RESEARCH & DEVELOPMENT

Determination of Bridge Deterioration Models and Bridge User Costs for the NCDOT Bridge Management System

Tara L. Cavalline, Ph.D., P.E.
Matthew J. Whelan, Ph.D.
Brett Q. Tempest, Ph.D.
Raka Goyal
Joshua D. Ramsey

Department of Engineering Technology and Construction Management
Department of Civil and Environmental Engineering
University of North Carolina at Charlotte
9201 University City Boulevard
Charlotte, North Carolina 28223-0001

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16. Abstract

The North Carolina Department of Transportation (NCDOT) currently oversees the design, construction, operation, maintenance, repair, rehabilitation, and replacement of more than 17,000 bridges. As funding to match the growing need for new infrastructure and for maintenance, repair, and rehabilitation (MR&R) of existing infrastructure becomes more difficult to obtain, maximizing the service life of existing bridges becomes increasingly critical. In support of data-driven planning, NCDOT's bridge management system (BMS) stores inventory data, including bridge characteristics, inspection data, and rating information, and uses deterioration models and economic models to predict outcomes and to provide network-level and project-level decisions. The objectives of this project were to provide NCDOT with revised, updated deterioration models and user cost tables for use in the BMS software. Existing data in NCDOT's BMS was reviewed and steps to address data anomalies were identified and implemented. Updated deterministic deterioration models were developed for the existing data on the family level, with components grouped into families using established *a priori* classifications. Additionally, a unique statistical regression methodology applying survival analysis techniques to better address characteristics of the historical condition rating data was developed and resulted in probabilistic deterioration models for bridge components and culverts that provide significantly improved predictive accuracy and precision over prior deterministic models. These models include transition probability matrices that account for the effects of design, geographic, and functional characteristics on deterioration rates over different condition ratings. These models were found to provide significantly improved prediction accuracy and precision over typical planning horizons used in network analysis. However, while this advanced model was found to best fit the historical condition rating data and provide unique insight on factors influencing deterioration over the life-cycle of each bridge component, it was also discovered that a simplified implementation of the probabilistic deterioration model was able to achieve similar performance without rigorously incorporating the effects of external factors on deterioration rates. To aid in implementation and technology transfer, a software application was developed to facilitate routine updating of both the deterministic and probabilistic deterioration models. Preliminary work to evaluate the relative impact of individual maintenance activities on element condition ratings was performed, including the development of histograms of condition rating changes from prior actions to aid in development of action effectiveness models. Inputs and methodologies utilized to compute user costs in NCDOT's BMS were updated and enhanced using relevant, current resources that were locally or regionally sourced when possible. Specifically, the updates and enhancements to the user cost models address ADT growth rates, vehicle operating cost, vehicle distribution, vehicle weight distribution, vehicle height distribution, accident injury severity, accident cost, and an equation useful in forecasting the number of annual bridge-related crashes. Analysis performed to generate the bridge-related crash prediction equation resulted in the identification of seven bridge characteristics that are most associated with bridge-related crashes. A sensitivity analysis on user costs indicated that, in NCDOT's BMS, user costs are most sensitive to accident costs.

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EXECUTIVE SUMMARY

The North Carolina Department of Transportation (NCDOT) currently oversees the design, construction, operation, maintenance, repair, rehabilitation, and replacement of more than 17,000 bridges across the state of North Carolina. As funding to match the growing need for new infrastructure and for maintenance, repair, and rehabilitation (MR&R) of existing infrastructure becomes more difficult to obtain, maximizing the service life of existing bridges becomes increasingly critical. Tools to assist in optimizing need-based scheduling of MR&R activities, as well as tools to assist with decision-making strategies, are integral to the efforts of NCDOT's Structures Management Unit. In support of performance-based and data-driven planning, a bridge management system (BMS) stores historical bridge data, including bridge characteristics, inspection data, and rating information, and uses deterioration models and economic models to predict outcomes and to guide network-level and project-level decisions. NCDOT's Structures Management Unit currently utilizes a BMS software program developed by AgileAssets Inc. Data in the BMS is input from NCDOT's data inventory of structures. Using deterioration models, condition states of bridge components are projected into the future to identify likely MR&R actions that should be considered in future funding cycles. Using a database of cost information, these MR&R options are evaluated on network-level to determine the most efficient use of MR&R funds to achieve level-of-service targets. Periodically, deterioration models and user costs used in the BMS software need to be updated.

The objectives of this project were to provide NCDOT with revised, updated deterioration models and user cost tables for use in the BMS software. As part of this work, a survey of BMS best practices nationwide was performed, along with a thorough review of relevant literature related to bridge deterioration modeling and user costs. In addition to directing the strategies pursued within this project for improvement of deterioration models, this literature review facilitated the development of recommendations related to the pending transition to expanded element-level condition ratings. In support of the development of updated models, 35 years of existing data from the NCDOT's BMS was analyzed after steps were taken to address identified data anomalies. Updated deterministic deterioration models were developed from this historical data for both bridge components and culverts, with components grouped into previously established families by material type, design type, geographic location, or average daily traffic (ADT), depending on the component type. Following recommendations from review of the state-of-art, new probabilistic models were developed using survival analysis techniques and proportional hazards assumptions. This unique statistical regression methodology resulted in the development of transition probability matrices for easily implemented probabilistic deterioration models that also account for the effects of design, geographic and functional characteristics on deterioration rates. These models were found to provide significantly improved prediction accuracy and precision over typical planning horizons used in short and long-term network analysis. However, while this advanced model was found to best fit the historical condition rating data and provide unique insight on factors influencing deterioration over the lifecycle of each bridge component, it was also discovered that a simplified implementation of the probabilistic deterioration model was able to achieve similar performance without rigorously incorporating the effects of external factors on deterioration rates. Implementation of these simplified models in the AgileAssets framework would require less development effort, while still realizing the most of the benefits of improved prediction accuracy afforded by probabilistic deterioration forecasting. These probabilistic models are also capable of incorporating the effect of maintenance activity within deterioration forecasts. Preliminary work to evaluate the relative impact of individual maintenance activities on component condition ratings (either improvement or sustainment of current rating) was performed. Work in this area is ongoing as part of a new project in progress to support prioritization indexes for bridge replacement, rehabilitation, and preservation projects. Lastly, the routines used for developing the deterministic deterioration models, proportional hazards probabilistic deterioration models, and simplified probabilistic deterioration models were integrated into a software application to permit NCDOT to routinely update these forecasting models as addition inspection data is added to the BMS.

Inputs and methodologies utilized to compute user costs were updated and enhanced using relevant, current resources that were locally or regionally sourced when possible. Specifically, the updates and enhancements to the user cost models address ADT growth rates, vehicle operating cost, vehicle distribution, vehicle weight distribution, vehicle height distribution, accident injury severity, accident cost, and an equation useful in predicting the number of annual bridge-related crashes. To generate this equation for prediction of bridge-related crashes, a statistical analysis of bridge-related crashes was performed to correlate crash frequency with bridge design, functional, and safety characteristics. This statistical analysis resulted in the identification of seven bridge characteristics that are most associated with bridge-related crashes. Additionally, this analysis provided useful information on bridge-related crashes and associated user costs for the North Carolina BMS. Due to a reduced occurrence rate of higher-severity accidents and locally sourced cost data, forecasted accident costs should be reduced using the new inputs. The results of a sensitivity analysis on user costs indicated that NCDOT's BMS user costs are most sensitive to accident costs. Since the cost associated with each accident is something that NCDOT cannot directly control, it is apparent that reducing the number of accident occurrences is the key way to reduce future user costs for the state bridge inventory.

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LIST OF ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Officials
ADT	average daily traffic
ADTT	average daily truck traffic
AIC	Akaike Information Criterion
ASCII	American Standard Code for Information Interchange
ATR	automatic traffic recording
BMIF	Bridge Management Inventory File
BMS	Bridge Management System
BNIP	Bridge Needs and Investments Process
CoRe	Commonly Recognized
CPI	Consumer Price Index
DMV	Division of Motor Vehicles
DOT	Department of Transportation
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
ft	foot
GVWR	gross vehicle weight rating
hrs	hours
IBMS	Indiana Bridge Management System
IRS	Internal Revenue Service
lbs	pounds
MDP	Markov Decision Process
mph	mile per hour
MR&R	maintenance, repair, and rehabilitation
NAICS	North American Industry Classification System
NAT	Network Analysis Tool
NBAIS	National Bridge Investment Analysis System
NBI	National Bridge Inventory
NBIS	National Bridge Inspection Standards
NC	North Carolina
NCDOT	North Carolina Department of Transportation
NCHRP	National Cooperative Highway Research Program
NYSDOT	New York State Department of Transportation
NYSTA	New York State Thruway Authority
NPV	net present value
NSC	National Safety Council
OPBRIDGE	Optimum Bridge Budget Forecasting and Allocation Module
OSHR	Office of State Human Resources
PHM	Proportional Hazards Model
PLAT	Project Level Analysis Tool
PMS	Pavement Management System
RP	Research Project
SQC	Synthesis Quality and Condition
SR	state route
SU	single unit
SV	single vehicle
TFU	Traffic Forecast Unit
TTST	truck tractor semi-trailer
US	United States
USACE	United States Army Corps of Engineers
VIF	Variance Inflation Factor
VOC	vehicle operating costs
W-to-P	Willingness-to-Pay
WIM	weigh-in-motion

1. INTRODUCTION AND RESEARCH OBJECTIVES

1.1 Introduction

Tools to assist in optimizing need-based scheduling of MR&R activities, as well as tools to assist with decision-making strategies, are integral to the efforts of NCDOT's Structures Management Unit. NCDOT uses in-house applications for inspection, data collection, and inventory management of its structures and pavements. As a component of the NCDOT asset management program, the bridge management system (BMS) facilitates performance-based and data-driven project planning by storing historical bridge data, including bridge characteristics, inspection data, and rating information, and uses deterioration models and economic models to predict future needs when optimizing network-level and project-level decisions. NCDOT's Structures Management Unit currently utilizes a BMS software program developed by AgileAssets Inc. Data currently in the BMS has been input from NCDOT's inventory of bridges. The database includes all National Bridge Inventory (NBI) data elements, as well as other elements defined within the NCDOT inspection routine. Yearly snapshots of data are available from the early 1981 to present day. Deterioration models currently used exist at the component-level for the deck, superstructure, and substructure elements. In an effort to account for explanatory factors, these deterioration models have been further grouped into families by material type, design type, geographic location, or ADT, depending on the component. Likewise, user costs models are incorporated in the BMS to consider detour costs and accident costs associated with individual bridge projects. These user costs models further incorporate formulas that use past data to predict ADT growth rates, vehicle operating cost, vehicle distribution, vehicle weight distribution, vehicle height distribution, and accident injury severity probabilities.

NCDOT periodically updates the data that supports the BMS. However, the efficacy of the BMS is highly dependent on the predictive capability of the deterioration models, as well as the validity of the cost data and computational methods. The last time BMS deterioration models and user cost data were evaluated was in 2002 (Duncan and Johnston 2002), and updates to both the deterioration models and user cost tables were recently identified by the NCDOT Structures Management Unit as an agency need. Based on the current state of the BMS, the needs of the Structures Management Unit at the time of inception of this project were as follows:

- Deterioration models used in the BMS needed to be revised to include data obtained during the past ten years. Additionally, some anomalies existing in the data contained in the BMS needed to be identified and reconditioning steps taken prior to developing the new, revised deterioration models.

- Methodologies utilized to generate the BMS deterioration models needed to be revisited and evaluated. During the past ten years, a number of other state DOTs have sponsored work to improve bridge deterioration forecasting. The findings of some of these studies were considered in development of the revised deterioration models. Specifically, areas considered for improvement as part of this project included:

    - *Use of probabilistic deterioration models.* Deterioration models utilized in the Agile Assets BMS software and the prior OPBRIDGE planning tool are deterministic. Other BMS software programs utilized by many states utilize probabilistic models, which have been shown to provide improved reliability and predictive accuracy over deterministic models.

    - *Development of deterioration models for NBI culverts*. Currently, the BMS only includes deterioration models to forecast the expected future condition of bridge components (deck, superstructure, and substructure). Deterioration models to facilitate condition rating forecasts for culverts receiving NBI condition ratings will allow for data-driven planning of culvert rehabilitation and replacement projects.

    - *Reliable incorporation of maintenance and preservation actions into deterioration models.* Previous work by Duncan and Johnston (2002) indicated that the role of maintenance activities in the deterioration models, and the impact on the usefulness of the BMS, was not entirely understood.

- The ability of the current BMS to effectively utilize data from element-based inspections, as well as incorporate this data into deterioration forecasting, evaluation, and decision-management, should be assessed. NCDOT will be moving to element-based inspections in the near future in order to comply with federal mandates aimed at moving states towards more uniform, data-driven, and performance-based transportation planning.

- Annual user costs also needed to be updated to reflect vehicle operating costs and accident costs. Updated reasonable estimates for traffic growth and inflation rates also needed to be included in the development of new user cost data tables.

The needs listed above were addressed (or partially addressed) as part of this project. The two needs listed below were also identified at the inception of this project, and are being addressed as part of ongoing research project 2016-05, "Guidelines for Prioritization for Bridge Replacement, Rehabilitation, and Preservation Project," and other work.

- Analysis of the historical impact of MR&R actions on component condition ratings would assist in improving the reliability of the condition state improvement inputs in the current BMS and allow for the development of action effectiveness models.

- The existing decision trees (and trigger condition states) that govern selection of preservation, maintenance, rehabilitation, and repair need to be reevaluated. Based on the current decision trees and BMS algorithms, only one MR&R action is identified per condition state. NCDOT desires that for a desired level of service, the decision tree and BMS provide multiple feasible MR&R options (if possible). Ultimately, NCDOT also desires a tool that could identify multiple feasible MR&R options that would achieve a desired level of service without a funding figure being specified. It is the understanding of the research team that this need has been at least partially addressed by the NCDOT Structures Management Unit through the development of a matrix-based decision tree.

1.2 Research Objectives

The objectives of this work were to provide NCDOT with revised, updated deterioration models and user cost tables for use in the BMS software. As part of this work, a survey of BMS best practices nationwide was performed, along with a thorough review of relevant literature related to bridge deterioration modeling and user cost predictions. Existing data from 35 years of NCDOT BMS records was parsed into an external database to facilitate the development of updated deterioration and user cost models after steps to address data anomalies were identified and implemented. Updated deterministic deterioration models that follow past practice and are therefore directly implementable into the BMS were developed, along with new probabilistic models that can be considered state-of-the-art. In developing these new deterioration models, the objective was to better account for the challenging nature of condition rating data as well as to better incorporate the influence of the most significant explanatory factors on deterioration rates. Furthermore, the research aimed to characterize the relative differences in predictive accuracy between deterministic and probabilistic models to inform decisions about revising the current approach to deterioration modeling used in the BMS. A cursory evaluation of commercially available software packages used for mechanistic modeling of service life was performed to determine if they could be utilized to further verify the deterioration models. Another objective of this work was to examine the effects of maintenance activity on deterioration models. A preliminary method for quantifying and evaluating the relative impact of individual maintenance activities on component condition ratings (either improvement or sustainment of current rating) was developed and demonstrated. Effort was made to isolate the effects of maintenance actions from naturally driven deterioration in bridge components and preliminary findings are presented. User cost models and required input data tables were updated using relevant, current resources identified through the comprehensive literature review. The review of methodologies to compute user costs suggested that the current methodologies are reasonable, but modifications could be made to support utilization of updated data sources. A statistical analysis of recent bridge related accident data was performed to produce updated expected frequencies of accidents of different severity types occurring on bridges, as well as to develop an updated equation useful in predicting bridge-related accidents. As part of updating user costs, traffic growth rates and inflation were also considered and incorporated into the updated required input tables.

2. SUMMARY OF KEY LITERATURE FINDINGS

2.1 Overview of Bridge Management Systems

National Bridge Inspection Standards (NBIS) were instituted in early 1970's following the collapse of Silver Bridge in Ohio due to corrosion-induced catastrophic failure. This legislation mandates that all states maintain bridge inventory and inspection records for each and every bridge in their jurisdiction. Each bridge record acts as a historical reference of any changes occurring in the physical condition of the bridge over time. These changes are measured and recorded through periodic inspections that must be performed no less frequently than on a biennial schedule. In this way, the deterioration, if any, of the overall condition of the bridge and its components is monitored so that remedial action can be taken as needed to preserve the bridge in good condition and ensure the safety of the traveling public.

While trying to achieve the objective of maintaining all individual bridges in their inventory, states continuously face the challenge of allocating increasingly limited funds and resources to most efficiently address network-level maintenance and re-construction as well as anticipating future funding needs. This challenge led to the evolution of Bridge Management Systems (BMS), which are systematic data-driven approaches for using the available bridge data, projected costs, and functional needs at the local and network-level to help objectively make such decisions. A BMS helps decision makers to interactively understand the trade-offs associated with allocating constrained funding to rehabilitation or maintenance work versus bridge replacement projects across the entire network of bridges to formulate optimal decisions based on economics, performance, and safety. North Carolina was one of the first states to develop a BMS (Chen and Johnston, 1987). Since then, many states, along with the federal government, have developed bridge management systems, although the majority of states now use the AASHTOWare Pontis software for some degree of bridge management (Markow and Hyman, 2009).

North Carolina Department of Transportation (NCDOT) currently maintains records for more than 17,000 in-service bridges with each record having over 200 items of operational and functional bridge information, including condition rating data from the most recent visual inspection. The digital recording of National Bridge Inventory (NBI) data for North Carolina bridges began in 1981, so there are now over 35 years of bridge records in NCDOT database. NCDOT currently uses a BMS software developed by AgileAssets Inc. However, while this software implements the constrained optimization analysis to provide scenarios for decision-making, the database relies on independent development of both deterioration models for the prediction of bridge maintenance needs and user costs for the prediction of required funds to accomplish projected maintenance actions. The two most important prediction tools of a BMS are bridge deterioration models and bridge-related cost models. The following sections provide a summary of key literature findings (and abbreviated reference list) related to deterioration models and user costs, the update and enhancement of which is the object of this project. The full literature review supporting this work, along with a complete list of references, is provided in Appendix A.

2.2 Summary Literature Review on Deterioration Modeling

Presented here is a summary literature review that provides an overview of the state-of-art in deterioration modeling revealed by this research, which was ultimately used to direct the development of probabilistic deterioration models for use in the NCDOT BMS. A more exhaustive literature review is provided in Appendix A of this report.

The deterministic deterioration models used currently by NCDOT are based on simple statistical properties that offer relative computational ease. However, they are associated with some critical inherent limitations. Primarily, they neglect the stochastic nature of the condition rating data, non-normal statistical properties, and the effect of censoring on the condition rating durations, which severely limits the prediction accuracy of such models. It has been found that deterministic regression techniques often provide reasonable results within the bounds of available data, but their projection beyond these bounds could be significantly misleading, thus severely limiting their predictive reliability and usefulness in a BMS. Probabilistic models have been shown to provide better extrapolation capabilities and can be easily integrated into dynamic BMS optimization processes resulting in more efficient and effective MR&R strategies (Butt et al., 1987). Furthermore, the *a priori* classification of bridges and bridge components commonly used in deterministic deterioration models to incorporate explanatory factors may overlook the impact of unobserved or unmodeled factors that influence deterioration rates. Stated another way, the statistical model may ultimately predict the average deterioration for a group of bridges well but inaccurately predict the deterioration of the bridges individually. This phenomenon is evident from a comparative study of deterioration models developed using two different approaches and applied to forty bridges in the Indiana bridge database. It was found that the magnitudes of prediction errors in models based on polynomial regression techniques were much higher compared to those in models based on a probabilistic Markov chain approach (Jiang, 2010).

The comparative lack of accuracy in model predictions has led to the gradual replacement of strict deterministic approaches with probabilistic approaches throughout the majority of the recent literature and BMS software implementations. Probabilistic models aim to capture the stochastic nature of the deterioration process and thereby improve the accuracy of prediction. The most prevalent probabilistic models used for bridge condition rating forecasting consider deterioration as a discrete time Markov process, called a Markov chain, with a finite number of states (Butt et al., 1987, Jiang et al., 1988). A Markov process is a stochastic process with the 'Markovian' property or assumption of time-independence in which the conditional probability P of a future condition state depends only on the present state and is independent of the past states. This can be represented for a discrete time, discrete state stochastic process X_t as given below (Morcous et al., 2003).

$$P(X_{t+1} = i_{t+1} | X_t = i_t, X_{t-1} = i_{t-1}, \dots, X_1 = i_1, X_0 = i_0) = P(X_{t+1} = i_{t+1} | X_t = i_t) \tag{2.1}$$

where i_t is the condition state at time t. In the context of bridge deterioration, the NBI condition ratings ranging from 0 to 9 represent the ten possible states of the bridge component being modeled with state 1 corresponding to a condition rating of 9 and state 10 to a condition rating of 0. The change of state is assumed to occur at discrete time intervals equal to the routine inspection period of 2 years. Consequently, the probabilities $P_{i,j}$ that a bridge component would transition from state i to another state j during a specified period are represented in a transition probability matrix. The form of this transition probability matrix most commonly utilized for bridge deterioration modeling is:

$$P = \begin{bmatrix} P_{99} & 1-P_{99} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & P_{88} & 1-P_{88} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & P_{77} & 1-P_{77} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & P_{66} & 1-P_{66} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & P_{55} & 1-P_{55} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & P_{44} & 1-P_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & P_{33} & 1-P_{33} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & P_{22} & 1-P_{22} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & P_{11} \end{bmatrix} \tag{2.2}$$

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 associated probabilities of each condition rating remaining unchanged between inspections is simply the $P_{i,i}$ probability values, which are found on the diagonal of the transition matrix. Since these probabilities are associated with the condition rating remaining the same, they are known as the "stay-the-same" transition probabilities. The transition matrix has zero values below the diagonal, because it is assumed that the deterioration takes place without rehabilitation and hence the probability of an improvement at any state is zero. Furthermore, for computational simplicity it is routinely assumed that a bridge component would not deteriorate by more than one state in a single inspection cycle. Graphically, we could represent the Markov chain and its possible state transitions and associated probabilities as shown in Figure 2.1.

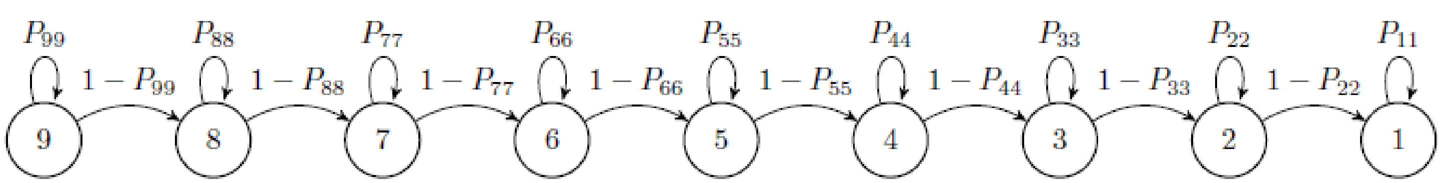


Figure 2.1: Typical Markov chain used in probabilistic bridge deterioration models

The transition probability of the lowest state, P_{11}, is one because there is no possibility of transitioning to a lower state that does not exist (Butt et al., 1987, Jiang et al., 1988, Madanat et al., 1995). The transition probability matrix can be used to predict the future condition of a specified bridge component if its present condition is known. The condition at any point in time is represented by a vector; for example, the initial vector Z_0 for a component in new condition will be [1 0 0 0 0 0 0 0 0 0] for the NBI condition rating scale of 0 to 9 with 9 signifying the good as new condition. Given the transition matrix P as defined above, the future state vector Z_t at time t is obtained using

$$Z_t = Z_0(P)^t \tag{2.3}$$

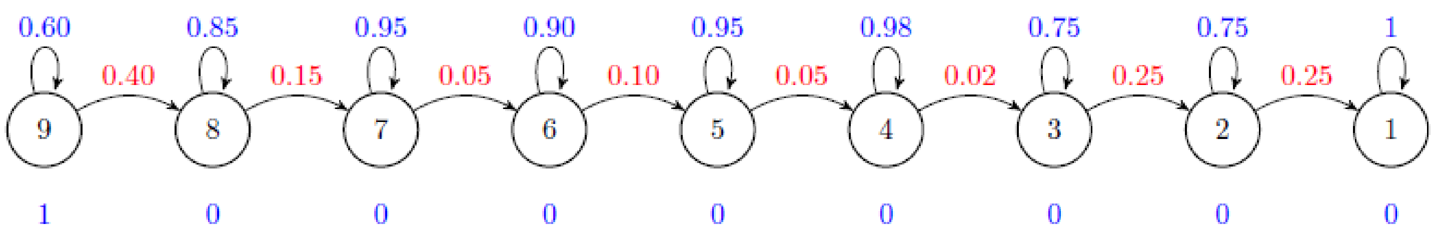
Application of this forward prediction will result in a vector of probabilities associated with each of the condition ratings. While these probabilities could be used to establish criteria or thresholds for decision trees, such methods are not as intuitive and consequently the expected value is typically used to reduce these probabilities to an estimate of the condition as a single rating. This expected value is simply calculated by multiplying the state vector by a column vector, R, that contains the ratings used in the scale (in other words 9 through 1). Mathematically, this matrix operation is:

$$E(t,P) = Z_t R = Z_0 (P)^t R \tag{2.4}$$

As an illustrative example of how the Markov chain works, consider a bridge component with a transition probability matrix of:

$$P = \begin{bmatrix} 0.60 & 0.40 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.85 & 0.15 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.95 & 0.05 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.90 & 0.10 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.95 & 0.05 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.98 & 0.02 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

If we consider the deterioration of a new bridge with a component condition rating of 9, the initial state vector would be: [1 0 0 0 0 0 0 0 0]. Graphically, the Markov chain associated with the example transition probability matrix, initial state vector, and expected value, are shown in Figure 2.2. Three annual cycles of condition rating forecasts are shown graphically in Figure 2.3, which illustrate the mechanisms of the probabilistic deterioration model that are carried out through application of equations 2.2, 2.3, and 2.4. In these graphical diagrams, the stay-the-same transition probabilities are represented in blue, while the probabilities associated with a decrease in condition rating are shown in red.



$$E = 9 * (1) = 9$$

Figure 2.2: Example Markov chain with an initial state vector expressing a condition rating of 9

Markov chain models are widely recognized as better than deterministic models as a result of accounting for the stochastic nature of the deterioration process. Moreover, these models have the advantage of computational simplicity and can be applied to both network level and project level bridge management systems. As a result, Markov chain-based deterioration models were adopted in the two U.S. national bridge management systems, AASHTOWare Pontis and BRIDGIT, that have been implemented in over forty states since their development in the late 1990s (Golabi and Shepard, 1997, Hawk and Small, 1998). Regarding these two commercial software programs, their difference is based on the optimization strategy employed. Pontis follows a top-down approach by doing network level optimization first before determining needs of individual bridges. BRIDGIT, on the other hand, implements a project-level based optimization prior to making network level recommendations (AASHTO, 2011a). BRIDGIT is better suited for use by smaller transportation departments with limited staff resources, but it can be run in parallel with Pontis to complement the decision process by providing an independent set of recommendations (Hawk and Small, 1998).

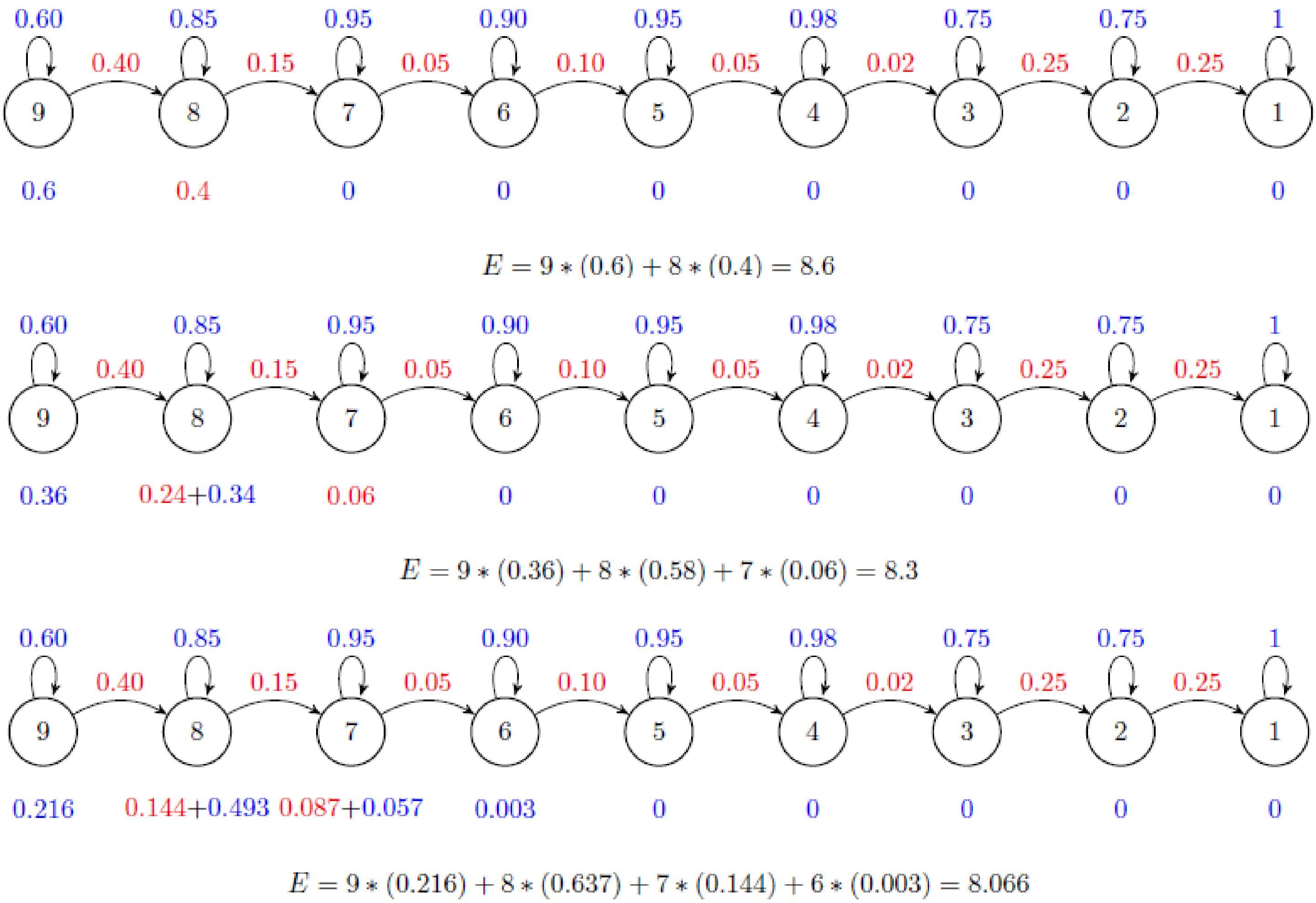


Figure 2.3: Example of three prediction cycles using the Markov chain transition probabilities

2.2.1 Conventional Approaches to Estimating Transition Probabilities

Most probabilistic deterioration models used in bridge management systems adopt the Markov chain approach illustrated above. However, deriving the transition probabilities included in each transition probability matrix for different bridge components has been approached by different techniques and was a key research component of the current project. The earliest methods for determining transition probabilities were developed mainly in construction of pavement deterioration models. One of these models defined the transition probability, $P_{i,j}$, simply as the percentage or proportion of pavement sections in condition state i that deteriorated to condition state j in one inspection period. Mathematically, this yields:

$$P_{i,j} = \frac{n_{i,j}}{n_i} \tag{2.5}$$

where n_i is the total number of pavement sections in condition state i and $n_{i,j}$ is the number of pavement sections whose condition state changes from i to j in one inspection period (Scherer and Glagola, 1994, Wang et al., 1994). In the early models, not only was the duration of the inspection cycles assumed to be the same, but the deterioration contributing factors of weather and traffic were also assumed to be the same in subsequent inspection cycles irrespective of the age of the pavement section. Consequently, the transition probabilities were not expected to change from one inspection cycle to the next. This type of process is deemed a homogeneous or stationary process and is known as a Markov Decision Process (MDP) (Frangopol et al., 2004, Jiang et al., 1988). The assumption of constancy of behavior within inspection cycles relative to factors producing deterioration over the life of an infrastructure component is not realistic as changes occur due to increases in traffic loads or modification of maintenance policies. This inadequacy was recognized after observing the deviation of the actual deterioration curve from the predicted deterioration curve based on MDP for a 30 year life of pavement (Butt et al., 1987). To overcome this limitation, a new model was developed in which the life of the pavement section was zoned into 6-year periods. The deterioration rate was assumed to be constant within each zone and a homogeneous Markov chain with a stationary transition matrix was developed specific to each zone. A non-homogeneous Markov chain was then developed to transition pavement sections from one zone to another. During such transitions, each subsequent zone takes the last state vector of the previous zone as its starting state vector. The deterioration curve developed using this model was found to more closely represent the actual deterioration curve (Butt et al., 1987). This model was also adopted for developing the Markov chain based bridge deterioration models for the Indiana bridge database, which were the earliest models of this kind developed in the U.S. (Jiang et al., 1988, Sinha et al., 1988), and continue to be used in the present-day Indiana Bridge Management System (IBMS) (Sinha et al., 2009).

In the previously mentioned models, a non-linear programming approach was used to calculate the transition probabilities. This approach is known as the expected value method and is still the most widely used method of calculating Markov chain transition matrix probabilities. In this method, the average condition rating of the bridge components in a particular zone or age group is first determined by applying a polynomial regression to all the bridges in that group in the form,

$$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 \tag{2.6}$$

where Y_t is the bridge component condition rating for a bridge at age t, and β_0, β_1, β_2 and β_3 are regression coefficients to be estimated. The transition probabilities are then calculated by minimizing the distance between the average condition rating $\widehat{Y_t}$ obtained through this regression and the theoretical expected value $E(t,P)$ of the condition rating based on the Markov chain at time t for the transition probability matrix P. The objective function to be minimized is thus given by

$$\min \sum_{t=1}^{N} \left| \widehat{Y_t} - E(t,P) \right| \tag{2.7}$$
$$\text{subject to: } 0 \le P_{i,j} \le 1 \text{ and } \sum_{j=1}^{k} P_{i,j} = 1 \text{ for } i,j = 1,2,\dots,k$$

where N is the number of years in one age group, and $P_{i,j}$ is the transition probability in the transition probability matrix, P, associated with moving from condition state i to condition state j over the inspection cycle (Butt et al., 1987, Jiang et al., 1988).

The unknown transition probabilities are the decision variables and the maximum number of these that can be estimated using the expected value method is the number of years in each age group (Madanat et al., 1995). The assumption that a bridge component does not deteriorate by more than one state in any one inspection cycle, as mentioned earlier, is helpful in this regard by reducing the probabilities of transition to other states to zero thereby significantly minimizing the number of decision variables that require estimation (Madanat et al., 1995). This assumption was recently applied to element level inspection data to determine transition probability matrices and develop deterioration models for use in Pontis for the Florida Department of Transportation (FDOT). The so-called “one-step method” was found not only to be simpler and require smaller sample sizes, but also more robust while having the same coefficient of determination as the regression model that did not use this assumption (Sobanjo and Thompson, 2013).

Despite the widespread use of Markovian models and the commonly used approaches for estimating transition probability matrices, a number of limitations have been identified in these models. These approaches do not model the effects of various explanatory variables, and therefore, as mentioned earlier, have to rely on pre-defined segmentation of the bridge population into homogeneous categories for meaningful statistical analysis. Moreover, the Markovian assumption of time independence is contrary to the time dependence of the deterioration process. This time dependence can indirectly be taken into account by dividing the bridges within each category further into various age groups. However, this grouping is ad hoc and fails to recognize the continuous nature of the underlying deterioration. The use of linear regression to calculate transition probabilities, as described in the expected-value method, is also deemed to be inappropriate by some researchers because the dependent variable, which in this case is the condition rating, is discrete and ordinal, and not continuous as presumed by linear regression (Bulusu and Sinha, 1997, Madanat and Ibrahim, 1995, Madanat et al., 1995, 1997, Mishalani and Madanat, 2002, Morcous et al., 2002).

2.2.2 Survival Analysis and Proportional Hazards Models

Duration models have been found to better model the stochastic nature of the deterioration process by accounting for duration dependence among other aspects of deterioration that could not be considered in earlier models. Likewise, the presence of censored observations in data does not lend well to deterministic modeling nor many conventional statistical regression techniques. However, survival analysis models can account for the effect of censored observations and are therefore suitable for analysis of bridge condition rating data (Greene, 1997, Hosmer and Lemeshow, 1999). The earliest time-based models were the state increment models developed for the pavement management and bridge management systems of the New York State Thruway Authority (NYSTA). In these models, the concept of state transition time was defined as the time between two consecutive changes of state or, in other words, the time taken by a bridge component to transition from an initial condition state to the next lower condition state (Ravirala and Grivas, 1995). A uniform distribution of transition time was assumed between minimum and maximum values of transition time, which were estimated on basis of expert elicitation. This assumed parametric distribution was then used to estimate the cumulative probability of the occurrence of a specified state transition event within any specified time, known as the "transition probability" (DeStefano and Grivas, 1998). The initial models were verified and enhanced by determining the transition probabilities using a non-parametric Kaplan-Meier approach and adding an elapsed-time parameter, respectively (DeStefano and Grivas, 1998). The revised models were then tested on a subset of 123 bridge decks located on the New York State Thruway and the resulting deterioration models were found to be more accurate than the original models. These models used life data analysis techniques on bridge inspection data for the first time. Previously, these techniques had long been used in engineering for reliability studies of industrial components, in the biomedical field for survival time analysis of patients diagnosed with a disease, and more recently, in the social sciences (Greene, 1997). Life data or duration data has typical characteristics like censored observations, which were taken into account in this study. Later researchers used survival analysis techniques to further develop the duration models (Mauch and Madanat, 2001, Mishalani and Madanat, 2002).

The Cox Proportional Hazards Model (PHM), a type of semi-parametric duration model, has been used in this study to model the deterioration rates of bridge components and their dependence on various exogenous explanatory factors. This model defines the hazard rate as a multiplicative function of a time dependent non-parametric baseline hazard function and a time-independent exponential function. Mathematically, the hazard rate is expressed in the proportional hazards model as:

$$h(t,\vec{z}) = h_0(t)e^{\vec{z}\vec{\beta}} = h_0(t)e^{(z_1\beta_1+z_2\beta_2+\cdots+z_n\beta_n)} \tag{2.8}$$

In this function, the time-independent exponential function represents the effects of covariates, or explanatory factors, on the hazard rate. The following summary describes survival analysis concepts important to interpreting the probabilistic models developed in this study. This description is largely based on comprehensive guidance for survival analysis provided in Hosmer and Lemeshow (1999).

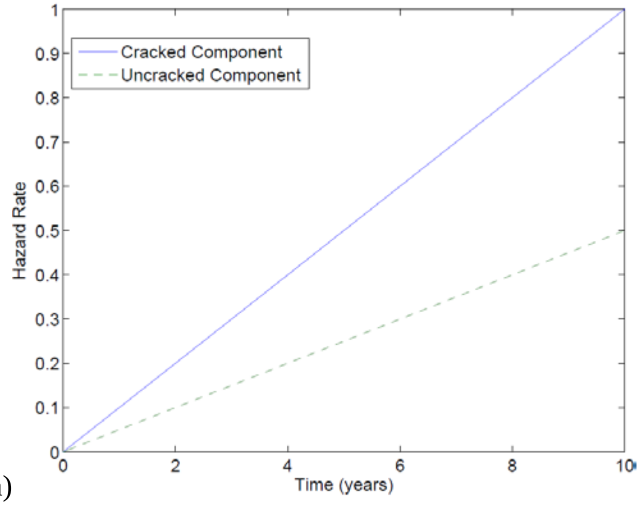
Hazard rate, or failure rate, is the instantaneous rate of failure or transition from one state to another. Hazard rate can be a function of time and include the effect of explanatory factors. If it is assumed, for the sake of simplicity, that the model contains only one covariate, z_1, the hazard rate for the Cox Proportional Hazards Model (Cox, 1972) is given by

$$h(t,\vec{z}) = h_0(t)e^{z_1\beta} \tag{2.9}$$

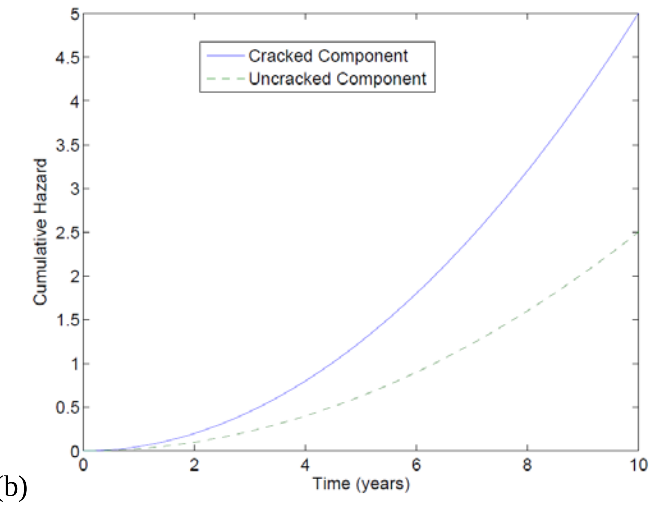
where β is the regression coefficient quantifying the effect of z_1 on the hazard rate. Due to the exponential form of the time independent component of the hazard rate function, the hazard rate is equal to $h_0(t)$ when $z_1 = 0$. Therefore, $h_0(t)$, known as the baseline hazard function, is the hazard rate of the subject under study when the covariate affecting it takes a value of zero. For example, in investigating fatigue failure of a structural component, consider the effect of a dichotomous variable such as presence or absence of cracking, which takes only two values: $z_1 = 0$ for uncracked components and $z_1 = 1$ for cracked components. In this case, the hazard ratio is given by

$$HR = \frac{h(t,1)}{h(t,0)} = e^{\beta(1-0)} = e^{\beta} \tag{2.10}$$

This hazard ratio expresses the risk of failure associated with an explanatory factor relative to the baseline case. For instance, $HR = 2$ in our example would indicate that cracked components are likely to fail at twice the rate of failure of the uncracked components. This is illustrated in Figure 2.4a using a hypothetical linear hazard rate function. It can be observed that, at any instance, the hazard rate of a cracked component has a value that is twice that of the hazard rate of an uncracked component. The hazard ratio of the Cox proportional hazards model thus lends itself to a quantifiable and easy interpretation of the comparative effect of the covariates under study.



(a)



(b)

Figure 2.4: (a) Hazard rate functions and (b) Cumulative hazard functions for a hypothetical example of fatigue failure of a structural component influenced by the presence of cracking as the explanatory factor

The cumulative hazard function, H, is an integration of the hazard rate based on an assumption of absolutely continuous survival time. For a single covariate PHM,

$$H(t, z_1) = \int_0^t h(t, z_1)dt = H_0(t)e^{\beta z_1} \tag{2.11}$$

where H_0 is the baseline cumulative hazard function, which takes the same value at any particular instant of time for different covariates in the same model. The cumulative hazard function incorporating the effect of covariate z_1 can be obtained by multiplying H_0 by the hazard ratio. The cumulative hazard functions for cracked and uncracked components are shown in Figure 2.4b. In this example, H for cracked components can be obtained by multiplying H_0 with $HR = 2$ when considering the cumulative hazard function for uncracked components as H_0.

Although the cumulative hazard function is typically not used directly, its importance to survival analysis is that it is the negative logarithm of the survival function. Alternatively, the survival function can be written in terms of the cumulative hazard function using (Hosmer and Lemeshow, 1999)

$$S(t, z_1) = e^{-H(t,z_1)} = \left[e^{-H_0(t)}\right]^{e^{\beta z_1}} = S_0(t)^{e^{\beta z_1}} \tag{2.12}$$

where S_0 is the baseline survival function. Continuing with the structural component failure example, a hazard ratio of $e^{\beta z_1} = 2 > 1$ implies that $S(t, z_1) < S_0(t)$ since the value of the baseline survival function is always between 0 and 1. This means that the survival probabilities associated with cracked components are lower than the survival probabilities associated with uncracked components. The survival functions of cracked and uncracked components based on the hypothetical hazard rate functions are plotted in Figure 2.5. A comparison amongst Figures 2.4 and 2.5 illustrates the nature of the relationship between the hazard rate function, cumulative hazard function, and survival function.

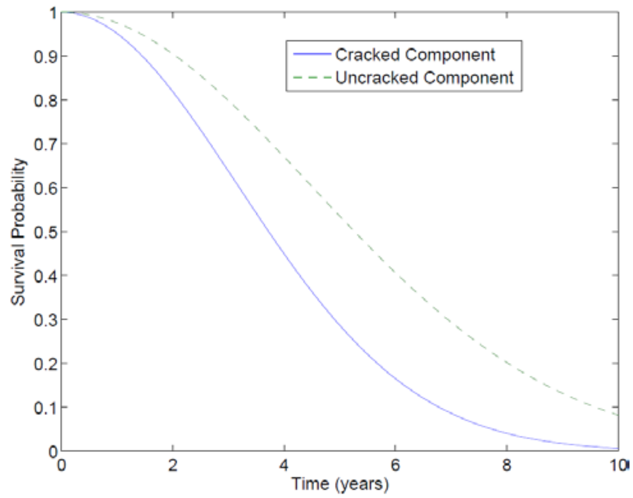


Figure 2.5: Survival functions for hypothetical example of fatigue failure of a structural component

It should be noted that hazard ratios express the relative difference in rate of failure, not the duration associated with a particular probability of failure. In other words, if we examine the survival functions from our hypothetical example, we see that the duration associated with the median probability of failure (0.5) is about 5.5 years for the uncracked component. Although the hazard ratio associated with the single explanatory factor is 2, the median probability of failure is about 3.8 years for the cracked component, which is not a factor of two. Also, proportional hazards models can be expanded to include more than one explanatory factor. In these cases, the survival function is expressed as

$$S(t,z) = S_0(t)^{e^{\beta_1 z_1+\beta_2 z_2+\cdots\beta_n\backslash z_n}} = S_0(t)^{e^{\beta_1 z_1}e^{\beta_2 z_2}\ldots e^{\beta_n z_n}} \tag{2.13}$$

and if the explanatory factors are limited to binary variables (either naturally or using reference-cell coding), the survival function for any component can be expressed as

$$S(t,z) = S_0(t)^{z_1 HR_1 * z_2 HR_2 * \ldots * z_n HR_n} \tag{2.14}$$

this simplifying approach is taken in the current study and permits for an easily implemented construction of transition probability matrices from proportional hazards analysis where the effect of explanatory factors are incorporated in the model through hazard ratios obtained by the statistical regression.

It is possible to determine the transition probabilities of Markovian state-based models from those of time-based models, including proportional hazards models, which will be illustrated later in this report. In fact, transition probabilities derived from time based models are found to give more accurate results particularly when inspection data are available for a sufficiently long and continuous time period (Mauch and Madanat, 2001). For the derivation of the transition probabilities, let $S_k(t,\vec{z})$ be the survival function of a bridge component associated with condition rating k for a bridge described by the vector of covariates $\vec{z}$. At any time t, the value of $S_k(t,\vec{z})$ is the cumulative probability that the structural component will remain in condition rating k up to time t. This probability is naturally 1 at $t = 0$ and decreases with each inspection cycle Δ. Therefore, the instantaneous probability that the structural component will remain at the same condition rating over the next annual reporting cycle at any time t (Mishalani and Madanat, 2002) is given by

$$P_{kk} = \frac{S_k(t+\Delta,\vec{z})}{S_k(t,\vec{z})} = \frac{S_k(t+1,\vec{z})}{S_k(t,\vec{z})} \ for\ \Delta = 1\ year \tag{2.15}$$

Duration models using the parametric Weibull distribution were developed for a subset of reinforced concrete bridge decks in the Indiana State bridge inventory (Mishalani and Madanat, 2002). This study illustrated a methodology for determining the state transition probabilities from transition time distributions. The results highlighted that deterioration rates of bridge components could exhibit different behavior at different condition states. For example, condition state 7 was found to exhibit the Markovian property of duration independence whereas condition state 8 had a hazard rate that was positively duration dependent (Mishalani and Madanat, 2002). All of these studies proposed using estimated duration distributions for computing accurate transition probabilities for the corresponding state-based models in order to construct the deterioration models (DeStefano and Grivas, 1998, Mauch and Madanat, 2001, Mishalani and Madanat, 2002).

Recently duration models using the Weibull distribution were developed for the New York State Department of Transportation (NYSDOT) (Agrawal et al., 2009, 2010). The deterioration models were constructed by calculating the expected duration spent in each condition rating. These duration based deterioration models were compared to Markovian models developed using the second level Markov process. The Weibull models were found to be more realistic and were therefore adopted for use in the NYSDOT BMS (Agrawal et al., 2009, 2010). A Weibull based enhancement was also used to improve the Markovian deterioration models recently updated for the FDOT database (Sobanjo and Thompson, 2011). Weibull based models, however, can only model monotonically increasing or decreasing hazard rate functions. They cannot model unimodal distributions frequently found in infrastructure deterioration (Yang et al., 2013). Moreover, they cannot take into account the effect of explanatory variables.

Duration models are considered appropriate only if more than 20 years of inspection data are available, otherwise state based models are considered more suitable (Mauch and Madanat, 2001). Consequently, it is only recently that sufficient NBI records have been available to facilitate use of these powerful statistical regression models. It is expected that duration modeling will be a very active and productive area of bridge management over the coming decades as researchers exploit the over three decades worth of condition rating data now available in the NBI. However, for element level data where only 10 years or less of inspection data is available duration models may not give reliable results. To overcome this limitation, various approaches have been recently suggested. One of these is a backward prediction model that can be used to generate past historical data from available inspection data (Lee et al., 2008). Likewise, an integrated algorithm that can match a suitable modeling technique to the available data has also been proposed (Bu et al., 2014).

2.3 Summary Literature Review on User Costs

A robust BMS will not only be able to utilize deterioration models to forecast bridge conditions, but will perform analyses to identify how these deficiencies affect the users of the bridge. All federal and state agencies have limited funding for transportation needs and many states rely on their BMS system to determine the bridge projects that are most vital to obtain maximum levels of service to the public (Rens et al. 1999). User costs are incurred by vehicles that are required to detour around a bridge due to load postings or low vertical clearance, as well as due to accidents occurring on bridges or bridge approaches (note that in this report, "accident" and "crash" are used synonymously). User costs can be up to five times the direct agency costs (Thompson et al., 1999), and therefore consideration of user costs can help agencies identify candidate bridge projects that could provide the greatest benefit to the public. Parameters included in computing these user costs periodically need to be updated or revisited to ensure their accuracy and validity. As part of this project, user cost inputs and computational methods for NCDOT's BMS were updated and enhanced as subsequently outlined in Chapter 4. A detailed discussion of the development and implementation of user costs in the NCDOT and other BMS, along with a review of literature on methods utilized to determine factors and inputs utilized in computation of user costs, is presented in Appendix A.3. For brevity, a brief summary of the computational methodology of user costs in NCDOT's BMS, along with an abbreviated background of its development and key assumptions is presented in this section of the report.

Currently, NCDOT BMS calculates user costs utilizing the methodology developed by Chen and Johnston (1987), shown in Equation 2.16. Development of Equation 2.16 by Chen and Johnston (1987), as well as the methods of identifying and computing inputs required for use of this equation, is generally considered by the BMS community to be groundbreaking, providing the foundation for the computation of user costs in a number of modern BMS (Thompson et al., 1999).

$$AURC(t) = 365\ ADT(t)\ [C_{WDA}U_{AC}+C_{ALA}U_{AC}+C_{CLA}U_{AC}+C_{CLD}U_{DC}DL+C_{LCD}(t)U_{DL}DL] \quad (2.16)$$

Where: $AURC(t)$ = annual user cost of the bridge at year t, \$/year

$ADT(t)$ = average daily traffic using the bridge at year t

C_{WDA} = coefficient for proportion of vehicles incurring accidents due to width deficiency

C_{ALA} = coefficient for proportion of vehicles incurring accidents due to poor alignment

C_{CLA} = coefficient for proportion of vehicles incurring accidents due to vertical clearance deficiency

C_{CLD} = coefficient for proportion of vehicles detoured due to a vertical clearance deficiency

$C_{LCD}(t)$ = coefficient for proportion of vehicles detoured due to a load capacity deficiency at year t

U_{AC} = unit cost of vehicle accidents on bridges, \$/accident

U_{DC} = unit cost for average vehicle detours due to vertical clearance deficiency, \$/mile

U_{DL} = unit cost for average vehicle detours due to load capacity deficiency, \$/mile

DL = detour length, miles

As shown in Equation 2.16, user costs computed in the NCDOT BMS are proportional to traffic volume and are influenced by bridge condition. Coefficients for proportions of vehicles incurring user costs are assumed to remain constant over time, with the exception of C_{LCD}, which will increase as bridge deterioration results in load posting. When considering both over-bridge and under-bridge computations, the coefficients, ADT, and detour length will vary, with C_{LCD} equal to zero for the under-bridge computation (Johnston et al., 1994). Detour lengths are provided in the NBI, but may contain some inaccuracies when considering detours that may involve load posted bridges or areas with large or multiple construction projects that impact use of one or more bridges associated with local detour routes. In these cases, the actual detour length may be longer than the detour length provided in the NBI.

ADT growth rates have historically been utilized to predict the ADT of a bridge at a future date. Using automatic traffic recording (ATR) data from 1974 to 1984, Chen and Johnston (1987) developed the first ADT growth rates for roadways of different types used in the NCDOT BMS. Limitations associated with this dataset (particularly for local and interstate routes) resulted in ADT growth rates for some types of roadways being assumed to be constant for bridges statewide. The ADT growth rates for the NCDOT BMS were later updated by Duncan and Johnston (2002) using the Bridge Management Inventory File (BMIF). The BMIF provided ADT data for all bridges from 1991 to 2000 (more robust than the original ATR dataset), allowing computation of an ADT growth rate for each of the four roadway classifications for each county. If values did not exist for a particular roadway in a county, the state average was utilized as the assumed value. Values were then reviewed by NCDOT's Traffic Forecast Unit (TFU), where personnel made some adjustments based on experience (Duncan and Johnston, 2002). These 2002 ADT growth rates are currently utilized as BMS inputs.

Detour costs for both vertical clearance and load capacity are determined using vehicle operating costs, which will vary based on operator wages and vehicle use characteristics. For simplicity, a procedure for obtaining vehicle operating costs that could easily be updated was developed by Chen and Johnston (1987). Sources for obtaining data to support these operator costs are the Internal Revenue Service (IRS), the North Carolina state government wage rates, and the North American Industry Classification system (NAICS) published by the US Census Bureau. Specific details on determination of these costs for the minimum weight (3 tons) and maximum legal gross weight (40 tons), along with associated assumptions including vehicle speed, fuel costs, and hours worked per operator per year, are provided in Appendix A (Section A.3.4.2). For vehicles weighing between three tons and 40 tons, a linear relationship between the vehicle weight and vehicle operating costs is assumed, and Equation 2.17 can be utilized to compute the vehicle operating cost for vehicles between three tons and 40 tons. In the BMS, the user cost for vehicles weighing three tons is utilized for all vehicles weighing less than three tons, and the user cost for vehicles weighing 40 tons is utilized for all vehicles weighing more than 40 tons (Chen and Johnston, 1987).

$$U_{DV} = U_{D3} + \frac{(U_{DNP} - U_{D3})}{(NP - 3)} \times (W_V - 3) \tag{2.17}$$

Where: U_{DV} = operating cost for vehicle V

U_{D3} = operating cost for vehicle weighing 3 tons or less

U_{DNP} = operating cost for vehicle weighing the maximum legal load

NP = maximum legal load (non-posted capacity of bridge)

W_V = weight of vehicle V

A load posting is implemented when the maximum legal weight of a vehicle is deemed unsafe for the structure, restricting the weights of vehicles that can pass. Optimally, a BMS should be able to predict when a bridge is nearing a load deficiency by analyzing the data input from previous inspections (Abed-Al-Rahim and Johnston, 1991). When a bridge has a load posting, vehicles at and above the posted weight must detour. To accommodate this in the NCDOT BMS user cost computations, an average vehicle operating cost (U_{DL}) is determined for all weight classes having to detour, as shown in Equation 2.18 (Chen and Johnston, 1987).

$$U_{DL} = (U_{DP} + U_{DNP})/2 \tag{2.18}$$

Where: U_{DL} = average operating cost for the detoured vehicles

U_{DP} = operating cost for a vehicle weighing the posted bridge capacity (smallest operating cost among detoured vehicles)

U_{DNP} = operating cost for vehicle weighing the maximum legal load (40 tons)

Load postings are provided for single vehicle trucks (SV), as well as truck tractor semi-trailers (TTSTs). Detours due to load capacity will be affected by the percentage of ADT that fall into these vehicle classifications, which vary with route functional classification as well as geographic location and other factors. The coefficient in Equation 2.1 for the proportion of vehicles detoured due to load capacity is computed using Equation 2.19. To accommodate this in the BMS, an input table of vehicle distributions by roadway functional classification is utilized. Proportions of TTST and SV (in percent) were determined using FHWA data (FHWA 1985) and data from other NCDOT sources (Johnston et al. 1994), but do not appear to have been updated by Duncan and Johnston (2002). Vehicle distribution percentages are then manipulated into a table of the cumulative percentage of trucks out of total vehicles (on each roadway type) that are heavier than the weight listed (Johnston et al. 1994) for input into the BMS.

$$C_{LCD}(t) = R_{SV}(t) + R_{TT}(t) \tag{2.19}$$

Where: R_{SV} = ratio of the number of single-unit trucks heavier than the bridge's SV posting to the total number of vehicles using the bridge

R_{TT} = ratio of the number of trailer combinations heavier than the bridge's TTST posting to the total vehicles using the bridge

To predict the number of vehicles detoured due to a load posting, bridge load capacity deterioration rates are utilized to forecast load posting over time. Chen and Johnston (1987) evaluated a number of approaches to determine deterioration rates that reasonably correlated bridge operating rating versus age, but encountered difficulty developing models due to scatter in the data and other factors. Ultimately, regression results, multi-year averaging, and engineering judgement were utilized to develop a table of estimated capacity deterioration rates in tons per year (Chen and Johnston, 1987).

User costs incurred due to detours resulting from vertical restrictions are computed using a truck height distribution. Chen and Johnston (1987) assumed that the distribution of truck heights varies with roadway type and developed a table of BMS inputs for the percentage of ADT detoured for vertical clearances ranging from 8 feet to 14.5 feet. This table provided different percentages for different roadway types as well as for SV and TTST. Research from the 1950's (Kent and Stevens, 1963) was utilized to develop this table, as presumably more reliable modern data was not available at the time. Chen and Johnston (1987) also utilized the assumption that, although operating cost likely varies with vehicle height, the relatively low number of vehicles assumed to be impacted by vertical height restrictions would justify use of the operating cost for the legal load limit (U_{DNP}) as an estimate of the vertical clearance detour unit cost (U_{DC}).

Two approaches have often been considered in determining accident (or crash) costs on bridges within a number of BMS, including the NCDOT BMS. They are the Willingness-to-Pay (W-to-P) approach and the Human Capital Approach (Chen and Johnston, 1987). Both approaches consider direct and indirect costs involved with bridge-related crashes. Direct costs for both are considered to be crash cost, emergency service, medical treatment, and legal and court fees as stated by the National Safety Council (NSC). The indirect costs, which can be more difficult to determine (Chen and Johnston, 1987), are considered to include compensation for pain and suffering and the costs of goods and services an individual will not be able to produce due to the crash. The Willingness-to-Pay approach also considers an indirect cost known as value of life, which includes possible long and short term loss in quality of life due to the crash. Both approaches provide a dollar value for fatalities (K), as well as for different crashes of different severity types (A-B-C, in order of level of seriousness) and crashes with property damage only (PDO). In updating NCDOT BMS crash costs, Duncan and Johnston (2002) also considered a third approach known as the comprehensive cost method, which incorporates 11 different components consisting of both direct and indirect costs, and is very similar to the Willingness-to-Pay method. The costs per crash values for the Human Capital approach are published by the FHWA every few years. Since this data does not include a cost parameter for value of life, the total cost of the five different crash types is less than the Willingness-to-Pay approach (Duncan and Johnston, 1987). Costs per crash values utilized for the Willingness-to-Pay approach are published annually by the NSC. Since this data is provided relatively frequently and includes value of life, Duncan and Johnston (1987) recommended that it be used to predict crash costs. Therefore, the Willingness-to-Pay approach continues to be the procedure utilized by the NCDOT BMS. Since NSC costs are not always updated annually, an appropriate CPI value can be utilized to extrapolate values between periodic updates to the NSC costs.

To compute crash costs in the BMS, costs per severity type are multiplied by the fraction of occurrence. Values are summed to produce one total cost per crash figure (U_{AC}). The values for fractions of occurrence for different severities of crashes were developed by Abed-Al-Rahim and Johnston (1991) using data from North Carolina crashes occurring between 1984 and 1989. The cost per crash is then multiplied by the number of annual crashes predicted to occur on or at each bridge. Development of the crash prediction equation utilized data from bridge-related crashes occurring in five North Carolina counties (Halifax, Harnett, Iredell, Guilford, and Wake) over a roughly six-year period during 1983-1989 (Abed-Al-Rahim and Johnston, 1991). A bridge-related crash was defined as any crash occurring on or near a bridge, as detailed in the road feature field of the crash report. As part of this work, each crash record for crashes occurring on or at a bridge was individually matched to the bridge at which it occurred. A total of 2,895 bridge-related crash records were obtained and reviewed, with 2,512 crashes occurring on Interstate, US, NC, or city routes. Of these, 2,104 crashes were matched to a specific bridge for a total of 72.7% of the total bridge-related crashes (Abed-Al-Rahim and Johnston, 1991). Statistical analysis was performed using a stepwise regression procedure to determine the bridge characteristics associated with the greatest influence on bridge-related crashes, using a significance level of 5 percent associated with the null hypothesis. The characteristics found to be significant were then fit with higher order polynomial models to determine an equation that could predict crashes on an individual bridge (Abed-Al-Rahim and Johnston, 1991). As can be seen in Equation 2.20, it was found that ADT, bridge length, and the difference in deck width between acceptable and actual level of service had the most significance (Abed-Al-Rahim and Johnston, 1991). The alignment appraisal is based on agency-collected data or data from other sources (Chen and Johnston, 1987). The width deficiency is based on the difference between the existing deck width and bridge clear deck width goals, as established by Johnston and Zia (1984).

$$NOACC = 0.783(ADT^{0.073})(LENGTH^{0.033})(WDIFACC + 1)^{0.05} \times 1.33 \tag{2.20}$$

Where: NOACC = number of accidents per year
ADT = average daily traffic
Length = bridge length, feet
WDIFACC = width difference between the goal clear deck width acceptable level of service and the actual clear deck width, but not less than zero, feet

Since some percentage of the total number of crashes reported could not be matched to a specific bridge, the number of crashes predicted by the statistical regression should be less than the reported number of crashes (as the sum of the dependent variables would be less than the reported total). To account for this difference, an adjustment factor of 1.33 was produced and multiplied by the resulting equation to correct for the difference. It is noted that in a few locations in other publications, the adjustment factor term is shown as subtracted from the accident prediction equation, which is likely a typographical error.

At the time of development of NCDOT's BMS, limited data on crashes resulting from vertical clearance issues existed, and studies on the role of vertical clearance deficiency in crashes were not available (Johnston et al., 1994). Therefore, it was assumed that the crash rate due to vertical clearance was linearly increasing with vertical deficiency from the desirable level of service goals (Johnston and Zia, 1984). Underpass accident data from NCDOT were assumed to be distributed to the bridges with vertical clearance deficiencies, and accident rates were computed for interstates, arterials, collector, and local roads (Chen and Johnston, 1987). An equation to compute the coefficient for proportion of vehicles incurring accidents due to a vertical clearance deficiency was developed as shown in Equation 2.21, and the bridge-related accident cost, U_{AC} was assumed to be reasonable for underpass accidents (Chen and Johnston, 1987).

$$C_{CLA} = \frac{UG - UCL}{ACCRU} \tag{2.21}$$

Where: UG = underclearance desirable goal, feet
UCL = bridge underclearance height, feet
ACCRU = accident rate by functional classification due to vertical clearance deficiency (7.4×10^6 vehicles/accident/ft deficiency for interstates, 37.3×10^6 vehicles/accident/ft deficiency for arterials, 8.0×10^6 vehicles/accident/ft deficiency for collectors, 1.1×10^6 vehicles/accident/ft deficiency for local roads)

As stated previously, efforts to estimate user costs for the NCDOT BMS as outlined above were groundbreaking in the BMS community, as evidenced by their publication in a Transportation Research Board Circular (Johnston et al., 1994). Johnston et al. (1994) acknowledged at the time, that some parameters of user costs could be defined with reasonable certainty due to the available data, while other parameters could not be defined due to absence of data. Additionally, many of the BMS inputs for user costs need to be periodically updated with recent data to ensure the accuracy of forecasted user costs. With approximately 20 to 25 years of additional data since the development of the user cost methodologies and inputs, enhancements could be made as part of this project and are presented along with updated input tables (where appropriate) in Chapter 4.

3. DETERIORATION MODELS

3.1 Bridge Record Database and Data Anomalies

Over the course of this project, the research team worked with data sourced primarily from NC Bridge Maintenance Inventory Files (1981-2009) as well as data sourced by directly exporting records from the AgileAssets BMS (2010, 2012-2015). Due to the unavailability of bridge data for 2011 in either NC Bridge Maintenance Inventory file format or in the AgileAssets database, condition rating data for this year was sourced from the publically available FHWA NBI ASCII file. Consequently, data parsing software routines were written over the course of the project to manage the importing of data from any of these three sources and assemble a continuous record of bridge condition rating data from 1981-2015. A post-processing script was also developed to search through individual bridge records to identify the presence of rebuilt bridges during this 35 year observation period. The reason for this post-processing is that the structure number is linked to location and, consequently, a rebuilt bridge retains the same structure number as the structure that was replaced. Since replacement structures potentially feature different design types, materials, and other design features than the original structure, the post-processing routine separates bridge records with replacement denoted by a change in the 'Year Built' item of the record into two separate bridge records for the purposes of the deterioration model development.

An important data anomaly was discovered while working with data sourced from the NC Bridge Maintenance Inventory Files that was corrected prior to finalizing both the updated deterioration models and the ADT growth rate projections. Specifically, there is a mis-keying error associated with county numbers in the 1983 and 1984 NCDOT Bridge Maintenance Inventory files. The county numbers for just these two years of records were found to be erroneous for the four counties: McDowell, Macon, Madison, and Martin. It appears that this error was a result of the special alphabetization rule that is associated with the prefix "Mc" (which is short for "Mac") that results in McDowell being alphabetized ahead of Macon. This data anomaly is summarized in Table 3.1. As a result of this error in the original source data, bridge histories reconstructed from the decades of inventory files were incorrect for many of the bridges in these four counties.

