DEVELOPMENT OF DETERIORATION CURVES FOR BRIDGE ELEMENTS IN MONTANA

FHWA/MT-22-003/9831-765

Final Report

prepared for
THE STATE OF MONTANA
DEPARTMENT OF TRANSPORTATION

in cooperation with
THE U.S. DEPARTMENT OF TRANSPORTATION
FEDERAL HIGHWAY ADMINISTRATION

October 2022

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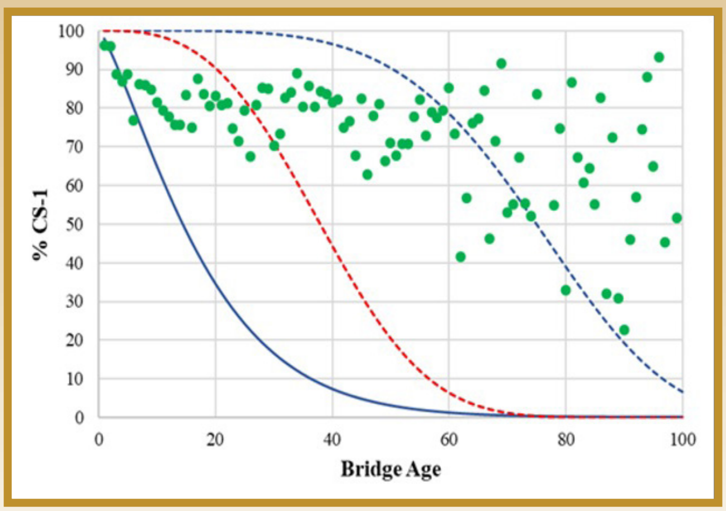

RESEARCH PROGRAMS

MONTANA
Department of Transportation

Development of Deterioration Curves for Bridge Elements in Montana

Final Report

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
FHWA/MT-22-003/9831-765		

4. Title and Subtitle
Development of Deterioration Curves for Bridge Elements in Montana

5. Report Date
October 2022

6. Performance Organization Code

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8. Performing Organization Report No.

9. Performing Organization Name and Address
Western Transportation Institute
Montana State University
205 Cobleigh Hall
Bozeman, MT 59717

10. Work Unit No.

11. Contract or Grant No.
MSU Project Number 4W8305
MDT Project Number 9831-765

12. Sponsoring Agency Name and Address
Research Programs
Montana Department of Transportation (SPR)
2701 Prospect Avenue
PO Box 201001
Helena MT 59620-1001

13. Type of Report and Period Covered
Final Report - April 2020 – October 2022

14. Sponsoring Agency Code
5401

15. Supplementary Notes:
Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration. This report can be found at https://www.mdt.mt.gov/research/projects/structures/deterioration-curves.aspx DOI: https://doi.org/10.21949/1518322

Recommended Citation:
Fick, D., and M. Bell. 2022. *Development of Deterioration Curves for Bridge Elements in Montana*. Helena, MT: Montana Department of Transportation. DOI: https://doi.org/10.21949/1518322

16. Abstract

The Federal Highway Administration has established measures for state departments of transportation to develop an asset management plan that includes deterioration forecasting to improve or preserve bridge conditions. The primary objective of this research was to support Montana's bridge management system by developing state-specific deterioration curves for bridges owned by the Montana Department of Transportation (MDT). The deterioration analysis used the National Bridge Inventory (NBI) data in combination with maintenance targets set by MDT. The deterioration curves developed for this research were designed to be compatible with AASHTOWare Bridge Management software (BrM).

This research utilized NBI element-level inspection data and a Weibull distribution to estimate the shape and spread of the deterioration curves. The input parameters required for BrM deterioration were calculated for six elements selected by MDT and reflected their maintenance priorities. The calculated deterioration curves for these elements predicted slower deterioration rates than those using BrM defaults. For steel girders, concrete abutments, and steel culverts, the deterioration curves were in reasonable agreement with the MDT maintenance experience. For reinforced concrete decks, prestressed concrete girders, and concrete culverts, the calculated deterioration curves predicted much slower deterioration rates than MDT's experience and the input parameters were revised. Differences in deterioration rates across Montana's five maintenance districts were investigated.

Results of this research will benefit state departments of transportation by providing baseline deterioration curves and trends that can be used to improve their optimization analyses. Recommended deterioration parameters for different bridge elements and transportation districts will enable MDT engineers to make efficient resource allocations for the selection and timing of preservation, rehabilitation, and replacement projects.

17. Key Words
Bridges, Deterioration, Structural deterioration and defects, Predictive models, Rehabilitation (Maintenance), Bridge management systems, Preservation.

18. Distribution Statement
No restrictions. This document is available through the National Technical Information Service, Springfield, VA 21161.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	56	

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1. Introduction

This final report summarizes the literature review, data review and processing, statistical analysis, and deterioration curve results for the Development of Deterioration Curves for Bridge Elements in Montana research project. The primary objective of this research was to establish deterioration curves for Montana bridges using inspection data and maintenance targets that could be implemented with AASHTO's Bridge Management software (BrM).

1.1 Background

Infrastructure in the United States includes 614,378 bridges, of which 9.1% were rated structurally deficient in 2016 and nearly 40% are over 50 years old [1]. Increasing traffic volumes and vehicle weights, along with harsh environmental exposure contribute to increased bridge deterioration and studies have shown that areas with higher levels of precipitation experience faster deterioration rates in bridge elements [2]. To maximize the impact of maintenance and preservation work, managers, planners, and decision-makers must have the data and tools available to determine the optimum strategy for bridges on a transportation network [3].

The Federal Highway Administration (FHWA) has established measures for state departments of transportation to implement the National Highway Performance Program (NHPP), which includes bridges that carry the National Highway System (NHS). As part of these measures, each state is required to develop an asset management plan to improve or preserve bridge conditions by maintaining a bridge management system that includes deterioration forecasting [4]. The objective is to assist bridge owners in prioritizing and efficiently performing maintenance, preservation, and/or re-construction on bridges. Achieving this objective requires the use of bridge inspection data to estimate bridge deterioration over time and to identify bridge work that will maximize service life and returns on investment.

The two formats of inspection data collected by state agencies and uploaded to the National Bridge Inventory (NBI) database are historical component-level data and the more recent element-level data. Component-level data (deck, superstructure, and substructure) records are available for years 1992-present from the NBI and are based on condition ratings of 0 through 9 for five components of bridge structures: bridge decks, superstructure, substructure, channels, and culverts. In 2015, State Departments of Transportation (DOTs) were required to submit inspection data that subdivided the area and length of a bridge element into different Condition State ratings using a scale of CS-1 to CS-4. Creating deterioration curves strictly from either NBI component- or element-level data is challenging because they inherently include incomplete/missing data fields, different time lengths, skewed distributions, and inspector bias. In addition, the inspection data does not include detailed documentation of bridge maintenance or rehabilitation and, therefore, represent the existing bridge condition rather than a strict deteriorated condition. To overcome these challenges, deterioration targets, based on MDT's experience, were used with the raw data trends and statistical analyses to calculate deterioration curves for Montana bridges.

The deterioration curves developed for this research were designed for implementation into AASHTO's BrM. This software was first developed during research sponsored by FHWA in the early 1990s as Pontis and was transferred to AASHTO for further development. BrM is a bridge management solution to assist engineers, managers, and decision-makers in the selection and timing of preservation, rehabilitation, and replacement projects for their structures [3]. BrM uses NBI element-level data and statistically derived input parameters to modify its default deterioration curves. A secondary objective of this research was to determine the BrM input parameters for deterioration curves developed using MDT's inspection data and estimated deterioration targets.

1.2 Summary of Work

The literature review identifies the current state-of-practice related to the use of stochastic and deterministic models to estimate deterioration rates of bridges. Different combinations of models, distributions, and statistical analyses were explored to select a strategy to develop deterioration curves for Montana bridges and input parameters for BrM. The review includes results and recent experiences of other state DOTs in their effort to develop deterioration curves for implementation into a bridge management system.

The data review and processing task considered both element- and component-level inspection data, from MDT's Structure Management System (SMS) and the NBI database, to identify representative datasets of different bridge types and deterioration indicators. These datasets were used to produce plots of bridge element ratings vs. age that characterize generalized trends from the unprocessed inspection data.

The statistical analysis task established a procedure that calculated deterioration curve parameters that were compatible with BrM using two different analysis approaches. Observations from the inspection data and results are summarized. With support from AASHTO's contractor for BrM and MDT, deterioration targets were established to confirm that the selected input parameters produced representative and reliable deterioration curves for bridge elements in Montana.

Using a time-based stochastic model, deterioration curves and parameters were developed using MDT's National Bridge Inventory (NBI) element inspection data. The data-based input parameters, calculated using the inspection data, resulted in deterioration curves that generally underestimated deterioration compared with the default curves in BrM. The deterioration trends were adjusted to reach approximate target values that represent reasonable deterioration trends based on MDT's experience. Recommendations were made for further refinements to the deterioration trends for concrete deck elements that would better reflect subtle differences observed in the five Montana maintenance districts.

2. Literature Review

The objective of the literature review was to identify different approaches to developing deterioration curves specific to Montana's climate, operation practices, and bridge design details. A review of other state departments of transportation efforts is included for insight on recent developments to more accurately perform state-wide investment optimization alternatives.

2.1 Bridge Deterioration Modeling

Estimating bridge deterioration can generally be classified into two groups, deterministic and stochastic modeling, and are described below.

2.1.1 Deterministic modeling

Deterministic modeling assumes that bridge deterioration is certain, and the models are based on a regression analysis of the condition data. The output in these models is fully determined by the parameter values and the initial conditions of the component or element being analyzed. Deterministic methods are based on the relationship of two or more variables related to the bridge's condition state. Linear regression does not provide enough accuracy for long-term performance of bridges, given its non-linear deterioration rate and may underestimate, or overestimate, the bridge condition at a specific time [5]. Nonlinear regression, such as polynomial curves for a condition state as a function of age provides a better estimate for most of the concrete bridges [6, 7]. The advantages of deterministic models are their simplistic approach to predict the future condition of the bridge, and their administration efficiency on a network level. The disadvantages are that they ignore uncertainty due to the stochastic nature of infrastructure deterioration, they can be expensive to update models when new data are available, and they ignore the interactions between the deterioration of different bridge element relationships.

2.1.2 Stochastic modeling

Stochastic modeling considers the bridge deterioration to be influenced by multiple factors and can capture the uncertainty of the deterioration process. The process includes some inherent randomness, as the same set of parameter values and initial conditions will result in an array of different outputs. The randomness is usually based on fluctuations observed over a certain time period and can either be classified as state-based or time-based.

2.1.2.1 <u>State-based approach</u>

State-based modeling predicts deterioration through the probability to transition from one condition state to another in a certain time interval. Markov chains have been extensively used in state-based models for analyzing the deterioration of road bridges using sets of measurable variables (e.g., age, ADT, climate, materials, etc.) [5, 8]. These models are developed by assuming bridges are inspected at fixed time intervals and the future bridge condition does not depend on past conditions [9]. One of the advantages of Markov models is their ability to include uncertainty from variations in the initial condition, applied stresses, inspection ratings, and the deterioration process itself. Other advantages include predicting future conditions based on present conditions and their computational efficiency [9]. The underlying assumption in these models is that the state of the system at a given time is not dependent on the intervention, or maintenance, history, thus assuming the effect of any improvement intervention over the bridge life is negligible[10].

Each Markov chain consists of an initial distribution matrix created from inspection data and/or expert opinions, and a probability transition matrix which represents the probability of moving from one condition state to the next within a unit of time [11]. The initial distribution matrix vector represents the current condition of a bridge element, and the future condition state can be calculated at any number of transition periods [12]. A method to solve the nonlinear problem using inspection data is through regression-based optimization. This method minimizes the sum of absolute differences between the regression curve that best fits the data and the conditions predicted using the Markov-chain model.

The advantage for the Markov model used in state-based models is that it provides a framework that accounts for uncertainty, it is compatible with the current bridge condition rating system, and the models are very practical at the network level. These models, however, are limited because the transition rates among condition states of bridge elements are time independent, they only provide a qualitative prediction of the future condition of the bridge elements (e.g., excellent, good, fair, poor), and the models cannot be used to assess the reliability of a structure in terms of strengths and stresses [11].

2.1.2.2 Time-based approach

The duration of a bridge element to remain in a specific condition for time-based models is considered a random variable using probability distributions to describe the deterioration process [13]. For applying stochastic models to small datasets, researchers suggest using component-level inspection [14]. Different probability distributions (e.g., Weibull, Gamma, etc.) are used to describe the deterioration process, and the amount of time a bridge element remains in a condition state is modeled as the dependent variable.

The advantages of time-based modeling are that Weibull-based methods utilize actual scatter in duration data for a particular condition rating and consider duration as a random variable. They have also been used to obtain an age-dependent probability of failure as an enhancement to the Markov model [15, 16]. The limitations to time-based modeling include the exclusion of interactions between bridge elements in relation to structural integrity, complexity in the estimation of condition states where there is a lack of data, and a requirement of at least 20 years of inspection data available [17, 18].

2.2 Models

Within both the deterministic and stochastic frameworks described above, physical or machine learning models can be used to estimate the transition of a bridge element from one condition state to another. These models can be used separately, or together, to analyze and predict the future outcome of bridge deterioration. Methods and assumptions for these two methods are described below.

2.2.1 Physical models

Physical models can be designed to increase the accuracy of probabilities used to estimate changes in bridge element conditions. This type of model is a physical experiment that captures the effect of a certain parameter on a selected bridge element in a controlled environment.

Physical experiments assume that bridge elements can be characterized by relationships between individual elements and other external conditions (e.g., weather, chloride deicers, etc.). They improve the accuracy of probability estimates because they can relate the estimated qualitative measurement to the physical parameters of the bridge. These parameters are critical to assessing the capacity and service life of the structure. For example, to model the chloride-induced corrosion of steel reinforcement, an existing interaction simulation can be mapped to condition states in which the results can be used to calibrate Markov probability matrices to fit the simulation results [19]. Advantages of using physical models is that they are suitable for project level analysis and they provide reliable quantitative deterioration predictions for bridge elements [5]. Some limitations of physical models are that they can be costly to conduct and difficult to apply to large bridge networks.

2.2.2 Machine learning models

Machine learning techniques for data analysis is a branch of artificial intelligence (AI) based on the idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention. These types of models can be used on bridges that have a limited amount of data. It has been found that using an artificial neutral network (ANN) backwards prediction model (BPM), it is possible to create artificial historical bridge condition states [20, 21]. There are many different types of machine learning models that are inspired by actual historical data and are used to approximate unknown functions and influential variables. These models can learn from the experiences of training data and apply algorithms to provide values for missing data. The AI systems learn to identify the relationships between different parameters and are used to develop a network that can be used to solve the problems for unknown datasets, or to update model parameters when new information is available [22, 23].

An advantage of machine learning is its ability to generate missing bridge condition state data to fill gaps, and the ability to apply case-based reasoning to different maintenance scenarios by retrieving bridge data with similar maintenance decisions from available data and conducting an analysis. Although, this is a way to generate missing data, AI still needs complementary tools to generate information for bridge deterioration. It is important to utilize large datasets to insure accuracy of AI for case adaptation [5].

2.3 State DOT Deterioration Analyses

Several states have recently completed research projects related to deterioration curve modeling using both deterministic and stochastic models. Research reports published by these departments of transportation that overlap with objectives of this research are summarized below.

2.3.1 Nebraska

Recently completed research by the Nebraska Department of Roads investigated developing state-specific deterioration models for use in BrM [12]. Using data from the Nebraska bridge management system, they developed deterioration models and identified deterioration trends related to concrete decks in different transportation districts based on AADT, epoxy coated rebar, and structure type.

2.3.2 *Wyoming*

The state of Wyoming developed deterioration models using both stochastic and deterministic models using the NBI inspection data and inspection data from WYDOT [14]. Two stochastic deterioration models were created for different bridge ages; one for the first 30 years and a second model for 30+ years in order to leverage the large amount of accumulated data. Results from the deterministic models of this investigation found that Lease Absolute Shrinkage and Selector Operator (LASSO) regression, a type of machine learning, can reduce human bias from the selection of explanatory variables. Wear surface, structure length, functional class, and ADT were identified as significant for deck condition rating. Superstructure ratings were influenced by deck structure type, bridge roadway width, functional class, and max. span length.

2.3.3 *Wisconsin*

Artificial neutral network (ANN) -based models were used to estimate the deterioration of bridge decks in Wisconsin. The study identified 11 significant factors that include age, design load, maintenance history, length, ADT, deck area, environment, number of spans, degree of skew, district, and the previous condition rating [22]. Researchers reported their model had the accuracy to predict the condition of bridge decks and therefore provide very important information for maintenance planning and decision making at both a project and network level.

2.3.4 *Indiana*

The Indiana Department of Transportation developed families of deterioration curves using the NBI database [24]. The condition ratings were used as the response variable and families were categorized by administration region, functional class, and superstructure material type. The explanatory variables were traffic volume, truck traffic, climatic condition, and design type and features. The study concluded that environmental variables contribute significantly to bridge deterioration. Major predictors were freeze index, freeze-thaw cycles, and average precipitation [24].

