NOVEL ELEMENT-DATA DRIVEN COACTIVE PRIORITIZATION FOR BRIDGE ASSET MANAGEMENT

by

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(Under the Direction of MI GEUM CHORZEPA)

ABSTRACT

This dissertation investigates element-level inspection data available in the National Bridge Inventory and proposes a novel coactive prioritization model for bridge asset management. The model accounts for time-dependent element interactions, referred to as coactiveness, in predicting bridge performance resulting from preventive maintenance, rehabilitation, or replacement (MRR) activities. The proposed coactive model hypothesizes that if one repairs one element, it should reduce the deterioration of other elements. Those improved elements, in turn, reduce the deterioration of the repaired element and so forth. Therefore, this study aims to enable data-driven time-dependent element interactions for MRR decision-making. The proposed model is used to analyze Georgia's bridges at first. It is concluded that accounting for element interactions that are present in the element-data yields more realistic, and thus less overly conservative, performance predictions. The results also indicate that the overall Bridge Health Index (BHI) improves by 20% over the subsequent 20 years when expansion joints are repaired utilizing the coactive prioritization mechanism. In a subsequent study, it is concluded that coactive relationships exist among elements in the Alabama and Florida bridge inventories. In Alabama, MRR on bridge deck elements are more influential than MRR on the expansion joint for the long-term bridge performance. It is concluded from this study that early preventive maintenance implemented in Florida most leverages the coactive mechanism. However, most states that do not have as much resources as Florida for early maintenance should benefit from the coactive model. Therefore, three additional bridge inventories of Virginia, Pennsylvania, and New York are investigated to study the effectiveness of employing the coactive model. They are known to have an excellent bridge preservation program. In this last study, both state-owned and NHS bridges are investigated. A game theory model is applied to decision-making, and payoffs of two major players, the Federal Highway Administration and a state agency are evaluated. The analysis confirms that long-term bridge performance predictions leveraging a coactive mechanism are effective in prioritizing elements for MRR decisions.

INDEX WORDS: Bridge; Bridge Asset Management; Bridge Health Index; Coactive; Depreciation; Element; Element Interactions; Game Theory; National Bridge Inventory; National Highway System; Prioritization Model.

COACTIVE PRIORITIZATION AND A NOVEL GAME THEORY MODEL FOR BRIDGE ASSET VALUATION AND MANAGEMENT

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DEDICATION

This dissertation is dedicated to the loving memory of my father, Abraham Oladepo Oyegbile.

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CHAPTER 1

1. INTRODUCTION

This chapter presents the background information, objectives, significance, and methodology employed in this study.

1.1 Background

The first subsection introduces the basic knowledge required to understand how bridge management practices in the United States. Bridge element performance and interactions are also presented as prerequisites to the Co-Active model presented in this dissertation.

1.1.1 U.S. Transportation Agencies' Bridge Asset Management Strategy

Due to the complexity of bridges, optimal management strategies are crucial to keeping them in a safe condition, particularly in places where a large network of bridges exist. In Georgia, for example, there are approximately 15,000 in-service bridges. To cope with such a huge network of bridges, Bridge Management Systems (BMSs) has been developing since the early 1990's to manage bridges efficiently (Guoping Bu, Lee, Guan, Blumenstein, & Loo, 2011). Bridge Management System, according to Federal Highway Administration (FHWA., 2017), is "a systematic process that provides, analyzes, and summarizes bridge information for use in selecting and implementing cost-effective bridge construction, rehabilitation, and maintenance programs." Thus, BMSs have been critical to the successful implementation of various bridge management programs, enhancing the capability of bridge maintenance agencies to preserve public investment and users' safety.

1.1.2 Bridge Performance Measures

Bridge performance analysis generally entails a rigorous process of obtaining useful information crucial to the optimization of short- and long-term investment plans for bridge maintenance, repair, and rehabilitation (MR&R). Developing a performance-based approach to bridge management is critical for establishing accountability and improving the effectiveness of decision-making processes (Campbell, Perry, Connor, & Lloyd, 2016; Hearn, 2015). The scope and application of such analysis largely depend on the bridge management program and, by extension, bridge performance measures. As such, the adoption of an appropriate bridge performance measure is a prerequisite to the attainment of bridge management performance goals. AASHTO sufficiency rating, NBI general condition rating, among others, have been routinely used as bridge performance measures since 1970's. The AASHTO sufficiency rating is a numeric value that indicates safety, functionality, overall adequacy, and ability of a bridge to remain in service. It was superseded by the Moving Ahead for Progress in the 21st Century, also known as MAP-21, legislation (Anderson, Rizzo, Huston, & Dewoolkar, 2017; Chase, Adu-Gyamfi, Aktan, & Minaie, 2016; Weidner et al., 2018). Unlike the sufficiency rating (SR) which provides a 'single-digit' rating for a complete bridge, general condition rating (GCR) separately describes the performance of the three major bridge components (deck, superstructure, and substructure).

While these approaches have been greatly streamlined, inherent deficiencies such as their inability to capture depreciation of bridge elements, particularly when the condition rating drops, have been well-documented in the literature (Fereshtehnejad et al., 2018; Jeong, Kim, Lee, & Lee, 2018; Jonnalagadda, Ross, & Khademi, 2016; Lake & Seskis, 2013). The NBI GCR approach provides information on the severity of a condition but does not provide a quantitative evaluation of the degree of the severity (Lake & Seskis, 2013).

1.1.3 Bridge Element Level Inspection Data and Bridge Health Index

Recently, a performance measure based on bridge health index utilizing element-based bridge inspection data has gained widespread attention in the United States. As the popularity of bridge health index increases, recent publications have recognized the potential benefits of the computation of bridge health index utilizing an element-based analysis and call for consideration of such performance analysis for infrastructure investments, including investments in highway bridge programs (Chase et al., 2016; Inkoom, Sobanjo, Thompson, Kerr, & Twumasi-Boakye, 2017; Thomas & Sobanjo, 2012, 2016; Thompson, Bye, Western, & Valeo, 2018).

1.1.4 Bridge Element Interactions and MRR Prioritization Strategy

National Cooperative Highway Research Program (NCHRP) Report 551, ‘‘Performance Measures and Targets for Transportation Asset Management’’ presents a step-by-step guide for identifying performance measures and establishing target values (NCHRP, 2006). However, a commonly accepted, comprehensive methodology for bridge element-based performance analysis that recognizes interdependencies among bridge elements does not exist. Research is therefore needed, to provide bridge engineering professionals with a streamlined methodology for the utilization of element-based inspection records, most especially at a network level, to aid them in the prioritization and selection of the most appropriate bridge improvement alternatives that could result in the highest yield on investment.

1.2 Problem Statement

A bridge performance evaluation entails a rigorous process of obtaining its element condition states. However, a performance measure (or BHI) is not the only factor that determines a bridge action (preventive maintenance, rehabilitation, or replacement) priority. Factors such as the bridge action costs (i.e., preventive maintenance, rehabilitation, or replacement costs), threshold BHI, and life cycle affect a bridge action prioritization plan. Thus, an efficient prioritization analysis incorporating such factors optimizes the allocation of limited funds because it enables cost-effective preventive maintenance, rehabilitation, or replacement (MRR) decisions (Phillips, 2017; Puls, Hueste, Hurlebaus, & Damnjanovic, 2018). Among the factors, the bridge service life is dependent on the complex interactions among elements. There are groups of elements that act together to affect the BHI. They are referred to as “Co-Active elements” in this dissertation. When one prioritizes these elements for a bridge action (e.g., deck treatment as preventive maintenance), the overall bridge performance significantly improves (Inkoom & Sobanjo, 2018; Sabatino & Frangopol, 2017), and the improvement should be quantifiable.

1.3 Research Objectives

This study aims to enable data-driven time-dependent element interactions for MRR decision-making. The specific aims of this dissertation are listed below and repeated in each chapter.

Chapter 1 aims to:

1. Review state-of-the-art strategies for bridge asset management in the United States.
2. Synthesize information regarding element-level bridge inspection data and bridge health index, and how element interactions influence decision making on prioritization strategies for bridge maintenance, rehabilitation, or replacement (MRR).
3. Present background information on the critical components of this dissertation.

Chapter 2 aims to:

1. Develop MATLAB codes that can be used to conduct a preliminary analysis of element-level bridge inspection data and obtain critical information that is influential to element and overall bridge performance.

2. Ensure that element-based inspection data are sufficient (in terms of quality and format) as an input file for Matlab® (©The MathWorks, Inc., 1994 – 2018), which is one of the primary software used for this study.

Chapter 3 aims to:

1. Review, analyze, and identify possible knowledge gaps and make suggestions for future research in the application of BHI as a performance measure in the bridge management system.
2. Compute BHI and definition of important concepts, namely, AASHTO CoRe elements, condition states, and element health index coefficient, are reviewed; second, sensitivity analysis of Caltrans BHI and Denver BHI; then, recommendations for the computation and improvement in the application of DBHI; finally, the conclusions are drawn from key findings for the advancement of frontiers of knowledge in the research field.

Chapter 4 aims to:

1. Analyze element-level bridge inspection data and develop age-bin based depreciation model for each element.
2. Determine how the age-bin based depreciation models compare with the depreciation models obtained from the National Bridge Inventory data.

Chapter 5 aims to answer the following research questions:

1. Can one define inter-dependent relationships among bridge elements' health indices?

2. How should one optimize a return on investment (ROI) in terms of bridge service life extension? That is, how should one quantify the effects of inter-element relationships as a function of time and evaluate bridge long-term performance?
3. Do inter-element relationships affect importance weighting factors and help prioritize actions (preventive maintenance, rehabilitation, or replacement) on bridge elements?

Specifically, Chapter 6 aims to answer the following three key questions by analyzing bridge inventories in three states:

1. Does Co-Activeness, among bridge elements, exist in the element data?
2. If exists, is the Co-Activeness quantifiable?
3. If exists and is quantifiable, are the U.S. state agencies leveraging Co-Activeness in their MRR strategies?

Chapter 7 aims to answer the following research questions:

1. Does the proposed Co-Active model have application to other U.S. state agencies?
2. Is there any difference in the performance of NHS state-owned and non-NHS state-owned bridges?
3. How should one quantify payoffs for two players, the FHWA and a state DOT, using a game theory?

Finally, Chapter 8 provides conclusions and recommendations for future studies.

1.4 Research Significance and Scope

The primary benefit of this study is to additionally accounts for the inter-dependencies that exist among elements in determining element weight factors, based on the concept of "Co-Active elements", and accounts for the time-value of element's depreciation. A Bridge Co-Active Prioritization Model (Br-CPM) is introduced. The Br-CPM determines how "Co-Active elements" affect a bridge health index and its service life at a discrete-time.

This study focuses on wide-area applications of the proposed Co-Active model, including complementary concepts such as the performance gap index, investment-to-depreciation ratio, and game theory.

1.5 Research Methodology

To accomplish the aforementioned objectives, analytical studies are deployed in five specific tasks. These are outlined below.

1.5.1 **Task 1. Perform Extensive Literature Review**

A thorough review of bridge management practices by state DOTs is conducted to provide insight into current issues, practices, and challenges pertaining long-term bridge performance in the United States.

1.5.2 **Task 2. Perform Preliminary Data Analysis**

A preliminary data analysis is conducted to understand bridge element performance. Task 2 results are presented in Chapter 2.

1.5.3 **Task 3. Conduct Sensitivity Analysis of the Bridge Health Index**

A sensitivity analysis of the bridge health index (BHI), which is the bridge performance measure used in the Co-Active model, is conducted. Task 3 results are presented in Chapter 3.

1.5.4 **Task 4. Comparatively Analyze the Element-and-NBI-based Bridge Deterioration Models**

The procedure for the age-bin based approach for developing element-level bridge depreciation models is presented. Then, the approach is used to analyze Georgia's element data; develop element and overall bridge depreciation models for approximately 15,000 in-service bridges in Georgia. The element depreciation models are developed as one of the major inputs for the Co-Active model. Lastly, a comparative analysis of the depreciation models obtained from element-level and NBI data is performed. Task 4 results are presented in Chapter 4.

1.5.5 **Task 5. Analyze Georgia's Bridges Using the Proposed Co-Active Model**

The proposed Co-Active model which accounts for time-dependent element interactions, referred to as Co-Activeness, in predicting bridge performance resulting from MRR activities, is used to analyze Georgia's bridges at first. Also, bridge element depreciation models are developed as one of the major inputs for the Co-Active model. Task 5 results are presented in Chapter 5.

1.5.6 **Task 6. Apply the Proposed Co-Active Model to Southeastern U.S. States**

This task includes the application of the proposed Co-Active model to bridge management in southeastern U.S. states: Alabama, Georgia, and Florida. Task 6 results are presented in Chapter 6.

1.5.7 **Task 7. Investigate the Strategic Move for Service Life Extension of Bridges by Employing a Co-Active Prioritization Mechanism**

Additional bridge inventories in three additional states which are known to have proactive maintenance strategies are investigated. A game theory approach to model a strategic interaction between two players, the FHWA and a state DOT, is presented. The payoffs of the two players in prioritizing element MRR are quantified based on a service life extension of bridges. Results from this task are presented in Chapter 7.

1.5.8 **Task 8. Conclusions and Recommendations**

Results from this task are presented in Chapter 8.

1.6 Organization of the Dissertation

This dissertation is divided into seven chapters that describe procedures for the applications for the proposed Co-Active model and present results from the application of the model, which include:

Chapter 1 presents a general background on the bridge element inspection data and element interactions. Additionally, research objectives and significance are described.

Chapter 2 describes a preliminary data analysis conducted to understand bridge element performance. These analyses include data characterization, data quality assessment, and data processing.

Chapter 3 outlines a sensitivity analysis of the BHI, which is the bridge performance measure used in the Co-Active model. Caltrans BHI and Denver BHI are analyzed to provide more insights to the application of the BHI.

Chapter 4 presents a stochastic bridge element depreciation modeling approach. In this chapter, the element depreciation predictions for approximately 15,000 in-service Georgia bridges are evaluated. Finally, a comparative analysis of age-bin based depreciation models, implemented in the Co-Active model in Chapter 5, and the models obtained from the National Bridge Inventory is presented.

Chapter 5 introduces a Co-Active model, which represents a time-dependent element interaction mechanism, and presents an analytical investigation of Georgia's bridge performance using the proposed Co-Active model. The formulation of the Co-Active model is presented. This chapter offers insight into the essential components of the Co-Active model. Co-Active parameters, contingency tables, and element HI using a multilinear approach are computed.

Chapter 6 presents the application of the proposed Co-Active model to Southeastern US states. Concepts such as performance gap index and investment-to-depreciation ratio are used to quantify element interactions and improve the application of the Co-Active model to bridge asset management.

Chapter 7 presents the analysis of bridge performance in Georgia, Virginia, Pennsylvania, and New York using the Co-Active model. In this Chapter, a game theory is introduced to enhance the application of the Co-Active model to bridge asset management.

Chapter 8 presents conclusions and recommendations for future studies.

CHAPTER 2

2. PRELIMINARY DATA ANALYSIS

2.1 Introduction

Element-based bridge inspection data include a quantitative assessment of each bridge element in four condition states (see Table 1). Table 2 illustrates how quantities are specified in the data. Such quantitative evaluation allows decision-makers to measure the extent of deterioration, determine current asset value, and prepare successful bridge management plans (AASHTO, 2019). Each condition state aggregates the cumulative effects of relevant defects. Thus, a preliminary data analysis is conducted to understand bridge element performance. It also ensures that element-based inspection data are sufficient (in terms of quality and format) as an input file for Matlab® (©The MathWorks, Inc., 1994 – 2018), which is the primary software used for this study.

2.2 Data Characterization

This section describes the characteristics of element-based bridge inspection records in Georgia. The purpose of data characterization is to obtain valuable information on the element inspection records that are relevant to bridge asset valuation.

2.3 Data Quality Assessment

Table 1 shows the four condition states defined in the AASHTO element inspection manual (2019). The quality assessment performed in this study is based on experience gained from the National Bridge Inventory (NBI) condition rating analysis, where bridges and components with incomplete entries were found and screened out. This analysis concluded with 46,176 (in Tape 2015); 83,370 (in Tape 2016); 87,624 (in Tape 2017); and 88,030 (in Tape 2018) element inspection records. Overall, these records are found to be complete with a few anomalies (i.e., incomplete and missing data and changes in element number assignments) observed in the 2015 and 2016 datasets.

Table 1 – Condition state definitions (AASHTO, 2019).

<table>
<tr><th rowspan="2">Defects</th><th colspan="4">Condition States for Element 12, Reinforced Concrete Deck</th></tr>
<tr><th>1</th><th>2</th><th>3</th><th>4</th></tr>
<tr><td>Delamination/ Spall/Patched Area (1080)</td><td>None</td><td>Delaminated. Spall 1 in. or less deep or 6 in. or less in diameter. Patched area that is sound.</td><td>Spall greater than 1 in. deep or greater than 6 in. diameter. Patched area that is unsound or showing distress. Does not warrant structural review.</td><td rowspan="3">The condition warrants a structural review to determine the effect on strength or serviceability of the element or bridge;

or,

a structural review has been completed and the defects impact strength or serviceability of the element or bridge.</td></tr>
<tr><td>Exposed Rebar (1090)</td><td>None</td><td>Present without measurable section loss.</td><td>Present with measurable section loss but does not warrant structural review.</td></tr>
<tr><td>Cracking (RC and Other) (1130)</td><td>None or insignificant cracks</td><td>Unsealed moderate width cracks or unsealed moderate pattern (map) cracking. Cracks from 0.012 to 0.05 inches wide.</td><td>Wide cracks or heavy pattern (map) cracking. Cracks greater than 0.05 inches wide.</td></tr>
<tr><td>Damage (7000)</td><td>Not applicable</td><td>The element has impact damage. The specific damage caused by the impact has been captured in condition state 2 under the appropriate material defect entry.</td><td>The element has impact damage. The specific damage caused by the impact has been captured in condition state 3 under the appropriate material defect entry.</td><td>The element has impact damage. The specific damage caused by the impact has been captured in condition state 4 under the appropriate material defect entry.</td></tr>
</table>

2.4 Data Processing

Unfortunately, element-based inspection data are not self-reliant. That is, there are important bridge variables that are comprehensively captured in the NBI but not captured by element-based inspection data. Among others, construction years are not available in the element inspection inventory ('Tape') as shown in Table 2. Therefore, element-based inspection data do not replace NBI data; rather, it is a supplementary data set that provides more details on each element's quantitative condition. In Section 6, element inspection-based and NBI-based condition scores are compared.

Table 2 – Element inspection records for selected bridges in Georgia.

STATE	STRUCNUM	EN	TOTALQTY	CS1	CS2	CS3	CS4
13	12105430	12	19393	19393	0	0	0
13	12105430	515	21426	21426	0	0	0
13	12105430	515	36	36	0	0	0
13	12105430	234	190	188	2	0	0
13	8100450	215	62	55	7	0	0
13	3150100	110	1956	1956	0	0	0
13	2101220	12	5630	5216	414	0	0
13	14100010	215	112	100	12	0	0
13	14100010	331	206	206	0	0	0
13	14100010	234	104	74	30	0	0
13	30350140	301	120	0	0	120	0

Other relevant attributes in the NBI include structure number, designated as STRUCNUM (Item no. 8); year built, designated as YEAR BUILT (Item no. 27); and year reconstructed (Item no. 106). In this study, NBI data for 2017 and Tape data for 2018 are used for the analysis. The Excel program developed for this study can process any combination of standardized NBI and Tape (or element-based) data.

The following three steps are used for data processing:

(1) extract year built from NBI data;

(2) replace year built by the year reconstructed if the year reconstructed is greater than year built; and

(3) align bridge identification numbers (IDs) in NBI data with bridge IDs in Tape (or element-based) data to extract year built/reconstructed.

This process is illustrated in Figure 1 with the first five rows of the element-based bridge inspection data from Table 2. There is a total number of 14,863 bridges in NBI 2017 and 14,684 bridges in Tape 2018. This querying process returns a total number of 14,039 bridges. It should be noted that NBI 2018 data was not available when this study was conducted.

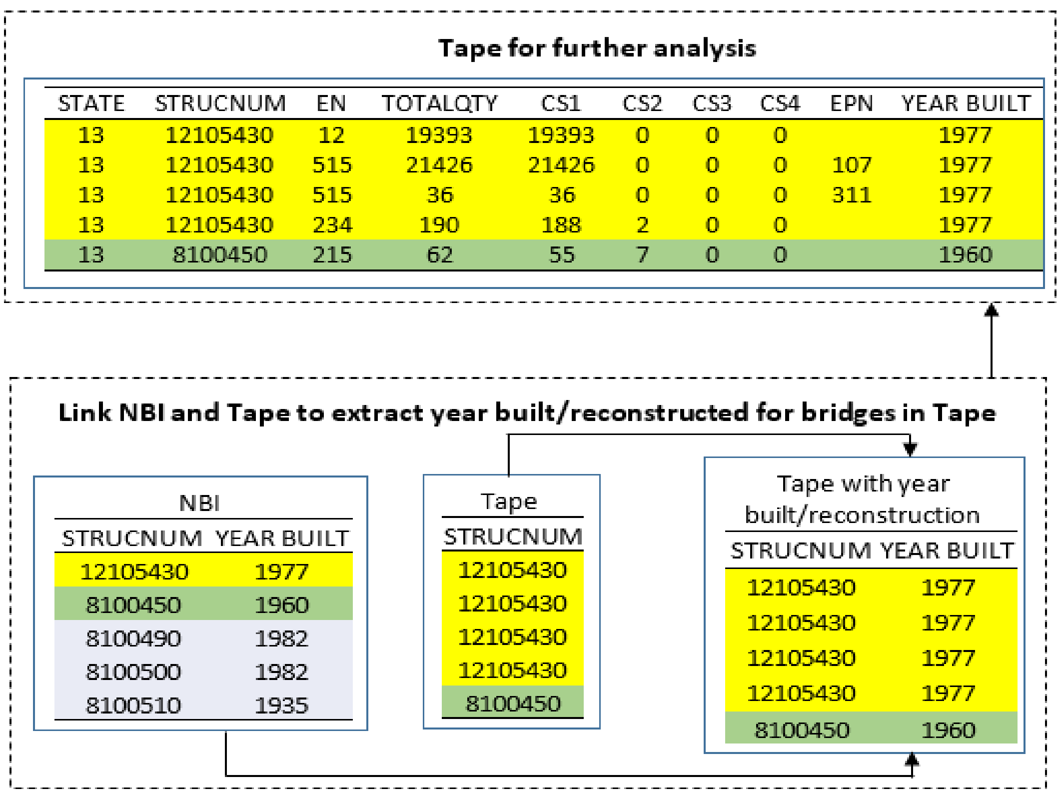


Figure 1 – Extraction of year built/reconstructed from NBI.

Note: EN = Element Number, and 'EPN' indicates the parent element number.

CHAPTER 3

3. SENSITIVITY ANALYSIS OF BRIDGE HEALTH INDEX TO DEPRECIATION OF CRITICAL ELEMENTS

3.1 Introduction

The application of the bridge management system is increasing due to the aging of the old and complexity of modern infrastructures, among others. As a result, various state departments of transportation and other agencies have developed measures of bridge performance for effective management and preservation of public equity. An important consideration is the minimization of the proportion of bridges that are structurally deficient and functionally obsolete. Bridge "health" (condition) index in most bridge management systems (e.g., AASHTOWare and OBMS) typically tracks the performance of bridges or network of bridges based on the available element-level/components inspection records. It aggregates the elements/components health indices for the overall performance of bridges. Several studies have been conducted to investigate the sensitivity of BHI, but none of them have focused on critical CoRe elements. This study reviews recent developments in the computation of BHI and investigates different scenarios that reflect the depreciation of critical CoRe elements and their potential impacts on the interpretation of BHI. The relative importance and contributions of various elements to the continuing functionality of bridges are clearly highlighted. This analysis also includes the newly introduced concept of element quantity distribution coefficients and its potential application in bridge depreciation modeling.

3.2 Objectives

The overarching goal of this study is to review, analyze, and identify possible knowledge gaps and make suggestions for future research in the application of BHI as a performance measure in the bridge management system. This chapter is organized as follows: first, the computation of BHI and definition of important concepts, namely, AASHTO CoRe elements, condition states, and element health index coefficient, are reviewed; second, sensitivity analysis of Caltrans BHI and Denver BHI; then, recommendations for the computation and improvement in the application of DBHI; finally, the conclusions are drawn from key findings for the advancement of frontiers of knowledge in the research field.

3.3 Computation of BHI

3.3.1 Computation of Caltrans BHI

To account for the depreciation in asset value over time, BHI assigns important weights to element quantities in their initial and lower CSs as shown in Equations 1 through 4.

$$HI = \frac{CV_e}{TV_e} \times 100 \tag{1}$$

$$CV_e = \sum_e H_e \, TV_e \tag{2}$$

$$WQ_e = \sum_e W_e \sum_i^{N_e} Q_{ei} \tag{3}$$

$$H_e = \frac{\sum_e Q_{ej} C_{ej}}{TV_e} \times 100 \tag{4}$$

Where,

HI = health index,

CV_e = current element e value,

TV_e = total element e value (e.g.,WQ_e or weighted value, WV_e)

W_e = weight given to element e (e.g., repair, replacement or failure cost, or based on expert opinion)

C_{ej}= index coefficient (linear or nonlinear) of element e in condition state i

Q_{ej}= quantity of element e in each condition state

N_e= number of condition states for element e

WQ_e= weighted quantity of element e without index coefficient

The element quantities and important weights are usually used for the aggregation of HI for a bridge or network of bridges based on the identified condition states (Shepard & Johnson, 2001). This aggregation makes use of the information obtained from component/element-based inspection inventories collected over a period. Important weights are usually applied to the element to account for the value (repair, failure or replacement cost), performance, and contributions to the overall health of the bridge. Ultimately, successful application of BHI as a decision-making tool for the management of bridges (e.g. in the allocation of resources for RR&R) largely depends on how accurately these important weights can represent the condition of each element and aggregates it for the whole bridge.

3.3.2 Computation of Denver BHI

Based on the analysis of the Caltrans BHI for bridges in Denver, Colorado, Jiang and Rens concluded that the current Caltrans BHI was subjective to a municipality's often imprecise cost data (X. Jiang & Rens, 2010a). Even though most of the bridges had been in use for many years and needed rehabilitation, Caltrans BHI performance of almost 90% of the bridges was between 90 and 100%. They also noted that the Caltrans BHI, in its current form, was not sensitive to the general deterioration of bridge elements. Furthermore, the element value, which is the product of the weight and the element quantity, did not indicate the effect of element damage on the bridge health and function. The result of the study served as the basis for developing an alternate BHI methodology, called Denver BHI. Jiang and Rens introduced new weight coefficient and proposed

Denver BHI as follow:

$$H_e = \frac{\sum_s \ k_s^n q_s}{\sum_s \ q_s} \times 100\% \tag{5}$$

$$w_e^{aj} = w_e AF_e \tag{6}$$

$$H = \frac{\sum_e \ H_e w_e^{aj}}{\sum_e \ w_e^{aj}} \times 100\% \tag{7}$$

where,

k_s^n is the nonlinear health index coefficient corresponding to the *s*th condition state

w_e^{aj} is the adjusted weight coefficient of element *e*

AF_e is the adjustment factor of element *e*

w_e is the weight coefficient assigned to each element

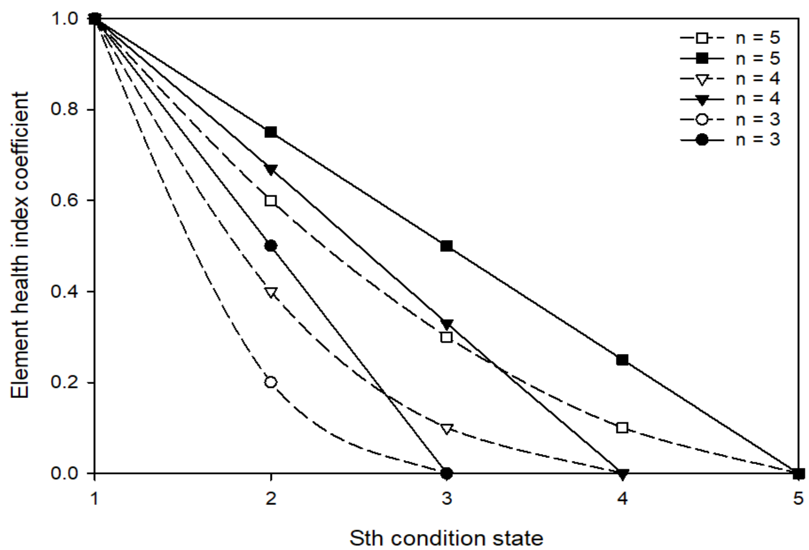


Figure 2 – Comparison of trends of linear "—" and nonlinear health index "----" coefficient of condition states, n = number of condition states (k_s^n).

This new approach is based on the application of the nonlinear index coefficient of condition states (Figure 2) and adjustment factor (Figure 3) to obtain new BHI. The weight coefficients are determined based on expert opinion. Weight coefficients define the contribution and relative importance of each element to the health and functionality of the bridge. In Caltrans BHI, it is a function of element cost.

Table 3 – Bridge Condition Indices (CI).

CI Zones		CI Scales
Action	Value	Condition description
Immediate action not required **(71-100)**	85 – 100	Excellent – no noticeable effects some aging or wear visible
Economic analysis of repair alternatives recommended to determine appropriate maintenance action **(41-70)**	70 – 84	Very good – only minor deterioration or defects evident.
	55 – 69	Good – some deterioration or defects evident, function not impaired.
	`40 – 54	Fair – moderate deterioration, function not seriously impaired.
Detailed evaluation required to determine the need for RR&R, safety evaluation recommended **(0-40)**	25 – 39	Poor – serious deterioration in at least some portion of structure, function seriously impaired.
	10 – 24	Very poor – extensive deterioration, barely functional.
	0 – 9	Failed – general failure or failure of a major component no longer functional.

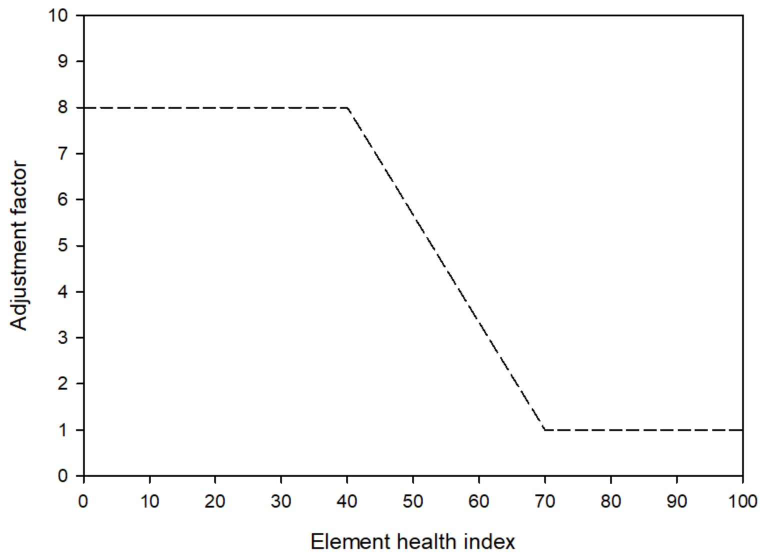


Figure 3 – Linear step curve for calculating Adjustment Factor (AF).

3.4 Sensitivity Analysis of BHI

3.4.1 Analysis of Caltrans BHI

As shown in Tables 4 and 5, the average value of the elements' HIs for bridge A is different from the HI obtained by aggregating CV_e and TV_e. The element-based inspection records for the computation of the bridge HI for bridges A and B are shown in Appendix A. The average values of elements' HI and aggregated HI are 89.21%, 91.69%, 67.69% and 99.42%, 90.48%, 81.44% for bridges A, B and C, respectively. This discrepancy in the values of overall bridge HI can be attributed to the fact that Caltrans BHI defines element value as a product of economic cost and element quantity. The Caltrans BHI directly relates the aggregated element quantity to the element HI and bridge HI. The implication is that elements with higher quantities assert greater influence than those with lower quantities on the bridge health, irrespective of their functionality. It is therefore recommended that, for the computation of bridge health index, element quantities in all the condition states are aggregated as a percentage of each element in 'good health'.

Table 4 – Linear weighting factor for the Condition States (CS).

No. of CSs	CS 1	CS2	CS3	CS4	CS5
5	1	0.75	0.50	0.25	0
4	1	0.67	0.33	0.00	NA
3	1	0.50	0.00	NA	NA

Table 5 – Computation of HI for Georgia bridge 100140 (Bridge A).

*Element key	Meas. Unit	Element Quantity	**Unit FC	Resulting CV_e	Resulting TV_e	HI_e (CV_e/TV_e) *100
12	ft.	6069	$600	$3,605,058	$3,641,400	99.00
215	ft.	52	$3,500	$182,000	$182,000	100.00
301	Sq.ft.	208	$556	$108,420	$115,648	93.75
311	ft.	28	$500	$9,845	$14,000	70.32
234	ft.	156	$8,740	$1,363,440	$1,363,440	100.00
225	ft.	24	$819	$19,656	$19,656	100.00
107	ea.	756	$65	$48,708	$49,140	99.12
313	ea.	16	$650	$6,721	$10,400	64.63
331	ft.	378	$456	$170,111	$172,368	98.69
515 (107)	Sq.ft.	4528	$300	$1,358,400	$1,358,400	100.00
515 (225)	Sq.ft.	10200	$300	$3,060,000	$3,060,000	100.00
515 (311)	Sq.ft.	28	$300	$5,850	$8,400	69.64
515 (313)	Sq.ft.	16	$300	$3,102	$4,800	64.63
			TOTAL	$9,941,311	$9,999,652	**Average HI 89.21%**

*CV_e = current element value; TV_e=total element value; HI_e=element HI; *Element descriptions in Appendix B; ** Unit failure costs obtained from literatures; CV_e $=\sum_{CS1}^{CS4} Quantity\ X\ weighting\ factor\ X\ \ unit\ FC$; TV_e = Element Quantity X Unit FC.*

Aggregation of health index: $HI_e = \left(\sum_e CV_e/TV_e\right)$X100

For bridge A in Table 5,

HI = ($9,941,311/$9,999,652) X 100% **= 99.42%**

For bridge B in Table 6,

HI = ($7,571,482/$8,368,242) X 100% = **90.48%**

For bridge C in Table 7,

HI = ($622,300/$764,144) X 100% = **81.44%**

Table 6 – Computation of HI for Colorado bridge D-03-V-150, bridge B (X. Jiang & Rens, 2010a)

Element key	HI_e **(%)**	TV_e **Value**	TV_e **%**	CV_e **Value**	CV_e **%**
14	100	$693,832	8.29	$693,832	9.16
101	97	$1,069,122	12.78	$1,037,048	13.7
106	100	$413,669	4.94	$413,669	5.46
205					
210	100	$2,398,570	28.66	$2,398,570	31.68
215	100	$866,047	10.35	$866,047	11.44
234	67	$1,531,772	18.3	$1,026,287	13.55
305	100	$63,610	0.76	$63,610	0.84
306					
314	34	$374,014	4.47	$127,165	1.68
326	100	$4,820	0.06	$4,820	0.06
331	100	$398,900	4.77	$398,900	5.27
333	100	$251,931	3.01	$251,931	3.33
334	94	$205,878	2.46	$193,525	2.56
338	100	$96,077	1.15	$96,077	1.27
TOTAL	**91.69**	$8,368,242	100	$7,571,482	100

*CV_e = current element value TV_e = total element value; HI_e = element HI = (CV_e/TV_e) *100*
TV_e = Element Quantity X Unit FC; CV_e = $\sum_{CS1}^{CS4} Quantity\ X\ weighting\ factor\ X\ unit\ FC$

Additional drawbacks of the current methodology for the computation of Caltrans BHI include:

- It is based on the current and original (i.e., ideal) value of the structure. It does not consider the life span of the structure, which may make its application to long term TAMP less efficient.
- It does not make provision for the historical bridge management practices (e.g., historic repair, rehabilitation, and or construction cost). The resulting deterioration models appear too idealistic. For example, a bridge element that is better maintained should have higher

importance weight compared to a similar element that is poorly maintained. However, this is presently not the case.

Table 7 - Computation of HI for sample bridge, bridge C (Shepard & Johnson, 2001).

Element key	HI_e (%)	TV_e Value	TV_e %	CV_e Value	CV_e %
14	50	$180,000	23.56	$90,000	14.46
101					
106	89	$350,000	45.8	$311,500	50.06
205	100	$36,000	4.71	$36,000	5.78
210					
215	100	$184,800	24.18	$184,800	29.7
234					
305					
306	0	$13,344	1.75	$0	0
314					
326					
331					
333					
334					
338					
TOTAL	**67.80**	$764,144	100	$622,300	100

*CV_e = current element value TV_e = total element value; HI_e = element HI = (CV_e/TV_e) *100*
TV_e = Element Quantity X Unit FC; CV_e = $\sum_{CS1}^{CS4} Quantity\ X\ weighting\ factor\ X\ unit\ FC$

3.4.2 Analysis of Denver BHI

Reference to the BHI values in Table 6, computed based on the element level bridge inspection record for 8th Avenue Viaduct Bridge D-03-V-150 in Colorado shown in Appendix A, the initial parametric analysis (not presented in this study) reveals that the computed values of Denver BHI largely depend on the HI of elements with higher weight coefficients. This makes sense because the condition of critical bridge elements such as bridge deck, piers, abutments, etc., are more important than 'auxiliary' components such as asphaltic wearing surface or railings. In other words, the structural integrity of a bridge is more of a function of the condition of critical elements. A bridge can still function without major safety concerns even when the wearing surface is not in good condition! So, the sensitivity analysis presented in this study revolves around the bridge elements with higher weight coefficients.

Considering the condition indices given in Table 3, the analysis is divided into two categories (a) sensitivity of the HI when HI of critical elements vary between 0 and 100 and (b) sensitivity analysis when HIs of critical elements are less than 50. The critical elements, selected after preliminary analysis of the causes of major bridge collapse around the world (Choudhury & Hasnat, 2015; Deng, Wang, & Yu, 2015; Peng, Dai, & Taciroglu, 2014; Shi, Zhou, & Ruan, 2016; Turner, Brandenberg, & Stewart, 2016) include:

1. Abutment
2. Pier wall and cap
3. Girder
4. Pot bearing

3.4.2.1 Sensitivity of the HI when HI of critical elements vary between 0 and 100

The major defects in the bridge from the inspection data shown in Appendix A2 are in RC pier cap and pot bearing. In addition to pier cap and bearing, effects of deterioration of pier wall, girder, and abutment are analyzed as a function of their HI. To analyze the effects of adjusted weights, a concept of element quantity distribution coefficients is introduced as shown in Table 8. Upper bound (UB) and lower bound (LB) concepts are introduced to account for the relative performance of quantities measured for each condition state. Apart from its application for the sensitivity analysis of the BHI, bridge maintenance agency's inspection engineers can find it useful for the development and 'fine-tuning' the deterioration models for a bridge or network of bridges. Because of its compatibility with the present AASHTO format for state and national bridge condition states reporting, it can also be adapted for element-based inspection.

Table 8 - Element quantities distribution coefficients for 210-RC pier wall.

	Condition State 1		**Condition State 2**		**Condition State 3**		**Condition State 4**	
	Distribution Coefficients							
	1	1		0		0		1
	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound
Quantities	82.295	82.295						
Distributions		-82.295	+82.295					
Distributed Quantities	82.295		82.295					

Table 9 shows the quantities (with and without distribution) for the computation of the DBHI for the bridge D-03-V-150. To demonstrate the application of distribution coefficients, we consider the quantity in CS1 for element 210 to be equally distributed between the bounds – upper and lower. We then applied a distribution coefficient of 0.5 across the boundary of CSs 1 and 2. Similarly, the quantities for abutment and steel open girders are distributed to account to deterioration. The sensitivity of the reduction in the element HI because of this distribution is analyzed for the critical elements.

Figure 4 shows the relationship between the deterioration of these critical elements and overall BHI. This result shows that the effect of the critical elements' deterioration follows the pattern of the linear step curve used for the calibration of the HI. The point of transition lies around 50% HI, which can be broadly divided into two parts - high and low performance. The upper part gives a good indication of the performance of a typical bridge. Because of the relative importance of critical elements at higher rates of deterioration, it is necessary to conduct a detailed analysis of the bridge behavior for the low-performance part of the curve.

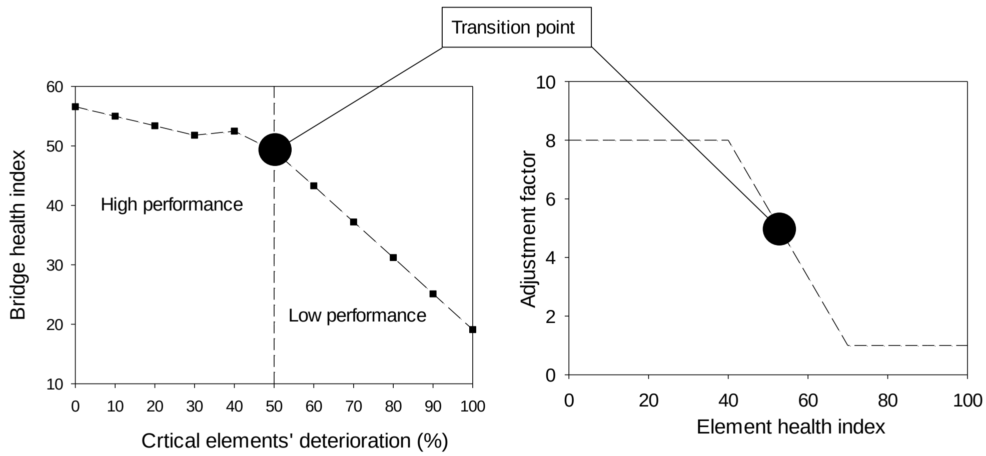


Figure 4 – Relationship between the critical element's deterioration, BHI, and adjustment factor.

3.3.2.2 Sensitivity of the overall BHI when HI of critical elements are less than 50 (i.e., more than 50% deterioration)

The following scenarios are considered for the analysis:

1. Reinforced concrete pier cap and pot bearing have deteriorated by 60% and 68%, respectively (Controls).
2. In addition to pier cap and pot bearing, reinforced concrete abutment has deteriorated by 80%.
3. Reinforced concrete pier cap and pot bearing are in good condition, but pier wall and abutment have deteriorated by 70% and 80%.
4. Reinforced concrete pier cap and pot bearing are in good condition, but pier wall or abutment has deteriorated by 80%.

Table 9 – Element quantities (with and without distribution) for the computation of the Denver BHI.

Undistributed quantities: HI = 56.6%					Element key	Distributed quantities: HI = 51.8%				
Condition States						**Condition States**				
CS5	**CS4**	**CS3**	**CS2**	**CS1**		**CS1**	**CS2**	**CS3**	**CS4**	**CS5**
0	0	0	0	8,895.28	14	8,895.28	0	0	0	0
	0	0	144.48	1,300.28	101	1,300.28	144.48	0	0	
	0	0	0	176.48	106	88.24	88.24	0	0	
	0	0	0	164.59	210	82.295	82.295	0	0	
	0	0	0	27.43	215	13.715	13.715	0	0	
	0	0	175.26	0	234	0	175.26	0	0	
		0	0	27.43	305	27.43	0	0		
		55	4	27	314	27	4	55		
		0	0	4	326	4	0	0		
	0	0	0	874.78	331	874.78	0	0	0	
		0	0	569.98	333	569.98	0	0		
0	0	89	0	633.38	334	633.38	0	89	0	0
	0	0	0	722.38	338	722.38	0	0	0	

The distribution of element quantities is also applied to obtain the deteriorated HI of the elements for each of the three scenarios. Tables 10 through 14 show the computation of BHI for the four scenarios. Scenario 2, as shown in Table 11, where the abutment has deteriorated by 80% and in addition to the significant deterioration of pier and pot bearing, one would expect a collapse or near-collapse condition for the overall bridge. Conversely, CI scale interpretation of the structure indicates otherwise – moderate deterioration, function not seriously impaired. This may be misleading considering the contribution of the critical elements such as abutment to the overall structural integrity of the bridge. In fact, the collapse of major bridges around the world has been attributed to the deteriorated condition of the abutment (Cook, 2014). Moreover, the CI zones action does not indicate any serious safety concerns - economic analysis of repair alternatives recommended to determine appropriate maintenance action. Scenario 3 gives similar observation, where abutment and pier wall has deteriorated to a level that they are barely functional. Yet, the condition interpretation indicates that the function is not seriously impaired. It is difficult, if not impossible, to imagine the continuing functionality of a bridge where the pier wall and abutment (bridge critical load transmission elements) have deteriorated by 70% and 80%, respectively.

Perhaps the most critical observation is the performance of the structure in scenario 4, where abutment has depreciated by 80%. The BHI is unexpectedly 64.8%. By interpretation, the bridge is still in good condition - function not impaired. How can a bridge continue to function when 80% of the abutment has depreciated? Surprisingly, this BHI is even higher than that of scenario 1 which is 56.6%. It appears that the DBHI, in its present form, is less sensitive to the individual element distress.

Table 10 – Computation of BHI for scenario 1 (Controls).

Element key	Element HI	Weight coefficient		Adjustment factor	Adjusted weight coefficient	$H_{e*} w_e^{aj}$
		Value	%			
14	100	6	6	1	6	6.00
101	94	12	13	1	12	11.28
106	100	12	13	1	12	12.00
210	100	15	16	1	15	15.00
215	100	12	13	8	12	12.00
234	40	15	16	8	120	48.00
305	100	7	7	1	7	7.00
314	32	6	6	8	48	15.36
326	100	4	4	1	4	4.00
331	100	2	2	1	2	2.00
333	100	2	2	1	2	2.00
334	91	2	2	1	2	1.82
338	100	1	1	1	1	1.00
	$\sum$	96	100		**243**	**137.46**

$H = \frac{\sum_e CV_e}{\sum_e TV_e} \times 100\% = \frac{\sum_e H_e w_e^{aj}}{\sum_e w_e^{aj}} \times 100\%$ = (137.46/243) X 100% = **56.6%**

Table 11 – Computation of BHI for scenario 2.

Element key	Element HI	Weight coefficient		Adjustment factor	Adjusted weight coefficient	$H_e * w_e^{aj}$
		Value	%			
14	100	6	6	1	6	6.00
101	94	12	13	1	12	11.28
106	100	12	13	1	12	12.00
210	100	15	16	1	15	15.00
215	**20**	12	13	8	96	19.20
234	40	15	16	8	120	48.00
305	100	7	7	1	7	7.00
314	32	6	6	8	48	15.36
326	100	4	4	1	4	4.00
331	100	2	2	1	2	2.00
333	100	2	2	1	2	2.00
334	91	2	2	1	2	1.82
338	100	1	1	1	1	1.00
	Σ	96	100		**327**	**144.66**

HI = (144.66/327) X 100% = **44.2%**

Table 12 – Computation of BHI for scenario 3.

Element key	Element HI	Weight coefficient		Adjustment factor	Adjusted weight coefficient	$H_e * w_e^{aj}$
		Value	%			
14	100	6	6	1	6	6.00
101	94	12	13	1	12	11.28
106	100	12	13	1	12	12.00
210	**30**	15	16	8	120	36.00
215	**20**	12	13	8	96	19.20
234	100	15	16	1	15	15.00
305	100	7	7	1	7	7.00
314	100	6	6	1	6	6.00
326	100	4	4	1	4	4.00
331	100	2	2	1	2	2.00
333	100	2	2	1	2	2.00
334	91	2	2	1	2	1.82
338	100	1	1	1	1	1.00
	Σ	96	100		**285**	**123.30**

HI = (123.30/285) X 100% = **43.3%**

Table 13 – Computation of BHI for scenario 4 (Abutment).

Element key	Element HI	Weight coefficient		Adjustment factor	Adjusted weight coefficient	$H_e *$ w_e^{aj}
		Value	%			
14	100	6	6	1	6	6.00
101	94	12	13	1	12	11.28
106	100	12	13	1	12	12.00
210	100	15	16	1	15	15.00
215	**20**	12	13	8	96	19.20
234	100	15	16	1	15	15.00
305	100	7	7	1	7	7.00
314	100	6	6	1	6	6.00
326	100	4	4	1	4	4.00
331	100	2	2	1	2	2.00
333	100	2	2	1	2	2.00
334	91	2	2	1	2	1.82
338	100	1	1	1	1	1.00
	Σ	96	100		**180**	**102.30**

HI = (102.30/180) X 100% = **56.8%**

Table 14 – Computation of BHI for scenario 4 (Pier wall).

Element key	Element HI	Weight coefficient		Adjustment factor	Adjusted weight coefficient	$H_e *$ w_e^{aj}
		Value	%			
14	100	6	6	1	6	6.00
101	94	12	13	1	12	11.28
106	100	12	13	1	12	12.00
210	**20**	15	16	8	120	24.00
215	100	12	13	1	12	12.00
234	100	15	16	1	15	15.00
305	100	7	7	1	7	7.00
314	100	6	6	1	6	6.00
326	100	4	4	1	4	4.00
331	100	2	2	1	2	2.00
333	100	2	2	1	2	2.00
334	91	2	2	1	2	1.82
338	100	1	1	1	1	1.00
	Σ	96	100		**201**	**104.10**

HI = (104.10/201) X 100% = **51.8%**

Table 15 – Summary of computed values of BHI for the three scenarios and their interpretations

CI Zones		CI Scales
Action	Scenario (BHI)	Condition description
Economic analysis of repair alternatives recommended to determine appropriate maintenance action	4 (56.8) - Abutment 1(56.6)	Good – some deterioration or defects evident, function not impaired.
	4 (51.8) – Pier wall 3(43.3), 2(44.2)	Fair – moderate deterioration, function not seriously impaired.

3.5 Discussion

As earlier observed, element quantity cannot adequately account for the contribution of an individual element to the continuing functionality of the bridge. For example, how can the quantities of a reinforced concrete bridge deck and pier be related to the overall health of the bridge? By comparison, bridge deck can be two or more times greater than a pier in terms of quantities. Yet, a drastic reduction in the strength or failure of a pier can result in the partial or complete collapse of a bridge (e.g., the collapse of I-40 bridge in Webber Falls, Oklahoma in 2002). The weight coefficient developed for Denver BHI assigns numerical values to each of the AASHTO CoRe elements. Table 3 shows the grouping based on the condition index used for the interpretation of the Denver BHI. The computation of HI using the Denver BHI method generally results in a lower HI compared to cost-based approaches.

The successful application of BHI as a decision-making tool depends on how accurately it can predict the short- and long-term performances of bridges. In computing the BHI, important weights are usually applied to reflect the changes in the 'value' of each element that deteriorates over a period. While the failure or replacement cost of each bridge CoRe element can be obtained from relevant sources, there is currently no consensus on the application of important weights to elements in each condition state. The nonlinear health index assigns the important weights more realistically than the linear health index, but the general application of this approach could be misleading. Hence, concepts like ‘pessimistic’ and ‘optimistic’ nonlinear health indices have been introduced recently.

Various authors have pointed out the effects of ‘boundary’ elements in the computation of BHI. The new concepts of upper bound (UB) and lower bound (LB) with distribution coefficients are introduced for the boundary condition states, which can be aggregated to obtain condition states compatible with the present 2019 AASHTO element-level inspection format. This new approach can enable bridge inspection engineers to differentiate between quantities with higher and lower performance values within each condition state and perform quantities distribution, where necessary, to fine-tune and improve the accuracy of the agency’s bridge deterioration models.

The computation of Denver BHI in its present form makes use of the numerical values (weight coefficients) assigned to bridge CoRe elements. These values are assigned based on the contribution of the elements to the health and continuing functionality of the bridge. In other words, it is an indicator stressing the effects of the deterioration of an individual element on the bridge health and function. While these values are more representative of the bridge condition than bridge quantities, its application needs further modification.

As shown in Table 10, the computation of DBHI makes use of the assigned values of weight coefficients, which is not ‘close bound’. The total value of the coefficients is 96. The implication is that the computation of the overall BHI is dependent on 96% health condition of the bridge. This can even be more problematic because there are more than 80 bridge CoRe elements identified in the 2019 AASHTO Bridge Manual. Thus, the total value of weight coefficients for different bridges can vary significantly due to the variations in the element’s compositions (i.e., the total value of the weight coefficients can be less-or-greater than 100) depending on the prevailing circumstances.

Table 16 – Modification of bridge Condition Indices (CI) for Denver BHI interpretations.

CI Zones	CI Scales	
Action	Value	Condition description
Immediate action not required **(71-100)**	85 – 100	Excellent – no noticeable effects some aging or wear visible
	70 – 84	Very good – only minor deterioration or defects evident.
Economic analysis of repair alternatives recommended to determine appropriate maintenance action **(41-70)**	55 – 69	Good – some deterioration or defects evident, function not impaired ***(check the critical elements)***.
	`40 – 54	Fair – moderate deterioration, function not seriously impaired
Detailed evaluation required to determine the need for RR&R, safety evaluation recommended **(0-40)**	25 – 39	Poor – serious deterioration in at least some portion of structure, function seriously impaired.
	10 – 24	Very poor – extensive deterioration, barely functional.
	0 – 9	Failed – general failure or failure of a major component no longer functional.

Instead of using the numeric values of individual elements' weight coefficients, the contribution of each element should be standardized as a percentage. Based on this, elements' weight coefficients for different types of bridges can be obtained as a redistributed percentage values of the initial coefficients. For a better interpretation of the DBHI, it is recommended that for computed values of DBHI between 40 and 69, the conditions of critical elements should be checked. This can be included as shown in Table 16. Finally, the modified bridge health index can be computed when additional parameters such as threshold health index and average bridge service life are considered (See Appendix E).

3.6 Conclusions

The successful application of BHI as a decision-making tool depends on how accurately it can predict the short and long-term performances of bridges. In computing the BHI, important weights are usually applied to reflect the changes in the "value" of each element that deteriorates with time. While the failure or replacement cost of each bridge CoRe element can easily be computed, there is currently no consensus on the application of important weights to elements in each state. The nonlinear health index assigns the important weights more realistically than the linear health index, but the general application of this approach could be misleading. Hence, concepts like "pessimistic" and "optimistic" have been introduced recently. Can the present nonlinear health index approach accurately represent the general condition of bridges? Is it too optimistic or pessimistic? These are the questions the need urgent answers for an improvement in the accuracy of BHI as a bridge performance measure. The important weights, including nonlinear health indices, should not be treated as a rule-of-thumb. They should be products of deterioration models developed for each bridge/element.

Various authors have pointed out the effects of "boundary" elements in the computation of BHI. The new concepts such as upper bound (UB) and lower bound (LB) with distribution coefficients are introduced for the boundary CSs, which can be aggregated to obtain CSs compatible with the present 2019 AASHTO format. This new approach can enable bridge inspection engineers to differentiate between quantities with higher and lower performance values within each CS and perform quantities distribution, where necessary, to fine-tune and improve the accuracy of the agency's bridge depreciation models.

CHAPTER 4

4. COMPARATIVE ANALYSIS OF ELEMENT- AND NBI-BASED STOCHASTIC BRIDGE DETERIORATION MODELS

4.1 Introduction

The rapidly growing gap between investment needs and available funds continues to threaten the functionality of a large network of bridge infrastructure, most especially in developed countries. Because of the limitation on resources, it is therefore important that bridge-owning agencies use proper planning and management strategies to make the best use of available funding. An important step in properly managing and preserving a bridge inventory is the prioritization of bridges for preservation (Puls et al., 2018). Thus, bridge managers are usually interested in the long-term performance of bridges and their associated elements. Prediction of such performance (i.e., condition of bridges) is usually captured using depreciation models. Bridge depreciation model, as an integral component of Bridge Management Systems (BMS), now constitutes one of the major requirements for the development of a long-term decision-making framework for effective bridge management. It aids the selection and performance of appropriate work for a bridge at the right point in time and cost-effectively (FHWA, 2018; Yanev & Richards, 2013).

