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ARTICLE

Survival Analysis Using Cox Proportional Hazards Regression for Pile Bridge Piles Under Wet Service Conditions

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ABSTRACT

This paper studies the deterioration of bridge substructures utilizing the Long-Term Bridge Performance (LTBP) Program InfoBridge™ and develops a survival model using Cox proportional hazards regression. The survival analysis is based on the National Bridge Inventory (NBI) dataset. The study calculates the survival rate of reinforced and prestressed concrete piles on bridges under marine conditions over a 29-year span (from 1992 to 2020). The state of Maryland is the primary focus of this study, with data from three neighboring regions, the District of Columbia, Virginia, and Delaware to expand the sample size. The data obtained from the National Bridge Inventory are condensed and filtered to acquire the most relevant information for model development. The Cox proportional hazards regression is applied to the condensed NBI data with six parameters: Age, ADT, ADTT, number of spans, span length, and structural length. Two survival models are generated for the bridge substructures: Reinforced and prestressed concrete piles in Maryland and reinforced and prestressed concrete piles in wet service conditions in the District of Columbia, Maryland, Delaware, and Virginia. Results from the Cox proportional hazards regression are used to construct Markov chains to demonstrate the sequence of the deterioration of bridge substructures. The Markov chains can be used as a tool to assist in the prediction and decision-making for repair, rehabilitation, and replacement of bridge piles. Based on the numerical model, the Pile Assessment Matrix Program (PAM) is developed to facilitate the assessment and maintenance of current bridge structures. The program integrates the NBI database with the inspection and research reports from various states' department of transportation, to serve as a tool for condition state simulation based on maintenance or rehabilitation strategies.

Keywords: Survival analysis of bridge structures; Cox proportional hazards regression; Bridge rehabilitation and maintenance; Bridge substructure protection; National bridge inventory; Simulation of bridge substructure condition state

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1. Introduction

Deterioration of bridge structures plays an essential role in maintaining the functionality of transportation networks as aging infrastructure becomes more prevalent nowadays. Bridges are unique because there are few substitutions to them when a failure occurs. Hence, any obstruction during a bridge's operational life will create major losses. Due to the complexity of bridge deterioration, prediction models derived using analytical methods struggle to provide accurate predictions of the deterioration process. Since large-scale datasets became available, engineers can perform statistical analysis with the aid of evolving computational power. In addition, deterministic models are gradually being replaced by probabilistic approaches, which account for uncertainties. Hence, a probabilistic-based model is preferred over a deterministic model in the prediction of a bridge condition rating.

Bridges under wet service conditions generally deteriorate faster than those on land. In a wet environment, the piles are the most vulnerable components of a bridge. Yet it is a critical part of the bridge integrity, especially in terms of seismic resistance [1-3]. Michael and Sagues concluded that in marine environments, bridge piles are highly susceptible to server localized corrosion [4]. The condition rating of a bridge can be considered as individual incidents throughout the lifespan of the bridge, and the defects in structural integrity can be viewed as hazards [5]. The Cox proportional hazards regression is widely used in clinical trials that describe the survival rate, hazard rate, and cumulative survival function [6]. In bridge studies, the survival function outlines the deterioration of bridges or bridge components over the lifespan of the structure [5]. Missing data in bridge inventory records can also be accounted for by survival models [7,8]. The deterioration of bridge structures can be modeled as a Markov process with discrete time, with the stochastic characteristic of bridge deterioration maintained [9,10]. The transition probability is key to the Markov chain. In bridge maintenance, the transition probability is the probability of a bridge component, will transition into the next condition rating. It is calculated by dividing the total number of bridge components in a particular condition state in the year prior by the number of bridge components in the same condition state in the current year [11].

Using modern computers and advanced programs, large-scale statistical analysis can investigate the deterioration trend of bridge structures with customized parameters deemed relevant by the user. Such an approach allows researchers to acquire probabilistic models for both a large area and a specific region [12]. The parameters can also be adjusted to reflect critical factors that may not be predominant in a larger-scale model.

The scope of this research is to study the deterioration of bridge substructures using the Long-Term Bridge Performance (LTBP) Program InfoBridge™ [13], and bridges with reinforced or prestressed concrete (RC/PC) columns/piles are chosen. The dataset is obtained from the National Bridge Inventory (NBI) [14] for bridge information from 1992 to 2020. This study primarily focuses on the bridges in the state of Maryland, with three additional northeast regions also included to facilitate the survival analysis, particularly for bridges in wet service conditions. The NBI dataset was condensed to only include items considered to be reverent to the deterioration model. The Cox proportional hazards regression was selected as the statistical tool to develop the survival model that reflects the deterioration of bridge piles. Results of the survival analysis are used to construct two Markov chains for visualization and prediction of pile deterioration.

The stakeholders of bridge structures rely on a robust and comprehensive bridge management system to secure the serviceability and longevity of the bridges [15]. However, there is a lack of existing studies in developing a tool for the assessment and prediction of bridge piles under wet service conditions. Robert et al. discovered that prestressed concrete piles deteriorate in marine environments as the jackets deteriorate, exposing prestressing strands and tie reinforcement that exhibit heavy corrosion due to high levels of chloride [16]. The challenge of monitoring pile deterioration is that the process is gradual and continuous throughout the lifespan of the structure. When deterioration becomes visible, the piles are severely compromised. Moreover, major corrosion can be hidden by jackets designed to protect the piles, and the deterioration of jackets can also boost the corrosion of the reinforcing steel. Therefore, there is a need for an automatic, robust, and reliable tool for assessing the integrity of piles. The tool needs to be easily implemented and user-friendly and can be applied to different regions as the service condition of the bridge structures dramatically affects the deterioration of piles.