In a second study, researchers conducted performance evaluations and life predictions of concrete bridge structures across design type. Exponential and polynomial functions were investigated as part of the modeling process. Some explanatory variables (e.g., age, ADTT, and freeze-thaw cycles) were found to have significant influence on the deterioration of concrete bridge superstructures' condition across all design types, while others (e.g., number of spans, skew, precipitation, and ADT) were only found to influence a few of the design types [25]. Using their models, researchers estimated cast-in-place concrete bridges in Indian had a service life of 53 to 71 years. The developed models were used to predict the future performance of the superstructure condition.

A third study looks at bridge surface and pavement maintenance activities on the condition ratings of assets. Deterministic linear models were used to assess performance jumps for preventative maintenance and logarithmic models were used for rehabilitation and replacement treatment [26]. The performance jumps showed that the asset's functional class, pre-treatment condition, and treatment type were significant predictors. For the post-treatment performance, deterioration rates were modeled from an elevated condition rate after the previous performance jump was applied to measure the extension in service life of the deck.

A fourth analytical study by Saeed [10] introduced a method to incorporate newly introduced explanatory variables to capture the types of maintenance activities and the degree to which they were effective by defining and quantifying the types of intervention. It demonstrates how the developed probabilistic modeling methodology can be implemented to predict the probability that a bridge component will be at a certain condition state at a given year [10].

2.3.5 New York

The City University of New York compared Markov chains and Weibull-based deterioration bridge models for the New York DOT. They found that the Weibull-based approach performed better probabilistically in terms of the observed bridge element conditions [16]. This may be to the inclusion of the duration dependency and right censoring characteristic of the data. This approach takes the scatter in the data at a particular age by calculating Weibull-distribution parameters. They recommend using this method on bridge elements in each state, as their equations were not applicable outside of New York.

Another study predicted long-term bridge deterioration ratings and patterns of bridge elements to optimize maintenance strategies. They developed an approach that incorporates a time-based model, a state-based model with a Elman neural network (ENN), and a backwards prediction model (BPM) using 40 bridges with 464 bridge substructure inspection records as inputs [27]. Although the two approaches were equal in predicting short-term condition states, and were more accurate than the standard Markov-based procedure for long-term predictions over a period up to 25 years. This method did not consider maintenance improvements, and researchers recommended further modeling to assess the true long-term estimates of condition states.

2.3.6 California

Purdue University used stochastic regression to model deterioration of prestressed concrete bridges in California. Using NBI data, researchers identified the variables affecting superstructure deterioration and built models to predict the bridge condition of four structure types: slab, stringer/multi-beam or -girder, t-beam, and box-beam or -girder. Using regression techniques and Monte Carlo simulation they identified eight variables (age, ADT, degree of skew, max. span length, structure length, roadway width, deck width, and average daily truck traffic) on the superstructure deterioration that have high coefficient of determination [28]. The Monte Carlo simulation calculated results for thousands of cases using different randomly selected values of the explanatory variables and was expressed as a probability distribution to simulate real-world processes. These models were validated using the Average Validity Percentage method.

2.3.7 Texas

This study used a semi-Markov process for life-cycle optimization models for highway bridge maintenance activities, because the traditional Markov process cannot capture the real time at which the bridge state transitions. Their models used bridge specific information (e.g., age, materials, environmental conditions, ADT, etc.) to model the service life deterioration behavior of bridges in a specific environment, assuming the state transition has the Markov property and the holding time in each state is assumed to follow a Weibull distribution [29]. Their proposed models were able to predict the repair effects of maintenance and captured the post-performance of the bridge. The models were based on steel bridges in Texas, but researchers concluded the approach is applicable to other types of bridges.

2.3.8 Pooled Fund

Twelve Midwest states are currently performing research related to deterioration modeling and developing new analytical tools to develop deterioration curves for bridge elements using inspection data from bridges in their own state. Research is specifically considering element-level deterioration, operation practices, maintenance activities, and historic design/construction details [30]. The study objective is to develop a select number of deterioration curves for the time-dependent deterioration of bridge elements that reflect Midwest environments.

2.4 Updated State Departments of Transportation Experiences

To further investigate the inspection data challenges experienced in this research, a second literature review was completed in search of more-recent publications documenting the experiences of other state departments of transportation. Results published by Washington state, Kentucky, and Georgia are summarized below.

2.4.1 Washington State

The Washington State Department of Transportation evaluated the potential implementation of BrM in 2018 within Washington's risk-based asset management framework [31]. The strategy estimated a timeline of 775 working days and a budget of $462,875 for deterioration modeling, consultant project support, hardware, and contingency.

2.4.2 Kentucky

In 2019, the Kentucky Transportation Cabinet (KYTC) reported their efforts to implement NBI element data into BrM [32]. An initial review of the data by the University of Kentucky concluded there were not enough data points in CS-3 and CS-4 to complete a reliable analysis. Researchers were unsuccessful in obtaining data from other states to fill in these gaps, due to a similar lack of data points. The unavailability of sufficient element-level data points resulted in the KYTC to postpone their deterioration modeling until such data becomes available.

2.4.3 Georgia

Rather than using NBI element data, the Georgia Department of Transportation used 25 years of historical NBI component data to successfully create depreciation models using the Markov chain approach [33]. Their results were able to estimate expected service lives and condition ratings of bridges over a 100-year timeline.

The results of Washington state and Kentucky illustrate the potential resources required and challenges associated with implementing BrM using NBI element data. The report from Georgia, however, provides incentive to pursue component-level data with Markov chains to estimate deterioration trends of Montana bridges.

2.5 Summary

Literature related to statistical analysis methods for modeling bridge deterioration and recent efforts by other state departments of transportation was reviewed. The most applicable information obtained from the literature review for this project includes:

- Time-based stochastic models introduce randomness and uncertainty and have been used successfully by other researchers to model deterioration curves.

- Five out of the 10 state agencies represented in the literature review identified significant factors that influenced the deterioration of concrete decks including ADT, functional class, transportation district, age, deck treatment, and freeze thaw cycles among others.
- New York state concluded that a Weibull statistical distribution characterized bridge deterioration better than a Markov approach.

3. Inspection Data Review and Processing

Inspection data from MDT's Structure Management System (SMS) and the Federal Highway Administration's (FHWA) National Bridge Inventory were used to create datasets of different bridge types and in different regions to review bridge deterioration trends of the raw, unfiltered inspection data. With input from MDT, selected bridge attributes were refined, and computer routines developed to create plots of bridge element ratings vs. age for different bridge groups.

3.1 MDT's Structural Management System Bridge Data

A component-level dataset was created by the research technical panel from MDT's SMS that contained 5,039 bridges with inspection dates going back to 1970. The attributes associated with each bridge included construction and maintenance activity, location, geometric design, materials, traffic use, and the current condition of the bridge deck using the National Bridge Inventory condition ratings of 0 to 9 as shown in Table 1. MDT maintains approximately 2,938 of these bridges with locations across Montana shown in Figure 1. The location of MDT maintained bridges generally consists of main traffic corridors, highways, and interstates (i.e., on-system routes).

Table 1: Description of the condition ratings used in NBI databases.

NBI scale	Condition	Description
9	Excellent	New condition, no noteworthy deficiencies
8	Very good	No repair needed
7	Good	Some minor problems, minor maintenance needed
6	Satisfactory	Some minor deterioration, major maintenance needed
5	Fair	Minor section loss, cracking, spalling, or scouring for minor rehabilitation, minor rehabilitation needed
4	Poor	Advanced section loss, deterioration, spalling or scouring; major rehabilitation needed
3	Serious	Section loss, deterioration, spalling or scouring that have seriously affected the primary structural components
2	Critical	Advanced deterioration of primary structural elements for urgent rehabilitation; bridge maybe closed until corrective action is taken
1	Imminent failure	Major deterioration or loss of section; bridge may be closed to traffic, but corrective action can put it back to light service
0	Failed	Out of service and beyond correctives action

The research technical panel also provided historical bridge deck ratings from their SMS. Approximately 75,000 rows of data exist for the 5,039 bridges with each row representing a different inspection year. The structural bridge identification numbers in this database were matched to the 2,938 bridges maintained by MDT to exclude ratings for bridge decks maintained by others. This data was used to further explore computer routines to investigate bridge characteristics and temporal periods where deterioration may vary due to different construction techniques and materials.

3.2 FHWA's National Bridge Inventory (NBI) Data

A complete dataset of NBI component-level data is available from the FHWA website (https://www.fhwa.dot.gov/bridge/nbi/ascii.cfm) for years 1992-present. This data includes condition ratings of 0 to 9 (Table 1) for the five components of bridge structures: bridge decks, superstructure, substructure, channels, and culverts.

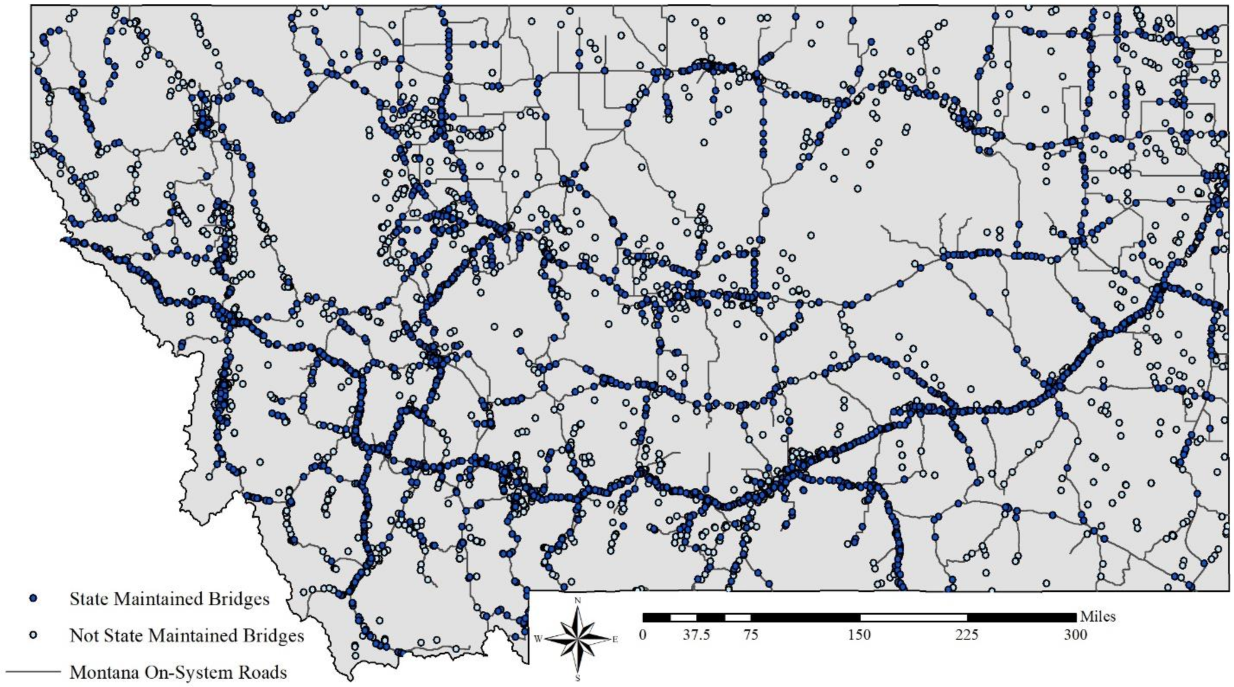


Figure 1: Locations of all the bridges in Montana.

In 2015 State Departments of Transportation (DOTs) were required to submit inspection data that subdivided the quantity of a bridge element into different condition state ratings shown in Table 2. This NBI element data contains the total area or length of the element and the condition state associated with the component area/length. The NBI Element data are available from the FHWA website (https://www.fhwa.dot.gov/bridge/nbi/element.cfm) and contains the years from 2015 to present [34].

Table 2: Condition State definitions

Condition State 1 (CS-1)	Good
Condition State 2 (CS-2)	Fair
Condition State 3 (CS-3)	Poor
Condition State 4 (CS-4)	Severe

There are currently no accurate methods to convert the NBI element condition state levels, CS-1 to CS-4 to the inspection data collected prior to 2015 which uses a 0-9 scale. Because of this, the historical data was evaluated independently and compared with deterioration predictions made with the more recent condition state ratings.

3.3 Preliminary Data Processing

Simple regression lines for concrete bridge deck ratings and age were created for the MDT SMS dataset that included all 5,039 bridges in Montana and is shown in Figure 2. The figure illustrates the importance of creating smaller, more specific groups of bridge rating datasets, where trends between bridge deck rating and bridge age can be more insightful. As the bridge datasets get smaller, such as concrete bridges in the Billings region or bridges with average daily traffic (ADT) of 10,000-19,999 as shown in Figure 3 and Figure 4 respectively, it is possible to more clearly see deterioration trends within a group.

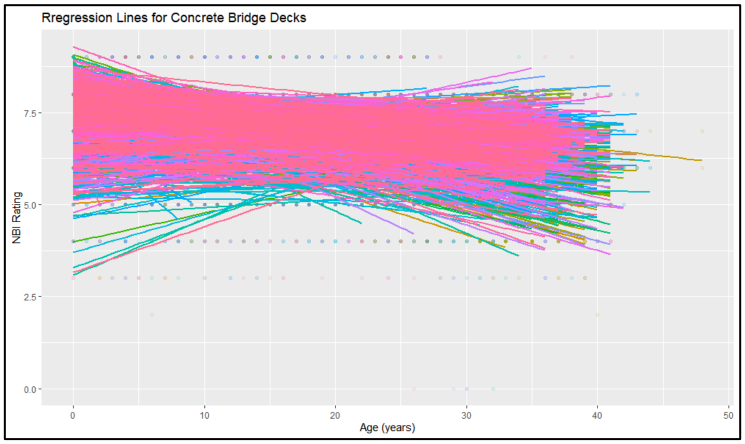


Figure 2: Regression lines for NBI values vs. age for decks of concrete bridges in Montana.

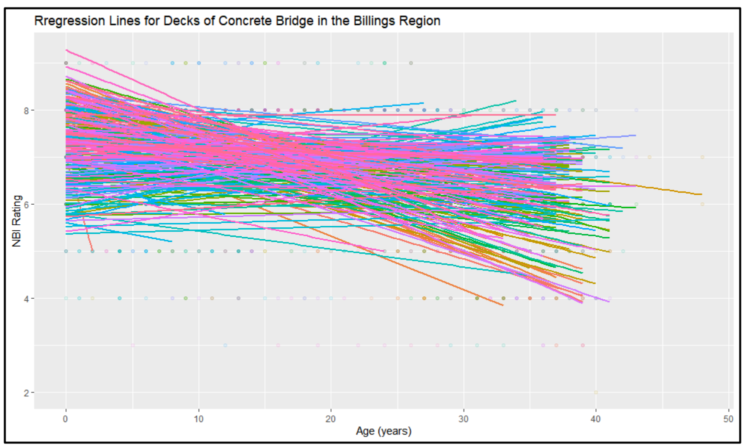


Figure 3: Regression lines for NBI values vs. age for decks of concrete bridges in Billings, Montana.

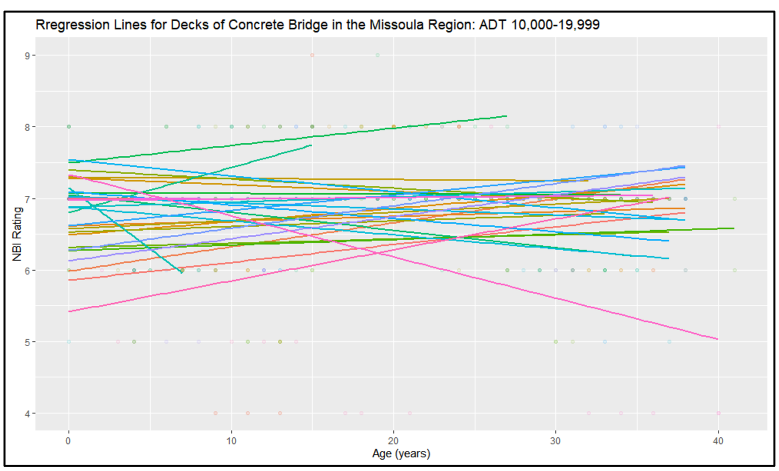


Figure 4: Regression lines for NBI values vs. age for decks of concrete bridges in Missoula, with an ADT of 10,000-19,999 vehicles.

The NBI bridge deck ratings vs. age plots shown in Figure 2 through Figure 4 do not represent true bridge deck deterioration because the effects of maintenance are included with the inspection ratings. The upward and/or neutral trend of some of the regression lines for the average bridge deck ratings reflects the inclusion of bridge deck maintenance in the NBI rating.

