Bridge Health Diagnostics using Machine Learning

by

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Abstract: As of 2022, there were 620,669 bridges in the United States. Each bridge is inspected according to the Federal Highway Administration's regulations to maintain safety and serviceability. These inspections are performed on varying schedules that are dependent on several factors. Over 100 types of characteristic data are collected during these inspections and are used to produce a structural evaluation rating (SER) for each bridge. These characteristics can include location, material, geometric, and other types of information about a bridge. This paper investigates the use of Pearson's Correlation, Decision Trees, and Random Forest models to determine and show relationships between individual characteristics and the SER. These machine learning methods allow for fast and accurate predictions of the SER based on the selected individual characteristics over varying periods of time. These models also provide visual interpretations of the relationship information produced. Using these models in conjunction with current inspection scheduling methods may maximize efficiency and improve reliability. The models may also be useful for characteristic selection during the design process. New and improved technologies allow engineers to keep safety as the base of everything they do.

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Chapter 1: Introduction

1.1: Research Objectives

The objective of this research is to propose machine learning methods for improvement and optimization of the inspection scheduling process of highway bridges. The proposed methods are analyzed to find the relationships between the characteristics of a bridge and its inspection rating. They will also provide an intuitive, visual approach to these relationships. While many concepts in the field of bridge engineering have been used for decades, bridge inspections are ever evolving with new technology. These new technologies allow engineers to process more information than ever before; however, this may also increase the time needed to address such volume. Introducing new methods will allow engineers and inspectors to make more informed decisions and provide more choices regarding how they conduct inspections.

In order to perform this research, machine learning methods were used to find the relationships between bridge characteristics and the Structural Evaluation Rating (SER). The methods investigated include Pearson's Correlation, K-Means Clustering, Principal Component Analysis, Decision Tree Modeling, and Random Forest Modeling. These methods were selected due to their ability to process large amounts of data in a short amount of time. The visual approaches to these relationships produced through these methods assist in these rankings and prioritizations by increasing their interpretability and creating workflows that can be followed for a specific bridge. Other methods may be more time-consuming due to preprocessing or computation time.

Computers have become an indispensable tool to engineers in nearly every aspect of day-to-day work. As new programs and information become available, it is important to use them to their full potential. Ultimately, bridge engineering is a discipline that is governed by the responsibility of public safety. Inspections are a time-consuming activity for engineers, inspectors, and motorists. Through new pathways to optimization and efficiency, companies and agencies will be able to choose methods that may reduce computational errors and the time a bridge remains in a deteriorated or altered state. By determining the characteristics that have a more significant effect on the inspection rating, future bridges may be designed to improve upon those specific areas. These relationships may also be implemented in new rating programs or advancing current ones. Organizations may also see benefits in their time-value by allowing the machine learning models to process information in the background.

1.2: Background Information

In 2022, the State of Ohio managed 27,003 bridges, the second-most of any state in the United States (FHWA, 2022a). The SER is an overall condition rating ranging from zero to nine, using the minimum value of the appraisal ratings. Bridges with individual components or an SER of four or less are rated as poor. The appraisal rating coding values for these components are described as follows: ≥ 7 "Good", 5-6 "Fair", and ≤ 4 "Poor", with detailed descriptions shown in Table 1.1. The SER as well as elemental characteristics of a bridge are the basis for condition rating and health diagnostics.

Table 1.1. Item appraisal rating codes

Code	Description
N	Not Applicable
9	Superior to present desirable criteria
8	Equal to present desirable criteria
7	Better than present minimum criteria
6	Equal to present minimum criteria
5	Somewhat better than minimum adequacy to tolerate being left in place as is
4	Meets minimum tolerable limits to be left in place as is
3	Basically intolerable requiring high priority of corrective action
2	Basically intolerable requiring high priority of replacement
1	This value of rating code not used
0	Bridge closed

Four-and-a-half percent of bridges in Ohio were considered poor, as shown in Fig. 1.1. In 2022, the estimated cost to replace all poor-rated NHS (National Highway System) and non-NHS bridges in Ohio was over one-billion dollars, while the estimated cost to rehabilitate the same bridges was over $700 million (Federal Highway Administration, 2022b).

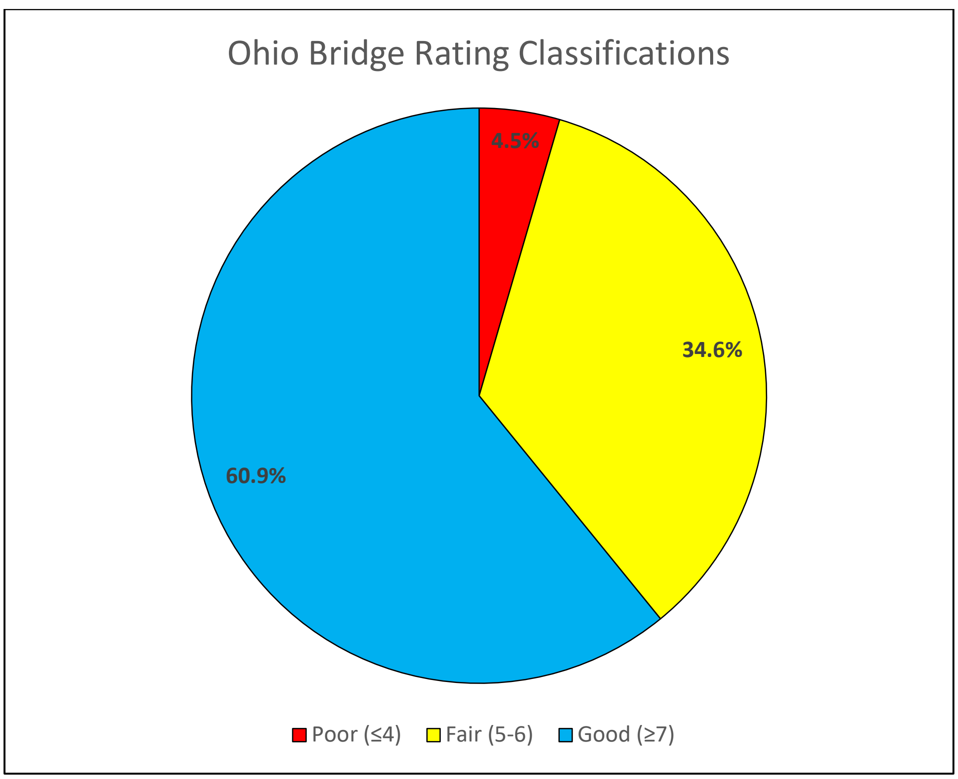

Fig. 1.1. Structural Evaluation Rating classifications for all Ohio bridges.

The Federal Highway Administration (FHWA) requires all states to adhere to the National Bridge Inspection Standards (NBIS), which were implemented beginning in 1971 (Hartmann & Weingroff, 2021). The catalyst for the inclusion of these standards was the fatal collapse of the Silver Bridge over the Ohio River on December 15, 1967. The regulations within these standards outline the inspection process and inspector qualifications, as well as requirements for inventories, reports, and ratings for any bridge located within the public transportation network. The collection of these inventories, the National Bridge Inventory (NBI), is a publicly available database containing data sets for each state annually dating back to 1992. This data is recorded to promote safety and allow agencies to make informed financial and practical decisions regarding the health and preservation of the country's transportation infrastructure.

Routine inspections are performed at least every 24 months, with approximately 83% of the nation's bridges falling within this timeframe (Gee & Henderson, 2007). State Departments of Transportation (DOTs) may require inspections more often than federally mandated. Increased inspection frequency may also be necessary when the structure exhibits unforeseen damage or deterioration, as well as other strength considerations. This is done visually and physically by teams of at least two inspectors. Bridges are accessed using snooper and/or bucket truck, rappelling and climbing, wading, or other terrain navigation methods. Hand tools, such as scrapers, brushes, probing rods, and borers may be used for measuring and identifying defects. General information and defects are recorded on inspection forms and photographed with a camera. Currently, the Ohio Department of Transportation (ODOT) uses 14 different inspection types with varying frequencies, which are listed in Table 1.2.

Table 1.2. Ohio Manual of Bridge Inspection (2014) inspection types and frequency

Inspection Type	Frequency
Initial	Infrequent, performed and inventoried before the bridge is first opened to traffic or there is a change or update in inspection responsibility.
Routine	Performed at a maximum interval of 24 months based on reliability criteria.
In-Depth	As-needed, generally for major or complex bridges often on a 60-month cycle or less.
Damage	As-needed.
Flood	As-needed.
Fracture Critical	Not to exceed 24-months for structures that fit the rigid definition.
Underwater	Not to exceed 60-months.
Cross Channel Profile	As-needed.
Scour Susceptibility Inspection and Evaluation	As-needed.
Special/Interim Safety (Cursory)	As-needed.
Quality Assurance	A rolling sample set of field and office visits performed regularly by FHWA, ODOT Central Office, CEAO or initiated by any Control Authority or NBIS Program Manager to verify quality inspections.
Complex	Routine, with often a 60-month in-depth inspection cycle.

Note: CEAO – County Engineers Association of Ohio

Since 2021, these inspection frequencies have outlined ODOT's prioritization using reliability-based inspection intervals (RBIs) (ODOT Office of Structural Engineering, 2021). This is performed using a bridge program called AssetWise. AssetWise tracks high-risk bridges by considering five critical features of any individual bridge. The first feature considered is the presence of at least one fracture critical member (FCM). Fracture critical members occur in steel bridges and can result in a total loss of structural integrity, if damaged. The second critical feature is the susceptibility to scour. Bridge scour occurs when water erodes or degrades the streambeds beneath piers and abutments. Scour holes can occur more suddenly than other types of bridge deterioration and affect the integrity and stability of the entire structure. The third critical feature is the presence of a posted load or restriction on the bridge. Posted loads or restrictions are used when the capacity of the structure to carry its design or current legal load reduces. The fourth critical feature considered is a general appraisal or deck condition rating of less than seven. The fifth critical feature is whether the bridge is a new construction or has had a rehabilitation in the past three years. New construction or rehabilitation inspections are necessary to confirm that the design plans and requirements have all been met by the contractors. Any issues or defects that are found during these inspections may be addressed prior to opening or reopening to traffic. This reassures that public safety is not at risk and decreases delays created by diverting traffic for longer than necessary. If any of these five critical features are present at the time of inspection, AssetWise will trigger the inspection interval adjustment. This adjustment is an increase in frequency from the standard 24-month interval to a 12-month interval. All other bridges that do not have these features are kept at the 24-month interval unless a non-routine inspection is required.

Through analyzing condition ratings of bridges in Ohio, it has been found that the average SER for Ohio bridges has gradually increased by nearly one point from 1992 to 2022, as shown in Fig. 1.2 for steel and concrete bridges. However, it is important to note that the construction of new bridges and closure of poorly rated bridges may artificially skew the average rating positively. New technologies, effective construction and inspection techniques, improving design methods and materials, rehabilitation of existing bridges, decommissioning of older bridges, and construction of new bridges, all play a role in this increase. New or improved design methods, such as those for gusset plates, can be utilized in the rehabilitation of older bridges as well as be implemented for new or rehabilitated bridges. These design methods can emerge through research or in the wake of disaster, as the inadequate gusset plate design contributed to the collapse of I-35W in 2007. New materials and production methods may also improve the SER by increasing their durability and strength, extending their design and service life. New materials may also see an increase in service life due to emerging inspection technology. Non-destructive testing, such as ground penetrating radar and ultrasonic surface waves, allows inspectors to see conditions within the element while minimizing damage, cost, and time (FHWA, 2021).

