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# Artificial Neural Networks, Non Linear Auto Regression Networks (NARX) and Causal Loop Diagram Approaches for Modelling Bridge Infrastructure Conditions

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ARTIFICIAL NEURAL NETWORKS, NON LINEAR AUTO REGRESSION  
NETWORKS (NARX) AND CAUSAL LOOP DIAGRAM APPROACHES FOR  
MODELLING BRIDGE INFRASTRUCTURE CONDITIONS

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A Dissertation  
Presented to  
the Graduate School of  
Clemson University

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In Partial Fulfillment  
of the Requirements for the Degree  
Doctor of Philosophy  
Civil Engineering

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by  
Srimaruthi Jonnalagadda  
August 2016

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Accepted by:  
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## **ABSTRACT**

The quality of highway bridge infrastructure in United States is of major concern. One in every four bridges in the US is deficient. This research applied Artificial Intelligence, Systems Dynamics and linear modeling techniques to investigate the causes and effects of bridge deterioration and to forecast bridge infrastructure condition and improvement costs. The main contribution of the research is the development and demonstration of these methods within the context of highway bridges. These methods provide bridge designers and policy makers new tools for maintaining, improving, and delivering high quality bridge infrastructure.

To start with, a comprehensive review of the current state of bridge deficiency in US was conducted. Through extensive data mining of the National Bridge Inventory (NBI), the causes and trends in bridge deficiency were identified. This exercise addressed questions such as: What is the current extent of bridge deficiency? Is deficiency getting better or worse? What are the biggest problems causing deficiencies? It was observed that though the general condition of bridges is improving, additional work needs to be done in fixing bridge deficiency and bridge functionally obsolescence in particular.

Subsequent to the review of bridge deficiency, four distinct but related modeling studies were conducted. These phases are: 1) Capacity Obsolescence/Sustainability assessment, 2) Causal Loop Diagram (CLD) and linear modeling for bridge improvement costs, 3) Artificial Neural Network (ANN) model for bridge condition ratings and bridge variable effects, 4) Non-linear auto regression (NARX) model for bridge inventory condition prediction.

In the first phase, a conceptual model was developed to minimize capacity obsolescence, one face of functional obsolescence. A framework was developed to minimize bridge capacity obsolescence while optimizing the use of embodied energy over the service life of bridges. The research demonstrated how design phase consideration of bridge obsolescence can contribute to sustainability of bridge infrastructure.

As a novel approach for studying bridge improvement costs, the second phase used a Causal Loop Diagram (CLD), a tool used in the field of System Dynamics. Using a CLD, the causes and effects for bridge deterioration were qualitatively described. A segment of the qualitative relationships described through the CLD were then analyzed quantitatively for the South Carolina bridge inventory. The quantitative model was based on linear modeling and was developed and validated using NBI data. The model was then applied to estimate future bridge inventory sufficiency ratings and improvement costs under possible funding scenarios.

For effective mitigation of bridge deficiency, it is important to identify the effects of different variables on bridge conditions and forecast bridge condition. In the third phase of modeling, Artificial Neural Networks (ANN) models were used to study the effects of bridge variables on bridge deck and superstructure condition ratings. The models considered prestressed concrete bridges in South Eastern United States. Simulations based on Full Factorial Design (FFD) were conducted using the developed ANN models. The simulations highlighted the effects of skew, span and age on bridge

condition ratings. Given sufficient source data, the approach can be broadly applied to consider other bridge types and design variables.

In the last phase, time based ANN learning algorithms were used to forecast bridge condition ratings and bridge improvement costs. Non Linear Auto Regression with Exogenous Inputs (NARX) model was developed using NBI data for South Carolina bridges over the last decade. The study estimated bridge condition ratings as a function of bridge geometry, age, structural, traffic attributes and bridge improvement spending.

This doctoral research contributed to the development of multiple qualitative and mathematical models for forecasting bridge inventory condition and improvement costs by applying ANN, CLD, and linear regression techniques. While the conclusions of these studies are bound by the scope of the data and methodical constraints of the research, the methods can be more generally applied to aid in better bridge management policies and contribute to sustainable bridge infrastructure in United States.

## **DEDICATION**

*“To my beautiful wife Sirisha, for her unconditional love, exemplary sacrifice and outstanding support through all the tough times in my life.”*

*My life is hers, this doctorate is hers !*

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This is the time to recollect the role of my elder brother Mr. Lakshmi Ganapathi in shaping my persona. Starting from my middle school days through all of my academic and professional life, his inspiring letters ignited my passion to dream big, work hard and achieve those dreams. He is a great inspirer and true leader. I attribute my success to his selfless guidance. May God shower blessings on him and his family at all times.

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## CHAPTER ONE

### INTRODUCTION

#### **Motivation**

Bridges are critical to transportation systems and have impact on the vitality of the communities and regions. The quality of bridge infrastructure in US has become a cause of concern for federal authorities, state transit authorities, bridge owners, and general public (Jansen 2016, Babcock, 2016). The ASCE Report Card for America's Infrastructure gave C+ grade to bridge infrastructure quality which means that the quality is 'mediocre' (ASCE, 2013). According to the National Bridge Inventory (NBI) (NBI, 2016), a collection of data on all bridges that are over 20ft length in U.S, nearly 24% of all bridges in US are categorized as 'deficient'. A '*deficient*' bridge means that the bridge is either *structurally deficient (SD)* or *functionally obsolete (FO)* (Ryan et al, 2012).

Bridges are categorized as deficient based on routine inspection ratings. The FHWA coding guide provides guidelines to bridge inspectors on conducting inspections and assigning ratings (FHWA, 1995). Some of the important items that affect a bridge over all rating are its deck condition, superstructure condition, substructure condition, structural capacity and bridge geometry. While condition ratings grade the bridge components with reference to their original built condition, appraisal ratings compare the bridge current standards with those of current design standards (Ryan et al, 2012). The ratings are assigned on a scale of 0 to 9 indicating worst to best respectively. Sufficiency Rating (SR) is another important rating measure used to assess the overall health of a bridge. SR is measured on a scale of 0 to 100 indicating worst to best, respectively.

Bridge ratings give a picture of the condition of individual bridges as well as the health of the entire inventory. Hence there has been great research interest in developing methodologies that aid in estimating the future condition of bridges. In the past, Markovian chains and regressions models have been successfully applied to forecast bridge conditions (Morcous, 2002). With the advent of advanced computing methods, there is also great interest in Artificial Intelligence (AI) techniques.

While methods such as probabilistic evaluation, decision trees, and linear regression models are available, AI-based methods were selected for this research because of the complex nature of bridge infrastructure systems. AI models are based on “learning” from source data, and they are well-suited for identifying patterns and relationships between bridge usage (traffic), age, material types, geometries, and other relevant variables.

Alternative methods and their limitations are mentioned in brief. Probabilistic methods estimate probability distribution of the outcome variable by defining transition probabilities based on current condition and a set of dependent variables. They do not consider condition history, and are not self-learning (Morcous 2002). Decision trees provide a simple white box classification, however, they become very complicated for systems with large sets of variables and outcome scenarios. Their ability to learn from noisy and incomplete data is poor (Podgorelec, 2002). Linear regression models are deterministic mathematical models that are suitable for linear modeling, however linear regression models are based on monotonic relation between dependent and independent variables (UCB, 2011). With dynamic, nonlinear and time history based supervised



learning, AI-based methods, such as artificial neural networks (ANN) and nonlinear auto regression networks (NARX) are well suitable for addressing the problems selected in this study.

Bridge infrastructure is part of a complex public transportation system, the condition of which depends on a numerous different variables. For instance, bridge quality depends on local aspects such as traffic on the bridge, the age, the geometry, the structural conditions, weather, etc. to global aspects such as geographical, geological, social, economic, demographics of the location, and policies of the local, state and federal governments. Because of the complexity of bridge infrastructure systems, there is need for models and techniques that account for numerous variables and their interactions over time. System Dynamics approach is one suitable for modeling complex transportation systems and are useful for making policy-level decisions (Shepherd, 2014).

This study is motivated by the desire to improve the quality of bridge infrastructure in US. Accurate forecasts of the bridge conditions and deterioration will help bridge agencies and authorities to rightly and timely prioritize bridge maintenance, repair and rehabilitation programs, thus improving the bridge infrastructure quality. The application of ANN to bridge infrastructure is interesting and encouraging. Application of Causal Loop Diagrams, a tool used in System Dynamics, is also promising as a means to capture the dynamics of bridge variable interactions, the cause and effects of deterioration. ANN and CLD models, as well as traditional linear regression and simulations based on full factorial designs were applied in this work.

In addition to forecasting bridge deterioration, this study is motivated to identify and quantify the impacts of key bridge attributes on the bridge quality. The knowledge of these impacts will help designers as well as policy makers in making better choices within engineering and economic constraints.

### **Objectives**

This research aimed to apply AI-based and CLD methods in a novel application, specifically to better understand bridge infrastructure conditions. These methods are applied to enhance understanding of bridge deterioration, to forecast the future health of bridge inventories, and to estimate costs of bridge improvements. Variables that cause bridge deterioration and their effects on bridge condition ratings were identified and studied.

The principal objectives of this study are:

- ✓ *Develop a conceptual model for minimizing capacity obsolescence*
- ✓ *Create a causal loop diagram to qualitatively describe the causes and effects that impact the quality of highway bridge inventories*
- ✓ *Develop a linear quantitative model for proportions of the bridge inventory CLD*
- ✓ *Create an approach for evaluating the effects of design variables on bridge condition; the approach utilizes artificial neural networks and simulations based on a full factorial design*
- ✓ *Apply the NARX modeling approach to assess bridge inventory conditions*

## **Organization**

This dissertation is organized into seven chapters, some of which were prepared as stand-alone papers for journals and conferences. Chapter two contains a review of the current status of US bridge infrastructure. Terminology and concepts associated with bridge deficiency are described, as are the NBI bridge condition rating criteria. Extensive mining of NBI data across 50 states of US was performed for this part of the study and the most common reasons for bridge deficiency were identified. This chapter provides background on the prevalence of bridge deficiency and its impacts and gives a context for the research presented in the subsequent chapters.

In chapter three, a conceptual model was developed to quantify bridge *capacity obsolescence*. Capacity Obsolescence (CO) is defined as the gap between evolving load demands on bridges and load carrying capacity of bridges. A design framework is demonstrated to optimize bridge capacity with embodied energy consumption. Recommendations were made to incorporate design stage intervention to minimize capacity obsolescence and improve sustainability of bridge infrastructure. A review of the sustainability impacts of bridge obsolescence was also done. Chapter three was published as a conference paper in the proceedings of Transportation Research Board 94th annual meeting.

In chapter four, causal loop diagrams were developed for bridge deterioration system to describe the cause and effects of technical, policy, and other variables on bridge infrastructure quality. In the first step, a qualitative CLD was presented. Next, a portion of the CLD was quantitatively modeled with data for bridges in South Carolina

using NBI records for years 2004 to 2013. The model was used to forecast bridge quality in terms of Sufficiency Rating (SR) and yearly costs of improvements needed for bridges until 2020. The forecast is done for several possible funding scenarios, and the effects of alternative funding scenarios on the future quality of the SC bridge inventory are evaluated.

In chapter five, a method is presented for assessing the impacts of design variables on bridge performance. The method used ANN models with a systematic grouping of simulations based on full factorial design (FFD) to evaluate bridge deck and superstructure condition ratings, and demonstrated for prestressed concrete bridges in South Eastern United States. The FFD based simulations were used to perform sensitivity analysis and evaluate the effects of skew, span and age of bridge on deck and superstructure ratings.

In chapter six, NARX model was developed for bridges in South Carolina to forecast bridge inventory quality as measured by sufficiency rating. Extensive data from NBI for the past decade are used to build a non-linear auto regression based ANN model. Average SR for bridge inventory for each year until 2020 are estimated for various levels of bridge improvement funding.

Finally, chapter seven provides an overall summary of the work and conclusions; recommendations for further research are also suggested.

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## CHAPTER TWO

### **THE STATE OF BRIDGE DEFICIENCY IN UNITED STATES**

#### **Abstract**

The ASCE Report Card for America's Infrastructure provides an annual grade on the overall condition of infrastructure sectors, including highway bridges. Noting that 25% of the 607,751 bridges in the United States were classified as deficient, the 2013 ASCE report card gave bridges a C+ grade. The objective of the current chapter is to give context to the ASCE grade by providing additional details on the state of bridge deficiency in the US. To that end, analyses of data from the National Bridge Inventory (NBI) are presented and discussed. These analyses investigate the prevalence of different types of bridge deficiency, and trends in the number and usage of deficient bridges in the past two decades. Trends at the national and state levels are discussed. Rules for classifying deficient bridges as functionally obsolete and structurally deficient are also summarized.

## **Introduction**

### *Deficiency of Bridges*

As of 2013, the average age of bridges in the US is 42 years, or close to the 50 year design life of most of the bridges built during the interstate era (ASCE, 2013). As the bridge inventory has aged, deficient bridges have become a major concern for federal, state, and local transportation officials. The annual infrastructure report card from American Society of Civil Engineers (ASCE) for 2013 (ASCE, 2013) gave a C+ to bridges. According to ASCE, this grade means that bridge infrastructure in US is “mediocre.” The objective of this paper is to provide details and context on the condition of US bridges that go beyond the overall grade given by ASCE. To that end, the first part of this paper describes the rules and procedures for classifying bridges as deficient. The *sufficiency rating* metric is also discussed. In the second part of the paper, changes to the overall number and usage of deficient bridges between 1992 and 2013 are discussed. The third part of the paper evaluates the different types of deficiency in the US bridge inventory. The most common types are identified and reported. The fourth and final part of the paper investigates if trends in bridge deficiency at the state level.

As per the Bridge Inspector’s Reference Manual (Ryan et al, 2012), deficient bridges are categorized as either *structurally deficient (SD)* or *functionally obsolete (FO)*. A SD bridge has load carrying elements that are in poor condition due to deterioration and/or damage. Bridges with inadequate waterway openings to the point of causing intolerable traffic interruptions are also categorized as SD. A SD rating does not

automatically mean that a bridge is unsafe; however, it does indicate that the bridge needs some kind of repair intervention for it to perform and provide service as intended.

Bridges classified as FO no longer meet the design standards of the highway system of which it is a part. Unlike structural deficiency, functional obsolescence does not indicate deterioration of components, but rather indicates constraints on the functional usage of the bridge due to changed requirements. Writing about infrastructure in general, Lemer (1996) defined obsolescence as “something that does not measure up to the current needs or expectations”. Lemer further observed that obsolescence is triggered by social, economic, technology and regulatory changes. Federal Highway Administration (FHWA) guidelines for FO classification are most directly linked to regulatory changes in bridges codes and design standards.

Bridges are characterized as SD or FO based on metrics obtained through routine bridge inspections. These bridge inspections are conducted based on the National Bridge Inspection Standards (NBIS, 2004). Details of the inspection procedures and standards are provided in Bridge Inspector’s Reference Manual (BIRM) (Ryan et al., 2012). A discussion of how bridge inspection data is used to categorize SD and FO bridges is provided later in this paper.

Data from bridge inspections is aggregated into the National Bridge Inventory (NBI), a database maintained by FHWA for all bridges having spans greater than 6.1m (20ft) (NBI, 2013). According to the 2013 NBI data, there are 607,751 bridges in the US, and approximately 25% of are categorized as deficient. Of these, 63,522 bridges are SD while 84,348 are FO. With one in four bridges categorized as SD or FO, there is



incentive to understand these deficiencies in greater detail and to investigate how the prevalence and usage of deficient bridges has changed over the past two decades.

*Previous studies on bridge deficiency*

Dunker and Rabbat were the first to publish a study of deficient bridges based on the NBI data (1990). Their study analyzed bridges built between 1950 and 1987 based on bridge type, material, and type of structural deficiency. The study reported that steel stringer and timber stringer bridges had the highest percentage of structural deficiency while prestressed concrete (PSC) bridges had the lowest. Out of the total 69, 885 steel stringer bridges built during this period, 23% were SD while only 3% of all PSC slab bridges (5,706) and 5% of the all PSC Tee bridges (5,017) built during this period were SD. The study also considered the most common types of structural deficiency. It was noted that poor deck condition was the most common structural deficiency in interstate bridges, and poor substructure condition was the most common deficiency in county bridges.

In 1988 revisions were made to the FHWA *Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges* (FHWA, 1995) leading to greater consistency of the NBI data across different states (Dunker and Rabbat, 1995). Using the revised NBI data, Burke (1994) published a study reporting that 44% of US bridges were deficient. A year after Burke's study, Dunker and Rabbat (1995) analyzed the revised NBI data and concluded that deck geometry, structural evaluation, and condition deficiencies were most prevalent types of bridge deficiency.

Based on NBI data, Bhide (2004) studied correlations between bridge material and physical condition. The author reported that 2.9% of the bridges built between 1990 and 2003 were SD. Even though reinforced concrete (RC) bridges accounted for 21.4% of total bridges built during this period, they accounted for only 9.2% of SD bridges. Steel bridges accounted for 25.8% of the bridges constructed during this period, but had a 62% share of SD bridges. At 22%, County highways had the highest percentage of SD bridges, though Interstate highways had the highest percentage SD bridges (28%) as measured by the area of bridge decks.

The FHWA is required by law to submit a biennial report to congress on the status of the nation's roads, bridges, and transit. Since 1999, the FHWA has submitted seven reports. The latest report from FHWA, *Status of the nation's highways, bridges and transit: Conditions and performance* (FHWA, 2013) indicates that the condition of US bridges has improved in recent years, with the total percentage of deficient bridges dropping from 31% in 2000 to 26% in 2010. Although the overall percentage of deficient bridges is improving, maintaining the condition of bridge infrastructure in US continues to be a major challenge for transit officials (Reid 2008, ASCE 2013). The aforementioned ASCE report card (2013) indicated that about 20.5 billion USD of annual funding is required to eliminate the backlog of deficient bridges by 2028.

The report card also makes the following relevant observations:

1. As of 2013, 11% of the nation's bridges are classified as SD while 14% are classified as FO.
2. 22 states have higher percentage of SD bridges than national average.

3. SD bridges account for one third of the total bridge decking area in the nation.
4. More than 30% of bridges have exceeded their design life of 50 years

This paper adds to the discussion of deficient bridges in three distinct ways. First, it uses recent NBI data to evaluate the prevalence of the different types and subtypes of deficiency. Second, evaluations are presented regarding changes to the quantity and usage of deficient bridges over the last two decades. Third, and finally, the paper reports changes in SD and FO bridges at the state-level. All data used in these comparisons comes from the NBI. Details of the NBI are discussed in the next section.

#### *National bridge inventory data*

In response to the tragic collapse of Silver Bridge in West Virginia on 15<sup>th</sup> December of 1967, the Federal-Aid- Highway act (US Congress, 1968) required that National Bridge Inspection Standards be established to ensure the safety of travelling public. The Act directed the states to maintain an inventory of Federal-aid highway bridges (FHWA, 2004). Shortly thereafter, in 1971, the National Bridge Inspection Standards (NBIS) were created to establish consistent procedures for bridge inspections and ratings. In 1978, the Surface Transportation Assistant Act (US Congress, 1978) extended the NBIS and mandated inspections for all public bridges (FHWA, 2004). The NBI data collected through the mandatory inspections is used by both FHWA and state transportation officials for setting priorities on repair, replacement, and rehabilitation of bridges (Bhide, 2004).

The NBI contains information about all bridges in US that have spans of 6.1 m (20 ft) or more. Individual bridges in the NBI are given a unique identifier called

‘structure number’, and information is reported for each bridge such as location, geometric data, inspection details, material type, and usage. Important aspects like fracture criticality and scour criticality are also captured in the data. In total, data is collected in 116 fields to provide vital statistics about each bridge. The NBI database is available online for each year since 1992, and includes information about bridges in 50 states as well as the District of Columbia and Puerto Rico. As mentioned previously, 1992 was the first year that data was collected using the revised 1988 standards.

## **Methodology**

### ***Categorizing deficient bridges***

Six items from the NBI are considered for the structural deficiency classification, while five items are considered for functional obsolescence (Table 1, Table 2). Each of the considered items is based on either an appraisal rating or a condition rating. An appraisal rating is an assessment comparing a bridge to current codes and standards, while a condition rating is an assessment comparing a bridge with new as-built conditions. A scale of 0 to 9 is used for rankings in both appraisal and condition ratings (Table 3). Additional details of the rating scales and their application to specific items are provided in the BIRM.

Table 1. Items and Criteria for Structural Deficiency<sup>a</sup>

Item #	Item Label	Structural Deficiency Criteria	Item description
Item 58	Deck condition	Condition rating $\leq 4$	Condition rating of the bridge deck
Item 59	Superstructure Condition	Condition rating $\leq 4$	Condition rating of the superstructure
Item 60	Substructure Condition	Condition rating $\leq 4$	Condition rating of the substructure including abutments
Item 62	Culvert Condition	Condition rating $\leq 4$	Condition rating of a culvert
Item 67	Structural Evaluation	Appraisal rating $\leq 2$	Appraisal rating with respect to structural load capacity
Item 71	Waterway Adequacy	Appraisal rating $\leq 2$	Appraisal rating with respect to passage of flow through the bridge

<sup>a</sup> Source Information: Bridge Inspector's Reference Manual

Table 2. Items and Criteria for Functional Obsolescence

Item #	Item Label	Functional Obsolescence Criteria	Item description
Item 67	Structural Evaluation	Appraisal rating =3	Appraisal rating of structural load capacity
Item 68	Deck Geometry	Appraisal rating $\leq 3$	Appraisal rating of deck geometry
Item 69	Under clearances	Appraisal rating $\leq 3$	Appraisal rating of under clearances
Item 71	Waterway Adequacy	Appraisal rating =3	Appraisal rating with respect to passage of flow through the bridge
Item 72	Approach Roadway Alignment	Appraisal rating $\leq 3$	Appraisal rating of approach road alignment

<sup>a</sup> Source Information: Bridge Inspector's Reference Manual

Table 3. Code Description for Condition & Appraisal Ratings<sup>a</sup>

Rating code	Guidelines for condition rating	Guidelines for appraisal rating
N	Not applicable	Not applicable
9	Excellent condition	Superior to present desirable criteria
8	Very good condition	Equal to present desirable criteria
7	Good condition	Better than present minimum criteria
6	Satisfactory condition	Equal to present minimum criteria
5	Fair condition	Better than minimum adequacy to tolerate
4	Poor condition	Meets minimum tolerable limits
3	Serious condition	Basically intolerable- requires corrective action
2	Critical condition	Basically intolerable- requires replacement
1	Imminent failure condition	This rating code value is not used
0	Failed condition	Bridge closed

<sup>a</sup> Source Information: Bridge Inspector's Reference Manual

***Sufficiency rating***

Sufficiency Rating (SR) is an aggregate metric that provides an overall measure of bridge health and condition. Federal and State transportation agencies rely on SR to prioritize repair, retrofit, and replacement of bridges. SR is reported as a value between 0 and 100, with higher values indicating good overall health. Out of 100 points, 55 points of the SR are based on structural adequacy and safety, 30 are based on serviceability and functionality, and 15 are based on essentiality for public use. A complete description of the algorithm used to calculate SR is given in the *Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges* from FHWA (1995).

Analyses reported in the subsequent sections were made using NBI data from the years 1992 through 2013, which data were downloaded directly from FHWA. Downloaded data were compiled into spreadsheets for analysis. NBI data prior to 2010 is distributed by FHWA in text files with non-delimited format. A sequential query language (SQL) algorithm was used to convert the non-delimited data into a more useable spreadsheet format. Data from 2010 and beyond is distributed by FHWA in ASCII delimited format, which was directly compiled in spreadsheets.

To analyze bridge information at national level, the data from individual states were consolidated in to single spreadsheet for each year from 1992 until 2013. Once the data were compiled, filters in the spreadsheets were applied to isolate the records of deficient bridges. Filters were also used to isolate bridge data based on the items (Table 1 and Table 2) associated with SD and FO classification. The Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges from FHWA (1995) was used to interpret the data codes and their values. All analyses reported in this paper assume that NBI data is accurate and closely reflects the actual condition of bridges as reported by bridge inspectors.

## **Results and Discussion**

### ***Functionally Obsolete Bridges (1992-2013)***

Figure 1 compares the rate of change for six different bridge metrics between 1992 and 2013. To aid in comparison, all values are normalized using 1992 as a baseline. Metrics include the total number of bridges, and the number of FO bridges. Average daily traffic (ADT) and average daily truck traffic (ADTT) on all bridges and on FO bridges are also

shown. Data presented in Figure 1 is based on all 50 states plus the District of Columbia and Puerto Rico.

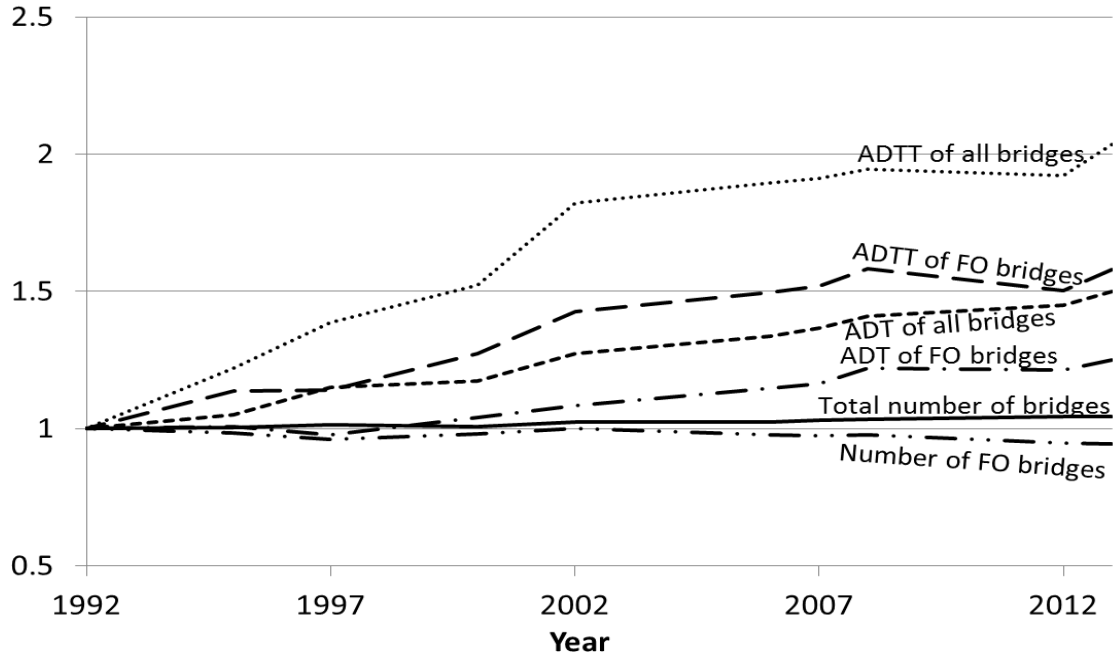


Figure 1. Change in Number and Usage of FO Bridges in US (1992-2013)

A steady increase in the total number of bridges and the average daily bridge traffic occurred over the period of 1992 and 2013. The total number of bridges increased by 4.3%, while the total bridge traffic increased by 50%. Truck traffic on all bridges grew at the fastest rate of any metric considered. Average daily truck traffic on all bridges was over two times greater in 2013 than in 1992.

