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EVALUATION OF BRIDGE DETERIORATION FACTORS: FROM DESIGN PARAMETERS TO COMMUNITY IMPACT

by

Lawrencia Maame Ofosua Akuffo

A Thesis

Submitted to the
Civil and Environmental Engineering
College of Engineering
In partial fulfillment of the requirement
For the degree of
Master of Science in Civil Engineering
at
Rowan University
August 16th, 2024

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Dedication

First and foremost, I dedicate this thesis to God Almighty. Through His grace, I have been blessed with the strength, wisdom, and perseverance needed to complete this journey. I am eternally grateful for His endless blessings and glory upon my life.

To my beloved mother, Doris Akuffo, for praying and sacrificing so much for me, and my sibling, Samuel Akuffo, your unwavering support and encouragement have been my anchor. You both stood by me through thick and thin, and your love has been a constant source of strength and inspiration.

To my late father, Lawrence Akuffo, who never stopped believing in me, till the end. Your faith in me and your enduring love continue to inspire me every day. This achievement is as much yours as it is mine.

To my fiancé, Stephan Komladzei, thank you for your patience, understanding, and unwavering support. Your love and companionship have been my refuge during the most challenging times, pushing me to fulfill my wildest imaginations and dreams.

To my advisor, Dr. Adriana Trias Blanco, your guidance, insight, and encouragement have been invaluable. Your dedication to my academic and personal growth has profoundly shaped my journey.

Finally, I express my gratitude to all those who contributed to this work, including my team members, committee members, and research participants. Your support, guidance, and feedback have been invaluable, and I am honored to have worked with you all.

Acknowledgment

My sincere appreciation goes out to everyone who helped me along the way while I worked on this thesis.

I would like to start by expressing my sincere gratitude to the Center for Research and Education in Advanced Transportation Engineering Systems (CREATES) for providing me with the chance to conduct this research and for their continuous support. Their commitment to furthering the field of transportation engineering has consistently served as an inspiration.

The New Jersey Department of Transportation (NJDOT) is also much appreciated for their crucial assistance with this study. This effort, which allowed me to delve extensively into the study of bridge infrastructure and its crucial importance to public safety, was made possible by the resources provided by the NJDOT Bridge Resource Program.

Lastly, I want to sincerely thank my advisor, committee members, mentors, and colleagues for their crucial advice and criticism during this process. Your knowledge and support have been invaluable in helping me finish this thesis.

Abstract

Lawrencia Maame Ofosua Akuffo
EVALUATION OF BRIDGE DETERIORATION FACTORS: FROM DESIGN PARAMETERS TO COMMUNITY IMPACT
2023-2024
Adriana Trias Blanco, Ph.D.
Master of Science in Civil Engineering

The structural health and economic variables influencing the state of bridges in New Jersey are thoroughly examined in this thesis. The predictive modeling of bridge conditions using stepwise selection and linear logistic regression approaches is the primary focus of the opening chapter. With its precise predictions about bridge condition, either being fair/good, our model identifies bridge features which affect the deterioration of bridges the most.

The second section of the analysis has two parts. We first started by examining the time-to-failure of bridges under various load scenarios (ADT/Live Loads, Environmental Loads/Conditions) and for different bridge materials in the first section. For the second part, we investigate the impacts of the median household income of the people living in a county on bridge conditions. This insight, combined with statistical analysis to find the time-to-failure of the bridges, suggests prioritizing specific bridge types in low-income areas to ensure longevity despite limited funds.

In the third chapter, we address the skew angle of the bridges and its influence on structural integrity because, from the previous analysis, we found that the skew angle has a 0.7% effect on the hazard/probability of deterioration of the bridge.

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Chapter 1

Introduction

Background

About 46,000 (7.5%) of the 617,000 public road bridges in the US were deemed to be in bad condition in 2019. These statistics and a few well-publicized accidents involving highway bridges have led to assertions that the United States is facing a bridge catastrophe. Bridges are essential parts of the transportation network because they allow cargo and people to move between different areas. However, due to a variety of factors like traffic volumes, environmental conditions, and material degradation, bridges, like all infrastructure assets, are susceptible to deterioration over time (Bhandari et al., 2023). Bridges must be periodically inspected for safety and longevity, and prompt maintenance and restoration plans must be put in place. The development of machine learning and data analytics techniques in recent years has made it possible to create models for evaluating the condition and health of bridges using readily available data sources, including the National Bridge Inventory (NBI) (Pugliese et al., 2021). By using historical data for the analysis, these models will hopefully help transportation agencies allocate resources more effectively and prioritize maintenance tasks.

Firstly, in order to manage missing values and outliers, the research requires thorough data pretreatment, including cleaning and filtering (Kwak & Kim, 2017). After that, prediction models are constructed using machine learning methods, with a focus on determining important variables that affect the bridge condition. The preprocessed data is also used to perform a comprehensive statistical analysis of bridges using Kaplan-Meier survival analysis and the Cox proportional hazards (PH) model to determine the time-to-failure of these bridges.

The Kaplan-Meier estimator provided survival probabilities over time, indicating the proportion of bridges that remain functional without failure. The Cox PH model was employed to assess the impact of various covariates on the probability of bridge failure find how long the bridges last before they reach the failure mode and together with household income, assess the impacts of the bridge condition in the county economically. In light of the fact that tolls, gas taxes, user fees, and user taxes, in addition to federal road funds, provide the majority of the funding for bridge reconstruction, this analysis sought to identify any relationships between how long a bridge takes to get to the failure mode, the percentage of good and fair bridges in each county and household income, and the features which affect bridge deterioration the most (Joseph Bishop-Henchman, 2013).

The results gave a clear correlation, showing that counties with lower household incomes had a greater percentage of bridges rated as fair. This highlights how important economic variables are in determining the state of bridges and emphasizes the necessity for creative methods to finance and priority in order to successfully overcome inequalities in infrastructure upkeep. Several performance indicators are used to assess the models' prediction accuracy, giving valuable information about how well the models predict the different bridge conditions (fair/good) (Steyerberg et al., 2010).

After determining the variables that lead to bridge deterioration, and doing a statistical analysis, we looked at the features that were identified to be contributors to the hazard/probability of failure and did a further analysis into two extreme features; we looked into the features that were identified by the Cox Proportional Hazard model and realized some interesting facts. Skew angle was identified as being the bridge feature with one of the lowest contributions to failure which was interesting because not much research has been done into it to ascertain why as it is often overlooked in favor of more significant features like prestressed concrete, which has the highest contribution to deterioration has no doubt, a substantial amount of research done to look at why this is so.

This study intends to improve our knowledge of the variables causing bridge deterioration and also determine how household income affects revenue collected for bridge rehabilitation, thus enabling proactive maintenance planning by utilizing predictive modeling approaches and time-to-failure analysis. The results should help transportation authorities optimize their infrastructure management procedures, which will ultimately guarantee the longevity, dependability, and safety of bridge assets.

Motivation and Context

Most of the bridge network in the United States is aging and degrading past its planned service life, posing a serious infrastructure concern. Nearly 40% of the nation's bridges are over 50 years old, and 9.1% are categorized as structurally inadequate, according to the ASCE Infrastructure Report Card. Although there have been initiatives to address this problem, such as a 3% drop in structurally flawed bridges over the past ten years, it is unclear if these efforts will be maintained or accelerated (ASCE’s 2021 Infrastructure Report Card, 2021).

Given the scope of the issue, replacing all outdated and inadequate bridges would not be a practical solution. Instead, in order to securely extend the lives of existing bridges, it is imperative to create quick, accurate, and affordable methods for detecting, predicting, and fixing problems with them (Capacci et al., 2022). In this process, assessment is essential because it allows for the early identification and characterization of flaws, which in turn allows for the development of efficient prognoses and repair plans (C. Crawford, 2023).

Bridge condition assessments have always placed a strong emphasis on load ratings which are based on the design considerations (FHWA's policy for Items of the Coding Guide) and traditional inspections, which are informed by practical and experience based information created by owner agencies (U.S. Department of Transportation Federal Highway Administration, 2018). However, there is a paradigm shift toward enhancing traditional approaches with nondestructive evaluation (NDE) and structural health monitoring (SHM) technologies due to advancements in sensing, simulation, and information technologies, as well as the urgency of aging infrastructure (Malekloo et al., 2022).

Notwithstanding the possible advantages of Non-Destructive Testing and Structural Health Monitoring technologies, there are obstacles to their general adoption, including as implementation-related costs and disruptions to the traveling public (Blabac et al., 2023). However, there is a rising understanding of the necessity of utilizing these technologies to raise the efficacy and efficiency of bridge condition assessment, which will ultimately increase the resilience and lifespan of the country's bridge infrastructure (United States Department of Transportation Federal Highway Administration, 2021)

Within this framework, machine learning modeling with data from the National Bridge Inventory (NBI), together with engineering analysis, offers a viable method for evaluating numerous bridges at once without much disruption to traffic and inconvenience to road users while also reducing cost. Models can be used to identify important elements impacting bridge conditions, prioritize maintenance interventions looking at bridge longevity and survival analysis, and provide guidance for decision-making processes related to bridge asset management by utilizing data-driven approaches like machine learning and statistical analysis (Mohamed Mansour et al., 2019).

The study also sought to create a well-balanced program that reflected the growing interdependence of the transportation system, the overall economy, and the flow of people and products (*NJDOT Local Bridges Fund*, 2017). Through the identification and comprehension of the variables affecting bridge conditions, this study aids in the creation of fair transportation systems that cater to the requirements of many populations. This knowledge also guides attempts to enhance infrastructure resilience and address the issues posed by growing transportation networks in the future through strategic planning and policy decisions (Saif et al., 2018).

Intellectual Merit

This study's use of predictive modeling tools to assess and estimate bridge conditions using data from the National Bridge Inventory (NBI); while using time-to-failure analysis and the correlation between household income and bridge condition to make prioritization of funds for rehabilitation and also throwing light on how much the skew angle contributes to deterioration, an often-overlooked feature, is what gives it its intellectual quality.

Approximately every two years, FHWA evaluates and assesses the performance and condition of the country's roadways and bridges, records the amount spent thus far by all governmental levels, and projects the amount of money that will be required in the future to maintain or enhance the current performance and conditions (*Issues For Congress*, n.d.; Liu & Xiang, 2024)

The objective of this work is to improve our comprehension of bridge deterioration patterns by obtaining valuable insights from a large dataset through the use of statistical analysis and machine learning methods. To be more precise, the approach entails thorough preparation of the NBI data in order to fix missing values and guarantee data integrity. By using stepwise selection, the most important elements affecting the condition of the bridge are found, offering important information on the main causes of bridge deterioration. This method not only makes it easier to estimate bridge conditions accurately, but it also establishes the groundwork for focused maintenance plans and infrastructure planning initiatives.

Additionally, this study attempts to shed light on the factors impacting infrastructure repair by examining the association between household income and bridge condition across various counties in New Jersey while considering the survival analysis of the bridges. Policymakers and transportation authorities need these insights to create fair and efficient plans for managing and investing in infrastructure (USDOT, 2023). All things considered, this study advances the use of machine learning techniques in transportation engineering and provides useful instruments for enhancing the sustainability and resilience of infrastructure.

Broader Impact

The utilization of National Bridge Inventory (NBI) data to estimate bridge conditions has the potential to have far-reaching effects that go beyond the domain of infrastructure management. This research improves our understanding of bridge deterioration trends and opens the door for creative structural engineering education applications by utilizing machine learning techniques and statistical analysis (*Bridge Selection and Data Preparation*, n.d.).