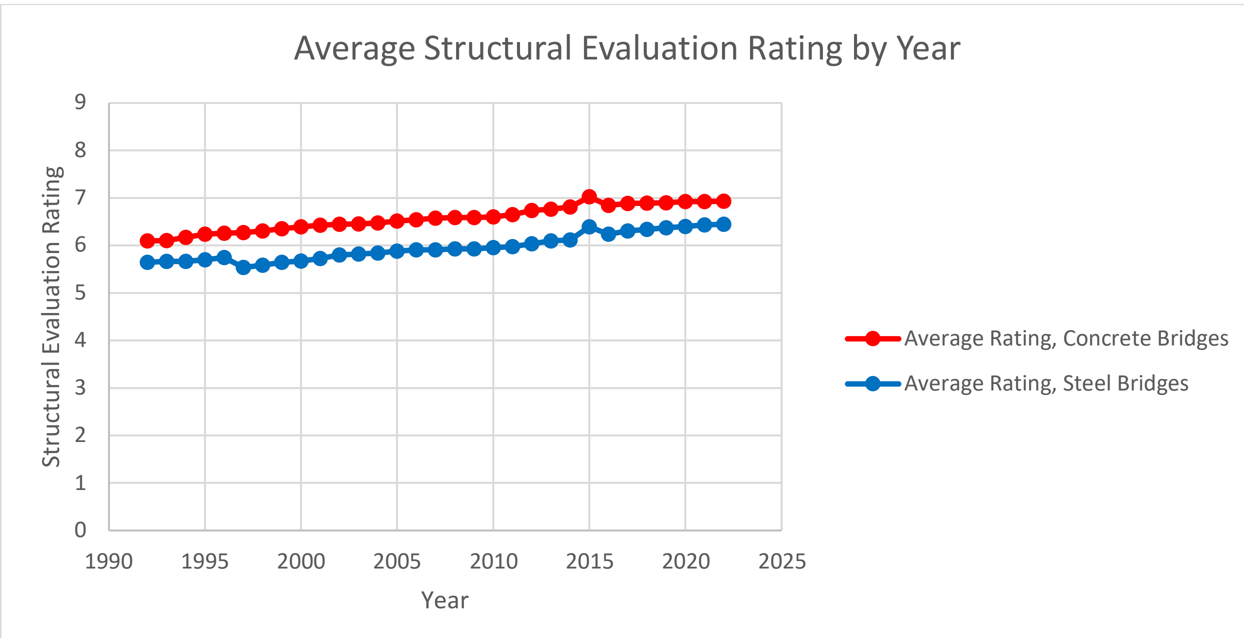

Fig. 1.2. Average Structure Evaluation Rating for Ohio bridges by year.

1.3: Literature Review

The physical deterioration of bridges is caused by many different factors. In many cases, unexpected or unintended events cause damage that needs immediately addressed. For example, there were over 13,000 vehicle-bridge collisions in 2021 (National Highway Traffic Safety Administration, 2023) These collisions can affect the columns, piers, beams, and other crucial components in varying severities up to the closure of the bridge. Bridges crossing over waterways also risk being impacted by vessels. When these events happen, experienced inspectors with the proper tools can determine the structural integrity of the system and make judgements on when the bridge will be safe to reopen. Corrosion also plays a significant role in the deterioration of bridge health, especially in steel bridges. Corrosion is a gradual erosion of metal materials within a bridge caused by a chemical reaction, often between water and steel. As portions of the steel are removed from the structure, the load bearing capacity of the components is significantly reduced. This can occur over many parts of a bridge but may be concentrated in areas such as joints or supports where water is able to pool. Ahn et al. (2013) found that carbon fiber reinforced polymer (CFRP) repairs applied to a corroded plate girder reduced the stress at the support. Repairs such as these are beneficial for keeping the capacity of the member at an acceptable level whether the repair is meant to be temporary or permanent. Physical deterioration is often easier to see than other types of damage, however new technologies allow engineers to see more than what a visual inspection may typically show.

Environmental factors also play a large role in the deterioration of bridges. While many environmental effects, such as potholes in the pavement in the Spring, are readily visible, many require more in-depth inspection to be identified. Palu and Mahmoud (2019) suggested that bridges in regions where there is a larger variation in temperature may experience an increase in expansion joint malfunctions as the climate changes. In areas with cold weather, freeze-thaw cycles and deicing agents may deteriorate concrete used on the deck and superstructure faster than others. Zhao et al. (2024) found that bridges damaged by freeze-thaw cycles showed worse deterioration when exposed to a salt solution similar to that of deicing salt. Bridges with substructure units underwater are susceptible to scour and other weathering from the movement of the water. Scour occurs when the moving water erodes sediments from around the bridge's foundations, leaving holes and compromising stability. Every component of a bridge has the potential to experience environmental deterioration. However, there are many methods of prevention and rehabilitation. Johnson and Niezgoda (2004) discussed the benefits and risks of using countermeasures against scour, such as riprap or stream realignment. Different concrete curing methods may help counter the effects of freeze-thaw and deicing agents. Expansion joints may be monitored and cleared out before clogging can occur. Engineers and inspectors can aid in this prevention by being thorough during design and inspection processes and taking the environment surrounding the bridge into account. It is important to consider information about the location and climate a bridge is constructed in to help increase its design service life. These environmental factors may also change how inspections are conducted. For example, bridges that are susceptible to scour may have underwater inspections done supplemental to the routine inspection. Proper documentation and consideration of these factors is paramount to successful inspection and prevention.

Technological advances are allowing inspectors and engineers to improve the efficiency and accuracy of their findings through the automation of computations as well. Clarke-Sather et al. (2021) found that report-writing and data compilation were the primary time-consuming activities for an inspection. If the inspection data for a bridge can be collected and analyzed during inspection in the field, the post-inspection time consumed by the inspector can be reduced. Automation through new technology for directly processing information through artificial intelligence may contribute to this reduction in the future. Abdallah et al. (2022) provided an in-depth review of the various inspection methods currently employed and outlined future frameworks that might be useful in planning. One of the main identified limitations for the future is the computation complexity. By providing methods of computation, such as machine learning that is easily interpretable, inspectors will be readily able to implement them with minimal training.

Galdelli et al. (2022) proposed the use of a remote visual inspection system. This robotic system employed a multi-camera system that captured images in nearly any condition and assisted in detecting flaws in areas that may be difficult for inspectors to access. The use of robotic systems in this study were consistent and efficient, making it beneficial in terms of cost and time. It was suggested that the data this system obtained over time might be useful when processed through machine learning as well. Unmanned aerial vehicles (UAVs) are also showing promising uses within the inspection process. UAVs are able to access portions of a bridge that would typically be difficult for inspectors to evaluate using snoopers, rappelling, or other traversal methods. A study by Duque et al. (2018) was conducted to compare the damage quantification accuracy between a UAV and typical field measurements. One of the disadvantages noted was the ability of the UAV to capture high-quality images when weather and/or lighting conditions were insufficient. Future work to identify the cost and time benefits of using UAVs in any condition will expand their applicability in the inspection process.

Machine learning and artificial intelligence overall have proven useful in many different applications. In manufacturing, machine learning can detect defects in products and optimize their production. Altmann et al. (2023) investigated the use of supervised and unsupervised machine learning models in manufacturing defect classification. Defects that occur within additive manufacturing of metals negatively impact their mechanical properties. Six hundred and thirty-five micrographs were processed to determine the features contained within their regions of interest. Altmann et al. analyzed these features and binary images using K-Means clustering and Random Forest models to determine the accuracy of defect detection. For each defect type, the Random Forest model outperformed the others, providing at least 90% accuracy. In cybersecurity, biometric systems and network protection are improved. Using electrocardiogram information, Patro et al. (2020) optimized their selected features to process them through machine learning classifiers. When compared to other existing feature classifying methods, the feature optimization method improved the recognition accuracy.

In bridge inspections, machine learning provides a low-cost, low-impact, and simple but efficient method for damage detection and health monitoring. Luo et al. (2023) introduced computer-vision methods and applications for defect detection, vibration measurements, and parameter identification. Li & Burgueño (2010) utilized five soft computing methods, including support vector machines and fuzzy neural networks, to determine their effectiveness in degradation predictions for abutment walls. By presenting multiple models with reasonable results for the same task, users of these methods will be able to choose which one is more applicable to their project.

The most significant way to help preserve the nation's bridges is through prevention. By detecting defects in the earlier stages of deterioration, ample time and resources may be available to remedy them. Inspections are the key to early identification. Technology is constantly changing, allowing engineers to utilize new tools that make the inspection process more efficient and reliable. Sensors, UAVs, and new physical tools have allowed bridge components that were previously difficult to see or analyze to be readily accessible. The introduction of machine learning into bridge inspection and health monitoring is only a small part of what may be available for use in the future. This research introduces three methods that have potential to be a part of that future.