The number of FO bridges decreased steadily between 2002 and 2013 after a small increase during the period of 1997 and 2002. Overall, the number of FO bridges decreased by 5.7% between 1992 and 2013. However, the usage of these bridges increased during this period. Total traffic on FO bridges grew by 25% and truck traffic



on FO bridges grew by 58%. Thus, the good news is that there are fewer FO bridges; the bad news is that the remaining FO bridges are carrying more and more traffic.

***Structurally Deficient Bridges (1992-2013)***

Figure 2 compares the quantity and traffic on SD bridges between 1992 and 2013. As was done in Figure 1, data in Figure 2 is plotted with respect to baseline values from 1992. The total number of bridges, the number of SD bridges, and the total traffic and truck traffic on bridges are plotted in Figure 2

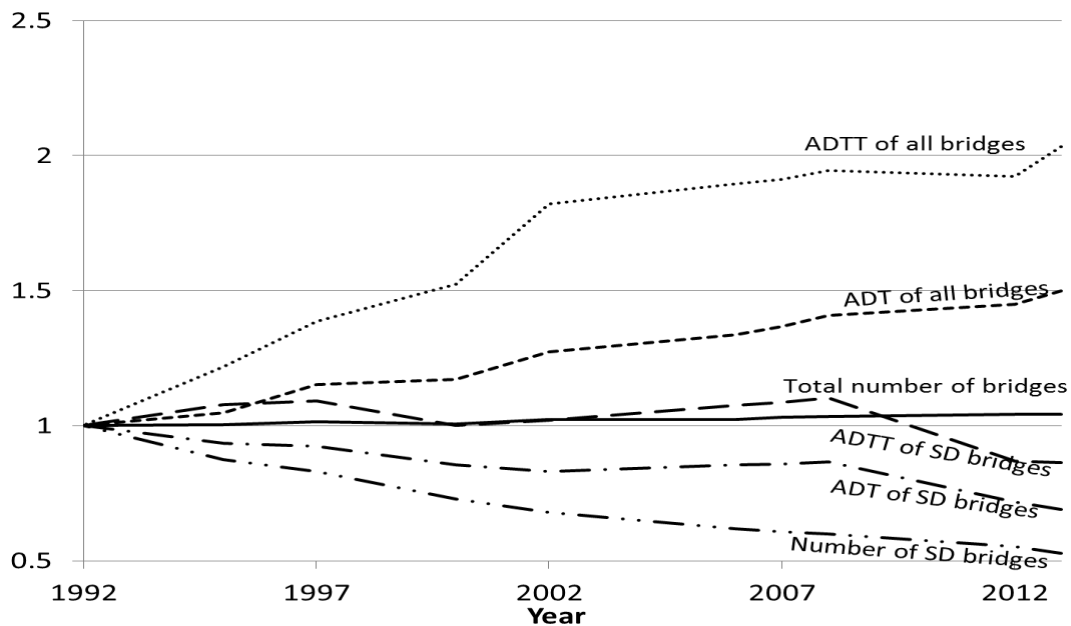


Figure 2. Change in Number and Usage of SD bridges in US (1992-2013)

Interpreting Figure 2, it is noted that the number of SD bridges has decreased steadily over the last two decades. As of 2013 there are approximately half as many SD bridges as there were in 1992. Total traffic and truck traffic on SD bridges have also decreased over this period. While total traffic on SD bridges decreased by 31.1%, the truck traffic decreased by 13.7%. These trends are opposite to those on FO bridges

wherein both normal traffic and truck traffic have increased. One possible explanation is that SD bridges carrying high traffic on important routes were prioritized for intervention, while FO bridges have not received the same degree of attention.

**Sufficiency Rating Of Bridges (1992-2013)**

The SR for a bridge is an indicator of its overall health and condition. Figure 3 presents aggregate data on SR for all bridges in the US over the period 1992-2103. Rather than presenting the data in terms of SR directly, it is presented in terms of 100-SR (referred as ‘insufficiency’ here after). This approach was taken so that the interpretation of Figure 3 is similar to that of Figure 1 and Figure 2; values less than 1.0 indicate an improvement in bridge conditions. Data in Figure 3 were normalized using 1992 as a baseline. The product of (100-SR) and ADT or ADTT is also presented. Although these later metrics do not have any physical meaning, they are useful in evaluating health and usage in a combined sense.

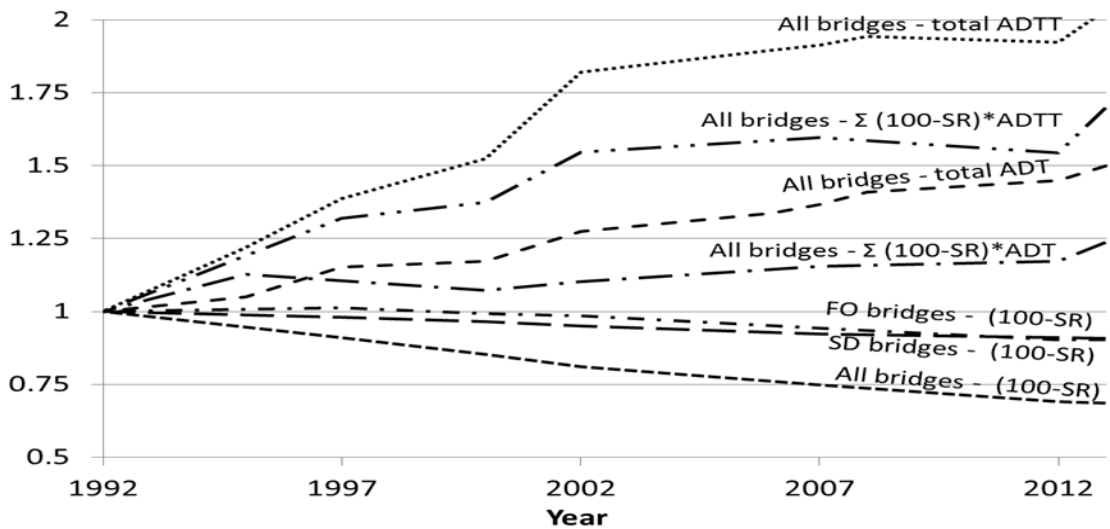


Figure 3. Change in insufficiency rating (100-SR) of FO & SD bridges in US

In terms of average SR, the overall health of bridges improved by 12.4% during the period between 1992 and 2013. The SR of FO and SD bridges also improved, suggesting that the worst FO and SD bridges were either replaced or were upgraded. However, though the average SR of SD bridges improved by 15.9%, the average SR for FO bridges improved by just 4.9% over the last two decades. The combined SR and traffic metrics indicate that traffic volume is increasing at a faster rate than SR is improving. This means that usage of relatively poor health bridges continues to increase. SR is included as an eligibility criterion for federal funding for bridge replacement. A bridge must have an SR less than 50 to be eligible. In 1992 the average SR for SD bridges was 36.6% while the same is 42.5% in 2013. While this data indicates 6% improvement, it also demonstrates that much of work is left to be done.

***Items Leading to FO and SD Classification (2013)***

Figure 4 and Figure 5 compare the prevalence of each of the items associated with FO and SD classifications. Data in the figures is for deficient bridges in US as of 2013. In some cases a single bridge may qualify as FO or SD based on multiple item ratings, for this reason the data are presented as exclusive and combined. Exclusive means that the FO or SD classification is based on a single item rating; combined means that the deficient item exists in combination with any other deficient items.

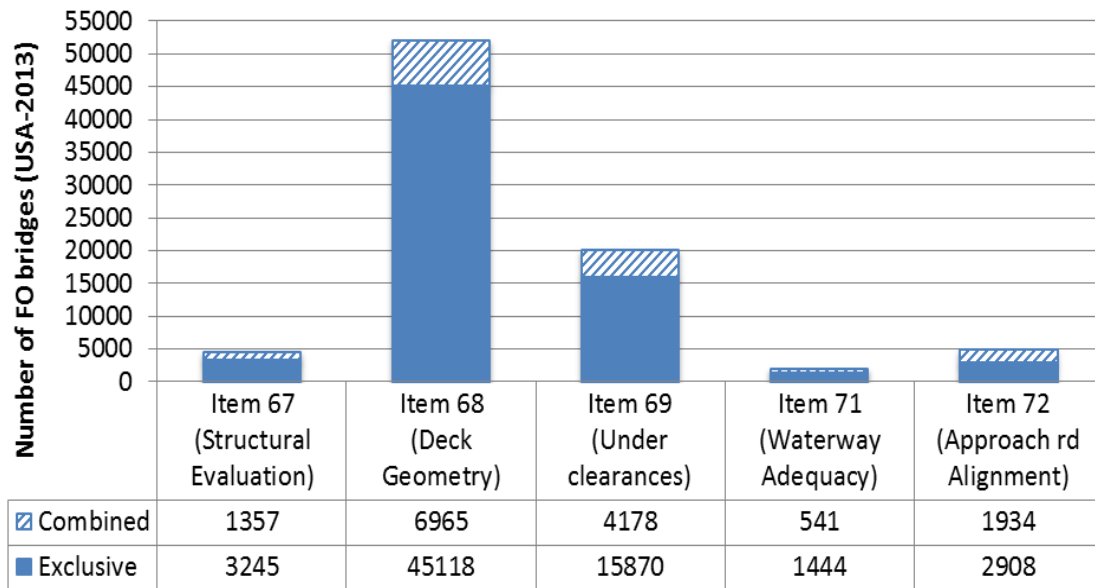


Figure 4. USA 2013: FO Bridges by Type of Obsolescence

Inadequate deck geometry was the most common type of FO in 2013. Inadequate deck geometry means that the bridge deck is narrow compared to current standards. This inadequacy is a safety concern. Deck geometry alone renders 45,118 bridges obsolete and another 6,965 bridges obsolete in combination with other causes. Inadequate under clearances are also safety concerns and are the second most common type of obsolescence. Under clearances alone account for obsolescence of 15,870 bridges and another 4,178 bridges in combination with items. When combined, inadequate deck geometry and inadequate under clearances account for 95% of all FO bridges. Thus geometric factors, i.e. the width, height, and pier/abutment spacing are the most significant factors causing FO highway bridges.

Capacity obsolescence, obsolescence due to inadequate structural capacity, affects 4,602 bridges, or approximately 6% of all FO bridges. A methodology for quantifying capacity obsolescence was developed by Jonnalagadda et al (2014). Inadequate approach

roadway alignment impacts 4,842 bridges. Waterway inadequacy is the least common cause of deficiency. This is because the number of bridges spanning over navigable waterways is relatively small as compared to other bridges.

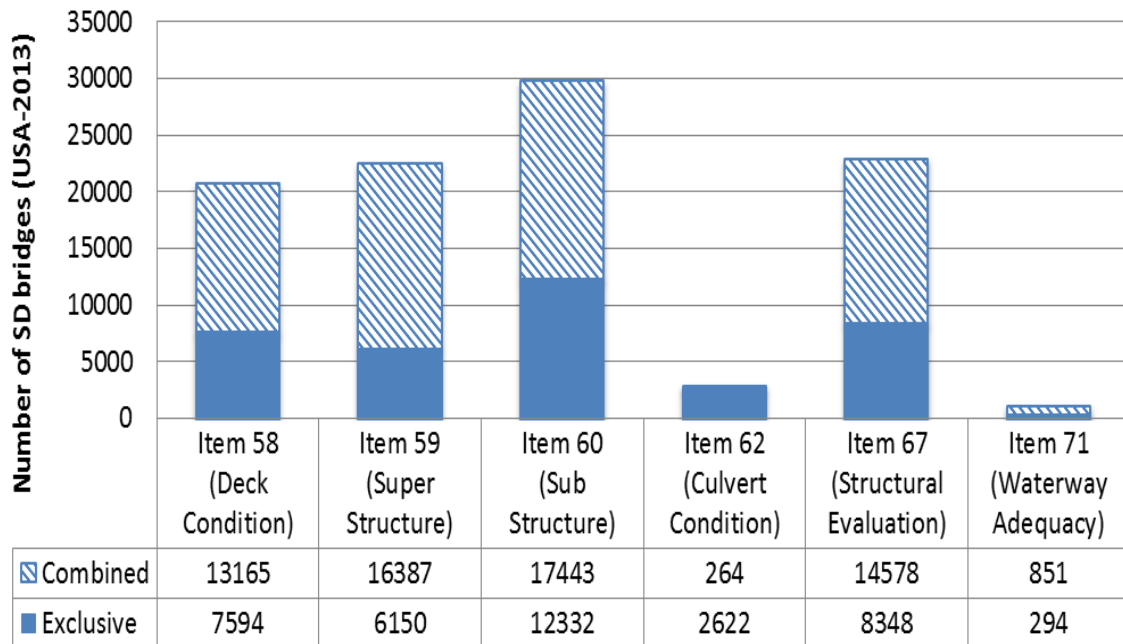


Figure 5. USA 2013: SD Bridges by Type of Structural Deficiency

For SD bridges, poor substructure condition is the most common item resulting in SD classification, impacting 12,332 bridges by itself and another 17,443 bridges in combination with other items. This is closely followed by inadequate structural capacity, poor superstructure condition, and poor deck condition, respectively. It is noted that SD bridges are likely to have multiple deficient items, whereas most FO bridges typically have a single deficient item. This means that in most cases, correcting an SD bridge requires repair or retrofit of multiple bridge components.

*Analysis of Bridge Deficiency at State Level (1992-2013)*

This section evaluates how quantity and usage of deficient bridges changed between 1992 and 2013 at the state level. The Federal Districts of Columbia and Puerto Rico were also considered in the evaluation. The evaluation was conducted to determine if the trends observed at the national level are consistent when analyzed for individual states. For each state, the percent change in the number of SD and FO bridges, and the percent change in ADT on SD and FO bridges were calculated. Distribution of these values for FO bridges is presented in Figure 6 and Figure 7. The distribution of these values for SD bridges is presented in Figure 8 and Figure 9. Negative percent change in the figures indicates a decrease or improvement in deficient bridges and deficient bridge traffic. Positive percent change indicates an increase or worsening.

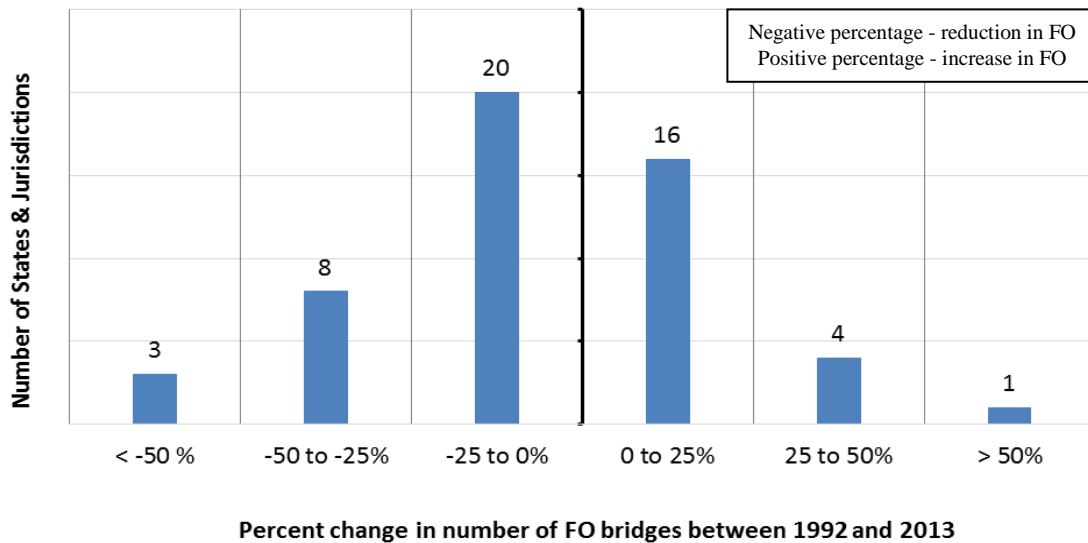


Figure 6. State & Jurisdiction Level Change in Number of FO bridges (1992-2013)

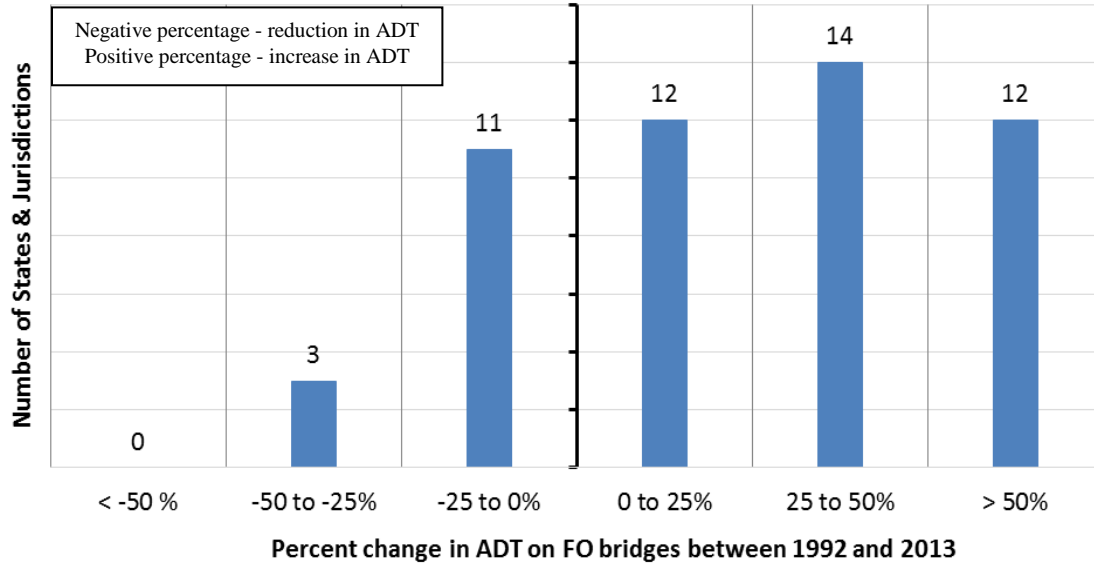


Figure 7. State & Jurisdiction Level Change in ADT on FO bridges (1992-2013)

The percent change in the number of FO bridges has an approximately normal distribution. With respect to FO bridges, Iowa is the best performing state while New York is the worst performing. The number of FO bridges in New York increased by 179% between 1992 and 2013, whereas Iowa saw a 64% decrease. Traffic on FO bridges shows a different trend. Fourteen states had reduced ADT on FO bridges as compared to 1992, and thirty eight states had increase in ADT on FO bridges. No trends were observed with regard to region or population of states having the largest increases in ADT on FO bridges.

Referring to Figure 8, forty two states had a reduction in the number of SD bridges between 1992 and 2013. Only ten states had an increased number of SD bridges as compared to 1992. The states of California, Wyoming, and Arizona had greater than 50% increases in number of SD bridges. California had the largest increase, 94%. With a

79% reduction in SD bridges in the last two decades, New York is the best performing state with respect to decreasing the number of SD bridges.

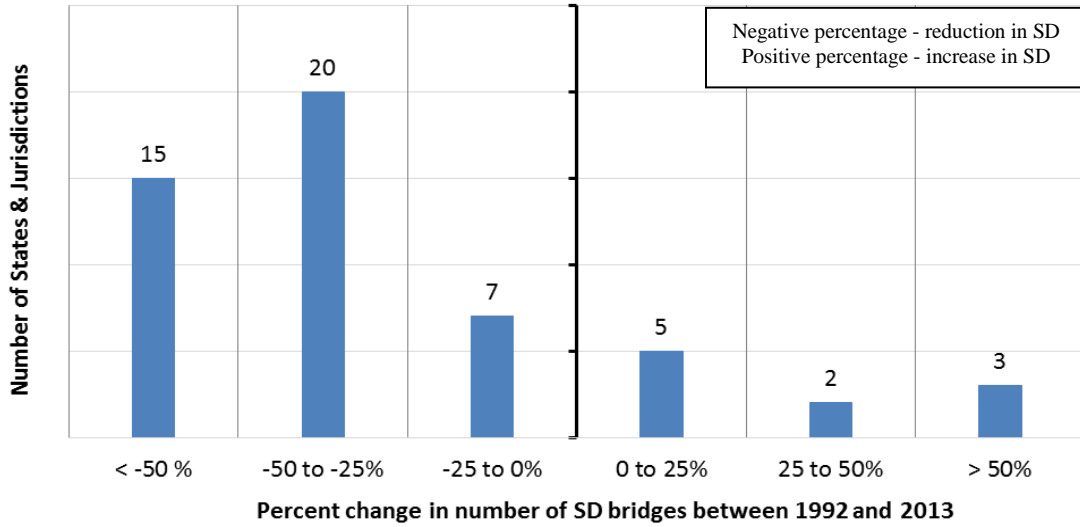


Figure 8. State & Jurisdiction Level Change in Number of SD bridges (1992-2013)

Referring to Figure 9, thirty four states had reduced ADT on SD bridges as compared to 1992; however, ten states had increases in ADT on SD bridges in excess of 50%. The remaining states (eight) had a moderate increase in ADT on SD bridges.

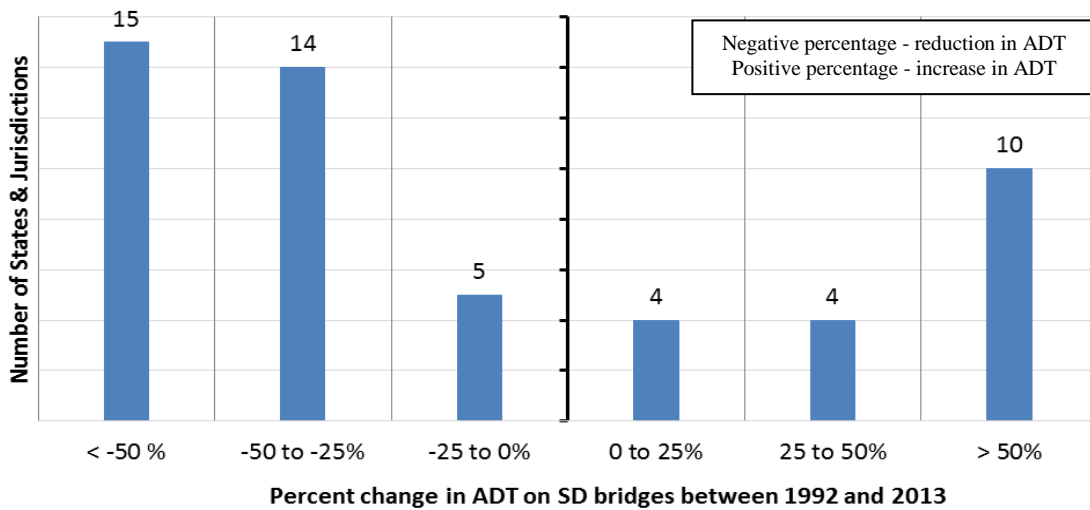


Figure 9. State & Jurisdiction Level Change in ADT on SD bridges (1992-2013)



## Summary and Conclusions

This paper evaluates the trends in the prevalence and usage of deficient bridges in United States. Deficient bridges include those that are structurally deficient or functionally obsolete. NBI data for all fifty states, plus the District of Columbia and Puerto Rico were consolidated and analyzed over the interval from 1992 to 2013. Metrics such as the number of deficient bridges, amount of traffic on deficient bridges and bridge sufficiency ratings were considered. Prevalence of the different types of deficiency was also considered. The following observations and conclusions are made:

- Between 1992 and 2013, the number of SD and FO bridges in the United States decreased by 47% and 5.7%, respectively. Also, the average sufficiency rating of the US bridges, which is currently at 81%, improved by a margin of 12.4% over the same period. By these metrics the overall health of US bridges is improving.
- Trends in the traffic usage of deficient bridges provided mixed results. The ADT on SD bridges decreased by 31%, whereas the ADT on FO bridges increased by 25% over the period considered. Thus the number of FO bridges is decreasing, but the remaining FO bridges are carrying increased traffic.
- Reduction in the number of FO bridges (5.7%) between 1992 and 2013 was lower than reduction in number of SD bridges (47%) over the same period.
- Although bridge quality is improving by many metrics, deficient bridges are still a major concern. In 2013, one in four bridges in the US was deficient, and the average SR of deficient bridges was 58.1%.

- Geometric features such as deck width and under clearances are the most common items of deficiency in FO bridges. At least one of these types of deficiency exists in 95% of the FO bridges.
- Poor substructure condition is the most common type of deficiency leading to SD ratings, followed closely by inadequate structural capacity, poor superstructure and poor deck condition. Many SD bridges have multiple deficiencies.
- The distribution and usage of deficient bridges is not uniformly distributed in the United States. Although the overall trend is towards improved bridges, some states have had distinct increases in the number and usage of deficient bridges.

### **Acknowledgement**

Students in the fall of 2014 Highway Bridge Design course at Clemson University assisted in data collection and analysis tasks. Julia Daniels, a student at the South Carolina Governor’s School for Math and Science also assisted in consolidating the NBI data.