Other factors that contribute to the challenge of creating true bridge deterioration curves from the inspection data include the variability of bridge inspector judgement and guidance provided by the FHWA for certain bridge types. In addition, only 22% of Montana bridge decks included a CS-3 rating and only 3% with CS-4 in 2020 and suggests a program that performs maintenance when poor condition element quantities (CS-3) are a relatively small percentage of the overall element quantity. For example, a 32 ft wide bridge deck with four, 2 ft wide wheel paths would represent 25% of the bridge deck area. If half of the wheel path area is rated as CS-3, or poor condition, the overall CS-3 bridge deck area would be approximately 12.5%. This would result in a bridge deck with an extremely rough ride and would be a candidate for an entire deck replacement because of complaints from the traveling public.

4. Statistical Analysis

To overcome the NBI element data challenges described in the previous section, a statistical analysis was used to create unbiased deterioration curves from the raw inspection data for six bridge elements (concrete decks, steel beams, prestressed concrete girder, concrete abutment, steel culverts, and concrete culverts). The calculated statistical parameters were refined using maintenance targets relative to MDT's experience and trends observed from the raw data.

Two methods, graphical and algebraic, were used to calculate parameters that define the Weibull distribution. The deterioration trends were compared with the deterioration curves calculated in BrM using its default parameters, which were determined to be a reasonable starting point representing a lower bound, or faster estimation of deterioration. Plots of raw inspection data, deterioration targets, and experience from MDT engineers were used to select the appropriate analysis method for further refinement.

The objective of the statistical analysis task was to select an appropriate analysis method and develop a method to adjust deterioration curve parameters based on raw inspection data to obtain deterioration curves that align with MDT's experience while working in the framework of BrM functionality.

4.1 BrM Deterioration Curves

BrM uses a Weibull distribution to define the bridge deterioration from CS-1 to CS-2, followed by a Markov model to estimate the deterioration curves from CS-2 to CS-4. The input parameters used by BrM to calculate the deterioration curves include the median years in CS-1, CS-2, and CS-3, and a Weibull shape factor (β). The shape factor defines the initial slope of the deterioration curve and the median years determines the length of time over which the deterioration occurs in each condition state. As shown in Figure 5, a higher β value produces less deterioration during early bridge ages followed by a steeper curve and faster deterioration expected as the bridge age increases. A β value between 0-1 ($0 < \beta \leq 1$), creates a concaved deterioration rate that is similar to deteriorations calculated using a Markov model.

A trial version of BrM was used to evaluate deterioration curves for bridge elements using the default input parameters, which represent average reported values from five states (Alabama, Idaho, New York, California, and Kentucky) in 2013. The default values for reinforced concrete bridge decks are shown in Table 3.

Table 3: BrM default input parameters for concrete bridge decks.

Parameter Estimates	Shape Factor	Median Years CS-1	Median Years CS-2	Median Years CS-3
BrM Default	1.3	14.4	42	14.9

Due to a lack of data related to bridges in CS-3 and CS-4, the statistical analysis for this research considered only the transition from CS-1 to CS-2 and was used as a starting point for the implementation of BrM by MDT.

4.2 Weibull Distribution

Bridge element deterioration does not have a normal distribution and is typically skewed towards bridges in good condition (CS-1) that exist at lower bridge ages. The Weibull distribution has been shown by DeLisle et al. [35] to provide a good overall fit for infrastructure deterioration data and was verified by Agrawal et al. [16]. The Weibull distribution used by BrM to evaluate the deterioration between CS-1 and CS-2 can be defined by a 2-parameter Weibull distribution [36] shown in the following equation:

$$y = \beta[-\ln{(x)}]^{1/\alpha} \qquad \text{Equation 1}$$

Where β is the shape factor, and α is the scale factor associated with the data. The effects of the shape factor (β) used in a Weibull distribution can be seen in Figure 5. Larger shape factors result in a faster deterioration rate.

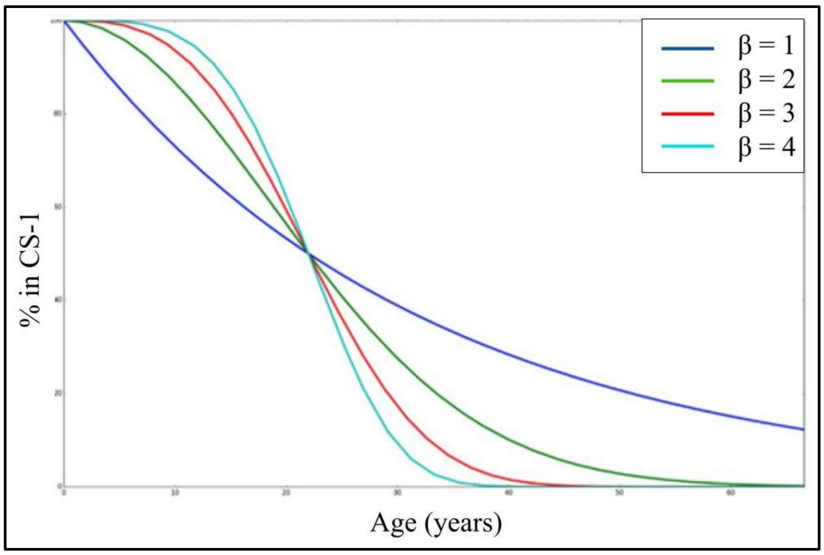


Figure 5: Effect of the shape factor (β) on Weibull Modeled Deterioration (adapted from [3]).

The median years in a Weibull distribution for this application locates the middle point, or half-life, of the bridge element deterioration. It can be calculated using the scale factor, α, and shape factor β using Equation 2.

$$median = \alpha(\ln 2)^{\frac{1}{\beta}} \qquad \text{Equation 2}$$

Two methods, graphical and algebraic, were investigated to estimate the shape factor (β) and the median number of years in CS-1 for the Weibull distribution used by BrM. The statistical analysis procedures were tested using the National Bridge Inventory (NBI) element inspection data for all reinforced concrete decks maintained by MDT. A single year of inspection data (2020) is used for the algebraic statistical analysis and is assumed to include a reasonable representation of the percentage of bridge deck area reported by inspectors as CS-1 for all bridge ages.

4.2.1 Graphical method

The graphical method to describe a Weibull distribution uses one-year time increments and the entire dataset to represent the deterioration of different bridge elements [37]. There are multiple observations for each time-step (i.e., there are multiple bridges that have the same age), so the condition state for bridges with the same ages are averaged leaving only one observation per time-step. The bridges are then arranged in ascending order by the average percentage of deck area in CS-1.

After the bridges are ranked, each time-step is assigned a probability. For this research, the probability (P) was calculated using the formula in Equation 3, where *Rank* and *n* are the ascending rank and number of observations, respectively. Using these assigned probabilities, the *x*- and *y*-values are calculated using Equation 4 and Equation 5 for each time step. Example results for the calculated probabilities and *x* and *y* values are shown in Table 4.

$$Probability = \frac{(Rank - 0.5)}{n} \qquad \text{Equation 3}$$

$$x = ln(CS1) \qquad \text{Equation 4}$$

$$y = ln(-ln\,(1-P)) \qquad \text{Equation 5}$$

Table 4: Example (top ten rows) of organized CS-1 bridge deck data used to estimate Weibull parameters.

Bridge Rank	**Average % Deck Area in CS-1**	**P *(Rank-.5)/n***	**Y *(ln(-ln(1-P)))***	**X_CS1 (*ln*(CS1p))**
1	22.6602	0.0051	-5.2857	3.1206
2	26.1263	0.0152	-4.1820	4.5657
3	32.0000	0.0253	-3.6661	3.4657
4	33.0384	0.0354	-3.3244	3.4977
5	41.5346	0.0455	-3.0679	3.7265
6	45.3344	0.0556	-2.8619	3.8141
7	45.9862	0.0657	-2.6896	3.8283
8	46.2039	0.0758	-2.5411	3.8331
9	51.6435	0.0859	-2.4105	3.9444
10	52.0168	0.0960	-2.2938	3.9516

A linear regression line of the calculated *x*- and *y*-values for the averages of bridges with the same age for the entire dataset is shown in Figure 6. The slope of the regression line through the data points is the shape factor (β). The scale factor (α) corresponds to the y-intercept, which can be estimated from the trend line or calculated by substituting $x = 0$ into the Weibull distribution Equation 1. A rearranged Equation 1 to solve for the scale factor, α, is shown in Equation 6. Once the values of α and β are known, the median number of years can be calculated using Equation 2.

$$\alpha = e^{\frac{-y}{\beta}} \qquad \text{Equation 6}$$

4.2.1.1 Evaluation of the graphical method

The graphical method is a true representation of the data using a Weibull distribution because it considers every line of data and adjustments are not made to fit the desired outcomes. For all reinforced concrete bridge decks maintained by MDT (*n* = 1,549), the graphical Weibull distribution plot in Figure 6 results in a shape factor, β = 4.74 and median years in CS-1 equal to 75. The age of the bridge deck was calculated using the "year built" field in the inspection data.

It is acknowledged that older bridges with recent bridge deck repairs or replacements would contribute to an underestimate of the bridge deterioration using the age calculated from the year-built data field. Because of the inconsistent recorded bridge deck maintenance in the inspection database, the year-built field was chosen to calculate the age to minimizing uncertainties introduced from the inclusion of bridge maintenance records.

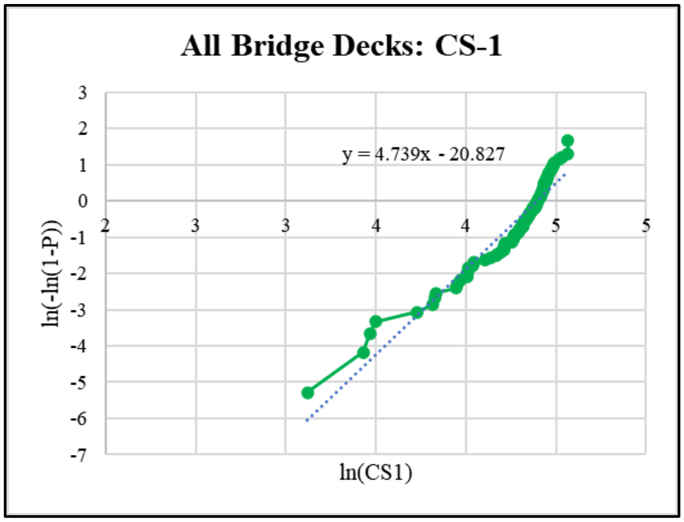


Figure 6: Weibull distribution - graphical representation of all bridge decks in CS-1.

Entering these parameters into BrM and using default values for median years in CS-2 and CS-3, the deterioration curves for CS-1 were calculated and are shown in Figure 7. The estimated deterioration curve is the dashed line and the solid line represents the deterioration curve using the BrM default values (β = 1.3, median years in CS-1 = 14.4). Compared with the default BrM deterioration curve, the estimated trend using values calculated from the graphical approach has a slower deterioration rate than the default BrM values that is caused by the large shape factor (β = 4.74) and a large median year value for CS-1 of 75. The trend suggests that reinforced concrete decks will have 95% of their surface area rated as CS-1 at a bridge age of approximately 45-years, as indicated by the green lines in Figure 7. This deterioration rate may not be unreasonable for low-volume roads based on MDT's experience. However, because all concrete bridge decks were used to create the BrM input parameters, this trend will underestimate the deterioration curves for bridge decks with higher traffic volumes.

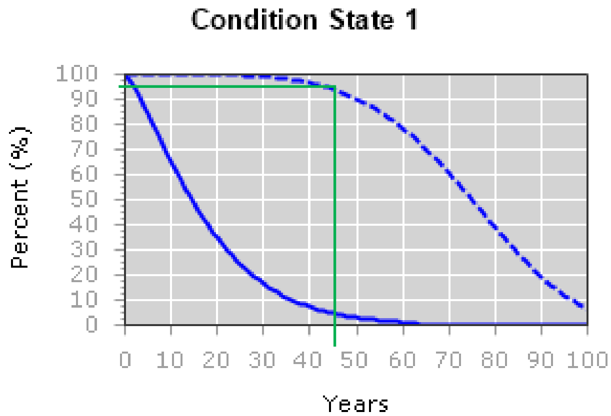


Figure 7: Deterioration curves for shape factor, β = 4.74, and median years in CS-1 equal to 75 (dotted line). The solid line is the BrM default deterioration curve.

4.2.2 Algebraic method

The second statistical method investigated was the algebraic method, which is similar to the graphical method but instead of including the entire dataset, only three bridge ages are used to calculate the Weibull parameters α and β. It allows for some flexibility to adjust the calculated input parameters by selecting different groups of bridge ages. The Weibull parameters are calculated using the same method as the graphical method with data from three bridge ages. Selecting different bridge ages allows deterioration trends to be modified to obtain Weibull parameters and deterioration curves that more-closely match expected values.

4.2.2.1 <u>Evaluation of the algebraic method</u>

The algebraic method uses only three lines of aggregated NBI element data from the complete dataset to estimate parameters for a Weibull distribution. To compare with the geometric method results presented above, the entire dataset was arranged (ranked) by percentage of bridge deck area rated in CS-1. Four arbitrarily selected lines of the reinforced concrete deck element data with ranks of 2, 25, 50, and 99 were selected to demonstrate how to calculate the Weibull parameters using the equations in Section 4.2.1 and how selecting different bridge deterioration ranks can influence the shape factor and/or median years in CS-1. The results are shown Table 5. The three lines of data used to estimate the BrM input parameters α and β were ranked 2, 25, and 50 and 2, 25, and 99. The two groups were selected to show how changing the selected bridge ranks will alter the parameter estimates.

Table 5: Four selected rows of CS-1 Weibull distribution data used for the algebraic method parameter estimates.

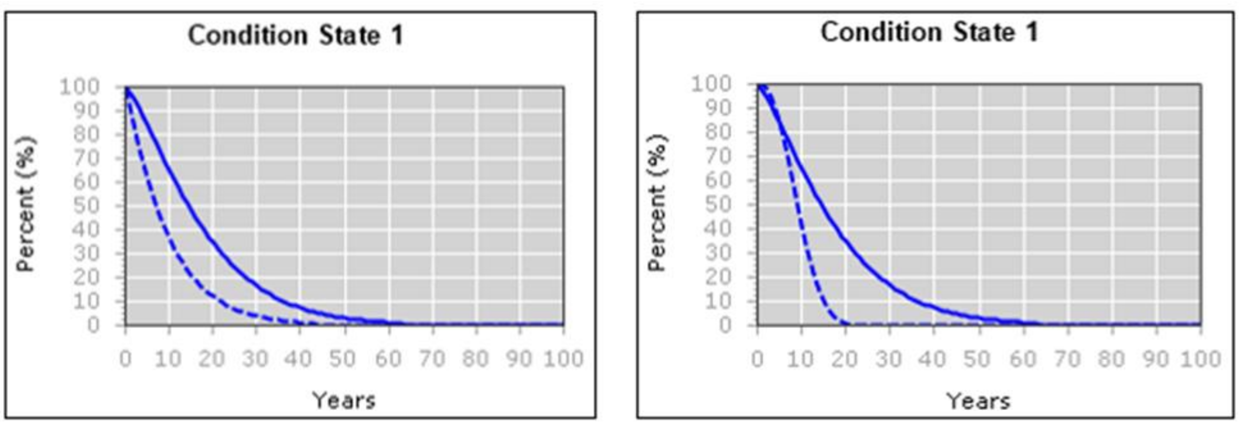
Bridge Rank	**Average % Deck Area in CS-1**	**P *(Rank-.5)/n***	**Y *(ln(-ln(1-P)))***	**X_CS1 (*ln*(CS1p))**
2	96.1263	0.0152	-4.1820	4.5657
25	96.0138	0.2475	-1.2577	4.5645
50	93.2127	0.5000	-0.3665	4.5349
99	30.8747	0.9949	1.6655	3.4299

The process for calculating the BrM input parameters using the algebraic method with three selected lines of data involves the incremental application of the Weibull equations described in Section 4.2. For example, an expression for β in Equation 1 using *x*- and *y*-values from the 2-year bridge-age data (Table 5) can be used to solve for α in Equation 2 using the median years in CS-1 for the selected 25-year bridge age. This substitution results in a calculated scale parameter, α, of 10.0 that represents data for the first and second selected bridge ages. The α value can then be substituted back into Equation 1 using *x*- and *y*- values for the third bridge age to calculate β. The median years in CS-1 is then calculated using Equation 2 with β and α from the first- and second- bridge ages selected.

The BrM input parameters calculated using the algebraic method and bridge ranks of 2, 25 and 50 and 2, 25, and 99 for all bridge decks maintained by MDT (n = 1,549) are shown in Table 6. The BrM-calculated deterioration curves using these input parameters are shown in Figure 8. Unlike the CS-1 deteriorations calculated using the graphical method (Figure 7), the dashed line in Figure 8 suggest a more aggressive deterioration trend than the BrM default values shown by the solid line.

Table 6: BrM input parameters using algebraic method.