Chapter 2: Data Preprocessing

In this research, the term “bridge” follows the FHWA guidelines, defined as “A structure of more than 6.1 meters (20ft) in length spanning an obstruction or depression” (Federal Highway Administration, 2023). The raw bridge data was obtained from the National Bridge Inventory repository. This repository contains links to the individual inspection year data. Within a link to an individual inspection year, three options are available for location data: individual files for highway bridges in 54 states and territories, a single file containing highway bridges in all 54 states and territories, or all records. Each state is responsible for the inspection of all public highway bridges it contains. State DOTs may enforce inspection methods and regulations of their own if the minimum requirements outlined in the NBIS are met as well. For this research, only Ohio bridges were considered for analysis. One of the main advantages of considering one state is that the inspection records and regulations are consistent across every year. Ohio manages more than 27,000 bridges each year, providing a larger amount of data compared to other individual states. All states must follow the FHWA inspection requirements at a minimum. However, states may also choose to follow their own guidelines that are stricter than the federally mandated ones. Considering Ohio for analysis also decreased the variability of inspection requirements from state to state. Other information to consider, such as climate or population, vary greatly between states as well. Once the year and state were selected, the raw data were saved as a delimited file. Delimited files are text files containing strings of data using field separators in between. A sample of the delimited text file from NBI is shown in Fig. 2.1 below.

```
STATE_CODE_001,STRUCTURE_NUMBER_008,RECORD_TYPE_005A,ROUTE_PREFIX_005B,SERVICE_LEVEL_005C,ROUTE_NUMBER_005D,DIRECT
010,KILOPOINT_011,BASE_HWY_NETWORK_012,LRS_INV_ROUTE_013A,SUBROUTE_NO_013B,LAT_016,LONG_017,DETOUR_KILOS_019,TOLL_
PR_WIDTH_MT_032,MEDIAN_CODE_033,DEGREES_SKEW_034,STRUCTURE_FLARED_035,RAILINGS_036A,TRANSITIONS_036B,APPR_RAIL_036
URE_KIND_043A,STRUCTURE_TYPE_043B,APPR_KIND_044A,APPR_TYPE_044B,MAIN_UNIT_SPANS_045,APPR_SPANS_046,HORR_CLR_MT_047
D_REF_054A,VERT_CLR_UND_054B,LAT_UND_REF_055A,LAT_UND_MT_055B,LEFT_LAT_UND_MT_056,DECK_COND_058,SUPERSTRUCTURE_CON
URAL_EVAL_067,DECK_GEOMETRY_EVAL_068,UNDCLRENCE_EVAL_069,POSTING_EVAL_070,WATERWAY_EVAL_071,APPR_ROAD_EVAL_072,WOR
ACTURE_LAST_DATE_093A,UNDWATER_LAST_DATE_093B,SPEC_LAST_DATE_093C,BRIDGE_IMP_COST_094,ROADWAY_IMP_COST_095,TOTAL_I
RECTION_102,TEMP_STRUCTURE_103,HIGHWAY_SYSTEM_104,FEDERAL_LANDS_105,YEAR_RECONSTRUCTED_106,DECK_STRUCTURE_TYPE_107
TICAL_113,FUTURE_ADT_114,YEAR_OF_FUTURE_ADT_115,MIN_NAV_CLR_MT_116,FED_AGENCY,DATE_LAST_UPDATE,TYPE_LAST_UPDATE,DE
FICIENCY_RATING,STATUS_NO_10YR_RULE,CAT10,CAT23,CAT29
39,        0100021,1,3,1,00032,0,09,001,85890,'N&W RR                   ',,'SR 32            ','0.9 MI W OF JCT SR
',99.99,1.335,1,0000000032,0,38561826,083400729,3,3,01,01,02,1983,2,0,4627,2015,5,12.2,0,42,0,1,1,1,N,4,N,0,0,A,1,
,,,,0,0,0,,,,,2,L,1,,1,0,0,1,2,N,N,13,0,,Y,N,6422,2039,0,N,5/4/2018,B,Z ,,,,,,,,,0,,97.4,0,F,6,756.48
39,        0100048,1,3,1,00032,0,09,001,85890,'N&W RR                   ',,'SR 32            ','0.9 MI W OF JCT SR
',99.99,1.335,1,0000000032,0,38561827,083400875,3,3,01,01,02,1983,2,0,4627,2015,5,12.2,0,42,0,1,1,1,N,4,N,0,0,A,1,
,,,,0,0,0,,,,,2,R,1,,1,0,0,1,2,N,N,13,0,,Y,N,6422,2039,0,N,5/4/2018,B,Z ,,,,,,,,,0,,97.4,0,G,7,756.48
39,        0100137,1,3,1,00032,0,09,001,58366,'CHERRY FORK CREEK        ',,'SR 32            ','2.98 MI E OF SR 24
',99.99,14.915,1,0000000032,0,38553380,083305013,3,3,01,01,02,1978,2,0,3881,2015,5,12.8,0,47,0,1,1,1,N,4,0,0,0,A,1
```
Fig. 2.1 Delimited text file sample.

The NBI website provides detailed instructions on how to import the delimited text file data into Microsoft Excel. The information contained herein was copied into a master Microsoft Excel workbook containing 31 worksheets, one for each year from 1992 to 2022. Each worksheet was given a corresponding name, such as “OH22”, defining the state and the last two digits of the year of data contained in the worksheet.

The raw data contains up to 134 columns, each one representing a different characteristic of the corresponding bridge. It also contains between 26,986 and 28,284 bridges in each year. Over time, new bridges are constructed while others are closed or demolished. This means that the same bridge may be processed in this analysis in all 31 years or may only appear in a smaller span of time. The data also contains up to 856,986 rows across all 31 years. Each row represents one bridge and all its recorded characteristics, and is labeled using its Structure Number (SN). The SN is a unique, numeric identifier for a bridge used for identification only. Each worksheet was sorted by the SN for consistency in organization.

2.1: Characteristic Information

The characteristic columns provided in the raw data sets include geospatial, physical, historical, and geometrical information. As new information and technologies became available, new characteristics were included in or removed from the inspection records. In order to maintain consistency in the characteristic relationships, only columns that are available across all 31 years were considered. This allows for comparisons to be drawn from the raw data as well as the results of this research over any time span within the 31-year boundary. Historic information, such as federal land designation, provides descriptions that are used to label bridges for administrative, organizational, or other uses. Geospatial information, such as location or latitude, provides information for locating a bridge in reference to known markers or Geographic Information Systems (GIS). While the location may be helpful in identifying climate information, the characteristics themselves are descriptors only. These categories of information do not contribute to the physical deterioration of bridges on their own and were excluded from analysis.

Bridge geometry is a highly variable trait that is directly related to the materials and loads bridge members contain or experience. Different configurations are necessary when considering the type of space a bridge spans over and the needs of the owner. While there are minimum requirements from various structure codes, many of these physical traits are determined by engineers or the owners. The NBI Coding guide references up to 134 of these characteristic columns that may be included in any given year. In order to focus on information that is presumed to have an effect on bridge performance as well as to streamline data processing, only eight important characteristics columns were used in the analysis that are directly related to the health of a bridge. The SN was used as a reference label in the analysis with no effect to the bridge health.

Bridges can be designed using many different types of materials, primarily including concrete and steel. These materials have substantially different mechanical properties and may behave differently in varying environmental conditions. In order to take these inherent differences into account, the column, labelled STRUCTURE_KIND_43A, was retained in order to split the data. Once this split occurred, this characteristic was no longer necessary to keep, and was subsequently discarded in the final workbooks. The SER is representative of the lowest rating of components between the deck, superstructure, and substructure. Each characteristic listed influences the corresponding component and its individual rating, therefore affecting the SER as well. Due to this relationship, the SER was retained for analysis as well. Definitions for the eight selected characteristics are listed below based on the NBI Coding Guide.

2.2: Selected Variable Information

Age is a variable computed by taking the difference between the applicable year and Item 27 – Year Built. Item 27 uses a four-digit code representing the year the structure was completed or the best estimate. Similarly, Age Reconstructed is a variable computed using the difference between the applicable year and Item 106 – Year Reconstructed. Item 106 is also coded as a four-digit value representing the year. If the structure has not been reconstructed, it is coded as 0000. Reconstruction is defined as work that is eligible for Federal-aid funding and meets other standard minimum requirements. Bridge members are considered reconstructed when the work that is done substantially alters the geometry or load bearing capacity of the bridge. Work done to temporarily keep a bridge operational until new designs can be implemented is also not considered a reconstruction. For example, resurfacing a bridge deck is considered a repair, while a bridge deck replacement that alters the lanes or adds sidewalks would be considered a reconstruction. A bridge's original age and age since reconstruction may show general deterioration of the materials used for construction and their physical properties. These characteristics may also show how long a bridge has been experiencing various loads, which can induce deterioration and damage.

Average Daily Traffic (ADT) is the most recent traffic volume of the inventory route or the closest estimate. This is coded as a six-digit number representing the volume up to one million vehicles. The ADT is an indicator of the amount of daily vehicular traffic the bridge experiences. Any increase in this amount affects bridge components, potentially expediting deterioration and decreasing overall life span.

Main Unit Spans is the number of spans within the main or major unit. This typically includes all spans of most bridges, a major unit of a sizeable structure, and or a unit that utilizes a different material or design than the approach spans. This is coded as a three-digit number. When multiple main unit spans are present, different beam patterns, lengths, or other design considerations may be used for each one. These differences may change the inspection method or damage experienced by the components.

Maximum Span Length is the length of the longest span in metric units taken along the centerline of the bridge. This measurement may be taken as the center-to-center of the bearing points or the clear distance between piers, bents, or abutments, and is coded using a five-digit number. Longer main unit spans may experience an increased deflection under load compared to shorter spans under similar load. These deflections should be monitored along with the superstructure, especially those containing fracture-critical members.

Structure Length is the length of the roadway in metric units measured from paving notch to paving notch from back-to-back of the backwalls. It is coded using six digits and is measured to the nearest tenth. The overall length of the structure does not consider the individual span lengths as differing parts. This is useful when considering how loads move throughout the entire structure from start to end, including support points.

Deck Width is the out-to-out deck width, measured as either the lateral clearance between superstructure members or the actual out-to-out width in metric units. This is coded as a four-digit number recorded to the nearest tenth and is dependent on whether the traffic runs directly on the wearing surface or top of slab. The deck width is determined by the needs of the area the bridge serves. Wider bridge decks allow for vehicular and pedestrian loads to be spread across the structure, rather than a thinner bridge with more concentrated traffic volumes.

Percent ADT Truck is a two-digit code representing the percentage of truck traffic based on Item 29 – Average Daily Traffic. This does not include vans, pickup trucks, or light trucks, and may be estimated based on road category. Trucks create larger, more concentrated loads than a typical vehicle. Accurate estimates of the percentage of trucks using the bridge in reference to the ADT allow engineers to design for the larger load capacity to help reduce stresses the bridge would experience over its service life.

With the removal of all other columns, the Steel Bridge Data and Concrete Bridge Data workbooks are prepared for analysis. Figure 2.2 below shows a sample of the final workbook.

	A	B	C	D	E	F	G	H	I	J
1	STRUCTURE_NUMBER_008	AGE	ADT_029	MAIN_UNIT_SPANS_045	MAX_SPAN_LEN_MT_048	STRUCTURE_LEN_MT_049	DECK_WIDTH_MT_052	STRUCTURAL_EVAL_067	AGE RECONSTRUCTED	PERCENT_ADT_TRUCK_109
2	0100021	39	4627	3	21.9	58.3	12.8	6	0	13
3	0100048	39	4627	3	21.9	59.1	12.8	6	0	13
4	0100137	44	3881	3	28.7	73.8	12.2	6	0	19
5	0100145	44	3881	3	28.7	73.9	12.2	7	0	19
6	0100226	44	3881	3	38.4	97.7	12.3	7	0	19
7	0100234	44	3881	3	38.4	97.5	12.2	7	0	19
8	0100331	50	2888	3	16.5	44.2	12.8	7	0	20
9	0100366	50	2888	3	16.5	44.4	12.8	6	0	20
10	0100420	50	2888	3	22.9	61.4	12.2	8	0	20
11	0100455	50	2888	3	22.9	61.6	12.2	8	0	20
12	0101397	23	3612	3	40	105.1	14.1	7	0	8
13	0101842	24	3294	3	24.4	55.9	14.3	7	0	10
14	0101869	92	1108	3	30.8	77.8	12.2	5	39	13
15	0102172	23	990	3	42.6	110.8	14.1	6	0	12
16	0102466	52	1489	3	13.1	36.3	11	6	0	11
17	0102520	49	1489	3	24.4	64.8	12.2	6	0	11
18	0102563	38	1489	1	13.1	13.7	8.5	7	0	11
19	0102776	20	1217	3	21	52	10.9	7	0	29
20	0102806	20	1939	3	15	40.8	10.8	7	0	29
21	0103004	63	1229	3	13.7	38.4	12.2	6	0	8

Fig. 2.2. Final Steel bridge data sample.

2.3: Complete Data and Materials

Some bridges did not contain a complete set of information on their characteristics, as shown in Fig. 2.3. In some cases, the characteristic was not applicable to an individual bridge, and was coded with an “N”. Any row containing an “N” was discarded in order to avoid the program trying to process information that did not apply. In other cases, there was no information recorded at all. This was especially prevalent in earlier inspection years. The lack of information may have been due to the bridge not exhibiting those characteristics. It also may have been due to a lack of accessibility to the bridge element or inspector error. Any rows containing blank cells were also discarded for the ease of data processing. This process was repeated for all 31 years. The remaining data only included those bridges containing complete sets of information.