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## CHAPTER THREE

### A METHOD FOR ASSESSING CAPACITY OBSOLESCENCE OF HIGHWAY

### BRIDGES

*A paper on this chapter is published in Transportation Research Board 94<sup>th</sup> Annual compendium of papers*

*Srimaruthi Jonnalagadda, Brandon E. Ross, Jeffery M. Plumblee, II*

#### **Abstract**

As of 2013, 14% of highway bridges were classified as functionally obsolete. This classification is given to bridges that have capacity and geometric conditions that do not satisfy modern requirements and thereby limit usage. The first part of this paper is a general discussion of obsolescence and sustainability of highway bridges, and describes the impact of obsolete bridges on economic, social, and environmental sustainability. The second part of the paper proposes a theoretical model for quantifying obsolescence due to load carrying capacity, a subcategory of functional obsolescence. The model includes features to account for increasing load demand and decreasing structural capacity over time. Historic trends for bridge design loads are discussed as they relate to the model, as are methods for calculating degradation of structural capacity. Limitations, applications, and possible extensions of the model are discussed. The third part of the paper applies the capacity obsolescence model to an example problem involving a simple span reinforced concrete bridge. The example demonstrates a methodology for simultaneously evaluating capacity obsolescence and environmental impact using multi-criteria decision analysis (MCDA). The paper concludes by suggesting future research to

advance the proposed methodology. The overall objectives of the paper are to propose a model for quantifying obsolescence and to demonstrate how obsolescence can be jointly considered with other bridge design criteria.

## **Introduction**

According to the 2013 data in the National Bridge Inventory (NBI) (1), approximately 67,000 highway bridges in United States are structurally deficient and 85,000 are functionally obsolete. The substandard quality of bridges is reflected in the C+ grade given for the overall condition of bridges in the ASCE infrastructure report card for 2013 (2). These statistics and ratings demonstrate the critical need to address the condition of the United States' bridge infrastructure. This paper focuses specifically on functional obsolescence, a topic that has received only limited attention in the existing literature. The effects of functional obsolescence on the sustainability of highway bridges are also discussed and a methodology is proposed for designing bridges to minimize obsolescence and maximize sustainability.

Functional obsolescence is a label applied to infrastructure that is unsuitable for current demands (3). Obsolescence (i.e. lacking relevance) is common to all sectors of civil infrastructure (4). According to the Federal Highway Administration (FHWA), bridges are categorized as functionally obsolete when their load carrying capacity, deck geometry, under clearance, water way adequacy, or approach roadway alignment no longer meet current demands (5). Details of the FHWA rating system used to categorize bridges are discussed in section 2.1.

Capacity obsolescence is a primary focus of this paper and is herein defined as the condition of having structural capacity that is insufficient to support current load demands. Although this terminology is not used in the FHWA rating system, capacity obsolescence is accounted for in the system criteria. According to the 2013 NBI, capacity

obsolescence affects about 5,200 bridges. The terms functional serviceability and capacity serviceability are proposed to denote the absence of functional obsolescence and capacity obsolescence, respectively. Functional serviceability and capacity serviceability are thus distinct from the classical concept of serviceability used in structural engineering.

Sustainable development is defined as “development that meets the needs of the present without compromising the ability of future generations to meet their own needs” (6). Sustainability is assessed in three domains: economic, environmental, and social. Because bridges are often the most complex and costly components of highway infrastructure, they can have large footprints on the economic, environmental, and social sustainability of a project. Though economic efficiency of bridge management and design have been well studied (e.g. 7, 8, 9, 10, 11), quantification of social and environmental costs is a relatively recent development. The life cycle analysis method for quantifying environmental sustainability is discussed in the section 2.2.

It has been proffered that sustainability and resilience will be the two metrics by which infrastructure will be evaluated in the next century (12). Resilience is a metric associated with the ability of an infrastructure asset or system to recover from an extreme event. Recent natural hazards such as Superstorm Sandy and Hurricane Katrina have exposed vulnerabilities in the United States’ civil infrastructure systems and have demonstrated a clear need for infrastructure resilience (4). While noting the critical import of resilience, the scope of this paper will be limited to sustainability and functional serviceability.

## **Background**

### *Functional and Capacity Obsolescence*

According to the FHWA Bridge Inspection Manual (5), bridges are classified as functionally obsolete based on structural evaluation, bridge deck geometry, under clearances, waterway adequacy and approach roadway alignment (Table 4). As part of a bridge condition appraisal, each item is rated on a scale of 0 to 9; with 0 meaning the item is completely unfit for use and the bridge is closed, and 9 meaning that the item is superior to the desirable condition. A bridge is categorized as functionally obsolete if any of the associated criteria are rated as a 3 or lower.

Item 67 in the FHWA rating system, structural evaluation, is used for assessing both structural deficiency and functional obsolescence. A poor rating on this item does not automatically trigger a structurally deficient rating; many additional criteria and rules are also used to determine structural deficiency in the FHWA system. A poor rating (3 or less) on the structural evaluation, however, is an automatic trigger for a functionally obsolete rating. Thus, it is possible for a bridge to be categorized as functionally obsolete due to the structural evaluation, but not be categorized as structurally deficient. In cases where a bridge qualifies as both deficient and obsolete, then structural deficiency is the priority classification; a structurally deficient bridge it is not classified as functionally obsolete until the structural deficiency has been repaired.

Although it is not labeled as such in the FHWA Bridge Inspection Manual, capacity obsolescence is directly related to the structural evaluation in item 67. As noted above, capacity obsolescence is defined as the condition of having structural capacity that is



insufficient to support current load demands. In this condition, a bridge can have restricted usage even if it is otherwise structurally sound and can still safely carry the original loads for which it was designed.

Whereas item 67 is associated with structural capacity, the remaining criteria for functional obsolescence (items 68 through 72) are associated with geometric conditions. These items account for the effects of geometric constraints on traffic moving on and under the bridge. The term geometric obsolescence is proposed herein to distinguish bridges that are categorized as functionally obsolete due to the geometric criteria accounted for in items 68 through 72.

Table 4. Itemized Evaluation Criteria for Functionally Obsolete Bridges (5)

Item #	Item description	Sub Items or evaluation criteria
67	Structural Evaluation	Item 59 (superstructure evaluation) Item 60 (substructure evaluation) Item 29 (comparison of ADT) Item 66 (inventory rating)
68	Deck Geometry	Item 51 (curb-to-curb width) Item 53 (vertical over clearance)
69	Under clearances	Item 54 (vertical under clearance) Item 55 (lateral under clearance-right) Item 56 (lateral under clearance-left)
71	Water way adequacy	Overtopping flood frequency Impact to traffic delays
72	Approach roadway alignment	Speed restrictions

Functional obsolescence as defined by FHWA is a subset of general obsolescence. Writing of civil infrastructure in general, Lemer (3) noted that obsolescence can be caused by changes in technology, regulations, social or economic conditions. Langston (13) noted that causes of obsolescence in buildings are due to physical, technological, social, functional, economical, legal and political changes. Many of these conditions also impact highway bridges but are beyond the scope of the FHWA rating system. The intent of this paper is to contribute towards the creation of a general framework whereby mitigation of obsolescence can be treated as a fundamental design goal, and whereby relevance can be considered as a paramount feature of infrastructure along with resilience and sustainability.

#### ***Environmental Sustainability of Highway Bridges***

Sustainability is assessed in three domains: economic, environmental, and social. Thus a sustainable highway bridge provides economic and social benefits, while limiting the environmental costs of its construction, operation, maintenance, and decommissioning. Bridges are often the most complex and costly components of highway infrastructure projects and have a significant impact on sustainability.

Life Cycle Assessment (LCA) is a commonly used tool for quantifying the environmental sustainability of a product, process, or system. Rules for conducting an LCA are defined by the ISO 14040 series (14). Embodied energy is one metric used to assess environmental sustainability in an LCA, and is the metric used in the example in section 4. Embodied energy includes all energy consumed in the production of building materials, energy needed for transportation of the materials, and energy required for

assembling the various materials to form the building (15). This metric also includes ‘recurrent energy’ that is required for maintenance, repairs and renovations (16).

Environmental impact and optimization of have been topics in recent literature on highway bridges. In one of the most comprehensive qualitative treatments of the subject, Steele et al. (17) discussed how design, durability, retrofit, and maintenance operations have significant impact on the environmental impact of bridges. Other authors have compared the environmental impact of alternate bridge designs (18) and materials (19). Sustainability in the context of highway bridges has been studied at the network level (20) and as it relates to resilience (21). One common theme in the literature is the need to consider environmental costs over the entire life span of a bridge. This paper adds to the body of knowledge by discussing how obsolescence affects sustainability of bridge infrastructure, and by presenting a methodology whereby obsolescence and sustainability can be jointly evaluated.

#### ***Impacts of Functional Obsolescence on the Sustainability of Bridge Infrastructure***

Functional obsolescence can have significant impacts on the economic, environmental, and social aspects of sustainability for highway bridge infrastructure. Functional obsolescence can necessitate major repair, retrofit, or replacement, even for bridges with remaining service life. These activities require economic, social, and environment investments that would otherwise be avoided in the absence of functional obsolescence. Table 5 summarizes some of the effects functional obsolescence has on the economic, social and environmental sustainability of bridges.

Table 5. Impacts of Functional Obsolescence on Sustainability

Sustainability Category	Impacts of functional obsolescence on sustainability of highway bridges
Economic	Limits ability to transport goods Businesses avoid areas lacking functional bridge infrastructure Economic costs for repair, retrofit and/or replacement of obsolete bridges Rerouting to avoid obsolete bridges affects travel and transport costs
Social	Reduced safety due to speed changes, alignment issues, and flooding potential Negative public perception of bridge infrastructure Reduced speeds and congestion cause longer travel time Social disruptions during repair, retrofit and/or replacement of obsolete bridges Geometric constraints discourage walking and cycling
Environmental	Rerouting and congestion due to obsolete bridges affect fuel consumption Environmental costs for bridge repair, retrofit, and/or replacement Geometric constraints discourage walking and cycling

## Methodology

### *Capacity obsolescence model*

Capacity obsolescence is graphically defined in Figure 10 for a hypothetical highway bridge. The approach taken in this figure is an adaptation of the general obsolescence framework proposed by Lemer (3). As the hypothetical bridge ages, its capacity is diminished and the load demand increases. For simplicity these effects are represented in as linear trends, however, they are likely to occur in discrete instances or at variable rates

throughout the bridge life. Models for evaluating these trends are discussed in the next sections. The intersection of capacity and demand defines the end of functional life; at time less than the functional life the bridge has capacity serviceability, and at time greater than the functional life the bridge is capacity obsolete. Capacity obsolescence is quantified as the area between capacity and demand lines occurring after the end of the functional life. This value accounts for both the degree and the duration of the capacity deficiency. As observed in Figure 10, capacity obsolescence is a function of initial capacity and demand, the rate of capacity degradation, the rate of load demand increase, and the length of time between the end of functional life and the end of service life.

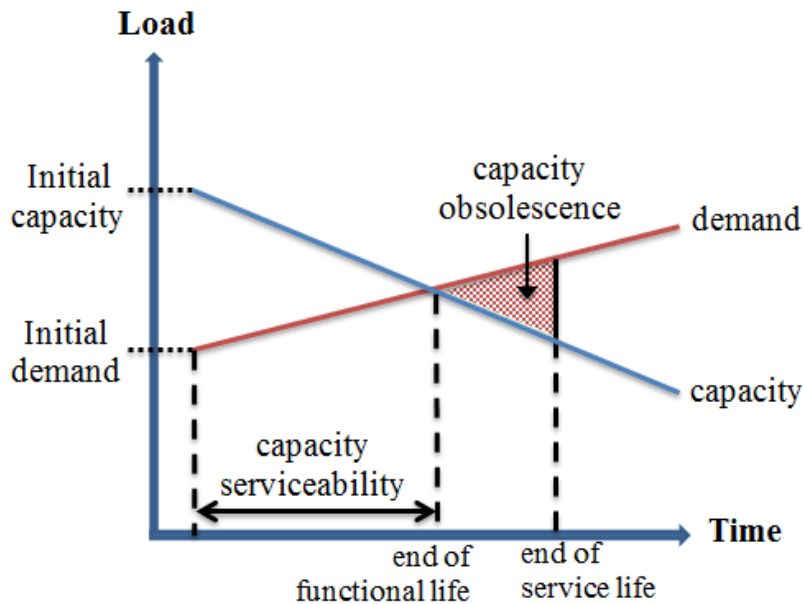


Figure 10. Graphical Representation of Capacity Obsolescence

The statistician George Box (22) famously quipped “...all models are wrong, but some are useful.” The observation that all models are wrong certainly holds true for the proposed model. As noted above, demand increases occur as discrete events based on

code and regulatory changes. Also, routine maintenance may prevent capacity degradation over time. Clearly the model is a simplification, but what are its uses? First, the model can be used to study the sensitivity of obsolescence and functional life over a range of possible changes to demand and capacity. Second, as demonstrated in section 4, the model provides a means to quantitatively assess obsolescence in order to evaluate tradeoffs with other design criteria such as sustainability. Increasing the rigor of the proposed model will improve its utility; to that end suggestions for future work to refine the model are presented in section 5.

Capacity obsolescence is used in this paper because load demand and structural capacity can be estimated using historic data and existing models. In a more general form (3), the proposed model can also be extended to quantify other causes of obsolescence. In the 2013 NBI (1) deck geometry is the most common trigger for the functionally obsolete label. Thus extension of the model to the other causes of obsolescence will provide even greater utility.

### ***Demand Increase***

Load demands on highway bridges in the United States have increased throughout the last century. Figure 11a shows changes in the weight of notional trucks in AASHTO bridge design codes. The H20 design truck was introduced in 1923 and had a total weight (across all axles) of 40 kip (178kN) (23, 24). The HS20 design truck was introduced in 1944 to account for truck trailers that were in use on the US highway system. The total weight for HS20 truck was 72 kip (320kN) (23, 24). In 1976 interim specifications, AASHTO added the design tandem for alternate military loading. In early 1980s, some

states increased the design loads to the HS25 truck. This truck had a total weight of 90 kip (400kN) but of the same axle spacing and weight proportions of HS20 (23). With the advent of probabilistic methods and publication of the AASHTO LRFD specifications (23), the HL93 truck was introduced in 1993. The HL93 truck has a total weight of 72kip (320kN) and is superimposed with a design lane load of 64 psf (0.003MPa). The uniform lane load is included to calibrate the notional load with load effects measured on select highway bridges (25). The 100 kip (444kN) load for HL93 shown in Figure 11a includes both the truck and lane loads. The “weight” of the lane load was calculated by multiplying the prescribed uniform load by the design lane width and truck length. A linear trend line fit to the data points in Figure 11.

Figure 11a indicates the weight of design trucks has increased at a rate of approximately 0.85kip per year (or 2% of the H20 truck weight) between 1923 and 1993. Ignoring the H20 truck, the rate has been 0.55kip per year between 1944 and 1993. Figure 11b shows changes to the federal GVW limit over the past century. The first GVW limit of 28 kip (124 kN) was introduced in 1913. In 1956 the limit was raised to a GVW of 73 kip (325 kN), and in 1975 it was raised to 80 kip (356 kN). A recent bill introduced in the US Congress proposed to raise the allowable GVW to 97 kip (431 kN) (26). Assuming the limit is raised as proposed, 97 kip (431 kN) is included in Figure 11b as the final data point. Figure 11c shows the state overweight permit limits for 15 different states as reported in 1913, 1933, 1994, and 2010 (24, 27). Note that only 3 of the 15 states represented in the figure had permit limits for 1913 and 1933. The limits range from a low of 28 kip (125 kN) in 1913 to a high of 200 kip (890 kN) in 2010.

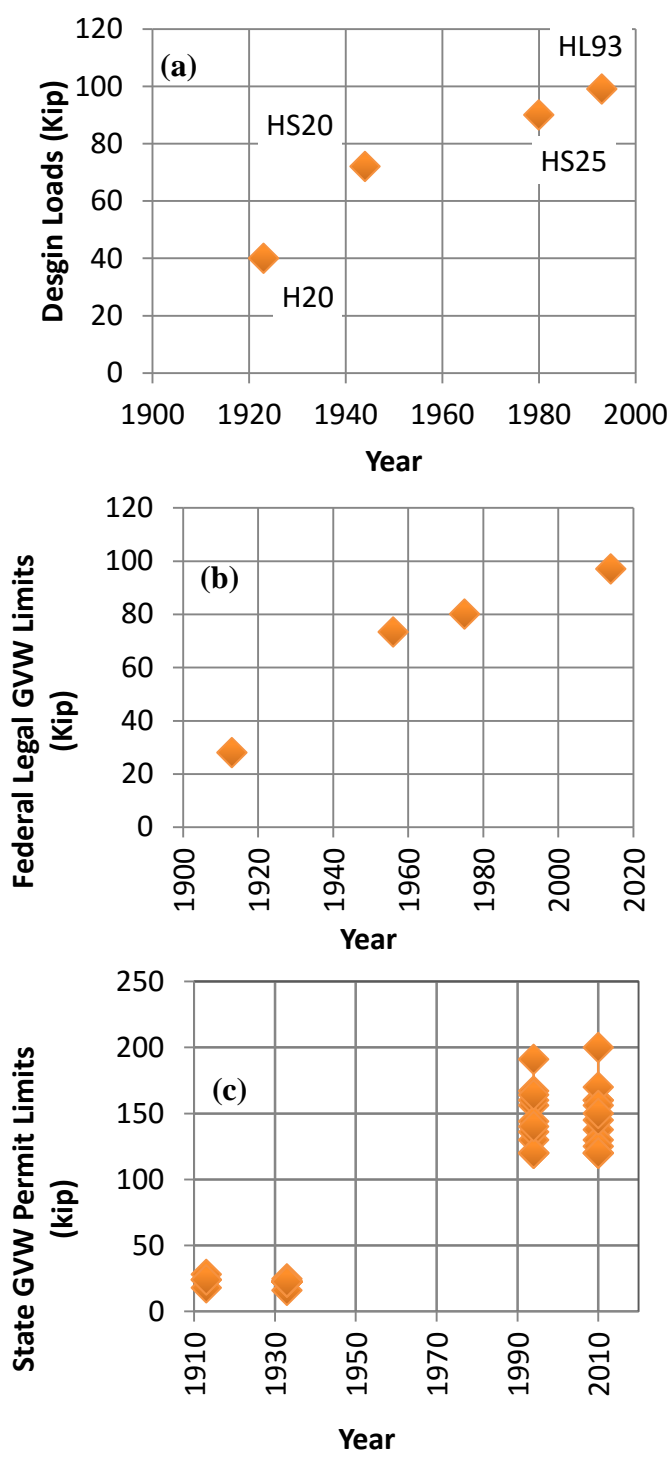


Figure 11. Evolution of highway bridge loads- (a) Design trucks (b) Federal GVW limits (c) State overweight permit limits.



The data plotted in Figure 11 show how design and permit loads for highway bridges have increased over the past century. This observation, however, does not mean that loads will continue to increase in the future. In calculations of capacity obsolescence, engineering judgment must be used when selecting a function to model future load demand. If historic trends are expected to continue, then use of a linear function with slope near 0.75 kip/year (3.3 kN/year) may be appropriate. In selecting a model for future load demand, the relationship between service life and extreme truck loading must also be considered. This relationship has nothing to do with changes to design or permit loads; it is based on the probabilistic concept that as the life span of a bridge increases, so does the likelihood that the bridge will experience an extreme truck loading. A procedure for assessing this effect can be found in National Cooperative Highway Research Program Report No. 538 (28).

### ***Capacity Degradation***

Without (and sometimes even with) proper maintenance, all bridges experience capacity degradation over their lifespan. The causes of degradation vary based on the bridge materials. Steel bridges lose capacity primarily due to corrosion (29). Fatigue can also cause degradation, but this mechanism is not a significant factor for bridges designed according to current AASHTO fatigue provisions (30). Concrete bridges primarily lose capacity due to corrosion of reinforcement and prestressing, and due to environmental stressors that attack the concrete such as freeze-thaw cycling and alkali-silica reaction (29, 31). Loss of capacity over time has also been reported for bridges made of timber (32) and masonry (33).

Recent works have made meaningful contributions to the area of modeling bridge degradation. As part of a larger effort to predict life-cycle performance of bridges, Okasha and Frangopol (29) numerically modeled the degradation of a steel girder bridge. Using reliability concepts, finite element modeling, and advanced computing techniques, the authors calculated linear degradation of girder flexural capacity of approximately 0.3% per year relative to the initial capacity. Sun et al. (34) modeled the degradation of a reinforced concrete bridge due to the effects of concrete carbonation and reinforcement corrosion. These degradation phenomena were modeled empirically and resulted in a nonlinear relationship between the age of the bridge and the degree of flexural capacity degradation. A 17% loss of flexural capacity was calculated over an assumed 100 year life span, with the majority of the loss occurring in years 30 through 60 due to reinforcement corrosion and the attendant loss of bond. Bridge degradation has also been quantified using bridge condition assessments such as the FHWA rating system (35, 36).

### ***Example***

#### *Description and Methodology*

This section presents an example whereby multi-criteria decision analysis (MCDA) was used to evaluate a bridge with regard to environmental sustainability and obsolescence criteria. The bridge in the example consisted of a 20 ft (6.1m) long simple span with rectangular reinforced concrete girders and a reinforced concrete deck, subjected to truck and lane loads (Figure 12). Flexural capacity of the interior girder was the subject of the example. The objective was to identify a girder design that minimized embodied energy and capacity obsolescence over a service life of 50, 75, or 100 years. The example was

designed to be relatively simple in order to illustrate how sustainability and obsolescence criteria can be simultaneously considered in bridge design; ideas for enhancing the rigor of the methodology are discussed in section 5.

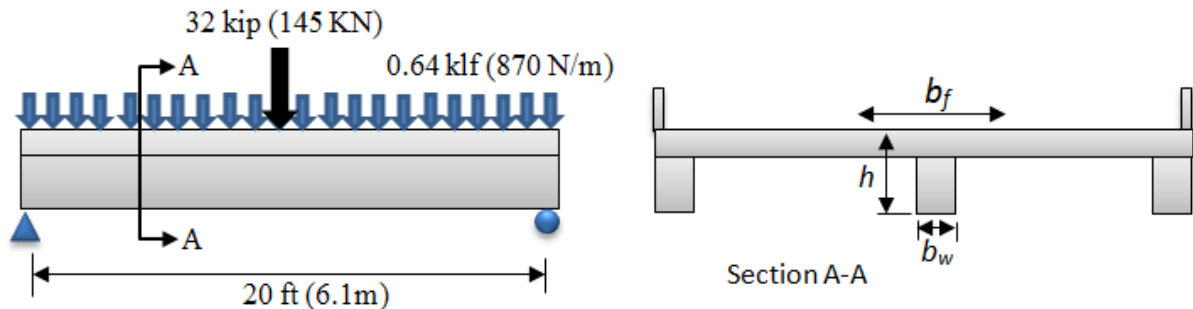


Figure 12. Girder Loading and Superstructure Cross Section

Design constraints and variables are listed in Table 6. Variables were treated discretely and resulted in a design space with 64 options (permutations). Each option was considered using the methodology from Koslowski (37). Other methods have been demonstrated for optimizing the environmental impact of reinforced concrete structures in problems with much larger design spaces (38, 39, 40). The range for each variable in the current example was selected based on typical values used on reinforced concrete design. For example, the minimum girder height (measured from the top of the slab) was 18" (0.45 m) which corresponds to a span-to-depth ratio of approximately 13. The flexural capacity was calculated considering the girders as T-beams. Shear capacity was not considered in the example.

To calculate capacity obsolescence, a demand increase of 0.6% per year (relative to the initial demand from the HL-93 loading) and a capacity degradation of 0.3% per year

(relative to the initial capacity) were used. These values are within the ranges discussed in sections 3.2 and 3.3. The initial flexural demand was calculated based on the loading condition shown in Figure 12. For the analysis, it was assumed that the entire axle load and a 10 ft (3 m) tributary of the uniform load were carried by the interior girder. The maximum moment occurring at midspan was used in the analysis. Only self-weight and truck loads were considered, and the appropriate load, dynamic load allowance, and resistance factors based on LRFD (41) were applied. Capacity obsolescence was calculated as the difference between the factored moment demand and the nominal flexural capacity reduced by the resistance factor.

The total embodied energy for each option was calculated by multiplying the material quantity by the unit embodied energy values presented in Table 6. As the deck was consistent across all options, only the embodied energy of the girders was considered. To facilitate comparison across different service lives, the total embodied energy of each option was divided by 50, 75, and 100 years to obtain three amortized values. These values represent the annual investment of embodied energy for each bridge design option. A bridge having a longer service life will require a smaller annual investment of embodied energy than an identical bridge having a shorter service. Discount rates were not considered in the example.

Table 6. Design Parameters and Variables

Concrete compressive strength	5000 psi (35 MPa)
Embodied Energy (Concrete)	1.3 MJ/kg (42)
Grade of steel	60 ksi (415 MPa)
Embodied Energy (Steel)	8.8 MJ/kg (42)
Unit weight of concrete	150 pcf (24 kN/m <sup>3</sup> )
Depth of beam	Varied from 18 in. to 33 in. (450 to 825 mm)
Width of beam	Varied from 8 in. to 12 in. (200 to 300 mm)
Reinforcement ratio	Varied from 0.008% to 0.016% (based on T-beam section)
Span of girder	20 ft (6.1 m)
Live load factor	1.75
Dead load factor	1.25
IM factor	1.33
Resistance factor	0.9
Deck slab thickness	8" (200mm)
Effective Flange width	60" (1.5m)

## Results and Discussion

Results from two typical design options are presented in

Figure 13. The demand curves for both options are nearly identical and vary only due to differences in girder self-weight. The capacity curves are different for each option, based on their associated design variables. The option shown in Figure 13a had a smaller initial capacity and a functional life of only 33 years; the option in Figure 13b had a larger initial capacity and a functional life of 87 years. The capacity obsolescence of option (a) was 700, 4,320, and 11,020 kip-ft-years (949, 5,861, 14,951 kN-m-years) for services lives of 50, 75, and 100 years, respectively. Because the functional life of option (b) was

87 years, it had a capacity obsolescence of zero for service lives of 50 and 75 years. The capacity obsolescence for a 100 year service life was 520 kip-ft-years (705 kN-m-years).