Bridge Rank	**β**	**median years in CS-1**
2, 25, 50	1.06	7
2, 25, 99	2.36	9



(a) β = 1.06 and median years in CS-1 = 7

(b) β = 2.36 and median years in CS-1 = 9

Figure 8: Estimated bridge deteriorations (dotted lines) for CS-1 using the algebraic method using (a) bridge ages of 2, 25, and 50 years and (b) using bridge ages of 2, 25, and 99 years.

4.3 Statistical Methods Assessment

The algebraic method for calculating the Weibull distribution parameters considering three arbitrarily selected lines of NBI element data represented a lower-bound, or faster deterioration than the default BrM curve (Figure 8). Deterioration parameters calculated using different lines of data (Table 6) resulted in shape factors of β = 1.06 and 2.36 and creates an arbitrary source of variation that was considered undesirable. Conversely, the input parameters calculated using the graphical method represented an upper bound, or slower deterioration, than the default BrM curve (Figure 7) and is a true representation of the data because every line of NBI element data are considered, without bias.

The preliminary results from the graphical method analysis revealed slower deterioration trends that suggested 95% of bridge deck areas remain in CS-1 for up to 45 years (Figure 7). Although these estimates may not be realistic for high volume bridges based on MDT's experience, a closer review of all NBI element inspection data does support the underestimated deterioration calculated using the graphical method.

A review of the reinforced concrete bridge elements rated in CS-1, CS-2, CS-3, and CS-4 can be used to support the slower deterioration parameters calculated using the graphical method. In 2020, approximately 14.9 million square feet of reinforced concrete deck area were inspected for 1,549 bridges in Montana, with bridge ages ranging from 1 to 99 years. For all bridge ages, the median percentage of bridge deck area rated as CS-1 was 75%. The median percentages for CS-2 and CS-3 were 22% and 3% respectively. The distribution of the 2020-year CS ratings is shown in Figure 9 below indicates 92.6% of all bridge decks have less than 15% of their total area in CS-3 and 99.8% of bridge decks did not include CS-4 rating. Figure 9 helps to visualize how the data are distributed between different condition states and confirms the challenge with trying to estimate deterioration trends with small percentages of bridge deck areas rated in CS-2, CS-3, and CS-4.

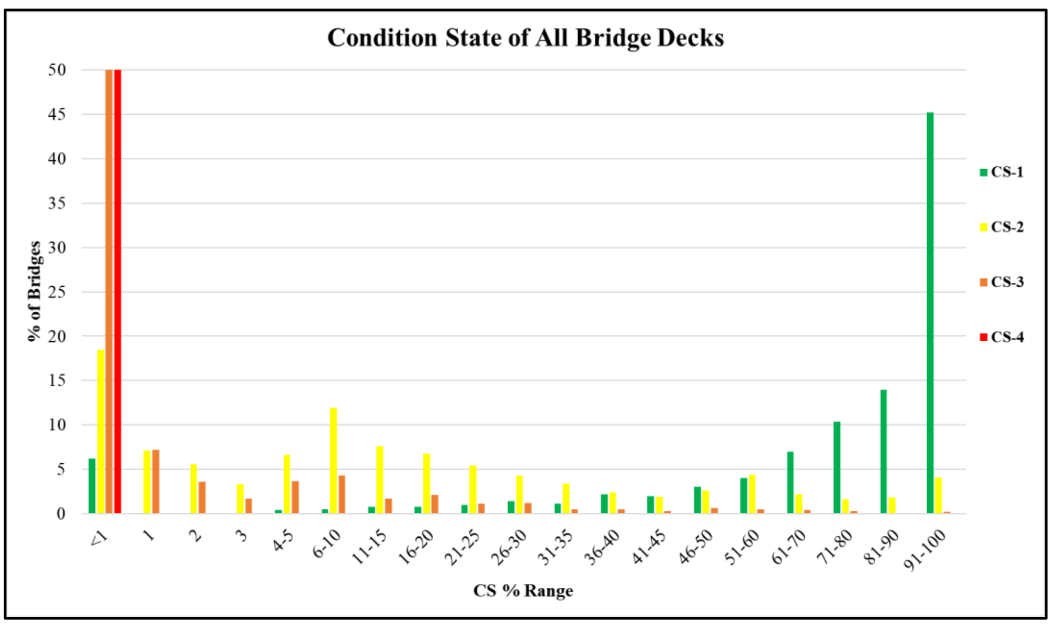


Figure 9: Percentage of bridges in each condition state based on the percent of the bridge deck element areas in each associated condition state.

The slower deterioration parameters calculated using the algebraic method are generally supported by the data and may represent actual deterioration for low-volume bridges. To represent bridges carrying higher-volume traffic, the deterioration trends can be intuitively accelerated by refining the calculated deterioration parameters. For these reasons, the graphical method was selected for further evaluation.

4.4 Deterioration Parameters for Other Datasets

Deterioration parameters (β and median years in CS-1) for reinforced concrete deck deterioration were calculated for additional datasets that included bridges without maintenance and interstate bridges with and without maintenance.

The deterioration curve calculated for 896 bridges maintained by MDT that did not have documented maintenance reported in the NBI element database is shown in Figure 10. Removing the bridges with reported maintenance slightly reduced the shape factor ($\beta = 3.80$ compared with $\beta = 4.74$) but kept the median years in CS-1 approximately the same (75.3 compared with 75.0). The reduced shape factor resulted in a faster deterioration in CS-1 with 95% of bridge deck areas remaining in CS-1 after approximately 35 years (compared with 45 years) as shown in Figure 7. A faster deterioration rate (smaller β) would be expected when bridges with reported maintenance are removed from the dataset. The calculated deterioration excluding bridge decks with recorded maintenance shown in Figure 10 approximately represents MDT's experience where it is not uncommon for low volume roads to have 95% of the bridge deck rated as CS-1 after 30 years.

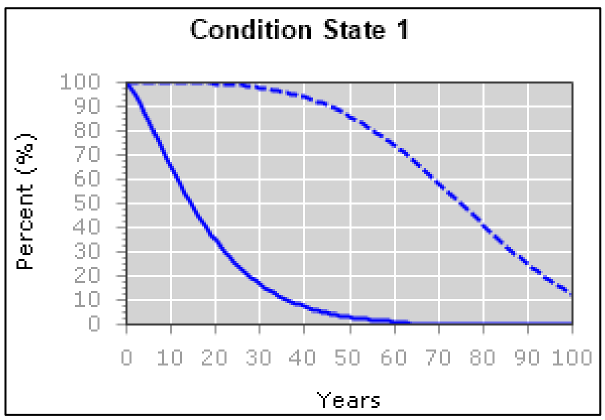


Figure 10: Deterioration curves for a shape factor of 3.8 and median years at CS-1 equal to 75.3 (dotted line). The solid line is the BrM default deterioration curve.

For bridges along Interstate-15, with and without reported maintenance, deterioration parameters were calculated using the graphical method and are shown in Table 7 with the statistical summary. Recognizing that higher shape factors (β) and higher median years in CS-1 contribute to slower deterioration trends, calculated curves would be slower than those shown in Figure 7 and Figure 10 for all MDT-maintained bridges. The underestimation of deterioration for the two interstate groups is likely due to the increased and potentially unreported maintenance activity in the inspection database and could also reflect the MDT's objective to prioritize maintenance for bridges with high traffic volumes.

4.5 Refined Analysis and Validation

The preliminary results to estimate input parameters from a Weibull distribution and MDT's current NBI element data resulted in varying degrees of confidence for identifying deterioration trends of reinforced concrete bridge deck elements. To improve the reliability and accuracy of the calculated deterioration parameters, observations from graphical presentations of the data were investigated.

Table 7: Statistics summary of data to estimate Weibull parameters using the graphical method for reinforced concrete deck elements from different bridge datasets.

Bridge Group	Min. Bridge Age	Max. Bridge Age	Number of Observations	% CS-1 Data Summary					Shape Factor (β)	Scale Factor (α)	Median Years in CS-1
				Min.	Max.	Mean	Median	Std. Dev.			
All Bridges	1	99	96	22.7	96.1	73.2	77.3	14.9	4.7	81	75
Bridges w/o Maintenance	3	97	92	22.7	96	74.7	79.4	16	3.8	82.9	75.3
Interstate-15	1	61	32	58.3	100	84.4	86.2	11.6	7.2	102.7	98
Interstate-15 w/o Maintenance	1	61	27	31.7	100	83.3	91	16.8	4.7	91.6	85

A method suggested by the developer and support contractor for BrM to interpret and identify deterioration trends was the use of 3-Dimensional (3D) plots of CS-1 ratings, bridge age, and element areas. Bridge age ranges are plotted on the horizontal (x-axis), total bridge element area on the vertical (y-axis), and the percentage of element area in a particular condition state plotted on the z-axis. The 3D plot for all reinforced bridge decks maintained by MDT for CS-1 is shown in Figure 11. The total deck area represents the total area for all bridges in the given age range. Large total deck area 'bars' shown on the vertical axis of Figure 11 represent groups of bridges in similar condition states based on the NBI element data without assumptions or bias.

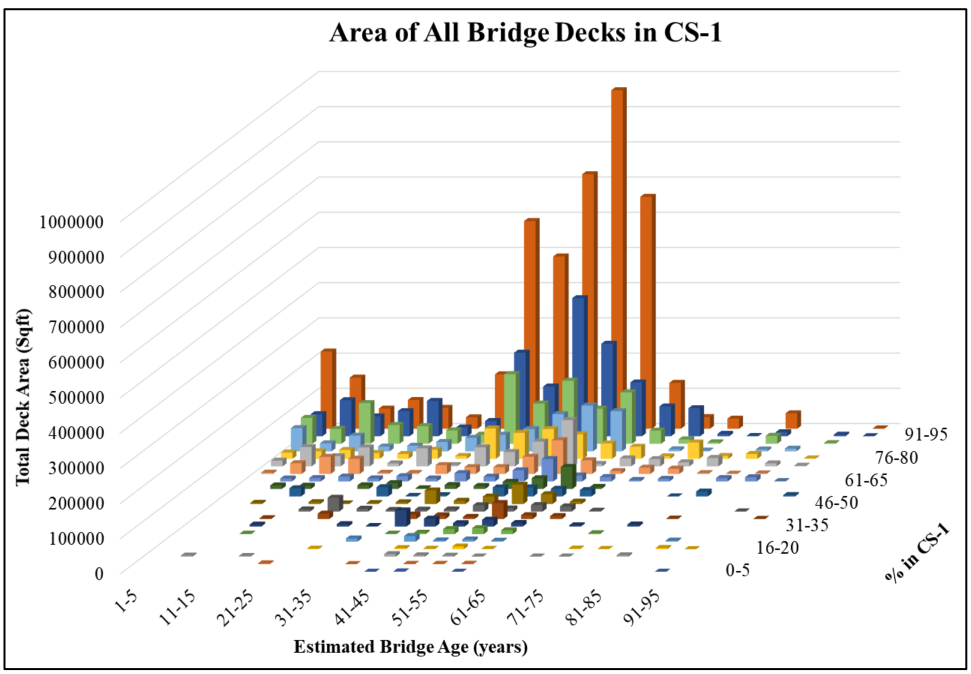


Figure 11: 3D graph of the total area of bridge decks in CS-1 for all bridges maintained by MDT in 2020.

One observation evident from Figure 11 is a downward trend in the orange bars that represent reinforced bridge deck areas with 95-100% of the deck area rated in CS-1. The trend starts from bridge ages of 1-5 years and decreases until it reaches bridge ages up to 30 years. This trend begins to reverse for bridges in the 31-35 age range and likely indicates deck maintenance or rehabilitation activities were completed. The largest areas of bridge decks rated as CS-1 could be estimated to be approximately 40 years represented by the largest orange bars in Figure 11. The same plot was created for the percentage of deck area rated as CS-2 and is shown in Figure 12. In this plot, the peak bridge deck areas are much smaller than the magnitude of the total deck area shown for CS-1 in Figure 11 and indicate smaller bridge deck areas rated as CS-2 in MDT's inspection database.

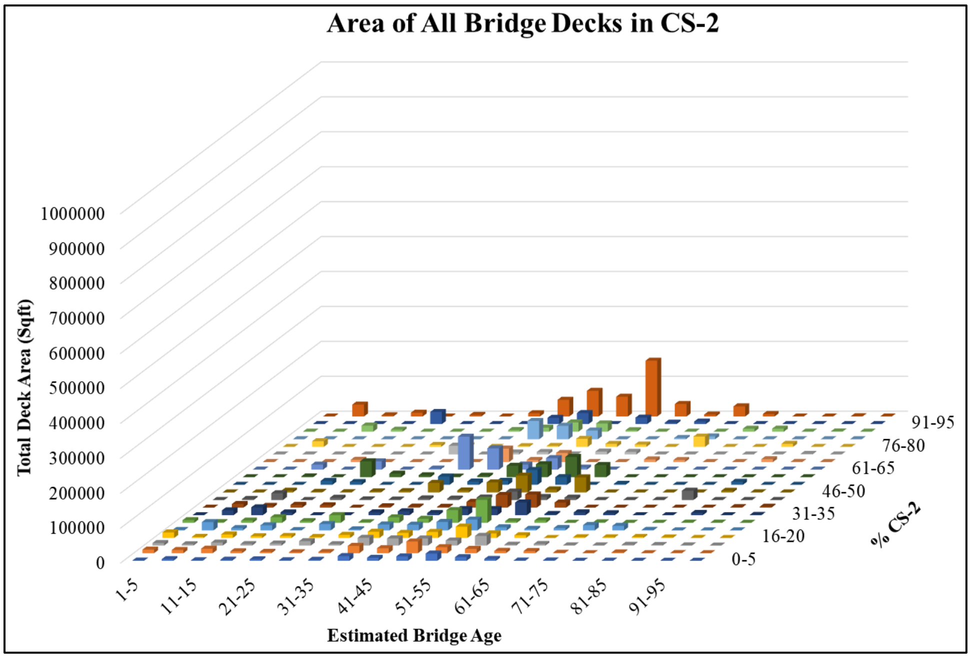


Figure 12: 3D graph of the total area of bridge decks in CS-2 for all bridges maintained by MDT in 2020.

The 3D plots show the total deck area in a condition state based on groups of estimated bridge ages and the percent of element rated in the condition state considered. The plots highlight bridge age groups where large areas of a considered element have high percentages of element areas in a selected CS. They are valuable because they show the bridge groups that may need maintenance relative to the entire MDT bridge inventory.

In search of more definitive trends in the 3D plots, the CS-1 deck ratings were normalized by ADT, number of bridges, age range, and condition state. Figure 13 shows the CS-1 deck area normalized by the total deck area in each of the age ranges. An improved trend was not observed for this case nor the other normalized 3D graphs.

4.5.1 Deterioration targets

The 3D plots used to identify deterioration and maintenance trends of bridge elements in Montana should be supported by benchmarks or target values to improve the confidence in the Weibull distribution parameters for CS-1. Based on MDT's bridge deterioration and NBI data experience, preliminary deterioration targets for concrete bridge decks shown in Table 8 were selected as an initial validation value for both observations from 3D graphs and the deterioration trends from calculated parameters using the graphical method. For simplicity, the targets focus on the percentage of the selected element remaining in CS-1. Focusing on CS-1 allows MDT the ability to adjust the triggers without making assumptions for the percentage of the element in CS-2 to CS-4 that will require maintenance. These targets were used to adjust the calculated input parameters for the Weibull distribution to improve the confidence based on MDT engineering maintenance experience.

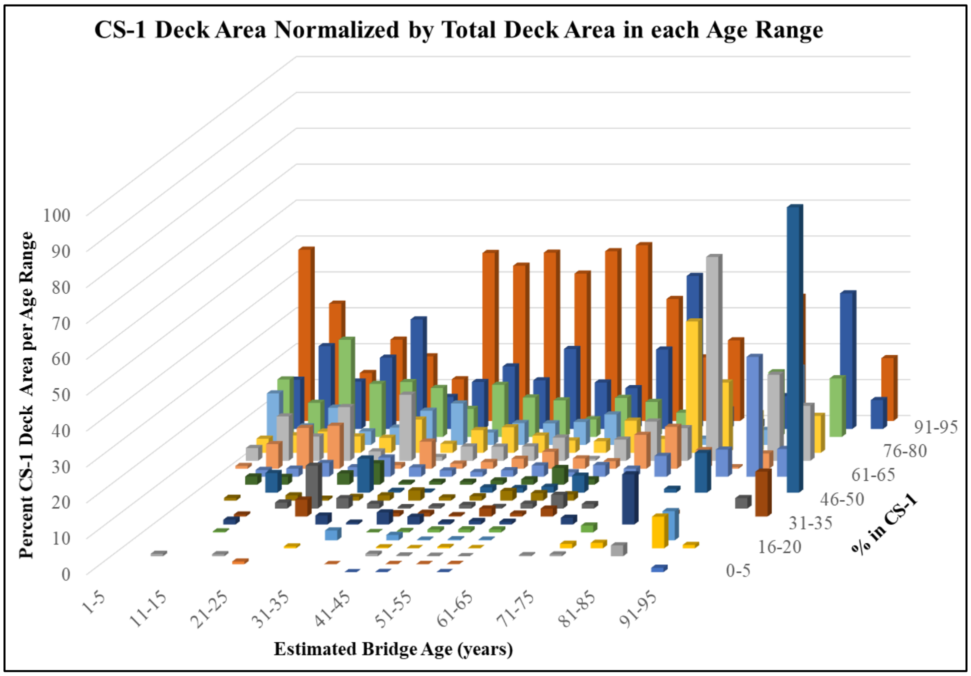


Figure 13: 3D graph of CS-1 deck area normalized by total deck area in each age range.