STRUCTUR	DECK_GEC	UNDCLREI	POSTING_	WATERWA	APPR_ROA	WORK_PR	WORK_DC	IMP_LEN_	DATE_OF_	INSPECT_I	FRACTURE
8	7	N	5	N	8				504	12	N
8	7	N	5	N	8				504	12	N
7	7	N	5	8	8				604	12	N
8	7	N	5	8	8				604	12	N
7	7	N	5	8	8				604	12	N
7	7	N	5	8	8				604	12	N
8	7	9	5	N	8				304	12	N
8	7	9	5	N	8				304	12	N
7	7	N	5	8	8				604	12	N

Fig. 2.3. Incomplete NBI bridge data sample.

With only complete sets of data remaining, four copies of the consolidated workbook were created in order to make comparisons between different bridge materials. The column "STRUCTURE_KIND_43A" of the data indicates the bridge material by code. Table 2.1 below shows the bridge material with its corresponding code number from this column (FHWA, 1995).

Table 2.1. Main structure material and/or design based on NBI Coding Guide

Code	Name
1	Concrete
2	Concrete Continuous
3	Steel
4	Steel Continuous
5	Prestressed or Post-tensioned concrete
6	Prestressed or Post-tensioned concrete continuous
7	Wood or Timber
8	Masonry
9	Aluminum, Wrought Iron, or Cast Iron
0	Other

The first workbook (Concrete Bridge Data) contained bridges utilizing concrete as the building material. These include concrete, concrete continuous, prestressed and post-tensioned concrete, and prestressed and post-tensioned concrete continuous spans. The second workbook (Steel Bridge Data) contained bridges with steel as the building material; these include steel and steel continuous spans. The third workbook (Steel and Concrete Bridge Data) contained both the steel and concrete spans together. The fourth workbook (Other Materials) contained bridges utilizing any other structural material including wood or timber, aluminum, wrought iron, cast iron, or other spans. Steel and concrete bridges make up the majority of the remaining bridges, especially those located on the highway network. The fourth workbook included multiple types of building materials and contained a relatively small amount of each and was therefore not considered for analysis.

These workbooks are used for the Pearson correlation analysis due to the ease of their year-to-year capabilities within the program. In order to run the decision tree and random forest models, copies of the workbooks were created and adjusted. In these copies, the data from each year was consolidated onto one sheet instead of 31. This was repeated to have one sheet of data for all 31 years, the last five years, and 2022 only, and was done for both concrete and steel bridge data. In total, six workbooks were created and used within the program. Table 2.2 provides the names and descriptions of each workbook. Table 2.3 below indicates the final number of bridges considered for analysis within each data set per year.

Table 2.2. Microsoft Excel workbook summary

Excel Workbook Name	Bridge Data Included
Concrete Bridge Data 2022	Concrete bridges in 2022 only
Concrete Bridge Data 2018 - 2022	Concrete bridges from the last five years
Concrete Bridge Data 1992 - 2022	Concrete bridges for all years beginning in 1992
Steel Data Bridge 2022	Steel bridges in 2022 only
Steel Data Bridge 2018 - 2022	Steel bridges from the last five years
Steel Bridge Data 1992 - 2022	Steel bridges for all years beginning in 1992

Table 2.3 Final number of Ohio bridges considered every year

Year	Concrete bridges	Steel bridges
1992	7,829	10,746
1993	7,834	10,684
1994	8,135	10,590
1995	8,464	10,515
1996	8,567	10,404
1997	10,520	14,261
1998	10,750	14,099
1999	10,900	13,954
2000	11,271	13,810
2001	11,452	13,694
2002	11,682	13,381
2003	11,752	13,318
2004	11,873	13,194
2005	12,160	12,984
2006	12,287	12,816
2007	12,553	12,666
2008	12,770	12,553
2009	13,006	12,393
2010	13,087	12,241
2011	12,895	11,892
2012	12,857	11,707
2013	13,045	11,519
2014	13,170	11,398
2015	13,303	11,293
2016	14,118	11,432
2017	13,635	11,086
2018	13,711	10,977
2019	13,731	10,883
2020	13,719	10,798
2021	13,575	10,455
2022	13,621	10,383
Total	368,272	372,126

Chapter 3: Data Analysis and Modeling

In this analysis, the goal is to accurately determine the SER as the output based on its relationship with the selected characteristics as the input. If the primary characteristics for deterioration can be determined, bridges exhibiting them may benefit from an increased inspection frequency. Supervised learning models achieve this by predicting an output based on the input. The system learns through training with a subset of labeled data. Using this training subset, the model recognizes patterns within the features that are used in producing an acceptable output. These models are useful in regression or classification analysis. Unsupervised machine learning models use unlabeled input data to identify patterns and structures contained within it. These models learn through clustering, association, or dimensionality reduction techniques, such as Principal Component Analysis (PCA). Based on the pattern recognition abilities of supervised and unsupervised models, both types of machine learning models were considered in this research.

3.1: K-Means Clustering

K-Means clustering is an unsupervised machine learning model, which aims to create optimized "clusters" of similar data. Each iteration adjusts the clusters to minimize the distances between the center of a cluster and each data point. The produced groupings may show previously unknown patterns within the data or confirm previous assumptions. K-Means clustering was attempted due to its ability to process large sets of data. It is considered one of the most popular algorithms due to its simplicity and interpretability. The distances between each data point and the centroid of each cluster are visible when plotted, making the distinction between each cluster and a data point more pronounced than other methods. The similarities between data points that share a cluster may be investigated once the final iteration has been processed. The disadvantage to using K-Means clustering for this research was that it may underperform when processing categorical data. It is also more sensitive to outliers than other methods. Bridges and their characteristics may undergo sudden changes due to closures, accidents, and other unexpected events. This introduces more opportunities for outliers to occur within the data set. Based on these disadvantages, other methods were selected for analysis.

3.2: Principal Component Analysis

Principal Component Analysis (PCA) is an unsupervised statistical model used to show the maximum spread of a data set along the principal axis while retaining the maximum number of features. By standardizing the data into a covariance matrix and their eigenvectors and eigenvalues, the principal components may be identified. Using the primary principal components, the original data may be plotted against the new principal component axes. This provides a greater understanding and visualization of the most important data set without losing its principal characteristics.

Principal component analysis is useful with data containing a large number of features. The dimensionality reduction that occurs decreases the model's complexity and helps to avoid overfitting. For this research, the features were manually reduced based on their physical relation to the bridge health. Similar to K-Means clustering, PCA is not suited for use with categorical data due to the linear relationship assumptions. Using PCA may be difficult to interpret when trying to identify the most important features compared to other methods. For these reasons, PCA was not finally chosen for this analysis.

3.3: Pearson's Correlation

A Pearsons's correlation is a linear measure of the strength of relationship between two variables. The two variables, x and y, are plotted against each other, and a best-fit line can be created based on the data points. The correlation coefficient, r, is a descriptor of the distance between these data points and the best-fit line. The value of these coefficients may range from -1 to 1. A negative value indicates a negative linear relationship, or a decrease in y as x increases. A positive value indicates a positive linear relationship, or an increase in y as x also increases. Coefficient values of 0 indicates no clear linear relationship between the data sets. Table 3.2 below describes the range of correlation coefficient, r, and its respective association.

Table 3.1. Pearson correlation relationship associations

Correlation Coefficient (r)	Association
±1.0	Perfect Positive or Negative Association
± 0.8 to 1.0	Strong Positive or Negative Association
± 0.4 to 0.8	Moderate Positive or Negative Association
± 0 to 0.4	Weak Positive or Negative Association
0	No Correlation

In order to determine the Pearson's correlation coefficients, the Jupyter's Notebook file utilizes Pandas, which is a Python code package that performs data manipulation and analysis. The Excel workbooks containing the bridge data are imported into a Pandas data frame. This data frame allows for any row or column to be referenced for calculation. The individual bridge characteristics may also be referenced into a smaller dataset as needed. If it is not specified within the code, the Pearson correlation method is defaulted.

Pearson's correlation uses covariances and standard deviations to determine the relationship coefficient of two selected variables. Covariance, ($Cov_{x,y}$), is a measure of variability between two random variables. The mean, or expected value, for variable x is calculated and multiplied with the expected value for variable y. These calculations are repeated and summed, and the summation is divided by one less than the number of data points. This process determines the expected value of the set. The covariance is calculated using Eq. 3.1 below.

$$Cov_{x,y} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{N-1} \tag{3.1}$$

The standard deviation ($\sigma_{x,y}$) measures the dispersion of a dataset compared to the mean, calculated as the square root of the variance. This calculation is shown using Eq. 3.2.

$$\sigma_{x,y} = \sqrt{\frac{\sum(x_i - \mu)^2}{N}} \tag{3.2}$$

With this information, the Pearson's correlation coefficient (r) can be determined using a ratio of the covariance and the product of the standard deviations. This is shown in Eq. 3.3.

$$r = \frac{Cov_{x,y}}{\sigma_x \sigma_y} \tag{3.3}$$

Once the code is run, the Pearson's Correlation coefficients are calculated for each selected characteristic. Although these coefficients are produced in a tabular format, a heatmap was also generated to provide an easily interpretable graphic. Coefficients and heatmaps were produced for each year from 1992 to 2022 for both Steel and Concrete bridges.

3.4: Decision Tree Modeling

A decision tree is a supervised non-parametric learning algorithm that categorizes and makes predictions about data using training subsets of that data. They provide an easily interpretable, visual approach to data analysis by providing a tree-structured flowchart using rule branches. By applying the rules to each node, every possible outcome is considered while maintaining the properties of the data.

To run this analysis, three Python libraries were utilized within the Jupyter Notebook file to produce the decision tree: pandas, sklearn, and graphviz. The entire dataset is imported into a Pandas data frame. The SER value is the target variable to be predicted using classes defined by the eight selected features defined earlier. A random state is applied to maintain the way the data is split through multiple executions. The dataset is then split into training and test sets, with 80% of the data being used to train the model and the remaining 20% of the data to test and validate the model.

The decision tree classifier algorithm can then be fit into the training data. A random state is applied to the algorithm to control the random behavior of the estimator during the split. This prevents the structure of the decision tree from varying when the model is used and allows the same output to be produced during any number of runs. Once the model is prepared with the training data, it can be fit to the test data. As it runs, the model is adapting and generalizing the test set to predict the SER. Once the model completes its predictions, the accuracy can be determined.

The explained variance (r^2), or "decision R-squared" of the data is also automatically computed by the program. Explained variance is a proportion of the variance in the dependent variable explained by the independent variables. To determine the explained variance, the total sum of squares (TSS) is calculated, representing the total variance in the dependent variable. The residual sum of squares (RSS) is also calculated, representing the unexplained variance in the dependent variable after fitting. The explained variance can then be found using Eq. 3.4.

$$r^2 = 1 - \frac{RSS}{TSS}. \tag{3.4}$$

This explained variance from 0 to 1, with higher values indicating a better fit of the model.