Table 3.1: Erroneous county numbers in select data sets due to alphabetization issue

FIPS Code	County	County No.	County No. in 1983 and 1984 NCDOT Bridge Maintenance Inventory Files
111	McDowell	58	55
113	Macon	55	56
115	Madison	56	57
117	Martin	57	58

In addition to this major data anomaly, the research team also noticed that there are a number of bridge records with inconsistently coded features in select years of the data. For instance, an item such as the main structure material type that, in the absence of reconstruction or replacement, should not change over the service life of the bridge was found in some records to change for a year or two and then revert back to the originally coded material type. To address such inconsistencies in the recorded data, the most frequently recorded values (mode) of the recorded descriptive feature items were calculated for each record to minimize errors resulting from occasional inconsistencies in the individual annual bridge records.

3.2 Update of Deterministic Deterioration Models

Bridge deterioration models used in the NCDOT BMS were last developed in 2002 as part of Research Project 2001-18 "Bridge Management System Update." In this prior research effort, a methodology was developed to produce deterministic deterioration models through statistical analysis of the duration of continuously observed condition ratings and the total number of years spent in each condition rating for individual bridge records. This methodology computes the expected duration spent in individual condition ratings by calculating the average of estimates generated from two analysis routines. The first routine extracts periods within individual bridge records where the condition rating remains continuously unchanged and then calculates the average of this continuously observed duration for all bridges within the deterioration model. To minimize the effect of data anomalies resulting from incorrectly coded data, any records where the continuously observed duration of the condition rating is only one year are removed from the data prior to averaging since the inspection cycle is biennial. The second routine analyzes the entire bridge record for each structure and then sums the total number of years that each condition rating is observed, regardless of whether the rating is continuous or not. As with the first analysis routine, any bridges that yield a total sum of less than two years are removed prior to obtaining the average across all bridges within the deterioration model.

In the current research effort, a software code was developed in MATLAB to implement the methodology developed in RP 2001-18 to produce updated deterministic deterioration models using the now 35 year history of condition ratings from 1981-2015. To provide a means of developing meaningful conclusions on the impact of updating the deterioration models, the research team followed the methodology as closely as possible and maintained the same *a priori* classification of bridges for each component type prior to developing each deterioration model. For bridge decks, NCDOT has relied on pre-classifying bridges based on the item 'Deck Material Type' and then further classifying bridges by average daily traffic. Historically, bridges have been categorized into five ADT categories, which were maintained in this analysis for consistency. Likewise, bridge substructures are pre-classified by substructure material type (using the 'Substructure Material' item from the AgileAssets BMS record or the 'Pier Substructure Material Type' from the NC Bridge Maintenance Inventory files) and then further classified by geographic region. Lastly, bridge superstructures are pre-classified by the 'Structure Type Main – Material' item, then by the 'Structure Type Main – Design' item, and finally by the 'State System' item, where State System 1 is comprised of urban, interstate, and primary routes and State System 2 is comprised of rural routes. For these superstructure categories, models can only be developed where there is sufficient data to analyze for each condition rating. Consequently, deterioration models are developed for only the predominant combinations of structural designs and materials found in the statewide inventory.

The updated deterministic deterioration models for bridge decks computed from 1981-2015 historical condition rating data are provided in Table 3.2. As can be seen in the data, timber decks have been found to exhibit the fastest deterioration rates, followed by steel decks, and lastly concrete decks. Additionally, it should be noted that the analysis reveals little difference in the calculated deterioration rates for bridge decks by average daily traffic, with the exception of steel decks. However, it should be additionally noted that there are relatively few steel deck bridges in the statewide inventory (these averages were regularly computed with often far less than 200 individual records per rating) and so the differences exhibited may be partially attributed to the sparsity of the dataset available for these cases. These models generally exhibit the same trends as the models developed in 2002, however there has been a notable increase in the expected duration of each individual condition rating for each model and, consequently, in the expected service life of the average bridge deck. The relative change in individual condition rating durations for each model, as well as the cumulative duration, since the 2002 analysis is presented in Table 3.3. Note that the 2001-18 analysis did not compute expected durations at condition rating 4, however in the current research it was found that sufficient data is available to yield this portion of the deterioration model. On average, the cumulative service life duration from condition rating 9 down to condition 4 was found to increase by 34% relative to the 2001-18 deterioration model estimates. While this may in part reflect improved bridge performance as a result of improved bridge designs and better preservation strategies, the significant increase in the expected durations expressed in the updated deterioration models is expected to also reflect better statistical averaging as a result of the longer period of condition rating data now available, which reduces the impact of data censoring on the analysis. However, these deterministic deterioration models are still believed to be influenced significantly by data censoring and may still be over-conservative in predicting deterioration rates. This will be discussed further in subsequent sections of this report.

Table 3.2: Updated deterministic deterioration models for bridge deck condition

Deck Material	ADT	9	8	7	6	5	4	Total Years
Timber	0 – 200	3.0	8.9	8.4	7.0	5.2	4.4	36.9
Timber	201 - 800	3.0	8.5	8.9	7.0	5.1	4.5	37.0
Timber	801 – 2000	3.2	7.7	8.5	6.9	4.9	4.1	35.3
Timber	2001 – 4000	2.6	7.9	8.5	6.5	5.5	3.9	34.9
Timber	>4000	3.3	8.6	7.1	5.6	5.9	5.3	35.8
Concrete	0 – 200	3.9	10.3	9.7	9.5	7.8	9.4	50.6
Concrete	201 – 800	4.0	10.0	9.8	10.7	8.4	7.9	50.8
Concrete	801 – 2000	3.8	9.2	9.6	11.1	8.3	8.0	50.0
Concrete	2001 – 4000	3.3	8.4	9.7	10.5	8.3	6.9	47.1
Concrete	>4000	4.0	7.2	9.1	10.3	7.7	8.3	46.6
Steel	0 – 200	4.9	15.6	9.1	7.0	4.1	5.1	45.8
Steel	201 – 800	3.6	13.4	9.0	7.7	5.1	3.7	42.5
Steel	801 – 2000	3.6	12.0	8.6	7.8	5.4	4.6	42.0
Steel	2001 – 4000	3.3	11.4	7.0	7.9	6.3	4.6	40.5
Steel	>4000	3.0	6.8	7.2	8.9	8.0	4.7	38.6

Table 3.3: Change in deck deterioration models relative to 2002 analysis

Deck Material	ADT	9	8	7	6	5	4	Total Years (9-5)
Timber	0 – 200	+0.4	+3.0	+2.8	+0.8	+0.9	N/A	+7.9
Timber	201 - 800	+0.3	+2.0	+2.6	+1.0	+0.8	N/A	+6.7
Timber	801 – 2000	+0.6	+1.7	+2.7	+0.8	+0.9	N/A	+6.7
Timber	2001 – 4000	-1.2	+1.8	+2.2	+1.5	+1.2	N/A	+5.5
Timber	>4000	-0.5	+1.2	+2.1	+0.5	+2.6	N/A	+5.9
Concrete	0 – 200	+1.1	+2.9	+3.4	+3.0	+2.5	N/A	+12.9
Concrete	201 – 800	+1.2	+2.5	+2.5	+3.4	+2.7	N/A	+12.3
Concrete	801 – 2000	+1.1	+2.2	+2.5	+3.4	+2.4	N/A	+11.6
Concrete	2001 – 4000	+0.5	+2.1	+2.7	+2.9	+2.0	N/A	+10.2
Concrete	>4000	+1.0	+1.9	+2.0	+2.8	+1.7	N/A	+9.4
Steel	0 – 200	+1.7	+6.4	+3.6	+2.3	+0.6	N/A	+14.6
Steel	201 – 800	+0.8	+4.7	+3.1	+1.9	+0.9	N/A	+11.4
Steel	801 – 2000	-0.3	+4.0	+2.7	+2.7	+0.9	N/A	+10.0
Steel	2001 – 4000	+1.3	+3.2	+1.6	+1.8	+0.6	N/A	+8.5
Steel	>4000	-	-0.4	+1.7	+2.9	+3.3	N/A	+7.5

The updated deterministic deterioration models for bridge substructures are provided in Table 3.4. Again, few significant differences are present in these models within the same material type, with the exception of steel substructures in the Coastal region that exhibit a notably faster rate of deterioration than steel substructures in the Piedmont and Mountain regions. Furthermore, as observed for the bridge deck models, the updated deterioration rates reflect a significantly slower rate of deterioration than predicted by the prior models developed in 2002 (Table 3.5). The increases in the cumulative service life duration from condition rating 9 down to rating 4 are similar to those observed for the bridge deck models and, on average, the expected duration increased by 30%. Updated superstructure deterministic deterioration models are presented in Table 3.6. Sufficient data was found to be available to develop deterioration models for steel multi-beam superstructures, prestressed concrete slab superstructures, and prestressed concrete tee-beam superstructures, which were not developed in the 2001-18 previous research report. Consistent with the observations in the updated bridge deck and substructure deterioration models, all updated superstructure deterioration models were found to exhibit a slower rate of predicted deterioration than estimated by the current 2002 models. On average, the expected cumulative service life duration from condition rating 9 down to rating 4 was found to increase by 23% for the superstructure deterministic deterioration models. Plots of all of the updated deterministic deterioration models can be found in Appendix B of this report.

Table 3.4: Updated deterministic deterioration models for bridge substructure condition

Substructure Material	Region	9	8	7	6	5	4	Total Years
Timber	Coastal	3.5	4.2	6.0	7.8	7.9	5.6	35.0
Timber	Piedmont	3.8	4.6	5.6	8.4	7.6	6.0	36.0
Timber	Mountain	2.9	4.6	7.5	10.4	6.1	4.9	36.4
Concrete	Coastal	3.0	5.0	8.0	10.7	7.9	6.3	40.9
Concrete	Piedmont	3.0	6.0	7.9	10.5	8.3	7.4	43.1
Concrete	Mountain	3.4	7.6	11.0	10.9	6.4	4.7	44.0
Steel	Coastal	4.1	7.8	6.4	8.1	5.7	5.7	37.8
Steel	Piedmont	4.7	9.6	8.2	8.5	6.5	5.6	43.1
Steel	Mountain	3.8	10.7	10.1	7.5	5.0	4.7	41.8
Prestressed Concrete	Coastal	4.0	8.9	7.9	9.6	6.7	7.9	45.0
Prestressed Concrete	Piedmont	3.3	9.2	9.6	10.6	7.5	6.3	46.5
Prestressed Concrete	Mountain	3.9	8.6	14.0	6.9	5.2	6.1	44.7

Table 3.5: Change in substructure deterioration models relative to 2002 analysis

Substructure Material	Region	9	8	7	6	5	4	Total Years (9-5)
Timber	Coastal	1.2	1	1.2	1.1	2.1	N/A	+6.6
Timber	Piedmont	1.4	0.8	0.6	1.3	2.3	N/A	+6.4
Timber	Mountain	-0.4	0.9	1.9	3.1	1.8	N/A	+7.3
Concrete	Coastal	-0.1	-1	1.9	4.3	2.3	N/A	+7.4
Concrete	Piedmont	-0.2	-0.5	0.8	3.6	2.5	N/A	+6.2
Concrete	Mountain	0.5	0.3	4.3	4.5	1.7	N/A	+11.3
Steel	Coastal	0.8	1.5	-0.1	1.6	-0.9	N/A	+2.9
Steel	Piedmont	1.9	2.2	1	1.8	0.8	N/A	+7.7
Steel	Mountain	0.7	3.6	2.8	1.4	0.3	N/A	+8.8
Prestressed Concrete	Coastal	0.9	2.8	1.4	2.7	0.3	N/A	+8.1
Prestressed Concrete	Piedmont	0.9	2.3	2.2	3.6	1.8	N/A	+10.8
Prestressed Concrete	Mountain	1.1	2.2	6.3	2.2	1.2	N/A	+13.0

Table 3.6: Updated deterministic deterioration models for bridge superstructure condition

Superstructure Material	Design Type	State System	9	8	7	6	5	4	Total Years
Timber	Multi-Beam	1	3.0	5.7	6.5	8.6	9.0	3.7	36.5
Timber	Multi-Beam	2	2.9	7.7	8.3	8.1	6.4	4.3	37.7
Concrete	Slab	1	2.0	6.7	9.7	12.1	7.4	6.8	44.7
Concrete	Slab	2	4.2	7.5	10.2	11.0	8.2	11.1	52.2
Concrete	Tee-Beam	2	2.0	7.2	12.1	11.6	8.4	10.0	51.3
Steel	Multi-Beam	1	4.2	11.5	8.1	7.8	5.8	5.6	43.0
Steel	Multi-Beam	2	3.3	10.3	11.2	8.0	5.2	4.6	42.6
Steel	Truss	1	3.0	5.1	6.8	7.1	7.3	6.6	35.9
Steel	Truss	2	5.1	5.8	6.8	7.6	6.8	6.0	38.1
Steel	Floor-Beam	1	4.0	5.7	6.4	7.1	7.6	5.0	35.8
Steel	Floor-Beam	2	3.6	7.2	8.4	7.2	5.2	4.6	36.2
Prestressed Concrete	Multi-Beam	1	4.5	10.4	6.6	7.6	5.4	5.3	39.8
Prestressed Concrete	Multi-Beam	2	4.2	13.2	7.0	5.1	3.7	2.8	36.0
Prestressed Concrete	Slab	1	3.8	8.7	7.1	8.2	4.3	5.1	37.2
Prestressed Concrete	Slab	2	3.7	9.1	7.3	7.6	3.8	3.5	35.0
Prestressed Concrete	Tee-Beam	1	3.0	3.7	6.0	11.5	5.9	4.4	34.5
Prestressed Concrete	Tee-Beam	2	2.6	8.2	9.7	8.9	6.3	5.7	41.4

Through early discussions with the Steering and Implementation Committee for this research project, it was revealed that the deterministic deterioration models developed in 2002 and currently implemented in the AgileAssets BMS are strongly believed to produce overly-conservative estimates of the deterioration rates associated with bridge components. The updated deterministic deterioration models confirm this suspicion and the implementation of these new models will aid in improving the accuracy of the condition rating forecasts used in network analysis for long-term bridge project planning. However, the original methodology used to develop deterministic deterioration models fails to adequately address two fundamental issues associated with the nature of bridge condition rating data that results in conservative estimates of component deterioration rates. Namely, the issues are: 1) censoring of recorded condition rating data; and 2) the skewed distribution of typical continuously observed condition rating data. These two issues will be presented briefly here to establish the motivation for the development of probabilistic deterioration models carried out in this research project.

Censoring is a term applied to instances when a particular event is not completely observed and it is a commonly encountered and unavoidable problem in analysis of any duration data. Bridge condition rating data has a large percentage of censored observations due to the discrete nature of the inspection records, variability in ratings due to inspector subjectivity, and the impact of maintenance actions on condition rating durations. Most of these instances are of the form classified as “right censored” observations, where the observed period is only known to be equal to or less than the actual duration. One common instance of such censoring occurs at the beginning and end of the period of recorded ratings. For example, consider a bridge component that had a condition rating of 7 at the beginning of the historical database in 1981 and stayed at that condition rating until 1987 when it changed to 6. In this case, all we know is that the time in condition rating 7 was at least 6 years as we cannot say for how long it was at that rating before the observation first began in 1981 when the state inventory was initiated. Similar censoring is encountered at the most recently observed year (2015) when the observed time in each current condition state can only be calculated at least as long as the actual duration, since the remaining duration spent at that condition rating will occur in the future. Lastly, condition rating durations are often prematurely interrupted by bridge reconstruction or replacement, which is another form of right censoring. For example, if an observed condition rating of 5 increases to 7 due to maintenance action, it is not possible to calculate how long the bridge component would have remained at rating 5 in the absence of maintenance. In all of these cases, the measurement of condition rating duration used in the development of the deterioration model is always less than or equal to the actual condition rating duration. Consequently, the deterministic deterioration models calculated on this data exhibit deterioration rates that are faster (more conservative) than actually expressed in the historical condition rating data. As the number of recorded years of bridge records increases, the effect of censoring is reduced. However, even with 35 years in the current bridge record database, censoring of condition rating data is still prominent. To illustrate the extent of this phenomenon, censoring percentages were calculated for concrete deck condition rating observations and are shown in Table 3.8. As can be seen, despite collection of over 35 years of condition rating data, the majority of observed condition rating durations are still censored observations. This issue prompted the research team to explore the use of Survival Analysis techniques, which use a maximum partial likelihood estimator that statistically accounts for the effect of censoring on the condition rating durations. In addressing this issue, the improved models should result in more accurate condition rating forecasts that alleviate the over-conservative prediction errors currently plaguing the NCDOT BMS network analysis.

Table 3.7: Change in superstructure deterioration models relative to 2002 analysis

Superstructure Material	**Design Type**	**State System**	**9**	**8**	**7**	**6**	**5**	**4**	**Total Years (9-5)**
Timber	Multi-Beam	1	-2	0.6	0.3	1.4	2.7	N/A	+3.0
Timber	Multi-Beam	2	0.2	2.1	2	1.4	1.8	N/A	+7.5
Concrete	Slab	1	0	1.6	2.6	4.9	1.8	N/A	+10.9
Concrete	Slab	2	2.2	1.7	4.2	3.3	3.3	N/A	+14.7
Concrete	Tee-Beam	2	-0.7	-0.4	4.6	4.1	2.6	N/A	+10.2
Steel	Multi-Beam	1	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Steel	Multi-Beam	2	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Steel	Truss	1	0	2.9	-2.5	0.6	3	N/A	+4.0
Steel	Truss	2	2.1	2.4	1.8	0	-0.1	N/A	+6.2
Steel	Floor-Beam	1	0.7	-2.6	-0.1	1.3	2.8	N/A	+2.1
Steel	Floor-Beam	2	0.9	-0.3	1	1.3	0.9	N/A	+3.8
Prestressed Conc.	Multi-Beam	1	0.6	2.3	0.1	1.4	0.4	N/A	+4.8
Prestressed Conc.	Multi-Beam	2	1.1	4.8	-0.5	-1.6	-1.5	N/A	+2.3
Prestressed Conc.	Slab	1	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Prestressed Conc.	Slab	2	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Prestressed Conc.	Tee-Beam	1	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Prestressed Conc.	Tee-Beam	2	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table 3.8: Severity of censoring in concrete deck condition rating data

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**
Percentage of Records with Censoring	86.5%	70.1%	67.1%	74.5%	81.5%	93.2%

The second issue challenging the use of the deterministic deterioration modeling methodology relates to the statistical distribution of condition rating durations. The issue relates to the use of statistical averaging to develop the expected condition rating durations, which is an approach best suited for sample distributions that are normally distributed. However, the probability distribution functions associated with condition rating data are found to exhibit a log-normal distribution, which is common with reliability data. An example of these log-normal probability distributions is provided for condition rating data obtained from concrete deck ratings in Figure 3.1, where it is apparent that the use of the statistical mean is not an appropriate measure. To address this issue, probabilistic deterioration models should be developed in place of the deterministic ones currently used in the AgileAssets BMS. Development of probabilistic models will account for these distributions in the statistical regression, thereby resulting in more accurate and precise condition rating forecasts in long-term network analysis.

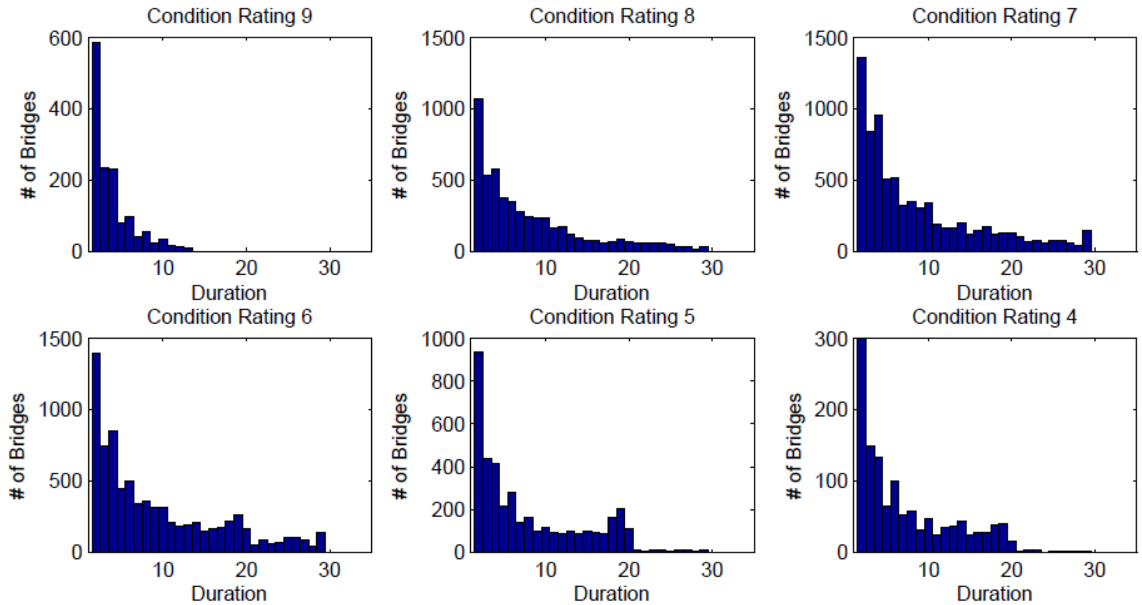


Figure 3.1: Histograms of condition rating durations from historical concrete deck data

3.3 Development of Probabilistic Deterioration Models

Review of literature on bridge deterioration modeling revealed that deterministic modeling approaches have long been replaced by probabilistic methods in most state BMS, as well as in the AASHTOWare Bridge Management software. In order to facilitate NCDOT's transition from deterministic deterioration models to the preferred probabilistic models, the research team developed a methodology for developing probabilistic deterioration models using proportional hazards assumptions to incorporate the effects of explanatory factors (design, geographic, and functional bridge features) on bridge component deterioration rates. The methodology produced offers unique contributions to the state-of-art in this respect, as the incorporation of these external factors in the proportional hazards model offers the ability to provide insight on the most significant factors influencing deterioration rates and quantify how the influence of these factors changes over the life cycle of each bridge component. In addition to the development of the modeling methodology, the research also developed the first strategy for efficiently incorporating the proportional hazards effects within a transition probability matrix to facilitate ease of implementation of this advanced model. Complete details on the development of the statistical regression methodology and rigorous treatment of both theoretical and applied aspects of the modeling approach are presented in a Ph.D. dissertation that stemmed from this research project (Goyal, 2015). In this project report, the presentation of the methodology and discussion of the results obtained from application to the historical statewide bridge inventory records is condensed for brevity. The focus of the material presented in this project report will be on the key aspects of the probabilistic deterioration models required to analyze and implement this strategy for condition rating forecasting. An overview of the effects of significant external factors on bridge deterioration rates revealed through application to the state database will also be presented to summarize key analysis results.

The general framework established for proportional hazards regression analysis of bridge condition rating data is presented schematically in Figure 3.2 and described briefly here to provide an overview of the statistical regression process. The routine begins with querying and extraction of relevant descriptive and condition-specific data from the historical bridge records. This data is preprocessed to extract all observations of the response variable, which is the observed continuous duration at the particular condition rating being analyzed (transition probabilities and hazard ratios are developed for each condition rating independently). Censoring information is compiled in a separate vector and indicates whether the extraction algorithm classifies the continuously observed condition rating data as either fully observed or censored. The BMS historical records also contain descriptive information on each structure, such as the design type, functional classification, geographic region, average daily traffic, percent average daily truck traffic, maximum span length, wearing surface, and other information that could be considered to potentially produce significant influence on deterioration rates of specific bridge components and are therefore treated as explanatory variables. To address missing and mis-coded information within individual records, median values calculated over the full recorded history for each bridge are used for these explanatory factors. Each of these variables is organized into categories designated by one or more design variables to which bridges are classified based on either binary or reference cell coding. It is important to note that a distinct set of dependent and independent proportional hazards regression inputs are associated with each condition rating for any subset of bridges analyzed. For example, in developing a deterioration model for timber decks, the full subset of bridges with timber decks is first isolated from the database and then unique individual sets of variables associated with historical observations within each condition rating are then extracted. The subsequent steps in the processes of multivariable proportional hazards regression, best subset selection, and development of survival functions are then performed individually on each of these condition rating specific sets associated with the component subset analyzed.

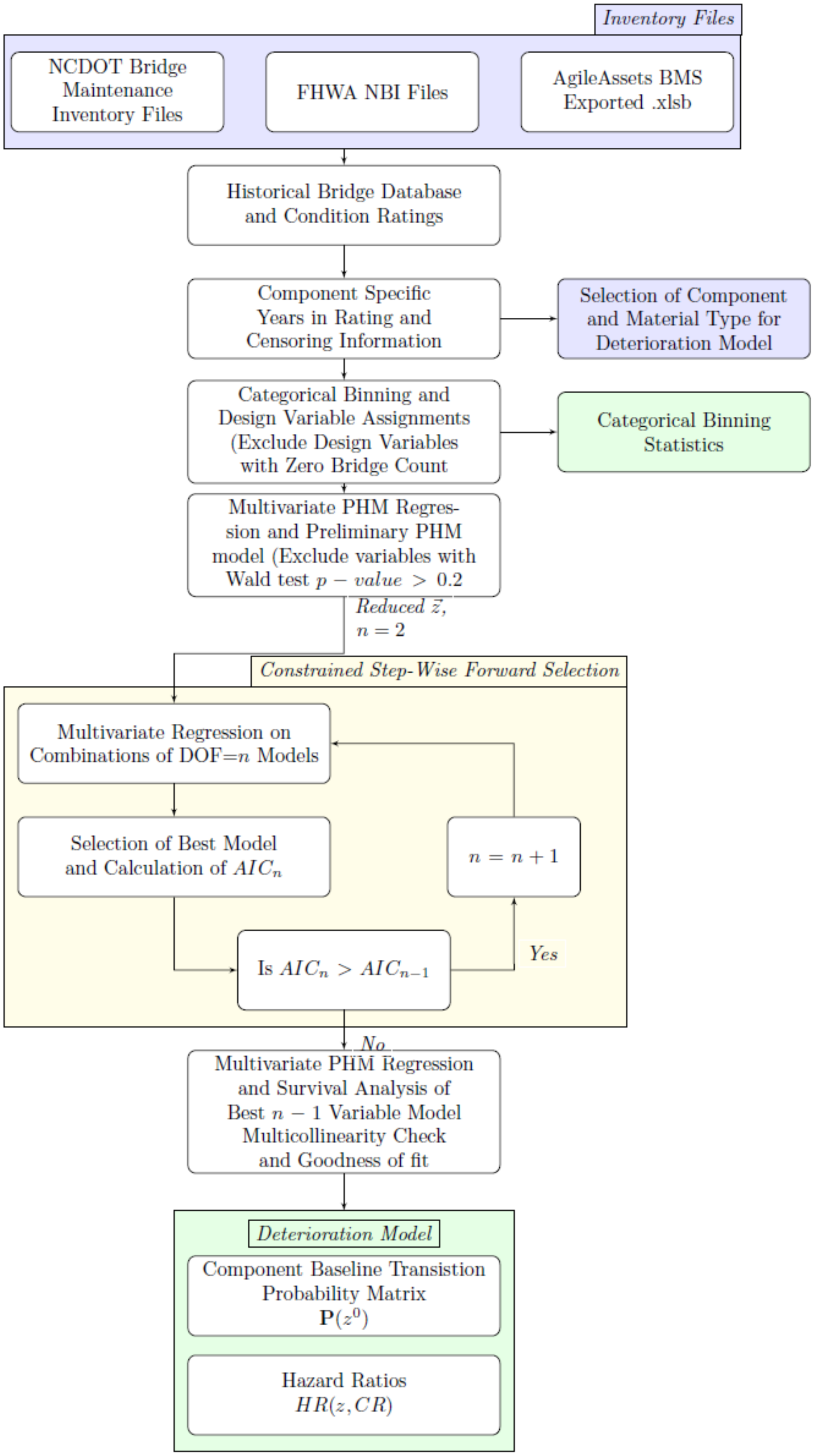


Figure 3.2: Flowchart of developed methodology for proportional hazards-based probabilistic deterioration modeling

An important step in the model development is best subset selection, which aims to reduce the explanatory factors included in the model to an optimally small set in order to facilitate ease of implementation, while balancing the desire to achieve a strong statistical fit to the condition rating data. In the methodology developed, an initial multivariable proportional hazards regression is carried out using only those design variables that are observed within one or more bridge records for the condition rating under study. For this initial multivariable model, only those variables that are statistically significant with a Wald statistic p-value of ≤ 0.2 are included in the benchmark multivariable model. This benchmark represents the best possible fit to the observed data under the proportional hazards assumptions with the largest number of factors included in the model. A model selection algorithm for determining the best subset of significant variables to achieve an optimal model fit with reduced degrees of freedom is then implemented on this benchmark multivariable model. This algorithm executes a constrained step-wise forward selection strategy based on a combination of maximizing the log partial likelihood and minimizing the number of covariates included in the model. The best subset of statistically significant covariates is then included in a multivariable proportional hazards regression to estimate the regression coefficients, hazards ratios, and baseline survival functions associated with that rating. At this point, the best subset model is also tested for potential collinearity issues using the Variance Inflation Factor (VIF) indicator. Additionally, the goodness-of-fit of the final model is assessed by developing Kaplan-Meier estimators on select categorical data at each condition rating for qualitative comparison (Figure 3.3). The survival functions developed using this best subset model incorporate the effects of the most significant explanatory variables on the deterioration rate over an individual condition rating.

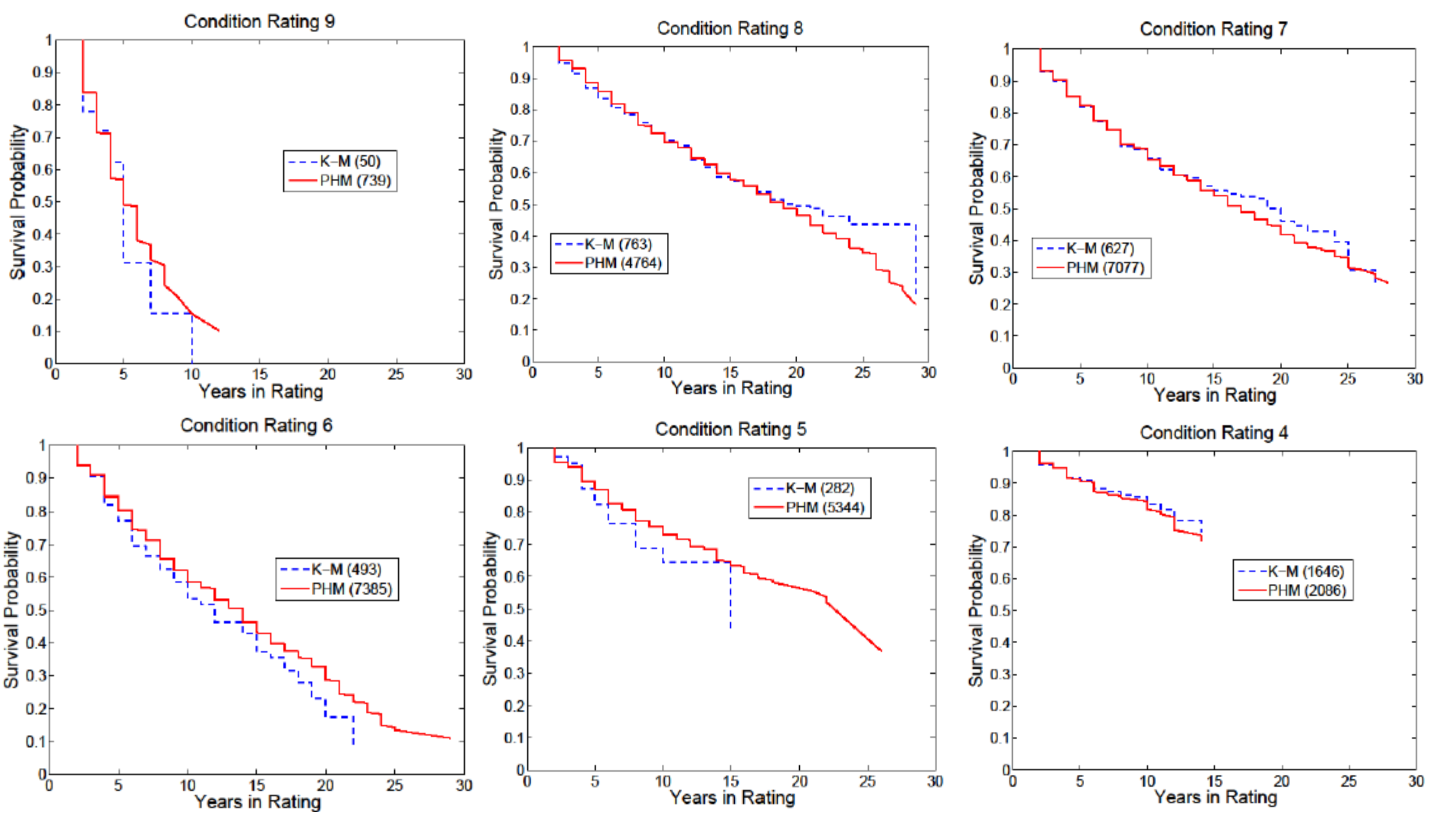


Figure 3.3: Comparison of survival functions in a fully developed proportional hazards model versus empirical functions developed from subsets of the condition rating data (serves to validate the reasonableness of the proportional hazards assumption)

The survival function for each condition rating is subsequently used to calculate the transition probabilities associated with staying at the same condition rating or deteriorating to a lower rating at the end of each annual prediction cycle. The transition probabilities associated with all condition ratings at the end of one annual prediction cycle are integrated into a single transition probability matrix applicable to that annual cycle. In this way, a set of non-stationary (time-dependent) transition probability matrices are developed. For ease of implementation, these non-stationary transition probability matrices can be averaged to yield a stationary transition probability matrix or Markov-chain. Comparisons between predictions formed using the advanced non-stationary matrices and simplified stationary matrices revealed no significant differences in predictions for planning horizons less than 20-25 years and therefore the simplified stationary approach is recommended for implementation. The process used for implementation of the proportional hazards probabilistic deterioration model for condition rating forecasting is presented schematically in Figure 3.4. This process will be illustrated by way of example in the following subsection of the report.

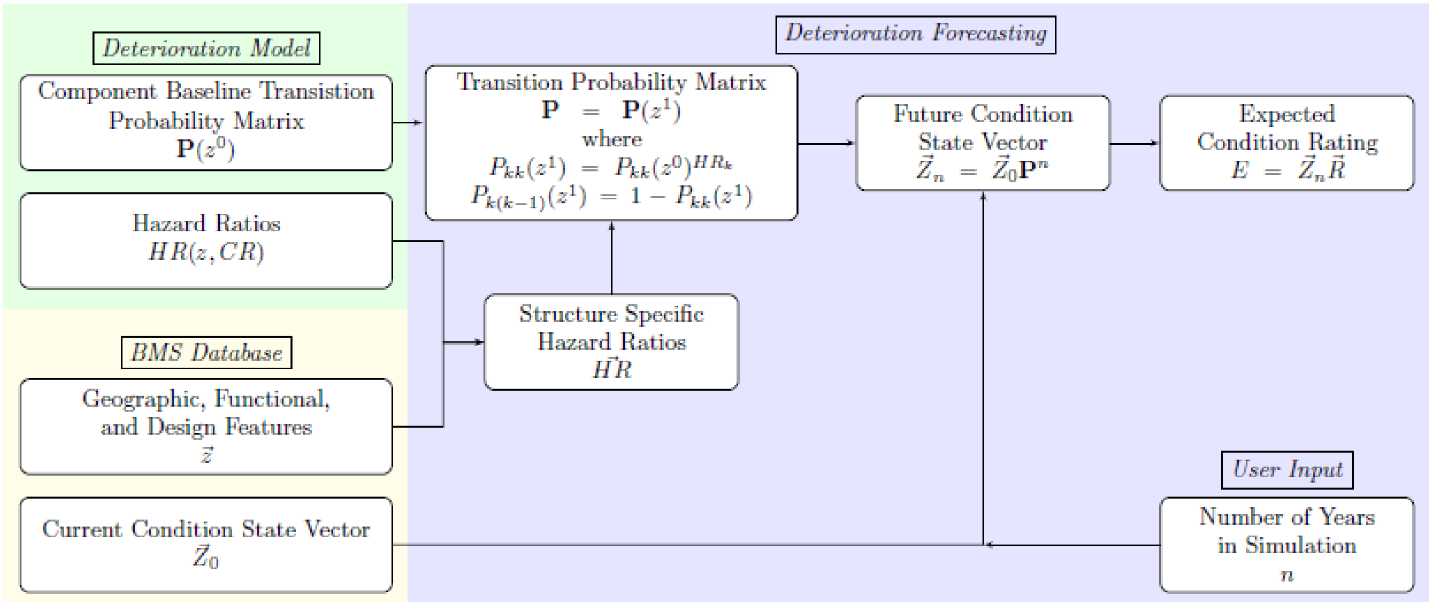


Figure 3.4: Schematic of process used for condition rating forecasts with proportional hazards probabilistic model

The probabilistic deterioration model yielded by the developed methodology for statistical regression of proportional hazards models consists of two primary inputs: 1) a baseline transition probability matrix, and 2) a set of hazard ratios associated with individual factors deemed to be significant to the predictive accuracy of the model by the best subset selection process. The baseline transition probability matrix is described by stay-the-same transition probabilities, like any other Markov-chain deterioration model. As an example, application of this methodology to concrete deck data from 1981 to 2015 produced the baseline stay-the-same transition probabilities presented in Table 3.9. These baseline stay-the-same transition probabilities are affected by the explanatory factors in the model through the hazard ratios developed by the statistical regression, shown in Table 3.10. As shown in this table, one of the unique aspects of the developed technique is that the influence of external factors can change over the service life of individual bridge components. Any factors that have a hazard ratio less than 1 are associated with a slower rate of deterioration, while those with a hazard ratio greater than 1 are associated with accelerated rates of deterioration. Factors that have a hazard ratio of 1 do not influence the deterioration rate for the specific condition rating(s) where the hazard ratio is indicated as 1. For example, this model indicates that concrete decks on multi-span bridges deteriorate at a faster rate than concrete decks on single-span bridges, but only within condition rating 7 and 6. Over the remaining condition ratings, the statistical regression found no significant difference between the deterioration rates of concrete decks on either multi-span or single-span structures. Likewise, bridges in State System 2 were found to deteriorate at a faster rate than those on State System 1 within condition rating 6, but at a slower rate within condition rating 5. More extensive discussion of the significant factors affecting deterioration rates of the different bridge components and different materials will be presented in a subsequent subsection of this report.

In developing the proportional hazards probabilistic deterioration models, all external factors were treated with binary or reference-cell coded variables. This was intentionally done to facilitate ease of implementation. By this approach, the effect of an external factor is included in the structure-specific deterioration model if it has the feature specified by the external factor identified in the model. For example, StateSystem2 is a binary classifier. If the bridge for which a prediction is being made is classified as being on State System 2, then the hazard ratios associated with the StateSystem2 factor are incorporated into the model and if the bridge is on State System 1, then they are not. All variables in the probabilistic model are treated this way, except ADT, ADTT, Maximum Span Length, and Age that are described with categories of classifiers. Consequently, the models produced contain categorical bins associated with these factors. In the case of concrete decks, the categorical bins developed are presented in Table 3.11. For example, if a bridge has a maximum span length greater than 6m, then the hazard ratios for MaxSpan3 are incorporated in the prediction model, if the bridge has a maximum span greater than 4m but less than or equal to 6m, then the hazard ratios for MaxSpan2 are incorporated in the prediction model and, if the bridge has a maximum span length less than or equal to 4m, then it is a member of the baseline category and no change to the prediction model for this factor is necessary. The effect of multiple external factors is easily incorporated in the model by taking the product of the hazard ratios associated with the individual factors. This is illustrated by way of example in the following subsection of the report.

Table 3.9: Baseline stay-the-same transition probabilities for concrete deck model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.8821	0.9643	0.9584	0.9668	0.9889	0.9933	0.75	0.75	1

Table 3.10: Hazard Ratios for explanatory factors in concrete deck model

Factor	**Rating 9**	**Rating 8**	**Rating 7**	**Rating 6**	**Rating 5**	**Rating 4**
StateSystem	1	1	1	1.1242	0.7722	1
Piedmont	0.6310	1.2238	1	0.7527	1.4339	1
Mountain	0.4603	1.2067	0.7522	0.8089	1	1
ADT3	1	1	1	1.1312	1	1
ADT4	1	1	1	1.2481	1	1.5508
MaxSpan2	1	1.4816	0.8044	1	1	1
MaxSpan3	0.4971	2.1793	1	1.3529	1	1
NumberSpans	1	1	1.5749	1.2997	1	1
Age2	4.5250	1.6839	1.1300	1.2616	1	0.2570
Age3	1	2.2851	1.4054	1.4602	1.6920	1
Age4	1	2.2802	2.2229	2.2785	1.3628	1

Table 3.11: Categorical bounds for explanatory factors in concrete deck proportional hazards model

Categorical Variable	**Range**
ADT3	3184-9090 Vehicles
ADT4	>9090 Vehicles
MaxSpan2	4-6 m
MaxSpan3	>6 m
Age2	14-23 years
Age3	23-33 years
Age4	>33 years

3.3.1 Implementing the Proportional Hazards Probabilistic Deterioration Model

Implementation of the proportional hazards probabilistic deterioration models is expedient due to the relationship between the survival function and the derived transition probabilities. As derived by the research team and presented in Goyal (2015), incorporating the effects of the significant explanatory factors into the probabilistic deterioration model simply requires raising the baseline stay-the-same transition probabilities by the power of the structure-specific hazard ratio associated with the condition rating. Mathematically, the transition probability matrix that accounts for the effects of design, geographic, and functions features takes the form:

$$P = \begin{bmatrix} P_{99}^{HR_9} & 1-P_{99}^{HR_9} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & P_{88}^{HR_8} & 1-P_{88}^{HR_8} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & P_{77}^{HR_7} & 1-P_{77}^{HR_7} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & P_{66}^{HR_6} & 1-P_{66}^{HR_6} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & P_{55}^{HR_5} & 1-P_{55}^{HR_5} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & P_{44}^{HR_4} & 1-P_{44}^{HR_4} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

where:

$[P_{99}, P_{88}, P_{77}, P_{66}, P_{55}, P_{44}]$ are the baseline stay-the-same transition probabilities (constants in model)
$[HR_9, HR_8, HR_7, HR_6, HR_5, HR_4]$ are the hazard ratios describing the effect of covariates (structure-specific)

The hazard ratios used in this model are computed from the matrix of hazard ratios produced through application of the developed deterioration methodology. Specifically, these hazard ratios are obtained as the product of the factor-specific hazard ratios provided from the proportional hazards model. In obtaining this product, only those factors associated with the specific bridge that is being modeled are included in the product used to calculate the hazard ratio. If the bridge has only the baseline features, then the hazard ratio is 1. This calculation is illustrated by example in the next subsection.

3.3.2 Example Calculation of a Structure-Specific Probabilistic Deterioration Model

To illustrate the implementation of the proportional hazards deterioration model, the use of the model outputs to generate a structure-specific transition probability matrix for condition rating forecasting are illustrated here. The proportional hazards probabilistic deterioration model that will be used for this example is the one presented previously in Tables 3.9, 3.10, and 3.11. Suppose that we wish to forecast the deterioration of a concrete deck for a bridge that is on State System 2, is located in the Mountain region, has no additional wearing surface, has an ADT of 200 vehicles, a maximum span length of 5 m, is a single-span structure, and is 25 years old. Revisiting the explanatory factors provided in Table 3.10 with the categorical bounds presented in Table 3.11, the descriptive features of this bridge indicate that the following factors should be incorporated into the structure-specific deterioration model: StateSystem2, Mountain, MaxSpan2, and Age3. Consequently, the hazard ratios used for this structure's transition probability matrix for each rating will be obtained by taking the product of only the hazard ratios associated with these factors over each condition rating. This is illustrated in Table 3.12, where the calculation of the hazard ratio for condition rating 7 is highlighted.

Table 3.12: Calculating hazard ratios for a specific structure using proportional hazards model

Factor	**Rating 9**	**Rating 8**	**Rating 7**	**Rating 6**	**Rating 5**	**Rating 4**
StateSystem2	1	1	1	1.1242	0.7722	1
Piedmont	0.6310	1.2238	1	0.7527	1.4339	1
Mountain	0.4603	1.2067	0.7522	0.8089	1	1
ADT3	1	1	1	1.1312	1	1
ADT4	1	1	1	1.2481	1	1.5508
MaxSpan2	1	1.4816	0.8044	1	1	1
MaxSpan3	0.4971	2.1793	1	1.3529	1	1
NumberSpans	1	1	1.5749	1.2997	1	1
Age2	4.5250	1.6839	1.1300	1.2616	1	0.2570
Age3	1	2.2851	1.4054	1.4602	1.6920	1
Age4	1	2.2802	2.2229	2.2785	1.3628	1
Hazard Ratios for Structure	HR_9	HR_8	HR_7	HR_6	HR_5	HR_4
	0.4603	4.0854	0.8504	1.3279	1.3066	1

The stay-the-same transition probabilities associated with this specific structure can then be determined by raising the baseline stay-the-same transition probabilities from this model (Table 3.12) to the power of the condition-specific hazard ratios. For this example, we have:

$$\begin{aligned} P_{ii}^{HR_i} &= [(0.8821)^{0.4603}, (0.9643)^{4.0854}, (0.9584)^{0.8504}, (0.9668)^{1.3279}, (0.9889)^{1.3066}, (0.9933)^{1}] \\ &= [0.9439, 0.8620, 0.9645, 0.9562, 0.9855, 0.9933] \end{aligned}$$

Which yield the following structure-specific transition probability matrix:

$$P = \begin{bmatrix} 0.9439 & 0.0561 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.8620 & 0.1380 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.9645 & 0.0355 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.9562 & 0.0438 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.9855 & 0.0145 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.9933 & 0.0067 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Suppose now that the deck condition rating for this structure is currently a 7, has been a 7 for the past 3 years, and it is desired to forecast what the condition rating of the deck will be in 5 years from now. To perform this prediction, we establish the initial state vector as:

$$\begin{array}{cccccccccc} & (9) & (8) & (7) & (6) & (5) & (4) & (3) & (2) & (1) \\ Z_0 = & [0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0] \end{array}$$

Which simply states that there is a 100% probability that the structure has a condition rating of 7 and zero probability of it having any other rating. (Note, however, that in practical application the research team has found that more accurate predictions are yielded if the state probabilities at a point of transition are set as 0.5 for the rating before the transition and after the transition. In other words, when the year at which the transition from rating 8 to rating 7 is identified, the corresponding state vector should be set to [0 0.5 0.5 0 0 0 0 0 0] to achieve better accuracy against the recorded ratings. The reason for this improvement in prediction accuracy is that the probabilistic deterioration model produces floating point precision numerical estimates, while the condition ratings are recorded on an integer scale.) With the initial state vector established, we can forecast the state vector at 'n' years into the future using the equation:

$$Z_n = Z_0(P)^n$$

In our example, since the bridge has been in rating 7 for 3 years already and we are trying to forecast the rating an addition 5 years into the future, 'n' should be set to 8. Therefore, the state vector associated with the condition rating probabilities at 5 years into the future are:

$$Z_n = [0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]\left(\begin{bmatrix} 0.9439 & 0.0561 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.8620 & 0.1380 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.9645 & 0.0355 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.9562 & 0.0438 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.9855 & 0.0145 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.9933 & 0.0067 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}\right)^8$$

$$= [0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]\begin{bmatrix} 0.6301 & 0.2228 & 0.1356 & 0.0108 & 0.0007 & 0 & 0 & 0 & 0 \\ 0 & 0.3048 & 0.5979 & 0.0882 & 0.0090 & 0.0002 & 0 & 0 & 0 \\ 0 & 0 & 0.7489 & 0.2140 & 0.0360 & 0.0011 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.6989 & 0.2853 & 0.0156 & 0.0002 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.8897 & 0.1077 & 0.0016 & 0.0007 & 0.0003 \\ 0 & 0 & 0 & 0 & 0 & 0.9476 & 0.0233 & 0.0166 & 0.0124 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.1001 & 0.2670 & 0.6329 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1001 & 0.8999 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$Z_n = [0 \quad 0 \quad 0.7489 \quad 0.2140 \quad 0.0360 \quad 0.0011 \quad 0 \quad 0 \quad 0]$$

Which means that the deterioration model predicts a 74.9% probability that the deck will still remain in condition rating 7 at 5 years into the future, a 21.4% probability that it will deteriorate to rating 6, a 3.6% probability that it will deteriorate to rating 5, and a 0.1% probability that it will deteriorate to rating 4. To reduce these probabilities to a single numerical prediction of condition rating, the expected value can be calculated by:

$$E = Z_n R$$

where R is a column vector indicating the condition ratings used during the inspection program. In our example, the expected condition rating would be:

$$E = [0 \quad 0 \quad 0.7489 \quad 0.2140 \quad 0.0360 \quad 0.0011 \quad 0 \quad 0 \quad 0] \begin{bmatrix} 9 \\ 8 \\ 7 \\ 6 \\ 5 \\ 4 \\ 3 \\ 2 \\ 1 \end{bmatrix} = 6.71$$

and therefore the predicted condition rating is 6.71.

3.3.3 Summary of Effects of Explanatory Factors on Bridge Deterioration Rates

The proportional hazards probabilistic deterioration modeling methodology allows for unique subsets of explanatory factors to be included in the model across different condition ratings, which improves the model fit and offers insight into how the effects of these factors change over the service life of bridge components. However, to distill the analysis to a more manageable and holistic perspective, only the general trends in the explanatory factors affecting deterioration rates across all components and their relative impact on deterioration rates are examined and summarized in this section. To reduce the state-dependent hazard ratios to a single index for ease of interpretation, weighted averages of hazard ratios expressed for each covariate across condition ratings 4 to 9 were computed for each material-specific component in this analysis. The weighting is specified in proportion to the number of total records available for individual condition ratings. This weighting scheme reflects the certainty expressed in each hazard ratio and provides weighting factors similar to those that would be developed by weighting based on duration spent in each condition rating. The weighted mean hazard ratios across all material-specific deck, superstructure, and substructure components for the significant variables identified in the proportional hazards regression are presented in Table 3.13. In this table, only factors appearing in at least two material-specific component models are presented. In order to rank the explanatory factors based on average significance, the variables have been sorted on the basis of the mean absolute deviation from unity (no effect) obtained by averaging across the mean weighted HRs for all material-specific components. As a reminder, hazard ratios greater than 1.0 indicate that the factor accelerates deterioration relative to the baseline category assignment, while a hazard ratio less than 1.0 indicates that the factor is associated with a slower rate of deterioration than the baseline category assignment.

Table 3.13. Weighted mean hazard ratios of explanatory factors on deterioration rates

The weighted mean hazard ratios indicate that most factors develop generally consistent effects across the different components and material types, although the amplitudes of the hazard ratios do vary by both material type and component. In all instances, increased age is associated with the most significant increase in the rate of deterioration and, on average, the regression coefficients indicate that bridge deterioration rates increase with age. Interestingly, the effect of age on the relative deterioration rates are similar for components of the same material and vary more significantly across the material types than the component types. The relative effect of age on deterioration rates is found to be more significant for steel and prestressed concrete components than for timber or concrete components. The positive correlation between the age at inspection and the observed rate of deterioration is well established in deterioration modeling literature (Busa et al., 1985, Chen and Johnston, 1987, Madanat and Ibrahim, 1995, Madanat et al., 1995).

Components on bridge designs with multiple spans are found to exhibit consistently greater deterioration rates than those on single span bridges, with the exception of steel and prestressed concrete substructure components. Evidence of increased rates of deterioration with an increase in number of spans has been documented in a number of previous studies (Busa et al., 1985, Madanat and Ibrahim, 1995, Madanat et al., 1995). Multi-span bridge decks necessarily include expansion joints with a known propensity for maintenance issues (Chang and Lee, 2002) that are likely to affect the overall general condition rating of the deck. Presence of joints was found to exacerbate deck deterioration in an earlier study (Yanev and Chen, 1993) and serves to support the higher deterioration rates predicted for multi-span bridge decks.

The presence of reconstruction was found to exhibit a mild to moderate effect on deterioration rates with the trend of increasing the deterioration rate for all material-specific components with the exception of timber superstructures and prestressed concrete substructures. Reconstructed bridges have been previously observed to have higher deterioration rates than original or rebuilt bridges (Sanders and Zhang, 1994, Yanev and Chen, 1993). Similarly to the effect of reconstruction, the impact of geographic region was moderately significant across the majority of models. Predominantly, bridge components in the Coastal region are found to deteriorate at a faster rate than bridge components in the Mountain and Piedmont regions, which are found to generally deteriorate at similar rates on average. This effect is found to be most significantly expressed in steel bridge components, although prestressed concrete substructures were also found to deteriorate at an accelerated rate in the Coastal Region. Prior precedent for geographic region as a factor influencing bridge deterioration rates is widespread in the research literature. Higher rates of deterioration in the Coastal region of North Carolina have been observed in earlier studies and are attributed to the salt laden atmosphere and humid marine environment in these regions, which exacerbate corrosion-driven deterioration mechanisms (Abed-Al-Rahim and Johnston, 1991, Chen and Johnston, 1987). Higher rates of deterioration on concrete bridge decks in northern Indiana compared to those in southern Indiana were found in earlier studies (Madanat and Ibrahim, 1995, Madanat et al., 1995, Mauch and Madanat, 2001, Mishalani and Madanat, 2002) and were attributed to the use of deicing salts in cold weather regions that contribute to corrosion of concrete deck reinforcement bars. Similar impact was found in a study on bridge deterioration rates in the state of Nevada with bridges in northern Nevada deteriorating much faster than those in southern Nevada on account of harsher winter environment and, consequently, increased freeze-thaw cycles and salt application (Sanders and Zhang, 1994). In an earlier study done on NCDOT bridges, it was noted that the western divisions of the state's Piedmont region experience more frequent ice and snow compared to the eastern Piedmont divisions, which in turn leads to higher rates of deterioration for these divisions due to the increased use of deicing and anti-icing salts (Abed-Al-Rahim and Johnston, 1991). This study recommended classifying regions into salt/non-salt and marine/non-marine regions instead of Mountain, Piedmont, and Coastal because of striking differences in deterioration rates observed for these classifications.

Maximum span length was found on average to be mildly to moderately significant across the material-specific components. However, this covariate expresses no clear trends across the different models except that increased span length is associated with increased deterioration rates of all deck materials. Notably, this increase in deterioration rates with an increased span length has been documented for concrete bridge decks in earlier studies (Freyermuth et al., 1970, Madanat and Ibrahim, 1995, Madanat et al., 1995). Interestingly, bridge decks on structures servicing secondary routes were found to consistently deteriorate at a slightly slower rate than those on interstate, urban, and primary routes. A lower rate of deterioration associated with State System 2 was also observed in an earlier study conducted on North Carolina bridges and is most likely attributable to the lower traffic volumes on secondary roads (Abed-Al-Rahim and Johnston, 1991). However, in the current study the opposite effect was identified for superstructure and substructure components, which, with the exception of concrete superstructures and substructures, were found to exhibit faster rates of deterioration in State System 2. A similar observation was previously made for prestressed concrete decks in North Carolina and was attributed to the potential variations in the design of prestressed concrete structures for low-volume routes (Abed-Al-Rahim and Johnston, 1991). An increased deterioration rate for concrete bridge decks located on secondary highways relative to interstates was also observed in another state, where the observation was attributed to lower design requirements and maintenance standards on secondary roads (Mauch and Madanat, 2001, Mishalani and Madanat, 2002).

The remaining covariates of ADT and ADTT are found to exhibit little or no average effect on deterioration rates of the bridge component ratings. Given the *a priori* classification used currently in the protocol for developing deterministic deterioration models for the NDOT BMS, it is important to emphasize the near absence of ADT as an explanatory factor with significant effect on the hazard rates in the proportional hazards models. This finding was not unexpected given the nature of the deterministic deck deterioration models, presented in Figure B.1, which generally indicate that the use of ADT as a pre-classifier for the deterioration models leads to poor development of independent models that clearly distinguish significant factors affecting deterioration. The lack of ADT as a significant factor in the deterioration models developed by proportional hazards regression serves to support the validity of the developed framework and illustrate the benefit offered by the multivariate regression technique in identifying and incorporating the most significant external factors.

The general consistency and presence of clear trends exhibited by the weighted mean covariate hazard ratios across the different components and different material types serves to support the plausibility of the results generated by the proportional hazards-based deterioration modeling framework. Furthermore, the plausibility of the general effects and trends of these effects across the different material types and components is well supported by prior literature.

3.3.4 Simplified Probabilistic Models

In developing proportional hazards probabilistic deterioration models, it was noted that hazard ratios associated with typical significant explanatory factors were often quite close to 1. Since the effect of these hazard ratios on the stay-the-same transition probabilities is based on raising the transition probability to the power of the hazard ratio, there is some likelihood that the actual effect of explanatory factors on the probabilistic prediction model is actually quite small and may not significantly affect the predictive fidelity of the probabilistic deterioration models. In this research project, the research team performed model assessment (detailed in the next subsection of the report), which revealed that simplified probabilistic deterioration models could achieve similar improvements in accuracy and precision as developed through use of the more advanced proportional hazards deterioration models. This suggests that, while the proportional hazards models due offer useful insight into the factors influencing deterioration rates over the service life of individual bridge components and do significantly improve the statistical fit of the regression model, the granularity of bridge component condition rating data may not warrant such an advanced prediction tool. Instead, simplified probabilistic models that are very simple to implement could be used in place of the advanced proportional hazards models for bridge component condition rating forecasts. However, the methodology developed for proportional hazards regression should be revisited when sufficient element level condition rating data is available since such element-level ratings will not suffer from the same granularity issues as component ratings and therefore the methodology may out-perform simplified prediction tools.

The simplified probabilistic deterioration models developed in this project use the same maximum partial likelihood estimator to account for the effects of censoring on condition rating duration data. Likewise, the transition probabilities are derived through construction of non-parametric survival functions, in this case using the empirical Kaplan-Meier estimator, to incorporate probabilities into the prediction model. However, for these simplified probabilistic models, the effects of explanatory factors are no longer explicitly incorporated into the model. Instead, the deterioration model developed is common to all of the bridge components in the classification used to develop the model through statistical regression. Since the simplified probabilistic deterioration model does not incorporate the proportional hazards assumptions, the model takes the form of a stationary Markov-chain. In other words, the transition probability matrix for the condition rating predictions reduces to the form:

$$P = \begin{bmatrix} P_{99} & 1-P_{99} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & P_{88} & 1-P_{88} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & P_{77} & 1-P_{77} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & P_{66} & 1-P_{66} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & P_{55} & 1-P_{55} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & P_{44} & 1-P_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

In this research program, simplified probabilistic deterioration models were developed for each bridge component after first pre-classifying the components by material type. This strategy follows an assumption that deterioration rates are most significantly affected by the material type, as deterioration of different materials are often driven by different mechanisms or affected by common mechanisms at the same rate. The stay-the-same transition probabilities required to implement these simplified probabilistic models are presented in Table 3.14.

Table 3.14: Simplified Kaplan-Meier probabilistic deterioration models

	P_{99}	P_{88}	P_{77}	P_{66}	P_{55}	P_{44}	P_{33}	P_{22}	P_{11}
Timber Deck	0.5937	0.8346	0.9380	0.9149	0.9454	0.9800	0.75	0.75	1
Concrete Deck	0.9468	0.9292	0.9622	0.9341	0.9837	0.9931	0.75	0.75	1
Steel Deck	0.8703	0.9399	0.9203	0.9007	0.9633	0.9891	0.75	0.75	1
Timber Substructure	0.7205	0.8733	0.9124	0.8969	0.9391	0.9771	0.75	0.75	1
Concrete Substructure	0.9810	0.9449	0.9622	0.9352	0.9803	0.9912	0.75	0.75	1
Steel Substructure	0.9685	0.9460	0.9599	0.9075	0.9753	0.9899	0.75	0.75	1
Prestressed Concrete Substructure	0.8942	0.9615	0.9513	0.9179	0.9744	0.9924	0.75	0.75	1
Timber Superstructure	0.5488	0.8356	0.9490	0.9062	0.9646	0.9779	0.75	0.75	1
Concrete Superstructure	0.9000	0.9198	0.9637	0.9388	0.9740	0.9892	0.75	0.75	1
Steel Superstructure	0.9666	0.9211	0.9494	0.9229	0.9572	0.9818	0.75	0.75	1
Prestressed Concrete Superstructure	0.9577	0.9361	0.9698	0.9125	0.9646	0.9866	0.75	0.75	1

3.4 Model Assessment and Comparison of Predictive Fidelity of Deterministic and Probabilistic Models

The primary objective of deterioration modeling is to predict future condition ratings of bridge components, which is critical to the accurate identification of MR&R projects within the network analysis tools used for data-driven transportation planning in the BMS. In order to compare and contrast the accuracy and precision of the deterioration models developed in this research program, model assessment was performed using a select 10 year time period of condition rating data extracted from the NCDOT historical bridge management database. Ideally, model assessment should be performed using data independent from the records used to develop the statistical models. However, due to the rate of collection of bridge condition rating data, assessment of the predictive fidelity of the developed deterioration models to future response data is not possible for several years. Consequently, past data was used for the assessment results presented in this report, with the period of bridge inspection records from 2000 to 2010 being used as the source. This data was subject to a pre-filtering algorithm to remove obvious cases where the deterioration model forecasts are not applicable, such as when a structure was replaced during this period, where data was not available for the entire duration of the observation period, or when reconstruction improved the condition ratings at any point over the observation period. Likewise, if the condition rating decreased by more than one rating over a single inspection cycle, then the data was likewise treated as anomalous and removed from the dataset used for the model assessment. This data preprocessing aims to reduce the dataset used for model assessment to only those structures exhibiting typical deterioration under either natural conditions or routine maintenance actions that do not improve the condition ratings.

In performing the model assessment, the condition ratings at 2000 were input to the deterioration models along with the duration already spent by the bridge component at that condition rating in order to incorporate that duration into the predictions generated by the respective deterioration models. Through this measure, the fact that a bridge that has already spent 10 years in a particular condition rating is more likely to deteriorate to a lower rating than one that has only spent a single year is incorporated into the model forecasting. The research team assessed model predictive accuracy for all of the different bridge component models; the results from the concrete deck deterioration models will be presented here because bridges with concrete decks represent a large percentage of the statewide inventory. The results and conclusions drawn from model assessment using data from other bridge components and material types was strongly consistent with those reflected in the following concrete deck analysis. A total of 6,104 bridge records for concrete decks remained after the pre-filtering algorithm was applied to the extracted 2000-2010 condition rating data. Statistics of this data, including the initial deck condition rating at 2000, the change in condition rating over the 10 year period, and the pre-existing durations that the decks had already experienced at the initial condition rating are presented in Figure 3.5. As can be seen in the histograms, the initial condition ratings at 2000 are fairly normally distributed between ratings 4 through 9 with the majority of decks rated either 6 or 7. By the end of the ten year observation period, roughly 63% of the records experienced no net change in condition rating, 32% decreased by 1 rating, 5% decreased by 2 ratings, and less than 0.4% decreased by 3 ratings.

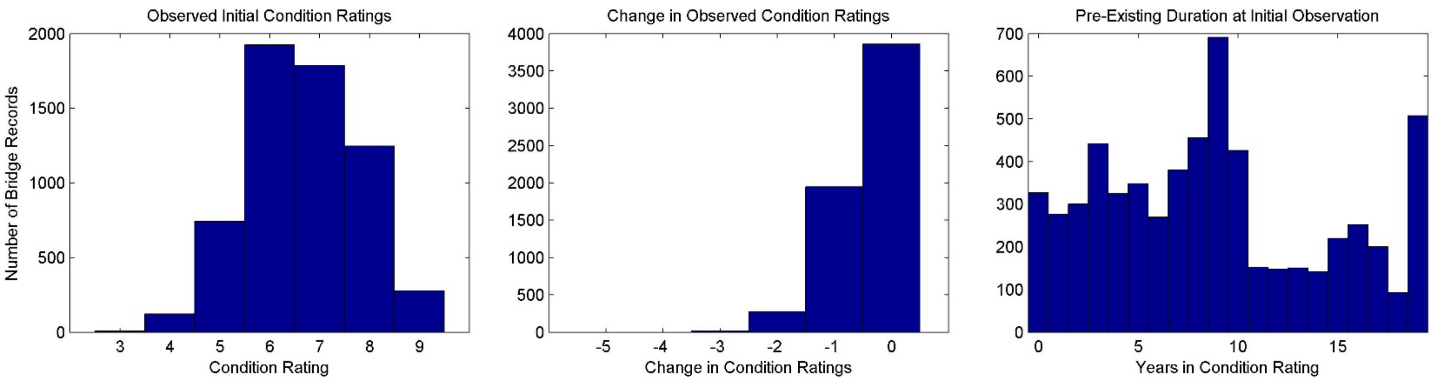


Figure 3.5: Characteristics of 2000-2010 concrete deck condition rating data used for model assessment

Assessment of the predictive accuracy of the current deterministic deterioration models (those developed in RP 2001-18), the deterministic deterioration models updated in this project, and the stationary proportional hazards-based probabilistic deterioration models developed in this study was performed. For each model, the initial condition rating and pre-existing duration at 2000 for each of the 6,104 concrete deck records were passed to the deterioration model with the bridge characteristic required for pre-classification and the predicted condition rating at 2010 was compared to the actual recorded condition rating from the NCDOT BMS database. Note that in applying the probabilistic deterioration models, the initial state vector probabilities were established at the transition between condition ratings and the probability was split 50/50 between the initial condition rating and the next higher rating (with the exception of components in rating 9, where the probability of the initial condition rating being 9 was set to 1). Improvements in predictive accuracy obtained through this approach were discovered empirically, but were later reasoned to be linked to the integer scale used by condition ratings, which differs from the floating point precision offered by the expected value computed in the probabilistic models.

Histograms of the prediction errors obtained from each model are presented in Figure 3.6. These results confirm the suspicion of Structures Management Unit analysts that the current deterministic deterioration models provide overly-conservative estimates of deterioration. For this case, the current deterministic deterioration models over-predict the change in condition rating by 2.46 condition ratings on average over this ten year period. The distribution of prediction errors obtained from the updated deterministic deterioration models reveals that the accuracy is improved, but the new deterministic models are still very conservative as they over-predict the change in condition ratings by 1.66 on average over the same period. However, the probabilistic deterioration models developed through the proportional hazards-based methodology developed in this research project are found to greatly improve the prediction accuracy, as the average prediction error is reduced to only -0.49 condition ratings, which is below the +/-1 integer precision of the condition rating scale. Furthermore, as reflected in the dispersion of the prediction errors and standard deviations presented across the three models, the probabilistic model yields significantly improved precision, as the spread in prediction errors is very tight around the mean for this model.