One effect is the creation of virtual laboratories that use data from actual bridges to provide students with immersive learning environments. Students can investigate and engage with real bridge structures through these virtual labs, learning about the mechanisms underlying degradation and damage under typical operating circumstances. In addition to improving students' comprehension of structural engineering principles, this practical method offers useful insights into the upkeep and administration of infrastructure (Roosendaal et al., 2010).

In addition, the incorporation of stress maps and real displacement onto structural members—possibly via the use of augmented reality technology—offers stimulating prospects for bridging the knowledge gap between engineering education and practical applications. Students can better understand the intricacies of structural behavior and the effects of maintenance decisions by seeing structural performance visualized in real-time. Through the promotion of a better comprehension of infrastructure resilience and sustainability, this immersive learning experience improves the relevance and applicability of structural engineering courses.

Overall, this research has wider implications that go beyond transportation engineering and include improvements in structural engineering education. This research equips upcoming generations of engineers with the knowledge and abilities required to tackle the difficulties of contemporary infrastructure management by utilizing cutting-edge technology and real-world data.

Objectives

The overarching objective of this research is to evaluate the impact of bridge deterioration on vulnerable communities due to unforeseen geometry and design parameter implications. To accomplish this, two specific goals have been established: (a) Investigate the impact of full-scale bridge geometry on deterioration patterns, and (b) Quantify the impact of girder design parameters on its structural capacity. The specific objectives selected to develop this study will contribute to understanding the impact of pre-inception decisions on the long-term performance of bridges.

Predictive Modeling for Bridge Condition Assessment

The goal of Section 1, presented in Chapter 3, is to create a framework for evaluating the state of bridges using data from the National Bridge Inventory (NBI).

- Determine the main causes of the decline in bridge condition.
- Create prediction models using NBI data to forecast the state of the bridge.
- Assess the predictive models' accuracy and dependability.
- Examine how predictive modeling could help guide decisions on bridge asset management.

Time-to-Failure and Analysis on The Impact of Median Household Income on Bridge Condition

The goal of Section 2, presented in Chapter 4, is to develop and validate time-to-failure models and to perform a detailed statistical analysis to identify significant factors affecting bridge longevity; while considering the impact of the median household income on the bridge condition of the different counties.

Time-To-Failure Analysis (Objectives)

- Estimate the survival probabilities of bridges using Kaplan-Meier survival analysis.
- Identify key factors influencing the probability of bridge failure through the application of the Cox proportional hazards model.
- Provide data-driven insights that will inform maintenance strategies and optimize resource allocation.

Impact of Median Household Income on Bridge Condition (Objectives)

- Investigate the relationship between median household income and bridge conditions using Pearson correlation analysis.
- Analyze the correlation between household income levels, and the proportion of bridges in good or fair condition.
- Provide data-driven insights to guide maintenance strategies and enhance resource allocation efficiency.

Skew Angle and Deterioration Rate Analysis

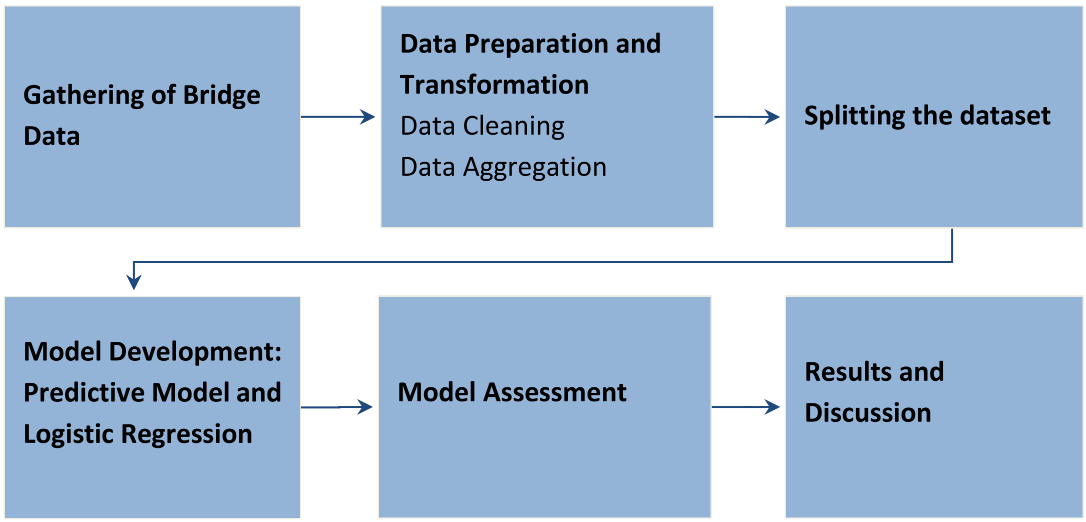
- Determine a correlation between the skew angle of bridges and their deterioration rate.
- Evaluate the correlation between the skew angle and the deterioration rate through ANOVa analysis.

Methodology

Predictive Modeling for Bridge Condition Assessment

Figure 1

Flow Chart for Predictive Analysis



- *Gathering of Bridge Data:* We acquired the National Bridge Inventory (NBI) dataset from the appropriate governmental bodies or agencies in charge of managing the bridge infrastructure. Extraction of pertinent features from the NBI dataset was also done. These attributes include traffic statistics (such as average daily truck traffic), environmental parameters (such as total precipitation), and bridge characteristics (such as primary span material, number of spans, and age).
- *Data Preparation and Transformation*: Using R programming, researchers cleaned the dataset to remove outliers, inconsistent values, and missing values. Exploratory Data Analysis (EDA) was used to learn more about the distribution and connections between

variables. To guarantee consistency and stability during model training, we normalized and scaled numerical features.

- *Splitting the dataset*: Using stratified random sampling, the preprocessed dataset was split into training and validation sets. To evaluate the predictive performance of the model, allocate 70% of the data for model training and 30% for model validation.
- *Model Development: Predictive Model and Logistic Regression*: We used an R package (caret) to implement a machine learning method called logistic regression. Creating a mathematical equation that defines y (the result variable) as a function of one or more predictor variables (x) is the aim of a regression model. Next, using new values for the predictor variables (x), this equation can be utilized to predict the outcome (y). (Haidara Saleh & Jamil Antone Layous, n.d.). Using results that indicate fair or poor conditions, stepwise selection was applied to determine which bridge condition predictions are the most important. Stepwise Selection examines the impact of eliminating each variable in the present model. It then eliminates the least informative variable, unless it continues to provide meaningful insight into the response. Utilizing a subset of characteristics from the training dataset, we trained the prediction model, then used cross-validation to optimize the model's selected parameters.
- *Model Assessment*: Using relevant assessment metrics, such as accuracy, specificity, sensitivity, and area under the receiver operating characteristic curve (AUC-ROC), we assessed the trained model's performance on the validation dataset. To evaluate statistical significance, we computed the model's accuracy of 95% confidence intervals.
- *Results and Discussion*: To determine the major elements impacting bridge condition, we have to interpret the model coefficients or feature importance scores. Examining

the effects of particular predictors on model forecasts and efforts to prioritize bridge maintenance was done. To guarantee dependability and generalizability, we validated

- model results using robustness tests and sensitivity analysis.

Identification of Knowledge Gaps

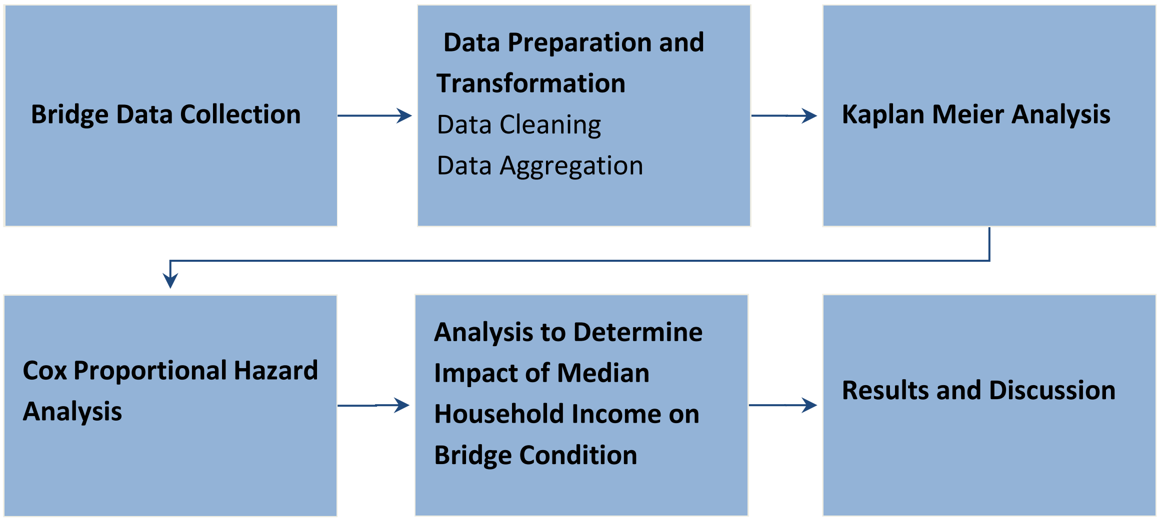
- Researchers determined any potential gaps in knowledge and study constraints, such as those related to the availability of data, model assumptions, and the generalizability of the results.
- They also spoke about how the research's conclusions may affect both current and upcoming investigations as well as real-world bridge infrastructure management.
- Suggestions will have to be made for filling in the gaps found and enhancing the predictive modeling methods used to assess the state of bridges.

Time-To-Failure of Bridges and Analysis Of Impact Of Median Household Income On Bridge Condition

Data for this study was obtained from the National Bridge Inventory (NBI), which includes detailed information on bridge characteristics, conditions, and environmental factors. Key variables considered in the analysis include bridge materials, average daily traffic (ADT), freeze-thaw cycles, total precipitation, and skew angle. The data was then cleaned to take out missing or inaccurate data.

Figure 2

Flow Chart For Time-to-Failure Analysis and Analysis of Impact of Household Income on Bridge Condition



- *Bridge Data Collection:* We acquired the National Bridge Inventory (NBI) dataset from the info bridge portal. To get a more accurate representation, we extracted bridge data from 1999 to 2024. (https://infobridge.fhwa.dot.gov/) This is because, for the time-to-failure analysis, we needed to account for the times that the bridge moved from good to fair, unlike the predictive model in the previous section, where we used data from 2023 since we were concerned with the most current data and not necessarily how long it took the bridge to move from good to fair condition.
- *Data Preparation and Transformation*: Using R programming, we cleaned the dataset to remove outliers, inconsistent values, and missing values. Exploratory Data Analysis (EDA) was used to learn more about the distribution and connections between variables.