The sum of squared error (SSE) is a measure of the variation within a cluster of data. It is taken as the total sum of the squared differences between actual (y) and predicted ($\hat{y}$) values, with the goal having the minimum value. If there is no variation and each observation is identical, the square error is zero. The following formula in Eq. 3.5 is used to calculate SSE.

$$SSE = \sum(y - \hat{y})^2 \tag{3.5}$$

Using the Pandas data frame, the Decision Tree model is created branch by branch. As the model processes the data, different branches are created with varying rules that must apply to the information passing through it. This data moves through the applicable Decision Tree branches until it has reached a leaf, which is the final classification the data can have. The SER based on the class relationships is predicted and compared to the actual independent variable value. A coefficient of determination is also produced for each leaf. The coefficient of determination measures the accuracy of the predictions in each leaf.

The Decision Tree is created and extracted from the program as a graphviz DOT file. A DOT file is a text file describing the attributes of an image. This analysis produces a large flowchart that displays all the information described above. Using the generated DOT file, the Decision Tree may be rendered as any graphic file necessary. For this analysis, a .png file was selected for displaying the Decision Tree.

3.5: Random Forest Modeling

Random forest modeling is a supervised learning algorithm made up of a network of decision trees. The basis of the model assumes that having multiple, uncorrelated decision trees can improve the probability of outputting an accurate prediction compared to using a single decision tree. Each decision tree in the random forest is trained using a subset of the data. These trees are produced using a bagging process, which randomized the data sets each tree uses. Multiple, randomized decision trees reduce the overfitting of the data set overall.

The Random Forest models use the same Python libraries and datasets as do the Decision Tree models. The SER is used as the target variable while the features are separated from it. Similar to the decision tree step above, these splits in the data are used to produce the same output over any number of runs while generalizing the data. The random forest classifier is initialized to include 100 decision trees as a default. Once fit, predictions can be made from the test set and an accuracy score is produced. A random forest regressor is then initialized to include 100 trees, which are fit into the data. The values of the test set are predicted, and an R-squared score is generated. The large set of decision trees are then combined to produce a single decision tree with a generalized output. This decision tree is then extracted as a graphviz DOT file and rendered into the appropriate format. This analysis used a .png file for the graphical representation.

3.6: Method Selection

Three of the methods of analysis were selected to identify and show the relationships between the SER and the selected characteristics: Pearson's Correlation, Decision Tree Modeling, and Random Forest Modeling. Although Decision Tree Modeling and Random Forest Modeling operate under similar conditions, their methods of processing training information differ. Utilizing both methods allows for comparison of the advantages and disadvantage between their application in predicting bridge health. Other statistical methods including K-Means clustering and PCA were also identified as potential options but were not utilized. These two methods do not provide benefits when categorical data is used compared to the selected methods. The disadvantage in using categorical data in analyses is the difficulty in finding distances between each category. While the selected characteristics for this analysis are discrete or continuous, other characteristics that may be considered in the future and are recorded during inspections may be categorical or ordinal. In order to allow other characteristics to be potentially analyzed, methods that could better accommodate them were utilized instead. Table 3.2 summarizes each method.

Table 3.2. Summary of supervised and unsupervised learning methods

Learning Method	Method Type	Summary
K-Means Clustering	Unsupervised	Clusters data based on similar features
Principal Component Analysis	Unsupervised	Transforms data into lower dimensional forms
Pearson’s Correlation	Statistic	Measures linear correlation between two sets of data
Decision Tree Modeling	Supervised	Categorizes data based on training information to make predictions
Random Forest Modeling	Supervised	Categorizes data based on multiple randomized training information to make predictions

Chapter 4: Results and Discussions

Both steel and reinforced concrete bridges undergo deterioration from fatigue, freeze-thaw cycles, corrosion, vehicular loads, and other environmental distresses. However, the average SER has been increasing in both bridge types over time. This can be attributed to more efficient and precise design methods, better inspection tools and techniques, and preventative maintenance. The SER may also be dependent on the inspectors, with 95% of condition ratings varying by two points and 68% varying within one point for each element (Phares et al., 2004). Utilizing machine learning becomes valuable for predicting the SER by removing inspector bias and only considering the raw data.

4.1: Pearson's Correlation Results

Pearson's Correlation coefficients for each characteristic were produced for every year. Figure 4.1 shows the correlation matrix for Concrete Bridge Data 2022. This heatmap assigns colors to each square based on the correlation each characteristic produced with one another. When compared with itself, a characteristic's correlation coefficient will be equal to 1, indicating a perfect relationship, which is expected. A correlation coefficient of 0 (zero) would indicate no relationship between the two parameters. The use of color and a text value provides a visual context of the correlation. Although the matrix shows potential relationships between characteristics, this research only considers correlations with the SER. The matrices are useful for seeing the correlations in individual years, as well as providing a more interpretable approach than only a table may offer. Matrices were produced using Concrete Bridge Data 1992 – 2022 and Steel Bridge Data 1992 - 2022 for each of their 31 years.

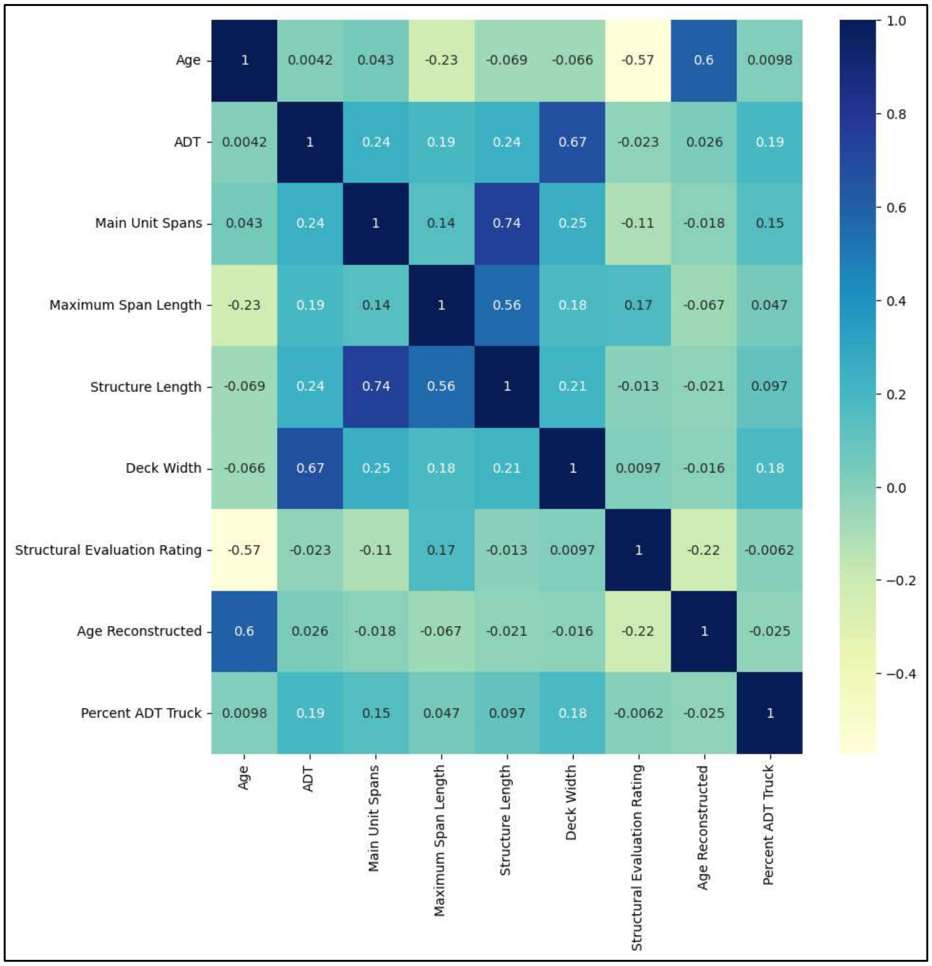

Fig. 4.1. Pearson's correlation matrix for Concrete Bridge Data 2022.

The Pearson's Correlation coefficients were produced for all 31 years of data. In order to find a typical value across the entire time span, the average coefficient for each characteristic was calculated. By only considering averages for the full timeframe, it is possible that many factors' importance may have been diluted. These averages may also be taken to consider smaller amounts of time, including individual years, to isolate changes and prevent this dilution in certain characteristics. For example, showing the coefficient from last year or an average coefficient of the last five years may differ from the last 31 years due to new technology or designs being incorporated. However, the consideration of all timeframes may be beneficial as each one provide a different view to consider and make decisions with. This process also allows for an easier comparison of the coefficients between concrete and steel bridges. Table 4.1 shows each characteristic's average Pearson's Correlation coefficient. Figure 4.2 compares these average coefficients based on material composition. This separation allows for characteristics that show a significant difference in relationship between material to be identified and potentially cross-examined. Figure 4.2 also highlights the overall performance of the characteristic as well. The visual interpretation of this figure may be considered a more intuitive approach to analysis than comparing numeric values within a boundary. In six out of eight characteristics, the sign of the coefficient remained the same for both materials. For the remaining two characteristics, ADT and Main Unit Spans, the coefficients for concrete bridges were both negative, while they were positive for the steel bridges. In unexpected cases such as the positive correlation between ADT and the SER for steel bridges, many unidentified factors may play a role in the values produced. For example, correlations closer to one or negative one would have more difficulty changing sign, as there is a larger numerical distance to cover to do so when compared to correlations that are nearly zero.

It is also possible that by taking the average across all 31 years would have produced an average coefficient that is not necessarily representative if the sign had been consistently changing. Both of these characteristics exhibited a weak relationship, which may make them more prone to changing positively or negatively. However, the coefficient signs remained the same every year for both characteristics. This suggests that using the comprehensive average does not necessarily change the unexpected results for these characteristics compared to other time considerations.

Table 4.1. Characteristic average 31-year correlation coefficient by material

	Average Correlation	
Characteristic	**Concrete bridges**	**Steel bridges**
Age	-0.5806	-0.4594
ADT	-0.0433	0.1585
Main Unit Spans	-0.0772	0.1336
Maximum Span Length	0.2110	0.1384
Structure Length	0.0202	0.1189
Deck Width	0.0123	0.2847
Age Reconstructed	-0.1871	-0.2163
Percent ADT Truck	0.0096	0.1816

