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Bridge management from data to policy

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by

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ABSTRACT

Bridge management involves all efforts to build, preserve, and operate bridge networks cost-effectively with an objective to deliver the best value for the public tax dollars spent. The dissertation consists of three complementary studies that address both bridge management policies and condition data that contribute to bridge management practices.

This dissertation begins with an overview of federal and state government bridge management efforts taken in conjunction with the federal bridge programs in the last 40 years. While the majority of the states have implemented a BMS, the level of implementation is varied, and the overall input from BMSs to network-level decisions remains minimal. Survey findings from 40 states indicate that federal funding eligibility is the major criterion that impacts state-level bridge management decisions. State transportation agencies need federal guidance on areas such as using decision support tools, implementing BMSs, and improving data quality. The findings from the study are useful to both practitioners and policy makers, and identify challenges and needs for bridge management at both federal and state level.

Following the policy study, a statistical comparison of field NBI condition ratings and ratings generated by FHWA's NBI Translator (BMSNBI) algorithm for Iowa bridges is presented. Statistical analysis indicates that the ratings generated by the NBI Translator algorithm are not representative of actual NBI ratings. Results from the research raise questions about the effectiveness of the algorithm.

Final study in this dissertation presents a new methodology to predict National Bridge Inventory (NBI) condition ratings from bridge management system (BMS) element condition data, based on Classification and Regression Trees (CART). The proposed methodology achieves significantly better accuracies than other methodologies reported in the literature for the data set used in this study. The CART prediction methodology uses simple and logical conditions of BMS element condition data to predict NBI condition ratings and has potential use for federal and state transportation agencies to summarize bridge condition data.

CHAPTER 1.
GENERAL INTRODUCTION

BACKGROUND

Infrastructure, in the simplest terms, is the "the basic physical and organizational structures and facilities needed for the operation of a society"[1]. Traditionally, infrastructure facilities with "high fixed costs, long economic lives, and strong links to economic development" are owned, maintained and operated by the public sector, to a great extent [2]. The facilities referred to as infrastructure include highways, roads, and bridges; airports and airways; rail systems; public transit; intermodal transportation; water supply; wastewater treatment; water resources; solid waste and hazardous waste services; energy generation and transmission facilities; schools; and so forth [3, 4].

In the United States, the Eisenhower Interstate Highway System forms the backbone of the highway infrastructure. Since the beginning of its construction in mid-1950s, the system has enhanced mobility and economic development nationwide [5]. The highway financing pattern in the United States was simultaneously designated by the Federal-Aid Highway Act of 1956. The Highway Trust Fund (HTF), established then, is the main transportation fund for financing the needs of the federal-aid highways. Tax revenues directed to the HTF are derived from excise taxes on highway motor fuel and truck-related taxes on truck tires, sales of trucks and trailers, and heavy vehicle use [6]. For the eligible projects, the states can use HTF funds up to 80% of the cost and match the rest by local funds [8].

Prior to the Highway Act of 1976, federal funds were limited only to new construction. Consequently the maintenance, rehabilitation and renewal activities by state and local transportation agencies were quite limited or deferred [5]. These needs, which have not received enough attention, have added to the increasing needs of the highway system in light of the increasing demand. Today, transportation agencies at all levels of government are substantially challenged to address the backlog of needs by the restricted resources available to them.

Beginning in 1988, the American Society of Civil Engineers (ASCE) has published a Report Card to grade the nation's infrastructure. The latest report from 2009 estimates that

$2.2 trillion needs to be invested over five years to bring the condition of the nation's infrastructure up to a good condition, which is double the amount of current estimated spending [3]. Although, the combined investment by all levels of government in highway and bridge infrastructure has increased over time and was estimated to be $78.7 billion dollars in 2006 [7], the gap between the needs and the available funds still remains wide and critical. ASCE estimates an annual investment need of $186 billion dollars over the next five years for highway and bridge infrastructure.

Congress expanded the span of federal-aid eligible activities by adding reconstruction to the list in 1981 legislation, with special emphasis on bridge rehabilitation and replacement [5]. By the late 1980s however, the efforts had not made much difference, and it was understood that a new approach would be needed to close the gap between infrastructure needs and available resources. Decision makers then began looking at management sciences such as finance, asset management and accounting for alternative solutions [8].

Infrastructure asset management, as defined by the FHWA and AASHTO, is "a systematic process of maintaining, upgrading, and operating physical assets cost-effectively. It combines engineering principles with sound business practices and economic theory, and it provides tools to facilitate a more organized, logical approach to decision-making" [9]. The major goals of infrastructure asset management are "to build, preserve, and operate the infrastructure systems cost-effectively with improved asset performance; to deliver the best value for the public tax dollars spent; and to enhance the credibility and accountability of the transportation agency to its governing executive and legislative bodies" [10].

The Intermodal Surface Transportation Efficiency Act of 1991 originally mandated that states should implement a variety of transportation management systems, including pavement and bridge management systems [11], and thus many transportation agencies across the country started implementing them.

Trends in public administration and transportation in the 1990s have also provided motivation to align transportation agency business practices with infrastructure asset management principles [11]. In April 1992, the American Society of Public Administration (ASPA) adopted "a resolution that endorses efforts by governments at all levels to develop and adopt performance measures." Later in 1999, the Governmental Accounting Standards

Board (GASB) issued Statement 34, which specifies that "governments' financial statements must show a value for their infrastructure investments and the costs associated with depreciation of those assets" [12]. Unlike previous experiences, the transportation agencies now needed to use either the depreciation method or a modified approach that allows an asset management system to be implemented [12]. Since infrastructure asset management focuses on explicit and clearly defined goals and the value and continued maintenance costs of assets over their life-cycle, these shifts in public policy were good motivators for transportation agencies to adopt an asset management philosophy and implement infrastructure asset management systems.

The origin of bridge management programs in the United States dates to the early 1970s. Bridge management systems (BMSs) were developed in the mid 1990s [13, 14]. Today, state transportation agencies have established bridge inspection programs and a majority of them have implemented a BMS.

Although the share of bridges classified as deficient fell from 34.2 percent in 1996 to 27.6 percent in 2006 [15], aging bridges still have substantial maintenance, rehabilitation, and replacement needs, and agencies are challenged with the backlog of these needs. ASCE's 2009 Report Card grades the nation's bridges at a grade of C (mediocre) [3] and estimates that a $ 17 billion annual investment on the construction and maintenance of bridges is needed, instead of the current $10.5 billion, to substantially improve the condition of the nation's bridges.

The collapse of the I-35 W Bridge in 2007 drew attention to the safety of bridges and elicited a self-assessment of bridge management activities by both the federal government and state transportation agencies. Many aspects of bridge management, such as federal bridge programs, bridge management at the state level, and tools and techniques used in bridge management, are being questioned to find answers to a basic question, "How can we do better?" This dissertation focuses on bridge management in the United States and focuses on bridge management policies and bridge management condition data, to suggest answers to the same basic question.

OBJECTIVES

The objectives of the research for this dissertation are:

- To provide an independent review and explanation of the issues regarding the federal bridge programs;
- To obtain information from state transportation departments on their bridge management practices and how these practices are influenced by the federal bridge programs;
- To synthesize inputs from the major stakeholders;
- To develop a statistical model to predict National Bridge Inventory (NBI) deck, superstructure, and substructure condition ratings based on BMS element condition data; and
- To provide timely input to the reauthorization and future policy debate.

DISSERTATION ORGANIZATION

This dissertation is divided into five chapters. Chapter 1 provides a general introduction that includes brief background information, dissertation objectives, and dissertation organization.

Chapters 2-4 comprise papers that have been either published or prepared for submission to peer reviewed journals. The papers are ordered in the dissertation as follows:

Aldemir Bektas B, Souleyrette R, Smadi O. *An Independent Look at Federal Bridge Programs: Findings from a National Survey*. Will be submitted to Transportation Research Record (TRR).

Chapter 2 presents findings from a national survey on bridge management and federal bridge programs. It includes a review of the issues and a discussion of the federal bridge programs to provide input to the reauthorization or restructuring of the federal transportation programs and future policy debate.

Aldemir Bektas B, Smadi O. *A Discussion on the Efficiency of NBI Translator Algorithm.* A paper presented in Tenth International Conference on Bridge and Structure Management and published in Transportation Research E-Circular E-C128.

Chapter 3 presents a statistical comparison between the field NBI condition ratings and the ratings generated by the BMSNBI algorithm for bridges in Iowa. The paper also includes a review of bridge inspections and bridge condition data in the United States.

Aldemir Bektas B, Carriquiry A, Smadi O. *CART Algorithm for Predicting NBI Condition Ratings*. A paper to be submitted to The Journal of Infrastructure Systems (ASCE).

Chapter 4 presents a new methodology to predict NBI condition ratings from BMS element condition data based on Classification and Regression Trees (CART). The statistical results point to a method of predicting NBI condition ratings that is more accurate than the previous algorithms in the literature.

Finally, Chapter 5 summarizes the major findings of the study and includes recommendations for future work.

Appendix A gives the summary results of the national survey in Chapter 2.

Appendix B includes the reports from the CART analyses in Chapter 3.

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CHAPTER 2.
AN INDEPENDENT LOOK AT FEDERAL BRIDGE PROGRAMS: FINDINGS FROM A NATIONAL SURVEY

A paper to be submitted to Transportation Research Record (TRR)

B. Aldemir Bektas[1], R. Souleyrette[2], O. Smadi[3]

ABSTRACT

This paper presents findings from a national survey on bridge management and an overview of the federal bridge programs in the United States. The collapse of the I-35W Minnesota Bridge in 2007 led to efforts by state and federal transportation agencies to improve the federal bridge programs. The main purpose of this study is to contribute to these efforts by providing an independent review of the issues regarding the federal bridge programs and synthesizing findings from a national survey to provide timely input to the reauthorization and future policy debate.

The responses to a national survey from 40 states indicated that network-level bridge management decisions at the state level are typically guided by federal funding eligibility. In general, states are pleased with the federal bridge programs, but they want to have more flexibility in using federal bridge funds. Although a majority of the states have implemented a bridge management system (BMS), less than half consider BMS recommendations for selecting bridge projects. Skepticism of the BMS simulation results, difficulties in BMS simulation modeling, and resource limitations are the most reported issues that obstruct BMS implementation at the national level.

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Ninety percent of the respondent states do not believe that National Bridge Inventory (NBI) data items cover their data needs for bridge management, and seventy percent believe that more detailed BMS element condition data should be utilized in the federal bridge funding allocation process. Development of clear performance measures and tools to guide network-level bridge management decisions and funding allocation remains a critical need. Using decision support tools, implementing BMSs, and improving data quality are the major areas in which federal guidance is needed at the state level.

INTRODUCTION

The I-35W Bridge over the Mississippi River collapsed on August 1, 2007 in Minneapolis, Minnesota, resulting in 13 fatalities and 145 injuries [1]. Although investigation of this failure later suggested that it was due to a design error [2], this event raised national concern on the condition of the nation's bridges and triggered a self-criticism among federal and state agencies to improve how they oversee and guide the management of bridge infrastructure.

Oversight and guidance of bridge management by the Federal Highway Administration (FHWA) is executed through two federal bridge programs: the Highway Bridge Program (HBP) and the National Bridge Inspection Program (NBIP). Current efforts to evaluate these programs are particularly important since the conclusions will provide input to Congress as they work on the next transportation bill to follow the "Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU)." SAFETEA-LU (Public Law 109-59) was enacted on August 10, 2005 and provided a five-year authorization of federal surface transportation programs for highways, highway safety, and transit. Authorization ran out in 2009 [3].

The main purpose of this study is to contribute to the efforts to improve the federal bridge programs from an academic perspective. It provides a review of the issues and related literature, investigates the practices of the policy implementers at the state level and their perception of the programs through a national survey, and suggests a set of recommendations by synthesizing these components. The objectives of this study are as follows:

- To provide an independent review and explanation of the issues regarding the federal bridge programs;
- To obtain information from state transportation departments on their bridge management practices and how these practices are influenced by the federal bridge programs;
- To synthesize inputs from the major stakeholders; and
- To provide timely input to the reauthorization and future policy debate.

This paper focuses on bridge management policy and implementation at the state and national levels rather than providing details of tools, methodologies, or techniques. We begin reviewing recent criticism and the background of federal bridge programs. Background information on the status and issues of bridge management system implementation in the United States is also included.

BACKGROUND

A review of recent evaluations regarding the federal bridge programs

After the collapse of the I-35 W Bridge in Minneapolis, the Secretary of Transportation asked the U.S. Department of Transportation (USDOT) Office of Inspector General (OIG) to evaluate FHWA's management of bridge safety and oversight of the HBP. Reports were issued in 2009 and 2010 [4, 5] by the USDOT Office of the Inspector General (OIG). Together with a report from 2006 on load ratings and postings on structurally deficient structures [6], these reports raise issues regarding federal bridge programs.