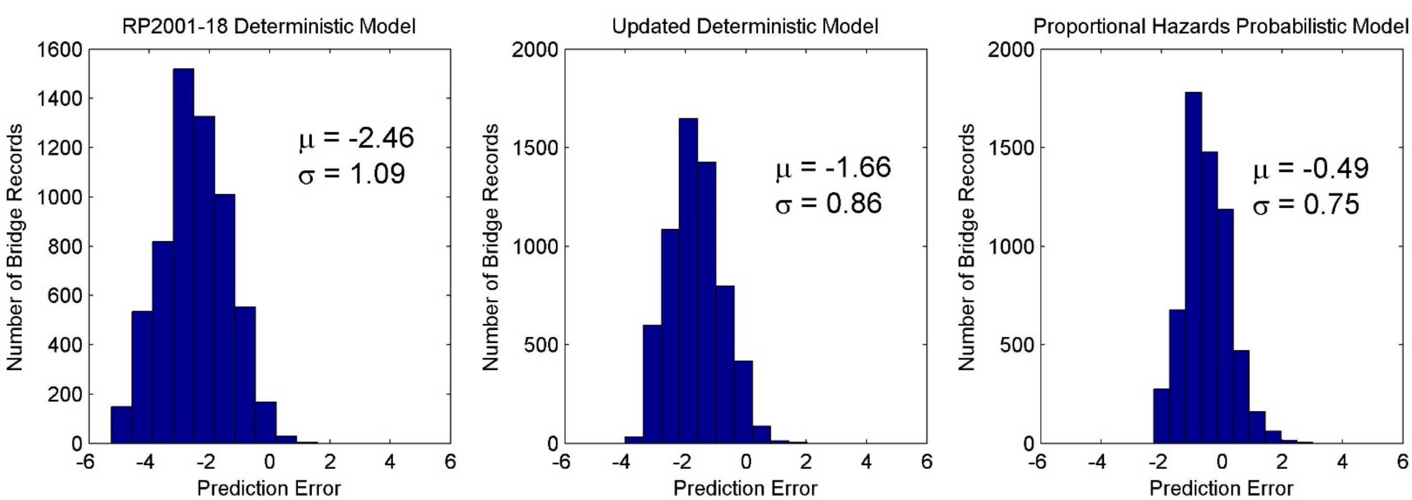


Figure 3.6: Comparison of prediction errors obtained from deterministic and probabilistic deterioration models

To further qualify the improvement offered by adopting the probabilistic deterioration models over the deterministic approach, empirical cumulative distribution functions were developed for the prediction errors developed with each model (Figure 3.7). These cumulative distribution functions allow for determination of the probability that each model will produce a prediction within a prescribed tolerance on the actual rating. Since condition ratings are integer values and since the accuracy of the actual condition rating is commonly taken as +/-1 rating, this measure was used to characterize the performance of the different deterioration models. The empirical cumulative distribution function for the deterministic deterioration model reveals that this model will only produce a prediction within +/-1 of the actual concrete deck condition rating about 22% of the time after 10 years. In contrast, the probabilistic deterioration model is able to achieve a prediction within +/-1 condition rating of the actual about 72% of the time. Clearly, the probabilistic model significantly out-performs the deterministic models and should be favored for implementation in the NCDOT BMS due to the significant improvement in prediction accuracy and precision.

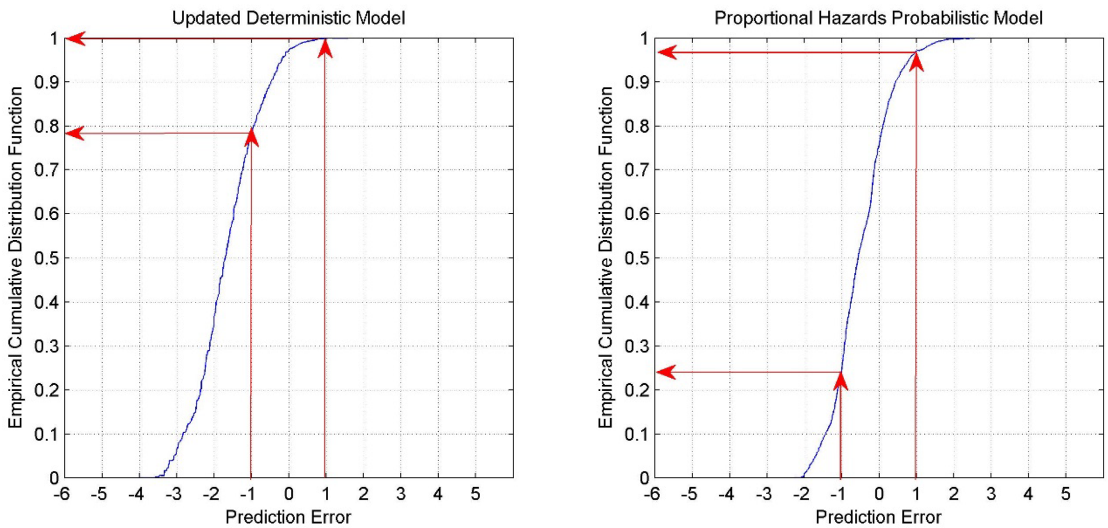


Figure 3.7: Empirical cumulative distribution functions used to assess prediction accuracy

As previously explained, the reasons for the improved performance of the probabilistic deterioration models relative to the deterministic deterioration models are the ability to account for the large degree of censoring in the condition rating data and the better statistical performance on non-normally distributed duration data. Additionally, the proportional hazards-based probabilistic models incorporate the effects of many more external factors than the limited tiers of classifiers used in the deterministic models provide. To explore the extent that the prediction accuracy is improved by the inclusion of the effects of external factors with hazard ratios, the research team compared the performance of the proportional hazards-based probabilistic deterioration models to a simplified probabilistic model that uses a stationary transition probability matrix without hazard ratios. This simplified model was developed using the Kaplan-Meier empirical estimator, which accounts for censoring in developing a survival function similar to proportional hazards models with the exception that covariates are not included in the model. This simplified model was developed using concrete deck condition rating data and develops a single, common model for all concrete decks. Comparison between the previously presented prediction errors developed using the proportional hazards probabilistic model and the prediction errors developed when using the simplified probabilistic model are shown in Figure 3.8. The results indicate that, in this case, the simplified model actually performs slightly better than the full proportional hazards model in terms of accuracy, precision, and portion of estimates that are correct within +/-1 condition rating, despite the fact that this simplified does not explicitly account for external factors beyond the material and component type. This suggests that the improvements relative to the deterministic models can be attributed to the nature of how the probabilistic models handled the condition rating data and account for censoring, more so than the ability to discriminate external effects on deterioration rates. The research team also believes that this reflects that the granularity of component condition rating data is too coarse to adequately reflect the effects of most geographic, design, and functional features on deterioration rates. However, it should also be emphasized that the proportional hazards deterioration model produces more normally distributed prediction errors, so it does better fit the underlying data than the simplified model, which produces a slightly skewed prediction error distribution. Furthermore, as sufficient element-level condition rating data becomes available to permit statistical regression, the developed proportional hazards technique may offer important advantages over the simplified probabilistic models.

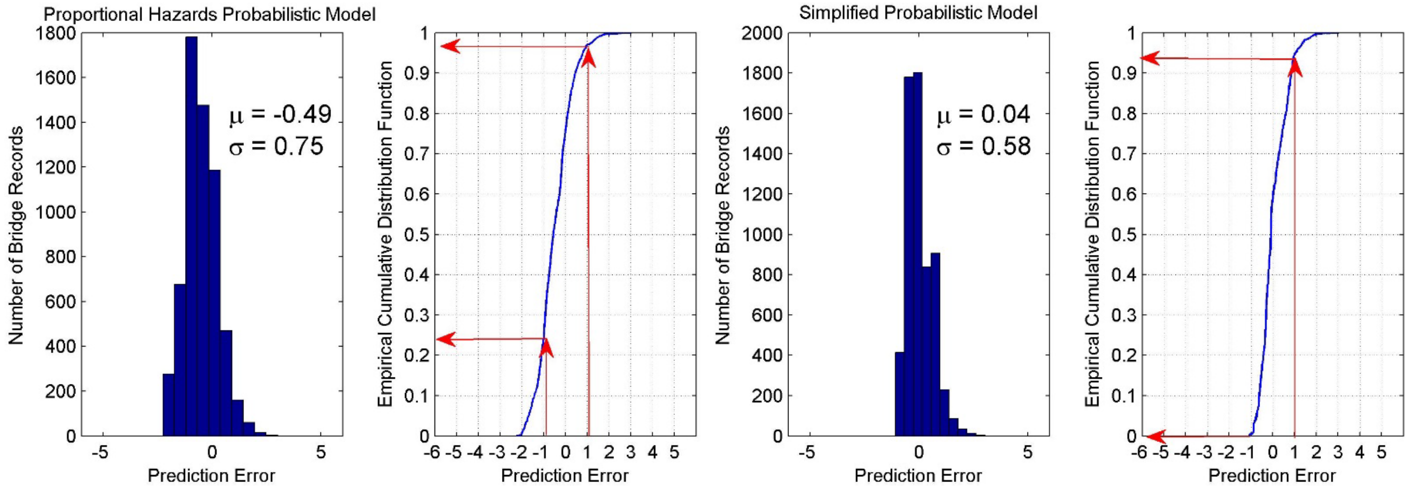


Figure 3.8: Comparison in prediction errors between proportional hazards and simplified probabilistic deterioration models

To further investigate the differences in performance amongst the deterioration models, analysis was performed using data from a 5-year period (2000-2005), a 10-year period (2000-2010), a 15-year period (2000-2015), and a 20 year period (1995-2015). The results are presented in Figure 3.9 and reveal important information on the performance of the individual deterioration models. First, the histograms of prediction errors from the deterministic deterioration models illustrate that the magnitude of the prediction errors grows as the planning horizon is increased, which confirms the overly-conservative nature of both the models currently used in the BMS and the updated deterministic deterioration models. Important differences between the performance of the proportional hazards probabilistic model and the simplified probabilistic model are also revealed in this analysis, although these differences are less obvious at first inspection. Foremost, it is important to recognize that the mean error in the proportional hazards probabilistic model remains nearly constant regardless of the length of the planning horizon. Furthermore, the fraction of predictions with essentially no prediction error increases as the length of the planning horizon is increased. This provides strong evidence of the enhanced predictive fidelity of the proportional hazards prediction models relative to the other modeling strategies examined. Furthermore, the mean error is slightly conservative (less than 0), which is desirable in condition rating forecasts since it provides improved likelihood that components most likely to need maintenance action will be identified in advance. In contrast, the mean error in the simplified probabilistic deterioration model tends to increase and become unconservative as the planning horizon is increased. Furthermore, when using the simplified probabilistic deterioration model, a greater percentage of positive prediction errors occurs as the planning horizon increases. These positive prediction errors correspond to cases where the actual recorded deterioration was more severe than predicted by the simplified probabilistic model. Consequent to these differences, this analysis supports a preference for the use of the proportional hazards probabilistic deterioration models over the simplified probabilistic deterioration models. Furthermore, regardless of whether proportional hazards or simplified probabilistic models are adopted, either probabilistic model provides improved accuracy and precision relative to the currently used deterministic deterioration modeling strategy.

At the initiation of the project, the team proposed comparing the output of deterministic bridge deterioration models with individual bridge lifecycle performance as predicted by the mechanistic modeling software packages Life365 and STADIUM. Both packages would primarily be useful in verifying the deterioration models for concrete components, as they primarily model chloride induced damages. The most advanced (and complex) of these software packages is STADIUM. Although STADIUM utilizes state-of-the practice techniques in its modeling, the software requires detailed concrete material inputs that are costly to obtain for even a single bridge, as they require coring and laboratory evaluation. In conversation with STADIUM technicians, the research group identified that the most appropriate way to evaluate this software would be to use a case study of the Wright Memorial Bridge that was recently completed by NCDOT and includes an existing bridge model in STADIUM. In order to compare mechanistic bridge deterioration model output with actual bridge condition, however, the effect of bridge maintenance to condition ratings needed to be evaluated, spurring the analysis presented subsequently in Section 3.7. Further investigation on use of mechanistic models to validate the deterioration models developed as part of this work was not performed due to the limitation of these mechanistic models to concrete components, and the cost for acquisition of the materials performance data required by the software.

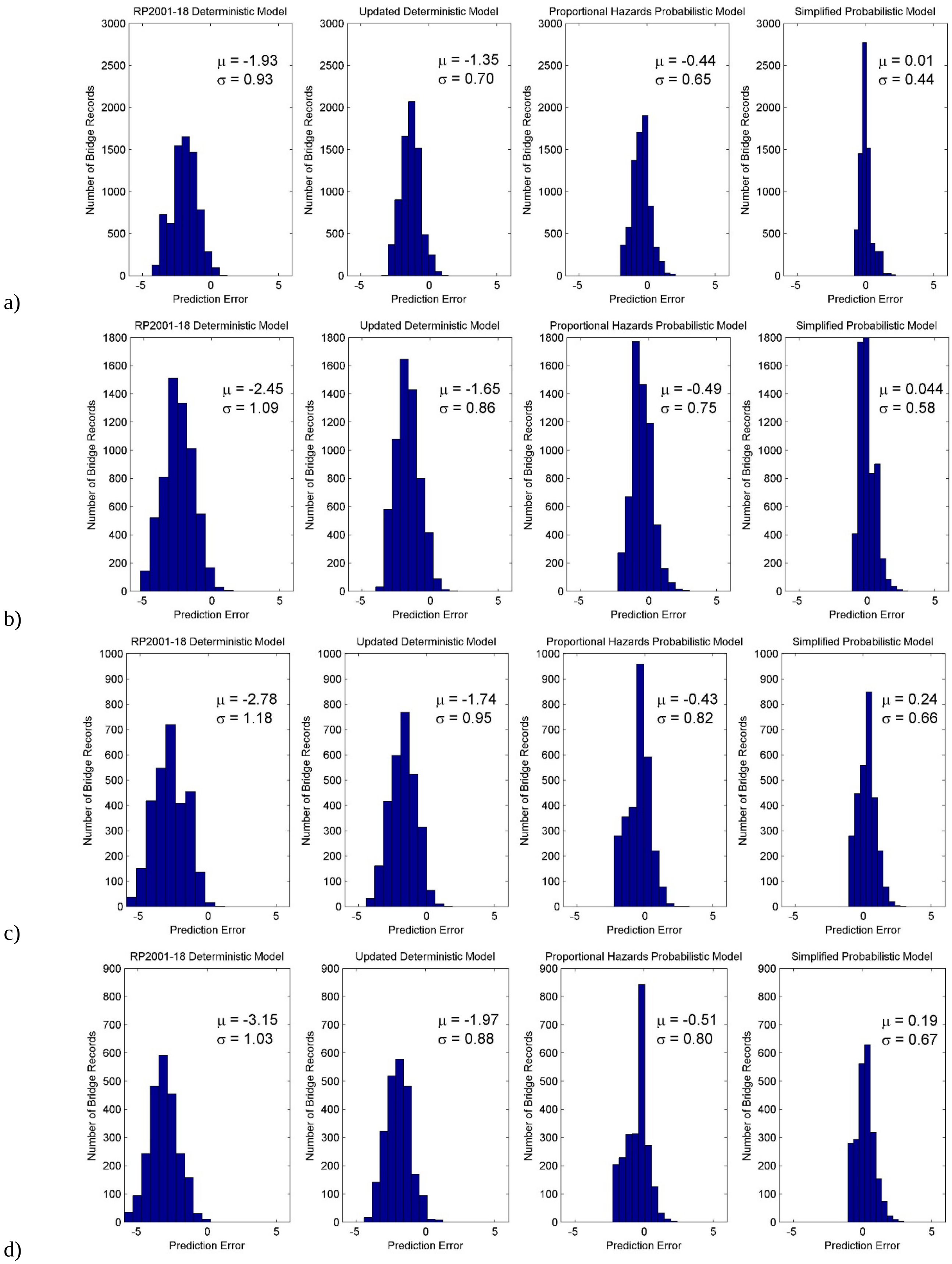


Figure 3.9: Comparison of prediction errors in concrete deck deterioration models over a) 5-year prediction (2000-2005); b) 10-year prediction (2000-2010); c) 15-year prediction (2000-2015); d) 20-year prediction (1995-2015)

3.5 Development of NBI Culvert Deterioration Models

Although the development of deterioration models for NBI culverts was not part of the original project scope, early discussions with the Steering and Implementation Committee revealed the desire for culvert deterioration models that would enable the use of network analysis for culvert MR&R planning. Consequently, the research team developed both deterministic and simplified probabilistic deterioration models for NBI culverts using the same strategies employed for bridge component deterioration modeling.

Preliminary assessment of pre-classification strategies for NBI Culvert deterministic deterioration models was performed using a single tier classification hierarchy due to the limited number of culverts in the statewide inventory relative to bridges. This preliminary assessment has led to the recommendation that the main material type be used as the pre-classifier for culverts. This classifier produced the best spread in the models and is consistent with the strategy employed in the bridge deterministic deterioration models, where the first tier of classification is based on material type. The vast majority of NBI culverts in the NCDOT inventory are classified with either concrete continuous or steel as the main structural material (Figure 3.10), however sufficient data exists to develop deterministic deterioration models for NBI culverts classified with concrete, prestressed concrete, aluminum/wrought iron/cast iron, or other as the main structural material.

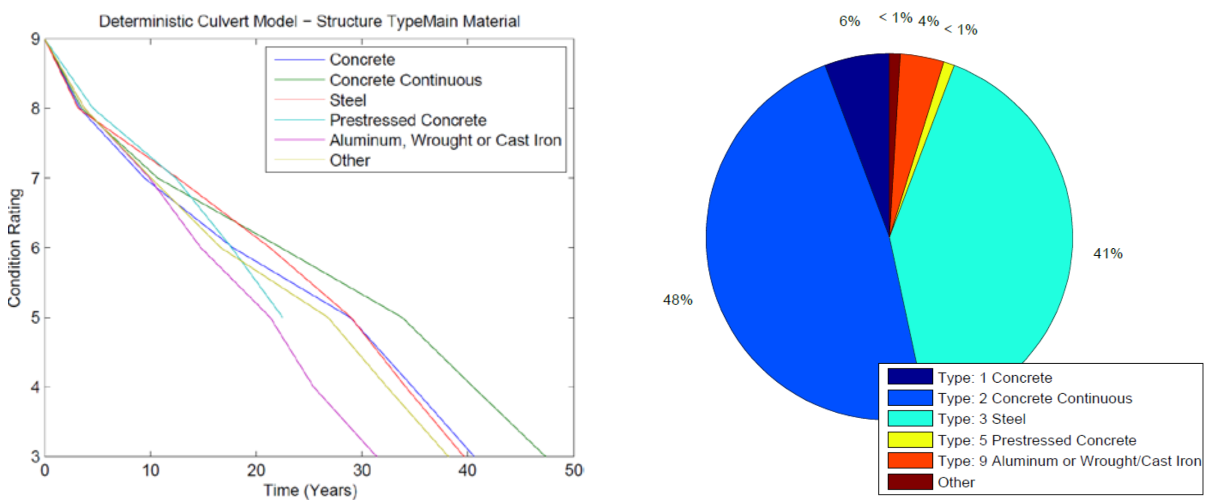


Figure 3.10. Deterministic deterioration models developed for NBI culverts and distribution of culvert types in NC

Table 3.15: Deterministic deterioration models for NBI culverts developed from 1981-2015 data

Culvert Material	9	8	7	6	5	4	Total Years
Concrete	3.3	6.1	8.3	11.1	5.9	5.8	40.5
Concrete Continuous	3.5	7.2	11.6	11.5	6.7	6.9	47.4
Steel	3.2	9.4	8.7	7.7	5.2	5.5	39.7
Prestressed Concrete	4.6	7.8	5.3	4.9	-	-	-
Aluminum, Wrought or Cast Iron	3.8	6.2	4.8	6.5	4.1	6.0	31.4
Other	3.8	6.3	6.6	10.1	5.6	5.8	38.2

As revealed in the model assessment routine applied to the bridge condition data, the accuracy and precision of deterministic deterioration models is severely limited due to the effects of censoring and the non-normal distribution of condition rating durations. The deterministic deterioration models for NBI culverts were provided above only because the the AgileAssets BMS currently does not support the implementation of Markov-chain probabilistic deterioration models. However, if this feature is added to the AgileAssets platform, a probabilistic deterioration model should be used to realize the benefits of improved prediction accuracy and precision. The stay-the-same transition probabilities developed for a stationary simplified probabilistic model for NBI culverts developed from 1981-2015 culvert condition rating data is presented in Table 3.16.

Table 3.16: Probabilistic deterioration model for NBI culverts

Condition Rating	9	8	7	6	5	4	3	2	1
Stay-the-Same Probability	0.8779	0.9520	0.9648	0.9293	0.9824	0.9876	0.75	0.75	1

3.6 Development of a Stand-Alone Graphical User Interface for Annual Updating of Deterioration Models

To enhance the implementation and technology transfer of research products developed through this project, the research team has packaged the software routines developed over the course of this research effort into a stand-alone graphical user interface software. This software will permit the NCDOT Structures Management Unit to routinely update deterioration models for use in the AgileAssets BMS as new annual bridge records become available. The intent is to provide this capability so that NCDOT can realize increased operational efficiency and cost savings benefits by maintaining accurate prediction models in the BMS at a more frequent interval and without the expense associated with regular research contracts currently used to perform such updates. The research team has developed a comprehensive user manual to accompany this software application, which is included as an appendix to this report. The research team welcomes the opportunity to continue supporting the NCDOT Structures Management Unit by offering technical support for the use of this software.

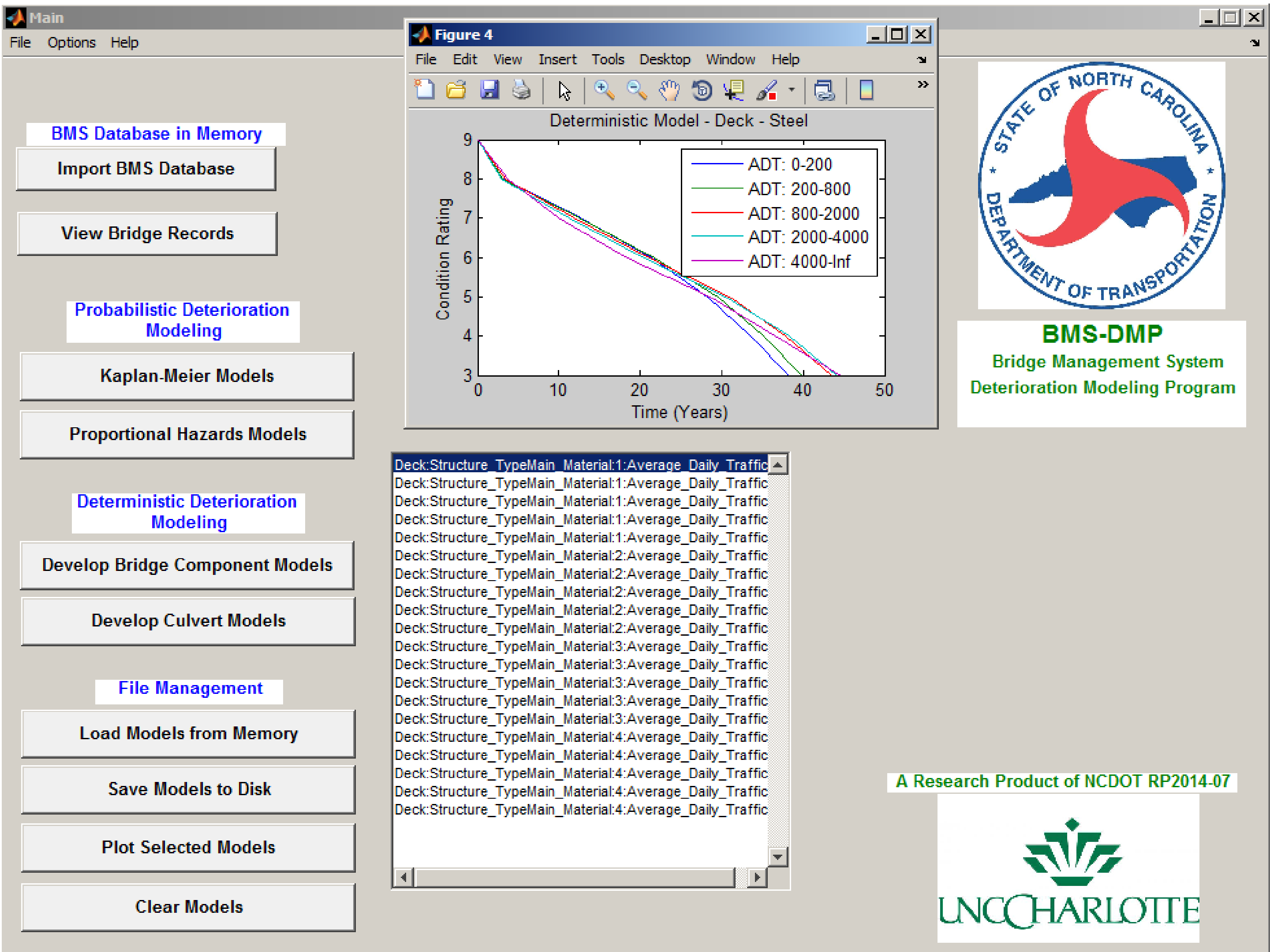


Figure 3.11. Screenshot of developed graphical user interface for deterioration model updating

3.7. Condition Improvement (Action Effectiveness) Models

Currently, the AgileAssets BMS attempts to model the improvement in condition ratings resulting from maintenance action on bridge components. In order to better inform the programming of these condition improvement indexes and explore the use of probabilistic methods of incorporating maintenance actions within forecasting models used in network analysis, the research team analyzed Maintenance Management System (MMS) data alongside the BMS condition rating data. This MMS data was provided to the research team as a spreadsheet containing select maintenance actions performed between 2003 and 2014.

A software routine was developed to correlate recorded maintenance actions with historical condition rating data. This routine matched the structure numbers in the MMS database to those in the BMS records and then extracted four years of deck, superstructure, and substructure condition rating data around the indicated year of maintenance action. This four year period included the year before the maintenance action, the year of the maintenance action, and the two years following maintenance action. This was done in order to minimize errors associated with the timing of the maintenance action and the potential change in condition rating following the next inspection cycle. Since the maintenance action might occur prior to inspection in the same year, the initial condition rating before the maintenance action was calculated as the lower of the condition rating recorded at the year of maintenance action and the condition rating recorded one year prior to the year of maintenance action. Likewise, since inspection in biennial, the condition rating after the maintenance action was determined by taking the maximum of the condition ratings recorded either during the year of maintenance action, one year after the maintenance action, or two years after the maintenance action.

Statistical analysis of the maintenance action data revealed that maintenance actions most frequently occur between condition ratings 4-7. A typical histogram of initial condition ratings during maintenance action is presented in Figure 3.12, which presents deck condition rating data from maintenance action "3325 – Maintain Concrete Deck." Consequent to the distribution of initial condition ratings at the time of maintenance, condition improvement probabilities for select maintenance action were only computed for condition ratings 4 through 7. Histograms of the condition improvement relative to the initial condition rating were developed for the maintenance action, similar to those presented in Figure 3.13 for action 3326. Using these histograms, condition improvement probabilities were computed for each condition rating and presented in tabular form (Table 3.17). These probabilities were used to estimate the expected value (average) condition rating improvement for the maintenance action as a function of the initial condition rating. This value is denoted in the table as "E.V." It should be recognized, however, that the mapping of BMS treatments to MMS work function codes often results in many different treatments being classified with the same MMS work function. For example, BMS treatments "3326 – Maintain Concrete Deck," "DC – Deck Rehabilitation – Deck Overlay (condition rating 4)," "DC – Deck Sealers\Joints (conditions 7-8)," "DC Minor Patching\Crack Sealing (condition 6)," and "DC – Patch Spalls\Epoxy Injection (condition 4)" are mapped to the single MMS work function "3326 – Maintain Concrete Deck." Consequently, the analysis performed has no means of distinguishing these different BMS treatments, which may be major rehabilitation action, minor rehabilitation action, or preservation actions. As a simplified means of distinguishing major repairs from preservation actions, an additional expected value (E^{+}) was computed that did not consider the cases where the condition remained unchanged following maintenance action. This modified expected value estimate could be used as the condition improvement associated with major rehabilitation BMS treatments at the respective condition ratings.

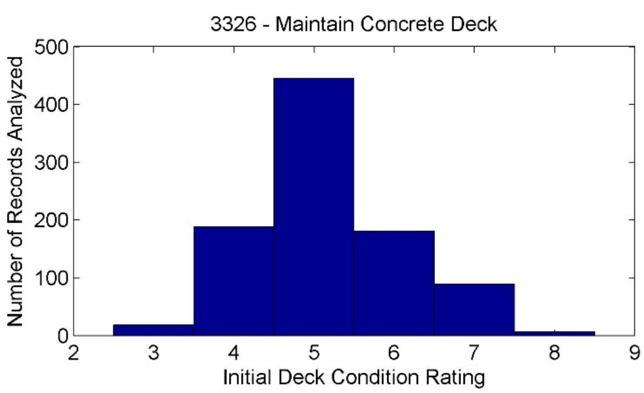


Figure 3.12: Frequency of Action 3326 – Maintain Concrete Deck Applied at Different Condition Ratings

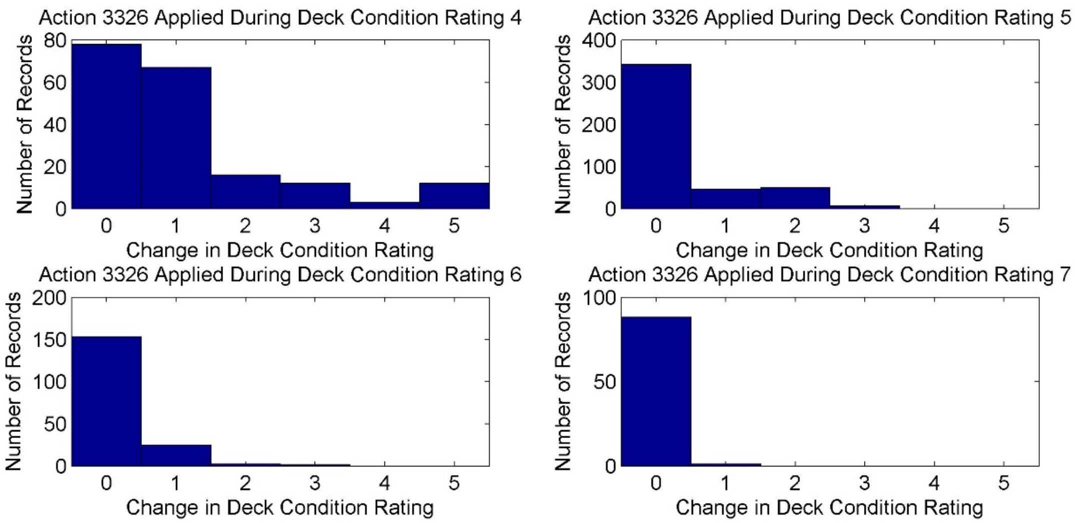


Figure 3.13: Histograms of Historical Condition Improvement following 3326 – Maintain Concrete Deck

Table 3.17: 3326 – Maintain Concrete Deck (1064 Records)

Initial Condition Rating	Distributions						E.V.	E^+
	0	+1	+2	+3	+4	+5		
Condition Rating 4	0.415	0.356	0.085	0.064	0.016	0.064	+1.10	+1.88
Condition Rating 5	0.769	0.106	0.112	0.014	0	*	+0.37	+1.60
Condition Rating 6	0.845	0.138	0.011	0.006	*	*	+0.18	+1.15
Condition Rating 7	0.989	0.011	0	*	*	*	+0.01	*

Analysis of the primary MMS work functions associated with maintenance, repair, and replacement of deck, substructure, and superstructure components are presented in Tables 3.18 through 3.24. Comparison of the condition improvement estimates obtained through this analysis to the current values programmed in the Agile Assets BMS suggest that the NCDOT may be overly optimistic in predicting condition rating improvement afforded by BMS treatments. In particular, many BMS treatments triggered at condition rating 4 have been assigned a condition improvement of +3 in the BMS, however the statistical analysis of past performance suggests that most actions at condition rating 4 have typically achieved just under a +2 improvement in the condition rating of the component subject to the BMS treatment. In order to enhance the agency's ability to establish condition improvements using analysis of past performance, it is recommended that the MMS work functions be expanded to include all BMS treatments to eliminate the mapping that condenses many BMS treatments into the same MMS work function. Alternatively, improved specificity of the maintenance actions actually performed or exploration of ways to incorporate the cost data into the statistical regression could be used to improve the analysis without necessarily changing the mapping of BMS treatments to MMS work functions.

Table 3.18: 3324 – Maintain/Repair/Replace Timber Deck Components (575 Records)

Initial Condition Rating	Distributions						E.V.	E^+
	0	+1	+2	+3	+4	+5		
Condition Rating 4	0.303	0.134	0.067	0.294	0.202	0	+1.96	+2.81
Condition Rating 5	0.505	0.081	0.296	0.086	0.032	*	+1.06	+2.14
Condition Rating 6	0.504	0.354	0.142	0	*	*	+0.64	+1.29
Condition Rating 7	0.940	0.060	0	*	*	*	+0.06	*

Table 3.19: 3344 – Repair/Replace Timber Substructure Components (1211 Records)

Initial Condition Rating	Distributions						E.V.	E^+
	0	+1	+2	+3	+4	+5		
Condition Rating 4	0.590	0.254	0.037	0.077	0.033	0.009	+0.74	+1.80
Condition Rating 5	0.816	0.093	0.065	0.015	0.011	*	+0.31	+1.70
Condition Rating 6	0.864	0.097	0.039	0	*	*	+0.18	+1.29
Condition Rating 7	0.970	0.030	0	*	*	*	+0.03	*

Table 3.20: 3348 – Maintain Concrete Substructure Components (818 Records)

Initial Condition Rating	Distributions						E.V.	E^+
	0	+1	+2	+3	+4	+5		
Condition Rating 4	0.423	0.423	0.080	0.029	0.022	0.022	+0.87	+1.51
Condition Rating 5	0.752	0.185	0.054	0.010	0	*	+0.32	+1.30
Condition Rating 6	0.829	0.147	0.023	0	*	*	+0.19	+1.14
Condition Rating 7	0.969	0.031	0	*	*	*	+0.03	*

Table 3.21: 3354 – Maintain Steel Substructure Components (145 Records)

Initial Condition Rating	Distributions						E.V.	E^+
	0	+1	+2	+3	+4	+5		
Condition Rating 4	0.638	0.255	0.064	0	0.021	0.021	+0.57	+1.58
Condition Rating 5	0.846	0.135	0.019	0	0	*	+0.17	+1.12
Condition Rating 6	0.905	0	0.095	0	*	*	+0.19	*
Condition Rating 7	1.0	0	0	*	*	*	0	*

Table 3.22: 3304 – Maintain/Replace Timber Superstructure Components (422 Records)

Initial Condition Rating	Distributions						E.V.	E^+
	0	+1	+2	+3	+4	+5		
Condition Rating 4	0.235	0.341	0.141	0.235	0.047	0	+1.52	+1.98
Condition Rating 5	0.754	0.143	0.064	0.034	0.005	*	+0.39	+1.60
Condition Rating 6	0.793	0.196	0.011	0	*	*	+0.22	+1.05
Condition Rating 7	1	0	0	*	*	*	0	*

Table 3.23: 3306 – Maintain Concrete Superstructure Components (651 Records)

Initial Condition Rating	Distributions						E.V.	E^+
	0	+1	+2	+3	+4	+5		
Condition Rating 4	0.343	0.434	0.091	0.071	0.061	0	+1.07	+1.63
Condition Rating 5	0.783	0.141	0.051	0.022	0.004	*	+0.33	+1.49
Condition Rating 6	0.832	0.150	0.019	0	*	*	+0.19	+1.11
Condition Rating 7	0.985	0.015	0	*	*	*	0.02	*

Table 3.24: 3314 – Maintain Steel Superstructure Components (886 Records)

Initial Condition Rating	Distributions						E.V.	E^+
	0	+1	+2	+3	+4	+5		
Condition Rating 4	0.537	0.270	0.031	0.093	0.050	0.019	+0.91	+1.96
Condition Rating 5	0.781	0.099	0.086	0.034	0	*	+0.37	+1.70
Condition Rating 6	0.829	0.124	0.038	0.01	*	*	+0.23	+1.34
Condition Rating 7	0.948	0.013	0.039	*	*	*	+0.09	*

As an improvement to using a fixed condition improvement index to predict the effect of maintenance action on the condition rating of bridge components, the action effectiveness could be accounted for using a probability of condition improvement in the transition probability matrix. To incorporate the typical improvements in condition rating associated with maintenance, the transition probability matrix could be expanded to

$$P = \begin{bmatrix} P_{99} & P_{98} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & P_{88} & P_{87} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & P_{78} & P_{77} & P_{76} & 0 & 0 & 0 & 0 & 0 \\ 0 & P_{68} & P_{67} & P_{66} & P_{65} & 0 & 0 & 0 & 0 \\ 0 & P_{58} & P_{57} & P_{56} & P_{55} & P_{54} & 0 & 0 & 0 \\ 0 & P_{48} & P_{47} & P_{46} & P_{45} & P_{44} & P_{43} & 0 & 0 \\ P_{39} & 0 & 0 & 0 & 0 & 0 & P_{33} & P_{32} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & P_{22} & P_{21} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & P_{11} \end{bmatrix}$$

The introduction of new transition probabilities below the main diagonal of the matrix would account for typical maintenance actions applied between condition ratings 4 through 7 and reconstruction performed at condition rating 3. Graphically, the potential condition state transitions represented by this modified transition probability matrix are presented in Figure 3.14. Derivation of the modified transition probabilities would be enabled through the previously generated condition improvement probabilities, as indicated by Table 3.25. However, since the Agile Assets BMS does not yet support the use of probabilistic deterioration models, the research team has not formally investigated the development of such transition probability matrices. If the current BMS is revised to permit the use of preferred probabilistic methods for deterioration modeling, then the research team recommends that further research be performed to integrate the condition improvement, or action effectiveness, probabilities into the transition probabilities of the deterioration models to develop an integrated analysis.

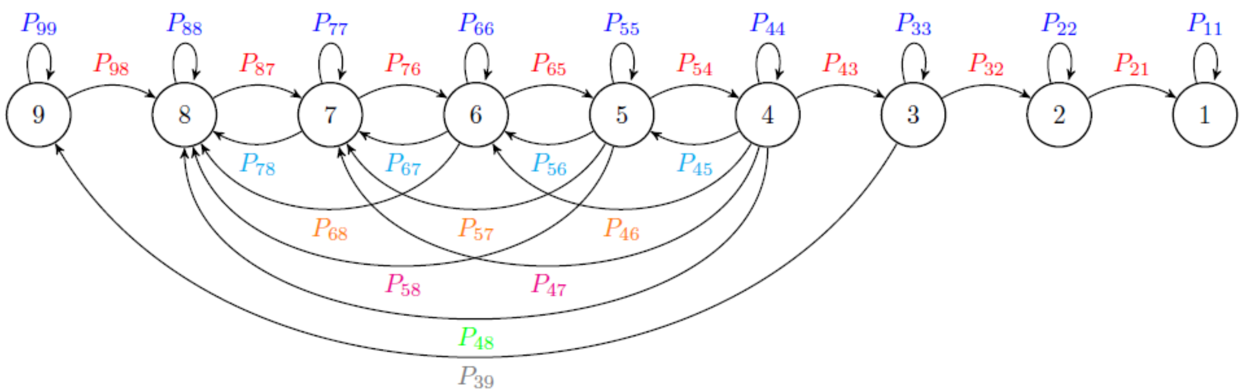


Figure 3.14: Suggested Markov chain probabilistic model modified to include maintenance action in forecasts (suggested future work pending enhancement of BMS to permit probabilistic methods)

Table 3.25: Sourcing condition improvement probabilities from the statistical analysis of past condition rating improvements associated with MMS work function

Initial Condition Rating	Distributions					
	0	+1	+2	+3	+4	+5
Condition Rating 4	I_{44}	I_{45}	I_{46}	I_{47}	I_{48}	*
Condition Rating 5	I_{55}	I_{56}	I_{57}	I_{58}	*	*
Condition Rating 6	I_{66}	I_{67}	I_{68}	*	*	*
Condition Rating 7	I_{77}	I_{78}	*	*	*	*

3.8 Summary of Key Recommendations for Deterioration Modeling in the NCDOT BMS

The research on deterioration modeling performed during this project revealed that deterministic deterioration models have been replaced by probabilistic models in many state and Federal BMS systems. Consequently, after updating the conventional deterministic models, a unique statistical regression methodology that applies survival analysis with a proportional hazards model was developed to provide a means of developing transition probability matrices for probabilistic deterioration models while accounting for the effects of design, geographic, and functional characteristics on bridge component deterioration rates. This model was found to provide significantly improved prediction accuracy and precision over typical network analysis planning horizons. However, while this advanced model was found to best fit the historical condition rating data and provide unique insight on factors influencing deterioration over the life-cycle of each bridge component, it was also discovered that a simplified implementation of the probabilistic deterioration model was able to achieve similar performance without rigorously incorporating the effects of external factors on deterioration rates. Consequent to the main findings of this component of the research, the following key recommendations for implementation are provided:

- Priority should be placed on implementing probabilistic deterioration models in the AgileAssets BMS using the Markov-chain approach. Since the proportional hazards-based probabilistic deterioration models provide the best statistical fit to the historical data, remain accurate yet slightly conservative over both short-term and long-term planning horizons, and reveal important insight on the key factors that affect deterioration of different bridge components, consideration should be given to incorporating the capability to perform deterioration forecasts with these models in the AgileAssets BMS. Additionally, these models are expected to be more powerful as element-level condition rating data becomes available in the BMS and therefore it is recommended that the full proportional hazards models be implemented to support longer-term improvements to the BMS. However, the research results also indicate that simplified probabilistic models are likely to provide improvements in accuracy and precision similar to proportional hazards probabilistic models for moderate planning horizons but with easier implementation/minimal programming requirements.

- In the interim before such methods are permitted in AgileAssets, the Structures Management Unit should use the updated deterministic deterioration models. However, model assessment performed in this study indicates that these deterministic deterioration models are still overly conservative and lack the precision offered by the improved probabilistic methods.

- Deterioration models should be updated on a more frequent basis to take full advantage of the value of the historical condition rating database. The stand-alone graphical user interface developed through this research effort provides a means for NCDOT to update either the deterministic or probabilistic deterioration models without having to contract research universities or independent consultants. This will allow NCDOT to focus future research efforts on improving the BMS as element-level data becomes available, rather than simply updating component deterioration models.

- As an improvement to using a fixed condition improvement index to predict the effect of maintenance action on the condition rating of bridge components, the action effectiveness could be accounted for as a probability of condition improvement in the transition probability matrix. If the current BMS is revised to permit the use of preferred probabilistic methods for deterioration modeling, then the research team recommends that further research be performed to integrate the condition improvement, or action effectiveness, probabilities into the transition probabilities of the deterioration models to develop an integrated analysis.

4. USER COST INPUTS

User costs are computed in the BMS as outlined in Section 2.3, in accordance with Equation 2.16. To update and enhance user cost predictions, more appropriate sources of input data used in several main components of Equation 2.16 were identified, and potential improvements to prediction models were developed. These improvements include updates of the ADT growth rates, updates to user cost prediction models for detours resulting from bridge capacity and vertical clearance limits, updates to the model utilized to forecast bridge-related accidents, and cost input values associated with both operating costs (due to detours) and accident costs. To develop these suggested improvements, relevant data from a number of sources were examined and utilized as described in the subsequent sections of this report. Much of this data was specific to North Carolina, available from several divisions of NCDOT including Traffic Engineering, Division of Motor Vehicles (DMV), and the Traffic Survey group. When data from North Carolina was not available, efforts were made to identify and analyze regional data, if possible. For cost values that could not be obtained in current (2014) cost figures, the Consumer Price Index (CPI) was used to adjust the most recently available cost to 2014 adjusted cost.

4.1 Average Daily Traffic and Growth Rates

The expected ADT growth rate is an input in the BMS that is used to predict the future ADT for user costs estimates in optimization scenarios. ADT growth rates currently utilized in NCDOT's BMS were identified as outlined in Section 2.3. These ADT growth rate values were primarily developed using traffic data from the Bridge Management Inventory File (BMIF) from 1991 to 2000, and were subsequently adjusted based upon expert opinion (Duncan and Johnston 2002). As part of the bridge inspection and NBI reporting programs, NCDOT biennially updates the ADT estimate for each bridge. At this point in time, most bridges in the BMS have nearly 30 years of ADT estimates. As part of this work, this extensive historical ADT data was used to compute a new recommended ADT growth rate for each roadway type (Interstate, Arterial, Collector, and Local) in every North Carolina county.

To identify the new recommended ADT growth rates, historical ADT values stored in the BMS for each bridge were compiled into a dataset for analysis. The dataset was screened to remove bridges with partial and non-recent ADT records. Only bridges that had a minimum of ten years of data and also had an ADT value recorded for 2010 or more recent were utilized in the analysis. The ADT for each bridge was plotted against time and an exponential curve was fit to the data. Based on the exponential best fit curve, the average growth rate for each bridge was identified. This percent growth rate was then compiled with the percent growth rate of other bridges in the same counties after grouping the bridges based on one of the four types of roadways. For each roadway type in each county, a histogram was produced so that the distribution of the growth rates could be evaluated and a representative value for the group (roadway type) was identified statistically. Examples of these histograms are provided in Appendix C (Figures C.1 through C.4). Some of these distributions could be visually classified as normally distributed (Figure C.4), while others could not (Figures C.1 through C.3). Also provided in Appendix C is a table indicating the number of ADT growth rates used in each roadway grouping by county as well as the distribution type (color coded) to indicate where the data was considered to be well distributed or not well distributed. Due to a number of roadways exhibiting non-normally distributed data, it is recommended that the median, rather than mean, values be used by NCDOT for the ADT growth rate estimate used in the BMS.

The recommended updated ADT growth rates are presented in Table 4.1. Since some counties do not have Interstate or Arterial routes, the statewide average for each respective route type is suggested for use in the BMS as a place holder (denoted as shaded cells in Table 4.1). In the event that these routes are constructed in the future, new ADT growth rates could be developed in a manner similar to the method outlined above as data becomes available.

ADT growth rates have significant influence in forecasting applications. Therefore, the changes in current ADT growth rates values from the previous ADT growth rate values (from Duncan and Johnston, 2002) are of interest. In Table C.2 in Appendix C, the changes in the updated ADT growth rate values relative to the currently utilized values are tabulated by county and roadway type. This information was plotted in a manner that facilitated a geographical overview of the net increase or decrease in the growth rate, shown in Figure 4.1. It can be observed that the ADT growth rates currently used in the BMS are predicting much higher user costs than would be predicted if the updated ADT growth rates are implemented, particularly for interstates in the Charlotte-Triad-Triangle urban corridor. Updated, recommended ADT growth rates for arterial routes tended to be lower than the values currently used in the BMS. For local and collector routes, many ADT growth rates were relatively unchanged from the values currently used in the BMS. Note that for counties without a bridge on an Interstate, a gray color was used in Figure C.2, since only a placeholder value is suggested for use in the NCDOT BMS.

Table 4.1: ADT growth rates suggested for use in BMS

County No.	County Name	Local	Collector	Arterial	Interstate
00	Alamance	2.55%	3.23%	2.30%	6.36%
01	Alexander	2.74%	2.98%	2.27%	3.64%
02	Alleghany	1.79%	2.35%	2.21%	3.64%
03	Anson	1.81%	2.33%	2.00%	3.64%
04	Ashe	1.69%	2.30%	3.82%	3.64%
05	Avery	2.92%	3.79%	1.05%	3.64%
06	Beaufort	2.31%	1.49%	2.45%	3.64%
07	Bertie	2.57%	2.85%	1.71%	3.64%
08	Bladen	2.95%	3.13%	1.43%	3.64%
09	Brunswick	5.26%	3.41%	2.85%	3.64%
10	Buncombe	3.20%	3.92%	3.46%	3.65%
11	Burke	2.60%	4.04%	2.48%	3.64%
12	Cabarrus	4.15%	5.07%	2.96%	4.42%
13	Caldwell	2.44%	2.11%	2.13%	3.64%
14	Camden	1.00%	3.31%	2.22%	3.64%
15	Carteret	0.61%	2.41%	1.74%	3.64%
16	Caswell	1.92%	2.39%	2.91%	3.64%
17	Catawba	3.79%	3.61%	3.38%	3.62%
18	Chatham	2.54%	3.03%	3.06%	3.64%
19	Cherokee	3.29%	2.97%	0.89%	3.64%
20	Chowan	1.57%	1.13%	1.46%	3.64%
21	Clay	3.15%	3.40%	4.21%	3.64%
22	Cleveland	2.63%	2.74%	2.38%	2.26%
23	Columbus	2.12%	2.56%	2.75%	3.64%
24	Craven	2.56%	2.94%	1.74%	3.64%
25	Cumberland	2.46%	2.57%	3.28%	2.34%
26	Currituck	2.67%	2.68%	3.59%	3.64%
27	Dare	6.34%	2.18%	2.28%	3.64%
28	Davidson	2.23%	2.87%	1.61%	2.43%
29	Davie	2.61%	2.88%	2.81%	3.42%
30	Duplin	2.63%	2.59%	0.34%	1.83%
31	Durham	3.08%	4.40%	2.84%	5.56%
32	Edgecombe	1.72%	0.79%	2.38%	3.64%
33	Forsyth	1.87%	2.39%	1.83%	4.52%
34	Franklin	3.55%	3.31%	2.38%	3.64%
35	Gaston	3.83%	3.43%	2.02%	6.60%
36	Gates	0.95%	2.68%	2.33%	3.64%
37	Graham	3.01%	3.68%	2.40%	3.64%
38	Granville	3.29%	4.05%	4.36%	2.96%
39	Greene	2.76%	2.37%	2.91%	3.64%
40	Guilford	2.57%	3.02%	2.31%	3.15%
41	Halifax	1.85%	0.96%	1.17%	2.96%
42	Harnett	3.89%	3.79%	1.92%	2.89%
43	Haywood	3.50%	2.33%	2.76%	2.76%
44	Henderson	4.28%	3.87%	1.67%	3.31%
45	Hertford	1.44%	2.79%	2.25%	3.64%
46	Hoke	2.48%	4.11%	2.90%	3.64%
47	Hyde	1.34%	4.21%	0.18%	3.64%
48	Iredell	3.24%	3.70%	3.58%	3.37%
49	Jackson	2.54%	4.20%	3.42%	3.64%

Table 4.1: ADT growth rates suggested for use in BMS (continued)

50	Johnston	2.78%	3.90%	1.60%	4.46%
51	Jones	2.31%	2.08%	2.07%	3.64%
52	Lee	3.28%	3.22%	3.86%	3.64%
53	Lenoir	1.90%	1.66%	1.51%	3.64%
54	Lincoln	3.36%	3.26%	2.03%	3.64%
55	Macon	2.67%	4.40%	6.07%	3.64%
56	Madison	2.85%	2.95%	4.55%	3.26%
57	Martin	1.75%	2.90%	1.51%	3.64%
58	McDowell	2.33%	1.76%	4.31%	3.28%
59	Mecklenburg	1.49%	4.49%	2.75%	4.87%
60	Mitchell	2.36%	2.12%	2.63%	3.64%
61	Montgomery	1.70%	3.22%	3.39%	4.36%
62	Moore	3.06%	4.37%	2.68%	3.64%
63	Nash	2.70%	3.15%	2.57%	2.96%
64	New Hanover	3.12%	3.66%	2.64%	3.79%
65	Northampton	0.89%	2.02%	0.47%	2.69%
66	Onslow	3.61%	2.74%	1.92%	3.64%
67	Orange	3.82%	3.67%	2.12%	2.57%
68	Pamlico	1.77%	3.17%	2.40%	3.64%
69	Pasquotank	2.81%	2.44%	1.35%	3.64%
70	Pender	2.61%	3.75%	2.40%	4.63%
71	Perquimans	2.14%	1.61%	2.16%	3.64%
72	Person	3.16%	2.90%	2.77%	3.64%
73	Pitt	1.78%	3.09%	2.77%	3.64%
74	Polk	3.07%	2.15%	4.64%	2.71%
75	Randolph	3.20%	2.45%	2.84%	4.01%
76	Richmond	1.70%	1.92%	2.95%	3.64%
77	Robeson	2.74%	3.22%	2.56%	2.26%
78	Rockingham	2.40%	1.75%	0.77%	3.64%
79	Rowan	3.24%	2.98%	2.06%	4.20%
80	Rutherford	2.49%	2.00%	2.55%	3.64%
81	Sampson	2.89%	2.77%	2.27%	3.64%
82	Scotland	2.36%	2.58%	1.93%	3.64%
83	Stanly	2.05%	2.57%	2.19%	3.64%
84	Stokes	3.23%	2.30%	3.03%	3.64%
85	Surry	3.05%	2.78%	2.61%	3.81%
86	Swain	2.20%	4.43%	3.37%	3.64%
87	Transylvania	3.74%	2.63%	2.45%	3.64%
88	Tyrrell	0.38%	1.10%	2.92%	3.64%
89	Union	3.86%	4.90%	2.84%	3.64%
90	Vance	2.27%	3.28%	1.18%	4.60%
91	Wake	4.11%	4.79%	2.59%	5.84%
92	Warren	2.54%	2.56%	2.40%	2.83%
93	Washington	1.73%	1.54%	0.33%	3.64%
94	Watauga	2.85%	4.97%	2.63%	3.64%
95	Wayne	1.57%	2.98%	0.90%	3.64%
96	Wilkes	2.57%	2.06%	2.06%	3.64%
97	Wilson	1.74%	2.19%	0.27%	2.93%
98	Yadkin	3.13%	3.23%	2.66%	3.39%
99	Yancey	2.86%	2.38%	3.63%	3.64%

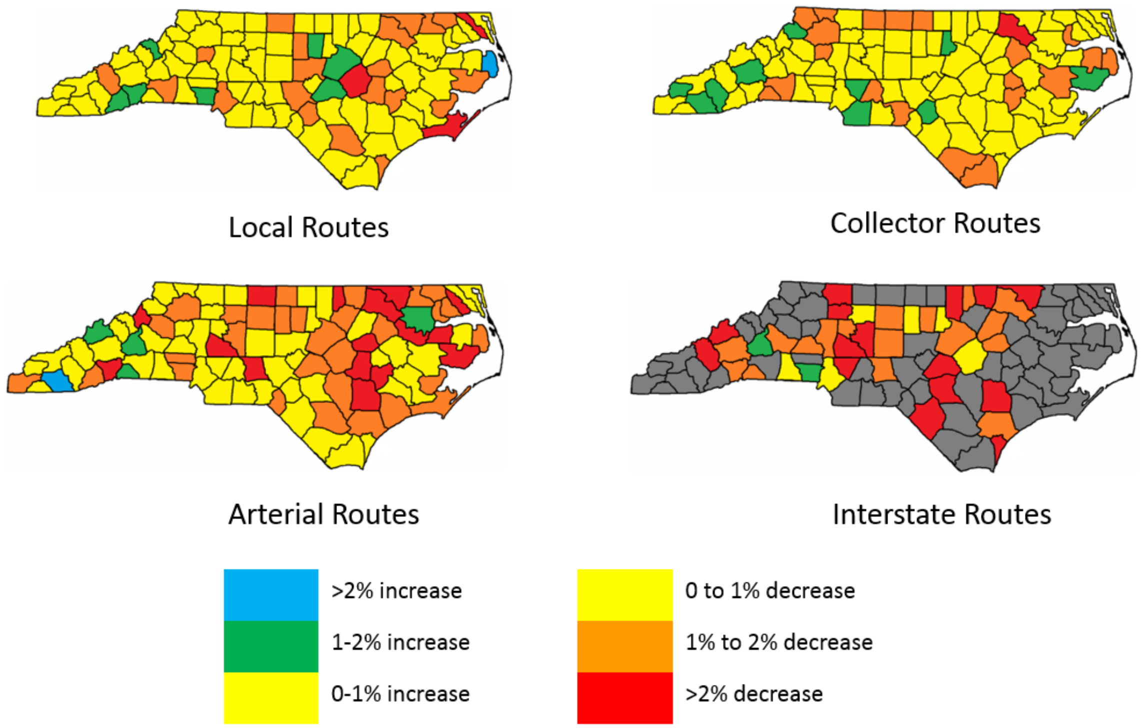


Figure 4.1: Relative increase/decrease of updated ADT growth rates from currently utilized estimates

4.2 Vehicle Operating Costs From Detours Due to Bridge Capacity and Vertical Clearance Limits

Like many states, North Carolina has a number of bridges with load postings and/or vertical clearance limits. This results in a significant number of vehicles (primarily trucks) detoured at these bridges due to loads in excess of the bridge posting or heights that exceed safe passage. To compute user costs associated with detours, it is necessary for the BMS to accurately predict the number of vehicles that are too heavy or oversized to traverse each individual bridge. This is accomplished in the software by multiplying the overall ADT by a percentage (in decimal form) of each type of vehicle class (SU and TTST) restricted from traveling over the bridge due to SV or TTST load posting or vertical clearance. To improve user cost predictions in the BMS, currently available data from North Carolina and other sources was utilized to update vehicle operating costs, as well as the distributions of traffic by height and weight on different types of roadways. Updated input tables for use in the BMS were prepared using techniques outlined in the following sections.

4.2.1 Vehicle Distribution by Functional Classification

FHWA currently classifies vehicles into 13 different classes. To estimate the percentile of different vehicle classes operating on different routes, data collected from North Carolina Weigh-in-Motion (WIM) stations on four different roadway types (Interstate, US, NC, and SR) was obtained from NCDOT. Due to roadway accidents and aging of the WIM systems, most of the North Carolina WIM stations are currently not in operation. To provide the most current data, NCDOT Traffic Survey Group personnel selected eight different WIM stations from the stations with operational data available within the range of 2007 to 2014. WIM stations at two locations for each roadway type were selected to provide a representative data set to estimate North Carolina vehicle classification percentages on the different roadways. WIM stations selected for this work are listed in Table 4.2 and are graphically shown in Figure 4.2.

Table 4.2: Descriptions of WIM sites used for traffic data

Roadway Type	County	Route	Location	Site
Interstate ★	Pender	I-40	0.70 miles west of NC 210	542
	Surry	I-77	2.25 miles south of NC 89 (West Pine St.)	515
US ★	Chatham	US 64	1.5 miles west of NC 87	508
	Forsyth	US 311	0.90 miles south of Ridgewood R. (SR 2698)	512
NC ★	Durham	NC 147	1.30 miles north of Ellis Rd. (SR 1954)	545
	Guilford	NC 68	0.5 miles north of SR 4464 (Bryan Blvd.)	555
SR ★	Onslow	SR 1245 (Byran Rd.)	0.05 miles north of Cypress Rd. (SR 1209)	532
	Mecklenburg	SR 1138 (Arrowood Rd.)	0.4 miles east of I-77	516

Figure 4.2: Map showing WIM sites used for traffic data

One year of continuous data from each site was provided by NCDOT for analysis. Since NCDOT's Traffic Survey Group also utilizes the vehicle classification counts for other purposes, the data had already been cleansed of anomalies and adjusted using correction factors typically utilized by NCDOT's Traffic Statistics Section. From the data provided, vehicle classes were grouped into three categories: cars (classes 1-3), SU (classes 4-7), and TTST (classes 8-13). These three categories were subsequently used to determine overall percentage of occurrence of each type of vehicle group on each specific roadway. After analyzing individual roadways, the vehicle distribution percentages obtained from the two WIMs on similar roadway types were averaged together. The averaged results for each roadway type are presented in Table 4.3. It is suggested that these percentages be used in the NCDOT BMS to update the input tables for vehicles required to detour due to either load postings or vertical clearance. The roadway grouping shown in Table 4.3 differs from the roadway grouping currently used for vehicles detoured due to weight or height. However, it is suggested that the grouping shown in Table 4.3 be used since it is consistent with the roadway grouping used in NCDOT's Pavement Management System (PMS). This would allow NCDOT to eventually move to corridor-level analysis (consideration of both roads and bridge together) to assist in condition forecasting and project selection.

Table 4.3: Vehicle distribution by functional classification

	Cars	SU	TTST
Interstate	81.64%	4.13%	14.23%
US	91.77%	3.85%	4.38%
NC	93.75%	3.70%	2.55%
SR	92.04%	7.50%	0.46%

4.2.2 Vehicle Weight Distributions

Weight distributions of different SU and TTST vehicles were updated as part of this work in order to provide updated BMS inputs. Current North Carolina vehicle weight distribution data provided by NCDOT's Traffic Survey Group was used to update the weight distribution estimates. Weight data from eight WIM stations listed in Table 4-2 were provided for a one-week span. This WIM data included weights on each vehicle class of 4 through 13 separately, as the WIM station is able to determine the vehicle class based on the number of axles and their spacing. Upon providing this data to UNC Charlotte, NCDOT personnel noted that this data should be considered “raw,” as anomalies had not been removed, and no correction factors for the weights had been applied. To provide a basis for weight ranges of different classes, Table 4-4 was used (U.S. Department of Energy, 2012). This table lists average weight ranges for commercial classes, which are grouped differently from the 13 vehicle classifications used by FHWA although the commercial classes are equal to the FHWA vehicle classes 4 through 13. Gross vehicle weight rating (GVWR) categories are also shown in Table 4.4.

Table 4.4: Vehicle weight ranges used for analysis of WIM data

Gross Vehicle Weight Ratings (lbs)	Federal Highway Administration	
	Vehicle Class	GVWR Category
<6,000	Class 1: <6,000 lbs	Light Duty <10,000 lbs
10,000	Class 2: 6,001-10,000 lbs	
14,000	Class 3: 10,001-14,000 lbs	Medium Duty 10,001-26,000 lbs
16,000	Class 4: 14,001-16,000 lbs	
19,500	Class 5: 16,001-19,500 lbs	
26,000	Class 6: 19,501-26,000 lbs	
33,000	Class 7: 26,001-33,000 lbs	Heavy Duty >26,001 lbs
>33,000	Class 8: >33,001 lbs	

Using the information in Table 4.4, the vehicle classes 4 through 13 were assigned minimum and maximum weight ranges, which bounded the expected weights for each class and thereby allowed for developing a method for cleaning the data set of anomalies. Table 4.5 shows the weight ranges utilized for grouping the vehicle classes, with SU classes separated in this initial step due to the wide variance in weight range of these vehicle classes.

Table 4.5: Minimum and maximum weight ranges

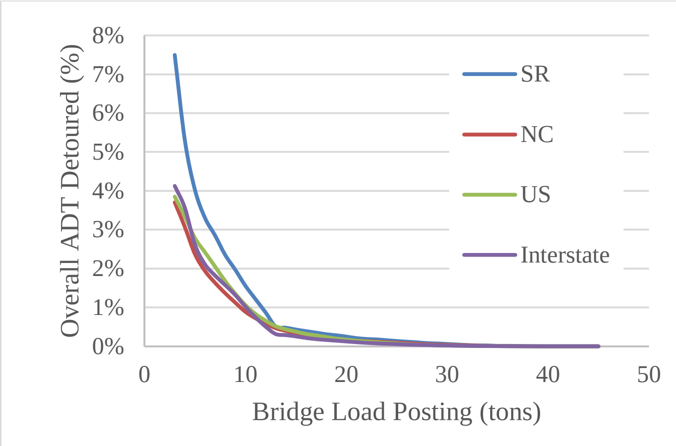
Vehicle Class	Minimum Weight (lbs.)	Maximum Weight (lbs.)
4 and 5	6,000	26,000
6 and 7	10,000	80,000
8 - 13	26,000	90,000

The WIM data obtained from each of the eight stations was filtered by weight to bound the data in records obtained within the minimum and maximum range developed for each respective class. The records for vehicles with weights within the range limits were then exported. These records were then grouped by vehicle classes 4 through 7 (SU) and vehicle classes 8 through 13 (TTST) and by weight. Data from WIM stations on similar roadway types were also combined prior to statistical analysis. Table 4.6 shows the cumulative percentage of truck weights distributed among the different roadway types. These percentages were then multiplied by the corresponding percentage of occurrence (shown in Table C.3) to determine the overall percent of ADT that is expected to be detoured at bridges with different load capacities across the four different roadway types. A table of the analysis results, which are recommended for input into the BMS, is presented in Table 4.6. These percentages are used in Equation 2.16 in decimal form (as a coefficient) to determine the overall ADT that must detour due to load restrictions (C_{LCD}).

Figures 4.3 and 4.4 provide a graphical representation of the overall percentage of ADT detoured due to load posting on the four roadway classifications for SU and TTST, respectively, using the updated data from Table 4.6. As expected, these plots illustrate that the majority of detours are associated with heavier vehicles. SU trucks must detour when the load posting is below 15 tons. It can be observed in Figure 4.3 that since SU vehicles represent a higher portion of traffic on SR routes, user costs from SU are highest on SR routes (when a bridge has a load posting below 15 tons). TTST traffic is most frequent on Interstates, and all TTST’s must detour if a load posting is below 13 tons. It can also be observed in Figure 4.4 that user costs due to TTST are most frequently incurred on interstates.