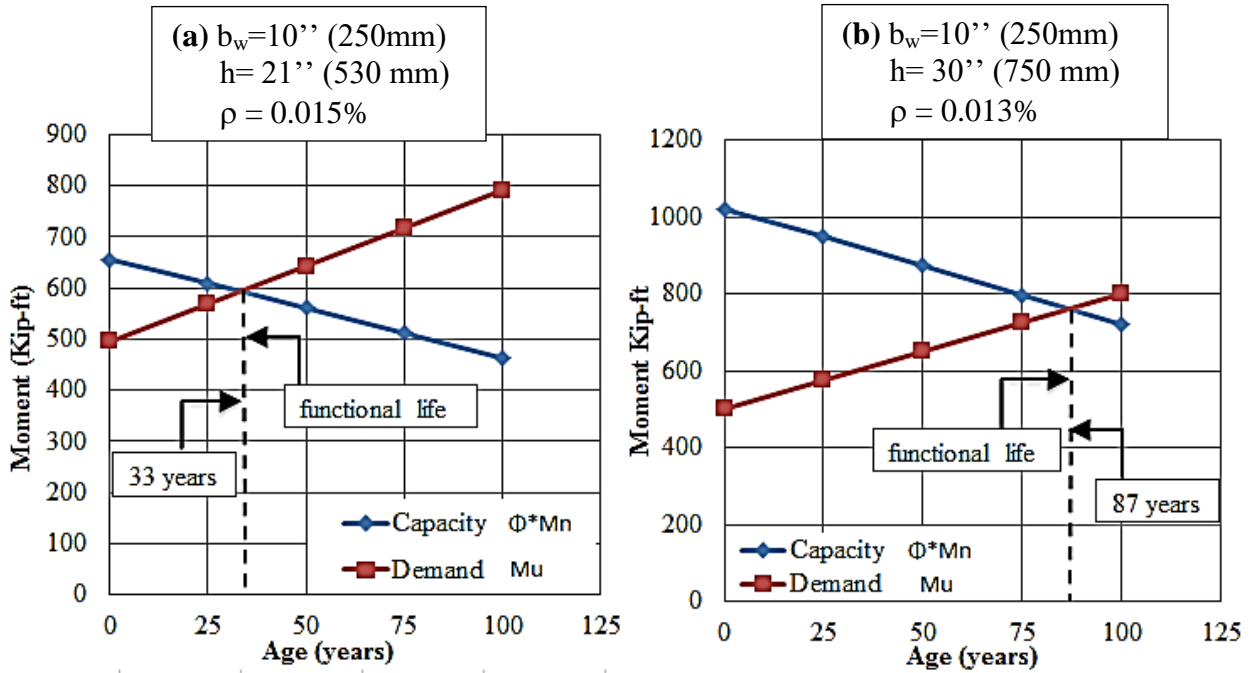


Figure 13. Capacity and demand over time for two representative options

Results for all 64 permutations of the design variables are plotted in Figure 14 according to their capacity obsolescence and annual embodied energy. Each individual permutation can be represented by up to three points, one for each service life. The solid lines Figure 14 are the Pareto fronts for each service life. Design options along a Pareto front cannot be improved for one objective without causing a negative effect on the other objective. Optimal designs for the example bridge are those that have minimum annual embodied energy and that remain functional throughout the designated service life. The optimal designs correspond to the points at which the Pareto front crosses the line of zero obsolescence.

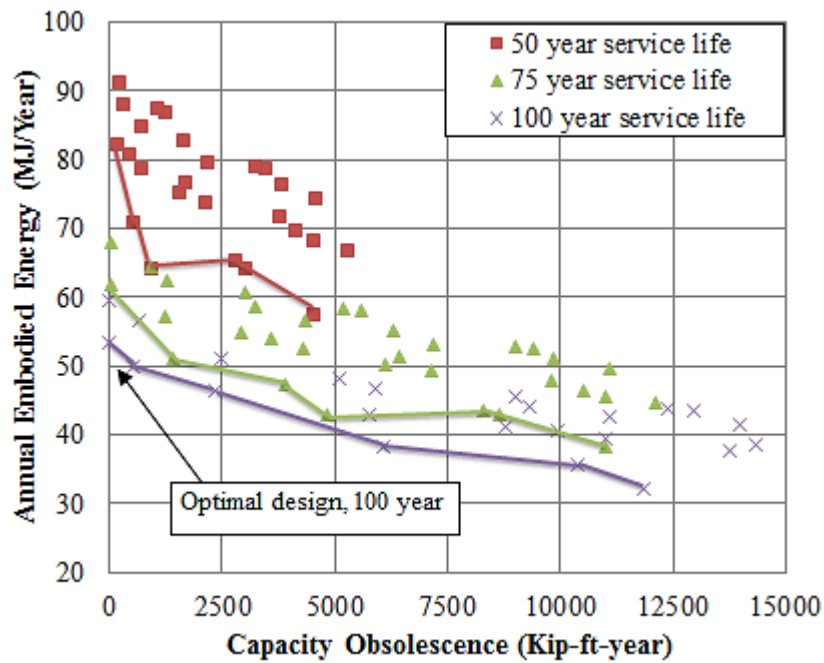


Figure 14. Multi-criteria analysis of the example bridge

As expected, longer services lives are associated with lower embodied energy, and consequently, greater environmental sustainability. In the example problem, changes in energy efficiency were greater between 50 and 75 years than between 75 and 100 years. There is a trade-off between energy and obsolescence. Girder designs with lower capacity obsolescence are larger and contain more embodied energy than smaller girder designs with higher obsolescence. MCDA methods, such as the Pareto front method demonstrated in Figure 14 and discussed above, can be used to navigate these tradeoffs. More rigorous MCDA methods such as multi-attribute utility theory (MAUT) or the analytic hierarchy process (AHP) can be used to evaluate problems with greater complexity.

### **Scope for further research**

In order to demonstrate application of MCDA and the capacity obsolescence model, the example in the previous section was designed to be relatively simple. Practical application of the methodology will require additional considerations and features.

Suggestions for future advancements are listed below:

- The example focused only on flexural capacity of girders. The methodology should be extended to include other components of the bridge and to other load effects and limit states.
- The effects of repair, maintenance and/or retrofit should be considered as they relate to the degradation model and embodied energy. As these events occur at discrete instances, a piecewise function might be utilized to model their effects on structural capacity.
- Capacity degradation and load increase were treated independently in the example. Work should be conducted to elucidate the interaction between these factors.
- The example only included embodied energy and capacity obsolescence. The methodology should be expanded to include other criteria such as economic cost and multi-hazard resilience, as well as geometric obsolescence.
- Probabilistic analysis should be used to assess uncertainties and variability. Application of robust design methodologies, such as those applied by Liu et al (43), would be an effective tool for selecting a designs with minimum sensitivity to uncertainty and variability.



- The methodology should be extended from a single bridge to infrastructure networks. This would be of benefit to agencies in prioritizing maintenance and replacement interventions. Existing works studying seismic resilience of bridge networks would likely be useful in this regard (20, 44).

### **Summary and conclusions**

The 85,000 functionally obsolete highway bridges in the United States have significant impact on the economic, social, and environmental sustainability of highway infrastructure. In spite of this condition, there is a dearth of information on methods for assessing obsolescence. In response, this paper qualitatively discussed the interactions between functional obsolescence and sustainability of highway bridges. A definition was proposed for capacity obsolescence (one type of functional obsolescence), and a model for quantifying capacity obsolescence was proposed. An example involving a simple span reinforced concrete bridge was presented to demonstrate a methodology for quantitatively evaluating capacity obsolescence and environmental impact using multi-criteria decision analysis. The example demonstrated the environmental benefits of designing for a longer service life. Concepts for advancing the methodology used in the example were suggested. The concepts and methods discussed and presented in this paper are presented as a foundation for future studies on functional obsolescence and sustainability of highway bridges.

## Acknowledgement

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## CHAPTER FOUR

### **APPLICATION OF CAUSAL LOOPS DIAGRAMS TO MODEL IMPROVEMENT COSTS FOR HIGHWAY BRIDGE INVENTORIES**

*This chapter is currently under review for publication*

*Srimaruthi Jonnalagadda, Brandon E. Ross*

#### **Abstract**

The quality of bridge infrastructure is affected by a variety of factors. Traffic and aging deteriorate bridges; maintenance and repair operations mitigate deterioration. The overall quality of a bridge inventory is also affected by new construction, and through removal or improvement of poor bridges. This study uses tools from the field of systems dynamics to study changes to the quality of bridge inventories. A causal loop diagram (CLD) is developed to qualitatively describe the relationships and actions impacting the quality and improvement costs of a bridge inventory. Relationships expressed in the CLD consider physical, economic, and policy factors. A quantitative linear-regression model is also developed, which is based on a portion of the CLD. Using South Carolina as a test subject, the model is used to calculate the inventory-level improvement costs as a function of annual improvement budget. Data from the National Bridge Inventory are used to develop the model. This paper is presented as a first step towards the use of system-based approaches to study highway bridge inventories. Recommendations are given for extending the proposed CLD and quantitative model.

## **Introduction**

The average age of highway bridges in United States in 2015 was approximately 42 years (1). As age and traffic demands increase, there is growing need for maintenance and improvement of highway bridges. This paper uses a system-based approach to study *improvement costs*, which are defined as the costs to repair or rehabilitate bridges to the point at which they provide an acceptable level of service (2). By using such an approach the relationships between physical phenomena, policy decisions, economic activity, traffic demands, and other relevant factors can be jointly considered and evaluated. The suitability of system-based models for studying transportation systems has been well established (3); however this approach has not previously been applied to study highway bridge inventories. Towards the goal of applying a system approach to bridge inventories, this paper has three objectives:

1. To develop a Causal Loop Diagram (CLD) of the system that governs the improvement costs of a highway bridge inventory (hereafter ‘bridge inventory system’);
2. To develop and apply a simplified quantitative model to predicting future improvement costs subject to variable levels of annual funding; and
3. To recommend future work for extending system modeling of bridge inventories

The first objective is conceptual in nature and is addressed in section 3 of this paper. Factors and relationships that impact improvement costs are identified and mapped onto a CLD for the bridge inventory system. For the second objective, a simplified quantitative model is developed to predict quality and improvement costs of the South Carolina

bridge inventory. The model is characterized as ‘simplified’ because it is not comprehensive of the entire bridge inventory system, is based on linear-regression (as opposed to more complex system dynamic modeling,) and because it focuses only on short-term analysis. Development of the simplified model is presented in section 4. Section 4 also presents a parametric study to determine the effects of annual improvement budget on the future improvement costs. The final objective flows from the first two. Recommended tasks towards quantitatively modeling the entire bridge inventory system are discussed in section 5. Summary and conclusions are presented in section 6.

## **Background**

### ***Bridge Improvement and Maintenance***

Bridge improvement is distinct from maintenance; the latter being defined as activities performed on a predetermined schedule to preserve bridges from future deterioration and damage (2). While improvements are aimed at enhancing the functional or structural condition of bridges, maintenance activities are aimed at delaying bridge deterioration. Both are critical factors when evaluating the condition of individual bridges, as well as the overall condition of bridge inventories. According to the Federal Highway Administration (FHWA) typical bridge improvements include (2):

- Widening of existing bridges with or without deck rehabilitation
- Bridge deck rehabilitation with only incidental widening
- Replacement of bridge or other structure due to substandard load carrying capacity



- Bridge deck replacement with only incidental widening
- Bridge rehabilitation because of general structure deterioration
- Other structural works including hydraulic replacements

The National Bridge Inventory (NBI) is a database of all bridges in the United States having spans over 20 feet. It is updated on a yearly basis and is available through FHWA (4). Estimated improvement costs are included as a data item for each bridge in the NBI. A year-over-year decrease in estimated improvement costs indicates that a bridge received treatments for improvement during the previous year. A year-over-year increase in improvement costs indicates the condition of the bridge worsened and that additional funds are required to bring the bridge up to an acceptable level of service.

### ***Sufficiency Rating***

*Sufficiency Rating* (SR) is another of the data items listed in the NBI, and is an overall indicator of a bridge's quality and condition. SR is reported as a value between 0 and 100, and is calculated from over 20 different data parameters listed in the NBI. Structural adequacy, safety features, serviceability, function, and criticality are all part of SR. A value of 100 indicates a bridge in effectively new condition; lower values indicate lesser degrees of sufficiency. A bridge with SR less than 80 is considered a candidate for rehabilitation, whereas a bridge with SR less than 50 is a candidate for replacement (5). Because it provides an overall measure of bridge health, SR was selected for use in the simplified model presented in section 4.

### *System Dynamics and Causal Loop Diagrams*

System Dynamics is defined as a perspective and set of conceptual tools that enable understanding of the structure and dynamics of complex systems (6). It is developed from system theory, information science, organizational theory, control theory, and tactical decision-making (3). System Dynamics approach is suitable for modeling complex transportation systems and are useful for making policy-level decisions (3).

Causal loops diagrams (CLD) are a fundamental tool in System Dynamics. CLD are used to organize variables that impact a complex system and to visualize the interaction between these variables. CLD provide a basis for understanding and measuring the effects of these variables and their interactions on the overall performance of the system (6). As a precursor to quantitative analyses, CLD can also be used to qualitatively map and rationalize relationships in complex systems. A qualitative CLD approach has been used to study such things as the process by which buildings are adapted over time (7) and the decision of individuals to use public or private transportation (8).

The study most relevant to the current research was conducted by Fallah-Fini et al. (9) in which a CLD was developed to describe the causal relationships between highway maintenance operations and highway deterioration. Using mathematical functions to describe casual relationships, the effects of three types of maintenance operations (preventive, corrective, and restorative) were considered and measured. The study concluded that the current decision-making strategies are not adequate for deriving

optimal highway performance. Based on the CLD and associated modelling, recommendations were made for optimizing highway maintenance.

## **Methodology**

### *Causal loop diagram for bridge inventory system*

Figure 15 presents a CLD of the system that controls the size, quality, and improvement costs of a highway bridge inventory. The figure is based on South Carolina; however, most aspects of the figure can be generalized to other jurisdictions. Arrows in the diagram represent causal relationships. A positive sign is placed next to the arrow if the factor on the originating end tends to increase or grow the item at the arrowhead end. A negative sign denotes decreasing or shrinking effect.

To aid in presenting the CLD, numbers are used to link components of the Figure 15 with discussions in the subsequent text. Numbering begins with improvement costs near the center and follows a roughly counterclockwise pattern through the figure. In addition to describing the components of the diagram, relevant sources of data are also mentioned in the subsequent text.

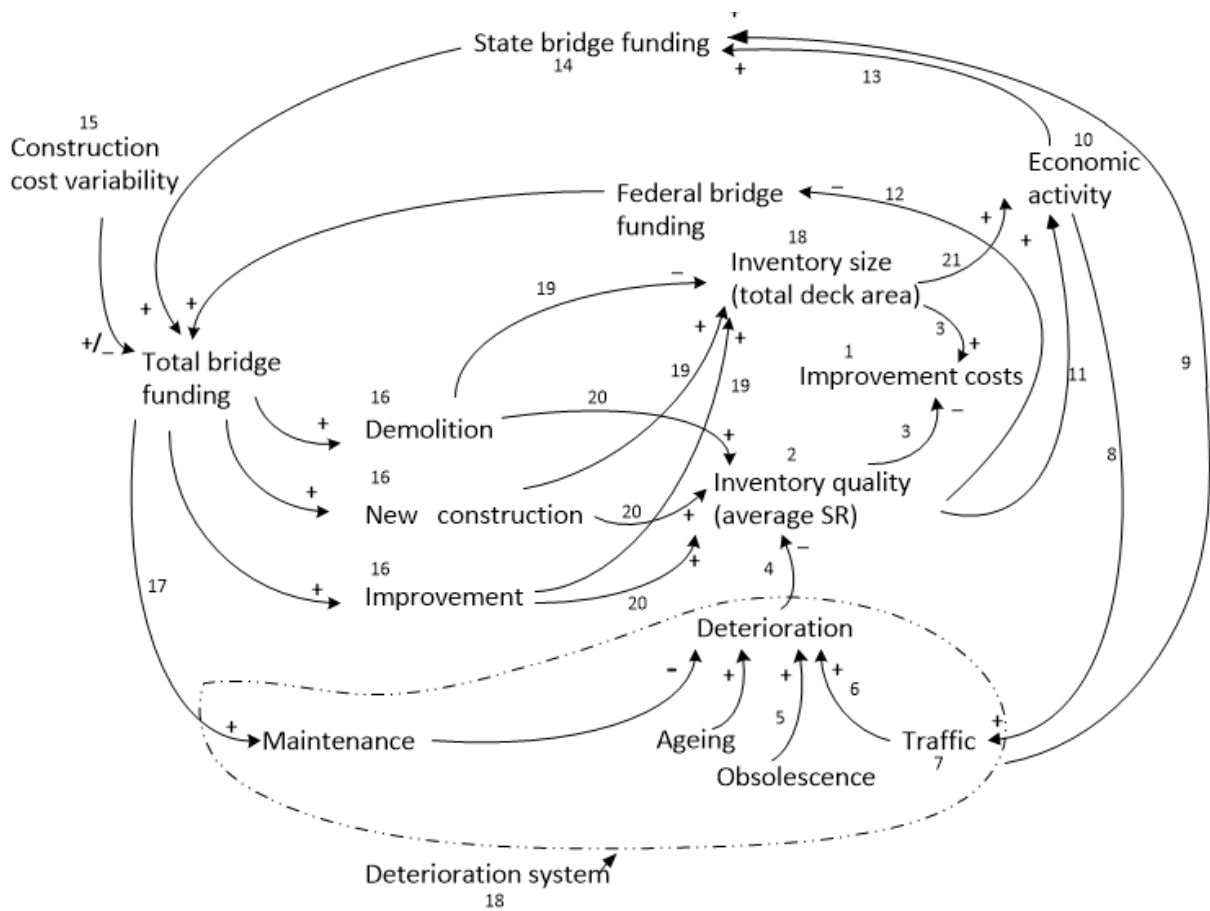


Figure 15. Causal Loop Diagram of the Bridge Inventory System

**Description of CLD**

1. The primary objective in creating Figure 15 was to map the factors and relationships that impact total improvement costs for the South Carolina bridge inventory. Thus each path through the diagram ends at improvement costs. Improvement cost data for individual bridges are available in the NBI.
2. Average SR provides one measure of inventory quality. Measures such as the percentage of structurally deficient and functionally obsolete bridges could also

- be used to measure inventory quality. Data on these measures are available in the NBI.
3. Total improvement costs for the inventory increase as the size and quantity of bridges increase; they decrease as the quality of the inventory improves.
  4. Deterioration adversely impacts the quality of bridges and occurs due to ageing, traffic, and obsolescence. Maintenance activities slow deterioration.
  5. Bridges are considered obsolete when they no longer meet current standards and functional demands (10). Strictly speaking, changing standards and demands do not cause a reduction in bridge quality. They do, however, impact the definition by which bridge quality is evaluated. For example, if the standard for calculating SR changes, then bridges failing to meet the new standard will be judged as having reduced quality.
  6. It is well understood that traffic, especially heavy truck traffic, has a negative impact on bridge quality. This impact has recently been studied in South Carolina by Chowdhury et al. (11).
  7. Traffic on individual bridges is measured as average daily traffic (ADT) and as percentage of truck traffic. Data on both measures are available at the bridge level in the NBI.
  8. It is reasoned that higher levels of economic activity lead to increased traffic as goods are trucked using the highway system.

9. As with many other states, South Carolina uses a fuel tax as a funding source for transportation infrastructure. It is reasoned that increased traffic results in increased fuel sales and taxes.
10. Measures such as Gross Domestic Product (GDP) are available for quantitatively describing the level of economic activity. Historic data on state-level GDP are available from Bureau of Economic Analysis (12).
11. The overall quality of transportation infrastructure has positive impact on economic activity (13). The specific impact of bridge quality on economic activity has not previously been studied, however, and is recommended as an area for future research.
12. Federal Highway Bridge Rehabilitation and Replacement Program (HBRRP) is a major source of funding for bridge repair and replacement (14). Individual bridges are candidates for federal bridge replacement aid when they have a SR 50 or lower. Data on total federal aid for highway is available (15); funding for bridges is a portion of the total aid.
13. It is reasoned that economic activity increases the tax base. The causal relationship between economic activity and state funding for bridges represents mechanism other than fuel taxes. Examples include special funding districts and one-time funding packages.
14. Data on the total transportation budget for South Carolina can be found from SC Office of the State Auditor (16). For recent years (2008 and later) State Transportation Improvement funding is also readily available (17).

15. The ability of transportation funds to impact physical improvements is a function of economic inflation and construction costs. The National Highway Construction Cost Index (NHCCI) is the price index that accounts for these factors (18).
16. Funding allows for new construction and for improvement or removal of poor bridges. The number of added, removed, and improved bridges can be obtained through year-to-year comparison of the NBI.
17. A portion of bridge funding is allocated to maintenance activities. Maintenance is distinct from other activities in that maintenance slows the rate of deterioration. Condition ratings in the NBI implicitly reflect maintenance activities, but specific data on maintenance activities are not explicit in the NBI.
18. In practice it can be challenging to separate the effects of maintenance, aging, and traffic because they do not occur in isolation. Thus, these factors are collectively considered as the ‘deterioration system’. Net deterioration from this system is reflected in the condition and sufficiency ratings in the NBI.
19. Total area of all bridge decks provides a measure of inventory size that captures the effects of both the number and physical size of bridges. Total deck area of the inventory changes as bridges are added and removed. Improvement activities also commonly increase the size of bridge decks. Deck area for an individual bridge can be calculated as the product of the structure length and deck width; these data are available in the NBI.
20. Inventory quality improves as new high-quality bridges are built and as existing poor-quality bridges are removed or improved.

21. It is reasoned that increasing the size of the bridge inventory has a positive effect on state economy as the bridges facilitate more efficient transfer of goods. To date, this relationship has not been rigorously studied.

*Comments on CLD*

The purpose of CLD mapping is to combine basic relationships into a graphical representation of a more complex system. Studying feedback loops in a CLD can be insightful for understanding long-term system behavior. For example, one loop in Figure 15 shows that increased bridge quality leads to increased economic activity, leads to increased funding, leads to increased bridge quality. This is referred to as a *reinforcing loop* because each relationship in the loop has positive impact. In an alternative loop we can see that increased bridge quality leads to increased traffic, leads to increased degradation, leads to decreased quality. This is referred to as a *balancing loop* because the negative factors and relationships balance the positive effects of the reinforcing loop. The net effect of reinforcing and balancing loops leads to system behavior, in this case inventory improvement costs.

Presentation of the CLD is made as a first step towards development of a quantitative model of the complete bridge inventory system. Additional research and data are needed in order to realize such as model. Some of the relationships shown in the CLD cannot be quantitatively described due to lack of data and/or establish theories. Limitations also exist in modeling the impacts of delays in the causal relationships. An example of a delay would be the time it takes between funding allocation and the subsequent increase



in inventory quality. Design, bidding, and construction time are responsible for such a delay.

Some casual relationships, such as those allocating funding, are highly dependent on policy. These relationships are difficult to predict due to the volatility of the political process. Rather than attempting to predict political outcomes, policy decisions are can be treated as *decision variables* in quantitative models to study the impacts of alternative policies. This is demonstrated in section 4, wherein the annual budget for bridge improvement is treated as a variable.

With some adjustments the CLD shown in Figure 15 can be used to describe the systems impacting other components of transportation infrastructure such as pavements, or to describe the quality of transportation infrastructure overall. The CLD was developed with consideration of the South Carolina bridge inventory; however CLD can also be used to map larger or smaller systems.

### ***Simplified improvement cost model***

#### ***Model Overview***

This section presents a simplified quantitative model for studying the total improvement costs of the South Carolina highway bridge inventory. The model is mapped in Figure 16 and is referred to as ‘simplified’ because it is based on only a portion of the larger CLD presented in Figure 15. The ‘simplified’ moniker is also used because the model is based on linear regression, and not more complex system dynamics approaches. The portion of the CLD selected for the simplified model was chosen because items and relationships can be quantified using data exclusively from the NBI. Calculations in the model are

made on a yearly basis, and utilize South Carolina NBI data from 2004-2014. This range was selected because improvement costs, an essential piece of the model, were not consistently reported in the NBI for South Carolina prior to 2004.

Annual funding for improvements is the only variable in the model. Funding for demolitions, new construction, and maintenance are treated as constants. This approach is taken so that the impact of improvement funding can be studied in isolation. Furthermore, this approach was taken for the practical reason that funding data for demolitions, new construction, and maintenance are not included in the NBI. Traffic is also treated as a constant in the model.

Note that the portion of the CLD used for the simplified model does not contain any feedback loops. Feedback loops in the bridge inventory system (Figure 15) are likely to impact long-term system behavior. For this reason, the simplified model is only considered viable for estimating improvement costs in the short-term future.