Notably, the forecast of long-term bridge performance expressed through a deterioration model has been identified as one of the main components of BMSs (Zambon, Vidovic, Strauss, Matos, & Amado, 2017). Most of these bridge deterioration models are data-driven, utilizing bridge condition states obtainable from the bridge performance inspection.

In the United States, the two major approaches for the bridge performance inspection include bridge overall-condition-rating, available in the National Bridge Inventory (NBI) inspections for bridge subsystems, and bridge health index, computed from the American Association of State Highway and Transportation Official (AASHTO) element inspections. While the NBI-based deterioration models have been extensively studied, only limited studies have been conducted on comprehensive element-based bridge deterioration models. There is no available information on how the granularity of the element-based inspections affects the overall bridge health index. Additionally, the two approaches have been independently investigated, and the potential impact of implementing the two approaches on the overall bridge management remains relatively unknown. Thus, this study provides a comparative analysis of the bridge deterioration predictive models developed from the two approaches.

This chapter is organized as follows. First, a brief literature review on the bridge deterioration models is presented. Second, the methodology for this study, including a proposed age-bin-based approach is described. Then, the results obtained from the study described in the methodology are presented. A discussion of the results is provided in the following section. Last, conclusions and future work are provided.

4. 2. Literature Review

4.2.1 Bridge Deterioration Prediction Techniques

Several models exist for quantifying bridge deterioration rates. Bridge inspection data have been collected and analyzed since the early 1970's to assist decision-makers in predicting the likelihood of future changes in bridge conditions. A statistical approach is often adopted to investigate structural performance trends in individual elements (M. Chang & Maguire, 2016). A predictive model that can describe the future state of a bridge component has enabled state agencies to prioritize and deploy resources to where they are most needed. A reliable prediction future performance index is expected to directly improve emergency response, management, and budget allocation (GP Bu et al., 2013; DeStefano & Grivas, 1998; Huang, Ong, & Alahakoon, 2015; Khatami, Shafei, & Smadi, 2016).

MAP-21 establishes a performance- and outcome-based program to help state agencies invest resources in projects that "collectively will ensure progress towards the achievement of the national goals." MAP-21 represents a strong commitment to a data-driven, risk-based approach to asset management in the United States. Pursuant to 23 U.S.C.150(c)(3)(A), transportation agencies are required to develop TAMPs which must contain deterioration models, as elaborated in 23 C.F.R. 515.17 and MAP-21 §1106 (Campbell et al., 2016; CFR., 2017; FHWA., 2012; USC., 2019).

At present, cutting-edge bridge management systems classify bridge deterioration models into two major categories: deterministic models and stochastic models (Agrawal, Kawaguchi, & Chen, 2010; Li, Sun, & Ning, 2014). For deterministic models, the measure of bridge condition is expressed without probabilistic considerations, whereas a stochastic approach reflects the uncertainties that each bridge condition represents.

Deterministic models assume that bridge deterioration is certain, and thus a regression analysis is commonly used to determine a decay rate. They generally describe a relationship between factors affecting the facility's deterioration (e.g., bridge age) and condition using a mathematical or a statistical formulation. These models calculate predicted conditions deterministically by ignoring the random error in predictions (Huang et al., 2015; Li et al., 2014; G Morcous, Lounis,

& Mirza, 2003). Such models aim to further improve the overall predictive performance of a system (Huang et al., 2015).

This study uses a stochastic modeling approach, more suitable for handling a large network of bridges such as the approximately 15,000 in-service bridge in Georgia. Moreover, a stochastic approach gives a more realistic deterioration model (M. Chang & Maguire, 2016; Manafpour, Guler, Radlińska, Rajabipour, & Warn, 2018). The Markovian modeling technique, a special stochastic approach long used for bridge deterioration modeling, is described in Section 2.2.

4.2.2 Markovian Bridge Deterioration Models

Markovian bridge deterioration models forecast BHIs based on the concept of condition transitions from one state to another state during a transition period. The Markov-chain approach is a special case of the Markov-process with discrete-time and state parameters. These models have been employed by most state-of-the-art bridge management systems, such as AASHTOWare BrM, BRIDGIT, and Ontario Bridge Management System (Guoping Bu et al., 2011). Bridge deterioration models based on the Markov-chain approach assume a static condition or progressive deterioration to a lower condition state. For example, in AASHTOWare BrM, bridge element deterioration is typically modeled as annual transition estimates across four discrete condition states.

There are two assumptions made in the Markov-chain process. First, the future state of a stochastic process depends only on the present condition (namely, a state independence assumption). The second assumption is that the transition probability between two states should be constant. A constant inspection period, where inspections are performed at predefined and fixed-time intervals, is required (Grussing, 2015; Li et al., 2014). The major advantages of the

Markov-process (Almeida, Teixeira, Delgado, & Engineering, 2015; M. Chang & Maguire, 2016; Huang et al., 2015) are as follows:

- It can reflect a stochastic bridge deterioration process based on variables such as initial conditions, assessment errors, and inherent uncertainties;
- A future-state prediction is based on the present state enabling an incremental approach; and
- It can be applied to a large network of bridges.

The procedure for developing Markovian bridge deterioration models is well documented in the literature (Agrawal et al., 2010; Guoping Bu et al., 2011; Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015; G Morcous, 2006). The most significant task in the Markov-chain process is to determine a transition probability matrix, P, which quantifies the probabilities of condition state transitions (Li et al., 2014). Element-based health indices (0 to 100) in the 2019 AASHTO Bridge Manual are distributed across four possible bridge element states. Condition states 1 and 4 correspond to the best and worst conditions, respectively. A change in condition state is assumed to occur at discrete time intervals that align with routine inspection periods. Consequently, the components, P_{ij}, of the probability matrix, P, represent bridge elements transitioning from state i to state j during a specified period (see Equation 8). The transition matrix has zero values below the diagonal because it is assumed that deterioration takes place without rehabilitation. Thus, the probability of improvement at any state is assumed to be zero (Cavalline et al., 2015). The values above the diagonal matrix indicate transitions to 'immediately' lower condition states. System states are "mutually exclusive and collectively exhaustive" after each transition so that the sum of each row is the unity (M. Chang & Maguire, 2016).

$$P = \begin{bmatrix} P_{11} & 1-P_{11} & & \\ & P_{22} & 1-P_{22} & \\ & & P_{33} & 1-P_{33} \\ & & & P_{44} \end{bmatrix} \tag{8}$$

For the NBI general condition rating, there are nine possible condition ratings distributed across nine possible bridge element states. The transition probability matrix, P, which is raised to the power t (time), is shown in Equation (9), where p9 indicates the probability of CR 9 remaining in CR 9, and q8 indicates the probability of CR9 transitioning to CR8; the other components in the matrix are zero (Agrawal et al., 2010) for each bridge or culvert group.

$$P^t = \begin{bmatrix} \boldsymbol{p1} & & & & & & & & \\ q1 & \boldsymbol{p2} & & & & & & & \\ & q2 & \boldsymbol{p3} & & & & & & \\ & & q3 & \boldsymbol{p4} & & & & & \\ & & & q4 & \boldsymbol{p5} & & & & \\ & & & & q5 & \boldsymbol{p6} & & & \\ & & & & & q6 & \boldsymbol{p7} & & \\ & & & & & & q7 & \boldsymbol{p8} & \\ & & & & & & & q8 & \boldsymbol{p9} \end{bmatrix}^t \tag{9}$$

4.3. Methodology

4.3.1 Overview

The granularity of element-based inspection data enables the development of deterioration models at the element level. These models are more quantitative and informative than the ones derived from the traditional NBI overall condition-rating-based approach for bridge subsystems. However, the element-based approach as currently implemented has its deficiencies. The main shortcoming relates to a lack of enough records. Many bridge authorities worldwide have similar problems using a BMS for accurate predictions of long-term bridge performance and budget planning (GP

Bu et al., 2013; Jeong, Kim, Lee, & Lee, 2017; Manafpour et al., 2018). While some state DOTs have collected element inspection data since the mid-1990's, most have only assembled element inspection data since 2013, in compliance with the MAP-21 Legislation. Georgia Department of Transportation (GDOT) falls into the second category and recently started the element-based inspection of all bridges to comply with the FHWA's element inspection requirements in Title 23 of the United States Code §144(b).

GDOT has collected bridge element inspection data since 2015, yielding two inspection records per bridge between 2015 and 2018, resulting from a biennial inspection process. Based on the experience of the authors, these inspection records are insufficient for developing meaningful deterioration models when a conventional approach is used. As an alternative method, this study has developed an age-bin-based approach for generating bridge deterioration models. This process must be validated once enough element-based inspection data are gathered. This study primarily utilizes GDOT's element inspection records between 2015 and 2018.

While element-based inspection data is relatively new, GDOT has sustained NBI inspection data for all bridges for more than 25 years. Section 4.3.3 describes the approach utilized to develop NBI overall condition-rating-based bridge deterioration models.

4.3.2 Development of Element-based Deterioration Models

4.3.2.1 Deterioration Models for Each Element

The procedure for the development of deterioration models for each element has been described in Chapter 3. The following subsection describes how element health indices are aggregated to develop deterioration models for each bridge.

4.3.2.2. Deterioration Models for Each Bridge

4.3.2.2.1 Aggregate Element Health Indices by Cost-based Weight Factors

A weighted average of element health indices determines an overall BHI. This study utilizes bridge element importance weights recommended for the management of bridges in Florida (See Figure 5). Element weights are determined based on element replacement costs, long-term costs, hazard vulnerability, and engineering judgment (Sobanjo & Thompson, 2016).

Element weights generally represent the relative contributions of each element to the overall structural health of a bridge. This study introduces the concept of dynamic element weights (DEW) to re-scale the weighted health index by 100. For instance, consider a bridge (#32150490) with associated elements in the age bin 1930. The BHI is computed as the weighted values of element health indices in each age bin. The weighted average is 121 and is generally greater than 100. The dynamic health index is calculated as the product of the element health index and its dynamic weight. This study aggregates dynamic health indices for elements in age bins between the years 1920 and 2020.

Table 17 – Element weight factors in age bin 1930 for bridge number 32150490.

Element key	Health index (HI)	Element weight (EW)	Dynamic element weight (DEW=HI*EW/100)	Element health (HI* EW)	Dynamic element health (HI* DEW)
301	61.36	12.00	7.36	736.32	451.81
234	88.42	13.00	11.49	1149.46	1016.35
227	44.29	11.00	4.87	487.19	215.78
331	81.27	14.00	11.38	1137.78	924.67
16	71.54	25.00	17.89	1788.5	1279.49
110	78.37	33.00	25.86	2586.21	2026.81
215	81.27	13.00	10.57	1056.51	858.63
∑		121.00	89.42	8941.97	6773.54
Bridge HI				73.90	75.75

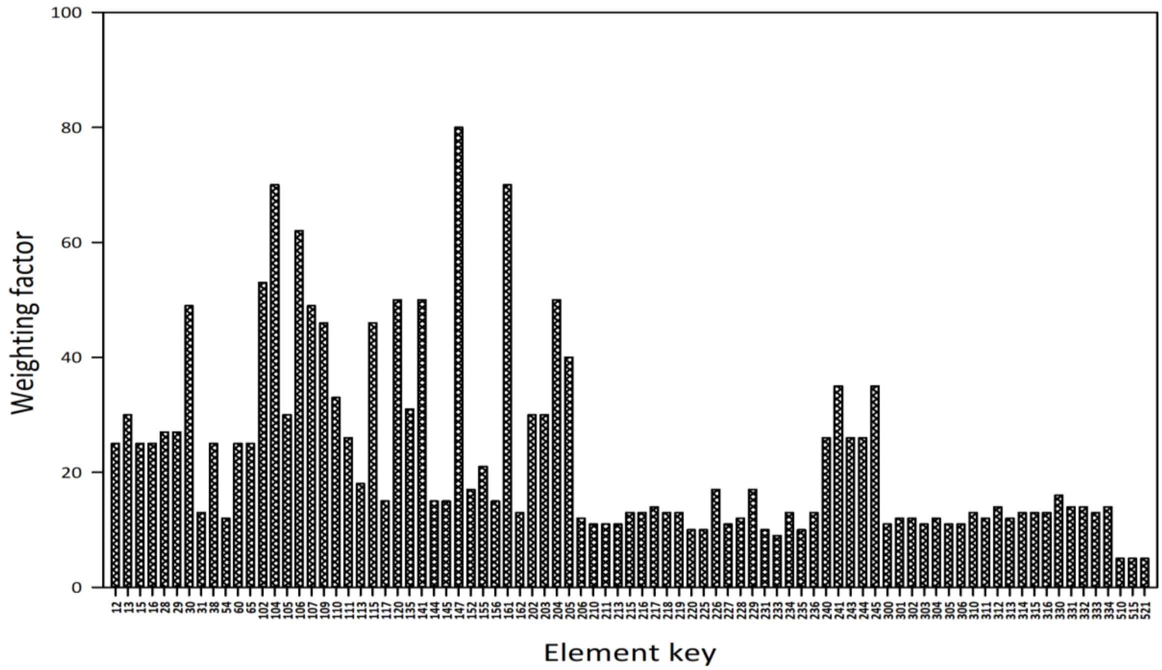


Figure 5 – FDOT bridge element important weights (Sobanjo & Thompson, 2016).

4.3.2.2.2 Develop Deterioration Models for Each Bridge

Deterioration curves for bridges in Georgia are developed using the Markovian approach.

4.3.3 Development of NBI-based Deterioration Models

4.3.3.1 Define NBI data and attributes

4.3.3.1.1 State Code (Item No. 1)

A total of 26 NBI data sets (1992-2017) containing the three-digit state code, ‘134’, Georgia, are downloaded from the NBI website (FHWA-NBI., 2018).

4.3.3.1.2 Structure Number (Item No. 8)

The GDOT bridge identification numbers are saved to develop deterioration models for each bridge in the NBI data.

4.3.3.1.3 Year Built (Item No. 27)

The construction year is saved to review the historic condition ratings. See Appendices A and B.

4.3.3.1.4 Structure Type (Item No. 43)

This NBI item indicates the type of structure for the main span(s). The kind of material (43A) is primarily used to recognize more distinct bridge characteristics in differentiating deterioration models in bridge superstructures. They are divided into five categories: Concrete (Codes 1 and 2), Steel (Codes 3 and 4), and Prestressed/Precast (Codes 5 and 6), Timber (Code 7), and Others (Codes 8, 9, and 0). Culverts are identified by Item No. 43B (Code 19) and independently analyzed from bridges.

4.3.3.1.5 Deck Structure Type (Item Number 107)

Item 107 provides the (material) type of bridge deck system whereas Item 43A is associated with the bridge superstructure type. They are similarly divided into five categories: Concrete (Code 1), Precast (Code 2), Steel (Codes 3 through 7), Timber (Code 8), and the Others (Code 9).

4.3.3.1.6 Condition Ratings – Deck, Superstructure, Substructure (Item Nos. 58 through 60)

The overall deck, superstructure, and substructure condition rating of bridges are used in this study. Code 9 indicates an excellent condition, and 7 indicates bridges in good condition whereas 0 indicates a failed condition.

4.3.3.1.7 Condition Rating - Culverts (Item Number 62)

For culverts, Items 58 through 60 are coded as ‘N’. Therefore, Item 62 is used to evaluate the overall condition rating of culverts.

4.3.3.2 Analyze Condition Rating Transition History

The frequency of condition rating transition occurrences is computed for three bridge components (deck, superstructure, and substructure) as well as culverts. For example, Figure 6 illustrates GDOT's historic trend in the bridge deck condition rating distribution, and Figure 7 shows the year-over-year condition rating (CR) transition probabilities over the past 25 years. The figure indicates the three most frequent CR changes (e.g., deterioration) in the GA inventory are: CR 7−> CR7, CR 8−>CR7, and CR6−>CR6. It also indicates that the CR transition trends have remained fairly unchanged over the past 25 years. The CR transition probabilities are determined by counting the CR transition occurrences between the years 1992 and 2017 in the bridge inventory.

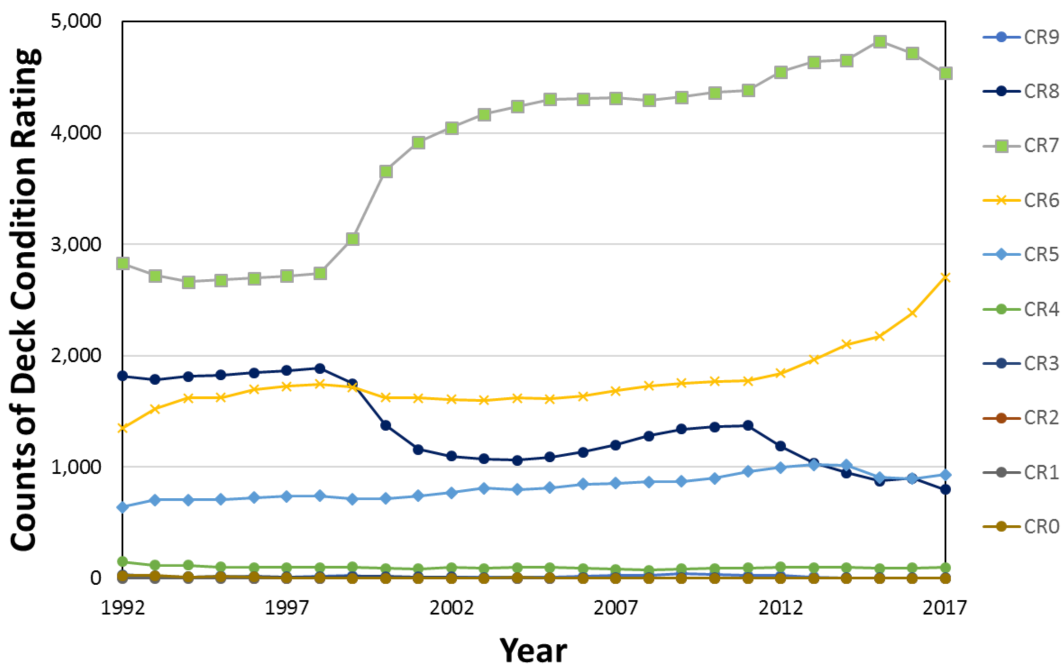


Figure 6 – Condition rating over the past 26 years.

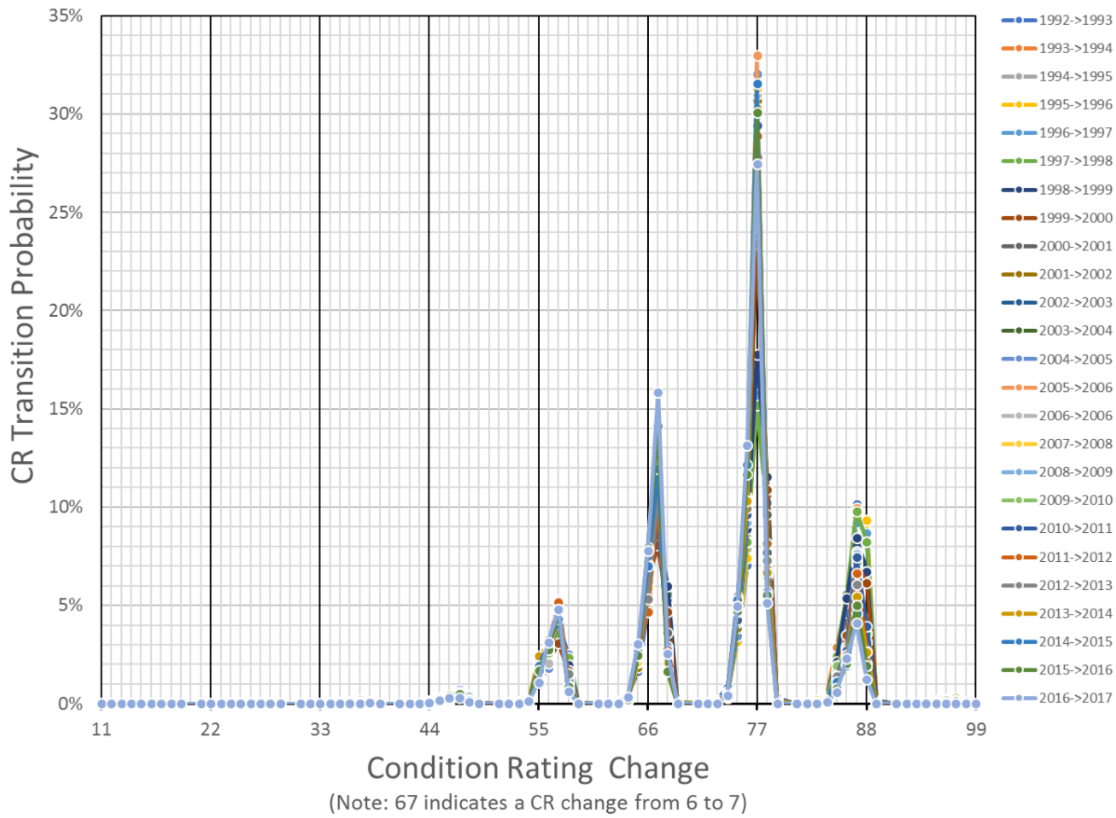


Figure 7 – CR transition frequencies.

4.3.3.3 Develop Deterioration Models for Each Component and Overall Bridge

The entire Georgia bridge inventory is used to derive a transition probability matrix for each bridge component and subgroup. Detailed information on the bridge components and subgroups analyzed can be found in our previous communication (Mi Geum Chorzepa & Oyegbile, 2019). As described in Section 4.3.2, the CR transition counts are used to compute the transition probability matrix, P. Finally, the transition probability matrix, P, described by Equation (8) in Section 4.2.2, is multiplied by a condition rating matrix to determine a deterioration model.

Once a deterioration model is constructed by the above procedure, a plot illustrating the lifecycle of each bridge is generated. Appendix B illustrates a sample plot for culverts and bridges, respectively. For culverts and bridges that were constructed before 1992, an initial condition rating of 8 is assigned, from which CR is linearly extrapolated to the condition ratings reported in 1992. Their construction year records predate the year when the oldest NBI database was recorded, and thus the bridge condition ratings are not available.

4.3.4 Comparison of Element and NBI-based Condition Scores

A Chi-square goodness of fit test is performed to compare element-based bridge deterioration models (developed based on FDOT's weight factors) and NBI overall condition-rating-based bridge deterioration models (see GDOT RP 18-30 final report, 2019 (Mi Geum Chorzepa & Oyegbile, 2019) for a network of bridges under consideration.

The formula for the Chi-square distribution is given as (GP Bu, Lee, Guan, Loo, & Blumenstein, 2014; Y. Jiang & Sinha, 1989):

$$\chi^2 = \sum_{i=1}^{k} \frac{(E(t)_i - A(t)_i)^2}{E(t)_i} \tag{10}$$

where, χ^2 = Chi-square distribution with k − 1 degrees of freedom (DOF); $E(t)_i$= value of condition rating in year i predicted using the element-based models, $A(t)_i$ = value of condition rating in year i predicted using NBI condition-rating-based models; and k = number of prediction years

The approach to the Chi-square hypothesis testing is shown in Figure 8. The test is performed using two bridge deterioration models (element-based and NBI condition-rating-based). NBI condition ratings are rescaled to a 100-point scale (e.g., an NBI condition rating of 9 is scaled to 100), while the health indices are reduced by 22%. This reduction is necessary for a fair comparison. NBI condition-rating-based models are aggregated using Equation (11) to determine a blended general condition rating (Blended GCR) as proposed by the Virginia DOT (VDOT, 2017).

$$\text{Blended GCR} = 0.25(\text{Deck GCR}) + 0.35(\text{Superstructure GCR}) + 0.40(\text{Substructure GCR}) \quad (11)$$

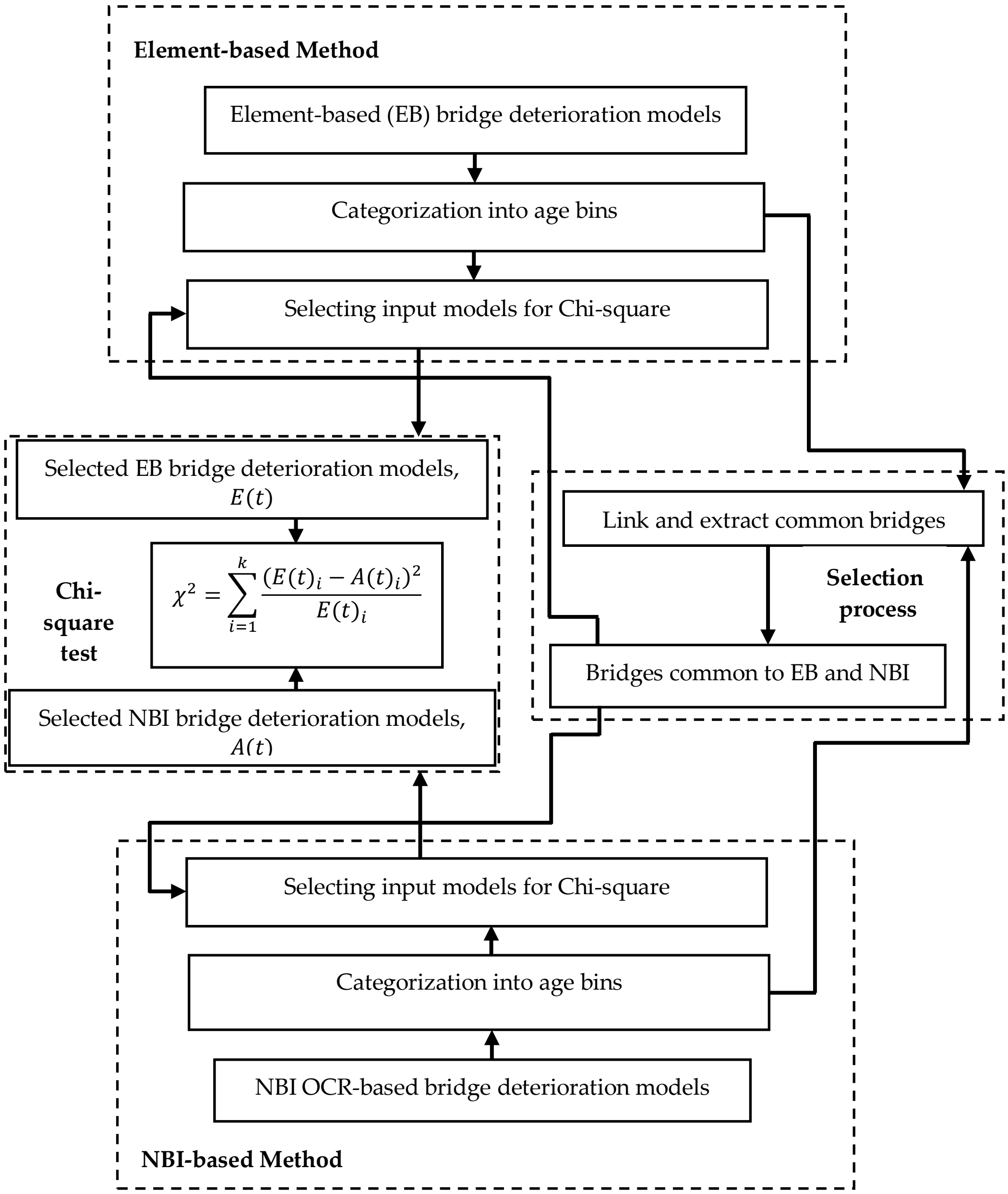


Figure 8 – Process chart for the Chi-Square test.

The difference between the Chi-square and the critical threshold values evaluates the null hypothesis: the two models are not correlated. The larger the difference between the Chi-square and the critical values, the closer the predictions between the Chi-square test parameters (i.e., $E(t)_i$ and $A(t)_i$).

4.4 Results

4.4.1 Element Performance Predictions

The age-bin approach yields a time-dependent health index history for each element.

4.4.1.1 Mathematical expression for describing element performance predictions

Table 18 shows the mathematical equations describing time-dependent element health indices and lists diagonal components (P11, P22, P33, P44) of the transition probabilities for bridge elements.

Table 18 – Equations for describing time-dependent element health index.

Category	Element key	Deterioration equation (Time T in Years)	Transition probabilities			
			P11	P22	P33	P44
Decks and Slabs	12	$0.1511T^3 - 2.4490T^2 + 6.9678\mathrm{T} + 94.2513$	0.9849	0.0049	0.7814	1.0000
	13	$-0.1092T^3 + 1.4851T^2 - 5.1516\mathrm{T} + 101.4598$	0.9998	0.0000	0.0000	1.0000
	15	$0.4884T^3 - 6.0982T^2 + 20.0941\mathrm{T} + 81.4156$	0.9949	0.0527	0.8042	1.0000
	16	$-0.1530T^3 + 1.2990T^2 - 4.6632\mathrm{T} + 103.5154$	0.9839	0.9323	0.8596	1.0000
	28	$0.4265T^3 - 4.0447T^2 + 5.7860\mathrm{T} + 100.4697$	0.9942	0.0000	0.0000	1.0000
	29	$-0.1226T^3 + 0.9684T^2 - 4.8706\mathrm{T} + 103.8687$	0.9825	0.0023	0.9268	1.0000
	30	$0.5547T^3 - 7.2746T^2 + 20.8149\mathrm{T} + 82.3411$	0.9735	0.3872	0.1274	1.0000
	31	$0.1666T^3 - 1.9874T^2 + 3.1748\mathrm{T} + 94.3892$	0.9827	0.0000	0.0000	1.0000
	38	$0.1355T^3 - 1.1674T^2 + 0.7712\mathrm{T} + 99.8981$	0.9972	0.0000	0.0000	1.0000
	54	$0.1192T^3 - 2.1480T^2 + 4.9265\mathrm{T} + 94.6867$	0.9748	0.0114	0.8600	1.0000
	60	$-0.1439T^3 + 2.8658T^2 - 15.4903\mathrm{T} + 115.0714$	0.9988	0.0000	0.0000	1.0000
	65	$-0.6910T^3 + 8.9121T^2 - 34.3159\mathrm{T} + 127.6112$	0.9893	0.0008	0.9839	1.0000
Girders	102	$-0.2733T^3 + 0.6392T^2 + 2.0611\mathrm{T} + 95.3792$	0.9639	0.8947	0.7985	1.0000
	104	$-0.1818T^3 + 2.1016T^2 - 7.1032\mathrm{T} + 104.1719$	0.9968	0.1156	0.9680	1.0000
	105	$-0.3058T^3 + 3.9018T^2 - 14.2819\mathrm{T} + 111.8641$	0.9989	0.0034	0.9660	1.0000
	106	$-0.2391T^3 + 2.3433T^2 - 7.7390\mathrm{T} + 105.5500$	0.9896	0.2662	0.9320	1.0000
	107	$-0.1793T^3 + 1.8265T^2 - 6.1996\mathrm{T} + 103.9503$	0.9936	0.0579	0.7892	1.0000
	109	$0.0048T^3 - 0.0280T^2 - 0.0829\mathrm{T} + 100.0693$	0.9999	0.0000	0.0000	1.0000
	110	$-0.0184T^3 - 0.0247T^2 + 0.6066\mathrm{T} + 97.7558$	0.9971	0.0242	0.7580	1.0000
	111	$-0.2454T^3 + 2.6258T^2 - 9.4648\mathrm{T} + 108.3868$	0.9924	0.0648	0.7871	1.0000
Stringer	113	$-0.3022T^3 + 5.7739T^2 - 30.3880\mathrm{T} + 130.2841$	0.9984	0.0000	0.0000	1.0000
	115	$-0.3162T^3 + 3.5916T^2 - 14.1909\mathrm{T} + 108.5664$	0.9817	0.0000	0.9684	1.0000
	117	$0.4058T^3 - 7.0331T^2 + 25.7675\mathrm{T} + 77.5086$	0.9559	0.8862	0.7874	1.0000

Table 18 Continued–Equations for describing time-dependent element health index.

Category	Element key	Deterioration equation (Time T in Years)	Transition probabilities P11	P22	P33	P44
Trusses/ Arches	120	$-0.0764T^3 + 1.1226T^2 - 8.0852T + 108.1244$	0.9888	0.0000	0.0000	1.0000
	135	$0.3726T^3 - 4.8292T^2 + 8.0359T + 94.8630$	0.9446	0.0032	0.7394	1.0000
	141	$-0.0136T^3 + 0.5720T^2 - 11.6083T + 111.0455$	0.9225	0.0000	0.9937	1.0000
	144	$0.2997T^3 - 2.8672T^2 - 2.0216T + 103.0959$	0.9510	0.0000	0.0000	1.0000
	145	$-0.0136T^3 + 0.5720T^2 - 11.6083T + 111.0455$	0.9225	0.0000	0.9937	1.0000
Floor Beams & Miscellaneous Superstructure Elements	147	$0.2575T^3 - 4.0389T^2 + 11.7925T + 91.7796$	0.9766	0.0166	0.8501	1.0000
	152	$-0.2929T^3 + 5.4006T^2 - 27.6338T + 127.6848$	0.9992	0.0000	0.0000	1.0000
	155	$-1.0000T^3 + 11.2215T^2 - 18.5911T + 27.3454$	0.0000	0.0755	0.0008	1.0000
	156	$0.2142T^3 - 3.1530T^2 + 6.4074T + 97.1074$	0.9718	0.0026	0.7784	1.0000
	161	$-0.1660T^3 + 3.6218T^2 - 24.6024T + 123.4673$	0.9752	0.0000	0.0000	1.0000
	162	$0.3427T^3 - 3.5559T^2 + 6.2069T + 98.0005$	0.9916	0.0000	0.0000	1.0000
Columns/Pier Walls	202	$-0.2229T^3 + 2.7735T^2 - 15.8273T + 116.0349$	0.9645	0.0125	0.9809	1.0000
	203	$1.6130T^3 - 19.1205T^2 + 54.1177T + 60.2429$	0.9520	0.0212	0.4622	1.0000
	204	$0.0410T^3 - 0.4741T^2 + 1.3183T + 99.0977$	0.9996	0.0282	0.7751	1.0000
	205	$-0.1974T^3 + 1.8931T^2 - 6.4979T + 102.9826$	0.9895	0.0184	0.8380	1.0000
	206	$-0.5789T^3 + 8.7546T^2 - 43.1680T + 143.6437$	0.9797	0.0000	0.0000	1.0000
	210	$0.1867T^3 - 2.1425T^2 + 4.7253T + 94.4143$	0.9927	0.0000	0.0000	1.0000
	211	$-0.3867T^3 + 4.8406T^2 - 17.5379T + 111.2257$	0.9959	0.0475	0.8097	1.0000
	213	$-0.3624T^3 + 5.4961T^2 - 24.2161T + 108.9389$	0.9914	0.0000	0.0000	1.0000
Abutments	215	$-0.0501T^3 + 0.5681T^2 - 2.8296T + 101.7064$	0.9958	0.0000	0.0000	1.0000
	216	$-0.0368T^3 + 0.3911T^2 - 3.0559T + 102.2274$	0.9932	0.0000	0.0000	1.0000
	217	$-0.1438T^3 + 2.5721T^2 - 14.8861T + 113.1101$	0.9921	0.1507	0.3741	1.0000
	218	$0.0999T^3 - 0.8046T^2 - 0.5969T + 102.1581$	0.9963	0.0000	0.0000	1.0000
	219	$-0.5122T^3 + 8.5317T^2 - 41.0527T + 123.9565$	0.7899	0.0000	0.9999	1.0000
Piles/Pier Caps/Footings	220	$-0.6389T^3 + 10.1743T^2 + 2.8321T + 135.1197$	0.9223	0.0000	0.0000	1.0000
	225	$0.0093T^3 + 1.5020T^2 - 15.8565T + 115.5996$	0.9895	0.0000	0.0000	1.0000
	226	$-0.1297T^3 + 1.3238T^2 - 7.8336T + 104.4685$	0.9718	0.0052	0.9838	1.0000
	227	$0.3511T^3 - 3.7013T^2 + 3.9339T + 96.3666$	0.9602	0.0328	0.8830	1.0000
	228	$-0.1313T^3 + 2.7077T^2 - 18.0713T + 114.9383$	0.9805	0.0000	0.0000	1.0000
	229	$-0.7298T^3 + 9.8749T^2 - 39.9382T + 132.1143$	0.9823	0.0000	0.9859	1.0000
	231	$-0.7233T^3 + 11.1874T^2 - 52.2665T + 142.4373$	0.9803	0.0000	0.0000	1.0000
Piles/Pier Caps/Footings	233	$-0.2144T^3 + 2.0851T^2 - 7.4290T + 105.5556$	0.9882	0.0477	0.9307	1.0000
	234	$-0.0294T^3 + 0.2793T^2 - 1.4889T + 100.7699$	0.9965	0.0309	0.7773	1.0000
	235	$-0.1744T^3 + 2.1612T^2 - 9.3287T + 108.7321$	0.9938	0.0563	0.7901	1.0000
	236	$0.1402T^3 + 0.5315T^2 - 15.7073T + 116.7351$	0.9606	0.0000	0.9999	1.0000
Culverts	240	$-0.0842T^3 + 2.3358T^2 - 18.6154T + 114.8947$	0.9732	0.1743	0.4373	1.0000
	241	$0.0136T^3 - 0.0723T^2 - 2.9892T + 100.0298$	0.9887	0.0000	0.0000	1.0000
	243	$-0.4643T^3 + 7.2809T^2 - 34.7551T + 134.1467$	0.9933	0.0000	0.0000	1.0000
	244	$-0.4346T^3 + 7.1332T^2 - 35.6148T + 131.7878$	0.9905	0.0008	0.0002	1.0000
	245	$0.1813T^3 - 2.4789T^2 + 2.3095T + 101.1617$	0.9695	0.3609	0.3189	1.0000
Joints	300	$-0.4704T^3 + 6.6107T^2 - 29.3921T + 112.2405$	0.9764	0.1710	0.6086	1.0000
	301	$-0.1202T^3 + 2.14401T^2 - 15.9017T + 109.8458$	0.9693	0.1029	0.2788	1.0000
	302	$-0.0154T^3 + 2.4377T^2 - 18.5906T + 104.2560$	0.9936	0.1302	0.5132	1.0000
	303	$-1.0185T^3 + 14.2996T^2 - 64.5428T + 158.1630$	0.9545	0.0320	0.6716	1.0000
	304	$-0.0565T^3 + 2.2024T^2 - 17.4749T + 117.9738$	0.9913	0.0000	0.0000	1.0000
	305	$-0.3536T^3 + 3.6514T^2 - 11.9816T + 105.1657$	0.9868	0.0346	0.8587	1.0000
	306	$0.0053 - 0.5761T^2 - 4.1493T + 95.4245$	0.9406	0.0221	0.6084	1.0000

Table 18 Continued – Equations for describing time-dependent element health index.

Category	Element key	Deterioration equation (Time T in Years)	Transition probabilities P11	P22	P33	P44
Bearings	310	$-0.0055T^3 - 0.1459T^2 + 0.5291\text{T} + 99.6494$	0.9967	0.0766	0.9125	1.0000
	311	$-0.0025T^3 - 0.3854T^2 + 0.8707\text{T} + 91.6961$	0.9868	0.0000	0.0000	1.0000
	312	$0.1135T^3 - 1.3667T^2 + 4.1231\text{T} + 96.7693$	0.9988	0.2028	0.2218	1.0000
	313	$-0.1253T^3 + 1.4890T^2 - 7.3435\text{T} + 102.3654$	0.9883	0.0000	0.0000	1.0000
	314	$-0.0836T^3 + 0.8993T^2 - 7.4061\text{T} + 107.9560$	0.9729	0.1267	0.9880	1.0000
	315	$-0.3162T^3 + 3.5916T^2 - 14.1909\text{T} + 108.5664$	0.9817	0.0000	0.9684	1.0000
	316	$-0.5684T^3 + 6.8948T^2 - 25.3556\text{T} + 120.6585$	0.9903	0.2095	0.9605	1.0000
Railings	330	$-0.4342T^3 + 4.8417T^2 - 15.4665\text{T} + 112.1704$	0.9957	0.0490	0.8068	1.0000
	331	$-0.0497T^3 + 0.6634T^2 - 2.8795\text{T} + 101.8070$	0.9983	0.1223	0.3533	1.0000
	332	$-0.0316T^3 + 1.1579T^2 - 10.0941\text{T} + 109.6748$	0.9917	0.0000	0.0000	1.0000
	333	$-0.6065T^3 + 6.9569T^2 - 22.9647\text{T} + 119.0347$	0.9951	0.0512	0.8047	1.0000
	334	$-0.6813T^3 + 7.5481T^2 - 23.6620\text{T} + 119.1135$	0.9942	0.0606	0.8077	1.0000
Wearing Surface and Protective Coating	510	$0.0737T^3 - 0.9915T^2 + 2.5419\text{T} + 95.5164$	0.9947	0.0000	0.0000	1.0000
	515	$-0.2595T^3 + 2.9795T^2 - 12.8247\text{T} + 107.3627$	0.9775	0.0137	0.9853	1.0000
	521	$-0.1805T^3 + 2.0346T^2 - 6.5042\text{T} + 105.3158$	0.9987	0.0303	0.8144	1.0000

4.4.1.2 Deterioration curves for each element

The long-term performance of bridge elements greatly influences the overall health of bridges in Georgia. For example, in Figure 9, a steel deck with corrugated material in a highly corrosive marine environment will deteriorate at a much faster rate than a reinforced concrete deck. Thus, bridge element deterioration models are invaluable for the development of short- and long-term planning strategies for the bridges considered in this study. Appendix C presents deterioration predictions for the remaining bridge elements in Georgia.

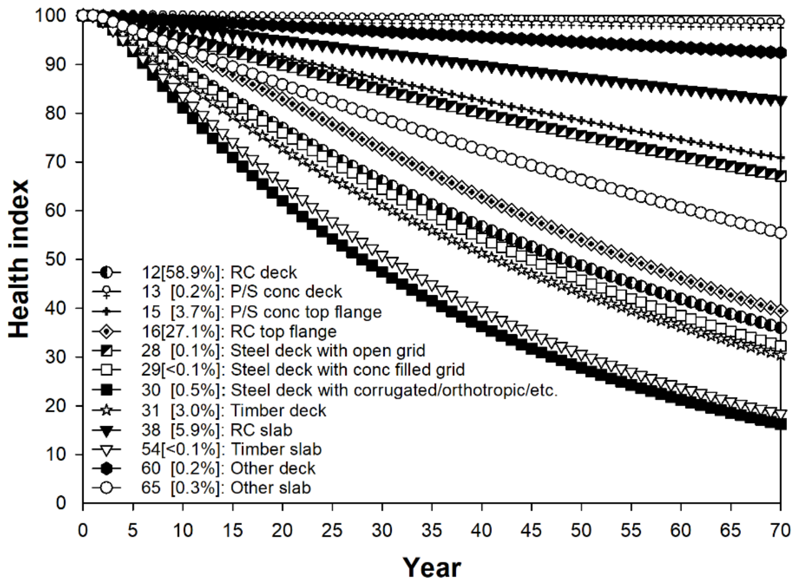


Figure 9 – Deck and slab elements in Georgia.

RC = Reinforced Concrete; P/S = Prestressed/Precast; conc = concrete; and Steel deck with corrugated = steel deck with corrugated panels

Note: In the brackets, the presence of each element within the Deck & Slab category is shown as a percentage.

Figure 9 illustrates the overall performance of deck and slab elements. In reviewing the figure, it is important to recognize that Georgia's bridge inventory consists of approximately 60% reinforced concrete decks (Element #12). Based on these results, long-term performance of bridge elements is mainly dependent on the following factors: (1) material type and properties; (2) resistance to environmental factors such as corrosion; (3) areas of applications, e.g., under water, surface, or concealed; and (4) design type. In reviewing the element-level deterioration prediction models in Appendix C, it is also important to recognize that the number of elements affects the results. Figures 10 and 11 show that Element #12's health scores vary each year, particularly for Inspection Area #6, when normalized by the number of elements as shown in Figure 11.

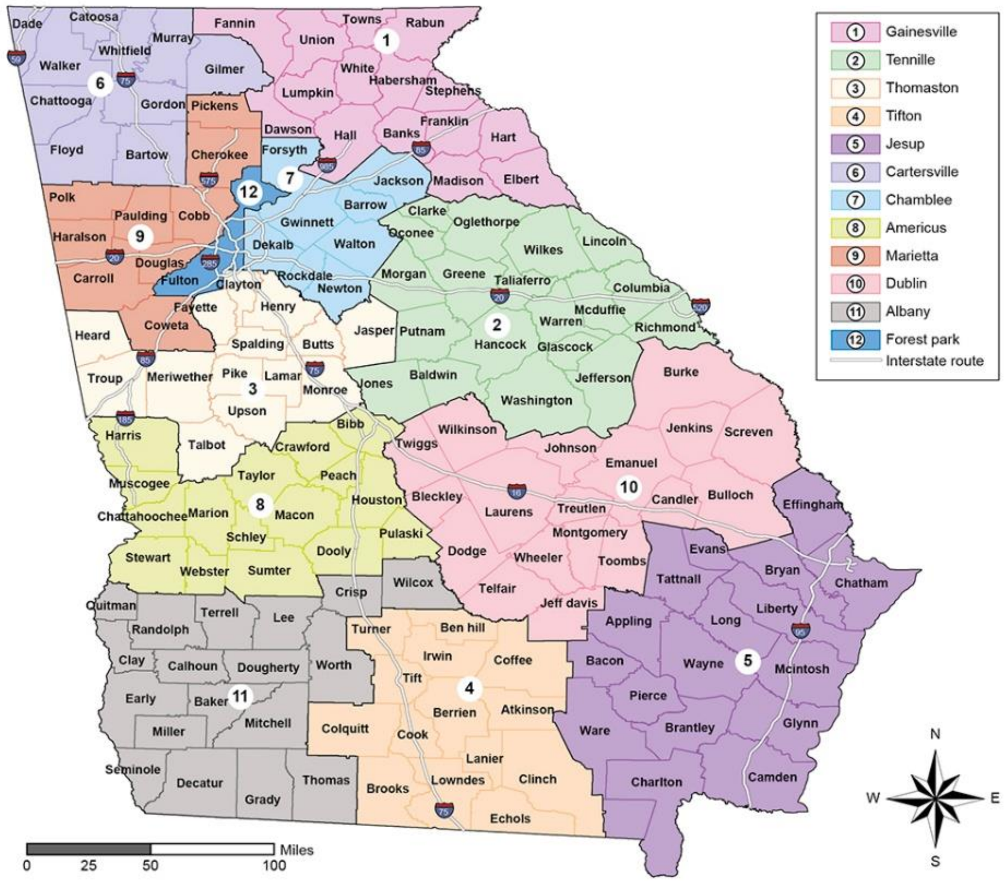


Figure 10 – Twelve (12) inspection areas in Georgia

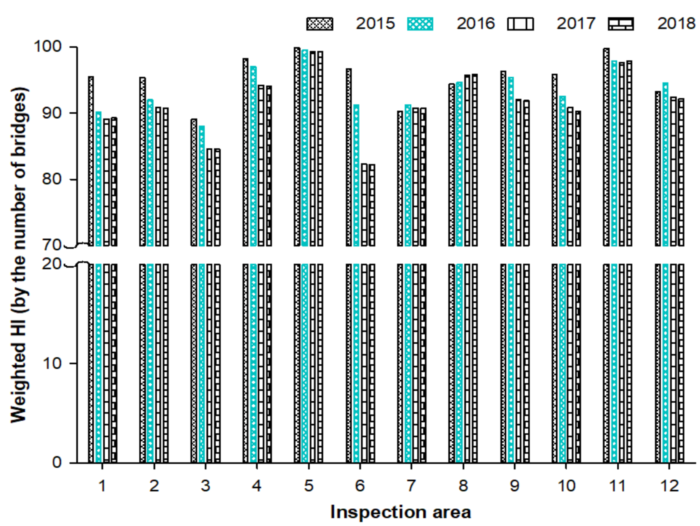


Figure 11 – Health index normalized by the number of bridges (Element No. 12).

4.4.2 Element-based Overall Bridge Performance Predictions

Deterioration models for 14,039 bridge structures have been developed. This number includes 9,019 bridges and 5,020 culverts. Figures 12 and 13 show the deterioration curves for both bridges and culverts and bridges only, respectively, in each of the 12 age categories. The deterioration curves for 'one-element' bridge structures (i.e., culverts only) are shown in Appendix C.

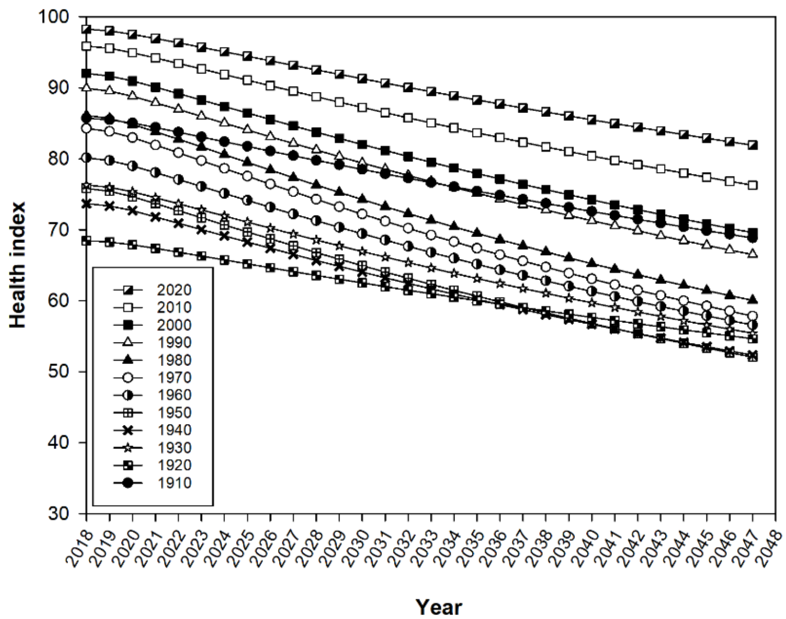


Figure 12 – Health index predictions of 14,039 bridges and culverts in Georgia.

Culverts generally have a faster deterioration rate than bridges (Perrin Jr & Dwivedi, 2006). Therefore, Figure can be misleading when reviewing the predictions for bridges and culverts together. In Figure 13, the HI predictions of bridges are isolated from Figure 12. Figure 13 indicates that older bridges yield slightly higher deterioration rates, which is reasonable based on Figure 14 and agrees with previous research findings (Bulusu & Sinha, 1997; George Morcous, Rivard, & Hanna, 2002; Qiao et al., 2016). In Figure 13, the uniquely slower deterioration of bridge structures in age categories 1920 and 1910 may be attributed to increased attention to maintenance over their service life and/or other reasons such as the limited number of bridges.

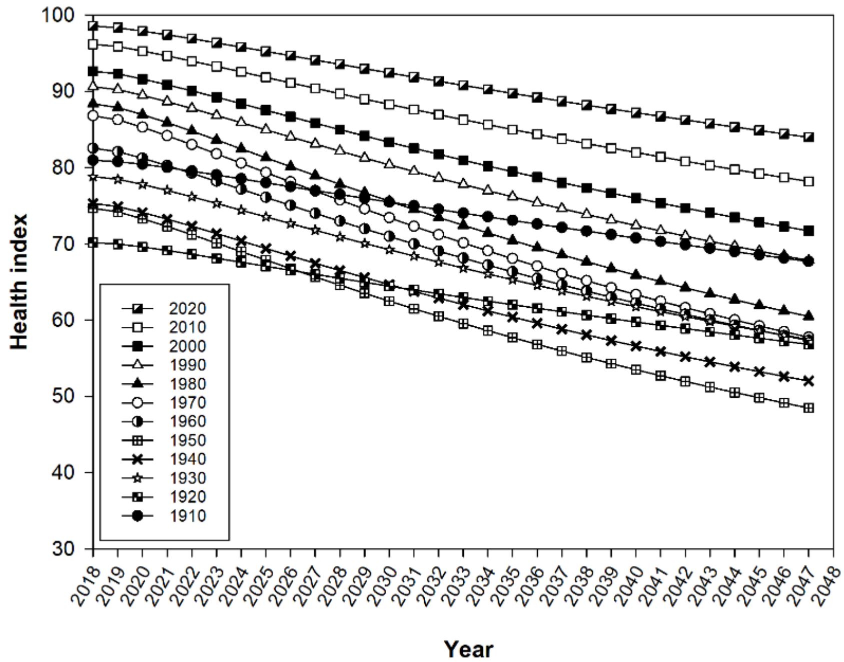


Figure 13 – Health index predictions of 9,019 bridges only in Georgia.

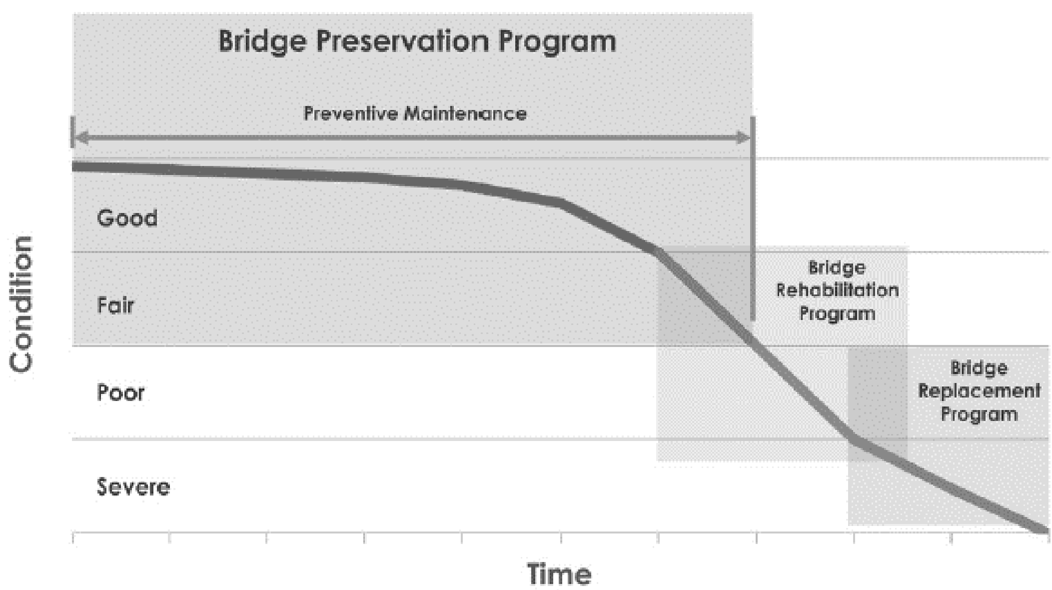
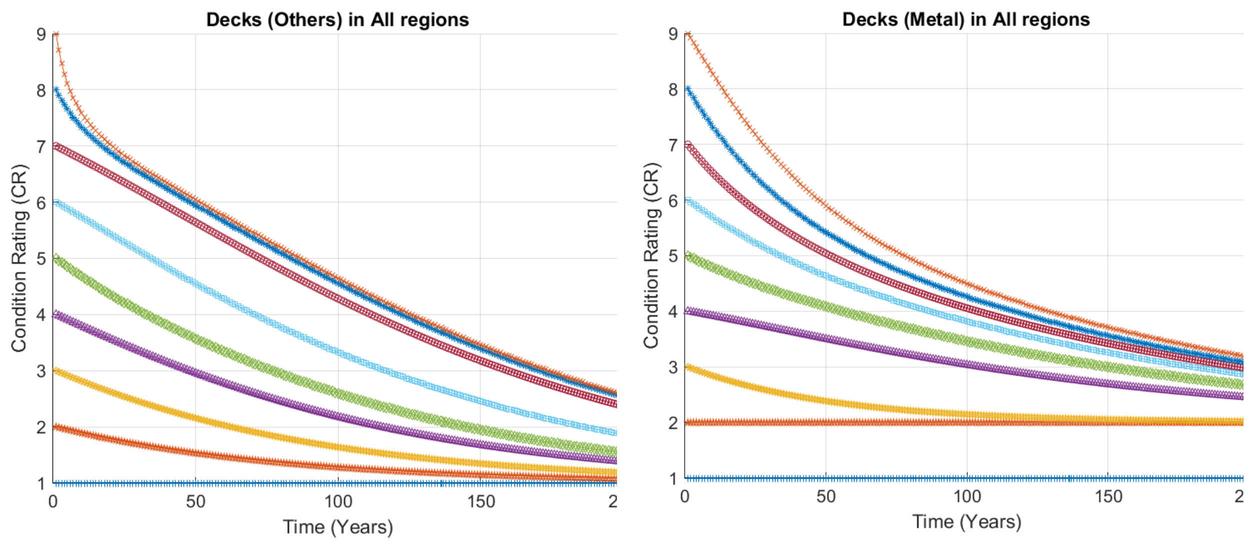


Figure 14 – Typical bridge condition over time (FHWA., 2018).

