Development of Deterioration Curves for Bridge Elements in Montana

Task 1 Report: Literature Review

by

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Abstract

With limited resources and funding, transportation agencies are required to develop strategies to efficiently allocate their funds for bridge maintenance. One strategy that is currently being implemented by many State departments of transportation is to estimate the structural integrity of bridges by modeling their deterioration rates at a component and/or element level analysis. Stochastic and deterministic models can be used to estimate deterioration rates by developing strategies specific to bridge inventories and inspection data collected. Based on the findings of this literature review, a framework for the analysis and deterioration modeling specific to the Montana Department of Transportation's criteria is identified and discussed.

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Literature Review

1. Introduction

The U.S. infrastructure includes 614,378 bridges of which 9.1% were rated structurally deficient in 2016 and nearly 40% are over 50 years old [1]. The increased traffic volumes and vehicle weights, along with harsh environmental exposure contributes to an increase in bridge deterioration. Studies have shown that areas with higher levels of precipitation experience faster deterioration rates in bridge elements [2]. As state Department of Transportations (DOT) have limited funding, they must allocate resources in an efficient way. 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.

One method to determine deterioration models for bridges is the use of component-level data (deck, superstructure, and substructure) records from the National Bridge Inventory (NBI) for bridges in the U.S. [5]. The NBI database includes component level data on the geometric and design parameters (e.g. span length, skew angle, deck width, material type, design load, etc.), operational conditions (e.g. average daily traffic [ADT], age, highway class, etc.), and structural condition of bridges in the states’ inventory. Each data field includes a score of 0-9, with 9 being excellent and 0 considered failed, based on a visual inspection either annually or bi-annually. A description of the ratings can be seen in Table 1. The NBI records, however, are limited because they are subjective, there is an extremely large amount of unbalanced and noisy data (e.g. incomplete/missing data fields, different durations between inspections, skewed distributions, inspector bias, etc.).

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

A second option includes the evaluation of bridge element-level deterioration. Bridge elements consist of smaller members that make up bridge components (e.g. steel reinforcement, bearings, connections, etc.). Providing a rating for the individual elements enables bridge owners to potentially make more efficient and targeted maintenance and rehabilitation decisions. This data follows similar scale ratings to the NBI database and includes similar limitations as component level data, with the exception that it is distributed over a larger number of members.

The objective of the literature review is 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. A priority for the review is to identify methods to accurately detect changes in deterioration trends, based on maintenance, rehabilitation, or construction that contribute to maintenance schedules during its service life.

2. Bridge Deterioration Modeling

Estimating bridge deterioration can generally be classified into two groups: deterministic and stochastic modeling. Each type of model has its benefits and challenges. Generally, deterministic models are easier to apply, but they lack in statistical accuracy when compared to more complex stochastic models. The potential increased accuracy of stochastic models comes at the expense of more costly implementation due to the data and analysis required.

2.1. Deterministic modeling

Deterministic modeling assume 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. Simple, linear regressions do not provide enough accuracy for long-term performance of a bridge, 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 concrete bridges [6, 7]. The advantages of deterministic modeling are their simplistic approach to predict the future condition of the bridge, and that they are practical to administer on a network level. The disadvantages are that they ignore uncertainty due to the stochastic nature of infrastructure deterioration, they can be resource intensive to update when new data is available, and they ignore the interactions between the deterioration of different bridge element relationships.

2.2. Stochastic Modeling

Stochastic modeling considers multiple factors of bridge deterioration 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.

2.2.1. State-based approach

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 using sets of measurable variables (e.g. age, ADT, climate, materials, etc.).

Markov models are a commonly used state-based stochastic technique for analyzing the deterioration of road bridges [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].

Analytical Studies 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].

2.2.2. Time-based approach

Time-based models the duration of time that a bridge remains in a specific condition as 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 is that they tend to be more realistic because Weibull-based methods utilize actual scatter in duration data for a particular condition rating and consider duration as a random variable, and they have been used to obtain an age-dependent probability of failure as an enhancement of 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].

3. Models

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

3.1. 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 add to the accuracy of statistical models because they relate the estimated qualitative measurement to the physical parameters of the bridge, thereby increasing the accuracy of probability estimates, i.e. Markov transition matrices. 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 include their suitability for project level analysis and their reliable quantitative deterioration predictions for bridge elements [5]. Limitations of physical models are the cost to conduct and analyze element level experiments, their potential irrelevance for large bridge networks, and the challenge to implement into a Bridge Management System (BMS).