A total of 979 bridges in the state of Maryland were chosen to be the primary focus of this study, complemented by bridges in the state of New York, North Carolina, Virginia, Delaware, and the District of Washington to expand the sample size. The goal of the study is to perform a survival analysis of bridge piles under wet service conditions and develop a pile assessment tool for simulating future pile conditions based on maintenance and rehabilitation strategies. Users can easily implement the computer program to assist in decision-making.

2. Materials and methods

2.1 Cox proportional hazards regression model

The deterioration of bridge substructures is controlled by various factors, such as geological location, usage, soil, and service condition [5]. The deterioration of bridge substructures is similar to that of clinical trial studies. In clinical trial studies, a certain outcome, for instance, death, is associated with various parameters in the treatment. The Cox proportional hazards regression model [6] is one of the most popular regression techniques in survival analysis. The model calculates the hazard rate given the subject has survived for a certain amount of time. The Cox proportional hazards regression is based upon three fundamental assumptions:

1) The survival times between each distinct individual are independent.

2) The predictors and the hazards share a multiplicative relationship.

3) The hazard ratio is constant over time.

The general expression of the Cox proportional hazards regression can be written as:

$$h(t) = h_0(t)\exp(b_1X_1 + b_2X_2 ++ b_pX_p) \quad (1)$$

where h(t) represents the hazard at time t, and X is the predictor and independent variable that affects the hazard rate over time t. $h_0(t)$ is the baseline hazard when all the parameters are equal to zero. The relevance of the predictors is quantified by the regression coefficients, b.

The hazard ratio relates the hazard ratio at time t and the individual item X and can be written as:

$$HR(X_i) = \frac{h(X_i,t)}{h_0(t)} = \exp[\sum_{i=1}^{p} X_{ij}b_j] \quad (2)$$

The Cox proportional hazards regression model is semi-parametric, meaning that the shape of the baseline hazard function is not assumed. The hazard ratio of the Cox proportional regression model provides a clear sign of the association between the predictor variable and the hazard rate. The hazard ratio of a variable can be calculated as $\exp(b_i)$, and the interpretation can be summarized below:

1) If hazard ratio > 1, increase in hazard.

2) If hazard ratio < 1, decrease in hazard.

3) If hazard ratio = 1, no effect on hazard.

Since the hazard rate is related to the survival rate, the survival rate at time t can be derived as:

$$S_{xi}(t) = S_0(t)^{HR(X_i)} \quad (3)$$

To complete the regression, the cumulative hazard function is calculated as:

$$H(t,X) = \int_0^t h(t,X)dt = e^{(Xb)} \int_0^t h_0(t)dt = e^{(Xb)}H_0(t) \quad (4)$$

Thus, the cumulative survival function can be calculated as follows [8]:

$$S(t,X) = e^{-H(t,X)} = e^{-e(Xb)H_0(t)} = [e^{-H_0(t)}]^{e(Xb)} = [S_0(t)]^{e(Xb)} \quad (5)$$

The cumulative survival function can be used to calculate the transition probability to construct a Markov chain. The Markov chain defined in this study has a time interval of one year [5]. Hence, the transition probabilities describe the probabilities of a bridge substructure remaining in one condition for a year, as shown by Mishalani and Madanat [11]. The transition probabilities are calculated as:

$$P_{kk}(t, X) = \frac{S_k(t+\Delta t,X)}{S_k(t,X)} = \frac{S_k(t+1,X)}{S_k(t,X)} \tag{6}$$

where Δt = 1 year.

The transition probabilities between substructure condition states can be modeled using a Markov chain [9,10]. It is assumed that the deterioration of the bridge substructure only goes in one direction: from a better state to a worse state. The process is irreversible without repair or rehabilitation. Once the bridge substructure rating reaches the failure state, it will remain in the failure state. The Markov chain uses the NBE condition state format, with an artificial condition state CS5 added solely for mathematical reasons. The Markov chain adopted in this research is illustrated in **Figure 1**.

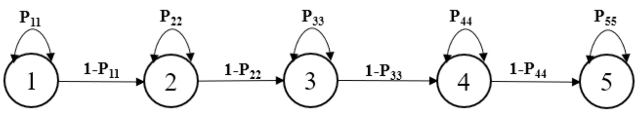


Figure 1. Markov chain for deterioration of bridge substructures.

2.2 Survival analysis of bridge structures

The general approach of this study adopts the mythology presented by the research report published by Goyal et al. [1]. Using LTBP Infobridge™ [13]. bridges with RC/PC columns/piles are selected. Then, two survival analyses were performed based on the filtered data from New York, North Carolina, Maryland, and Virginia. The first analysis focuses on 979 bridges in the state of Maryland. All 979 bridges are constructed with RC/PC columns/piles. The number of Maryland's bridges with prestressed concrete piles in wet service conditions is relatively small to represent the entire population. Hence, additional states (NY, NC, and VA) in the northeast are included to facilitate the second survival analysis where the hollow prestressed concrete pile is adopted in wet service conditions.

The NBI dataset provides bridge information for all states starting from 1992, which makes it the most comprehensive dataset on LTBP Infobridge™ [13]. Meanwhile, the National Bridge Element (NBE) [14] is a great complementary tool to the NBI dataset, as NBE offers detailed information on specific bridge elements. Items in the NBE dataset represent the condition of the primary structural component of a bridge and can be used as indicators in the assessment of the overall condition rating of the structure. However, unlike the NBI dataset, some bridges' NBE datasets are not provided in the LTBP Infobridge™ database. In Maryland, only 1,972 bridges have NBE data among all 5,430 bridges. In this study, the NBE dataset is used as a filter to identify bridges that meet the criteria of this research. The locate the bridges with reinforced or prestressed columns/piles and bridges with RC/PC columns/piles in wet service condition, the following NBE items are used in **Table 1**.