4.4.3 NBI-based Bridge Component Performance Predictions

Figure 15 shows the deterioration curves for all concrete and metal bridge decks in Georgia, based on a 1-9 CR scale. Comprehensive NBI-based deterioration curves for all networks of bridges in Georgia can be found in the GDOT RP 18-30 final report, 2019 (Mi Geum Chorzepa & Oyegbile, 2019).



(a) (b)

Figure 15 – Deterioration models for bridge decks: (a) Concrete; (b) Metal.

4.4.4 Element versus NBI-based Predictions

Overall, element-based bridge prediction models yield steeper deterioration curves (see Appendix D). Due to this discrepancy, the predictions of the two models are not well correlated although they have similar trends. The outcomes of the hypothesis test for 9,019 bridges are presented in Table 19, which summarizes the distribution of discretized Chi-square values at 99 DOFs, a Chi-square critical value of 123.23, at a significance level ($\alpha = 0.05$).

Table 19 – Discretization of χ^2 using percentages at a significance level of 0.05.

χ^2 percentage	Bridge count in each age category												
	2020	2010	2000	1990	1980	1970	1960	1950	1940	1930	1920	1910	1900
10	128	366	301	255	98	61	53	0	13	0	0	0	0
20	112	245	192	169	76	70	59	3	8	3	0	0	0
30	25	135	70	71	41	33	42	14	8	6	0	0	0
40	18	85	72	67	29	20	25	11	9	2	0	0	0
50	13	31	27	33	25	19	18	7	5	2	0	0	0
60	3	21	18	31	13	9	19	4	2	4	2	0	0
70	2	28	12	20	10	14	15	2	3	2	2	0	0
80	4	29	13	18	13	7	18	1	4	2	3	0	0
90	4	16	11	14	7	3	11	1	1	2	1	1	0
100	2	25	8	16	14	7	11	2	3	1	1	1	0
>100	68	467	635	874	979	1023	794	269	155	48	18	1	2

Note: χ^2 percentage = Chi-square percentage.

Table 20 – Description of discretized χ^2 in form of percentages.

χ^2 percentage	Description
10	0<=χ^2 percentage <=10
20	11<=χ^2 percentage <=20
30	21<=χ^2 percentage <=30
40	31<=χ^2 percentage <=40
50	41<=χ^2 percentage <=50
60	51<=χ^2 percentage <=60
70	61<=χ^2 percentage <=70
80	71<=χ^2 percentage <=80
90	81<=χ^2 percentage <=90
100	91<=χ^2 percentage <=100
>100	χ^2 percentage >=101

Table 20 gives the discretized Chi-square percentage values. Equation (12) is used to calculate the Chi-square in the form of a percentage. Figure 16 shows the percentage error ─ the NBI and element-based data are not correlated.

$$\text{Chi-square percentage} = \left(\frac{\chi^2}{\chi^2\text{critical}}\right) * 100 \tag{12}$$

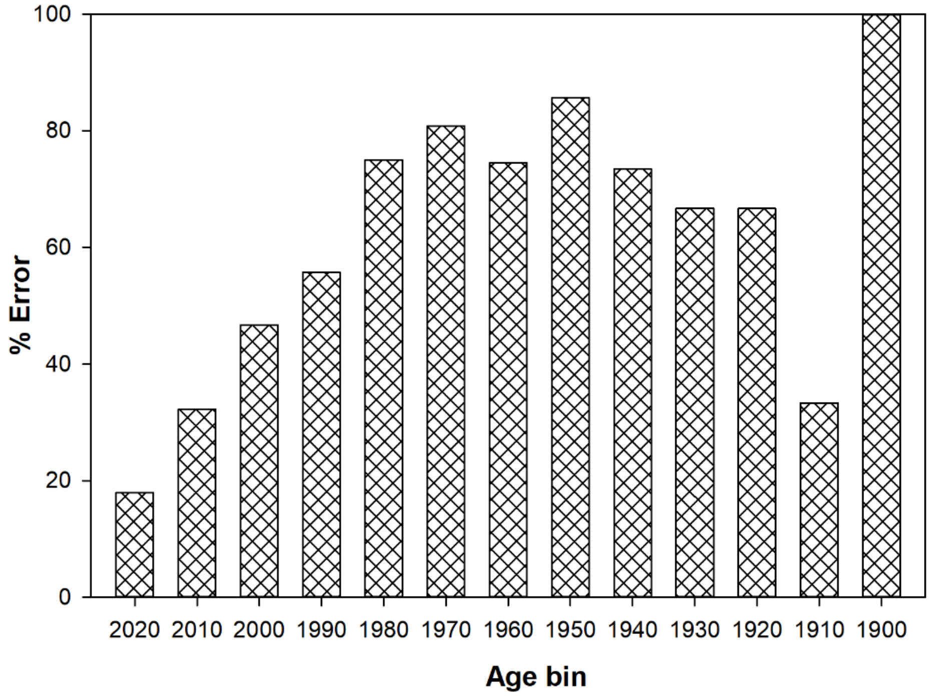


Figure 16 – Chi-Square percentage (% error) in each age bin.

4.5 Discussion

The performance of BMSs for optimal bridge MR&R strategy relies heavily on the efficiency bridge deterioration models. Efficient bridge deterioration models are valuable for future investment and design decisions. In this study, element- and NBI-based stochastic bridge deterioration models have been developed and compared for 14,039 bridges. For the element-based approach, due to the insufficiency of the inspection data, deterioration models for bridge elements are developed by classifying bridges in 12 age-bins. The projected long-term performance of the bridge elements in each category (e.g., decks and slabs) shows a strong correlation to the design and material types, which agrees with previous research findings on the field bridge performance (Lee, 2002; Pyc, 1998). For example, steel decks, if not adequately protected, may deteriorate at faster rates than reinforced concrete decks. Presently, steel decks with corrugated metal have the fastest deterioration rates among bridge decks in Georgia.

The deterioration models give a good estimate of the element average service lives in Georgia. For the element-based overall bridge deterioration models, culverts generally have faster deterioration rates than bridges, with shorter service lives. The results obtained also show the uniquely slower deterioration of much older bridge structures, which may be attributed to increased attention to maintenance over their service life and/or other reasons such as the limited number of bridges.

The comparative analysis of the two deterioration models provides useful guides to decision-makers on the application of the models in the BMSs. Overall, element-based bridge prediction models yield steeper deterioration curves. Further review of the results shows an increasing steepness of the element-based bridge prediction models as the bridges become older, excluding much older bridges in lower age-bins. This shows that the older the bridges, the more the likelihood of discrepancies between the two models. This can be attributed to the fact that the element-based data offers far more detailed information regarding the bridge health status/performance reliability, most especially for older bridge structures where more defects and higher deterioration rates are expected. Due to the observed discrepancy between NBI and element-based bridge condition ratings, if both NBI and element-based inspection records were to be maintained, consistent criteria must be applied to close the gap.

4.6 Conclusions

Through this study, the authors have assessed bridge health indices (BHIs), developed deterioration prediction models for bridge elements and bridges, and compared element-based and NBI-based bridge deterioration models for a network of bridges in Georgia. Based on the findings of this study, the following conclusions are made:

1. The projected long-term performance of bridge elements, particularly decks and girders, shows strong correlations with two important factors, namely: (1) design types (i.e., prestressed and reinforced concrete) and (2) material types (i.e., concrete, steel, and timber). In terms of design, prestressed concrete members as a whole yield the best long-term element health index. For material types, bridge elements with concrete materials tend to lose their health index at slower rates than those with other materials (see Appendix C).
2. Culverts (see Figure C.10) overall have faster deterioration rates, in the range between 35 and 85% HI reductions in 70 years, than bridges (see Figure 13) showing about 15-25% HI reductions over 70 years, regardless of age. Steel culverts depreciate relatively faster (see Figure C.10) although only less than 10% of the culverts are made of steel.
3. Most bridge elements' deterioration rates tend to be slower as time passes (see Appendix C). This prediction trend is not anticipated but consistent with the findings of a previous study (Mi Geum Chorzepa & Oyegbile, 2019).
4. The results of the Chi-square test accept the null hypothesis that the element- and NBI- based bridge condition prediction models are not correlated; element-based BHIs are generally 22% higher than NBI condition scores when rescaled to 100.
5. Similar to NBI deterioration models (Mi Geum Chorzepa & Oyegbile, 2019), element-based forecasting trends indicate that bridges deteriorate slower as time passes (see Appendix D), which is not expected. That is, deterioration curves are steeper in the short term.

CHAPTER 5

5. COACTIVE PRIORITIZATION BY MEANS OF CONTINGENCY TABLES FOR ANALYZING ELEMENT-LEVEL BRIDGE INSPECTION RESULTS AND OPTIMIZING RETURNS

5.1 Introduction

Transport infrastructure represents the complex, fixed, and crucial asset of a transport system. In order to manage constructed facilities such as in-service bridges, one needs to understand how bridges perform over time. A bridge generally consists of 30–80 elements, each of which is assessed in the recently-mandated Element-level Bridge Inspection (AASHTO, 2019). In order to analyze data from the Inspection process, transportation agencies usually calculate a Bridge Health Index (BHI). This is an element-priority-weighted average performance measure of bridges' conditions. Therefore, a bridge performance evaluation entails a rigorous process of obtaining elements' condition states. However, a performance measure (or BHI) is not the only factor that determines a bridge action (preventive maintenance, rehabilitation, or replacement) priority. Factors such as the bridge action costs (i.e., preventive maintenance, rehabilitation, or replacement costs), threshold BHI, and life cycle affect a bridge action prioritization plan. Thus, an efficient prioritization analysis incorporating such factors optimizes allocation of limited funds because it enables cost-effective preventive maintenance, rehabilitation, or replacement (MRR) decisions (Phillips, 2017; Puls et al., 2018). Among the factors, the bridge service life is dependent on the complex interactions among elements. There are groups of elements that act together to affect the BHI. They are referred to as "Co-Active elements" in this dissertation. When one prioritizes these elements for a bridge action (e.g., deck treatment as a preventive maintenance), the overall bridge performance significantly improves (Inkoom & Sobanjo, 2018; Sabatino & Frangopol, 2017), and the improvement is quantifiable.

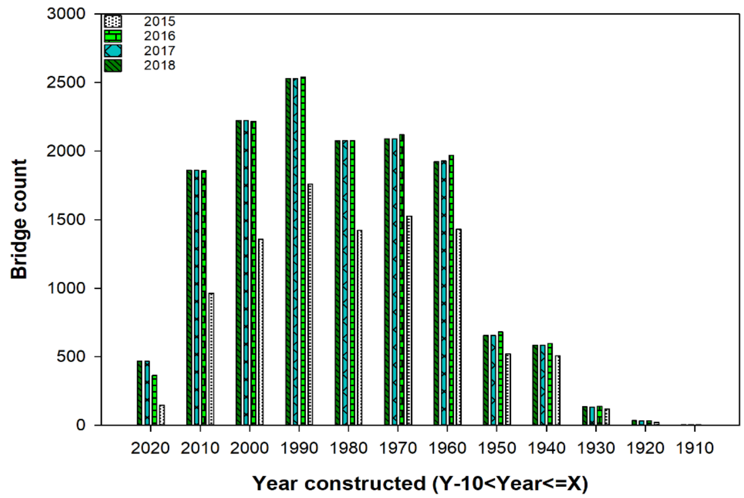
5.1.1 General Background on Bridge Elements

Elements in this dissertation refer to commonly recognized (CoRe) structural elements that constitute a bridge (AASHTO, 2019). This study develops a methodology based on the concept of "Co-Active elements". The word, "Co-Active", is used to represent a small group of elements that act together to improve a BHI over time. The term, 'Co-Activeness', measures the degree of inter-dependency among "Co-Active elements".

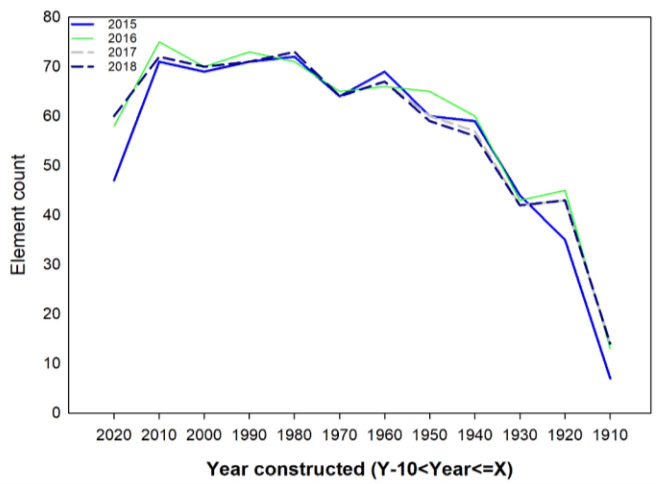
The average service life of bridges in Georgia is 80–100 years. With the existing prediction models, however, BHIs rapidly decrease and do not yield the expected service lifecycle. This is because the existing approach for bridge performance evaluation and MRR prioritization in the U.S. does not consider how elements' inter-dependencies affect the BHI, resulting in overly conservative predictions. For example, replacing a damaged expansion joint is inexpensive. It has an insignificant impact on the overall performance of the bridge in the short term, relative to other elements such as a column. However, as de-icing salt and/or contaminated water ingresses through the damaged expansion joint over time, it accelerates the deterioration of other critical elements beneath it. The deterioration rate of an adjacent element, deck, may also increase when debris accumulates in the expansion joints and restricts normal expansion and contraction of the deck. Thus, "Co-Active elements" are a group of elements, including expansion joint and other elements such as bearing and cap beam, which are affected by a deterioration of an expansion joint.

5.1.2 Motivation

The Georgia Department of Transportation (GDOT) element-level bridge inspection data, which has been maintained over the past four years, between 2015 and 2018, serves as an input for the analyses performed in this study



(a)



(b)

Figure 17 – Bridge and element counts in the Georgia (GA) bridge inventory. (a) The number of bridges constructed in 12 age bins. (b) The number of elements in a bridge by year constructed.

Figure 17 illustrates that the inspection data contains 14,570 bridge structures (including culverts), with an average age of 40 years. The figure shows a steady increase in the number of bridges and elements in each age bin with a 10-year increment, based on Georgia's bridge inspection results for the years 2015 through 2018. Figure 17a shows that 2074 bridges constructed between 1970 and 1980 and were reported in the inspection year 2018. For the bridges built between 1980 and 1990 (designated as "1990" in the x-axis), 2530 bridges containing 72 elements, were reported in the same inspection year, 2018. Figure 17b shows an increase in the number of elements in recently constructed bridges and indicates that a bridge can contain up to 75 elements.

5.1.3 Research Goals

This study aims to answer the following three key research questions:

3. Can one define inter-dependent relationships among bridge elements' health indices?
4. How should one optimize a return on investment (ROI) in terms of bridge service life extension? That is, how should one quantify the effects of inter-element relationships as a function of time and evaluate bridge long-term performance?
5. Do inter-element relationships affect importance weighting factors and help prioritize actions (preventive maintenance, rehabilitation, or replacement) on bridge elements?

5.1.4 Research Scope

An analytical study consisting of three parts is designed for the implementation of a Bridge Co-Active Prioritization Model (Br-CPM). Each of the three parts below provides answers for Section 1.2:

- In Part 1, inter-element relationships are defined and described as a function of time (time-dependent Co-Active coefficient).
- In Part 2, collaboration factors are computed to determine the Prioritization Coefficient (PC), by applying Co-Active coefficients from a contingency table.
- In part 3, bridge elements and overall health indices are assessed.

5.1.5 Significance

Due to the complexity of bridges, elements make varying degrees of structural contributions to BHIs. Element importance-weighting factors measure how important each element is, in terms of its contribution to the BHI. Hence, these factors are critical components for measuring bridge performance. Previous studies focus on estimating element weight factors based on the cost and functional importance of each element (Adhikari, Moselhi, & Bagchi, 2013; Inkoom et al., 2017; X. Jiang & Rens, 2010a, 2010b; Sobanjo & Thompson, 2016). This study additionally accounts for the inter-dependencies that exist among elements in determining element weight factors, based on the concept of "Co-Active elements", and accounts for the time-value of element's depreciation. Finally, a Bridge Co-Active Prioritization Model (Br-CPM) is introduced. The Br-CPM determines how "Co-Active elements" affect a bridge health index and its service life at discrete time

5.2 Literature Review

The scope and application of bridge MRR prioritization analysis largely depend on state Departments of Transportation (DOTs) bridge management program and how they measure bridge performance. The American Association of State Highway and Transportation Officials (AASHTO) sufficiency rating (SR) and National Bridge Inventory (NBI) general condition rating (GCR) among others have been routinely used as bridge performance measures since the 1970s. The AASHTO SR is a performance measure, which indicates safety, functionality, overall adequacy, and ability of a bridge to remain in service (Anderson et al., 2017; Chase et al., 2016; Weidner et al., 2018). Contrary to the AASHTO SR, the NBI GCR gives condition ratings of the three major bridge components (deck, superstructure, and substructure).

While bridge performance evaluation approaches such as AASHTO SR and NBI GCR have been widely implemented, inherent deficiencies exist (Fereshtehnejad et al., 2018; Jeong, Kim, Lee, & Lee, 2018; Jonnalagadda et al., 2016; Lake & Seskis, 2013). The NBI GCR approach provides information on the severity of a bridge condition in terms of the condition rating (CR) but does not provide a quantitative evaluation (Lake & Seskis, 2013). For example, in GCR, 310 m^2 bridge decks with a 150 m^2 and 125 m^2 spalling area are both classified as a CR of '4' (Verhoeven & Flintsch, 2011) on the scale of 10 (excellent). However, based on the percentage of deteriorated areas, they may be given more precise and quantitative condition scores, 3.51 and 4.49, respectively.

Recently, the Element-level Bridge Inspection (AASHTO, 2019) data has enabled a quantitative performance analysis. One of the key strengths of element level inspection, which can be performed by the visual inspection of bridges, is its ability to simultaneously capture the severity and extent of deterioration of an element (Chase et al., 2016). As a result, BHIs are determined based on bridge elements' conditions, which makes them effective for the prioritization of MRR activities. Although element-level data result from visual inspections, they provide a numerical score based on physical quantities of each element in four condition states. The link that the health index provides between the condition and asset value allows bridge managers to translate the condition to dollar amounts. The Virginia Department of Transportation has been very successful in optimizing MRR activities and has saved millions of dollars by using bridge health index (Matteo, 2016; Matteo, Milton, & Springer, 2016; Shepard & Johnson, 2001). The relative importance of elements, together with their conditions, may enable state DOTs to make bridge action decisions. Hence, elements such as decks, piers, abutments, girders, and stay cables are classified as critical elements. These critical elements relatively have more significant effects on the BHI (Enright & Frangopol, 2000; Mehrabi, 2006; Spyrakos & Loannidis, 2003; Yianni, Rama, Neves, Andrews, & Castlo, 2017). Identification, proper monitoring, and adequate maintenance of critical elements can help reduce elevated risks in bridges (De Risi, Di Sarno, & Paolacci, 2017; Yarnold & Weidner, 2016).

As the popularity of element-level inspection grows, most bridge management professionals are optimistic about its potential benefits, knowing that the bridge performance can be better assessed when detailed information is available. Yet, due to the uncertainties surrounding the determination of each element important weight, accurate predictions of BHIs remain challenging. Without a quantitative description of how critical each element is, the computation of a BHI using the broad classification of elements as critical and non-critical elements may be misleading. Studies on the application of element-level inspections indicate that the BHI, as a bridge performance measure, is better assessed by using various element important weight factors such as repair cost, reliability indices, or other agency-priority weights (Chase et al., 2016; Inkoom et al., 2017; Salim, Liew, & Shafie, 2014; Thomas & Sobanjo, 2012, 2016; Thompson et al., 2018). Jiang and Rens (X. Jiang & Rens, 2010b) suggested that element important weight factors should not be solely based on repair or replacement cost. Patidar et al. (Patidar, Labi, Sinha, & Thompson, 2007) used multiple factors (risk, condition, cost, and priority) to determine element weight factors. More recently, Inkoom et al. (Inkoom et al., 2017) analyzed element weight factors based on the bridge element's replacement costs, long-term maintenance costs, and vulnerability to natural and manmade hazards.

A few studies that account for the relationships between elements are available in the literature (Hearn, 2015; Kosgodagan-Dalla Torre et al., 2017). The fault tree and impact tree methods have been used to analyze how one element affects the other elements (Dori, Wild, Borrmann, & Fischer, 2013; LeBeau & Wadia-Fascetti, 2000; Sianipar & Adams, 1997). However, these methods are probability-based analyses with hypothetical quantities and did not use actual quantities measured from the Element-level Bridge Inspections. The National Cooperative Highway Research Program (NCHRP) Report 551 presents a step-by-step guide for identifying performance measures (NCHRP, 2006) but is silent on inter-dependencies among elements.

5.3 Methodology

This section identified and computed Co-Active parameters that influence the overall BHIs. These parameters include Co-Active correlation coefficients and collaboration factors. Contingency tables are used for determining the Co-Active correlation coefficients, which are in turn used to assess the bridge health index.

5.3.1 Development of Contingency Tables

As presented earlier, the existing approach for bridge MRR prioritization considers elements independently, resulting in overly conservative predictions. This section describes how contingency tables are effectively used to prioritize MRRs.

5.3.1.1 Identify Groups by Bridge Types

Bridge structures are usually made up of different types and a number of elements due to the inherent variations. For example, a steel deck with corrugated material in a highly corrosive marine environment will deteriorate at a much faster rate than a reinforced concrete deck. Therefore, bridge groups having the same type and number of elements are identified. For this study, the three most common groups were identified among 9044 in-service bridges (excluding culverts) in the state of Georgia, U.S.A.

These groups consisted of bridges, which were categorized primarily based on the type of material used for the girder/beam element:

1. Steel open girder/beam bridge (SO107): This group consisted of bridges with steel open girder (I section) as the means of supporting the overlying reinforced concrete deck, and in transmitting loads from the reinforced concrete deck into the underlying substructure. There were 598 bridges in this group. The last three numbers, ‘107’, in ‘SO107’, is an element identification number for steel open girder/beam bridge element. The first two letters, ‘SO’, means steel open, added to emphasize this group and make it unique in representation.
2. Prestressed concrete open girder/beam bridge (PC109): In this group, each bridge contained prestressed concrete as the open girder/beam element’s material. The open girder/beam element in this bridge group performed similar functions as described in the group ‘SO107’, steel open girder/beam bridge. There were 1439 bridges in this group. Figure 18 shows a typical in-service prestressed concrete girder/beam bridge, which is the most common type in Georgia.

3. Reinforced concrete open girder/beam with pile foundation bridge (RC110): Unlike the other two groups, bridges in this group contained reinforced concrete as a construction material for the open girder/beam element. Also, each bridge contained a pile foundation. There were 1098 bridges in this group.

Figure 18 – Typical bridge in the ‘PC109’ group.

5.3.1.2 Create 12 Age Bins for Bridges in Each Group

Bridges were categorized by 12 age bins shown in Figure 19 because ages should affect bridge performance. While bridges in the steel open girder/beam bridge (SO107) group were evenly distributed around the southern part of Georgia, there was a cluster of bridges around Atlanta, in inspection areas 7, 9, and 12, for the other bridge groups, prestressed concrete girder/beam bridge (PC109), and reinforced concrete open girder/beam with pile foundation bridge, RC110 (Figure 19). The element health indices by age for bridges in the first bridge group, steel open girder/beam bridge (SO107), were presented later to illustrate the procedure for determining the Co-Active parameters, which were required for the implementation of the Br-CPM. In this study, the significance of the output from the proposed Br-CPM and the prioritization coefficient (PC) is clearly shown, in terms of decision making regarding how to optimize return on investment (ROI) on element’s preventive maintenance, rehabilitation, or replacement (MRR).

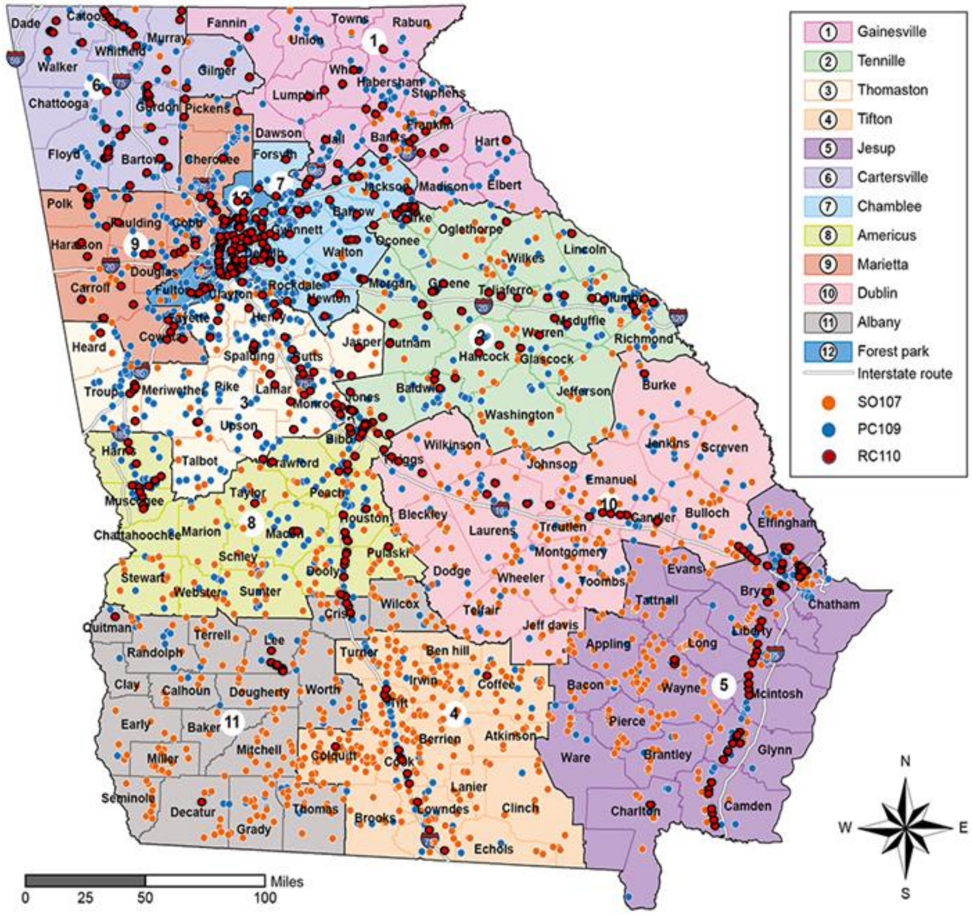


Figure 19 – Geographical locations of the identified bridge groups (SO107, PC109, and RC110) in twelve (12) inspection areas in Georgia. Notes: SO107 = Steel open girder/beam bridge; PC109 = Prestressed concrete girder/beam bridges; RC110 = Reinforced concrete open girder/beam bridge.

5.3.1.3. Compute Health Indices for Elements in Each Age Bin

In this study, the bridge health index (BHI) used as a bridge performance measure. Prior to the implementation of BHI in the Co-Active model, sensitivity analysis is performed to determine the efficiency of the BHI, using element-based inspection data. The results obtained from the sensitivity analysis have been presented separately in Chapter 4.

The procedure for computing element health indices is described by the following 3 steps.

Step 1. *Compute each element's percentage quantities in 4 condition states for an age bin*

Table 21 shows the reinforced concrete deck element (No. 12) condition states (CSs) for 15 bridges in age bin 1940. In the table, there were four CSs, with one and four being the good and severe conditions, respectively. In each CS, the area of distress was quantified. The quantities in each CS were combined to determine the total quantity for the 15 bridges as shown in the "Row A", at the bottom of Table 21. The last row, "Row B", presents the percentage quantities in each CS. They were determined by taking the quantities in each CS and dividing by the total quantity, 4283 m^2

Table 21 – A typical element-level inspection in Georgia (reinforced concrete deck for age bin 1940).

STRUCNUM	EN	TOTAL QTY (m^2)	CS1 (m^2)	CS2 (m^2)	CS3 (m^2)	CS4 (m^2)
20700220	12	310	0	264	46	0
19950080	12	67	67	0	0	0
28500340	12	1526	0	0	1526	0
19950740	12	42	0	42	0	0
26300160	12	499	487	11	0	0
6300860	12	191	0	0	191	0
19950490	12	36	0	36	0	0
19900470	12	328	0	317	10	0
20700210	12	310	0	294	16	0
25550440	12	85	0	85	0	0
19950520	12	279	0	0	279	0
19950680	12	80	0	80	0	0
17100110	12	232	0	231	0	0
19950620	12	72	72	0	0	0
20700140	12	226	0	213	13	0
Row A—Quantity Sum		4283(a)	626(b)	1573(c)	2081(d)	0(e)
*Row B—% Quantity		100	14.62(f)	36.73(g)	48.59(h)	0(i)

Notes: STRUCNUM = structure number; EN = element number; TOTALQTY = total quantity; CS1 = condition state 1 (good); CS2 = condition state 2 (fair); CS3 = condition state 3(poor); CS4 = condition state 4 (severe); *The last row, "Row B", corresponds to age-bin 1940 in Table 22.

Step 2. *Compute each element's percentage quantities in 4 condition states for all age bins*

Repeating the process described in Step 1, each element's % quantities were calculated for a group of bridges in each age bin as shown in Table 22.

Table 22 – Percentage quantities for element 12 (Reinforced concrete deck).

Age-bin	% Quantities in each condition state				
	1 (Good)	2 (Fair)	3 (Poor)	4 (Severe)	
2020	99.52	0.48	0	0	
2010	90.39	8.10	1.51	0	
2000	76.17	22.27	1.56	0	
1990	75.41	21.26	3.33	0	
1980	60.19	39.70	0.11	0	
1970	25.61	62.58	11.81	0	
1960	18.57	70.63	10.8	0	
1950	24.77	54.96	20.28	0	
**1940	14.62	36.73	48.59	0	(See "Row B", in Table 1)
1930	0	0	0	0	
1920	0	0	0	0	
1910	0	0	0	0	

Notes: **This row was obtained from Table 21.

Step 3. *Compute element health indices for all age bins*

This study utilized a multi-linear function shown in Figure 20 and computed the element HI. The multi-linear function was defined by the element's percentage quantities (see Table 22) and gave Table 23 as output. For example, the element's percentage quantities in each age bin in Table 22 (e.g., 14.62, 36.73, 48.59, and 0, in age bin 1940) were used to characterize the multilinear function with 4 points shown in Figure 20. Table 23 summaries the numerical values of the five areas (A, B, C, D, and E) shown in Figure 20.

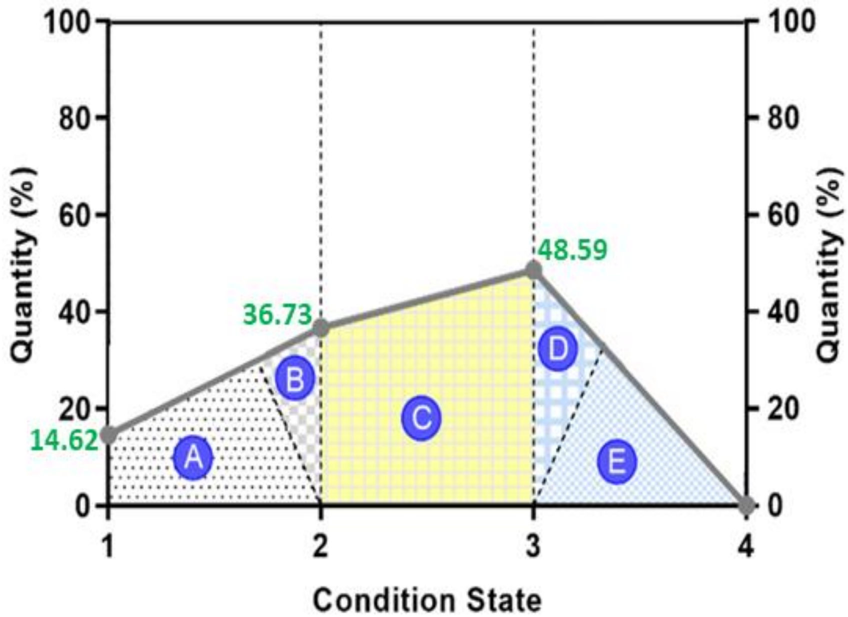


Figure 20 – Multilinear function to aggregate element percentage quantities (age bin 1940).

Table 23 – Computation of element 12 health indices, HI_{12} (reinforced concrete deck).

(a) Age-bin	**Aggregated Percentage Quantity**					**HI_{12}**
	(Area 'A')	**(Area 'B')**	**(Area 'C')**	**(Area 'D')**	**(Area 'E')**	
2020	49.90	0.10	0.20	0	0	99.80
2010	47.40	1.90	4.80	0	0.70	96.20
2000	43.80	5.40	11.90	0	0.80	91.40
1990	43.40	4.90	12.30	0.10	1.60	90.50
1980	40.00	9.90	19.90	0	0.10	86.40
1970	29.80	14.30	37.20	0.60	5.30	70.50
1960	28.20	16.40	40.70	0.50	4.90	68.50
1950	28.30	11.60	37.60	1.70	8.40	67.00
1940	20.20	5.50	42.70	8	16.40	51.20
1930	0	0	0	0	0	0
1920	0	0	0	0	0	0
1910	0	0	0	0	0	0
(b) Weighing factors (Inkoom et al., 2017b)	2.0	0.24	0.20	0.12	0.0	

In Table 23, the product of each area (A through E) and its corresponding weighting factor (Inkoom et al., 2017) (see part 'b') was calculated to determine HI for element 12 (reinforced concrete bridge deck) in the last column. For example, the HI for a group of reinforced concrete decks in age bin 1940 was 51.20 $(= (20.20 \times 2.0) + (5.50 \times 0.24) + (42.70 \times 0.20) + (8 \times 0.12) + (16.40 \times 0.0))$.

5.3.1.4 Develop deterioration prediction for each element

An age-bin analysis approach, utilizing element HIs computed in Step 3 (Table 23), was used to develop deterioration predictions presented in this study using the Markov-chain method (Guoping Bu et al., 2011). The Markov-chain method requires condition state (CS) transition probabilities in each element and bridge. For each transition probability matrix, three unknowns ($P_{11},\ldots P_{33}$) were estimated by minimizing the sum of errors between predicted and aggregated health indices (M. Chang & Maguire, 2016):

$$\hat{P} = min\left[\sum_{j=1}^{N} |y_{n,j} - R_{p,n}|\right] \text{ subject to } 0 \leq p_{ii} \leq 1 \text{ for } i = 1,2,\ 3,\ ..\ ,\ ns \qquad (13)$$

where, min min denotes minimization; *N* denotes the number of bridges or elements belonging to a subset; ns is the number of condition states; $y_{n,j}$ is the observed (aggregated) health index at an nth age-bin of jth bridge; and $R_{p,n}$ is the predicted health index.

As a result of the process described from this section, HIs of bridge elements were described as a function of time. That is, deterioration models, which describe HIs as a function of time, were developed for each bridge element. Detailed procedure and deterioration predictions for Georgia's bridge elements are presented in Chapter 5.

5.3.1.5 Develop contingency tables and determine element co-active coefficients

A contingency table was developed to provide interactions among Co-Active elements, describing correlation coefficients for pairs of Co-Active elements. It is expressed in a 2 × 2 table.

Equation (14) defines the Co-Active correlation coefficients. It measures how much one element HIs, ‘X’, affects the other element HIs, ‘Y’, based on the Pearson correlation coefficient (Embrechts, McNeil, & Straumann, 2002).

$$\rho(X, Y) = \frac{\mathrm{Cov}[X, Y]}{\sqrt{\sigma^2[X]\sigma^2[Y]}} \tag{14}$$

where, $Cov[X, Y]$ is the covariance between the two elements’ HIs and $\sigma^2[X]$ $\sigma^2[Y]$ denotes their variances in each age bin. In the case of non-Co-Active elements, $\rho(X, Y) = 0$ since $Cov[X, Y] = 0$.

5.3.2 Computation of Element Collaboration Factors

5.3.2.1 Existing Element Weight Factors

This study adopted the element weight factors recommended by Sobanjo and Thompson (Sobanjo & Thompson, 2016). In their approach, element weight factors are determined based on element replacement unit costs, element long-term unit costs, and more.

5.2.2 Collaboration Factors

The collaboration factors are defined by Equation (15) and used for a prioritization model (see Section 5). With the ‘N_e^{CA}’ number of Co-Active elements, the number of 2-element interactions is $\frac{1}{2}(N_e^{CA}!/(N_e^{CA} - 2)!) + N_e^{CA}$. Collaboration factors were determined by multiplying the Co-Active coefficients by the (importance) weight factors developed by Sobanjo and Thompson (Sobanjo & Thompson, 2016) including the cost and risk. They were used in the neighboring state, Florida, to weigh elements and determine the overall BHI. This collaboration factor plays an important role in decision making at discrete times (see Section 5.5.1).

$$W_e^C = \sum_{i}^{N_e^{CA}} \rho_e^{\mathrm{CA}} W_e \tag{15}$$

where,

W_e^C = Collaboration factor,

W_e = Weight factor (Sobanjo & Thompson, 2016) given to element, 'e',

ρ_e^{CA} = Co-Active correlation coefficient between two elements' HIs (from Equation (14)),

N_e^{CA} = the number of Co-Active elements.

5.3.3 Bridge Health Index Assessment

Figure 21 is a flowchart showing how one element's change in HI affects the other elements. For example, when an expansion joint's HI changed from 60 to 100 in Year 20, it affected HIs of the other elements (e.g., cap beam, bearing, column, and girder) due to the proposed Co-active model. The number in each arrow shows the Co-Active correlation coefficient between the expansion joint and each element. The overall BHIs were determined by a weighted average of element HIs.

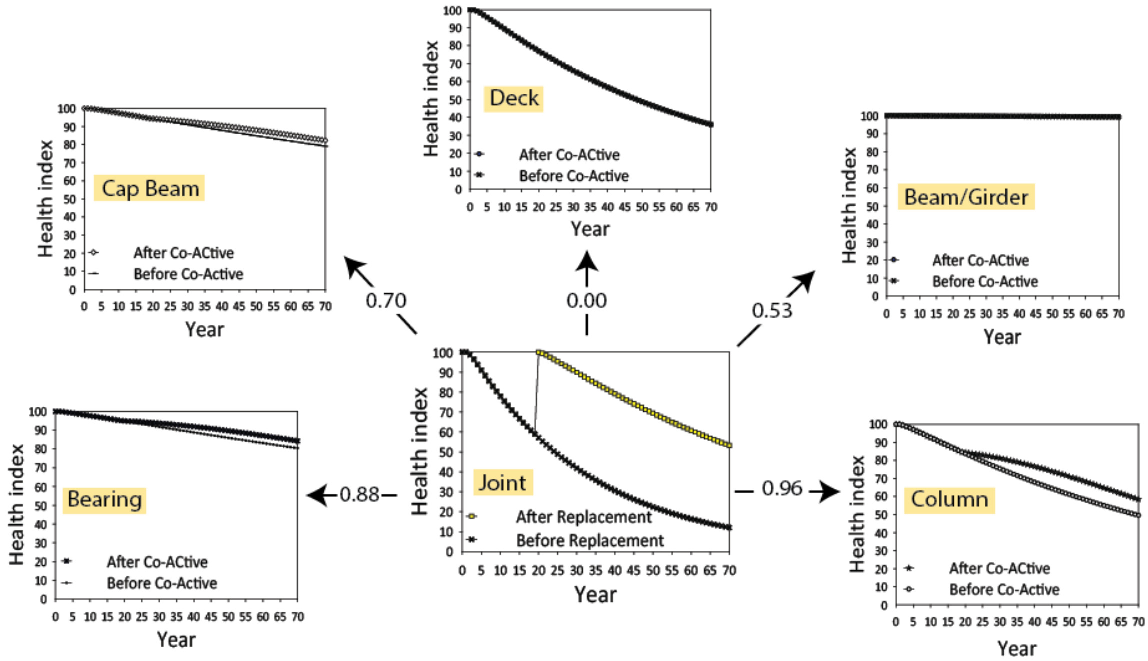


Figure 21 – Flowchart showing how one element's HI change affects a time-history of other elements.

5.4 Analytical Investigation of Co-Active Elements in Three Bridge Groups

This section presents the Co-Active coefficients, obtained from the contingency tables, and collaboration factors for the three major bridge groups identified in this study.

5.4.1 Contingency Table for Co-Active Coefficients

Table 24 lists bridge elements by age for bridges in the steel open girder/beam bridge (SO107) group. They were determined by the methodology described in Section 5.1.4. Figure 22 shows the contingency table representing Co-Active coefficients for Co-Active elements in the group 'SO107' bridges. The small graphs in Figure 22 below the diagonal were bivariate scatter plots of two elements' health indices, which were used for the calculation of the Co-Active coefficients. Each graph shows a relationship (e.g., a linear trend) between two elements.

For example, the Co-Active coefficient in "Row 1", "Col. 4", in Figure 23 (designated as 'A', shown in Table 25) was calculated by Equation (16).

$$\rho(\text{No.}\,12, \text{No.}\,311) = \frac{\text{Cov}[{}_{\text{HI}}12, {}_{\text{HI}}311]}{\sqrt{\sigma^2[{}_{\text{HI}}12]\sigma^2[{}_{\text{HI}}311]}} = 0.90 \tag{16}$$

where, ${}_{\text{HI}}12$ and ${}_{\text{HI}}311$ represent the health indices of deck and bearing elements, respectively. For example, ${}_{\text{HI}}12$= [95.26, 92.30, 90.15, 83.73, 89.15, 77.76, 73.51, 63.32, 61.28] and ${}_{\text{HI}}311$ = [88.41, 95.95, 87.42, 93.99, 89.25, 84.22, 78.77, 66.45, 69.66] come from the second and fifth columns of Table 24.

Table 24 – Element health indices by age for bridges in the 'SO107' group.

Age-bin	Deck	Expansion Joint	Beam/ Girder	Bearing	Cap Beam	Pier/ Column
2020	95.26	83.58	97.65	88.41	99.92	100.00
2010	92.30	74.34	98.92	95.95	93.28	97.68
2000	90.15	75.05	98.97	87.42	95.67	96.20
1990	83.73	53.36	98.02	93.99	95.79	95.34
1980	89.15	67.42	97.87	89.25	96.87	94.82
1970	77.76	67.50	95.03	84.22	94.57	94.60
1960	73.51	60.03	91.82	78.77	92.86	89.23
1950	63.32	34.68	82.26	66.45	93.14	81.31
1940	61.28	59.72	80.71	69.66	74.41	89.06

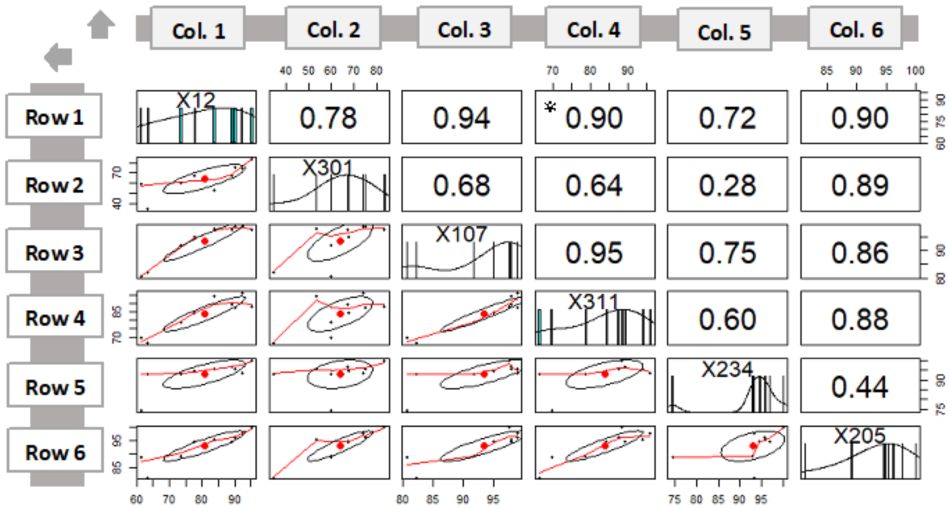


Figure 22 – Contingency table for the Co-Active elements in the 'SO107' group. Notes: * = Co-Active coefficient corresponding to "Row 1", "Col. 4".

Figures 23 and 24 show the contingency tables for the Co-Active elements in the other two groups, PC109 and RC110.

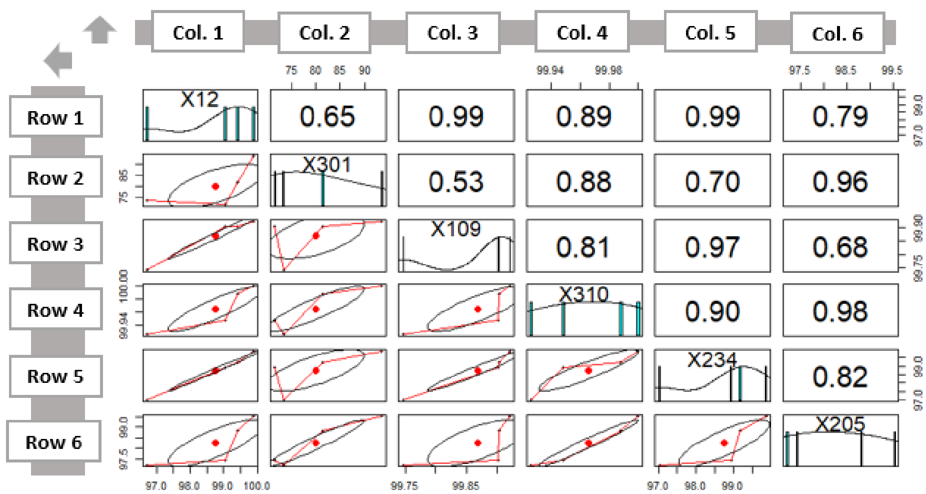


Figure 23 – Contingency table for the Co-Active elements in the 'PC109' group.

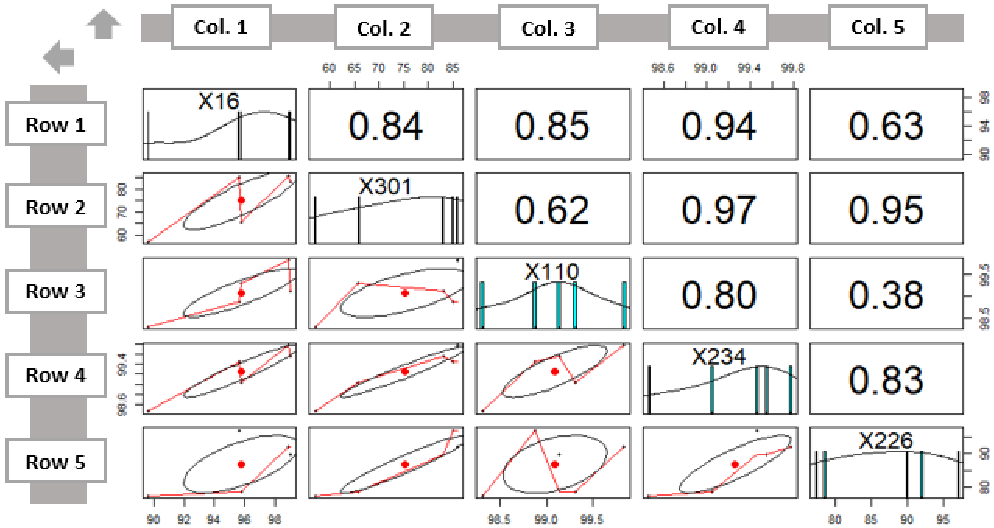


Figure 24 – Contingency table for the Co-Active elements in the 'RC110' group.

The aggregated Co-Active coefficient (see part '(b)' of Table 25) for each element was determined by combining all coefficients in each column. For example, an aggregated Co-Active coefficient for the reinforced concrete deck was 5.24 $5.24\ (= 1.00 + 0.78 + 0.94 + 0.90 + 0.72 + 0.90)$.

5.4.2 Collaboration Factors

Table 25 shows the Co-Active coefficients and collaboration factors calculated for the six Co-Active elements in the group 'SO107' bridges. The collaboration factor was computed as the product of weight factors and the Co-Active coefficient for each element (see part '(d)' of Table 25).

This process primarily applies weight factors based on relative costs of elements and inter-dependency that exists among them. For example, the collaboration factor for the reinforced concrete deck was 136.58 $[= (1.00 * 25) + (0.78 * 12) + (0.94 * 49) + (0.90 * 12) + (0.72 * 13) + (0.90 * 40)]$. Tables 26 and 27 show the Co-Active prioritization parameters in the other two groups, PC109, and RC110. Element ranking changes when Co-Active coefficients were considered in conjunction with importance weight factors (part '(d)' of Tables 25 through 27).

Table 25 – Co-Active prioritization parameters in the 'SO107' group.

(a) On the element below	The Effect of the Following Element's Condition Change					
	Deck	**Expansion Joint**	**Beam/ Girder**	**Bearing**	**Cap Beam**	**Pier/ Column**
Deck	1.00					
Expansion Joint	0.78	1.00				
Beam/Girder	0.94	0.68	1.00			
Bearing [a] =	'A' = 0.90	0.64	0.95	1.00		
Cap Beam	0.72	0.28	0.75	0.60	1.00	
Pier/Column	0.90	0.89	0.86	0.88	0.44	1.00
(b) Aggregated Co-Active coefficient	5.24 (Rank 1)	3.49 (Rank 2)	3.56 (Rank 3)	2.48	1.44	1.00
(c) Importance weight (Sobanjo & Thompson, 2016) factor, [c]=	25.00 (Rank 3)	12.00	49.00 (Rank 1)	12.00	13.00	40.00 (Rank 2)
(d) Collaboration factor = [c][a]	136.58 (Rank 1)	92.24 (Rank 3)	104.55 (Rank 2)	55.00	30.60	40.00

Table 26 – Co-Active prioritization parameters in the 'PC109' group.

On the element below.	The Effect of the Following Element's Condition Change					
	Deck	**Expansion Joint**	**Beam/ Girder**	**Bearing**	**Cap Beam**	**Pier/ Column**
Deck	1.00					
Expansion Joint	0.65	1.00				
Beam/Girder	0.99	0.53	1.00			
Bearing	0.89	0.88	0.81	1.00		
Cap Beam	0.99	0.70	0.97	0.90	1.00	
Pier/Column	0.79	'B' = 0.96	0.68	0.98	0.82	1.00
(b) Aggregated Co-Active coefficient	5.31 (Rank 1)	4.07 (Rank 2)	3.46 (Rank 3)	2.88	1.82	1.00
(c) Importance weight (Sobanjo & Thompson, 2016) factor	25.00 (Rank 3)	12.00	46.00 (Rank 1)	13.00	13.00	40.00 (Rank 2)
(d) Collaboration factor	134.38 (Rank 1)	95.32 (Rank 3)	96.34 (Rank 2)	63.90	45.80	40.00

Table 27 – Co-Active prioritization parameters in 'RC110' group.

(a) On the Element Below	The Effect of the Following Element's Condition Change				
	Deck	Expansion Joint	Beam/ Girder	Cap Beam	Pile
Deck	1.00				
Expansion Joint	0.84	1.00			
Beam/Girder	0.85	0.62	1.00		
Cap Beam	0.94	0.97	0.80	1.00	
Pile	0.63	0.95	0.38	0.83	1.00
(b)Aggregated Co-Active coefficient	4.26 (Rank 1)	3.54 (Rank 2)	2.18 (Rank 3)	1.83	1.00
(c) Importance weight (Sobanjo & Thompson, 2016) factor	25.00 (Rank 2)	12.00	33.00 (Rank 1)	13.00	17.00 (Rank 3)
(d) Collaboration factor	86.06 (Rank 1)	61.22 (Rank 2)	49.86 (Rank 3)	27.11	17.00

5.4.3 Effect of Co-Active Elements on the Bridge Health Index

A bridge generally consists of 30–80 elements. In order to analyze data from the recently mandated Element-Level Bridge Inspection program, transportation agencies in the U.S. will need to calculate a Bridge Health Index (BHI). This is a weighted average measure of the elements' conditions. To illustrate how the proposed Co-Active model works, 1439 bridges from the Georgia Element-Level Bridge Inspection results, representing the group 'PC109', prestressed concrete open girder/beam bridges, were investigated (see Figures 25 and 26). Group PC109 was selected for the Co-Active model because it was the most dominant bridge group in Georgia. The effect of collaboration factors for the 'PC109' group is presented in the following sub-section, 'Results.' However, all groups were analyzed in the following section, "Analysis and interpretation of results and implementation".

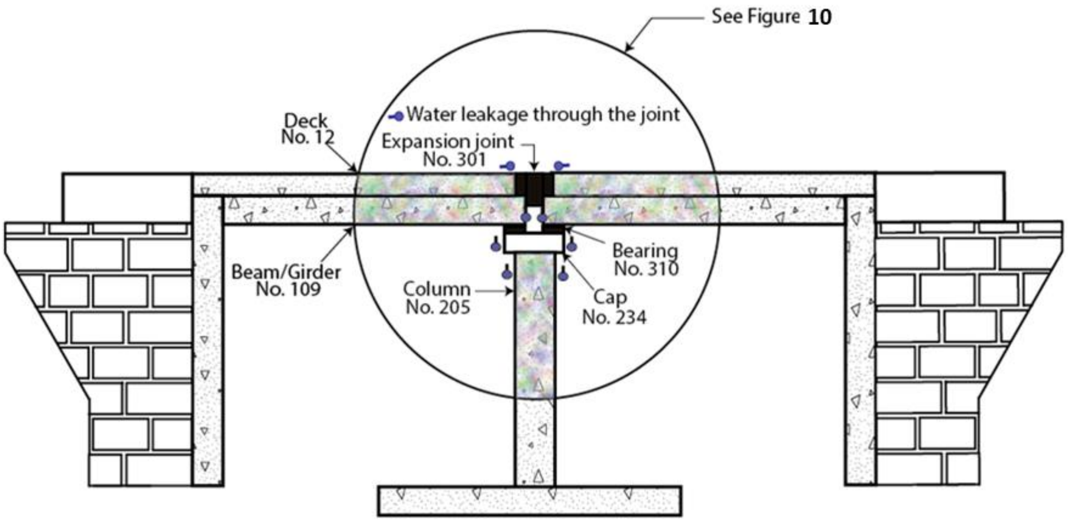


Figure 25 – A two-span bridge with a group of Co-Active elements in the group PC109.