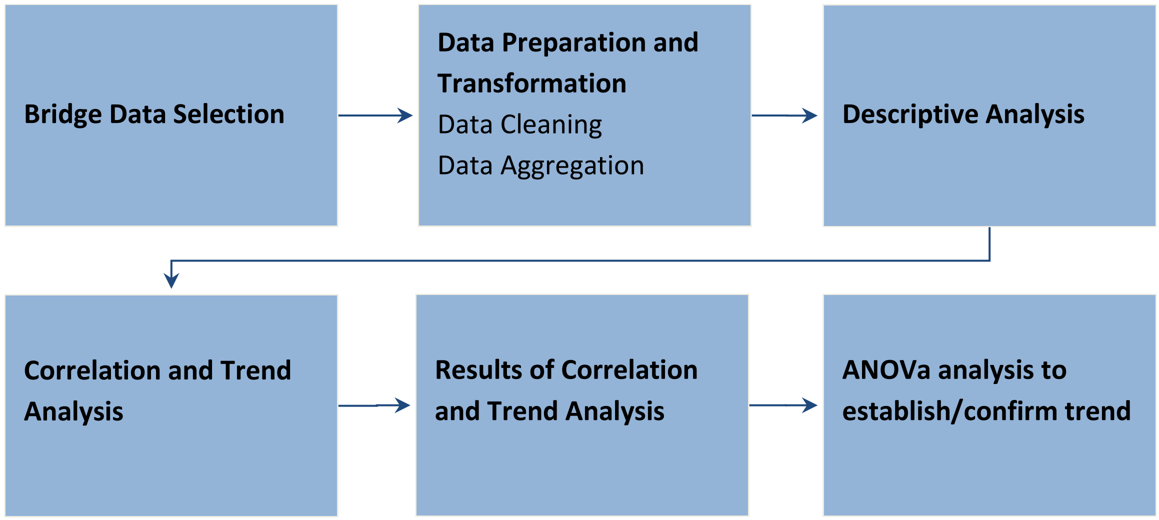
- *Kaplan Meier Analysis*: This was applied to determine the probability of a bridge failure developing over time. The capacity of Kaplan-Meier to handle censored data—cases in which the event of interest (like failure or deterioration) has not yet happened for any participants by the study's conclusion—is what sets it apart from other methods. This flexibility is particularly useful for the dependability study of infrastructure, such as bridges, as it allows for a more thorough and accurate analysis of survival data in situations when not every subject has experienced the event. (N. Dudley et al., 2016)
- *Cox Proportional Hazard Analysis: the Cox Proportional Hazards (Cox PH) model was* chosen because is its capacity to examine the effects of several factors on the hazard or chance of an event happening with the least amount of presumption regarding the underlying survival distribution. The Cox PH model is very flexible to different survival data types since it does not require a particular form of the baseline hazard function, unlike many other models. (N. Dudley et al., 2016)
- *Median Household Income and Impact on Bridge Condition:* The analysis gives a clear picture of the median household income of the various counties, which is then tied to the condition of the bridges in these counties. This analysis was done by extracting household income data from the Census Bureau. The Pearson correlation was the statistical tool that was used to find the correlation between median household income and bridge conditions.(Peter Samuels & Mollie Gilchrist., 2014)

Skew Angle and Deterioration Rate Analysis

The data used in this study was collected from the InfoBridge web portal, led by the Federal Highway Administration of the United States of America (10). The following steps were taken to collect and process the data for this study (Figure 2).

Figure 3

Data Collection and Processing Flowchart



- *Bridge Data Selection*: the bridges selected for this study were all in New Jersey. Aside from the fact that New Jersey has over 6,000 bridges, a representative sample size for a more accurate analysis, the climatic conditions, age, materials used, and maintenance culture of the different counties and owners also differ across the state, giving a more varied data set. Not all bridges in New Jersey are skewed. Skewed configurations are occasionally required when safety and alignment difficulties (congested locations, natural or manmade impediments, complicated intersections, etc.) mandate critical highway and highway bridge design considerations. For this study, all the bridges, including ones with skew angle of 0, were considered to establish the correlation between skew angle and bridge deterioration.

- *Data Preparation and Transformation*: Data collected from field assessments, performance monitoring, NDE testing, possibly laboratory analysis, and other sources is combined and structured in a defined format. This process is part of cleaning the data to correct errors, inconsistencies, or missing information and assuring data quality and integrity. The data for this analysis was cleaned using the structure number to identify the bridges. The year built, deck condition rating, years it takes to deteriorate a scale down, and skew angle were then selected for the various structure numbers. This eliminated data entries with missing information and could not be attributed to any specific bridge. The data was transformed by converting raw data into a more structured and usable form using various operations and calculations. Data cleaning, aggregation, summarization, and the creation of derived variables are examples of this.

- *Data cleaning*: Data cleaning is the process of discovering and repairing or deleting errors, inconsistencies, and inaccuracies in a dataset. It is also known as data cleansing or data scrubbing. It is a vital stage in data preparation to assure the data's quality and dependability for analysis, modeling, or other data-driven tasks. We cleaned the data by remedying missing values; we removed rows and columns with excessive missing data depending on its impact on the analysis. We also removed duplicates and identified outliers with extreme values to be either removed or transformed to fit the data needed for our analysis. Finally, we removed the redundant data which did not contribute to the data analysis.
- *Data aggregation*: A mathematical process that summarizes or combines several values within a dataset to produce a single representative value is known as an aggregation function, also known as an aggregate function or summary function. We used the average/mean to find one representative value for the years it takes for the condition rating to drop by one. Count was used to determine the number of occurrences or data

points inside a specific category, thus the total number of bridges. We used variance, a measure of the spread of data points around the mean that measures the dispersion or variability of values within a dataset, and standard deviation, a measure of the average distance between data points and the mean that quantifies the dispersion or variability of values within a collection for the hypothesis testing.

- *Data Summarization*: Data summarization is the process of condensing and displaying a dataset or a subset of data simply and informally. It is also known as data aggregation or summarizing statistics. Data summarization provides a high-level overview of the dataset's properties, patterns, and insights. Histogram was employed to display the distribution of numerical data by dividing the data range into intervals and representing the frequency or count values in each category/interval.

- *Descriptive Analysis*: Descriptive analysis techniques are used to understand the fundamental properties and trends in data. This includes summarizing data using statistical measurements, creating visualizations (e.g., charts and graphs), and detecting noteworthy patterns or outliers. Excel was used in the descriptive analysis of this data. The deck condition rating was first plotted against the skew angle to see how the bridges deteriorate according to the skew angle. A trend was then established for how long it takes the condition rating to drop by one point for all the bridges, and finally, a graph of how long the condition ratio takes to drop by one point is plotted against the skew angle.

- *Correlation and Trend Analysis*: the correlation and trend analysis intended to establish a relationship between the two variables (deck condition rating and skew angle). The degree and direction of the association between two variables are assessed using correlation analysis. This scenario investigates the relationship between bridge deck condition rating and skew angle. A positive connection suggests that as the skew angle grows, so does the bridge deck condition rating. A negative connection, on the other hand, indicates that a larger skew angle is connected with a poorer bridge deck condition grade. The process of assessing the pattern or direction of change in the bridge deck condition rating regarding the skew angle over time or across a sample of bridges is known as trend analysis. This analysis aids in the identification of any systematic trends or tendencies in the data. One method is to categorize bridges based on their skew angle ranges (e.g., 0-5 degrees, 6-10 degrees, etc.) and then compute the time it takes for the bridge deck condition rating to drop by one point for each group. We can examine the trend and identify any regular trends by charting these average years over the skew angle range

Thesis Structure for Each Section

Chapter 1: Introduction

- An overview of the significance of assessing the bridge conditions and the requirement for predictive modeling techniques, time-to-failure analysis, an analysis to see the impact of median household income on bridge condition and skew angle analysis.
- An explanation of the preparation procedures and the dataset from the National Bridge Inventory (NBI).

- A description of the study's goals, which include the creation of prediction models and the examination of variables that indicate the time-to-failure and condition of bridges therefore impacting the economy of the counties.
- A discussion of the research's importance in directing maintenance schedules and tackling the problems associated with bridge deterioration.

Chapter 2: Literature Review

- A summary of the body of research on predictive modeling, time-to-failure analysis, and the impact of median household income on bridge condition for bridge condition assessment, emphasizing the application of machine learning approaches like logistic regression, stepwise selection methods, Kaplan Meier, Cox PH and Pearson Correlation analysis while looking into research that talks about the Skew Angle of a bridge and its effects on deterioration of the bridge.
- A review of studies examining the association between different factors, including age, traffic volume, and bridge material, and condition of the bridge.
- The significance of precise bridge condition assessment in guaranteeing dependable and secure transportation infrastructure is examined.

Chapter 3: Predictive Modeling for Bridge Condition Assessment Approach

- An explanation of the process followed in the creation of prediction models for bridge condition evaluation.
- A description of how the dataset was divided into training and testing subsets, along with how stepwise selection was used to find important predictors.

- Information on the model evaluation measures that were applied, such as the Receiver Operating Characteristic (ROC) area under the curve (AUC), sensitivity, specificity, and accuracy.

Chapter 4: Time-to-Failure Analysis

a) Using Kaplan-Meier and Cox Proportional Hazards Models:

- Detailed explanation of the methodology followed in conducting the time-to-failure analysis of bridge conditions using Kaplan-Meier survival analysis and Cox proportional hazards (PH) modeling.
- Description of the steps taken to preprocess the National Bridge Inventory (NBI) data to ensure it was suitable for survival analysis.
- Methodology for applying the Kaplan-Meier estimator to analyze survival probabilities and identify critical failure points over time.
- Description of the process for developing the Cox PH model, including the identification and selection of covariates that significantly influence the probability of bridge failure.
- Explanation of how hazard ratios (HRs) were interpreted for different covariates, including their statistical significance (p-values).
- Interpretation of survival curves and hazard functions to provide insights into bridge longevity and factors that affect bridge failure.

b) Correlation Analysis Using Pearson Correlation for Bridge Condition and Median Household Income:

- Detailed explanation of the process used to analyze the relationship between bridge condition and median household income using Pearson correlation analysis.

- Description of how the relevant data was extracted from the NBI and census bureau.
- Explanation of how the dataset was divided into appropriate subsets to analyze the correlation between bridge conditions (categorized as good, fair, or poor) and median household income in different regions.
- Description of preprocessing steps, including normalization of income data and categorization of bridge conditions.
- Discussion of the Pearson correlation coefficient (r) as the primary measure for evaluating the strength and direction of the relationship between bridge condition and median household income.
- Explanation of the statistical significance (p-value) of the correlation coefficient and its interpretation.
- Analysis of the results, including plots and correlation matrices, to visually and statistically interpret the relationship between bridge conditions and household income levels.

Chapter 5: Skew Angle Analysis

- A comprehensive overview of the procedure for applying statistical tools to examine the connection between bridge Skew Angle and Deterioration Rate.
- Explaining the process used to extract the useful information from the Federal Highway Administration's Long-Term Bridge Performance Online Portal.
- An explanation of the dataset's division into suitable subsets in order to examine the relationship between deterioration rate and skew angle
- An explanation of the preprocessing procedures, such as the classification of skew angles and setting up the statistical analysis

- Examining the relationship between Skew Angle and Deterioration Rate with ANOVA as the main statistical tool.
- An explanation and interpretation of the ANOVA results' statistical significance (p-value)
- Plots and statistical interpretation are included in the analysis of the data to assess the relationship between skew angle and degradation rate.

Chapter 6: Interpretation and Conclusions

- An analysis of the different modeling findings, including the models' accuracy and the importance of the predictor variables and time-to-failure analysis, while looking at the effects of the skew angle on deterioration rate.
- An examination of the correlation between household income and bridge condition in the counties of New Jersey, with a focus on the budgetary implications for bridge maintenance.
- Interpretation of the results in light of planning and policy-making for bridge repair.
- An examination of the research's wider effects on economic growth, equitable access to transportation resources, and transportation infrastructure.

Chapter 7: Future Work

- A highlight of the major conclusions and how they will affect further study and application.
- Suggestions for additional research into particular indicators of bridge condition as well as methods for enhancing financing and regulations for bridge repair.