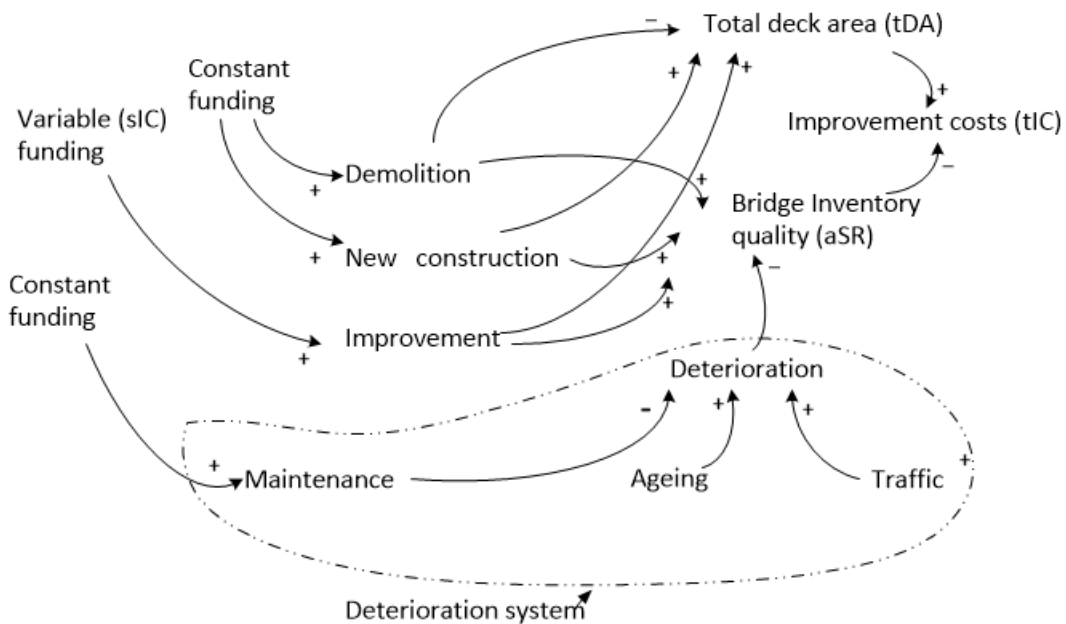


Figure 16. Simplified Model for Total Improvement Costs

**Source Data**

Data used to develop the model are shown in Table 7. The total number of bridges in the inventory was determined by simply counting the number of records in the NBI for each year. The numbers of removed and new bridges were determined by comparing data from adjacent years. The number of improved bridges for a given year was determined by comparing changes in improvement costs for each bridge from the previous year. If improvement costs for a given bridge changed downward from the previous year, then that bridge was added to the count of improved bridges. Structured Query Language (SQL) programs were written to automate these processes.

Table 7. Data for South Carolina Bridges (based on NBI data)

Year	Number of bridges				tDA <sup>+</sup> (m <sup>2</sup> )	sIC <sup>+</sup> (USD)	tIC <sup>+</sup> (USD)	aSR <sup>+</sup>	ΔSR <sup>+</sup>
	Total	Improved	removed	new					
2004	9224	163	14	125	5790539	75.6	1422	75.4	1.38
2005	9168	186	104	48	5875774	142	1492	76	0.90
2006	9202	103	123	157	6046437	56.8	1340	76.2	2.25
2007	9184	126	21	3	6129313	80.7	1317	76.48	0.19
2008	9184	104	30	30	6373756	94.2	1247	76.83	0.32
2009	9188	99	27	32	6422431	47.5	1188	77.06	0.47
2010	9187	118	1	0	6473146	72	1136	77.56	-0.26
2011	9202	107	22	36	6525932	61	1079	77.9	0.39
2012	9204	100	55	58	6555825	54	1067	77.95	1.06
2013	9261	120*	23	80	6581745	*	999	78.35	*

*\*Data not available, assumed + Explained below*

The *total Deck Area (tDA)* is the summation of deck area from all bridges for a given year, and was calculated using Equation 1.

$$tDA = \sum_{b=1}^{b=n} L_b * D_b \quad \text{Equation 1}$$

Where:  $n$  = number of bridges  
 $L_b$  = length of bridge (m)  
 $D_b$  = width of deck (m)

*Spent improvement cost (sIC)* is the total amount spent on all bridge improvements in a given year. This value is calculated indirectly from NBI data. As noted above, year-to-year comparisons were used to identify improved bridges. Once the improved bridges were identified, the *sIC* for a given year was calculated using Equation 2.

$$sIC_t = \sum_{b=1}^{b=p} (IC_{bt} - IC_{bt-1}) \quad \text{Equation 2}$$

Where:  $p$  = number of improved bridges  
 $IC_{bt}$  = Improvement cost for bridge ‘b’ at year ‘t’  
 $IC_{bt-1}$  = Improvement cost for bridge ‘b’ at year ‘t-1’

The *Total Improvement Cost (tIC)* is the funding required to bring all bridges to a satisfactory level of service. Data for *tIC* in Table 7 were calculated for each year from the NBI as the summation of the improvements cost for each bridge.

*Average Sufficiency Rating (aSR)* is calculated directly from the NBI data for each year as the average SR of the entire inventory.

*Net deterioration ( $\Delta SR$ )* is listed for each year in Table 7, this parameter will be defined and discussed in section 4.6. Table 8 lists additional calculated values that are used in the simplified model for improvement costs.

Table 8. Calculated constants for simplified model (based on NBI data 2004-2013 unless otherwise noted)

Item	Variable	Value
Average cost of improvements per unit area (m <sup>2</sup> ) of bridge deck*	$uIC$	1250 \$/m <sup>2</sup>
Average number of newly built bridges per year	$Q$	56
Average number of removed bridges per year	$R$	46
Average deck area of new bridges	$\overline{bDA}$	1565 m <sup>2</sup>
Average deck area of removed bridges	$\overline{rDA}$	650 m <sup>2</sup>
Average deck area added due to improvements	$\overline{IDA}$	630 m <sup>2</sup>
Average SR of new bridges	$bSR$	80
Average SR of removed bridges	$rSR$	61
Average change in SR of improved bridges	$\Delta ISR$	23
Average net deterioration in SR (see discussion in section 4)	$a\Delta SR$	0.75 unit SR /year

\*Based on personal communication with Wilson. B, SCDOT, Feb 2016

The Arthur Ravenel Bridge on US 17 near Charleston, SC, was omitted from the data shown in Table 7 and Table 8. This bridge is a 2.5 mile long signature cable stayed

bridge and is an outlier in the SC bridge inventory. Data from all other bridges were included.

### ***Total Improvement Cost***

A linear equation was developed to describe the relationship between total improvement costs, inventory quality, and inventory size:

$$tIC = [-m(aSR) + b] * tDA \quad \text{Equation 3}$$

- Where:
- $tIC$  = total improvement costs for all bridges (USD)
  - $tDA$  = total deck area of all bridges (m<sup>2</sup>)
  - $aSR$  = average sufficiency rating of entire bridge inventory
  - $m$  = constant taken as 31.4 (\$/m<sup>2</sup> per unit SR)
  - $b$  = constant taken as 2618 (\$/m<sup>2</sup>)

The rationale for the above formulation is that improvement cost is directly related to the size of the bridge inventory (large inventories have greater improvement costs) and inversely related to SR (poor quality bridges cost more to improve). The linear model is compared to data from 2004-2013 in Figure 17; each data point in the figure represents one year. Values for slope ( $m$ ) and intercept ( $b$ ) are based on fit with the data.

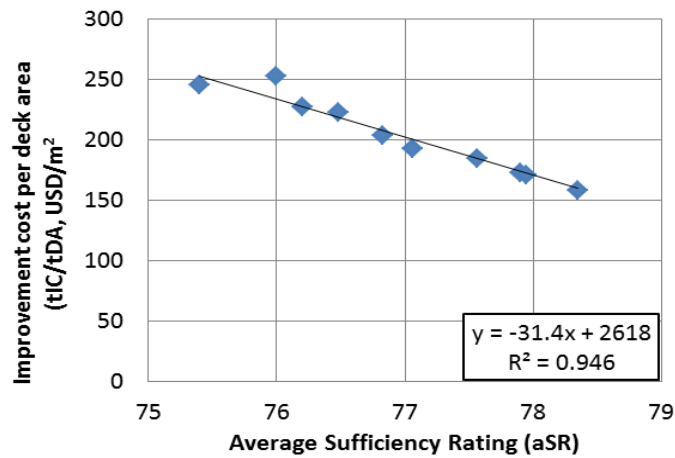


Figure 17. Relationships between Improvement Costs, Inventory Size, and Sufficiency Ratings

Equation 3 correlates well with data ( $R^2=0.946$ ), indicating the linear model adequately captures the relationship between improvement costs, inventory size, and Sufficiency Ratings. The intercept value of equation 3 is 2618  $\$/m^2$ . This is the theoretical cost to improve one square meter of deck having an SR of 0 to an SR of 100. The intercept value is approximately the same amount as needed for each square meter of new bridge construction (Wilson. B, SCDOT, Personal Communication, Feb 2016). If building a new bridge is analogous to improving a bridge from an SR of 0 to an SR of 100, then the similarity between intercept value and new construction cost gives further support for the validity of equation.

### **Total Deck Area**

Referring to Figure 17, total deck area increases with new bridges and improvements, and decreases with removals. Accordingly, Equation 4 is used to estimate  $tDA$  in future years:

$$tDA_i = tDA_{i-1} + IDA_i + bDA_i - rDA_i \quad \text{Equation 4}$$

- Where:  $tDA_i$ = total deck area of bridges at year 'i'  
 $tDA_{i-1}$ = total deck area of bridges at year 'i-1'  
 $IDA_i$ = deck area added through improvements in year 'i'  
 $bDA_i$ = deck area added by new bridges at year 'i'  
 $rDA_i$ = deck area added by removed bridges at year 'i'

The deck area added through improvements is a function of the annual budget for improvement ( $sIC$ ). For the prediction phase (2014 through 2020),  $sIC$  is calculated as:

$$IDA_i = \frac{sIC_i}{uIC} \quad \text{Equation 5}$$

The total deck area of newly built bridges and removed bridges during any year 'i' are estimated using Equation 6 and Equation 7.

$$bDA_i = q_i (\overline{bDA}) \quad \text{Equation 6}$$

$$rDA_i = r_i (\overline{rDA}) \quad \text{Equation 7}$$

### **Average Sufficiency Rating**

Referring to Figure 17, bridge quality is negatively impacted by the deterioration system, and positively impacted by bridge improvements, new construction, and removal of poor



bridges. These factors are included in the Equation 8 for calculating average SR of the inventory ( $aSR$ ):

$$aSR_i = aSR_{i-1} + bSR \frac{q_i}{N_i} + rSR \frac{r_i}{N_i} + \Delta ISR \frac{p_i}{N_i} + \Delta SR_i \quad \text{Equation 8}$$

Where:  $aSR_i$ = average SR of entire bridge inventory at year 'i'  
 $aSR_{i-1}$ = average SR of entire bridge inventory at year 'i-1'  
 $p_i$ = number of bridges improved at year 'i'  
 $N_i$ = total number of bridges at year 'i'

The value of  $aSR$  for a given year is based on the previous years' value and changes due to removals, new construction, improvements, and net deterioration. For the predictions in this paper, changes due to removed bridges, new bridges, and net deterioration are treated as constants based on the values given in Table 8. Calculations for determining net deterioration are discussed in detail in the next section. The number of improved bridges for a given year is calculated using Equation 9.

$$p_i = \frac{IDA_i}{IDA} \quad \text{Equation 9}$$

### ***Net Deterioration***

Referring to Figure 16, *net deterioration* is defined as the combined effect of the deterioration system on inventory quality. In the simplified model net deterioration is the reduction of  $aSR$  due to the deterioration system. The deterioration system includes traffic, aging, and maintenance. The NBI data do not provide a means of isolating these effects individually, but do allow a means of determining the combined (net) effect of all

three. This is accomplished by considering the year-over-year change in  $aSR$  less the effects of new, removed and improved bridges:

$$\Delta SR_t = aSR_t - aSR_{t-1} + bSR * \frac{q_t}{N_t} + rSR * \frac{r_t}{N_t} + ISR * \frac{p_t}{N_t} \quad \text{Equation 10}$$

Equation 10 can be derived by rearranging Equation 8. The subscript ‘t’ is used in Equation 10 to denote that it is based on years 2004-2013, whereas Equation 8 uses subscript ‘i’ to denote future years. Yearly values of  $\Delta SR$  calculated using Equation 10 are reported in Table 7. The value for average net deterioration ( $a\Delta SR$ ) reported in Table 8 calculated by averaging the yearly  $\Delta SR$  values reported in Table 7.

#### ***Parametric Study***

The simplified model was used to parametrically study the effects of annual improvement spending. Four possible funding scenarios were considered: 0, 40, 80, and 120 million USD annually. The average spent improvement cost in recent years (Table 7) was approximately 60 million USD. Hence, the scenarios range from zero funding to a level that is approximately double the funding from recent years. Average SR ( $aSR$ ) and total Improvement Costs ( $tIC$ ) were projected from 2014 to 2020 for each scenario.

Table 8 presents input and output data for the scenario of  $sIC$  equal to 40 million USD per year. Input data for the other scenarios were similar; only the  $sIC$  and number of improved bridges varied. The number of improved bridges for each scenario was determined using Equation 9. Constant values for new and removed bridges were based on average values from recent years (Table 7). Total deck area was calculated for each year using Equation 4 through Equation 7. Output data included  $tIC$  and  $aSR$ , which were calculated using Equation 3 and Equation 8, respectively.

The analysis implicitly treats maintenance activities and traffic levels as constant. A value of 0.75 was used yearly net deterioration ( $\Delta SR$ ) in Equation 8. As discussed in section 4.6, this value is based on NBI data from 2004 through 2013, and includes the effects of maintenance, aging, and traffic. By using 0.75 as net deterioration in the parametric studies, it is assumed that maintenance and traffic will continue at a level similar to 2004 to 2013.

## Results and Discussions

Table 9. Projections for South Carolina bridge inventory (*Scenario: sIC=40 USD Millions*)

Year	Input data				Output data			
	Number of bridges				tDA (m <sup>2</sup> )	sIC (USD millions)	tIC (USD millions)	aSR
	Total	improved	removed	New				
2014	9271	51	46	56	6647486	40	1015	78.46
2015	9281	51	46	56	6713226	40	991	78.62
2016	9291	51	46	56	6778966	40	967	78.78
2017	9301	51	46	56	6844706	40	942	78.94
2018	9311	51	46	56	6910446	40	917	79.10
2019	9321	51	46	56	6976186	40	891	79.25
2020	9331	51	46	56	7041926	40	865	79.41

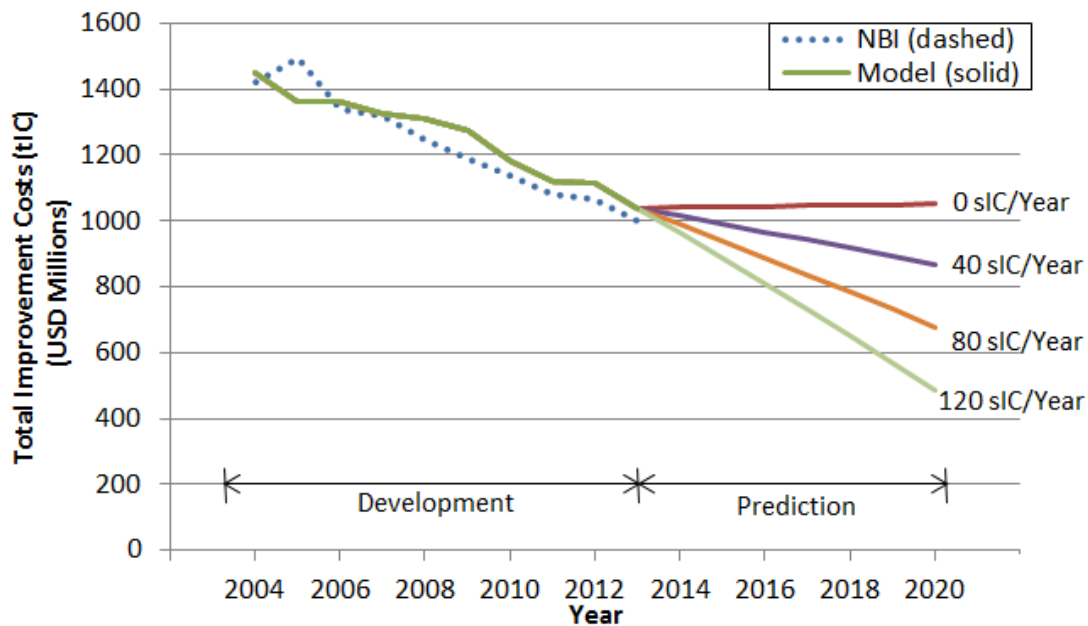


Figure 18. Total Improvement Costs (*tIC*)

Figure 18 presents total improvement costs as a function of time. Data from the NBI and model are presented for years 2004 through 2013. NBI data in the figure match the values from Table 9; model values for the same period were calculated using Equation 3 and data from Table 9. Data from 2014 through 2020 are predictions from the parametric study. Four lines are shown, one for each funding level. As the annual funding level increases, the total improvement costs for the inventory decreases. It is estimated that total improvement costs for the South Carolina inventory can be reduced by 50% by 2020 if annual funding for improvements is set at 120 million USD per year. This estimation assumes that traffic, maintenance, new construction, and demolition will continue at the same pace through 2020.

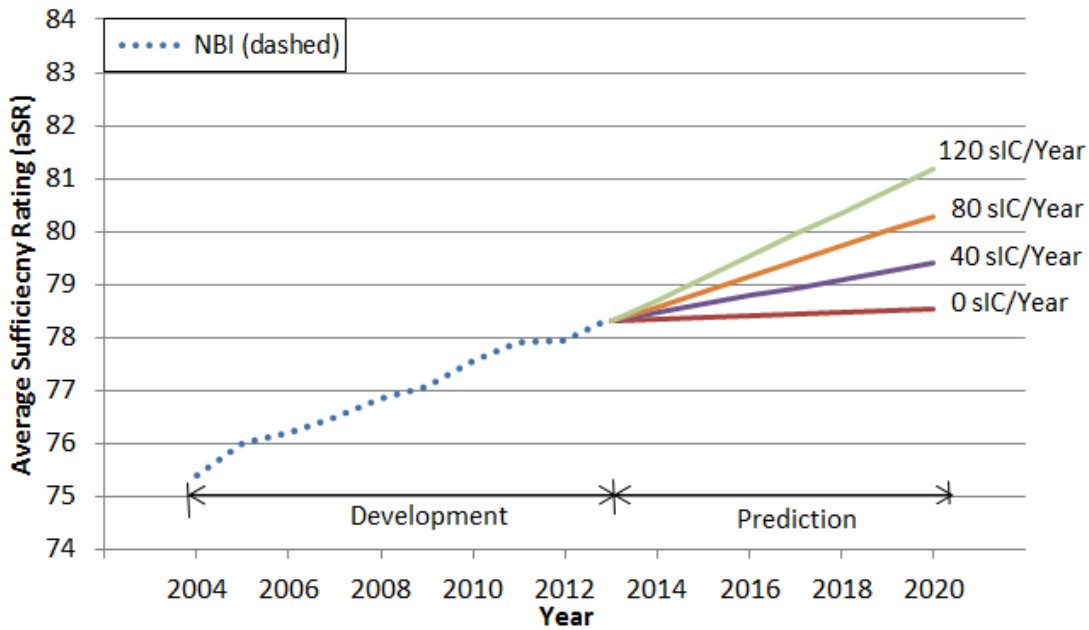


Figure 19. Average Sufficiency Rating (*aSR*)

Figure 19 compares the average SR of the South Carolina inventory under different levels of improvement funding. Average SR is approximately constant at 78.5 between 2014 and 2020 for the scenario where no funds are spent on improvement. In this scenario, the positive effects of bridge removals and new construction are approximately equal to the negative effects of the deterioration system. Thus adding and removing bridges at a rate equal to the average rate from 2004 to 2012 would likely be sufficient for maintain average SR in the near future. Improving average SR will require spending on improvements, or an increased rate of new bridge construction and/or removal of poor bridges. Assuming rates of new construction and removal stay constant, it is estimated that an annual improvement budget near 80 million USD per year would increase the average SR of bridges in South Carolina to 80 by 2019.

## **Recommendations for future work**

This paper is intended as a starting point for the application of System Dynamics to evaluate highway bridge inventory systems. Additional works are required to practically apply a system-based approach in more rigorous and comprehensive studies. The following recommendations and comments are made in this regard:

- Inclusion of bridge-specific models is recommended to improve modeling of traffic, maintenance, and aging effects. NBI data are insufficient for such modeling; maintenance and inspection records would be required. Detailed bridge-specific funding data would also be of great use.
- Delays in casual relationships should be considered. For example, the time required for economic activity to impact funding for bridges.
- The simplified model was based entirely on linear relationships, and in this sense was not a system dynamics model. Nonlinear models should also be considered as they may be appropriate for describing some relationships in the system. Nonlinear behavior of the overall system due to feedback loops should also be considered.
- A multidisciplinary approach is required in order to model the entire bridge inventory system. Public policy models are required to relate economic activity to funding. Similarly, relationships are needed to relate economic activity to traffic levels, and bridge inventory size and quality to economic activity.

- The simplified model was based on a limited data set covering only 10 years. Creating and validating a model that captures the effects of feedback loops, obsolesce, and construction cost variation will require additional years of data.
- The CLD and simplified models are based on average sufficiency rating of the bridge inventory. Alternative measures such as average deck condition ratings, or percentage of structurally deficient and functionally obsolete bridges might also be considered.

### **Summary and conclusions**

A systems-based approach was used to study the system controlling the size and quality of the South Carolina highway bridge inventory. To begin, the system was qualitatively described using a causal loop diagram that included physical, economic, and policy factors. Second, a simplified linear regression model, based on a segment of the CLD, was developed and applied to study the effects annual improvement funding on inventory quality and total improvement costs. The model was developed exclusively using data from the National Bridge Inventory. Alternative funding scenarios were analyzed using the simplified model. Finally, recommendations and comments were made with regard to future system-based modeling of bridge inventory systems.

With regard to the South Carolina highway bridge inventory, the following conclusions and observations are made from the parametric study:

- Total improvements costs are linearly related to total deck area and average sufficiency rating. The proposed linear model had strong correlation,  $R^2 = 0.95$ , with the available data from 2004 through 2013.

- The combined effects of traffic, aging, and maintenance resulted in a deterioration of average Sufficiency Rating by an average of 0.75 SR points per year from 2004 to 2013. Deterioration was completely offset during this period, however, a net improvement in average SR was realized due to the effects of new construction, and removal and improvement of poor bridges.
- Under the assumed conditions (constant traffic, maintenance, new construction, and demolitions), it is estimated that an annual improvement budget of 120 million USD per year will decrease the total improvement costs by 50% by 2020.
- For each 10 million USD spent on annual improvements between 2014 and 2020, the total improvement cost in 2020 is estimated to decrease by 46 million USD, and the average SR in 2020 is estimated to increase by 0.14 SR points.

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## CHAPTER FIVE

### **A MODELING APPROACH FOR EVALUATING THE EFFECTS OF DESIGN VARIABLES ON BRIDGE CONDITION RATINGS**

*This chapter is currently under review for publication*

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#### **Abstract**

While routine inspections are commonly used to assess the structural integrity, safety, and maintenance needs of individual highway bridges, data from these inspections can also be used to study performance of bridges at the inventory level. This paper presents a novel method by which inspection data can be used to evaluate design variables and inform future designs. In particular, inspection data from prestressed concrete bridges in Southeastern United States were used to develop artificial neural networks (ANN) models for estimating the condition rating of bridge decks and superstructures as a function of skew angle and span length, as well as, bridge age, width, and traffic level. Once developed and validated, the ANN models were used for an array of simulations that were designed using a full factorial approach. The objective of the simulations was to identify skew angles and span lengths that correlate with the highest inspection ratings. It was determined that deck ratings are highest for smaller skew angles and shorter span lengths, whereas superstructure ratings are minimally impacted by larger skews and unrelated to span length. The conclusions of this study will be helpful in understanding

the implications of bridge design variables on the long term performance of bridge decks and superstructures. Though the trends and conclusions noted in this study are to be seen within the scope of the data considered, the approach demonstrated in this paper can be applied to address other questions of bridge performance.

## **Introduction**

Routine bridge inspections provide a wealth of information on the condition and performance of individual bridges, but also provide rich data for analyzing bridge inventories and for identifying design variables that correspond to high-performing bridges. As the quality and quantity of inspection data increase, what approaches can be used to learn from this information? This paper presents a methodology, using Artificial Neural Network (ANN) modeling and full factorial-based simulations (FFS), to analyze bridge inspection data. The ANN is built using data from the National Bridge Inventory (NBI) (NBI, 2016), a database compiled by the United States Federal Highway Administration (FHWA) for all bridges in the US that are longer than 6.1 meters (20 feet). The NBI is updated yearly and includes 116 different pieces of data for each bridge, including inspection data that documents the condition of different bridge elements. Similar inspection data inventories are available in other countries such as Denmark, Germany, UK, Finland, Canada, France (Hearn, 2007), Korea, China, and Japan (Jeong et al, 2016). India currently is in the process of building a bridge inventory (Arora, 2016). Typical data items in these inventories include physical characteristics, structural characteristics, traffic counts, component structural ratings, overall sufficiency

ratings, etc. The FHWA coding guide (FHWA, 1995) describes each of these fields and how to interpret the code values for these fields in NBI databases.

ANN and other artificial intelligence networks have previously been trained using bridge inspection records (discussed in Section 2.1); however, these applications have focused on predicting the future condition of existing bridges. ANN methods also offer the potential to identify relationships between design variables and ratings, which information can be used to inform future designs. The novel ANN-FFS approach demonstrated in this paper was created for such a purpose; to provide a systematic means of evaluating large sets of inspection data so that future designs can be informed by “lessons learned” from existing bridges. To that end, this paper has three technical objectives:

1. To apply the ANN-FFS approach to assess the sensitivity of prestressed concrete bridge deck and superstructure condition ratings to changes in skew and span length;
2. To compare findings of the current study with results of other researchers who used alternative methods;
3. To suggest values of skew and span length that are likely to lead to longer lasting decks and superstructures.

Identifying relationships between design variables and inspection ratings is insufficient to determine causation. Hence the results of the current study are compared to findings from other researchers who used structural analysis models, small field studies, and laboratory studies. In this manner, possible explanations for the relationships observed in the ANN-

FFS analysis are identified and analyzed. Prestressed concrete superstructures and reinforced concrete bridge decks were selected for the current study because they are common in the southern eastern United States. While applied here to study prestressed concrete bridges, the ANN-FFS methodology has potential for addressing questions related to other bridge types. Information gleaned from bridge inspection records can be used as one more piece in the puzzle of improving performance and extending the life of highway bridges. Design engineers can use such information to create designs that balance the likelihood of high condition ratings (increased longevity) against functional and economic criteria. Maintenance engineers can use the information to target their inspections and maintenance interventions on bridges having the highest likelihood of poor condition ratings.