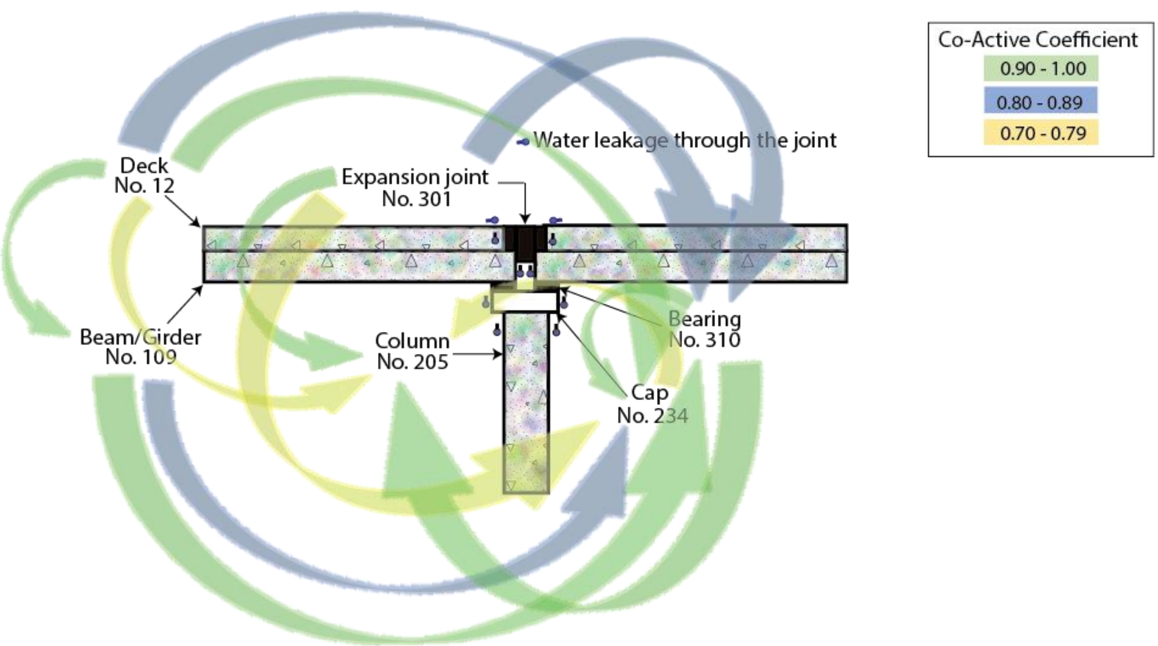


Figure 26 – Dominant inter-dependencies among the Co-Active elements in the group PC109.

Figure 26 shows the complex interactions that existed among the six Co-Active elements in the prestressed concrete open girder/beam bridge (PC109) group. The arrow originating from one bridge element (e.g., expansion joint) to another one (e.g., bearing) shows that the long-term performance of bearing was dependent on the expansion joint's performance, based on the computed Co-Active coefficients shown in Table 26. In other words, if the condition of the expansion joint deteriorates/appreciates, it is likely going to affect the bearing element's long-term performance. Furthermore, the four arrows originating from the expansion joint show that the long-term performance of bearing, cap beam, and column was dependent on expansion joint's deterioration/appreciation rates. The arrows shown in the figure are given in different colors to indicate the rates at which changes in the condition of an element affects the other dependent bridge elements.

For example, the green color arrows show the most dominant inter-dependent relationship between pairs of Co-Active elements, having Co-Active coefficients between 0.90 and 1.00. Thus, the green color arrows originating from the expansion joint shows that the long-term performance of the pier/column was most dependent on the changes in the condition of the expansion joint. By investing in the expansion joint's MRR, the long-term performance of other elements (beam/girder, bearing, cap, and column) also improves over time.

Figure 27 shows the deterioration models (or time-history of HIs) for the six Co-Active elements and an overall bridge. The deterioration models were developed using the Markovian modeling approach (Agrawal, Kawaguchi, & Chen, 2010). In this study, the overall BHI represents HI predictions for bridges that pertained to the six elements. In Georgia for instance, at least 1439 bridges pertained to these six elements. The elements' deterioration models were aggregated to obtain an overall bridge model using element weight factors. For each element deterioration model, there were year-to-year depreciation factors (DFs) for each element's HIs (i.e., the element's deterioration rates). For example, if the reinforced concrete column's HIs were 89.06 and 88.16 in the Years 2014 and 2015, respectively, the Year 2014–to–2015 DF was 0.01 (= (89.06–88.16)/89.06).

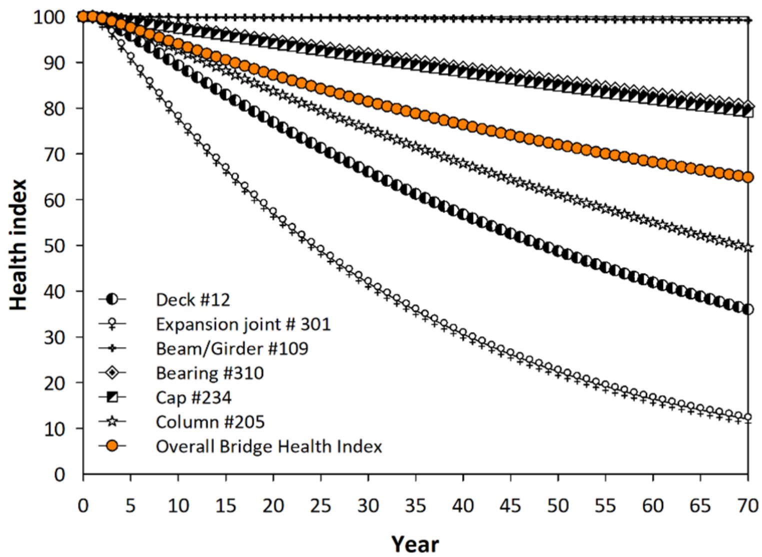


Figure 27 - Bridge overall and element health index prediction models (group PC109).

When one of Co-Active elements is maintained, rehabilitated, or replaced (MRR), it affects the DFs for the other Co-Active elements, the elements' HIs, and the overall BHI. However, the extent to which the MRR of a Co-Active element affects the other elements' DFs is quantified by $AF_e^{acting}\rho_e^{\mathrm{CA}}$, where AF_e^{acting} is the appreciation factor calculated for an element (e.g., expansion joint) being maintained, repaired, and rehabilitated. AF_e^{acting} is 2.0 if an element HI increases from 50 to 100 and 5.0 if it increases from 20 to 100. ρ_e^{CA} is the Co-Active coefficient between the acting element (e.g., expansion joint) and its co-active elements (e.g., column). The depreciation factor for the affected element (e.g., column) decreases due to the Co-Active relationship with the expansion joint:

$$DF_e^{affected}(1 - AF_e^{acting}\rho_e^{\mathrm{CA}}) \tag{17}$$

To illustrate how this equation works, a case study, involving the replacement of an expansion joint in the Year 20 (threshold element HI is 75), was considered. The following sub-section presents the results, which show the effects of Co-Active elements on the bridge performance over time. A comparison of the analysis results (with and without the application of the Co-Active model) was also presented. The purpose of this comparison was to determine the impact of the Co-Active model, in terms of projected overall BHI obtained after the bridge element's repair or replacement.

3.4.3.1. Results Obtained without Co-Active Model

Figure 28 shows the overall bridge and element HIs, before applying the Co-Active model, when an expansion joint was replaced in Year 20. The HI of 100 indicates an excellent condition.

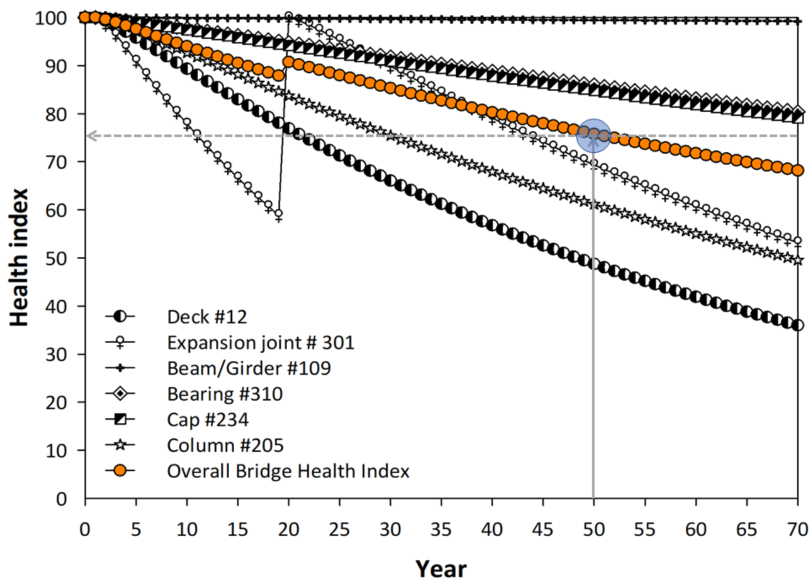


Figure 28 - Effect of an expansion joint No. *301* replacement (before applying the Co-Active approach).

3.4.3.2. Results Obtained with Co-Active Model

Figure 29 shows the overall bridge and element HIs, after applying the Co-Active model, when an expansion joint is replaced in Year 20. $DF_e^{affcted}$ represents the initial slope of an affected element (e.g., bearing) in the depreciation model, which is reduced by $AF_e^{acting}\rho_e^{CA}$ computed from the expansion joint's HI change and Co-Active relationship with the affected elements (e.g., bearing and cap) shown in Figure 29.

The Co-Active model considers the effects of the complex systems of interaction, which is a function of key parameters that define elements' inter-dependent relationships, on the BHIs over time. By using the Co-Active model, bridge performance life improved from 50 to 60 years, an increase of 20% (see Figures 28 and 29). The 20% increase in the bridge performance life indicates the indirect effects of an expansion joint's replacement on the other elements' performance, which the current methodology in Figure 28 was unable to capture.

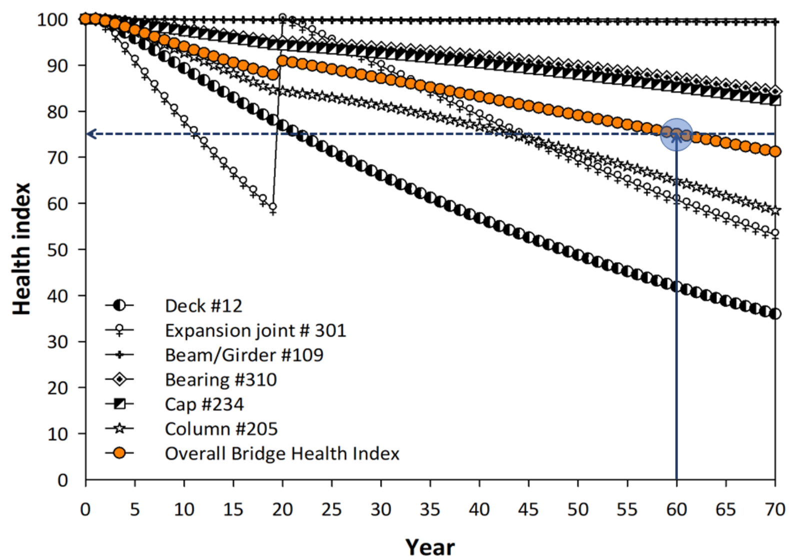


Figure 29 – Effect of an expansion joint No. *301* replacement (after applying the Co-Active approach).

When one of the Co-Active elements (e.g., an expansion joint) was replaced or repaired, its overall bridge performance improved. However, after the replacement or repair, the expansion joint's HI, in fact, decreased over time as it deteriorated. Consequently, the Co-Active coefficients should vary as a function of time and have a diminishing effect on the overall bridge HI. Therefore, the effect of Co-Active coefficient on the elements' HIs and overall BHI predictions was dependent on three main factors:

- The year in which a Co-Active element was maintained, rehabilitated, or replaced (MRR).
- The condition of a Co-Active element (i.e., an element HI) before MRR and the type of MRR action. The more the performance gap (i.e., the difference between an element's HI before and after MRR), the more influential the element's MRR was on the HI predictions.
- The inter-dependencies among the Co-Active elements. The elements' inter-dependency was a function of their Co-Active coefficients. The higher the value of an element Co-Active coefficient, the more dependent the element was.

5.5 Analysis and Interpretation of Results and Implementation

5.5.1 Prioritization for Bridge Maintenance

The bridge element "prioritization coefficient (PC)" is a numerical value, which defines the relative maintenance priority of Co-Active elements at a discrete-time. While health indices should be time-dependent, decision making occurs at discrete times. Therefore, the proposed element 'PC' analysis informs state DOTs which elements are most influential for long-term bridge performance based on bridge health index depreciation models similar to one shown in Figure 29. The effective bridge preventive maintenance actions (e.g., deck treatment, beam painting, etc.) are intended to delay the need for costly rehabilitation or replacement while bridges are still in good or fair condition and before the onset of serious deterioration (FHWA, 2018).

Thus, it is recommended that the results from the previous section are further analyzed by means of 'PC' defined by Equation (18). The 'PC' accounts for a performance target (e.g., a threshold health index) and associated performance gaps. Consequently, the 'PC' analysis helps prioritize preventive maintenance activities, rehabilitation, or replacement. In this equation, the subscript, ‘e’, indicates an element.

$$PC_e = \left[HI_e^{threshold} - HI_e \ \right] \times \frac{W_e^C}{100} \tag{18}$$

where,

PC_e = Prioritization coefficient,

HI_e = Health index,

$HI_e^{threshold}$ = Threshold health index,

W_e^C = Collaboration factor.

The prioritization coefficients (PCs) for varying BHI thresholds (50, 75, and 90) in Year 2018 are shown in Figure 30 for the case studied (prestressed concrete open girder/beam bridges) in the preceding section. Figures 31 and 32 show the PCs for the other bridge groups (steel open girder/beam bridges and reinforced concrete open girder/beam with pile foundation bridges) previously identified in this dissertation.

When ‘PC’ is negative, it means that the element meets the performance level, having a specific prioritization requirement (see Table 28). As the ‘PC’ approaches zero, elements may require preventive maintenance activities. When ‘PC’ is positive, the first part of Equation (18) represents a “performance gap” in an element. The second part, including the weighed element collaboration factors, accounts for how Co-Active elements work together to affect the overall bridge performance. When the ‘PC’ is positive and higher in value, elements are prioritized because the performance gap is larger, and the collaboration factor is higher. The higher the positive value of an element’s ‘PC’, the more influential it is in closing the “performance gap” and in meeting the agency’s performance target. However, if the agency’s benchmark HI target is lower (or 50), all elements' condition would need a minimum improvement although elements with less negative 'PC' will be prioritized.

Table 28 – Prioritization Coefficients (PC) scales.

Negative (-) PC		**Positive (+) PC**	
Coefficient	**Description**	**Coefficient**	**Description**
PC ≥ 100	**Very Low Priority**	**PC ≥ 100**	**Very High Priority**
90 ≤PC < 100 80 ≤ PC < 90 70 ≤ PC < 80 60 ≤ PC < 70	Low Priority	90 ≤PC < 100 80 ≤ PC < 90 70 ≤ PC < 80 60 ≤ PC < 70	High Priority
50 ≤ PC < 60 40 ≤ PC < 50	Medium Priority	50 ≤ PC < 60 40 ≤ PC < 50	Medium Priority
30 ≤ PC < 40 20 ≤ PC < 30 10 ≤ PC < 20	High Priority	30 ≤ PC < 40 20 ≤ PC < 30 10 ≤ PC < 20	Low Priority
0 ≤ PC < 10	Very High Priority	0 ≤ PC < 10	Very Low Priority

For example, in Figure 30, when the threshold BHI was 75, the 'PC' for expansion joint was 8, which was the highest 'PC', and it was the only positive 'PC'. The pier/column's 'PC' was negative but approached zero. This indicates this element would soon need attention. By comparison, the 'PCs' of beam/girder, bearing, and cap beam in the 'PC109' group (Figure 30) show that these elements were less critical than similar elements in the 'SO107' group (Figure 31). Furthermore, due to the relatively lower magnitude of negative 'PCs', when the threshold BHI was 50, most elements in the 'RC110' group (Figure 32) would become critical, sooner than similar elements in the other groups.

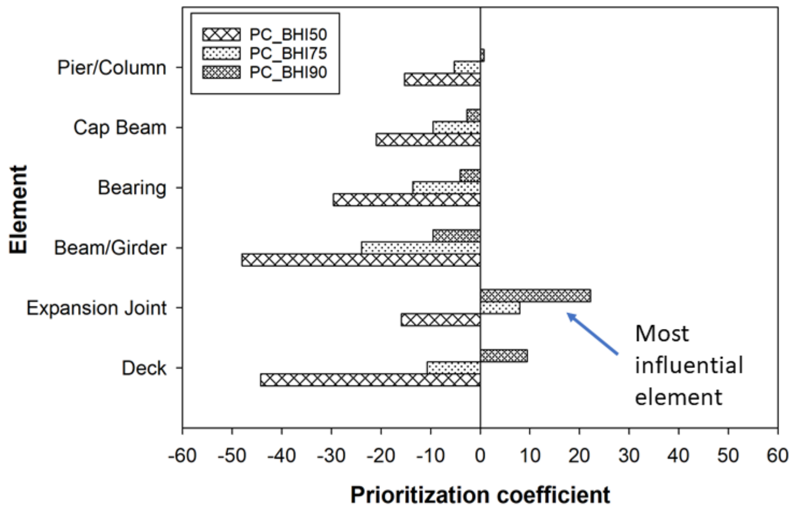


Figure 30 – Prioritization coefficients in the 'PC109' group for Bridge Health Index (BHI) thresholds (50, 75, and 90). Notes: negative value of 'PC' = the element meets the performance level; positive value of 'PC' = the element does not meet the performance level.

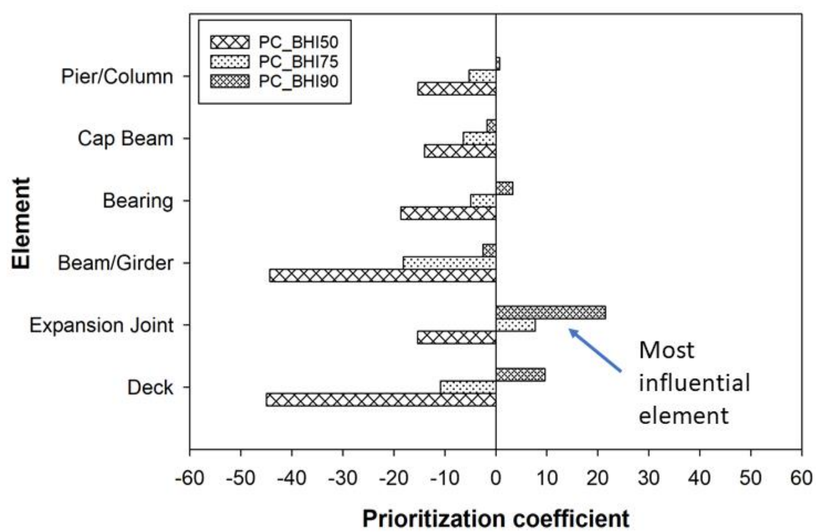


Figure 31 – Prioritization coefficients in the 'SO107' group for BHI thresholds (50, 75, and 90).

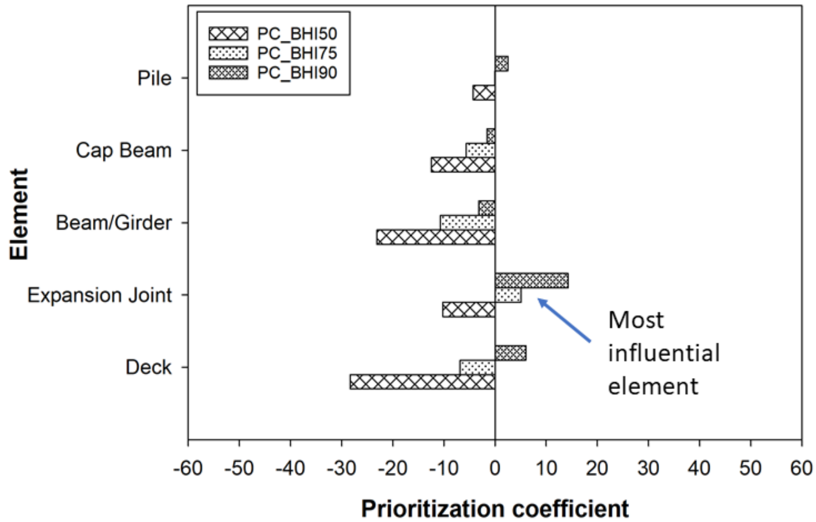


Figure 32– Prioritization coefficients in the 'RC110' group for BHI thresholds (50, 75, and 90).

3.5.2 Discussion of Results

The return on the investment (ROI) in terms of bridge service life extension is optimized when an element with the highest prioritization coefficient is replaced or repaired. This Co-Active approach and associated long-term ROI is not currently being considered by transportation agencies. Among the group of six Co-Active elements analyzed, the prioritization coefficient of the expansion joint appears to be the highest. This shows that the deterioration of expansion joints in Georgia bridges is most influential on the performance of the adjacent and underlying elements, for the group of bridges studied. The prioritization coefficient is a resourceful parameter for closing performance gaps and prioritizing elements for preventive maintenance activities, rehabilitation, or replacement.

For the three study bridge groups (steel open girder/beam bridge (SO107), prestressed concrete open girder/beam bridge (PC109), and reinforced concrete open girder/beam with pile foundation bridge (RC110), it was concluded that the expansion joint was the most influential element for improving the overall BHI when the threshold BHI target of 75 was used. This means that by investing on expansion joint replacements in Year 20, for the prestressed concrete open girder/beam bridge (PC109) group, which contained 1439 in-service bridges in Georgia, the overall BHI would improve by 20% over the subsequent 20 years. The results from the prioritization analysis also suggest that expansion joints were the most critical element when a threshold BHI of 75 was considered.

In addition to the expansion joint and deck, the third most influential element was bearing, in the steel open girder/beam bridge (SO107), and pile, in the reinforced concrete open girder/beam with pile foundation bridge (RC110). Although the cap beam element met the performance level in all the three bridge groups. Yet, the element's PCs were not the same for the three studied groups. The relative difference in the element's PCs, among the three study groups, had great potential for influencing the decision-making process on the element's MRR. As per the element's MRR requirements, the cap beam was more critical in reinforced concrete open girder/beam with the pile foundation bridge (RC110) group than in the steel open girder/beam bridge (SO107) and prestressed concrete open girder/beam bridge (PC109) groups. This means that the cap beam element would require MRR sooner in reinforced concrete open girder/beam with pile foundation bridge group (which contained bridges that were evenly distributed around the southern part of Georgia) than in the other two bridge groups, having a cluster of bridges around Atlanta (see inspection areas 7, 9, and 12 in Figure 19).

5.6 Conclusions

In this study, "Co-Active" bridge elements that act together to improve the overall bridge health index (BHI) were defined. The main advantage of using a "Co-Active" model lies in the fact that transportation agencies will be able to assess which element's preventive maintenance, rehabilitation, or replacement (MRR) optimizes a return on investment (ROI), in terms of bridge service life. Optimization of the ROI was achieved when the Co-Active element with the highest prioritization coefficient was selected for MRR.

It was concluded that long-term gains from bridge investments (preventive maintenance, rehabilitation, or replacement) became apparent when the “Co-Active” elements were identified to extend the service life of bridges. The “Co-Active” elements extended the service life of bridges through complex systems of interaction, which is a function of key parameters that define elements’ inter-dependent relationships over time. This study shows how to determine “Co-Active” coefficients and factors that enhance bridge performance by means of analyzing contingency tables. The “Co-active” model proposed in this study determines the effects of “Co-Active” elements on the bridge performance over its life cycle.

In addition to the proposed “Co-Active” model, a prioritization coefficient (PC) was introduced to account for a performance target and identify performance gaps established by a transportation agency. The proposed PC effectively found most influential MRR items in closing the performance gaps that might be present in a bridge inventory.

CHAPTER 6

6. NOVEL PRIORITIZATION MECHANISM LEVERAGING TIME-DEPENDENT ELEMENT INTERACTIONS AND CAUSALITY TO ENHANCE DEPRECIATION PREDICTIONS FOR BRIDGE ASSET MANAGEMENT

6.1 Introduction

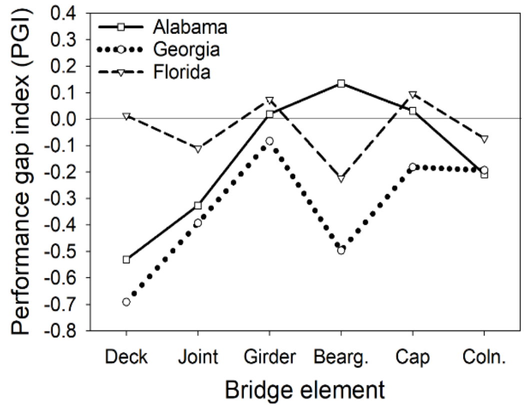
Transportation infrastructure is one of the most crucial components of overall infrastructure systems. Development of a bridge management strategy is vital in order to sustain the performance of critical transportation infrastructure such as bridges while using available funds efficiently (Karaaslan, Hiasa, & Catbas, 2018). In the United States, two major approaches exist for bridge inspection: 1) condition-rating of three major bridge components, i.e., deck, superstructure, and substructure and 2) element-based inspection, which allows a more comprehensive bridge performance assessment of element conditions and quantities (AASHTO, 2019). Regardless of the inspection methods employed, a bridge inspection enables transportation agencies to allocate funding for preventive maintenance, rehabilitation, or replacement (MRR) and to sustain the mobility for any events possibly including a national emergency. However, prioritization is often necessary due to limited resources.

6.1.1 Research Motivation

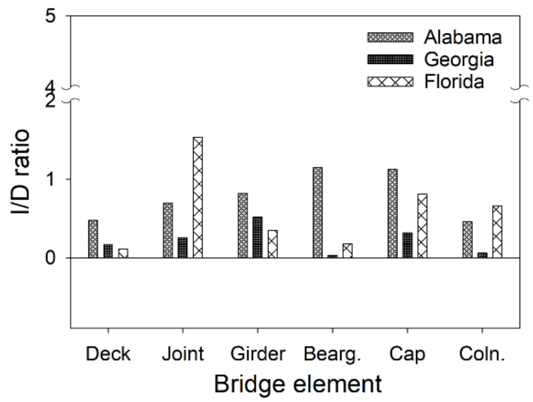
Each state Department of Transportation (DOT) in the United States maintains between 780 and 54,131 bridges in its inventory, and each bridge’s health relies on the health of 60-80 elements (e.g., deck, girder, and column) with different performance characteristics. Most transportation agencies make asset management decisions with budgetary constraints. Therefore, an efficient prioritization mechanism is essential for decision making. Here, a prioritization is defined as an element-level MRR ranking for which the long-term performance of a bridge is optimized. Many transportation agencies in North America have adopted a bridge management system (BMS) such as AASHTOWare. In most systems, however, performance gaps in a bridge inventory are determined by establishing a target performance (or threshold health index). Additionally, they predict future conditions by delineating depreciation rates from existing conditions and MRR strategies. Such predictions are overly conservative because element interactions, although present in a bridge inventory, are not considered in quantifying bridge depreciation. In Georgia, for example, deterioration predictions indicate that bridges on average last 65-75 years. However, well-maintained bridges serve for a longer period, 100-125 years. Logically, if one repairs one element, it should reduce the deterioration of other elements. Those improved elements, in turn, reduce the deterioration of the repaired element and so forth. This study proposes a novel prioritization mechanism that leverages time-dependent element interactions. They collectively measure a bridge's performance and yield more accurate depreciation rates for long-term performance predictions. Figure 33 shows the 12,723 bridge locations investigated to verify the proposed Co-Active approach. Depreciation is often used interchangeably with deterioration for bridge asset management. This dissertation adopts this perspective.

6.1.2 Performance of Bridges in Three Southeastern States

The bridges shown in Figure 33 are part of the National Highway System (NHS). In this study, health indices for bridge elements in Alabama, Georgia, and Florida are computed using bi-annual element-level bridge inspection data available in the National Bridge Inventory. For the purpose of quantifying a performance gap in this study, the element conditions are assessed in terms of 2 indicators: performance gap index (PGI) and investment-to-depreciation (I/D) ratio.



(a) PGI



(b) I/D Ratio

(c) NHS Bridge Locations

Figure 33 – Existing bridge conditions in Southeastern US states: Alabama, Georgia, and Florida.
(a) NHS bridge element performance gap index (PGI); (b) Investment-to-depreciation (I/D) ratio; and (c) NHS bridge locations

The performance gap index (PGI) is a proportional measure which represents the predicted long-term bridge performance, in relation to the exemplary long-term performance. Figure 34 shows a typical comparison between exemplary and actual bridge element performance as measured by the Bridge Health Index (BHI). The exemplary curve (see ‘Area E’ in Figure 34) characterizes a state’s target long-term performance curve.

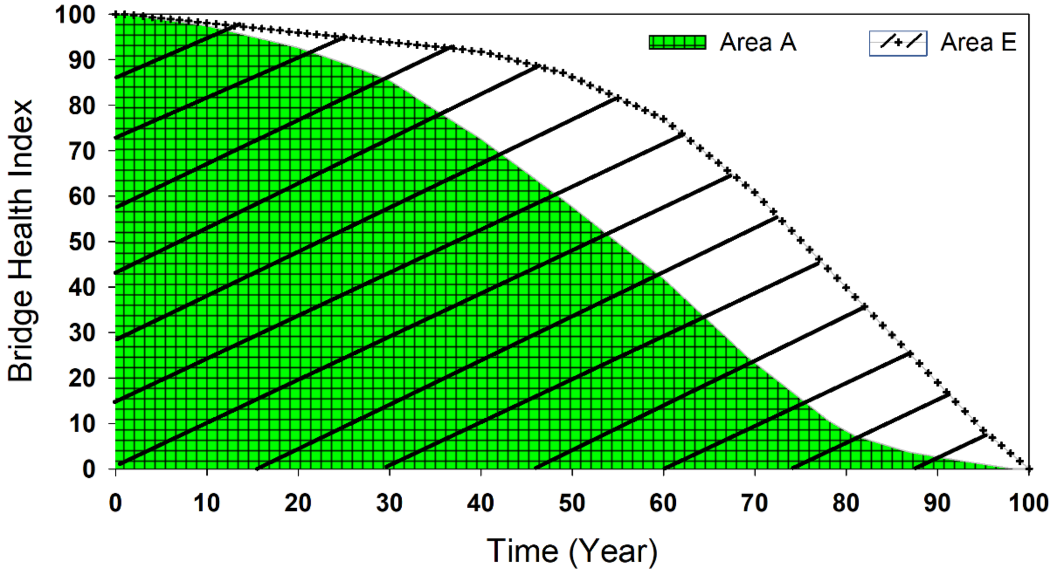


Figure 34 – Exemplary and actual bridge performance.

This study hypothetically adopts the curve presented by the Federal Highway Administration (2018). It is indicated as ‘Area E’ in Figure 34. The PGI compares areas under the curves of exemplary and actual time-history of bridges’ health indices, indicated as ‘Area E’ and ‘Area A’, respectively, and is computed by (Area A-Area E)/Area E. For example, a PGI of -0.7 for the deck elements in Figure 33(a) indicates that the area under the predicted deck performance curve is 30% of the area under the exemplary deck performance. In other words, the element performance is not desirable with a large performance gap (70%).

The investment-to-depreciation (I/D) ratio is the other indicator. It represents the ratio of a net positive change to health indices resulting from MRR to a net negative change in element health indices due to deterioration. Thus, an I/D ratio greater than 1 for an expansion joint in Florida (see Figure 33b) indicates that the average increase in health index by MRR is greater than the average reduction from depreciation. An element I/D ratio of 1 indicates that state agencies improve an element as much as it naturally and physically depreciates due to usage.

In Figure 33, the PGI and I/D ratios are calculated for a group of six selected elements in Alabama, Georgia, and Florida. There is a smaller performance gap in Florida than in Georgia and

Alabama, which is indicated by a higher PGI in the figure. Alabama has the highest I/D ratio for deck, followed by Georgia. The I/D ratio and the associated PGI for expansion joints are higher in Florida than in Georgia and Alabama. This means that Florida is the most diligent in the maintenance of expansion joints. The PGI reflects sustained long-term performance of elements. Thus, an element with a low I/D ratio could still have high PGI; however, a low I/D ratio indicates that PGI may decline in the future if no investment is made. Overall, the element conditions in Florida appear to be better than Alabama and Georgia. Based on a review of the two performance indicators, one may undertake MRR for elements. However, an investment strategy for prioritizing elements that extend bridge service life is not straightforward. The following section describes complex interactions among elements that collectively influence the overall bridge performance.

6.1.3 Research Goals and Scope

This study aims to account for element interactions, referred to as "Co-Activeness" hereafter, in predicting the long-term performance of bridges by analyzing element data available in the National Bridge Inventory. Element data refer to element-level bridge inspection results, which are generally aggregated to bridge health indices to represent the overall bridge health. Specifically, this study aims to answer the following three key questions by analyzing bridge inventories in three states:

1. Does Co-Activeness, among bridge elements, exist in the element data?
2. If exists, is the Co-Activeness quantifiable?
3. If exists and is quantifiable, are the U.S. state agencies leveraging Co-Activeness in their current maintenance, rehabilitation, or replacement (MRR) strategies?

   In order to answer these questions, an analytical study is designed in five parts:

   - Part 1: Co-Activeness is numerically quantified to investigate if strong correlations exist among elements.

- Part 2: Depreciation curves representing long-term performance of bridge elements in each of the 3 states are developed through an extensive data analysis employing the Markov method.
- Part 3: The Co-Active parameters quantified in Part 1 are used to adjust the element depreciation prediction models developed in Part 2.
- Part 4: Elements' Co-Active performance is aggregated to evaluate the effects of two hypothetical investment (or MRR) scenarios. For comparison, the performance gap index (PGI) and investment-to-depreciation (I/D) ratio are re-evaluated after employing the Co-Activeness mechanism.
- Part 5: Existing MRR strategies apparent in the element data of Alabama, Georgia, and Florida are reviewed in light of the findings.

6.2 Literature Review

Bridge performance analysis is becoming increasingly important due to aging infrastructures (K. Chang, Lim, Chi, & Hwang, 2019; Ferguson, Godson, & Gleason, 2019; Maizuar, Zhang, Miramini, Mendis, & Duffield, 2020). Bridge performance measures must be identified (Alsharqawi, Zayed, & Dabous, 2018), for decision-making on MRR, in addition to the condition assessment of bridges. As a result, various state departments of transportation (DOTs) and other agencies have developed measures of bridge performance for effective management and preservation of public equity (Adarkwa & Attoh-Okine, 2017; Garder, Aaleti, Zhong, & Sritharan, 2019). Understanding the bridge "health index" (or condition) in most bridge management systems typically enables a transportation agency to assess the performance of bridges or a network of bridges based on the available element-level inspection records (Campbell et al., 2016; Jeong, Kim, Lee, Lee, & Maintenance, 2018). Once the assessment is made, it is possible to aggregate the element health indices (HIs) to determine the overall bridge health index (BHI). Typically, a transportation agency reports a performance gap when a BHI falls below an established threshold. For example, the Virginia Department of Transportation has set a target health index of approximately 95.5 (VDOT, 2020). Additionally, BHI enables a transportation agency to develop performance prediction models. These models are beneficial in evaluating the long-term performance of bridges and bridge elements.

Overall, bridge performance prediction models must be time-dependent. However, because they are time-dependent, multiple years of condition scores are required before the effects of annual investment on bridge MRR can be determined. In this study, an alternative approach, an age-bin based bridge element deterioration model is adopted. Most transportation agencies are often interested in determining which bridge actions (or MRR strategies) optimize spending on a bridge or a network of bridges. Bridge asset management models are usually developed based on the bridge performance models and predict the effect of annual or projected investments on bridge MRR (Shim, Lee, & Kang, 2017). One of the major deficiencies of this approach is that it does not account for the influence of element performance interactions and causality on the long-term bridge performance.

6.3 Methodology

6.3.1 Quantification of Element Co-Activeness (Part 1)

In this study, Co-Activeness is quantified with a Co-Active coefficient. This parameter represents interactions among elements and is computed for a group of six selected elements previously identified in Figure 33. Equation (19) defines the Co-Active correlation coefficient. It measures how much one element's HIs, a vector 'X', affects the other element's HIs, a vector 'Y', in a bridge inventory based on the Pearson correlation coefficient (Embrechts et al., 2002), where $Cov[X, Y]$ is the covariance between the two elements' HIs, and $\sigma^2[X]$ and $\sigma^2[Y]$ denote the variances. In the case of elements with no correlation, $\rho(X, Y) = 0$.

$$\rho(X, Y) = \frac{Cov[X, Y]}{\sqrt{\sigma^2[X]\sigma^2[Y]}} \tag{19}$$

6.3.1.1 Development of element depreciation predictions (Part 2)

An age-bin analysis approach is used to develop deterioration prediction models for Georgia (M.G. Chorzepa, Durham, Kim, & Oyegbile, 2019). This methodology, used for Georgia, is employed to develop depreciation predictions for Alabama and Florida. This approach primarily employs the Markov-chain method (Guoping Bu et al., 2011) and is developed to overcome the limited element-data available as they have been collected bi-annually for each bridge since 2015. The age-bin approach for developing deterioration prediction models are briefly described as below.

The first step in developing a model is to compute and aggregate element Health Indices (HIs)

The computation of bridge element health indices follows the procedure available in the literature (Inkoom & Sobanjo, 2018; Sobanjo & Thompson, 2016). This study utilizes the element inspection records for the 3 states to compute element health indices. The computed element health indices are then aggregated and grouped into twelve age-bins with a 10-year interval as shown in Table 29. The element health indices within age bins represent element performance scores over the last 100 years.

Table 29 – Age-bin-based health index predictions for selected elements in Georgia.

Element #	Health Index											
	2020	**2010**	**2000**	**1990**	**1980**	**1970**	**1960**	**1950**	**1940**	**1930**	**1920**	**1910**
12	99.47	98.43	97.35	92.90	88.01	79.33	74.64	70.91	73.46	88.49	84.30	76.36
38	99.92	97.41	94.04	95.77	92.55	85.83	81.17	99.44	68.84	77.43	67.26	55.00
107	99.16	98.43	95.62	97.20	96.52	94.21	87.79	79.71	78.72	81.54	81.60	73.44
205	98.00	97.09	93.78	93.61	95.73	89.45	80.87	71.83	90.38	76.82	42.93	59.69
215	99.19	98.23	97.25	95.97	94.96	94.71	92.89	89.56	83.72	81.27	62.92	53.63

The second step is to apply the Markovian model to the aggregated element Health Indices (HIs) The Markovian modeling approach is used because it is more suitable for the large bridge inventories available in the 3 states investigated in this study. This Markovian approach typically requires calculating a transition probability matrix (Inkoom & Sobanjo, 2018; Sobanjo & Thompson, 2016). for each element. Using the transition probability matrices estimated for an element, the Markovian model evaluates element deterioration predictions. This procedure is repeated for each element in each state.

6.3.1.2 Adjustment to the Depreciation Curves Accounting for Co-Activeness (Part 3)

A Co-Active model accounts for the effect of element interactions (i.e., Co-Activeness) in developing the depreciation predictions resulting from an element MRR. The Co-Active model leverages on element interactions and more accurately predicts bridge performance. The following sections explain how one can use the proposed model.

6.3.1.3 Evaluation of Two Hypothetical Investment Scenarios (Part 4)

Two hypothetical cases involving an expansion joint replacement and a deck repair for the next 25 years show how the proposed mechanism affects the bridge service life from MRRs. Additionally, the PGI and I/D ratio are evaluated for the MRR strategies.

6.3.1.4 Review of Existing MRR Strategies (Part 5)

Biannual changes, from bi-annual inspections, in the element health indices (i.e., increase or decrease in the element HIs) are computed for all elements in the 3 states. The existing MRR strategies apparent in the element data are discussed in light of the findings.

6.4 Results Employing the Proposed Co-Active Mechanism

6.4.1 Co-Active Parameters

This section presents the results obtained from studying the three-state element data. Tables 30 through 32 show the Co-Active parameters for Alabama, Georgia, and Florida. These parameters include co-active coefficients and aggregated Co-Active parameters (Parts ‘a’ and ‘b’ in Tables 30 through 31). The Co-Active coefficients are calculated using Equation (20). For example, the Co-Active coefficient for Alabama, designated as ‘A’ in Part ‘a’ of Table 30, is calculated as follows:

$$\rho(Deck,\ Joint) = \frac{Cov\left[HI_{deck}, HI_{joint}\right]}{\sqrt{\sigma^2[HI_{deck}]\sigma^2\left[HI_{joint}\right]}} = 0.96 \qquad (20)$$

In Equation (20), HI_{deck} and HI_{joint} represent the age-bin aggregated health indices of deck and expansion joint elements, respectively. $Cov\left[HI_{deck}, HI_{joint}\right]$ is the covariance between deck’s and expansion joint’s HIs, and $\sigma^2[HI_{deck}]\ and\ \sigma^2\left[HI_{joint}\right]$ denote their variances. The aggregated Co-Active parameter (see part ‘(b)’ in Table 30) is obtained by combining all Co-Active coefficients for each element. For example, the aggregated Co-Active parameter for deck in Alabama is 5.02 (= 1.00 + 0.96 + 0.89 + 0.50 + 0.71 + 0.96).

The correlation matrix shown in Tables 30 through 31 is assumed asymmetric in this study. That is, it is assumed that there is a uni-directional cause and effect for maintenance such as one associated with a water intrusion. However, an asymmetric matrix may also be considered if there is strong evidence that the bearing element affects the deck condition and that the column significantly affects the deck element. The cause and effect question addressing meaningful bridge element interactions must be identified after carefully reviewing service and maintenance records. Asymmetric matrix was considered for this study, and for the six elements selected in the three states, it was concluded that the asymmetric matrices better represent element interactions observed in in-service bridges. Therefore, the results from asymmetric element interactions are presented in this dissertation.

As shown in Table 30, the expansion joint and deck are highly interactive and affect the underlying elements. The expansion joint and deck with the underlying elements are more interactive in Georgia than Alabama and Florida. Among the three states, the expansion joint and deck elements in Florida have the least interactions with the underlying elements. This aspect is further discussed in the later section. The element interactions for the three states are graphically illustrated in Figure 35. It should be recognized that the Co-Active parameters only describe the interactions among elements present in each state's element data. It is important to recognize, however, the conditions of Co-Active elements mainly drive the overall bridge health indices. That is, the element interactions are reflected in predicting bridge health indices in order to account for the Co-Activeness recognized in the data; however, current element conditions (or bridge inspection results) primarily characterize the bridge performance deterioration.

Table 30 – Co-Active parameters for Alabama.

	The Effect of the following element's condition change					
(a) On the element below	**Deck**	**Expansion Joint**	**Beam/ Girder**	**Bearing**	**Cap Beam**	**Pier/ Column**
Deck	1					
Expansion Joint	0.96	1				
Beam/Girder	0.89	0.82	1			
Bearing	0.50	0.36	0.61	1		
Cap Beam	0.71	0.57	0.75	0.86	1	
Pier/Column	0.96	0.93	0.96	0.54	0.68	1
(b) Aggregated Co-Active parameter	5.02	3.68	3.32	2.4	1.68	1

Table 31- Co-Active parameters for Georgia.

	The Effect of the following element's condition change					
(a) On the element below	**Deck**	**Expansion Joint**	**Beam/ Girder**	**Bearing**	**Cap Beam**	**Pier/ Column**
Deck	1.00					
Expansion Joint	0.65	1.00				
Beam/Girder	0.99	0.53	1.00			
Bearing	0.89	0.88	0.81	1.00		
Cap Beam	0.99	0.70	0.97	0.90	1.00	
Pier/Column	0.79	0.96	0.68	0.98	0.82	1.00
(b) Aggregated Co-Active coefficient	5.31	4.07	3.46	2.88	1.82	1.00

Table 32 - Co-Active parameters for Florida.

	The Effect of the following element's condition change					
(a) On the element below	**Deck**	**Expansion Joint**	**Beam/ Girder**	**Bearing**	**Cap Beam**	**Pier/ Column**
Deck	1.00					
Expansion Joint	0.37	1.00				
Beam/Girder	0.41	0.70	1.00			
Bearing	0.21	0.34	0.03	1.00		
Cap Beam	0.88	0.49	0.58	0.00	1.00	
Pier/Column	0.85	0.61	0.72	0.08	0.89	1.00
(b) Aggregated Co-Active coefficient	3.72	3.14	2.33	1.08	1.89	1.00

Figure 35 shows the complex interactions that exist among the six Co-Active elements for the three states. The arrowtail (i.e., the origin of each arrow) represents the influential element, and the arrowhead (i.e., end of each arrow) shows the dependent element being affected by the influential element (i.e., defines the causality). In Figure 35, each arrowhead shows the Co-Active coefficient between two elements. For example, in Figure 35, the arrow originating from the beam/girder and terminating at the cap beam shows that the cap beam is highly dependent on the changes in the condition of the beam/girder, as evident with the Co-Active coefficient of 0.97. As indicated earlier, the arrows may go both ways if one must define such causality. Among the three states, changes in the deck conditions in Alabama appear most influential on the long-term performance of the expansion joints. Similarly, the changes in the conditions of expansion joints are most influential on the long-term performance of the underlying elements in Georgia (see Figure 36a).

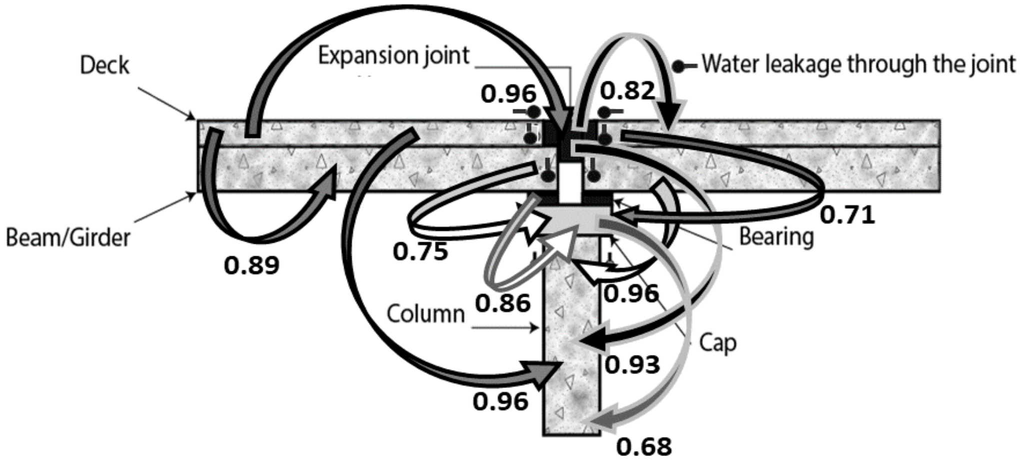
Overall, the development of element interactions enables transportation agencies to depict data-driven element interactions for decision-making on bridge investment. The following section presents two hypothetical cases. They show how investments on MRR of two critical elements (expansion joints or decks) affect the long-term bridge performance when the proposed Co-Active mechanism is employed.

6.4.2 Effects of MRR on Bridge Performance

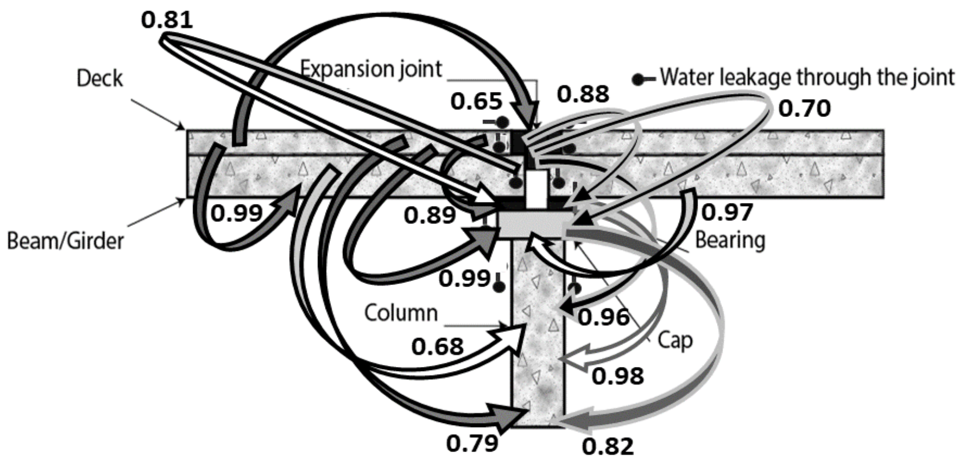
6.4.2.1 Case 1. Expansion Joint Replacement

When an element is maintained, rehabilitated, or replaced (MRR), it affects the deterioration rate. Additionally, it affects the other elements' HIs as well as the overall BHI. In this study, the extent to which the MRR of an element affects the other elements' depreciation rate is affected by the Co-Active coefficients shown in Tables 30 through 32. Thus, the Co-Active mechanism leverages on element interactions and brings a deterioration rate close to real-world observations.

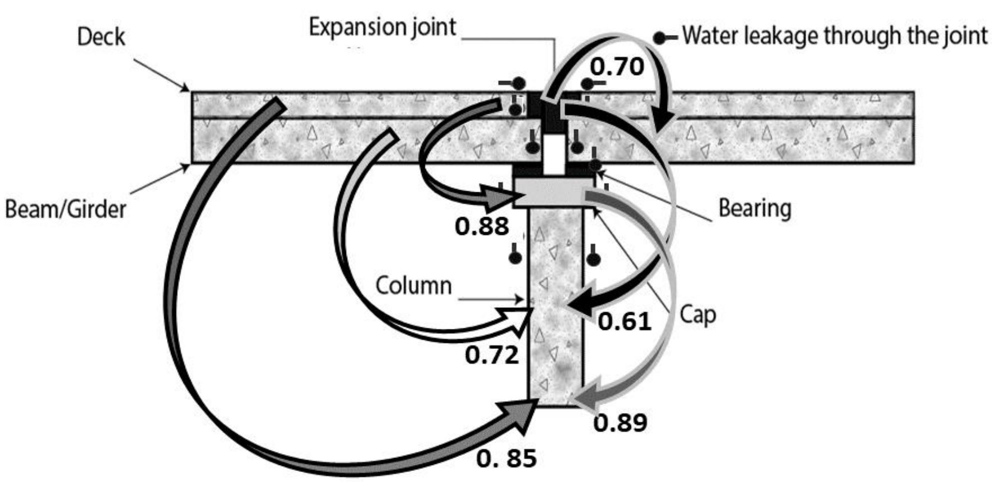
To illustrate how this novel mechanism works, a case study, involving a replacement of all expansion joints in the inventory is considered. Figure 36 shows the overall bridge and element HI predictions, not including and including the Co-Active mechanism, when an expansion joint is replaced in (future) Year 25 holding everything else equal. The HI of 100 indicates an excellent condition. As shown in Figures 36 (b), (d), and (f), the depreciation rates of the other elements are affected by the expansion joint replacements.



(a) Alabama



(b) Georgia



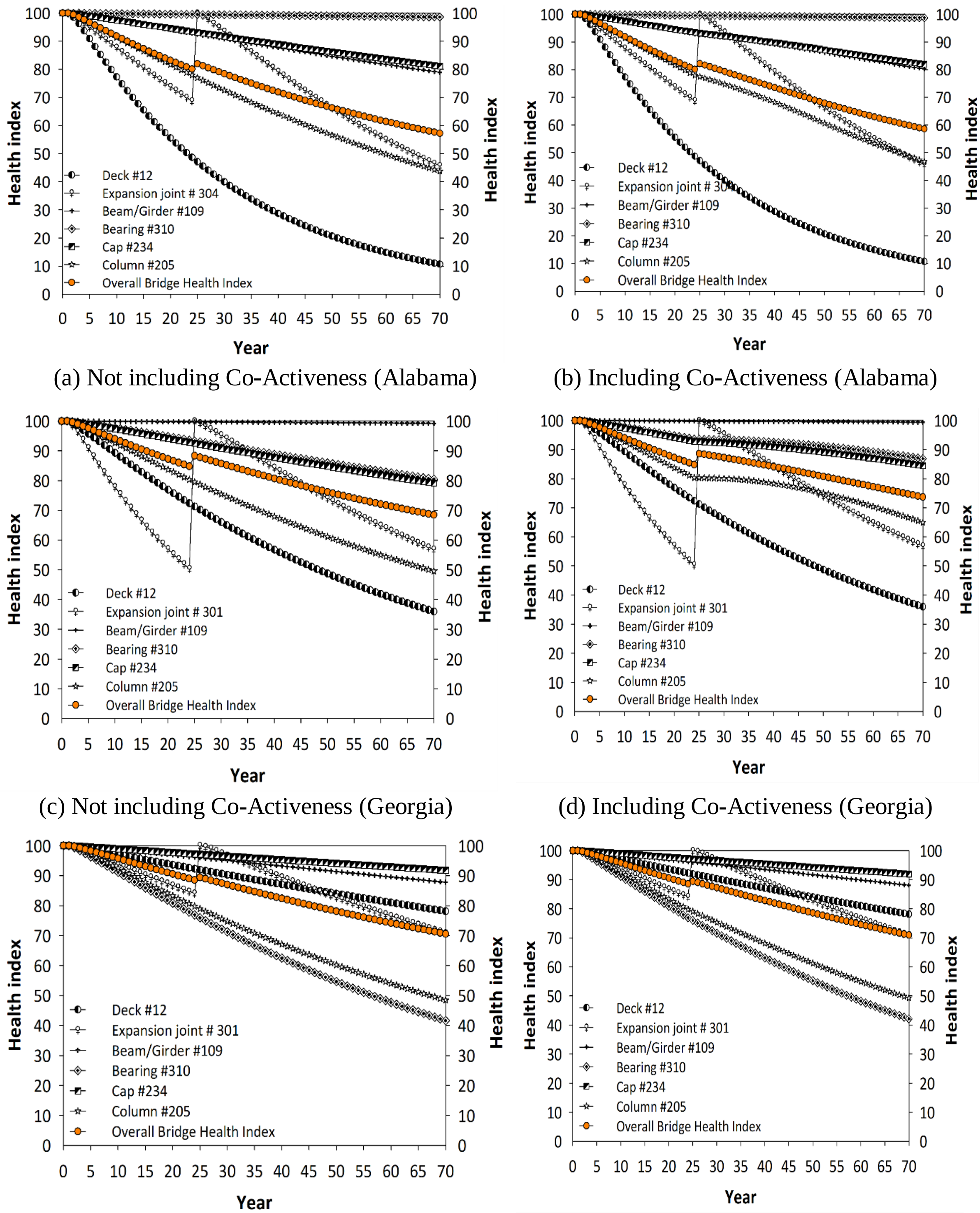
(c) Florida

Figure 35 – Graphical illustration showing element interactions:

Alabama; (b) Georgia; (c) Florida.

As shown in Figure 36, element interactions do not have significant effects on the deterioration predictions for elements in Alabama and Florida. The element interactions in Georgia improve the deterioration predictions and enhance the overall bridge performance by extending the service life by about 5 years. This is significant because the extension applies to 3,324 bridges in Georgia. The figure also shows that the deterioration predictions are dependent on the magnitude of the Co-Active parameters.

Figure 37 presents the PGI and I/D ratio calculated for the expansion joint replacement scenario. For Alabama, the Co-Active analysis (including element interactions) marginally improves the element and overall bridge PGIs. For Georgia, on the other hand, the Co-Active analysis improves HI of the other elements and overall bridge PGIs more than it did in Alabama. The Co-Active analysis has no impact in Florida. Overall, the Co-Active mechanism extends the bridge service life by 5 years and improves the overall bridge PGI and I/D ratios in Georgia (see Figure 37).