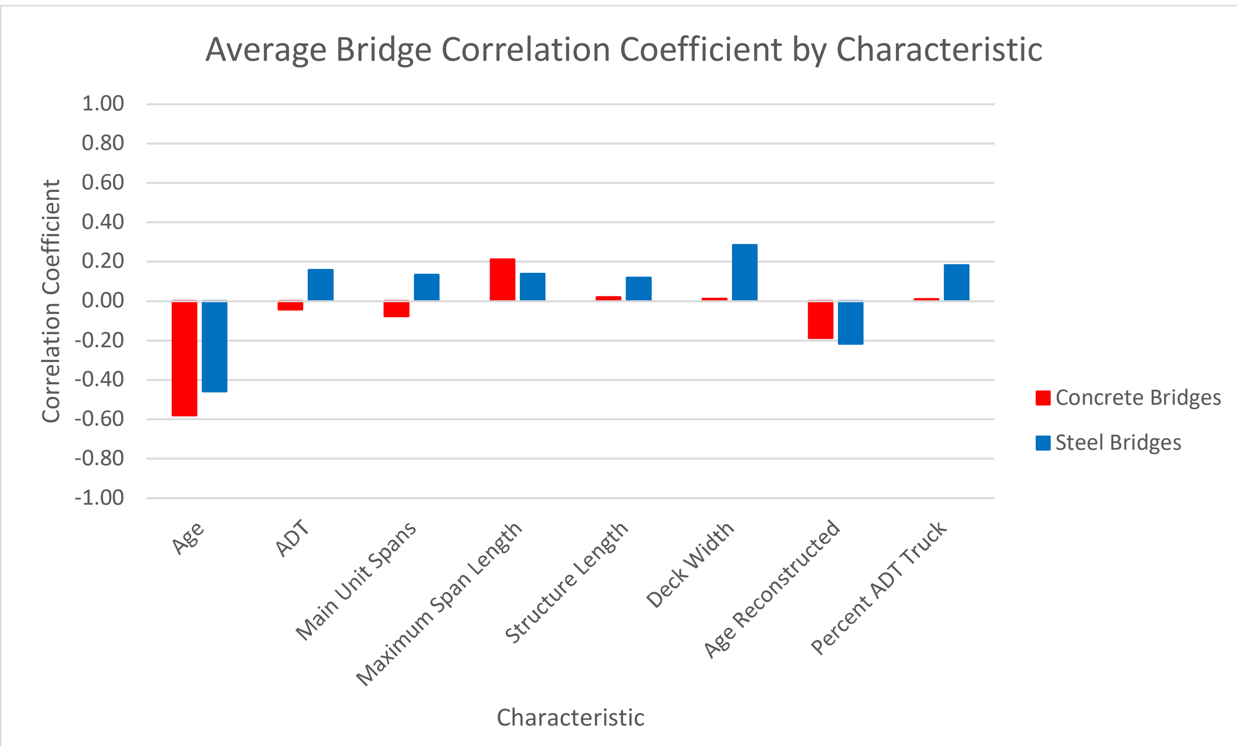

Fig. 4.2. Average of 31-year correlation coefficients based on the material of construction.

Figures 4.3 and 4.4 show the fluctuations of correlation coefficients each year. From these graphs, it can be easily visualized which characteristics had positive or negative correlations, as well as which ones had correlations of nearly zero, or no relationship. Overall, these figures presented herein allow for a visual approach to be used to make distinctions between different materials and characteristics. Trends, or lack thereof, may be more noticeable in graphical form when compared to the tables. These graphics may also show insights into changes that were made to specifications, environmental events, or other changes in data recording and their effect on the correlation. For example, if a new tool or technology is employed in a selected year, the following years may show a positive or negative trend. This would help to isolate such occurrences and allow engineers to make other potential modifications based on them. Different years or spans of time may also be used to only analyze a boundary where certain bridges or characteristics appear.

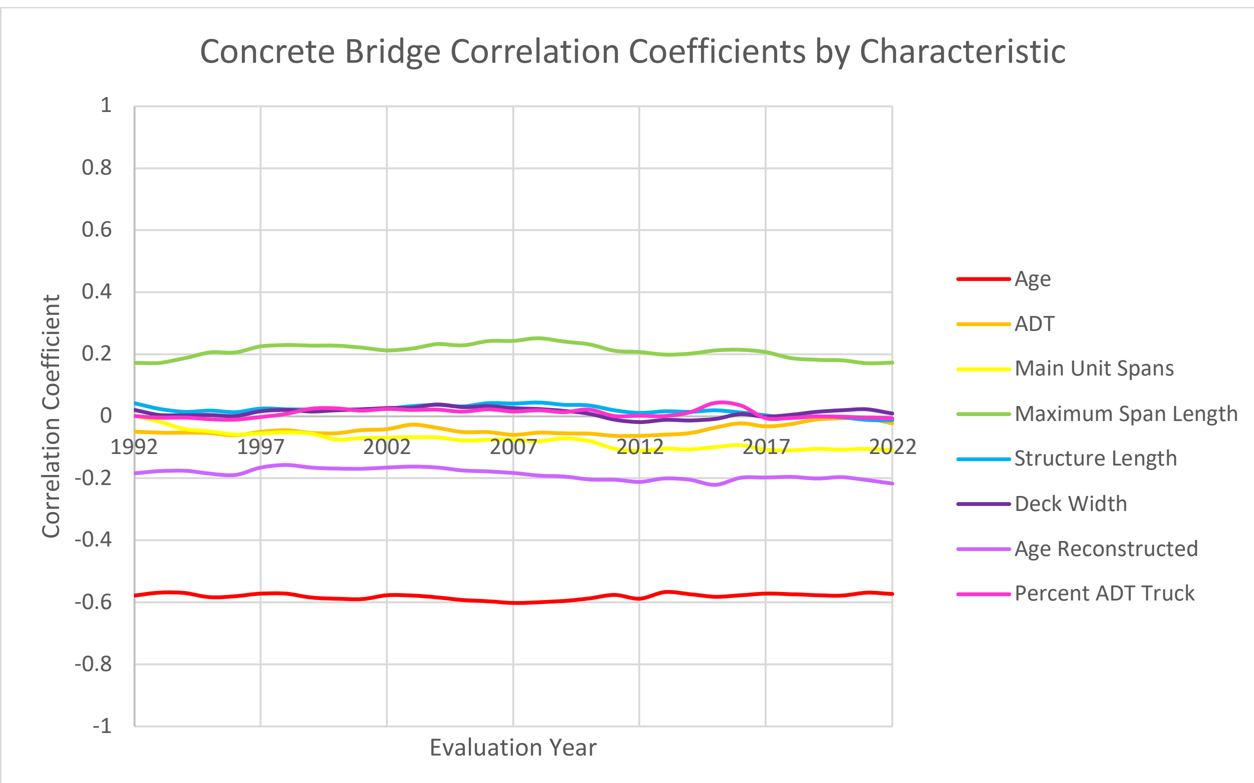

Fig. 4.3. Pearson's correlation coefficients over time for Concrete bridges.

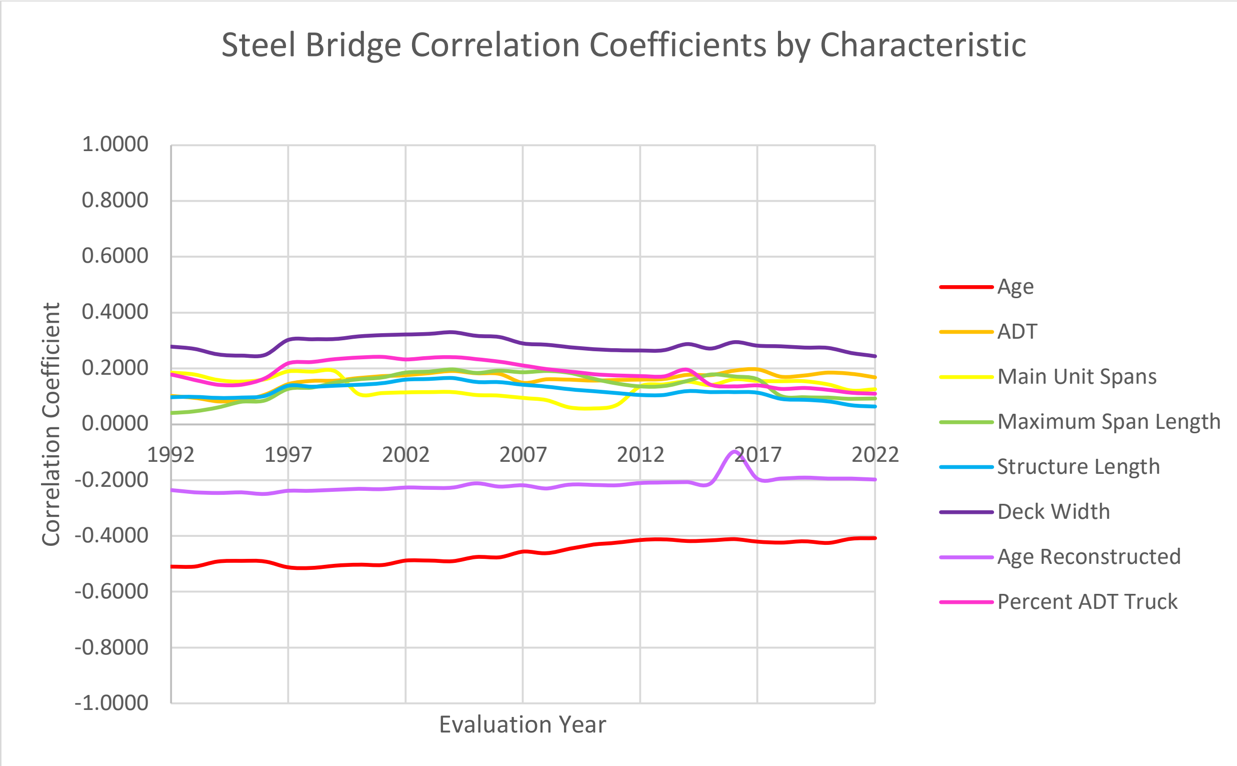

Fig. 4.4. Pearson's correlation coefficients over time for Steel bridges.

The age and age reconstructed consistently produced negative correlations in both material cases over 31 years. The correlation between age and the SER was the strongest relationship evaluated, although it is only considered moderate. The age of bridge reconstruction is considered a weak relationship, while it is the third strongest relationship over the entire timeline. As bridges age, they are continually exposed to weather, chemicals, impacts, and repeated loading, decreasing the SER. This degradation is shown in the coefficients through their negative values. When caught early by inspection, degraded components may be replaced individually, or the entire bridge may be reconstructed. LeBeau and Wadia-Fascetti (2010) suggested that earlier inspections at a lower age of a bridge may be significant in detecting deterioration/corrosion in strands/rebars in order to prevent or reduce further deterioration. Investigations into deterioration rates of bridge elements by Agrawal et al. (2010) did not consider incidences that would cause drastic changes in the SER, such as rehabilitation or miscodings. Information based on rehabilitations or accidents is typically reflected in the inspection report generated after the applicable event, and may be shown in this analysis through an atypical change in the elemental relationship. Full reconstructions upgrade nearly every component of the bridge and can alter any characteristic, effectively resetting its age to the year of restoration.

All relationships aside from age were considered to be weak or have no correlation. Although they are weak, the characteristics may still be ranked in comparison to one another. The Pearson's correlation coefficients for both steel and concrete bridges ranked the ADT as the 5th strongest relationship to the SER. However, the concrete bridge data produced a negative correlation, while the steel bridge data produced a positive one. The ADT represents repeated vehicle loading that bridges experience. Tabatabai et al. (2011) have shown that the failure rates of bridge decks increase when ADT increases for bridges of the same age. It was suggested that increases in ADT deteriorate the decks through more frequent load cycles and an increased use of deicing agents. It was also found that failure rates increase when the age increases at a steady ADT. In steel bridges, vehicular traffic causes cyclic damage over time, also known as fatigue. Saberi et al. (2016) suggested that the changes in cyclical loading from the heavy-truck traffic volume decreases the remaining service life. While it would be expected that a higher ADT would negatively correlate with the SER, both cases showed weak to no correlation.