- In the 2006 report, some errors in the calculation of load ratings and in the posting of maximum weight limits were identified [6]. As a result of the analysis, the report projected that 10.5 percent of the load rating calculations for structurally deficient structures on the National Highway System (NHS) were inaccurate.
- The 2009 report reviewed audits of 10 FHWA Division Offices and observed that the new Risk Assessment Tools for Bridge Load Ratings and Postings, suggested by FHWA in a February 2007 memo, were either not being used or were being used inconsistently. The OIG suggested that FHWA incorporate systematic data-driven oversight to address nationwide bridge safety risks and to encourage states to expand

their use of bridge management systems. However the OIG also reported that the FHWA lacks the statutory authority to require this.

- In the 2010 report, the OIG concluded that FHWA lacks sufficient data to evaluate states' use of HBP funds and cannot link expenditures of HBP to the investments on deficient bridges. Since deficiency (number of deficient structures or total deck area of deficient structures) and sufficiency ratings are the only significant performance measures guiding the HBP, tracking the connection between HBP and spending on deficient structures is critical for FHWA to show the use of apportioned funds for the intended use.

The U.S. Government Accountability Office (GAO) also contributed to the evaluation. In 2008, the GAO published a report [7] on the condition of the national bridge network and federal investment in it. The GAO concluded that the HBP lacks "focus, performance measures, and sustainability."

The GAO noted that it is difficult to determine the impact of HBP funds in reducing the number of deficient bridges and increasing the average sufficiency ratings from 1998 through 2007 [7] because HBP is not the only funding source for states' expenditures on bridges, and local funding on bridges is not well documented. The report generally agreed with the proposed legislation under review at that time by the U.S. Senate Committee on Environment and Public Works. The National Highway Bridge Reconstruction and Inspection Act of 2008 (S.3338) recommended a risk-based prioritization process for selecting bridge projects, five-year performance plans, and implementation of BMSs. This bill was not reported out of the Committee.

On July 21, 2010, the U.S. House Subcommittee on Highways and Transit held a hearing on "Oversight of the Highway Bridge program and the National Bridge Inspection Program" as part of the effort to prepare for the reauthorization of Federal surface transportation programs under SAFETEA-LU. Testimony was given by the USDOT OIG, FHWA, GAO, and AASHTO. The GAO's testimony [8] emphasized its previous findings. The USDOT OIG [9] acknowledged FHWA's response to its recommendations from the three reports they published in the last four years. Central to these was to implement a pilot risk-assessment program to identify high-priority bridge risks. However, a lack of progress in obtaining data from the states on their expenditure of HBP funds was also noted.

FHWA's statement [10] noted the achievements of the federal bridge programs over the last 30 years, such as a reduction in the percentage of the Nation's deficient bridges from 19.4 percent to 12 percent since 1994. Efforts such as domestic and international scans on bridge inspections, the Bridge Research and Technology Program, providing training on bridge inspections and BMS implementation assistance, and NBIS Compliance Reviews by FHWA that aim to improve and monitor bridge management practices nationwide were also acknowledged. FHWA concurred with the majority of the recommendations from the earlier USDOT IG and GAO reports, and reported

- the development of a new NHI course on Load and Resistance Factor Rating methodology;
- the development of additional NBI data reports to identify load rating issues and data quality problems;
- the initiation of a risk assessment program for load rating and posting practices;
- the continuation of the efforts to assist states in their BMS implementation;
- the implementation of a pilot program for data-driven, risk-based oversight of the NBIP;
- working with AASHTO to update the standards for element-level data; and
- the beginning of on an enhancement to the Financial Management Information Systems (FMIS) to improve tracking of HBP spending and bridge projects.

AASHTO's testimony focused on the necessity of a new vision for the HBP and the importance of addressing the overall health of the bridge network based on asset management rather than a "worst-first" approach [11]. Referring to the USDOT's 2006 Conditions and Performance report [12], which estimated a backlog of over $ 19 billion of bridge needs, the testimony stated that the level of funding is far below the needs to reconstruct or rehabilitate all deficient structures in the country. AASHTO suggested a balanced asset management approach of addressing immediate problems, replacing old bridges, and conducting preventive maintenance.

Background on federal bridge programs

The content of existing federal bridge programs has also been influenced by previous bridge collapses. Prior to the collapse of the Silver Bridge in Ohio in 1967, the focus of the U.S. bridge program was [7] on building and enhancing the infrastructure. The collapse evoked national concern about the safety and conditions of the national bridge network.

The 1968 Federal-Aid Highway Act set the state transportation authorities in action to collect and maintain an inventory of federal-aid highway system bridges. Congress later established two major federal bridge programs: the Special Bridge Replacement Program (SPRB, 1970), which assists states in replacing and rehabilitating bridges, and the National Bridge Inspection Program (NBIP, 1971) to ensure periodic national inspections [7]. The SBRP was enhanced and renamed by subsequent federal programs: first by the Highway Bridge Replacement and Rehabilitation Program (HBRRP) and later by the Highway Bridge Program (HBP).

The NBIP establishes standards and requirements for the inspection and evaluation of bridges in the United States. National Bridge Inspection Standards (NBIS) were first issued in 1971 [7], and these standards are used to guide state transportation agencies in complying with the responsibilities for inspecting bridges, maintaining a current bridge inventory, and reporting bridge condition data to FHWA. The HBP provides funding to enable states to improve the condition of bridges through replacement, rehabilitation, and systematic preventive maintenance and is the primary source of federal funding for bridges. The allocation of HBP funds is based on an apportionment process, which is dependent on the data from the NBIP.

As a requirement of the NBIP, states are required to inspect all bridges longer than 20 feet and report both condition and updated inventory data to FHWA on an annual basis. The NBI data that the states are obliged to submit are specified in the Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges [13] and includes 94 NBI items. The NBIP is intended to identify the nation's structurally deficient or functionally obsolete bridges, to evaluate overall conditions of bridges in the national network, and to form a statistical basis for developing the cost-to-repair estimates that are used in HBP apportionment formulae [14]. NBI includes condition ratings for deck, superstructure, substructure, and culverts and includes the primary data items that determine the deficiency status for bridges. NBI condition ratings are assigned on a scale of zero to nine (with nine being excellent and zero being failing), according to the specifications in the Recording and Coding Guide [13]. Table 2-1 gives a brief summary of NBI condition rating guidelines [13].

Table 2-1: NBI condition rating guidelines in brief

Code	**Description**
N	NOT APPLICABLE
9	EXCELLENT CONDITION
8	VERY GOOD CONDITION (No problems noted)
7	GOOD CONDITION (Some minor problems)
6	SATISFACTORY CONDITION (Minor deterioration in structural elements)
5	FAIR CONDITION (Sound structural elements with minor section loss)
4	POOR CONDITION (Advanced section loss)
3	SERIOUS CONDITION (Affected structural elements from section loss)
2	CRITICAL CONDITION (Advanced deterioration of structural elements)
1	IMMINENT FAILURE CONDITION (Obvious movement affecting structural stability)
0	FAILED CONDITION (Out of service)

The FHWA defines deficiency under two categories: structural deficiency or functional obsolescence. Structural deficiency (SD) indicates poor conditions and deterioration in structural elements, while functional obsolescence (FO) indicates design or configuration that is no longer adequate for the traffic. Deficiency status affects both allocation of federal funding and eligibility to use federal bridge replacement funds. This classification is summarized in Table 2-2.

Sufficiency rating (SR) in conjunction with deficiency status determines whether a structure is eligible for rehabilitation only or eligible for both rehabilitation and replacement (Table 2-3).

Table 2-2: Deficiency status classification[15]

Structurally Deficient	Functionally Obsolete
A condition rating of 4 or less for: Deck (Item 58) OR Superstructure (Item 59) OR Substructure (Item 60) OR Culvert (Item 62)	An appraisal rating of 3 or less for: Deck geometry (Item 68) OR Underclearance (Item 69) OR Approach roadway alignment (Item 72)
OR	**OR**
An appraisal rating of 2 or less for: Structural condition (Item 67) OR Water adequacy (Item 71)	An appraisal rating of 3 for: Structural evaluation (Item 67) OR Water adequacy (Item 71)

Table 2-3: HBP funding eligibility for NBI bridges

Bridge Classification	Sufficiency Rating	Eligibility for HBP funds
Not deficient	81-100	Not eligible
Deficient (Structurally Deficient OR Functionally Obsolete)	50-80	Eligible for Rehabilitation
	0-49	Eligible for replacement or rehabilitation

SR is a value between 0 to 100, where “100” represents an entirely sufficient bridge and “0” represents an entirely insufficient bridge. The formula for calculating SR uses 20 of the 94 NBI data items with an emphasis on condition ratings. These items are summarized by the FHWA as shown in Figure 2-1 [13].

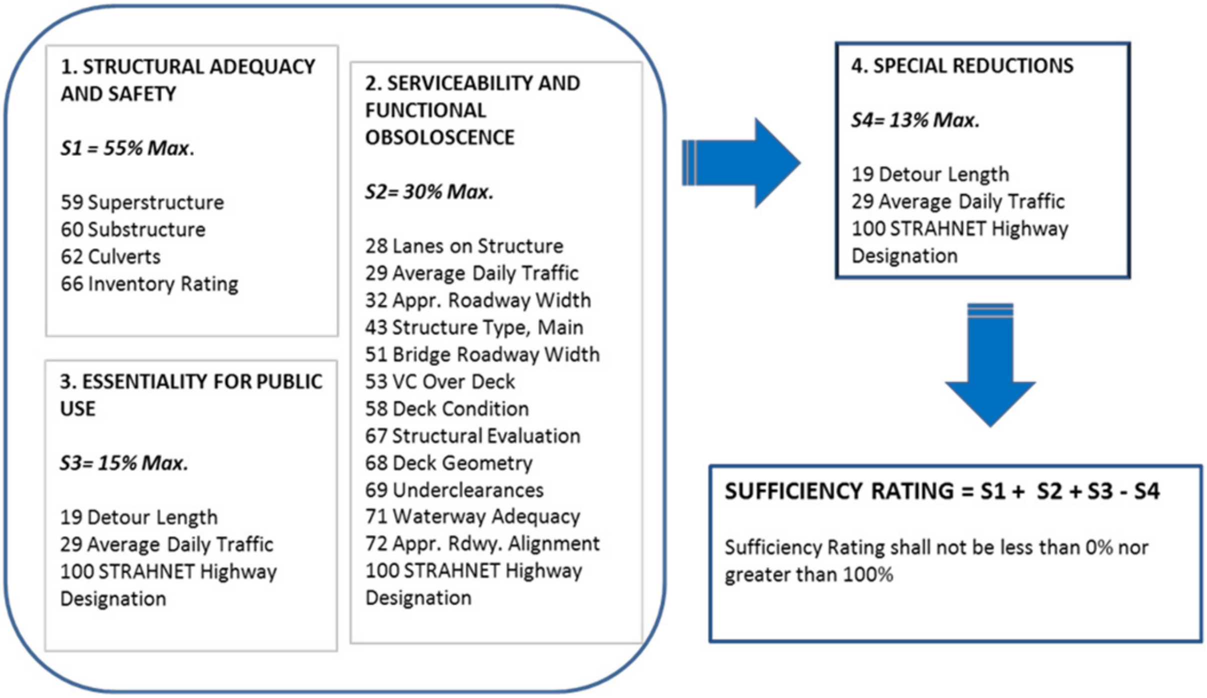

Figure 2-1: NBI items used in sufficiency rating calculation

Apportionment and use of HBP funds

HBP eligible activities were later expanded in SAFETEA-LU to include systematic preventative maintenance [16], although states can use HBP funds for this purpose only if they have a systematic process of choosing such activities. The final decision of eligibility is determined by mutual agreement between the FHWA division office and state DOT.

FHWA's apportionment process for the allocation of HBP funds between states (U.S. Code, Title 23, Chapter 1, § 144) includes the following steps [17]:

- Gathering NBI data and bridge construction unit costs (BCUC)
- Identifying HBP eligibility based on deficiency status
- Computing state apportionment factors
- Computing the funds that go to each state (Some standard adjustments for each state)

To compute the state apportionment factors, rehabilitation and replacement needs for eligible deficient structures for each state are calculated by multiplying deck areas by corresponding replacement and rehabilitation BCUC. The bridge investment requirement at the national level is simply the total of needs at the state level. The state apportionment factor is calculated by dividing the state investment required by the national investment required.

Regardless of the apportionment factor, states receive a minimum of 0.25 percent of total funds, and no state can receive more than 10 percent of total funds [17].