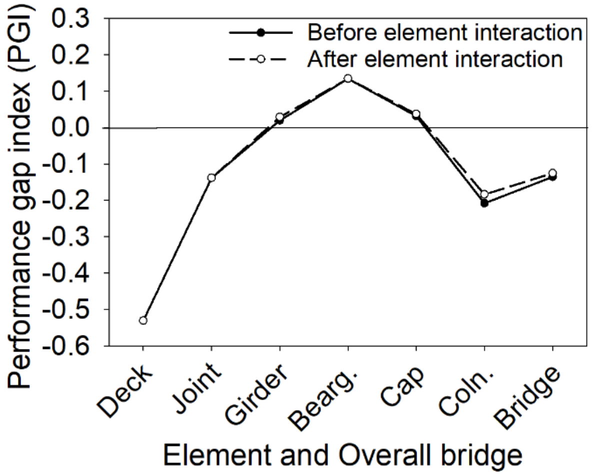


(a) Not including Co-Activeness (Alabama) (b) Including Co-Activeness (Alabama)

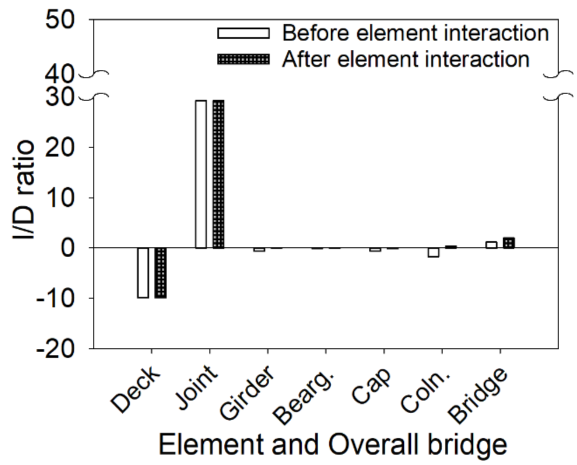
(c) Not including Co-Activeness (Georgia) (d) Including Co-Activeness (Georgia)

(e) Not including Co-Activeness (Florida) (f) Including Co-Activeness (Florida)

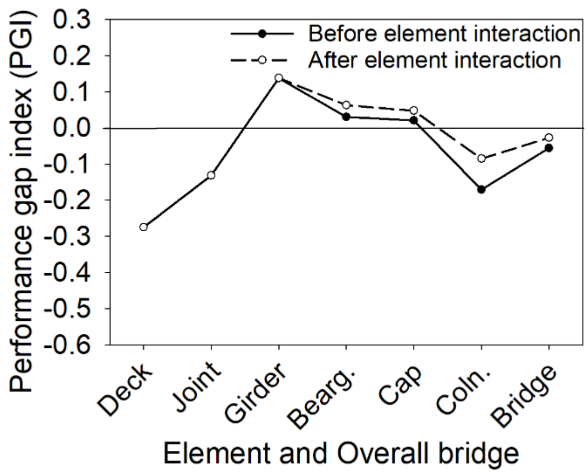
Figure 36 – The Effect of an expansion joint replacement not including and including the Co-Active mechanism: (a) and (b) in Alabama, (c) and (d) in Georgia, and (e) and (f) in Florida.



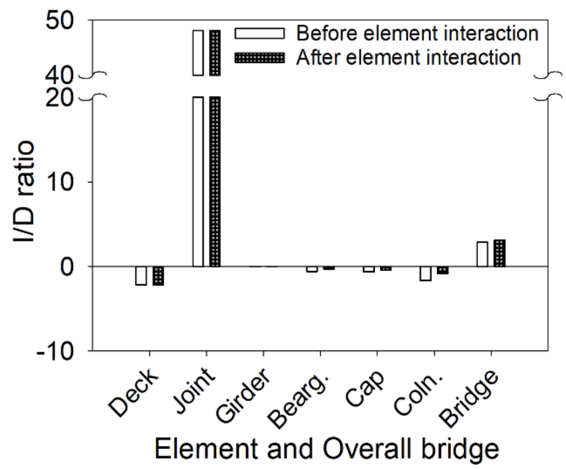
(a) PGI Including Co-Activeness (Alabama)



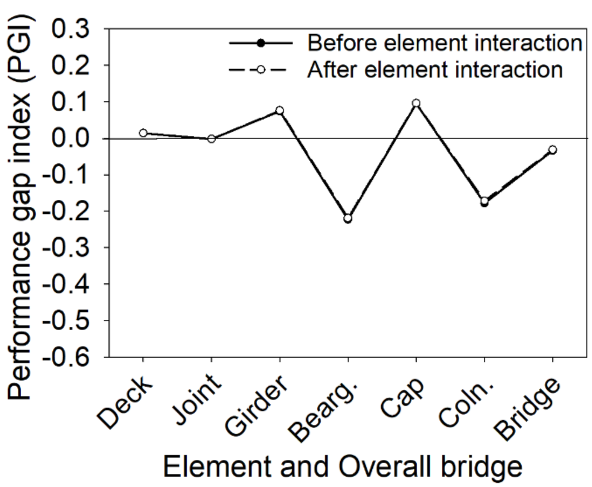
(b) I/D Including Co-Activeness (Alabama)



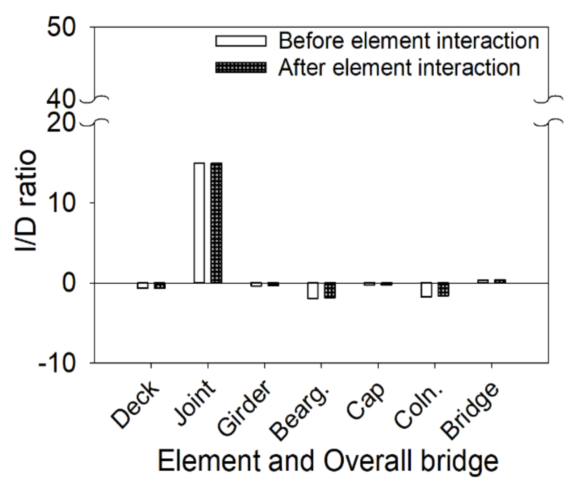
(c) PGI Including Co-Activeness (Georgia)



(d) I/D Including Co-Activeness (Georgia)



(e) PGI Including Co-Activeness (Florida)



(f) I/D Including Co-Activeness (Florida)

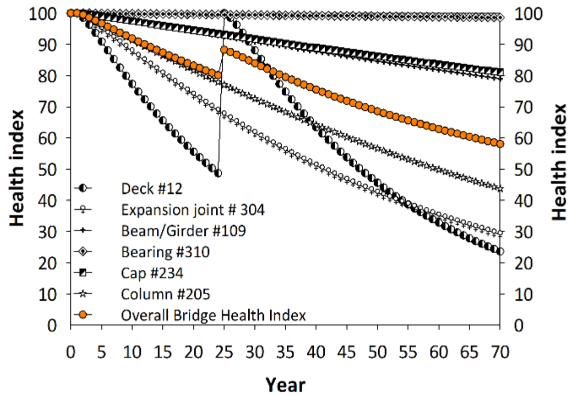
Figure 37 – Case 1: Performance gap index and I/D ratio for Southeastern US states:

(a) and (b) in Alabama; (c) and (d) in Georgia; (e) and (f) in Florida.
(b)

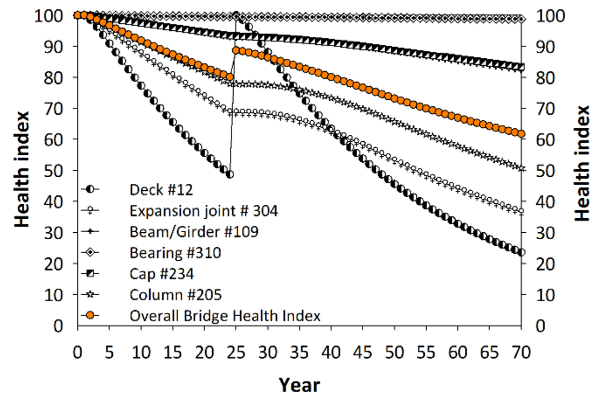
6.4.2.2 Case 2: Deck Repair

Figure 38 shows the overall bridge and element HI predictions, with and without employing the Co-Active mechanism, when all deck elements in the inventory are repaired in Year 25, holding everything else equal. As shown in Figure 38, element interactions do not have significant effects on the deterioration predictions for elements in Georgia and Florida. The element interactions in Alabama improve the deterioration predictions and enhance the overall bridge performance by extending the service life by about 4 years. In Figure 38, it is important to recognize that the increase in the deck HIs has slowed the deterioration rate of the other elements, notably expansion joints and columns. Similar to the findings from the first scenario, it is concluded that the Co-Active analysis has no impact in Florida. This will be further discussed in the following section.

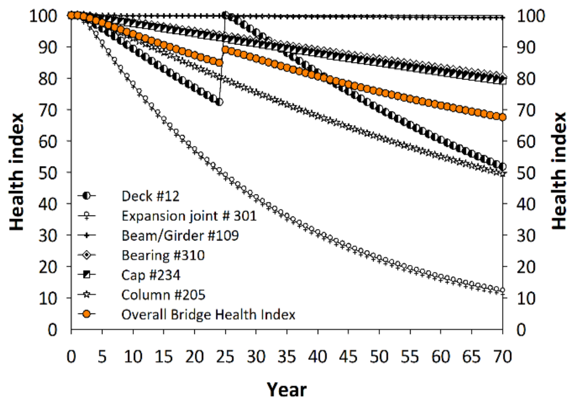
Figure 39 shows the corresponding performance gap index and investment-depreciation (I/D) ratio computed for the analysis presented in Figure 38. The Co-Active analysis improves HIs of the other elements and overall BHIs as well as PGIs in Alabama, while it marginally improves the PGIs in Georgia. The Co-Active analysis has no significant impact on the Florida data. Additionally, the Co-Active analysis improves the element I/D ratios for the expansion joints, piers, and overall bridges in Alabama.



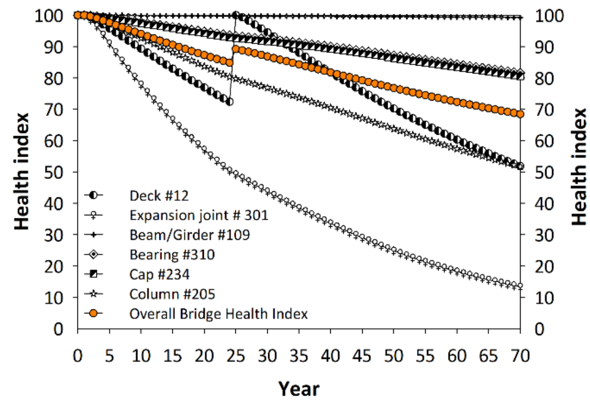
(a) Not including Co-Activeness (Alabama)



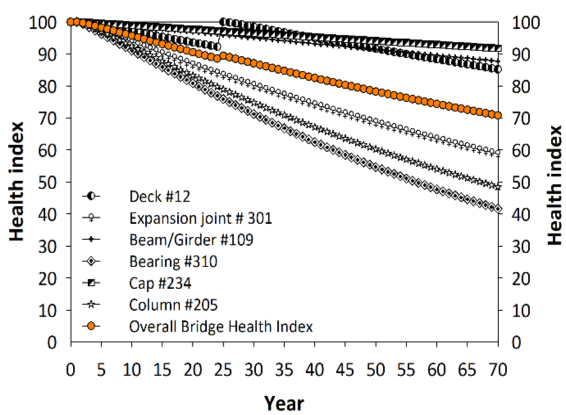
(b) Including Co-Activeness (Alabama)



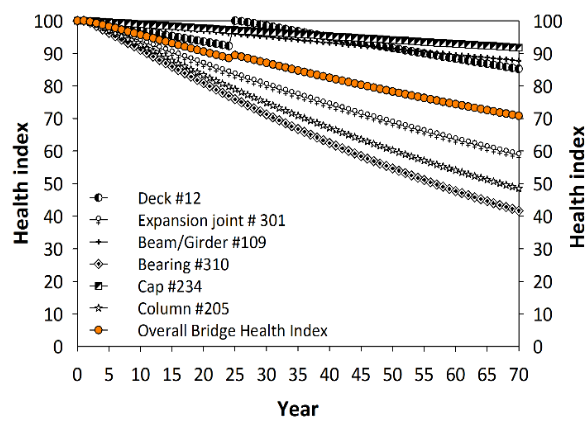
(c) Not including Co-Activeness (Georgia)



(d) Including Co-Activeness (Georgia)

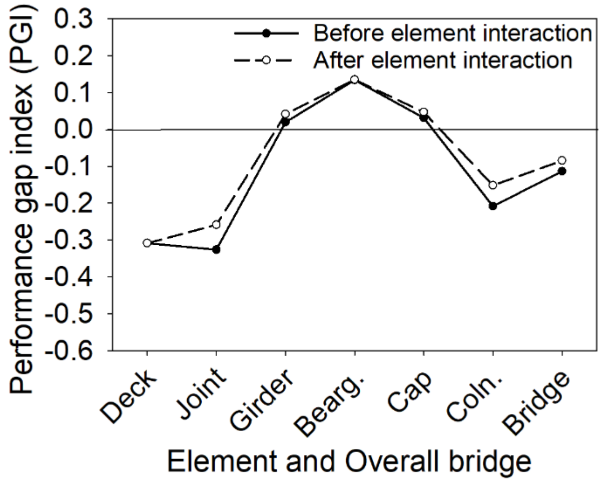


(e) Not including Co-Activeness (Florida)

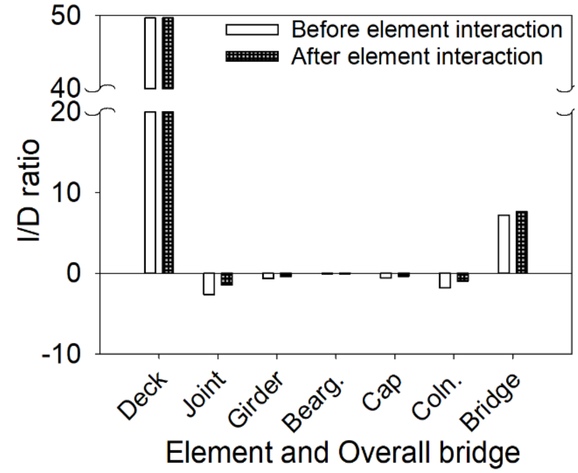


(f) Including Co-Activeness (Florida)

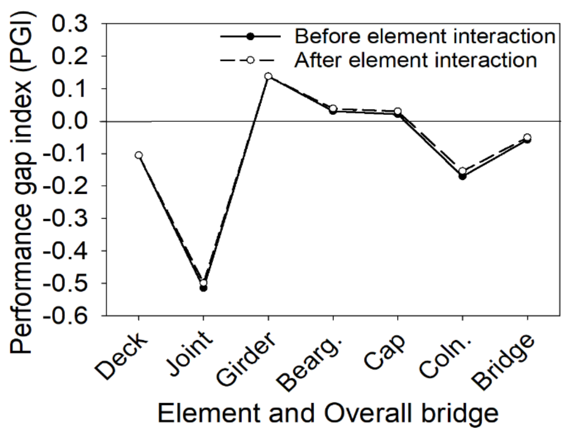
Figure 38 – The effect of a deck repair not including and including the Co-Active mechanism: (a) and (b) in Alabama, (c) and (d) in Georgia, and (e) and (f) in Florida.



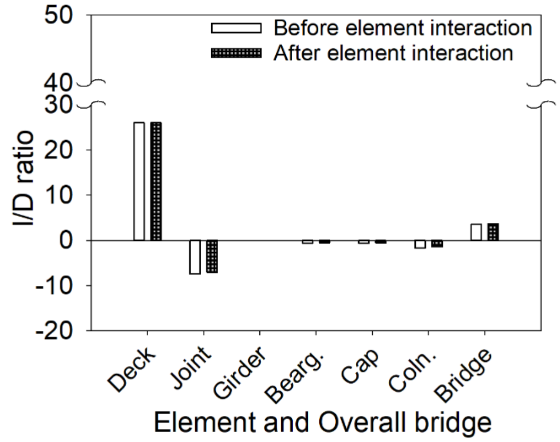
(a) PGI Including Co-Activeness (Alabama)



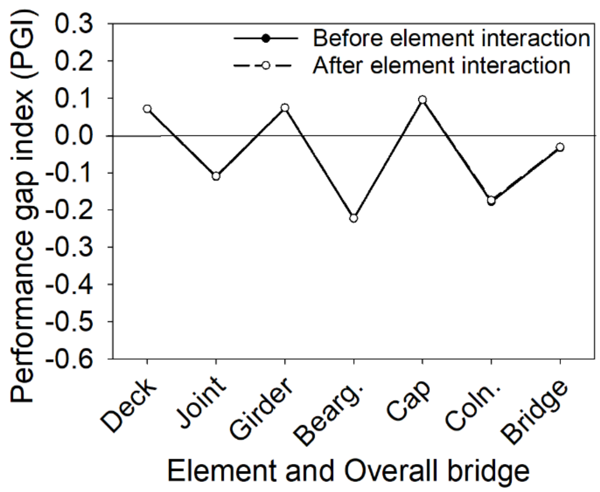
(b) I/D Including Co-Activeness (Alabama)



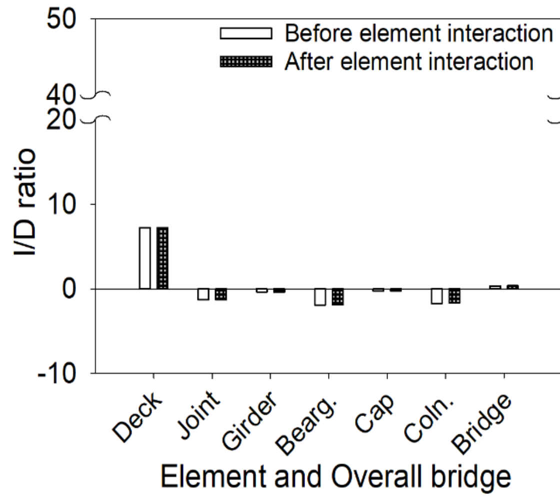
(c) PGI Including Co-Activeness (Georgia)



(d) I/D Including Co-Activeness (Georgia)



(e) PGI Including Co-Activeness (Florida)

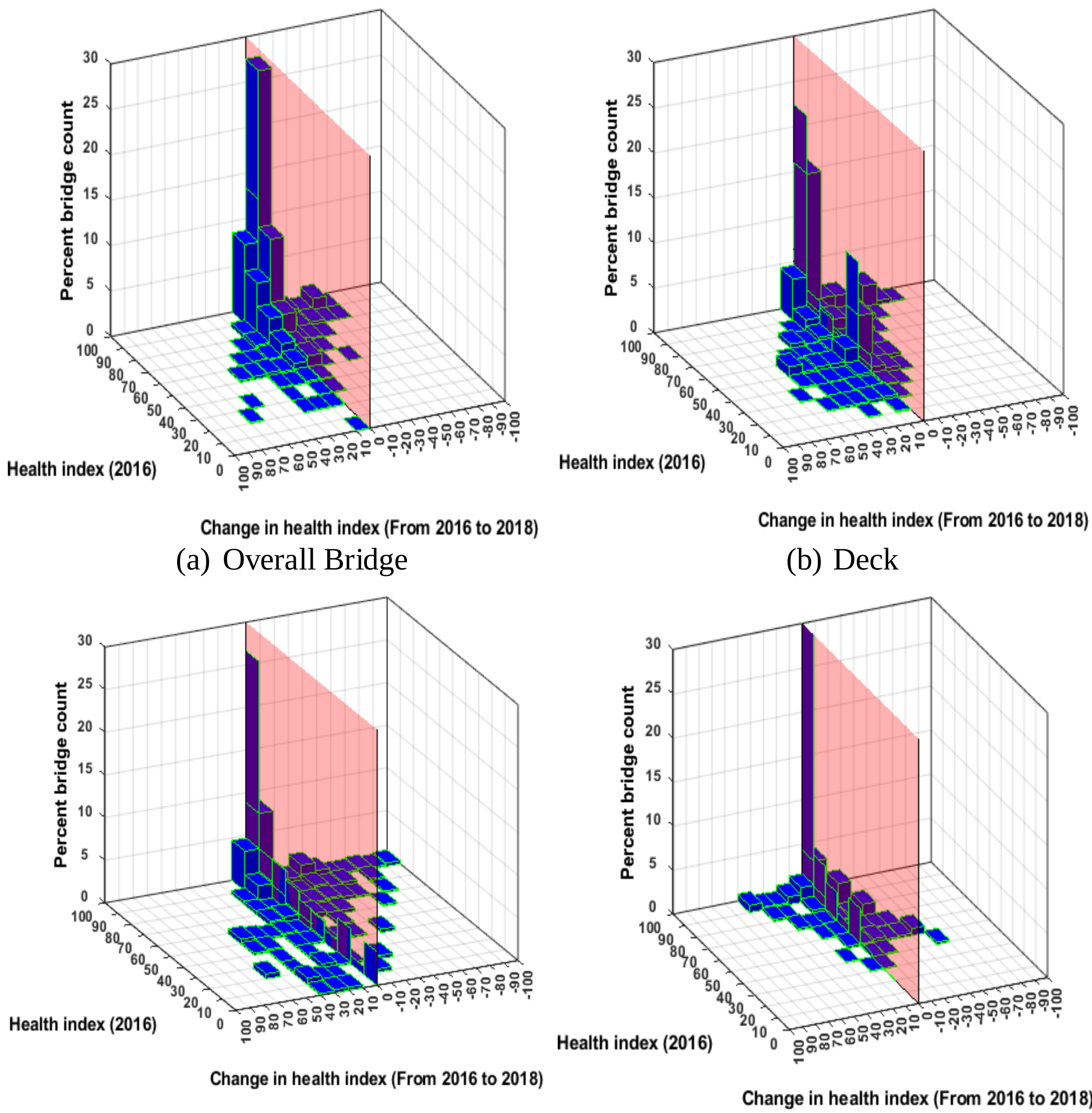


(f) I/D Including Co-Activeness (Florida)

Figure 39 – Case 2: Performance gap index and I/D ratio for Southeastern US states: (a) and (b) in Alabama; (c) and (d) in Georgia; (e) and (f) in Florida.

6.5 Analysis of MRR Strategies and Discussion of Results

In the previous section, hypothetical scenarios are studied to identify critical elements that need to be prioritized for asset management decision making. In Figures 40 through 42, the increase or decrease in the element health indices is graphically presented to review and deduce each state's MRR approach. This step answers the third research question: if a state agency can leverage the Co-Active mechanism for decision making.



(a) Overall Bridge (b) Deck

(c) Expansion Joint (d) Bearing

Figure 40 – Biannual bridge performance for Alabama.
(a) Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.

The bar charts show the element (or bridge) health indices in 2016 versus the change in health indices from 2016 to 2018 on a horizontal plane, and present a percentage of elements/bridges in the inventory in the vertical axis. Figure 40 shows that Alabama focuses on the maintenance of decks with health indices (HIs) between 20 and 70. Additionally, it actively carries out preventive maintenance for relatively new decks (i.e., decks with HIs between 90 and 100). In terms of performance, decks with high HIs (i.e., HIs between 80 and 100) are depreciating faster than those in the other states as indicated by the change in HIs (see Figure 40b). Alabama appears to invest more in expansion joints, particularly invests heavily in expansion joints with HIs between 40 and 60 (see Figure 40c). However, the Co-Active analysis presented in this study informs that Alabama could benefit more (i.e., extend the bridge service life in the long-term) if it were to increase investments on decks. The data also show that newly installed expansion joints (or expansion joints with HIs between 80 and 100) are depreciating faster than those with HIs lower than 80. Alabama may move on to the expansion joint element after or while addressing deck MRR.

Figure 41 presents the bridge MRR strategy for Georgia. It focuses on the maintenance of decks and expansion joints with HIs between 0 and 60. As a result, decks and expansion joints with higher HIs (about 50 to 100) are depreciating faster. The current MRR strategy appears to negatively affect the overall bridge performance (see Figure 41a) because bridges with higher HIs (about 60 to 100) are also depreciating faster than bridges with relatively lower HIs. Based on the review of Georgia’s element data and Co-Active analysis findings, Georgia should be able to optimize its long-term bridge performance by investing more in expansion joints, particularly focusing on joint replacements and early preventive maintenance.

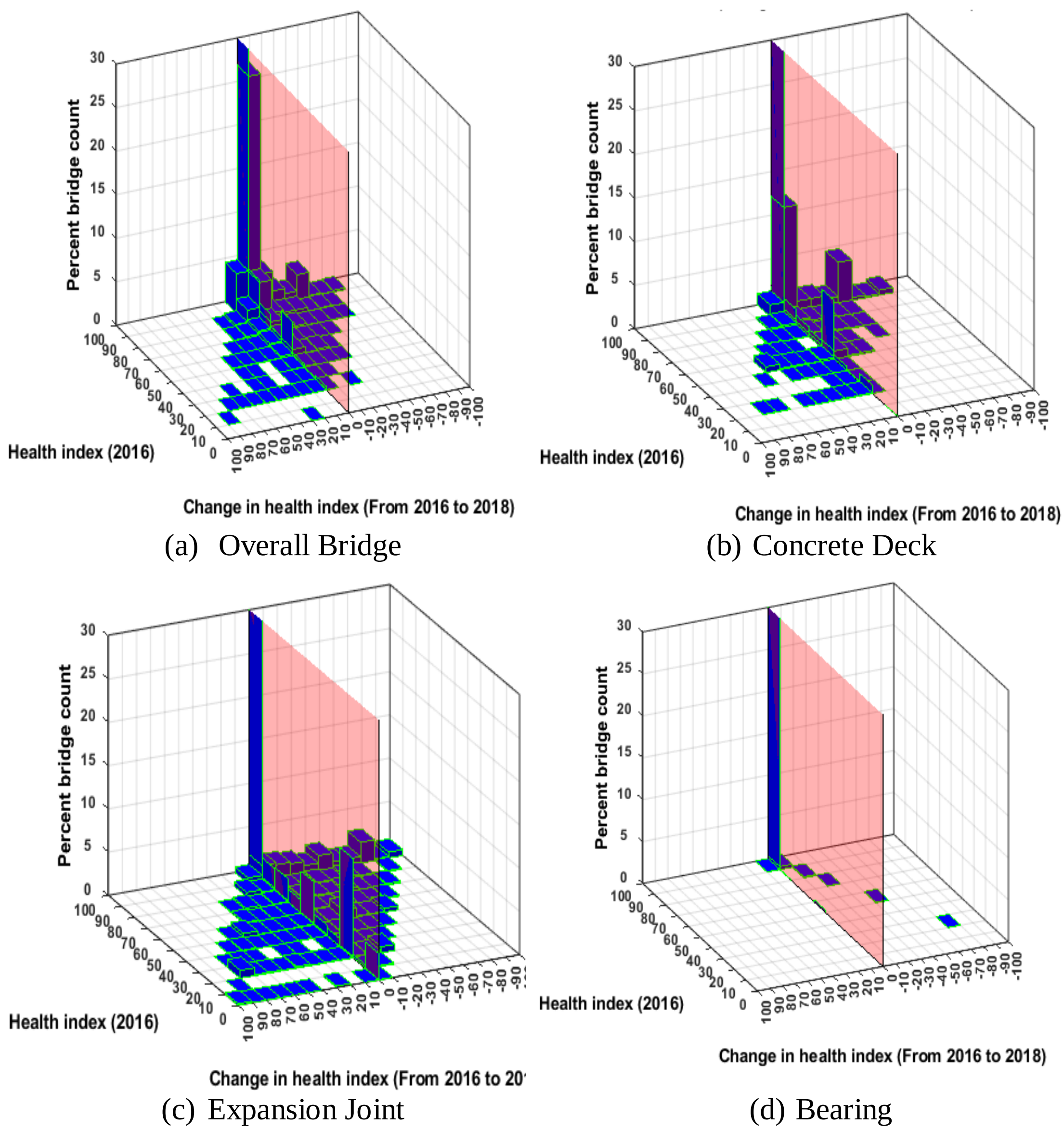
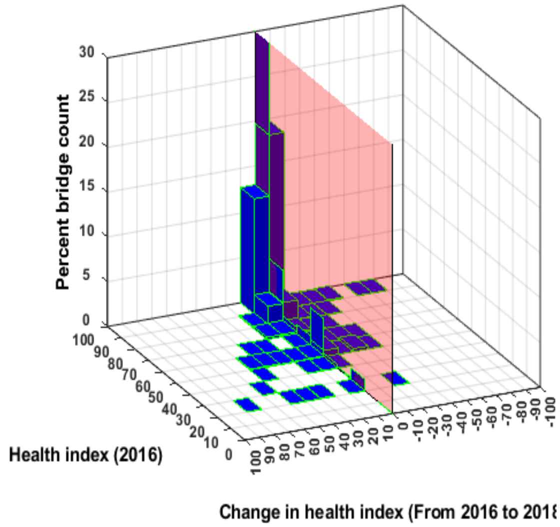


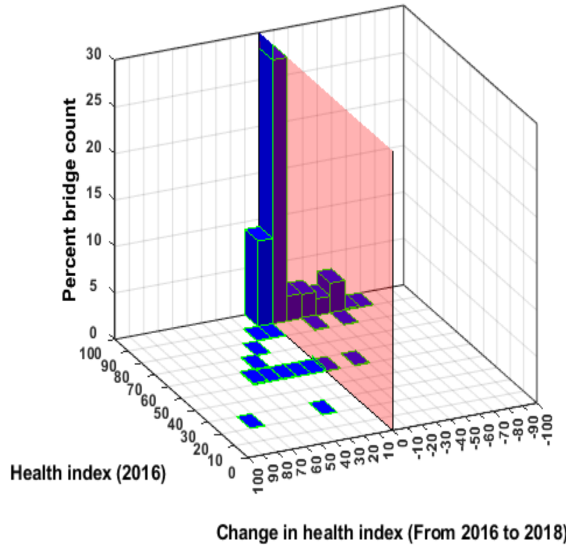
Figure 41 – Biannual bridge performance for Georgia.

(a) Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.

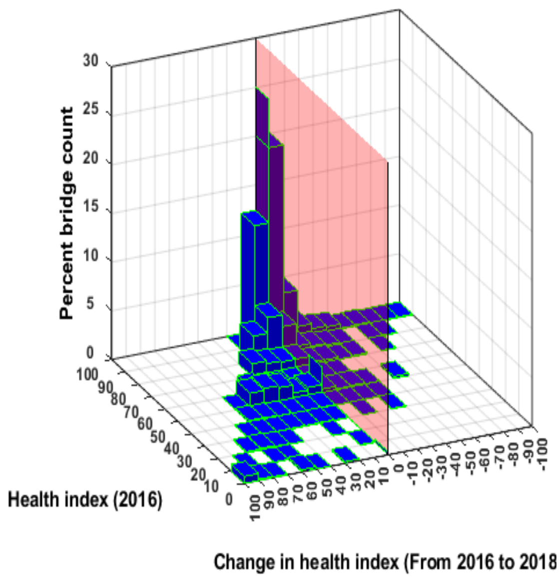
Compared to Florida's strategy shown in Figure 42(c), Georgia's investment in expansion joints is relatively lower. Similarly, investments on decks' preventive maintenance and minor repairs made early in their service life should increase in order to effectively extend the bridge service life. This particular finding for Georgia is significant because the U.S. DOT requires less than 10% of the total deck area in a state is allowed to be structurally deficient, leading to allocating resources to decks.



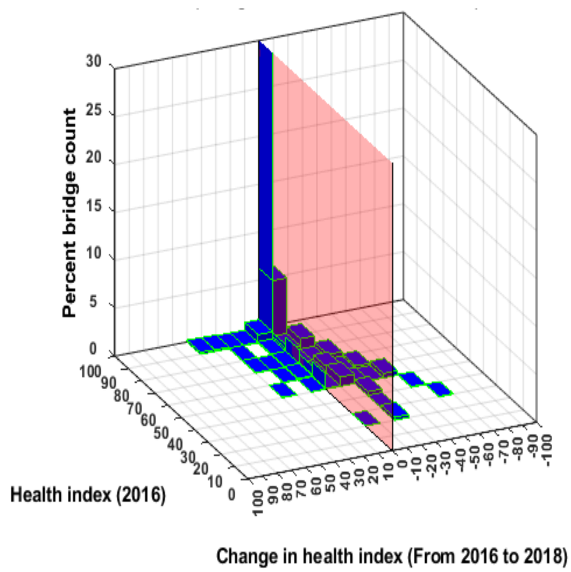
(a) Overall Bridge



(b) Concrete Deck



(c) Expansion Joint



(d) Bearing

Figure 42 – Biannual bridge performance for Florida.

(a) Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.

Figure 42 shows how Florida's MRR strategy affects bridge/element health indices. Similar to the other two states, Florida focuses extensively on repairs and rehabilitations of decks and expansion joints. However, it invests more into newer elements than Georgia and Alabama do. In other words, Florida's bridge MRR strategy effectively delays a progressive deterioration through purposeful preventive maintenance early in-service life. This strategy appears highly effective in improving the overall bridge performance as evident in Figure 42a, although this outcome may result from more resources allocated. Similar to Georgia, bridges with high HIs (i.e., bridges with HIs between 80 and 100) are also depreciating fast. However, Florida appears to recognize the depreciation and invest heavily in bridges with high HIs, in addition to MRR on bridges with relatively lower HIs.

6.5.1 Summary of Results

Although one element is not selected over the other elements for asset management, a prioritization of elements exists in the inventories.

1. MRR on the bridge deck is more influential than MRR on the expansion joint for the long-term performance of bridges in Alabama.
2. MRR on the expansion joint is more influential than MRR on the bridge deck for the long-term bridge performance in Georgia.
3. The element interactions do not have significant effects on the long-term bridge performance in Florida. This may be attributed to the bridge management strategy (i.e., early preventive maintenance) in Florida.
4. Florida's strategy leverages Co-Activeness in bridge maintenance, repair, and rehabilitation (MRR).

In Georgia, where the expansion joint is the most influential element, the PGI for column improved by 50% as a result of an expansion joint replacement. The percentage reduction in the I/D ratio was also higher than in the column element. This shows that the condition of expansion joints in Georgia is most critical to the long-term performance of columns. Therefore, by investing in expansion joint replacements, Georgia also benefits, indirectly, in closing the performance gaps in critical elements such as a column. For the bridge management in Alabama, the PGI for column and expansion joint improved by 25% and 20%, respectively, when a deck was replaced in Year 25. Alabama bridge management strategy slows the depreciation of columns and expansion joints by allocating more resources on the deck's MRR (AASHTO, 2019). The Florida outcome, resulting from early preventive maintenance, is anticipated but is significant because it provides evidence that the Co-Active model well characterizes element interactions and bridge performance.

6.6 Conclusions

The proposed Co-Active mechanism used in bridge performance predictions leverages time-dependent element interactions that affect depreciation rates of bridges. In this study, the element data from three southeastern US states (Alabama, Georgia, and Florida) are investigated to illustrate the capability of the proposed model. It is concluded that Co-Activeness exists in the element data, and the extent of Co-Activeness among elements are numerically quantifiable. Two indicators, the investment-to-depreciation (I/D) ratio and performance gap index (PGI), is used to measure a long-term bridge performance gap. Based on the findings of this study, the following conclusions are made:

- Accounting for element interactions (i.e., Co-Activeness) that are present in the element-data yields more realistic, and thus less overly conservative, performance predictions.
- Long-term bridge performance predictions reflecting a Co-Active mechanism that is present in a bridge inventory are effective in prioritizing elements for maintenance, rehabilitation, and repair decisions.

- State agencies with relatively lower bridge health indices are more likely to benefit from using the proposed method that accounts for the Co-Active mechanism because condition changes in one element are more likely to significantly influence the bridge health indices.
- Early preventive measures undertaken for a bridge inventory have a similar effect as leveraging the proposed Co-Active mechanism. That is, early MRR measures enables states to fully leverage the Co-Activeness in bridge long-term performance.

CHAPTER 7

7. A STRATEGIC MOVE FOR SERVICE LIFE EXTENSION OF BRIDGES BY EMPLOYING A CO-ACTIVE PRIORITIZATION MECHANISM

7.1 Introduction

Transportation asset management often requires a data-driven decision-making process to effectively preserve the long-term performance of transportation assets. This data-driven decision-making process is dependent on the information obtainable from the quantitative analysis of transportation assets inspection records. Thus, there has been an increasing interest in the performance analysis of transportation asset among agencies around the world because each nation's infrastructure is essential for supporting economic development and sustainability and boosting the public health and safety (Contreras-Nieto, Shan, Lewis, & Hartell, 2019). Among this infrastructure, bridges constitute the most expensive assets, by mile, for transportation agencies across the United States and around the world. Also, bridges are a crucial component of the overall transportation system. The collapse or breakage of a bridge generally causes considerable damage and social loss to the users. Therefore, it is critical to preserve a certain level of bridge performance (Kim, Lee, & Lee, 2018). Bridge preservative measures include preventive maintenance, rehabilitation, or replacement (MRR). For an effective application of these preservative measures, bridge agencies need to implement a bridge management strategy that effectively prioritizes bridges for actions, most especially for large bridge networks such as those available in the United States.

7.1.1 Research Motivation

Most of the bridges in the United States were constructed between the 1950s and the 1970s, with an average lifespan ranges from 50 to 100 years. Consequently, an increasing number of these bridges are getting old, resulting in a decrease in the overall bridge structural and functional performance, and thus requiring much more frequent inspections, repairs, or rehabilitation to keep them safe and functional. Also, due to constrained construction and maintenance budgets, bridge owners now have a difficult task of balancing the condition of their bridges with the cost of maintaining them (Kim et al., 2018). Particularly, bridge managers are facing ever-increasing challenges in prioritizing investment to maintain the safety and functionality of deteriorating bridges (W. Zhang & Wang, 2017).

The main purpose of investment in bridge preventive maintenance, rehabilitation, or replacement (MRR) is obtaining the highest return while the risk associated with it is minimum (Agdas, Rice, Martinez, & Lasa, 2016; Andrijcic & Haimes, 2017; Sabatino & Frangopol, 2017). Thus, significant research efforts have focused on the development of bridge prioritization strategies that optimize return on investment on bridge MRR. Recently, most studies on the bridge prioritization for MRR adopt a risk-based approach (Contreras-Nieto et al., 2019; Kim et al., 2018; Puls et al., 2018; W. Zhang & Wang, 2017). They often determine the risk associated with the continuing usage of a bridge based on its current and projected performance. However, consideration for risk alone does not provide a comprehensive solution to bridge asset management. To better manage bridge inventories, therefore, tools that can accurately predict the future condition of a bridge, as well as its remaining life, are required (Lu & Phares, 2018). The effects of the changes in the condition of each element, how these changes relate to the element interactions, and how element interactions impact the long-term bridge performance, needs to be fully understood. These element conditions can be assessed by computing element health indices from the recently mandated element-level inspection data (AASHTO, 2019). Once a bridge prioritization approach is developed, its efficacy may be determined by estimating the return on investment in terms of bridge service life. Within this context, a strategic move is defined in this study as the purposeful step taken by a bridge agency to enhance the return on investment on bridge MRR. This strategic move is implemented in a game theory approach, together with a Co-Active model, which accounts for time-dependent element interactions, referred to as Co-Activeness, in predicting bridge performance resulting from MRR activities.

7.1.2 Research Goals and Scope

This study investigates the feasibility of implementing a proposed Co-Active model in multiple states with a game theory approach, which models a strategic interaction between two players, the FHWA and a state DOT. Specifically, this study aims to answer the following three key questions by analyzing bridge inventories in four states (Georgia, Virginia, Pennsylvania, and New York):

1. Does the proposed Co-Active model have an application to other U.S. state agencies?
2. Is there any difference in the performance of NHS state-owned and non-NHS state-owned bridges?
3. How should one quantify payoffs for two players, the FHWA and a state DOT, using a game theory?

7.2 Literature Review

The two major challenges to an effective transportation asset management include 1) bridge deterioration predictions and 2) limited budget as the bridge MRR has to compete for resources with other transportation assets, such as pavements, rail lines, and ports (Contreras-Nieto et al., 2019). Therefore, the development of an efficient bridge prioritization strategy, which effectively balances deterioration predictions and available funds, has become a critical component of transportation asset management plans in many state DOTs in the United States (Lu & Phares, 2018). A study conducted by Elbehairy, Elbeltagi, Hegazy, and Soudki (2006) investigated the application of two evolutionary-based optimization techniques that are capable of handling large-size problems, namely Genetic Algorithms and Shuffled Frog Leaping, to optimize bridge decks maintenance and repair decisions. A risk-based year-by-year optimization strategy, coupled with the use of a pre-processing function to allocate repair funds first to critical bridges, was recommended. Another approach by X. Zhang and Gao (2012) proposed an optimization model and the search algorithm that was consequently applied to three bridge decks maintenance scenarios. The optimization model was developed to determine the optimal length of the maintenance period based on the proposed maintenance policy, to minimize the system's life cycle cost per unit time. W. Zhang and Wang (2017) developed a decision model for bridge network management and project prioritization that enables the operational performance of a transportation system to be optimized, given the safety requirements mandated by AASHTO and the inevitable budgetary constraints imposed by limited resources. More recently, Kim et al. (2018) in their study presents a prioritization model that reflects both existing structural conditions and possible future risk factors. In their study, bridge risk was defined as a risk factor that can deteriorate the functionality of a public bridge, and it was used as an index for determining the maintenance priority by quantitatively deriving the risk. All of the previous efforts relating to prioritization of bridges for MRR are commendable because they all attempted to maximize return on investment of bridge MRR. However, these prioritization models are mainly risk-based. In this study, the feasibility of implementing a proposed Co-Active model in multiple states in the U.S. is investigated. The Co-Active bridge prioritization model additionally accounts for the effects of time-dependent element interactions on the long-term bridge performance. Also, the model is implemented alongside a game theory approach, which quantifies payoffs for two players, FHWA and state DOTs. The model is further used to investigate the performance of NHS and non-NHS bridges.

7.3 Methodology

7.3.1 Overall Approach

This study investigates the feasibility of implementing the proposed Co-Active model in multiple states with a game theory approach. Therefore, bridge inventories in four states which are known to have proactive maintenance strategies are investigated. Title 23 of the United States Code §150(c)(3), in compliance with MAP-21 Legislation, requires state DOTs to establish, as part of their governance of performance measures, "minimum standards for States to use in developing and operating bridge and pavement management system". For bridges on the National Highway System (NHS), Title 23 of the United States Code §119(f) stipulates that no more than 10% of the total NHS bridge deck area be structurally deficient (U.S.C., 2018). However, other important factors for measuring bridge performance such as the average life cycle must be considered.

7.3.2 Game Theory Approach

This study uses a game theory approach to model a strategic interaction between two players, the FHWA and a state DOT. A sequential game with two FHWA's strategic moves, one imposing the 10% deck requirement and the other with a reallocated 0.5% in deck requirement (from 10% to 10.5%) while requiring states to maintain all joints in superior conditions. Both NHS bridges and non-NHS bridges are investigated to review the effectiveness of FHWA's strategic moves.

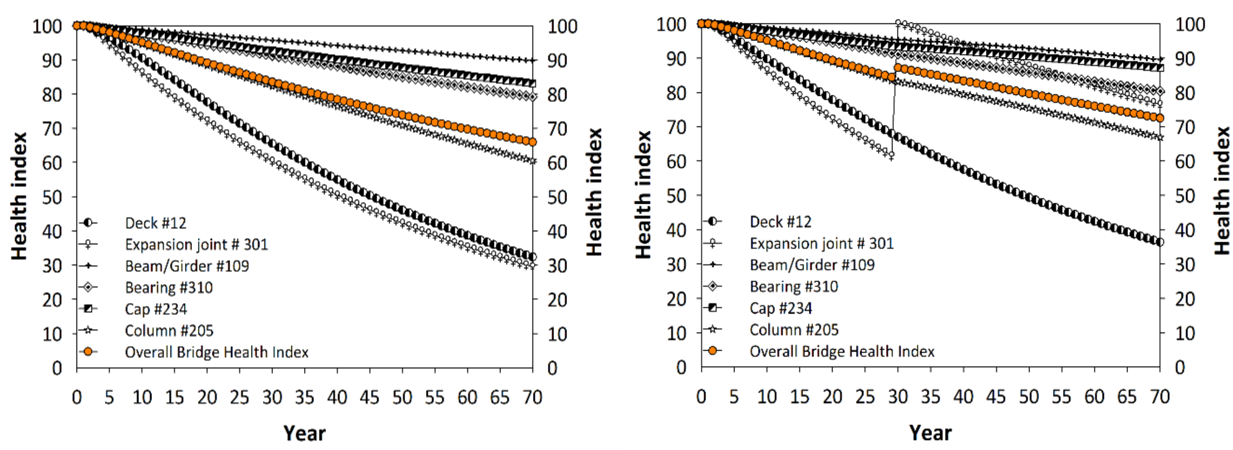
7.3.3 Payoffs

The payoffs of the two players in prioritizing element MRR are quantified based on a service life extension of bridges when a threshold bridge health index (BHI) is set at 70. A threshold BHI is set at 60 for New York, due to the observed bridge performance in the state. The cost of reducing deck MRR by 0.5% is assumed equivalent to the cost of rehabilitating all expansion joints and joint seals in a bridge inventory. This reduction is calculated based on the total quantity of deck areas and the total linear footage of joints.

7.4 Results

7.4.1 Analysis of Georgia DOT's Element Data

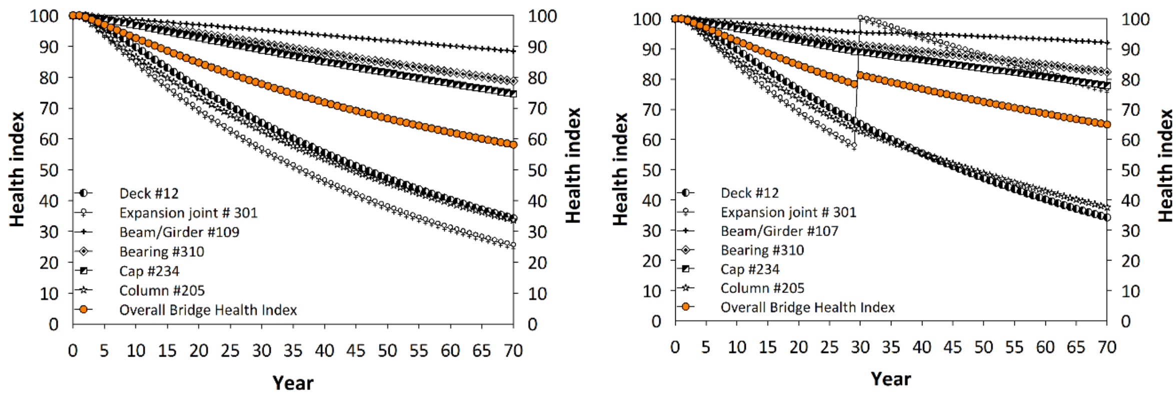
Figure 43a shows the average service life of NHS bridges in Georgia when no joints are rehabilitated or replaced. Figure 43b presents the NHS bridge performance when additional resources are allocated to expansion joints and joint sealant rehabilitation and/or replacements. The Co-Active model is used in this figure. The average service life has been extended by 10 years because the service life is 65 and 75 years in Figures 43 (a) and (b), respectively, for the HI threshold of 70. Similarly, Figure 44 shows the non-NHS bridge performance. Figure 45 illustrates a payoff of the two players, FHWA and state DOT.



(a) Bridge Performance Prediction (Georgia)

(b) Prediction with the proposed joint requirement (Georgia)

Figure 43 – NHS bridge performance prediction (a) Current projection and (b) Projection with joint MRR in Georgia.



(a) Bridge Performance Prediction (Georgia)

(b) Prediction with the proposed joint requirement (Georgia)

Figure 44 – Non-NHS bridge performance prediction (a) Current projection and (b) projection with joint MRR in Georgia.

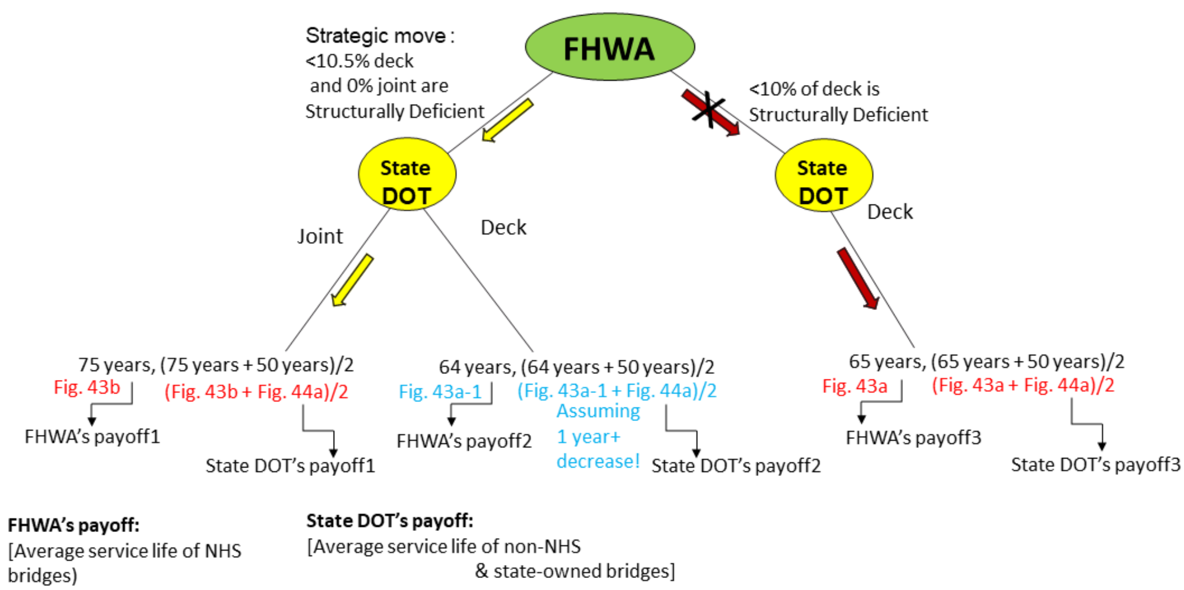


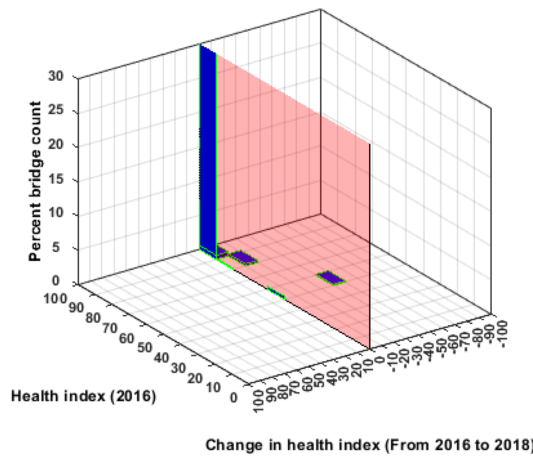
Figure 45 – Game tree illustrating a strategic move and payoffs of 2 players in Georgia.

In comparison with NHS bridges, non-NHS but state-owned bridge performance and performance predictions are investigated. In the absence of a strategic incentive and resources, non-NHS bridges are not as well maintained as the NHS bridges (see Figures 46 and 47).

(a) Overall Bridge

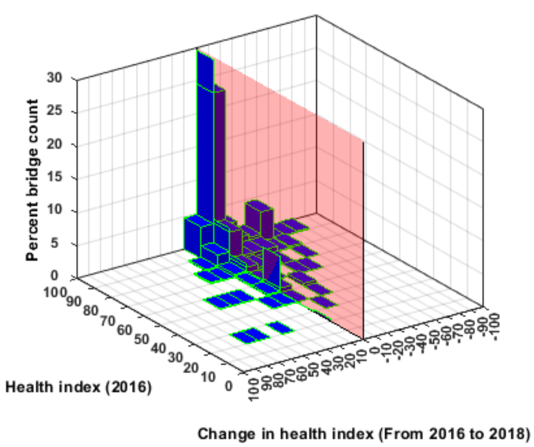
(b) Deck

(c) Expansion Joint



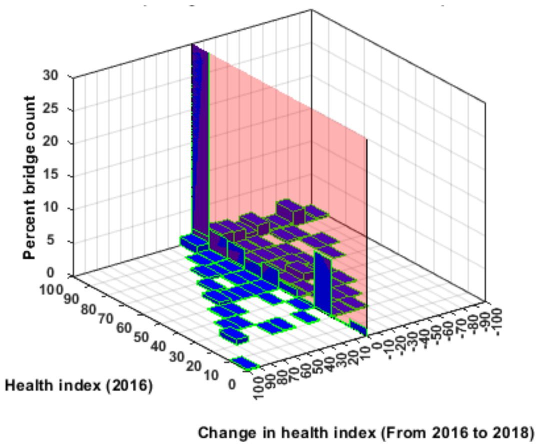
(d) Bearing

Figure 46 – NHS bridge performance in Georgia.
(a) Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.

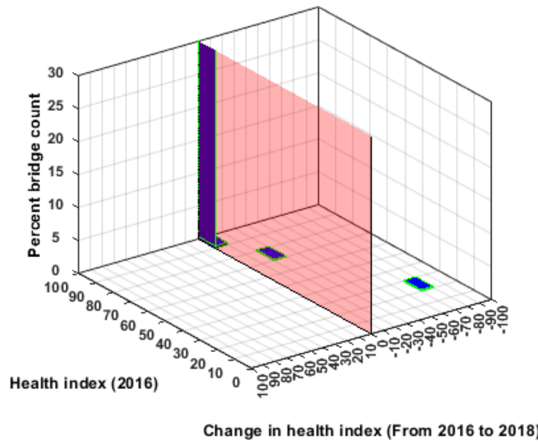


(a) Overall Bridge

(b) Deck

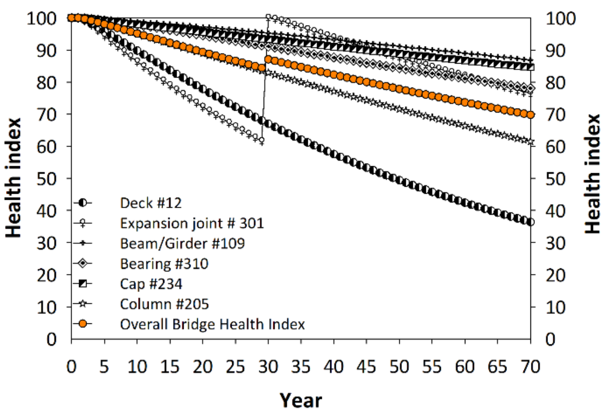


(c) Expansion Joint

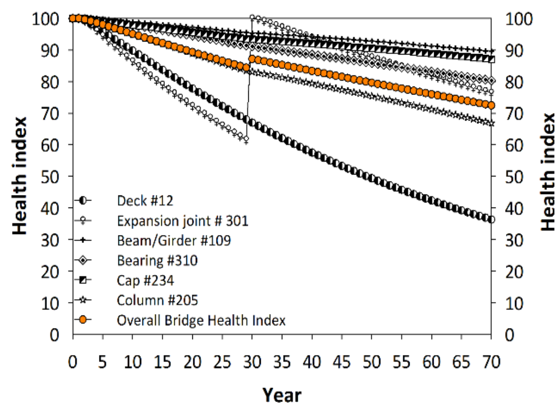


(d) Bearing

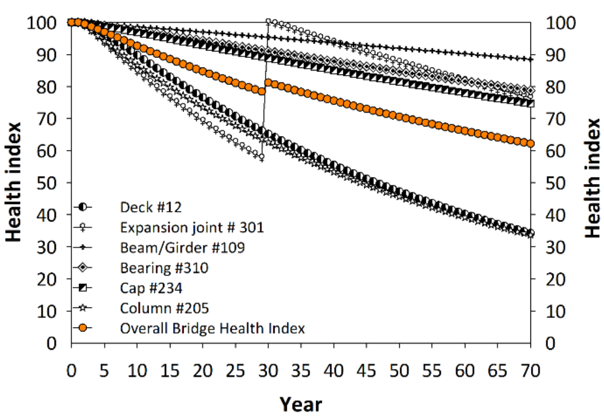
Figure 47 – Non-NHS bridge performance in Georgia.
(a) **Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.**



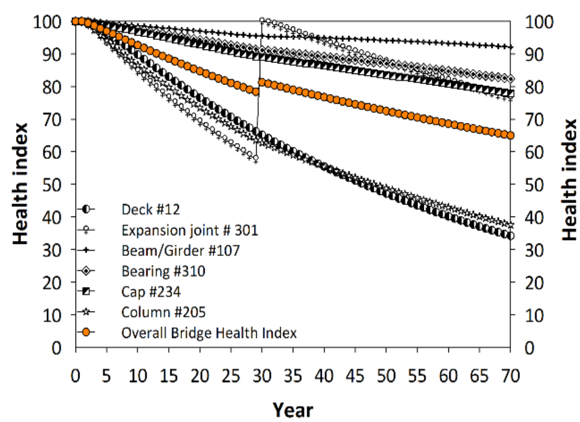
(a) Not Including Co-Activeness (NHS)



(b) Including Co-Activeness (NHS)



(c) Not Including Co-Activeness (non-NHS)



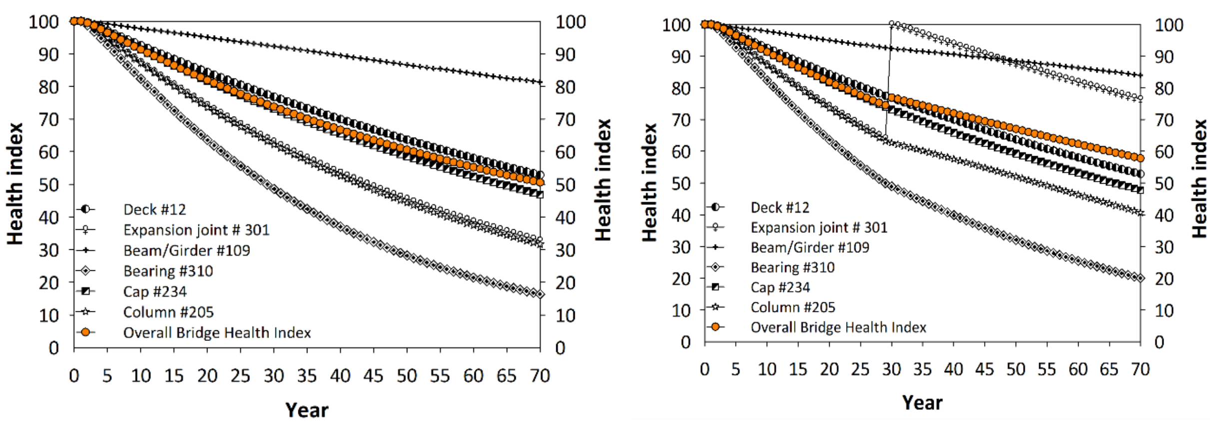
(d) Including Co-Activeness (non-NHS)

Figure 48 – The effect of an expansion joint replacement not including and including the Co-Active mechanism: (a) and (b) in NHS bridges, (c) and (d) in Non-NHS bridges in Georgia.