The number of main unit spans a bridge contains were the fourth strongest relationship for concrete bridges and the seventh strongest for steel bridges. The maximum span length was the second strongest factor for concrete bridges, and sixth strongest for steel bridges. While longer spans may experience similar load distributions as short spans on the same bridge, the total load including self-weight and vehicular loading including impact increases in longer spans. These added loads increase the deflection at midspan and creates higher stresses within the section. The structure length was the sixth strongest factor for concrete bridges and eighth strongest factor for steel bridges. The structure length only considers the length between paving notches and not the number of supports or individual span lengths. This length may not reflect the moments, forces, or stresses experienced within each span. Bridges with longer structure lengths may be designed with more components to bear the necessary loads, such as larger decks, an increased number of piers and/or girders, and superstructure anchorage. Longer spans may introduce more points of failure or deterioration compared to short span bridges. It would be expected that both material types produce a negative correlation. Similar to the ADT analysis, both materials show weak or no correlation with the SER, which may be dependent on other factors such as years considered. This characteristic alone also does not consider these potential differences, which may be length dependent. Other characteristics in conjunction with structure length may apply these considerations in a way that shows relational improvement.

The deck width was the seventh strongest for steel bridges and second strongest for concrete bridges. Although it is ranked second strongest for concrete bridges, both cases only show a weak positive correlation. Bridge decks experience the most exposure through loading, weather, and other agents, such as deicers. Deck width typically depends on the type of traffic the bridge is intended to receive when designed, rehabilitated, or reconstructed. On major highways or arterials, more vehicular lanes may be necessary to relieve traffic congestions. In large cities, bike lanes and pedestrian lanes or sidewalks are added to accommodate non-vehicular travel to increase pedestrian safety. Shoulders and barriers are also used to assist drivers who may need to exit the moving lanes in a safe manner in case of emergency. These design considerations are highly dependent on the needs of the area the bridge will serve and the requests of the owner. Although larger decks may potentially introduce more points of deterioration or failure, the factors listed above may change load distributions in a way that is beneficial when considering the SER. Bridges with wider decks that have larger shoulders or pedestrians lanes will have less live loads applied than other bridges that are equal in deck width but carry vehicular lanes only, with little change in the dead load. This suggests that the positive relationship for deck width may be influenced by the loads it is designed for.

Beyond the age and age reconstructed, the characteristic relationships between concrete and steel bridges vary in their relationship ranking. Many of the selected characteristics exhibit assumed correlations that are different or unexpected from those that were produced. The differences in coefficient values are small, making them more sensitive to fluctuations in ranking. It is possible that other considerations, such as length of time, may have a more realistic impact on the correlation. Although concrete and steel bridges may experience different forms or modes of deterioration, the material differences show little connection based on geometry.

Overall, the Pearson's correlations provide a valuable look into the relationship between the selected characteristics and the SER. Although many of these characteristics showed weak or no correlation, this information is still helpful in visualizing how the characteristics have changed in their relationships over time. Isolating each characteristic allows for more in-depth analyses into potential ways to positively influence the SER. As other characteristics are investigated, previously unknown connections may be uncovered. This isolation also allows inspectors to select bridges exhibiting strongly correlated characteristics into their inspection considerations.

This research has affirmed that age is a prominent factor for the SER and overall bridge health, highlighting the need to care for the aging infrastructure system. Preventative maintenance on older bridges can help to extend their design life and continue to provide a safe form of travel. This analysis also highlights the benefits of extensive documentation. Proper inspection data recording provides a way for engineers to look into the past to plan for the future.

4.2: Decision Tree and Random Forest Model Results

Using decision tree and random forest modeling, the program was able to associate the selected characteristics to the correct SER reliably for both bridge types. Two time spans were processed: all recorded years from 1992 to 2022 and the last five recorded years from 2018 to 2022. The corresponding accuracy scores are shown in Table 4.2.

Table 4.2. Decision Tree and Random Forest Model accuracy percentage by material

		Concrete bridges	Steel bridges
1992 - 2022	Decision Tree	82.1%	82.9%
	Random Forest	87.9%	86.2%
2018 - 2022	Decision Tree	79.2%	81.7%
	Random Forest	88.0%	88.5%

The performance of both models was comparable between the Concrete Bridge Data and Steel Bridge Data, with the maximum difference of 2.5% occurring in the five-year Decision Tree model. This indicates that both model types are effective in their SER prediction abilities regardless of the material. The total amount of bridges that fall into these two categories differs by approximately 4,000.

The time frames considered also produced comparable accuracies. The largest difference in model performance between Concrete Bridge Data 1992-2022 and Concrete Bridge Data 2018-

2022 was 2.9%, which occurred in the decision tree model. In both Steel Bridge Data and Concrete Bridge Data cases, the accuracy was over 79% for both model types. The Decision Tree model for the 31-year data set slightly increased in accuracy while the Random Forest model accuracy slightly decreased when compared to Concrete Bridge Data 2018-2022 and Steel Bridge Data 2018-2022. Their explained variances are shown in Table 4.3.

Table 4.3. Decision Tree and Random Forest Model explained variance values by material

		Concrete bridges	Steel bridges
1992 - 2022	Decision Tree	0.786	0.809
	Random Forest	0.877	0.881
2018 - 2022	Decision Tree	0.705	0.740
	Random Forest	0.838	0.861

The explained variance may range from zero to one, with a value of one indicating a perfectly fit model. The 31-year data set produced the largest explained variances for both models, as well as both material types. The five-year data set shows a slight decrease, although all values are above 0.7. The 31-year data set processed more than 740,000 bridges. The same bridge may have been considered within a range of years. However, over time bridges may be opened or closed, changing the amount of data each year includes. The preprocessing done for this research may have also removed bridges that appear within a certain time range due to incomplete data. As bridges are rehabilitated and experience fluxes in characteristics, such as ADT, the recorded information and SER may change, making repeated bridges a valuable asset.

The Random Forest model outperformed the Decision Tree model in every case presented. Random Forests combine the output information from 100 decision trees to determine how they split. The randomized changes in each decision tree within the forest decrease the variance through averaging, rather than relying on the output of only a single tree. This averaging also helps to decrease noise that processing large data can produce.

Overall, the Random Forest model using Concrete Bridge Data 1992-2022 and Steel Bridge Data 1992-2022 each yielded the most significant results. As inspection data is collected in the future, the models may become more refined in their prediction abilities if combined with previous data. Both model types can be used for predictions using other features as well. Although they utilize continuous or discrete data, these models are able to convert the data into categorical information, if necessary.

The visuals shown in Figs. 4.5 and 4.6 are samples of the Concrete Bridge Data Decision Tree and Random Forest outputs. Three types of nodes are shown: root, internal and leaf. The root node is the starting node within the free, where the rest of the tree grows from. Internal nodes are those that continue to produce nodes from itself. Leaf nodes are endpoints of the tree with no nodes produced from it.

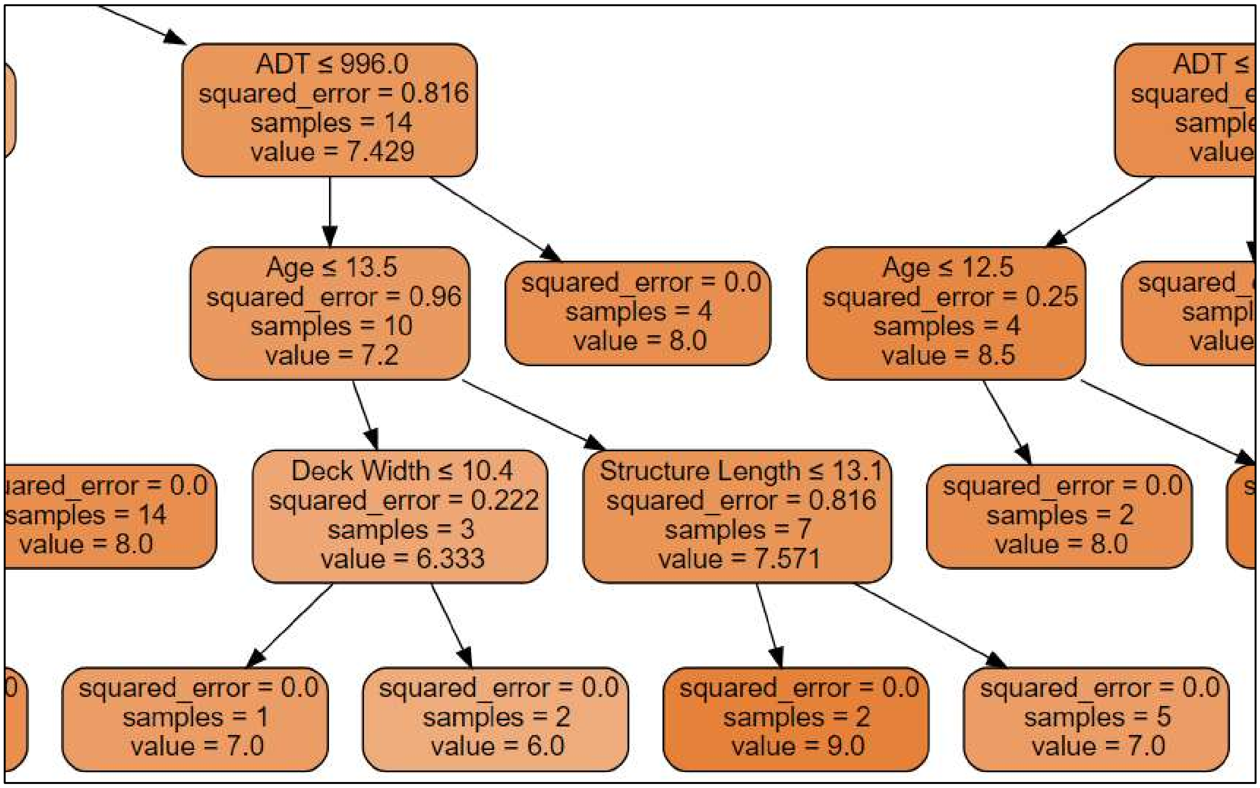

Fig. 4.5. A partial representation of the Decision Tree model for Concrete Bridge Data 1992-2022.