Total HBP funds available for distribution in FY 2009 was $4.3 billion [18]. Funds allocated by the HBP are not direct cash amounts, but rather are made available to the states through reimbursement for suitable projects, which include replacement, rehabilitation, painting, seismic retrofitting, systematic preventive maintenance, and installation of scour countermeasures (U.S. Code, Title 23, Chapter 1, § 144). Typically, states must provide matching funds of up to 50 percent of project costs by law. In 2006, HBP funded 45% of total capital outlays by all levels of government on bridge rehabilitation [19].

Bridge Management Systems in the United States

The aftermath of the two bridge failures, first the Silver Bridge in 1967 and later in 1983 the Schoharie Creek Bridge [20, 21], and the increasing gap between the available funds and needs of the national bridge network stimulated increasing research to develop bridge management systems in mid-1980s.

Shortly thereafter, the Intermodal Surface Transportation Efficiency Act of 1991 required states to develop and implement BMSs. A BMS is a software package that provides a rational and systematic approach to all the activities related to managing a network of bridges [22], such as inspecting and storing bridge condition data, predicting future needs of the bridge network, selecting maintenance and improvement actions cost-effectively, and tracking maintenance activities. Although development of BMSs was made optional by the National Highway System Designation Act of 1995, many states decided to continue implementing them [23].

Some states set out to develop their own tools, while many decided to implement available systems. The FHWA developed the Pontis Bridge Management System in 1989 [24], which later became the most popular bridge management tool in the United States [25]. The BRIDGIT bridge management system was later developed by the National Cooperative Highway Research Program (NCHRP) but has not become as popular as Pontis [26]. Today, although Pontis is licensed in 44 states [27], the level of implementation varies.

The bases of the Pontis BMS modeling approach are principles of operations research and economic analysis. Pontis addresses preservation decisions separately from improvement decisions [28]. The main inputs for Pontis preservation modeling are element-level condition data, cost models, and deterioration models. In Pontis, bridges are represented as a set of structural elements based on AASHTO's Commonly Recognized (CoRe) elements. For each element a set of possible conditions is defined (up to five, where the first represents the perfect condition and the last represents the worst) and a set of feasible actions is assigned to each condition (such as do nothing, paint, replace).

Pontis models separate functional improvements (widening, raising, strengthening, and replacement) from preservation. Preservation cost models are developed by assigning the costs to each feasible action of each element along with the failure cost of each element. Costs are assigned typically through expert elicitation. Deterioration models are based on Markov transition probabilities. Dynamic optimization models are used to identify the optimal bridge preservation policy, which minimizes the total life-cycle costs given the cost and deterioration models. Improvement models have bridge-level formulas and inputs (e.g., cost of raising, user benefit of replacement).

Currently, the most acknowledged performance measure based on current BMS elements is the Health Index (HI) [29]. HI is a single number (from 0-100) that reflects the condition distribution for the different elements on a structure [28]. This index reflects a weighted condition distribution of the BMS elements with weights determined by expert assignments or element failure costs. HI values typically accumulate at the higher end of the 0-100 range, and therefore relative HI values do not always convey a clear notion of relative performance.

Some states that are experienced Pontis users and that have been using the tool for developing their bridge programs for a while discovered a problem in the program results over long durations. When simulations are performed over a long term, the condition of the network converges to a condition level lower than what agencies would target in practice [30, 31]. So, when decision making is based only on cost minimization, the agencies cannot achieve a desired future network condition. This phenomenon is addressed by Patidar et al. [32] in the recent "Multi-Objective Optimization for Bridge Management Systems" study, which is the outcome of a NCHRP project.

This new approach is based on multi-objective optimization and considers more than one performance criterion. Each performance criterion is represented with a utility function, which is measured on a zero to one scale and has a unitless measure. The benefits of bridge actions (i.e., project benefits) are represented by the utility value. Utility functions can be defined for a variety of measures, such as condition, load capacity, risks, or functional needs. The total utility of a project is equal to the weighted sum of all component utilities. Final prioritization in this approach is based on a total utility/cost ratio. This new methodology will be used in the new version of Pontis (5.2), planned for release in 2011.

New AASHTO Bridge Element Inspection Manual

At present, two types of condition inspections are prevalent in the United States: the obligatory NBI condition inspections and the optional BMS element condition inspections. Because each relies on different methodologies and rating systems, they require separate condition inspections. State DOTs allocate resources to both inspections whilst the mutual goal of both inspections is to assess condition.

In 2010, the AASHTO Subcommittee on Bridges and Structures approved a new element-level bridge inspection manual intended to replace this methodology. The new AASHTO Bridge Element Inspection Manual [33] replaces the AASHTO Guide to Commonly Recognized Structural Elements. The new manual classifies two sets of bridge elements differently as the National Bridge Elements (NBE) and the Bridge Management Elements (BME).

The NBE proposed refined condition ratings for the primary structural components of bridges, including decks, superstructures, substructures, and culverts defined in the Federal Highway Administration's Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges[33]. The intention of introducing NBEs is to eventually replace the NBI condition inspections with NBE condition inspections to provide a more detailed and objective condition assessment of the Nation's bridges.

Pontis 5.2 is expected to combine the new AASHTO element definitions and multi-objective optimization, but the modeling is still in process. The shift to NBE from NBI condition ratings was discussed and received positive comments at the recent Pontis User Group meeting (September 21-22, 2010, Newport, Rhode Island). However, at this time, it is unclear when the shift to NBE may take place. Until the HBP apportionment process is changed to be compatible with the new NBEs, NBI data will still need to be reported to meet federal requirements.

The NBI Translator (BMSNBI)

Since the early 1990s, the NBI Translator has been available as a built-in module within Pontis BMS [34] to map element-level condition data to NBI condition ratings. Ideally, for the States that have BMS element condition inspections, use of the NBI Translator would eliminate the need for NBI condition inspections. States have the option to report translated NBI condition ratings to the FHWA; however, the majority of states continue to collect both types of condition data due to reported skepticism of the accuracy of the algorithm [35].

The NBI Translator is frequently criticized for estimating lower ratings than the field NBI ratings at the upper end of the condition ratings [36]. Since the lower end governs deficiency status, the effect on HBP apportionments may be negligible; however, it is well documented that a true estimation between the two rating systems has not been possible [35-37].

The NBI Translator algorithm is also used within the National Bridge Investment Analysis System (NBIAS), which is used to project future investment needs for repair, rehabilitation, and replacement of bridges in the national network [19]. These projections are part of the Condition and Performance Report on the nation's highways, bridges, and transit systems, prepared by FHWA and submitted to Congress biennially. The NBIAS follows the principles of the Pontis BMS, uses the same deterioration and cost models, and incorporates benefit-cost analysis into bridge investment evaluation. Utilization of these models also requires Pontis BMS element-level condition data. Therefore, the NBIAS uses the NBI Translator algorithm for a back-translation to create representative Pontis BMS elements for structures based on reported NBI condition ratings. This same algorithm is also used to predict future conditions in NBIAS scenario analysis.

METHODOLOGY

The focus of this study was a survey of state bridge management engineers, who typically oversee all bridge management activities for the state. The purposes of the survey were to analyze bridge management practices and identify how consistently state DOTs implement federal bridge programs, and to explore how bridge management at the state level is influenced by the federal bridge programs. The survey design was based on the results of a literature search [20, 24-27], targeting computer-mediated survey research. A preliminary draft was reviewed by a diverse group of experts from academia, FHWA, state DOTs, and consultants from the bridge management community.

The first section of the survey focused on the bridge management data that is maintained by the state. This included identifying the data items collected, the data items used for bridge management, methods of data entry and storage, and methods to ensure quality control and quality assurance (QC/QA).

The second section targeted BMS implementation. The survey asked whether the state is implementing a BMS, the challenges in implementation, the benefits realized so far, improvements needed, and the state's current and future plans for using a BMS for decision support.

The third section included questions on how the state developed its bridge program (the list of selected bridge projects). This section identified all of the agency processes involved in preparing the list of bridge rehabilitation, replacement, and maintenance projects, as well as how the state agency assessed condition and risk, how it used a BMS (or other decision support tools), how it involved local agencies, and how it used economic methods such as benefit-cost analysis or life-cycle cost analysis (LCCA).

The final section explored the respondents' perceptions of federal bridge programs. This included identifying issues, comments, and suggestions they have and how the federal bridge programs affect the way they manage their bridge network. This section also asked for recommendations to improve federal bridge programs and to identify the primary areas in bridge management where the states need more federal guidance.

A review of the recent literature and related recent surveys [23, 38-41] on the subject were studied to form the conceptual design. The main concern regarding the online survey study was the level of response from the states, because this was an independent study and participation was voluntary. A combination of 52 closed- and open-ended questions was included in this survey. Open-ended questions were picked for salient issues such as network-level prioritization and comments on federal bridge programs.

FHWA shared the recent annual NBIS Compliance Reviews conducted by their division offices (2007 and 2008) and a recent Bridge Management Systems Survey to be sent to the states at the time the survey was being prepared. These documents were reviewed to avoid duplicate questions and to minimize shared content. Some of the common content was kept in the survey if there was value in asking the question as an independent party (e.g., challenges in implementing BMSs, data quality concerns).

The survey was sent to one person, typically the state Bridge Management Engineer, who oversees all bridge management activities for the state. Initial response was from 23 states in a week. It took three months for the survey to be completed, with an 80 percent response rate (40 states).

The survey results were analyzed to explore the relationships between identified problems regarding the federal bridge programs and the bridge management practices at the state level. A synthesis of the issues and findings are given in the discussion section, along with a list of recommendations on improvement of federal bridge programs.

SURVEY RESULTS

The major findings from the survey are presented in this section.

Bridge management data

Ninety percent of respondent states do not believe the NBI data items (required by the NBIP) cover all their needs for bridge management. When they were asked which additional data items they thought were necessary for bridge management, respondents indicated AASHTO CoRe element condition data (32 states), condition information on paint or protective coatings (26 states), condition information on deck joints and wearing surfaces (25 states), and condition information on bearings (20 states). Other common necessary data items included condition data on deck drainage systems, scour history, scour condition, and seismic vulnerability, to name a few.

The list of items collected specifically by some state agencies is extensive. Thirty-seven states collect agency-specific items. When these items were reviewed, some common information collected under different definitions was observed.

The majority of states (29) use both NBI condition data and BMS element-level condition data when assessing the condition of bridges, 6 states use only NBI condition data, and 5 states use only element-level condition data. One issue observed from the responses was that condition assessment from both systems does not always provide systematic input to the development of the bridge programs. For example, using NBI condition ratings to identify project candidates eliminates the opportunity to use BMS element-level condition data. Even though BMS data can subsequently be used to compare between single structures, it is not typically used to assess the condition of the entire bridge network.

In addition to inspection and inventory data, effective decision making in bridge management needs other sources of information such as traffic and cost data [42]. Often these other data items are collected and stored by different offices within the agency. Four respondents indicated that inspection data are maintained in multiple database systems. Of these, two indicated that duplicate data are being archived but not used.

US Code 23 CFR 650.313 requires states to assure systematic quality control and assurance procedures, and the FHWA provides states a framework for a Bridge Inspection QC/QA Program to help them comply with this requirement. Survey questions relating to this framework were designed to determine how states comply with the regulations. Thirty-seven respondents reported having a QC program, and 36 respondents reported having a QA program. Implementation of the framework, however, varies, and in general, has not yet been systematized.

Only 23 respondents reported having in-house training for bridge inspectors. The majority of the QA programs reported were for NBI inspections (29 states), but 21 states have QA programs for BMS inspections as well. Fifteen respondents report QA reviews for all inspections, while 20 report random inspections. Data samples for the random reviews range from 0.5 percent to 20 percent of all inspections.

Bridge program development

A bridge program development is a key process that combines all efforts in bridge management and transforms them into a tool to support funding decisions. Ideally, this is a systematic process that is based on quality data, effective models, and economic methods that result in the most cost-effective decisions. Survey results on bridge program development process indicate the following:

- Seven respondents reported having no set criteria for prioritizing bridge projects. Three others reported criteria that are vague (e.g., "all/any available data/information is used by the bridge committee")
- Local agency involvement varies. Nineteen respondents involve local agencies in the development of state bridge programs (21 do not). Some local agencies are partners in decision making.
- Twenty-seven respondents listed set criteria for prioritizing bridge projects. Figure 2-2 presents the frequency of reported criteria. Most common are NBI condition data, deficiency status, and traffic.