Table 8: Target deterioration conditions for reinforced concrete decks.

Target	Years
97.5% CS-1	10
90% CS-1	20
80% CS-1	25
70% CS-1	30

4.6 Adjustments to BrM Input Parameters

Using experience with NBI element data from other states, the BrM development and support contractor suggested that in general, shape factors (β) for joint elements are estimated to be 1.0, with most other elements described by a shape factor $\beta = 1.5$. Some state departments of transportation have found that shape factors as large as 4 do a reasonable job of capturing deterioration trends for some bridge elements. With these values in mind, Weibull distribution shape factors calculated using the graphical method were adjusted using three-dimensional bar graphs and deterioration targets (Table 8).

The shape factor calculated from the graphical method (β = 4.7) and median years in CS-1 of 40 determined from Figure 11 were used to calculate deterioration curves in BrM. The initial parameters were then adjusted to accelerate the concrete deck deterioration to approximately meet the selected target of 80-90% bridge deck areas rated as CS-1 after 40 years. BrM defaults and adjusted median years in CS-1 and CS-2 using the 3D charts as a reference are shown in Table 9. Because of the low number of bridges rated with a CS-3 rating, an estimate to the median years could not be obtained, and the default BrM value of 15 years was used.

Table 9: Initial and adjusted BrM input parameters.

BrM defaults			Adjusted values		
Shape Factor (β)	Median years in CS-1	Median years in CS-2	Shape Factor (β)	Median years in CS-1	Median years in CS-2
1.3	14	42	2.4	45	20

4.7 Deterioration Adjustments through Environmental Factors

With an increased level of confidence in the deterioration curves for reinforced concrete decks, calculated with support from deterioration targets and 3D graphs, further refinements for MDT's five maintenance districts were evaluated.

Four environmental factors can be applied in BrM to adjust the deterioration trends to reflect a more benign or severe environment. These values are an additional method for adjusting the deterioration produced from the recommended input parameters described above. Because of the relatively large maintenance inputs and frequency associated with reinforced concrete bridge decks, the environmental factors were only investigated for this element.

The environmental levels within BrM and their associated factors used to adjust the deterioration curves are shown in Table 10. The default environment is moderate, with a factor of 1.0, and represents no environmental adjustment to the deterioration curve. The environmental factor adjusts the median years in a condition state to either increase or decrease the deterioration rate. A benign environmental factor (2) doubles the length of time an element stays in a condition state, whereas a severe factor (0.7) will shorten the number of years by 0.7. The effect of these environmental factors on the shape of the deterioration curves for concrete decks can be seen in Figure 14.

Table 10: Default values of Environmental Factors in BrM.

Environmental Factors	
Benign	2
Low	1.5
Moderate	1
Severe	0.7

To evaluate the effect of applying different environmental factors, bridge datasets were created for each of the five MDT transportation districts. Three-dimensional plots were created for each district for bridge deck areas rated as CS-1. The bar graph trends were compared with calculated

CS-1 deteriorations using different environmental factors to identify an appropriate environmental factor for each maintenance district.

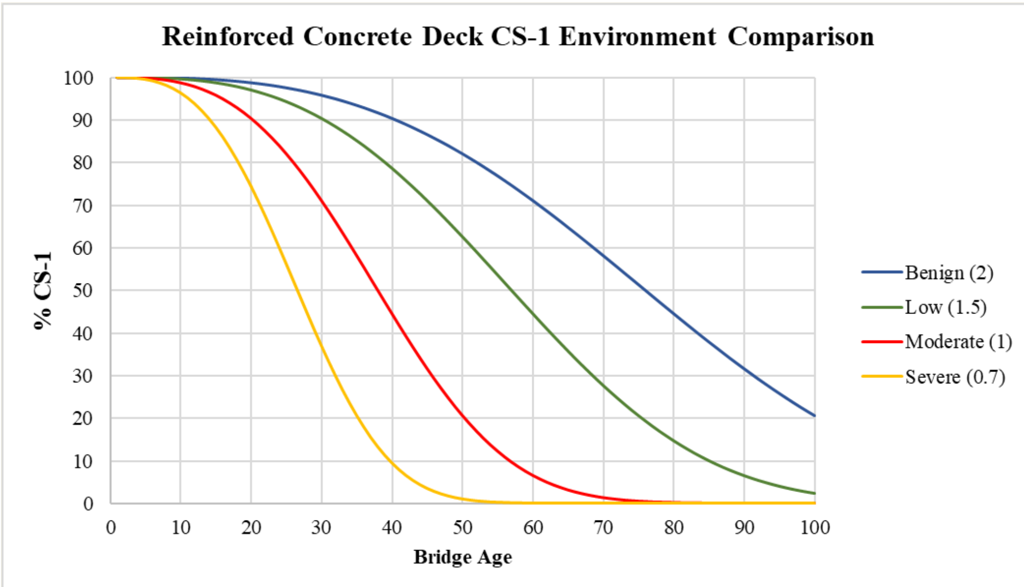


Figure 14: Comparison of the four environmental factors influence on CS-1 deterioration rate for reinforced concrete bridge decks.

The 3D plot for reinforced concrete decks rated as CS-1 in the Billings district are shown in Figure 15. The largest areas of bridge decks rated as CS-1 for all bridges occurred at approximately 40 years (Figure 11). The peak for the largest areas of bridge decks rated as CS-1 in the Billings district increases to approximately 50 years (Figure 15). To capture this slower deterioration, a ‘low’ environmental factor of 1.5 (Table 10) was applied resulting in the deterioration curve shown in the inset of **Error! Reference source not found.**.

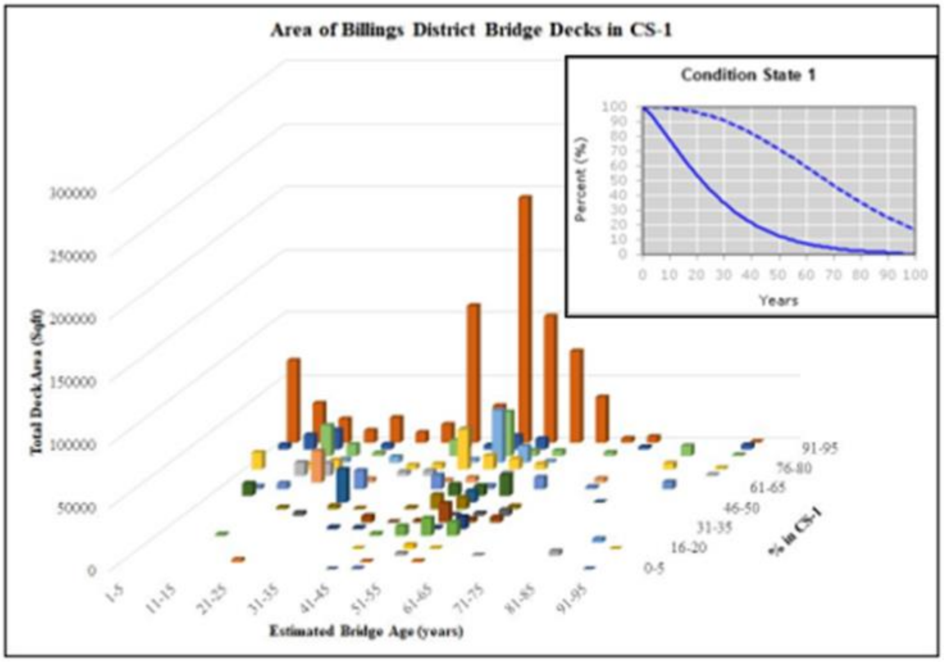


Figure 15: 3D graph for the area of bridge decks in Billings District with a CS-1 rating. A benign environmental factor is applied to the deterioration rate.

In contrast, Figure 16 shows the CS-1 ratings of bridge decks in the Butte district. The large bridge deck areas rated as CS-1 drop off more quickly, indicating a faster deterioration rate. Applying a ‘severe’ environmental factor (0.7) to this group approximately captures a faster deterioration shown in the inset of Figure 16.

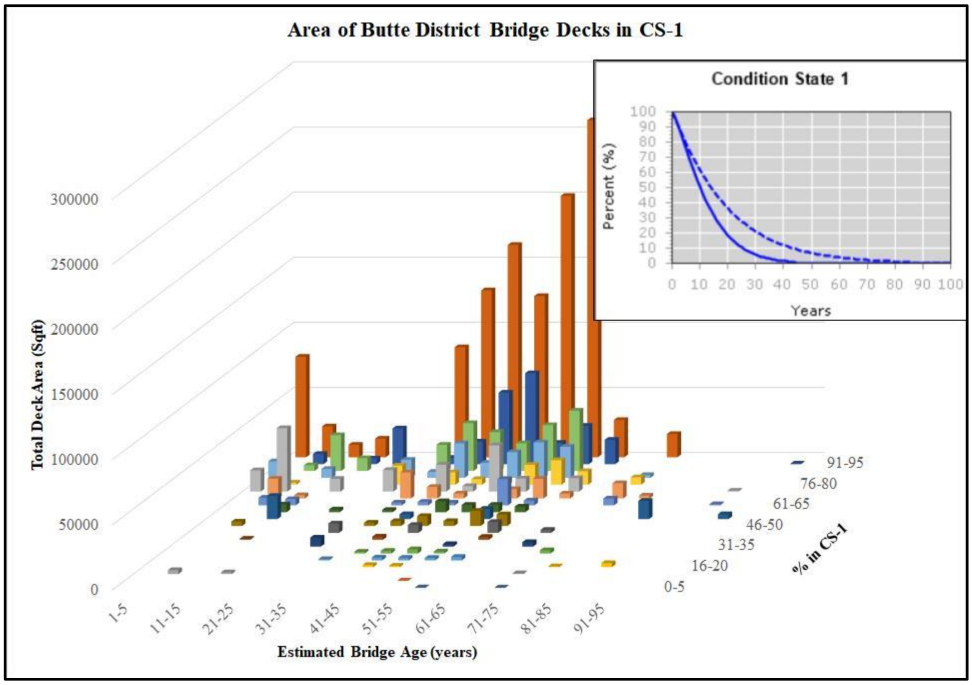


Figure 16: 3D graph for the area of bridge decks in the Butte District with a CS-1 rating. A severe environmental factor is applied to the deterioration rate.

The bridge decks in the Glendive transportation district deteriorate slower than the Billings or Butte districts as shown in Figure 17 relative to Figure 15 and Figure 16. The peak deck areas rated in CS-1 move horizontally to reflect the increased ages of these bridge decks that are still rated as CS-1. Applying a benign environmental factor (2.0), a slower deterioration curve is achieved shown in the inset of Figure 17.

A similar process was used for the Great Falls and Missoula districts, where environmental factors of low (1.5) and moderate (1.0), respectively, provided a reasonable adjustment to the deterioration curves using the 3D plots as a reference. The 3D plots for deck areas in the Great Falls and Missoula districts rated as CS-1 are shown in **Error! Reference source not found.**. A summary of the selected environmental factors used to adjust the CS-1 deterioration rates for bridges in the five MDT maintenance districts can be seen in Table 11.

A second method used to determine the appropriate environmental factor for the five Montana maintenance districts involved recalculating the shape factor (β) for datasets of bridges in each district. β-factors that are larger than the state-wide calculated value would have a steeper or faster deterioration as shown above in Figure 5. Similarly, smaller β-factors would result in a flatter or slower deterioration rate. The state-wide and district-specific shape factors are shown in Table 12.

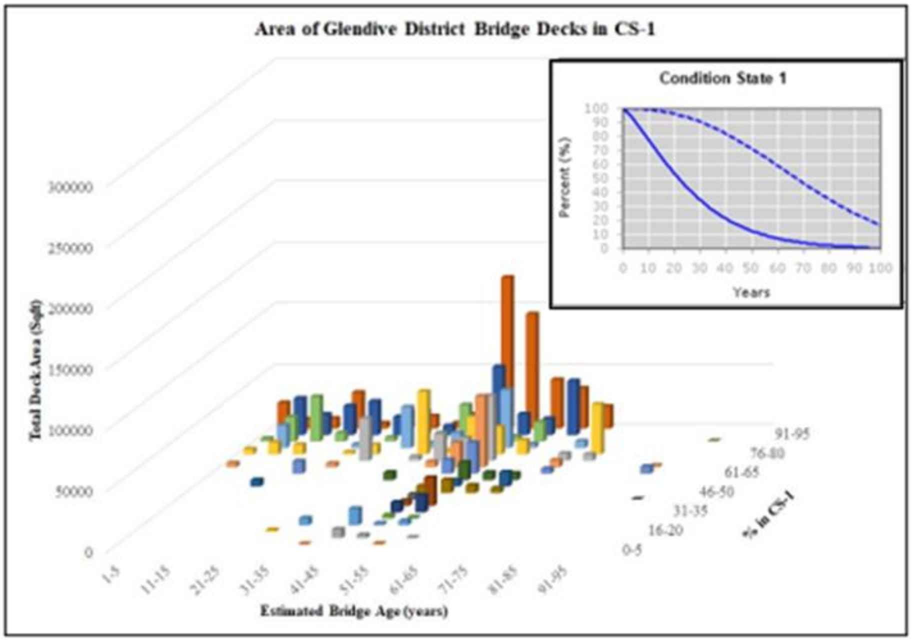


Figure 17: 3D graph for the area of bridge decks in the Glendive District with a CS-1 rating. A benign environmental factor is applied to the deterioration rate.

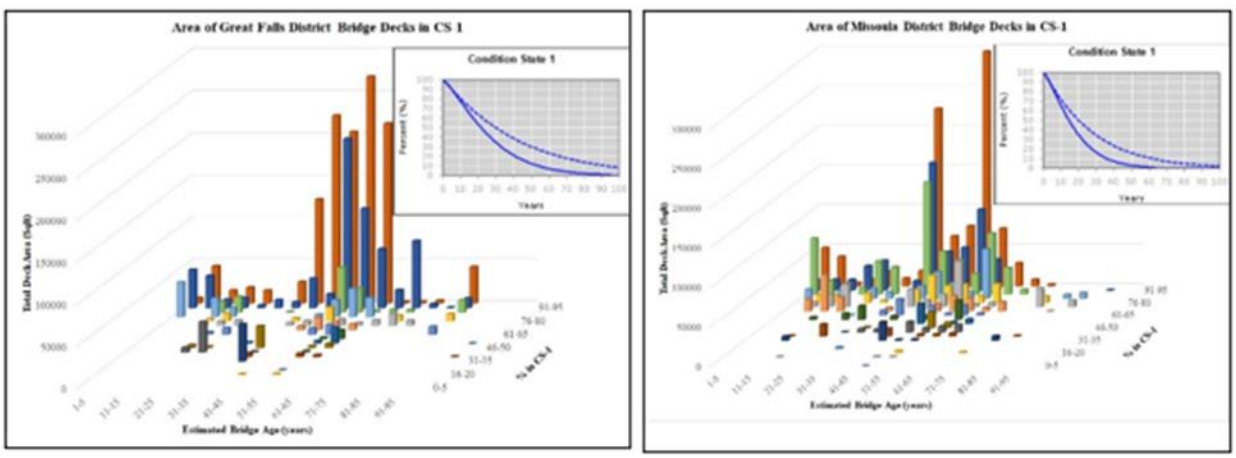


Figure 18: 3D plots for the area of bridge decks in the Great Falls (a) and Missoula (b) districts with a CS-1 rating. A low environmental factor is applied to the Great Falls deterioration curve and a severe environmental factor for the Missoula deterioration curve.

Table 11: Estimates for the deterioration rates of concrete bridge decks for transportation district bridge groups with different environmental factors applied.

Transportation District	**Environmental Factor**	**% in CS-1**		
		@30 yrs	**@50 yrs**	**@70 yrs**
Billings	Benign	95	85	70
Glendive	Benign	95	70	45

Great Falls	Low	50	30	15
Missoula	Severe	55	10	0
Butte	Severe	55	10	0

Table 12: Calculated values for shape factors using the graphical method in relation to the adjusted WTI values with recommended environments.

Region	Graphical-Method Shape Factor (β)	Recommended Environment	BrM Environment Factor
State-wide	4.8	Moderate	1.0
Billings	3.8	Low	1.5
Butte	3.2	Low	1.5
Glendive	5.0	Moderate	1.0
Great Falls	6.5	Severe	0.7
Missoula	6.5	Severe	0.7

The shape factor, β, calculated using the graphical method for all concrete decks in Montana was 4.8 (Table 12). Because the calculated shape factor for concrete decks in the Glendive district is approximately the same as the state-wide factor, a moderate environment is recommended. Calculated shape factors for concrete decks in the Missoula and Great Falls maintenance districts are larger than the state-wide factor and therefore a severe environment may be appropriate. Shape factors for concrete decks in both Butte and Billings districts are less than the state-wide factor and a low environment may more accurately adjust the deterioration in these districts.