## **Background**

### *Artificial Neural Networks for Bridge Condition Evaluation*

Artificial Intelligence techniques, ANN being one type, are effective for modeling the behavior of complex systems with multiple factors that dynamically influence system performance. Neural networks simulate the thinking and learning behavior of biological systems (Mitchell, 1997). The approach was first proposed in 1943 by mathematician Walter and neuro-physician Warren (McCulloch and Pitts, 1943). Since that time, the application and sophistication of ANN models have expanded widely (Burke et al 1997, Abbass et al 2002, Gniadecka et al 2004).

A neural network is a collection of processing units called neurons arranged in layers to form a computing network (Priddy and Keller, 2005). The network can have single or multiple layers, with multi-layered networks yielding better results for more complex systems. Referring to Figure 20, the first layer is called input layer. Input data are passed from the input layer to an intermediate hidden layer, wherein the data are assigned mathematical weights and processed by neurons. The neurons pass information to transfer function which generates the net input based on input variable values and their weights. The net input is passed to an activation function in the output layer, wherein the output value is calculated. To train the network, the process is repeated many times, with different weights and functions being used for each pass. The model is trained until the error between model outputs and source data are within an acceptable range.

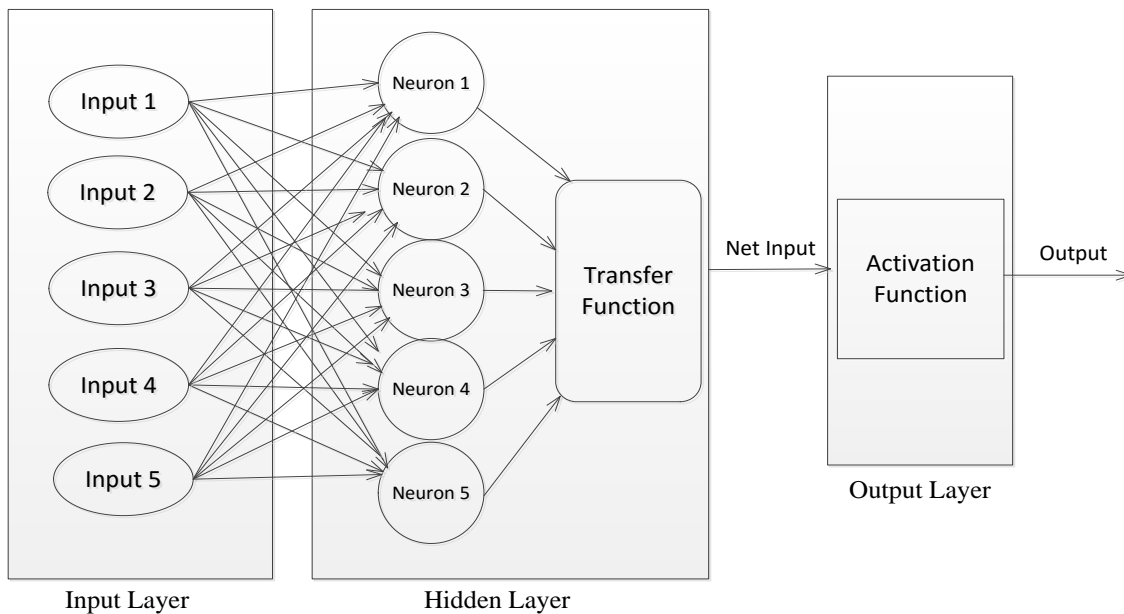


Figure 20. A multi layered neural network

ANN computing has been applied to a range of civil engineering problems, including evaluation and analysis of bridges. For example, Chen and Shah (1992)

developed ANN models to predict changes in frequencies and displacements of bridge piers due to dynamic loads. Sobanjo (1997) demonstrated the application of ANN for modeling bridge deterioration on a pilot basis. With a small data set of 50 bridges, the study predicted condition rating of superstructures considering only the age of bridge as variable. Tokdemir (2000) developed an ANN model to predict bridge sufficiency ratings in California based on 28 bridge attributes. Morcous (2002) applied ANN to forecast concrete bridge deck conditions and compared the results with other Artificial Intelligence methods. Huang (2010) applied ANN for developing deck condition prediction models for bridges in Wisconsin. The study suggested that age and maintenance history are relevant to deck deterioration. In a study conducted for Michigan Department of Transportation, Winn and Burgueno (2013) developed ANN models for predicting condition ratings for deck surfaces in the state of Michigan. Contreras-Nieto et al (2016) compared results from ANN, linear regression, and decision tree models to predict superstructure ratings of bridges in the state of Oklahoma. It was concluded that among the three approaches, ANN models gave the best prediction and that age is the most significant factor in predicting superstructure ratings.

This paper adds to the body of knowledge on bridge condition evaluation by combining artificial neural networks modeling with full factorial-based simulations to create a framework for evaluating the impacts of design variables on condition ratings. Through this approach, complex interactions between input variables are inherently considered and overarching trends can be identified. Whereas previous researchers used ANN to forecast the condition of existing bridges and bridge components, the current



study presents a methodology for systematically identifying the sensitivity of bridge deck and superstructure performance to design variables through a large set of simulations. The results of such analyses can be used by designers as they seek to balance structural efficiency, functionality, and bridge longevity.

### ***Full Factorial Approach***

Full Factorial Design is an approach used within the ‘Design of Experiments’ (DoE) philosophy, and is commonly used to design experimental programs that involve many different variables. The approach is useful for elucidating the effects of combinations of variables on a system response and can be an efficient alternative to one-factor-at-a-time analysis (Antony, 2014; Montgomery, 2008). In civil engineering the full factorial approach has been used to study mix designs for concretes and mortars (Yeh 2006, Correia 2010). Rather than using a full factorial approach to design experiments, this paper uses full factorial to design an array of simulations in which all possible combinations of the variables are investigated. If ‘N’ is the number of variables and ‘K’ is the number of levels, then a full factorial array requires that  $K^N$  simulations be conducted to include each unique combination. In this manner the combined effects of skew, span, age, and other input variables can be considered.

### ***Condition Ratings***

Bridge inspection data in the NBI are given as *condition ratings*, which describe the physical condition of the superstructure, substructure, and bridge deck. Inspectors rate components on a scale of 0 to 9, as shown in Table 10 below.

Table 10. Condition ratings for bridge components (Ryan et al, 2012)

Rating code	Condition rating guidelines
N	Not applicable
9	Excellent condition
8	Very good condition - No problems noted
7	Good condition- Some minor problems
6	Satisfactory condition- Structural elements show some minor deterioration
5	Fair condition- All primary structural elements are sound but may have minor section loss, cracking, spalling, or scour
4	Poor condition- Advanced section loss, deterioration, spalling, or scour
3	Serious condition- Loss of section, deterioration, spalling, or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present
2	Critical condition- Advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken
1	Imminent failure condition- Major deterioration or section loss present in critical structural components, or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic but corrective action may put bridge back in light service
0	Failed condition- Out of service; beyond corrective action

Previous research by Phares et al. (2004) quantified the variability in the condition ratings reported during bridge inspections. By having multiple inspectors rate the same bridge components it was determined that ratings are normally distributed and, depending on the situation, have a standard deviation between approximately 0.5 and 1 rating point. Variability of the ratings was observed to be greater from bridge decks and for bridges in relatively poor condition. In the current study, data are evaluated in an average sense, thus mitigating the effects of variability in individual bridge inspection ratings.

#### *Effects of skew and span length on condition ratings*

Many different approaches have been used to study the effects of design variables on performance and behavior of bridge decks and superstructures. This section summarizes those studies that are most germane to the current research.

Barr et al. (2001) modeled a 3-span continuous prestressed concrete girder bridge using finite elements to compare live load distribution as a function of skew angle. Select results of the study are presented in

Figure 21, which shows variation in distribution factor (DF) ratio ( $DF_{skew}/DF_{zeroskew}$ ) with respect to bridge skew angle. It can be observed from the figure that distribution factors are relatively consistent for small skew angles, but decrease for skew angles greater than 20 degrees. Khaloo and Mirzabozorg (2003) and Bishara et al (1993) arrived at similar conclusions. As the distribution factor decreases, a greater portion of the load is shared through the bridge deck to the girders. This effect is considered in distribution factors presented in the AASHTO LRFD Bridge Design Specifications (AASHTO, 2012), which are referenced as “LRFD” in Figure 21

Because large skew angles result in decreased girder load distributions, it is reasoned that the decks in bridges with large skew should wear out at faster rates. In bridges with large skew angles the deck is “working harder” to distribute loads, and thus experiences greater distress and lower condition ratings. This effect has been observed in bridges with integral abutments in New York State (Alampalli and Yannotti 1998). The analyses presented in Section 4 elucidate if the effects of skew are also reflected in the inspection ratings of prestressed bridges in the southeastern US.

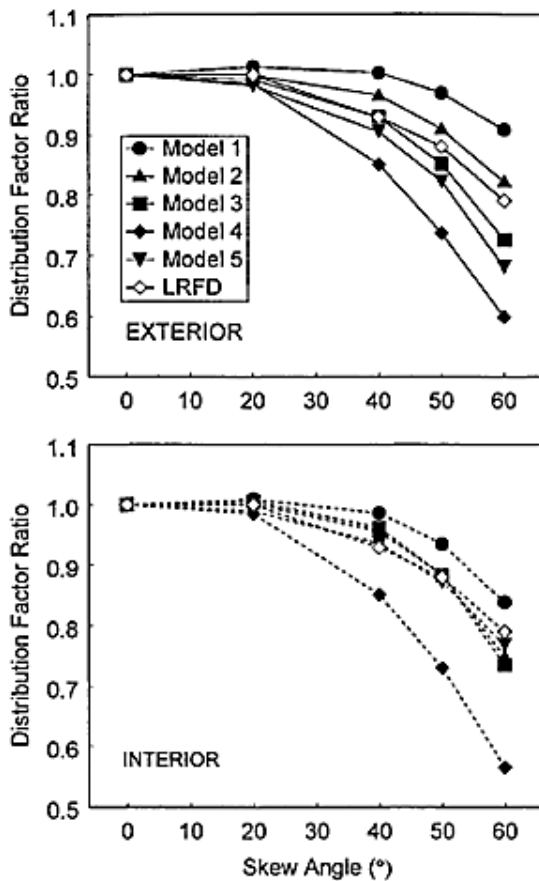


Figure 21. Effects of skew angle on live load distribution (*reproduced from Barr et al, 2001 with permission from ASCE*)

The effects of span length on transverse cracking of bridges with concrete decks and composite steel girders have been studied by Ducret et al. (1999) through laboratory experiments, French et al (1999) through a field study, and Saadeghvaziri and Hadidi (2005) through finite element modeling. Each study concluded that higher longitudinal girder stiffness (relative to the deck stiffness) provides greater restraint and thus causes increased deck cracking. The current research investigates if a similar phenomenon is at work in prestressed concrete bridges. It is reasoned that as span length increases, larger members are used (or members are spaced closer together), member stiffness increases relative to the deck, deck restraint is increased, transverse cracking is increased, and deck ratings decrease. The ANN-FFS method is used to determine if less cracking and high deck ratings are associated with short spans in prestressed concrete bridges.

## **Methodology**

### ***Source Data***

Quality source data is essential for creating models that provide useful results. This section describes the datasets and the filtering processes used to create the ANN models. Separate datasets were used for creating models to estimate DR and SSR. All data were taken from the 2014 NBI for the states of Alabama, Georgia, Louisiana, Mississippi, North Carolina, South Carolina and Tennessee. Data from multiple states were used to create a sufficiently large dataset for training and validating the ANN models. Each of the states has a similar climate and, with the exception of Tennessee, includes both coastal and inland bridges. Design, construction, and maintenance policies vary from state to state; therefore one limitation is that the analyses are based on the aggregate performance

of bridges in all of the states that comprise the dataset. The data filter process for deck and superstructures is presented in Figure 22 and Figure 23, respectively. Filtering steps are discussed in the following paragraphs.

Because of their prevalence in the Southeastern US, this study focuses on bridges with prestressed concrete (PSC) superstructures. The first filter removed bridges with superstructures other than PSC. The NBI does not differentiate between types of prestressed concrete superstructures, thus the dataset represents a range of different member types (girders, boxes, segments, etc.), and includes both precast/prestressed and post-tensioned structures. Subsequent steps were taken to focus the dataset on prestressed girder bridges.

The second filter for the superstructure dataset removed bridges that are older than 25 years or younger than 15 years. In contrast, the age filter for the bridge deck dataset is based on a range of 5 to 15 years. These ranges were selected based on the relative life of bridge components; decks typically degrade at an earlier age as compared to superstructures

The third filter for both datasets removed bridges having maximum spans less than 28m (90 ft) or greater than 62m (200 ft). Depending on the range of interest, different span lengths could be filtered for, provided that the resulting dataset yields sufficient information for model training and validation. This study focuses on girder bridges; however, the NBI does not provide a means of differentiating between girders and other superstructure types. The low end filter for span length eliminated bridges using prestressed boxes and slabs, which are sometimes used for shorter span bridges up

to 30m (100 ft) in the study region (SCDOT design manual, 2006). Prestressed I girders and bulb tees are common for spans up to 50m (Castrodale, 2004) though they are more recently used for spans up to 60m (FDOT, 2009). In order to target I-girder bridges, a span range of 30m to 40m is considered in the simulation phase of this research, as discussed in Section 3.3.

The fourth filter removed bridges that have decks other than concrete. Both precast and cast-in-situ decks are included in the study. The fifth filter removed bridges having deck protection systems. Deck protection improves the performance of decks; however this study was interested in deterioration of decks without protection.

The sixth filter removed bridges that have received improvement treatments (significant upgrades or repairs). Improved bridges were identified by looking for year-over-year reduction in *Bridge Improvement Cost* values reported in the NBI. Past years' NBI data were also checked for increases in condition ratings, as this also suggests improvement treatments. Excluding improved bridges is necessary to create a comparable dataset for training of ANN models.

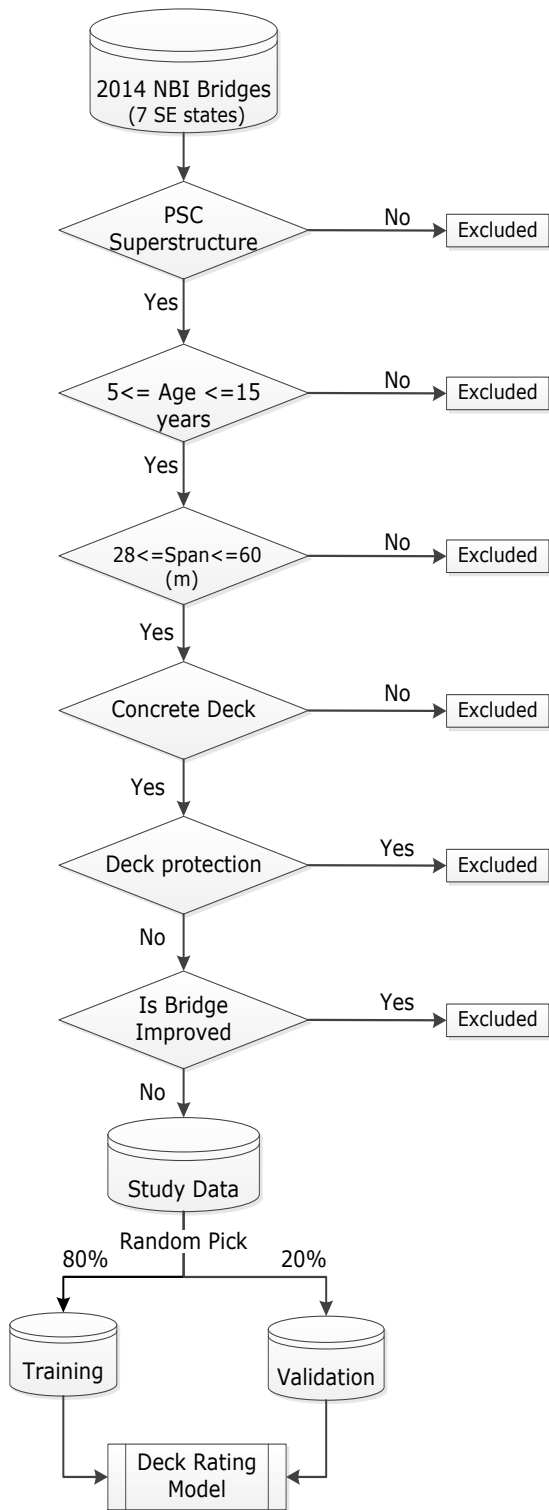


Figure 22. Data for deck model

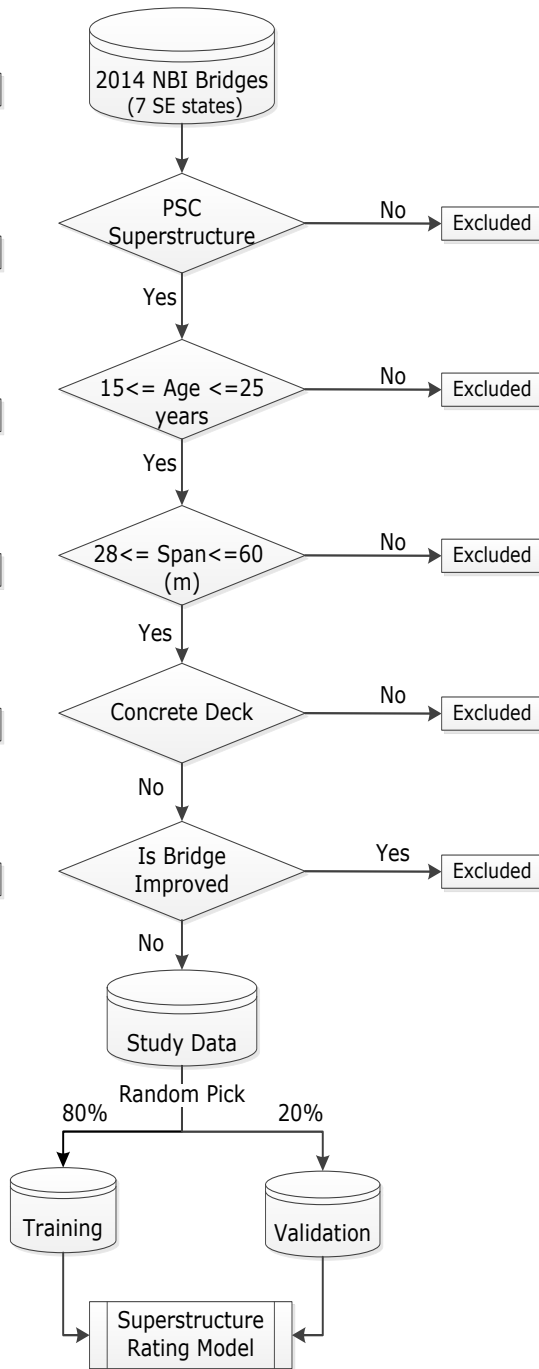


Figure 23. Data for superstructure model



After all filters were applied, a total of 520 and 450 bridges comprised the DR and SSR datasets, respectively. Both dataset were then randomly subdivided into training sets consisting of 80% of the bridges and validation sets with the other 20% of bridges. The training sets were used to develop, train and validate the ANN models, while the validation sets were used for additional validation of the developed models.

### ***Model Training and Validation***

Two models were developed in this study. The DR model predicted the deck condition rating as output variable. The SSR model predicted the superstructure condition rating as output variable. Input variables for both the models included skew angle, maximum span length, deck width, average daily traffic (ADT), average daily truck traffic (ADTT), and age.

Models were built using the Mathworks® Matlab neural network toolbox (Mathworks®, 2015). A multi-layered feed forward neural network with error back propagation was selected for this study. The model was a two-layered neural network with 40 neurons, and the Levenberg-Marquardt training function was selected for optimization.

Table 11 summarizes the goodness of fit for the DR and SSR models; fit is reported using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Lower MAE and MAPE values indicate smaller errors and more accurate models. As shown in the table, the models are reasonably accurate; MAPE values are low and MAE values are within the range of scatter inherent in inspection data as reported by Phares et al (2004). A linear-regression model was also constructed from the source data..

As reported in Table 11, the ANN model has less error than the linear model for all datasets.

Table 11. Model Validation

Dataset		ANN		Linear Regression	
		MAE	MAPE	MAE	MAPE
DR	Training	0.35	4.7%	0.46	6.2%
	Validation	0.34	4.4%	0.44	5.8%
SSR	Training	0.32	4.5%	0.53	7.9%
	Validation	0.54	7.5%	0.57	8.1%

***Test Bridges and Full Factorial Simulations***

Three bridge types were used in the analyses: low-volume, medium-volume, and high-volume. These types were selected to cover the range of bridges within the dataset, while also representing commonly occurring bridges. Using the full factorial approach, unique combinations of variables were simulated using the validated ANN models.

The upper level for maximum span length was set at 40m for the simulations. This was done to limit the analysis range to match common span lengths of prestressed girders in the study region. Levels used for widths were selected such that the low- and medium-volume bridges are two-lane and the high-volume bridge is three lane.

Table 12 lists the variables and levels considered for each bridge type. Values for each level were chosen such that they fall between the 25 percentile and 75 percentile values of the datasets. This is done so that the analyses do not include extreme variable values

and do not rely on extrapolation from the source data. Six different levels were considered for each of the six variables. For a full factorial array,  $6^6$  or 46,656 simulations were conducted for each bridge types. In other words, each possible permutation of the variables and levels presented in Table 12 was used in a simulation.

The upper level for maximum span length was set at 40m for the simulations. This was done to limit the analysis range to match common span lengths of prestressed girders in the study region. Levels used for widths were selected such that the low- and medium-volume bridges are two-lane and the high-volume bridge is three lane.

Table 12. Variables and levels used in simulations

Bridge Types	Variable levels						
	Skew (deg.)	Max span (m)	Width (m)	ADT	ADTT	Age (years)	
						DR	SSR
Low-volume	0, 10, 20, 30, 40, 50	30,32, 34,36, 38,40	10,10.5,11, 11.5,12,12.5	500,700, 900,1100 1300,1500	50,60,70 80,90,100	8,9,10, 11,12,13	18,19,20 21,22,23
Medium-volume	0, 10, 20, 30, 40, 0	30,32, 34,36, 38,40	10,10.5,11, 11.5,12,12.5	2000,3200, 4400,5600, 6800,8000	500,600, 700,800, 900,1000	8,9,10, 11,12,13	18,19,20 21,22,23
High-volume	0, 10, 20, 30, 40, 50	30,32, 34,36, 38,40	17,18,19 20,21,22	10K,12K, 14K,16K, 18K,20K	800,1050, 1300,1550 1800,2050	8,9,10, 11,12,13	18,19,20 21,22,23

### ***Benefits and Limitations***

Two limitations of the methodology are mentioned here. First, results from the ANN-FFS methodology are based on average performance over the considered study region, variables, and range of levels. While useful for identification of overall trends, results of

the approach are not necessarily applicable at the level of a specific bridge. Bridge-specific studies can still be made using ANN models and one-factor-at-a-time methodologies; however, this is not the focus of this paper. Second, the approach provides results that are strictly empirical. Bridge inspection data are evaluated at a high level, but the results do not provide information on the physical phenomena which lead to the inspection ratings. For this reason it is important to use caution when inferring causation from the ANN-FFS analysis results. This paper studies causation by combining results of the ANN-FFS analysis with the results of previous researchers who used physical experiments and structural analysis models.

Regarding the benefits of such an approach, note that, ANN models can be superior to linear regression methods, as they are capable of learning and representing nonlinear relationships in a system. Results in Table 11 demonstrate superiority for ANN to linear regression for the current study. The methodology also provides a systematic method for analyzing large sets of inspection data, and compliments other research methods such as structural modeling, small field studies, and laboratory work.

## **Results and Discussions**

Figure 24, Figure 25, and Figure 26 present the estimated DR (left) and SSR (right) for the low-, medium-, and high-volume bridges, respectively. To explain the construction and interpretation of the figures, reference is made to Figure 24a. In this plot DR is shown as a function of skew for low-volume bridges. Using the full factorial approach, data in the plot come from each of the 46,656 unique simulations. Six different levels were used for skew starting at 0 degrees and ending at 50 degrees. One-sixth or 7,776 of

the simulations were associated with each level of skew. As observed from the 0 degree level of skew in the plot, the simulation outputs ranged from a high DR of 8.9 to a low of 5.7, with an average of 7.8. Range and average are shown for each level of skew and are also based on 7,776 unique simulations. The dashed line in the plot consists of straight-line segments connecting the average output from each level. The line is useful for evaluating the overall trend between DR and skew. Each individual plot in Figure 24, Figure 25, and Figure 26 was created in the same manner.

In practice, individual bridges ratings are reported as integer values between 0 and 9. However, the ANN models output ratings as decimal numbers. While inconsistent with practice, these decimal values provide useful information as they are based on the aggregate performance of all bridges in the source data. Thus, we assume that an average increase of 0.5 rating points is significant because it is spread over the entire dataset.

Within the given analyses, the greatest changes in ratings were observed for skew, span, and age; accordingly these effects are reported in Figure 24, Figure 25, and Figure 26 and in Table 13. In general the average ratings decrease with increases in skew, span, and age. The only exceptions to this trend were span length and SSR for medium- and high-volume bridges. The improvements in ratings for these exceptions were modest relative to the decreases observed in the other cases.

Deck ratings are of primary interest due to the relatively short service life of bridge decks. Recall from the background material on the effects of skew that load distribution changes as a function of skew angle and that one goal of the current study is to determine if these changes impact deck condition. Comparing Figure 21 to Figure 24a,

Figure 25a, Figure 26a, it is noted that the relationship between skew and the DF ratio follows the same trend as the relationship between skew and DR. For skew angles less than 20 degrees, DF ratio and DR are constant or gradually changing. As the skew angle increases beyond 20 degrees, both DF ratio and DR rapidly decrease. It is concluded that increased load distribution associated with large skews, leads to increased load demand in bridge decks, which causes increased deck distress and lower ratings. This conclusion is consistent with the results of the research study conducted by Bishara et al (1993). Increased torsional effects in skew bridges are also noted as another possible factor contributing to the observed relationship between skew and DR.