Bridge Management Systems

Eighteen respondents reported the use of a BMS (Pontis or other) to develop their bridge program. Figure 2-3 shows the percentage of projects in bridge programs derived from BMS recommendations, as reported by these 18 respondents. The most common benefits reported from the BMSs in order of importance were the bridge condition data inventory with historic data and deterioration models; identifying, programming and tracking maintenance activities; and systematic analyses.

The responses indicate that the decision support capabilities of BMSs are being used by only a few states. The few states at this more advanced BMS implementation level are typically content with the benefits realized. The same respondents indicated the value of identifying and programming preventive maintenance and rehabilitation activities and commented on how this approach helped them to improve more of their bridge network condition instead of only targeting bridge replacement projects to a small portion of the network. Improvements that are necessary for states to use BMSs more effectively can be generalized under one area: modeling. The majority of the responses to the questions regarding BMSs that included the modeling issues referred to Pontis BMS, since it is the dominant BMS used by the states.

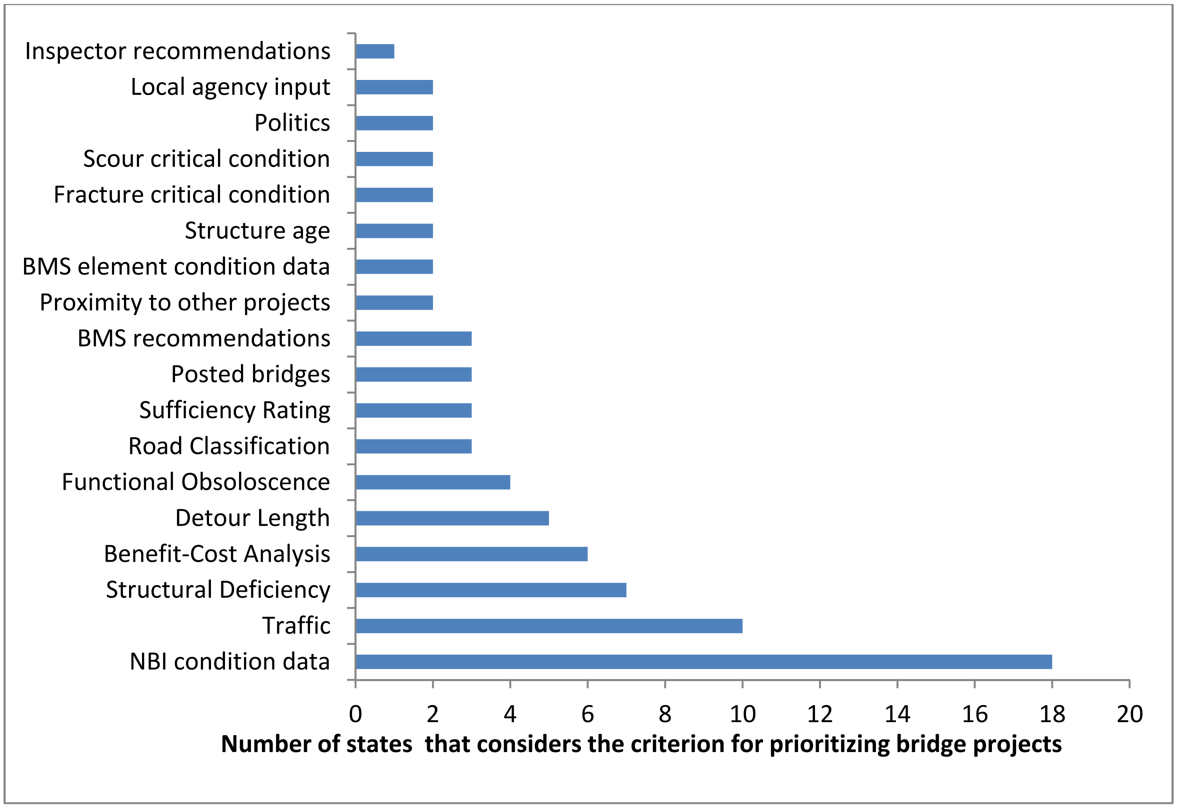

Figure 2-2: Criteria used for prioritizing bridge projects

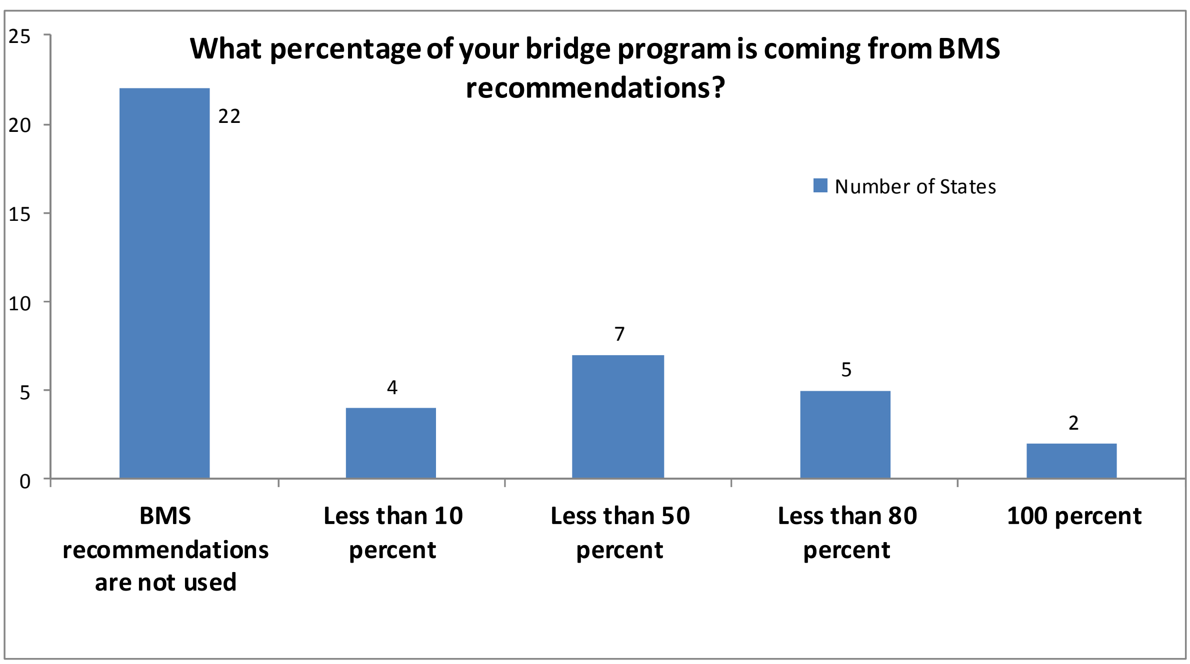

Figure 2-3: Percent of program bridge projects derived from BMS recommendations

Pontis model cost numbers are different from real construction costs, and each agency needs to customize and develop its own cost models [30, 43]. Having historical element-level condition data helps states to improve their deterioration models [44]. However, developing both cost and deterioration models takes time and requires good data inventory and agency commitment. Coordination between departments in the agency is also needed since cost information is typically kept by another department. The results of the survey are consistent with the literature; 11 respondents identified developing the deterioration and cost models as a major difficulty in implementing BMSs.

The survey reported that difficulties in implementing a BMS differed depending on level of implementation. The states at earlier stages of implementation were typically challenged by management buy-in (most reported), inspection and data requirements, development of deterioration and cost models, questions on whether Pontis simulation results are realistic, the amount of time required to learn and implement the BMS, and internal resistance from the agency staff.

At later stages of implementation, the limited number of staff in these departments was an issue. Since it takes considerable time to train new employees, turnover can be troubling. Also, uncertainties regarding the national direction for bridge management and the expected improvements for the Pontis BMS were noted by the respondents as impairing agency commitment to implementation. Experienced states reported that despite the initial challenge of developing agency procedures and policies to support the BMS, they now see the value and perceive the challenges as the necessities of implementing a good BMS. As the inspectors and management get more experienced, these difficulties also lessen.

The most common criteria used in the development of the bridge programs by the states are reported as NBI data, and mostly NBI condition ratings. Sufficiency ratings and deficiency status, which are mainly based on NBI condition data and are the main influencers of HBP fund allocations, are also the most common information used by the states to identify candidate projects. This step is typically followed by a prioritization process by the central office; local agencies affect this prioritization in 25 percent of the states.

As indicated earlier, 29 respondents reported using BMS element-level condition data when they are evaluating bridge conditions. However, except for 11 respondents, the effect of BMS element-level condition data in bridge program development could not clearly be seen, either because the process was guided by NBI data only or the BMS element-level condition data were used only for individual assessment of bridges and not network-level comparisons. Thirty percent of the respondents had some form of a prioritization method (e.g., ranking structurally deficient structures by sufficiency rating, ranking based on a combined index of vulnerabilities and condition, or ranking by the use of multi-objective utility functions).

Whether states had a systematic process for the development of their bridge programs was another concern. From the explanations provided for several questions, seven states have a clear and systematic process for developing bridge programs. Other methods are based on BMS recommendations (5 states), proximity of bridges to other large projects (4 states), structural vulnerabilities (3 states), and economic analyses (2 states). The typical method is to identify candidates based on structural deficiency and sufficiency ratings, combined with engineering judgment.

Figure 2-4 summarizes the reasons 28 respondents report for not using a BMS for bridge program development. Skepticism of BMS simulation results and the challenge of developing the cost and deterioration models are the primary reasons cited. Some respondents report difficulty in advancing the level of implementation due to lack of resources and staff limitations, while a few respondents are satisfied with their own systems. Two respondents reported resistance within the agency as the major reason. Eighty percent are planning to use a BMS for this purpose in the future.

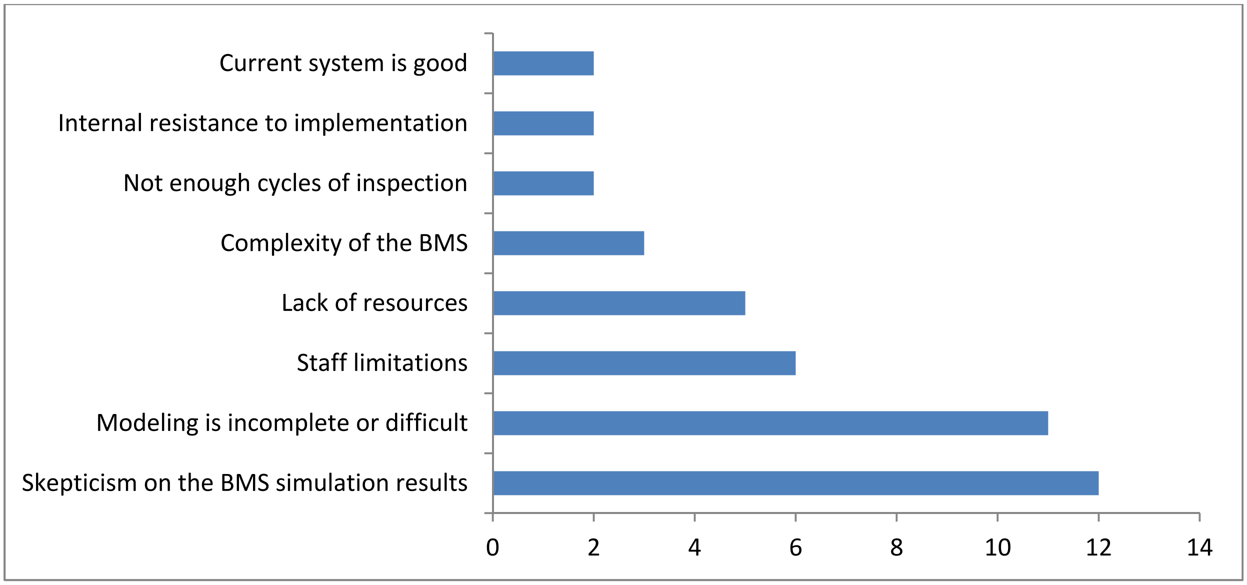

Figure 2-4: Reasons reported for not using BMS for bridge program development

Thirty-two respondents confirmed addressing risks such as scour and seismic safety while developing bridge programs. Addressing these vulnerabilities, however, was not as pronounced in the responses to earlier questions. For example, addressing vulnerabilities was indicated by only five respondents in the development of bridge programs and prioritization criteria.

Twenty-five of the forty respondents do not consider LCCA when evaluating project alternatives for new design and improvements. Although LCCA has long been recognized as a technique to help transportation agencies in project-level investment decisions, there is no consensus on methodology or cost parameters [45]. These parameters may include agency, user, and vulnerability costs, and analysts must have reliable estimates of these costs as well as probabilities that these costs will be incurred. Similar to the modeling of deterioration and cost models, LCCA is a dynamic process and model estimates need to be updated.

States' perception of the federal bridge programs

The final section of the survey investigated respondents' perceptions of the federal bridge programs, how they benefit from the programs and the types of challenges they may have.