Table 1. National bridge element items.

Item number	Description
204	Prestressed Concrete Column
205	Reinforced Concrete Column
226	Prestressed Concrete Pile
227	Reinforced Concrete Pile

In the NBI dataset, item 92B (underwater inspection) is used to select bridges that are under wet service conditions, including lakes, rivers, bay areas, and oceans. The items listed in **Table 2** are processed and converted into parameters that serve as predictors for the Cox proportional hazards regression. Among them, item 60 (substructure condition) is the target output of the model. Hence, the purpose of the regression is to study the association of the variables with the substructure condition. Then, the condensed NBI data was processed to prepare the parameters for the Cox proportional hazards regression.

Table 2. Nation bridge inventory items for Cox proportional hazards regression.

NBI item number	Description
27	Year built (age of the bridge)
29	Average daily traffic
45	Number of spans in main unit
46	Number of approach spans
48	Length of maximum span
49	Structure length
109	Average daily truck traffic (%)

Per MDOT State Highway Administration, the NBI substructure condition rating is converted into the NBE condition state format before processing Cox proportional hazards regression, with one additional condition state (CS5: failure) added. The added condition state is only necessary for mathematical reasons in the Markov chain developed in the latter section. The conversion follows the instruction of the MDOT State Highway Administration and is displayed in **Table 3**. The NBI condition ratings are based on the recording and coding guide by the Federal Highway Administration [17]. When a bridge is in condition rating 9 to 8, there is no defect. In ratings 7 to 6, minor defects become visible. At 5, the main structural components are in good condition while they may exhibit slight deterioration in certain areas, such as section loss, cracks, and scour. Starting from rating 4 the bridge shows advanced section loss and deterioration and will quickly enter critical conditions. In practice, bridges reaching a condition rating of 4 or below demand immediate attention and rehabilitation effort.

Table 3. Nation bridge element items.

NBI condition rating	NBE condition rating
9-8	CS1
7-6	CS2
5	CS3
4 or less	CS4
failure	CS5 (failure)

With the condensed NBI dataset established, a series of scripts were created in MATLAB to perform the Cox proportional hazards regression. The MATLAB scripts are streamlined: First, import bridge data from 1992 to 2020; next, select bridges that meet the research criteria using structural number/ID; then, perform data cleaning and prepare the NBI data for regression; finally, perform Cox proportional hazards regression to obtain cumulative survival function, calculate transition probability and construct the Markov chain. An example of the condensed data in MATLAB is shown in Appendix A for bridge number 100000210108014.

To prepare the data for regression, censoring information, and data normalization need to be included. Censoring is crucial for acquiring an accurate model since it is not always possible when the event is completely observed. In this study, a bridge may exhibit substructure condition state 7 in the year 1992. There is no definitive information of when did this bridge reach substructure condition state 7, and for exactly how long has the bridge been in that condition state, since the NBI record starts in the year 1992. Because of the reconstruction or repair of the bridge, the natural deterioration process is interrupted. Hence, substructure condition state 7 for this bridge is censored. While only the fully observed substructure condition states remain effective, data normalization is required to limit the bias of predictor variables in terms of their impact on the event of interest. For instance, the value of average daily traffic usually contains a larger number compared to that of the age of the structure; the value of span length is also considerably greater than that of the number of spans. Parameters with large fluctuations will also introduce bias without proper treatment. The regression may be biased without balancing and normalizing these parameters. Hence, the parameters are normalized into a standard 1 to 10 scale before being processed by the Cox proportional hazards regression model.

3. Results

3.1 Results of survival analysis of Maryland bridges with RC/PC columns and piles

Two survival analyzes were performed using the Cox proportional hazards model. The first case generates the cumulative survival function for 979 bridges in Maryland with RC/PC columns and piles. The second case calculates the cumulative survival function for the same type of bridges in wet service conditions in New York, Maryland, Virginia, and North Carolina. The following data visualizations are based on results for Maryland bridges. **Figure 2** shows the occurrence of each rating of the substructure condition.

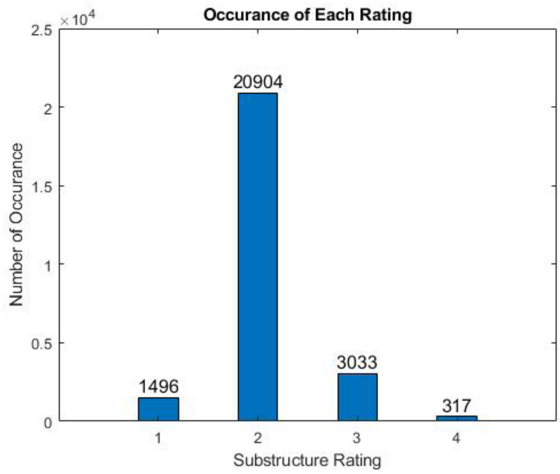


Figure 2. Occurrence of each substructure condition rating.

Based on the graphs above, most of the bridges in Maryland stay in substructure condition rating CS2 (20904), while CS4 has the least occurrence (317) over the past 29 years. The NBI dataset was fitted by the Cox proportional regression, and four cumulative survival functions are generated. The cumulative survival function reflects the probability of the bridge substructure staying in a specific condition rating each year. Likewise, it can also be interpreted as the percentage of bridge substructures remaining in a condition state at a year. At CS1, the deterioration rate of the substructure is considerably faster as the cumulative survival function displays a faster drop. This observation shows that a new bridge exhibits an accelerated deterioration rate when the substructure is still in the best condition ratings. The substructure condition ratings of bridges constructed with reinforced or prestressed concrete columns/piles stabilize in CS2 and CS3. A bridge structure will spend most of its service life in these two condition states, where the deterioration of the substructure remains steady. Conversely, the deterioration rate accelerates rapidly in CS4. Under substructure condition rating CS4, the substructure is considered in "poor" condition. As deterioration accumulates over the life span, the substructure experiences an increased rate of drop in structural integrity, as shown by the steeper slope and sudden drop in the cumulative survival function. Overall, the substructure condition rating exhibits an accelerated deterioration rate in CS1 and CS4 and stabilizes during CS2 and CS3. cumulative survival function of the bridges over 29 years are plotted in **Figure 3**.