Table 4.6: Percentage of ADT detoured by bridge load posting level

Bridge Posting (tons)	SR		NC		US		Interstate	
	SU	TTST	SU	TTST	SU	TTST	SU	TTST
3	7.50%	0.46%	3.70%	2.54%	3.85%	4.38%	4.13%	14.23%
4	5.31%	0.46%	3.07%	2.54%	3.34%	4.38%	3.56%	14.23%
5	4.03%	0.46%	2.37%	2.54%	2.79%	4.38%	2.62%	14.23%
6	3.30%	0.46%	1.94%	2.54%	2.42%	4.38%	2.11%	14.23%
7	2.85%	0.46%	1.63%	2.54%	2.05%	4.38%	1.82%	14.23%
8	2.35%	0.46%	1.37%	2.54%	1.68%	4.38%	1.58%	14.23%
9	1.97%	0.46%	1.12%	2.54%	1.35%	4.38%	1.32%	14.23%
10	1.56%	0.46%	0.89%	2.54%	1.06%	4.38%	1.02%	14.23%
11	1.21%	0.46%	0.72%	2.54%	0.83%	4.38%	0.75%	14.23%
12	0.87%	0.46%	0.58%	2.54%	0.66%	4.38%	0.51%	14.23%
13	0.51%	0.46%	0.47%	2.54%	0.52%	4.38%	0.32%	14.23%
14	0.48%	0.44%	0.40%	2.41%	0.44%	4.03%	0.29%	14.07%
15	0.43%	0.41%	0.33%	2.24%	0.38%	3.65%	0.26%	13.84%
16	0.39%	0.37%	0.27%	2.08%	0.32%	3.31%	0.22%	13.53%
17	0.35%	0.33%	0.23%	1.92%	0.28%	3.01%	0.19%	13.14%
18	0.31%	0.29%	0.21%	1.79%	0.24%	2.76%	0.16%	12.72%
19	0.28%	0.26%	0.18%	1.66%	0.20%	2.53%	0.14%	12.32%
20	0.25%	0.22%	0.16%	1.54%	0.17%	2.33%	0.13%	11.91%
21	0.21%	0.20%	0.15%	1.44%	0.14%	2.16%	0.11%	11.50%
22	0.19%	0.17%	0.13%	1.35%	0.12%	2.03%	0.09%	11.10%
23	0.18%	0.15%	0.12%	1.27%	0.10%	1.88%	0.08%	10.72%
24	0.16%	0.14%	0.11%	1.19%	0.09%	1.75%	0.07%	10.33%
25	0.14%	0.13%	0.09%	1.12%	0.07%	1.62%	0.06%	9.94%
26	0.12%	0.12%	0.08%	1.07%	0.05%	1.49%	0.04%	9.55%
27	0.10%	0.11%	0.07%	1.02%	0.04%	1.37%	0.04%	9.17%
28	0.08%	0.10%	0.05%	0.96%	0.03%	1.25%	0.03%	8.77%
29	0.07%	0.09%	0.04%	0.90%	0.03%	1.13%	0.02%	8.37%
30	0.06%	0.08%	0.04%	0.84%	0.02%	1.01%	0.02%	7.98%
31	0.05%	0.07%	0.03%	0.76%	0.02%	0.90%	0.01%	7.57%
32	0.03%	0.06%	0.02%	0.70%	0.01%	0.80%	0.01%	7.15%
33	0.02%	0.06%	0.02%	0.63%	0.01%	0.70%	0.01%	6.71%
34	0.02%	0.05%	0.01%	0.57%	0.01%	0.60%	0.01%	6.27%
35	0.01%	0.04%	0.01%	0.51%	0.00%	0.52%	0.01%	5.78%
36	0.01%	0.04%	0.00%	0.44%	0.00%	0.44%	0.00%	5.25%
37	0.01%	0.03%	0.00%	0.38%	0.00%	0.38%	0.00%	4.63%
38	0.00%	0.02%	0.00%	0.31%	0.00%	0.32%	0.00%	3.94%
39	0.00%	0.02%	0.00%	0.25%	0.00%	0.26%	0.00%	3.17%
40	0.00%	0.01%	0.00%	0.19%	0.00%	0.20%	0.00%	2.37%
41	0.00%	0.01%	0.00%	0.14%	0.00%	0.15%	0.00%	1.70%
42	0.00%	0.00%	0.00%	0.09%	0.00%	0.11%	0.00%	1.16%
43	0.00%	0.00%	0.00%	0.05%	0.00%	0.07%	0.00%	0.71%
44	0.00%	0.00%	0.00%	0.02%	0.00%	0.03%	0.00%	0.34%
45	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%



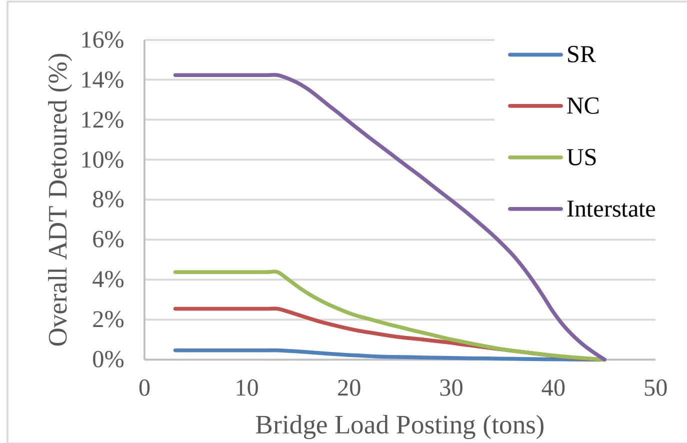


Figure 4.3: SU portion of ADT detoured due to load posting

Figure 4.4: TTST portion of ADT detoured due to load posting

4.2.3 Vehicle Height Distributions

Current input parameters in NCDOT's BMS are based on vehicle height data from the 1950's (Kent and Stevens 1963). The foundation of existing vehicle height distributions currently utilized in the BMS is that "heights of duals were assumed to be well distributed between 8.0 and 13.5 feet; and between 10 and 13.5 feet for trailer combinations" (Chen and Johnston, 1987). As part of this project, more current data was sought to modernize the inputs associated with BMS user costs for detours due to vertical clearance.

NCDOT does not currently have data to support development of a height spectrum for vehicles utilized today. A review of literature identified a report published for FDOT by Sobanjo and Thompson (2004). In this study, vehicle scanners and a laser range finder were used to sample the heights of trucks on roadways of different functional classifications in Florida. In total, Sobanjo and Thompson (2004) produced a dataset comprised of the height data obtained from 273,532 trucks. After binning the data into height ranges, a cumulative percentage of trucks that would need to detour due to vertical clearance was computed (shown in Appendix C as Table C-4). Since the study by Sobanjo and Thompson (2004) was extensive and heights of truck traffic in Florida could reasonably be expected to represent the distribution of truck traffic heights in North Carolina, the results from the Sobanjo and Thompson (2004) report, shown in Table C.4, were used to update the percentage of trucks detoured due to height in NCDOT's BMS.

The significance that this updated truck height distribution will have in the predicted percentages of trucks detoured due to vertical clearance on bridges (and subsequent user costs) is illustrated in Figure 4.5. Figure 4.5 provides the percentage of vehicles that would have to detour around a bridge due to vertical clearance using the data previously used in NCDOT's BMS (labeled "old") and the new suggested data (labeled "new"). These percentages of detours are a step function since both the previous and new data provide percent detoured in bins of height ranges. Note that the previous method provided data for SU and TTST, while the new approach provides data on all trucks (both SU and TTST together). It can be seen in Figure 4.5 that by using the previous truck height data from Kent and Stevens (1963), the NCDOT BMS has been underestimating the percent of vehicles that would have to detour due to height, and therefore has underestimated user costs associated with detours due to height. For design purposes, it could also be of interest to NCDOT that the findings of Sobanjo and Thompson (2004) indicate that over 99 percent of vehicles are under 14 feet in height.

The data obtained by Sobanjo and Thompson for FDOT was used to create an updated table for NCDOT's BMS detour to height prediction model. From this table, the percentages of trucks expected to be operating at various heights (Table 4.6) were then multiplied by their percentage of occurrence (Table 4.3) to determine the total percentage of vehicles estimated to be detoured due to vertical clearances. This updated estimate is presented in Table 4.7. Percentages are used in Equation 2.16 in decimal form (as a coefficient) to determine the overall ADT that will detour due to height (C_{CLD}) and are recommended for use in the NCDOT BMS.

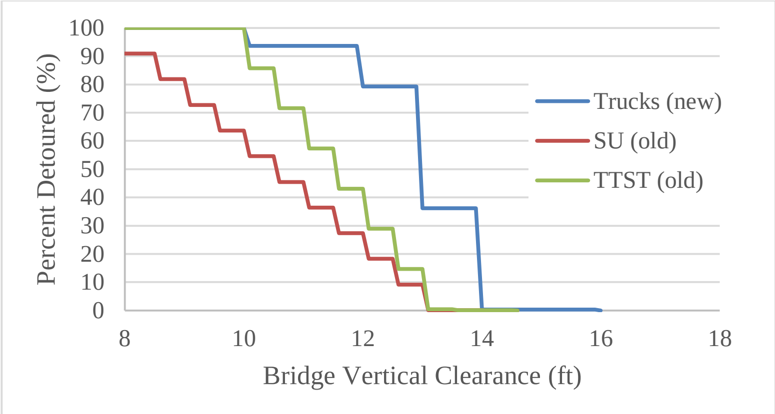


Figure 4.5: Percentage of trucks detoured due to vertical clearance

Table 4.7: Percentage of ADT expected to be detoured by bridge vertical clearance posting level

	SR		NC		US		Interstate	
Height (ft)	**SU**	**TTST**	**SU**	**TTST**	**SU**	**TTST**	**SU**	**TTST**
< = 10	7.50%	0.46%	3.70%	2.54%	3.85%	4.38%	4.13%	14.23%
10.1-11.9	7.02%	0.43%	3.47%	2.38%	3.61%	4.10%	3.87%	13.34%
12-12.9	5.94%	0.37%	2.94%	2.01%	3.05%	3.47%	3.27%	11.28%
13-13.9	2.71%	0.17%	1.34%	0.92%	1.39%	1.58%	1.49%	5.15%
14-15.9	0.02%	0.00%	0.01%	0.01%	0.01%	0.01%	0.01%	0.03%
> 16	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

4.2.4 Vehicle Operating Costs

As shown in Equation 2.16, percentages of vehicles detoured due to load posting or vertical clearance are multiplied by an associated vehicle operating cost per mile, supplied from state and government sources, to determine an overall detour cost. Currently, vehicle operating costs used in the NCDOT BMS are based on values computed for two vehicles: a passenger car (3-tons) and a vehicle at maximum allowable load (40-tons). As part of this project, vehicle operating costs for the minimum and maximum vehicle weights were updated using current locally calibrated data. Additionally, an effort was made to obtain an intermediate value for vehicle operating costs, with the intent of identifying if the currently utilized linear relationship between user vehicle operating cost and vehicle weight was applicable.

Vehicle operating costs at the 3-ton vehicle weight and 40-ton vehicle weight were determined using the methodology developed by Duncan and Johnston (2002). To obtain user costs at the 3-ton weight limit (the minimum used in the BMS), the North Carolina State government employee wage rate for a Vehicle Operator I was obtained from the North Carolina Office of State Human Resources ($23,975). This employee wage rate is noted as Grade 53 (OSHR, 2014). This value was then divided by the product of the estimated number of hours worked in a year (1920 hrs) and an assumed average speed (40 mph). Lastly, the value was added to the Internal Revenue Service (IRS) standard mileage rate for business use ($0.56), which is published yearly (IRS 2014), resulting in a vehicle operating cost for a 3-ton vehicle of:

$$[\$23{,}975 / (1920 \text{ hrs} \times 40 \text{ mph})] + \$0.56 = \$0.87 \text{ per mile}$$

To determine user costs at the 40-ton weight limit (maximum in the BMS), information published by the U.S. Census Bureau was utilized. This organization publishes a report called the Service Annual Survey which uses the North American Industry Classification System (NAICS) to sort data. This report contains a section on transportation of cargo using tractor-trailers. In this section of the most recent version of this report available for this project, “2010 Service Annual Survey,” a table is provided that contains a value for the estimated motor carrier revenue ($183,496 million) and another table that provides the estimated total distance traveled during 2010 (76,740 million miles) (U.S. Census Bureau, 2012). The revenue was divided by the distance traveled to produce a vehicle operating cost for the maximum legal weight vehicles.

For any values not current, the appropriate CPI (2015) was used to adjust to current costs as follows for the vehicle operating cost at 40 tons:

$$(\$183{,}496 / 76{,}740 \text{ miles}) = \$2.39 \text{ per mile (year 2010)}$$
$$\text{CPI inflation: year 2014 / year 2010} = 2.20/2.03 = 1.083$$
$$\$2.39 \text{ per mile} \times 1.083 = \$2.59 \text{ per mile}$$

As mentioned previously, a study was conducted to determine vehicle operating costs for vehicles with an operating rate between the minimum (3-ton) and maximum (40-ton) values. The method developed in this prior study used the U.S. Army Corps of Engineers' (USACE) Construction Equipment Ownership and Operating Expense Schedule report for Region III, which includes North Carolina. This report is published annually and includes operating costs for a wide variety of different machines and equipment in units of dollars per hour. After reviewing this report, a 3-axle dump truck was chosen as an intermediate point for computation of a vehicle operating cost. The USACE lists its average operating costs for the vehicle at $60.87 per hour (USACE, 2014). This value was divided by the assumed average speed (40 mph), resulting in an operating cost of $1.52 per mile for the vehicle. To determine the operator costs, the method used for the minimum value (3-ton vehicle) was utilized with the wage rate for a Vehicle Operator III, since driving a larger vehicle such as a dump truck is a skilled operation that requires a special driver license. The North Carolina Office of State Human Resources lists this wage rate at $26,159 (OSHR, 2014). This rate was divided by the product of the estimated number of hours worked in a year (1920 hrs) and assumed average speed (40 mph), which results in an operating cost of $0.34 per mile. The two values were added together to produce a vehicle operating cost of $1.86 per mile. North Carolina law governs the maximum weight permitted for a vehicle and its load by the number of axles the vehicle has and by the distance between the axles. A 3 axle dump truck has an average spacing of 22 feet from the two furthest axles, allowing for a gross vehicle weight of 26.25 tons. Values for the vehicle operating costs at the three weights are presented in Table 4.8. This table also shows the increase in cost over time.

Table 4.8: Vehicle operating costs over time

Vehicle Operating Costs at each individual weight (U_{DV}) ($ per mile)			
	Year		
Weight	**2002**	**2010**	**2014**
3 tons	0.60	0.81	0.87
26.25 tons	N/A	N/A	1.86
40 tons	1.95	2.39	2.59

To determine the vehicle operating costs at intermediate weights, the three costs (from year 2014) were plotted against their respective weights. This was done once for weights between 3 ton and 26 ton, and then for weights between 27 ton and 40 ton, with piecewise linear trend lines drawn between data points. This best fit line can be used to interpolate intermediate values for the vehicle operating costs of vehicles with other operating weights. The equation for the best fit line shown in Equation 4.1 can be used to compute the vehicle operating costs, U_{DV}, between the weights of 3 and 26 tons, while the best fit line shown in Equation 4.2 can be used to compute the vehicle operating costs, U_{DV}, for vehicles weighing between 27 and 40 tons.

$$U_{DV} = 0.0426 \times (W) + 0.7423 \tag{4.1}$$

$$U_{DV} = 0.0531 \times (W) + 0.4664 \tag{4.2}$$

Where: U_{DV} = Vehicle operating costs at weight X ($/mile)
W = Weight (tons)

In order to determine the average operating costs for all vehicles that would have to detour around a bridge posted at a specific weight, U_{DL}, the vehicle operating cost associated with vehicles with weights equal to the posted weight is added to the maximum allowable weight, and then divided by two, providing the U_{DL} used in Equation 2.16. Figure 4.6 provides a comparison of the average operating cost (U_{DL}) estimated for vehicles between 3 and 40 tons using the traditional method (two point linear interpolation) and using the proposed method of adding a third intermediate point. It can be seen in Figure 4.6 that the two approaches provide similar vehicle operating costs throughout. Given the similarity between the two approaches, it seems the two point linear interpolation method currently used in NCDOT's BMS is acceptable and a modification to this approach is not suggested at this time.

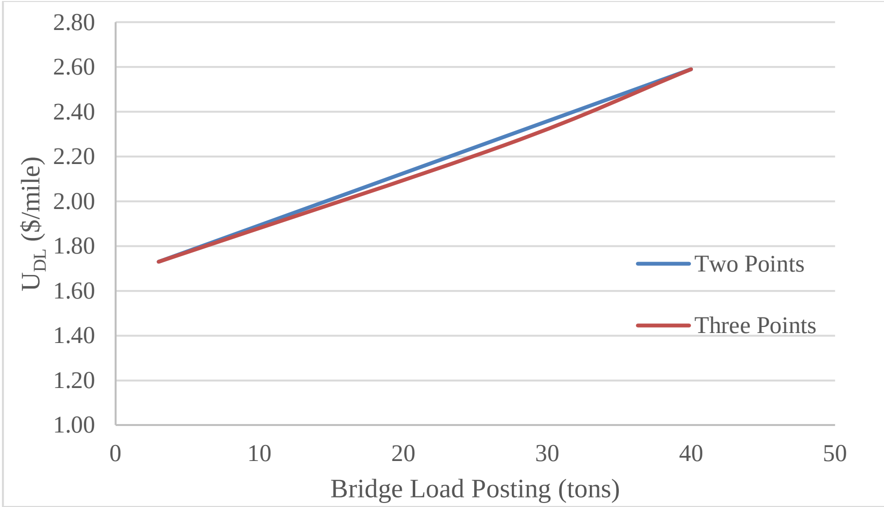


Figure 4.6: Average vehicle operating cost for detoured vehicles

4.3 Accident Costs

Accident costs due to vehicular crashes are a significant component of user costs and, therefore, accurate forecasting of bridge-related accidents (or "crashes") is required to inform reliable decision making. Currently, accident costs (or "crash costs") are calculated in the BMS utilizing the percentage of accidents that are forecasted to occur on a bridge, which produces an expected accident rate for each bridge. These accident rates are then multiplied by the corresponding accident costs predicted using the NSC methodology and the corresponding occurrence of each severity type. Since more severe crashes (with fatalities and severe injuries) incur significantly higher costs, overall accident costs are particularly sensitive to the predicted number of higher severity crashes. Percentages of accident severity types occurring on bridges have not been updated in the BMS since the original tables were generated by previous researchers (Abed-Al-Rahim and Johnston, 1991) and needed to be updated using more recent crash data. Additionally, accident costs specific to North Carolina have recently become available and use of these locally calibrated cost values in the BMS would provide more accurate predictions of user costs.

NCDOT collects crash data using standard Crash Report Forms completed by responding officers. Data on bridge-related crashes can be identified by screening the database for several key codes on the Crash Report Forms. The "Road Feature" input on the North Carolina crash report form allows officers to identify "Bridge" or "Bridge approach," along with other non-bridge-related features. Bridge-related crashes are also identifiable by the codes for "Collision with fixed object," where options include "Bridge rail end" and "Bridge rail face." The accuracy of the data reported on a Crash Report Form is influenced by the discretion of the officer completing the form and it is likely that some fields are more accurate than others. As described previously, NCDOT classifies crash types by severity with the rating designated by the most severe injury. Therefore, a crash producing one "A" injury and three "B" injuries will be considered an "A injury" crash.

4.3.1 Bridge Related Accidents by Injury Severity

NCDOT's Traffic Engineering Division provided records on all crashes (both bridge-related and non-bridge-related) occurring over a period of five years (2009-2013) in all counties in North Carolina. Crashes that occurred on a bridge, bridge approach, or on a bridge rail were extracted and the number of crashes of each severity was totaled for each of the five crash severity types (K-A-B-C-PDO). The percentage of each crash type was used to produce the expected frequency of each severity type occurring on bridges. Table 4.9 shows the average number of injuries per bridge-related crash, along with the values that were previously used (Abed-Al-Rahim and Johnston, 1993). From Table 4.9, it is noted that the proportion of bridge-related crashes with fatality has been reduced in half. The relative occurrences of the two most severe injuries types (A and B) have also decreased significantly. From a user cost perspective, the reduction in crash rates for the most severe types of crashes (K, A, and B) will significantly reduce the overall user cost predicted per crash, since the costs associated with these severity types are disproportionally larger than those associated with low severity or property damage only crashes.

Table 4.9: Comparison of bridge-related crash frequencies between 1991 and 2013

Avg. # of injuries per bridge-related crash		
Severity	**Year**	
	1991	**2013**
K	0.02	0.01
A	0.13	0.02
B	0.20	0.13
C	0.34	0.40
PDO	N/A	N/A

4.3.2 Bridge Related Accident Costs

To compute accident costs in the BMS, costs per severity type are multiplied by the fraction of occurrence. Values are summed to produce one total cost per crash figure (U_{AC} in Equation 2.16). Since NSC costs are not always updated annually, an appropriate CPI value can be utilized to extrapolate values between periodic updates to the NSC costs, if NSC costs are utilized. Recently, NCDOT has been retaining a private consultant to produce an annual report on Standardized Crash Cost Estimates for North Carolina (NCDOT, 2013). The locally-calibrated crash cost values provided in this report can be used in lieu of the crash costs obtained via the NSC methodology. As part of this work, the effects of using the locally-calibrated crash costs and updated crash severity frequencies on the cost per crash were explored. In Table 4.10, the cost per crash is computed using the outdated accident frequencies along with the W-to-P costs computed using both the NSC values and the locally-calibrated W-to-P costs. Using the locally-calibrated cost data and the outdated crash severity frequencies, the cost per crash is decreased by approximately $10,000 per crash, or roughly 7%.

Table 4.10: Bridge-related crash costs computed using outdated severity frequency and two cost sources

Crash Severity	Avg. # of injuries per bridge-related crash	W-to-P Cost per injury, NSC Updated with CPI	Cost per bridge-related crash	Avg. # of injuries per bridge-related crash	W-to-P Cost per injury, Locally-calibrated Values	Cost per bridge-related crash
K	0.02	$4,687,150	$93,743	0.02	$4,287,340	$85,745
A	0.13	$237,177	$30,883	0.13	$216,026	$28,083
B	0.20	$60,630	$12,126	0.20	$55,322	$11,064
C	0.34	$28,921	$9,833	0.34	$26,325	$8,951
PDO	N/A	$2,582	$2,582	N/A	$5,388	$5,388
		Total (U_{AC}) = (currently utilized in NCDOT BMS)	$149,166		Total (U_{AC}) =	$139,231

In Table 4.11, the cost per crash is computed using the updated accident frequencies along with the W-to-P costs computed using the both the NSC values and the locally-calibrated W-to-P costs. Using the locally-calibrated cost data and the updated crash severity frequencies, the cost per crash is decreased by approximately $3,300 per crash, or roughly 5%. More importantly, however, it is noted that regardless of the source of the cost data, updating the BMS to include the more recent crash frequency inputs will result in a much lower cost per crash than is obtained using the outdated crash frequencies. The most significant change in per crash cost is linked to the decrease in proportion of fatal and high severity accidents. The cost per crash value computed using updated crash severity frequencies and locally-calibrated costs ($70,796) is less than half of the cost per crash computed using the earlier crash frequency statistics and non-locally-calibrated costs ($149,166). This indicates that current BMS inputs result in a significant overestimation of user costs for bridges with higher crash rates. Consequently, it is suggested that the updated crash frequency values and locally-calibrated cost data be implemented into the BMS to improve the prediction accuracy.

Table 4.11: Bridge-related crash costs computed using updated severity frequency and two cost sources

Crash Severity	Avg. # of injuries per bridge-related crash	W-to-P Cost per injury, (NSC Updated with CPI)	Cost per bridge-related crash	Avg. # of injuries per bridge-related crash	W-to-P Cost per injury, (NC Values)	Cost per bridge-related crash
K	0.0103	$4,687,150	$48,370	0.0103	$4,287,340	$44,244
A	0.0172	$237,177	$4,069	0.0172	$216,026	$3,706
B	0.1258	$60,630	$7,630	0.1258	$55,322	$6,962
C	0.3987	$28,921	$11,531	0.3987	$26,325	$10,496
PDO	N/A	$2,582	$2,582	N/A	$5,388	$5,388
		Total (U_{AC}) =	$74,182		Total (U_{AC}) =	$70,796
					(Suggested for future use in NCDOT BMS)	

4.3.3 Development of Bridge-Related Accident Prediction Model

The methodology currently utilized by NCDOT's BMS predicts crash costs by multiplying the cost per crash by the number of annual crashes predicted to occur on or at each bridge (Abed-Al-Rahim and Johnston, 1991). Data from bridge-related crashes occurring in five North Carolina counties (Guilford, Halifax, Harnett, Iredell, and Wake) over a roughly six-year period during 1983-1989 was utilized to develop an equation that could be used to predict the number of annual crashes associated with individual bridges. A bridge-related crash was defined as any crash occurring on or near a bridge, as detailed in the road feature field of the crash report. As part of this work, each crash record for crashes occurring on or at a bridge was individually matched to the bridge at which it occurred. A total of 2,895 bridge-related crash records were obtained and reviewed, with 2,512 crashes occurring on Interstate, US, NC, or city routes. Of these, 2,104 crashes were matched to a specific bridge, for a total of 72.7% of the total bridge-related crashes (Abed-Al-Rahim and Johnston, 1991). Statistical analysis was performed using a stepwise regression procedure to determine the bridge characteristics associated with the greatest influence on bridge-related crashes, using a significance level of 5 percent associated with the null hypothesis. The characteristics found to be significant were then fit with higher order polynomial models to determine an equation that could predict crashes on bridges (Abed-Al-Rahim and Johnston, 1991). As discussed previously, Abed-Al-Rahim and Johnston (1991) found that ADT, bridge length, and the difference in deck width between acceptable and actual level of service had the most significance.

As part of the current research, a similar analysis was performed to identify the characteristics and features of bridges currently most influential in affecting the rate of North Carolina's bridge-related crashes, and to produce an updated prediction equation. Crash reports in the same five counties from the previous study (Guilford, Halifax, Harnett, Iredell, and Wake) over five years (2009-2013) were utilized. The five counties were originally selected based upon geographic region, population density, and distribution of highway functional classes (Abed-Al-Rahim and Johnston, 1991). A total of 2,416 bridge-related crashes occurred in the five selected counties during this five-year time frame (an average of 483 crashes per year), which is notably similar to the number of bridge-related crashes occurring in the same counties in the roughly six-year timeframe between 1983 and 1989 (total of 2,895, an average of 483 per year). Crashes were denoted as either occurring on a bridge, on a bridge approach (within 500 ft.), or on a bridge railing in the crash report. As in many other states, North Carolina crash reports are not directly linked to structure numbers assigned by the NCDOT. Although automated bridge matching has been performed in other studies (Mehta et al., 2015), the potential for mismatching of crashes to bridges exists due to discrepancies between NBI bridge coordinates and crash reporting data, and further examination is required after the automated process to verify that the crash occurred on the bridge and not beneath the bridge. For this work, a manual matching procedure was utilized, as performed in the original study (Abed-Al-Rahim and Johnston, 1991).

Crashes were manually matched to bridges using features coded in the crash reports that indicate the "facility carried," "road measured from," and "road measured to." Tools utilized to facilitate matching of bridges to crash reports included maps sourced from the NCDOT Geographic Information Systems (GIS) unit and Google Maps. Similar to the previous study (Abed-Al-Rahim and Johnston, 1991), there were a number of instances where crashes could not be matched to bridges using the limited data provided in the crash reports. In the previous study, researchers indicated that likely explanations for "unmatchable" crashes could have been that recorded locations were incorrectly coded on crash reports, a culvert being denoted as a bridge in the crash report, or the crash occurring under the bridge instead of on the bridge or approach (Abed-Al-Rahim and Johnston, 1991). To maintain consistency in the analysis, crashes occurring on culverts in the 2009-2013 dataset were excluded from the analysis. A number of reported crashes were also not successfully matched because the crash occurred near two closely-spaced but separate bridges, such as when separate bridges service the same roadway for each direction, and the direction of traffic was not stated in the crash report to allow for identification of the exact bridge the crash occurred on. Other matches were simply not found because of incorrect location information recorded on the crash report or because the crash did not occur on or near a bridge and was accidentally mis-coded by the responding officer. For the current study, 1,938 of the 2,416 reported crashes, or 80.2% of the total crashes that occurred in the subject counties analyzed over the five year span, were successfully matched to a specific bridge. This percentage is comparable to, but higher than, the percentage of matches obtained in the previous study (72.7%).

Once the crash records were matched to bridges, statistical regression of the crash data in the five counties using the bridge characteristics as independent variables was performed to identify the bridge features most influential in the rate of bridge-related crashes. Specific bridge characteristics included in the analysis as potential independent variables were determined based on a review of the literature (Abed-Al-Rahim and Johnston, 1991, Chen and Johnston, 1987, Abed-Al-Rahim and Johnston, 1993, Wang, 2010) as well as relevant items available in the NCDOT BMS. The following thirteen bridge characteristics were included as potential variables in the stepwise regression: ADT, Approach Alignment Appraisal, Approach Roadway Width, Bridge Deck Width, Bridge Roadway Width, Deck Geometry Appraisal, Structure Length, Structure Appraisal, Through Lanes On, Average Index (BMS), Total Horizontal Clearance, WDIFACC (width difference between goal clear deck width for acceptable level of service and actual clear deck width), and Functional Classification (referenced as categorical data).

Spreadsheets and statistical analysis software (Minitab) were used to perform the statistical regression. Functional Classification includes six categories listed in the NCDOT BMS as: Interstate, US Route, NC Route, SR Route, Municipal Road not in contact with State System road, and Municipal Road over State System. Since this data is associated with a nominal scale, reference cell coding was used to develop design variables for each classification. This reference cell coding was used to determine an independent regression coefficient depending on the bridge functional classification.

To begin the multiple linear regression analysis, a multicollinearity check was performed on all of the independent variables using the variance inflation factor (VIF) with a threshold of 10 (Rawlings et al., 1998). Multicollinearity checks were repeated until all remaining independent variables were shown to be uncorrelated. This resulted in identification of several correlated variables related to width. Bridge roadway width and bridge deck width were removed from the analysis, with the correlated variable of approach roadway width allowed to remain with the other 10 independent variables for further analysis. A best subset stepwise regression was computed using the remaining eleven independent variables. In Minitab, a best subset regression provides the two best fitting models with X number of variables, up to the regression model containing all of the variables. These best subset results provide different coefficient of determination values along with the Mallows C_p. The Mallows C_p is a statistic that provides an approximation of the quality of fit for a particular model, penalized by the number of independent variables included in the model. Use of the Mallows C_p to determine the model size balances the objectives of developing an effective prediction model with minimizing the number of independent variables required. The model associated with the smallest Mallows $C_{p,}$ should be used in the final regression model. The Mallows C_p should be approximately equal to (or approaching) the number of variables in the output.

Results indicated that seven variables: Average Daily Traffic, Approach Roadway Width, Deck Geometry Appraisal, Structure Length, Average Index (BMS), Total Horizontal Clearance, and Functional Classification have the greatest influence on bridge-related crashes and should be retained in the final regression model. Once the seven variables associated with the final regression model were identified, multiple linear regression analysis was performed to generate a prediction equation for bridge-related crashes specific to individual bridges in North Carolina, shown in Equation 4.3. With Functional Classification coded as a categorical variable, the intercept value will vary based on the bridge's Functional Classification coding, listed in Table 4.12. Once the final bridge crash prediction equation was produced in Minitab, the equation was manipulated algebraically to provide an estimate that predicts the annual number of crashes. To normalize the prediction equation to an annual rate, the linear coefficients were divided by 5, since 5 years of crash data was used in the analysis. Since some percentage of the total number of crashes reported could not be matched to a specific bridge, the number of crashes predicted by the statistical regression should be less than the reported number of crashes (as the sum of the dependent variables would be less than the reported total). To account for this difference, an adjustment factor (AF) was produced and multiplied by the resulting equation to correct for the difference. This is consistent with the approach taken by Abed-Al-Rahim and Johnston (1991). To compute the AF for the current analysis, the number of crashes identified as occurring on a culvert (29), a closed bridge (1), private bridge (2), and railroad bridge (1) were subtracted from the total number of reported crashes (2,416). This value was then divided by the total number of crashes linked to a bridge (1,938), which produced an AF of 1.23.

$$NOACC = ((FC+(0.000066\times ADT) - (0.01679\times ARW) - (0.2611\times DGA) + (0.001434\times SL) - (0.2016\times AI) + (0.05936\times THC))/5) \times 1.23 \quad (4.3)$$

Where: NOACC = Number of Accidents (or Crashes), per year
FC = Functional Classification (values from Table 4.12)
ADT = Average Daily Traffic
ARW = Approach Roadway Width
DGA = Deck Geometry Appraisal
SL = Structure Length
AI = Average Index (BMS)
THC = Total Horizontal Clearance

Table 4.12: Functional classification code for prediction equation

Code	Functional Classification	Intercept Value
0	Interstate	0
1	US Route	0.4622
10	NC Route	0.4549
100	SR Route	0.3336
1000	Municipal Road not in contact with State System road	0.1921
10000	Municipal Road over State System	0.5530

Equation 4.3 can be manipulated to incorporate the adjustment factor (1.23) and number of years of data (5), to provide a cleaner final equation that can be used in North Carolina's BMS to predict the annual number of bridge-related crashes. This is shown in Equation 4.4.

$$NOACC = 0.246\times FC + (0.00001624\times ADT) - (0.004130\times ARW) - (0.06423\times DGA) + (0.0003528\times SL) - (0.04959\times AI) + (0.01460\times THC) \quad (4.4)$$

As is current practice in the BMS user costs equation, the number of predicted crashes on any bridge cannot be less than zero. Applying this constraint in the analysis, and utilizing Equation 4.4, the number of bridge-related crashes occurring on all bridges statewide was calculated. By using the prediction equation on the bridges contained in all 100 counties in North Carolina (a total of 13,928 bridges), the total predicted number of crashes per year was 3,304 crashes. Over the last 5 years, the actual annual average number of crashes was 2,985 crashes per year (obtained by dividing a total of 14,923 crashes that were reported statewide over 5 years). This demonstrates that Equation 4.4 is reasonably plausible, as it predicts the statewide number of crashes within 11 percent of the actual reported total. Utilizing this equation to predict the number of crashes occurring on bridges in the 95 North Carolina counties not used in the regression analysis yields a prediction of 2,807 crashes annually. The actual annual average number of crashes in those 95 counties over the last 5 years was 2,502 crashes per year (obtained by subtracting 2,416 crashes from 14,923 then dividing by 5 years). This again shows that the prediction equation provides plausible results.

An important result of this analysis was that bridge characteristics that could be most closely linked to bridge-related crashes (i.e. the characteristics showing the strongest predictive capability) were identified and could be compared to those identified as influential in the analysis performed nearly 25 years ago (Abed-Al-Rahim and Johnston, 1991). Bridge characteristics that were determined to be influential in bridge-related crashes in both the previous analysis and in this analysis are ADT (higher traffic associated with increased incidence of crashes) and structure length (longer structures associated with increased incidence of crashes). Variables not utilized in the previous prediction equation that are suggested for use in the new prediction equation include approach roadway width, deck geometry appraisal, total horizontal clearance, Average Index (BMS), and Functional Classification. The currently suggested variables of approach roadway width, deck geometry appraisal, and total horizontal clearance are consistent with a term in the previously utilized equation "width between goal width and actual width" (Abed-Al-Rahim and Johnston, 1991), and also with findings in other studies indicating the significance of different width parameters (Turner, 1984, Mak and Calcote, 1983, Ghandi et al., 1984, Wang, 2010). Based on the negative coefficients, the statistical model indicates that having a larger approach roadway width and increased deck geometry appraisal helps decrease the incidence of bridge-related crashes.

Regular and preventative maintenance to maintain or improve condition ratings should help reduce bridge-related crashes, since the Average Index (BMS) is developed from the average of the deck, superstructure, and substructure condition ratings. As evidenced by the intercept values, interstate bridges are associated with lower incidences of bridge-related crashes, relative to bridges on municipal roads, US, and NC routes. Also of note, Abed-al-Rahim and Johnston (1991) concluded "Although alignment is believed to be significant this was not confirmed by analysis of the data available." Approach Alignment Appraisal was also not found to be a statistically significant predictor in this study.

While the effects predicted by the significant independent variables are plausible and supported by prior research, the predictive equation developed has a relatively poor fit, with an R^2 value of 0.36. However, this is similar to the R^2 value reported for the previous prediction equation (0.34). Some reasons for the poor model fit arise from the fact that only recorded characteristics related to each bridge could be considered as coefficients. Crashes can be the result of numerous causes, or contributing causes, such as weather, speed, time of day, and human factors such as cell phone use (it is noted that cell phone use was likely not a human factor during the original study). These factors cannot be easily accounted for within a predictive crash forecasting tool for use within the BMS.

In conclusion, the average number of bridge-related crashes occurring in counties included in the study remained relatively constant, and the frequency of fatal and high-severity injury bridge-related crashes decreased significantly. Paired with locally-sourced per-crash cost data, use of updated, lower crash frequencies will result in significantly lower, more accurate, user cost predictions in the state BMS. The updated bridge-related crash prediction equation developed through statistical regression provides plausible results linking crash rates to bridge characteristics recorded in the BMS and identified several key factors influential in predicting bridge related crashes. These include ADT and structure length, which were also identified as influential in previous studies. Approach alignment, suspected by previous researchers to influence bridge-related crashes but not confirmed, was again found to not be a significant predictor. However, Average Index (BMS), a composite bridge condition rating, was found to be a significant predictor, indicating that regular and preventative maintenance should reduce bridge-related crashes. Also of note, interstate bridges are associated with lower incidences of bridge-related crashes, relative to bridges on other roadway types.

4.4 Results of Updates to User Costs

Ultimately, a number of user costs and BMS input tables were updated as part of this work. In some cases, new methodologies to obtain these user costs were utilized. In other cases, previous methods used to obtain these values were deemed to currently be appropriate, and new, updated values were obtained. In order to evaluate the new recommended user cost inputs and methodologies, a sensitivity analysis on user costs was completed.

4.4.1 Recommended Changes to User Costs Equation

Equation 2.16 shows the original NCDOT BMS user costs equation based on research conducted by Chen and Johnston (1987). As part of this work, it is recommended that this equation be modified as shown in Equation 4.5, and utilized in the NCDOT BMS to predict user costs for bridges.

$$AURC(t) = 365ADT(t)\,[\overbrace{C_{WDA}U_{AC}}^{\text{Accident cost due to width}}+\overbrace{C_{ALA}U_{AC}}^{\text{Accident cost due to alignment}}+\overbrace{C_{CLA}U_{AC}}^{\text{Accident cost due to under vertical clearance}}+\overbrace{C_{CLD}U_{DC}DL}^{\text{VOC due to vertical clearance}}+\overbrace{C_{LCD}(t)U_{DL}DL}^{\text{VOC due to load capacity}}] \quad (2.16)$$

Where: $AURC(t)$ = annual user cost of the bridge at year t, \$/year

$ADT(t)$ = average daily traffic using the bridge at year t

C_{WDA} = coefficient for proportion of vehicles incurring accidents due to width deficiency

C_{ALA} = coefficient for proportion of vehicles incurring accidents due to poor alignment

C_{CLA} = coefficient for proportion of vehicles incurring accidents due to vertical clearance deficiency

C_{CLD} = coefficient for proportion of vehicles detoured due to a vertical clearance deficiency

$C_{LCD}(t)$ = coefficient for proportion of vehicles detoured due to a load capacity deficiency at year t

U_{AC} = unit cost of vehicle accidents on bridges, \$/accident

U_{DC} = unit cost for average vehicle detours due to vertical clearance deficiency, \$/mile

U_{DL} = unit cost for average vehicle detours due to load capacity deficiency, \$/mile

DL = detour length, miles

$$AURC(t)=365ADT(t)[\overbrace{CLCD(SU)(t)UDLDL}^{\text{VOC due to load capacity for SU}}+\overbrace{CLCD(TTST)(t)UDLDL}^{\text{VOC due to load capacity for TTST}}+\overbrace{CCLD(t)UDCDL}^{\text{VOC due to vertical clearance}}] + \overbrace{NOACC(t)UAC}^{\text{Annual total Accident cost}} \qquad (4.5)$$

Where: AURC = annual user cost of the bridge at year t, \$/year
ADT = average daily traffic using the bridge at year t
CLCD = coefficient for proportion of vehicles detoured due to a load capacity deficiency at year t
CCLD = coefficient for proportion of vehicles detoured due to a vertical clearance deficiency
UAC = unit cost of vehicle accidents on bridges, \$/accident
U_{DC} = unit cost for average vehicle detours due to vertical clearance deficiency, \$/mile
U_{DL} = unit cost for average vehicle detours due to load capacity deficiency, \$/mile
DL = detour length, miles
NOACC = number of annual accidents per year at year t (see Equation 4.4)

Comparing Equations 2.16 and 4.5, some changes to the user costs equation are recommended based on the results of this work. An extensive analysis of recent bridge-related accidents resulted in the development of an updated bridge-related accident prediction equation. As part of this work, the characteristics most influential on bridge-related accidents were identified and are included in Equation 4.4, which is in turn utilized in Equation 4.5. It is noted that the accident cost is also no longer multiplied by the ADT and 365 days, since NOACC, predicted by Equation 4.4, predicts the annual number of bridge-related accidents. Accident costs due to the vertical clearance under a bridge are not specifically included in Equation 2.16, as data currently included in the BMS does not support this calculation. However, accidents occurring as a result of vertical clearance issues would be considered as part of the accident prediction equation (Equation 4.4), which is incorporated into Equation 4.5. Also included in Equation 4.5 are vehicle operating costs separated into two separate components (for SU and for TTST). This is now possible because the current BMS provides load postings for both SU and TTST. Since these load postings can be different for SU and TTST, treating the user costs associated with these types of vehicles separately (as shown in Equation 4.5) should result in more accurate prediction of user costs.

4.4.2 User Costs Sensitivity Analysis

When forecasting an outcome in the future, such as bridge user costs, inputs will not always remain constant due to economic and inflation uncertainties. Sensitivity analysis is used to analyze an equation to determine which inputs (when varied) have the greatest effect on the outcome of an equation. In this case, the sensitivity analysis was performed to determine which cost inputs have the greatest impact on the resulting user costs for a given set of parameters. This is completed using different constraints (distributions and parameters) in an equation, which change the array of results produced. Ultimately, factors deemed most influential in user costs provide data to support design and MR&R decisions that could reduce user costs associated with vehicle operating costs due to detours or accident occurrences) as well provide a listing of key input values that should be updated regularly (or more frequently) to more accurately predict bridge user costs.

Since changes in economic behavior and inflation largely drive cost, accident costs and vehicle operating costs (VOC) were identified as the two variables to be evaluated in the sensitivity analysis. Similar to the sensitivity analysis performed by Abed-Al-Rahim and Johnson (1991), the sensitivity of the user costs was evaluated using the variance of the user cost increase predicted over a 20 year timeframe. In order to perform the sensitivity analysis, a representative subset of bridges was selected. To provide continuity for comparison between prior and current work to develop and enhance NCDOT's BMS, a method similar to work previously done by Abed-Al-Rahim and Johnston (1991) was utilized. In the sensitivity analysis performed for this work, as well as for the 1991 study, four counties were selected for testing: Guilford, Halifax, Harnett, and Haywood. A total of 969 bridges, representing roughly 7 percent of the statewide inventory, are located in these four counties. Similar to the method and constraints utilized by (Abed-Al-Rahim and Johnston, 1991), a 20-year horizon was used for the sensitivity analysis, with a 6 percent rate of return, and net present value (NPV) utilized as the evaluation method.

The sensitivity analysis was performed using an add-on program within Excel, called @RISK, developed by Palisade Corporation. A base inflation rate was required for prediction in @RISK as the base percentage of increase in accident and VOC costs at each year. Using the CPI (2015), a median inflation rate of 2.50 percent was calculated from the annual indexes of years 1999 through 2014. Each inflation rate is assigned a distribution and parameter type in @RISK with which it will vary in the analysis, with the inflation rate being the mean value of increase. A normal distribution was assigned to the inflation rate along with a standard deviation of 1.04 percent, which was calculated using the CPI (2015) annual indexes for year 1999 through 2014.

Time dependent variables incorporated into the sensitivity analysis included: ADT, Deck Geometry Appraisal, Coefficient of vehicles detoured due to load posting, Average Index (BMS), Cost / accident (U_{AC}), and Vehicle Operating Cost (VOC), using both U_{DC}= Cost / mile and U_{DL}= Cost / mile as variables. To establish the time-dependent relationships necessary to run the sensitivity analysis, work being performed as part of the effort to update deterioration models was utilized. For brevity, much of the supporting data and tables showing these time-dependent relationships are shown in Appendix C. A more detailed discussion of the assumptions and constraints utilized in the sensitivity analysis, as well as treatment of the time-dependent relationships utilized in this sensitivity analysis, is provided in Ramsey (2015), although a synopsis is provided herein.

Deck geometry appraisal is listed as Federal Item 68 in the FHWA Recording and Coding Guide (FHWA, 1995). The FHWA Recording and Coding Guide provides two comparative methods by which to appraise a bridge deck geometry (vertical clearance or number of lanes). This method consists of identifying the appropriate deck geometry appraisal rating from three different tables in which a bridge is rated, with the lowest appraisal rating from the table used for the condition rating assignment. In one method, a bridge is given a deck geometry appraisal rating based on its vertical clearance and functional classification, therefore it is assumed that this rating will remain constant for the bridge's service life. The other method to determine a bridge's appraisal rating is based on the total number of lanes. A bridge with three or more lanes is assigned a deck geometry appraisal rating based on its number of lanes and roadway width. If a deck geometry appraisal rating is assigned in this manner it is also assumed to remain constant for the bridge's service life, unless major reconstruction occurs. Bridges with two lanes and two-way traffic are differentiated by their ADT and assigned a lower deck geometry appraisal rating with increasing ADT. Using tables provided by the FHWA (1995) for Federal Item 68, bridges analyzed in this study that fit the two-lane, two-way traffic classification were assigned future appraisals based on the their future ADT (discussed above) and their bridge roadway width. A snapshot of the deck geometry appraisal forecast is provided in Appendix C, Table C.5.

Average Index (BMS) is calculated as the average of the deck, superstructure, and substructure condition ratings for a particular bridge. As part of ongoing work being completed for updating the BMS, a new set of deterministic models were developed using the Duncan and Johnston (2002) methodology to determine the deterioration rates of these condition ratings (Goyal, 2015). Table 4.13 provides a sample table (for timber decks) that illustrates the typical number of years that a timber deck condition remains at each condition rating prior to changing to the next lower rating. Utilizing updated deterministic models, these tables were prepared for each condition rating for timber, steel, concrete, and prestressed concrete deck bridges based on different ADT bins. Tables for deck, substructure, and superstructure condition deterioration rates, illustrating the typical number of years the each component can be expected to remain at each condition rating, are provided in Appendix C, Tables C.6 through C.15. The bins were then averaged for each condition rating associated with the deck, substructure, and superstructure over each material type. This average was used to provide a slope, which serves in this analysis to compute the expected change in each condition rating over time.

Using these material-specific deterministic models to predict how long each part of the bridge structure (deck, superstructure, and substructure) can be expected to remain at each condition rating, a predicted condition rating for deck, superstructure, and substructure of each bridge was computed for the 20-year timeframe of the sensitivity analysis. Snapshots of this work are provided in Appendix C, Tables C.16 through C.20. The Average Index (BMS) was additionally computed at each year for each structure. A snapshot of this calculation is provided in Table 4.14. It is noted that the lowest rating that a bridge component could be assigned at any point in the 20-year timeframe was a condition rating of 3.

Table 4.13: Expected deck condition rating durations (in Years in Rating) for Timber Decks

Timber Deck (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Timber 0-200	2.9361	8.4615	7.3584	6.9167	4.9352	4.302
Timber 200-800	3.0151	8.3017	7.9498	6.8142	4.8426	4.4534
Timber 800-2000	3.0517	7.4764	7.8105	6.8052	4.5854	4.203
Timber 2000-4000	2.6429	7.3468	7.8414	6.217	4.9135	3.959
Timber >4000	3.1667	8.9063	6.7352	5.2826	5.5646	5.1196
Timber Average	2.9625	8.09854	7.53906	6.40714	4.96826	4.4074
Slope	0.33755	0.123479	0.13264	0.156076	0.20128	0.22689

Table 4.14: Snapshot of typical Excel spreadsheet showing prediction of average index (BMS) deterioration

	Averge Index (BMS)										
Structure No.	year 0	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	5.67	5.67	5.33	5.33	5	5	4.67	4.67	4.33	4	4
400002	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5	5	4.33	4.33
400003	5	4.67	4.67	4.33	4.33	4.33	3.67	3.67	3.67	3.67	3.67
400004	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5.33	5	5	4.33
400005	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5.33	5	5	4.33
400006	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5.33	5	5	4.33
400007	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5.33	5	5	4.33
400009	6.67	6.33	6.33	5.67	5.33	5.33	5.33	5.33	5.33	5	5
400010	5	4.33	4.33	4.33	4	3.33	3.33	3.33	3.33	3.33	3.33
400011	7	6.67	6.67	6.67	6.33	6	6	6	6	6	5.67
400012	4	3.67	3.67	3	3	3	3	3	3	3	3
400013	5	5	4.67	4.67	4	4	4	3.67	3.67	3.33	3.33
400015	5.67	5.33	5.33	5	4.67	4.67	4.67	4.67	4.33	4.33	3.67
400016	5.67	5.33	5.33	5	5	4.33	4.33	4.33	4.33	4.33	4.33
400017	5	5	5	4.67	4.33	4	4	3.67	3.67	3.33	3.33
400018	5	5	5	4.67	4.33	4	4	3.67	3.67	3.33	3.33
400019	7	6.33	6.33	6.33	6	6	6	6	5.67	5.67	5.67
400020	7	7	7	7	6.67	6	6	6	6	6	6
400021	7	6.67	6.67	6.67	6.67	6.67	6	6	6	6	5.67
400022	5.67	5	5	5	5	4.67	4.33	4.33	4	4	4
400023	7	6.67	6.67	6.67	6.67	6.33	6	6	5.67	5.67	5.67
400024	7	7	7	7	6.33	6	6	6	6	6	6
400025	5.33	5.33	5.33	5	4.67	4.67	4.33	4.33	4	4	4
400027	5.67	5	4.67	4.67	4.67	4.33	4.33	4.33	4.33	4	3.67
400028	5	5	5	5	4	4	4	4	4	4	4
400030	5	4.33	4.33	4.33	4	4	3.33	3.33	3.33	3.33	3.33
400031	6.33	6.33	6.33	6.33	6	5.67	5.33	5.33	5.33	5	5
400032	5.67	5	4.67	4.67	4.67	4.67	4.33	3.67	3.67	3.67	3.67

User costs incurred due to detours resulting from load postings will be affected as deterioration of a bridge results in lower load postings (TTST and SU) over time. The estimated future bridge capacity reduction is currently predicted based on the substructure condition rating, as outlined by Johnston et al. (1994). Based on the substructure material type and condition rating at each year (as determined as part of this project and presented by Goyal, 2015), the capacity of the bridge will either remain constant or will be reduced. As part of work to update deterioration models included in this project, an updated table that provides the predicted reduction in capacity of a bridge based on its substructure condition rating was developed and is presented in Table 4.15. The load capacity for each bridge was predicted for the 20-year horizon, with a snapshot for TTST shown in Appendix C, Table C.17, and a snapshot for SU provided in Appendix C, Table C.18. Both SU and TTST loads were constrained so that they would not go below 3 tons, which is the minimum load a bridge must hold to remain open to traffic.

Table 4.15: Predicted load capacity deterioration rates

Load Capacity Deterioration Rates (tons/year)				
Substructure Condition Rating	**Bridge Main Structural Material**			
	Timber	**Concrete**	**Steel**	**Prestressed**
5-9	0	0	0	0
4	0	0.22	0.06	0.84
3	0.57	1.67	0.61	1.61

The result of the @RISK Monte Carlo simulation used to perform the sensitivity analysis is a series of predicted NPV user costs for bridges in Guilford, Halifax, Harnett, and Haywood over the 20 year horizon with the uncertainties due to accident and VOC costs. The @RISK output for the range of predicted NPV is shown in Figure 4.7 as a probability density histogram prepared from the 1,000 analyses performed on the user costs equation in @RISK. From Figure 4.7, it can be noted that the uncertainty in change of both the accident and vehicle operating costs will have a large effect on the resulting predicted NPV user costs. This is depicted in the x-axis where the predicted NPV user costs range from 645 million dollars to 967 million dollars. In Figure 4.7, values on the y-axis indicate the probability density of the histogram, where the area of each bar is the proportion of samples within it, the y-axis is scaled so that the total area of the histogram bars is 1. It is noted that the standard deviation is over 47 million dollars.

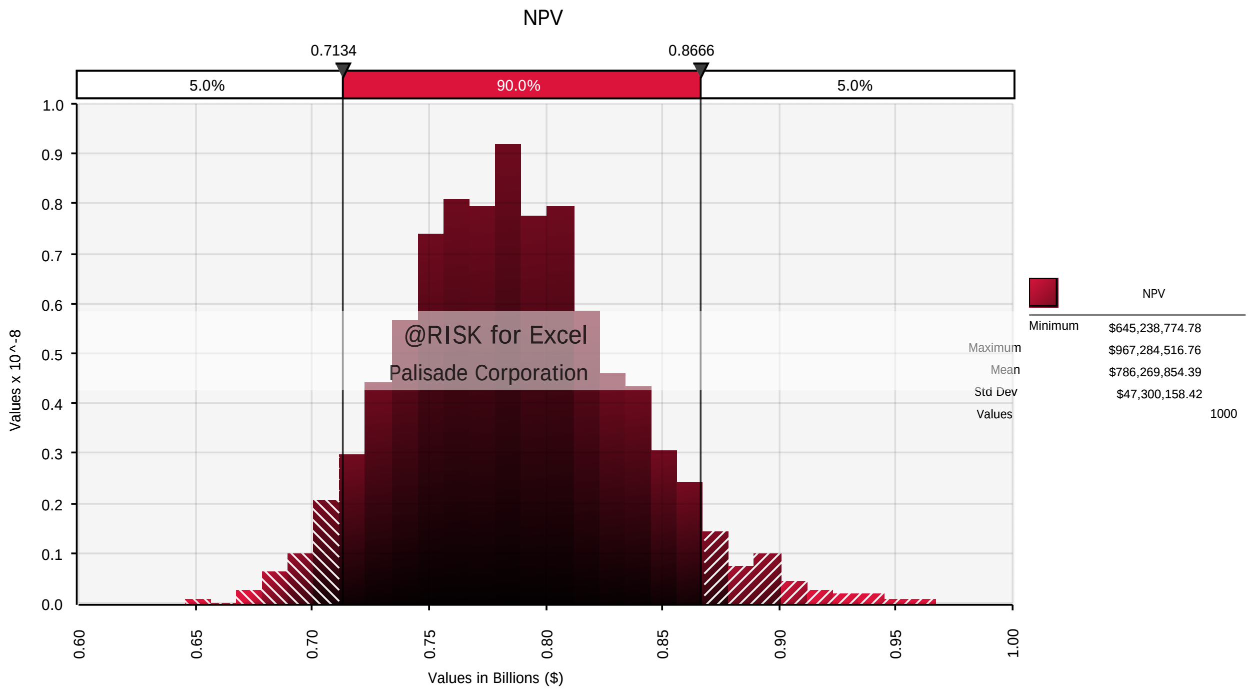


Figure 4.7: @RISK output showing user NPV costs, 20-year horizon for bridges in (Guilford, Halifax, Harnett, and Haywood)

To illustrate how user costs are affected by each variable (the sensitivity to each variable), @RISK computes how each uncertain variable affects the predicted NPV user costs. The @RISK output is formatted to show the variance in costs from the lowest (bottom of the chart) to the highest (top of the chart). The results of the sensitivity analysis of the user costs based on accident costs and vehicle operating costs (VOC), compared separately, is shown in Figure 4.8. The results indicate that accident costs have a much larger effect on the resulting predicted NPV user costs than the VOC. For clarity, the ranges of computed values (corresponding to the bars in Figure 4.8) are provided in Table 4.16.

Ultimately, the results of this sensitivity analysis should allow NCDOT to identify ways to reduce user costs. Since user costs are most sensitive to accidents, and because the cost associated with an accident is something that NCDOT cannot directly control, it is apparent that reducing accidents themselves is the key to reducing future user costs for the state's bridges. To develop an updated bridge accident prediction equation, bridge characteristics most associated with recent bridge-related accidents were identified as part of this work. This sensitivity analysis reinforces that an increased focus on addressing factors that most greatly influence bridge-related accidents will significantly reduce user costs, as well as improve the safety North Carolina's bridges.

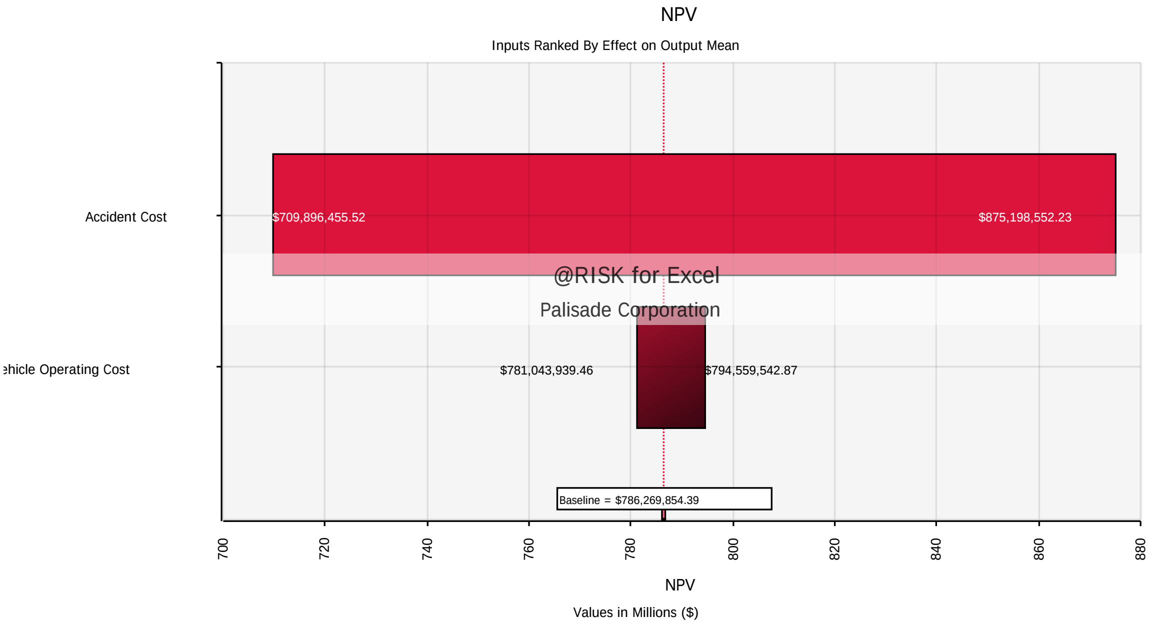


Figure 4.8: @RISK output showing sensitivity analysis

Table 4.16: @RISK output showing NPV output change

Change in Output Statistic for NPV			
Rank	**Name**	**Lower**	**Upper**
1	Accident Cost	$ 709,896,455.52	$ 875,198,552.23
2	Vehicle Operating Cost	$ 781,043,939.46	$ 794,559,542.87

5. SUMMARY AND CONCLUSIONS

Advancements in optimized bridge management, including deterioration forecasting and user cost prediction methodologies, have been achieved over the past decade that have significantly matured the state-of-art of BMS practices nationwide. Federal and state initiatives to leverage performance-based metrics for transportation planning have likewise resulted in increased interest and reliance on intelligent asset management software, such as the NCDOT BMS, to provide data-driven decision making capabilities. Research performed specifically within this project will be significant to both NCDOT and the larger community involved in bridge structures as it provides resources to facilitate implementation of nationwide BMS best practices in probabilistic deterioration models and provides updated, enhanced capabilities for predicting user costs. Provisions for incorporation of data obtained via element-based inspections in the NCDOT's BMS have been suggested where appropriate. Ultimately, when implemented into NCDOT's BMS, the contributions of this project will result in improved accuracy of both predicted bridge condition states and anticipated user costs in network-analysis, which in turn will result in more effective allocation of resources for maintenance, repair, replacement, rehabilitation, and preservation of North Carolina's bridge infrastructure.

In summary, key contributions of this work related to updates and enhancements of the deterioration models include:

- Updated deterministic deterioration models for both bridge components and culverts that are immediately implementable into NCDOT's BMS.

- Development of a unique statistical regression methodology that applies survival analysis with a proportional hazards model to provide a means of developing transition probability matrices for probabilistic deterioration models that account for the effects of design, geographic, and functional characteristics on bridge component deterioration rates. These models were found to provide significantly improved prediction accuracy and precision compared to the deterministic deterioration models over typical planning horizons used in network analysis.

- An analysis that indicates that a simplified implementation of the probabilistic deterioration model was able to achieve similar performance to the proportional hazards probabilistic model without explicitly incorporating the effects of external factors on deterioration rates. However, the analysis does reveal that the proportional hazards probabilistic models developed as part of this work were found to best fit the historical condition rating data, ensure consistent and slightly conservative prediction errors over both short and long term planning horizons, and provide unique insight on factors influencing deterioration over the life-cycle of each bridge component. Consequently, implementation of the proportional hazards probabilistic models is the recommended course of action, with the implementation of the simplified probabilistic models being a secondary recommendation if resources for modifying the current AgileAssets approach are limited.

- A Windows-based graphical user interface (GUI) software to assist in developing and refining deterioration models in the future. This software provides the capability to develop both the conventional deterministic, proportional hazards probabilistic deterioration models, and simplified probabilistic deterioration models using annual bridge reports sourced from either the NC Bridge Maintenance files, NBI files, or exported datasets from the AgileAssets BMS.

Although it is premature to provide recommendations on modifications to trigger points for MR&R decision trees, groundwork has been laid that demonstrates a methodology for quantifying the improvement effectiveness of MR&R actions on deterioration rates. Preliminary work performed as part of this project to develop action effectiveness histograms lays the foundation for incorporation of MR&R actions into the probabilistic deterioration model. Ongoing work as part of Research Project 2016-05 will allow the research team to further explore the validity of this method given the data available to quantify action effectiveness. Ultimately, this effort should provide new insight into revisions to decision trees and condition state triggers, resulting in improved suggestions for MR&R activities, more effective allocation of resources, and more accurate forecasts of budget needs. If the current BMS is revised to permit the use of preferred probabilistic methods for deterioration modeling, then the research team recommends that further research be performed to integrate the condition improvement, or action effectiveness, probabilities into the transition probabilities of the deterioration models to develop an integrated analysis.

Key contributions of this work related to updates and enhancements of BMS user costs include:

- Updated ADT growth rates based on statistical analysis of a fairly robust dataset of historical ADT records. Also prepared is a graphical summary of where updated ADT growth rates were found to be higher or lower than the growth rates sourced from prior NCDOT research and currently utilized in the BMS.

- Updated inputs for prediction of vehicle operating costs incurred due to detours caused by bridge load postings and vertical clearance restriction. To obtain these inputs, reliable sources of current data (often North Carolina specific) were utilized to provide an updated distribution of vehicle types on roadways of different classifications, an updated vehicle weight distribution, and an updated vehicle height distribution. Analysis performed as part of this work demonstrated that the BMS is currently under-predicting the portion of traffic incurring user costs due to vertical height limitations.

- Updated vehicle operating costs for the minimum (3-ton) and maximum (40-ton) weight vehicles utilized for this computation in the BMS. Additionally, a vehicle operating cost for a vehicle of 26-tons (typical 3-axle dump truck) was computed. Using this third point, the two-point linear interpolation method currently utilized by NCDOT's BMS to compute user vehicle operating costs between the minimum and maximum weight vehicles was validated as a reasonable approach.

- Updated inputs for prediction of accident costs for bridge-related crashes. Recent data on bridge-related crashes in North Carolina were utilized to produce the expected frequency of each severity type occurring on bridges. It was found that the average number of bridge-related accidents occurring per year in the five counties included in the prior study has remained constant, even with a significant increase in population (and subsequently higher ADT) over the 25 year period, which is promising. It was also determined that the frequency of fatal (K) bridge-related crashes has decreased significantly (by a factor of approximately 2) over the past 25 years. The frequency of high severity injury (A) crashes has decreased by a factor of 6.5 over the past 25 years and the frequency of moderate severity injury (B) crashes has decreased by a factor of 1.6. The reduction in the frequency of these high-cost accidents will result in BMS predictions with significantly lower user costs attributed to bridge-related accidents.

- Updated input data for cost per bridge-related crash based on recent North Carolina-sourced data for accident costs of different severity. An analysis was also provided to illustrate the impact of using the updated crash frequencies and accident cost data. It was shown that the impact of the new, locally sourced cost data on the calculation of user costs is nominal, particularly when compared to the impact associated with changes in the frequency of fatal and severe crashes.

- Development of a new equation useful in predicting the number of annual bridge-related crashes. The analysis of bridge-related crashes performed to develop this equation resulted in the identification of seven bridge characteristics that are most associated with bridge-related crashes. These seven characteristics are ADT, approach roadway width, deck geometry appraisal, structure length, Average Index (BMS), total horizontal clearance, and functional classification. When compared to the crash prediction equation currently utilized in the BMS, ADT and structure length remain influential in predicting bridge-related crashes, with higher ADT and longer structures associated with higher incidences of crashes. Approach alignment, suspected by previous researchers to influence bridge-related crashes but not confirmed by past data, was again found to not be significant. Average Index (BMS) was found to be a significant predictor of bridge-related crashes. Regular and preventative maintenance to maintain or improve condition ratings should reduce bridge-related crashes, since the Average Index (BMS) is developed from the average of the deck, superstructure, and substructure condition ratings. Interstate bridges are associated with lower incidences of bridge-related crashes, relative to bridges on municipal roads, US, and NC routes.

- Results of a sensitivity analysis on user costs indicated that NCDOT's BMS user costs are most sensitive to accident costs. Since the cost associated with each accident is something that NCDOT cannot directly control, it is apparent that reducing the number of accident occurrences is the key way to reduce future user costs for the statewide inventory of bridges.

In conclusion, the revised deterioration models (both updated deterministic models and proportional hazards-based probabilistic models) and user cost inputs and methodologies developed as part of this work will increase the effectiveness of the BMS's ability to effectively perform economic analyses of bridges to establish MR&R priorities and to assess intervention options. This will assist in project candidate selection and MR&R decision making on the network-level and project-level.

6. RECOMMENDATIONS

Recommendations for implementation of the products and findings of this research project include:

- Priority should be placed on implementing probabilistic deterioration models in the AgileAssets BMS using the Markov-chain approach. Since the proportional hazards-based probabilistic deterioration models provide the best statistical fit to the historical data, remain accurate yet slightly conservative over both short-term and long-term planning horizons, and reveal important insight on the key factors that affect deterioration of different bridge components, consideration should be given to incorporating the capability to perform deterioration forecasts with these models in the AgileAssets BMS. Additionally, these models are expected to offer more powerful predictive capability as element-level condition rating data becomes available in the BMS. Therefore, it is recommended that the full proportional hazards models be implemented to support longer-term improvements to the BMS. However, the research results also indicate that simplified probabilistic models are likely to provide improvements in accuracy and precision similar to proportional hazards probabilistic models for moderate planning horizons but with easier implementation/minimal programming requirements. If resources for improving the Agile Assets BMS are constrained, then these simplified probabilistic models will still offer significant improvements in deterioration forecasting accuracy and precision as well as allow for probabilistic incorporation of maintenance action effectiveness.

- In the interim before such methods are permitted in the Agile Assets BMS, the Structures Management Unit should use the updated deterministic deterioration models. However, model assessment performed in this study indicates that these deterministic deterioration models are still overly conservative and lack the precision offered by the improved probabilistic methods.

- Culvert deterioration models should be introduced to the BMS to extend network level-of-service analysis to culvert replacement and rehabilitation actions.

- Deterioration models should be updated on a more frequent basis to take full advantage of the value of the historical condition rating database. The stand-alone graphical user interface developed through this research effort provides a means for NCDOT to update either the deterministic or probabilistic deterioration models without having to contract research universities or independent consultants. This will allow NCDOT to focus future research efforts on improving the BMS as element-level data become available, rather than simply updating component deterioration models.

- In order to enhance the agency's ability to establish condition improvements using analysis of past performance, it is recommended that the MMS work functions be expanded to include all BMS treatments to eliminate the mapping that condenses many BMS treatments into the same MMS work function. Alternatively, improved specificity of the maintenance actions actually performed or exploration of ways to incorporate the cost data into the statistical regression could be used to improve the analysis without necessarily changing the mapping of BMS treatments to MMS work functions.

- User cost updates and enhancements developed and recommended for implementation as part of this work are predicated on the assumption that the methodology developed by Chen and Johnston (1989), Abed-Al-Rahim and Johnston (1991), and Duncan and Johnston (2002) is actively used within the Agile Assets BMS. It is recommended that NCDOT verify that computational methodology utilized in the BMS software is consistent with these approaches as published.

- Updated inputs for ADT growth rates, vehicle distribution percentages, proportions of vehicles detoured due to vertical height restriction and load posting, vehicle operating costs, accident costs, and crash frequencies by severity should be immediately implemented into the BMS.

- The new recommended equation for prediction of user costs in the BMS (Equation 4.5) should be incorporated into the BMS software. This new equation is the result of modifications to the accident prediction equation and the availability of load postings for both SU and TTST in the BMS. This new equation would allow accident costs incurred due to vertical clearance issues to be included in the user cost forecasting, as well as more accurate user costs incurred by vehicles detoured due to load postings.

- Record bridge accident data in BMS to help with user cost predictions and prioritization of bridge replacement projects.