Finally, Figure 48 shows that the proposed Co-Active mechanism yields less conservative deterioration predictions. Therefore, the results presented in Figure 43 were a more realistic comparison, which resulted in a 2-3-year service life extension for the bridges in Georgia.

7.4.2 Analysis of Virginia DOT's Element Data

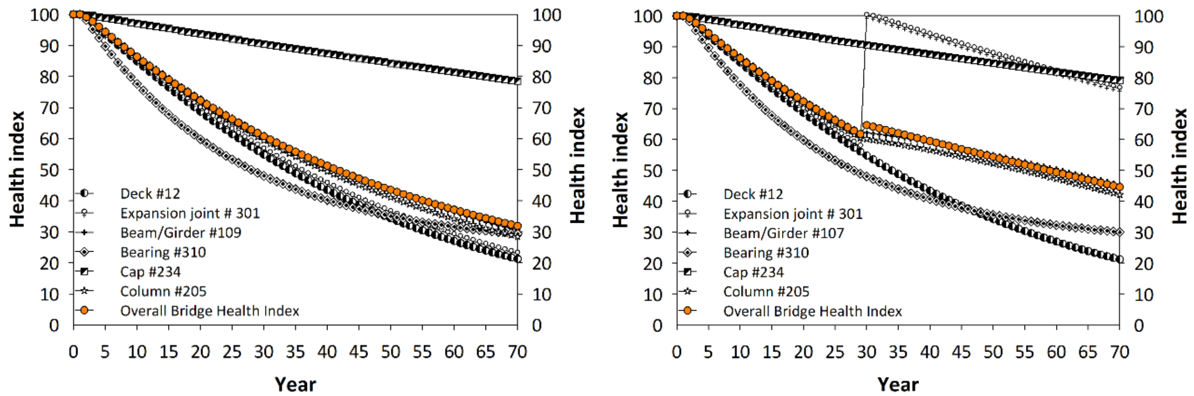
Figure 49a shows the average service life of bridges in Virginia when no joints are rehabilitated or replaced. Figure 49b presents the bridge performance when additional resources are allocated to expansion joints and joint sealant rehabilitation and/or replacements. The Co-Active model is used in this figure. The average service life has been extended by 10 years because the service life is 35 and 45 years in Figures 49 (a) and (b), respectively, for the health index threshold of 70. Figure 51 illustrates a payoff of the players for the existing and new strategies.



(a) Bridge Performance Prediction (Virginia)

(b) Prediction with the Proposed Joint requirement (Virginia)

Figure 49 – NHS bridge performance prediction (a) Current projection and (b) projection with joint MRR in Virginia.



(a) Bridge Performance Prediction (Virginia)

(b) Prediction with the proposed joint requirement (Virginia)

Figure 50 – Non-NHS bridge performance prediction (a) Current projection and (b) Projection with joint MRR in Virginia.

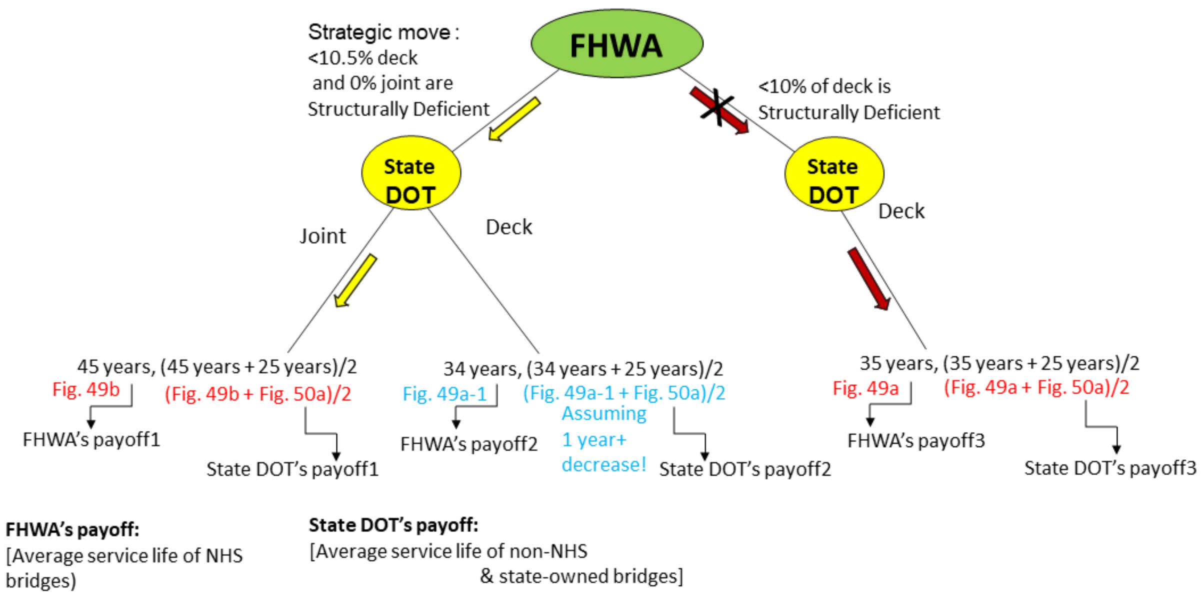
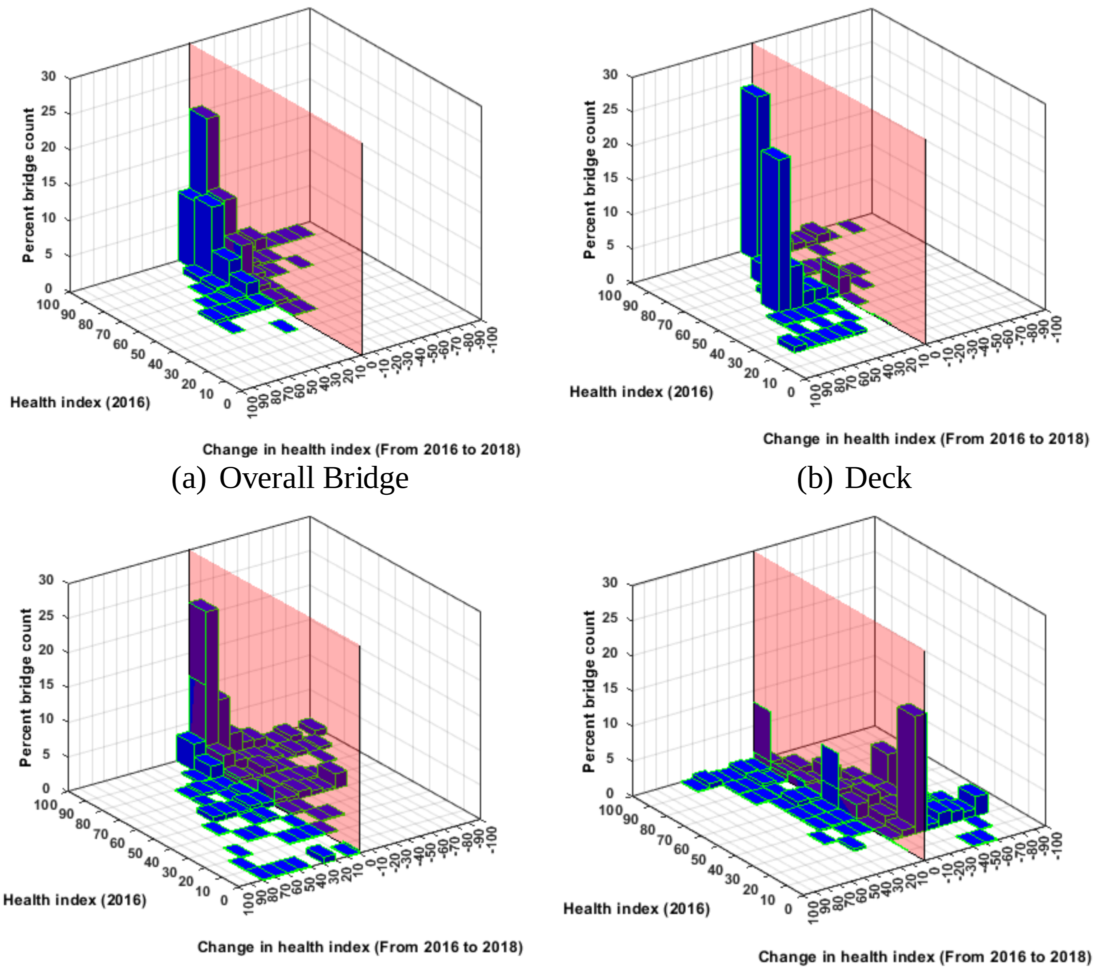


Figure 51 – Game tree illustrating a strategic move and payoffs of 2 players in Virginia.



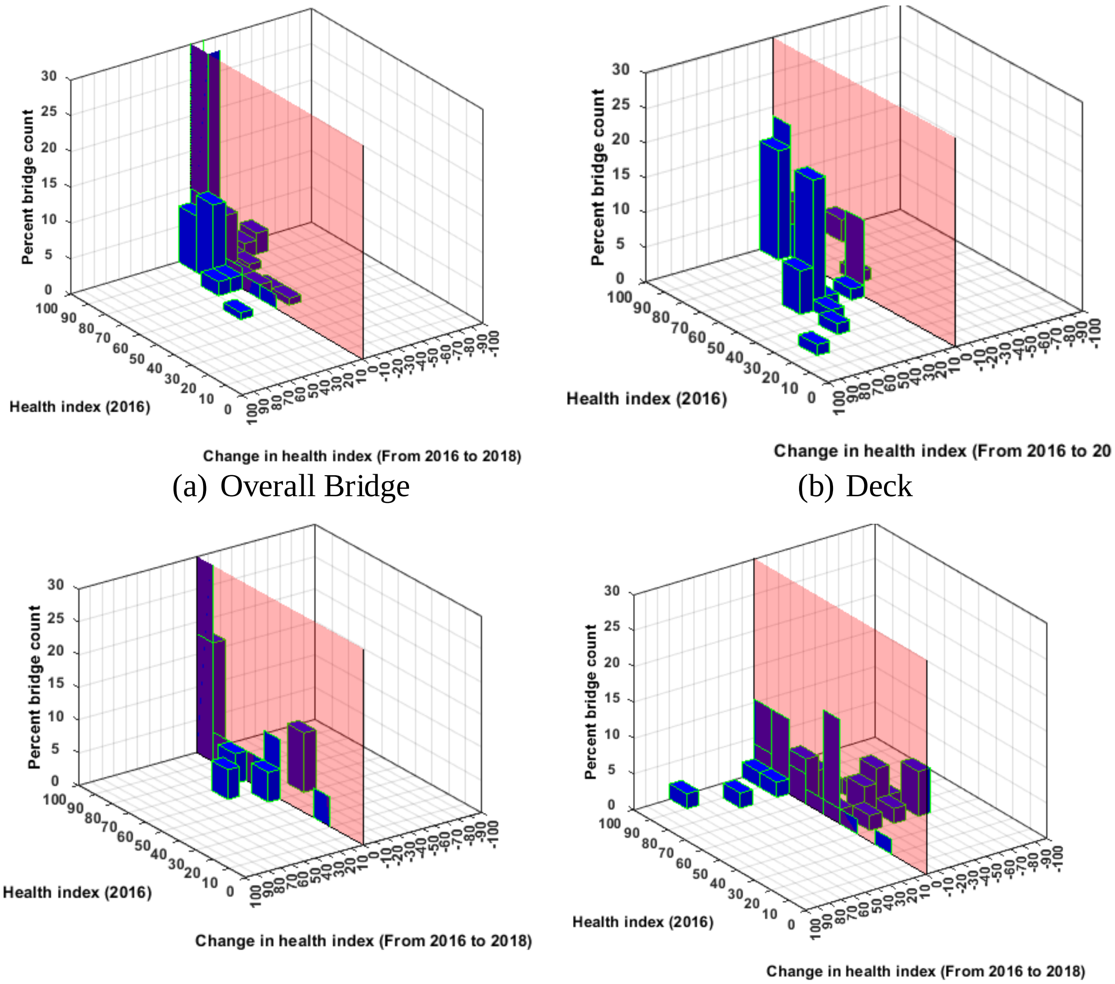
(a) Overall Bridge (b) Deck

(c) Expansion Joint (d) Bearing

Figure 52 – NHS bridge performance in Virginia.

(a) Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.

Similarly, non-NHS but state-owned bridge performance and performance predictions are investigated, in comparison with NHS bridges. In the absence of a strategic incentive and resources, non-NHS bridges are not as well maintained as the NHS bridges (see Figures 52 and 53).

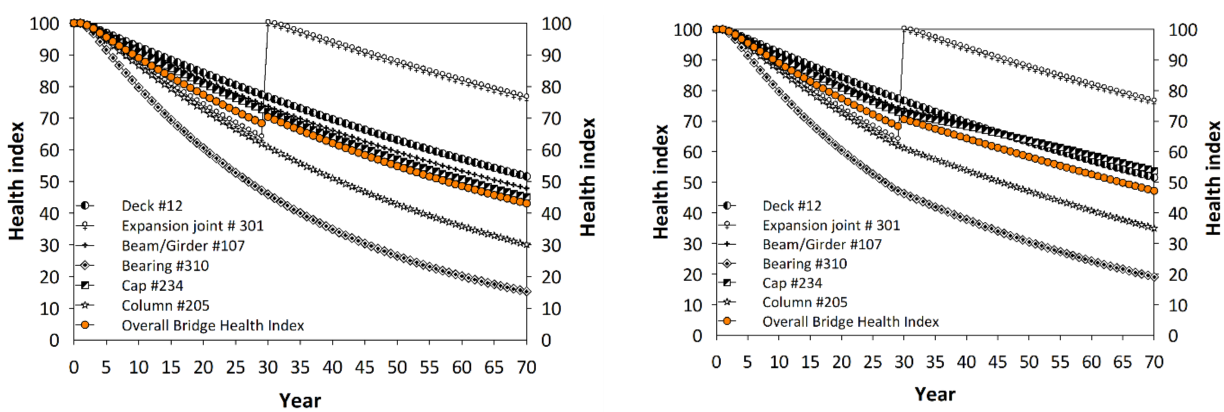


(a) Overall Bridge (b) Deck

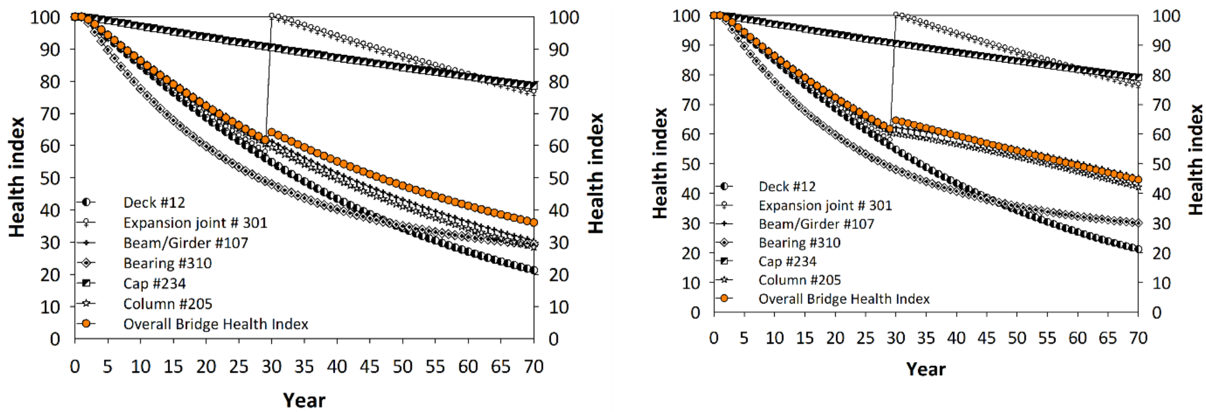
(c) Expansion Joint (d) Bearing

Figure 53 – Non-NHS bridge performance in Virginia.
(a) Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.

Finally, Figure 54 shows that the proposed Co-Active mechanism yields less conservative deterioration predictions.



(a) Not Including Co-Activeness (NHS) (b) Including Co-Activeness (NHS)

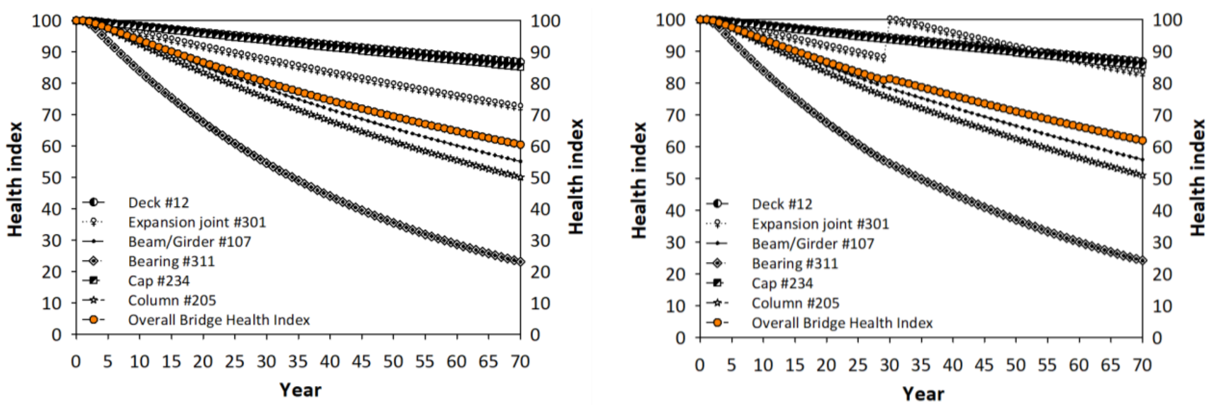


(c) Not including Co-Activeness (non-NHS)   (d) Including Co-Activeness (non-NHS)

Figure 54 – The effect of an expansion joint replacement not including and including the Co-Active mechanism: (a) and (b) in NHS bridges, (c) and (d) in Non-NHS bridges in Virginia.

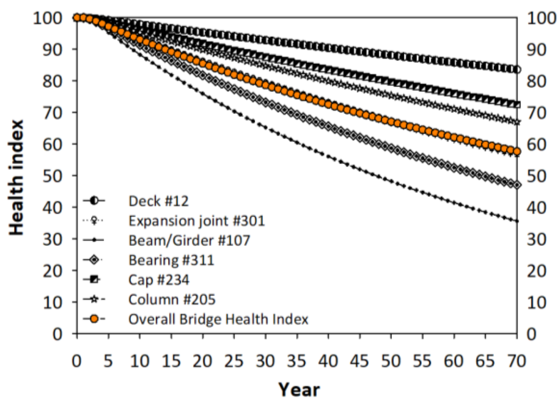
7.4.3 Analysis of Pennsylvania DOT's Element Data

Figure 55a shows the average service life of bridges in Pennsylvania when no joints are rehabilitated or replaced. Figure 55b presents the bridge performance when additional resources are allocated to expansion joints and joint sealant rehabilitation and/or replacements. The Co-Active model is used in this figure. The average service life has been extended by 5 years because the service life is 50 and 55 years in Figures 55 (a) and (b), respectively, for the HI threshold of 70. Figure 57 illustrates a payoff of the players for the existing and new strategies.

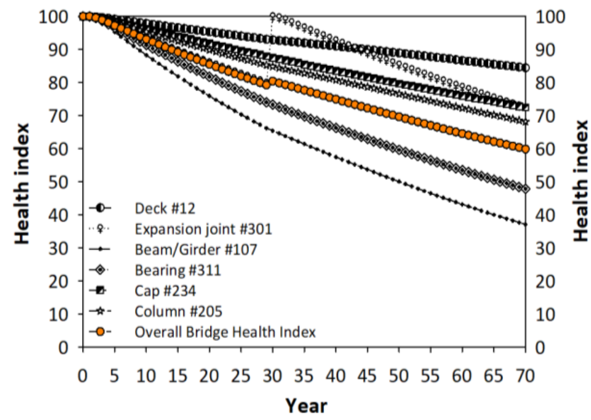


(a) Bridge Performance Prediction (Pennsylvania)   (b) Prediction with the Proposed Joint Requirement (Pennsylvania)

Figure 55 – NHS bridge performance prediction (a) current projection and (b) projection with joint MRR in Pennsylvania.



(a) Bridge Performance Prediction (Pennsylvania)



(b) Prediction with the Proposed Joint Requirement (Pennsylvania)

Figure 56 – Non-NHS bridge performance prediction (a) Current projection and (b) projection with joint MRR in Pennsylvania.

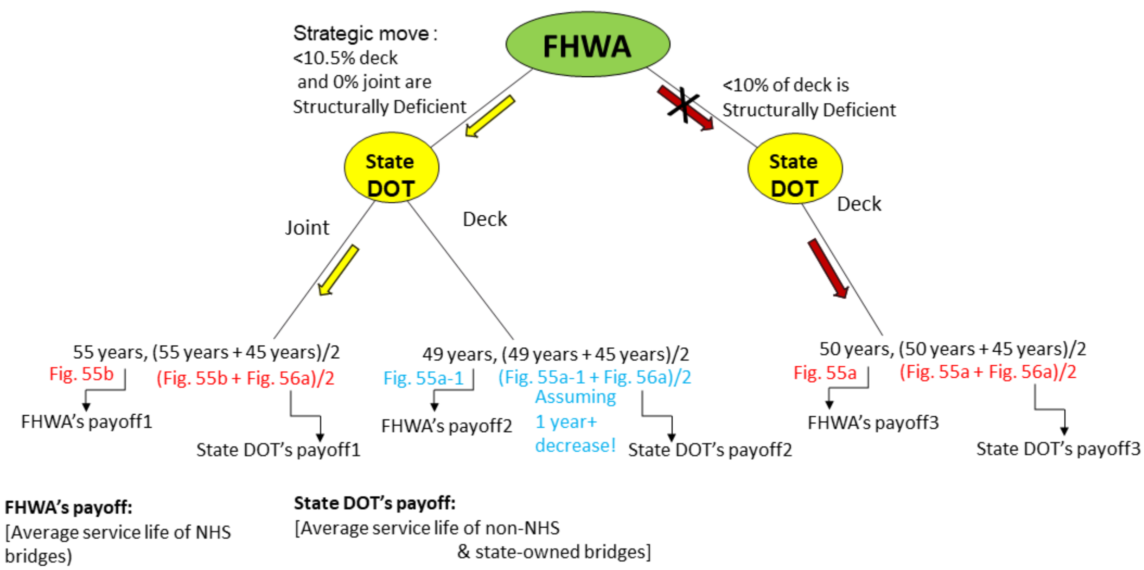
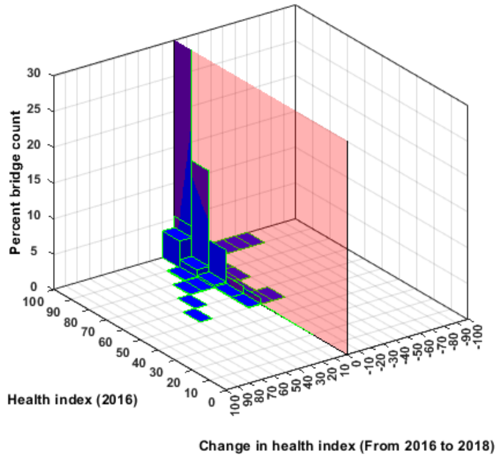
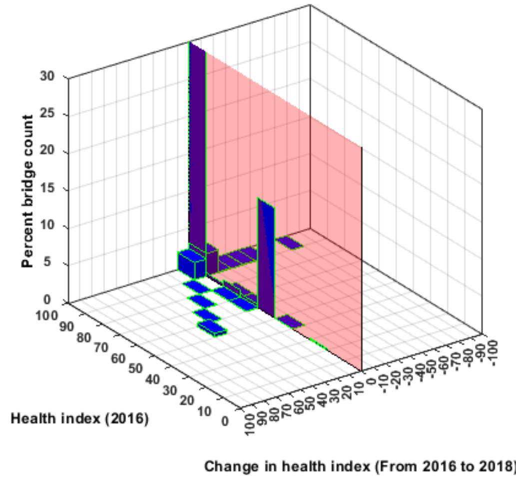


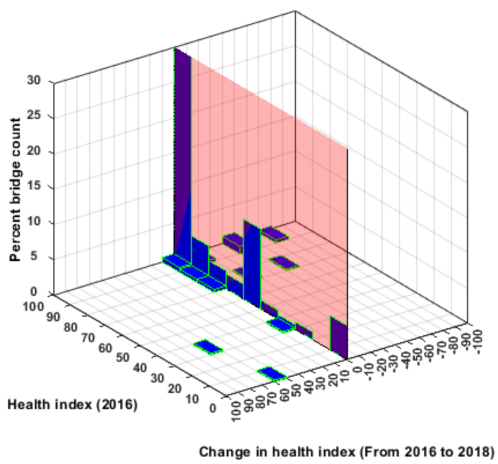
Figure 57 – Game tree illustrating a strategic move and payoffs of 2 players in Pennsylvania.



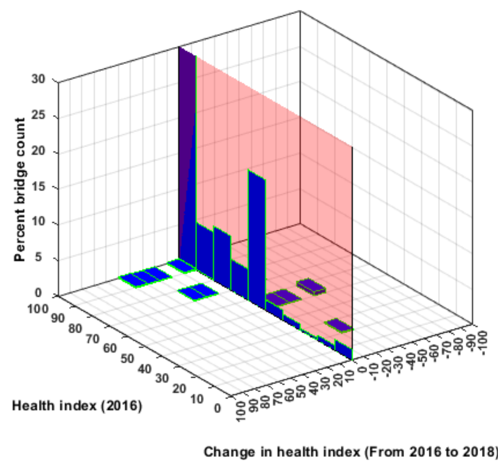
(a) Overall Bridge



(b) Deck

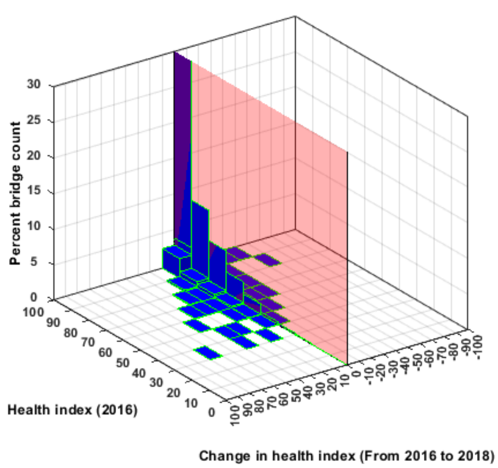


(c) Expansion Joint



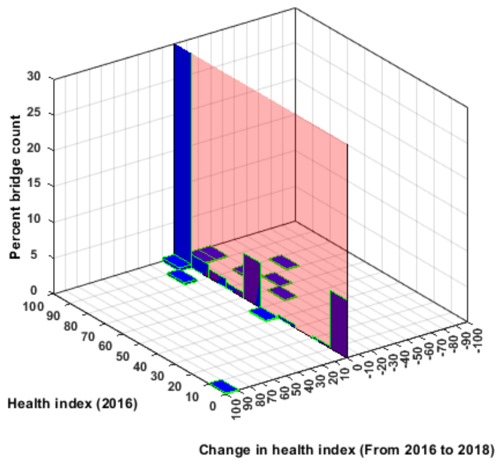
(d) Bearing

Figure 58 – NHS bridge performance in Pennsylvania.
(a) Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.

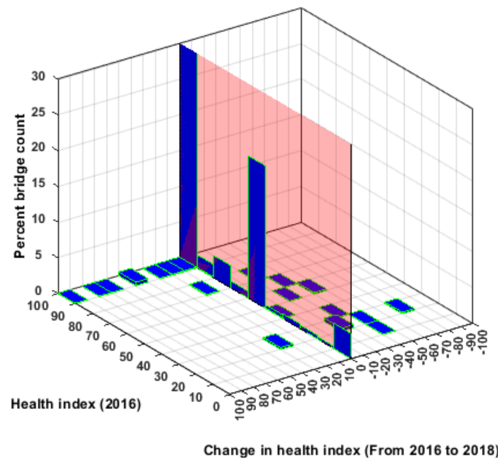


(a) Overall Bridge

(b) Deck



(c) Expansion Joint

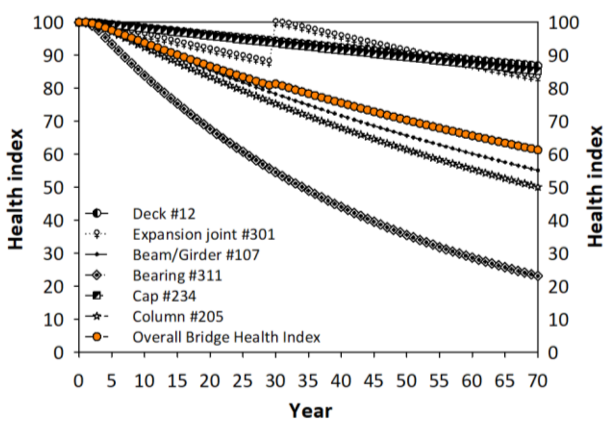


(d) Bearing

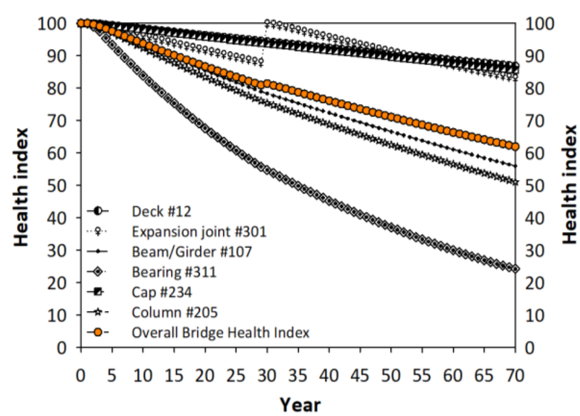
Figure 59 – Non-NHS bridge performance in Pennsylvania.
(a) Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.

In comparison with NHS bridges, non-NHS but state-owned bridge performance and performance predictions are investigated. In the absence of a strategic incentive and resources, there is no significant difference between the maintenance of non-NHS bridges and the NHS bridges (see Figures 58 and 59).

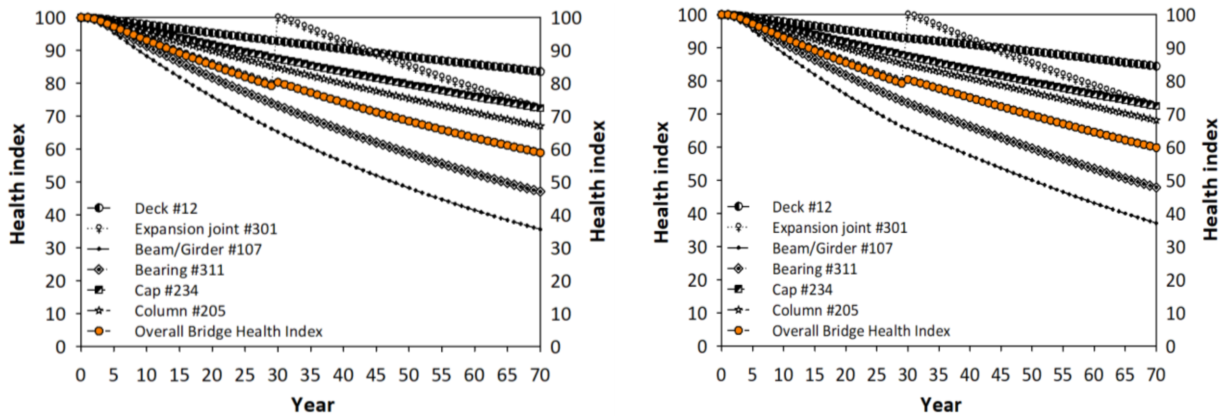
Finally, Figure 60 shows that the proposed Co-Active mechanism yields less conservative deterioration predictions.



(a) Not Including Co-Activeness (NHS)



(b) Including Co-Activeness (NHS)

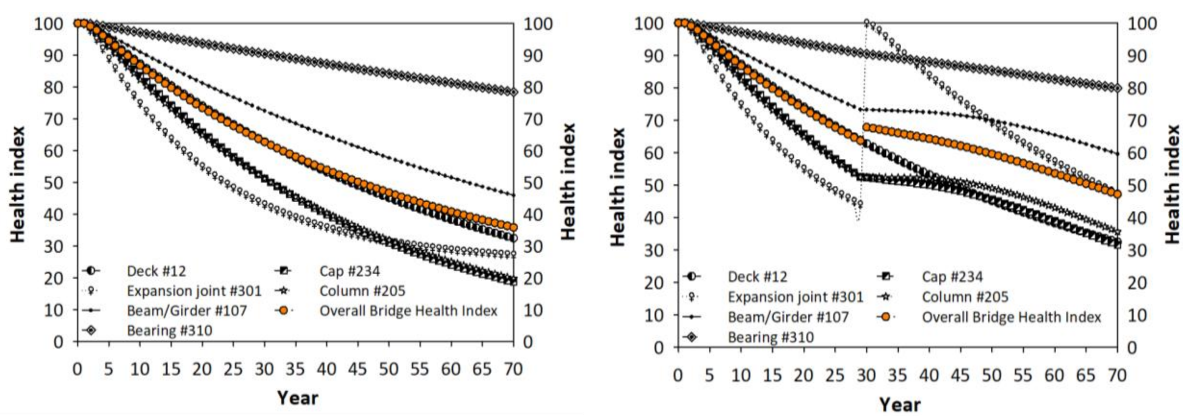


(c) Not including Co-Activeness (non-NHS) (d) Including Co-Activeness (non-NHS)

Figure 60 – The effect of an expansion joint replacement not including and including the Co-Active mechanism: (a) and (b) in NHS bridges, (c) and (d) in Non-NHS bridges in Pennsylvania.

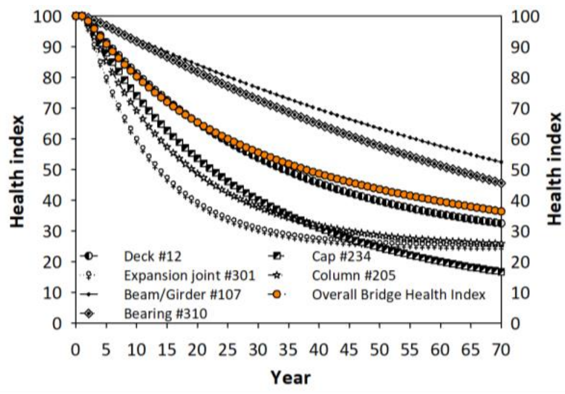
7.4.4 Analysis of New York DOT's Element Data

Figure 61a shows the average service life of bridges in New York when no joints are rehabilitated or replaced. Figure 61b presents the bridge performance when additional resources are allocated to expansion joints and joint sealant rehabilitation and/or replacements. The Co-Active model is used in this figure. The average service life has been extended by 15 years because the service life is 35 and 50 years in Figures 61 (a) and (b), respectively, for the health index threshold of 60. Figure 63 illustrates a payoff of the players for the existing and new strategies.

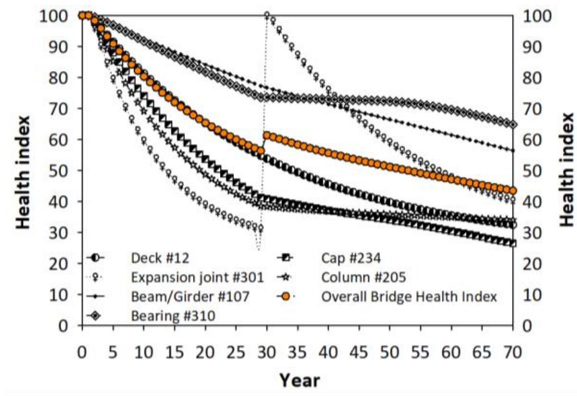


(a) Bridge Performance Prediction (New York) (b) Prediction with the Proposed Joint Requirement (New York)

Figure 61 – NHS bridge performance prediction (a) Current Projection and (b) Projection with joint MRR in New York.



(a) Bridge Performance Prediction
(New York)



(b) Prediction with the proposed joint requirement
(New York)

Figure 62 – Non-NHS bridge performance prediction (a) Current projection and (b) Projection with joint MRR in Pennsylvania.

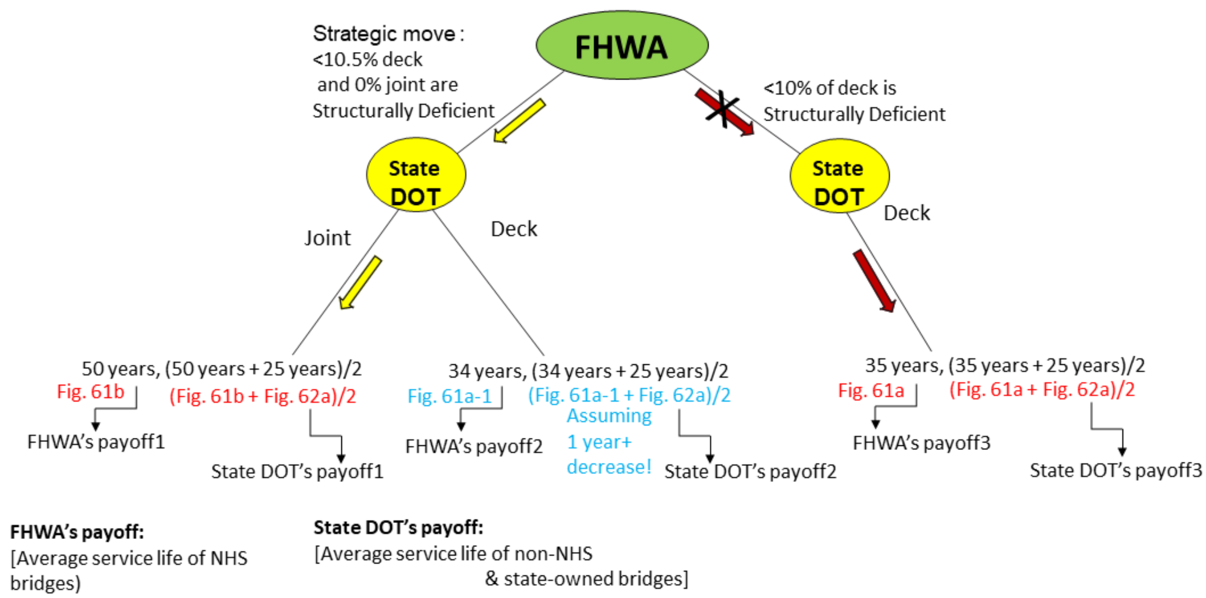
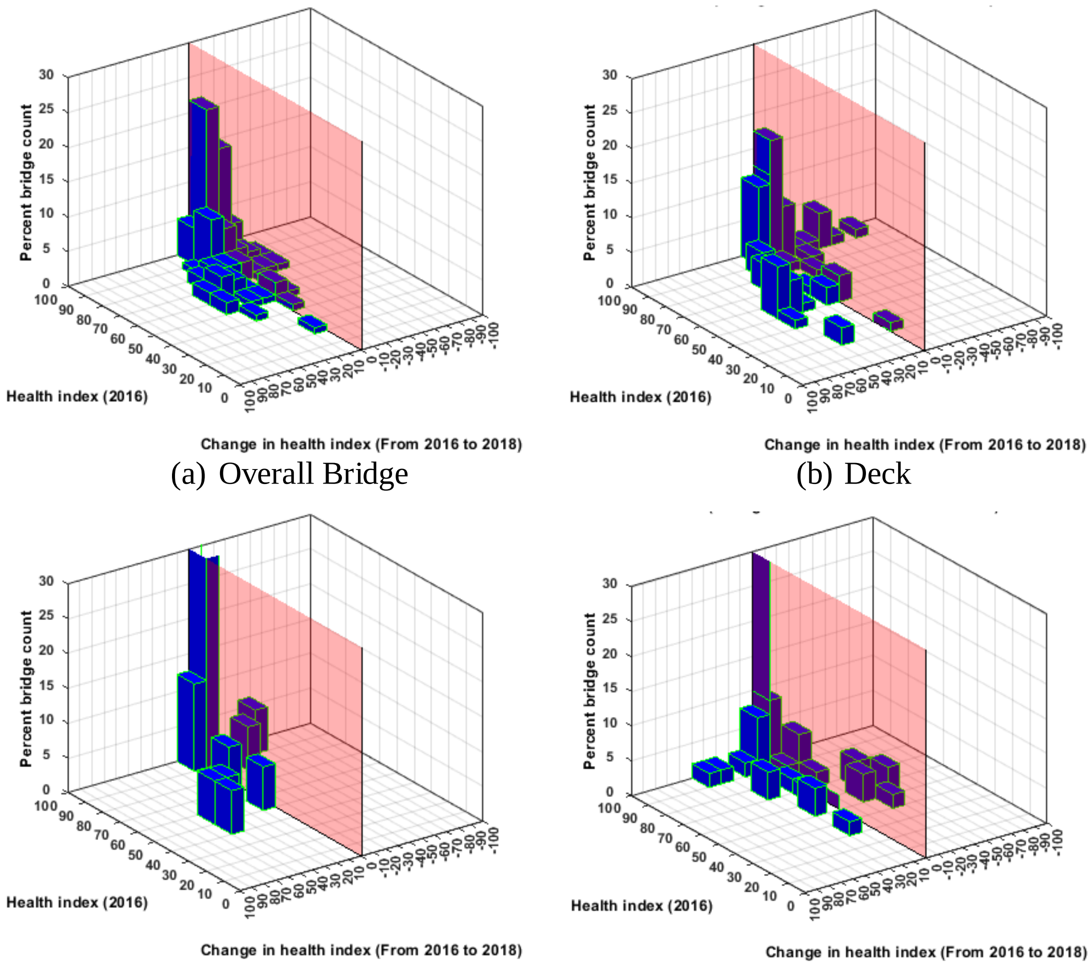


Figure 63 – Game tree illustrating a strategic move and payoffs of 2 players in New York.

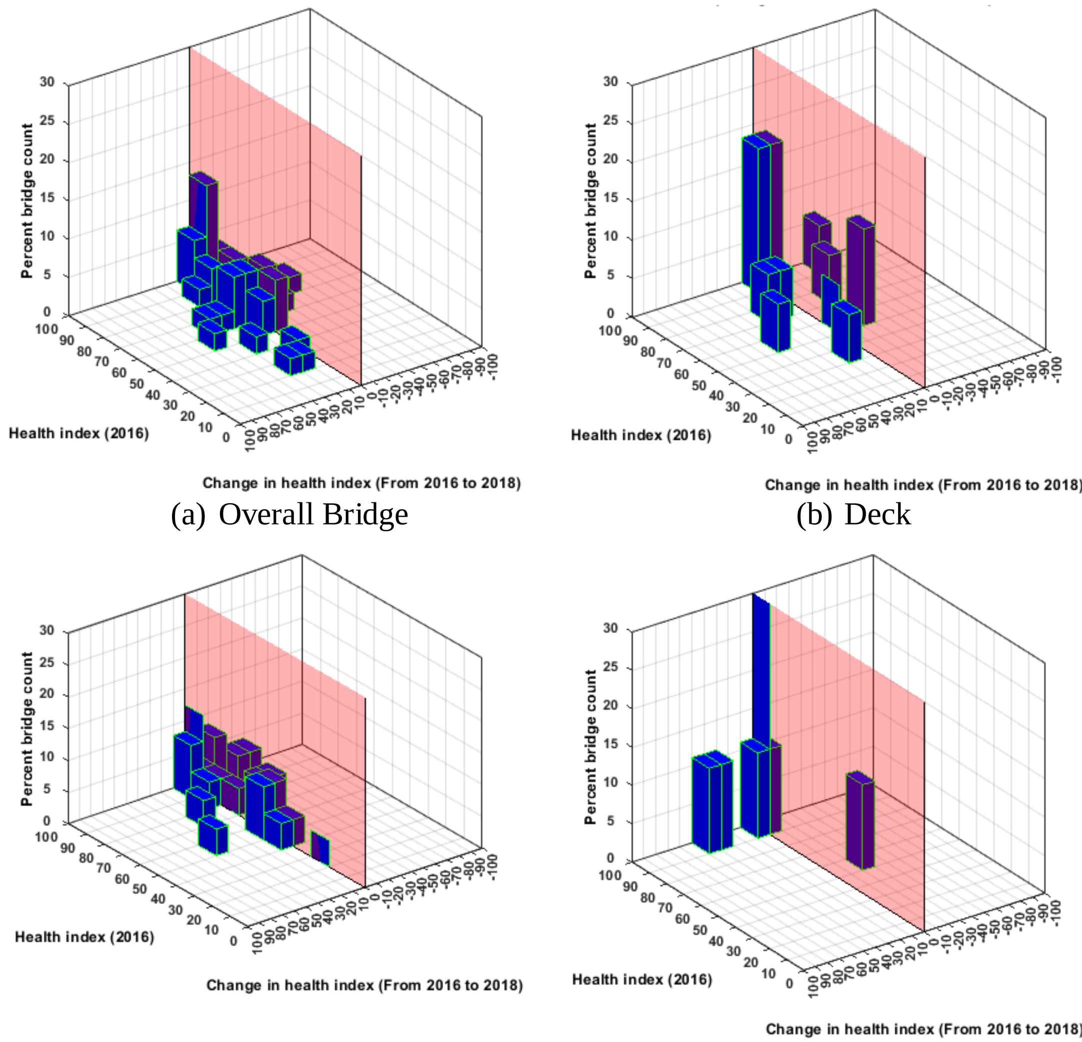


(a) Overall Bridge (b) Deck

(c) Expansion Joint (d) Bearing

Figure 64 – NHS bridge performance in New York.
(b) Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.

In comparison with NHS bridges, non-NHS but state-owned bridge performance and performance predictions are investigated. In the absence of a strategic incentive and resources, non-NHS bridges are not as well maintained as the NHS bridges (see Figures 64 and 65).

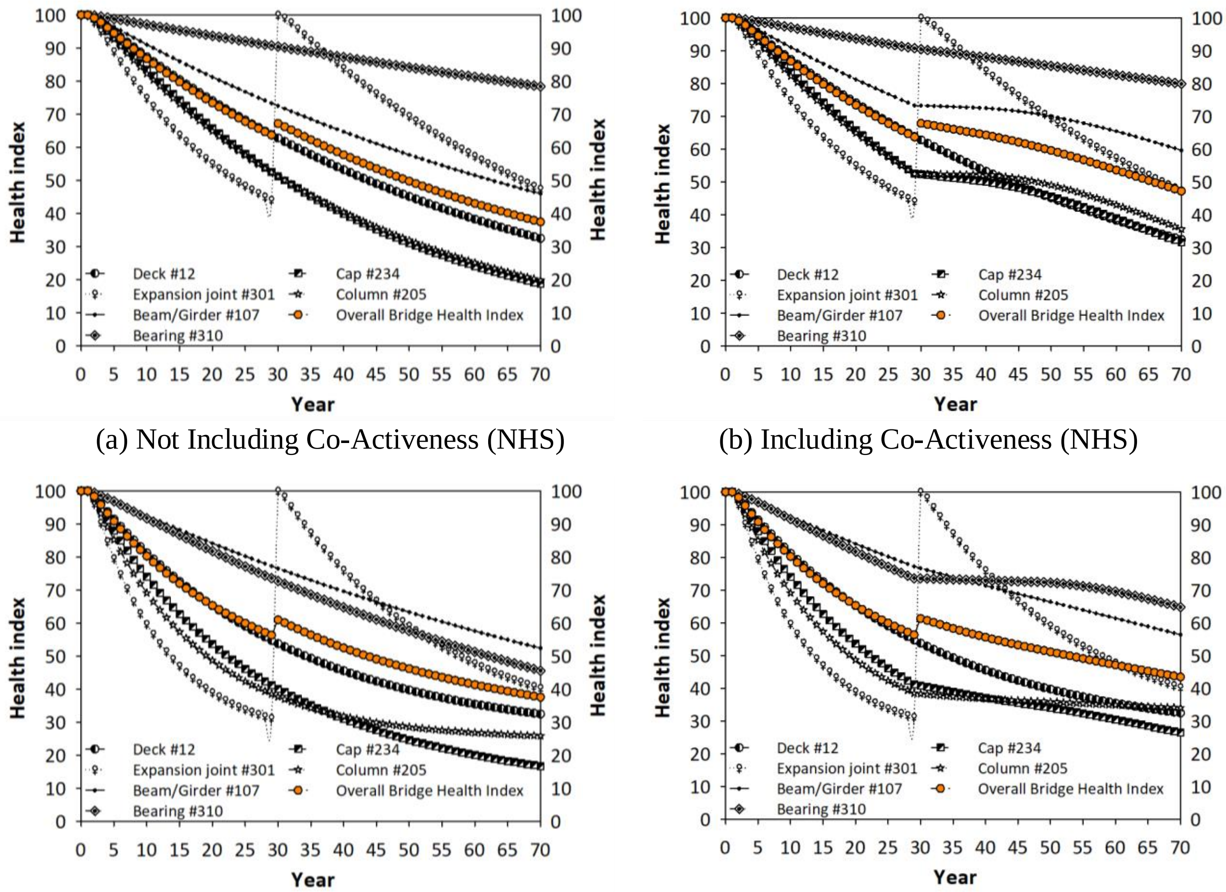


(a) Overall Bridge (b) Deck

(c) Expansion Joint (d) Bearing

Figure 65 – Non-NHS bridge performance in New York.
(b) Overall bridge; (b) Concrete deck; (c) Expansion joint; (d) Bearing.

Finally, Figure 66 shows that the proposed Co-Active mechanism yields less conservative deterioration predictions.



(a) Not Including Co-Activeness (NHS)
(b) Including Co-Activeness (NHS)
(c) Not Including Co-Activeness (non-NHS)
(d) Including Co-Activeness (non-NHS)

Figure 66 – The effect of an expansion joint replacement not including and including the Co-Active mechanism: (a) and (b) in NHS bridges, (c) and (d) in Non-NHS bridges in New York.

7.5 Discussion of Results

The bridge performance analysis presented in this study integrates a Co-Active model and a game theory approach for optimizing return on investment (ROI) on bridge maintenance, rehabilitation, or replacement (MRR) actions. This Co-Active approach and the strategic move associated with the game theory approach are not currently being considered by transportation agencies. The game theory approach modeled a strategic interaction between two players, the FHWA and a state DOT. In each of the four states investigated, the Co-Active model leverages on element interactions and gives a realistic long-term bridge performance prediction. The proposed Co-Active model and the game theory approach is most effective in prioritizing bridge actions in New York, where the bridge average service life is extended by 15 years. This may be attributed to the relatively lower bridge health indices and high Co-Activeness among the elements in the New York bridge inventory. The effectiveness of the Co-Active model in the Georgia and Virginia bridge inventories is similar. In both states, the bridge average service life is extended by 10 years. The proposed Co-Active model and the game theory approach indicates that the bridge average service life is extended by 5 years in Pennsylvania. This lower value of service life extension in Pennsylvania, compared to the other states investigated in this study, may be attributed to Pennsylvania's bridge management strategy, which currently leverages the proposed Co-Activeness mechanism in their bridge MRR, even though bridges in Pennsylvania are exposed to aggressively deteriorating environment condition similar to what is obtainable in Virginia and New York.

7.6 Conclusions

The element data from four U.S. states (Georgia, Virginia, Pennsylvania, and New York) are investigated to determine the feasibility of implementing a proposed Co-Active mechanism in multiple states with a game theory approach. It is concluded that Co-Activeness exists in the element data, and the extent of Co-Activeness among elements affects the long-term bridge performance. Based on the findings of this study, the following conclusions are made:

- The Federal Highway Administration (FHWA) requires that states have less than 10% of the total deck area that is structurally deficient. Therefore, the FHWA has a minimum risk benchmark, which can be described as a "worst-case scenario", for its investments on the nation's NHS bridges. However, criteria for obtaining the highest return on investment (ROI) on bridge maintenance, rehabilitation, and replacement (MRR) is needed.

- Long-term bridge performance predictions reflecting a Co-Active mechanism that is present in a bridge inventory are effective in prioritizing elements for MRR decisions.
- Investments on the bridge MRR is optimized when the Co-Active mechanism that exists in a bridge network is determined and considered in the long-term bridge performance predictions.
- By applying a game theory approach, it is possible to identify an inherent and particular payoff structure between FHWA and a state DOT. The 10% limit on deck maintenance in current requirements may not be most cost-beneficial for extending the service life in the long term. By reallocating 0.5% (from 10% to 10.5%) of the FHWA's deck requirement, both FHWA and state DOTs will be able to allocate additional resources to expansion joints and joint seals. The outcome of such a strategic move yields higher a payoff for the players.
- State agencies with relatively lower bridge health indices are more likely to benefit from using the proposed method that accounts for the Co-Active mechanism because condition changes in one element are more likely to significantly influence the bridge health indices.

8. CONCLUSIONS AND RECOMMENDATIONS

8.1 Conclusions

This dissertation investigates element-level inspection data available in the National Bridge Inventory and proposes a novel Co-Active prioritization model for bridge asset management. The model accounts for time-dependent element interactions, referred to as “Co-Activeness”, in predicting bridge performance resulting from preventive maintenance, rehabilitation, or replacement (MRR) activities. Based on the findings of the studies presented in this dissertation, the following conclusions are made:

- Co-Activeness exists in the element data, and the extent of Co-Activeness among elements are numerically quantifiable.
- Accounting for element interactions (i.e., Co-Activeness) that are present in the element-data yields more realistic, and thus less overly conservative, performance predictions.
- Inter-dependent relationships among Co-Active elements are highly affected by Co-Active coefficients. They are determined from the element-data in a state bridge inventory and increase when the degree of dependency among elements is strong.
- In the first study, involving the performance analysis of Georgia’s bridges (see Chapter 5), overall Bridge Health Indices (BHIs) improve by 20% in the subsequent 20 years when expansion joints are replaced, which is an outcome of applying the proposed Co-Active prioritization mechanism deduced from Georgia’s element-data.