The majority of respondents acknowledged the NBIP as the principal source of information on the condition of bridges and the condition assessment of their bridge networks. Half of respondents also noted the NBIP and the data collected for NBI strongly influenced their network-level prioritization. While a few respondents indicated that the HBP does not affect their bridge management process to any great degree, the majority reported that bridge management is driven by HBP requirements for eligible projects. The relaxation in HBP to fund preventive maintenance projects was well received by some states and evaluated to be a very positive move. For example, one respondent stated,

> "The relaxing of rules that used to require a bridge be eligible before bridge money can be spent on it has helped…In many ways this has helped focus the need on maintaining bridges rather than waiting until they deteriorate to the point that a lot needs to be spent to upgrade them. You can get more done with limited resources that way."

On the other hand, some respondents criticized that the HBP program does not encourage preservation activities. Several respondents were aware of the recent change and wanted to use HBP funds for preventive maintenance, but evaluated the requirements to be too restrictive or commented on the difficulty of complying with these requirements due to lack of time and personnel.

When respondents were asked whether federal bridge programs provide enough flexibility to agencies, 13 of the 40 respondents stated that they do not believe federal bridge programs provide enough flexibility. Eight of the 13 respondents commented that flexibility to use HBP funds for preventive maintenance was too restrictive. Final eligibility to use HBP funds on project-specific preventive maintenance depends on mutual agreement between the state FHWA division office and the state DOT. Some respondents reported that the interpretation of requirements by the FHWA division offices may vary and that the requirements should be more objective.

Thirty-one of the respondents are familiar with how FHWA uses NBI data in allocating Federal bridge funds (apportionment factors for states depend on the rehabilitation and replacement needs of eligible deficient structures identified by NBI condition ratings). Twenty-nine respondents believe that NBI data is not sufficient for allocating federal bridge funds. Twenty-seven respondents believe that BMS element-level condition data should be incorporated into the allocation of federal bridge funds and preparation of the required Condition and Performance Reports. Nine respondents suggested that the new National

Bridge Elements (NBE) as suggested by AASHTO would improve the condition assessment for the Nation's bridges and federal bridge programs.

Respondents were also asked if they have any suggestions to improve allocation of federal bridge funds and preparation of the Condition and Performance Reports. Several of these suggestions are quoted below:

> "Quantifying all funds spent on bridges is difficult to summarize. Funds are expended in a variety of manners to address transportation needs throughout the State. The obvious and easiest to quantify are those funds spent directly for the repair, rehab and replacement of bridges. The FY 2010 Program will improve or replace approximately *** bridges. However, we also spend funds indirectly on bridges through congestion management projects, roadway resurfacing projects where bridges are included separately from other bridge funding categories. State funds are expended for a variety of bridge maintenance needs that are not included in typical program accounting."

Quantifying the funds spent not only on bridges but also on other transportation assets or programs is important to analyze the relationship between investment and effect. This quantification is challenging since a variety of alternative resources can be used for any transportation project. However, it can provide valuable information to determine the effectiveness of federal programs and investment decisions. Unless the documentation and reporting of expenditures is required to a level of detail for all activities, by funding source and by structure, tracking of expenditures from the HBP is difficult. Whether such a requirement would be reasonable or feasible at the national level is another issue.

> "Federal apportionment is only moderately fair and accurate because there is a wide variation in the way each state inspects and reports bridge data."

> "Without independent review of all bridge inspections or processes, there is no other way for FHWA to report to congress. The question is "are all states getting similar inspection results when seeing a bridge with similar conditions?" The main problem is this method punishes states that do preventive maintenance as they will receive less than those who 'let the bridges go.'"

While variation to an extent is inevitable, the need to having a more objective and consistent framework to inspect and assess bridge conditions is also acknowledged by the

FHWA as well as the bridge management community. The recent efforts to have national consistency and a more objective and detailed framework to inspect and assess bridge conditions are supported by the FHWA.

"The NBI feeds the analysis done for the Condition and Performance Report but does not necessarily determine how much congress allocates to transportation. The data and impact relationship cannot be directly measured."

The Condition and Performance Reports are informative but not compulsory documents. Yet they have an important mission to provide the major input from the FHWA to Congress. While not the only criteria, they are part of the criteria that guide Congress in resource allocation.

"We recently lost funds because our state's bridges were in good shape. To get there, we had to sell BONDS and part of our future. States that are willing to be creative to generate funds should not be punished."

This comment points out a major shortcoming in the current resource allocation model. The model does not have a component that motivates improving the conditions of bridges; rather, with increasing deficient deck area the amount of HBP apportionment for a state can increase.

"The funding should be partially based on the amount spent on preventive maintenance. If you are not trying to preserve, why should you get a larger piece of the pie by letting the bridges deteriorate to get more money?"

The current HBP apportionment process does not include bridge preservation needs in the calculation of national bridge investment requirements. Although the necessity of timely preventive maintenance and preservation activities is acknowledged by the FHWA [46], the apportionment process does not address this necessity.

The final question of the survey asked respondents to identify the subject areas they felt needed additional guidance from FHWA. The most common issues are presented in

Figure 2-5. Using decision support tools for supporting bridge program development was cited most often, while bridge management implementation, funding restrictions, developing QC/QA programs, and data quality are other areas states reported to struggle with in bridge management.

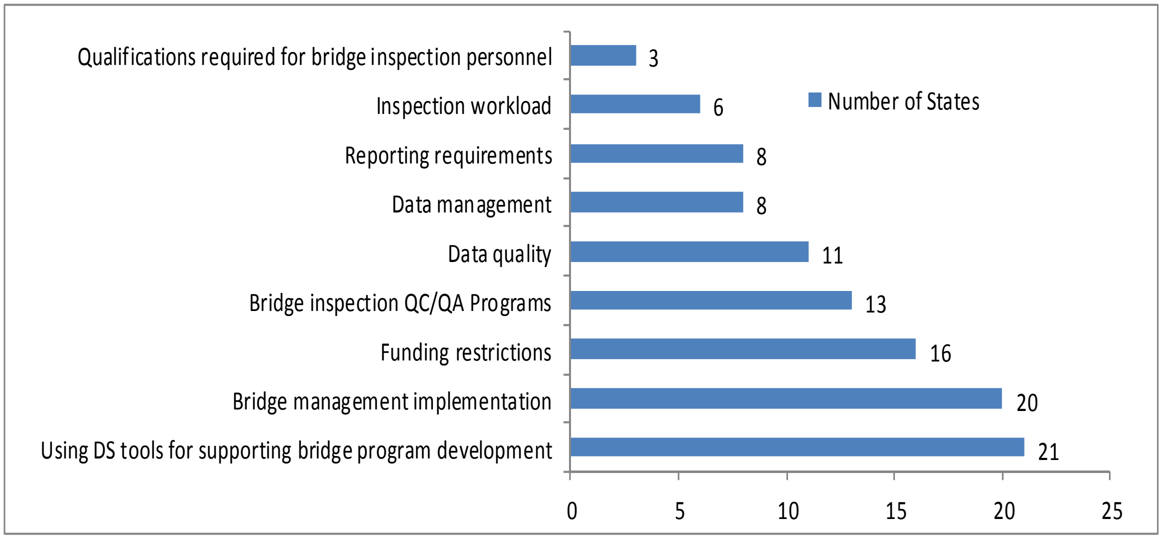

Figure 2-5: States' need for additional guidance in bridge management

Summary of major findings

The major findings from the survey can be summarized as follows:

- Ninety percent of the states do not believe NBI data items cover all their needs for bridge management.
- States as well as the federal government are concerned with data quality, but bridge inspection QC/QA programs typically are not yet completely established.
- Seven states have no set criteria to prioritize their bridge needs and for other states the criteria are open-ended. Reported criteria are governed by NBI condition data, HBP eligibility, and road capacity.
- The majority of states have implemented a BMS, typically Pontis; however, the level of implementation is varied. With few exceptions, states are challenged with implementation of BMS for decision support, especially due to difficulties in developing deterioration and cost models.
- General skepticism of the recommendations from the BMS discourages implementation and augments internal resistance to the necessary efforts to fully implement a BMS.
- States have extensive amount of BMS element-level condition data, but often the data are not processed and used, especially for network-level assessment.

- States desire more flexibility in the HBP to use funds for preventive maintenance.
- Use of economic analysis techniques such as LCCA or benefit-cost analysis is limited.

DISCUSSION

Bridge Inspections and Condition Data

The extensive amount of data collected by the states typically does not translate into information to support bridge management decision making. Investigating the differences between actual data collected and the data used may help transportation agencies identify redundant or duplicate data items. Ensuring that the data collection is rational [23] can save the states both crew time and resources and help them in their challenges to keep up with the inspection workload. How the data are transformed into concise, relevant inputs to various decision making processes should guide efforts from inspection to reporting. Effective communication of how these inputs guide the decision making with stakeholders such as policy makers, planners, budgeters, and the public is also essential for the accountability of bridge management programs.

Survey results suggest that although BMS element-level condition data based on AASHTO CoRe elements have been collected in the United States since the 1990s, not many states process or use this information extensively in bridge management. Project selection and prioritization are typically driven by NBI condition data, as they drive federal funding. However, although NBI is the only enforced and most nationally available source of data, it cannot sufficiently support all questions regarding bridge management at the state and federal levels.

The possible shift from NBI condition ratings to NBE as intended with the new AASHTO Bridge Inspection Manual will not be without its problems. Management of this transition at the state and federal level is critical for its ultimate success and sustainability. The NBE definitions in the new AASHTO Manual are pretty consistent with the AASHTO CoRe elements. However, significant changes to the condition state language have been made. The states that already collect CoRe element condition data will need to revise their inspection manuals and condition state definitions. NBE is proposed to replace the NBI condition ratings with element-level detail for decks, superstructures, substructures, and culverts. The element-level condition data for these primary structural components (e.g., pre-stressed concrete arch, reinforced concrete abutment) are to be represented by percentages of total quantity in four condition states. Many of these elements are in common with the AASHTO CoRe elements by structural use, and the element numbers are kept the same for ease of transition. However, the condition language and condition states are revised considerably to better capture defects and make them more objective.

While the change in bridge inspection approach is a potentially positive move from a condition assessment point of view, the transition has its challenges. The first challenge is how to migrate already available and very valuable historic BMS condition data to the NBE condition data. The number of condition states in the current CoRe elements can be 3, 4, or 5, but in the proposed NBE every element will be in 4 condition states. Other significant changes include the separation of wearing surfaces from decks, separation of steel protective coatings from steel, and incorporation of smart flags into condition state language. These issues regarding this migration are known by the developers of the new manual and are currently under investigation. The possible shift process needs time, but on the other hand these present circumstances and the resulting ambiguity leaves states anticipating the coming changes.

The NBI Translator (BMSNBI)

Within the data section of the survey, respondents were asked whether they use the NBI Translator (BMSNBI) algorithm to translate BMS element-level condition data to NBI condition ratings. Only three states report translated ratings to FHWA, and three other states use translated ratings for internal purposes. To a great extent, HBP funding eligibility is governed by the NBI condition ratings. Therefore, whether translated ratings adequately represent field NBI condition ratings is an issue. Reported concerns [35-37] about the accuracy of the translation between two condition systems therefore suggests concerns about the accuracy of investment projections. If NBEs are to be implemented, use of the NBI Translator algorithm within the NBIAS to synthesize BMS elements from NBI condition ratings will no longer be necessary. National bridge investment projections, needs, and performance measures could then be based on simulation results from the NBE data.

The FHWA QC/QA framework is a positive initiative, however additional guidelines in querying, processing, and using the data will be needed to improve overall data quality. Some inaccuracies and data quality problems are obvious at the bridge level but become less recognizable when the network as a whole is queried (e.g., queries for periodic checks to identify errors such as improved condition data when no improvement action was applied to the structure). Without using and processing the data, it is difficult or impossible to identify quality issues. In an agency where BMS implementation is not openly endorsed by all levels of management, there is little motivation to do element inspections in the field or to process and use the BMS element condition data.

Highway Bridge Program

Many states and FHWA acknowledge the value of a national bridge management policy that is based on modern asset management principles and balances bridge preservation, rehabilitation, and replacement activities based on objective data. Efforts at both the state and federal levels are needed to advance the framework and tools to get there, but this is a vision that would lead to cost-effective investments of tax dollars and sustainable bridge management programs. However, state-level management buy-in is key to have an established framework to achieve that vision, as NBEs and BMS implementation will require full-time staff, horizontal communication, and data sharing, training, and patience. Without it, it will be difficult for FHWA to encourage BMS implementation among the states, since executive-level endorsement is crucial for the implementation of asset management tools [47] (and any other strategic change such as the new NBE).