As mentioned previously, NCDOT is currently supporting Research Project 2016-05 to develop new prioritization indices for bridge replacement, rehabilitation, and preservation actions. Following recommended practice outlined in NCHRP Report 590, prioritization indices will be developed through decision-analysis guided by practitioner input to locally calibrate the index to the preferences, goals/objectives, risk attitudes, and needs of the State. The developed indexes will provide a data-driven and objective means of quantitatively computing relative priority of specific bridge projects from performance metrics that can be derived largely from design, functional, geographic, traffic, and condition data readily available in the existing asset management programs. In addition to producing a recommended revision to the current bridge Priority Replacement Index (PRI), the research project will also develop prioritization indexes associated with bridge rehabilitation projects and preservation actions, as well as the first culvert priority replacement index. Work from this project (Research Project 2014-07) to evaluate the effects of MR&R activities on deterioration rates (such as the action effectiveness histograms) will facilitate improved long-term economic and planning benefits. If the current BMS is revised to permit the use of preferred probabilistic methods for deterioration modeling, then the research team recommends that further research be performed to integrate the condition improvement, or action effectiveness, probabilities into the transition probabilities of the deterioration models to develop an integrated analysis.

Ultimately, it is understood that a key goal of NCDOT's continued updates and enhancements to the BMS is to facilitate identification of multiple feasible MR&R options that would achieve a desired level of service without a funding figure being specified. Building upon work completed as part of Research Project 2014-07, additional research to be conducted within Research Project 2016-05 should provide more insight into recommended changes in current BMS practice resulting from expansion of condition rating datasets following implementation of element-level rating.

Sensitivity analysis performed in this project revealed that user costs are highly influenced by bridge-related crashes and associated accident costs. Further study of crash causes and identification of design or operational tactics that could reduce the occurrence of bridge-related crashes could be performed. For example, preventative maintenance to existing bridges has been shown to reduce user costs. Recommended future work could include a study of past maintenance, repair, and rehabilitation work and its effect on Average Index (BMS), and subsequently accident rates. The costs of more severe injuries and fatalities are significantly higher than those of less severe and property-damage-only accidents. Study of the bridge-related characteristics associated with fatal and very severe accidents could be useful.

Overall, improvements to the NCDOT BMS could be made to facilitate more synergistic project decision making across the full suite of asset management programs. For instance, the NCDOT Pavement Management System (PMS) currently uses four roadway classifications: Interstate, US, NC, and SR. In contrast, the NCDOT utilizes eleven functional classifications to describe roadways served by the bridge system. Developing and implementing a field in the NCDOT BMS that allows for the BMS functional classification to be mapped to a corresponding PMS roadway classification would allow for more synergistic use of the BMS and PMS to support network-level project cost predictions and optimization.

7. IMPLEMENTATION AND TECHNOLOGY TRANSFER PLAN

Updated deterministic deterioration models and most user cost input tables developed as part of this work are directly implementable into the BMS software in the format provided in this report. Other suggested changes, such as implementation of the proportional hazards-based probabilistic deterioration models and modifications to the key user cost equation (Equation 4.5) will need to be addressed by the developers of the Agile Assets BMS software. Project personnel are willing to meet with NCDOT, Agile Assets, and others to assist with implementation as requested. The research results also indicate that simplified probabilistic models, which implement a standard Markov-chain deterioration model similar to those used by other state and federal BMS softwares, are likely to provide improvements in accuracy and precision similar to proportional hazards probabilistic models for moderate planning horizons but with easier implementation/minimal programming requirements.

A stand-alone Windows-based software application for developing and refining deterioration models across user-defined components and families was transferred as a digital executable file to permit application of the deterministic and/or probabilistic methods implemented and refined over the course of the research project. A user manual was developed and supplied to assist with technology transfer to NCDOT and other interested parties. This user manual is provided in Appendix D. Project personnel can work with NCDOT to provide training, both in person or via recorded video, as requested.

8. REFERENCES

Note: References listed below are cited in the body of the report. A full list of references utilized to support this work is provided at the end of Appendix A, which contains the complete Literature Review for this project.

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APPENDICES

FOR
FINAL REPORT

North Carolina Department of Transportation
Research Project No. 2014-07

Determination of Bridge Deterioration Models and Bridge User Costs for the NCDOT Bridge Management System

By

Tara L. Cavalline, Ph.D., P.E.
Assistant Professor

Matthew J. Whelan, Ph.D.
Assistant Professor

Brett Q. Tempest, Ph.D.
Assistant Professor

Raka Goyal
Graduate Research Assistant

Joshua D. Ramsey
Graduate Research Assistant

University of North Carolina at Charlotte
9201 University City Boulevard
Charlotte, NC 28223

October 26, 2015

APPENDIX A – LITERATURE REVIEW AND REFERENCES

A.1 Overview

National Bridge Inspection Standards (NBIS) were instituted in early 1970's following the collapse of Silver Bridge in Ohio due to corrosion. This legislation mandates that all states maintain bridge inventory and inspection records for every bridge in their jurisdiction. Each bridge record acts as a reference for any changes occurring in the physical condition of the bridge with time. These changes are measured and recorded through periodic inspections that must be performed no less frequently than on a biennial schedule. In this way the deterioration, if any, of the overall condition of the bridge and its components is monitored so that remedial action can be taken as needed to preserve the bridge in good condition and ensure the safety of the traveling public.

While trying to achieve the objective of maintaining all bridges in their inventory, states continuously face the challenge of allocating limited funds to meet the increasing needs of individual bridges. This challenge led to the evolution of Bridge Management Systems (BMS), which are systematic approaches for using the available bridge data, projected costs, and functional needs at the local and network-level to help objectively make such decisions. A BMS helps decision makers to interactively understand the trade-offs of allocating constrained funding to rehabilitation or maintenance work versus bridge replacement across the entire network of bridges in order to formulate optimal decisions based on economics, performance, and safety. North Carolina was one of the first states to develop a BMS (Chen and Johnston, 1987). Since then, many other states, along with the federal government, have developed BMS systems, although the majority of states now use the AASHTOWare Pontis software for some degree of bridge management (Markow and Hyman, 2009).

North Carolina Department of Transportation (NCDOT) currently maintains records for over 17,000 in-service bridges with each record having over 200 items of operational and functional bridge information, including condition rating data from the most recent visual inspection. The digital recording of NBI data for North Carolina bridges began in 1981, so there are now over 35 years of bridge records in NCDOT database. NCDOT currently uses a BMS software developed by AgileAssets, Incorporated. However, while this software implements the constrained optimization scenarios to provide scenarios for decision-making, the database relies on independent development of both deterioration models for the prediction of bridge maintenance needs and user costs for the prediction of required funds to accomplish projected maintenance, repair, and rehabilitation (MR&R) and reconstruction/replacement actions.

A.2 Deterioration Modeling

Bridge deterioration models represent the estimated deterioration of specific bridge components over time. These predictive models are developed on the basis of historical condition ratings of bridge components characterizing the extent of physically observable signs of deterioration as recorded by bridge inspectors during scheduled biennial inspections. Deterioration models form an important component of bridge management systems by predicting future MR&R needs at the bridge and network level. Consequently, the efficacy of a BMS in optimally allocating MR&R budgets to ensure the preservation of bridge components and the safety of the traveling public is directly affected by the accuracy of the bridge deterioration models. With the increased reliance on optimized, data-driven BMS planning to address infrastructure maintenance needs of large bridge inventories under constrained budgets, the importance of having accurate deterioration models cannot be overemphasized.

Since the introduction of BMS frameworks in the early 1980s, approaches for deterioration modeling have continuously developed in complexity from the earliest purely deterministic methods. Currently, the most widely prevalent in US are the Markov chain based probabilistic approaches, which have also been incorporated in the AASHTOWare Pontis and Bridgit commercial BMS software applications adopted by many states. However, the growth of the historical condition rating database has recently permitted duration-based probabilistic approaches to be investigated as well as the integration of these approaches with the earlier Markovian models. The different strategies for developing deterioration models from condition rating data are discussed in the following sections alongside their assumptions, advantages, and limitations.

A.2.1 Deterministic Models

Deterioration of bridge components is associated with many factors including age, environment, design characteristics, and traffic conditions. It manifests itself in observable defects like corrosive loss in steel components, delamination in concrete, cracking, and scour of foundation systems. Deterioration models are a way of linking observable symptoms of deterioration to the various explanatory factors affecting deterioration to enable prediction of deterioration behavior and planning of suitable corrective actions. Early studies formulated mathematical relationships between observed deterioration quantified by condition ratings with specific classifiers, such as component and material type, using statistical measures like mean, standard deviation, and linear regression coefficients. These studies ignored the random errors inherent in statistical prediction and therefore all these models are classified as deterministic models. A typical deterministic deterioration model is shown in Figure A2.1, where the ordinate is the condition rating that is plotted against the average age of the bridges at that condition rating, which forms the abscissa.

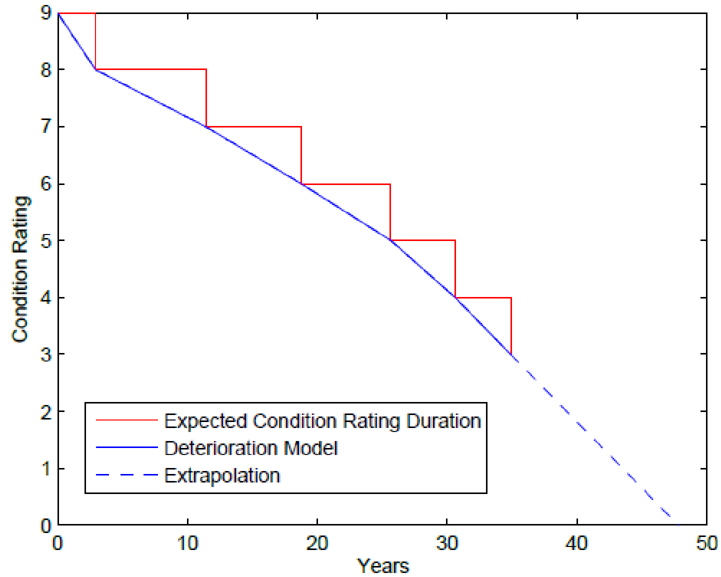


Figure A.2.1: A deterministic bridge deterioration model

The earliest deterministic models devised in 1987 for the North Carolina bridge inventory used two parameters: the average age of bridges at a particular condition rating and the average age of bridges when the condition rating dropped by one point (Chen and Johnston, 1987). The researchers did not use data regression as their efforts to do so proved ineffective on account of substantial scatter in condition rating data due to alteration in natural deterioration patterns caused by maintenance and repair activities. As an alternative, they used *a priori* classification of bridges and bridge components into categories based on factors believed to significantly affect the deterioration of the particular bridge components. Through this heuristic classification, all of the three primary bridge components analyzed (deck, superstructure, and substructure) were initially grouped by primary material type under the logical expectation that the deterioration rates would be strongly associated with characteristics of the long-term durability of the construction materials. As a secondary level of classification, bridge decks were further sub-classified into bins by average daily traffic (ADT), superstructures were sub-classified by both structural design type and highway functional classification, and substructures were sub-classified by geographical region. Statistical analysis of the then-limited historical condition rating data indicated deterioration of bridge condition with age, but ultimately was found unreliable for development of deterioration models due to ill-conditioning of the data caused by characteristics of the bridge age distribution and effects of maintenance activities. The deterioration models ultimately adopted at the time of this study were based on the results of an opinion survey of professional bridge inspectors and supervisors (Chen and Johnston, 1987). These heuristic deterioration models were used in the development of the Optimum Bridge Budget Forecasting and Allocation Module (OPBRIDGE) that produced North Carolina's original BMS (Isa Al-Subhi and Johnston, 1989).

A later study proposed the use of the average change in condition ratings over multiple years to model deterioration and to improve the performance of the North Carolina BMS (Abed-Al-Rahim and Johnston, 1991). The categorization of bridge components on the basis of expected explanatory factors was expanded to include geographic classifications in an attempt to account for the perceived dependence of deterioration rates on the presence of marine environment and de-icing salt applications. The study developed illustrative sets of deterioration models that were consistent in terms of predicting deterioration with respect to various material and environmental factors as well as other considerations (Abed-Al-Rahim and Johnston, 1991). Updating of the bridge deterioration models in OPBRIDGE was, however, implemented much later using the average durations of bridge components at particular condition ratings (Duncan and Johnston, 2002). Both of these models, while still deterministic, had the advantage of using time series data of bridges in addition to the cross-sectional data used exclusively by the earlier models. The NBI data is cross-sectional as it is comprised of inspection records that report only the condition ratings of all the nation's bridges in the current year. Time series data on the other hand represents the historical condition data of a particular bridge as it changes over time. In early studies that were disadvantaged by insufficient time series data for analysis, the cross-sectional condition rating data of all bridges of various ages was aggregated to represent the expected deterioration of a single representative bridge.

A.2.1.1 Linear and Nonlinear Regression Models

During the early 1990's, similar deterministic deterioration modeling studies were carried out using NBI bridge inventories for the whole nation as well as those of individual states, some of which are reviewed here. Linear regression was used in a study by the Transportation Research Center of the U.S. Department of Transportation (DOT) to correlate the relationship of bridge condition ratings with other bridge characteristics recorded in the NBI database in a linear statistical model (Busa et al., 1985). An improved piecewise linear regression was used in other studies performed for the Wisconsin DOT and the New York State DOT (Fitzpatrick et al., 1981, Hyman and Hughes, 1983). Deterioration of bridges in the New York City Metropolitan area was modeled as function of age using two methods: 1) the average rate of change for each condition rating and 2) the average condition rating of bridges of all ages (Yanev and Chen, 1993). Nonlinear regression models were also developed for the first time using time-series data for Pennsylvania bridges (West et al., 1989). Most of these studies developed composite deterioration curves with respect to age with minimal or no classification of bridges into categories based on characteristics like structural design or environment.

In subsequent years, several studies used nonlinear statistical regression along with classification of bridges into relatively homogeneous groups on the basis of potential determinants of deterioration identified through literature review and discussions with the members of the bridge engineering community. To produce a representative sample of diverse environments, one of these studies analyzed superstructure deterioration with respect to age and ADT for all of the steel and prestressed concrete bridges in the national inventory as well as individually for the seven states of Colorado, Illinois, Iowa, North Carolina, Pennsylvania, Tennessee, and Texas (Veshosky et al., 1994). This study found that there was no statistically significant difference in the rates of deterioration of steel superstructures relative to prestressed concrete superstructures. In general, age was found to be the most statistically significant factor followed by ADT, although the impact on the rate of deterioration was found to decrease with time. Another study was performed for bridges within the state of Nevada that correlated condition ratings with age while accounting for all other factors through a priori classification of bridges (Sanders and Zhang, 1994). Explanatory factors investigated in these studies included material type, structure type, ADT, maintenance responsibility, rehabilitation status, and geographical region. A particular challenge faced when increasing the number of variables in both of the studies was the reduced number of bridges in each category. The classification of condition rating data into such datasets of limited sample size ultimately compromised the reliability and applicability of the statistical models. To overcome this problem, investigation of some combinations of variables necessarily had to be abandoned whereas others were combined into larger, more generalized groups that would lend themselves to a more statistically significant analysis. This was especially true for Nevada, as it is a sparsely populated state with a relatively small bridge inventory.

A.2.1.2 Limitations and Contributions of Deterministic Models

While deterministic deterioration models based on simple statistical properties offer relative computational ease, they are associated with some critical inherent limitations. Primarily, they neglect the stochastic nature of the deterioration process as well as the subjectivity and uncertainty present in the condition rating data. For instance, it was found that although the polynomial regression techniques gave reasonable results within the bounds of available data, their projection beyond these bounds could be significantly misleading, thus severely limiting their predictive reliability and usefulness in BMS. Probabilistic models have been shown to provide better extrapolation capabilities and can be easily integrated into dynamic BMS optimization processes resulting in more efficient and effective MR&R strategies (Butt et al., 1987). Furthermore, a priori classification of bridges and bridge components may overlook the impact of unobserved or unmodeled factors that influence deterioration rates. Stated another way, the statistical model may ultimately predict the average deterioration for a group of bridges well but inaccurately predict the deterioration of the bridges individually. This phenomenon is evident from a comparative study of deterioration models developed using two different approaches and applied to forty bridges in the Indiana bridge database. It was found that the magnitudes of prediction errors in models based on polynomial regression techniques were much higher compared to those in models based on a probabilistic Markov chain approach (Jiang, 2010).

The comparative lack of accuracy in model predictions has led to the gradual replacement of strict deterministic approaches with probabilistic approaches throughout the majority of state BMS implementations. However, despite their limitations, studies using deterministic approaches succeeded in deriving some common inferences about bridge deterioration behavior. For instance, the statistical analysis of condition rating data revealed that decks deteriorate faster than the superstructure or the substructure components of a bridge (Chen and Johnston, 1987, Sanders and Zhang, 1994). Likewise, similar components may deteriorate at different rates depending upon various factors, including geographical location and ADT (Chen and Johnston, 1987, Veshosky et al., 1994). Decks with higher ADT tend to deteriorate faster than those with lower ADT and, perhaps inter-related, bridges on secondary highway systems comprising local roads and minor collector roads tend to deteriorate at a lower rate than those on primary systems and interstates (Abed-Al-Rahim and Johnston, 1991, Chen and Johnston, 1987). Impact of saltwater in coastal regions, freeze-thaw cycles, and the use of de-icing salts in cold climatic regions were found to measurably exacerbate deterioration (Abed-Al-Rahim and Johnston, 1991, Sanders and Zhang, 1994). Bridges with expansion joints were found to deteriorate faster than continuous span bridges without joints (Yanev and Chen, 1993). With respect to maintenance actions, rehabilitated bridges tend to deteriorate faster than new bridges (Sanders and Zhang, 1994, Yanev and Chen, 1993).

A.2.2 Markov Chain Models

Probabilistic models aim to capture the stochastic nature of the deterioration process and thereby improve the accuracy of prediction. These models are discrete time and state as the infrastructure condition in these models is represented by discrete condition states at fixed inspection intervals. The earliest probabilistic models considered deterioration as a discrete time Markov process, called a Markov chain, with a finite number of states (Butt et al., 1987, Jiang et al., 1988). The Markov chain models are also called incremental models or state-based models as they model the change in condition or "state" over fixed increments of time. The change in state during a fixed time increment is treated as a random variable that captures the uncertain and random nature of deterioration. Aggregating these random variables over time provides a more realistic representation of deterioration as a stochastic process rather than a purely deterministic one like in the models presented earlier (Madanat and Ibrahim, 1995, Papoulis and Pillai, 2002).

A.2.2.1 Markov Decision Processes

A key component of the Markovian approach is the definition of the states in the system such that they capture the complete status of the system and all the information necessary for the decision making process. Consideration of all N number of bridges in a particular state inventory, a number of which may run in the tens of thousands, each with n possible states corresponding to the NBI condition ratings, would make the total state space of size n^N, which would be computationally burdensome. This problem has been resolved by pre-classifying the bridges into categories with similar characteristics according to variables like material and design type, traffic loading, and geographical and climatic regions, as described earlier in the deterministic approaches. This allows for a tractable representation of the bridge system. A Markov model is then constructed for each class of bridges with the capability to generate models for individual bridges in each class. As mentioned earlier, this process may result in problems associated with limited data at the lower levels of the classification hierarchy when the number of classes increases to the extent that there are not enough bridges in each class to enable a statistically significant analysis (Scherer and Glagola, 1994).

A Markov process is a stochastic process with the 'Markovian' property or assumption of time-independence in which the conditional probability P of a future condition state depends only on the present state and is independent of the past states. This can be represented for a discrete time, discrete state stochastic process X_t as given below (Morcous et al., 2003).

$$P(X_{t+1} = i_{t+1} | X_t = i_t, X_{t-1} = i_{t-1}, \ldots, X_1 = i_1, X_0 = i_0) = P(X_{t+1} = i_{t+1} | X_t = i_t) \quad \text{(A2.1)}$$

where i_t is the condition state at time t. In the context of bridge deterioration, the NBI condition ratings ranging from 0 to 9 represent the ten possible states of the bridge component being modeled with state 1 corresponding to a condition rating of 9 and state 10 to a condition rating of 0. The change of state is assumed to occur at discrete time intervals equal to the routine inspection period of 2 years. Consequently, the probabilities $P_{i,j}$ that a bridge component would transition from state i to another state j during a specified period are represented in a transition probability matrix given below.

$$
P = \begin{bmatrix} P_{1,1} & P_{1,2} & \dots & P_{1,10} \\ P_{2,1} & P_{2,2} & \dots & P_{2,10} \\ . & . & \dots & . \\ . & . & \dots & . \\ . & . & \dots & . \\ P_{10,1} & P_{10,2} & \dots & P_{10,10} \end{bmatrix} \tag{A2.2}
$$

where $i = 1, \dots, 10$ and $j = 1, \dots, 10$. The indices, i and j, can take any value between the lowest and the highest condition state for the particular bridge inventory database. The size of this matrix, however, is specific to the discrete integer range of condition states in the rating system used. For example, the New York State Department of Transportation (NYSDOT) implements its own visual inspection program that assigns condition ratings within the range from 1 to 7, resulting in 7 condition states and therefore a 7x7 transition probability matrix. Similarly, the condition ratings range from 1 to 5 for the Commonly Recognized (CoRe) Structural Elements defined by the American Association of State Highway and Transportation Officials (AASHTO) and the Federal Highway Administration (FHWA), resulting in 5 condition states and a 5x5 transition matrix. Each row of the matrix 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 associated probabilities of each condition rating remaining unchanged between inspections is simply the $P_{i,i}$ probability values, which are found on the diagonal of the transition matrix. The transition matrix has zero values below the diagonal, because it is assumed that the deterioration takes place without rehabilitation and hence the probability of an improvement at any state is zero. Furthermore, for computational simplicity it is routinely assumed that a bridge component would not deteriorate by more than one state in a single inspection cycle. The practical influence of these simplifying assumptions on the transition matrix is shown in the reduced form shown below:

$$
P = \begin{bmatrix} P_{kk} & P_{k(k-1)} & 0 & 0 & \dots & 0 & 0 \\ 0 & P_{(k-1)(k-1)} & P_{(k-1)(k-2)} & 0 & \dots & 0 & 0 \\ . & . & . & . & \dots & . & . \\ . & . & . & . & \dots & . & . \\ 0 & 0 & 0 & 0 & \dots & P_{22} & P_{21} \\ 0 & 0 & 0 & 0 & \dots & 0 & P_{11} \end{bmatrix} \tag{A2.3}
$$

where k is the highest condition state and 1 is the lowest condition state, and $P_{k(k-1)} = 1 - P_{kk}$, $P_{(k-1)(k-1)} = 1 - P_{(k-1)(k-1)} \dots P_{21} = 1 - P_{22}$ and $P_{11} = 1$. The transition probability of the lowest state P11 is one because there is no possibility of transitioning to a lower state that does not exist (Butt et al., 1987, Jiang et al., 1988, Madanat et al., 1995). The transition probability matrix can be used to predict the future condition of a specified bridge component if its present condition is known. The condition at any point in time is represented by a vector; for example, the initial state vector Z_0 for a component in new condition will be [1 0 0 0 0 0 0 0 0 0] for the NBI condition rating scale of 0 to 9 with 9 signifying the good as new condition. Given the transition matrix P as defined above, the future state vector Z_t at time t is obtained using

$$
Z_t = Z_0(P)^t \tag{A2.4}
$$

Since the initial state vector is a known quantity, it is necessary to determine the transition matrix to completely define the Markov chain (Jiang et al., 1988). An illustrative Markovian bridge deterioration model is shown in Figure A2.2, where all of the transition probabilities $P_{i,i}$ on the diagonal of a 5x5 transition matrix are 0.8. The Y-axis represents the initial state, Z_0, when the probability of being in condition state, 5, is 1, and that of being in all the other states is zero. A vertical line drawn parallel to the Y-axis at any time, t, on the X-axis represents the state vector, Z_t, comprised of the probabilities of being in each of the 5 states, and the expected condition rating at that time, respectively, using equations A2.4 and A2.8. The accuracy of a Markovian model depends nearly exclusively on the accuracy of the transition matrix. Various methods have been developed to calculate the transition probabilities.

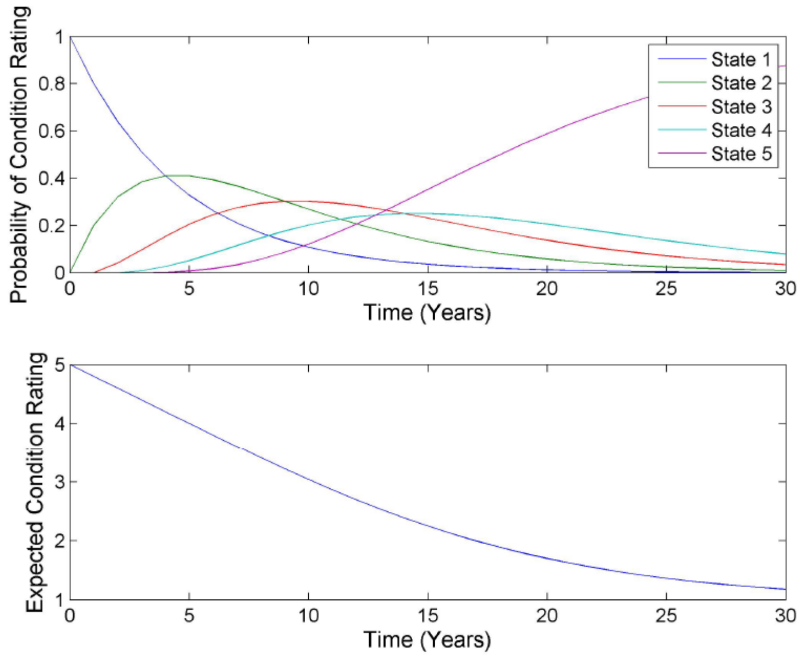


Figure A.2.2: A probabilistic bridge deterioration model

The earliest methods for determining transition probabilities were developed mainly in construction of pavement deterioration models. One of these defined the transition probability, $P_{i,j}$, simply as the percentage or proportion of pavement sections in condition state i that deteriorated to condition state j in one inspection period. Mathematically, this yields:

$$P_{i,j} = \frac{n_{i,j}}{n_i} \tag{A2.5}$$

where n_i is the total number of pavement sections in condition state i and $n_{i,j}$ is the number of pavement sections whose condition state changes from i to j in one inspection period (Scherer and Glagola, 1994, Wang et al., 1994). An inspection cycle is representative of a specified duration of weather and traffic causing deterioration in the pavement condition. In the early models, not only was the duration of the inspection cycles assumed to be the same, but the deterioration contributing factors of weather and traffic were also assumed to be the same in subsequent inspection cycles irrespective of the age of the pavement section. Consequently, the transition probabilities were not expected to change from one inspection cycle to the next. This type of process is deemed a homogeneous or stationary process and known as a Markov Decision Process (MDP) (Frangopol et al., 2004, Jiang et al., 1988).

The assumption of constancy of behavior within inspection cycles relative to factors producing deterioration over the life of an infrastructure component is not realistic as changes occur due to increases in traffic loads or modification of maintenance policies. This inadequacy was recognized after observing the deviation of the actual deterioration curve from the predicted deterioration curve based on MDP for a 30 year life of pavement (Butt et al., 1987). To overcome this limitation, a new model was developed in which the life of the pavement section was zoned into 6-year periods. The deterioration rate was assumed to be constant within each zone and a homogeneous Markov chain with a stationary transition matrix was developed specific to each zone. A non-homogeneous Markov chain was then developed to transition pavement sections from one zone to another. During such transitions, each subsequent zone takes the last state vector of the previous zone as its starting state vector. The deterioration curve developed using this model was found to more closely represent the actual deterioration curve (Butt et al., 1987). This model was also adopted for developing the Markov chain based bridge deterioration models for the Indiana bridge database, which were the earliest models of these kind developed in the U.S. (Jiang et al., 1988, Sinha et al., 1988), and continue to be used in the present-day Indiana Bridge Management System (IBMS) (Sinha et al., 2009).

In the previously mentioned models, a non-linear programming approach was used to calculate the transition probabilities. This approach is known as the expected value method and is still the most widely used method of calculating Markov chain transition matrix probabilities. In this method, the average condition rating of the bridge components in a particular zone or age group is first determined by applying a polynomial regression to all the bridges in that group in the form,

$$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 \tag{A2.6}$$

where Y_t is the bridge component condition rating for a bridge at age t, and β_0, β_1, β_2 and β_3 are regression coefficients to be estimated. The transition probabilities are then calculated by minimizing the distance between the average condition rating $\widehat{Y_t}$ obtained through this regression and the theoretical expected value $E(t, P)$ of the condition rating based on the Markov chain at time t for the transition probability matrix P. The objective function to be minimized is thus given by

$$\min \sum_{t=1}^{N} \left| \widehat{Y_t} - E(t, P) \right| \tag{A2.7}$$
$$\text{subject to: } 0 \le P_{i,j} \le 1 \text{ and } \sum_{j=1}^{k} P_{i,j} = 1 \text{ for } i, j = 1,2, \dots, k$$

where N is the number of years in one age group, and $P_{i,j}$ is the transition probability in the transition probability matrix, P, associated with moving from condition state i to condition state j over the inspection cycle (Butt et al., 1987, Jiang et al., 1988). In terms of equations (A2.3) and (A2.4), if the condition states are represented in a column vector R, $E(t, P)$ in equation (A2.7) is given by (Madanat et al., 1995)

$$E(t, P) = Z_t R \tag{A2.8}$$

The unknown transition probabilities are the decision variables and the maximum number of these that can be estimated using the expected value method is the number of years in each age group (Madanat et al., 1995). The assumption that a bridge component does not deteriorate by more than one state in any one inspection cycle, as mentioned earlier, is helpful in this regard by reducing the probabilities of transition to other states to zero thereby significantly minimizing the number of decision variables that require estimation (Madanat et al., 1995). This assumption was recently applied to element level inspection data to determine transition probability matrices and develop deterioration models for use in Pontis for the Florida Department of Transportation (FDOT). The so-called "one-step method" was found not only to be simpler and require smaller sample sizes, but also more robust while having the same coefficient of determination as the regression model that did not use this assumption (Sobanjo and Thompson, 2011).

A limitation of the expected-value method is that it cannot handle the case where the condition ratings in a particular age group remain the same or tend to increase instead of decreasing. In such a case, the non-linear optimization statement provided in equation (A2.7) may result in a unity or close to unity transition matrix P and, consequently, the deterioration curve flattens out at this point. This problem has been resolved by introducing a second level Markov process (Agrawal et al., 2010). In this second level process, the average condition rating, $\widehat{Y_t}$, in equation (A2.7) is derived from the first level Markov chain predictions instead of the originally used polynomial regression. The objective function is then minimized to determine a single transition matrix for the total number of years in all age groups combined. The deterioration curve generated by this second level transition probability matrix is found to follow the original data but continues realistically to exhibit a decreasing trend even in case where the original curve derived from the first level Markov process stops decreasing beyond a certain age (Agrawal et al., 2010).

A.2.2.2 Commercial BMS Packages and Element-Level Models

The Markov chain models are widely recognized as better than deterministic models by accounting for the stochastic nature of the deterioration process. Moreover, these models have the advantage of computational simplicity and can be applied to both network level and project level bridge management systems. As a result, MDP-based deterioration models were adopted in the two U.S. national bridge management systems, AASHTOWare Pontis and BRIDGIT, that have been implemented in over forty states since their development in the late 1990s (Golabi and Shepard, 1997, Hawk and Small, 1998). Regarding these two commercial softwares, their difference is based on the optimization strategy employed. Pontis follows a top-down approach by doing network level optimization first before determining needs of individual bridges. BRIDGIT, on the other hand, implements a project-level based optimization prior to making network level recommendations (AASHTO, 2011b). BRIDGIT is better suited for use by smaller transportation departments with limited staff resources, but it can be run in parallel with Pontis to complement the decision process by providing an independent set of recommendations (Hawk and Small, 1998).

AASHTOWare Pontis requires the use of element level condition rating data and development of deterioration levels for each element. This is much more detailed data than available in the NBI as each bridge component (deck, superstructure, and substructure) is comprised of numerous elements that currently do not get independently recorded condition ratings. Bridge inspections at the element level were formalized by AASHTO in 1997 through its Guide for Commonly Recognized (CoRe) Elements, which has been recently updated (AASHTO, 2011a). Most states did not have sufficient bridge condition rating data for their bridge inventories when they implemented Pontis. To overcome this limitation, Pontis provides for development of the initial transition probability matrix using "expert elicitation" data. Expert elicitation data is comprised of responses from qualified transportation engineers and inspectors to a questionnaire asking for their estimate of transition probabilities of various elements in a bridge inventory. For example, in Florida, this took the form of "do-nothing" probabilities developed by asking bridge engineers to estimate the median number of years, Y, that an element would take to transition out of a given condition state. This was established as the duration at which the probability of staying in the same condition state dropped to 50%. The unknown "stay-the-same" transition probability P was then calculated using (Sobanjo and Thompson, 2001)

$$P^{Y} = 50\% \tag{A2.9}$$

which implies

$$P = 0.5^{\frac{1}{Y}} \tag{A2.10}$$

Under the assumptions that an element can transition by only one state at the most in any given inspection cycle and that there is no possibility of transitioning to a better state in absence of any maintenance action, it is possible to ascertain the remaining transition probabilities described in equation (A2.3). Transition matrices obtained from this approach were used to develop the first deterioration models in Pontis. However, as new inspection data of element-level condition ratings become available, Pontis uses a Bayesian approach to update the initial transition probabilities. Using this approach, updated posterior transition probabilities are developed by taking a weighted average of the prior transition probabilities and those derived from the observed inspection data (Bulusu and Sinha, 1997, Golabi and Shepard, 1997). This leads to an improvement in the accuracy of the models over time as the process continues (Golabi and Shepard, 1997). The same concept is also used in BRIDGIT (Hawk and Small, 1998).

Recently, with the availability of sufficient element-level inspection data, FDOT estimated its transition probability matrices entirely from historical inspection data using regression and the one-step methods mentioned earlier instead of the expert elicitation process used in the 2001 study (Sobanjo and Thompson, 2011). The median transition times Y were also calculated from the transition probabilities P using the inverse of equation (A2.9)

$$Y = \frac{\ln(0.5)}{\ln(P)} \tag{A2.11}$$

It was found that the average ratio of the transition times for the new deterioration models to those of the earlier models was 1.97, indicating that expert opinion tends to overestimate the probabilities associated with deterioration (Sobanjo and Thompson, 2011). The Colorado Department of Transportation also recently estimated its transition probability matrices from its historical data using the percentage prediction method. The median transition times were also calculated using equation (A2.11) (Hearn, 2012). The median transition times for prestressed concrete superstructure elements were found to be unreasonably high, often exceeding 100 years, in both of these studies (Hearn, 2012, Sobanjo and Thompson, 2011).

The limitation encountered when applying regression techniques to historical element level inspection data has been the lack of sufficient condition rating data available for each element. Pontis has the ability to handle as many as 160 elements each having up to four deterioration models corresponding to the each of the specified four environments (benign, low, moderate, and severe). To have sufficient sample sizes for meaningful regression analysis, the elements have to be grouped by component (deck, superstructure, substructure) or environment or both. Since grouping results in loss of corresponding sensitivity, for example, collapsing of all environmental categories into one would result in loss of sensitivity to environmental factors, different levels and types of classifications have to be examined to obtain a complete picture (Sobanjo and Thompson, 2011).

It is pertinent to mention the role of the NBI translator at this point. The NBI translator works on the concept of assigning relative weights to the condition ratings of elements constituting a particular bridge component (deck, superstructure, or substructure), and aggregating them to obtain a single condition rating for that bridge component (Sobanjo and Thompson, 2011). An NBI translator program was developed by FHWA to help transportation agencies convert the element level inspection data to the format required for NBI submittals and consequent consideration for federal funding eligibility (Markow and Hyman, 2009). However, the translator was found to have some shortcomings that resulted in inaccuracies in condition rating prediction, especially for bridges in very good condition. This was because it could not distinguish effectively between the highest (6 to 9) and the lowest (0 to 3) NBI condition ratings. Moreover, it assigned too much weight to the fraction of elements in the poorer condition states thereby resulting in unreasonably rapid deterioration rates associated with the NBI condition ratings (Patidar et al., 2007). These inaccuracies were found to affect all performance measures based on NBI ratings that were developed for use in the optimization programming and budgeting decision support tools in the BMS. This was especially true for newly developed BMS software products like the Multi-Objective Optimization System (MOOS) developed by the National Cooperative Highway Research Program (NCHRP) Project 12-67 (Patidar et al., 2007), and the Project Level Analysis Tool (PLAT) and Network Analysis Tool (NAT), both developed by FDOT. All of these optimization tools were found to be highly sensitive to any changes in deterioration or unit cost inputs. To overcome these issues, FDOT has further improved upon its version of the NBI translator by applying multiple regression and optimization techniques to two years of bridge inspection data from the Florida bridge inventory to estimate the relative weights of element condition ratings. Reviews of initially translated ratings were performed by studying randomly selected bridges and corrections applied to the translator algorithms as necessary. Although the final developed version had similar issues with regard to the lowest and the highest condition ratings, it performed significantly better than the FHWA translator and produced more accurate translated ratings as compared to the actual NBI inspected ratings (Sobanjo and Thompson, 2011).

Pontis also has an action effectiveness model to determine the effect of MR&R activities. Any MR&R action is assumed to produce an immediate transition to a better condition state, defined by a set of action effectiveness transition probabilities. These “do something” probabilities are also obtained through the expert elicitation process (Sobanjo and Thompson, 2001). The action effectiveness transition probabilities are used once to arrive at the new condition state vector immediately following the action, after which deterioration is assumed to resume according to the process defined by the deterioration transition probability matrix for the component. Thus, any MR&R action has the effect of resetting the deterioration curve to a prior state in time (Golabi and Shepard, 1997).

Although Pontis has been licensed by 46 states, it is mostly used solely for managing bridge inspection data. Only 17 states, or less than 37%, are using the Pontis BMS capabilities for network level planning, project planning, or both (Markow and Hyman, 2009). Many of these states, including Idaho, Virginia and South Dakota, have modified and customized the Pontis framework instead of adopting it completely in its original format (FHWA, 2010b,c). The percentage of states using the deterioration modeling capabilities of the BMS is even lower at less than 20%. This has been attributed to various reasons including lack of trained staff for using these models, lack of data analysis and preprocessing tools needed to generate the models, or lack of credibility of the available predictive models (Markow and Hyman, 2009). Some states, including Ohio, Michigan and New York, develop their own deterioration models outside of Pontis and input them into Pontis for optimization and decision making.

At the national level, a National Bridge Investment Analysis System (NBIAS), is used by FHWA to predict nationwide future bridge conditions and investment requirements, based on the complete NBI database. The prediction models use element-level data and the Markovian models derived from Pontis. Since the NBI data do not contain element level data, a series of stochastic models, known as the Synthesis, Quantity, and Condition (SQC) models, are applied by NBIAS to “synthesize” element-level condition data from the NBI data (FHWA, 2010a, Markow and Hyman, 2009). These SQC models are based on statistical analysis of over 10,000 bridges nationwide to form a representative sample of various structural and material configurations. These models enable NBIAS to create a statistical model consisting of a typical assortment of elements with estimated quantities and condition state distributions for each structure based on its functional descriptors in the NBI database. NBIAS was first used in 1999 for preparing bridge-related need estimates for the Conditions and Performance report submitted biennially to the U.S. Congress. It has replaced the Bridge Needs and Investment Process (BNIP) model developed earlier by the FHWA in 1991 (FHWA, 2010a, Markow and Hyman, 2009).

A.2.2.3 Limitations of Markovian Models and Proposed Improvement

Despite the widespread use of Markovian models and the commonly used approaches for estimating transition probability matrices, a number of limitations have been identified in these models. These approaches do not model the effects of various explanatory variables, and therefore, as mentioned earlier, have to rely on pre-defined segmentation of the bridge population into homogeneous categories for meaningful statistical analysis. Moreover, the Markovian assumption of time independence is contrary to the time dependence of the deterioration process. This time dependence can indirectly be taken into account by dividing the bridges within each category further into various age groups. However, this grouping is ad hoc and fails to recognize the continuous nature of the underlying deterioration. The use of linear regression to calculate transition probabilities, as described in the expected-value method, is also deemed to be inappropriate by some researchers because the dependent variable, which in this case is the condition rating, is discrete and ordinal, and not continuous as presumed by linear regression (Bulusu and Sinha, 1997, Madanat and Ibrahim, 1995, Madanat et al., 1995, 1997, Mishalani and Madanat, 2002, Morcous et al., 2002).

Different models and approaches for calculating infrastructure transition probabilities have been proposed progressively with a view toward addressing the abovementioned limitations. The discrete nature of the dependent variable was first addressed through applying Poisson regression instead of linear regression in the estimation of transition probabilities (Madanat and Ibrahim, 1995). In addition to improving the predictive ability of the previous model, this model also permitted the development of a relationship between deterioration and the various explanatory variables affecting it. Further, it eliminated the need for segmenting the bridge population into homogeneous groups so that the statistical advantage of having the entire dataset for estimation was obtained. The model was extended into a negative binomial regression model to relax the constraining assumption of equality of variance and mean in Poisson regression. Both models were applied to a subset of bridges in the Indiana State Bridge inventory to estimate the infrastructure transition probabilities. The results were found to be very close to the actual observed frequencies (Madanat and Ibrahim, 1995). Another model developed around the same time also accounted for the ordinality of the dependent variable and the time-dependence of the deterioration process. This model, known as the ordered probit model, was used to derive non-stationary transition probabilities for a subset of bridges also from the Indiana State Bridge Inventory. The results were compared to those obtained from the expected value method by using a chi-square test on a sample of concrete bridge decks in condition state 7. The probabilities calculated using the ordered probit model were found to be more accurate in prediction than prior models (Madanat et al., 1995).

The above mentioned models, however, are still considered deficient in their ability to address the two issues of heterogeneity and state-dependence found in panel data, or longitudinal data (Bulusu and Sinha, 1997, Madanat et al., 1997). Panel data is multidimensional data. It comprises of data sets combining cross-sectional and time-series data such as those being used for deterioration modeling where the deterioration behavior of a number of facilities is observed across time (Greene, 1997). Such data may have persistent facility specific unobserved factors, referred to as “heterogeneity”, for example, construction quality, that if not accounted for may bias the model coefficient estimates. State dependence, on the other hand, is when the transition probability of moving from one state to another is dependent on the history of the deterioration. Such dependence is likely to make some facilities more deterioration prone than others in the same condition rating (Madanat et al., 1997). The issue of heterogeneity was addressed by developing the binary probit (Bulusu and Sinha, 1997) and random-effects (Madanat et al., 1997) models. Although no appreciable difference was observed in the coefficient values of explanatory variables, these models were found to improve significantly the goodness of fit and predictive abilities relative to the previous models (Bulusu and Sinha, 1997, Madanat et al., 1997). The issue of state-dependence is, however, still unresolved. Madanat et al. (1997) found that state dependence was present and correlated heavily with the elapsed time in the condition state. However, once the effect of heterogeneity is accounted for, it is difficult to distinguish between the effects of time non-homogeneity as captured in non-homogeneous Markov chain models and true state dependence (Madanat et al., 1997).

All of the above-mentioned model improvements were tested only on sample subsets of bridges and have not been applied to complete state-wide bridge inventories for actual use in a BMS. However, by investigating and exposing the weaknesses of the state-based models, these models served as precursors to the time-based or duration models discussed in the following section.

A.2.3 Duration Models

Duration models are those that model the time or duration that a bridge component remains in a particular condition state. In these models, the duration until the occurrence of the event of deterioration to the next lower condition state is treated as a random variable, instead of the event itself as done in the state-based Markovian models. Duration models have been found to better model the stochastic nature of the deterioration process by accounting for duration dependence among other aspects of deterioration that could not be considered in earlier models. The earliest time-based models were the state increment models developed for the pavement management and bridge management systems of the New York State Thruway Authority (NYSTA). In these models, the concept of state transition time was defined as the time between two consecutive changes of state, or in other words, the time taken by a bridge component to transition from an initial condition state to the next lower condition state (Ravirala and Grivas, 1995). A uniform distribution of transition time was assumed between minimum and maximum values of transition time, which were estimated on basis of expert elicitation. This assumed parametric distribution was then used to estimate the cumulative probability of the occurrence of a specified state transition event within any specified time, known as the `transition probability' (DeStefano and Grivas, 1998). The initial models were verified and enhanced by determining the transition probabilities using a non-parametric Kaplan-Meier approach and adding an elapsed-time parameter, respectively (DeStefano and Grivas, 1998). The revised models were then tested on a subset of 123 bridge decks located in the New York State Thruway and the resulting deterioration models were found to be more accurate than the original models. These models used life data analysis techniques on bridge inspection data for the first time. Previously these techniques have long been used in engineering for reliability studies of industrial components, in the biomedical field for survival time analysis of patients diagnosed with a disease, and more recently, in the social sciences (Greene, 1997). Life data or duration data has typical characteristics like censored observations, which were taken into account in this study. Later researchers used survival analysis techniques to further develop the duration models (Mauch and Madanat, 2001, Mishalani and Madanat, 2002). The problem of censored observations in duration data and the basic concepts of survival analysis are described in the following subsections before continuing further with the review of duration models in bridge deterioration.

A.2.3.1 Censored Data

‘Censoring’ is the term applied to instances when a particular event is not completely observed, and it is a commonly encountered and unavoidable problem in analysis of any duration data. Bridge condition rating data has a large number of censored observations, the reason being that discrete time measurements are made during the continuously ongoing deterioration process. A commonly occurring type of censored observation is the right censored observation where the observed period is known to be less than a certain value. There are many instances of right censored observations in condition rating data, such as at the beginning and end points of the data. For example, let's consider a bridge component that had a condition rating of 7 at the beginning of the observation period in 1981 and stayed at that rating until 1987 when it changed to 6. In this case, all we know is that the time in condition state 7 was at least 6 years as we cannot say how long it was at that rating before the observation first began in 1981 when the state inventory was initiated. Similar is the case for condition ratings observed at the most recent observation period (currently 2013), when we only know that the observed time in the state is at least as long as the actual time, since the remaining duration in that state has yet to be observed.

Likewise, the condition rating of a bridge component may increase during its lifetime because of maintenance actions. This represents a premature interruption of the natural deterioration processes. For example, if an observed condition rating of 5 increases to 7 due to maintenance, we do not know how long the bridge component would have stayed at rating 5 in the absence of maintenance. Therefore, the actual duration of condition rating 5 for the structure is again not fully observed and only known to be as long as or longer than the observed duration, making it a right-censored observation.

In addition to right censoring of data, bridge condition rating data is also subject to a form of censoring due to the discrete interval of inspection recording. Condition ratings are required to be recorded at least every two years in the USA. Therefore, although deterioration itself is a continuous process, the accuracy of the time measurement is limited to the two year inspection interval. This type of discrete measurement results in a type of incomplete observation of data known as interval censoring. For example, if a bridge component is observed to be at condition rating 6 since 1992, and remains at the same condition rating during inspections in 1994 and 1996, but deteriorates to condition rating 5 in 1998, all we can say is that the time that it stayed in condition rating 6 is between four years and six years.

Presence of censored observations in data does not lend well to deterministic modeling or many conventional statistical regression techniques. However, survival analysis models can account for the effect of censored observations and are therefore suitable for analysis of bridge condition rating data (Greene, 1997, Hosmer and Lemeshow, 1999).

A.2.3.2 Survival Analysis Concepts

Analysis of duration or life data, known as survival analysis, is a category of statistical analyses that models the time until the occurrence of an event of interest. In such analysis, the duration observed is referred to as survival time or time until failure. In analyzing bridge condition rating data, this time, T, would be the duration that a bridge component stays at a particular condition rating until it deteriorates to a lower rating. If T has a cumulative distribution function, $F(t)$, at time, t, then the probability that T exceeds t is given by the Survivor or Survival function, $S(t)$, given by (Greene, 1997),

$$S(t) = 1 - F(t) = P(T \geq t) \tag{A2.12}$$

The survival function or cumulative survival rate, is a non-increasing function of time that takes a value of one at $t = 0$ and a value of zero at $t = \infty$. Given that the survival time exceeds t or $T \geq t$, the probability that the failure event will occur in the next small interval of time, Δt , or when $t \leq T \leq t + \Delta t$, is given by the hazard function $l(t, \Delta t)$, where,

$$l(t, \Delta t) = P(t \leq T \leq t + \Delta t \quad | \; T \geq t) \tag{A2.13}$$

The hazard function is usually characterized by using the hazard rate function, $h(t)$, which is the instantaneous rate of failure at time t and is given by

$$h(t) = \frac{lim_{\Delta t \to 0}(P(t \leq T \leq t + \Delta t) \;\; | \; T \geq t)}{\Delta t} = -\frac{d}{dt} \ln S(t) \tag{A2.14}$$

The hazard rate of a bridge deck at a particular condition rating is a measure of the risk of dropping to a lower rating at any given time, t. The hazard rate is also known as the conditional failure rate and depends on when the observation was made. If the hazard rate is constant and does not vary with time, it implies that the process is memoryless, like the Markovian processes discussed earlier. This is also known as duration independence and can be modeled using an exponential distribution,

$$S(t) = e^{-\lambda t} \tag{A2.15}$$

where $h(t) = \lambda$ (a constant). In general, the hazard rate function may have an upward or a downward slope depending on whether the risk of failure increases or decreases with time. This is termed as positive or negative duration dependence, respectively (Greene, 1997).

Let $f(t)$ be the probability density function of T associated with $F(t)$. It is the probability of failure in a small interval of time per unit time, and is also known as the unconditional failure rate. The probability density function, the cumulative density function, survival rate and hazard rate are related as follows,

$$h(t) = \frac{f(t)}{S(t)} = \frac{f(t)}{1 - F(t)} \tag{A2.16}$$

The sum total of risk or hazard up to any time, t, is given by the cumulative or integrated hazard function, $H(t)$, and it is a useful tool in survival analysis. Its relationship to the survival function is given by,

$$H(t) = \int_0^t h(x)dx = -\ln S(t) \tag{A2.17}$$

The cumulative hazard function is zero at time $t = 0$ and infinity at $t = \infty$ (Lee and Wang, 2003).

Duration data can be modeled using non-parametric, fully parametric, or semiparametric methods. Non-parametric methods are strictly empirical or distribution-free as they are not constrained by any pre-imposed structure. A commonly used nonparametric approach is the Kaplan-Meier estimator, also known as the product limit estimator, which was used for developing duration based bridge deterioration models by DeStefano and Grivas (1998), as mentioned earlier. Although this approach is simple and flexible, it is not possible to relate exogenous explanatory factors to the dependent variable using this approach.

A.2.3.3 Parametric Duration Models

Parametric models are those that follow a theoretical distribution mathematically defined by one or more parameters. The exponential distribution that applies to the constant hazard rate model is one such parametric distribution. A parametric generalization of the exponential distribution that allows for a duration dependent hazard rate is the Weibull distribution. The Weibull distribution is characterized by a shape parameter, γ, and a scale parameter, λ, that determine the shape and the scale of the distribution, respectively. Estimation of these distribution parameters is done by maximizing the statistical likelihood function. The survivorship function for a Weibull distribution is given by

$$S(t) = e^{-(\lambda t)^{\gamma}} \tag{A2.18}$$

A limitation of the non-parametric and parametric distributions relative to the semi-parametric distributions is that they cannot directly model the effect of exogenous variables. This limitation can however be overcome by defining λ of the Weibull distribution as an exponential function of the exogenous variables (Greene, 1997, Mishalani and Madanat, 2002).

It is possible to determine the transition probabilities of Markovian state-based models from those of time-based models. In fact, transition probabilities derived from time based models are found to give more accurate results particularly when inspection data are available for a sufficiently long and continuous time period (Mauch and Madanat, 2001). Duration models using the parametric Weibull distribution were developed for a subset of reinforced concrete bridge decks in the Indiana State bridge inventory (Mishalani and Madanat, 2002). This study illustrated a methodology of determining the state transition probabilities from transition time distributions. The results highlighted that deterioration rates of bridge components could exhibit different behavior at different condition states. For example, condition state 7 was found to exhibit the Markovian property of duration independence whereas condition state 8 had a hazard rate that was positively duration dependent (Mishalani and Madanat, 2002). All of these studies proposed using estimated duration distributions for computing accurate transition probabilities for the corresponding state-based models in order to construct the deterioration models (DeStefano and Grivas, 1998, Mauch and Madanat, 2001, Mishalani and Madanat, 2002).

Recently duration models using the Weibull distribution were developed for the New York State Department of Transportation (NYSDOT) (Agrawal et al., 2009, 2010). The deterioration models were constructed by calculating the expected duration spent in each condition rating using

$$E(T_i) = \eta_i \Gamma\left(1 + \frac{1}{\beta_i}\right) \tag{A2.19}$$

These duration based deterioration models were compared to Markovian models developed using the second level Markov process. The Weibull models were found to be more realistic and were therefore adopted for use in the NYSDOT BMS (Agrawal et al., 2009, 2010). A Weibull based enhancement was also used to improve the Markovian deterioration models recently updated for the FDOT database (Sobanjo and Thompson, 2011). Weibull based models, however, can only model monotonically increasing or decreasing hazard rate functions. They cannot model unimodal distributions frequently found in infrastructure deterioration (Yang et al., 2013). Moreover, they cannot take into account the effect of explanatory variables.

A.2.3.4 Semi-Parametric Duration Models

Semi parametric models, on the other hand, support multivariate analysis while not making any assumptions about the shape of the distribution. A commonly used semi-parametric approach is the Cox Proportional Hazards Model (Cox, 1972), which defines hazard rate, $h(t,\vec{z})$, at time t and for covariates, $\vec{z}$, in terms of two components: 1. A non-parametric baseline hazard function, h_0, which varies only with time, and 2. A time-independent multiplier function using the exponential function to represent the effects of the covariates, $\vec{z}$, through regression coefficients, $\vec{\beta}$, as given by,

$$h(t,\vec{z}) = h_0(t)e^{\vec{z}\vec{\beta}} = h_0(t)e^{(z_1\beta_1 + z_2\beta_2 + \cdots + z_n\beta_n)} \tag{A2.20}$$

Here, $\vec{z}$ is a row vector of covariates or explanatory factors and $\vec{\beta}$ is a column vector of the corresponding regression coefficients that define the effect of the covariates on the hazard rate. The baseline hazard rate is the underlying model for the default factors or with covariates set to zero. The multiplier function associated with the covariates adjusts the hazard rate proportionally to the values of the covariates. The Hazard Ratio, HR, defined as the relative risk of instantaneous failure of any two items observed at time t associated with covariate sets $\overrightarrow{z^1}$ and $\overrightarrow{z^2}$, is constant, as shown below, thus giving the model its name (Kumar and Klefsjo, 1994).

$$HR = \frac{h(t,\overrightarrow{z^1})}{h(t,\overrightarrow{z^2})} = constant \tag{A2.21}$$

Semiparametric models do not restrict the shape of the distribution but give it better structure than non-parametric models by relating it to various explanatory variables. Model parameters are estimated by maximizing a partial likelihood function derived from the distribution. The use of semi-parametric Cox proportional hazards regression was illustrated for the Indiana state bridge inventory using a subset of reinforced concrete bridge decks in condition states 6, 7, and 8 (Mauch and Madanat, 2001). Different condition ratings were found to have different hazard functions, which served to recognize the change in the nature of deterioration of reinforced concrete from one condition state to the next. For example, for decks in condition state 8 and 7, deterioration may be primarily caused by chemical processes like chloride ingress and corrosion, whereas for decks at condition state 6, it may be due more to mechanistic processes like delamination cracking. The regression coefficient estimates were also found to be different and not all parameter estimates were significant for each condition state. Ultimately, the hazard ratios helped quantify the relative effect of explanatory variables on the deck deterioration rate at different condition states (Mauch and Madanat, 2001), and can be used to improve bridge classification over a priori groupings.

To overcome the limitations inherent in fully parametric models, an integrated modeling approach to combine the advantages of semiparametric and parametric models has also been proposed (Yang et al., 2013). This approach suggests first determining the shape of the distribution using the semi-parametric Cox proportional hazards method, and then fitting a mixed Weibull model to it for ease of determining transition probabilities and application to BMS. The mixed Weibull model was shown to produce significantly better results than the two-parameter Weibull model used in earlier studies (Yang et al., 2013).

A.2.3.5 Limitations

Duration models are considered appropriate only if more than 20 years of inspection data are available, otherwise state based models are considered more suitable (Mauch and Madanat, 2001). Consequently, it is only recently that sufficient NBI records have been available to facilitate use of these powerful statistical regression models. It is expected that duration modeling will be a very active and productive area of bridge management over the coming decades as researchers exploit the over three decades worth of condition rating data now available in the NBI. However, for element level data where only 10 years or less of inspection data is available duration models may not give reliable results. To overcome this limitation, various approaches have been recently suggested. One of these is a backward prediction model that can be used to generate past historical data from available inspection data (Lee et al., 2008). Likewise, an integrated algorithm that can match a suitable modeling technique to the available data has also been proposed (Bu et al., 2014).

Other bridge deterioration modeling approaches found in the literature review include Artificial Neural Network techniques (Lee et al., 2008), case based reasoning (Morcous et al., 2002), and fault tree modeling (Sianipar and Adams, 1997). A two level approach using probabilistic duration models at the network level and a mechanistic approach at the project level for safety critical bridges has also been proposed to improve the effectiveness of the BMS (Cusson et al., 2011, Lounis and Madanat, 2002, Morcous et al., 2010).

A.3 User Costs in Bridge Management Systems

All federal and state agencies have limited funding for transportation needs, and many states rely on their BMS system to identify bridge projects that are most vital to obtain maximum levels of service to the public (Rens et al., 1999). Most BMS can be used not only to forecast bridge conditions, but to perform analyses to identify how these deficiencies affect the users of the bridge. Once a bridge is considered either structurally deficient or functionally obsolete, a cost is burdened by the public (or a portion of the public) who can no longer use the bridge because of its deficiencies (Chen and

Johnston, 1987). Costs are incurred as the result of detours due to bridge deficiencies related to load postings, inadequate deck width, poor alignment, and limited vertical clearance (Chen and Johnston, 1987, Son and Sinha, 1997). Additional user costs are incurred at bridges due to accidents, which may be associated with characteristics such as bridge deck width, approach configuration, traffic speed, or other factors (Abed-Al-Rahim and Johnston, 1991). These user costs can be significant in magnitude, and have been found to be up to five times the direct agency costs in some instances (Thompson et al. 1999). Currently, NCDOT calculates and forecasts user costs using a methodology was developed by Chen and Johnston (1987), is shown in Equation A3.1.

$$AURC(t) = 365\ ADT(t)\ [C_{WDA}U_{AC}+C_{ALA}U_{AC}+C_{CLA}U_{AC}+C_{CLD}U_{DC}DL+C_{LCD}(t)U_{DL}DL] \qquad (A3.1)$$

Where: $AURC(t)$ = annual user cost of the bridge at year t, $/year

$ADT(t)$ = average daily traffic using the bridge at year t

C_{WDA} = coefficient for proportion of vehicles incurring accidents due to width deficiency

C_{ALA} = coefficient for proportion of vehicles incurring accidents due to poor alignment

C_{CLA} = coefficient for proportion of vehicles incurring accidents due to vertical clearance deficiency

C_{CLD} = coefficient for proportion of vehicles detoured due to a vertical clearance deficiency

$C_{LCD}(t)$ = coefficient for proportion of vehicles detoured due to a load capacity deficiency at year t

U_{AC} = unit cost of vehicle accidents on bridges, $/accident

U_{DC} = unit cost for average vehicle detours due to vertical clearance deficiency, $/mile

U_{DL} = unit cost for average vehicle detours due to load capacity deficiency, $/mile

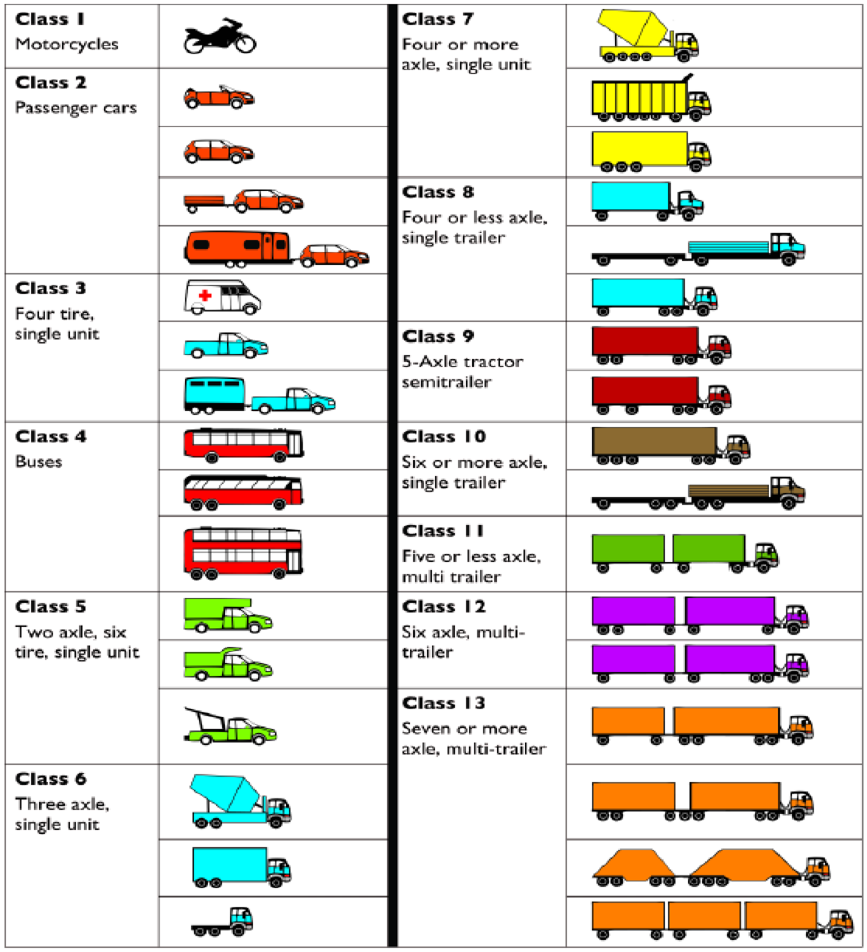
DL = detour length, miles

From Equation A3.1, in the NCDOT BMS, user costs are incurred by vehicles that are required to detour around a bridge due to load postings or low vertical clearance, as well as due to accidents related to narrow deck widths and poor alignments. The detour costs for both vertical clearance and load capacity are determined using vehicle operating costs, percent of vehicles detoured, and detour length. In computing the cost of accidents related to poor alignment, the alignment appraisal is based on agency-collected data or data from other sources (Chen and Johnston, 1987). The width deficiency is based on the difference between the existing deck width and bridge clear deck width goals, as established by Johnston and Zia (1984).

As stated previously, many agencies currently utilize the AASHTOWare Pontis BMS developed by the American Association of State Highway and Transportation Officials (AASHTO). In the development of AASHTOWare Pontis, cost considerations were largely based on the cost methodologies developed for the NCDOT BMS (Thompson et al., 1999). In recent years, other agencies have modified or enhanced the source data or methodologies utilized in the NCDOT BMS in order to support computation of user costs in their BMS. For example, in a research project to support the Indiana Bridge Management System (IBMS), which has a cost analysis component largely based on the work of Chen and Johnston (1987), Son and Sinha (1997) explored the incorporation of the effect of poor deck surface conditions to user costs. These poor deck conditions were found to cause vehicles to reduce speed on bridges adding to the travel time, which increases user costs (Son and Sinha, 1997).

A.3.1 Average Daily Traffic Growth

Computation of all user costs in the NCDOT BMS are dependent on an accurate forecast of traffic. A bridge with a higher volume of traffic will have an increased user cost associated with it, if deficiencies are present in that bridge. Traffic forecasting in the BMS utilizes Average Daily Traffic (ADT) data, which is the total traffic volume a roadway experiences over the course of an average day. ADT considers the traffic resulting from 13 different vehicle classifications, as denoted by the FHWA (2013), shown in Figure A.3.1. A bridge's ADT includes both single-unit (SU) and multi-unit (MU) vehicles as well as all other vehicle classifications, and the portion of the ADT that can be attributed to trucks is referred to as the Average Daily Truck Traffic (ADTT). Although all 13 vehicle classifications are typically affected by user costs, passenger vehicles are not affected nearly as much as vehicles in heavier weight classes (Chen and Johnston, 1987). Since load posting related detours typically affect tall and heavy weight vehicles such as trucks, the ADTT (or some portion of the ADTT) is the likely set of vehicles that may incur a detour. Other types of detours, like those due to construction projects, would affect all types of vehicles. In contrast, user costs attributable to accidents can be incurred by all types of vehicles. Currently, the NCDOT BMS does not utilize ADTT data inputs.



Source: *Federal Highway Administration.*

Figure A.3.1: FHWA vehicle classification

Projected ADT is used by a BMS when estimating user costs in future years, and ADT growth rates are BMS inputs typically used to facilitate this prediction. In the initial development of NCDOT's BMS, Chen and Johnston (1987) used ADT values provided by NCDOT to develop ADT growth rates for four different types of roadways (interstate, arterial, collector, and local roads), grouped by county. The source of the data used to predict the original ADT growth rates was automatic traffic recording (ATR) data from 1974 to 1984 (Chen and Johnston 1987). Data was available from a total of 59 ATR stations that were placed at roadways of different classifications, although only seven of the 59 ATR stations were situated on interstates. It was found that in many instances, insufficient data was available to support development of specific ADT growth rates by county or division. Therefore, interstate ADT growth rates were considered equal for the state, and arterial ADT growth rates were assumed to be the same for all counties in a division (for each of the 14 divisions in the state). Since no ATR stations were located on local routes, the population growth rate of the county was used to determine the ADT growth rate. For collector roads, the ADT growth rate were assumed to be the average of the local and arterial growth rates for each county.

The ADT growth rates for the NCDOT BMS were later updated by Duncan and Johnston (2002) using the Bridge Management Inventory File (BMIF). The BMIF provided ADT data for all bridges from 1991 to 2000. This more robust dataset allowed Duncan and Johnston (2002) to compute an ADT growth rate for each of the four roadway classifications for each county. Duncan and Johnston (2002) noted that if values did not exist for a particular roadway in a county, the state average was utilized as the assumed value. Values determined by Duncan and Johnston (2002) were then reviewed by NCDOT's Traffic Forecast Unit (TFU), where personnel adjusted some values based on experience. A snapshot of the breakdown of ADT growth rates for a portion of North Carolina counties is shown in Table A.3.1 (Duncan and Johnston, 2002).