Chapter 2

Literature Review

Predictive Modeling for Bridge Condition Assessment

Predictive modeling has been widely used in infrastructure management to forecast the condition and lifespan of bridges. Techniques such as linear regression, logistic regression, and machine learning algorithms have been employed to develop models that assist in maintenance planning and resource allocation.

Bridge condition assessment is a crucial component of infrastructure management that affects economic productivity, public safety, and traffic efficiency. In the past, manual data collection and analysis techniques have been used to augment the visual inspections carried out by qualified engineers in traditional methods of bridge inspection and evaluation. Although these techniques have been the foundation of bridge maintenance procedures for many years, they are fundamentally constrained by their subjectivity, reliance on human judgment, and incapacity to handle massive amounts of data quickly (Omar & Nehdi, 2018; Xia et al., 2022).

Over the years, the state of practice in bridge condition assessment has changed dramatically due to the necessity for efficient methods to maintain public safety and manage aging infrastructure. More advanced methods of evaluating bridge condition have been available for study and use thanks to developments in data analytics and technology.

Assessing and evaluating the state of the bridge appropriately and precisely is a crucial part of maintaining bridges that are already in place. Condition evaluations, which can be completed in a variety of methods, are essential for learning about a bridge's true state and the extent of any potential damages. They also serve as the foundation for choices about future maintenance (Björnsson et al., 2019).

The application of data-driven methodologies and machine learning to improve bridge condition assessment has gained popularity in recent years. Research like the one mentioned above has shown how predictive modeling methods may be used to evaluate sizable datasets, like the data from the National Bridge Inventory (NBI), and pinpoint the main variables affecting bridge condition. Researchers have developed prediction models with outstanding accuracy and predictive power by using variables including main span material, bridge age, traffic patterns, and environmental considerations, along with techniques like stepwise selection (Hurtado et al., 2024).

The use of R programming for model construction and data preprocessing indicates a move in the direction of more advanced analytical techniques for bridge evaluation. This methodology facilitates the combined use of heterogeneous datasets, encompassing structural attributes, traffic intelligence, and environmental factors, to enhance comprehension of the intricate interplay impacting bridge state across temporal dimensions (Gomez-Cabrera & Escamilla-Ambrosio, 2022; Ilbeigi & Ebrahimi Meimand, 2020).

The results of research like this one show that although traditional assessment techniques still have a place in bridge management, data-driven approaches have the ability to supplement and improve current techniques. These methods open the door to more proactive and well-informed repair priority efforts by offering insights into the critical factors impacting bridge deterioration and enabling focused investigations.

In summary, the literature points to a shift in bridge condition assessment techniques toward ones that are more comprehensive and data-driven, driven by advances in computational techniques, technology, and the growing availability of large-scale infrastructure datasets. In order to identify and solve structural faults more accurately, efficiently, and reliably, the field of bridge assessment is going to gain from ongoing research into new approaches and instruments.

Knowledge Gap

- ***Integration of Multiple Data Sources***: Predictive models may be more accurate and reliable if they incorporate data from multiple sources, including as inspection reports, sensor data, and previous maintenance records, even if the NBI offers a comprehensive dataset for bridge state assessment. Subsequent studies want to investigate strategies for integrating heterogeneous data sources efficiently to enhance predictive capabilities.

- ***Integration of Advanced Data Analytics Techniques***: Although the study shows that machine learning techniques are useful for predicting bridge conditions, the application of advanced analytics techniques, such as deep learning, ensemble learning, and explainable AI, has the potential to improve model accuracy and interpretability even further. By revealing intricate connections between bridge characteristics and condition outcomes, these methods may contribute to the development of more reliable predictive models.

- ***Validation and Model Generalization***: By dividing the dataset into training and validation sets, the study's validation methodology offers preliminary understandings of model performance. To evaluate the generalizability of predictive models, additional validation is required on separate datasets and in various geographical areas. In order to guarantee consistency and relevance across a range of bridge assets, future research ought to concentrate on verifying model performance in a variety of scenarios.

- ***Interpretation and Actionability of Results***: Although the study finds important predictors of bridge condition, it is still difficult to turn these results into practical advice for those who maintain bridges. Subsequent investigations ought to prioritize the creation of frameworks and decision-support instruments that streamline the integration of predictive model results into practical maintenance approaches.

Time-to-Failure Analysis

Survival analysis methods, including the Kaplan-Meier estimator and Cox proportional hazards model, have been applied to assess the time-to-failure of structural components. These two closely comparable statistical techniques are commonly used in time-to-event studies (N. Dudley et al., 2016). Cox analysis is multivariate, whereas Kaplan-Meier is a univariate method. Numerous well-known elements of parametric and nonparametric statistical methods, such as confidence intervals, independent and dependent variables, and null hypothesis testing, are used in both. These methods provide insights into the factors that influence the durability and performance of bridges over time.(N. Dudley et al., 2016)

The likelihood of survival and the anticipated service life of bridge decks would alter with age. According to the conditional probability theory, the additional information obtained from the fact that a bridge deck has previously lasted a certain number of years changes (increases) the initial likelihood of surviving at succeeding years. (Nabizadeh et al., 2020).

Various factors, including material properties, environmental conditions, traffic loads, and design characteristics, impact the condition and longevity of bridges. Understanding these factors is crucial for developing effective maintenance and rehabilitation strategies. High performance concrete (HPC) was created to satisfy the demands of the transportation sector when building bridges even though the relationship between material characteristics and field performance is still not entirely clear. (Vinit Barde et al., n.d.). Even though prestressed and reinforced concrete have been used severally to build both old and new bridges, modern concrete materials are becoming more and more crucial to the construction of concrete bridges because they make it easier to strengthen and repair already-existing bridges, quickly replace damaged sections of existing bridges, and design new, difficult bridge projects as compared to older materials.(Lantsoght, 2022).

Environmental factors also greatly affect bridge health and the focus should not be on just the bridge materials. There has been sufficient studies to determine the impact of environmental factors on bridge deterioration but not so much on its impact on performance ratings of the bridge. (Hung et al., 2023)

Knowledge Gap

- ***Modeling Uncertainty***: One significant challenge in bridge reliability is the uncertainty in load predictions. Traffic loads and environmental conditions can vary significantly over time, introducing variability into predictive models. This uncertainty makes it difficult to accurately forecast the loads that bridges will encounter. Additionally, predicting the degradation of bridge materials under various environmental conditions adds another layer of complexity. Material degradation is influenced by a wide range of factors, many of which are not fully understood, making it challenging to anticipate how different materials will perform over time.

- ***Environmental and Climate Effects***: The long-term impacts of climate change on bridge failure remain poorly quantified, adding to the uncertainty in predictive models. As climate change progresses, it will likely alter environmental conditions in ways that could significantly affect bridge performance. Moreover, localized environmental factors such as salinity and freeze-thaw cycles can have specific, and often severe, impacts on bridge materials and structures. The limited understanding of how these localized conditions affect bridges complicates efforts to design and maintain resilient infrastructure.
- ***Load and Resistance Factors*****:** Dynamic loads, such as those from moving vehicles and seismic activity, present another area where more research is needed. These loads can significantly impact bridge failure, but their effects are not yet fully understood. Furthermore, there is variability in the material properties and construction quality that affects the resistance of bridges. This variability introduces additional uncertainty into models predicting bridge performance and lifespan, highlighting the need for a better understanding of these factors.
- ***Interdependencies and Network Effects*****:** Bridges are not standalone structures; their reliability is interconnected with the broader transportation network. Understanding these interdependencies is crucial for comprehensive time-to-failure assessments. Additionally, bridge failures can have cascading effects on other critical infrastructure,

such as water and electricity systems. The interactions between bridge failure and these other infrastructures are not well-studied, which could lead to underestimating its broader impacts.

- ***Lifecycle Cost Analysis*****:** A more comprehensive approach to lifecycle cost analysis is necessary to make better-informed decisions regarding bridge maintenance and repair. Current models often do not fully integrate the costs associated with failures and ongoing maintenance. By developing models that encompass these factors, decision-makers can more accurately assess the economic impacts of different maintenance strategies and make more cost-effective choices.
- ***Behavior Under Extreme Events*****:** The performance of bridges under extreme events, such as earthquakes, floods, and hurricanes, requires more detailed study. Understanding the failure mechanisms and performance of bridges in these scenarios is essential for improving their design and resilience. Additionally, the reliability of bridges in the face of man-made threats, such as terrorism and sabotage, is not well understood. Research in this area is crucial to developing strategies to protect critical infrastructure from intentional harm.

Skew Angle Analysis

Bridges are essential for transportation infrastructure, and engineers and policymakers are concerned about their long-term performance and safety. President Eisenhower established the United States Interstate Highway System in the 1950s to improve commercial and military mobility. Its almost 50,000 miles were mainly constructed in 35 years and are now part of the country's over 4 million miles of highways (7). Bridges serve an important role in transportation by connecting divided locations such as rivers, valleys, or gaps in the topography. They are critical infrastructure for both urban and rural areas, allowing for the efficient flow of people, products, and services (8).

Several research has been conducted to investigate the relationship between bridge skew angle and the rate of deterioration. Researchers conducted a study on 313 bridges in Korea and discovered that the skew angle was an important factor in the decline of bridge decks. The study found that bridges with skew angles above 45 degrees deteriorated faster than those with less than 45 degrees (9).

Another study examined data from bridges and discovered that the skew angle was an essential determinant of bridge deterioration. The study found that bridges with skew angles above 20 degrees experienced much more bearing damage than bridges with skew angles below twenty degrees (6). There are various probable factors for why bridges that have large skew angles may deteriorate at a faster rate. For example, the geometry of the bridge may result in uneven loading on the bridge components, which can hasten wear and tear (3,18). Bridges with large skew angles may also be more subject to environmental variables like wind and water, which may lead to rust and other forms of degradation. Also, gravity load paths are important for how bridge skew angles behave (6,10).

Investigating the relationship between bridge skew angle and deterioration rate is critical in furthering our understanding of bridge performance. More research is needed to investigate this link and find effective solutions to reduce the influence of significant skew angles on bridge deterioration. Gaining a comprehensive understanding of the mechanisms underlying this correlation will ultimately ensure the safety and efficiency of transportation networks for years to come.

Knowledge Gap

- ***Repair and Maintenance Activities***: The kinds, frequency, and potential interactions of these interventions with bridge skew angles are not mentioned. Gaining a deeper understanding of this relationship may help bridges with significant skew angles last longer.
- ***Integration of Structural Health Monitoring (SHM)*****:** Real-time data from structural health monitoring systems is not included in this work, which could provide a more dynamic knowledge of how skew angle influences bridge deterioration under real-time settings.
- ***Non-Linear interactions***: Although non-linear interactions could offer a better view of the relationship between these factors (skew angle and deterioration rate), the study assumes a linear relationship between skew angle and deterioration rate and does not investigate the plausibility of such correlations.
- ***Regional Comparison***: The study does not compare its findings with bridges in other climates or locations, even as it applies its findings to bridges in New Jersey. The findings' applicability to other regions may be impacted by this gap.

Chapter 3

Predictive Modeling for Bridge Condition Assessment

A predictive model was built using the training data and stepwise selection was used to find significant components with p-values less than 0.05.

Through the application of sophisticated statistical methods like logistic regression, and ROC curve analysis, we were able to find the features that cause bridge deterioration and forecast the performance of the structure going forward.