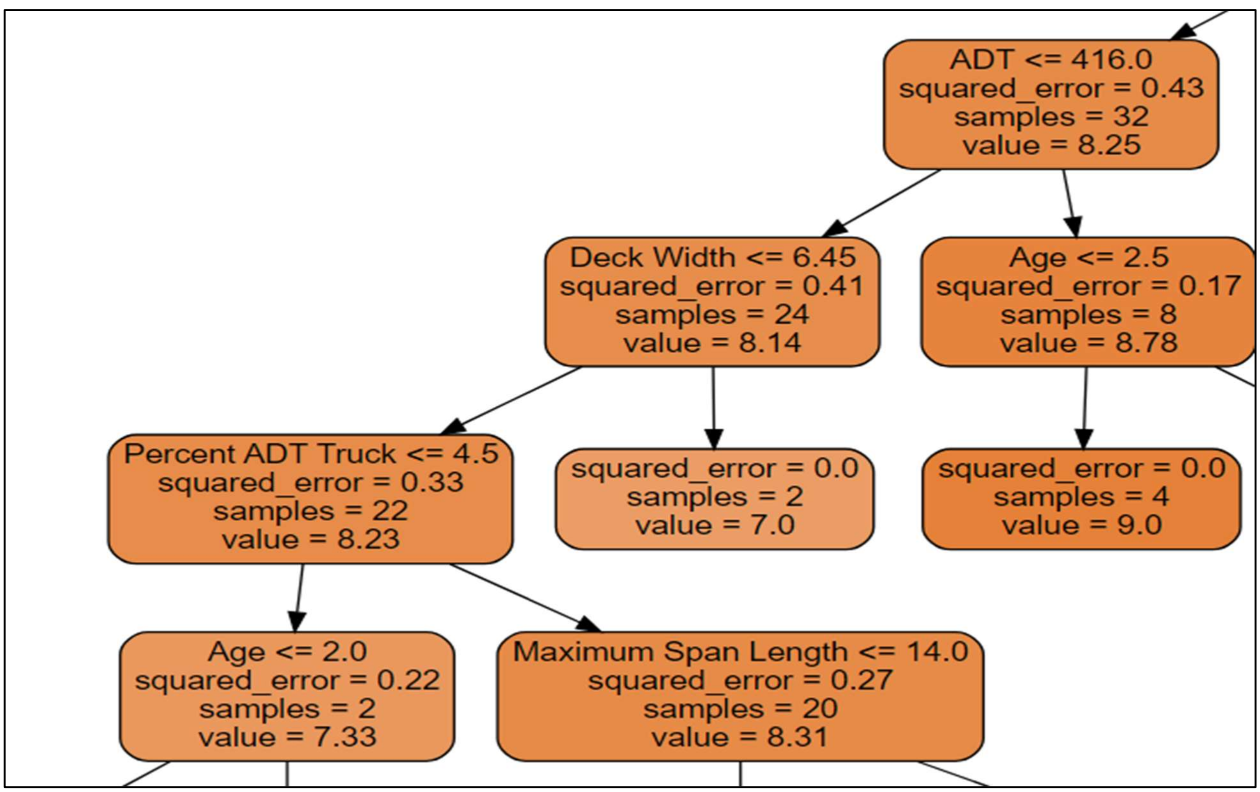

Fig. 4.6. A partial representation of the Random Forest model for Concrete Bridge Data 2018-2022.

It is possible to follow the characteristics through the tree based on their bounds. The characteristics used for this analysis primarily include quantitative data, which allows the splits to be greater than or less than a certain value. If the reader knows this information for a specific bridge, the leaf node containing the predicted SER can be traced. Each node contains up to four pieces of information. The characteristic that is being split and its bounds are labeled in the first row. The second row contains the squared error value of the node. Squared error values that are closer to zero indicate a good fit for the SER prediction based on the split. The third row shows the number of bridges that are sampled within a node. This number will decrease through each internal node in a branch, until the leaf node, where no other splits in the sample occur. The fourth row contains the average SER of the samples contained only within the specific node.

The decision tree and random forest visuals produced with the data processed are extremely large and are difficult to present in a single page for better visualization. Individual nodes also may not have an accurate split when the tree is maximized. In order to combat this, it is possible to regulate the size of a tree. One of the methods is called pruning. Pruning decreases the size of a tree by preventing or removing nodes that do not meet a given threshold, typically the number of samples it contains. The depth of a tree may also be manipulated. A tree's depth is the length of a tree from root node to leaf node. The maximum depth trees, such as the ones produced for this analysis, allow the algorithm to classify the data as much as possible. Allowing a tree to grow to its full depth may increase overfitting, but also increases the classification accuracy. Both of these methods must be balanced to maximize the variance while minimizing overfitting.

The goal of these models is to recognize the patterns that allow for the SER to be accurately predicted based on the selected characteristics. The branches of the produced trees show every combination of characteristics that lead into an SER. Both the Decision Tree and Random Forest models operate under the same premise. For example, in Fig. 4.5, the upper node splits conditionally based on the ADT. The following nodes split in the same manner, until only bridges with the exact same characteristic path remain with their average SER. While the Random Forest model performed better than the Decision Tree Model in every case, both are shown to be reliable methods of decision-making. If implemented into similar programs, the amount detail presented through these models would provide new criteria and reasoning for the change in inspection frequency.

Due to the size of the rendered Random Forest models, sample paths for steel and concrete bridge data have been organized in Tables 4.4 and 4.5. Each row of these tables includes all information in a single node from the produced models. The path selected for the Concrete Bridge Data 2022 model started with a decision between a bridge age greater than or less than 31.5 years. This node contained 6896 samples, with a squared error of 1.64 and an average SER of 6.94. Moving down the branch by to the left, or the "True" option, the next node was a decision between an age greater than or less than 12.5 years. Here, 3270 samples were included with a squared error of 1.04 and an average SER of 7.64. The branch continues through the series of choices shown in Table 4.4, until the leaf node is reached. The leaf node in this case only contained five bridges, which all exhibit the same ten characteristics. These five bridges produced a squared error of 0.0 and an average SER of 8.

In the shown path, the squared error trends downward as new conditions are added. This suggests that the predictability of the SER increases as information becomes known and available. The sample size will always decrease when moving through a branch, as the number of bridges is being split into two paths. At least one bridge will be shown in every leaf node produced, although many contain more than that, as shown here. The average SER in the leaf node for this subset of bridges trended upward until a final value of eight was reached.

Table 4.4. Random Forest branch sample information for Concrete Bridge Data 2022

Characteristic Boundary	Boundary Decision	Squared Error	Sample	Value
Age ≤ 31.5		1.64	6896	6.94
Age ≤ 12.5	True	1.04	3270	7.64
Age ≤ 21.5	False	0.92	2325	7.34
Deck Width ≤ 9.05	False	0.97	1325	7.19
Structure Length ≤ 11.5	True	0.91	632	7.36
Deck Width ≤ 6.3	True	1.18	226	7.13
Age ≤ 25.5	True	0.76	20	7.67
ADT ≤ 272.0	False	0.43	9	8.2
Structure Length ≤ 7.9	True	0.16	7	7.8
ADT ≤ 26.5	False	0.1	6	7.89
	False	0.0	5	8

The Steel Bridge Data 2022 Random Forest model path selected began with a decision of a deck width greater than or less than 7.25 meters. This node contained 5264 samples, with a squared error of 1.81 and an average SER of 6.42 Following the false, or “less than” branch, led to the next node where a decision regarding age was reached. Here, 4247 bridges remained, with a squared error of 1.42 and an average SER of 6.68. This path contained ten decisions leading into the lead node. In this leaf node, only one bridge remained with an average SER of 8.0.

Similar to the path selected for the concrete bridge data, the squared error trended toward zero, although outliers did exist in some nodes. This may be due to less information being available for less common characteristics, such as Percent ADT Truck. The sample size decreased through each node until only one bridge with the exact characteristics remained. The average SER showed no clear trend for this path.

Table 4.5. Random Forest branch sample information for Steel Bridge Data 2022

Characteristic Boundary	Boundary Decision	Squared Error	Sample	Value
Deck Width ≤ 7.25		1.81	5264	6.42
Age ≤ 19.5	False	1.42	4247	6.68
Age ≤ 8.5	True	0.74	405	8.04
Structure Length ≤ 199.2	True	0.47	149	8.53
ADT ≤ 880.0	True	0.42	145	8.56
Deck Width ≤ 10.0	False	0.49	90	8.42
Percent ADT Truck ≤ 6.0	True	1.01	12	7.79
Main Unit Spans ≤ 2.0	True	0.96	5	7.2
Percent ADT Truck ≤ 1.5	True	0.4	3	8.0
ADT ≤ 4080.5	False	0.19	2	7.75
	False	0.0	1	8.0

One benefit of utilizing the Decision Tree and Random Forest model is the ability to quickly visualize how many bridges fall into a certain characteristic subset. The tables shown above only include a single example of the potential paths produced from each dataset. Every bridge within the datasets has a place within the trees, so all possible combinations are available for analysis or selection. For example, if an engineer begins designing a bridge and needs to choose the number of main unit spans, the models provide the ability to see a predictive SER above or below their intended design.

By evaluating each node individually, the identification of where significant deviations in the average SER occur is easily visualized. This may be helpful for inspectors to optimize their inspection schedules. ODOT's AssetWise automatically flags bridges meeting their designated criteria using conditional statements. These conditional statements only consider a single characteristic. However, the use of Random Forest models would allow for entire sets of characteristics to be identified as a group for a similar purpose. By creating boundaries and paths to specify bridges that may be prone to deterioration and lower SERs, inspection frequencies may be adjusted to smaller windows than before.

Documentation and research are some of the most important components of the bridge engineering process. These models provide easily accessible and accurate information to the engineer to help make repair/rehabilitation decisions. Showing that a decision was made by considering multiple perspectives adds a level of reliability that is much greater than using a single method. The models proposed above may serve as a standalone option for flagging and selection, or as supplementation to current methods.

Chapter 5: Conclusion

In this paper, NBI bridge data for Ohio bridges from 1992 to 2022 were used to develop supervised learning and statistical models. Raw bridge data was imported from the NBI repository into Microsoft Excel. Using Microsoft Excel, the data was formatted into columns and rows using the applied delimiters. Bridges that were missing inspection information or included information that did not apply were discarded. Physical and geometric traits were primarily selected as the information that may have a relationship with the SER. Eight of these characteristics were chosen to be used in the analysis, while the rest were discarded. The remaining data was split into four different workbooks based on the bridge material: concrete bridges, steel bridges, concrete and steel bridges, and other bridges. Only the concrete and steel bridge workbooks were considered for this analysis due to the amount of data they contained. Over 700,000 sets of data remained after simplification. Once the NBI information was completely processed, three copies of the concrete bridge workbook and three copies of the steel bridge workbook were created in order to consolidate the data from each year onto one sheet. These workbooks each contained data from all 31 years, the last five years, and the last one year only.

Python language in Jupyter Notebook and its extensions were used to process the data. Three supervised learning methods were considered to determine the relationships, including Pearson's Correlations, Decision Tree Model, and Random Forest Model. The Pearson's Correlations showed the relationship of the individual characteristics to the SER over a 31-year period. Bridge age was found to be the primary characteristic for deterioration in both bridge types, while others had little to no correlation. Some characteristics produced unexpected results based on their correlations. The consideration of varying time frames had little effect on these unexpected results, although they did have effects on the program's accuracy. The Decision Tree and Random Forest models allowed for visual interpretations of the relationships over two different spans of time, as well as the ability to accurately predict the SER based on the shown relationships. The most significant results were produced when considering a comprehensive set of inspection data. This highlights the necessity of proper data collection and record-keeping.

All three methods have shown to be valuable in determining the SER based on inspection information. Pearson's Correlation information allows for certain characteristics to come into focus in bridge health. Further investigation into how each characteristic interacts with the SER can uncover ways to make positive strides in decision making. Seeing improvements in relationships will also show engineers times where certain events may have had a profound effect on the design or inspection processes. Future programs could be initialized that select bridges with specific characteristics for increased inspections in conjunction with or akin to the checklist used by AssetWise. Selecting bridges using multiple nodes of a Decision Tree or Random Forest model rather than a single characteristic could narrow down the number of bridges that may be caught in a generalized set for increased inspections while maintaining accuracy. However, if both methods were to be used together, the most severe cases could be identified within the larger flagged set. This would allow inspectors to put these bridges at the front of an already-optimized inspection schedule. With safety being the top priority while inspecting bridges, utilizing multiple tools to support the decisions being made is invaluable. Machine learning is becoming an important part of many different industries. Bridge engineering is a discipline that is reliant on data, oftentimes needing to process it in short timeframes. Inspections are a subset of the field where accuracy and timeliness make difference in public safety. Implementing new or improved technologies will make a difference in the future of damage detection and prevention, bridge health diagnostics, and inspection/repair/rehabilitation priorities.

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