Table A.3.1: A portion of the ADT growth rate table used in NCDOT BMS (Duncan and Johnston, 2002)

```
**************************************************************
TABLE 1  GEOGRAPHIC AREA (1=COASTAL, 2=PIEDIMONT, 3=MOUNTAIN)
**************************************************************
TABLE 2  YEARLY ADT GROWTH RATES FOR BRIDGES OF VARIOUS
         FUNCTIONAL CLASSIFICATIONS (%).
**************************************************************
CO # COUNTY NAME AREA LOCAL   COLLECTOR  ARTERIAL INTERSTATE
---- ----------- ---- -----   ---------  -------- ----------
 00  ALAMANCE      2   3.82       3.50      3.50       6.81
 01  ALEXANDER     3   4.57       4.28      2.86       5.38
 02  ALLEGHANY     3   2.75       3.99      2.75       5.38
 03  ANSON         2   2.67       2.86      2.98       5.38
 04  ASHE          3   2.50       3.61      2.97       5.38
 05  AVERY         3   3.42       3.52      3.50       5.38
 06  BEAUFORT      1   2.50       2.55      2.93       5.38
 07  BERTIE        1   3.45       3.28      0.48       5.38
 08  BLADEN        1   4.93       2.50      3.00       5.38
 09  BRUNSWICK     1   5.96       4.56      3.50       5.38
 10  BUNCOMBE      3   2.50       2.55      3.50       5.47
 11  BURKE         3   2.72       3.37      3.01       5.19
```

Methods to identify ADT growth rates currently utilized in the NCDOT BMS, as described previously, are heavily reliant on date collected in the 1990's data, as well as expert opinion. However, ADT for each bridge is reported biennially to the NBI (FHWA, 2012). Therefore, it is possible that the ADT for each bridge could be used to predict its own future ADT growth rate to be utilized in forecasting of more accurate user costs.

A.3.2 Vehicle Operating Costs

Vehicle operating costs are user costs incurred by the public when vehicles desiring to travel over a bridge are required to detour around the bridge due to the bridge being posted at a reduced load capacity. Vehicle operating costs are also incurred when vehicles that desire to travel either on or under a bridge must detour due to lack of vertical clearance either on or under a bridge. These expenses can be a result of fuel consumption, oil consumption, tire wear, maintenance and repair, and vehicle depreciation (Zaniewski et al., 1982). The following sections present a summary of how the NCDOT's BMS forecasts traffic affected by detours due to bridge load postings and height restrictions, as well as the means of identification of data utilized in computation of vehicle operating costs. A summary of treatment of these parameters in other state BMS is also included, as applicable.

A.3.2.1 Detour Resulting from Bridge Capacity and Vertical Clearance Limits

User costs associated with detours are computed by multiplying the detour length by the unit cost for vehicle detours and the coefficient of the proportion of vehicles that must detour. The NBI coding guide defines the detour length as the total additional length of travel a vehicle must go in order to remain on course (FHWA, 1995). Detour length is a required component of the NBIS, and is therefore easily incorporated into most BMS. It has been noted, however, that the actual detour length may be longer than that posted in the NBI since posting signs are located at the bridge and not where the detour runoff is actually located (Chen and Johnston, 1987).

A load posting results in the restriction of certain vehicles from using a bridge when vehicles' weights exceeds the safe capacity of a bridge (Hearn, 2014). These restrictions typically occur in older bridges that have experienced section loss or material degradation. Environmental effects, such as climate and geography, are some of the main causes of section loss and material degradation (Chen and Johnston, 1987). Bridges that do not receive regular maintenance will have a higher likelihood of deteriorating quickly (Sobanjo and Thompson, 2013). A bridge can have either one or two load postings, the first being for SU vehicles and the second being for tractor-trailer semi-trailer (TTST) vehicles.

Chen and Johnston utilized data published by FHWA, NCDOT, and various other sources to develop a vehicle classification distribution that could be utilized to compute the percent of trucks detoured due to load posting (Chen and

Johnston 1987), shown as Table A.3.2. The proportion of legal weight vehicles required to detour due to bridge capacity was assumed to be dependent upon the type of roadway system on which the bridge is located. This percentage does not consider vehicle classifications one through three, since their weight, which is considered three tons or less, is the minimum weight a bridge must hold in order to be operational (Chen and Johnston, 1987). The percentage of trucks detoured (in decimal form) is multiplied by proportion of the total traffic (ADT) that is trucks. Chen and Johnston (1987) utilized traffic data from portable counting stations at selected locations provided by the Planning and Research Branch of NCDOT to develop a table that provides percentages of total traffic that are cars and light trucks, SV Duals or TTST for the four roadway functional classifications. The resulting table of vehicle proportions on each of the four roadway functional classifications (shown in Table A.3.3) is used in conjunction with data on truck weight distributions (Table A.3.2) to produce the total percent of vehicles detoured due to bridge capacity. The original proportions of TTST and SV (in percent) were determined using FHWA data (FHWA, 1985) and data from other NCDOT sources (Johnston et al., 1994), but do not appear to have been updated by Duncan and Johnston (2002).

Table A.3.2: Percent detoured due to load posting (Chen and Johnston, 1987)

Bridge Posting (tons)	Interstate		Princ. Art.		Minor Art.		Major Coll.		Minor Coll.		Local	
	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST
3	4.40	12.50	6.00	6.60	4.60	3.30	2.60	1.10	2.60	0.80	2.40	0.60
4	3.87	12.45	5.21	6.57	4.11	3.29	2.32	1.09	2.32	0.80	2.14	0.60
5	3.35	12.40	4.41	6.54	3.61	3.28	2.04	1.09	2.04	0.79	1.88	0.60
6	2.82	12.36	3.62	6.50	3.12	3.26	1.76	1.08	1.76	0.79	1.63	0.59
7	2.30	12.31	2.82	6.47	2.62	3.25	1.48	1.08	1.48	0.78	1.37	0.59
8	1.77	12.26	2.03	6.44	2.13	3.24	1.20	1.07	1.20	0.78	1.11	0.59
9	1.52	12.24	1.70	6.33	1.78	3.19	1.00	1.05	1.00	0.77	0.92	0.58
10	1.26	12.02	1.36	6.23	1.43	3.14	0.80	1.04	0.80	0.76	0.74	0.57
11	1.10	11.65	1.22	5.97	1.28	3.01	0.72	0.99	0.72	0.73	0.67	0.54
12	0.95	11.28	1.08	5.70	1.13	2.87	0.64	0.95	0.64	0.69	0.59	0.52
13	0.82	10.74	0.97	5.39	1.02	2.71	0.57	0.90	0.57	0.66	0.53	0.49
14	0.71	10.04	0.90	5.02	0.94	2.53	0.53	0.84	0.53	0.61	0.49	0.46
15	0.60	9.34	0.82	4.66	0.86	2.35	0.48	0.78	0.48	0.57	0.45	0.42
16	0.51	8.89	0.76	4.41	0.79	2.22	0.45	0.73	0.45	0.54	0.41	0.40
17	0.42	8.35	0.69	4.16	0.73	2.09	0.41	0.69	0.41	0.51	0.38	0.38
18	0.35	8.04	0.63	3.95	0.66	1.99	0.37	0.66	0.37	0.48	0.34	0.36
19	0.30	7.71	0.58	3.78	0.60	1.90	0.34	0.63	0.34	0.46	0.31	0.34
20	0.24	7.37	0.52	3.61	0.55	1.82	0.31	0.60	0.31	0.44	0.28	0.33
21	0.21	7.06	0.44	3.50	0.47	1.76	0.26	0.58	0.26	0.43	0.24	0.32
22	0.18	6.75	0.37	3.39	0.39	1.71	0.22	0.56	0.22	0.41	0.20	0.31
23	0.16	6.46	0.30	3.28	0.32	1.65	0.18	0.55	0.18	0.40	0.17	0.30
24	0.15	6.17	0.25	3.17	0.26	1.60	0.15	0.53	0.15	0.39	0.14	0.29
25	0.13	5.89	0.20	3.06	0.21	1.54	0.12	0.51	0.12	0.37	0.11	0.28
26	0.11	5.61	0.16	2.96	0.17	1.49	0.10	0.49	0.10	0.36	0.09	0.27
27	0.09	5.32	0.13	2.86	0.13	1.44	0.08	0.48	0.08	0.35	0.07	0.26
28	0.08	5.01	0.10	2.75	0.10	1.39	0.06	0.46	0.06	0.33	0.05	0.25
29	0.07	4.68	0.07	2.64	0.08	1.33	0.04	0.44	0.04	0.32	0.04	0.24
30	0.06	4.35	0.05	2.52	0.05	1.27	0.03	0.42	0.03	0.31	0.03	0.23
31	0.05	3.95	0.03	2.38	0.04	1.20	0.02	0.40	0.02	0.29	0.02	0.22
32	0.04	3.56	0.02	2.25	0.02	1.13	0.01	0.37	0.01	0.27	0.01	0.20
33	0.04	3.11	0.01	2.09	0.01	1.05	0.00	0.35	0.00	0.25	0.00	0.19
33.6	0.00	2.81	0.00	1.98	0.00	1.00	0.00	0.33	0.00	0.24	0.00	0.18
34		2.60		1.91		0.96		0.29		0.23		0.16
36		1.74		1.56		0.78		0.24		0.19		0.14
36.6		0.00		0.00		0.00		0.00		0.00		0.00

Table A.3.3: Vehicle proportions on functional classifications (Chen and Johnston, 1987)

Functional Classification	Proportion of Total Vehicles (%)		
	Cars & Light Trucks	SV Duals	TTST
Interstate	83.1	4.4	12.5
Principal Arterial	87.3	6.0	6.6
Minor Arterial	92.1	4.6	3.3
Major Collector	96.3	2.6	1.1
Minor Collector	96.5	2.6	0.8
Local	97.0	2.4	0.6

To predict the number of vehicles detoured due to a load posting, bridge load capacity deterioration rates are utilized to forecast load posting over time. Chen and Johnston (1987) evaluated a number of approaches to determine deterioration rates that reasonably correlated bridge operating rating versus age, but encountered difficulty developing models due to scatter in the data and other factors. Ultimately, regression results, multi-year averaging, and engineering judgement were utilized to develop a table of estimated capacity deterioration rates in tons per year, shown as Table A.3.4 (Chen and Johnston, 1987).

Table A.3.4: Estimated bridge load capacity deterioration rates (Chen and Johnston, 1987)

Lower Rating of Superstructure and Substructure	Deterioration Rate (Tons/Year)		
	Timber	Concrete	Steel
6 - 9	0.00	0.00	0.00
5	0.30	0.20	0.20
4	0.60	0.30	0.30
3 or less	1.00	0.50	0.50

One factor affecting detour costs that can be difficult to determine and incorporate into a BMS is an accurate prediction of the number of (or the percentage of) vehicles with weight over the legal weight limits (Dey et al., 2014). Currently, the FHWA has a mandated maximum allowable gross weight of 80,000 pounds for vehicles, while also allowing the purchase of special permits for vehicles over this weight limit on certain roads. Detours of overweight vehicles are not currently specifically considered in NCDOT’s BMS.

Low vertical clearance on or under a bridge will also cause a portion of traffic passing on or under a bridge to detour due to the height restriction. The NCDOT BMS predicts a portion of vehicles that will detour due to excessive height. Johnston et al. (1994) notes that only a small portion of bridges have vertical clearance shorter than average truck heights, so relatively few vehicles will be required to detour due to vertical clearance. Chen and Johnston (1987) assumed that the distribution of trucks is well distributed, and data from a report by Kent and Stevens (1963) was used to predict the percentage of trailer heights over the standard height (13.5 feet). Using this data and Table A.3.3, Chen and Johnston (1987) produced an additional table used in the NCDOT BMS that estimates the percentage of vehicles that must detour due to height restrictions (Table A.3.5). It is of note that the Kent and Stevens (1963) report used to determine the percentage of vehicles of each height is entitled “Dimensions and Weights of Highway Trailer Combinations and Trucks – 1959,” indicating that this data may not accurately reflect the current geometric characteristics of North Carolina truck traffic.

Table A.3.5: Percent detoured due to vertical clearance (Chen and Johnston, 1987)

Vertical Clearance (feet)	Interstate		Princ. Art.		Minor Art.		Major Coll.		Minor Coll.		Local	
	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST	SV	TT ST
8.0	4.40	12.50	6.00	6.60	4.60	3.30	2.60	1.10	2.60	0.80	2.40	0.60
8.5	4.00	12.50	5.45	6.60	4.18	3.30	2.36	1.10	2.36	0.80	2.18	0.60
9.0	3.60	12.50	4.91	6.60	3.76	3.30	2.13	1.10	2.13	0.80	1.96	0.60
9.5	3.20	12.50	4.36	6.60	3.35	3.30	1.89	1.10	1.89	0.80	1.75	0.60
10.0	2.80	12.50	3.82	6.60	2.93	3.30	1.66	1.10	1.66	0.80	1.53	0.60
10.5	2.40	10.72	3.27	5.66	2.51	2.83	1.42	0.94	1.42	0.69	1.31	0.51
11.0	2.00	8.94	2.73	4.72	2.09	2.36	1.18	0.79	1.18	0.57	1.09	0.43
11.5	1.60	7.17	2.18	3.78	1.67	1.89	0.95	0.63	0.95	0.46	0.87	0.34
12.0	1.20	5.39	1.64	2.85	1.26	1.42	0.71	0.47	0.71	0.34	0.66	0.26
12.5	0.80	3.61	1.09	1.91	0.84	0.95	0.47	0.32	0.47	0.23	0.44	0.17
13.0	0.40	1.83	0.55	0.97	0.42	0.48	0.24	0.16	0.24	0.12	0.22	0.09
13.5	0.00	0.06	0.00	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
14.0	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14.5	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Other agencies have slightly different methods of approaching the computation of user costs due to detours. For example, the Indiana Department of Transportation's (IDOT) BMS (IBMS) computes detour due to excessive weight using a methodology similar to the NCDOT BMS, yet has a different approach for determining the portion that must detour. For the IBMS, Son and Sinha (1997) developed a system of three categories to determine the percent of vehicles that must detour due to weight. The first category includes vehicle classes in which the minimum weight of the vehicle class is greater than the load posting. In this category, all vehicles must detour, as reflected in Equation A3.2.

$$\text{If } PL < W_{MIN}(j)$$
$$N_L(j) = PADT(j) \times ADT \tag{A3.2}$$

The second category includes vehicle classes in which the maximum weight of a vehicle class is less than the load posting, which results in no vehicles in the category having to detour (Equation A3.3).

$$\text{If } PL > W_{MAX}(j)$$
$$N_L(j) = 0 \tag{A3.3}$$

The third category is utilized for load postings that are between the minimum and maximum weights associated with a vehicle class, thereby causing only a portion of the vehicle class to detour (Equation A3.4).

$$N_L(j) = \frac{(W_{MAX}(j) - PL)}{(W_{MAX}(j) - W_{MIN}(j))} \times PADT(j) \times ADT \tag{A3.4}$$

Where: $W_{MAX}(j)$ = maximum weight of vehicle type j, tons
$W_{MIN}(j)$ = minimum weight of vehicle type j, tons
PADT(j) = proportion of ADT of vehicle type j
PL = posted load limit or load capacity, tons
J = vehicle type

Once the percent detour ($N_L(j)$) is found, the equation used to produce the user costs is the same as the one used by the NCDOT BMS (Equation A3.1). However, the IBMS groups vehicles into four different classifications for vehicle operating cost. In these four groups, a maximum and minimum weight is predicted for each group and these weights are then used in the equation to estimate how many vehicles must detour (Son and Sinha, 1997).

A.3.2.2 Determination of Vehicle Operating Costs

In the NCDOT BMS, vehicle operating cost is currently calculated utilizing vehicle characteristics and the operator's wage rates for said vehicle, using a methodology developed by Duncan and Johnston (2002). In their initial work, Chen and Johnston (1987) computed the vehicle operating costs for vehicles of minimum weight (three tons) and vehicles of maximum legal gross weight (40 tons). For the NCDOT BMS, the vehicle operator cost for vehicles between these two weights is linearly interpolated (Chen and Johnston, 1987). To estimate the operator costs for vehicles weighing three tons or less, Duncan and Johnston (2002) first assumed the cost would be equal for all vehicles weighing three tons and less. They also assumed that the vehicle operating cost would be the sum of vehicle cost and operator cost. The vehicle cost is taken as the standard mileage rate for all business mileages, which is published by the Internal Revenue Service (IRS) and is routinely updated to reflect changes in the fuel cost of fuel. The estimate for operator cost utilizes the North Carolina state government vehicle operator I minimum wage rate as a basis. This minimum salary rate per year is divided by the product of the assumed 1,920 hours worked by a person in a year and a travel speed of 40 miles per hour (Duncan and Johnston, 2002), to obtain the operator cost per mile of detour. The operator cost and vehicle cost are then added to predict the vehicle operating cost of a three ton vehicle (U_{D3}), which is used in Equation A3.5.

$$U_{DV} = U_{D3} + \frac{(U_{DNP} - U_{D3})}{(NP - 3)} \times (W_V - 3) \tag{A3.5}$$

Where: U_{DV} = operating cost for vehicle V
U_{D3} = operating cost for vehicle weighing 3 tons or less
U_{DNP} = operating cost for vehicle weighing the maximum legal load
NP = maximum legal load (non-posted capacity of bridge)
W_V = weight of vehicle V

To predict operating cost for vehicles at the maximum legal weight, Duncan and Johnston (2002) used data from the North American Industry Classification System (NAICS) 484, published by the U.S. Census Bureau. NAICS 484 provides data on a variety of aspects (including costs and mileage) of overland transportation of cargo by means of tractor trailers. This report provides information on the estimated motor carrier revenue yearly in North America (U.S., Canada, and Mexico), as well as the estimated miles driven per motor carrier. To calculate the vehicle operating cost, the total annual revenue is divided by the total annual number of miles driven obtain the vehicle operating cost as a cost per mile of vehicles weighing 40 tons (U_{DNP}) used in Equation A3.5.

For vehicles weighing between three tons and 40 tons, the NCDOT BMS assumes a linear relationship between the vehicle weight and vehicle operating costs (Chen and Johnston, 1987). Equation A3.5 presents this linear relationship between vehicle weight and estimated vehicle operating cost at the weight. Chen and Johnston (1987) proposed using the average of the vehicle operating cost at the weight for the load posting (U_{DV}) and the vehicle operating cost at the maximum legal weight limit (U_{DNP}), to calculate U_{DL}, used in Equation A3.1. The operating cost for vehicles less than three tons is assumed to be the operating cost of a three ton vehicle. Also, vehicles weighing more than the maximum legal load (40 tons) are assumed to have an operating cost equal to the operating cost of the maximum legal weight vehicle.

When a bridge has a load posting, vehicles at and above the posted weight must detour, so an average vehicle operating cost (U_{DL}) is determined for all weight classes having to detour. To accommodate this in the NCDOT BMS user cost computations, average vehicle operating cost (U_{DL}) is determined for all weight classes having to detour, as shown in Equation A3.6 (Chen and Johnston, 1987).

$$U_{DL} = (U_{DP} + U_{DNP})/2 \tag{A3.6}$$

Where: U_{DL} = average operating cost for the detoured vehicles
U_{DP} = operating cost for a vehicle weighing the posted bridge capacity
(smallest operating cost among detoured vehicles)
U_{DNP} = operating cost for vehicle weighing the maximum legal load (40 tons)

As stated previously, load postings are provided for single vehicle trucks (SV), as well as truck tractor semi-trailers (TTSTs). Detours due to load capacity will be affected by the percentage of ADT that fall into these vehicle classifications, which vary with route functional classification as well as geographical location and other factors. The coefficient in Equation 2.1 for the proportion of vehicles detoured due to load capacity is computed using Equation A3.7. To accommodate this in the BMS, the input table of vehicle distributions by roadway functional classification is utilized. Vehicle distribution percentages are then manipulated into a table of the cumulative percentage of trucks out of total vehicles (on each roadway type) that are heavier than the weight listed (Table A.3.2) for input into the BMS.

$$C_{LCD}(t) = R_{SV}(t) + R_{TT}(t) \tag{A3.7}$$

Where: R_{SV} = ratio of the number of single-unit trucks heavier than the bridge's SV posting to the total number of vehicles using the bridge

R_{TT} = ratio of the number of trailer combinations heavier than the bridge's TTST posting to the total vehicles using the bridge

Other state agencies have different means of deriving this vehicle operating cost for their BMS. In 1982, the FHWA sponsored research in which 11 different vehicle classifications were analyzed to determine the overall unit operator cost for five different components (fuel consumption, oil consumption, tire wear, maintenance and repair, and vehicle depreciation) (Zaniewski, et al. 1982). The vehicles were tested on 51 different geometric test sections as well as at differing speeds to ensure accurate results (Zaniewski et al., 1982). The findings of this study have been incorporated into the IBMS by Son and Sinha (1997), after grouping the 11 different vehicle classes into a subset of four: passenger car, single unit truck, bus, and tractor trailer.

A.3.2.3 Needs for Improvement and Enhancement of Vehicle Operating Cost Prediction

Review of the literature indicated that several enhancements could be made to improve the vehicle operating costs computed in NCDOT's BMS. A key need lies in the estimating percentage of vehicles required to detour due to vertical clearance, which is currently based on pre-1960 data on trucks (Kent and Stevens, 1963). Data that characterizes current-day truck heights should be utilized to update the percentage of vehicles required to detour due to vertical clearance to improve user costs estimates based on this statistic. Likewise, there is also a need to update the percentages of vehicles of each weight that must detour due to bridge postings. NCDOT has sponsored research projects focused on developing improved truck forecast models by utilizing Weigh-in-Motion (WIM) stations and the NCDOT's Traffic Forecasting Unit (TFU) (Stone et al., 2009). Other reports on WIM data also exist (Ramachandran, 2009). Predictions obtained from these models, or recent WIM data, could be used to provide better input data regarding the percentage of vehicles in each weight class that travel different types of roadways, therefore improving the user costs predicted by the BMS.

The NCDOT BMS currently computes vehicle operating cost for two vehicle weights (three ton and 40 ton), with linear interpolation of the vehicle operating cost for all vehicles between these two weights. It is possible that this relationship is not linear and an effort to develop a more accurate relationship between vehicle weight and operating cost is needed. After base values for three ton (and lighter) vehicles and maximum legal weight vehicles are updated to present time, additional published information could be utilized to determine the operating costs of vehicles of intermediate weights. This would allow for more accurate forecasting of the operating costs of vehicles with weights between three tons and 40 tons.

Due to both higher operating costs and higher probability of a detour due to a bridge posting, heavier weight vehicles will have a greater impact on user costs than lighter weight vehicles (Johnston et. al., 1994). North Carolina has experienced a significant increase in truck traffic over recent years (Stone et. al. 2006). However, the NCDOT BMS currently uses data from the 1980's to predict the portion of SU and TTST that must detour as well the percent ADTT associated with different roadway classifications. Therefore, there is a need to identify a better procedure to more accurately predict the number of vehicles (particularly in heavier weight classes) affected by functional deficiencies on North Carolina bridges. Additionally, NCDOT has recently sponsored research that has resulted in the development of new truck traffic forecasting tools. A report published for the NCDOT titled "North Carolina Forecasts for Truck Traffic" (2006-28) explores the rapid increase in truck traffic in North Carolina (Stone et al., 2006). The findings of this research project, as well as those of another NCDOT research project (2008-11), could be utilized to better incorporate truck traffic estimates into the prediction of user costs in the BMS. As part of NCDOT research project 2008-11, Stone et al. (2011) combined vehicle classes four through seven as SU vehicles and vehicle classes eight through 13 as MU. Through this research, data collected on various roadways was used to predict the SU and MU portion of volume on different road classifications, thus providing an ADTT. Models developed as part of this work could possibly be utilized in the future to provide a more accurate set of ADTT estimates for the BMS, thereby improving user cost predictions.

Vehicles within a single vehicle class can have a range of weights. Since detours based on bridge postings depend on vehicle weight (not necessarily vehicle class), a means of better incorporating vehicle weight into computation of the percent of vehicles detoured would improve the fidelity of cost predictions. This would alleviate inaccuracies in cost computation that occur when an entire class of vehicles is assumed to detour when in reality only a portion of that class of vehicles would actually be required to detour as a result of the load posting.

Vehicle operating costs for maximum weight vehicles currently depend on travel miles and revenue for motor carriers on a North American basis. Specific data for North Carolina motor carriers could be utilized to compute a more accurate vehicle operating cost for these heavier-weight vehicles. Since user costs for detours are highly dependent on the vehicle operator costs for these heavier vehicles, use of North Carolina data would improve the quality of these cost predictions. Chen and Johnston (1987) also utilized the assumption that although operating cost likely varies with vehicle height, the relatively low number of vehicles assumed to be impacted by vertical height restrictions would justify use of the operating cost for the legal load limit (U_{DNP}) as an estimate of the vertical clearance detour unit cost (U_{DC}).

Travel time costs due to detour are not currently included in the NCDOT BMS user costs. Travel time cost can include cost to a business for a paid employee or an unpaid consumer's personal time spent traveling (Wang, 2010). The possibility of including travel time costs in NCDOT's BMS should be considered. The methodology utilized in the IBMS could provide a starting point for incorporating this consideration into the NCDOT BMS. The IBMS uses an approach developed by Son and Sinha (1997), shown below in Equation 2.8. In this equation, it is assumed that unit travel time costs are broken into four different categories that encompass the 13 vehicle classifications. Unit travel time cost for use in this equation were derived by the Texas Transportation Institute (TTI). The average speeds used for calculation are based on an estimation that is dependent upon the roadway classification.

$$TTC_L = \sum U_{TTCL}(J) \times \frac{DL}{SP(j)} \times N_L(j) \qquad \text{(A3.8)}$$

Where: $U_{TTCL}(j)$ = unit travel time cost for each vehicle of type j, \$/hour
$SP(j)$ = average speed of vehicle type j on detour, miles/hour
TTC_L = daily travel-time cost due to load capacity, \$/day
DL = detour length
$N_L(j)$ = number of type j vehicles to detour because of load capacity, per day

The AASHTOWare Pontis BMS software also accounts for travel time costs when predicting overall user cost. In order to assist FDOT enhance their BMS user costs, Thompson et al. (1999) investigated the travel time costs utilized by the IBMS as well as another approach known as the Highway Economic Requirements Systems (HERS) approach. As outlined above, the IBMS travel time costs for the four different vehicle groups were derived by a study from the Texas Transportation Institute (TTI). The HERS travel time costs are based on values for labor wages, fringe benefits, and spoilage cost. Thompson et al. (1999) recommended the HERS approach for incorporation of travel time costs into BMS. In future work, the appropriateness of the HERS approach for the NCDOT's BMS could be investigated as a means for introducing travel time costs, if desired by NCDOT personnel.

A.3.3 Accident Costs

A.3.3.1 Causes of Bridge-Related Accidents

Accurate forecasting of user costs associated with bridge-related accidents (or crashes) is dependent on reasonable predictions of crashes based on data available in the BMS. Bridge-related crashes have historically been linked to both a high percentage of crashes and a disproportionate number of injuries and fatalities (Brinkman and Mak, 1986). Although some crashes are caused by driver error, other factors can also contribute to crashes. Early bridge-related crash research in the 1950's indicated that average daily traffic (ADT), approach curvature, and bridge width strongly influence bridge-related crashes (Raff, 1953). Studies in the 1970's and 1980's supported these findings, while identifying other factors that could be utilized to better predict crashes or develop a Bridge Safety Index (BSI) for prioritization of work. Ten factors selected from data collected at 25 selected bridges and researcher experience were utilized in the development of a BSI for narrow bridges by Ivey et al. (1979). These factors included bridge structural and approach geometry characteristics, guardrail and bridge rail conditions, sight conditions, traffic characteristics (mix and volume/capacity ratio), and a qualitative assessment of "Distractions and Roadside Activities." The authors recommend that states establish and develop weighting factors for the BSI based on their own data (Ivey et al., 1989). A study of rural, two-lane undivided bridges by Turner (1984) found that ADT, bridge relative width (bridge minus road), and approach roadway width were most influential in predicting crashes on these types of bridges. It was also found that the reduced shoulder width on two-lane undivided bridges leads to higher crash rates (Turner, 1984). Turner (1984) also developed a probability table that allows prediction of bridge crash rates based on bridge shoulder reduction. Mak and Calcote (1983) also found that bridge width, particularly as quantified by shoulder reduction, significantly influenced crash rates on two-lane undivided bridges. Significant variables influencing bridge-related crashes in a study by Ghandi et al. (1984) again included bridge width, along with bridge length, speed, mixture of traffic, and grade continuity. The BSI developed in this work included those variables, along with ADT and shoulder reduction. Work by Chen and Johnston using 1980's data from North Carolina bridges found that other factors increasing the likelihood of bridge-related crashes include low vertical clearance and poor alignment (Chen and Johnston, 1987). In addition to traffic rates and bridge length that were found to be highly influential in other studies, location (urban/rural) was also shown to have possible influence on bridge-related crashes in North Carolina (Abed-Al-Rahim and Johnston, 1993).

Analysis of 1990's crash data from Florida bridges indicated that the crash rate was a function of bridge length, number of lanes, narrowness, ADT, approach alignment, deck condition, and functional class (Thompson et al., 1999). More recent research on Florida bridges confirmed the factors influencing crashes identified in the previous study and found that, along with number of lanes, ADT, and bridge length, functional classification as an urban arterial affects crash rates (Wang, 2010). The three model types used were linear regression models, Poisson regression models, and negative binomial regression models. Research concluded that negative binomial regression produced the best prediction of crashes rates due to bridge deficiencies (Wang, 2010).

Although many studies continue to link traffic and geometric factors to bridge-related crashes, other less readily quantifiable characteristics still play a role in crash occurrence. In a study of four urban bridges in or near New York City, the crash rate per 100 million vehicle miles was computed and compared to the crash rate per 100 million vehicle miles for the approach roads (Retting et al., 2000). Although all four bridges had higher crash rates than their approach roads, bridges judged to have greater inspection and maintenance activity, along with smoother transitions from road to bridge, had smaller differences between the bridge crash rate and the approach road crash rate. "Following too close" was the most commonly reported factor on crash reports and debris on the roadway was stated as an issue in approximately 10% of police reports used in the study (Retting et al., 2000). A significant portion of crashes did not appear to be influenced by weather (77% in dry conditions) or darkness (71% during daylight) (Retting et al., 2000).

In recent years, more specific types of bridge-related crashes, as well as more advanced modeling techniques, have been the subject of study. Risk analysis models, often utilized to evaluate the likelihood of crashes of all types, were used to develop a vehicle-bridge collision risk analysis model for run-off-road (ROR) truck crashes on overpass bridges for interstates in South Dakota (Qin el al., 2015). Monte Carlo simulation, along with roadway, weather, and traffic volumes, were used in the analysis, which found that volume of truck miles traveled, along with "sharp horizontal curves, high annual snowfall precipitation, and a concrete pavement surface" are associated with increased ROR truck crash frequencies (Qin et al., 2015). To meet the emphasis of facility-specific safety performance functions (SPFs) specified by the Highway Safety Manual, Mehta et al. developed SPFs for crashes occurring on major highway (state or interstate) bridges in Alabama (Mehta et al., 2015). Using negative binomial regression, this study found that the seven characteristics most linked to crashes on Alabama interstate/state route bridges were AADT, bridge length, shoulder width, percentage of trucks, and variables associated with conformance of rails, approach guard rails, and transitions to desirable safety standards (Mehta et al., 2015). The authors cite the use of data available in the NBI as a strength of the work, although caution that the models may require recalibration before being transferred to other states (Mehta et al., 2015).

A.3.3.2 Accident Costs and Crash Forecasting Models in NCDOT BMS

Johnston (2010) states that bridge related accidents are a small portion of total accidents, but the severity of these bridge related accidents are higher than other non-bridge related accidents. This is also emphasized by Sobanjo and Thompson (2013) who stated that vehicle crashes on bridges as well as on bridge elements are more likely to be deadly than other vehicle accidents. Abed-Al-Rahim and Johnston (1991) reported studies finding that the severity of bridge related accidents can be two to 50 times more severe than non-bridge related accidents. One factor that can result in increased accident rates are narrow deck width bridges that reduce lane width (Wang, 2010). Chen and Johnston (1987) report that other factors that increase the likelihood of accidents include low vertical clearance and poor deck alignment.

Accident costs can be calculated by grouping them as accidents that solely result in property damage, accidents that are injury producing, and accidents resulting in one or more fatalities (Wang 2010). NCDOT classifies accident types within their BMS in this manner (Abed-Al-Rahim and Johnston, 1991). In the NCDOT BMS, a scaled, lettering system is used to indicate the severity of the accident. Crashes incurring one or more fatalities are designated with K, while A, B, and C crashes are crashes that resulted in personal injury (in decreasing severity from A to C), but no fatalities. PDO is used to designate a crash that resulted in property damage only.

Two approaches have often been considered in determining crash costs on bridges within a number of BMS, including the NCDOT BMS (Chen and Johnston, 1987). These are the Willingness-to-Pay approach and the Human Capital Approach. Both approaches consider direct and indirect costs involved with bridge-related crashes. Direct costs for both are considered to be crash cost, emergency service, medical treatment, and legal and court fees as stated by the National Safety Council (NSC). The indirect costs, which can be more difficult to determine (Chen and Johnston, 1987), are considered to include compensation for pain and suffering and the costs of goods and services an individual will not be able to produce due to the crash. The Willingness-to-Pay approach also considers an indirect cost known as value of life, which looks at possible long and short term loss in quality of life due to the crash. Both approaches provide a dollar value for each severity type (K-A-B-C-PDO). In updating NCDOT BMS crash costs, Duncan and Johnston (2002) also considered a third approach known as the comprehensive cost method, which looks at 11 different components consisting of both direct and indirect costs, which is very similar to the Willingness-to-Pay method. The costs per crash values for the Human Capital approach are published by the FHWA every few years. Since this data does not include a cost parameter for value of life, the total cost of the five different crash types is less than the Willingness-to-Pay approach (2002). The costs per crash values for the Willingness-to-Pay approach are published by the NSC. Since data is provided more frequently and includes value of life, Duncan and Johnston (2002) recommended that it be used to predict crash costs.

To compute crash costs in a BMS forecasting analysis, a means of predicting the average number of crashes occurring on a bridge is required. For NCDOT's BMS, this prediction methodology was developed by Abed-Al-Rahim and Johnston (1991). In this methodology, data compiled by NCDOT was utilized to determine the percentage of crashes of all vehicular crashes occurring on bridges. At the time of this work, North Carolina required that all vehicular crash data be stored for seven years. These crash reports provided data on whether the crash occurred on the bridge or under the bridge, or on a bridge element, along with information on the severity of crash. Using this data, Abed-Al-Rahim and Johnston (1991) were able to produce an estimate of the average number of crashes for each severity type, K-A-B-C-PDO, on North Carolina bridges. These estimates are then multiplied by their corresponding costs per severity type crash value within the Willingness-to-Pay approach to produce the crash costs on bridges. These five different cost items are then summed up and averaged to produce an overall average annual bridge-related crash cost for the user cost models.

To compute accident costs in NCDOT's BMS, the accident cost value is multiplied by a coefficient expressing the expected rate of accidents occurring on a bridge. This coefficient is determined for individual bridges by an equation using bridge characteristics as inputs associated with the likelihood of future contributions to an accident. Chen and Johnston (1987) developed the equation used to determine the coefficient by conducting a literature review that showed bridge accident trends typically occur due to clear deck width and approach roadway alignment (Hilton, 1973). According to prior work, alignment contributed to bridge accidents at a rate of at most half of the rate attributed to clear deck width (Ivey et al., 1979). Using that understanding Chen and Johnston (1987) developed Equation A3.9 to predict the coefficient of accidents as a function clear deck width and approach roadway alignment.

$$C_{WDA} + C_{ALA} = (6.28\times10^{7.5}CDW^{-6.5}[1+0.5(9-ALI)/7])\times10^{-6} \tag{A3.9}$$

Where: $C_{WDA} + C_{ALA}$ = coefficient for proportion of vehicles incurring accidents due to width deficiency and poor alignment

CDW = clear deck width

ALI = alignment appraisal rating (scale of 1 to 9)

Later research by Abed-Al-Rahim and Johnston (1991) attempted to link bridge accidents to features of the corresponding bridge to determine what bridge characteristics cause accidents. However, they note that there was no way to merge the two files directly since bridges were not identified on common bases within the accident reports and the North Carolina Bridge Inventory (NCBI) file. So in order to match accidents to the bridge where the accident occurs, Abed-Al-Rahim and Johnston (1991) had to manually match accidents to bridges using information from the accident data records on county number, mile-marker, route type, route number, reference road, direction toward road, distance from reference point, and direction from reference road. Due to this large undertaking, only five counties were selected for accident and bridge matching: Guilford, Harnett, Halifax, Iredell, and Wake county; these counties were picked as an overall representation of the state with high and low population density (Abed-Al-Rahim and Johnston, 1991).

Abed-Al-Rahim and Johnston (1991) looked at accidents from 1983 through 1989. The records available totaled 2,895 accidents for the five counties, of which they were able to match 2,104 accidents to bridges with confidence. Once all the bridges with reported accidents were matched, Abed-Al-Rahim and Johnston (1991) used Statistical Analysis

Software (SAS) to develop a prediction model for bridge related accidents based on the bridges' characteristics. A stepwise selection procedure was used first to explore the characteristics that have the most significant effect on accident rates (Abed-Al-Rahim and Johnston, 1991). This procedure identified bridge clear deck width, approach roadway width, ADT, alignment appraisal rating, bridge length, and functional classification the most significant explanatory factors. These factors were then grouped into a number of different groupings and subgroupings and tested to determine their significance, through which ADT, bridge length, and the difference between clear deck width for an acceptable level of service and actual clear deck width were found to be the most significant. Using this information, the resulting Equation A3.10 was formed and recommended for use in the NCDOT BMS. Abed-Al-Rahim and Johnston (1991) note the strength of the regression was low with an R^2 value of 0.33, but justified the use of the model on the basis that the estimated number of accidents per year was close to actual accidents per year.

$$NOACC = 0.783(ADT^{0.073})(LENGTH^{0.033})(WDIFACC + 1)^{0.05} \times 1.33 \qquad (A3.10)$$

Where: NOACC = number of accidents per year
ADT = average daily traffic
Length = bridge length, feet
WDIFACC = width difference between the goal clear deck width acceptable level of service and the actual clear deck width, but not less than zero, feet

Equation A3.10 includes a factor of 1.33 subtracted from the accident prediction equation, and is shown as published in Abed-Al-Rahim and Johnston (1991) and Abed-Al-Rahim and Johnston (1993). However, as described in these same publications, the 1.33 factor serves as an adjustment factor (denoted in both publications as AF) to account for the proportion of accidents that could not be manually matched to a specific bridge in their effort. Therefore, it is assumed that the subtraction sign is printed in error, and the adjustment factor for unmatchable accidents AF (in this case, equal to 1.33) should be multiplied by the remainder of the equation to predict the yearly accidents.

At the time of development of NCDOT's BMS, limited data on crashes resulting from vertical clearance issues existed, and studies on the role of vertical clearance deficiency in crashes were not available (Johnston et al., 1994). Therefore, it was assumed that the crash rate due to vertical clearance was linearly increasing with vertical deficiency from the desirable level of service goals (Johnston and Zia, 1984). Underpass accident data from NCDOT were assumed to be distributed to the bridges with vertical clearance deficiencies, and accident rates were computed for interstates, arterials, collector, and local roads (Chen and Johnston, 1987). An equation to compute the coefficient for proportion of vehicles incurring accidents due to a vertical clearance deficiency was developed as shown in Equation A3.11, and the bridge-related accident cost, U_{AC} was assumed to be reasonable for underpass accidents (Chen and Johnston, 1987).

$$C_{CLA} = \frac{UG - UCL}{ACCRU} \qquad (A3.11)$$

Where: UG = underclearance desirable goal, feet
UCL = bridge underclearance height, feet
ACCRU = accident rate by functional classification due to vertical clearance deficiency
(7.4×10^6 vehicles/accident/ft deficiency for interstates, 37.3×10^6 vehicles/accident/ft deficiency for arterials, 8.0×10^6 vehicles/accident/ft deficiency for collectors, 1.1×10^6 vehicles/accident/ft deficiency for local roads)

In BMS used by other state agencies, accident costs are computed or considered in a manner that differs from that utilized by NCDOT's BMS. The Florida Department of Transportation (FDOT) sponsored research on the effect of the number of lanes on a bridge, ADT, and bridge length on accident rates (Wang, 2010). Using these parameters and Florida bridge accident data, models were produced to predict accident rates based on number of lanes, ADT, and length. The three types of regression techniques used were linear regression models, Poisson regression models, and negative binomial regression models. The research concluded that negative binomial regression produced the best prediction of accidents rates due to these bridge characteristics (Wang, 2010). Other BMS systems, such as that used in Indiana (IBMS), do not account for bridge related accident costs in their user costs (Sinha et al., 2009). These accident costs are not considered in the IBMS total user costs since traffic safety is considered in their project selection module. Therefore, Sinha et al. (2009)

believe that considering accident costs separately in the BMS would essentially incorporate these costs into the project planning and prioritization analysis twice.

A.3.3.3 Needs for Improvement and Enhancement of Accident Cost Prediction

Supporting data for the computation of accident costs in the NCDOT BMS should be updated using more current data. Using the existing methodology developed by Abed-Al-Rahim and Johnston (1991), costs per average accident across the range of severity categories should be updated to current values. Additionally, other approaches for determining accident costs should be investigated. Currently, the approach used in the NCDOT BMS uses the NSC Willingness-to-Pay values. Since the NSC Willingness-to-Pay values are not published annually, the Consumer Price Index (CPI) is used to project updated cost values to current values. The Traffic Safety Division of NCDOT publishes reports annually with Willingness-to-Pay costs per accident based solely on North Carolina data. Use of these accident costs for accidents solely in North Carolina would be an enhancement to the NCDOT BMS. Additionally, the coefficients used for the average number of accidents per severity type occurring on bridges were determined from data collected in the 1980's. There is a need to update these inputs using more up-to-date, local statistics on accident rates. The equation utilized to predict bridge-related accidents could also be updated using more recent data.

A.3.4 Summary

A majority of current BMS have a history traceable to NCDOT's BMS. Researchers (Chen and Johnston, 1987, Abed-Al-Rahim and Johnston, 1991, Johnston et. al., 1994, Duncan and Johnston, 2002, Johnston, 2010) have periodically updated NCDOT's BMS, including an update as recently as 2010. However, data tables used to compute user costs in NCDOT's BMS need to be updated to improve the fidelity of user costs predictions. In some cases, new data is available to enhance the existing methodology used to compute detour and accident costs. Since these methods were first developed, NCDOT has made a number of advances in the collection and characterization of traffic data and accident data. Additionally, research by other agencies has yielded new approaches to computing user costs. Approaches discussed in this literature review could be used in conjunction with updated and enhanced data to improve the cost predictions of the NCDOT BMS.

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APPENDIX B – SUPPORTING MATERIAL FOR DETERIORATION MODEL UPDATES

Updated Deterministic Deterioration Models

Updated Deterministic Deck Deterioration Models

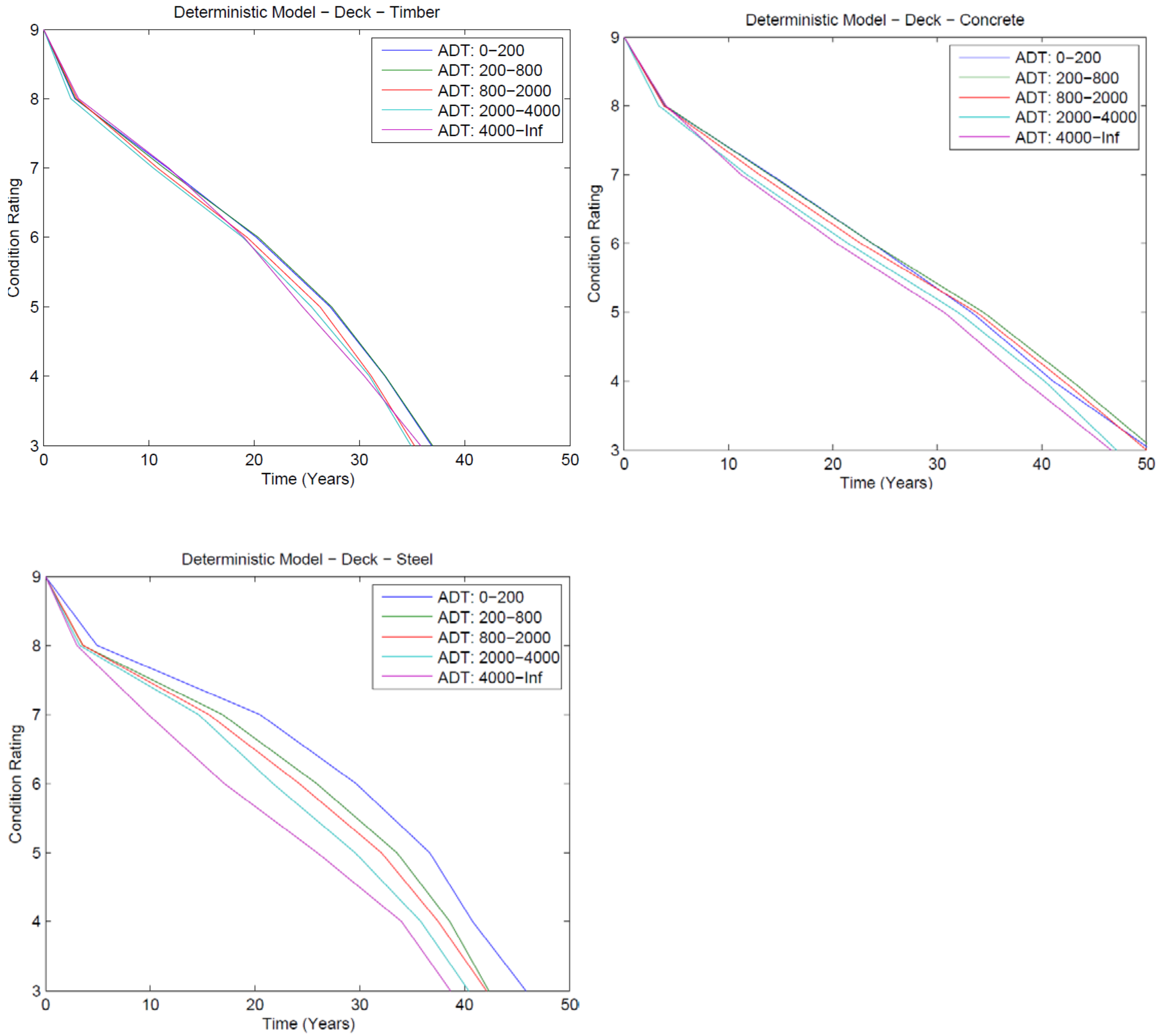


Figure B.1: Updated deterministic deterioration models for bridge decks: a) timber, b) concrete, c) steel

__Updated Deterministic Substructure Deterioration Models__

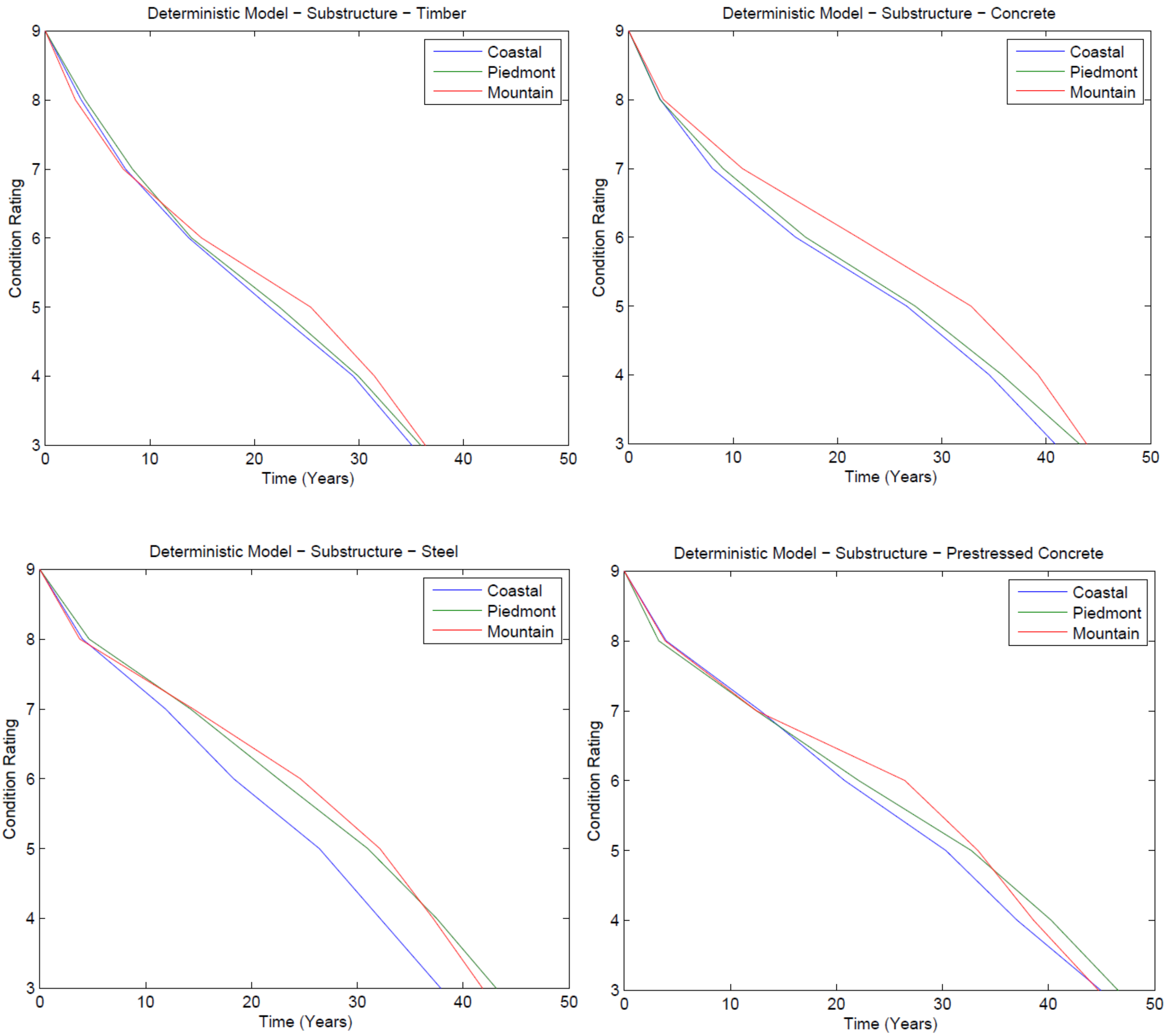


Figure B.2: Updated deterministic deterioration models for bridge substructures: a) timber, b) concrete, c) steel, d) prestressed concrete

Updated Deterministic Superstructure Deterioration Models

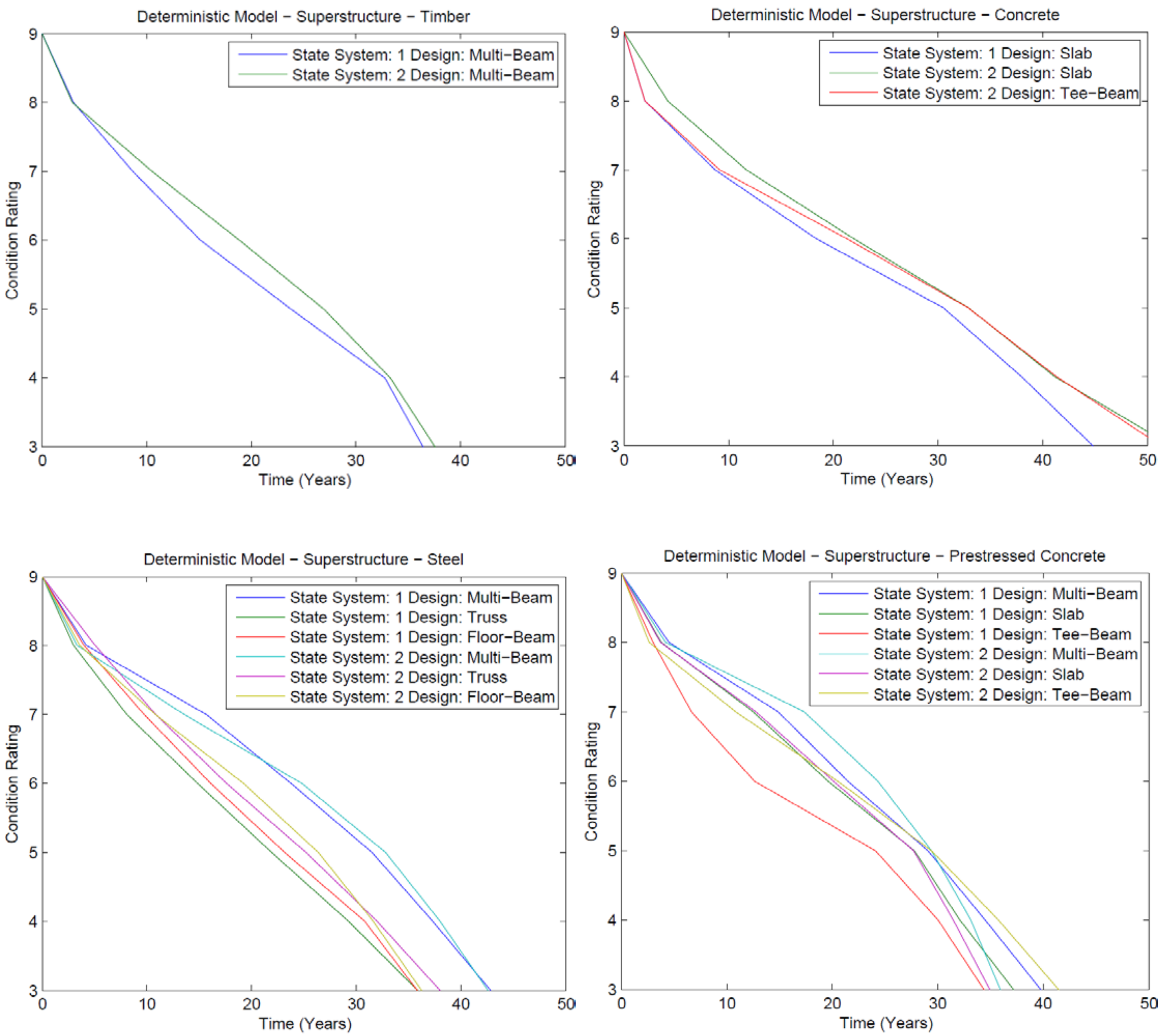


Figure B.3: Updated deterministic deterioration models for bridge superstructures: a) timber, b) concrete, c) steel, d) prestressed concrete

Proportional Hazards Probabilistic Deterioration Models

Proportional Hazards Probabilistic Deck Deterioration Models

Table B.1: Baseline stay-the-same transition probabilities for concrete deck model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.8821	0.9643	0.9771	0.9668	0.9889	0.9933	0.75	0.75	1

Table B.2: Hazard ratios for explanatory factors in concrete deck model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	1	0.7722	1.1242	1	1	1
'Piedmont'	1	1.4339	0.7527	1	1.2238	0.6310
'Mountain'	1	1	0.8089	0.7522	1.2067	0.4603
'ADT3'	1	1	1.1312	1	1	1
'ADT4'	1.5508	1	1.2481	1	1	1
'MaxSpan2'	1	1	1	0.8044	1.4816	1
'MaxSpan3'	1	1	1.3529	1	2.1793	0.4971
'NumberSpans'	1	1	1.2997	1.5749	1	1
'Age2'	0.2570	1	1.2616	1.1300	1.6839	4.5250
'Age3'	1	1.6920	1.4602	1.4054	2.2851	1
'Age4'	1	1.3628	2.2785	2.2229	2.2802	1

Table B.3: Categorical variable assignments for concrete deck model

Categorical Variable	**Range**
ADT3	3184-9090
ADT4	>9090 Vehicles
MaxSpan2	4-6 m
MaxSpan3	>6 m
Age2	14-23 years
Age3	23-33 years
Age4	>33 years

Table B.4: Baseline stay-the-same transition probabilities for timber deck model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.8060	0.9373	0.9512	0.9516	0.9663	0.9523	0.75	0.75	1

Table B.5: Hazard ratios for explanatory factors in timber deck model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	0.4489	1	1	1	1	1
'Reconstruction'	1	0.7790	1.2929	1	0.8424	1
'Piedmont'	1	1.3633	1	1	1	1
'Mountain'	1	1.4237	1.1427	0.8572	1.2772	1
'ADT4'	1	1	1	1.1380	1	1
'ADTT3'	1	1	1	1	1.1396	1
'ADTT4'	1	1	1	1	1.2962	1
'MaxSpan2'	1	1	1.1991	1.1707	1	1
'MaxSpan3'	1	1	1.1936	1.1652	1	1
'NumberSpans'	1	1	1.2180	1.2845	1.1188	1
'Age2'	0.7420	1.3024	1.3322	1.7146	2.4383	2.2889
'Age3'	1	1.8139	2.0758	1.2643	2.2100	2.5027
'Age4'	1	1.5639	2.2652	0.7873	3.0445	2.4453

Table B.6: Categorical variable assignments for timber deck model

Categorical Variable	**Range**
'ADT4'	>468
'ADTT3'	13-29
'ADTT4'	>29 Vehicles
MaxSpan2	2-3 m
MaxSpan3	>3 m
Age2	20-28 years
Age3	28-35 years
Age4	>35 years

Table B.7: Baseline stay-the-same transition probabilities for steel deck model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.8679	0.9627	0.9294	0.9170	0.9831	0.9596	0.75	0.75	1

Table B.8: Hazard ratios for explanatory factors in steel deck model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	1	1	0.8284	1	1	1
'Reconstruction'	1	1	1.4149	1	1	1
'Piedmont'	1	1	1	0.7190	0.7046	1
'Mountain'	1	1	1	0.6243	1	1
'MaxSpan2'	1	3.2796	1	1	1	1
'MaxSpan3'	1	2.8375	1	1	1	1
'NumberSpans'	1	1	1	1.3759	1.4117	1
'Age2'	1	1	1	1.4838	2.9947	1
'Age3'	1	1	1.3772	1.6133	3.0940	1
'Age4'	1	1	2.5928	1.8681	5.4984	1

Table B.9: Categorical variable assignments for steel deck model

Categorical Variable	**Range**
MaxSpan2	3-4 m
MaxSpan3	>4m
Age2	12-19 years
Age3	19-27 years
Age4	>27 years

Proportional Hazards Probabilistic Substructure Deterioration Models

Table B.10: Baseline stay-the-same transition probabilities for timber substructure model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.8487	0.9703	0.9610	0.9403	0.9501	0.9676	0.75	0.75	1

Table B.11: Hazard ratios for explanatory factors in timber substructure model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	1	1.0938	1.2317	1.5391	2.4151	1
'Reconstruction'	1	1	1.3106	1.2304	1.5729	1
'Piedmont'	0.7885	1.1155	1	1	1	1
'Mountain'	0.4579	0.7773	0.9283	1	1	1
'MaxSpan2'	0.7423	1	1	1.1824	1	1
'NumberSpans'	1	1.1901	1.2725	1	1	1
'Age2'	1	1	1.1269	1.5812	1.8008	1
'Age3'	1	1.0999	1.4267	1.7256	2.3522	1.7887
'Age4'	1	1	2.0540	1.8987	2.8342	2.2859

Table B.12: Categorical variable assignments for timber substructure model

Categorical Variable	**Range**
MaxSpan2	2-3 m
Age2	21-29 years
Age3	29-36 years
Age4	>36 years

Table B.13: Baseline stay-the-same transition probabilities for concrete substructure model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.9852	0.9459	0.9829	0.9422	0.9846	0.9878	0.75	0.75	1

Table B.14: Hazard ratios for explanatory factors in concrete substructure model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	1	0.8552	1	1	1	1
'Reconstruction'	1	1	1.1604	1.4223	1	1
'Piedmont'	1	1	0.7637	1	1	1
'Mountain'	1	1	0.8394	0.8209	0.7299	1
'ADT3'	1	1	0.7999	1	1	1
'ADT4'	1	1	0.7465	0.7889	0.7285	1
'ADTT2'	1	1	1	1.2434	1	1
'ADTT3'	1	1	1	1	1	2.3050
'ADTT4'	1	0.7553	1	1	1	1
'MaxSpan3'	0.4903	1	1.17104	1	1.4807	1
'NumberSpans'	1	1.6742	1.4123	1.2295	1	1
'Age2'	1	1	1	1.9588	1	7.1643
'Age3'	1	1.3929	1.2179	2.6069	1.7775	1
'Age4'	1	1	1.4528	2.5803	1	1

Table B.15: Categorical variable assignments for concrete substructure model

Categorical Variable	**Range**
'ADT3'	1100-5102
'ADT4'	>5102
'ADTT2'	19-88
'ADTT3'	88-514
'ADTT4'	>514 Vehicles
MaxSpan3	>5m
Age2	15-26 years
Age3	26-39 years
Age4	>39 years

Table B.16: Baseline stay-the-same transition probabilities for steel substructure model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.9327	0.9615	0.9594	0.9181	0.9624	0.9902	0.75	0.75	1

Table B.17: Hazard ratios for explanatory factors in steel substructure model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	2.1952	1	1	1	1.3811	1
'Reconstruction'	1	1	1.3957	1.7470	1	1
'Piedmont'	1	1	0.6133	0.7130	1.1912	0.4134
'Mountain'	1	1	0.7035	0.5572	0.7895	0.4889
'IntegralConcrete'	1	1	0.0369	1	0.0825	1
'LatexConcrete'	1	1	1.6572	1	1	1
'Timber'	1	1	0.5426	1	1	1
'ADT2'	1	1	1	1	1	1.5025
'ADTT2'	1	1.4179	1	1	1	1
'MaxSpan2'	1	1	1	1	1.1835	1
'MaxSpan3'	1	1	1	1	1.5193	1
'NumberSpans'	1	0.5707	1	1	0.8048	1
'Age2'	1	1	1	1	2.2677	14.4085
'Age3'	1	1	1.8157	1.5236	2.5633	1
'Age4'	1	1	2.9335	2.3828	3.5905	1

Table B.18: Categorical variable assignments for steel substructure model

Categorical Variable	**Range**
'ADT2'	745-3249
'ADTT2'	54-261 Vehicles
MaxSpan2	5-8 m
MaxSpan3	>8m
Age2	10-15 years
Age3	15-23 years
Age4	>23 years

Table B.19: Baseline stay-the-same transition probabilities for prestressed concrete substructure model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.8927	0.9704	0.9618	0.9166	0.8900	0.9868	0.75	0.75	1

Table B.20: Hazard ratios for explanatory factors in prestressed concrete substructure model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	1	1.4646	1	1	1	1
'Reconstruction'	1	0.3001	1	1	1	1
'Piedmont'	1	1	0.7891	1	1	1
'Mountain'	1	1	1	0.4990	1	2.2735
'ADT4'	1	1.5079	1	1	1	1
'NumberSpans'	1	0.2450	1	1	1	1
'Age2'	1	1	1	1.2953	1.7396	1
'Age3'	1	1	1	1.6525	2.4379	1
'Age4'	0.6261	1	1.4979	2.7497	5.2532	1

Table B.21: Categorical variable assignments for prestressed concrete substructure model

Categorical Variable	**Range**
ADT4	>11092 Vehicles
Age2	15-23 years
Age3	23-32 years
Age4	>32 years

Table B.22: Baseline stay-the-same transition probabilities for timber superstructure model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.7585	0.8975	0.9634	0.9579	0.9592	0.9804	0.75	0.75	1

Table B.23: Hazard ratios for explanatory factors in timber superstructure model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	1	1	1.4124	1	1	1
'Reconstruction'	1	1	1	1	0.7063	1
'Piedmont'	0.6211	1	0.7464	1	1	1
'ADT3'	1	0.4526	1	1	1	1
'ADTT3'	1	1.9368	1	1	1	1
'MaxSpan3'	1	1	1	1.3050	1	1
'NumberSpans'	1.8609	1	1.4350	1	1	1
'Age2'	1	1	1.2072	1.9363	2.5232	1
'Age3'	1	1	1.8232	2.1459	1.7157	2.2511
'Age4'	1	0.7151	2.4080	1	3.5598	1.9337

Table B.24: Categorical variable assignments for timber superstructure model

Categorical Variable	**Range**
ADT3	239-555
ADTT3	15-34 Vehicles
MaxSpan3	>2 m
Age2	22-28 years
Age3	28-36 years
Age4	>36 years

Table B.25: Baseline stay-the-same transition probabilities for concrete superstructure model

Condition Rating	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.9290	0.9847	0.9709	0.9881	0.9850	0.75	0.75	1

Table B.26: Hazard ratios for explanatory factors in concrete superstructure model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	0.8161	1	1	1	1	1
'Piedmont'	1	1	1	1	1.5343	1
'Mountain'	1	1	1	0.7914	1	1
'MaxSpan2'	1	1.5204	1	1	1	1
'MaxSpan3'	1	1.9963	1	1	1	1
'NumberSpans'	1	1.8622	1.6206	1.8489	1	1
'Age2'	1	1	1.2863	2.0594	1	1
'Age3'	0.3866	1	1.9205	2.4341	1.5123	1
'Age4'	1	1	2.1611	3.0011	1	1

Table B.27: Categorical variable assignments for concrete superstructure model

Categorical Variable	**Range**
MaxSpan2	3-5 m
MaxSpan3	>5 m
Age2	32-46 years
Age3	46-58 years
Age4	>58 years

Table B.28: Baseline stay-the-same transition probabilities for steel superstructure model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.9735	0.9499	0.9717	0.9504	0.9699	0.9795	0.75	0.75	1

Table B.29: Hazard ratios for explanatory factors in steel superstructure model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	1	1.3108	0.95008	1.1619	0.9160	1
'Reconstruction'	1	1	1.5024	1.5072	1	1
'Piedmont'	1	1	0.8894	0.8646	1.1395	1
'Mountain'	1	1	1	0.8026	1.1393	1
'IntegralConcrete'	1	1	1	0.0824	1	1
'EpoxyOverlay'	1	1	1	4.9239	1	1
'ADT2'	1	1	1.1258	1.1395	1	1
'ADT3'	1	1	1.1212	1.1632	1	1
'ADT4'	1	1	1	1.2772	1	1
'ADTT4'	0.8807	1	1	1	1	1
'MaxSpan2'	1	1	1	0.9201	0.8636	1
'MaxSpan3'	1	1	1.2868	0.8165	1	1
'NumberSpans'	1	1	1	1.2448	1	1
'Age2'	1	1	1	1.5831	2.4509	1
'Age3'	1	1	1.3960	2.0567	3.1086	17.2275
'Age4'	1	1.3850	2.7749	3.0084	3.7593	12.2736

Table B.30: Categorical variable assignments for steel superstructure model

Categorical Variable	**Range**
'ADT2'	282-1015
'ADT3'	1015-5179
'ADT4'	>5179
'ADTT4'	>454 Vehicles
MaxSpan2	3-5 m
MaxSpan3	>5 m
Age2	17-26 years
Age3	26-35 years
Age4	>35 years

Table B.31: Baseline stay-the-same transition probabilities for prestressed concrete superstructure model

Condition Rating	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
Stay-the-Same Probability	0.9113	0.9675	0.9670	0.9631	0.9534	0.8438	0.75	0.75	1

Table B.32: Hazard ratios for explanatory factors in prestressed concrete superstructure model

Factor	**Rating 4**	**Rating 5**	**Rating 6**	**Rating 7**	**Rating 8**	**Rating 9**
'StateSystem'	1	1	1.2500	0.8544	1.2166	1
'Piedmont'	1	1	0.7253	0.6885	1	0.4271
'Mountain'	1	1	1	0.5793	1	1
'ADT3'	1	0.6429	1	1	1	1
'ADT4'	1	0.4555	1	1	1	0.6122
'ADTT2'	1	1	1	1.2039	1	1
'ADTT3'	1	1	1	1.3342	1.1494	1
'MaxSpan2'	1	1	1	0.6898	1.2744	1
'MaxSpan3'	1	1	1	0.4887	1.6047	1
'NumberSpans'	1	1	1.5081	1	1	1
'Age2'	1	1	1	1	2.4399	9.4572
'Age3'	1	1	1	1.4089	2.0105	10.5458
'Age4'	1	1	2.4619	2.8898	3.0841	1

Table B.33: Categorical variable assignments for prestressed concrete superstructure model

Categorical Variable	**Range**
ADT3	1636-5432
ADT4	>5432
'ADTT2'	36-141 Vehicles
'ADTT3'	141-738 Vehicles
MaxSpan2	4-6 m
MaxSpan3	>6 m
Age2	7-12 years
Age3	12-19 years
Age4	>19 years

APPENDIX C – SUPPORTING MATERIAL FOR USER COST UPDATE

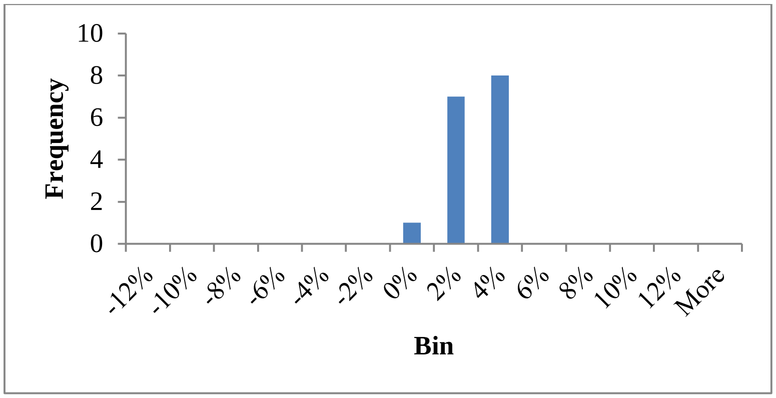


Figure C.1: Anson County bridges on arterial roadways - histogram of ADT growth rates

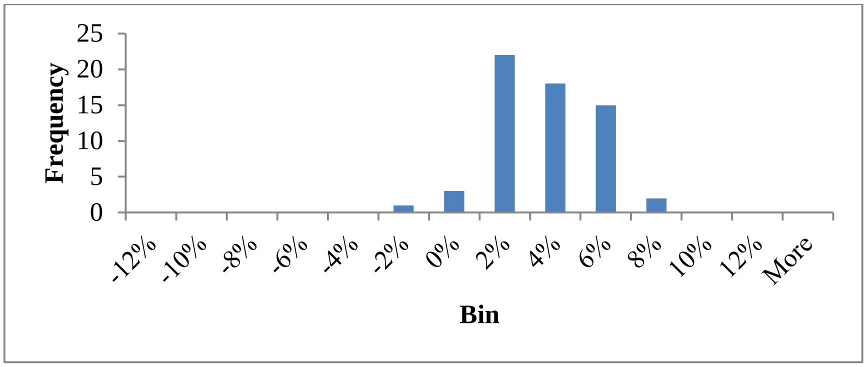


Figure C.2: Forsyth County bridges on collector roadways - histogram of ADT growth rates

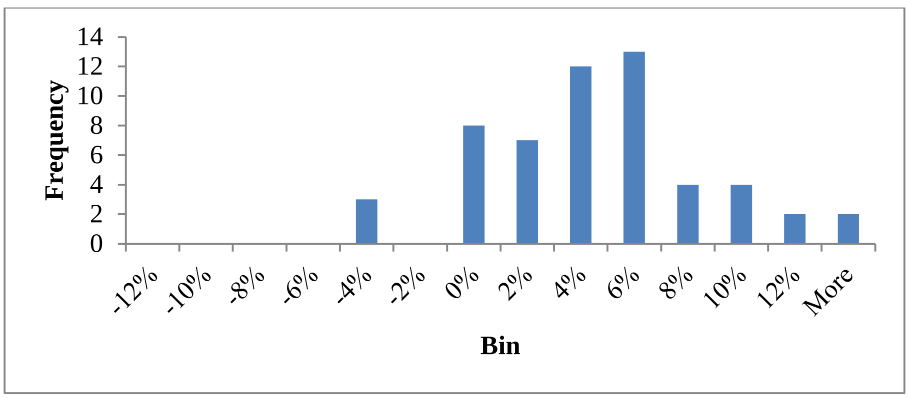


Figure C.3: Gaston County bridges on local roadways - histogram of ADT growth rates

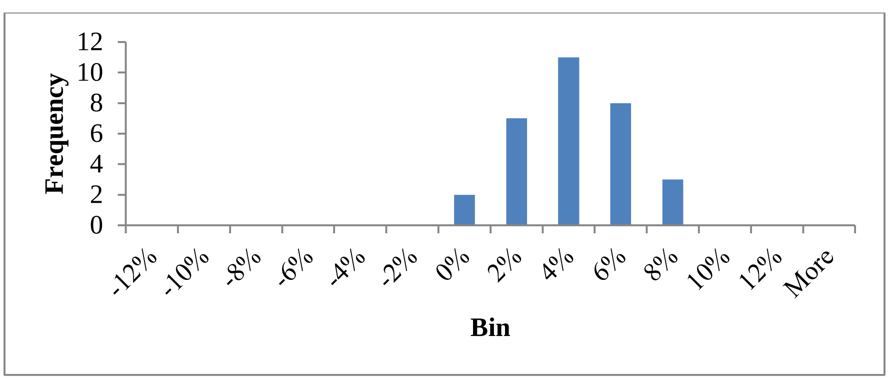


Figure C.4: Orange County bridges on collector roadways - histogram of ADT growth rates

Table C.1: Number of ADT growth rate values used and distribution type

Note: Green indicates the data was considered to be well distributed (N>15), yellow indicates the data was considered to be not well distributed (N>15), orange indicates the data was considered to be well distributed (N<15), red indicates the data was considered to be not well distributed (N<15), and gray indicates that no data was available.