The two methods used to estimate appropriate environmental factors were similar for Billings (benign/low), Glendive (benign/moderate), and Missoula (severe/severe). Inferred shape factors for the Butte and Great Falls districts, however, were not similar using the two methods. The differences in the estimated environmental factors will be evaluated using specific deterioration curves created for each maintenance district in Section 5.8.

4.8 Statistical Analysis Summary

The graphical method for calculating Weibull distribution parameters based on the NBI element data was selected for determining initial deterioration parameters for Montana bridge decks. Calculated values were compared with 3D plots and deterioration targets to make adjustments that were in reasonable agreement with MDT maintenance experience and BrM default values. The integrated approach calculates the Weibull distribution shape factor (β) and median years in CS-1 using NBI element data and adjusted to meet the deterioration targets estimated by MDT engineers and trends evident in three dimensional plots of the NBI element data. Deterioration parameters were further refined for reinforced concrete deck elements through BrM environmental factors to reflect the subtle differences observed in deterioration rates for the five maintenance districts. This methodology for determining revised deterioration parameters that better represent MDT bridge elements provides a starting point, with a reasonable level of confidence, for calculating deterioration trends and parameters for other bridge elements described in the next section.

5. Development of Deterioration Curves

The graphical method was used to calculate a shape factor and median year estimates for CS-1 using a Weibull distribution for the six bridge elements shown in Table 13. Using approximate maintenance targets estimated by MDT (also shown in Table 13), and observable trends from plots of raw data, refinements were made to the calculated parameters for reinforced concrete decks, prestressed girders, and concrete culverts. For steel girders, concrete abutments, and steel culverts, the calculated parameters were reasonable estimates to their deterioration and further adjustments were not made.

Table 13: NBI elements and CS-1 established maintenance targets.

Element	NBI Element Number	CS-1 Target	Years
Reinforced Concrete Deck	12	97.5%	10
		90%	20
		70%	30
Steel Girder	107	70%	40
Prestressed Concrete Girder	109	95%	40
Concrete Abutment	215	90%	50
Steel Culverts	240	75%	50
Concrete Culvert	241	95%	30
		75%	50

5.1 Deterioration Curve Calculations by BrM

BrM uses a Weibull distribution to model deterioration in CS-1 and a Markov chain for later-age deterioration modeling. The graphical analysis selected for this research calculates the shape factor and median years in CS-1 using a Weibull distribution. This research did not perform a Markov distribution to characterize the deterioration of reinforced concrete decks beyond CS-2 because of the small percentage of bridges deck areas rated in these condition states as shown in Figure 19.

The maximum percentage of all bridges with concrete deck areas rated in CS-2, CS-3, and CS-4 occurs with less than 1% of concrete deck area rated in these categories as shown in Figure 19. A second maximum occurs when 6-10% of reinforced concrete deck areas are rated CS-2 and CS-3 which represents only 10% and 5% of all bridges, respectively. The characteristics of the recorded inspection data shown in Figure 19 for CS-2 and CS-3 reveal only subtle changes in condition states for a small percentage of the total number of bridges in Montana. Therefore, a comprehensive statistical analysis was not performed to estimate the median years in CS-2 and CS-3. Rather, BrM default values for median years in CS-2 = 42 and CS-3 = 14.9 were used. In some cases, the median years in these condition states were adjusted to achieve desired late-age deterioration that aligned with graphical evidence and MDT's experience.

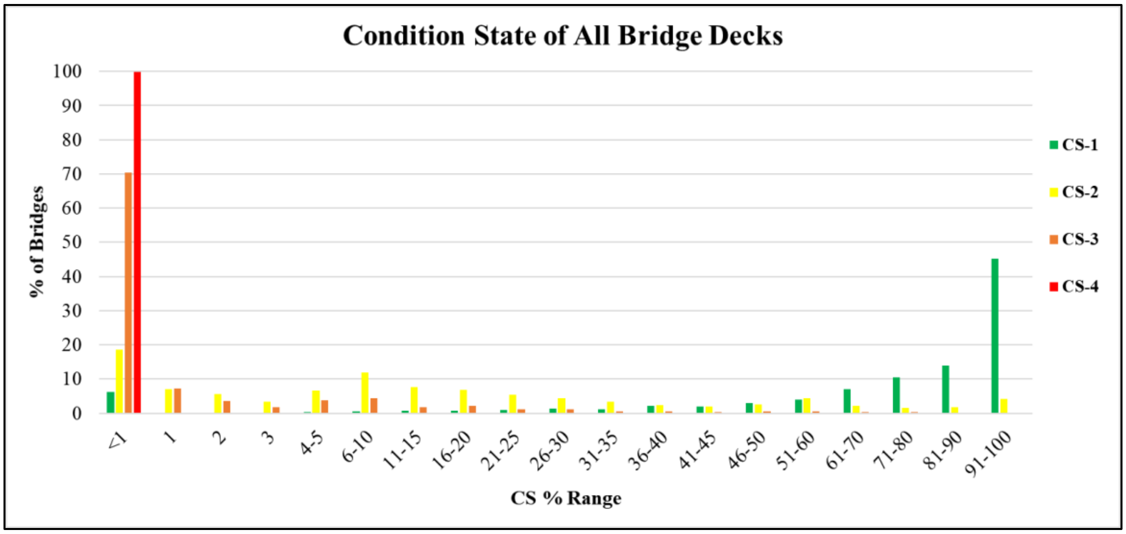


Figure 19: Distribution of condition state data for reinforced concrete bridge decks.

5.2 Reinforced Concrete Bridge Decks

For all reinforced concrete bridge decks maintained by MDT (n = 1,549), the graphical method resulted in a shape factor, β = 4.74, and median years in CS-1 equal to 75. The BrM-calculated deterioration curves using calculated and default parameters (Table 3) are shown by the dashed and solid lines, respectively, in Figure 20.

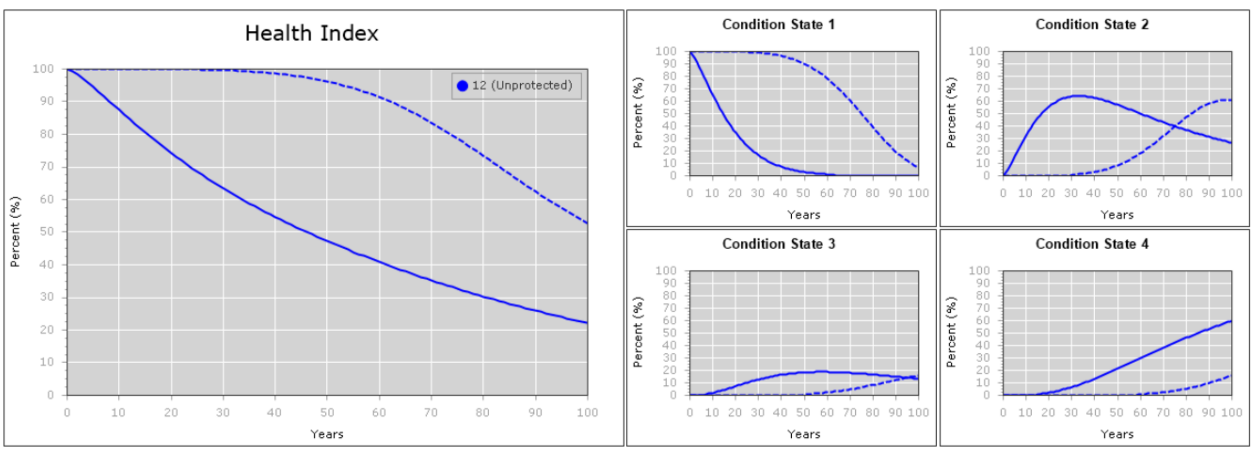


Figure 20: Comparison of reinforced concrete deck deterioration rates between BrM default values (solid line) and the graphical estimates (dashed line).

The graphical method derived deterioration curve for CS-1, shown in the top center plot of Figure 20, suggests reinforced concrete decks will have 95% of their surface area rated as CS-1 at a bridge age of approximately 45-years. This is an optimistic estimate for the deterioration rate of concrete decks state-wide in Montana and can be considered an upper-bound deterioration that represents the deterioration of decks on low-volume roads. This deterioration rate also reflects maintenance performed on these bridges because there are many bridges over 60 years old with 90% of deck areas rated as CS-1.

To adjust the data-based input parameters determined using the graphical method, target deteriorations shown in Table 13 above, were used. The targets are based on CS-1 to avoid over-emphasizing the deterioration rates of a smaller number of bridges with smaller deck areas rated in either CS-2 or CS-3 (Figure 19). By using CS-1 ratings, a combined percentage of deck areas rated below CS-1 are indirectly considered. For example, a bridge with 95% of its deck area in CS-1 indicates that 5% of the bridge deck area is rated in either CS-2, CS-3, and/or CS-4 and provides a more-reliable indicator of bridge deterioration.

The target values in Table 13 were approximately represented by a deterioration curve calculated using a shape factor, $\beta = 3$ and median years in CS-1 equal to 38. The parameters for median years in CS-2 and CS-3 where not changed and the BrM defaults (CS-2 = 42 years, CS-3 = 14.9 years) were used. A comparison of the three estimates can be seen in Figure 21. Adjusting the BrM input parameters to the values shown in Table 14 increased the deterioration rate to a trend that lies between the default and graphical method curves and represents a deterioration that matches target values (Table 13) for reinforced concrete bridge decks.

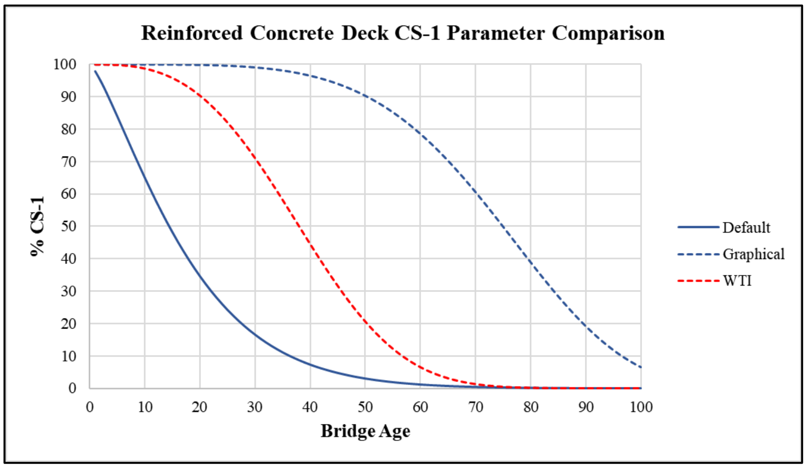


Figure 21: Comparison of the three different parameter estimates for concrete bridge decks in CS-1.

Table 14: Parameter values for reinforced concrete bridge decks.

Parameter Estimates	Shape Factor	Median Years CS-1	Median Years CS-2	Median Years CS-3
BrM Default	1.3	14.4	42.0	14.9
Graphical	4.8	75	42	14.9
WTI Refinement	3.0	38	42	14.9

To evaluate the data-based and refined input parameters, the average percentage of deck areas rated as CS-1 for all bridges are plotted as green points with the deterioration shown in Figure 22. While the averages do not provide a reliable method to validate the calculated deterioration curves, they do confirm the variability in CS-1 ratings as the bridge age increases, which is likely influenced by maintenance activities.

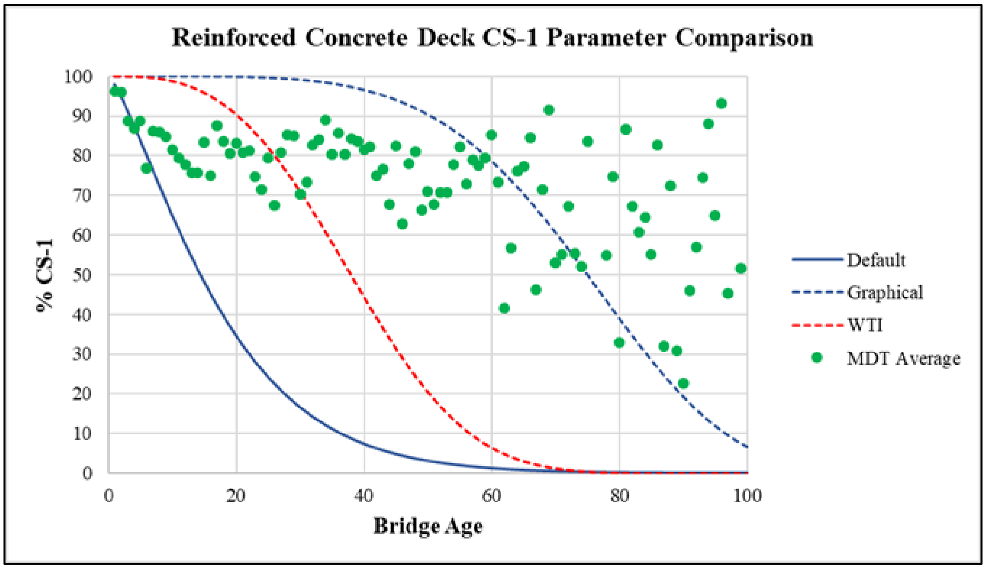


Figure 22 Average concrete deck areas rated as CS-1 shown with graphical method and refined deterioration curves.

5.3 Steel Girder

For all bridges with steel beams maintained by MDT (*n* = 875), the graphical method resulted in a shape factor, β = 2.4 and median years in CS-1 equal to 64. The BrM-calculated deterioration curves using the graphical method and default parameters (β = 1.8, CS-1 = 28.5) are shown by the dashed and solid lines, respectively, in Figure 23. Input parameters used to generate the curves are shown in Table 15.

Unlike the reinforced concrete deck condition state distribution data (Figure 19), a large percentage (25%) of steel girder bridges reach a deterioration level where over 91-100% of the girder area is rated as CS-2, as shown in Figure 24. This suggests that deterioration trends could be refined using trigger conditions based on CS-2. It also indicates that a Markov chain might be successful to estimate the median years in CS-2 and CS-3 more accurately. However, because the CS-1 maintenance target for steel girders shown in Table 13 (70% CS-1 at 40 years) is reasonably captured by the deterioration curve shown in the top center of Figure 23 calculated using the graphical method input parameters, further refinement was not investigated.

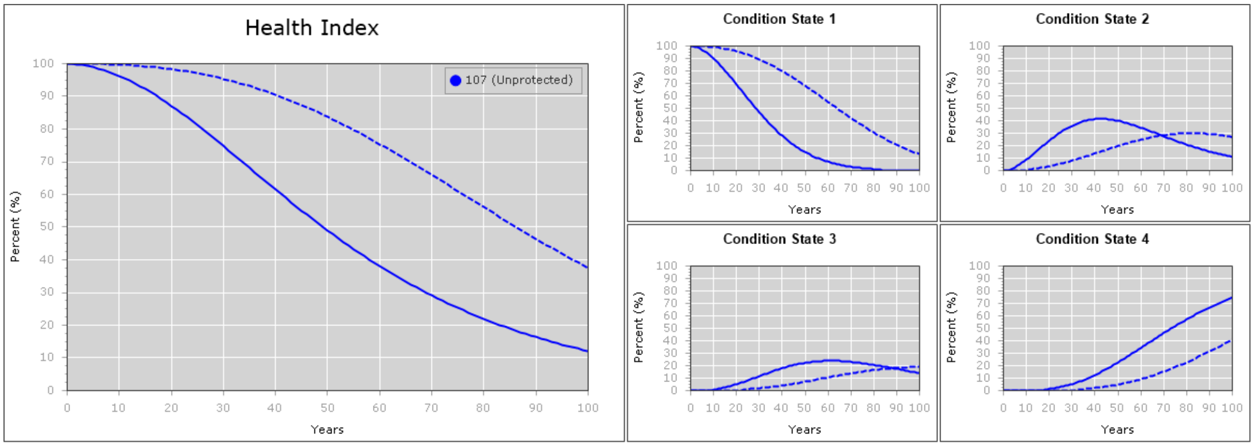


Figure 23: Comparison of steel girder deterioration rates between BrM default values (solid line) and the graphical estimates (dashed line).

Table 15: Parameter values for steel girders.