Logistic Regression

The logistic regression model used for binary classification (fair/poor condition) can be expressed as:

$$P(Y=1|X) = \frac{1}{1+e^{-(\beta 0+\beta 1X1+\beta 2X2+\cdots+\beta kXk)}}$$

Where:

- (Y) is the binary outcome (0 for good condition, 1 for fair/poor condition).
- (Xi) are the predictor variables (e.g., main span material, number of spans, age of the bridge).
- (βi) are the coefficients estimated by the model.(Haidara Saleh & Jamil Antone Layous, n.d.)

Stepwise Selection Criteria

Predictors are added or removed repeatedly using the stepwise selection approach according to their statistical significance (p-value < 0.05). The Akaike Information Criterion, or AIC, is frequently used to determine which model is best:

$$AIC = 2k - 2\ln(L)$$

Where: k is the number of parameters, and L is the model's likelihood.

Metrics for Model Evaluation

Confusion Matrix. The confusion matrix is typically represented as follows:

Table 1

Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

The predictive analysis technique is the confusion matrix. in the field of machine learning. The confusion matrix is used to evaluate the effectiveness of a machine learning model based on categorization. Additionally, we might state that a confusion matrix is a summarized table of the number of accurate and inaccurate predictions that a classifier (or classification model) produces for tasks involving binary classification. When N is the number of target classes, a N x N matrix called a confusion matrix is used to assess how well a classification model performs. A person might visualize the confusion matrix and use the diagonal values to measure the number of accurate classifications to assess the model's accuracy.(Haidara Saleh & Jamil Antone Layous, n.d.)

i. **Accuracy** = $\frac{TP+TN}{TP+TN+FP+FN}$

Accuracy: The proportion of accurately anticipated cases—both true positives and true negatives—to all instances is known as accuracy.

ii. **Specificity**= $\frac{TN}{TN+FP}$

Specificity: The proportion of real negative results to the total of false positive results. derived from the confusion matrix calculation

iii. **Sensitivity**= $\frac{TP}{TP+FN}$

The ratio of true positives to the total of true positives and false negatives is known as sensitivity (also known as recall or true positive rate), computed using the confusion matrix as well.

iv. A graphical representation called the Receiver Operating Characteristic (ROC) curve is used for the assessment of the binary classifier's performance (that is the performance of the model to see if it can truly produce the results for the bridge condition when certain features have been put into it). At different threshold values, it shows the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity). The classifier's performance over all threshold values is summed up by a single scalar statistic called the Area Under the ROC Curve (AUC).

True Positive (TP): The quantity of positive cases that were accurately anticipated. Stated otherwise, these are the cases where the model properly predicts a positive outcome and the actual class is positive.

TN (True Negative): The quantity of negative cases that were accurately anticipated. These are the cases where the model predicts the class as negative even though the actual class is negative.

FP (False Positive): The quantity of positive cases that were mispredicted. These are the cases where the model predicts a class as positive even though the actual class is negative. Another name for this is a Type I mistake.

FN (False Negative): The quantity of negative cases that were predicted incorrectly. These are the cases where the model predicts a class as negative even though the actual class is positive.

Findings and Interpretation

Training and Testing Accuracy of the Model Performance

Across the entire dataset, the model's accuracy was 83.4%, with a 95% confidence interval of (0.8169, 0.8513). 60.8% was the specificity and 91.85% was the sensitivity.

Model Accuracy

The model's accuracy is 83.4%. This means that 83.4% of the predictions made by the model were correct. Accuracy is calculated as the number of correct predictions divided by the total number of predictions. The 95% confidence interval for this accuracy is (0.8169, 0.8513), suggesting that we can be 95% confident that the true accuracy of the model lies between 81.69% and 85.13%. The confidence interval provides an estimate of the precision of the accuracy measurement, indicating the model's reliability in its predictions.

Specificity

Specificity, also known as the true negative rate, measures the proportion of actual negative cases (e.g., bridges in good condition) that were correctly identified by the model. In this case, the specificity is 60.8%, meaning that 60.8% of the bridges that were actually in good condition were correctly identified as such by the model. Specificity is calculated as the ratio of true negatives to the sum of true negatives and false positives. While the model performs well in identifying bridges in fair condition, it is less effective at correctly identifying bridges in good condition, with around 39.2% of bridges in good condition being incorrectly classified as fair.

Sensitivity

Sensitivity, also known as the true positive rate or recall, measures the proportion of actual positive cases (e.g., bridges in fair condition) that were correctly identified by the model. The sensitivity of the model is 91.85%, indicating that the model correctly identifies most of the bridges that are actually in fair condition. Sensitivity is calculated as the ratio of true positives to the sum of true positives and false negatives. This high sensitivity suggests that the model is highly effective at detecting bridges that require maintenance, ensuring that they are not overlooked.

Notable Characteristics Found

The main span material (concrete, prestressed concrete, steel, wood, or timber), the number of spans in the main unit, the age of the bridge, the maximum span's length, the average daily truck traffic (ADT), and the total amount of precipitation were significant factors influencing the bridge's conditions.

Table 2

Significant Bridge Features Affecting Bridge Condition

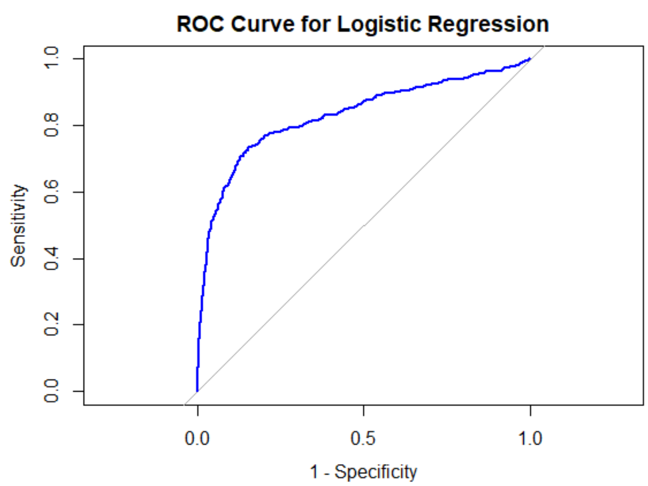
Coefficients	Estimate	Standard Error	Pvalues(α=0.05)
Main Span Material-Other material main span	-1.08E+01	1.59E+02	0.945659
Main Span Material-Masonry	1.72E-01	1.14E+00	0.880189
Main Span Material-Prestsressed Concrete Continuous	-6.48E-01	6.61E-01	0.327098
Main Span Material-Steel Continuous	-1.13E+00	5.62E-01	0.04384
Main Span Material-Concrete	-1.15E+00	5.55E-01	0.038458
Deck Area	-4.51E-06	1.93E-06	0.019554
Main Span Material-Concrete Continuous	-1.52E+00	6.31E-01	0.015935
Length of Maximum Span	1.45E-03	5.42E-04	0.0073
Average Daily Truck traffic	-2.54E-02	8.81E-03	0.003932
Main Span Material-Wood or Timber	-1.75E+00	5.80E-01	0.002531
Total Precipitation	-1.24E-03	4.07E-04	0.002392
Main Span Material-Steel	-1.83E+00	5.53E-01	0.000969
Main Span Material-Prestressed Concrete	-1.94E+00	5.54E-01	0.000473
Number of Spans in Manin Unit	-7.67E-02	2.05E-02	0.000186
Bridge Age/year	-5.26E-02	1.66E-03	< 2E-16
Intercept	5.15E+00	8.01E-01	1.26E-10

AUC Value and ROC Curve

With an AUC value close to 1, the ROC curve showed that the model had a strong discriminatory power and could effectively distinguish between various bridge conditions.

Figure 4

ROC Curve



Analysis of the Findings

The predictive model successfully pinpointed the primary causes of bridge deterioration, offering insightful information for repair scheduling. The model's dependability is demonstrated by its excellent accuracy and AUC value.

An Overview of the Results

Using NBI data, this thesis ranked and identified the important structural factors influencing bridge deterioration. When predicting bridge conditions, the built predictive model showed excellent accuracy and dependability. Disparities in bridge conditions according to household income were brought to light by an analysis to determine the impact of median household income on bridge condition.

Practical Implications

Given the high sensitivity, the model is highly effective at identifying bridges in fair condition, which is useful for maintenance planning as it ensures that bridges needing attention are not overlooked. However, the lower specificity suggests that the model has a tendency to falsely identify some bridges in good condition as fair. This could lead to unnecessary inspections or maintenance activities for some bridges that are actually in good condition. Balancing between high sensitivity and moderate specificity is crucial for optimizing resource allocation and maintenance activities.

Chapter 4

Reliability Analysis

Time-To-Failure Analysis of Bridges And Analysis To Determine The Impact Of Median Household Income on Bridge Condition

The Kaplan-Meier survival analysis was conducted to estimate the survival probabilities of bridges over time. The Cox proportional hazards model was applied to identify significant covariates influencing the probability of bridge failure. An analysis was also done to find the relationship between median household income and the bridge condition so that together with the time-to-failure analysis, more informed decisions can be made with regards to funding allocation.

Mathematical Framework for Time-To-Failure Analysis Methodology

Kaplan-Meier Survival Analysis

The Kaplan-Meier estimator is used to estimate the survival function from lifetime data. Modeling of survival data usually employs the hazard function or the log hazard. In simpler terms:

- ***Cumulative Distribution Function, P(t)*** tells us how likely the bridge is to fail by a certain age. For example, if P(50) = 0.35, it means there is a 35% chance the bridge will fail within 50 years
- ***Probability Density Function, p(t)*** shows us how likely the bridge is to fail at an exact age.

- ***Survival function, S(t)*** tells us how likely the bridge is to keep standing beyond a certain age, thus the age of a bridge before it fails. If a bridge lasts 50 years before it needs to be replaced, its survival time is 50 years.
- ***Hazard Function*** gives us the probability of failure at any given moment, assuming the bridge has made it that far. The hazard function tells you the probability of the bridge failing right now, considering it hasn't failed yet.

The Kaplan-Meier estimator is a non-parametric statistical method used to estimate the survival function from lifetime data. Thus, it helps us understand and visualize the likelihood of an event (such as failure, death, or breakdown) happening over time. Here's what it does and why it's useful:

What the Kaplan-Meier Estimator Does

- ***Estimates Survival Probability***: It calculates the probability that a subject (e.g., a bridge) will survive past a certain point in time. This is shown as a survival curve, which is a step function that changes at each time an event (like a failure) occurs.

- ***Handles Censored Data***: In many real-world scenarios, not all subjects will have experienced the event by the end of the study. For instance, some bridges might still be in good condition when the study ends. The Kaplan-Meier method can handle this incomplete information (called censored data) and still provide reliable estimates.

- ***Provides Confidence Intervals***: It also gives a measure of uncertainty around the survival probabilities by providing confidence intervals. This helps in understanding the reliability of the estimates.

- ***Compares Survival Between Groups***: You can use the Kaplan-Meier method to compare survival curves between different groups. For example, you might compare the survival of bridges made with different materials or in different environments to see if one group has a significantly different survival rate.

How It Works (in Simple Terms)

- ***Initial Setup***: You start with a group of subjects (e.g., bridges) and track them over time.
- ***Tracking Events***: As time goes on, you record when each event (failure) happens.
- ***Survival Calculation***: At each event time, you update the probability of survival by multiplying the previous probability by the fraction of subjects that survived past the latest event.
- ***Step Function***: The result is a step function that drops at each event time, showing the probability of survival at various points in time.