For national and state-level network assessments, developing performance measures based on the proposed NBE is a potential need. New performance measures with balanced distributions over their defined range are needed. Such performance measures will also serve the national agenda to identify "quantifiable performance measures" and to have "data-driven, risk based" oversight of the Nation's bridges. New performance measures based on NBEs also have also the potential to enhance the HBP apportionment model.

In the survey, 34 respondents reported spending $4.5 billion on bridge replacement, rehabilitation, and preservation. This compares to nearly the same amount spent from HBP for all states in 2009. If the expenditures from the HBP were tracked, it would be possible to investigate the link between expenditure and performance. The GAO recommended FHWA track HBP funding, and FHWA responded positively. However, several challenges exist. First, states have discretion in their spending, and FHWA does not have the authority to require such information. Another challenge is a provision in the Intermodal Surface Transportation Efficiency Act of 1991 that allows up to 40 percent of a state's bridge program apportionment to be transferred to the National Highway System (NHS) or the Surface Transportation Program (STP). Whether to share the amount of transfers from the HBP is, again, at the states' discretion.

Since 1992, the amount of transfers from HBP to other transportation programs, as reported by 35 states, equals $4.5 billion [48]. This amount is almost equal to last year's total HBP apportionment and reflects only the amount for 70% of the states that reported these transfers. It is well known that bridge management needs at the state level goes beyond all available federal and local funds. States also spend funds from other large "core" formula program apportionments on their states' bridges or spend more than required for the minimum matching share [14]. Therefore, it appears that the reason states transfer these funds are not because they do not spend more on bridges, but because either they want to allocate funds to projects that are not eligible for HBP funds or they prefer to use apportioned funds through more flexible transportation programs.

In several questions in the survey, respondents reported that they need more flexibility in spending HBP funds, but, at the same time, more documentation is necessary to track the HBP funds and their impact on the national network. This is an inherent conflict between FHWA and the state transportation departments and a challenge for the FHWA: providing national consistency without being perceived as rigid, and being flexible in achieving the goals of a national bridge management policy without being overly flexible. This hard-to-achieve balance will be will be debated during the next reauthorization.

Successful bridge management practices at state departments of transportation depend significantly on staff experience and expertise, due to the sophisticated nature of tools, long implementation times, and customization needed for each agency. Side comments from the survey emphasized the negative impact of staff fluctuation on the bridge management programs. Institutional memory loss in strategic planning and decision making programs is a significant problem [49]; knowledge management literature [50, 51] is available to assist state transportation departments as they consider the sustainability of their bridge programs.

CONCLUSIONS

This study presented an overview of federal and state government bridge management efforts taken in conjunction with the federal bridge programs in the last 40 years. Survey results from 40 states identify challenges and needs for bridge management at both federal and state level, useful to both practitioners and policy makers.

State transportation agencies collect extensive amounts of data on bridges, including generally both NBI and BMS condition inspections. However, systematic transformation of the extensive data into information to guide bridge management decisions is limited. Further, survey results indicate that ninety percent of the states do not believe that federally required NBI data items cover their data needs for bridge management.

HBP eligibility, NBI condition data, and road capacity guide network-level bridge management decisions. While the majority of state agencies have implemented BMS, the level of implementation is varied and the overall input from BMSs to network-level decisions is, as of yet, minimal.

Advancing implementation of BMSs in support of decision making at the national level has many challenges. A modeling approach that is consistent with states' expectations and verified by data and experience is yet to be achieved. Current models are complex and require continuous updates to verify assumptions and model inputs. Simplified network-level tools and methodologies are needed that summarize available data into objective information to guide bridge management decisions. Such tools that also consider economic analysis can support cost-effective, network-level decisions for both state and federal governments.

Questions remain and further research is needed on technical, institutional, and managerial aspects.

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CHAPTER 3.
A DISCUSSION ON THE EFFICIENCY OF NBI TRANSLATOR ALGORITHM

A paper presented at the Tenth International Conference on Bridge and Structure Management and published in Transportation Research E-Circular E-C128.

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ABSTRACT

The National Bridge Inventory (NBI) database is an extensive source of information on highway bridges in the United States. Among more than 100 NBI elements—deck, superstructure, substructure, and culverts—condition ratings are of special interest for bridge engineers and managers. The data for these condition ratings come from biannual bridge inspections in the field. As a part of their bridge management programs, many states have been collecting element-level condition data (mostly Pontis inspections) for more than 15 years. Element-level data provide more detailed condition data on sub-elements of the aforementioned general NBI element categories. Due to having such detailed condition data at hand, there has been an interest in developing algorithms that have the capability of estimating the NBI condition ratings from the Pontis element inspection data. If a sound estimation tool could be developed, the biannual NBI inspections done for these condition ratings would be deemed unnecessary. The NBI Translator is one of the algorithms that have been developed to achieve that goal and also works as a built-in module within Pontis.

Recently, there has been some concern as to the degree of accuracy of this algorithm by users of both Pontis and the translator. This paper presents a literature review on bridge management systems and bridge inspections in the United States. In addition, background on the NBI Translator algorithm and discussions on the efficiency of the tool are provided. A comparison study between the generated and actual values of the NBI ratings for bridges in Iowa is also included. The paper concludes with a discussion on how to improve the algorithm and use the translated results in a simplified network-level tool for bridge management decision making.

Keywords: asset management—bridge management—element condition ratings—NBI translator—NBI ratings

INTRODUCTION

In the past 40 years, there has been a shift from constructing new infrastructure to maintaining and managing the built infrastructure in the United States. Assessment of the deficiencies in the nation's infrastructure gained significant importance during this period. As the infrastructure gets older, more resources are required to maintain it at an acceptable level of service. Since the funds eligible for maintenance and rehabilitation activities are limited, effective resource allocation is now more necessary than ever. Agencies are required to keep condition data on their pavements, bridges, and other infrastructure elements and justify their reasons for decision making and funding requests.

As an important segment of the infrastructure system, bridges and their management have also been in the spotlight for the last four decades. Unlike pavements, the failure of bridge structures may result in disasters. Agencies in the United States learned from these incidents and started implementing an extensive and comprehensive approach to bridge management.

The biannual National Bridge Inventory (NBI) rating is an effort to support bridge management and to form a basis for funding bridge improvements in the United States. Agencies have also been collecting lower level detailed condition data for their bridge management systems. Modeling NBI ratings from lower level element condition data has been a topic of interest due to the significant resource savings it will facilitate (1). There have been efforts, but the degree of efficiency of the models is under consideration.

BRIDGE INSPECTIONS AND BRIDGE MANAGEMENT SYSTEMS IN THE UNITED STATES

On December 15, 1967, the Silver Bridge on U.S. Highway 35 suddenly collapsed into the Ohio River during rush hour (2). At the time of this tragic event, there were 37 vehicles crossing the bridge, and 31 of them fell into the river. Forty-six lives were lost during this event, and nine people had severe injuries (3). In addition to the loss of life, an important road connecting West Virginia and Ohio was no longer in service. The catastrophe evoked concern over the reliability of the national network of bridges in the United States.

The 1968 Federal-Aid Highway Act put the states in action to collect and keep an inventory for Federal-aid highway system bridges. In the early 1970s, the National Bridge Inspection Standards (NBIS) that form the basis of bridge inspection and inventory in the United States today were developed and implemented by the Federal Highway Administration (FHWA). This legislation guided the data collection on bridge condition all over the nation. After the collapse of the Silver Bridge, the failure of the Mianus River Bridge in 1983 and Schoharie Creek Bridge in 1987 were two other unfortunate events that drew attention to the importance of keeping the nation's bridges in sufficient condition and keeping up-to-date condition data (4).

In general, bridges are inspected every two years, and the condition ratings are reported to the FHWA. The inspection data are compiled by the FHWA into the NBI. After the analysis of the data, reports on bridge conditions are prepared and submitted to Congress. Decisions on the distribution of federal funding through programs such as the Highway Bridge Replacement and Rehabilitation Program are based on these reports (5).

In addition to the biannual NBI inspections, many states also collect element-level bridge condition data for the bridge management systems. Along with the Intermodal Surface Transportation Efficiency Act of 1991, which required the states to develop and implement bridge management systems, most of the states realized the importance and advantages of implementing bridge management systems. Although development of bridge management systems was made optional later in 1995 by the National Highway System Designation Act, many states decided to implement bridge management systems and took action (6). Forty-eight states were reported to be implementing a bridge management system as of September

1996 (7). Efforts to develop efficient national bridge management tools encouraged research in the area. A research project initiated by FHWA resulted in the development of Pontis Bridge Management System which later became the most popular bridge management tool in the United States. Forty-two states reported that they considered implementing Pontis Bridge Management System. Few states preferred to develop their own bridge management systems (Pennsylvania, Alabama, New York, and North Carolina). The state of Maine implemented BRIDGIT which was developed as a result of a National Cooperative Highway Research Program (NCHRP) Project (6).

PONTIS BRIDGE MANAGEMENT SYSTEM

As previously stated Pontis (8) is the most popular bridge management system in the United States that aims to help transportation agencies in the decision making process regarding maintenance, rehabilitation, and replacement of bridge structures. Agencies are now aware that the aging highway system has considerable improvement needs; however, funding resources are limited. Therefore, they need to make the best possible decisions for improvement, and these decisions should be based on facts. The Pontis input data structure is a relational database that contains complete bridge inventory and inspection data. FHWA and American Association of State Highway and Transportation Officials (AASHTO) adopted Commonly Recognized (CoRe) Elements for Bridge Inspection in order to standardize element-level condition data collection within the United States. Bridges are presented by the CoRe elements in Pontis, and the percentage of condition states for bridge elements are inspected and stored in the database. For each bridge element, specific condition states and related deterioration models were developed. Based on this detailed element inspection data, the program keeps track of current situation, simulates future condition, identifies bridge and network-level needs and makes project recommendations in order to gain maximum benefits from scarce funds.

Although Pontis has been extensively used for maintaining bridge element condition data inventory, not all states benefit from the tool for resource allocation and identifying future projects literally for the time being. Implementing a bridge management system is a big organizational change, and it takes time to prepare the organization for such a strategic change and customize the implementation.

NBI CONDITION RATINGS AND BRIDGE ELEMENT CONDITION DATA

The FHWA Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges (Coding Guide) helps inspectors with the data collection process. States are encouraged to use the coding guide for standardization purposes (5). The Structure Inventory and Appraisal Sheet (SI&A) lists the NBI items necessary for inspecting individual structures, and these items can be divided into three main categories: inventory items, condition rating items, and appraisal rating items. The NBI condition rating for an element is an evaluation of its current condition when compared to its new condition. In order to make the NBI condition ratings as objective as possible, the inspectors are provided with the general condition rating guidelines listed in Table 3-1. NBI condition rating elements are different from bridge management system elements. Three subsystems of bridges and culverts receive overall condition ratings in NBI inspections (5):

- Item No. 58 Deck
- Item No. 59 Superstructure
- Item No. 60 Substructure
- Item No. 62 Culverts

Table 3-1: NBI general condition rating guidelines*

Code	Description
N	NOT APPLICABLE
9	EXCELLENT CONDITION
8	VERY GOOD CONDITION (No problems noted)
7	GOOD CONDITION (Some minor problems)
6	SATISFACTORY CONDITION (Minor deterioration in structural
5	FAIR CONDITION (Sound structural elements with minor section loss)
4	POOR CONDITION (Advanced section loss)
3	SERIOUS CONDITION (Affected structural elements from section loss)
2	CRITICAL CONDITION (Advanced deterioration of structural elements)
1	"IMMINENT" FAILURE CONDITION (Obvious movement affecting
0	FAILED CONDITION (Out of service)

*Adapted from (Dunker and Rabbat 1995)

While the NBI condition ratings are assigned according to the 0-9 scale given in Table 3-1, element-level data collected for bridge management systems are assigned on a scale of 1 to 3, 1 to 4, or 1 to 5 based on the particular element. Of 106 CoRe bridge elements, 21 CoRe elements describe bridge decks, 35 CoRe elements describe superstructures, 20 CoRe elements describe substructures, and 4 CoRe elements describe culverts. In addition, smart flags are defined to describe special defects in miscellaneous bridge elements such as each beam, column, or girder. The rest of the CoRe elements are a variety of items such as bridge railings, joints, or bearings (1). Condition State 1 for an element is the best condition, while condition states 3, 4, or 5 present the worst conditions for particular elements. In Table 3-2 condition state definitions of an unprotected concrete deck from Pontis element configurations are provided as an example (9). The percentage/quantity of an element for each defined condition state is recorded during Pontis inspections.