The hazard ratio of each predictor variable was calculated and shown in **Table 4**. The hazard ratios give a direct indication of the association between the predictor variables and the substructure condition rating. If the hazard ratio is greater than one, that

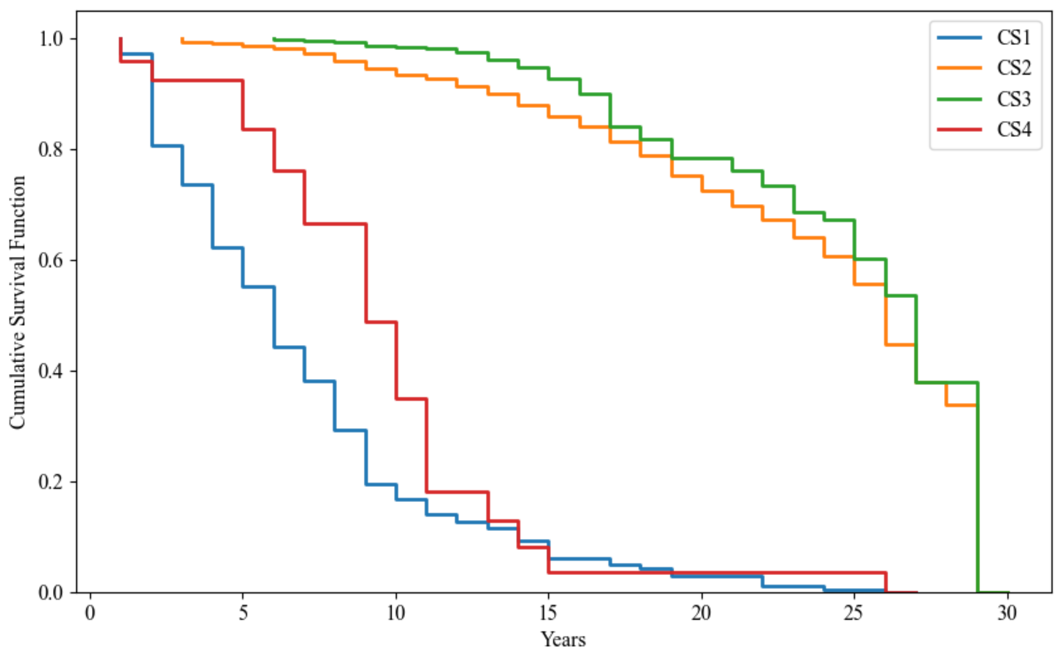


Figure 3. Cumulative survival function for Maryland bridge.

translates to an increase in hazard; when the hazard ratio is smaller than one, it shows a reduction in hazard. The value of the hazard ratio reflects the increase in hazard when the predictor variable increases by one unit, and vice versa. Note that for bridges under wet service conditions, the dataset does not distinguish seawater and freshwater because this classification is not available in the National Bridge Inventory data portal. Hence, results for bridges in wet service conditions are based on the general condition where the bridge is water-crossing. For instance, if the age of the bridge increase by one unit, there is an increase of 2.5% in hazard at CS1. The hazard ratios contradict the four condition states. At CS1, an increase in age, ADT, number of spans, and ADTT results in an increase in hazard, while longer maximum length and structure length result in a hazard reduction. At CS2, the structure length is the only variable that offers a hazard reduction, and the reduction is greater than that in CS1. At CS3, the maximum span length becomes the only variable with a hazard ratio smaller than one, however, it has almost no effect on the deterioration rate. At CS4, the number of spans and ADTT are identified as the only two variables with a hazard ratio greater than one, while others are smaller than one.

Table 4. Hazard ratios of predictor variables for Maryland bridge.

Parameter	CS1	CS2	CS3	CS4
Age	1.025689	1.06883	1.075101	0.811192
ADT	1.030079	0.913986	1.053165	0.643571
Number of spans	1.168937	1.318656	1.158964	1.785335
Max span length	0.980824	1.357925	0.284489	0.975701
Structure length	0.843096	0.609547	1.41E-06	0.739896
ADTT	1.036217	1.04808	0.930124	1.832976

The transition probability is calculated based on the cumulative survival function according to Equation (6). Under the NBE condition status rating, the Markov chain was developed to account for the transition from CS1 to CS5, with CS5 being an artificial condition state solely for mathematical purposes. The Markov chain for Maryland bridges is shown in **Figure 4**. Based on the results, there is a 77.7% of chance that a Maryland bridge will remain in CS1 for a year and a 22.3% of chance to transition into CS2. Then, it has a 96% of chance staying in CS2 and a 4% of chance deteriorating into CS3. Next, the bridge has a 95.7% of chance remaining in CS3 for another year, and a 4.3% of chance degrading into CS4. Finally, at CS4, the structure has a 76.1% of chance remaining in CS4 and a 23.9% of chance of failure. Once the structure reaches failure (CS5), it cannot transition into any other condition state. The Markov chain also reflects the same trend observed in the cumulative survival functions: the deterioration rate accelerates at CS1 and CS4 but stabilizes at CS2 and CS3.