When we talk about the "survival time" of something, like a bridge, we are interested in how long it lasts before it fails. We can use some mathematical functions to help us understand and predict this survival time.

$$h(t) = \lim \Delta t \rightarrow 0 = \frac{Pr[(t \leq T < t + \Delta t) | T \geq t]}{\Delta t}$$

$$= \frac{f(t)}{S(t)}$$

Cox Proportional Hazards Model

The Cox proportional hazards model is a regression model for survival data, which assesses the effect of covariates on the hazard rate.

The Cox proportional hazards model, (or simply the Cox model), is a statistical technique used in survival analysis to investigate the relationship between the survival time of subjects and one or more predictor variables. Here is an overview of what the Cox model does:

Key Features of the Cox Model

- ***Assessing Hazard Ratios*:** The Cox model estimates the hazard ratio (HR) for each predictor variable, which quantifies the effect of that variable on the hazard or probability of the event occurring. An HR greater than 1 indicates an increased probability, while an HR less than 1 indicates a decreased probability.

- ***Handling Censored Data*:** In survival analysis, data can be censored, meaning that for some subjects, the event of interest (e.g., failure, death) has not occurred by the end of the study period. The Cox model effectively handles such censored data.

- ***Time to Event Analysis*:** The Cox model focuses on the time until the event occurs. It is particularly useful for studying the impact of various factors on the timing of events like failure of a bridge, patient survival times, or time to equipment failure.

- ***No Need for Baseline Hazard Specification*:** Unlike some other survival models, the Cox model does not require the specification of the baseline hazard function. Instead, it assumes that the effect of the predictors on the hazard is multiplicative and constant over time.

Components of the Cox Model

- ***Survival Function*:** S(t)The probability that a subject will survive beyond time (t).

- ***Hazard Function*:** h(t)The instantaneous rate at which events occur, given survival up to time (t).

- ***Cox Proportional Hazards Model*:** The model expresses the hazard function as:

  h(t|X))= $ho(t)^{(\beta 1X1+\beta 2X2+\cdots \beta pXp)}$

  where:

- h(t|X) is the hazard at time t given covariates X.
- ho(t) is the baseline hazard function (common to all subjects).
- β1,β2,…,βp are the coefficients for the predictor variables X1,X2,…,Xp.

- ***Hazard Ratios (HR)*:**Each coefficient βi in the model is exponentiated to give a hazard ratio exp(βi). This HR represents the effect of a one-unit increase in the predictor Xi

  on the hazard, holding all other predictors constant.

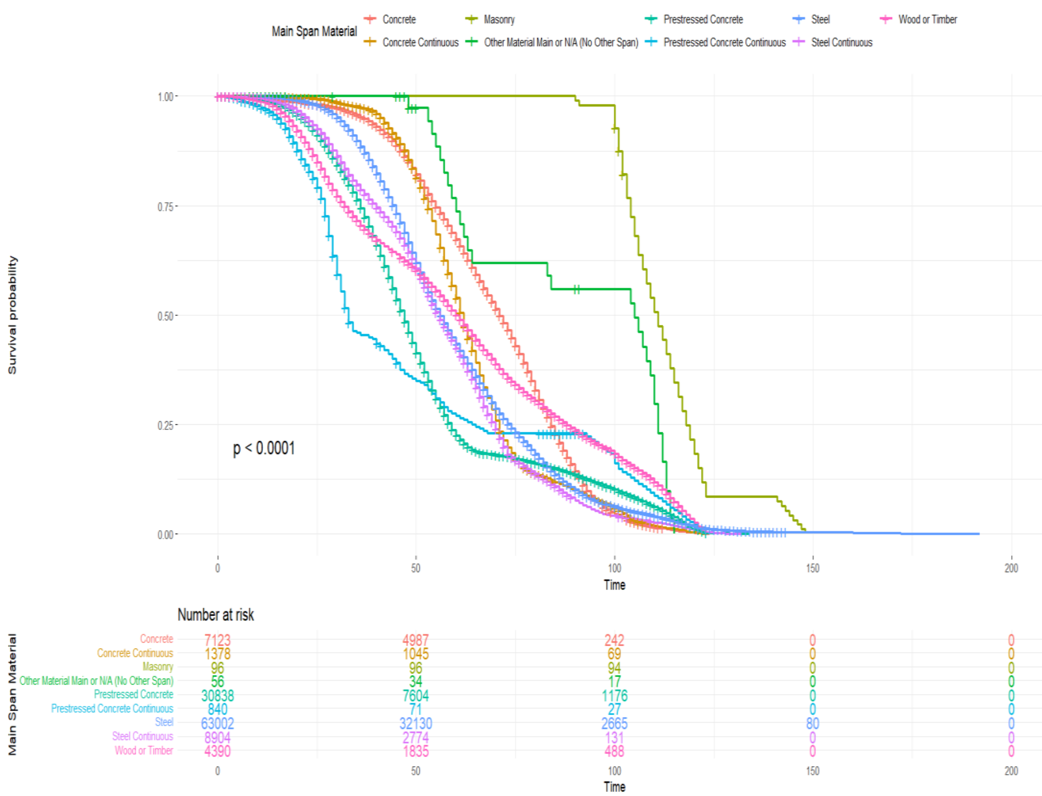
- ***Significance Testing*:**The p-values associated with each coefficient test the null hypothesis that the coefficient is zero (no effect). A small p-value indicates that the predictor has a statistically significant effect on the hazard.

Kaplan-Meier Analysis Results

The Kaplan-Meier survival curves showed varying survival probabilities for different bridge materials and conditions. Critical failure points were identified, indicating periods of increased probability for bridge failure. The periods of increased probabilities are marked with horizontal lines on the graph. The graph also shows the number at risk-of-failure or experiencing-the-failure-event below the plot. The number at risk of failure for each material is indicated at 0,50,100,150 and 200 years. So, on the extreme left, we have the initial number of bridges at risk of going to the fair (failure), then at 50 years, the bridges that did not go to the fair are censored, leaving only the bridges at risk of going to the fair(failure). This goes on till the 150-year mark, when almost all the bridges have either failed or have been censored.

Figure 5

Kaplan Meier Curve for Bridge Materials



The following table shows the median time to failure for the different bridges, the number of bridges at the beginning of the analysis, the events or the number of bridges whose rating dropped to 5(fair), the rmean which is the average time until an event occurs (in this context, a bridge failure) for the bridges within each material category, the standard error associated with the rmean, providing a measure of the variability or uncertainty in the estimation of the rmean.

These metrics are useful for understanding the durability and expected lifespan of bridges made from different materials and for comparing the time-to-failure across these categories. Prestressed Concrete Continuous takes approximately 33years to reach failure but Masonry takes about 111years to reach failure and this is important when selecting bridges for low income areas or for a guided allocation of funds for rehabilitation.

Table 3

Time-To-Failure for the Different Materials

Main Span Material	records	n.max	n.start	Events	rmean
Concrete	7123	7123	7123	5448	69.79093
Concrete Continuous	1378	1378	1378	1202	64.17755
Masonry	96	96	96	93	112.88277
Other Material Main or N/A (No Other Span)	56	56	56	32	88.67235
Prestressed Concrete	30838	30838	30838	17467	53.03632
Prestressed Concrete Continuous	840	840	840	233	50.25412
Steel	63002	63002	63002	47682	60.86235
Steel Continuous	8904	8904	8904	4221	56.79163
Wood or Timber	4390	4390	4390	2891	62.62734
		se(rmean)	**median**	**0.95LCL**	**0.95UCL**
Concrete		0.2597181	71	71	72
Concrete Continuous		0.4967833	62	61	63
Masonry		1.2632614	111	108	114
Other Material Main or N/A (No Other Span)		4.3293248	105	64	111
Prestressed Concrete		0.1936645	47	47	47
Prestressed Concrete Continuous		2.2244289	33	31	41
Steel		0.1056178	56	56	57
Steel Continuous		0.3367471	56	55	57
Wood or Timber		0.5788708	61	59	62

Cox Proportional Hazards Model Results

The Cox PH model revealed significant associations between covariates and probability of bridge failure. Prestressed Concrete (HR = 1.87) and Prestressed Concrete Continuous (HR = 1.93) were associated with higher hazard ratios, indicating increased probability of failure. This means that Prestressed Concrete has an 87% probability of failure, while prestressed continuous concrete has a 93% probability of failure. Environmental factors, such as the number of freeze-thaw cycles (HR ≈ 0.993) and total precipitation (HR ≈ 0.9999), were associated with reduced failure probability. The baseline is 1, so numbers below one for freeze-thaw and precipitation mean the occurrence of temperature and precipitation rather have a low/reduced failure probability. The table below gives the *p values* for the components in column 1, and all the *p values* are significant because the total number of bridges used in this analysis is huge, n= 116000, and such a huge number means the slightest change in any feature will be recorded as significant because a large sample size means a greater sensitivity of the model.

Table 4

Cox Proportional Hazard Results

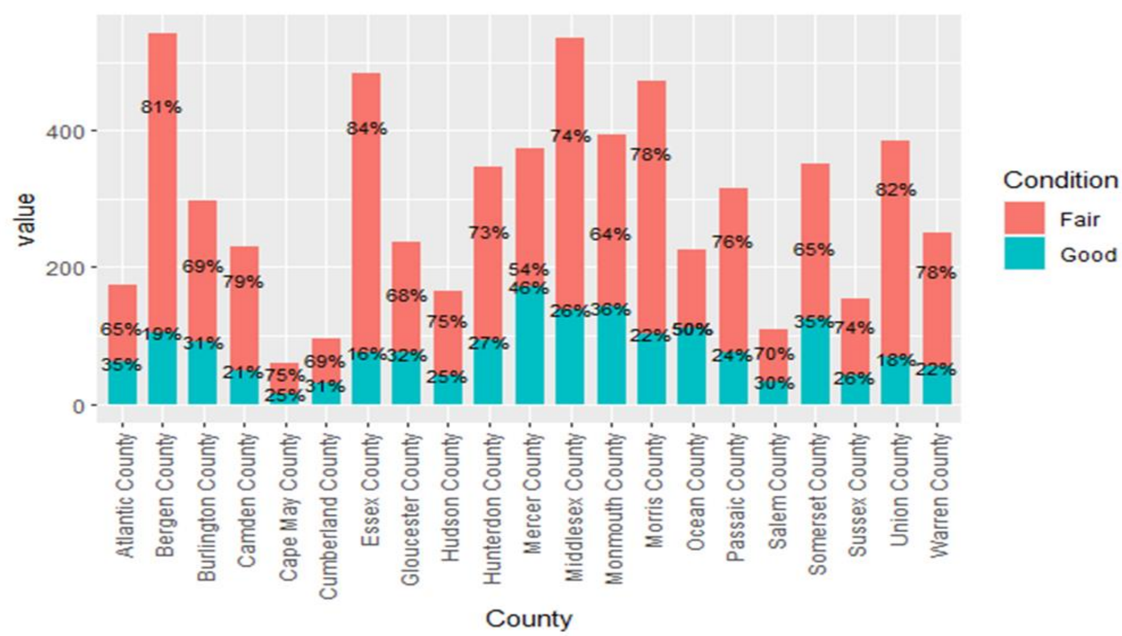
Column1	coef	exp(coef)	se(coef)	z	Pr(>|z|)
Average.Daily.Traffic	1.12E-06	1.000001122	1.04E-07	10.75854248	5.40E-27
factor(Main.Span.Material)Concrete Continuous	0.227588066	1.255568007	0.031927722	7.12822758	1.02E-12
factor(Main.Span.Material)Masonry	-1.073546183	0.341794301	0.104874512	-10.23648327	1.36E-24
factor(Main.Span.Material)Other Material Main or N/A (No Other Span)	-0.419894012	0.657116463	0.177352191	-2.367571605	0.017905255
factor(Main.Span.Material)Prestressed Concrete	0.623918939	1.866227362	0.015648213	39.8715775	<0.0001
factor(Main.Span.Material)Prestressed Concrete Continuous	0.655727327	1.926543234	0.06696245	9.792463173	1.21E-22
factor(Main.Span.Material)Steel	0.222473329	1.249162502	0.014464156	15.38100984	2.19E-53
factor(Main.Span.Material)Steel Continuous	0.305130612	1.356802206	0.020723414	14.72395478	4.52E-49
factor(Main.Span.Material)Wood or Timber	0.185420413	1.203724395	0.023171325	8.002149841	1.22E-15
Number.of.Spans.in.Main.Unit	0.004920736	1.004932863	0.000305721	16.09551025	2.74E-58
Skew.Angle..degrees.	0.007056249	1.007081202	0.000156592	45.06147868	<0.0001
Structure.Length..ft..	0.000174657	1.000174672	1.80E-05	9.678232289	3.73E-22
Deck.Area..sq..ft..	-2.14E-06	0.999997857	2.51E-07	-8.526713285	1.51E-17
Length.of.Maximum.Span..ft..	0.000530985	1.000531126	3.73E-05	14.25028683	4.46E-46
Average.Daily.Truck.Traffic..Percent.ADT.	0.027851974	1.028243466	0.000766762	36.32412075	6.73E-289
Number.of.Freeze.Thaw.Cycles	-0.006757174	0.993265604	0.000228534	-29.56743887	3.92E-192
Total.Precipitation	-0.000103613	0.999896392	1.48E-05	-6.982071767	2.91E-12