Table 3-2: Condition state definitions of unprotected concrete deck

Code	Description
1	No damage
2	Distress <= 2%
3	2-10% distress
4	10-25% distress
5	Distress >=25%

The Pontis condition inspection data with extensive detail down to each individual element made agencies and experts in the field question the redundancy of NBI inspections for the same inspected bridges. Pontis inspection results provided agencies with much more detailed condition data for the aforementioned NBI items. Using the data at hand for other data requirements when possible is essential because data collection is a time- and resource-consuming process. For the year 1986, NBI costs were estimated to be approximately $150 to 180 million (10). Although NBI data and Pontis inspection data have discrepancies in item definition and rating scales, researchers have been trying to make a translation from bridge element condition data to high-level NBI ratings to reduce the huge cost and time spent for data collection (11-13). Hearn et al. (11) developed an estimator model for the purpose, which was later developed as a software tool known as the NBI Translator or BMSNBI. The Pontis program has this software tool as a built-in module, and the tool can be used for translation from a defined set of element inspection states for specified bridges in the Pontis environment.

NBI TRANSLATOR

The NBI Translator was developed at the University of Colorado at Boulder, with the collaboration of the Colorado Department of Transportation (DOT) (11, 13). The translator generates condition ratings for deck (Item 58), superstructure (Item 59), substructure (Item 60), and culverts (Item 62) "by linking CoRe elements to corresponding NBI fields and mapping bridge management system condition states to NBI rating scale" (11). Bridge inspection data that contains both the NBI ratings and element-level condition state data of approximately 35,000 bridges were used to calibrate the NBI Translator (13).

Generation of NBI condition ratings is realized in four main steps (13). First, CoRe elements are grouped into matching NBI fields. Then, NBI condition ratings are generated for individual elements based on the quantities of that element in the different condition states. This table-driven procedure is shown in Figure 3-1 (adapted from 13).

Requirements on element quantities			NBI Rating
P_1	$\geq$	$M_{1,9}$	9
P_1+P_2	$\geq$	$M_{2,9}$	
$P_1+P_2+P_3$	$\geq$	$M_{3,9}$	
$P_1+P_2+P_3+P_4$	$\geq$	$M_{4,9}$	
P_1	$\geq$	$M_{1,8}$	8
P_1+P_2	$\geq$	$M_{2,8}$	
$P_1+P_2+P_3$	$\geq$	$M_{3,8}$	
$P_1+P_2+P_3+P_4$	$\geq$	$M_{4,8}$	

Figure 3-1: Table for NBI Generation modify according to the guide

Hearn, Cavallin, and Frangopol (13) describe the table-driven element NBI generation as follows: Percentages of element quantities in condition states are denoted by P_i and taken from element inspection records. Each row in Figure 3-1 checks the sum of percentages for a minimum required sum. These minimum required sums, denoted by $M_{i,j}$, are called mapping constants. As previously mentioned, number and definition of condition states differ for CoRe elements for each material and use. For example, the condition states for steel deck are different from reinforced concrete deck. Overall, 20 different maps are required for generating NBI ratings. The four requirements for each NBI rating should be satisfied at the same time to assign that particular NBI rating to that particular element. The calibration process estimates these mapping constants. After assigning the NBI ratings for all elements, NBI ratings for each item (deck, superstructure, substructure, and culverts) are calculated by a weighted combination of element ratings. While the weights for deck and superstructure fields are based on relative quantity, the weights for substructure field are based on number of spans. Finally, NBI condition ratings are modified based on the smart flag condition reports. Smart flags may reduce the NBI ratings by a maximum of three points.

The objective of the calibration process is to find the mapping constants that will lead to the minimum difference between the NBI ratings given by inspectors and the generated NBI ratings from the element condition data.

Discussions on the NBI Translator Algorithm

Although the PC-based version of the NBI Translator algorithm has been available since 1994, the traditional NBI inspections for bridge subsystems are still being done since the translator results are not accepted as satisfactory. In some of the states that have access to the NBI Translator through Pontis, bridge engineers reported that they have concerns regarding the efficiency of the tool. A recent study (14) on bridge management involving 17 state DOTs reported a general skepticism about the estimation accuracy of the NBI Translator. Among these states, only Oklahoma has been using the rating translator. However, due to the variance of the generated ratings, they are in the process of stopping the use of the translator. In another study, Scherschligt (15) reports that the Kansas DOT evaluated NBI Translator results as an alternative to performance measures for bridge prioritization. The coefficient of determination between generated and real ratings was only 25%. This implies that the translator was able to explain only 25% of the variation in the NBI ratings in the best case. The Kansas DOT decided that the translator results were statistically insufficient and inconsistent. Therefore, they eliminated the NBI Translator results from their alternatives of performance measures.

A study by Al-Wazeer, Nutakor, and Harris (1) proposes an alternative for NBI generation to improve the results of NBI Translator. Based on data from Wisconsin and Maryland, artificial neural network (ANN) models were developed, and results of ANN models were statistically compared with the NBI Translator results. The statistical comparison was based on the differences between the predicted and the actual observed NBI ratings. NBI error ranges were defined, such as the following:

- NBI Error = 0 (the difference between the predicted and the actual observed NBI rating is zero)
- NBI Error = 1 (the difference is equal to the absolute value of one)
- NBI Error = 2 (the difference is equal to the absolute value of two)
- NBI Error > 2 (the absolute value of the difference is greater than two)

Comparisons based on the aforementioned error ranges showed that the ANN model had a higher estimation capability with respect to the NBI Translator model for a particular state when the data used for ANN training is from the same state. The superiority of the ANN model to NBI Translator cannot be generalized, since the statistical results are valid for only the data used in the study. However, the study drew attention to the importance of customizing the prediction model for each state.

STATISTICAL COMPARISON OF ACTUAL AND GENERATED RATINGS FOR IOWA BRIDGES

For the state of Iowa, NBI generation from the element-level condition data was performed using the built-in NBI Translator in Pontis software. Six hundred and eighty data points were used for the analysis of culvert ratings, and 3,038 data points were used for the analysis of substructure, superstructure, and deck ratings. Before using NBI Translator for Iowa bridges, it was customized according to the element configuration of the Iowa Bridge Management System. This customization was done by modifying the driver file, Elements.prn, in the Pontis program folder, which defines the elements to be included in NBI generation (13). First, the list of elements defined in the original Elements.prn file in the program folder and Iowa elements defined in the Pontis inspection manual were compared to find the differences. Some elements that were included in the original Elements.prn file were not being used in the Iowa Pontis system; therefore, those elements were discarded in the modified Elements.prn file. Some elements had different numbers in the Iowa system, and they were also renumbered accordingly in the driver file.

The Elements.prn file contains seven fields of information. These information fields are element ID (element number), element NBI field (e.g., deck, superstructure), element material (e.g., unpainted steel, masonry, smart flag), element type (e.g., slab, truss bottom chord), element dimension (e.g., each, square feet), and element name in both long and short forms (13). There were some elements in the Iowa Pontis elements that were not defined within the original Elements.prn file. In order to include these elements in the NBI generation, all seven fields of information for each element were coded into the modified Elements.prn file. The list of codes necessary for modifying Elements.prn file is provided by Hearn et al. (11). After making all the modifications to the driver file, the modified file in the Pontis program folder is replaced by the modified version and used in NBI generation.

Figures 3-2 though 3-5 summarize the findings of the comparison. For each rating item, the percentage distribution of actual and generated ratings among the data set are presented as clustered column charts. Figure 3-2 shows that the NBI Translator estimates lower deck ratings than the actual observed deck ratings. While 34% of actual deck ratings have values of 8 and 9, the NBI Translator estimates no deck rating within this range.

Figure 3-3 shows the comparisons for superstructure ratings. While 19% of the actual ratings are equal to 9, no observation equal to 9 appears in the generated ratings. The percentages of generated 5, 6, and 8 ratings are greater than the actual case, while the percentage of generated 7 ratings is lower than the actual case.

For the substructure ratings, once again, the NBI Translator algorithm tends to estimate lower values than the actual assigned ratings (Figure 3-4). The percentages of 4, 5, and 6 ratings are very close for substructures. However, approximately 45% of the actual ratings that are equal to 8 and 9 are lost in the generated ratings. For culverts, the algorithm generates 20% more 8 ratings, 22 % more 7 ratings, and 19 % fewer 6 ratings than the actual case. Once again, no 9 rating is generated by the algorithm (Figure 3-5).