Referring to Figure 24b, Figure 25b, Figure 26b, 20 degrees also appears to be a significant point in the relationship between skew and SSR. Values of SSR are highest at zero skew, decrease as skew increases to 20 degrees, and are effectively constant at skew angles greater than 20 degrees. This observation may also be due to changes in load distribution. As skew increases 20 degrees, loads are spread between more and more girders, distress on individual girders is reduced, and SSR is constant. For the range of variables considered, the effects of skew on SSR are smaller than those on DR. It is concluded that skew angles less than 20 degrees are optimal for the longevity of decks and superstructures.

As mentioned previously, previous researchers have studied the effects of transverse deck cracking in steel girders bridges with composite bridge deck, and have concluded that higher longitudinal girder stiffness (relative to the deck stiffness) provides greater restraint and thus causes increased deck cracking. This phenomenon can be

associated with span length, because greater spans required stiffer girders. The data presented in Figure 24c, Figure 25c, and Figure 26c support the notion that similar effects are present in prestressed girder bridges; in each Figure, DR is highest when the span length is lowest. Although the causes of deck deterioration with increased span length cannot be definitively determined from the evidence presented, it is deemed plausible that this observation is due in part to effect of increased longitudinal superstructure stiffness in longer spans. Increased stiffness leads to increased deck restraint, and consequently to transverse deck cracking and lower ratings. Another possibility is that ratings decrease with larger spans because they have greater deck area and greater opportunity for damage. However, this possibility is considered secondary; inclusion of total structure length (which also increases opportunity for damage) was found to decrease the accuracy of the ANN model. Both possibilities are recommended for future study. In discussing the effects of span length, it is also noted that average SSR show little change with respect to span length.

With the exception of DR on high-volume bridges, age has the greatest effect on ratings in this study. The effects of age on SSR can be observed by comparing the ranges of SSR values. The range of SSR for a given skew or span is much wider (~1 point) as compared to range at a given age (~0.5 points). Decreased scatter in ranges shown in Figure 24f, Figure 25f, and Figure 26f demonstrate the criticality of age in the estimating SSR; this observation is consistent with previous research on the effects of age on SSR (Contreras-Nieto et al 2016).

The relationship between age and DR in high-volume bridges is curious (Figure 26e). Why does age appear to have a smaller effect on deck ratings in high-volume bridges? Neural networks learn from data, and the relationships represented in the ANN models may not indicate causation. This may be culpable in some of the trends observed in high-volume bridges. It is possible that bridges with the highest levels of traffic are prioritized for maintenance, and that increased maintenance accounts for the relationship observed in the results. While the source data was filtered to account for improvement interventions, it does not include information on maintenance. Inclusion of maintenance records (not available in the NBI) as an input for the ANN models would allow for testing of this possibility. Such efforts are a recommended extension of the current research.



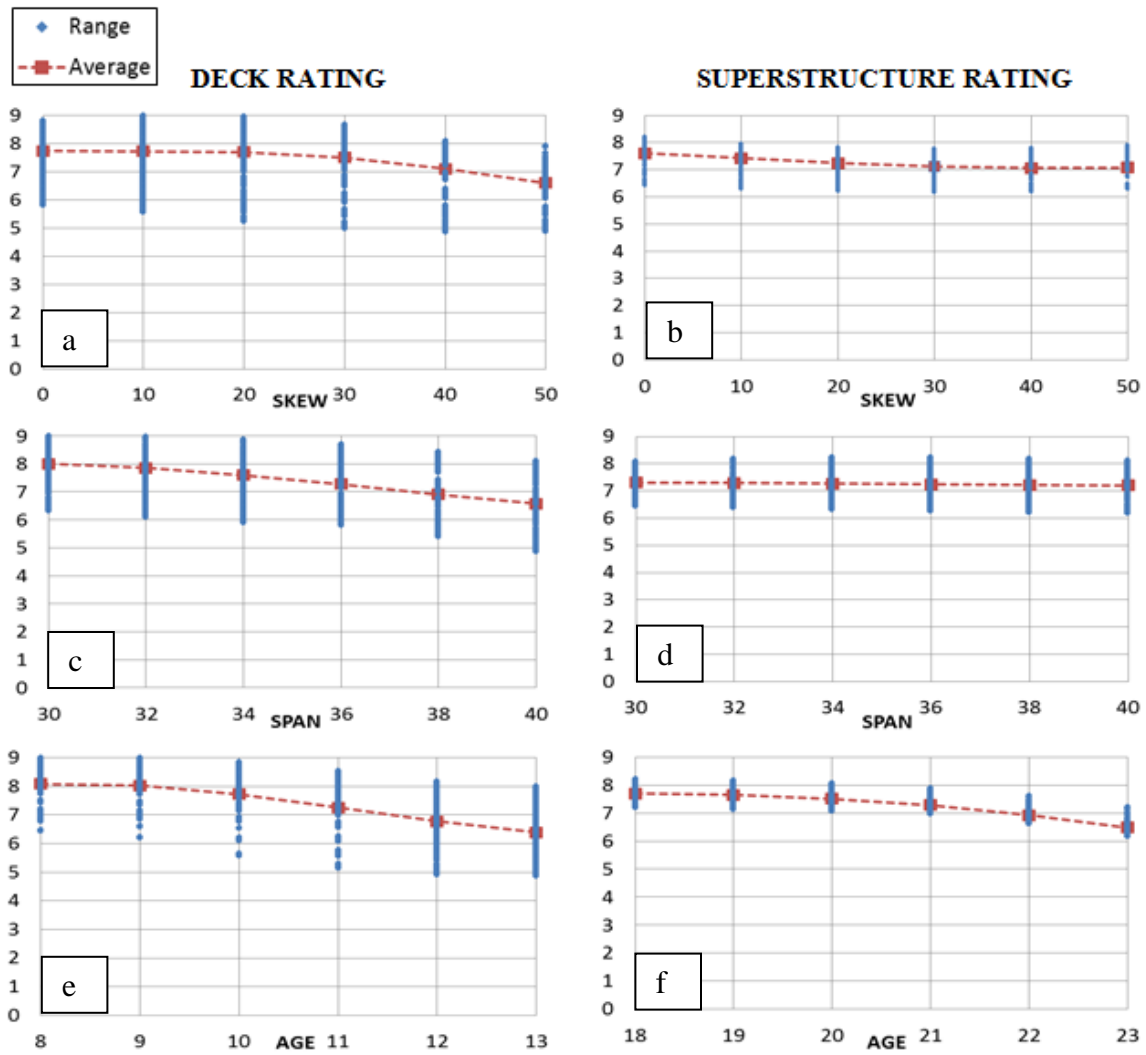


Figure 24. Deck and superstructure ratings for low traffic volume bridges

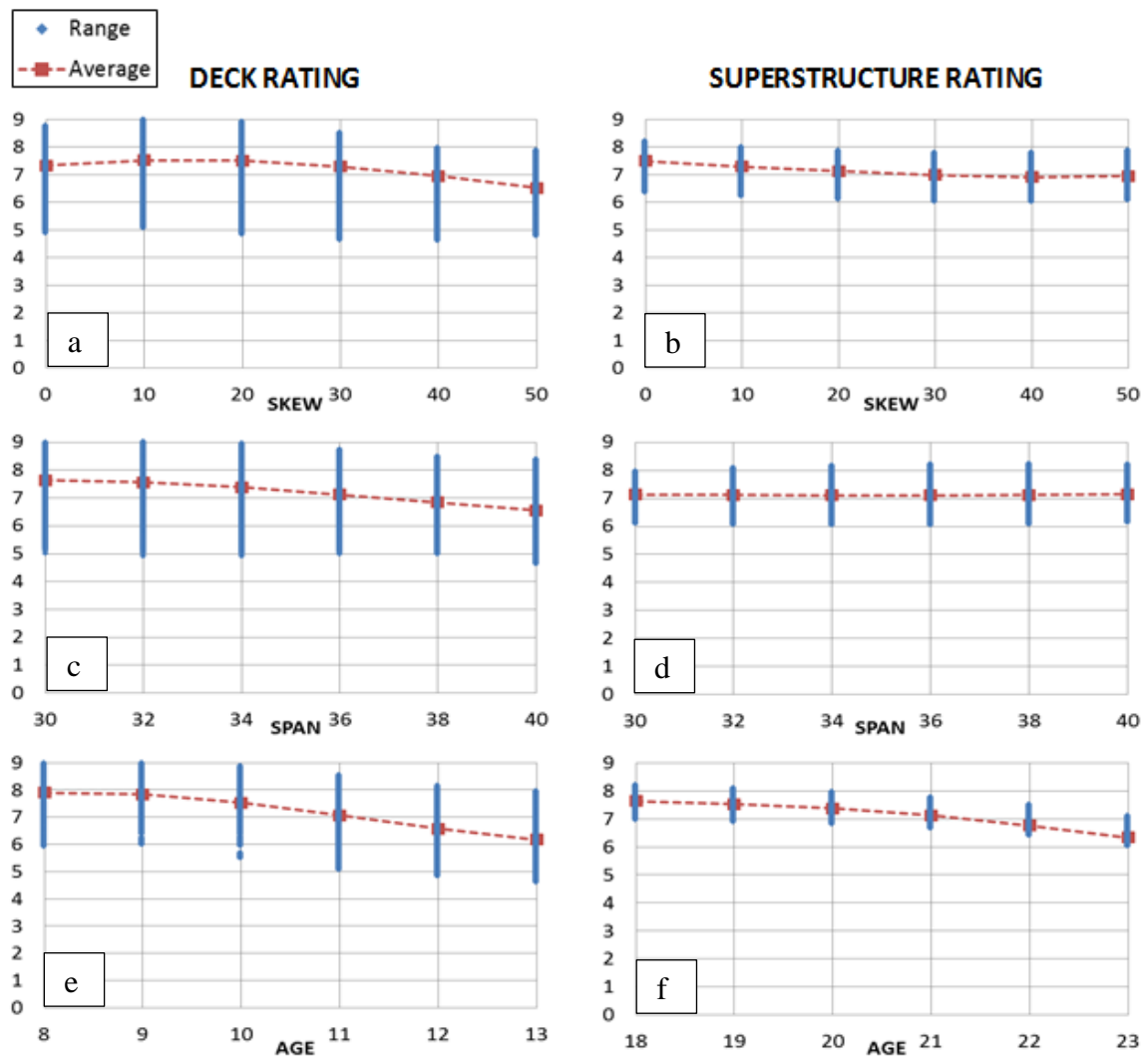


Figure 25. Deck and superstructure ratings for medium traffic volume bridges

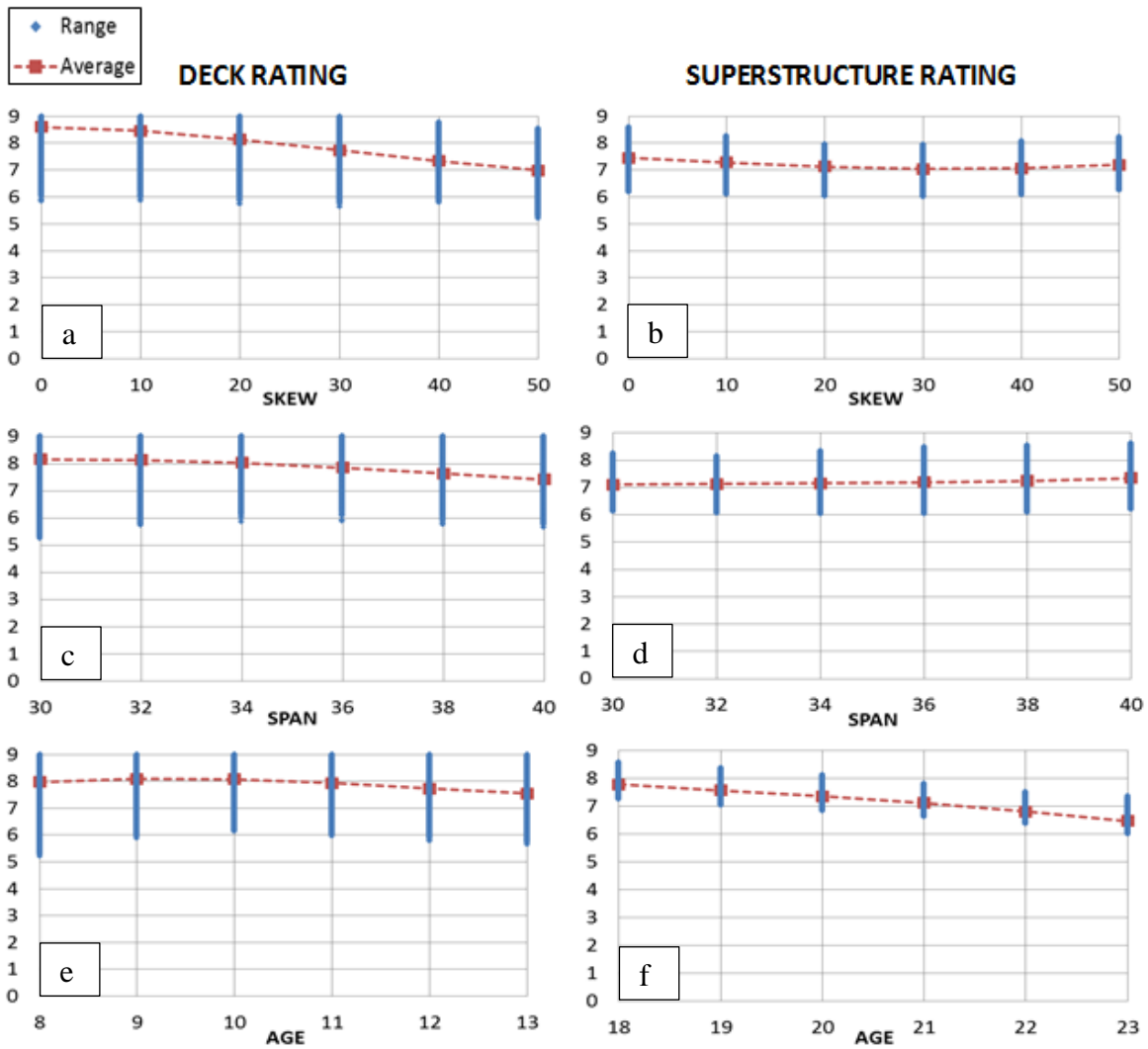


Figure 26. Deck and superstructure ratings for high traffic volume bridges

Table 13. Percent change in ratings over the considered range of variable values

Bridge Type	Ratings	Percent change over tested range		
		<i>Age</i>	<i>Skew</i>	<i>Span</i>
Low-volume	DR	-20.9	-14.7	-17.9
	SSR	-15.7	-7.0	-1.4
Medium-volume	DR	-21.8	-10.9	-14.1
	SSR	-17.0	-7.2	0.0
High-volume	DR	-5.3	-18.7	-9.1
	SSR	-16.8	-3.5	3.3

### Summary and Conclusions

An approach for analyzing bridge inspection data using Artificial Neural Networks and a systematic array of simulations was presented and demonstrated using inspection data from prestressed concrete bridges in the Southeastern United States. Skew angle, span length, age, total traffic, truck traffic, and width were inputs to the ANN models, which estimated the condition rating of bridge decks and superstructures. While the demonstrated methodology can be broadly applied, the conclusions are specific to the range of variables studied on prestressed concrete bridges in Southeastern United States.

Salient observations and conclusions are as follows:

- The ANN models accurately estimated condition ratings for the given source data. Mean absolute percent error in the estimates were 4.4% to 4.7% for deck ratings, and 4.5% to 7.5% for superstructure ratings. The mean absolute errors were always 0.57 or lower, which is within the range of scatter inherent in bridge condition ratings.

- Skew angle has little impact on deck condition ratings for small skews; however, ratings are negatively impacted by skew angles greater than 20 degrees. This observation is consistent with previous researchers (Barr et al. 2001, Khaloo and Mirzabozorg 2003) who have identified 20 degrees as the boundary between different load distribution behaviors. For bridges with large skew, load distribution through deck increases, which causes increased deck distress and lower ratings.
- Higher deck ratings correspond with shorter spans. One plausible explanation is that as span length increases, larger members are used (or members are spaced closer together), member stiffness increases relative to the deck, deck restraint is increased, transverse cracking is increased, and deck ratings decrease. This phenomenon has been observed in steel girder bridges with composite decks (Ducret et al 1999, French et al 1999, Saadeghvaziri and Hadidi 2005), however, additional research is required to confirm if this phenomenon also impacts prestressed concrete bridges.
- Superstructure ratings are negatively impacted by skew angle; however the effect is less pronounced than that for deck ratings. The effect of skew on superstructure ratings is diminished for skews greater than 20 degrees. This observation is attributed to the aforementioned relationship between skew angle load distribution.

## Acknowledgements

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## CHAPTER SIX

### **NON-LINEAR AUTO REGRESSION MODEL TO EVALUATE THE EFFECTS OF IMPROVEMENTS ON BRIDGE INVENTORY CONDITION**

#### **Abstract**

The ability to accurately forecast bridge condition is imperative for developing better bridge management systems. While methods such as ‘feed forward’ and ‘back propagation’ Artificial Neural Networks forecast bridge condition reasonably well, these algorithms cannot learn from time series data. In this study, time series data based non-linear auto regression (NARX) algorithm was applied for modeling bridge condition. A model was developed using twenty five attributes pertaining to bridge structural, geometry, age, traffic, and bridge improvement spending as input variables to estimate the future average Sufficiency Rating (SR) for the bridge inventory and study the effects of improvement spending on the inventory condition. The model was built using inspection records for bridges in SC that existed between 1992 and 2013. The average SR of the inventory is projected for various possible bridge improvement funding scenarios. It is concluded that NARX model can accurately estimate SR for bridge inventory, and is a suitable method for using large set of variables and data to assess the condition of bridge inventories.

## **Introduction**

Factors such as geometry, age, structural system, traffic, maintenance interventions, and improvement interventions have impact on bridge conditions. As discussed in chapter five of this report, improvements intervention decisions are often based on how conditions ratings of a bridge compare with a specified threshold (Ryan et al, 2012). While maintenance activities prevent bridges from deterioration, improvements are used to bring bridges to a better condition (FHWA, 1995). Bridge condition ratings and sufficiency ratings improve due to bridge improvement activities. However, the scale and size of these improvement activities depends on annual money spent on bridge improvements.

This chapter investigated the combined effects of bridge variables and annual bridge improvement money on bridge inventory. The time variant NARX neural network model was developed using twenty five bridge specific factors and annual bridge improvement money spent as overall variable to forecast Sufficiency Rating (SR) for the South Carolina bridge inventory.

The specific objectives of this chapter are:

1. To demonstrate a novel approach for forecasting bridge inventory condition using NBI inspection records for bridges; and
2. To forecast the average SR of bridges in SC considering combined effects of bridge variables and annual bridge improvements budget.

## **Background**

A review of literature and previous research on Artificial Neural Network applications in civil engineering and bridges is presented in the chapter five of this dissertation. Background information in this chapter focuses on time variant neural networks and their applications. Details of the NARX model, a type of time-dependent ANN modelling, are discussed.

### *Time Variant Neural Networks*

Traditional neural networks are not effective in learning patterns from dynamic systems over time. Time variant neural networks consider dynamic relationships between inputs and outputs that change through time. Very little research has been conducted so far on the application of these algorithms to bridge and structural engineering. In a research study by Barai and Pandey (1997) where the damage in steel truss bridges is estimated using data on vertical displacements, the prediction performance of time delay neural networks is proven to be superior to that of static models. The study compared the performance of traditional neural networks and time delay neural networks. Similarly time series based neural networks had better prediction of pavement cracking index as compared to traditional models (Lou et al, 2001). Nevertheless, most of the applications of ANN in civil engineering have been based on traditional neural networks that do not consider pattern changes in time due to lack of computing resources (Barai and Pandey 1997, Lou et al 2001). It is noted that this limitation is diminished as computer resources have advanced significantly since time-series neural networks were first applied in civil engineering.

### *NARX networks*

NARX networks are sophisticated versions of traditionally used time series based neural networks. NARX models are recurrent dynamic networks with feedback connections enclosing several layers of the network (Mathworks®, 2014). By using multi layered structure, NARX models can learn and predict behavior of complex nonlinear systems. These networks can model nonlinear relationships among variables in time. In a NARX model, the response variable (called ‘target’) at any time in future is not only a function of historic values of independent variables but also is a function of historic values of target itself. Multi-layered parallel processing abilities make NARX a fit for learning from huge nonlinear data even in the presence of noise.

Being relatively new, there has been only limited application of NARX models in civil engineering. Examples of the use of NARX neural networks can be found in other fields (e.g. Basso et al 05, Pisoni et al 09, Napoli & Piroddi 10) Palumbo and Piroddi (2001) applied NARX neural networks to model nonlinear response of buttress dam scale models subjected to seismic-like excitations. Ruslan et al (2014) concluded that NARX model was successful in predicting flood water levels and flood location 10 hours ahead of time. Hidayat et al (2011) applied NARX neural networks for developing models for fatigue life assessment of materials.

The application of NARX models to the field of bridge engineering is very minimal. Zolghadri et al (2015) applied linear regression, auto regression and NARX networks to correlate temperature changes with natural frequencies while studying dynamic characteristics of bridges for long term structural health monitoring. The NARX

models gave the best fit out of the three models. Lin et al (2012) proposed a neural network based health monitoring system for bridges. It was demonstrated that NARX models can find fundamental frequency of bridge decks using data collected from earthquakes, and that NARX models can identify nonlinear relationships which cannot be achieved by traditional methods like linear regression or conventional neural networks. However, no research is conducted so far on the application of NARX networks in the area of bridge infrastructure condition prediction or bridge management.

In NARX model, the historic data of the response variable is used to estimate its future values. Thus the response of the systems does not depend on past values of dependent variables alone. Equation 11 shows the mathematical representation for NARX model. The target variable value of  $y$  at any time 't' can be predicted from input variable 'x' values and target 'y' values for 'n' historic years until time 't' as shown below.

$$y(t) = f\{y(t-1) \dots \dots y(t-n), x(t), x(t-1) \dots x(t-n)\} \quad \text{Equation 11}$$

Figure 27 shows graphical interface of NARX model and its architecture as represented in Matlab®.

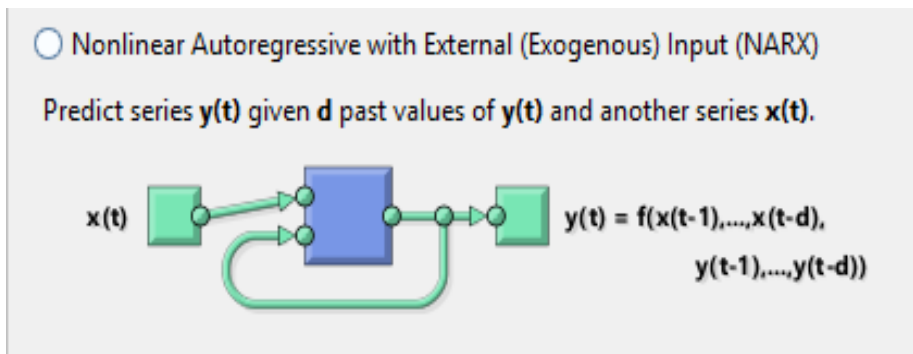


Figure 27. NARX Model (Mathworks®, 2015)

## **Methodology**

### ***NBI Bridge Data***

In time-variant neural network models, data records for the same set of bridges are required over multiple years in the past. Hence, this study required data for a set of bridges in South Carolina that were in service during the period between 1992 and 2013. Bridges that were newly built, reconstructed, removed, or replaced since 1992 were excluded from this dataset. For this exercise, MS SQL query interface tool in MS Excel is utilized. The query programs identified bridges that were continuously in service between 1992 and 2013 and aggregated NBI data for these bridges including structural, traffic, and inspection ratings. In total about 8250 (89%) bridges in South Carolina are considered for this study.

Records of bridges with information on 120 fields were aggregated from NBI ASCII files for each bridge in this dataset for each of the years between 2004 and 2013. The biggest challenge was to arrange the bridge records in the same order for every year because NARX models learn from time series patterns. Out of 116 fields total NBI data fields, twenty six fields were chosen as input parameters often called as ‘input variables’. The complete list of variables is given in Table 14. The SR of these bridges is the forecasted variable (here in called as ‘target’) considered as the outcome of interest in this study.

### ***Bridge Improvement Costs and Spent Costs***

Improvement activities are performed on bridges to improve their condition. Typical bridge improvements include repair and rehabilitation of deck or other components of the bridge. The list of activities that are categorized as bridge improvements is provided in the FHWA coding guide (FHWA, 1995). A detailed discussion about bridge improvements is presented in section two of chapter four. An improvement cost is assigned to each bridge in the NBI that needs improvements. Improvement cost is defined as the cost of any of the improvement activities performed on the bridges as per FHWA procedures. One of the input variables in the NARX model is ‘total improvement money spent’. This value is distinct from improvement costs, but can be indirectly calculated from the improvement costs listed in the NBI. The calculations are made as follows.

The estimated ‘total Improvement costs’ for each bridge are captured in field 96 (TOTAL\_IMP\_COST) of the NBI record format. When money is spent on a bridge for improvements, the estimated ‘total improvement costs’ of that bridge for subsequent years will reduce by an amount that is assumed to equal to money spent on improvements. Also, when bridges are improved, their ratings increase significantly. Using these criteria the bridges that were improved are identified to calculate the improvement costs. The total money spent annually on bridge improvements is calculated by summing up the money spent on individual bridges. Based on historic data it was found that on an average about 80 million USD is spent annually on bridge improvements in SC in recent years.