Data Analysis Results for Correlation Between Median Household Income and Bridge Condition

The relationship between median household income and the condition of bridges was investigated using data that was obtained from the U.S. Census Bureau and NBI. The median household income data was obtained from census.gov, and the percentage of bridges classified as either 'fair' or 'good' within each county was calculated using R statistical functions. To explore the correlation between median household income and the proportion of fair bridges, Pearson's correlation coefficient was computed. The analysis yielded a Pearson correlation coefficient of -0.45, indicating a moderate negative correlation. This suggests that as the percentage of fair bridges in a county increase, the median household income tends to decrease.

Figure 6

Percentage of Fair to Good Bridges In Each County



Discussion

Interpretation of Findings

The predictive model and time-to-failure analysis provide valuable insights into the factors affecting bridge conditions and failure probability. The identified predictors can guide maintenance strategies and resource allocation to enhance the longevity and safety of bridge networks.

Implications for Infrastructure Management

The results underscore the importance of considering both structural and environmental factors in bridge maintenance and rehabilitation. Infrastructure managers can prioritize maintenance efforts based on the identified risk factors and allocate resources more effectively.

Sociological Evaluation

The percentage of bridges in fair condition and household income had a negative connection ($r = -0.45$), according to a Pearson correlation analysis. The negative coefficient supports the hypothesis that areas with lower median household incomes are associated with a higher proportion of bridges in fair condition. This finding aligns with the broader understanding that infrastructure quality is often lower in economically disadvantaged areas, which can have significant implications for public policy and resource allocation in bridge maintenance and improvement programs.

Implications for Maintenance and Funding Allocation

The results emphasize how crucial it is to take the median household income of road users into account when allocating funds for bridge maintenance and constructing new bridges because some funds are generated from road tolls, user taxes, and gas taxes and areas to supplement the road fund. Some bridges last longer than others from the time-to-failure analysis in the previous chapter, hence such bridges should be prioritized when selecting/designing bridges for areas with low household income or during maintenance scheduling, bridges which do not last long can be prioritized in the allocation of funds to ensure more bridges are in the fair conditions even when there is not enough funds to go around all the bridges. The general standard and safety of bridge infrastructure can be raised by decision-makers by allocating resources to regions that require them more.

Chapter 5

Skew Angle and Bridge Deterioration Analysis

Literature Review

Bridges are essential for transportation infrastructure, and engineers and policymakers are concerned about their long-term performance and safety. President Eisenhower established the United States Interstate Highway System in the 1950s to improve commercial and military mobility. Its almost 50,000 miles were mainly constructed in 35 years and are now part of the country's over 4 million miles of highways (FHWA, 2020). Bridges serve an important role in transportation by connecting divided locations such as rivers, valleys, or gaps in the topography. They are critical infrastructure for both urban and rural areas, allowing for the efficient flow of people, products, and services (Nowak & O. Iatsko, n.d.)

Several research has been conducted to investigate the relationship between bridge skew angle and the rate of deterioration. Researchers conducted a study on 313 bridges in Korea and discovered that the skew angle was an important factor in the decline of bridge decks. The study found that bridges with skew angles above 45 degrees deteriorated faster than those with less than 45 degrees (Kong, 2015).

Another study examined data from bridges and discovered that the skew angle was an essential determinant of bridge deterioration. The study found that bridges with skew angles above 20 degrees experienced much more bearing damage than bridges with skew angles below twenty degrees (Singh, 2016). There are various probable factors for why

bridges that have large skew angles may deteriorate at a faster rate. For example, the geometry of the bridge may result in uneven loading on the bridge components, which can hasten wear and tear ((US Department of Transportation, 1995),(Solae et al., 2020)). Bridges with large skew angles may also be more subject to environmental variables like wind and water, which may lead to rust and other forms of degradation. Also, gravity load paths are important for how bridge skew angles behave ((Singh, 2016),(Diaz Arancibia et al., 2020).

Investigating the relationship between bridge skew angle and deterioration rate is critical in furthering our understanding of bridge performance. More research is needed to investigate this link and find effective solutions to reduce the influence of significant skew angles on bridge deterioration. This will ultimately ensure the safety and efficiency of transportation networks for years to come by gaining a comprehensive understanding of the mechanisms underlying this correlation.

Results

After examining the dataset, we determined the correlation coefficient between the skew angle and the number of years it takes for the bridge deck condition rating to drop by one. In our study, we discovered a correlation coefficient of -0.116 for a condition rating of 9 to 8, -0.210 for a condition rating of 8 to 7, -0.841 for a condition rating of 7 to 6, 0.0069 for a condition rating of 6 to 5, -0.398 for a condition rating of 5 to 4, and -0.4191 for a condition rating of 4 to 3.

The correlation coefficient always has a value between 1 and -1, and it is used as a general indicator of the strength of the association between variables. A positive number indicates a positive correlation (as one variable grows, so does the other), a negative value shows a negative correlation (as one variable increases, so does the other), and a value close to 0 indicates a weak or no association. A correlation coefficient's absolute value indicates the size of the correlation: the bigger the absolute value, the stronger the correlation (Papadopoulos, 2022). This is shown in Table 1.

Table 5

Correlation Coefficient Table

Correlation Coefficient	Correlation Type	Correlation Strength
-0.7 to -1	Negative	Very Strong
-0.5 to -0.7	Negative	Strong
-0.3 to -0.5	Negative	Moderate
0 to -0.3	Negative	Weak
0	Zero	None
0 to 0.3	Positive	Weak
0.3 to 0.5	Positive	Moderate
0.5 to 0.7	Positive	Strong
0.7 to 1	Positive	Very Strong

The negative correlation coefficient indicates that the skew angle and the bridge deck condition rating have an inverse association. This demonstrates that the bridge deck condition rating drops faster as the skew angle increases. However, the correlation coefficients suggest a varying association, implying that other factors may significantly impact the bridge deck condition rating ((Peter Samuels & Mollie Gilchrist., 2014),(George Casella & Roger L. Berger, 2002)). Generally, bridges have a fast deterioration rate between conditions 9 and 7, slowing the progression between conditions 7 and 5. To then experience a faster decline after condition 5 is reached. This trend is presented in Table 2, where the red-to-green scale represents fast to slow deterioration progress.

Table 6

Bridge Skew Angle and Years It Takes Condition Rating To Drop By 1 Step

	Condition Rating						
Skew Angles	9 to 8	8 to 7	7 to 6	6 to 5	5 to 4	4 to 3	Average
0	3.3	6.1	9.6	8.2	6.0	4.7	6.3
5	3.5	6.3	9.7	9.6	5.5	3.4	6.3
10	3.2	6.7	10.5	8.2	5.4	6.3	6.7
15	3.1	6.6	9.5	10.7	6.7	6.8	7.2
20	2.9	7.6	9.9	8.7	6.4	4.1	6.6
25	3.1	7.9	9.8	8.7	5.9	4.3	6.6
30	3.3	6.6	8.7	10.0	4.9	4.7	6.4
35	3.0	6.4	9.3	10.3	5.2	5.6	6.6
40	3.5	6.8	9.4	8.2	7.1	4.2	6.5
45	6.5	5.4	8.3	6.9	6.1	5.4	6.4
50	2.0	6.6	8.4	8.7	4.8	6.1	6.1
55	2.8	6.5	8.7	9.4	6.3	3.0	6.1
60	2.0	8.3	8.6	9.9	4.5	3.3	6.1
65	3.0	3.8	8.0	-	4.0	2.0	4.2
Average	3.2	6.5	9.2	9.0	5.6	4.5	

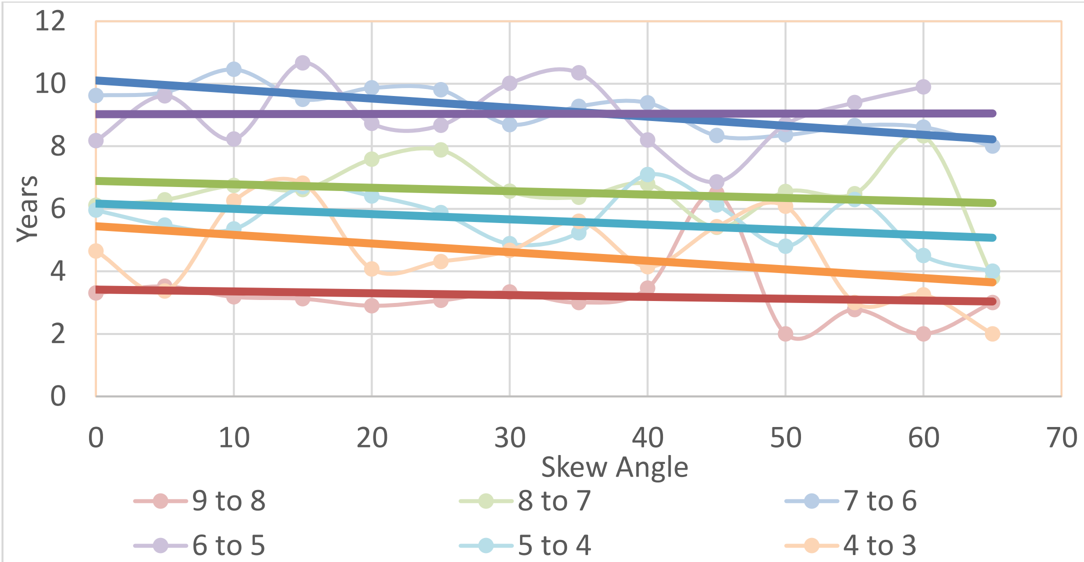
The graph in

Figure 7 depicts the relationship between the years it takes for a bridge to entire condition or quality of the bridge is represented by the condition rating, with higher numbers signifying better conditions. The graph's trend line has a rightward slope from left to right, showing a clear pattern in the data. This implies that when the condition rating reduces (going to the right on the X-axis), the bridge deteriorates by one point in fewer years. In other words, bridges with lower condition ratings deteriorate faster than those with better condition ratings. This graph gives valuable information about the relationship between bridge conditions and the pace of deterioration.