Parameter Estimates	Shape Factor	Median Years		
		CS-1	CS-2	CS-3
BrM Default	1.8	28.5	19.5	13.5
Graphical	2.4	64.0	19.5	13.5
WTI Refinement	-	-	-	-

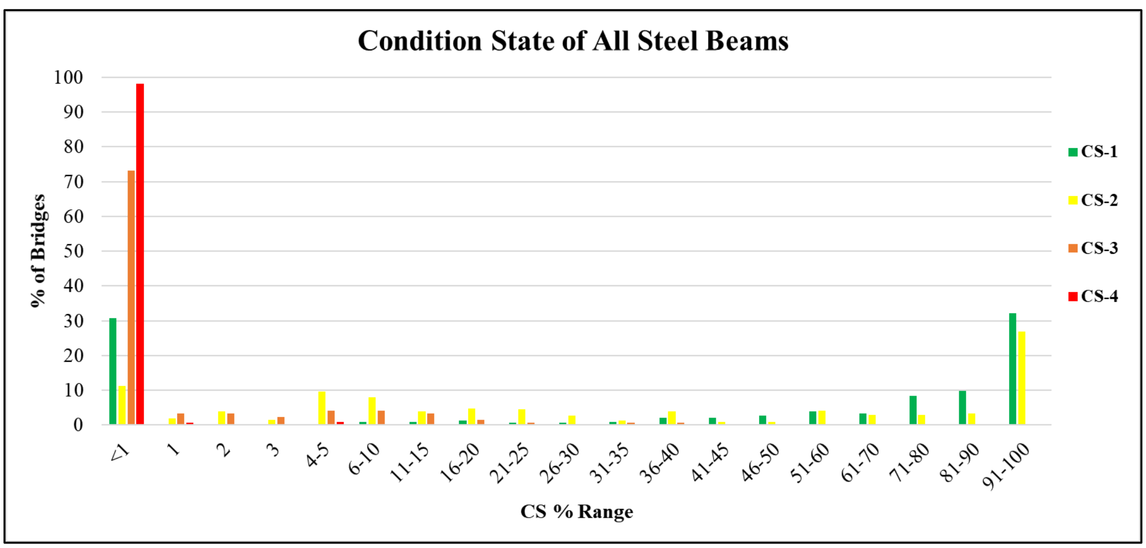


Figure 24: Distribution of condition state data for steel girder/beam.

5.4 Prestressed Concrete Girder

For all bridges with prestressed concrete girders maintained by MDT (n = 2,021), the graphical method resulted in a shape factor, β = 61.5 and median years in CS-1 equal to 100. The BrM-calculated deterioration curves using the graphical method and default parameters (β = 2, CS-1 = 55) are shown by the dashed and solid lines, respectively, in Figure 25.

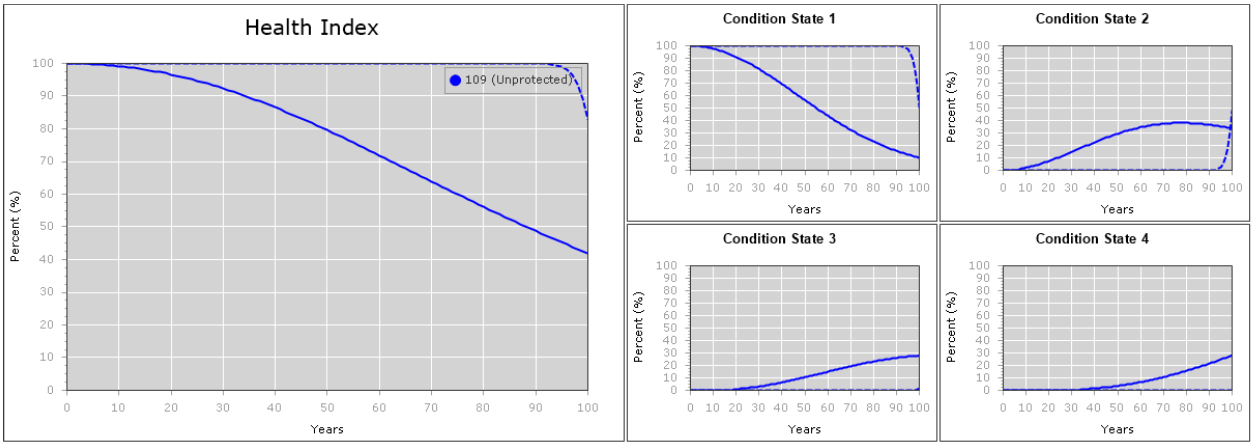


Figure 25: Comparison of prestressed concrete girder deterioration rates between BrM default values (solid line) and the graphical estimates (dashed line).

The graphical-method deterioration curve indicates no deterioration of prestressed girders until 90 years. This deterioration trend is supported by the lack of distributed condition state inspection data shown in Figure 26. All prestressed concrete girder bridges had greater than 80% of their total area rated as CS-1 and 98% of bridges had less than 5% of concrete girder area rated as CS-2. The inspection data suggests that routine maintenance is not regularly performed on prestressed concrete girders.

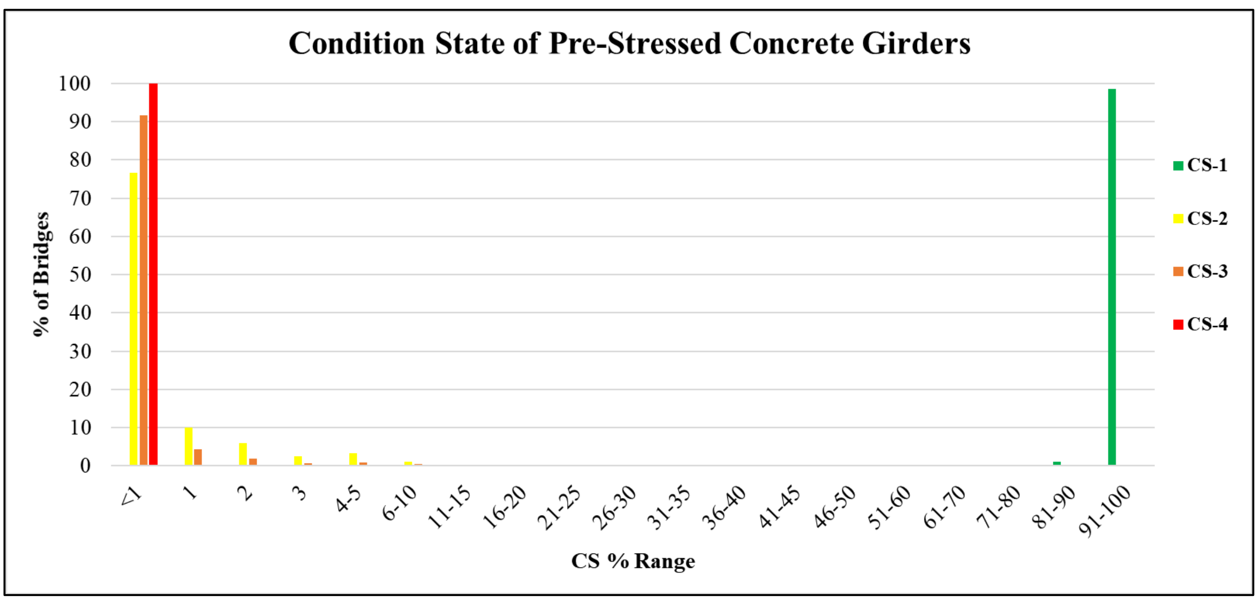


Figure 26: Distribution of condition state data for prestressed concrete girders.

The deterioration curves shown in Figure 25 likely under-estimate the deterioration rates of prestressed concrete girders and can be considered an upper-bound. Adjusting the input parameters to meet the deterioration targets shown in Table 13 resulted in a shape factor, $\beta = 5$ and median years in CS-1 equal to 75. The median years in CS-2 and CS-3 were reduced from the default values from 25.2 to 20 years for both condition states. A comparison of the refined curve with the default and graphical method curves can be seen in Figure 27. The input parameters used to calculate the three deterioration curves are shown in Table 16.

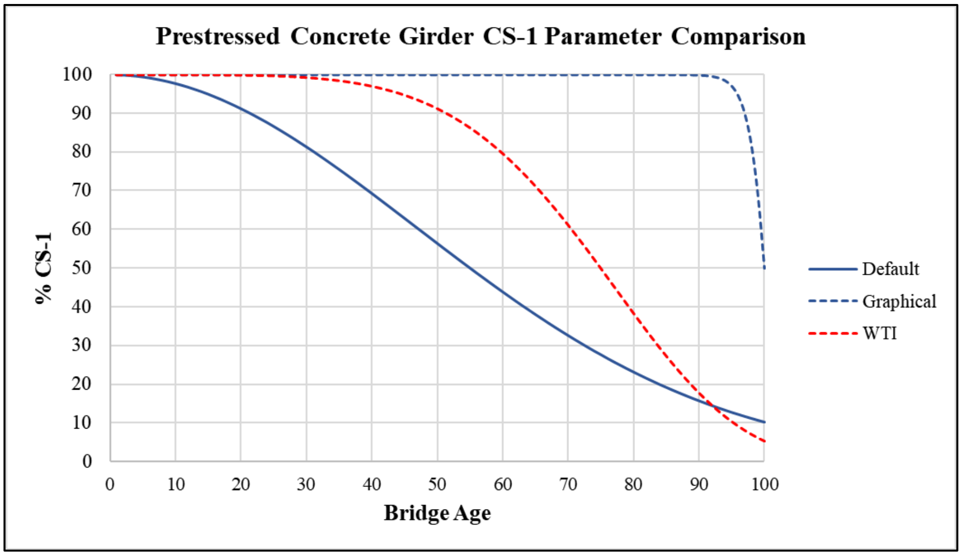


Figure 27: Comparison of the three parameter estimates for prestressed concrete girders in CS-1.

Table 16: Input parameter values for prestressed concrete girders.

Parameter Estimates	Shape Factor	Median Years CS-1	Median Years CS-2	Median Years CS-3
BrM Default	2.0	55	25.2	28.6
Graphical	61.5	100	25.2	28.6
WTI Refinement	5.0	75	20	20

5.5 Concrete Abutments

For all reinforced concrete bridge decks maintained by MDT (n = 3,116), the graphical method resulted in a shape factor, β = 3.9 and median years in CS-1 equal to 85. The BrM-calculated deterioration curves using the graphical method and default parameters (β = 2, CS-1 = 65.6) are shown by the dashed and solid lines, respectively, in Figure 28. The graphical method input parameters produce a deterioration curve that passes through the estimated maintenance target shown in Table 13 (90% CS-1 at 50 years).

The distribution of condition state data for concrete abutments shown in Figure 29 reveals a similar trend to reinforced concrete decks (Figure 19). A second peak occurs for the percentage of bridges with 6-10% of the abutment area rated CS-2. The relatively small areas and small percentages of changing condition states suggest further analyses will not improve the graphical method deterioration curves (Figure 28). Therefore, no additional refinements were made to the BrM input parameters shown in Table 17.

5.6 Steel Culverts

For all steel culvert bridges maintained by MDT (n = 213), the graphical method resulted in a shape factor, β = 2.3 and median years in CS-1 equal to 74. The BrM-calculated deterioration curves using the graphical method and default parameters (β = 1.8, CS-1 = 51.5) are shown by the dashed and solid lines, respectively, in Figure 30.

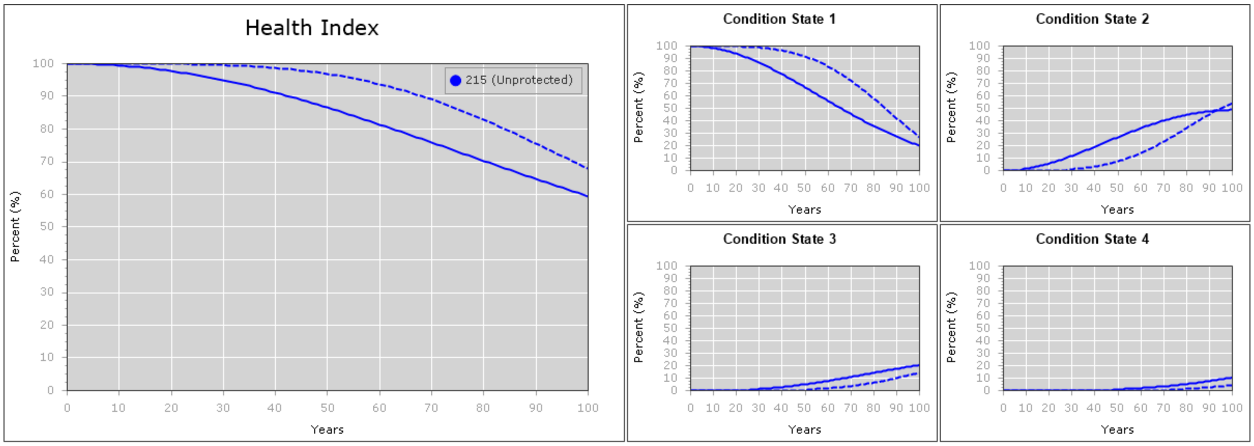


Figure 28: Comparison of reinforced concrete abutment deterioration rates between BrM default values (solid line) and the graphical estimates (dashed line).

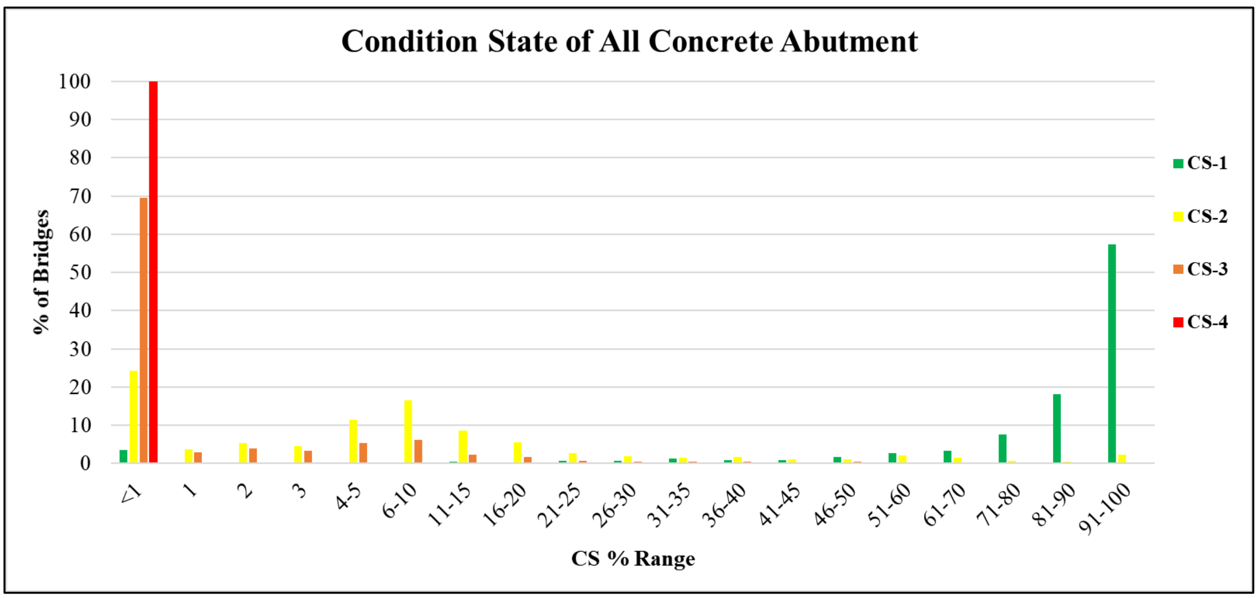


Figure 29: Distribution of condition state data for concrete abutments.

Table 17: Input parameter values for concrete abutments.

Parameter Estimates	Shape Factor	Median Years CS-1	CS-2	CS-3
BrM Default	2.0	65.6	56.2	45.4
Graphical	3.9	85	56.2	45.4
WTI Refinement	-	-	-	-

The distribution of condition state data for steel culverts can be seen in Figure 31 and is not unlike the distribution for other bridge elements. The graphical method input parameters produce a deterioration curve that passes through the estimated maintenance target shown in Table 13 (75% CS-1 at 50 years) and is close to the BrM default curve for steel culverts. For these reasons, refinements to the parameters shown in Table 18 were not made.

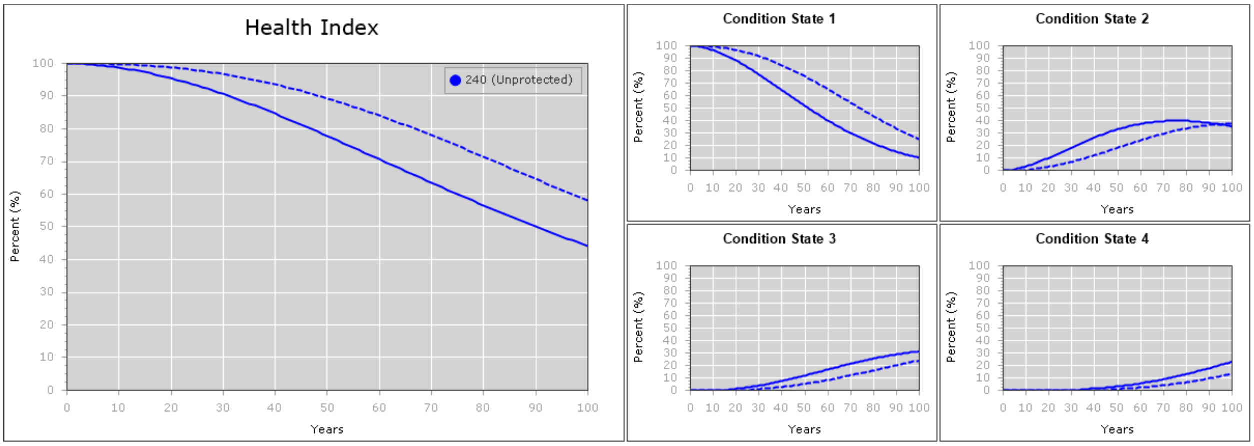


Figure 30: Comparison of steel culvert deterioration rates between BrM default values (solid line) and the graphical estimates (dashed line).