County No.	County Name	Local	Collector	Arterial	Interstate
00	Alamance	68	58	19	3
01	Alexander	47	16	5	
02	Alleghany	77	4	2	
03	Anson	86	32	16	
04	Ashe	187	24	4	
05	Avery	74	8	3	
06	Beaufort	63	42	15	
07	Bertie	28	16	26	
08	Bladen	35	35	14	
09	Brunswick	40	35	28	
10	Buncombe	265	72	56	86
11	Burke	85	60	30	14
12	Cabarrus	65	43	41	8
13	Caldwell	110	20	18	
14	Camden	7	7	4	
15	Carteret	12	28	10	
16	Caswell	46	13	5	
17	Catawba	67	35	45	10
18	Chatham	70	40	33	
19	Cherokee	83	38	25	
20	Chowan	12	8	12	
21	Clay	34	17	2	
22	Cleveland	127	45	33	2
23	Columbus	75	58	33	
24	Craven	36	33	33	
25	Cumberland	57	28	72	15
26	Currituck	7	3	7	
27	Dare	8	5	11	
28	Davidson	85	51	69	21
29	Davie	29	14	8	8
30	Duplin	67	57	11	10
31	Durham	49	24	89	34
32	Edgecombe	40	47	33	
33	Forsyth	116	61	83	25
34	Franklin	38	31	8	
35	Gaston	55	36	75	5
36	Gates	12	7	5	
37	Graham	69	15	1	
38	Granville	52	33	3	7
39	Greene	24	12	5	
40	Guilford	167	69	126	37
41	Halifax	65	26	13	8
42	Harnett	38	27	10	2
43	Haywood	187	48	35	21
44	Henderson	149	33	42	10
45	Hertford	20	10	7	
46	Hoke	17	11	3	
47	Hyde	16	22	11	
48	Iredell	136	51	11	54
49	Jackson	163	27	28	

Table C.1 (continued): Number of ADT growth rate values used and distribution type

50	Johnston	92	61	32	32
51	Jones	26	13	1	
52	Lee	19	13	17	
53	Lenoir	31	24	25	
54	Lincoln	65	22	25	
55	Macon	150	35	16	
56	Madison	140	66	8	4
57	Martin	44	12	26	
58	McDowell	102	48	8	22
59	Mecklenburg	106	28	137	103
60	Mitchell	95	21	1	
61	Montgomery	77	13	3	10
62	Moore	74	22	25	
63	Nash	67	73	62	12
64	New Hanover	9	5	22	8
65	Northampton	29	20	7	2
66	Onslow	21	30	22	
67	Orange	59	31	20	21
68	Pamlico	15	23		
69	Pasquotank	14	7	10	
70	Pender	40	28		2
71	Perquimans	17	10	4	
72	Person	39	15	6	
73	Pitt	69	45	33	
74	Polk	85	19	12	7
75	Randolph	136	61	37	13
76	Richmond	56	20	30	
77	Robeson	85	84	30	14
78	Rockingham	86	62	32	
79	Rowan	97	38	22	8
80	Rutherford	209	29	34	
81	Sampson	80	53	25	
82	Scotland	14	23	38	
83	Stanly	59	29	13	
84	Stokes	56	21	4	
85	Surry	130	41	30	29
86	Swain	75	6	16	
87	Transylvania	98	32	11	
88	Tyrrell	14	3	2	
89	Union	109	66	16	
90	Vance	18	22	13	6
91	Wake	168	55	109	54
92	Warren	52	11		2
93	Washington	9	13	1	
94	Watauga	133	12	6	
95	Wayne	42	31	37	
96	Wilkes	235	31	8	
97	Wilson	51	35	22	8
98	Yadkin	82	18	12	6
99	Yancey	130	24	4	

Table C.2: Change in ADT growth rates

Note: Yellow is a difference of plus or minus 1 percent, orange is minus 1 percent to minus 2 percent, red is minus 2 percent and less, green is plus 1 percent to plus 2 percent, and blue is plus 3 percent and greater.

		Local			Collector			Arterial			Interstate		
County No.	County Name	2001 (%)	2014 (%)	Diff. (%)	2001 (%)	2014 (%)	Diff. (%)	2001 (%)	2014 (%)	Diff. (%)	2001 (%)	2014 (%)	Diff. (%)
00	Alamance	3.82	2.55	-1.27	3.50	3.23	-0.27	3.50	2.30	-1.20	6.81	6.36	-0.45
01	Alexander	4.57	2.74	-1.83	4.28	2.98	-1.30	2.86	2.27	-0.59	5.38	3.64	-1.74
02	Alleghany	2.75	1.79	-0.96	3.99	2.35	-1.64	2.75	2.21	-0.54	5.38	3.64	-1.74
03	Anson	2.67	1.81	-0.86	2.86	2.33	-0.53	2.98	2.00	-0.98	5.38	3.64	-1.74
04	Ashe	2.50	1.69	-0.81	3.61	2.30	-1.31	2.97	3.82	0.85	5.38	3.64	-1.74
05	Avery	3.42	2.92	-0.50	3.52	3.79	0.27	3.50	1.05	-2.45	5.38	3.64	-1.74
06	Beaufort	2.50	2.31	-0.19	2.55	1.49	-1.06	2.93	2.45	-0.48	5.38	3.64	-1.74
07	Bertie	3.45	2.57	-0.88	3.28	2.85	-0.43	0.48	1.71	1.23	5.38	3.64	-1.74
08	Bladen	4.93	2.95	-1.98	2.50	3.13	0.63	3.00	1.43	-1.57	5.38	3.64	-1.74
09	Brunswick	5.96	5.26	-0.70	4.56	3.41	-1.15	3.50	2.85	-0.65	5.38	3.64	-1.74
10	Buncombe	2.50	3.20	0.70	2.55	3.92	1.37	3.50	3.46	-0.04	5.47	3.65	-1.82
11	Burke	2.72	2.60	-0.12	3.37	4.04	0.67	3.01	2.48	-0.53	5.19	3.64	-1.55
12	Cabarrus	3.61	4.15	0.54	3.50	5.07	1.57	2.86	2.96	0.10	7.75	4.42	-3.33
13	Caldwell	2.50	2.44	-0.06	2.50	2.11	-0.39	3.92	2.13	-1.79	5.38	3.64	-1.74
14	Camden	4.43	1.00	-3.43	3.47	3.31	-0.16	3.16	2.22	-0.94	5.38	3.64	-1.74
15	Carteret	3.50	0.61	-2.89	2.59	2.41	-0.18	3.25	1.74	-1.51	5.38	3.64	-1.74
16	Caswell	1.44	1.92	0.48	3.92	2.39	-1.53	4.24	2.91	-1.33	5.38	3.64	-1.74
17	Catawba	3.42	3.79	0.37	2.93	3.61	0.68	2.84	3.38	0.54	5.00	3.62	-1.38
18	Chatham	4.21	2.54	-1.67	3.49	3.03	-0.46	2.58	3.06	0.48	5.38	3.64	-1.74
19	Cherokee	4.28	3.29	-0.99	2.87	2.97	0.10	2.25	0.89	-1.36	5.38	3.64	-1.74
20	Chowan	2.50	1.57	-0.93	2.50	1.13	-1.37	2.60	1.46	-1.14	5.38	3.64	-1.74
21	Clay	2.40	3.15	0.75	2.47	3.40	0.93	3.50	4.21	0.71	5.38	3.64	-1.74
22	Cleveland	2.59	2.63	0.04	3.15	2.74	-0.41	2.79	2.38	-0.41	2.96	2.26	-0.70
23	Columbus	2.50	2.12	-0.38	3.87	2.56	-1.31	2.32	2.75	0.43	5.38	3.64	-1.74
24	Craven	2.41	2.56	0.15	2.22	2.94	0.72	2.50	1.74	-0.76	5.38	3.64	-1.74
25	Cumberland	2.50	2.46	-0.04	2.50	2.57	0.07	3.50	3.28	-0.22	5.00	2.34	-2.66
26	Currituck	2.50	2.67	0.17	2.5%	2.6%	0.18	3.15	3.59	0.44	5.38	3.64	-1.74
27	Dare	3.50	6.34	2.84	3.50	2.18	-1.32	4.00	2.28	-1.72	5.38	3.64	-1.74
28	Davidson	2.45	2.23	-0.22	2.99	2.87	-0.12	3.50	1.61	-1.89	5.84	2.43	-3.41
29	Davie	3.37	2.61	-0.76	3.25	2.88	-0.37	3.50	2.81	-0.69	4.50	3.42	-1.08
30	Duplin	2.55	2.63	0.08	2.55	2.59	0.04	3.50	0.34	-3.16	4.50	1.83	-2.67
31	Durham	3.39	3.08	-0.31	3.25	4.40	1.15	3.50	2.84	-0.66	5.00	5.56	0.56
32	Edgecombe	2.50	1.72	-0.78	2.50	0.79	-1.71	3.50	2.38	-1.12	5.38	3.64	-1.74
33	Forsyth	2.50	1.87	-0.63	2.55	2.39	-0.16	3.50	1.83	-1.67	3.60	4.52	0.92
34	Franklin	3.43	3.55	0.12	2.82	3.31	0.49	3.50	2.38	-1.12	5.38	3.64	-1.74
35	Gaston	2.50	3.83	1.33	2.50	3.43	0.93	3.50	2.02	-1.48	5.07	6.60	1.53
36	Gates	2.50	0.95	-1.55	2.69	2.68	-0.01	3.55	2.33	-1.22	5.38	3.64	-1.74
37	Graham	2.50	3.01	0.51	2.50	3.68	1.18	3.02	2.40	-0.62	5.38	3.64	-1.74
38	Granville	3.00	3.29	0.29	3.45	4.05	0.60	3.75	4.36	0.61	5.00	2.96	-2.04
39	Greene	2.50	2.76	0.26	3.50	2.37	-1.13	3.50	2.91	-0.59	5.38	3.64	-1.74
40	Guilford	2.50	2.57	0.07	3.55	3.02	-0.53	3.50	2.31	-1.19	5.00	3.15	-1.85
41	Halifax	3.50	1.85	-1.65	3.00	0.96	-2.04	3.50	1.17	-2.33	4.04	2.96	-1.08
42	Harnett	2.50	3.89	1.39	3.50	3.79	0.29	3.00	1.92	-1.08	5.03	2.89	-2.14
43	Haywood	4.63	3.50	-1.13	3.00	2.33	-0.67	3.61	2.76	-0.85	5.62	2.76	-2.86
44	Henderson	3.20	4.28	1.08	3.11	3.87	0.76	4.01	1.67	-2.34	5.01	3.31	-1.70
45	Hertford	2.50	1.44	-1.06	3.38	2.79	-0.59	3.75	2.25	-1.50	5.38	3.64	-1.74
46	Hoke	3.52	2.48	-1.04	2.50	4.11	1.61	3.50	2.90	-0.60	5.38	3.64	-1.74
47	Hyde	2.47	1.34	-1.13	2.50	4.21	1.71	3.50	0.18	-3.32	5.38	3.64	-1.74
48	Iredell	3.67	3.24	-0.43	3.50	3.70	0.20	3.33	3.58	0.25	4.50	3.37	-1.13
49	Jackson	2.81	2.54	-0.27	3.00	4.20	1.20	3.50	3.42	-0.08	5.38	3.64	-1.74
50	Johnston	6.68	2.78	-3.90	3.21	3.90	0.69	3.50	1.60	-1.90	4.24	4.46	0.22

Table C.2 (continued): Change in ADT growth rates

		Local			Collector			Arterial			Interstate		
County No.	County Name	2001 (%)	2014 (%)	Diff. (%)	2001 (%)	2014 (%)	Diff. (%)	2001 (%)	2014 (%)	Diff. (%)	2001 (%)	2014 (%)	Diff. (%)
51	Jones	2.50	2.31	-0.19	2.50	2.08	-0.42	3.00	2.07	-0.93	5.38	3.64	-1.74
52	Lee	2.50	3.28	0.78	3.50	3.22	-0.28	3.50	3.86	0.36	5.38	3.64	-1.74
53	Lenoir	3.06	1.90	-1.16	3.38	1.66	-1.72	4.11	1.51	-2.60	5.38	3.64	-1.74
54	Lincoln	2.60	3.36	0.76	3.34	3.26	-0.08	3.50	2.03	-1.47	5.38	3.64	-1.74
55	McDowell	2.54	2.33	-0.21	2.54	1.76	-0.78	3.00	4.31	1.31	5.17	3.28	-1.89
56	Macon	2.58	2.67	0.09	3.00	4.40	1.40	3.00	6.07	3.07	5.38	3.64	-1.74
57	Madison	2.50	2.85	0.35	3.20	2.95	-0.25	2.59	4.55	1.96	5.38	3.26	-2.12
58	Martin	2.50	1.75	-0.75	3.50	2.90	-0.60	3.55	1.51	-2.04	5.38	3.64	-1.74
59	Mecklenburg	2.67	1.49	-1.18	4.74	4.49	-0.25	2.90	2.75	-0.15	4.93	4.87	-0.06
60	Mitchell	1.05	2.36	1.31	1.18	2.12	0.94	2.97	2.63	-0.34	5.38	3.64	-1.74
61	Montgomery	2.02	1.70	-0.32	3.77	3.22	-0.55	5.84	3.39	-2.45	6.25	4.36	-1.89
62	Moore	5.01	3.06	-1.95	4.78	4.37	-0.41	3.43	2.68	-0.75	5.38	3.64	-1.74
63	Nash	3.00	2.70	-0.30	3.00	3.15	0.15	3.09	2.57	-0.52	4.50	2.96	-1.54
64	New Hanover	4.84	3.12	-1.72	3.06	3.66	0.60	3.50	2.64	-0.86	6.50	3.79	-2.71
65	Northampton	2.17	0.89	-1.28	2.05	2.02	-0.03	3.50	0.47	-3.03	5.25	2.69	-2.56
66	Onslow	3.06	3.61	0.55	3.25	2.74	-0.51	3.50	1.92	-1.58	5.38	3.64	-1.74
67	Orange	2.42	3.82	1.40	3.20	3.67	0.47	3.50	2.12	-1.38	4.56	2.57	-1.99
68	Pamlico	3.50	1.77	-1.73	4.16	3.17	-0.99	3.50	2.40	-1.10	5.38	3.64	-1.74
69	Pasquotank	2.50	2.81	0.31	2.50	2.44	-0.06	4.93	1.35	-3.58	5.38	3.64	-1.74
70	Pender	3.00	2.61	-0.39	3.50	3.75	0.25	3.50	2.40	-1.10	6.50	4.63	-1.87
71	Perquimans	2.50	2.14	-0.36	2.50	1.61	-0.89	3.50	2.16	-1.34	5.38	3.64	-1.74
72	Person	2.50	3.16	0.66	2.75	2.90	0.15	3.50	2.77	-0.73	5.38	3.64	-1.74
73	Pitt	2.55	1.78	-0.77	2.55	3.09	0.54	3.04	2.77	-0.27	5.38	3.64	-1.74
74	Polk	2.50	3.07	0.57	3.28	2.15	-1.13	3.50	4.64	1.14	4.42	2.71	-1.71
75	Randolph	3.50	3.20	-0.30	2.71	2.45	-0.26	3.67	2.84	-0.83	5.47	4.01	-1.46
76	Richmond	2.63	1.70	-0.93	3.20	1.92	-1.28	3.50	2.95	-0.55	6.25	3.64	-2.61
77	Robeson	3.06	2.74	-0.32	3.08	3.22	0.14	3.49	2.56	-0.93	4.50	2.26	-2.24
78	Rockingham	3.88	2.40	-1.48	2.85	1.75	-1.10	3.20	0.77	-2.43	6.25	3.64	-2.61
79	Rowan	3.00	3.24	0.24	3.50	2.98	-0.52	4.63	2.06	-2.57	6.91	4.20	-2.71
80	Rutherford	4.09	2.49	-1.60	3.25	2.00	-1.25	3.50	2.55	-0.95	5.38	3.64	-1.74
81	Sampson	2.50	2.89	0.39	2.50	2.77	0.27	3.50	2.27	-1.23	6.25	3.64	-2.61
82	Scotland	2.50	2.36	-0.14	3.50	2.58	-0.92	3.50	1.93	-1.57	5.38	3.64	-1.74
83	Stanly	2.50	2.05	-0.45	3.64	2.57	-1.07	3.08	2.19	-0.89	5.38	3.64	-1.74
84	Stokes	2.50	3.23	0.73	3.55	2.30	-1.25	3.55	3.03	-0.52	5.38	3.64	-1.74
85	Surry	2.60	3.05	0.45	2.60	2.78	0.18	3.50	2.61	-0.89	6.25	3.81	-2.44
86	Swain	2.50	2.20	-0.30	3.50	4.43	0.93	3.55	3.37	-0.18	5.38	3.64	-1.74
87	Transylvania	2.50	3.74	1.24	2.50	2.63	0.13	3.50	2.45	-1.05	5.38	3.64	-1.74
88	Tyrrell	0.84	0.38	-0.46	2.50	1.10	-1.40	2.50	2.92	0.42	5.38	3.64	-1.74
89	Union	3.00	3.86	0.86	3.00	4.90	1.90	3.50	2.84	-0.66	5.38	3.64	-1.74
90	Vance	3.25	2.27	-0.98	3.25	3.28	0.03	3.50	1.18	-2.32	5.82	4.60	-1.22
91	Wake	3.00	4.11	1.11	5.00	4.79	-0.21	4.00	2.59	-1.41	6.50	5.84	-0.66
92	Warren	2.50	2.54	0.04	3.15	2.56	-0.59	3.50	2.40	-1.10	7.51	2.83	-4.68
93	Washington	2.50	1.73	-0.77	2.50	1.54	-0.96	3.00	0.33	-2.67	5.38	3.64	-1.74
94	Watauga	2.50	2.85	0.35	3.00	4.97	1.97	3.50	2.63	-0.87	5.38	3.64	-1.74
95	Wayne	2.82	1.57	-1.25	3.00	2.98	-0.02	3.50	0.90	-2.60	5.38	3.64	-1.74
96	Wilkes	2.50	2.57	0.07	3.20	2.06	-1.14	3.50	2.06	-1.44	5.38	3.64	-1.74
97	Wilson	3.39	1.74	-1.65	2.81	2.19	-0.62	2.92	0.27	-2.65	4.50	2.93	-1.57
98	Yadkin	2.50	3.13	0.63	3.25	3.23	-0.02	3.50	2.66	-0.84	6.25	3.39	-2.86
99	Yancey	2.50	2.86	0.36	2.65	2.38	-0.27	4.35	3.63	-0.72	5.38	3.64	-1.74

Table C.3: Truck weight distribution cumulative percent

	SR		**NC**		**US**		**Interstate**	
Weight (tons)	**SU**	**TTST**	**SU**	**TTST**	**SU**	**TTST**	**SU**	**TTST**
> 3	100%	100%	100%	100%	100%	100%	100%	100%
> 4	70.78%	100%	82.93%	100%	86.87%	100%	86.36%	100%
> 5	53.74%	100%	64.09%	100%	72.34%	100%	63.39%	100%
> 6	44.05%	100%	52.31%	100%	62.82%	100%	51.07%	100%
> 7	38.03%	100%	44.08%	100%	53.28%	100%	44.12%	100%
> 8	31.37%	100%	36.88%	100%	43.59%	100%	38.17%	100%
> 9	26.28%	100%	30.34%	100%	35.15%	100%	31.98%	100%
> 10	20.80%	100%	23.99%	100%	27.59%	100%	24.73%	100%
> 11	16.20%	100%	19.48%	100%	21.62%	100%	18.10%	100%
> 12	11.66%	100%	15.75%	100%	17.19%	100%	12.29%	100%
> 13	6.81%	100%	12.62%	100%	13.45%	100%	7.67%	100%
> 14	6.39%	94.39%	10.70%	94.67%	11.36%	92.10%	6.98%	98.84%
> 15	5.75%	88.27%	8.96%	88.17%	9.80%	83.32%	6.19%	97.22%
> 16	5.21%	80.10%	7.31%	81.78%	8.28%	75.52%	5.21%	95.02%
> 17	4.69%	71.68%	6.22%	75.56%	7.29%	68.84%	4.50%	92.30%
> 18	4.15%	63.52%	5.56%	70.30%	6.22%	63.00%	3.97%	89.38%
> 19	3.78%	56.38%	4.85%	65.34%	5.14%	57.89%	3.51%	86.59%
> 20	3.33%	48.72%	4.39%	60.71%	4.47%	53.18%	3.03%	83.65%
> 21	2.82%	44.13%	3.93%	56.61%	3.73%	49.39%	2.56%	80.81%
> 22	2.51%	37.50%	3.58%	53.30%	3.20%	46.30%	2.15%	77.99%
> 23	2.36%	32.14%	3.21%	50.07%	2.72%	43.03%	1.84%	75.28%
> 24	2.09%	29.34%	2.85%	46.84%	2.29%	39.91%	1.60%	72.57%
> 25	1.82%	27.55%	2.49%	44.08%	1.87%	37.09%	1.35%	69.82%
> 26	1.57%	26.02%	2.13%	41.97%	1.37%	34.07%	1.08%	67.11%
> 27	1.36%	23.21%	1.78%	40.01%	1.12%	31.32%	0.93%	64.43%
> 28	1.09%	20.92%	1.40%	37.62%	0.89%	28.56%	0.79%	61.60%
> 29	0.97%	19.64%	1.19%	35.35%	0.67%	25.72%	0.59%	58.78%
> 30	0.79%	17.60%	0.98%	33.09%	0.51%	23.00%	0.47%	56.03%
> 31	0.65%	15.82%	0.81%	30.05%	0.39%	20.67%	0.36%	53.20%
> 32	0.42%	13.52%	0.66%	27.63%	0.28%	18.24%	0.30%	50.24%
> 33	0.30%	13.27%	0.47%	24.94%	0.23%	16.00%	0.20%	47.17%
> 34	0.27%	11.48%	0.30%	22.35%	0.20%	13.81%	0.17%	44.02%
> 35	0.15%	9.44%	0.19%	19.92%	0.12%	11.77%	0.14%	40.57%
> 36	0.15%	8.67%	0.09%	17.29%	0.07%	10.07%	0.09%	36.88%
> 37	0.09%	6.38%	0.07%	14.93%	0.05%	8.66%	0.05%	32.55%
> 38	0.03%	5.36%	0.04%	12.29%	0.02%	7.37%	0.04%	27.65%
> 39	0%	3.57%	0.01%	9.89%	0.01%	5.97%	0.02%	22.30%
> 40	0%	3.06%	0%	7.48%	0%	4.59%	0%	16.65%
> 41	0%	2.30%	0%	5.37%	0%	3.49%	0%	11.95%
> 42	0%	1.02%	0%	3.45%	0%	2.54%	0%	8.15%
> 43	0%	0.26%	0%	1.96%	0%	1.62%	0%	4.98%
> 44	0%	0%	0%	0.81%	0%	0.78%	0%	2.36%
> 45	0%	0%	0%	0%	0%	0%	0%	0%

Table C.4: Sampled distribution of truck heights from Sobanjo and Thompson (2004)

Height (ft.)	**Percent Detoured**
< = 10	100%
10.1-11.9	93.7%
12-12.9	79.25%
13-13.9	36.2%
14-15.9	0.245%
> 16	0%

Table C.5: Snapshot of deck geometry appraisal forecast

Structure No.	Deck Geometry Appraisal 0	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	4	4	4	4	4	4	4	4	4	4	4
400002	5	5	5	5	5	5	5	5	5	5	5
400003	9	9	9	9	9	9	9	9	9	9	9
400004	6	6	6	6	6	6	6	6	6	6	6
400005	6	6	6	6	6	6	6	6	6	6	6
400006	6	6	6	6	6	6	6	6	6	6	6
400007	6	6	6	6	6	6	6	6	6	6	6
400009	5	5	5	5	5	5	5	5	5	5	5
400010	2	2	2	2	2	2	2	2	2	2	2
400011	4	4	4	4	4	4	4	4	4	4	4
400012	6	6	6	6	6	6	6	6	6	6	6
400013	9	9	9	9	9	9	9	9	9	9	9
400015	9	9	9	9	9	9	9	9	9	9	9
400016	4	4	4	4	4	4	4	4	4	4	4
400017	2	2	2	2	2	2	2	2	2	2	2
400018	2	2	2	2	2	2	2	2	2	2	2
400019	2	2	2	2	2	2	2	2	2	2	2
400020	9	9	9	9	9	9	9	9	9	9	9
400021	7	7	7	7	7	7	7	7	7	7	7
400022	2	2	2	2	2	2	2	2	2	2	2
400023	6	6	6	6	6	6	6	6	6	6	6
400024	4	4	4	4	4	4	4	4	4	4	4
400025	4	4	4	4	4	4	4	4	4	4	4
400027	5	5	5	5	5	5	5	5	5	5	5
400028	5	5	5	5	5	5	5	5	5	5	5
400030	2	2	2	2	2	2	2	2	2	2	2
400031	5	5	5	5	5	5	5	5	5	5	5
400032	4	4	4	4	4	3	3	3	3	3	3
400033	6	6	6	6	6	6	6	6	6	6	6

Table C.6: Expected deck condition rating durations for concrete decks

Concrete Deck (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Concrete 0-200	3.7451	9.5058	7.9186	9.5769	6.6521	8.5954
Concrete 200-800	3.7467	9.4109	8.3469	10.8644	7.3464	7.7575
Concrete 800-2000	3.8162	8.7405	8.4399	11.0959	7.3481	8.0029
Concrete 2000-4000	3.1431	8.1471	8.5608	10.7817	7.6112	6.8569
Concrete >4000	3.725	6.7675	7.9295	10.4082	6.6865	8.11
Concrete Average	3.63522	8.51436	8.23914	10.54542	7.12886	7.86454
Slope	0.27509	0.117449	0.12137	0.094828	0.14027	0.12715

Table C.7: Expected deck condition rating durations for steel decks

Steel Deck (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Steel 0-200	4.7125	13.9435	8.0621	8.0815	3.5468	5.8889
Steel 200-800	3.4	12.8483	7.9489	8.0594	4.02	3.5222
Steel 800-2000	4.4167	12.0412	7.6999	7.9808	4.9801	4.5533
Steel 2000-4000	3.5347	11.5146	6.8626	8.1006	5.0948	4.3061
Steel >4000	2.9	6.8583	6.7492	8.4368	7.0507	4.2552
Steel Average	3.79278	11.44118	7.46454	8.13182	4.93848	4.50514
Slope	0.26366	0.087404	0.13397	0.122974	0.20249	0.22197

Table C.8: Expected superstructure condition ratings for timber superstructures

Timber Superstructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Timber State System 1, Mulit-Beam	3	5.2143	6.3492	8.3945	8.3754	3.6382
Timber State System 2, Multi-Beam	2.8718	7.3554	7.5268	7.9011	6.0105	4.1333
Timber Average	2.9359	6.28485	6.938	8.1478	7.19295	3.88575
Slope	0.34061	0.15911	0.14413	0.12273	0.13903	0.25735

Table C.9: Expected superstructure condition ratings for concrete superstructures

Concrete Superstructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Concrete State System 1, Slab	2	6.3377	9.0555	11.9508	6.5447	6.7905
Concrete State System 2, Slab	4.2	7.6139	9.7329	11.0284	7.2725	9.7722
Concrete State System 1, Tee-Beam	n/a	6.3637	9.8673	11.6001	7.0814	7.7721
Concrete State System 2, Tee-Beam	2	6.9713	11.4245	11.6894	7.3262	9.8259
Concrete Average	2.73333	6.82165	10.0201	11.5672	7.0562	8.54018
Slope	0.36585	0.14659	0.0998	0.08645	0.14172	0.11709

Table C.10: Expected superstructure condition ratings for steel superstructures

Steel Superstructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Steel State System 1, Multi-Beam	4.4206	11.4589	7.4071	7.8273	5.0145	5.2466
Steel State System 2, Multi-Beam	3.2702	10.0682	10.3105	7.97	4.4272	4.2707
Steel State System 2, Truss	5.2083	5.6058	6.668	7.3878	6.5156	5.9543
Steel State System 1, Floor-Beam	n/a	6.1688	6.4777	6.6292	6.5335	4.767
Steel State System 2, Floor-Beam	3.1429	6.9651	7.6751	6.7853	4.8972	4.4541
Steel Average	4.0105	8.05336	7.70768	7.31992	5.4776	4.93854
Slope	0.24935	0.12417	0.12974	0.13661	0.18256	0.20249

Table C.11: Expected superstructure condition ratings for prestressed superstructures

Prestressed Superstructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Prestressed State System 1, Multi-Beam	4.582	10.888	5.5108	7.8039	4.3542	5.0316
Prestressed State System 2, Multi-Beam	4.2044	13.3114	5.3833	5.7458	2.5653	3.5833
Prestressed State System 1, Slab	3.8018	9.218	5.9944	9.049	3.232	5.875
Prestressed State System 2, Slab	3.8508	9.8914	6.2964	7.998	2.886	3.5833
Prestressed State System 2, Tee-Beam	2.6481	8.8033	9.5877	9.0104	5.6423	5.4577
Prestressed Average	3.81742	10.4224	6.55452	7.92142	3.73596	4.70618
Slope	0.26196	0.09595	0.15257	0.12624	0.26767	0.21249

Table C.12: Expected substructure condition ratings for timber substructures

Timber Substructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Timber Coastal	3.5714	3.7829	4.8219	7.1158	7.55	5.1827
Timber Piedmont	3.8571	3.716	4.7011	7.2793	7.1357	5.4644
Timber Mountain	2.4828	4.5874	6.996	9.3507	5.1218	3.6215
Timber Average	3.3038	4.02877	5.50633	7.91527	6.6025	4.7562
Slope	0.3027	0.24821	0.18161	0.12634	0.15146	0.2103

Table C.13: Expected substructure condition ratings for concrete substructures

Concrete Substructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Concrete Coastal	7.6667	6.3412	7.5895	11.1303	7.2854	8.5743
Concrete Piedmont	4.25	5.3788	8.8016	11.1221	7.9547	8.82
Concrete Mountain	5.3	6.2894	11.8728	11.3939	6.0848	5.1627
Concrete Average	5.7389	6.00313	9.4213	11.2154	7.1083	7.519
Slope	0.1742	0.16658	0.10614	0.08916	0.14068	0.133

Table C.14: Expected substructure condition ratings for steel substructures

Steel Substructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Steel Coastal	3.3794	7.0468	6.6435	8.7156	7.1533	5.9018
Steel Piedmont	4.3031	8.6568	7.6843	8.8638	6.6995	5.9895
Steel Mountain	3.6946	8.1939	9.1922	9.7371	5.2814	4.2883
Steel Average	3.7924	7.96583	7.84	9.1055	6.37807	5.3932
Slope	0.2637	0.12554	0.12755	0.10982	0.15679	0.1854

Table C.15: Expected substructure condition ratings for prestressed substructures

Prestressed Substructure (Years in Rating)						
	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
Prestressed Coastal	3.6537	7.4576	5.5805	8.5565	6.1615	5.815
Prestressed Piedmont	4.1304	9.0317	6.205	9.6623	5.6743	4.903
Prestressed Mountain	3.621	9.9501	7.434	9.6117	5.0374	3.8633
Prestressed Average	3.8017	8.81313	6.4065	9.27683	5.6244	4.8604
Slope	0.263	0.11347	0.15609	0.1078	0.1778	0.2057

Table C.16: Snapshot of spreadsheet showing prediction of deck deterioration

Structure No.	Deck Structure Type	Deck Condition	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	1	7.69	7.571528109	7.45016	7.32878	7.20741	7.08604	6.96467	6.86984	6.77501	6.68018	6.58536
400002	1	6.11	6.012272103	5.91744	5.77717	5.63689	5.49662	5.35634	5.21607	5.07579	4.93552	4.80837
400003	1	4.35	4.225246982	4.09809	3.97094	3.84379	3.71663	3.58948	3.46233	3.33518	3.20802	3.08087
400004	1	5.01	4.869725117	4.74257	4.61542	4.48827	4.36111	4.23396	4.10681	3.97965	3.8525	3.72535
400005	1	5.01	4.869725117	4.74257	4.61542	4.48827	4.36111	4.23396	4.10681	3.97965	3.8525	3.72535
400006	1	5.01	4.869725117	4.74257	4.61542	4.48827	4.36111	4.23396	4.10681	3.97965	3.8525	3.72535
400007	1	5.01	4.869725117	4.74257	4.61542	4.48827	4.36111	4.23396	4.10681	3.97965	3.8525	3.72535
400009	2	7.31	7.189428109	7.06806	6.94668	6.85186	6.75703	6.6622	6.56737	6.47254	6.37772	6.28289
400010	1	5.49	5.345225117	5.20495	5.06468	4.9244	4.79725	4.67009	4.54294	4.41579	4.28864	4.16148
400011	1	7.45	7.332528109	7.21116	7.08978	6.96841	6.87358	6.77876	6.68393	6.5891	6.49427	6.39945
400012	1	4.01	3.882846982	3.75569	3.62854	3.50139	3.37423	3.24708	3.11993	2.99278	3	3
400013	1	5.49	5.347925117	5.20765	5.06738	4.9271	4.79995	4.67279	4.54564	4.41849	4.29134	4.16418
400015	1	5.01	4.869725117	4.74257	4.61542	4.48827	4.36111	4.23396	4.10681	3.97965	3.8525	3.72535
400016	2	5.62	5.482025117	5.34175	5.20148	5.0612	4.92093	4.79377	4.66662	4.53947	4.41231	4.28516
400017	1	5.63	5.490425117	5.35015	5.20988	5.0696	4.92933	4.80217	4.67502	4.54787	4.42071	4.29356
400018	2	5.69	5.549325117	5.40905	5.26878	5.1285	4.98823	4.86107	4.73392	4.60677	4.47961	4.35246
400019	2	7.01	6.888628109	6.7938	6.69897	6.60414	6.50932	6.41449	6.31966	6.22483	6.13	6.03518
400020	1	7.60	7.482028109	7.36066	7.23928	7.11791	6.99654	6.90171	6.80688	6.71206	6.61723	6.5224
400021	1	7.68	7.557328109	7.43596	7.31458	7.19321	7.07184	6.95047	6.85564	6.76081	6.66598	6.57116
400022	1	5.63	5.488625117	5.34835	5.20808	5.0678	4.92753	4.80037	4.67322	4.54607	4.41891	4.29176
400023	2	7.65	7.531328109	7.40996	7.28858	7.16721	7.04584	6.92447	6.82964	6.73481	6.63998	6.54516
400024	1	7.57	7.443828109	7.32246	7.20108	7.07971	6.95834	6.86351	6.76868	6.67386	6.57903	6.4842
400025	6	7.71	7.571733272	7.43777	7.3038	7.16983	7.03587	6.9019	6.77893	6.65595	6.53298	6.41
400027	1	5.27	5.124925117	4.98465	4.8575	4.73034	4.60319	4.47604	4.34889	4.22173	4.09458	3.96743
400028	1	5.56	5.417825117	5.27755	5.13728	4.997	4.86985	4.74269	4.61554	4.48839	4.36124	4.23408
400030	1	5.49	5.350325117	5.21005	5.06978	4.9295	4.80235	4.67519	4.54804	4.42089	4.29374	4.16658
400031	1	7.68	7.559628109	7.43826	7.31688	7.19551	7.07414	6.95277	6.85794	6.76311	6.66828	6.57346
400032	8	7.01	6.877357469	6.72128	6.56521	6.40913	6.25305	6.09698	5.9409	5.73962	5.53835	5.33707
400033	2	7.58	7.461428109	7.34006	7.21868	7.09731	6.97594	6.88111	6.78628	6.69146	6.59663	6.5018

Table C.17: Snapshot of spreadsheet showing prediction of substructure deterioration

Structure No.	Structure Type Main	Substructure Condition	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	302	5.2612	5.1044	4.9476	4.7622	4.5768	4.3914	4.2060	4.0205	3.8351	3.6497	3.4643
400002	302	6.0304	5.9206	5.7638	5.6070	5.4502	5.2934	5.1366	4.9799	4.7944	4.6090	4.4236
400003	302	6.5709	6.4611	6.3513	6.2414	6.1316	6.0218	5.9120	5.7552	5.5984	5.4416	5.2848
400004	302	7.01	6.8824	6.7726	6.6628	6.5530	6.4432	6.3333	6.2235	6.1137	6.0039	5.8940
400005	302	7.01	6.8824	6.7726	6.6628	6.5530	6.4432	6.3333	6.2235	6.1137	6.0039	5.8940
400006	302	7.01	6.8824	6.7726	6.6628	6.5530	6.4432	6.3333	6.2235	6.1137	6.0039	5.8940
400007	302	7.01	6.8824	6.7726	6.6628	6.5530	6.4432	6.3333	6.2235	6.1137	6.0039	5.8940
400009	501	7.3957	7.2396	7.0835	6.9274	6.8196	6.7118	6.6040	6.4962	6.3884	6.2807	6.1729
400010	522	5	4.7943	4.5885	4.3828	4.1770	3.9713	3.7655	3.5598	3.3541	3.1483	2.9426
400011	302	7	6.8902	6.7804	6.6705	6.5607	6.4509	6.3411	6.2312	6.1214	6.0116	5.9018
400012	402	4.4586	4.2732	4.0878	3.9023	3.7169	3.5315	3.3461	3.1607	2.9753	3.0000	3.0000
400013	402	5.4709	5.3141	5.1573	5.0005	4.8438	4.6583	4.4729	4.2875	4.1021	3.9167	3.7312
400015	402	5.6235	5.4667	5.3099	5.1531	4.9964	4.8109	4.6255	4.4401	4.2547	4.0693	3.8838
400016	501	7.3957	7.2396	7.0835	6.9274	6.8196	6.7118	6.6040	6.4962	6.3884	6.2807	6.1729
400017	502	5.6183	5.4405	5.2627	5.0849	4.9071	4.7014	4.4956	4.2899	4.0841	3.8784	3.6727
400018	502	5.5527	5.3749	5.1971	5.0193	4.8415	4.6358	4.4300	4.2243	4.0185	3.8128	3.6071
400019	501	7.5714	7.4153	7.2592	7.1031	6.9470	6.8392	6.7314	6.6236	6.5159	6.4081	6.3003
400020	602	7.6034	7.4473	7.2912	7.1351	6.9790	6.8712	6.7634	6.6556	6.5479	6.4401	6.3323
400021	302	7	6.8902	6.7804	6.6705	6.5607	6.4509	6.3411	6.2312	6.1214	6.0116	5.9018
400022	302	5.01	4.8532	4.6678	4.4824	4.2970	4.1115	3.9261	3.7407	3.5553	3.3699	3.1844
400023	501	7.6431	7.4870	7.3309	7.1748	7.0187	6.8626	6.7548	6.6471	6.5393	6.4315	6.3237
400024	602	7.5652	7.4091	7.2530	7.0969	6.9408	6.8330	6.7252	6.6174	6.5097	6.4019	6.2941
400025	302	4.6017	4.4163	4.2309	4.0454	3.8600	3.6746	3.4892	3.3038	3.1184	2.9329	3.0000
400027	522	7.01	6.8539	6.7461	6.6383	6.5305	6.4227	6.3149	6.2071	6.0993	5.9915	5.8137
400028	104	5.5432	5.4025	5.2618	5.1212	4.9805	4.8475	4.7145	4.5815	4.4485	4.3155	4.1825
400030	302	5	4.8146	4.6292	4.4437	4.2583	4.0729	3.8875	3.7021	3.5167	3.3312	3.1458
400031	502	5.6117	5.4339	5.2561	5.0783	4.9005	4.6948	4.4890	4.2833	4.0775	3.8718	3.6661
400032	302	5	4.8146	4.6292	4.4437	4.2583	4.0729	3.8875	3.7021	3.5167	3.3312	3.1458
400033	501	7.5637	7.4076	7.2515	7.0954	6.9393	6.8315	6.7237	6.6159	6.5082	6.4004	6.2926

Table C.18: Snapshot of spreadsheet showing prediction of superstructure deterioration

Structure No.	SuperStructure Type - Material (det)	Superstructure Condition	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	3 - Steel	5.6760	5.4934	5.3109	5.1283	4.9458	4.7433	4.5408	4.3383	4.1358	3.9333	3.7308
400002	3 - Steel	7.0952	6.9655	6.8288	6.6922	6.5556	6.4190	6.2824	6.1458	6.0092	5.8726	5.6900
400003	3 - Steel	5.0100	4.8274	4.6249	4.4225	4.2200	4.0175	3.8150	3.6125	3.4100	3.2075	3.0050
400004	3 - Steel	7.2491	7.1194	6.9896	6.8530	6.7164	6.5798	6.4432	6.3066	6.1699	6.0333	5.8967
400005	3 - Steel	7.2491	7.1194	6.9896	6.8530	6.7164	6.5798	6.4432	6.3066	6.1699	6.0333	5.8967
400006	3 - Steel	7.2491	7.1194	6.9896	6.8530	6.7164	6.5798	6.4432	6.3066	6.1699	6.0333	5.8967
400007	3 - Steel	7.2491	7.1194	6.9896	6.8530	6.7164	6.5798	6.4432	6.3066	6.1699	6.0333	5.8967
400009	5 - Prestressed Concrete	6.0000	5.7323	5.4647	5.1970	4.9293	4.7168	4.5044	4.2919	4.0794	3.8669	3.6544
400010	5 - Prestressed Concrete	5.0000	4.7875	4.5750	4.3625	4.1501	3.9376	3.7251	3.5126	3.3001	3.0876	2.8751
400011	3 - Steel	7.5336	7.4039	7.2741	7.1444	7.0146	6.8849	6.7483	6.6117	6.4751	6.3384	6.2018
400012	4 - Steel Continuous	4.4586	4.2561	4.0536	3.8511	3.6486	3.4462	3.2437	3.0412	2.8387	3.0000	3.0000
400013	4 - Steel Continuous	5.2899	5.1073	4.9248	4.7223	4.5198	4.3173	4.1148	3.9123	3.7098	3.5074	3.3049
400015	4 - Steel Continuous	7.3325	7.2028	7.0730	6.9433	6.8067	6.6701	6.5334	6.3968	6.2602	6.1236	5.9870
400016	5 - Prestressed Concrete	5.0000	4.7875	4.5750	4.3625	4.1501	3.9376	3.7251	3.5126	3.3001	3.0876	2.8751
400017	5 - Prestressed Concrete	5.5588	5.2911	5.0235	4.7558	4.5433	4.3308	4.1183	3.9058	3.6934	3.4809	3.2684
400018	5 - Prestressed Concrete	5.6295	5.3618	5.0942	4.8265	4.6140	4.4015	4.1890	3.9765	3.7641	3.5516	3.3391
400019	5 - Prestressed Concrete	7.0000	6.8738	6.7475	6.6213	6.4950	6.3688	6.2426	6.1163	5.9901	5.7224	5.4547
400020	6 - Prestressed Concrete Continuous	7.6240	7.4714	7.3189	7.1663	7.0137	6.8612	6.7349	6.6087	6.4824	6.3562	6.2300
400021	3 - Steel	7.6499	7.5202	7.3904	7.2607	7.1309	7.0012	6.8715	6.7348	6.5982	6.4616	6.3250
400022	3 - Steel	7.0100	6.8803	6.7436	6.6070	6.4704	6.3338	6.1972	6.0606	5.9240	5.7414	5.5588
400023	5 - Prestressed Concrete	7.0000	6.8738	6.7475	6.6213	6.4950	6.3688	6.2426	6.1163	5.9901	5.7224	5.4547
400024	6 - Prestressed Concrete Continuous	7.5260	7.3734	7.2209	7.0683	6.9157	6.7895	6.6633	6.5370	6.4108	6.2845	6.1583
400025	3 - Steel	5.5205	5.3379	5.1554	4.9728	4.7703	4.5678	4.3653	4.1629	3.9604	3.7579	3.5554
400027	5 - Prestressed Concrete	5.0000	4.7875	4.5750	4.3625	4.1501	3.9376	3.7251	3.5126	3.3001	3.0876	2.8751
400028	1 - Concrete	5.5188	5.3771	5.2354	5.0936	4.9519	4.8348	4.7177	4.6006	4.4835	4.3665	4.2494
400030	3 - Steel	5.0100	4.8274	4.6249	4.4225	4.2200	4.0175	3.8150	3.6125	3.4100	3.2075	3.0050
400031	5 - Prestressed Concrete	7.6974	7.5448	7.3923	7.2397	7.0871	6.9346	6.8083	6.6821	6.5558	6.4296	6.3034
400032	3 - Steel	5.2988	5.1162	4.9337	4.7312	4.5287	4.3262	4.1237	3.9212	3.7187	3.5163	3.3138
400033	5 - Prestressed Concrete	7.0000	6.8738	6.7475	6.6213	6.4950	6.3688	6.2426	6.1163	5.9901	5.7224	5.4547

Table C.19: Snapshot of TTST load capacity deterioration prediction

	TTST Load Capacity Deterioration										
Structure No.	year 0	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	99	99	99	99	99	99	99	99	99	98	97
400002	99	99	99	99	99	99	99	99	99	99	99
400003	99	99	99	99	99	99	99	99	99	99	99
400004	99	99	99	99	99	99	99	99	99	99	99
400005	99	99	99	99	99	99	99	99	99	99	99
400006	99	99	99	99	99	99	99	99	99	99	99
400007	99	99	99	99	99	99	99	99	99	99	99
400009	99	99	99	99	99	99	99	99	99	99	99
400010	99	99	98	97	96	96	94	92	91	89	88
400011	99	99	99	99	99	99	99	99	99	99	99
400012	99	99	99	99	98	97	96	95	95	94	93
400013	99	99	99	99	99	99	99	99	99	99	98
400015	99	99	99	99	99	99	99	99	99	99	99
400016	99	99	99	99	99	99	99	99	99	99	99
400017	99	99	99	99	99	98	97	96	96	95	93
400018	99	99	99	99	99	98	97	96	96	95	93
400019	99	99	99	99	99	99	99	99	99	99	99
400020	99	99	99	99	99	99	99	99	99	99	99
400021	99	99	99	99	99	99	99	99	99	99	99
400022	99	99	99	99	99	99	99	98	97	96	95
400023	99	99	99	99	99	99	99	99	99	99	99
400024	99	99	99	99	99	99	99	99	99	99	99
400025	99	99	99	99	99	98	97	96	95	95	94
400027	99	99	99	99	99	99	99	99	99	99	99
400028	99	99	99	99	99	99	99	98	98	98	98
400030	19	19	19	19	19	19	19	18	17	16	15
400031	99	99	99	99	99	98	97	96	96	95	93
400032	99	99	99	99	99	99	99	98	97	96	95

Table C.20: Snapshot of SU load capacity deterioration prediction

	SU Load Capacity Deterioration										
Structure No.	year 0	year 1	year 2	year 3	year 4	year 5	year 6	year 7	year 8	year 9	year 10
400001	99	99	99	99	99	99	99	99	99	98	97
400002	99	99	99	99	99	99	99	99	99	99	99
400003	99	99	99	99	99	99	99	99	99	99	99
400004	99	99	99	99	99	99	99	99	99	99	99
400005	99	99	99	99	99	99	99	99	99	99	99
400006	99	99	99	99	99	99	99	99	99	99	99
400007	99	99	99	99	99	99	99	99	99	99	99
400009	99	99	99	99	99	99	99	99	99	99	99
400010	41	41	40	39	38	38	36	34	33	31	30
400011	99	99	99	99	99	99	99	99	99	99	99
400012	99	99	99	99	98	97	96	95	95	94	93
400013	99	99	99	99	99	99	99	99	99	99	98
400015	99	99	99	99	99	99	99	99	99	99	99
400016	99	99	99	99	99	99	99	99	99	99	99
400017	99	99	99	99	99	98	97	96	96	95	93
400018	99	99	99	99	99	98	97	96	96	95	93
400019	99	99	99	99	99	99	99	99	99	99	99
400020	99	99	99	99	99	99	99	99	99	99	99
400021	99	99	99	99	99	99	99	99	99	99	99
400022	99	99	99	99	99	99	99	98	97	96	95
400023	99	99	99	99	99	99	99	99	99	99	99
400024	99	99	99	99	99	99	99	99	99	99	99
400025	40	40	40	40	40	39	38	37	36	36	35
400027	99	99	99	99	99	99	99	99	99	99	99
400028	99	99	99	99	99	99	99	98	98	98	98
400030	15	15	15	15	15	15	15	14	13	12	11
400031	99	99	99	99	99	98	97	96	96	95	93
400032	99	99	99	99	99	99	99	98	97	96	95

APPENDIX D – GRAPHICAL USER INTERFACE USER'S MANUAL

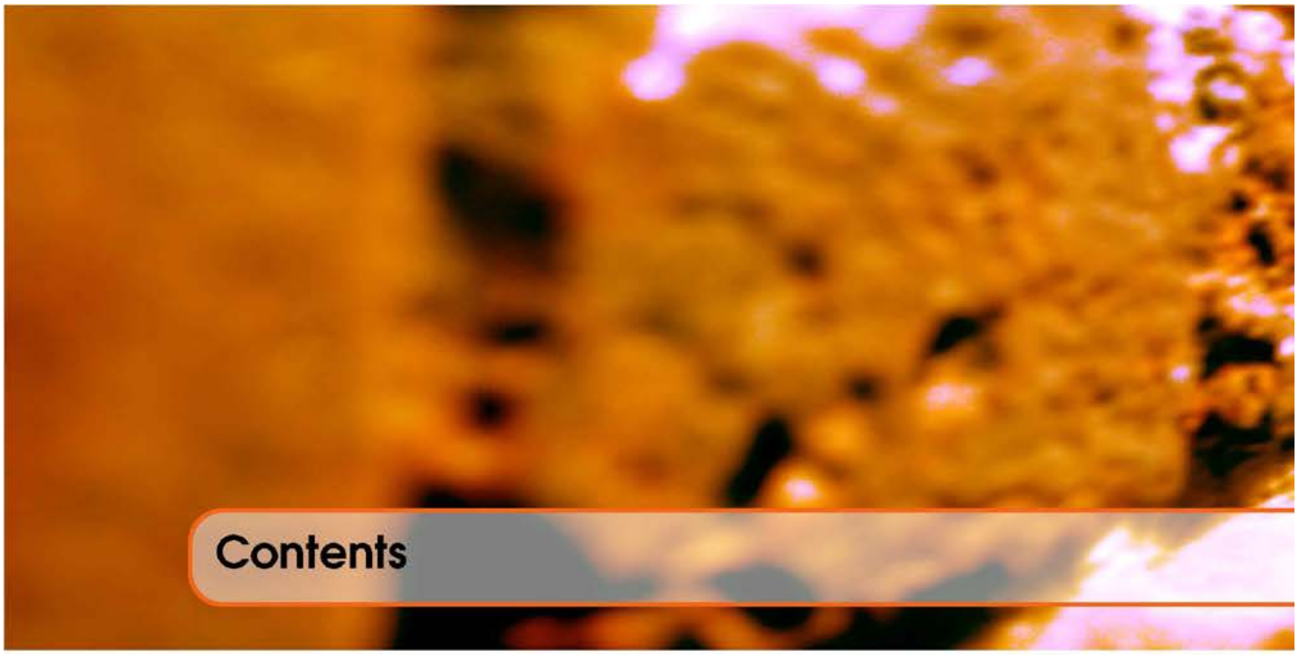
NCDOT Bridge Management System Deterioration Modeling Program (BMS-DMP)

User's Manual

UNIVERSITY OF NORTH CAROLINA AT CHARLOTTE

UNCC.EDU

First printing, August 2015



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II Getting Started

III Data Management

Introduction

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1.1 Software Description

The Bridge Management System Deterioration Modeling Program (BMS-DMP) is a product of NCDOT RP 2014-07 *Determination of Bridge Deterioration Models and Bridge User Costs for NCDOT Bridge Management System.* The purpose of this software is to provide a tool for yearly updates to the bridge deterioration models used in the North Carolina Bridge Management System (BMS), which is currently managed by the AgileAssets system. This software tool operates independently from the AgileAssets system, although it uses data sourced from the database to develop deterioration models to forecast future condition states from historical data.

This software program is a Windows-based stand-alone executable software that was written and compiled in the MATLAB computing environment and operates on a free MATLAB Runtime library that is packaged with the executable file. The software is capable of analyzing data sourced from Excel spreadsheets exported from the AgileAssets database, National Bridge Inventory (NBI) files, or North Carolina Bridge Maintenance Inventory files. Using multiple year databases, the software can:

- Develop deterministic deterioration models for components receiving general condition ratings (GCR)
- Develop deterministic deterioration models for culverts
- Export the deterministic deterioration models in a syntax directly compatible with the AgileAssets piecewise-linear deterioration model
- Develop probabilistic deterioration models for components receiving general condition ratings (GCR). While these probabilistic deterioration models are not directly supported by the AgileAssets system yet, they have been shown to yield more accurate and precise predictions than the currently used deterministic deterioration models that are supported by the AgileAssets database.

The purpose of this user's manual is to provide an overview of the functionality of the software application and a walk-through on how to use key features for annual updating of the NCDOT BMS. While some details on the deterioration modeling methodology is provided in this user manual, it is not meant to provide exhaustive coverage of the methodology and the interested reader is direct to the final project report for RP 2014-07.

1.2 Technical Issues and Software Updates

This software was developed out of academic research as a means of facilitating technology transfer. The software routines incorporated in the graphical user interface have been used and reviewed extensively by the research team over the course of the two year research effort. However, it is likely that the codes are not 100% free of software bugs. Should you encounter any abnormal results, errors, system hangs, or other unintended behavior, please carefully report the conditions that produced the error and report it to the authors of the code using the contact information below. The authors intend to continue to develop and provide technical support to the NCDOT over the next two years, as the software has relevant use in a funded follow-up research project.

1.3 Contact Information

This software was primarily written by Dr. Matthew Whelan and graduate research assistant Raka Goyal of the Department of Civil and Environmental Engineering at the University of North Carolina at Charlotte. Technical support and other questions should be directed to:

Matthew J. Whelan
Department of Civil and Environmental Engineering
University of North Carolina at Charlotte
9201 University City Boulevard
Charlotte, NC 28223-0001
Email: mwhelan3@uncc.edu
Phone: 704-687-1239

Getting Started

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2. Getting Started

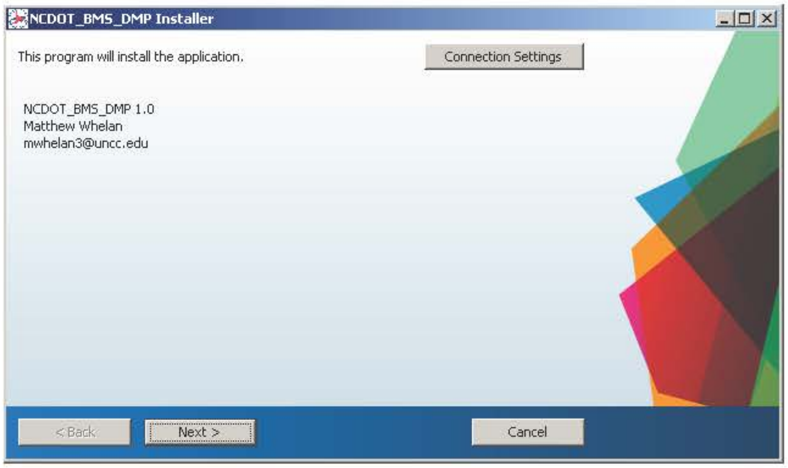
2.1 Installing the Software

The BMS-DMP software was written in the MathWorks MATLAB software environment and has been compiled as a royalty-free executable software application. This software application does not require the user to purchase MATLAB or have a full installation of MATLAB installed locally, however the user must install the MATLAB Compiler Runtime for version R2013b to run the current version of the BMS-DMP software.

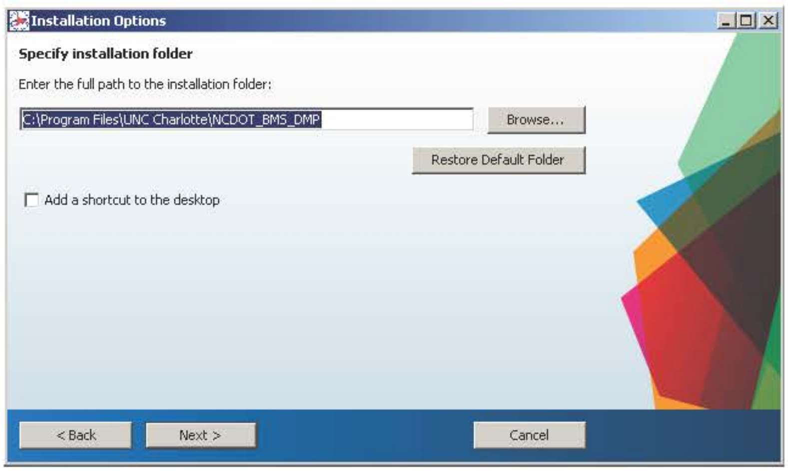
Step 1: Install MATLAB Compiler Runtime R2013b
The installation executable for the MATLAB Compiler Runtime is included with the files provided for the BMS-DMP software and can be installed by running the "MCR_R2013b_win64_installer.exe" file. Alternatively, the MATLAB Compiler Runtime can be installed from:
http://www.mathworks.com/products/compiler/mcr/
but if the runtime is sourced from this site it is necessary that the R2013b (8.2) 64-bit Windows version of the runtime be installed.

R While installation of the MATLAB Compiler Runtime software is necessary to run the BMS-DMP software, the remaining installation step are optional and should only be followed if the user desires to install the software on the computer as a regular application. If desired, the software can be run as an executable from the "Run_Live" folder. However, in order for the software to operate properly, this folder and the files contained in it must be run from an external drive or other media device that permits for files to be written to the folder.

Step 2: Install BMS-DMP Software Application
To install the BMS-DMP software application to a local computer, navigate to the "for_redistribution" folder on the installation disk. Then run the "MyAppInstaller_web.exe" executable. Once the installation application begins, the following window should appear as a prompt. Click "Next" to continue with the installation.



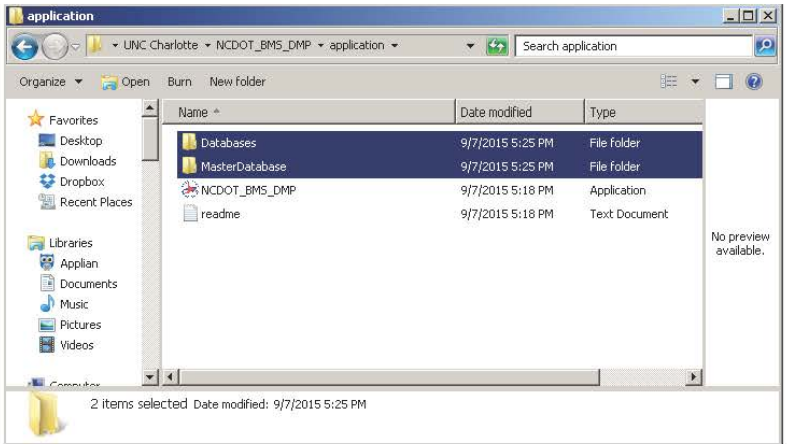
During installation, you will be prompted to enter the location where you would like the software installed. If you choose a location other than the default folder, take note of that location as it will be necessary to copy database files to this folder after the installation. Also, if you would like to add a shortcut for this application to your desktop, check the box next to "Add a shortcut to the desktop."



After proceeding with the installation by clicking "Next", the software should install and an icon for the software should appear in your Start Menu and, if selected as an option in the prior window, the desktop.

Step 3: Transfer Database Files to Software Directory

Database files (NC Bridge Maintenance Files, NBI Files, and Exported Annual Data from the Agile Assets BMS) as well as pre-compiled Master Database Files are not installed with the software but must be transferred to the local computer after the software is installed. Folders containing these database files are found in the installation media within the folder titled "Run_Live." Copy the folder titled "Databases" and the folder titled "MasterDatabase" to the "application" folder within the directory where the BMS-DMP software was installed.

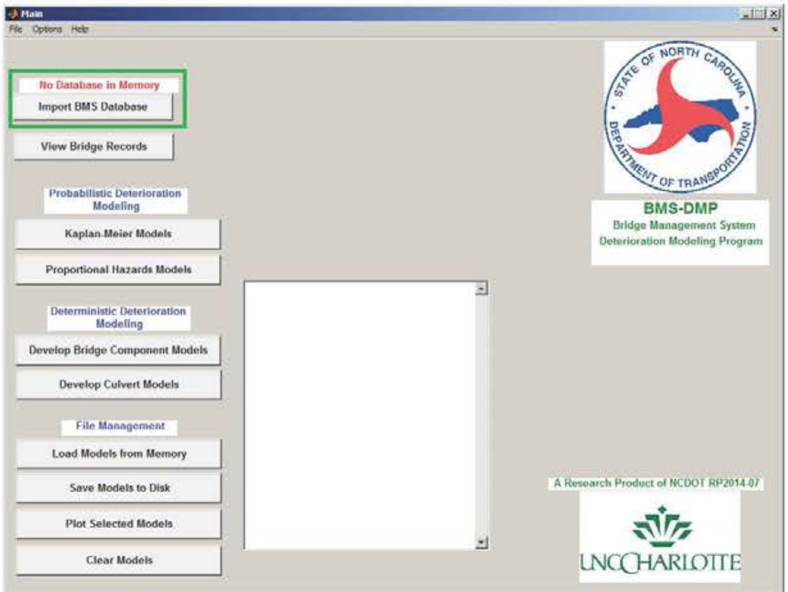


Step 4: Verify Installation by Opening the Software Application
The BMS-DMP Software can be opened by either clicking on the icon "NCDOT_BMS_DMP" in this installation application folder or by selecting the application from the start menu under "All Programs → UNC Charlotte → NCDOT_BMS_DMP." After clicking the icon, wait as the software may take a moment to load. Once the software is initialized, the user will be presented with the main application window.