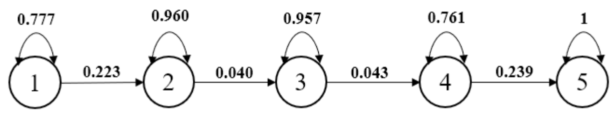


Figure 4. Markov chain for Maryland bridge.

3.2 Results of survival analysis of bridge structures with pre-stressed piles/columns

The survival analysis based on bridges constructed with pre-stressed piles/columns was carried out similarly. To obtain an adequate amount of bridge structures within regions where water-induced deterioration may be an issue, the sample comprises 330 bridges from New York, Virginia, Maryland, and North Carolina. The results are shown in **Figures 5 and 6**.

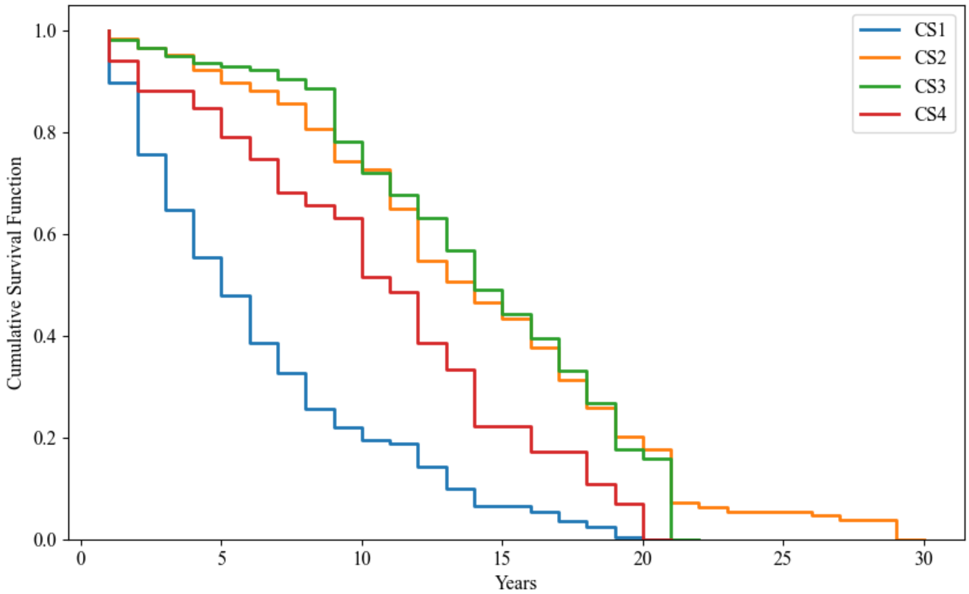


Figure 5. Cumulative survival function for bridge with pre-stressed piles/columns.

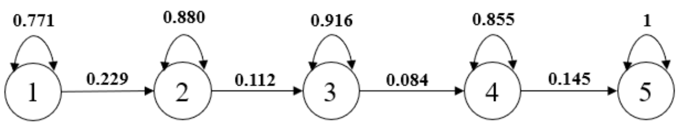


Figure 6. Markov chain for bridges with pre-stressed piles/columns.

3.3 Pile assessment matrix program (PAM)

Overview

To facilitate the simulation of bridge piles based on rehabilitation and maintenance strategies, the Pile Assessment Matrix Program (PAM) was developed to offer users an accessible tool to model the condition rating of piles in the future to assist in decision-making. PAM is constructed to incorporate the NBI database with research reports for state DOTs, forming a framework for pile condition rating simulation. To ease accessibility, the program is developed using Visual Basic for Applications so the users can simply operate the program in MS Excel. The workflow of PAM is presented in **Figure 7**.

The current version of PAM has integrated the NBI dataset of Maryland up to the year 2020, with the corresponding survival rates generated based on the same dataset. Hence, the numerical model is region-specific. As the NBI dataset gets updated each year, users can easily update the program database by adding the latest dataset to the program. There are two options regarding the preset for survival rates of bridge piles: One based on the reinforced/prestressed concrete bridges and the other based on the prestressed concrete bridges with hollow cross sections. The user can choose the appropriate option based on the bridge inventory being managed. In addition, the user is free to enter their survival rates carried out from other studies. Though the program is primarily a simulation tool for forecasting pile condition ratings, it also serves as a condensed database for the bridge inventory system. The user can access the bridge's age, length, longest span length, number of spans, number of approach spans, annual average daily traffic, and the total number of piles of a bridge by entering the structure ID. The general steps for using PAM can be summarized in **Figure 8**.