Apart from improvements, bridges are subjected to routine maintenance activities. These activities are performed on a predetermined schedule to prevent bridge deterioration. The NBI bridge records do not provide information about bridge maintenance activities. However, the records include the effects of bridge maintenance activities. It is assumed in this study that the level of maintenance activities will remain at the same levels as in the past. Also, the effects of bridges that are newly built or removed or replaced during the period of study are not considered.

#### *Inputs and target variables*

A NARX model was developed in this study for estimating the average sufficiency rating of the SC bridge inventory. Twenty five bridge specific attributes such as age, ADT, design load, skew, design type, material, clearances, condition ratings, etc. are chosen as inputs. The money spent on bridge improvement is a global input to the model. This means that each bridge was assigned the same value for ‘improvement money spent.’ The method for calculating this value was discussed in the previous section.

The variables of study are listed in Table 14.



Table 14. Variables for the model

Detour Length	Railings Condition	Vertical Under Clearance
Maintenance Agency	Bridge Transitions	Operating Rating
Function Class	Structure Material	Inventory Rating
Age (Year Built)	Structure Design	Structural Evaluation
Average Daily Traffic	Structure Length	Deck Geometry
Average Daily Truck	Maximum Span	Waterway Evaluation
Design Load	Deck Width	Approach Road Evaluation
Skew Angle	Horizontal Under	Strategic Highway Network
Deficiency Status	Improvement Money Spent (Global)	Sufficiency Rating <i>(Response or Target variable)</i>

For NARX models, ‘time’ is the third data dimension, with bridges and input variables being the first two dimensions. Input data is fed into the model for each of the years from 2004 until 2013. MatLab® programs are developed to import data from Excel® sheets for each of the years into a 3D cell arrays. Cell arrays are special data structures that can store data as multiple objects of 2D arrays. A figure depicting 3D cell array data for the models is presented in Figure 28.

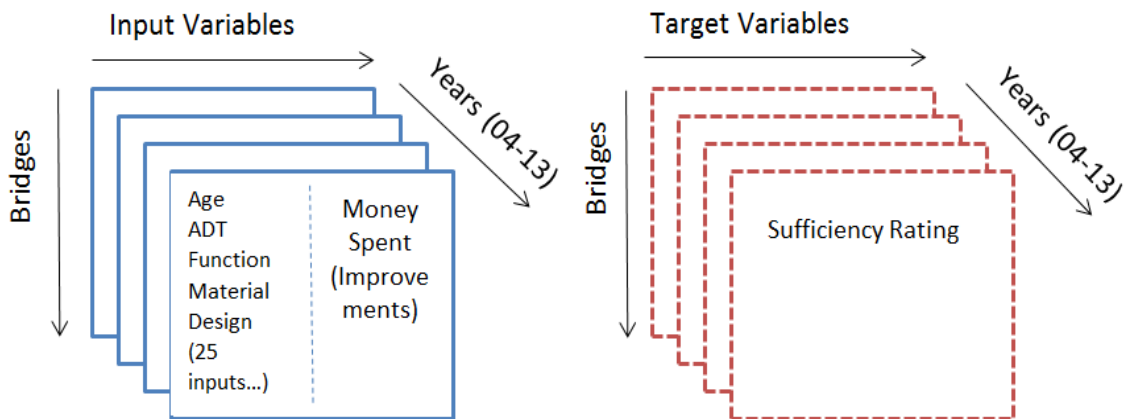


Figure 28. 3D data model for NARX network

### ***Training, validation & prediction***

NARX modelling was conducted in three phases. The ‘training phase is also known as development phase, and is used by the model to learn from the source data. In the ‘validation’ phase the trained model is tested for its reliability by comparing the model outputs with known values from the source data. During the ‘prediction phase’, simulations are performed on the developed model to forecast the effects of variable inputs (spent improvement costs) on future outputs (sufficiency rating).

A schematic figure showing these three phases for this study is shown in Figure 29. The years 2004 to 2009 are used for developing and training the model from the source data. During the training phase, source was split so that 70 percent was used for learning and 30 percent for statistical validation and testing purposes; the 30 percent allows for automated checking of model reasonableness during training. In this manner, validation begins in the training phase. The validation phase includes years 2010 to 2013. This is manual validation phase which is in contrast with the MatLab® neural

networks auto validation that is performed during the training phase with 30% of training records done for the purpose of checking for error convergence. During the validation phase, the model results are compared with NBI reported values. If the results are acceptable then the developed model can be reasonably used for predictions; if not the model is re-trained.

Once trained and validated, the model was deployed to perform simulations for forecasting the future SR for the years 2014 to 2020. In this study nine possible scenarios for bridge improvements funding are considered. The amounts range from no spending to highest spending of 160 million USD with increments in multiples of 20 million USD. The model forecasts the average SR of the bridge inventory for each of these nine scenarios.

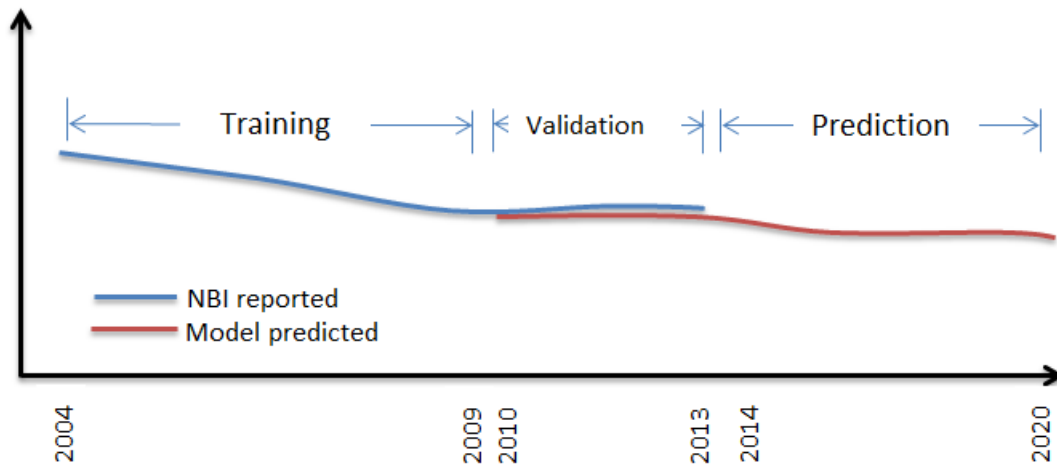


Figure 29. Schematic drawing of validation, training & prediction phases

### *Training and Validation Details*

The model is developed using MatLab® programming tool. The ANN tool box plugin is used for generating the scripts for data imports and creating the architecture of the network and running training algorithms. As in Figure 30, a multi-layered NARX network is developed. After training several times, the network shown in Figure 30 with about 20 neurons using Bayesian Regulation algorithm is found to give the smallest error.

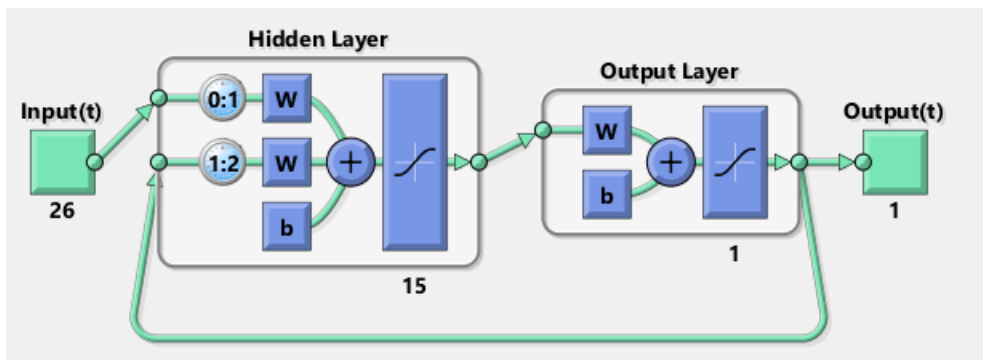


Figure 30. Network Architecture (MatLab®)

Table 15 summarizes the error between the validation data and NARX results. Recall that validation begins during the training phase as the Matlab toolbox uses a portion of the source data to create the model and another portion to calculate the error and stop the training. This occurs automatically during the model development iterations and continues until the model converges. A manual validation is also performed during the validation phase from 2010-2013. The NARX model calculates SR for each individual bridge in the dataset. Table 15 reports the statistical errors in predicting average SR at individual bridge level as well as inventory level. These are the average errors for all years within the given phase.

The error in the model at individual bridge level is 5.6% (MAPE) during the training phase and 9.5% (MAPE) during the validation phase. This indicates a good fit between the model predicted ratings and the actual NBI reported ratings at the bridge level. The model has even better fit, when applied to calculate the average SR of the entire inventory. Error in the model at the inventory level is 0.46% (MAPE) during the training phase and 0.52% (MAPE) during the validation phase. These results indicate that the model is acceptable for estimating the average SR of bridges at inventory level.

Table 15. Model Error

Phase	Level	MSE (Mean Square Error)	MAPE (Mean Absolute Percent Error)
Training (validation in MatLab, 2004-2009)	Bridge	19.62	5.6 %
	Inventory	0.21	0.46 %
Validation (manual validation, 2010-2013)	Bridge	89.02	9.5 %
	Inventory	0.17	0.52%

Comparison of the NBI reported ratings and model projected ratings shown in Figure 31 also demonstrate the validity of the NARX model. The trends are very similar. As shown, the model is able to capture the nonlinear relationship between time and average SR during the validation phase.

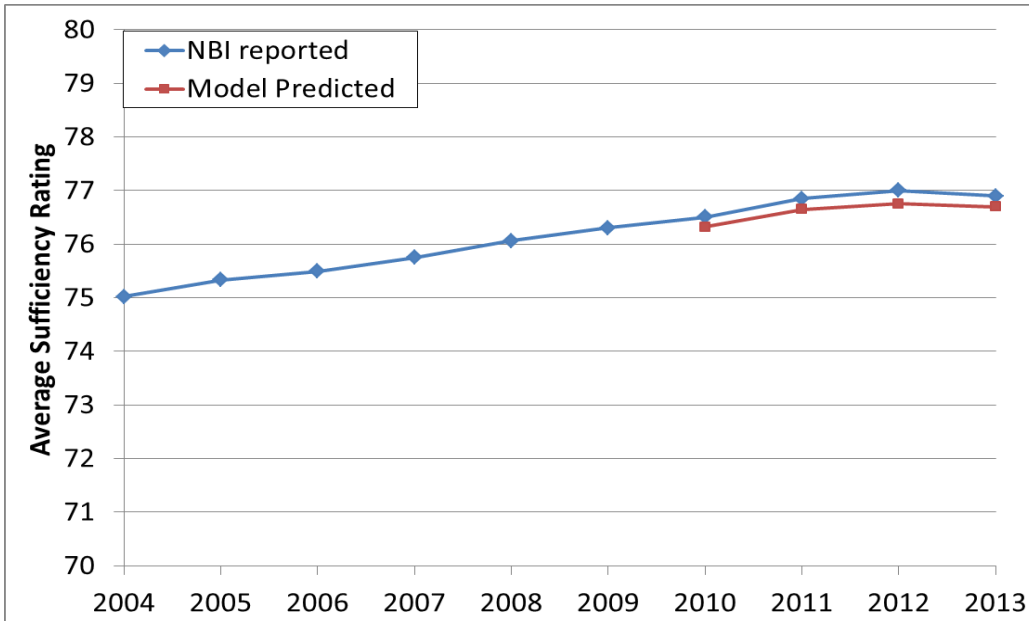


Figure 31. Comparison of NBI data and Model during validation phase (2010-2013)

## Results and Discussions

The NARX model is used to evaluate nine hypothetical funding situations ranging from \$0 to \$160 million per year on total spent improvement costs for the inventory. The model predicted the sufficiency ratings for each individual bridge in the data set for each year in the validation and prediction phases (2014-2020). The average SR of the inventory was calculated as the average of the model-calculated SR for all bridges in the inventory.

In recent years approximately 80 million USD is spent annually in South Carolina on bridge improvements. For clarity, forecast of budgets greater than 80 million are shown in Figure 32, whereas forecasts with smaller budgets are shown in Figure 33. As can be seen Figure 32, increased spending on bridge improvements consistently improved

the inventory health. The model calculated average SR in 2020 increased by approximately 0.2 points for every 20 Million USD of annual improvement spending above the current spending of 80 million USD. It may be noted that if the current level of spending is continued into the next few years, we could see a deterioration of bridge inventory health. From the figure it can be observed that at least about 120 million USD annual spending is necessary to sustain the current level of bridge inventory ratings.

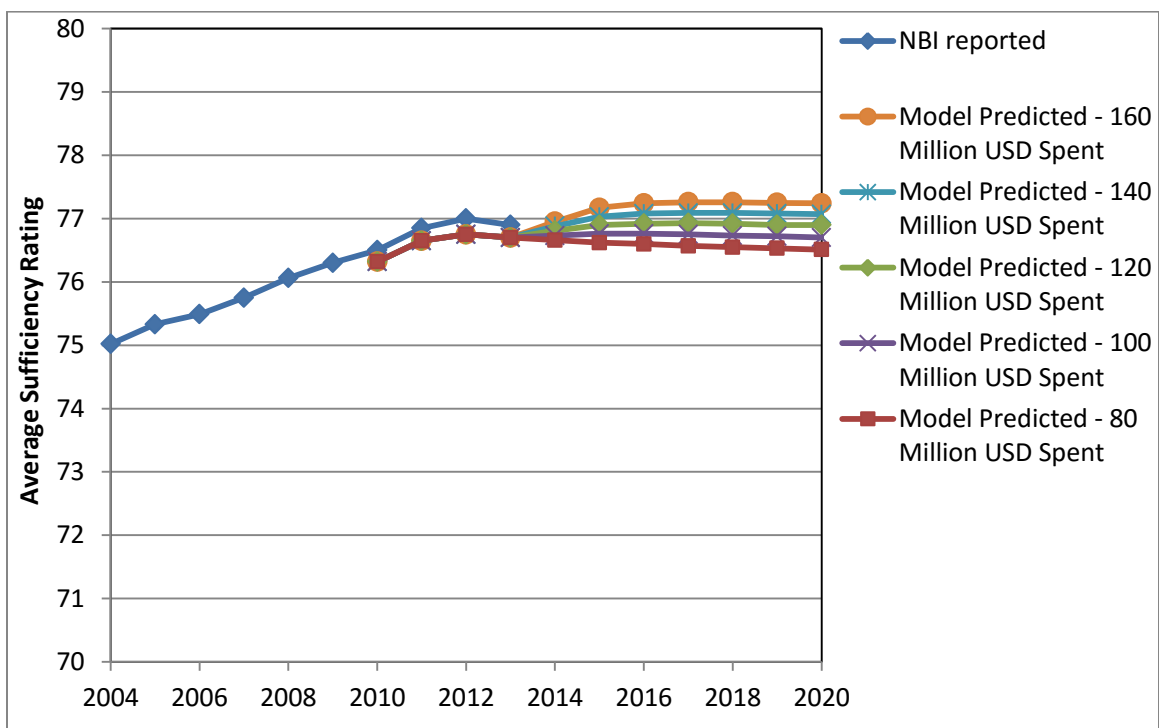


Figure 32. Average SR over time for increased spending on improvements

However, at times of poor economy or shifting priorities it is possible that funding for bridge improvements may be reduced. In Figure 33, the average SR for the bridges in the study is plotted with time for four scenarios of decreased funding. Figure 33 presents the model predicted average SR for funding from the current 80 Million USD going down to zero funding in decrements of 20 Million USD. The model calculated average

SR in 2020 dropped by 0.24 points for every 20 Million USD of annual improvement spending less than current spending. The plot indicates the rapid deterioration of bridge health in the years 2013-2016 if spending on bridge improvements is reduced. The average SR of these 8250 bridges will drop by almost 1 point in the hypothetical event of no improvement treatments are made between 2015 and 2020.

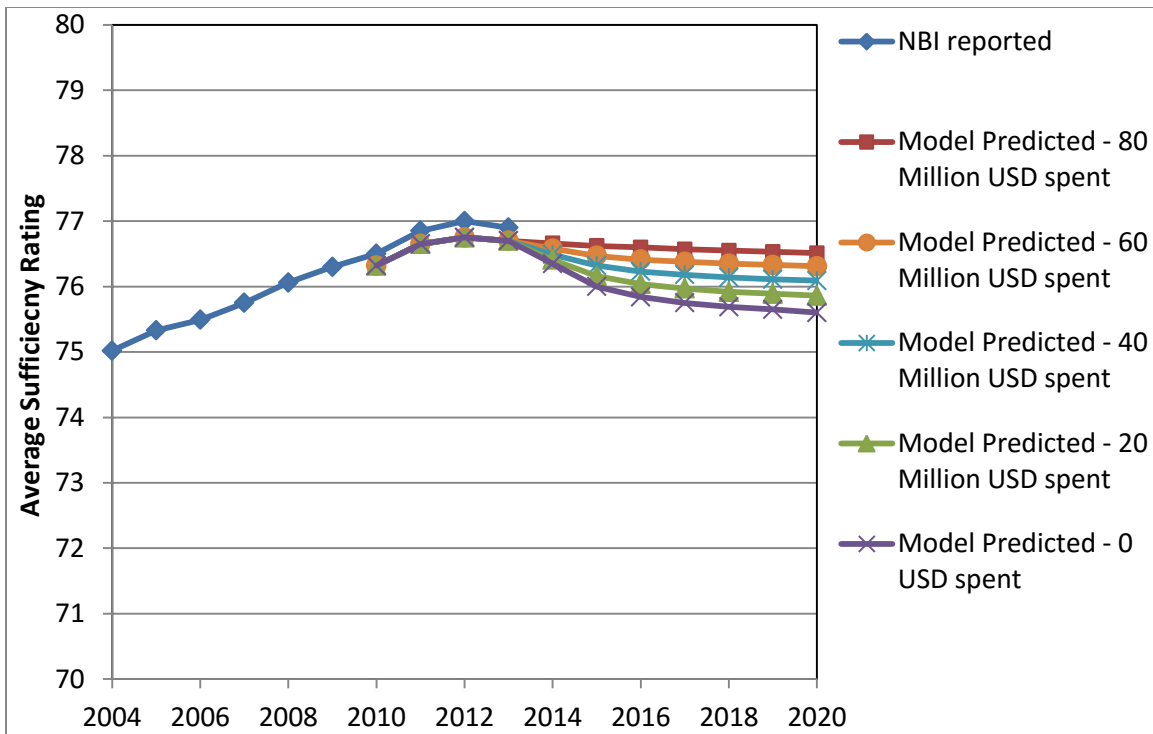


Figure 33. Average SR over time for decreased spending on improvements

It is of interest to compare and contrast the NARX model with the simplified CLD model presented in chapter three. In addition to different methodologies, the major difference between the models is the source data used in model development. While CLD model source data included all bridges in South Carolina (including new bridges, removed and replaced bridges), the NARX model was based on a fixed set of bridges that existed between 1992 and 2013. This difference is necessary because the NARX



model requires the same number of bridges for each year. Another difference is the types of data used as inputs. While CLD model used inventory size and improvement spending as the variables of study, the NARX model used 25 bridge attributes and improvement spending as variables.

Difference in the results between models is attributed to differences in source data and methodology, particularly that the NARX model was based 1011 fewer bridges and utilized much more robust mathematics. One similarity is that both models implicitly include the effects of maintenance and aging. As discussed in chapter three, maintenance and aging effects are necessarily reflected in the NBI data used to build the models.

The values of average SR vary between the CLD and NARX models; variation is also seen in the relative impact of money spent on improvements. For every 10 million USD in annual improvement spending between 2015 and 2020, the CLD model predicted an increase of 0.14 points in average SR for 2020 as against 0.1 point by the NARX model. This difference is attributed to the causes mentioned in the last two paragraphs.

## **Summary and Conclusions**

A time variant NARX model was developed to study the effects of bridge improvement spending on the sufficiency rating of bridges in SC. The model considered 8,250 bridges in SC that were in service between 1992 and 2013. Twenty five attributes related to geometry, structural, traffic, maintenance and condition and bridge improvement spending were considered as inputs for the model. Once trained and validation, the model was used to predict the average SR for the bridge inventory for nine funding scenarios

varying from zero to 160 Million USD per year. This range includes scenarios above and below the recent spending level in South Carolina of approximately 80 Million USD per year for bridge improvement.

The following conclusions are made after analyzing the model results:

1. The NARX model has very small error when compared to the validation data, particularly at the inventory level. The average error (MAPE) in model prediction at the inventory level 0.52% during the validation phase between 2009 and 2013.
2. The model predicted that average SR is positively impacted by bridge improvement spending. Increased spending on improvements improved bridge sufficiency ratings while decreased spending brought them down.
3. The model-calculated average SR in 2020 (end of the prediction phase) increased by approximately 0.2 points for every 20 Million USD of annual improvement spending above the current 80 million dollar level.
4. The model-calculated average SR in 2020 (end of the prediction phase) reduce by 0.24 points for every 20 Million USD of annual improvement spending less than the current 80 million dollar level

This research demonstrates that time variant NARX models can be used to provide accurate estimates of bridge inventory condition. The benefit of NARX is that these networks learn from time history. Conventional neural networks do not have the ability to learn from time history. Deterministic methods and Markovian models only use

current condition to model future deterioration; they cannot consider the effects of condition history while predicting future condition (Morcous, 2002).

NARX is a novel modeling technique for evaluating the quality of bridge inventories, which can be applied for developing tools that help bridge agencies in bridge management and policy decisions.

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## CHAPTER SEVEN

### **CONCLUSIONS AND RECOMMENDATIONS OF THE STUDY**

This research is motivated by the prevalence of bridge infrastructure deficiency across United States. With limited resources available for maintaining and improving bridge infrastructure, well-designed bridge management and prioritization are essential for success in tackling bridge deficiency. The ability to forecast bridge condition and understand the effects of relevant variables is vital for prioritization of bridge maintenance, planning bridge management activities, and determining effective designs for new bridges.

This research focused on developing and demonstrating alternative methods for assessing bridge condition and deterioration, and for identifying the causal relationships that impact bridge quality. The study considered powerful Artificial Intelligence based computing, traditional linear regression methods, and systems dynamics tools to assess bridge condition under the influence of factors such as aging, design variables, and funding for improvements. The study also provided insights in to the interactions between variables and their effects on the overall health of a bridge inventory. A brief summary of the highlights and conclusions of each chapter are provided below.

To start with, a thorough review on the state of bridge deficiency was made in chapter two. The various causes of structural deficiency and functional obsolescence were analyzed, and the itemized bridge condition and appraisal ratings were reviewed. The traffic growth on deficient bridges was also analyzed over the years 1992 through 2013. It was noted that in the last two decades the number of structurally deficient

bridges reduced by 47% while the number of functionally obsolete bridges dropped by just 5.7%. Traffic usage on FO bridges increased by 25% though the number of FO bridges came down. The most common traits leading to FO ratings are geometric factors of bridges such as deck width and under clearance. These trends indicate that the problem of bridge functional obsolescence has not received as much attention as structural deficiency. Although bridge quality is improving as compared to last two decades, one in every four bridges in US is still deficient.

With the observations of chapter two in mind, a concept for evaluating capacity obsolescence of bridges was developed in chapter three. The concept is based on the evolution of vehicular loads on highway bridges in US, and also considers deterioration of bridge structural capacity overtime. An example was used to demonstrate how capacity obsolescence and embodied energy consumption can be jointly considered during design to enable longer functional lives for bridges.

In order to understand the effects of various bridge and economic variables on bridge condition, tools from the field of systems dynamics were applied in chapter four. A causal loop diagram was made to qualitatively describe the factors impacting the size and quality of bridge inventories. A simplified linear regression model was then used to quantitatively model the portion of the CLD associated with data from the NBI. From the quantitative model, it was concluded that for every 10 million USD spent on annual improvements between 2014 and 2020, the total improvement cost in 2020 is estimated to decrease by 46 million USD, and the average SR in 2020 is estimated to increase by 0.14

points. Recommendations were made to expand the model if and when relevant source data are available.

In chapter five, a method for using bridge inspection data to assess in impacts of design variables was demonstrated. The effects of bridge attributes like skew, span, age and traffic on bridge condition deterioration were investigated. Prestressed concrete bridges in seven South Eastern states were chosen for study. The method used a multi layered feed forward neural network model to estimate deck and superstructure condition ratings. Once the model was developed, a systematic array of simulations was conducted based on a full factorial design approach. It was concluded that age typically has the most significant effect on both deck and superstructure ratings followed by skew and span. While deck deterioration is faster at higher skews, superstructure deterioration is relatively slower at higher skews. This can be partially attributed to changes in girder load distribution factors and the relative stiffness of girders and decks in composite decks. At about a skew angle of 25 degree, there is a considerable change in the effects. These findings confirm the results from experimental and analytical model studies conducted by previous research studies. The study gives insights for designers in choosing values of skew and span for best performing decks and superstructures within the design space.

Chapter six demonstrated the application of time-variant NARX neural networks to assess the effects of improvement spending on the average sufficiency rating of bridge inventory. The NARX model considered 8,250 bridges in SC that were in service between 1992 and 2013, and was based on 26 bridge specific variables such as geometry,

clearances, traffic, loads, ratings, detour length etc. To consider the effects of bridge improvements on the SR, the money spent on bridge improvements for each year is included in the model as input variable. It was found that NARX approach was successful in capturing nonlinear relationship between time and average SR of the inventory. A parametric study was conducted with the validated model and it was concluded that the average SR of the inventory improves by 0.15 points for every 20 Million USD of increased annual spending over the study period (2013-2020). Furthermore, average SR reduces by 0.19 points over the study period for every 20 Million USD reduced annual improvement spending. This study demonstrated the feasibility of the NARX neural network approach for forecasting bridge conditions.

To conclude, this dissertation presented alternative methodologies for evaluating the performance of highway bridges. Both conventional and time variant neural network models were employed to study the effects of bridge variables and improvements on bridge condition. Additionally, linear regression methods and tools from systems dynamics tool were also utilized. Applying these methods, designers and policy makers can use large sets of bridge inspection data to make informed decisions regarding bridge design and inventory management. The author hopes that this study will emphasize the importance of treating bridge deficiency in United States and contribute alternative methodologies to developing solutions for the same.