3.2. 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 shown that an artificial neutral network (ANN) backwards prediction model (BPM) can 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 use as much data that is available to insure AI can successfully implement case adaptation [5].

3.3. Summary

Deterministic models do a reasonable job of capturing the deterioration of the bridge elements and are easy to use. However, stochastic models that introduce randomness and uncertainty are better at predicting deterioration rates over a longer time period. There are multiple ways of modeling bridge deterioration rates. The completeness of data and resources available to conduct the analysis, or experiment are considerations for selecting a model. If relevant information is not available, machine learning techniques are often used instead to create synthetic data to complete a dataset or run consecutive analyses on a dataset that builds off each additional model to increase the accuracy of the predictors.

4. State DOT Deterioration Analyses

Several states have recently completed research projects related to deterioration curve modeling using the methods described above. Efforts similar to the objectives, datasets, and resources of this research are summarized below.

4.1. Nebraska

Recently completed research by the Nebraska Department of Roads investigated developing state-specific deterioration models for use in AASHTOWare Bridge Management Software (BrM) [12]. This software is a bridge management solution to assist engineer, managers, and decision-makers in the selection and timing of preservation, rehabilitation, and replacement projects for their structures [3]. Using data from the Nebraska BMS they developed deterioration models and identified deterioration trends related to concrete decks in different transportation districts and were specific to AADT, epoxy coated rebar, and structure type.

4.2. Wyoming

The state of Wyoming developed deterioration models using both stochastic and deterministic methods with the National Bridge Inventory 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 where identified as significant indicators for deck condition ratings. Superstructure ratings where influenced by deck structure type, bridge roadway width, functional class, and max. span length.

4.3. 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 project and network levels.

4.4. 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 and freeze index, freeze-thaw cycles, and average precipitation were found to be major predictors [24].

In a second study, researchers looked at bridges in Indiana to conduct performance evaluations and life predictions of concrete bridge structures across different design types. 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 the models created in their study, they identified that cast-in-place concrete bridges in Indiana 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 model 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 are 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.

4.5. 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 are not applicable outside of New York.

Another study predicted long-term bridge deterioration ratings and patterns of bridge elements to optimize maintenance strategies in New York. 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]. The two approaches were similar 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 recommended further modeling to assess the true long-term estimates of condition states.

4.6. California

The 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 (e.g. slab; stringer/multi-beam or -girder; T-beam; and box-beam or -girder). Using regression techniques and Monte Carlo simulation, they identified eight variables (e.g. age, ADT, degree of skew, max. span length, structure length, roadway width, deck width, and ADTT) on the superstructure deterioration that had a high coefficient of determination [28]. The Monte Carlo method was a type of machine learning that used the fitted probability of each variable. The simulation calculates results for thousands of cases using different randomly selected values of explanatory variables which were expressed as a probability distribution to simulate real-world processes. These models were validated using the Average Validity Percentage method.

4.7. Texas

This study uses a semi-Markov process for life-cycle optimization models for highway bridge maintenance activities to improve the traditional Markov model's ability to capture real time bridge-state transitions. Their models used bridge specific information (e.g. age, materials, environmental conditions, ADT, etc.) to realistically model the service-life deterioration behavior 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 predicted the repair effects maintenance and captured the post-performance of the bridge. The models were built only using steel bridges in Texas, but their approach is applicable to other types of bridges built with other materials.

4.8. Pooled Fund

Several states are currently participating in research related to deterioration modeling and new analytical tools to develop deterioration curves for bridge elements using bridge inspection data from their own state. This pooled-fund study of 12 midwest states is investigating 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.

5. Recommendations and Next Steps

1. Filter the data as needed, examples include.
    a. State highways only—data from local roads and other agencies are filtered out
    b. Bridges of span 20 ft or less were excluded
    c. Missing data results in the removal of the observation, or applications of machine learning are applied to fill the gaps.
2. Divide data into groups of similar bridge types, geographical regions, climate conditions, etc.
3. Identify, from the bridge condition data, whether any of the three bridge intervention categories (repair, rehabilitation, and replacement/reconstruction) occurred at any specific year and the effectiveness of such interventions in terms of changes in the condition ratings of the bridge components (from a lower to a higher condition state after the intervention).
4. Explicitly account for the recuperation effect of these past interventions on the bridge infrastructure condition using deterministic LASSO regression models and other forms of machine learning.
5. Introduce into the deterioration model the change in condition state after maintenance interventions and the length of time that a specific intervention remains effective. Its efficacy maintenance activities and the effect on the probability of the component being in a given condition will change as age progresses.

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