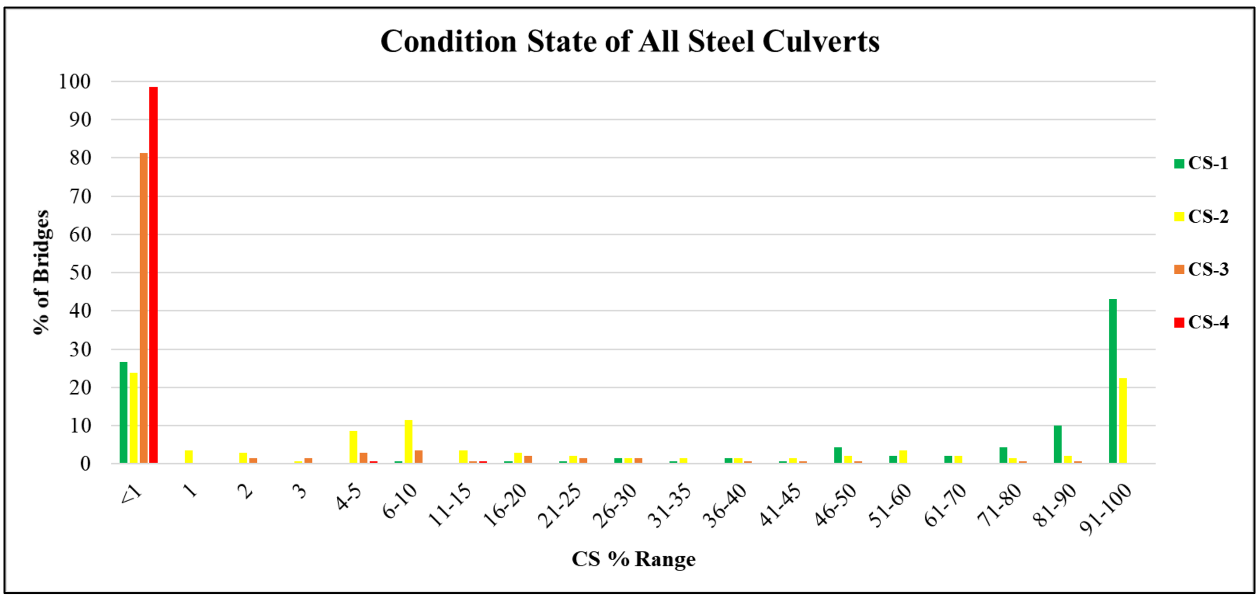


Figure 31: Distribution of condition state data for steel culverts.

Table 18: Input parameter values for steel culverts.

Parameter Estimates	Shape Factor	Median Years CS-1	Median Years CS-2	Median Years CS-3
BrM Default	2.0	65.6	56.2	45.4
Graphical	3.9	85	56.2	45.4
WTI Refinement	-	-	-	-

5.7 Concrete Culverts

For all concrete culvert bridges maintained by MDT (*n* = 77), the graphical method resulted in a shape factor, β = 7.4 and median years in CS-1 equal to 113. The BrM-calculated deterioration curves using the graphical method and default parameters (β = 2, CS-1 = 45.6) are shown by the dashed and solid lines, respectively, in Figure 32.

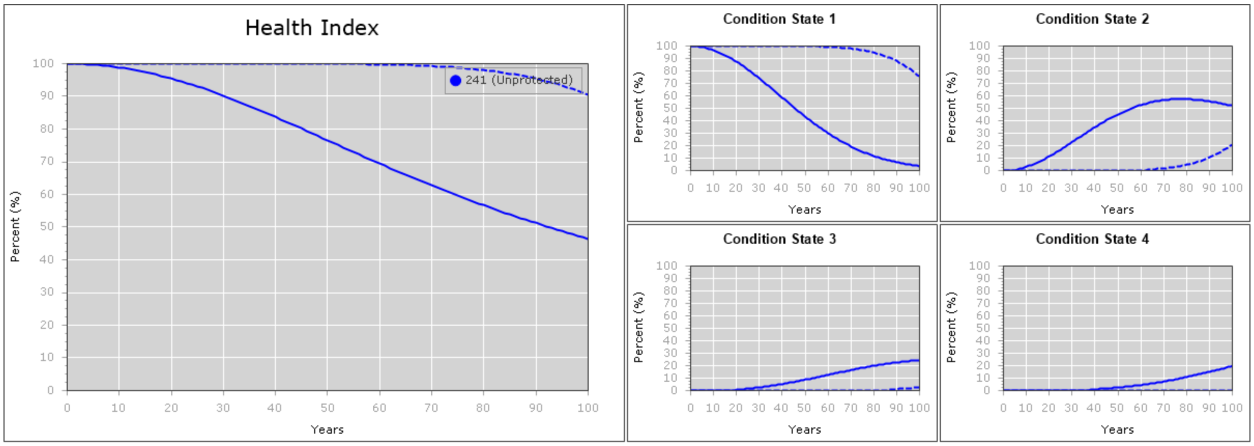


Figure 32: Comparison of concrete culvert deterioration rates between BrM default values (solid line) and the graphical estimates (dashed line).

The distribution of condition state data for concrete culverts shown in Figure 33 is similar to the distributions for prestressed concrete girders (Figure 26), where a gap with little or no CS percentages exists between 10 and 80%. While the gap for concrete abutments was smaller (20-50%) and did include small percentages of culverts in these ranges, it resulted in a trend that under-estimated deterioration when compared with the selected targets shown in Table 13. These target values were used to select a shape factor, $\beta = 3.5$ and median years in CS-1 equal to 60. The parameters for median years were reduced to CS-2 = 40 years and CS-3 = 20 years to further accelerate the late-age deterioration. A comparison of the three estimates can be seen in Figure 34 with input parameters for the three curves shown in

Table 19.

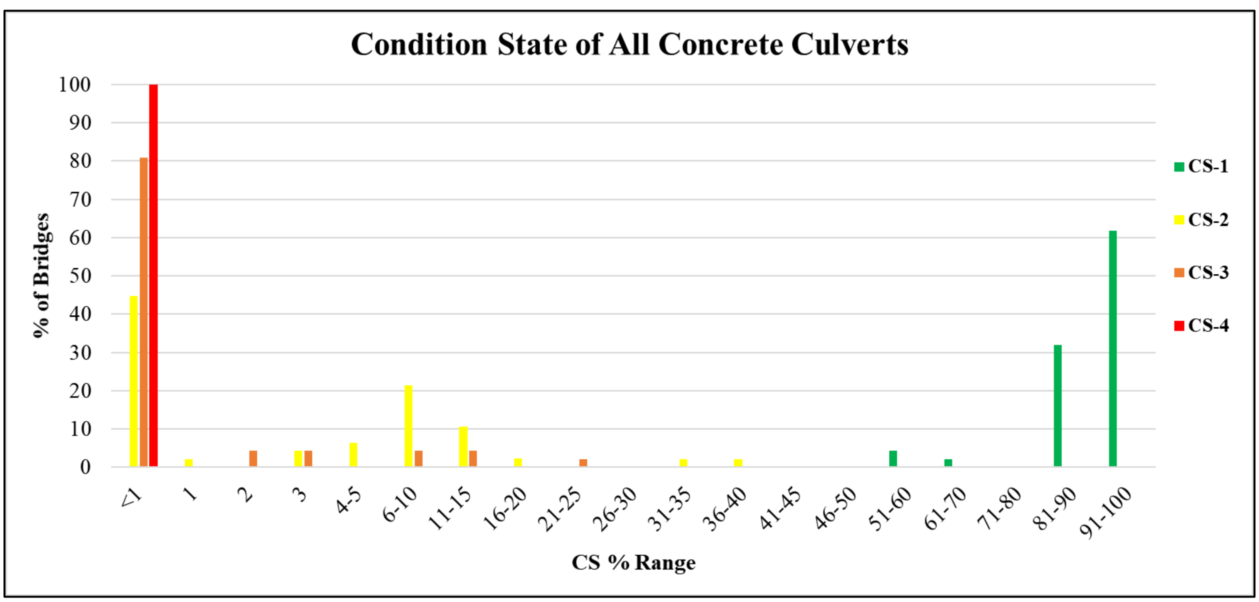


Figure 33: Distribution of condition state data for concrete culverts.

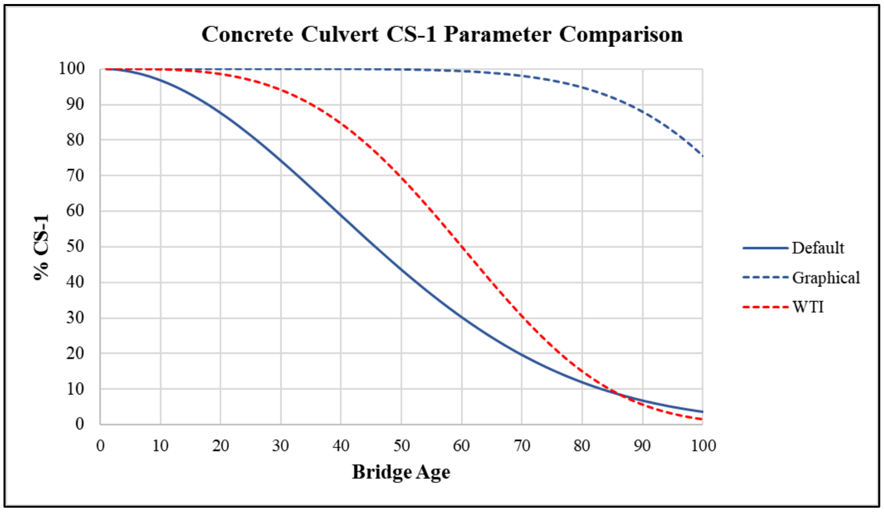


Figure 34: Comparison of the three different parameter estimating methods for concrete culverts in CS-1.

Table 19: Parameter values for concrete culverts using the three methods.

Parameter Estimates	Shape Factor	Median Years CS-1	Median Years CS-2	Median Years CS-3
BrM Default	2	45.6	56.5	34.8
Graphical	7.5	113	56.5	34.8
WTI Refinement	3.5	60	40	20

5.8 Environmental Factors

The estimated deterioration rates plotted as a utility index for reinforced concrete decks using the WTI refined input parameters for the five Montana maintenance districts are shown without environmental adjustment in Figure 35. The utility index is a customized health index within BrM that considers user-defined elements and condition states. Figure 35 includes only the CS-1 concrete deck ratings.

The estimated environmental factors for reinforced concrete decks previously estimated in Table 11 using the 3D graphs for the five maintenance districts match the deterioration rates calculated in BrM shown in Figure 35. These rates use only on the NBI element inspection data, which includes the effects of maintenance. Therefore, it is important to note, faster or slower deterioration rates in these districts may also be related to maintenance practices and frequencies for each district, as much as, or in combination with, environmental conditions present.

5.9 Summary

A Weibull distribution was applied using the graphical analysis method to six different NBI bridge elements (concrete decks, steel girders, prestressed concrete girders, concrete abutments, steel and concrete culverts). Deterioration curves were compared with those calculated using default input parameters and maintenance targets estimated by MDT. The input parameters calculated using the graphical method for concrete decks, prestressed concrete, and concrete culverts were adjusted to create a more aggressive deterioration rate that more closely matched the maintenance targets. Adjustments to the data-based input parameters for steel girders, concrete abutments, and steel culverts were not made because of estimated maintenance targets were reasonably represented. A summary of the default BrM, graphical method, and refined input parameters can be seen in Table 20.

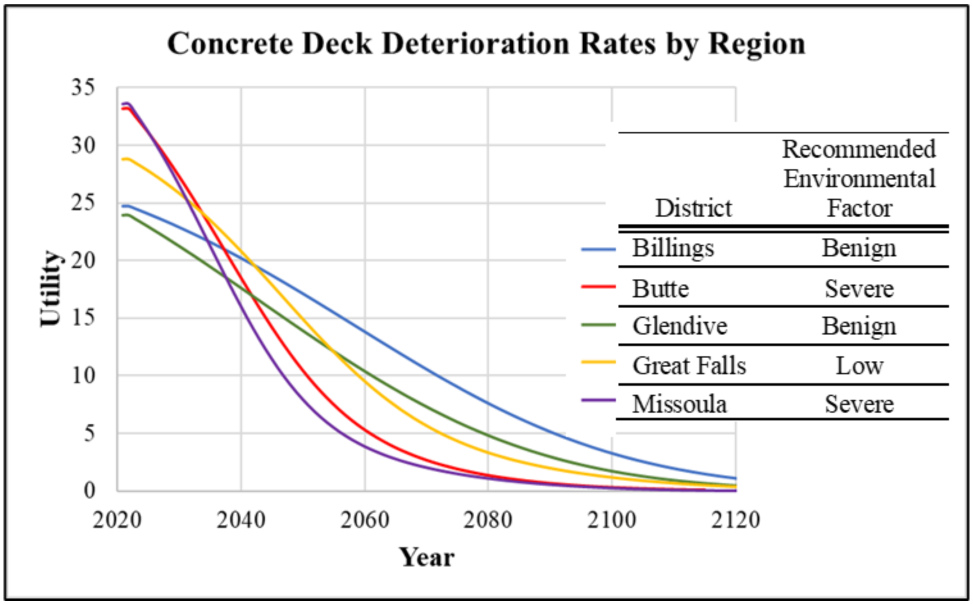


Figure 35: Deterioration rates based on region.

Table 20: Input parameter evolution from the default, graphical, and adjusted values.

Element	BrM Defaults				Graphical Method		WTI Refined Values			
	β	CS-1	CS-2	CS-3	β	CS-1	β	CS-1	CS-2	CS-3
Concrete decks	1.3	14.4	42	14.9	4.8	75	3	38	42	14.9
Steel Girder	1.8	28.5	19.5	13.5	2.4	64	2.4	64	19.5	13.5
Concrete Girder	2	55.0	25.2	28.6	61.5	100	5	75	20	20
Concrete Abutment	2	65.6	56.2	45.4	3.9	85	3.9	85	56.2	45.4
Steel Culvert	1.8	51.5	33.1	39.1	2.3	74	2.3	74	33.1	39.1
Concrete Culvert	2	45.6	56.5	34.8	7.5	113	3.5	60	40	20

6. Conclusions

Weibull Distribution parameters to model deterioration from CS-1 to CS-2 for six different bridge elements were calculated using NBI element data and a time-based stochastic statistical model. For the six bridge elements considered, the calculated parameters were an upper bound, or represented a slower deterioration than would be expected. The calculated distribution factor (β) and median years in CS-1 were refined using an integrated approach that compared the calculated parameters with 3D plots and deterioration targets estimated by MDT.

The Weibull distribution parameters calculated for concrete decks, prestressed concrete, and concrete culverts were adjusted to create a more aggressive deterioration rate that more closely matched the maintenance targets. Adjustments to the data-based parameters for steel girders, concrete abutments, and steel culverts were not made because the estimated maintenance targets were reasonably represented. A summary of the default BrM, graphical method, and refined input parameters is shown in Table 21 below.

Table 21: BrM input parameter summary

Element	BrM Defaults				Graphical Method		WTI Refined Values			
	β	CS-1	CS-2	CS-3	β	CS-1	β	CS-1	CS-2	CS-3
Concrete decks	1.3	14.4	42	14.9	4.8	75	3	38	42	14.9
Steel Girder	1.8	28.5	19.5	13.5	2.4	64	2.4	64	19.5	13.5
Concrete Girder	2	55.0	25.2	28.6	61.5	100	5	75	20	20
Concrete Abutment	2	65.6	56.2	45.4	3.9	85	3.9	85	56.2	45.4
Steel Culvert	1.8	51.5	33.1	39.1	2.3	74	2.3	74	33.1	39.1
Concrete Culvert	2	45.6	56.5	34.8	7.5	113	3.5	60	40	20

Deterioration parameters were further refined for reinforced concrete deck elements through four environmental factors available in BrM to reflect the subtle differences observed in deterioration rates for the five maintenance districts. The environmental factors are a second alternative for adjusting the deterioration parameters recommended above and are summarized in the Table below.

Table 22: Environmental factor summary

Region	Graphical-Method Shape Factor (β)	Recommended Environment	BrM Environment Factor
State-wide	4.8	Moderate	1.0
Billings	3.8	Benign	2.0
Butte	3.2	Severe	0.7
Glendive	5.0	Benign	2.0
Great Falls	6.5	Low	1.5
Missoula	6.5	Severe	0.7

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