- In the subsequent study, it is concluded that such Co-Active mechanism also exists in Alabama (see Chapter 6). In Alabama, MRR on bridge deck elements are more beneficial than MRR on the expansion joints for the long-term bridge performance.
- In Florida, a Co-Active mechanism is present; however, the Co-Active model had no significant impact on the service life extension because MRR strategies, primarily involving preventive maintenance, implemented in Florida are already leveraging the Co-Active mechanism.
- As anticipated, the Florida study confirms (see Chapter 6) that the proposed Co-Active mechanism mathematically characterizes cascading and causal effects in a bridge inventory. That is, in states implementing proactive early maintenance strategies, a Co-Active mechanism is already being leveraged whereas in states prioritizing repairs and rehabilitation, due to limited resources, they should be able to fully leverage the proposed Co-Active model.
- In order to further investigate the feasibility of implementing the Co-Active model in multiple states, bridge inventories in three additional states which are known to have proactive maintenance strategies are investigated. The analysis of Virginia, Pennsylvania, and New York’s bridge inventory (see Chapter 7) confirms that long-term bridge performance predictions leveraging a Co-Active mechanism are effective in prioritizing elements for MRR decisions.
- The Federal Highway Administration (FHWA) requires that states have less than 10% of the total deck area that is structurally deficient. By applying a game theory approach, it is possible to identify an inherent and particular payoff structure between FHWA and a state DOT. The 10% limit on deck maintenance in current requirements may not most cost-

beneficial for extending the service life in the long term. By reallocating 0.5% (from 10% to 10.5%) of the FHWA's deck requirement, both FHWA and state DOTs will be able to allocate additional resources to expansion joints and joint seals. The outcome of such a strategic move yields a higher payoff for the players.

8.2 Recommendations

The inter-dependent relationships among "Co-Active" elements define how the performance of one element affects the other bridge elements. Bridge asset managers should be able to optimize a return on investment (ROI), with respect to bridge actions (i.e., preventive maintenance, rehabilitation, or replacement), by understanding and defining inter-dependent relationships among elements. The "Co-Active" coefficients, which define the relationships among elements, vary from 0.28 to 0.99. Future research should, therefore, focus on identifying additional groups of Co-Active elements and improving the "Co-Activeness" of elements. Future work should consider applying the proposed Co-Active mechanism to geographically different areas of the U.S. with additional groups of bridge elements that may be Co-Active. Each state should investigate and define the cause and effect relationship (or Co-Activeness) in its element-based inspection data.

The results presented in Chapter 7 are limited to the NHS and non-NHS bridge inspection and asset management in the United States. Future work should consider applying the proposed Co-Active mechanism to locally owned bridges, which are known to have much-limited resources for MRR. The cause and effects of the differences between the performances of NHS and non-NHS bridges should be investigated in detail. Additional pairs/groups of players and strategic moves should also be identified for a broader implementation of the proposed game theory approach. Furthermore, developing depreciation predictions with limited data requires extensive data analysis for each state. The limited collection period of the element data should improve over time, and the proposed Co-Active model should be calibrated and improved based on future data.

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Appendix A – Bridge Inspection Records.

Table A.1 – A typical GDOT element-based bridge inspection record for Sweetwater Creek Trib. (100140).

Element Description	Unit	Element Quantity	Condition States State 1	State 2	State 3	State 4
12-RC Deck	ft.	6069	5887	179	3	
215-RC Abutment	ft.	52	52			
301-Pourable Joint Seal	Sq.ft.	208	182		26	
311-Movable Bearing	ft.	28	9	7	12	
234-RC Pier Cap	ft.	156	156			
225-Steel Pile	ft.	24	24			
107-Steel Open Web Girder/Beam	ea.	756	741	5	10	
313-Fixed Bearing	ea.	16	4	2	10	
331-RC Bridge Railing	ft.	378	363	15		
515-Steel Protective Coating (107)	Sq.ft.	4528	4528			
515-Steel Protective Coating (225)	Sq.ft.	10200	10200			
515-Steel Protective Coating (311)	Sq.ft.	28	11		17	
515-Steel Protective Coating (313)	Sq.ft.	16	4	2	10	

RC = reinforced concrete

Table A.2 – Element based inspection record for Colorado bridge D-03-V-150 (Jiang & Rens, 2010a).

Element Description	Unit	Element Quantity	Condition States State 1	State 2	State 3	State 4	State 5
14-P conc deck/AC ovly	in.	8,895.28	8,895.28	0	0	0	0
101-Unpnt stl box girder	in.	1,444.76	1,300.28	144.48	0	0	
106-Unpnt stl opn girder	in.	176.48	176.48	0	0	0	
210-R/conc pier wall	ft.	164.59	164.59	0	0	0	
215-R/conc abutment	ft.	27.43	27.43	0	0	0	
234-R/conc cap	in.	175.26	0	175.26	0	0	
305-Elastomeric flex Jt	in.	27.43	27.43	0	0		
314-Pot bearing	ea.	86	27	4	55		
326-Bridge wingwalls	ea.	4	4	0	0		
331-Conc bridge railing	ea.	874.78	874.78	0	0	0	
333-Other bridge railing	ea.	569.98	569.98	0	0		
334-Metal rail coated	ea.	722.38	633.38	0	89	0	0
338-Conc curbs/SW	ea.	722.38	722.38	0	0	0	

Appendix B – CR History and Deterioration Models for Culvert and Bridge.

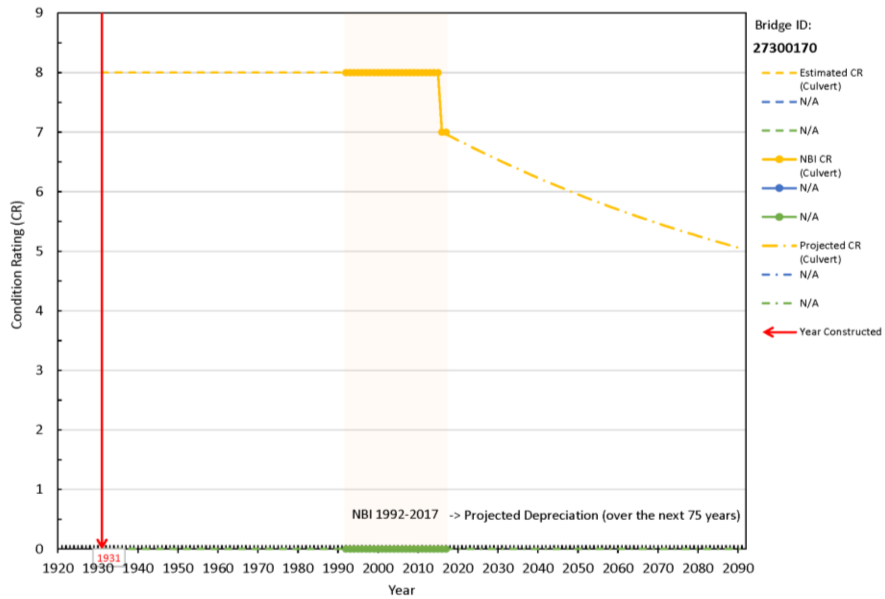


Figure B.1 – CR History and a deterioration model for a culvert.

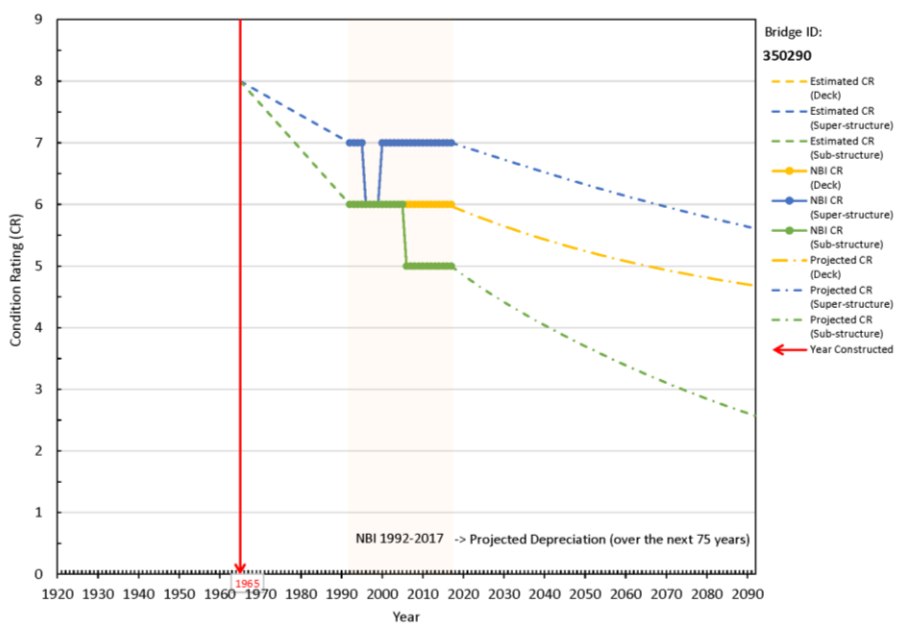
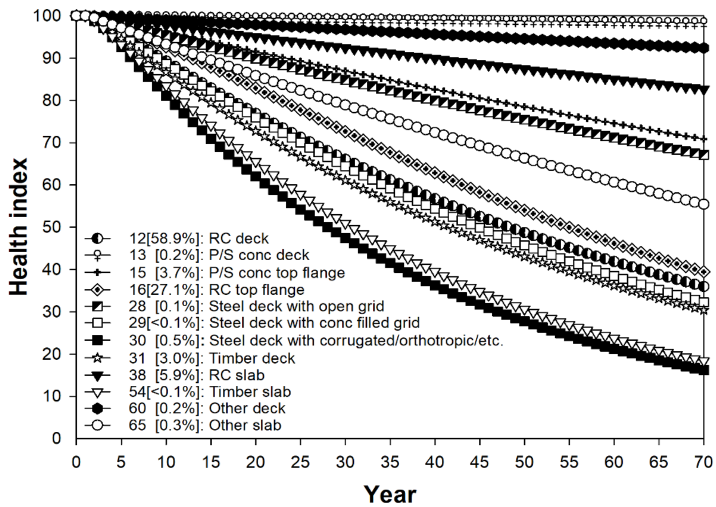


Figure B.2 – CR History and a deterioration model for a bridge.

Appendix C – Element Deterioration Prediction Models for Georgia.



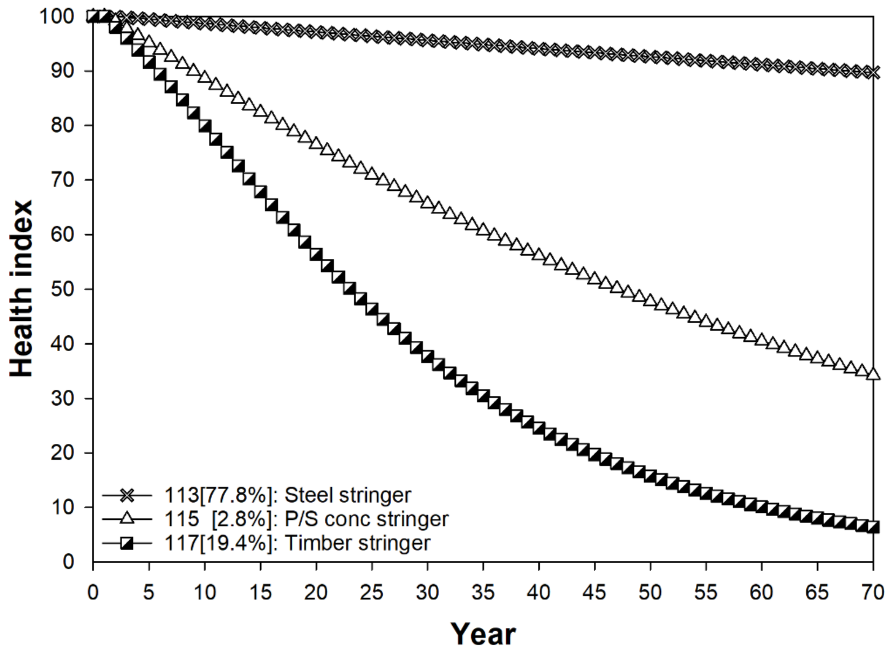
RC = Reinforced concrete; P/S conc = Prestressed concrete; conc = concrete; and Steel deck with corrugated = Steel deck with corrugated panels

Figure C.1 – Deck and slab elements in Georgia.

Note: In the brackets, the presence of each element within the category is shown as a percentage.

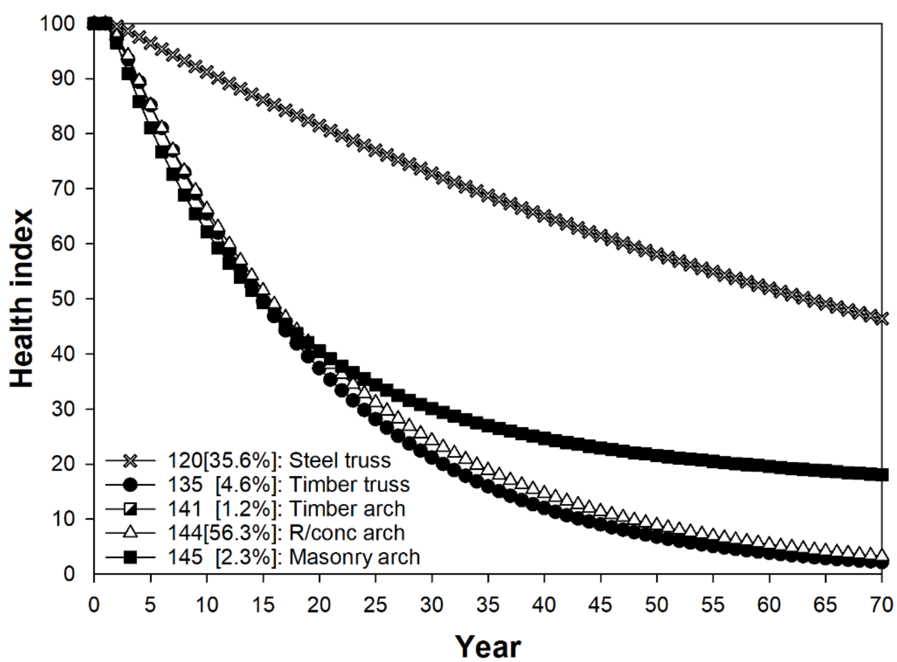
P/S conc = Prestressed concrete; R/conc = Reinforced concrete; and conc = concrete

Figure C.2 – Girders in Georgia.



P/S conc = Prestressed concrete

Figure C.3 – Stringer elements.



R/conc = Reinforced concrete

Figure C.4 – Trusses and arches.

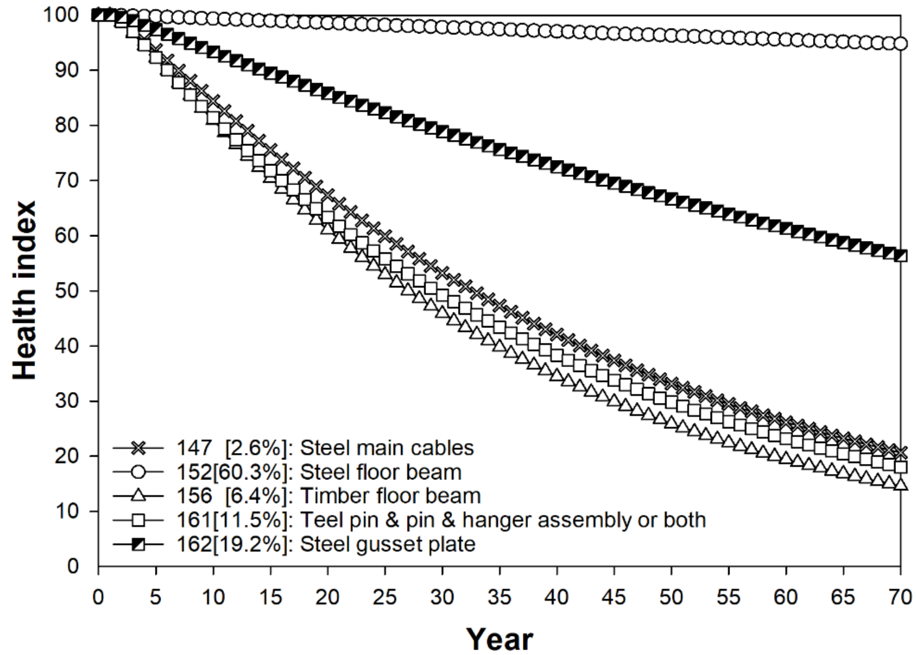
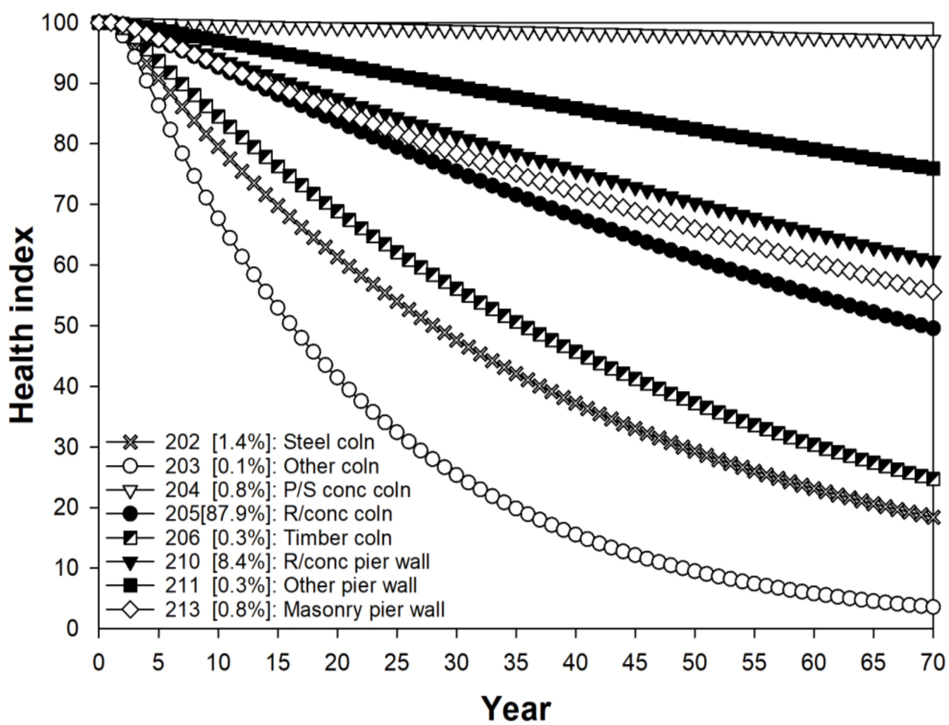
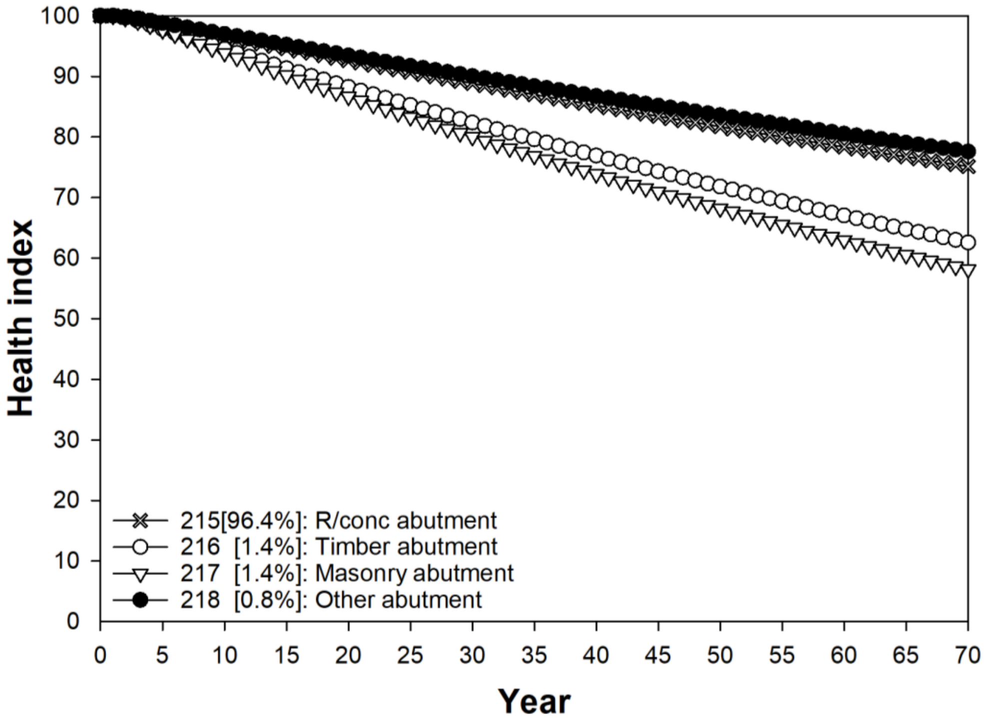


Figure C.5 – Floor beams and miscellaneous superstructure elements.



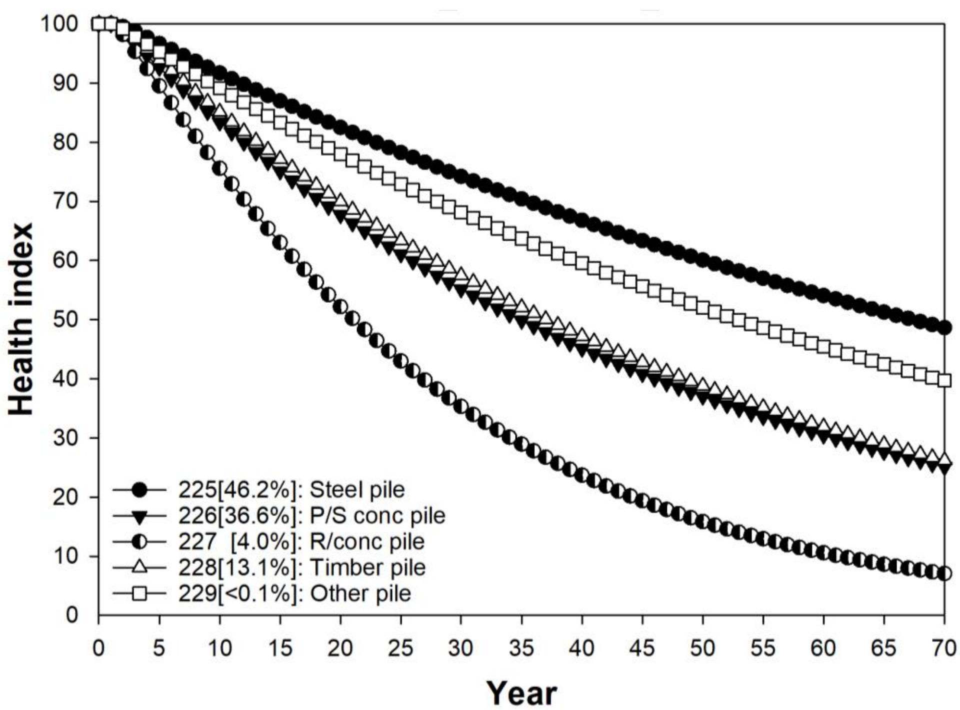
coln = column; P/S conc = Prestressed concrete; and R/conc = Reinforced concrete

Figure C.6 – Columns and pier walls.



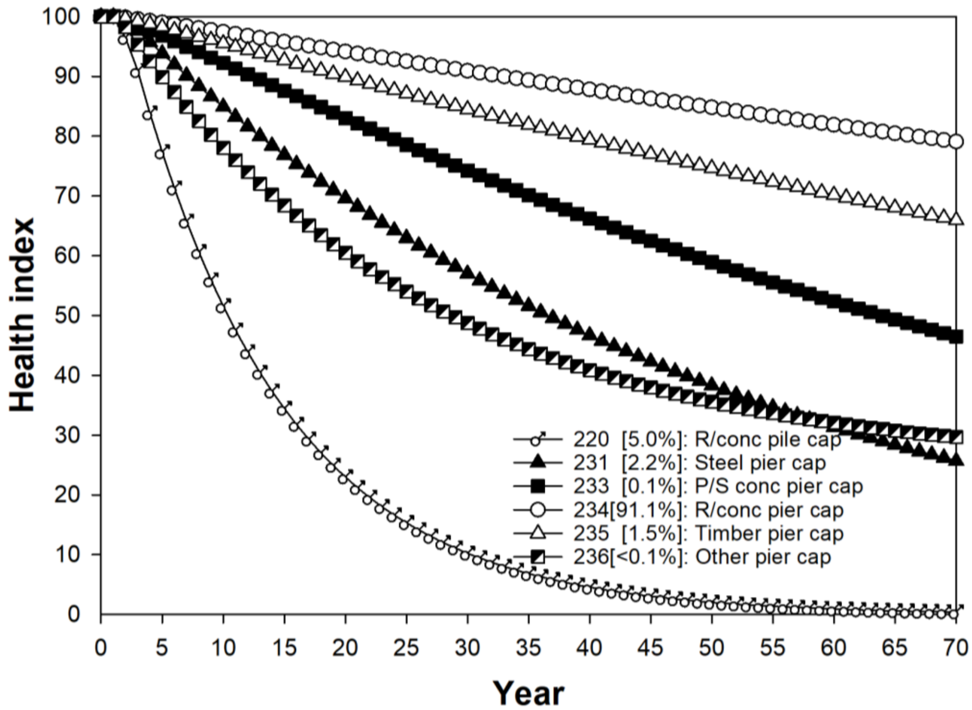
R/conc = Reinforced concrete

Figure C.7 – Abutments.



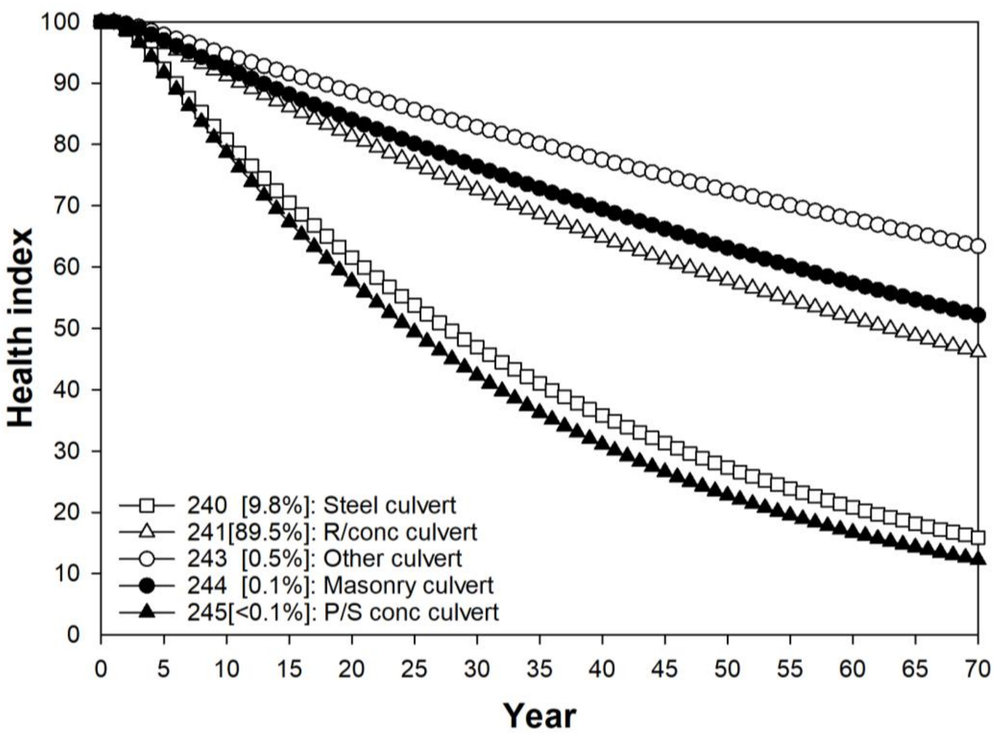
P/S conc = Prestressed concrete and R/conc = Reinforced concrete

Figure C.8 – Piles.



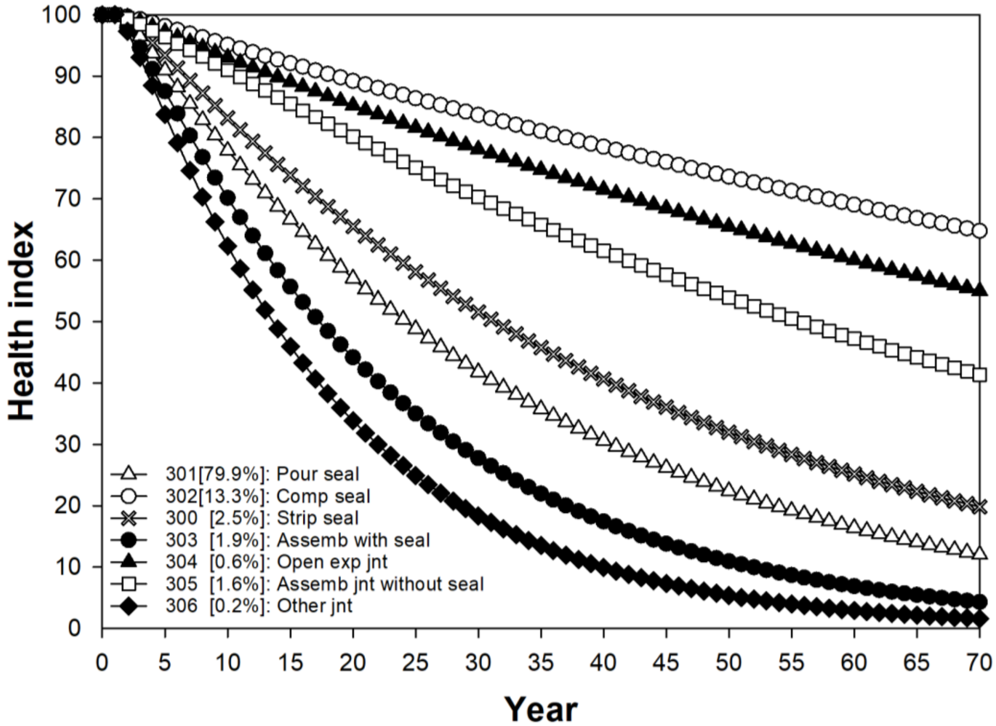
R/conc = Reinforced concrete and P/S conc = Prestressed concrete

Figure C.9 – Pier caps and footings.



R/conc = Reinforced concrete and P/S conc = Prestressed concrete

Figure C.10 – Culverts.



Pour = Pourable; Comp = Compression; Assemb = Assembly; exp = expansion; and jnt = joint

Figure C.11 – Joints in Georgia.

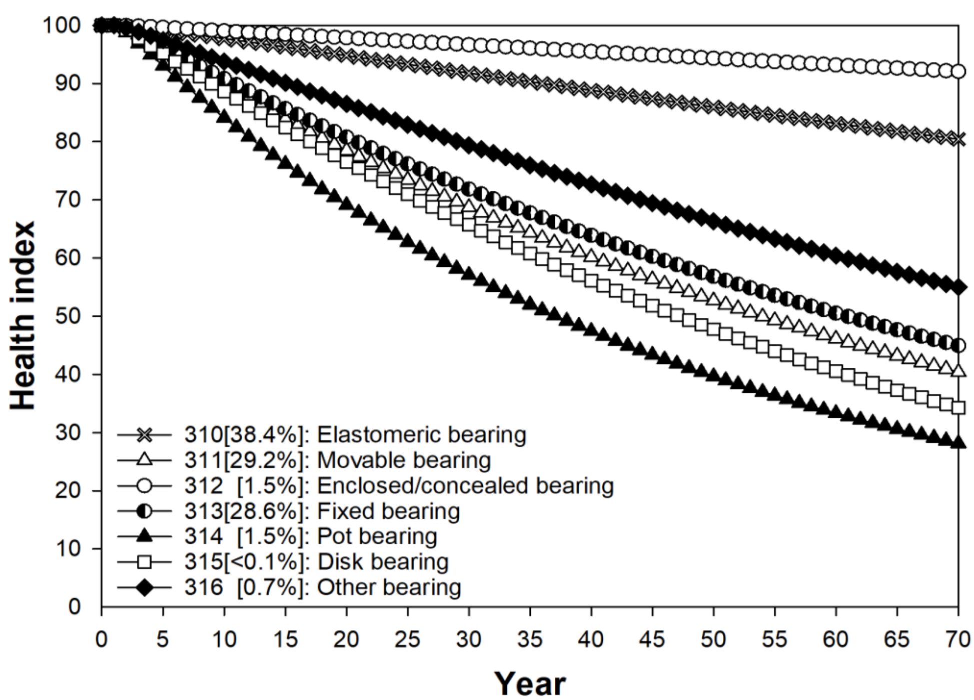
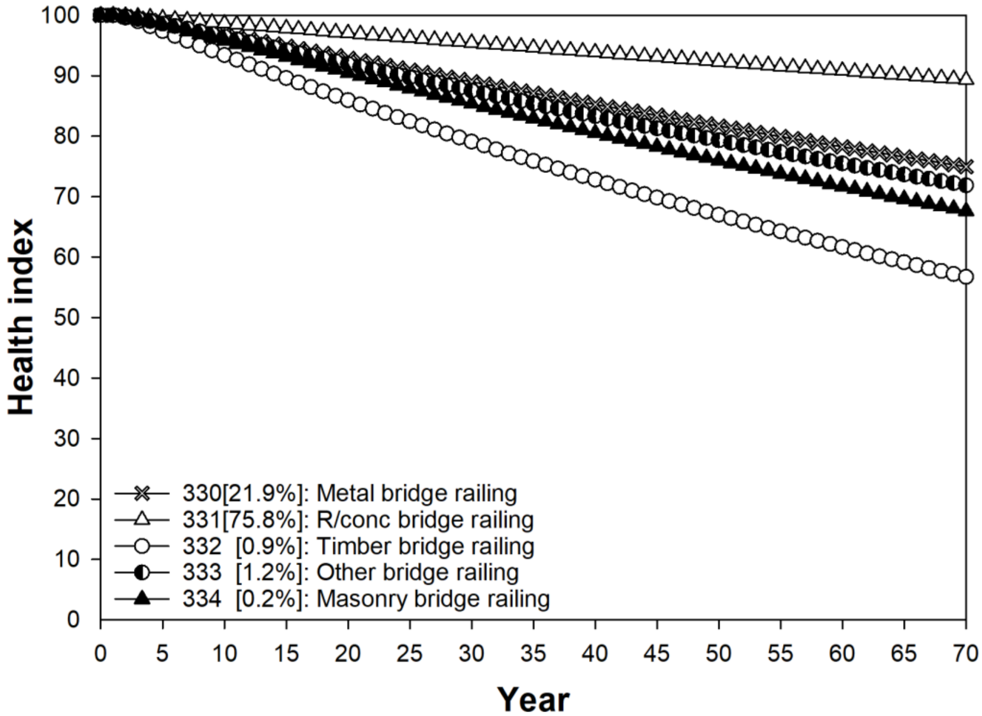
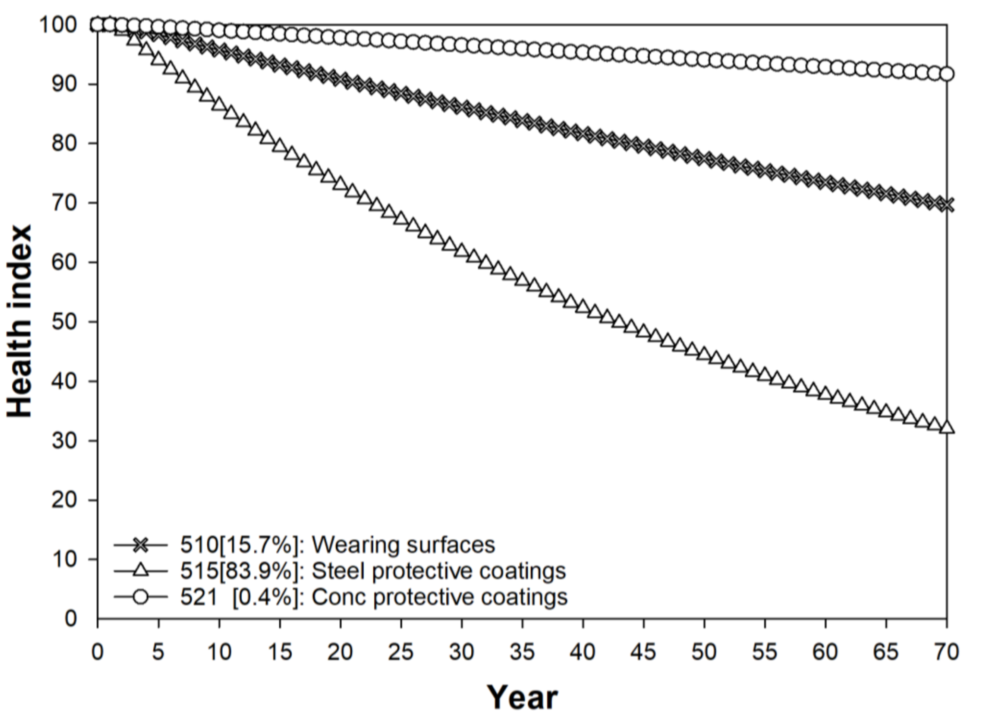


Figure C.12 – Bearings in Georgia.



R/conc = Reinforced concrete

Figure C.13 – Railings in Georgia.



Conc = Concrete

Figure C.14 – Wearing surface and protective coating in Georgia.

Appendix D: Element versus NBI-Based Bridge Deterioration Predictions.

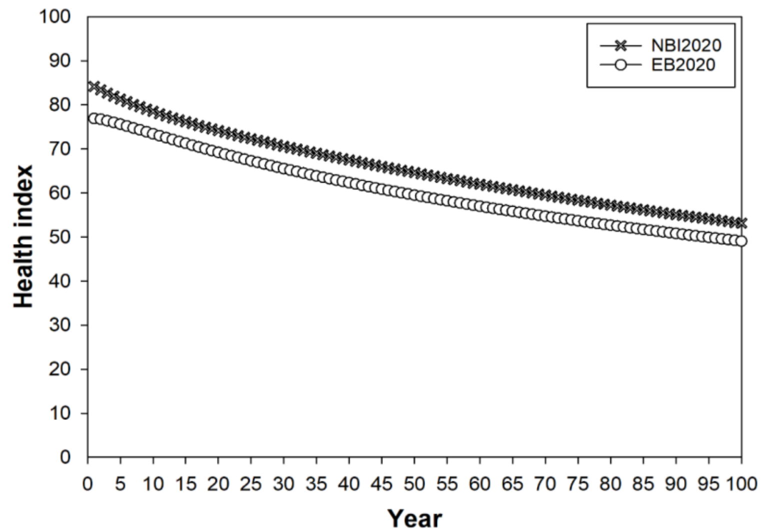


Figure D.1 – Element-based vs. NBI-based bridge deterioration models (Age Bin 2020).

Note: NBI condition ratings are rescaled to the 100-scale (e.g., an NBI condition rating of 9 is scaled to 100), and the health indices are reduced by 22% for a fair comparison.

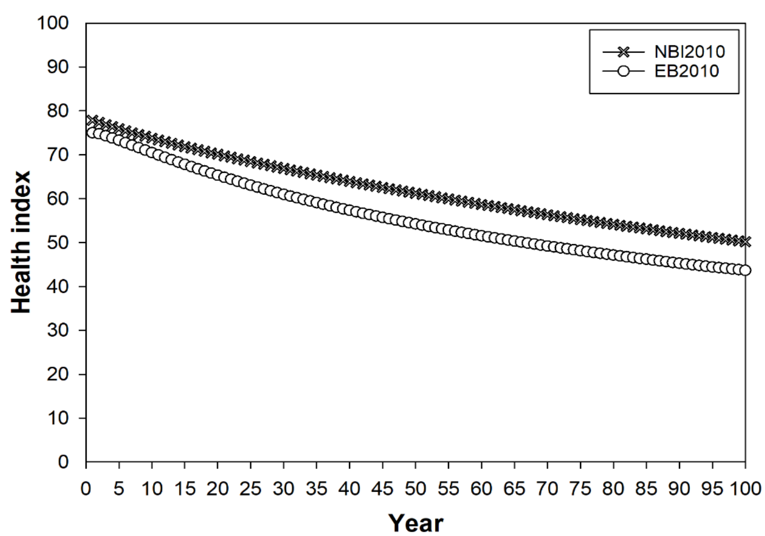


Figure D.2 – Element-based vs. NBI-based bridge deterioration models

(Age Bin 2010).

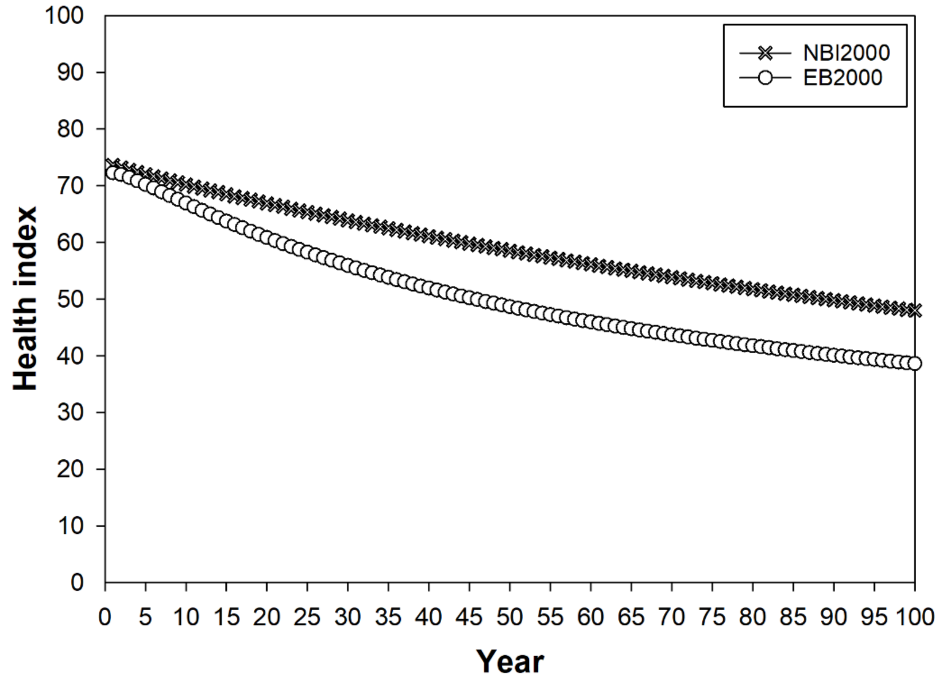


Figure D.3 – Element-based vs. NBI-based bridge deterioration models (Age Bin 2000).

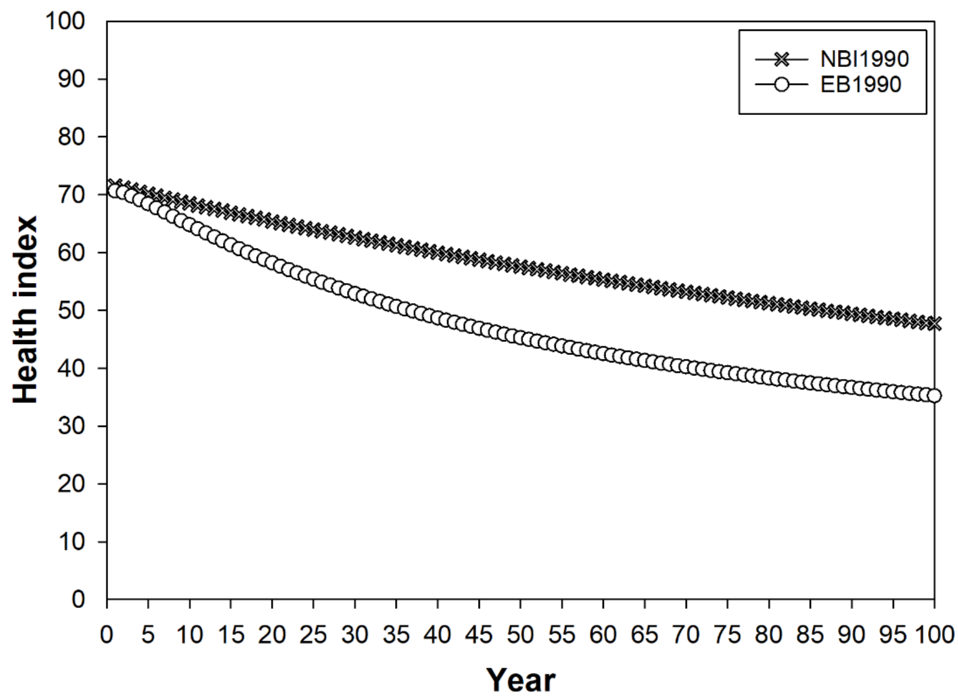


Figure D.4 – Element-based vs. NBI-based bridge deterioration models (Age Bin 1990).

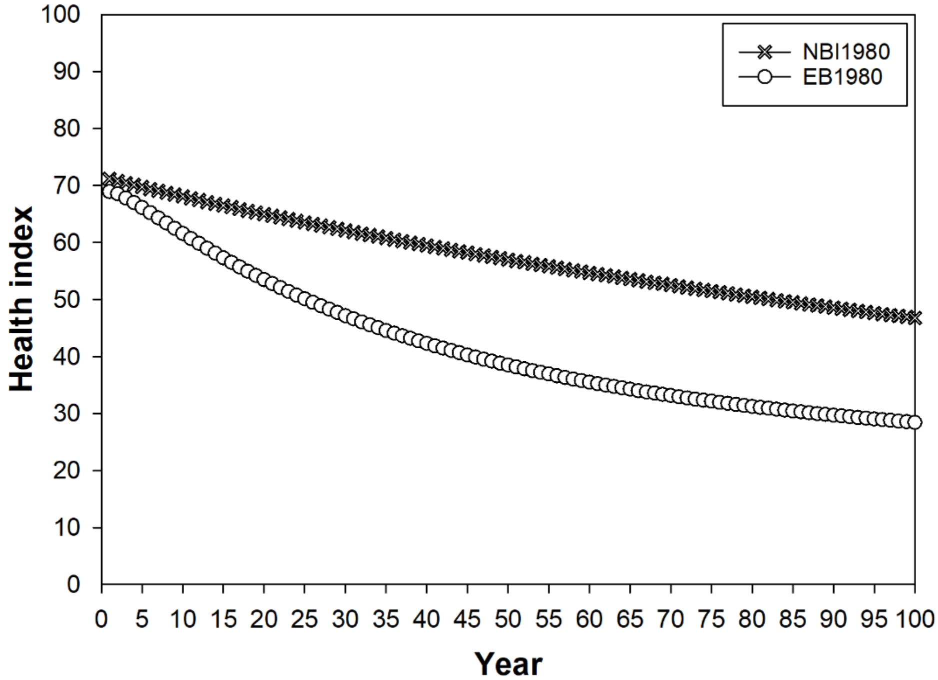


Figure D.5 – Element-based vs. NBI-based bridge deterioration models (Age Bin 1980).

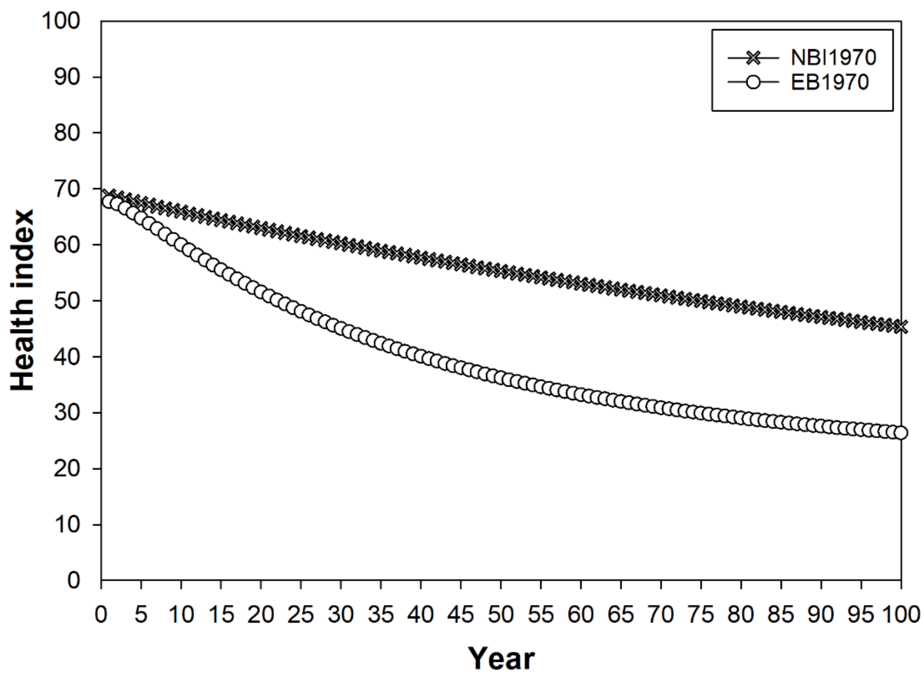


Figure D.6 – Element-based vs. NBI-based bridge deterioration models (Age Bin 1970).

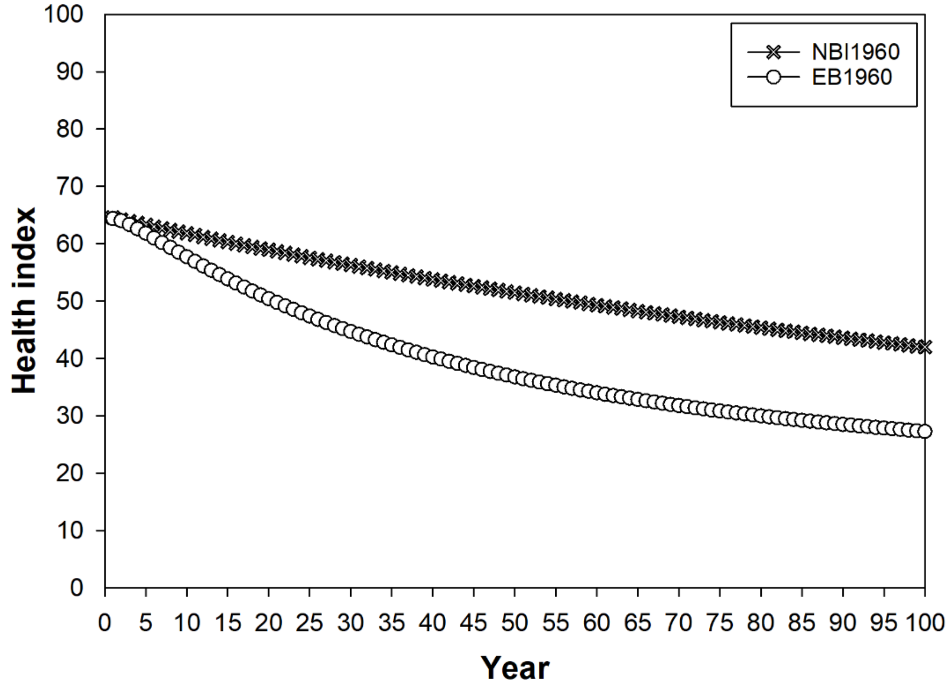


Figure D.7 – Element-based vs. NBI-based bridge deterioration models (Age Bin 1960).

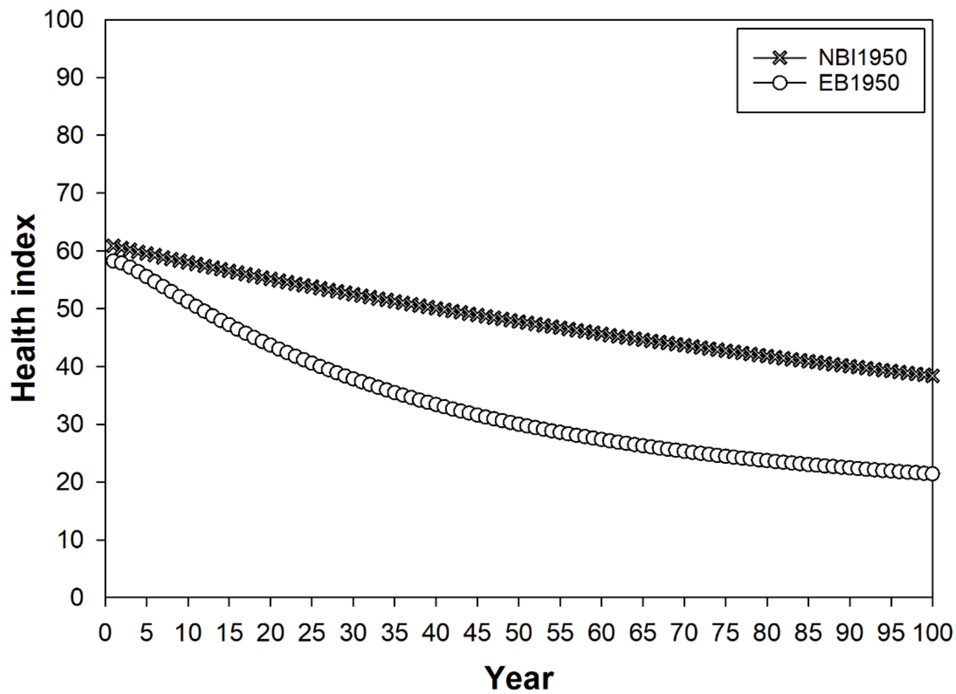


Figure D.8 – Element-based vs. NBI-based bridge deterioration models (Age Bin 1950).

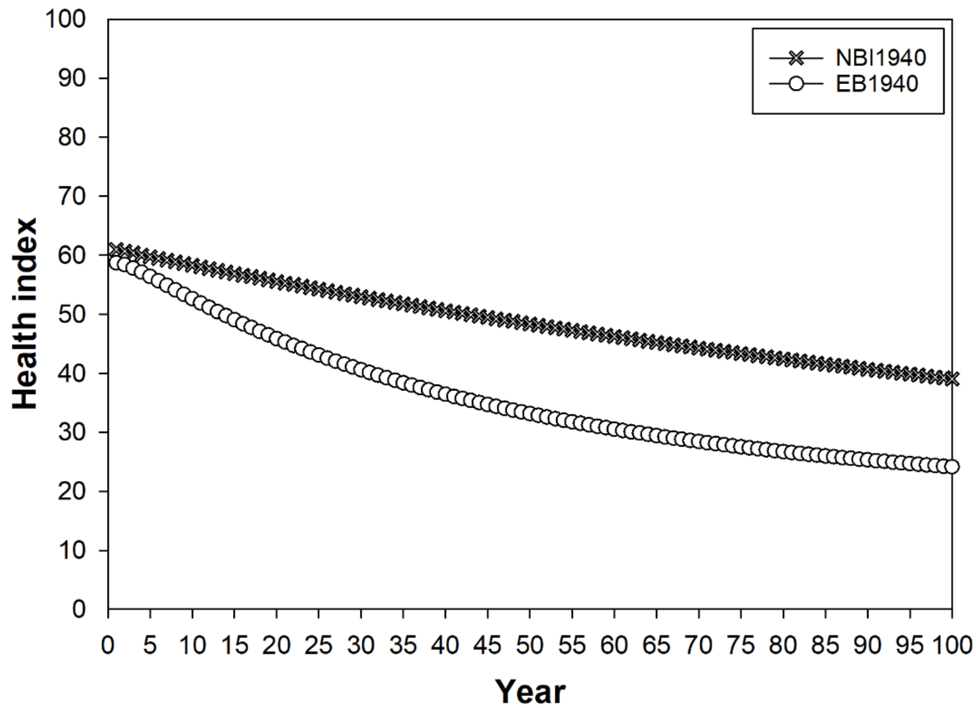


Figure D.9 – Element-based vs. NBI-based bridge deterioration models (Age Bin 1940).