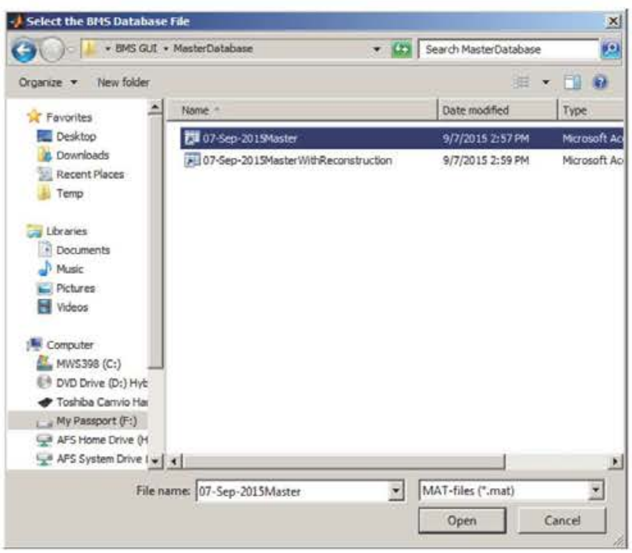
2.2 Loading the Master Database File into the Software

To begin using the BMS-DMP software application for development of bridge and culvert deterioration models, it is necessary to first load a "Master Database File" into the software memory. This Master Database File contains the complete history of BMS records to-date and can be updated as subsequent years are added to the BMS (the procedure for expanding the Master Database File is outlined in Part III of the User Manual). A Master Database File containing all bridge and culvert records from 1981-2015 (35 years) is provided with the software in the "MasterDatabase" folder. To load a Master Database File into the software application, simply click the button on the main window of the application titled "Import BMS Database."

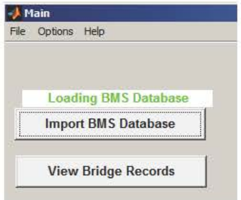
R Note: once a Master Database file is created and saved locally to the user's computer, there is no need to preprocess external sources and assemble a new Master Database file until more years of data are available. This software comes prepackaged with a Master Database file that contains NC bridge records from 1981-2015. When additional years of bridge records become available, the Master Database file can be updated using the guidance provided in Part III: Database Management.



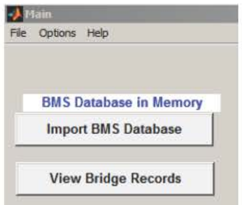
Upon clicking this button, you will be presented with a file dialog box requesting that you select the Master Database File. Navigate to the "MasterDatabase" folder and select the file of your choice.



Loading a Master Database File into the software will take 10-20 seconds. While this database is being loaded into memory, the main window will indicate that the database is being loaded by changing the text above the "Import BMS Database" button to a green "Loading BMS Database."



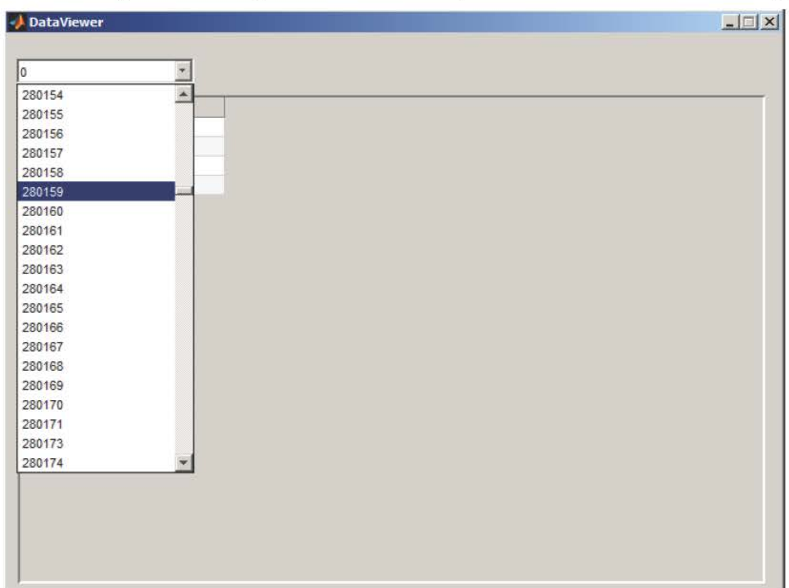
Once the Master Database has been loaded into the software, this text will change to a blue "BMS Database in Memory."



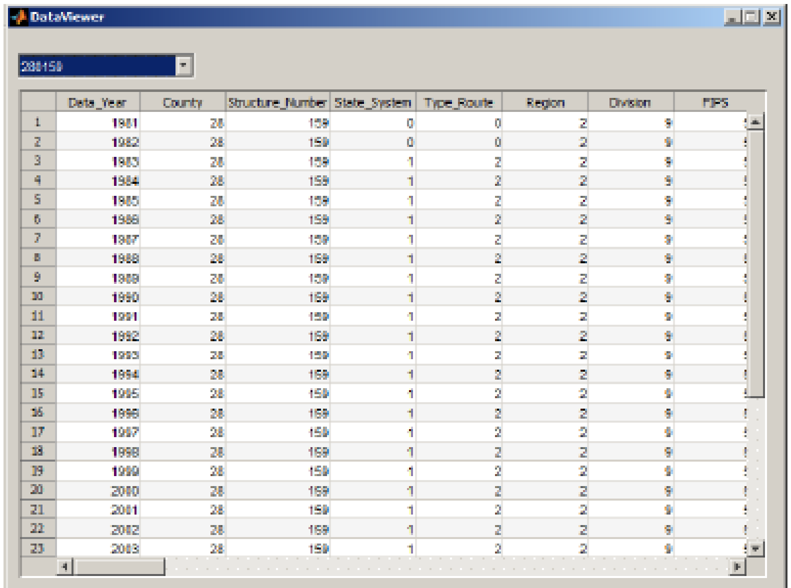
At this point, the user can view the bridge records in the Master Database File or directly proceed with the construction of deterioration models (Part IV: Sections 4 and 5).

2.3 Viewing Bridge Records in the BMS-DMP Software

After the Master Database File is loaded into the software, the individual bridge records can be accessed by clicking on the "View Bridge Records" button that is directly under the "Import BMS Database" button. Viewing of the individual bridge records can be used to ensure that complete records were properly parsed and imported into the Master Database File. It is recommended that whenever new years are added to the Master Database File (explained in the next section of this manual), bridge records should be spot-checked to ensure that the bridge records consist of a continuous record up to the latest year included in the update without instances of missing years.



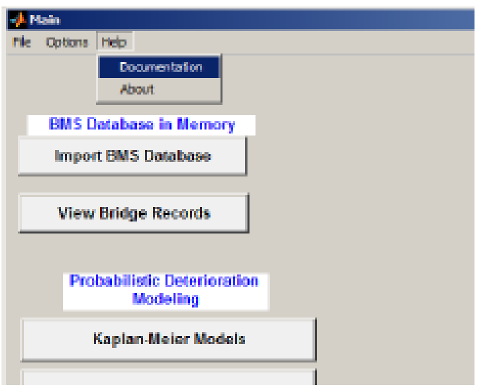
After selecting the bridge number, the complete bridge record reassembled from the annual database files will be presented to the user in tabular form. Note that both a vertical and horizontal scroll bar are present to allow the user to inspect all of the data for each bridge record that is held in the Master Database File. Any entries missing from the original annual database file will be indicated with 'NaN'.



	Data_Year	County	Structure_Number	State_System	Type_Route	Region	Division	FIPS
1	1981	28	159	0	0	2	9	[illegible]
2	1982	28	159	0	0	2	9	[illegible]
3	1983	28	159	1	2	2	9	[illegible]
4	1984	28	159	1	2	2	9	[illegible]
5	1985	28	159	1	2	2	9	[illegible]
6	1986	28	159	1	2	2	9	[illegible]
7	1987	28	159	1	2	2	9	[illegible]
8	1988	28	159	1	2	2	9	[illegible]
9	1989	28	159	1	2	2	9	[illegible]
10	1990	28	159	1	2	2	9	[illegible]
11	1991	28	159	1	2	2	9	[illegible]
12	1992	28	159	1	2	2	9	[illegible]
13	1993	28	159	1	2	2	9	[illegible]
14	1994	28	159	1	2	2	9	[illegible]
15	1995	28	159	1	2	2	9	[illegible]
16	1996	28	159	1	2	2	9	[illegible]
17	1997	28	159	1	2	2	9	[illegible]
18	1998	28	159	1	2	2	9	[illegible]
19	1999	28	159	1	2	2	9	[illegible]
20	2000	28	159	1	2	2	9	[illegible]
21	2001	28	159	1	2	2	9	[illegible]
22	2002	28	159	1	2	2	9	[illegible]
23	2003	28	159	1	2	2	9	[illegible]

2.4 Help Documentation

This manual can be accessed by the user by selecting "Documentation" from the "Help" menu. This will open this user manual in pdf form.



Data Management

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3. Data Management

3.1 Preparation of External Database Sources

Data for the BMS-DMP software is currently sourced from 3 databases:

Years	Source
1981-2009	NC Bridge Maintenance Inventory Files
2011	FHWA NBI File
2010, 2012-2015	AgileAssets Performance Master .xls Export

The preferred source for data is the NC Bridge Maintenance Inventory files, as these files provide the most information within each individual bridge record. Exported data from the AgileAssets Performance Master contains most of the same fields (one of the most significant exceptions is the "Year Reconstructed" field) and therefore is preferred when NC Bridge Maintenance Inventory files are not available for a year in the record. As a last resort, FHWA NBI files can be used for years when records from NC Bridge Maintenance Files or the AgileAssets Performance Master are missing. Currently, the only year that FHWA NBI files are necessary is 2011.

3.1.1 NC Bridge Maintenance Inventory Files

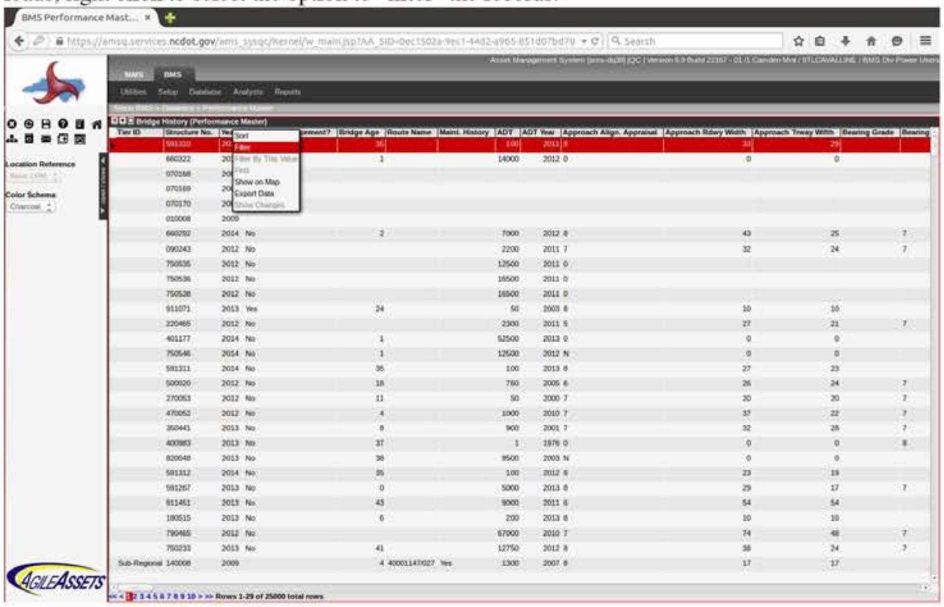
Packaged with the BMS-DMP software are the NC Bridge Maintenance Inventory files from 1981-2009. Each file is simply named using the year (eg. 1992.TXT). If it is desired that these files be replaced or supplemented with additional files, this naming structure should be maintained.

3.1.2 FHWA NBI Files

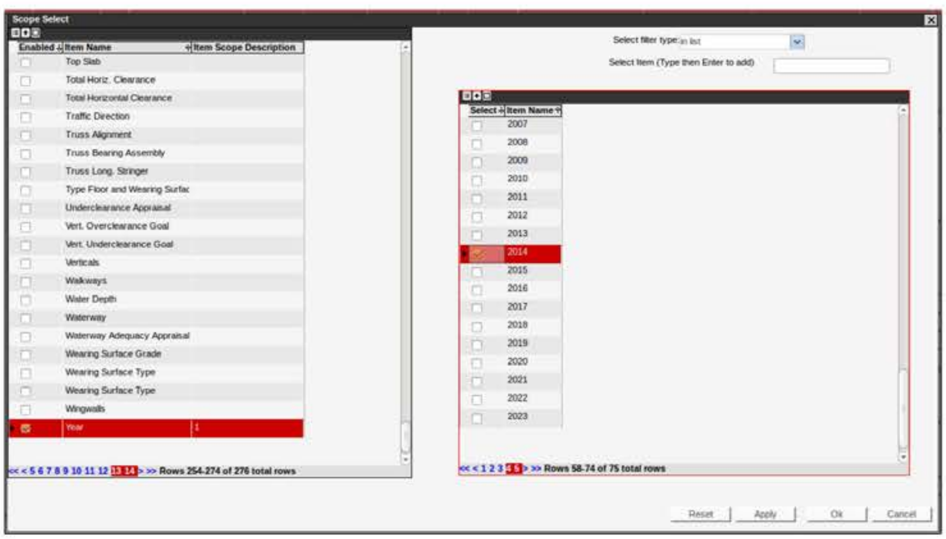
Also packaged with the BMS-DMP software is the North Carolina NBI file for 2011. To distinguish the NBI ASCII files from the NB Bridge Maintenance Inventory ASCII files, the NBI files are named using the structure NC(two-digit year).txt (eg. NC11.txt). Although it is recommended that NBI files be used only when necessary, if it is desired that additional NBI files be added to the database, then this naming structure should be maintained.

3.1.3 Exporting Yearly Database Records from the AgileAssets Performance Master

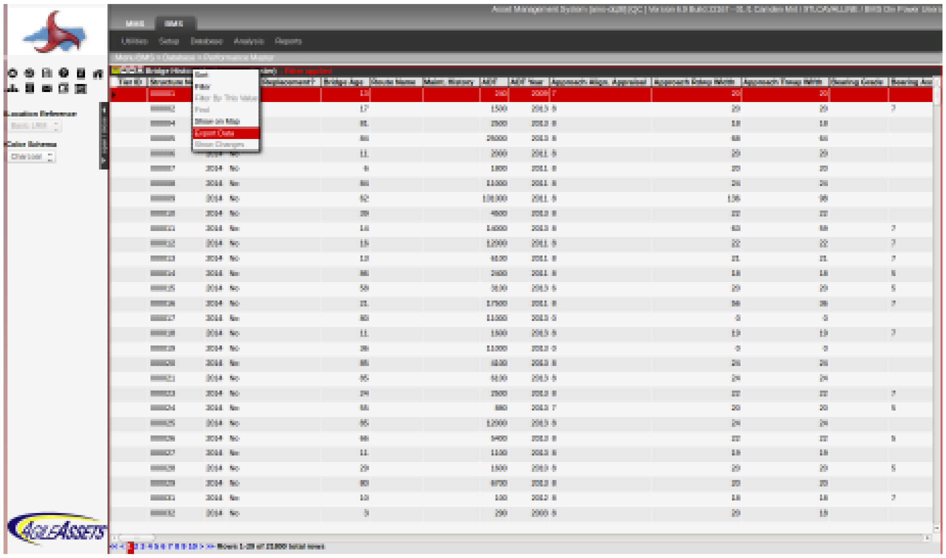
Yearly database files can be sourced from the AgileAssets database using the Performance Master. Within the BMS, navigate to "Database", then "Performance Master." Once the Performance Master loads, right click to select the option to "filter" the records.



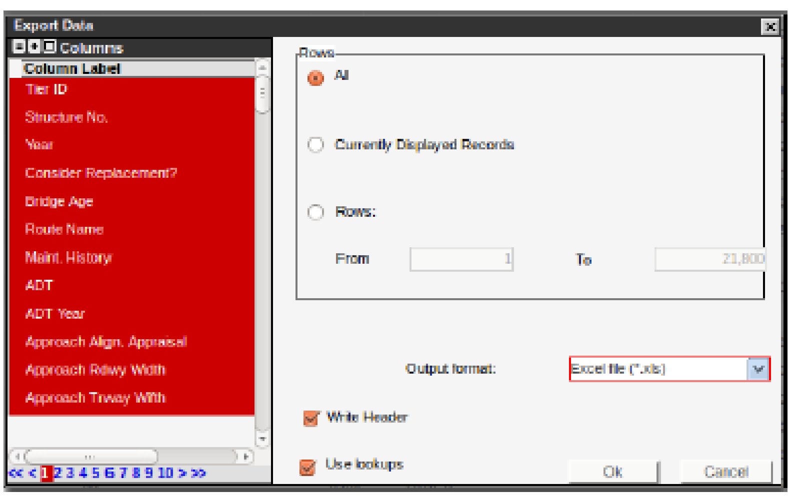
A "Scope Select" window will open that will allow you to specify which items to use for the filtering and the corresponding criteria for each item. Scroll down the menu of items and select "Year," then set the filter type to "in list." This will then allow you to select the year for which you would like to limit the data prior to exporting. Select one year, then click "Apply" and then "Ok".



After filtering the data to a single year of records, the Performance Master should only show records from the selected year, which should total approximately 21,000 to 22,000 total records. To export these record from the Performance Master, right-click again in the Performance Master window and select "Export."



This will bring up an "Export Data" window. The default options should be used, which are to export all rows in Excel file (*.xls) format with a header and lookups. Select "Ok" to begin exporting the data. You will be prompted to either open or save the file. Choose to save the file to your computer.



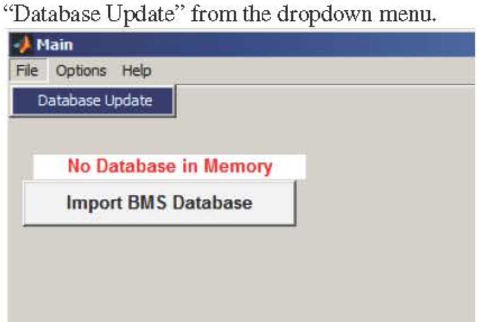
The exported yearly databases from the AgileAssets database should be simply named with the year of the record (eg. 2012.xls). The packaged software contains the AgileAssets database records for years 2010 and 2012-2015 in this Excel format.

3.2 Developing the Master Database File in the BMS-DMP Software

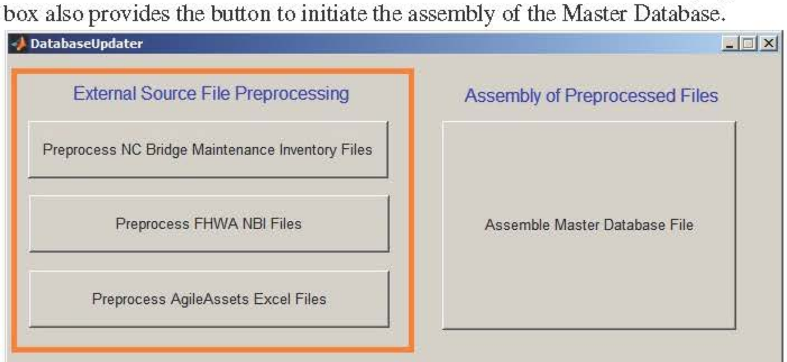
The developed software application was designed such that the Master Database of all yearly records could be updated on an annual basis to produce regularly updated deterioration models for use in the AgileAssets BMS. The software is also designed such that prior yearly records could be replaced if an alternative source is desired. This is accomplished by a two-stage assembly of the Master Database. The first step is a routine that preprocesses the externally sourced databases to extract the items used by the deterioration modeling software. Once preprocessed and formatted to the software syntax, the yearly databases are locally saved as .mat database files. The second step is an assembly routine that aggregates the individual .mat database files. The following walk-through addresses how to run the preprocessing routines and assemble a new Master Database file.

3.2.1 Preprocessing External Database Sources

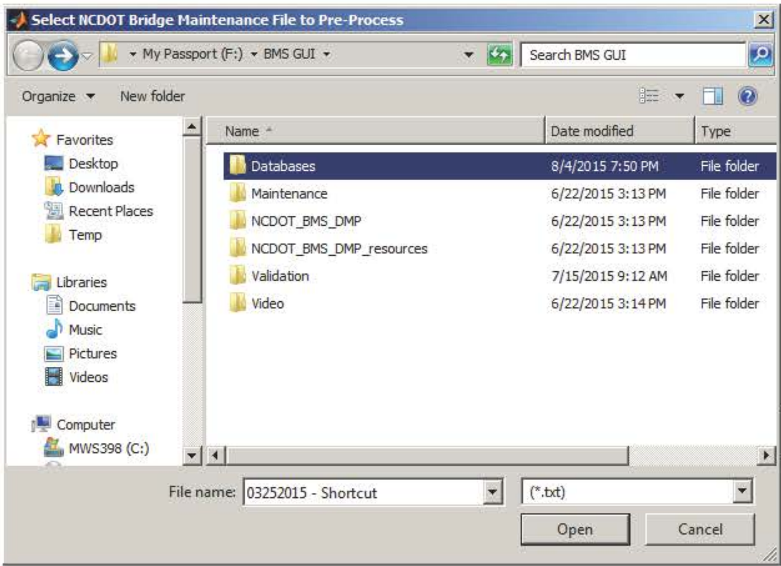
Database updating is initiated from the "File" Menu on the main window of the GUI. Select "Database Update" from the dropdown menu.



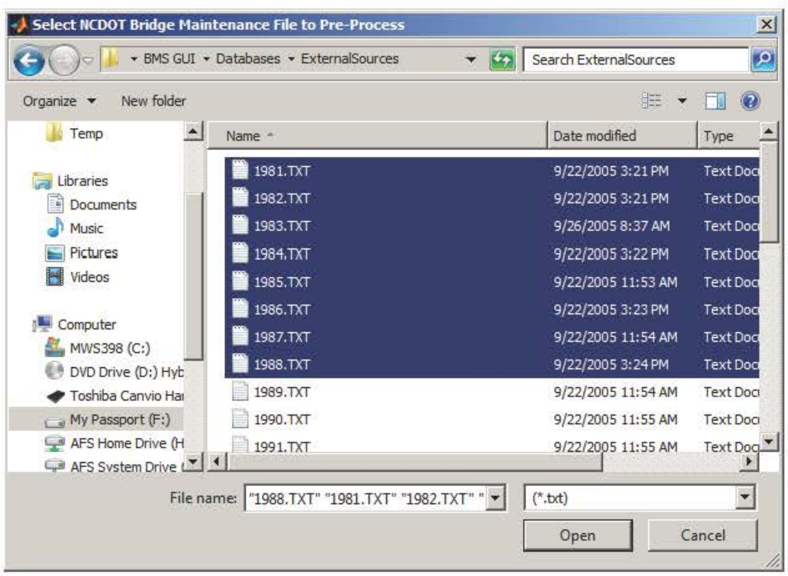
Selecting this feature will open a new dialog box that allows for the preprocessing of any of the 3 external source database files. After all external source files have been preprocessed, this dialog box also provides the button to initiate the assembly of the Master Database.



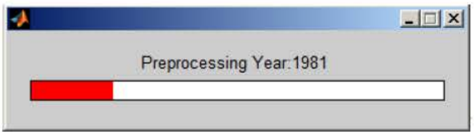
To begin preprocessing an external database file, click the corresponding button associated with the file type. For instance, by clicking the "Preprocess NC Bridge Maintenance Inventory Files" button, a file explorer window opens in the directory of the main software application. The external database source files packaged with the software are stored in the '/Databases/ExternalSources/' folder, so select the Databases folder:



And then select the ExternalSources folder, and within that folder select one or more of the NC Bridge Maintenance Files that you would like to preprocess.



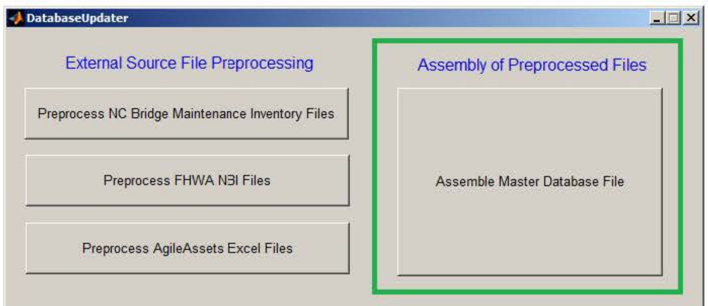
Preprocessing these database files will take time (especially the preprocessing of the AgileAssets .xls files), so a progress bar is provided to let you know where the software is at in this process. Once the process is completed, this progress bar will automatically close, which lets you know that you can move on to the next task.



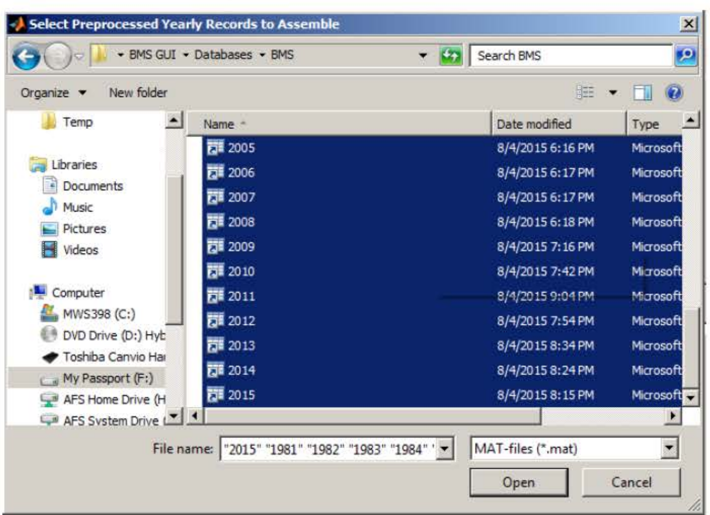
Preprocessing of FHWA NBI Files and AgileAssets .xls spreadsheets proceeds exactly the same way as demonstrated for the NC Bridge Maintenance Files. When the software performs this preprocessing, the yearly output is saved as .mat database files in the '/Databases/BMS/' folder.

3.2.2 Assembling the Master Database File

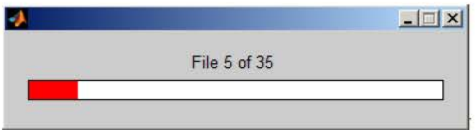
Once preprocessing of files is completed (or if the Master Database is to be assembled from the packaged .mat database files), the assembly of a Master Database record containing all recorded years of BMS records can be developed by clicking the "Assemble Master Database File" button.



Clicking this button will open another file explorer and request that the user select the .mat database files that should be used to develop the Master Database file. These files should have been automatically saved in the "/Databases/BMS/" folder so navigate the file explorer to that folder and then select all of the files to be used to construct the Master Database (normally, this would be all of the files in this folder).



Since this process will take a few minutes, a progress bar is provided to indicate where the software is at in this assembly routine. When the assembly is completed, this progress bar will automatically close.



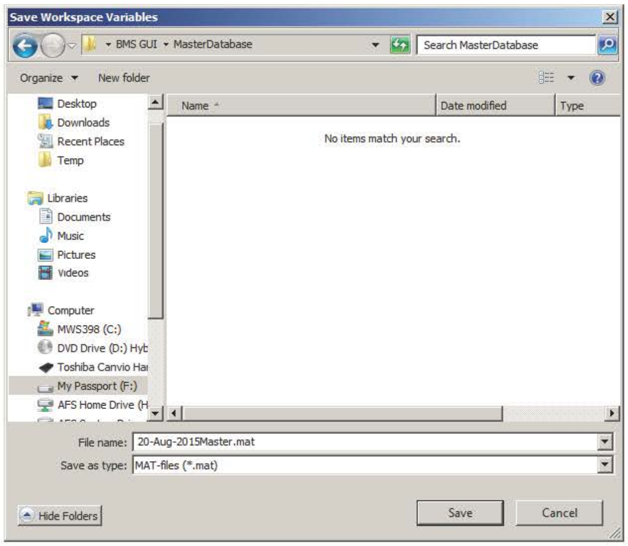
Note that there is a post-processing stage in this database assembly where the compiled bridge records are further processed to separate bridges that have been rebuilt into a new bridge record. Additionally, bridge records can be separated upon the instance of reconstruction, which was used by the research team to examine the influence of reconstruction on deterioration rates of bridge components. For development of deterministic deterioration models, it is recommended that the database be post-processed to separate records only after rebuilding. The reason for this is that reconstruction does not impact the condition of all three bridge components and therefore separating records after the occurrence of reconstruction may artificially shorten some of the observed continuous duration condition ratings. However, since a small percentage of the bridge records are affected by separate by reconstruction (less than 4%), the use of either post-processing technique should produce very similar deterioration models.

The identification of a rebuilt bridge is performed by comparing the "Year Built" item in each year to prior years in the record. To handle data anomalies, several measures are taken in this pre-processing step. Specifically, in order for a new bridge record to be developed to indicate a rebuilt bridge:

- The new Year Built must occur at least twice in the bridge record, which is done to minimize the effect of anomalies in the records
- The new Year Built must be at least 2 years greater than the original Year Built. Again, this criteria is used to minimize the effect of anomalies in the records on the post-processing routine.
- The new Year Built must be greater than the first year that the bridge data was recorded. The research team found that there are several records where the Year Built item changes within the record, but the new Year Built occurs before the start of the bridge record. Consequently, such records should not be separated into two instances since these instances are clear inconsistencies in the recorded data rather than correct indications of rebuilding during the period of recorded bridge inspections.

The identification of bridges with reconstruction and corresponding separation of records is handled similarly with the same measures taken to minimize the impact of miscoded data.

When all preprocessed yearly database files have been assembled into the Master Database file, a save dialog will be presented to the user. Save the Master Database file in a convenient location with a name that you will be able to associate with the contents of the database file. The default filename will be the date followed by "Master" if the database has been separated only by rebuilding or "MasterWithReconstruction" if the database has been separated by both rebuilding and reconstruction.



At this point, the development of the Master Database file has been completed. In order to use this new database file, the user must load the file into the BMS-DMP software using the "Import BMS Database" on the main window of the software. As previously mentioned, since the Master Database file is saved locally to the user's computer, it is not necessary to redevelop this file using the step outlined in this chapter each time that the software is used. Rather, the user can directly load the already developed database file into the software using the "Import BMS Database" button. The only time that the database file needs to be updated is when additional yearly data is available for statistical analysis.

IV Deterioration Modeling

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4. Deterministic Models

4.1 Overview of Methodology

Research performed in RP 2014-07 indicated that the current methodology for developing deterministic models suffers from 1) severely over conservative prediction of deterioration rates due to a failure to account for censoring of data and 2) poor discrimination of external factors influencing deterioration, as the pre-classification strategies currently used often do not produce significantly different models with in the same material-type. It is strongly recommended that probabilistic models be used to perform condition rating forecasting in network analysis and multi-objective optimization schemes. However, this capability to develop deterministic models is provided in the software because the current AgileAssets software does not provide the capability to implement Markov chain models or other probabilistic deterioration models.

The deterministic deterioration modeling approach implemented in the BMS-DMP was originally developed by [**AbedAlRahim91**] and updated in [**Duncan02**]. Specifically, the deterministic deterioration modeling approach adopted in the software follows the final recommended approach in [**Duncan02**], where the duration in an individual condition rating is computed by two approaches (referred to as "Program 1" and "Program 2") and the average duration computed by these approaches is used to develop the final model.

Definition 4.1.1 — Program 1. This routine examines each individual bridge history record and determines the longest continuous duration that the bridge remains in the specified condition rating. At the end of the observation period, the rating is allowed to either decrease or increase. The observed duration is required to be greater than one to be considered in the analysis.

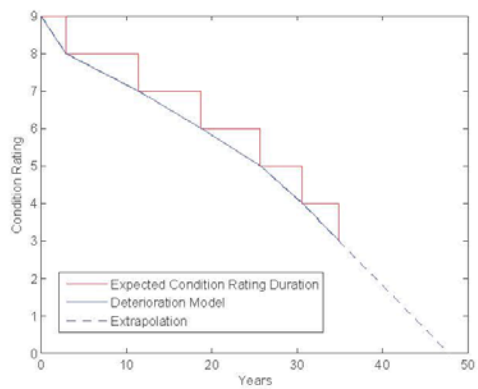
Definition 4.1.2 — Program 2. This routine examines each individual bridge history record and determines the total number of years that a condition rating appears over the entire recorded life of the bridge. In contrast to Program 1, the condition rating does not need part of a continuous series of years where the rating does not change to be included in this measure. However, as with Program 1, the observed duration is required to be greater than one to be considered in the analysis.

The result of the deterministic deterioration modeling algorithm is a piece-wise linear prediction model that forecasts the condition rating as a function of time. Due to limited bridge records with data for condition ratings below 4, the deterioration model only includes estimates for the duration associated with condition ratings 4-9. Below condition rating 4, a linear extrapolation has been used in the prior literature to facilitate condition rating forecasting to lower ratings by projecting the slope of the deterioration model between condition ratings 4 and 5.

■ **Example 4.1** Suppose that the following deterministic deterioration model is generated.

Rating	9	8	7	6	5	4
Years in Rating	2.936	8.462	7.358	6.917	4.935	4.302

In this case, the piece-wise linear prediction model is developed as:



To use this deterioration model for forward prediction, the current condition rating and current number of years that the bridge has been continuously rated in that rating can be used to locate the current point on the deterioration model. Then, the future condition rating at any point in time can be estimated by tracing the deterioration model forward over the total number of years in the planning period. ■

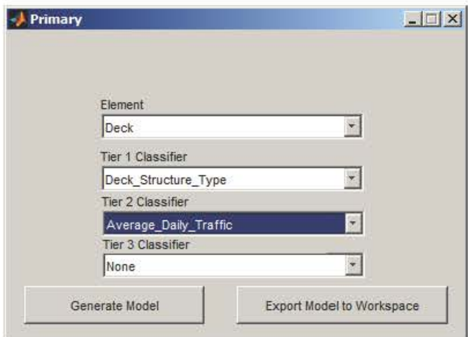
The deterministic deterioration modeling software routines can be applied to either primary (GCR) bridge components or culverts. In time, as element-level rating data becomes available, the software should be expanded to included element deterioration models as well. However, at the time of this project, the fields associated with the new element-level rating requirements have not been added to AgileAssets framework and, therefore, the capability for producing element-level deterioration models could not be built into the software.

4.2 Deterioration Modeling of Primary Components

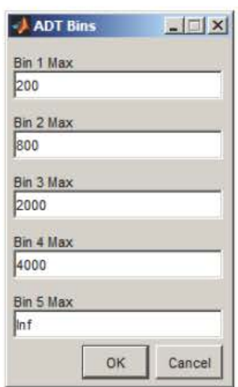
Currently, NCDOT uses pre-classification of bridges prior to deterministic deterioration modeling in an effort to incorporate the effects of external factors on deterioration rates of different bridge components. This section details how to develop deterministic deterioration models for each of the three main bridge components using the classification strategies currently used in the AgileAssets BMS. However, the software is flexible enough that NCDOT can explore the use of alternative classification tiers using the software, if desired. To start the development of deterministic deterioration models for bridge components, simply click the “Develop Bridge Component Models” button under the Deterministic Deterioration Modeling heading on the main window of the BMS-DMP software program. Then click ”Generate Model”.

4.2.1 Bridge Decks

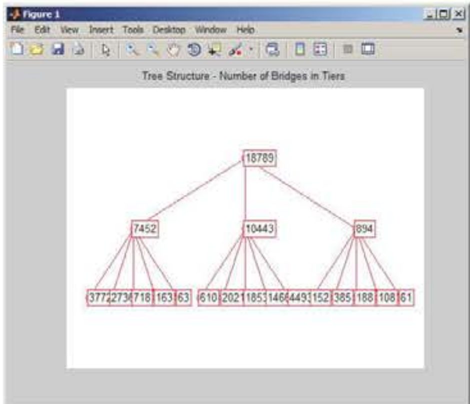
To-date, the pre-classification strategy used for bridge deck deterioration models was based on first grouping bridges by deck material type (Timber, Concrete, or Steel) and then based on average daily traffic. To develop deck deterministic deterioration models using this pre-classification strategy, use the drop-down menus to select the following element and classifiers.



For average daily traffic, the grouping was based on five ranges: 1) 0-200 vehicles, 2) 200-800 vehicles per day, 3) 800-2000 vehicles per day, 4) 2000-4000 vehicles per day, and 5) >4000 vehicles per day. Consequently, if average daily traffic is used as a pre-classifier, these values are established as the default. However, the user is presented with a dialog box that permits for adjusting these bounds, if desired. This dialog box, presented with the default values, is shown below. Once the desired bounds are established, click 'OK' to proceed with the development of the deterministic deterioration models.



When the development of the deterministic deterioration models completes, a series of figures and tables will be presented on the screen. One figure will present the distribution of records present for analysis of each model. This can be used to assess whether a sufficient number of records are present in each model to ensure reasonable confidence in the developed models. For example, in the tree developed for the deck deterioration models, it can be seen that there are only 894 records for bridges classified with steel decks and after further classifying by ADT, there are only 61 records of steel deck bridges with ADT greater than 4000 vehicles.

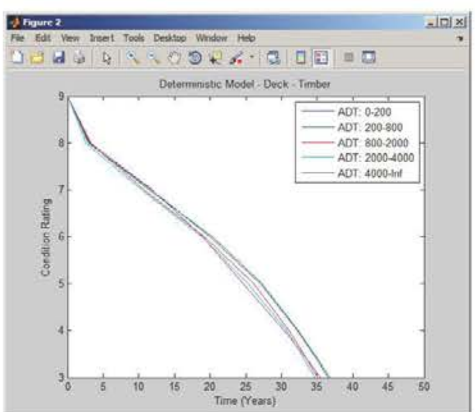


Further statistics on the data used for development of the individual models is provided in the form of tables. These tables indicate the number of continuously observed condition ratings observed for the model development at each condition rating, the number and percentage of censored records, the expected duration estimate computed by Program 1 (P1) and Program 2 (P2), and the final expected duration estimate computed for the deterioration model.

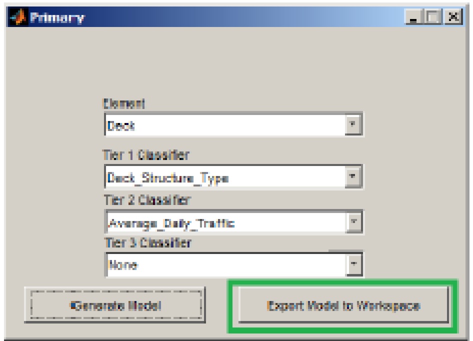
Deck Tier1: Timber Tier2: ADT: 0-200

	Rating 9	Rating 8	Rating 7	Rating 6	Rating 5	Rating 4
# of Instances	412	2238	3524	3726	2774	1107
# Censored	36	543	2368	2302	2098	1018
% Censored	8.7379	24.2627	67.1964	61.7821	75.6309	91.9603
Years in Rating (P1)	2.9175	7.9004	6.7971	6.0357	4.5306	4.1319
Years in Rating (P2)	2.9926	9.8163	9.9897	7.9916	5.8849	4.7198
Years in Rating	2.9550	8.8583	8.3934	7.0136	5.2078	4.4258

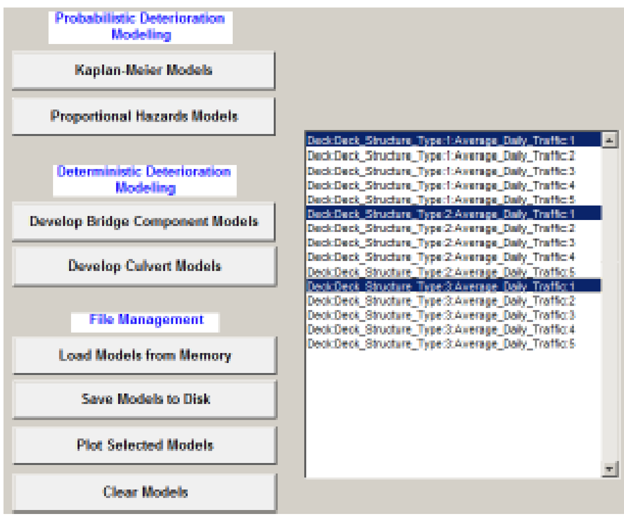
Additionally, the deterministic deterioration models are plotted in groups according to the top tier classifier. For example, the timber deck deterioration models developed on the 1981-2015 data are presented below. The complete set of deterministic deterioration models developed by RP2014-07 are provided in the final project report **[Cavalline15]**.



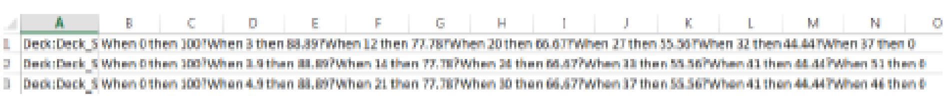
After models are developed, they may be exported to the listbox on the main window of the software by clicking the button "Export Model to Workspace".



Once the developed models have been exported to the workspace, they will appear in the listbox on the main window of the software. From here, individual models or sets of models can be plotted or saved to disk using the buttons under the "File Management" heading.



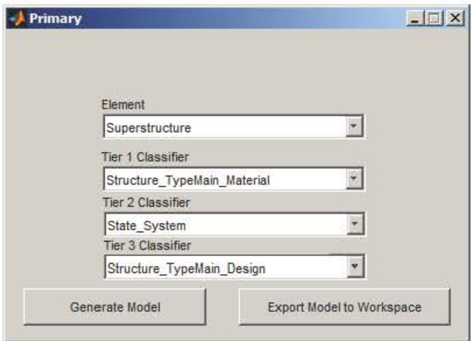
When saving the models to disk, the models are saved to an .xlsx Excel spreadsheet file. The first column of this file will contain the model name and the second column will contain the deterministic deterioration model written in the syntax compatible with the current AgileAssets software. An example output file is shown below.



	A	B
1	Deck:Deck_S	When 0 then 100?When 3 then 88.89?When 12 then 77.78?When 20 then 66.67?When 27 then 55.56?When 32 then 44.44?When 37 then 0
2	Deck:Deck_S	When 0 then 100?When 3.9 then 88.89?When 14 then 77.78?When 24 then 66.67?When 33 then 55.56?When 41 then 44.44?When 51 then 0
3	Deck:Deck_S	When 0 then 100?When 4.9 then 88.89?When 21 then 77.78?When 30 then 66.67?When 37 then 55.56?When 41 then 44.44?When 46 then 0

4.2.2 Bridge Superstructures

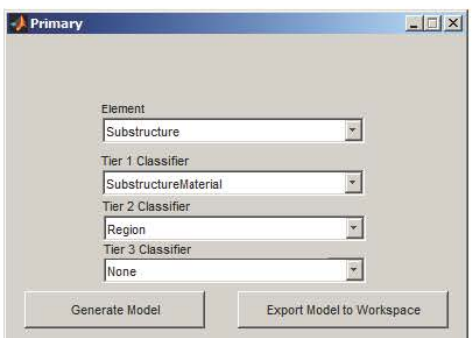
To-date, the pre-classification strategy used for bridge superstructure deterioration models has been based on first grouping bridges by substructure material type (Timber, Concrete, Steel, and Prestressed Concrete), then by state system, and then by structure design type (Multi-Beam, Slab, Tee-Beam, Truss, or Floor-Beam). To develop superstructure deterioration models using this classification, the element and tier classification assignments should be specified as shown below.



The development of these models parallels the development of prior models. Note that not all categories of superstructure deterioration models have a sufficient number of records present to develop a model (for instance, there are few, if any, concrete truss bridges in the inventory). The software yields models only for those classifications for which at least one record is present for each condition rating between 4 and 9. The final deterministic deterioration models for superstructures are provided in the final project report.

4.2.3 Bridge Substructures

To-date, the pre-classification strategy used for bridge substructure deterioration models has been based on first grouping bridges by substructure material type (Timber, Concrete, Steel, and Pre-stressed Concrete) and then by geographic region (Coastal, Piedmont, Mountain). To develop substructure deterioration models using this classification, the element and tier classification assignments should be specified as shown below. The development of these models parallels the development of prior models. The final deterministic deterioration models for substructure are provided in the Appendix of this report.



4.3 Deterioration Modeling of Culverts

One of the unique research contributions of RP2014-07 was the first development of deterministic deterioration models for NBI culverts for use in the NCDOT BMS. This routine adopts the same deterministic deterioration modeling approach used for bridge component models, where the expected duration in each condition rating is computed as the average of the "Program 1" and "Program 2" analyses. To construct deterministic deterioration models for culverts using the BMS-DMP, click the front panel button on the main window titled "Develop Culvert Models", which is found under the heading "Deterministic Deterioration Modeling."

After opening this interface, a user menu will open similar to the one provided for developing bridge component deterioration models (Figure 4.1). However, since there are far less culverts in the state inventory than bridges, this deterministic modeling routine was developed with only one tier of culvert pre-classification. Relevant fields coded in the AgileAssets BMS that could be linked to different deterioration rates are: Superstructure Material, State System, and Functional Classification. The NCDOT Bridge Maintenance Inventory files contain additional information on culverts, such as culvert type, number of barrels, barrel span, and barrel height. Each of these features are permitted as potential pre-classifiers for developing culvert deterioration models. After selecting the desired classifier, simply click "Generate Model" to pass the instruction to the statistical engine to develop the deterioration model.

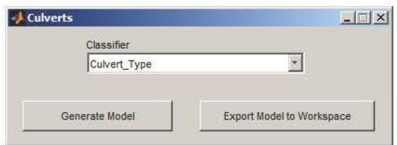
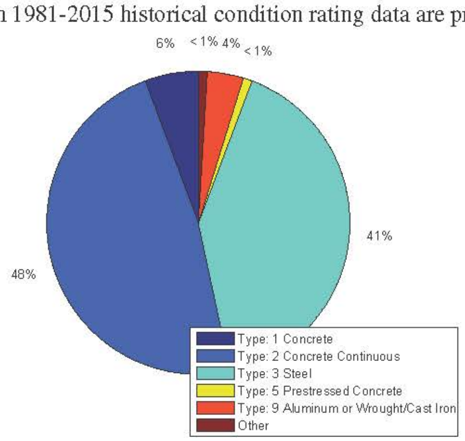


Figure 4.1: Culvert deterioration modeling user menu with single tier pre-classification

Preliminary assessment of the classification tiers in the current research project has lead to the recommendation that "Structure_TypeMain_Material", which is the main material of the culvert construction, should be used for culvert pre-classification. This recommendation is based on the observation that this classifier provides the most significant discrimination between different culvert deterioration models developed. The distribution of the NBI culverts by material type in the state inventory is shown below. The recommended culvert deterministic deterioration models constructed from 1981-2015 historical condition rating data are provided in the Appendix of this report.



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5. Probabilistic Models

5.1 Overview of Methodology

Probabilistic models have been preferred for deterioration modeling for many years and form the basis of the majority of commercial and federal bridge management system implementations. However, at this point in time, the AgileAssets does not support implementation of probabilistic models. Despite this current limitation, the modeling technique developed in this research project for constructing probabilistic models uniquely accounts for the effects of censoring on condition rating data and has been shown to yield more accurate and precise estimates of future condition rating over typical planning horizons than deterministic models. Consequently, the BMS-DMP includes routines for developing probabilistic models and strongly encourages the revision of the AgileAssets software to permit direct usage of these models.

The BMS-DMP software currently adopts the Markov chain approach to probabilistically modeling deterioration of bridge components. In the conventional Markov chain, the probability of a specific component being rated at any condition rating is given by a state vector, Z.

■ **Example 5.1** For example, for a new bridge at condition rating 9, this state vector would be:

$$Z = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Which simply states that there is a 100% probability that the component is at condition rating 9. Alternatively, if a component has just transitioned from condition rating 6 to condition rating 5, it may be best to assume a 50% probability that the component is still at condition rating 6 and a 50% probability that the component is at condition rating 5. This essentially assigns an effective rating of 5.5 and would be represented with an initial state vector of:

$$Z = \begin{bmatrix} 0 & 0 & 0 & 0.5 & 0.5 & 0 & 0 & 0 & 0 \end{bmatrix}$$

■

The probability of the component being in any of the condition ratings after n years is then computed by:

$$Z_n = Z(\mathbf{P})^n \qquad (5.1)$$

where **P** is the transition probability matrix and contains entries that describe the probability of the bridge component transitioning from any one rating to any other, including the probability of staying at the same rating. There are two common assumptions that simplify this transition probability matrix when applied to bridge condition rating data:

1. It is assumed that, when bridge deterioration occurs, the drop in condition rating occurs by only one condition rating at a time
2. It is assumed that deterioration model is developed to capture natural deterioration and, therefore, the probability of any component improving in condition rating is 0.

By these two assumptions, the transition probability matrix takes the form:

$$\mathbf{P} = \begin{bmatrix} P_{99} & P_{98} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & P_{88} & P_{87} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & P_{77} & P_{76} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & P_{66} & P_{65} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & P_{55} & P_{54} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & P_{44} & P_{43} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & P_{33} & P_{32} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & P_{22} & P_{21} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & P_{11} \end{bmatrix} \tag{5.2}$$

where P_{ii} is the probability that a component at condition rating i will remain at condition rating i over one year and P_{ij} is the probability that a component at condition rating i will deteriorate to the next lower condition rating, j, over one year.

The state vector computed for year n of the planning horizon presents the probabilities associated with the component being rated at any condition rating in the condition rating scale. To obtain a simple estimate or "best guess" of the condition rating from these probabilities, the expected value is typically used. This expected value, E, is simply computed as:

$$E = Z_n R \tag{5.3}$$

where R is a column vector of the scale of the condition ratings.

■ **Example 5.2** For example, suppose that a state vector at year n is computed as:

$$Z_n = \begin{bmatrix} 0 & 0 & 0.3 & 0.35 & 0.25 & 0 & 0 & 0 & 0 \end{bmatrix}$$

This state vector would mean that there is a 30% probability of the component being rated at 7, a 35% probability of it being rated at 6, a 25% probability of it being rated at 5, and a 10% probability of it being rated at 4. To obtain the expected value, the operation would be:

$$E = Z_n R = \begin{bmatrix} 0 & 0 & 0.3 & 0.35 & 0.25 & 0.10 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 9 \\ 8 \\ 7 \\ 6 \\ 5 \\ 4 \\ 3 \\ 2 \\ 1 \end{bmatrix} = 5.85$$

■

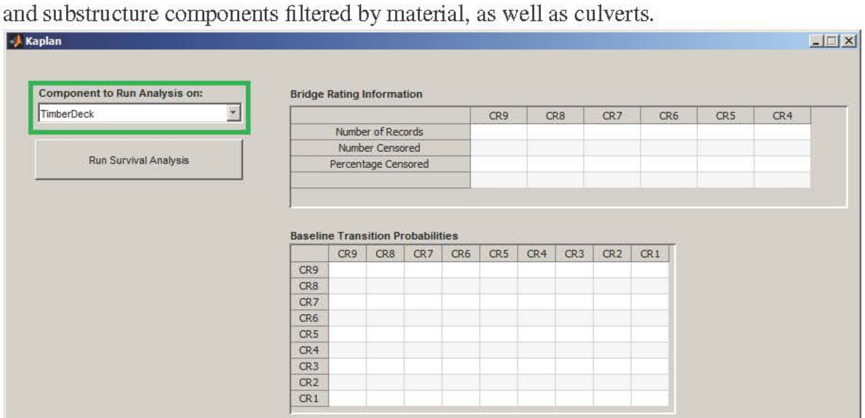
The challenge with developing probabilistic deterioration models is simply to estimate the non-zero transition probabilities in this matrix by statistical regression of historical condition rating data. In the BMS-DMP, duration-based statistical regression techniques based on survival analysis have been implemented since they can account for the effect of censoring on condition rating durations and therefore result in more accurate and precise models than those based on standard linear or nonlinear regression. The software provides two methodologies for developing probabilistic models using survival analysis techniques: 1) Kaplan-Meier Models and 2) Multi-Variate Proportional Hazards Models.

The Kaplan-Meier method yields a simpler model that does not explicitly account for the effects of significant external factors on deterioration rates. Consequently, this method is appropriate only for developing a general model to be applied to a subset of bridge components (eg. all Timber decks). However, due to its simpler form, this would be an easier model to implement in the BMS. In contrast, the Multi-Variate Proportional Hazards methodology developed in this research effort statistically analyzes historical condition rating data to discover the factors that have most significantly affected bridge deterioration over the service life of bridge components. This results in a more robust model that produces more accurate and precise forecasts of condition ratings at the expense of a more complex model to implement. However, it should be emphasized that the methodology developed in this research project incorporates the effect of significant factors on the transition probability matrices by simply raising baseline transition probabilities to a power. Consequently, even the implementation of the Multi-Variate Proportional Hazards models is relatively straightforward and computationally simple.

Illustrative use of the probabilistic deterioration models for condition rating forecasting is provided in the final project report [**Cavalline15**]. Additionally, details on the development of the proportional hazards probabilistic deterioration modeling methodology and extensive analysis of the models and hazard ratios developed through application to 1981-2015 data can be found in the Ph.D. dissertation that stemmed from this research project [**Goyal15**].

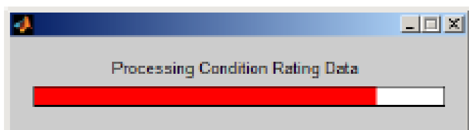
5.2 Simplified Probabilistic Models

The simplest technique for estimating transition probabilities for the deterioration model while still accounting for the significant effect of censoring on condition rating durations is by survival analysis with the Kaplain-Meier empirical estimator. Development of this simplified probabilistic models is enabled by clicking the "Kaplan-Meier Models" button on the main window of the user interface after loading the BMS database into memory. This will open a new window, where the component to be analyzed should be selected. These components include the deck, superstructure, and substructure components filtered by material, as well as culverts.

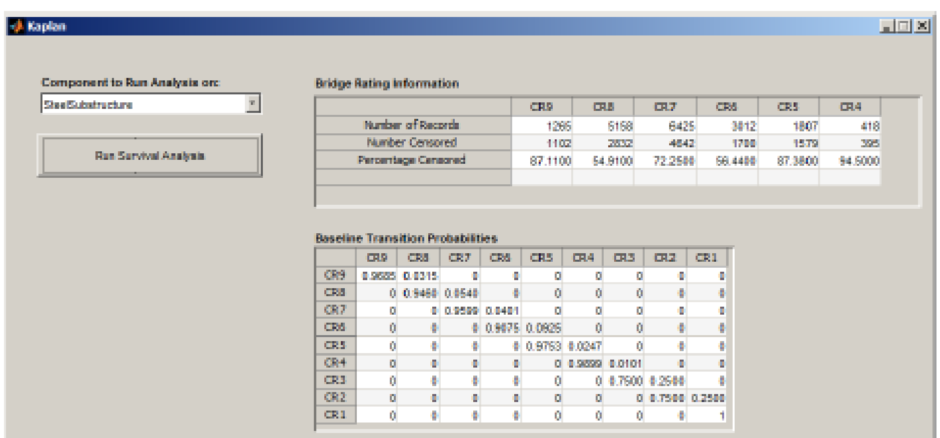


After selecting the desired component to construct the model for, click the ”Run Survival Analysis" button. You will then be prompted with a question box that asks if you would like to overwrite the existing condition rating databases with the new analysis. Normally, it is best practice to select ’Yes’ to ensure that the analysis is performed on the most current data loaded through the BMS database file. However, if the analysis was recently performed on the same dataset, this step can be bypassed to save time.

After making this selection, the processing of data and statistical regression of the simplified probabilistic model will be performed. A progress bar will be presented that provides feedback on the status of this analysis. For the simplified probabilistic models, this analysis should take less than a minute.



When this process completes, the tables in the simplified probabilistic modeling window will be populated with statistics on the condition rating data analyzed for development of the probabilistic model and the estimated stationary transition probability matrix for the simplified probabilistic model. This matrix serves as a Markov chain transition probability matrix for all bridge components in the family that the analysis was set to run on and implicitly considers the effects of explanatory factors rather than explicitly accounting for them with additional hazard ratios.



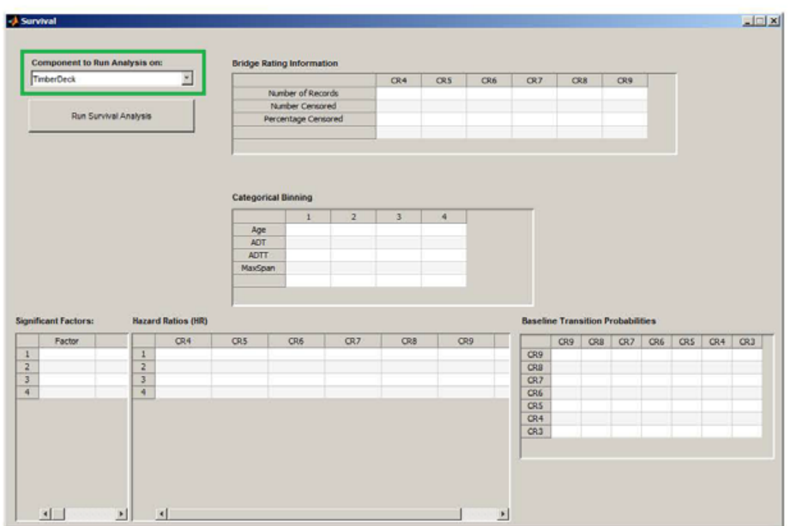
5.3 Proportional Hazards Probabilistic Models

Research performed in RP2014-07 revealed that improved prediction accuracy, precision, and stability of the prediction accuracy over both short and long-term analysis cycles was achieved using probabilistic models that incorporate the effects of explanatory factors (age, state system, geographic region, maximum span length, number of span, etc.) into the deterioration model. Adopting the proportional hazards model for these explanatory factors is convenient for implementation since the structure-specific transition probability matrices can be assembled using:

$$\mathbf{P} = \begin{bmatrix} P_{99}^{HR_9} & 1-P_{99}^{HR_9} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & P_{88}^{HR_8} & 1-P_{88}^{HR_8} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & P_{77}^{HR_7} & 1-P_{77}^{HR_7} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & P_{66}^{HR_6} & 1-P_{66}^{HR_6} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & P_{55}^{HR_5} & 1-P_{55}^{HR_5} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & P_{44}^{HR_4} & 1-P_{44}^{HR_4} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.75 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.4}$$

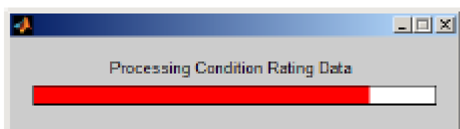
where P_{ii} are baseline stay-the-same transition probabilities associated with condition rating i and are common to all structures in the same model and HR_i are the structure-specific hazard ratios associated with the effects of the explanatory factors at condition rating i. Example assembly and forecasting with a proportional hazards probabilistic deterioration model is presented in the final report **[Cavalline15]**.

Development of the proportional hazards probabilistic models is enabled by clicking the "Proportional Hazards Models" button on the main window of the user interface after loading the BMS database into memory. This will open a new window, where the component to be analyzed should be selected. These components include the deck, superstructure, and substructure components filtered by material.

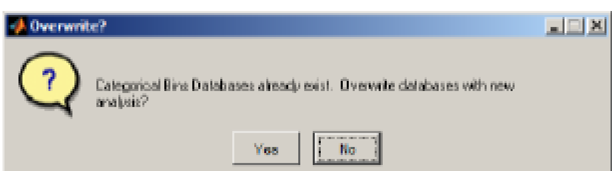


After selecting the material-specific component to analyze, click the "Run Survival Analysis" button to begin the statistical regression. As in the case of the simplified probabilistic deterioration model development, the user will be prompted with a question box that asks if you would like to overwrite the existing condition rating databases with the new analysis. Normally, it is best practice to select 'Yes' to ensure that the analysis is performed on the most current data loaded through the BMS database file. However, if the analysis was recently performed on the same dataset, this step can be bypassed to save time.

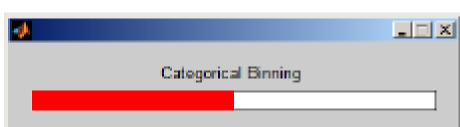
After making this selection, the processing of data and statistical regression of the simplified probabilistic model will be performed. A progress bar will be presented that provides feedback on the status of this analysis. For the simplified probabilistic models, this analysis should take less than a minute.



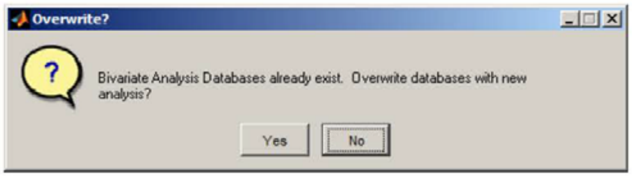
Once the pre-processing of condition rating data is completed, the user will be prompted with an additional question box that asks if you would like to overwrite the categorical bins used for reference cell coding of nominal scale variables (Age, ADT, ADTT, Maximum Span Length). Normally, it is best practice to select 'Yes' to ensure that the categorical binning is performed on the most current data loaded through the BMS database file. However, if the analysis was recently performed on the same dataset, this step can be bypassed to save time.



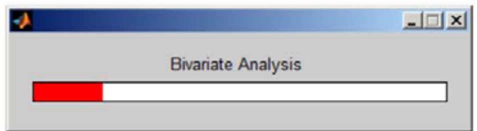
If the user choses to redevelop the categorical bounds, a progress bar is provided to inform the user of the status of this analysis as the new categorical bins are calculated.



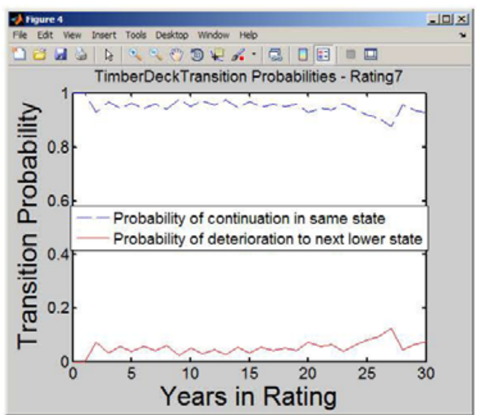
Finally, the user is prompted with a question box that asks if the bivariate analysis should be overwritten. Again, best practice is to select "Yes", unless the analysis was previously performed with the same data and the user is only looking to pull up the deterioration model again without having to wait for the analysis to be performed.



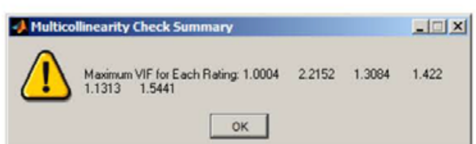
As this best subset selection can take a minute or more to perform, a progress bar is provided to indicate the status of the analysis to the user.



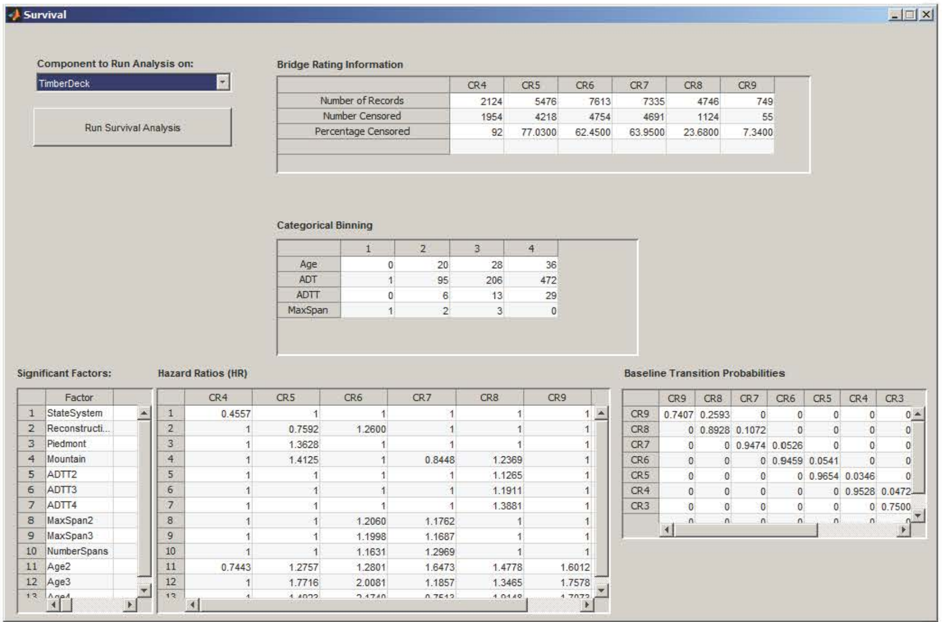
As the model development completes, the user will be presented with baseline survival functions for the individual condition ratings as well as the estimated transition probabilities for each condition rating over time. These transition probabilities should be nearly constant over time to enable a stationary (constant) transition probability to be used for the condition rating forecasting. The research team has found that these probabilities are sufficiently constant when applied to 1981-2015 condition rating data to allow for the use of a stationary transition probability matrix.



Additionally, the software indicates whether the model identifies any potential issues with collinearity amongst the variables included in the final model. If any of the computed VIF's are greater than 10, then an additional window is presented to the user to indicate where the collinearity issue exists. Normally, collinearity is not an issue when the proportional hazards regression is applied to bridge condition rating data.



At this point, the user can close any windows or dialog boxes generated during the statistical regression. The final proportional hazards probabilistic model will be contained in the Survival window, as shown in the following image.



As with the simplified probabilistic modeling, the characteristics of the data used to develop the deterioration model are presented under “Bridge Rating Information." This information only provides an indication of the extent and quality of the data used to develop the model and is not required for implementing the deterioration model for condition rating forecasting. The remaining tables include the information required to implement the proportional hazards probabilistic model. The “Categorical Binning" table provides the bounds associated with reference cell coded (binned) variables. Te “Baseline Transition Probabilities" table presents the matrix of the baseline transition probabilities for the model, which provide the P_{ii} terms in the matrix equation (5.4). Lastly, the “Hazard Ratios (HR)" table provides the hazard ratios associated with the "Significant Factors" identified in the model over condition ratings 4-9. These hazard ratios are used to develop structure specific hazard ratios, HR_i, for use in equation (5.4). Again, the implementation of this probabilistic deterioration model is presented in the final project report [**Cavalline15**].

Abed-Al-Rahim, I. J. and Johnston, D. W. (1991). "Analysis of Relationships Affecting Bridge Deterioration and Improvement." Final Report NC/R&D/93-001, Department of Civil Engineering, North Carolina State University, Raleigh, North Carolina.

Cavalline, T.L., Whelan, M.J., Tempest, B.Q., Goyal, R., and Ramsey, J.D. (2015) "Determination of Bridge Deterioration Models and Bridge User Costs for the NCDOT Bridge Management System." Final Report FHWA/NC/2014-07, Department of Engineering Technology and Construction Management, University of North Carolina at Charlotte, Charlotte, North Carolina.

Duncan. S. and Johnston, D. W. (2002). "Bridge Management System Update." Final Report FHWA/NC/2005-06, Department of Civil Engineering, North Carolina State University, Raleigh, North Carolina.

Goyal, R. (2015). "Development of Survival Based Framework for Bridge Deterioration Modeling with Large-scale Application to the North Carolina Bridge Management System." PhD. Dissertation, University of North Carolina at Charlotte. Charlotte, North Carolina.