Based on these data, a statistical study was performed using Analysis of Variance (ANOVa) to investigate the potential influence of skew angle on bridge deterioration because the bridges represented in the graph belonged to different skew groups (the skew angles were grouped in 5s, i.e., 0-5, 6-10 and so on) and they behaved differently. The ANOVa study sought to evaluate whether there was a statistically significant difference in the rate of deterioration between bridges with different skew angles. The investigation found a statistically significant influence of skew angle on bridge deterioration, showing

Figure 7

Graph of Years vs. Condition Rating



ANOVa Data Analysis

A hypothesis test was performed to establish and study the association between bridge condition rating and skew angle. Formulation of Hypothesis: (a) Null hypothesis (H0): There is no significant relationship between bridge skew angle and condition rating; (b) Alternate Hypothesis (Ha): There is a significant relationship between bridge skew angle and condition rating. Significance Level: the significant level of this test is $\alpha = 0.05$ (confidence interval = 0.95) (George Casella & Roger L. Berger, 2002).

The value of the negative correlation coefficient indicates an inverse association between the bridge condition rating and the skew angle. This means the deterioration will occur faster for bridges with larger skew angles. The magnitude and direction of the correlation reveal information about the link between two variables, as seen in Table 3.

The skew angle is categorical, meaning it has been grouped from 0-5 degrees, 6-10 degrees, and so forth, providing us with between 13 and 14 counts for each deterioration rating group. Then, since the condition rating is continuous, the analysis of variance is the most suitable non-parametric test to be used. Excel was used for the ANOVA test, and this test provided the test statistic and p-value. The hypothesis test findings show a statistically significant association between bridge condition rating and skew angle ($p<0.05$). See Table 4 below (George Casella & Roger L. Berger, 2002). This suggests that there is evidence that the two variables are associated and that the observed correlation is unlikely to have happened by chance alone.

The findings show a statistically significant relationship between these factors ($p<0.05$). As a result, the null hypothesis is rejected, and we conclude that there is evidence of a substantial link between bridge condition rating and skew angle.

The ANOVa table's "Count" values assisted us in understanding the distribution and balance of bridge data across multiple groups or categories of skew angles being compared. It enabled comparisons between skew angle groups with varied sample sizes and provided insights into the statistical findings' reliability. Summing the squared differences between each skew angle data point and the mean of the skew angle yields the sum of squares. It measures the total amount of variation within the different skew angle groups. The sum of squares is used to calculate the significance of differences between groups or factors, with the following calculations in the ANOVa table, such as mean squares and F-statistics, are derived from it.

The terms "between groups" and "within groups" in the ANOVa refer to two independent sources of variance being investigated. In this study, these sources of variation helped assess the differences or effects of skew angles on the bridges. The F-statistic, or the ratio of between-group variation to within-group variation, is used to determine the significance of variations across groups. If the F-statistic exceeds a critical value, it indicates that the differences between groups are unlikely to arise by chance. In this case, the F-statistic is 2.333, which is way above the significance level of $\alpha = 0.05$. This indicates that the difference in deterioration among the different skew angle categories did not occur by chance and, on the contrary, are correlated.

Table 7

ANOVA Test

Groups	**Count**	**Number of bridges**	**Sum (Rating/degrees)**	**Average (year)**	**Variance (year)**
9 to 8	14	1007	45.173	3.226	1.102
8 to 7	14	4874	91.530	6.537	1.176
7 to 6	14	8945	128.310	9.165	0.519
6 to 5	13	4766	117.491	9.037	1.145
5 to 4	14	1320	78.694	5.621	0.784
4 to 3	14	594	63.641	4.545	1.900

Table 8

ANOVA Results

Source of Variation	SS	Df	MS	F	P-value	F crit
Between Groups	394.879	5	78.975	71.525	1.637 E-27	2.333
Within Groups	85.020	77	1.104			
Total	479.900	82				

By connecting the graph's condition rating information with the statistical data from ANOVa, it is possible to conclude that the skew angle significantly influences the bridge deterioration rate.

Chapter 6

Conclusions and Recommendations

Predictive Modeling for Bridge Condition Assessment

Synopsis of Results

This thesis used NBI data to identify and rank important structural variables influencing bridge deterioration. The predictive model created showed excellent accuracy and dependability for predicting bridge conditions. A correlation analysis showed differences in bridge conditions based on household income.

Overall, the model demonstrates strong predictive performance with high accuracy and sensitivity, though it could benefit from improvements in specificity. These metrics help in assessing the model's reliability and can guide further refinement to balance between identifying all bridges needing maintenance (high sensitivity) and minimizing false alerts (improving specificity). This balance is essential for effective infrastructure management and optimal resource allocation in bridge maintenance and repairs.

Time-to-Failure Analysis and Analysis of the Impact of Median Household Income on Bridge Condition

This study developed a predictive model and conducted a time-to-failure analysis to assess the condition and failure probability of bridges in New Jersey. Significant predictors were identified, and their impacts on bridge conditions were quantified. This information, used together with the results of the correlation analysis between median household income and bridge condition, can aid in better allocating road funds.

Policy Consequences

According to the study, median household income should be taken into account when allocating funds for bridge repair in order to maintain a fair distribution of resources. Infrastructure safety and quality can be increased by concentrating on areas with lower household incomes.

Skew Angle and Bridge Deterioration Analysis

Correlation is a statistical measure of the relationship between two variables in bivariate data, meaning it is a linear connection between two independent variables. The correlation coefficient is a numerical measure that reflects the strength of a statistical association. The results of this study indicate that the skew angle significantly influences the bridge deterioration rate. Even though additional research and analysis are required to investigate the underlying mechanisms and potential confounding factors that may influence the association between bridge condition rate and skew angle, this research provides substantial evidence of their interrelation. Other pertinent variables, such as traffic volume, bridge age, or maintenance history, must be considered to understand the factors influencing bridge condition because there are many sources of uncertainty in structural design, which could also impact deterioration (22, 23). The study effectively established a relationship between bridge skew angle and deterioration rate. This finding stresses the need to consider bridge skew angle in project planning and infrastructure design to maintain bridge longevity and structural integrity.

Overall Conclusion

In summary, this thesis has presented a comprehensive examination of the structural health and economic variables influencing the state of bridges in New Jersey. The predictive modeling in the first chapter highlighted the critical factors affecting bridge conditions, providing a valuable tool for resource allocation and maintenance prioritization. The second chapter delved into the time-to-failure of bridges under various load scenarios and bridge materials; and the economic impacts on bridge conditions, revealing significant insights into the interplay between economic factors and infrastructure quality. The third chapter's focus on the skew angle of bridges underscored its influence on structural integrity, offering practical recommendations for optimal bridge design.

By integrating these three areas of analysis—predictive modeling, time-to-failure under load scenarios and bridge materials, and the impact of skew angles—the thesis offers a holistic approach to bridge management. This multidisciplinary perspective not only enhances our understanding of the factors that contribute to bridge deterioration but also provides actionable strategies for improving bridge reliability and longevity, particularly in economically disadvantaged areas. This comprehensive approach ensures that limited resources are effectively utilized, leading to more resilient and well-maintained bridge infrastructure.

Recommendations

Enhanced predictive maintenance is a crucial step that should be adopted. Utilizing the predictive modeling framework developed in this thesis allows for the proactive identification of bridges at risk of deterioration. This proactive approach ensures timely maintenance and repair, optimizing resource allocation and extending the lifespan of the infrastructure.

Targeted resource allocation is essential for addressing disparities in bridge quality across different economic regions. Maintenance and upgrades should be prioritized for bridges in low-income areas, where the study has shown a higher proportion of bridges in fair condition. This strategy ensures an equitable distribution of infrastructure quality and helps bridge the gap in maintenance standards.

Based on the findings, it is recommended that infrastructure managers incorporate the identified predictors into their maintenance and rehabilitation strategies. Further research could explore additional factors and extend the analysis to other regions.

Additionally, specific maintenance strategies should be implemented based on the different materials and load scenarios analyzed. For instance, focusing on bridges that endure higher average daily traffic (ADT)/live loads and environmental loads can significantly improve overall reliability. These material and load-specific strategies can tailor maintenance efforts to the unique demands of each bridge.

The findings on skew angles should be incorporated into bridge design standards. Bridges with skew angles between 15 and 30 degrees should be prioritized, as this range maximizes structural integrity and minimizes stress concentrations, thereby reducing the likelihood of deterioration. This consideration will ensure that new bridges are designed with long-term resilience in mind.

Developing a comprehensive management plan that integrates median household income data, predictive models, and structural health indicators is also recommended. This holistic approach ensures that all relevant factors are considered in the decision-making process, leading to more robust and sustainable bridge management practices.

Policy and funding advocacy is vital for addressing the correlation between low household income and higher proportions of fair bridges. Advocating for increased funding for bridge maintenance in low-income areas can provide the financial support needed to enhance infrastructure quality in these regions.

Finally, establishing a continuous monitoring system that feeds data back into the predictive models is essential. This system allows for ongoing refinement and improvement of maintenance strategies, ensuring that the management plan evolves in response to new data and changing conditions. By implementing these recommendations, transportation authorities can improve the overall condition and longevity of bridges, ensuring safe and reliable infrastructure for all communities.

Chapter 7

Future Work

Bridge Condition Assessment

For future work, researchers can look into enhancing the predictive model by apply more complex machine learning methodologies. Also, a deeper understanding of the temporal features of bridge deterioration can also be developed by doing longitudinal research.

We can also employ cutting-edge methods like Kaplan-Meier survival analysis and the Cox proportional Hazards model, just as it has been used with this current study to effectively create a time-to-failure model, to also generate new data and test the reliability of bridges with new construction methods, etc.

Also, we integrated the impact of median household income by doing an analysis; which yielded significant insights into how the economic factors of a community/county affect the bridge longevity and maintenance requirements. The thesis gives a comprehensive framework that policymakers can employ for making decisions during funding allocation for bridge development. This is especially important in areas where toll money is used to support roads, since building bridges in underprivileged areas with short lifespans may result in early failures and little financing for rehabilitation.

An interesting discovery was made during the time-to-failure analysis: it was found that the skew angle had a 0.7%. This surprising finding led to a more thorough examination of the connection between skew angles and structural degradation, a topic that has not gotten much attention in the literature to date. Future research can be aimed at understanding how skew angles contribute to the overall structural integrity of bridges as there is still a lot that is unknown; has been made possible by the study's investigation of this feature, which could have significant consequences for bridge design and building procedures.

For my doctoral research, I plan to concentrate on employing Abaqus, an advanced modeling software, to further explore the reasons for the identification of prestressed girders as the primary factor influencing deterioration rates in the time-to-failure investigations since it had a really high hazard ratio. The objective is to evaluate the remaining load-bearing capability of prestressed girders and identify the underlying reasons causing their fast deterioration through a thorough investigation. This will in effect, ensure that maintenance and replacement efforts are strategically prioritized to extend the service life of prestressed girders and improve the overall resilience of bridge infrastructure.

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