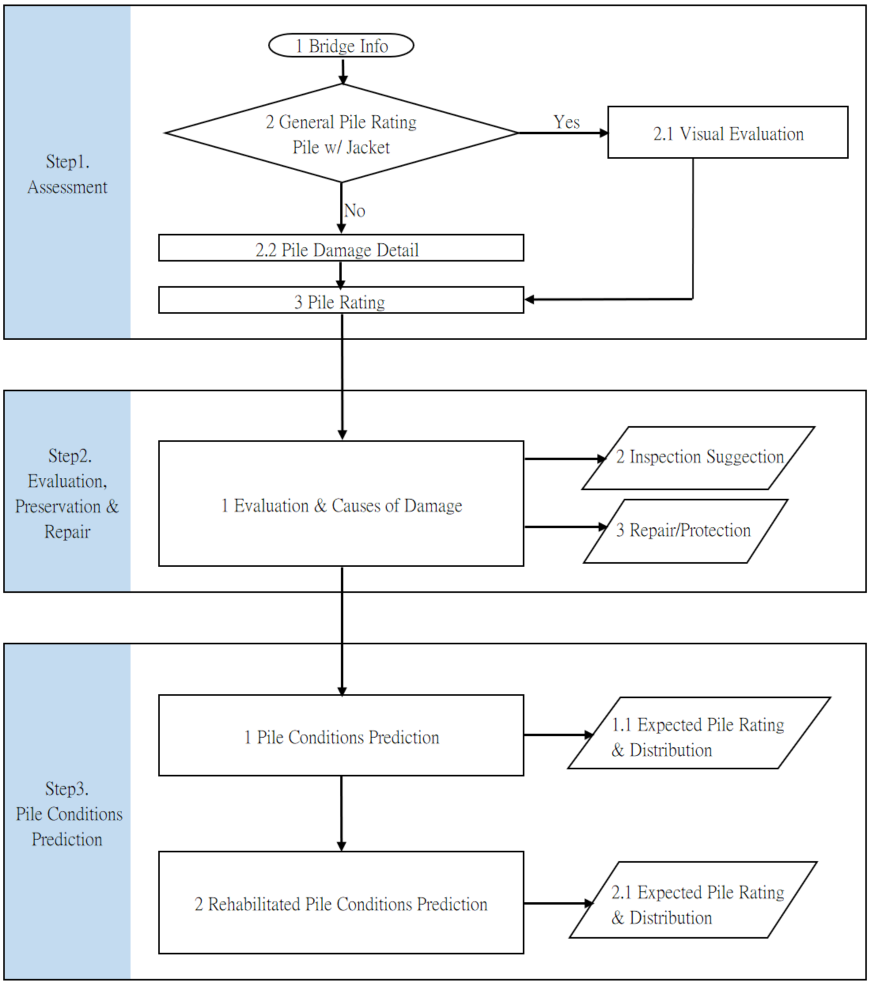


Figure 7. Flowchart of workflow in PAM.

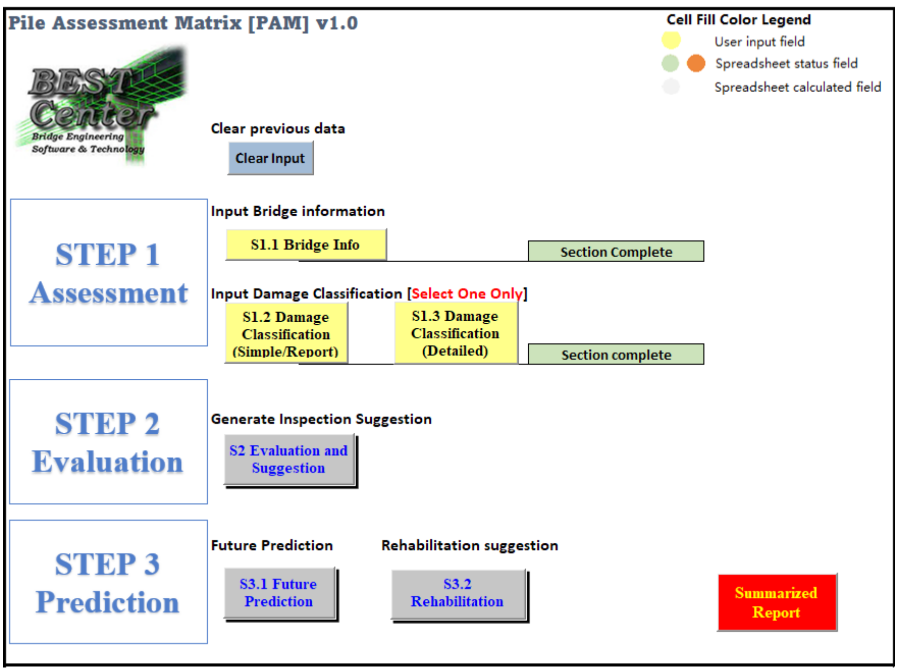


Figure 8. General steps in PAM.

Assessment of pile condition using PAM

Users can enter information regarding the current condition of the bridge pile based on inspection reports. There are two options for describing the pile conditions. The simplified method has the user entering the number of piles in each condition state, and the detailed approach enables more data entries on the pile conditions, including the overall condition of the bents and deterioration of specific categories.

Evaluation and recommendation

Based on the pile conditions, PAM can offer recommendations on potential location and cause of pile damage. These suggestions are based on various reports from DOTs across the U.S. **Table 5** and **Figure 9** show the reference guide for the potential cause of damages. Suggestions on the following inspection are also generated to focus on vulnerable components that may require immediate attention for repair.

Prediction of pile condition

The key functionality of PAM is to simulate the pile condition ratings based on the initial pile condition and maintenance strategies. The transition probabilities between condition ratings are calculated during the survival analysis. But the user has the freedom to specify the transition probabilities manually to suit the specific use case. As shown in **Figure 10**, PAM will estimate the percentage of piles in each condition rating and calculate the future values based on the specified time interval. The expected ratings are also listed for reference. A series of pie charts will be generated at the end of the simulation to visualize the change in pile conditions over time (shown in **Figure 11**). Likewise, simulation of the pile conditions also allows inputs regarding rehabilitation. The transition probability will adjust based on the rehabilitation implemented. **Figure 12** shows a summary report of a simulation.

Table 5. Common deteriorations.

Symptoms	**Damage**	**Cause**
Cracking w/rusted stains	Loss and exposed material	Corrosion of reinforcing steel
Longitudinal cracking above water level	Loss of material & exposure in splash and tidal zone	Freeze/Thaw
Softening of concrete	Loss and exposed material	Sulfate attack
Cracking	Loss and exposed material	Chemical reaction of aggregates with water
Hairline cracking and spall at the top of the pile	Loss and exposed material	Overloaded structure
Hairline circumferential cracks	Loss and exposed material	Overloaded structure
Exposed foundations	Loss of foundation soil & exposed footing	Erosion due to bridge scour or major flooding
Localized major cracking	Exposed material, impact damage, large section loss	Abnormal events (earthquakes, ship collisions, etc.)