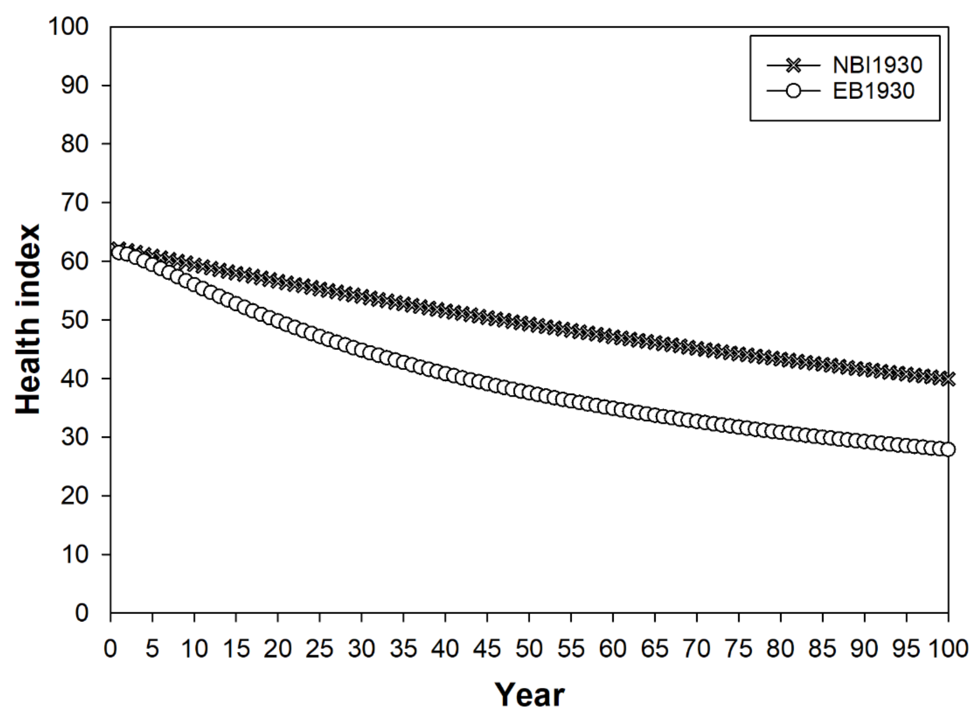


Figure D.10 – Element-based vs. NBI-based bridge deterioration models (Age Bin 1930).

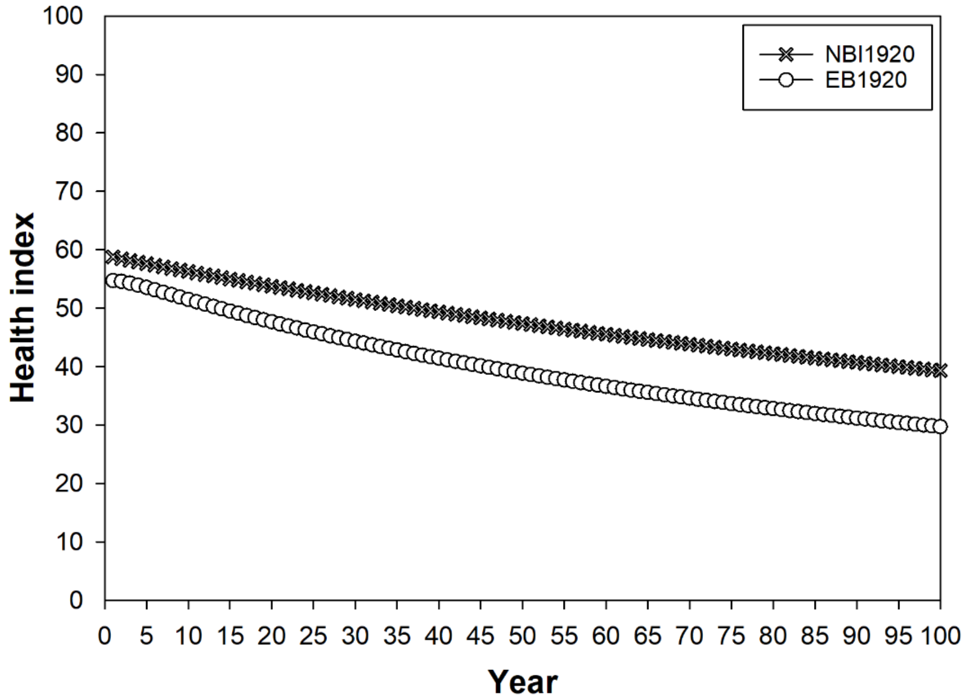


Figure D.11 – Element-based vs. NBI-based bridge deterioration models (Age Bin 1920).

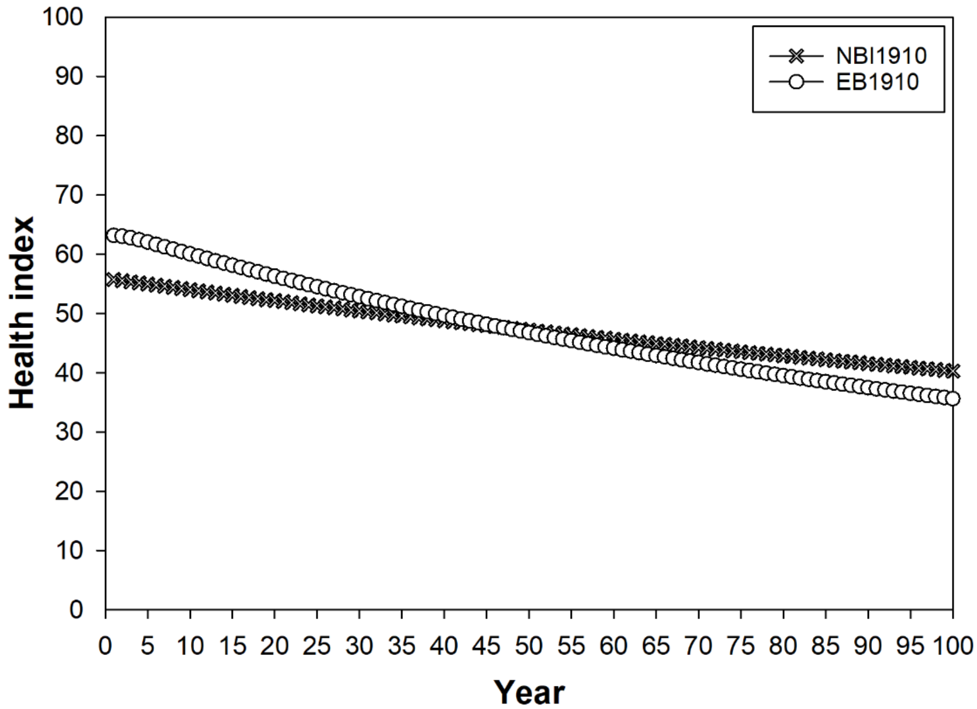


Figure D.12 – Element-based vs. NBI-based bridge deterioration models (Age Bin 1910).

Appendix E – MHI Predictions and Associated Parameters.

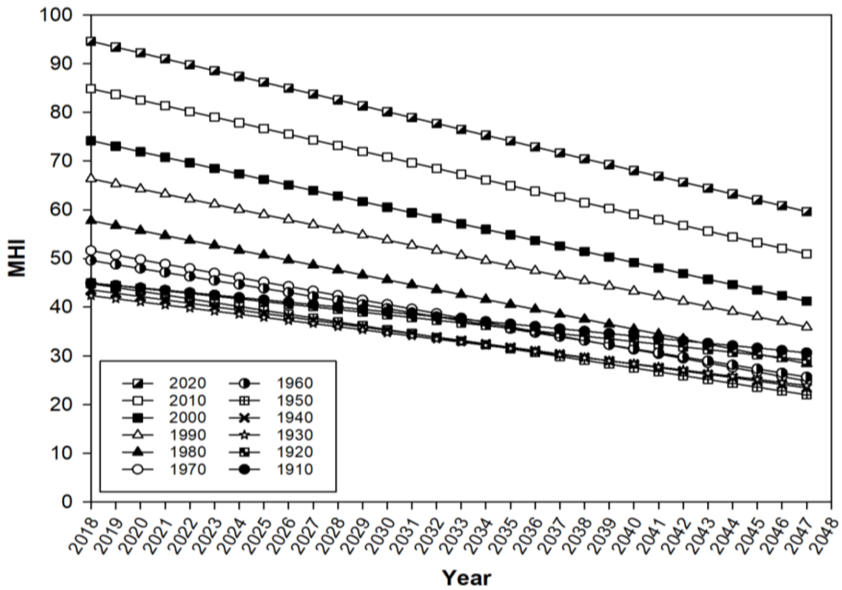


Figure E.1 – Model 1 MHI predictions for bridges & culverts (100yr & Threshold=50).

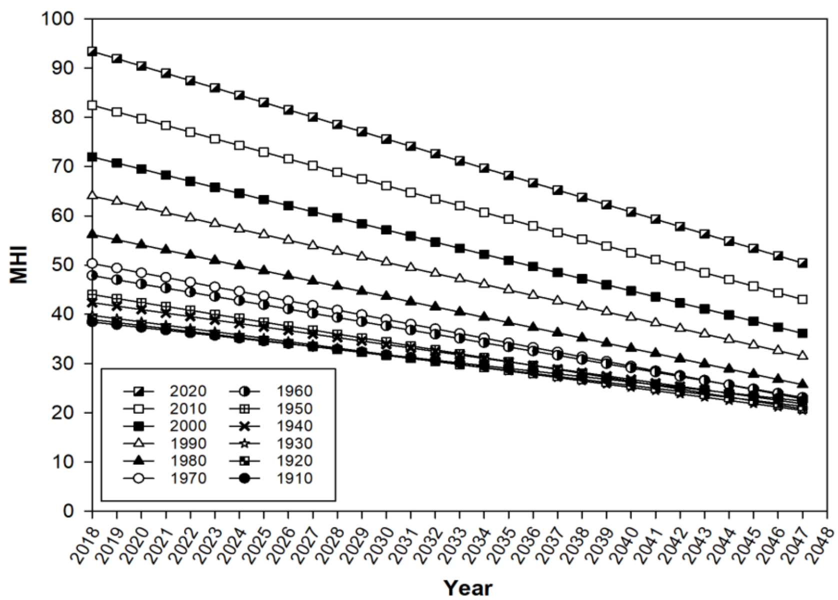


Figure E.2 – Model 1 MHI predictions for bridges & culverts (70yr & Threshold=50).

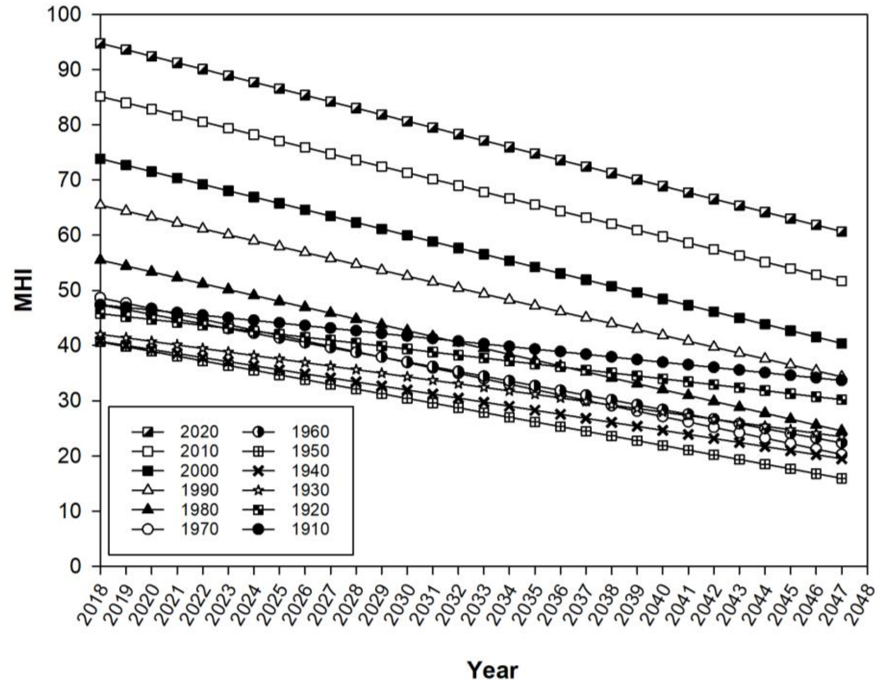


Figure E.3 – Model 1 MHI predictions for bridges only (100yr & Threshold=50).

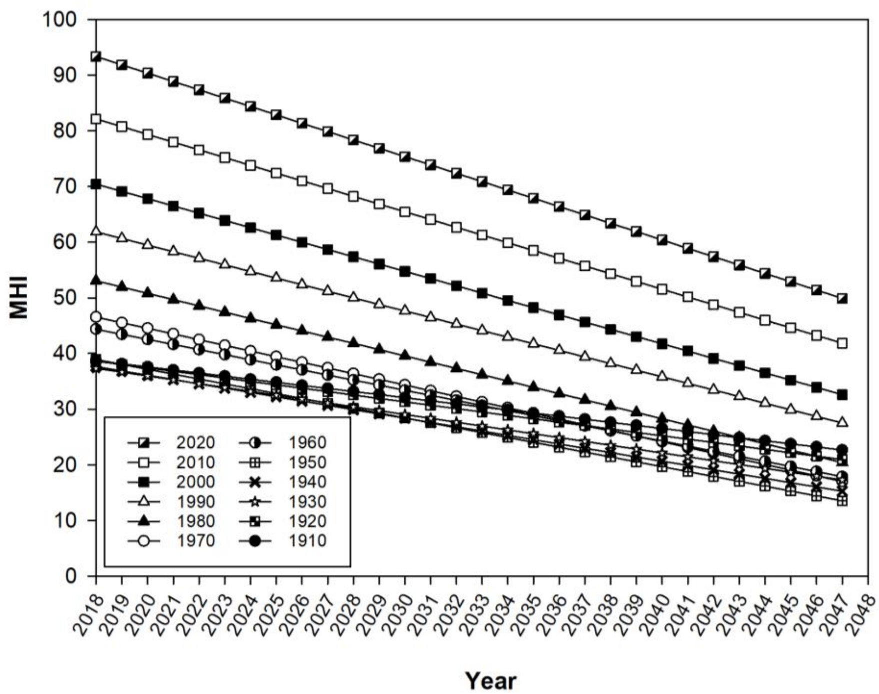


Figure E.4 – Model 1 MHI predictions for bridges only (70yr & Threshold=50).

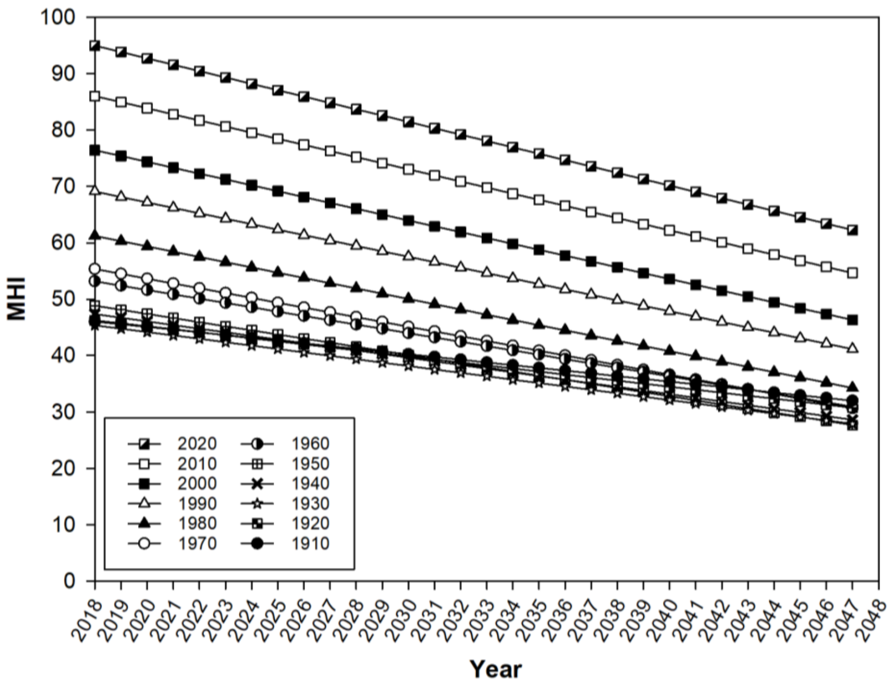


Figure E.5 – Model 2 MHI predictions for bridges & culverts (100yr & Threshold=45).

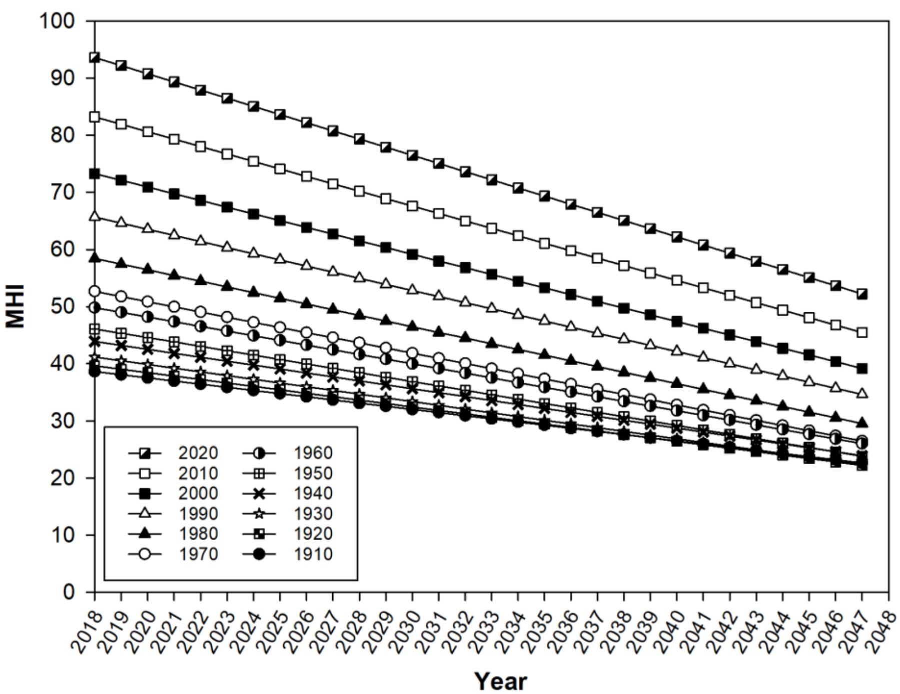


Figure E.6 – Model 2 MHI predictions for bridges & culverts (70yr & Threshold=45).

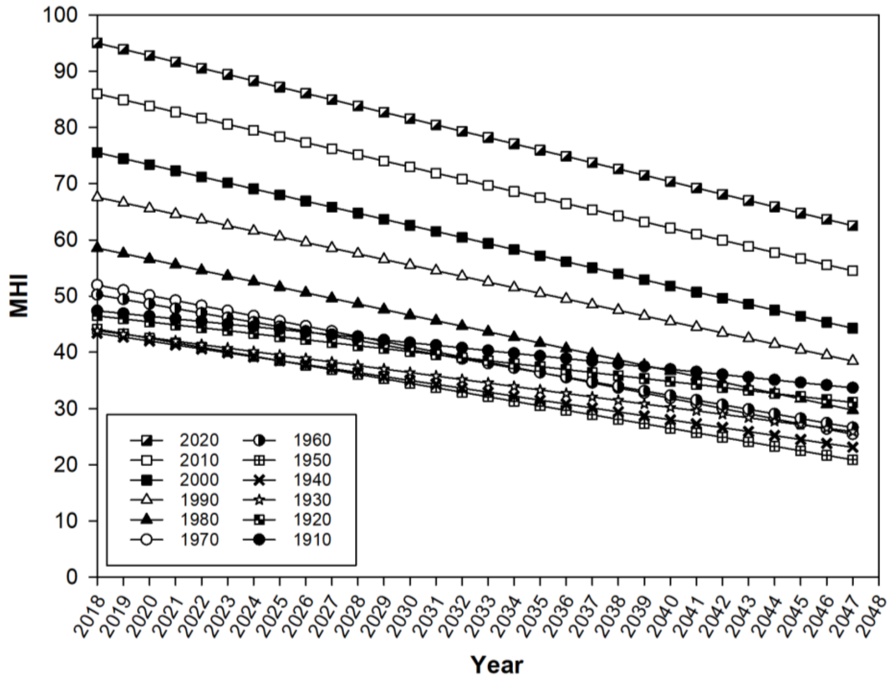


Figure E.7 – Model 2 MHI predictions for bridges only (100yr & Threshold=45).

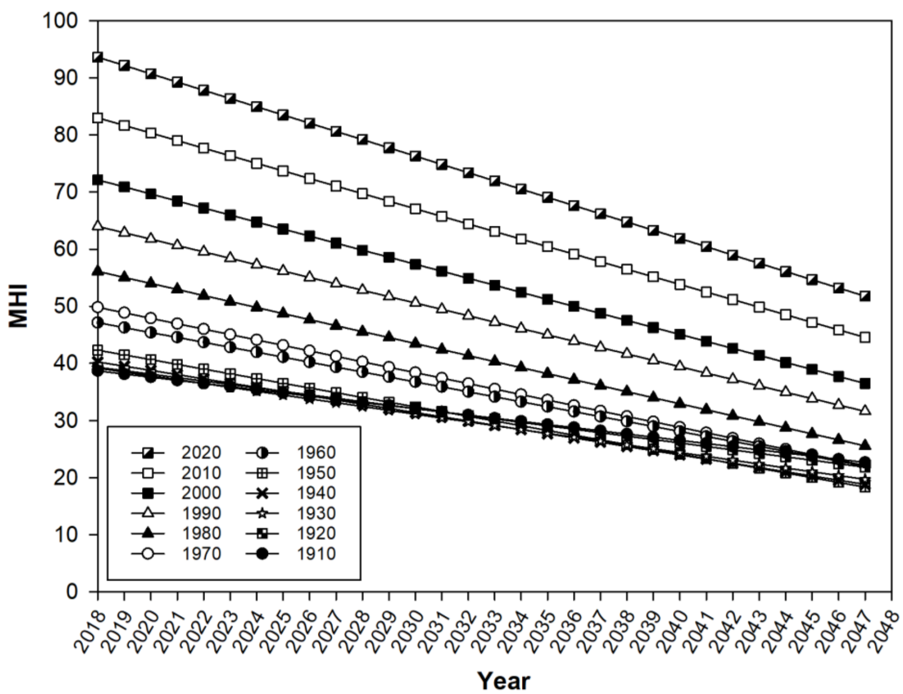


Figure E.8 – Model 2 MHI predictions for bridges only (70yr & Threshold=45).

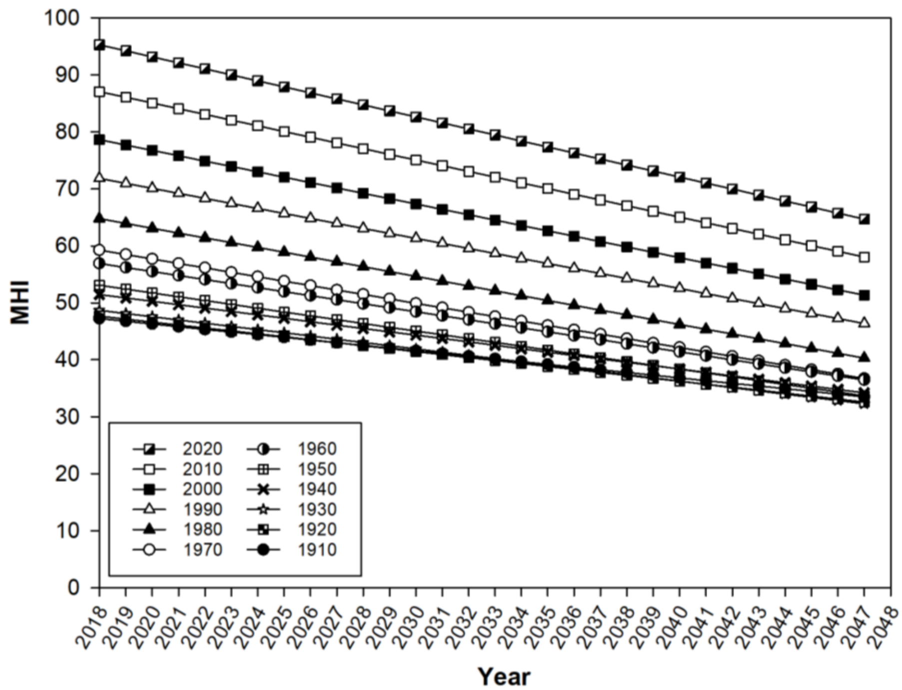


Figure E.9 – Model 3 MHI predictions for bridges & culverts (100yr & Threshold=40).

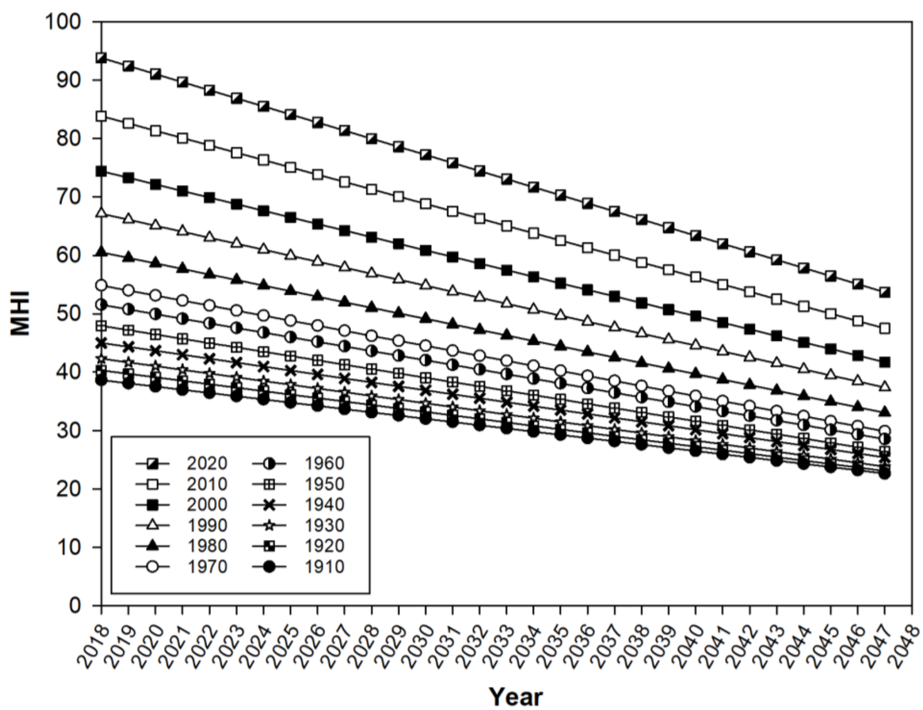


Figure E.10 – Model 3 MHI predictions for bridges & culverts (70yr & Threshold=40).

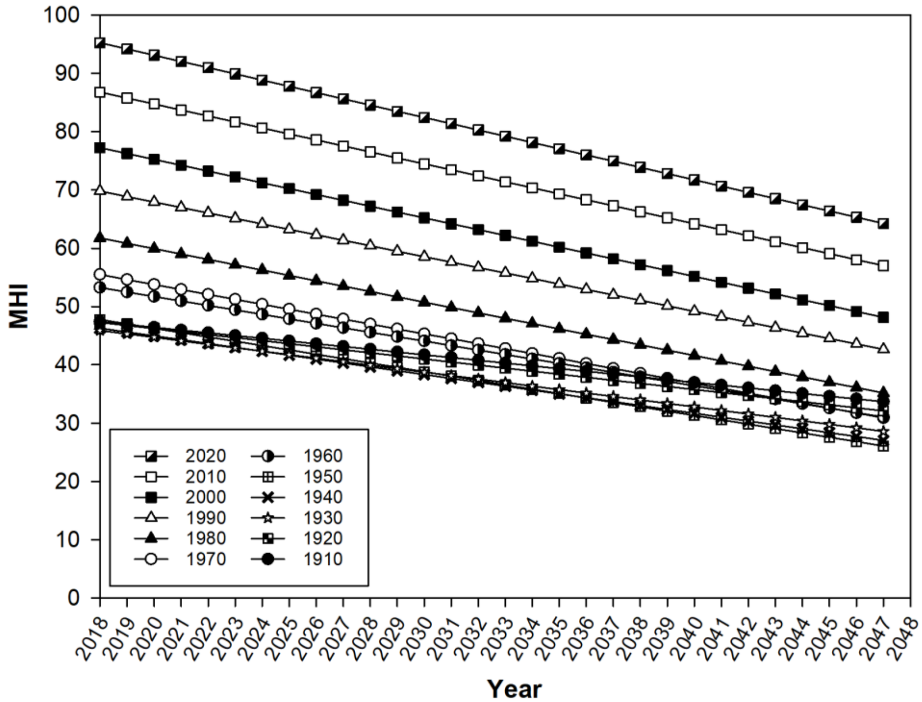


Figure E.11 – Model 3 MHI predictions for bridges only (100yr & Threshold=40).

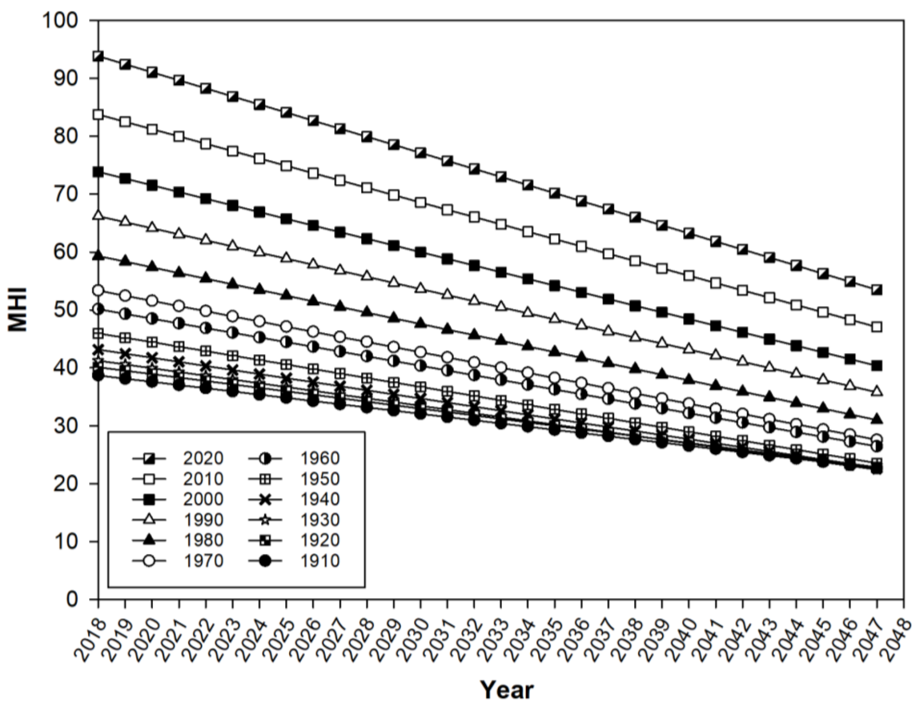


Figure E.12 – Model 3 MHI predictions for bridges only (70yr & Threshold=40).

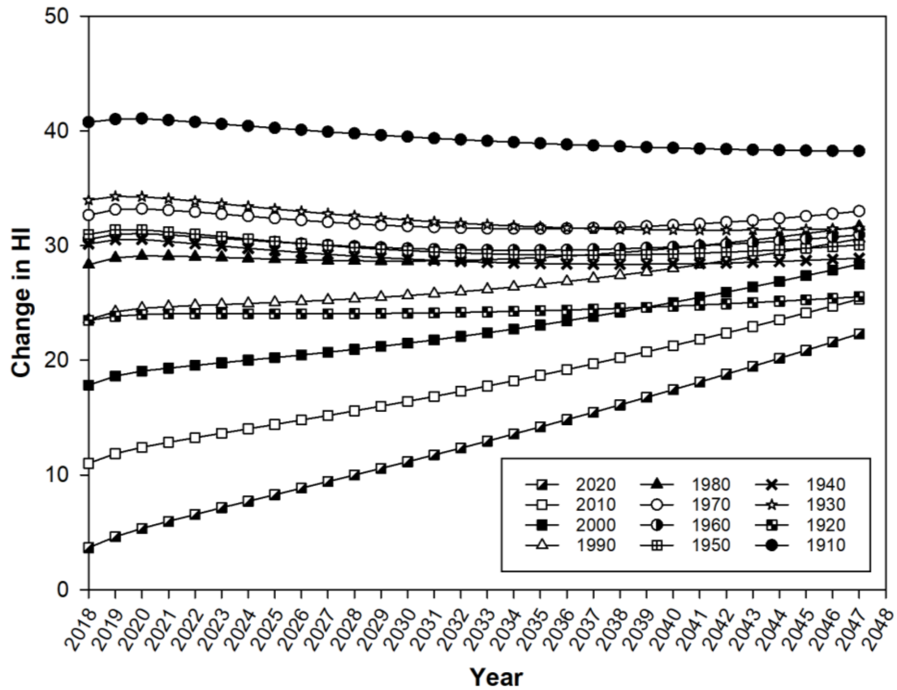


Figure E.13 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges & culverts for model 1 (100yr & Threshold=50).

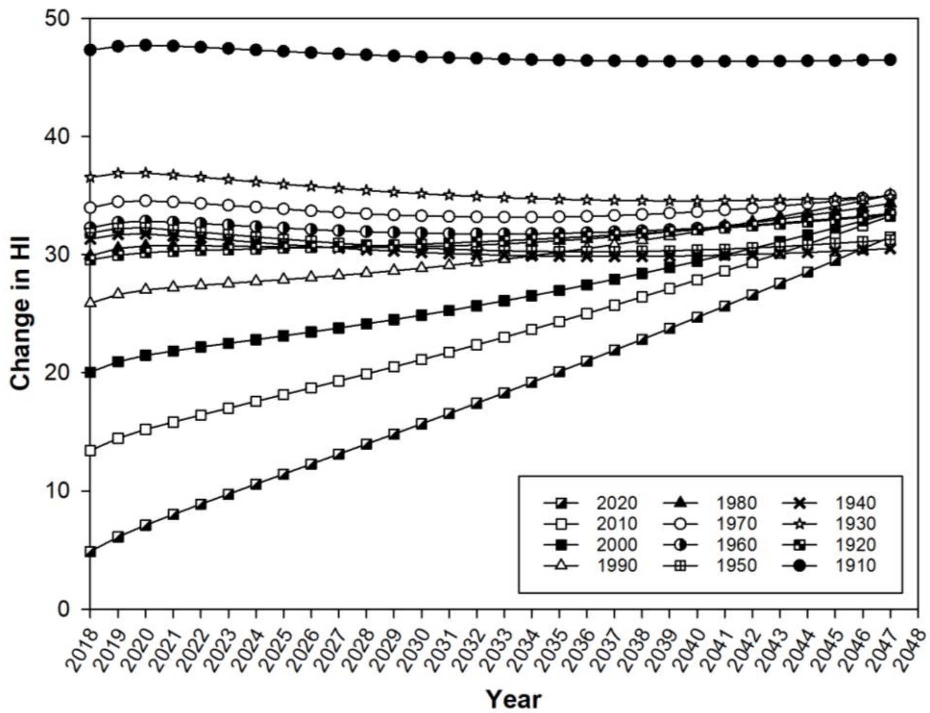


Figure E.14 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges & culverts for model 1 (70yr & Threshold=50).

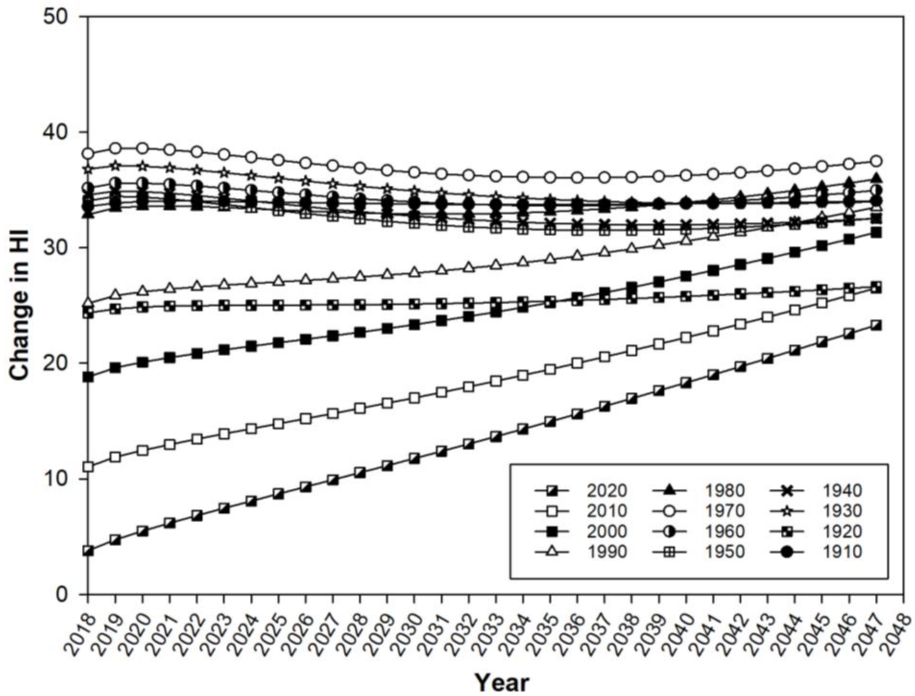


Figure E.15 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges only for model 1 (100yr & Threshold=50).

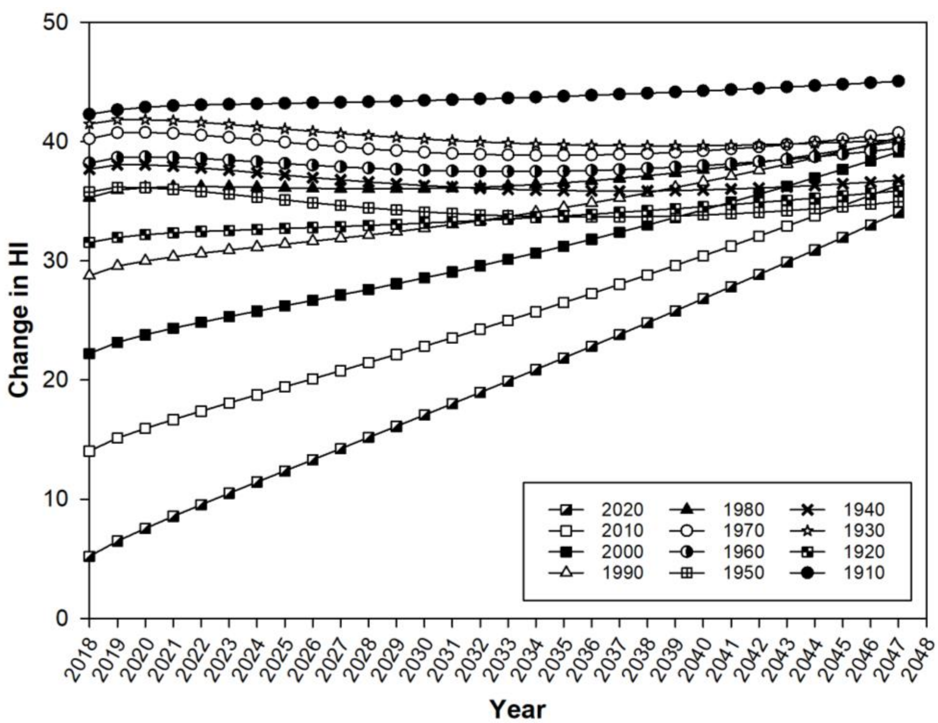


Figure E.16 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges only for model 1 (70yr & Threshold=50).

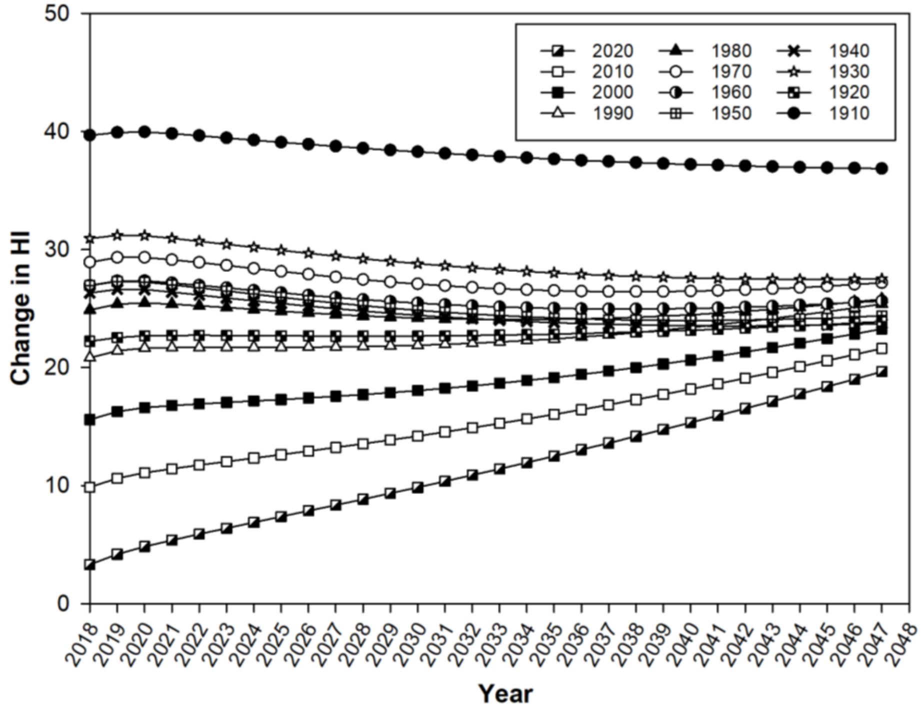


Figure E.17 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges and culverts for model 2 (100yr & Threshold=45).

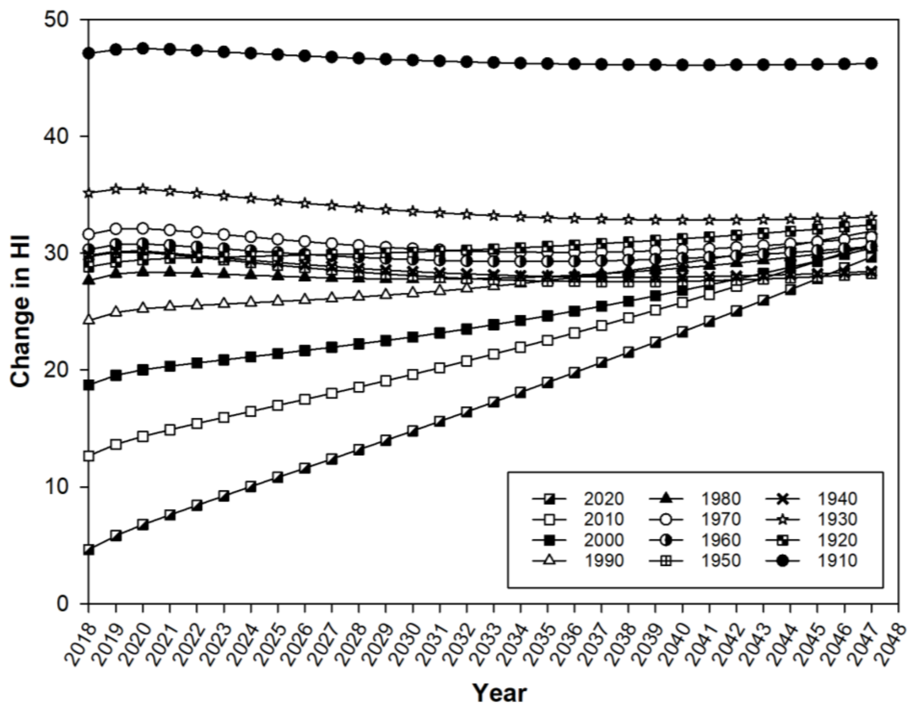


Figure E.18 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges and culverts for model 2 (70yr & Threshold=45).

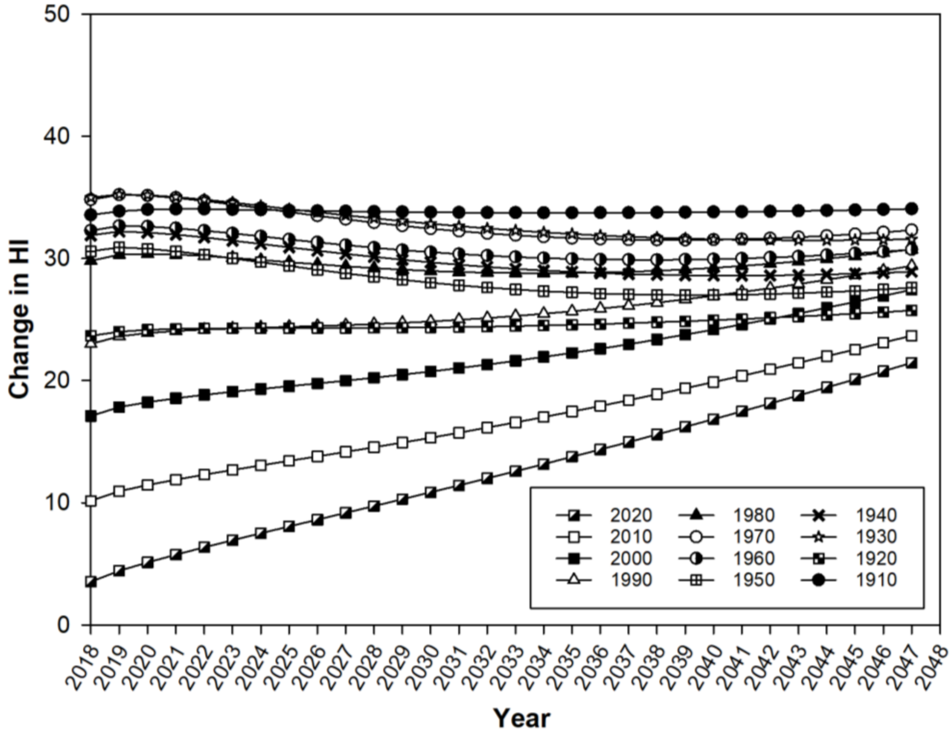


Figure E.19 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges only for model 2 (100yr & Threshold=45).

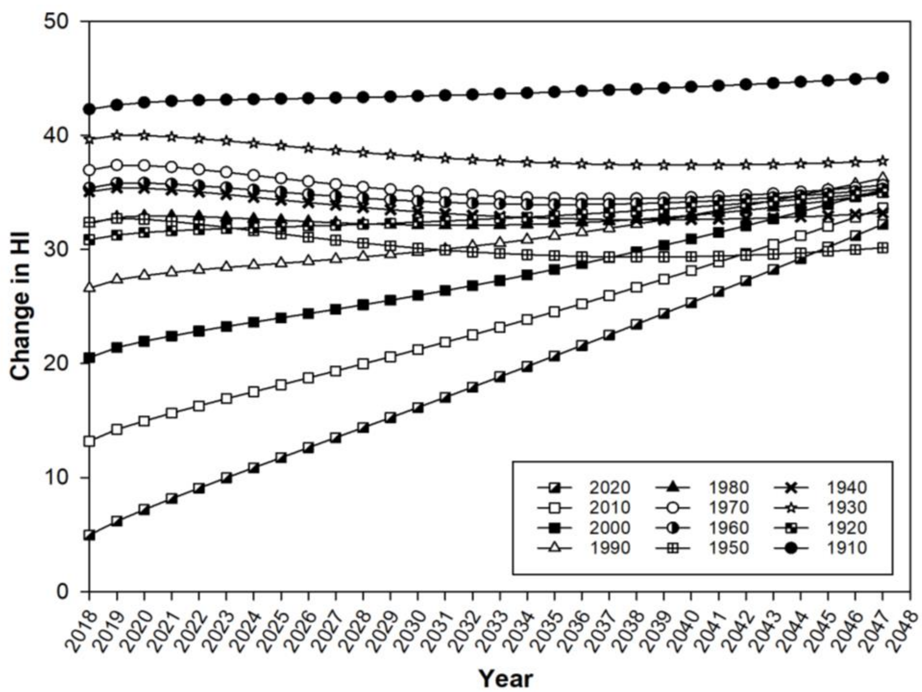


Figure E.20 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges only for model 2 (70yr & Threshold=45).

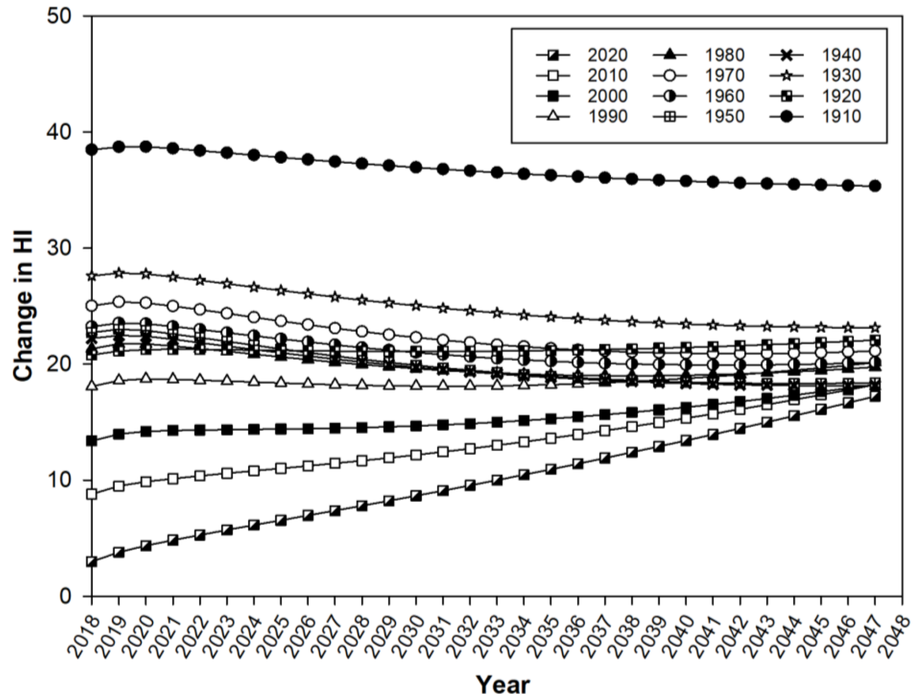


Figure E.21 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges & culverts for model 3 (100yr & Threshold=40).

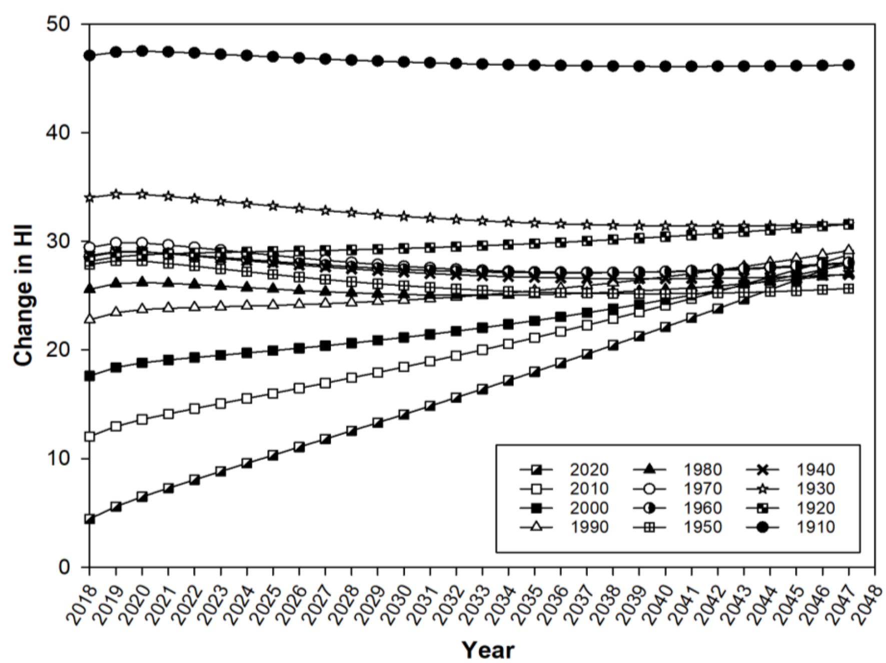


Figure E.22 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges & culverts for model 3 (70yr & Threshold=40).

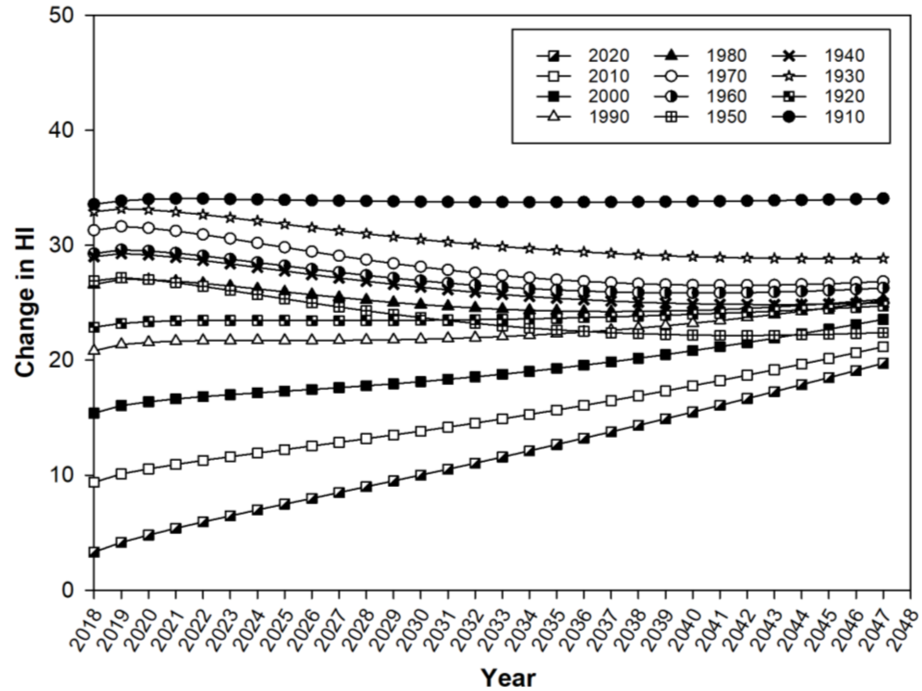


Figure E.23 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges only for model 3 (100yr & Threshold=40).

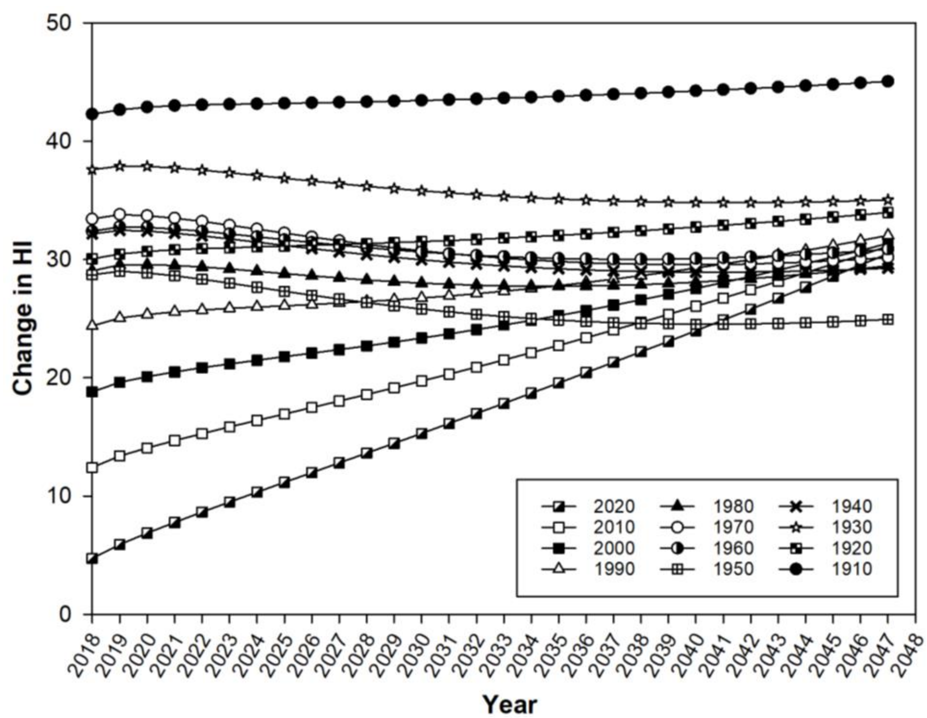


Figure E.24 – Health Indices (HIs) - Modified Health Indices (MHIs) of bridges only for model 3 (70yr & Threshold=40).