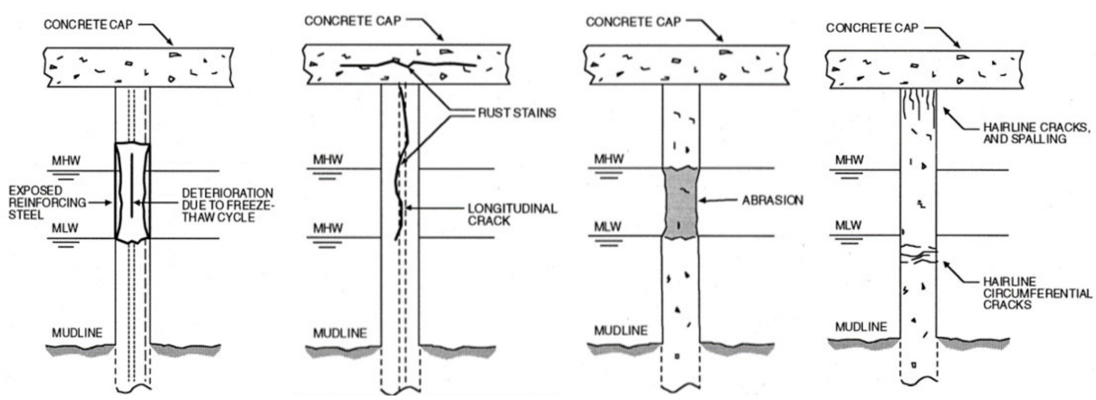
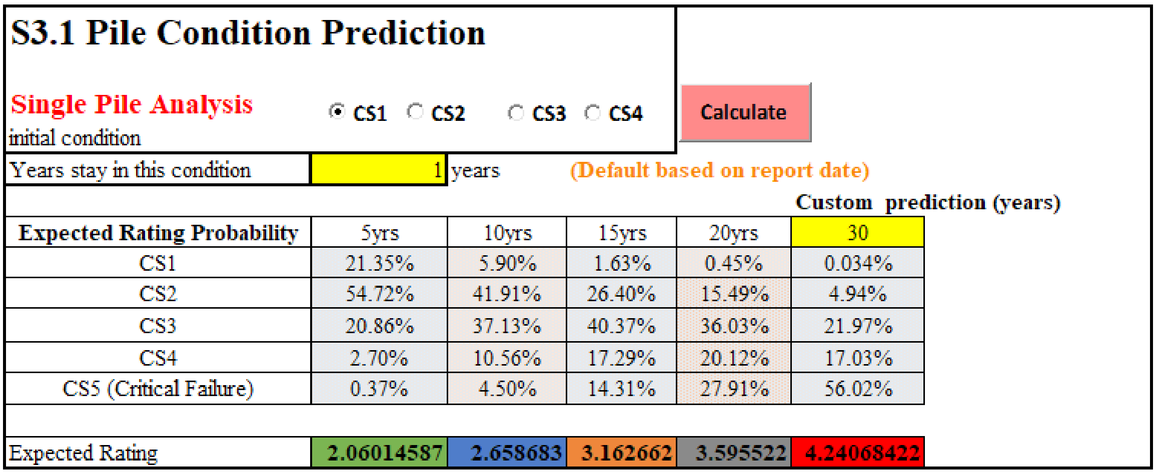


Figure 9. The common cause of damage.



S3.1 Pile Condition Prediction

Single Pile Analysis ◉ CS1 ○ CS2 ○ CS3 ○ CS4 **Calculate**

initial condition

Years stay in this condition: 1 years (Default based on report date)

Custom prediction (years)

Expected Rating Probability	5yrs	10yrs	15yrs	20yrs	30
CS1	21.35%	5.90%	1.63%	0.45%	0.034%
CS2	54.72%	41.91%	26.40%	15.49%	4.94%
CS3	20.86%	37.13%	40.37%	36.03%	21.97%
CS4	2.70%	10.56%	17.29%	20.12%	17.03%
CS5 (Critical Failure)	0.37%	4.50%	14.31%	27.91%	56.02%
Expected Rating	2.06014587	2.658683	3.162662	3.595522	4.24068422

Figure 10. Estimated percentage of pile ratings.

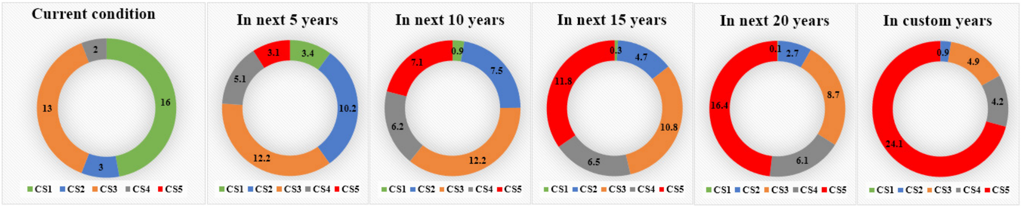


Figure 11. Change of pile ratings over time.

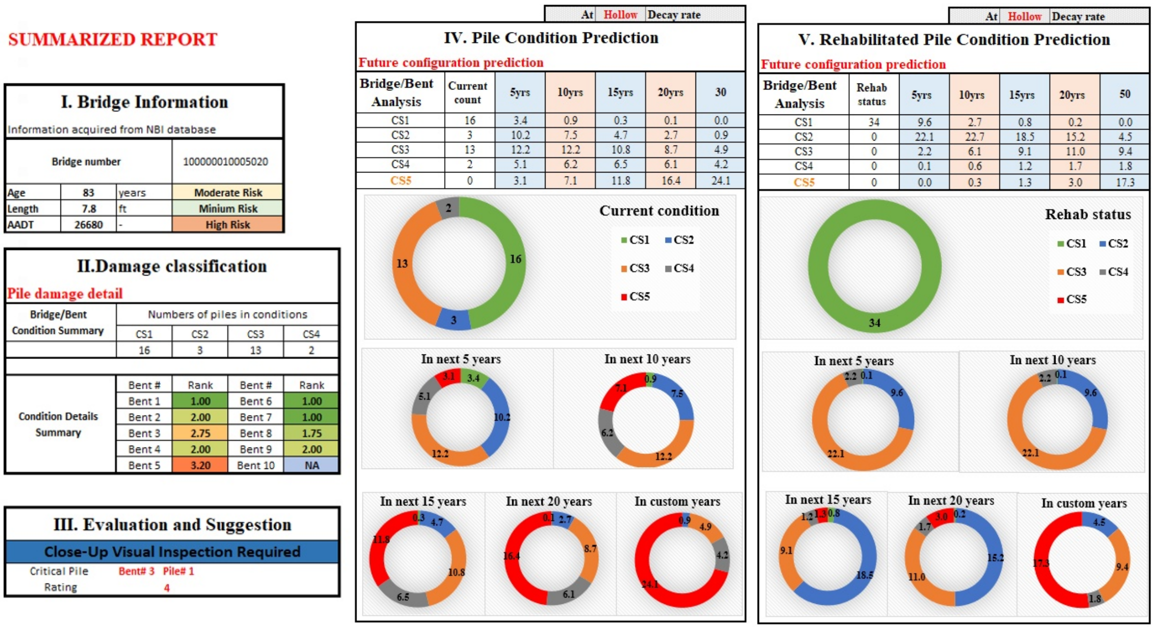


Figure 12. Summary report on pile condition simulation.

4. Discussion

Survival analysis carried out by the Cox proportional hazards regression model offers flexibility for users to generate various models based on specific criteria. The choice of predictor variables can be defined based on the project, and the dataset can also be chosen to reflect the structural deterioration in a certain region. For this study, there are six predictor variables included in the regression. The collection of predictor variables can always be expanded as deemed necessary. Whereas a larger number of predictor variables does not guarantee improvement in the accuracy as irrelevant data may introduce noise into the sample. Hence, further statistical analysis can be performed to identify any predictor variables that are not important. Results in this study might be improved by performing an in-depth analysis of the statistical correlation of the predictor variables and identifying the best subset for the algorithm.

The deterioration rate of newly built bridges with substructure condition state CS1 is faster than expected. One potential explanation is not all bridges are built with encapsulation of the columns or piles. In certain situations, pile jackets are installed after repair, or substantial damage has been found on the substructures. This effect can be observed with bridges in wet service conditions when a 68.3% probability is calculated compared to 77.7% of the general case. Bridges in wet service conditions are more susceptible to damage such as corrosion, spalling, and chloride contamination.

5. Conclusions

Two survival analyses were accomplished using the NBI, NBE dataset, and the Cox proportional hazards regression model. Two sets of cumulative survival functions were plotted to reflect the deterioration process of bridges constructed with reinforced RC/PC columns/piles. The associated Markov chains were developed based on the transition probabilities calculated from the cumulative survival function. The Markov chains are used as a probabilistic basis for a separate program forecasting the bridge substructure condition states. The key findings of this research are summarized below:

1) The deterioration of bridge substructures with RC/PC columns/piles can be modeled using Cox proportional hazards regression. The condition states of the bridge piles are treated as individual incidents, similar to those in medical trials.

2) The choice of predictor parameters affects the results. Though the NBI database offers a wide range of bridge parameters, only a portion of them is significant concerning the efficiency and accuracy of the survival analysis. When selecting the predictor variables, only the most relevant parameters are included, based on the specific subject on which the survival analysis is performed. For instance, the direction of traffic may not be important when calculating the survival rate of the piles.

3) The deterioration rates of bridge substructures with reinforced or prestressed columns/piles are fastest during the best or worst condition states (CS1 and CS4) but stabilize in the intermediate condition states (CS2 and CS3). That is, when the piles are in pristine condition, they tend to deteriorate faster as the material is settling into the surrounding environment and numerous chemical reactions are initiated. As the fresh materials interact with the environment, the deterioration starts to slow down, and the outer portion of the piles will start to show visible cracks without major damage. At last, deterioration of the piles accelerates again when they are in the worst condition state because at this point most of the protections have been consumed and the structure is severely exposed to the surrounding environment, promoting faster reactions between the materials and moisture contents.

4) In wet service conditions, bridge substructures experience an accelerated deterioration rate. This is mostly caused by chloride-induced reactions between the piles and water.

5) The Pile Assessment Matrix (PAM) is a computer program designed to facilitate the assessment and simulation of bridge piles under wet service conditions. The program is region-specific as the survival rates are dependent on the geological locations of the bridges. The user can use the default setting if the target bridge inventory is similar to those of Maryland. Otherwise, the user can manually specify the survival rates based on the particular use case. The main functionality of PAM is to simulate the pile conditions in the future and offer potential causes of deterioration and recommendations for future inspection.

Author Contributions

Naiyi Li—Collecting and organizing data, and performing survival analysis.

Kuang-Yuan Hou—Collecting and organizing data, and developing an assessment program.

Yunchao Ye—Developing an assessment program.

Chung C. Fu—Collaborating and guiding research efforts, interacting with funding agencies.

Conflict of Interest

There is no conflict of interest.

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