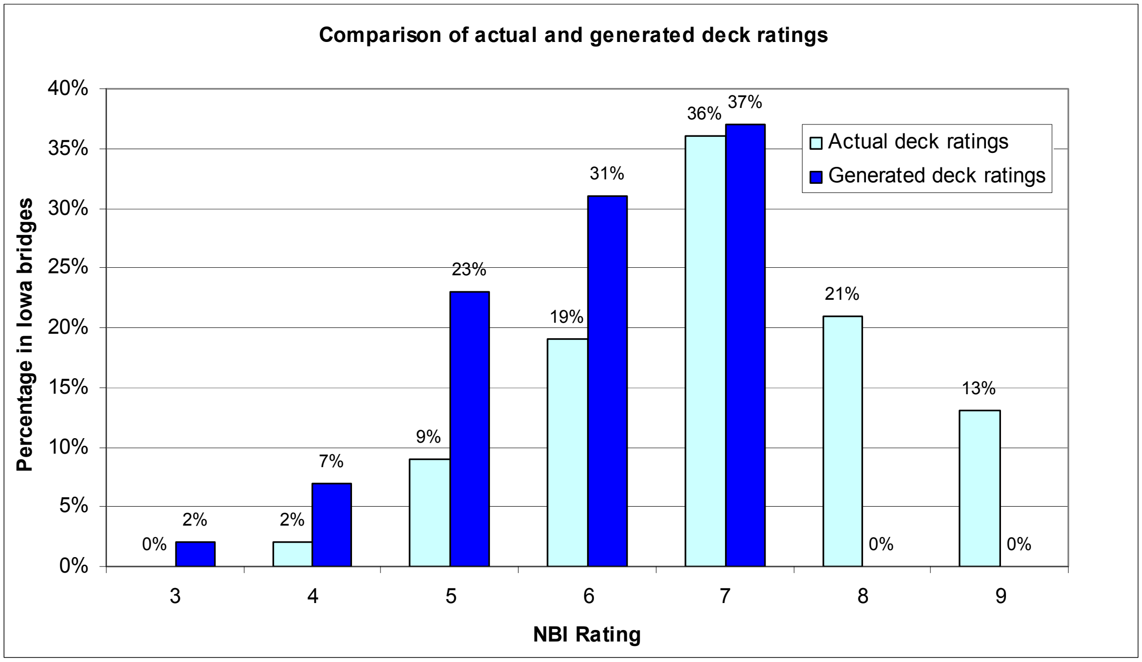

Figure 3-2: Comparison of actual and generated deck ratings

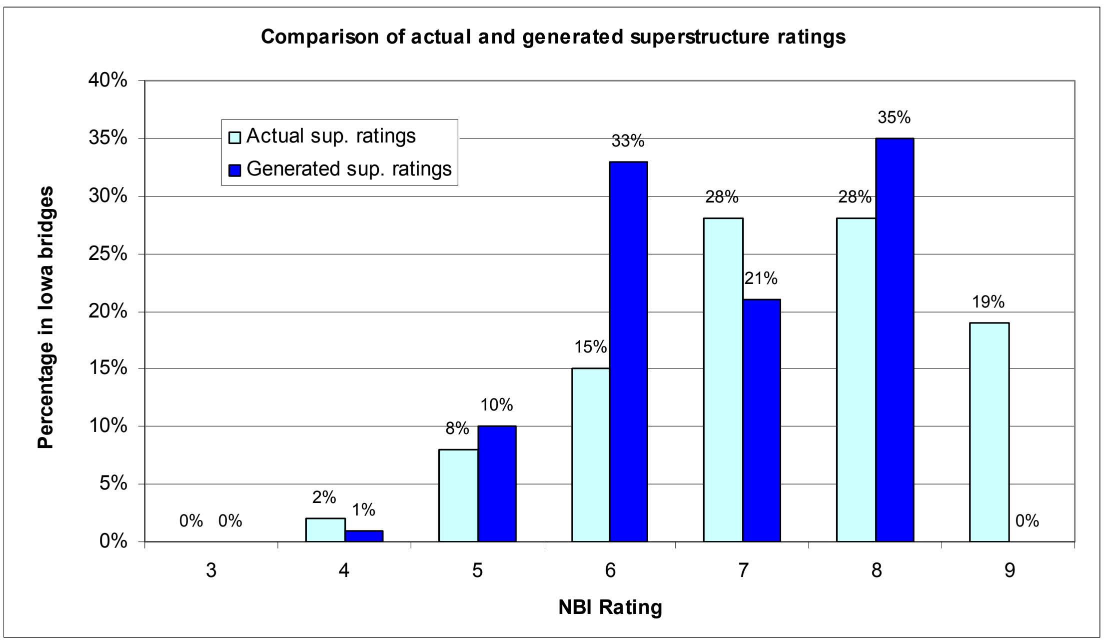

Figure 3-3: Comparison of actual and generated superstructure ratings

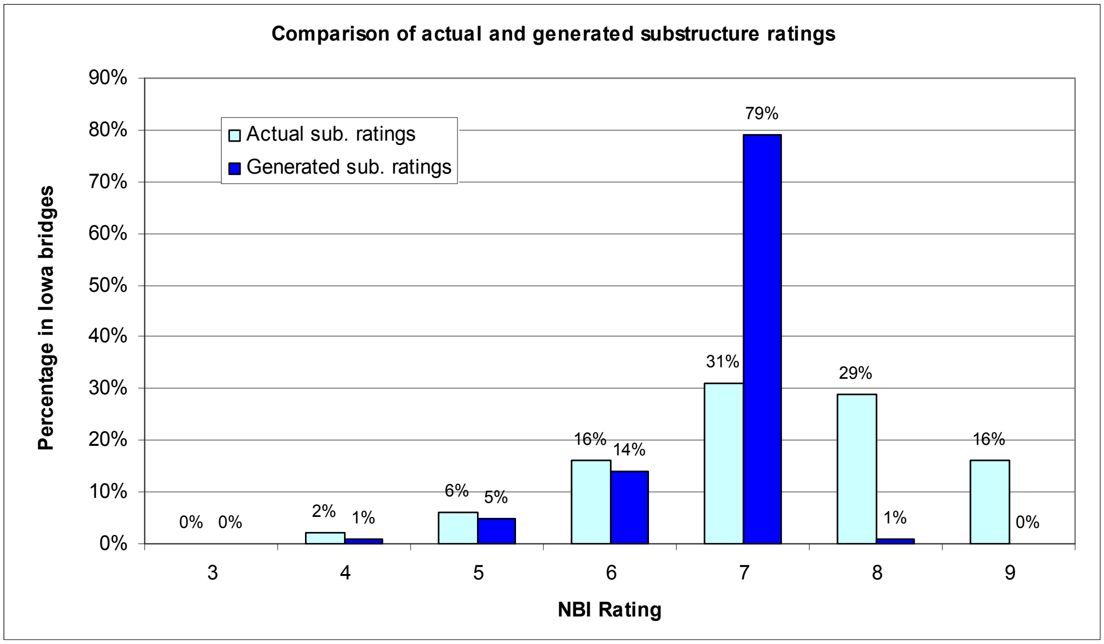

Figure 3-4: Comparison of actual and generated substructure ratings

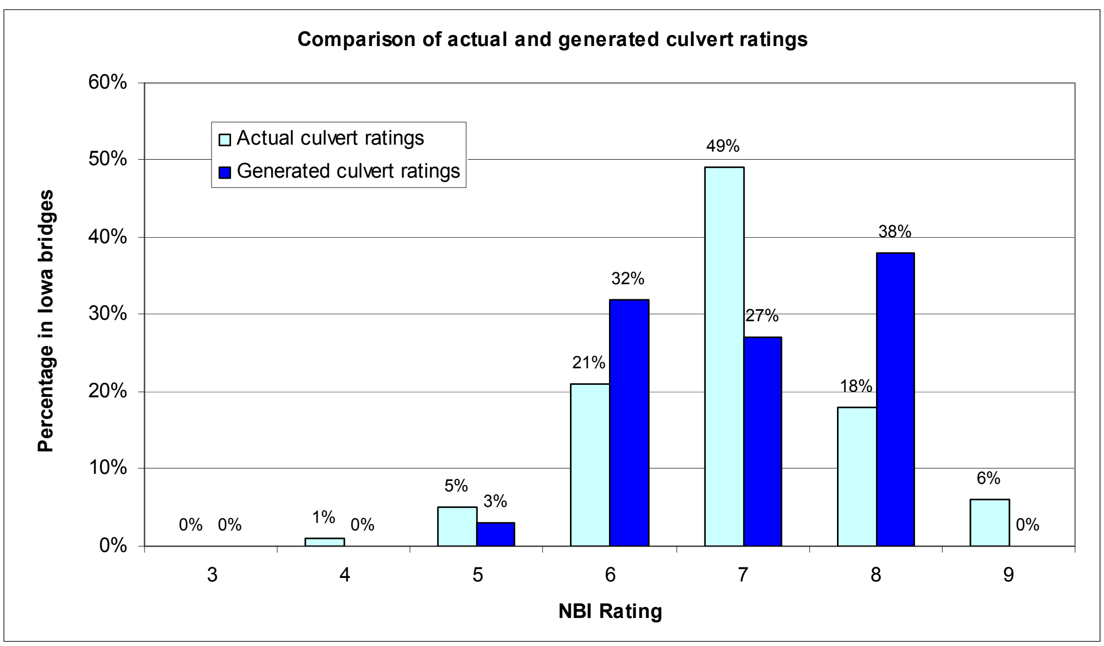

Figure 3-5: Comparison of actual and generated culvert ratings

HOW TO IMPROVE THE TRANSLATOR

Ideally it would be desirable to have an entirely objective system to collect bridge condition data. This would enable developing objective and standard performance indicators to evaluate bridge conditions that are efficient for all of the states. However routine bridge inspections are usually completed using only visual inspections, and in this context they are considerably dependent on the subjective assessments of the bridge inspectors (16). Although national and local agencies provide guides and guidelines to assist bridge inspectors in the data collection process and make bridge inspections as objective as possible, the ratings have subjectivity. Visual inspection methods have been criticized due to their subjectivity in the literature (17-19). However, they are still the most common bridge inspection methods due to budget constraints and lack of convenient and feasible alternative methods.

The current NBI Translator algorithm was developed based on element-level condition data and NBI ratings from 11 different states and from approximately 35,000 bridges. This extensive data was used to come up with a general translator algorithm that could be used in all states regardless of the location. Data from different states was banded together and used as the input data to develop this general algorithm. This approach is absolutely reasonable when the objective is to develop a general estimator; however, it is not useful in order to detect individual inspection practices of different organizations. A general estimator developed based on such an input structure may fail to sufficiently identify the variability that comes from the custom practices of different states. As mentioned in an earlier section, in a recent study where an alternative algorithm (1) was proposed, it was reported that when custom input data was used for the same state, this alternative algorithm had a higher estimation capability. Developing a customized estimator based on state-specific data may result in a more efficient and sufficient estimator and motivate agencies to use such a tool to estimate the NBI ratings, which will eventually have significant impact on bridge inspection costs.

The discrete characteristic of the NBI condition ratings make it impossible to use the ordinary least squares regression to develop an estimator where the NBI condition ratings are the dependent variables and element-level condition data are the independent variables. Also, when evaluated from a statistical point of view, the structure of potential predictor variables is complex. For each general NBI rating category, there is a set of CoRe elements that are elements of that category, and the condition data is presented as the percentages of those elements in different condition states. Because of these issues with the data, there is not a straightforward statistical model to be used to develop an alternative algorithm, but the data has potential to come up with a generalized linear model. Our current research focuses on developing an estimator based on a generalized linear model. The main challenge with the research is to define the most appropriate input structure for the model. After the model is developed, there is a plan to test the model with the data from other states and discuss its potential as an alternative algorithm.

CONCLUSIONS

This research paper reviewed bridge condition data and management in the United States and focused particularly on the estimation of NBI ratings from already-collected bridge-element condition data. The best known algorithm for the purpose, which is also available within the most popular bridge management software in the United States, was investigated and evaluated using a case study for Iowa bridge data.

The results of the statistical comparison for Iowa bridges showed that the generated ratings by NBI Translator algorithm with its current configuration are not representative of the actual NBI ratings. The results from this research support the concerns about the efficiency of the translator algorithm that have been previously reported. A more customized model for Iowa can lead to a more efficient model for estimating the NBI ratings. Using mapping constants specific to only Iowa bridge data instead of using the mapping constants calibrated with the data from 11 different states to create the translator algorithm may be an option. An improved and more customized algorithm may yield better estimates of NBI ratings. As a follow-up to another study in the literature, an ANN model can be developed for Iowa as another future research alternative. No matter what model is used, the current NBI rating system is prone to variation from the subjectivity of inspector decisions and might be hard to correlate to the more objective element-level condition data. Ultimately, an algorithm that calculates a 0 to 9 rating in an objective and consistent manner might be what is needed for improved bridge management data and decision making tools.

Whichever rating system an agency uses, the objective is to make consistent and objective decisions regarding bridge maintenance, rehabilitation, and/or replacement. Future research will cover the development of a simplified network-level tool utilizing consistent objective data to aid the decision makers and bridge managers in making resource allocation decisions and funding needs based on realistic and easy to use models.

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CHAPTER 4.
CART ALGORITHM FOR PREDICTING NBI CONDITION RATINGS

A paper to be submitted to The Journal of Infrastructure Systems (ASCE)

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ABSTRACT

This paper presents a new methodology to predict National Bridge Inventory (NBI) condition ratings from bridge management system (BMS) element condition data using Classification and Regression Trees (CART). Methodologies and use of two types of bridge condition data collected in the United States are first discussed. The algorithms and accuracy of predictions for FHWA's BMSNBI (NBI Translator) and two other proposed methods from the literature are then briefly summarized. The paper also discusses the need for and uses of translated NBI ratings and potential problems due to the reported accuracy concerns. The CART analyses were conducted with the bridge condition data from three states, using 2006 to 2010 data. The statistical results point to a more accurate prediction method than the previous algorithms in the literature. Comparisons of predictions by the CART algorithm and the BMSNBI indicated better accuracy of the CART algorithm on the same sample data sets. The CART algorithm also achieved higher accuracies than the other proposed methods when similar accuracy measures were compared. The methodology also provides an easy to use prediction framework based on logical conditions of BMS element condition data. The methodology does not assume expert weights for the BMS elements on their impact to relevant NBI condition ratings, but rather defines BMS element categories as predictor variables. Therefore, the results also reveal potential information about the statistical impact of BMS element categories on the NBI condition ratings.

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INTRODUCTION

Bridge condition data in the United States

Bridge condition information is the fundamental information essential for decision makers to make well-informed bridge management decisions. Transportation agencies collect bridge condition data to assess the current condition and identify the future needs for maintenance, repair, rehabilitation, and reconstruction activities, whichever decision making methodology they might use. This data is also used by the federal government to evaluate national needs and to make funding allocation decisions.

Federal Highway Administration (FHWA) implemented National Bridge Inspection Standards (NBIS) in the early 1970s [1]. The NBIS forms the basis of bridge inspection and bridge management in the United States today. Typically, bridges are inspected every two years in the United States, and data on 116 NBI (National Bridge Inventory) items are reported annually to the FHWA by the state transportation agencies. This data is compiled into the NBI by the FHWA, and condition and performance reports based on the NBI data are prepared and submitted to Congress [2]. Allocation of federal funding for bridges is based on the NBI information, including condition and appraisal ratings [1].

NBI data are collected and recorded according to the guidelines in FHWA's Recording and Coding Guide [3]. NBI items 58 through 66 constitute the NBI condition ratings, and four of them are especially important and more frequently utilized by the bridge management community because they directly affect the Highway Bridge Program (HBP) funding eligibility criteria. These NBI condition ratings are deck, superstructure, substructure, and culvert condition ratings (items 58, 59, 60, and 62, respectively).

NBI condition ratings are assigned on a scale of zero to nine and according to the specifications in the Recording and Coding Guide. Table 4-1 gives a summary of these specifications.

Table 4-1: NBI general condition rating guidelines [3]

Code	Description
N	NOT APPLICABLE
9	EXCELLENT CONDITION
8	VERY GOOD CONDITION (No problems noted)
7	GOOD CONDITION (Some minor problems)
6	SATISFACTORY CONDITION (Minor deterioration in structural
5	FAIR CONDITION (Sound structural elements with minor section loss)
4	POOR CONDITION (Advanced section loss)
3	SERIOUS CONDITION (Affected structural elements from section
2	CRITICAL CONDITION (Advanced deterioration of structural
1	"IMMINENT" FAILURE CONDITION (Obvious movement affecting structural stability)
0	FAILED CONDITION (Out of service)

In addition to NBI condition data, many states also collect element condition data to use in their bridge managements systems (BMSs). The Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 required states to develop and implement bridge management systems. Although the implementation of BMSs was later made optional by the National Highway System Designation Act of 1995, many states continued in their efforts to implement a BMS [3]. This intent to develop and implement BMSs motivated research in the area, and a research project initiated by FHWA resulted in the development of Pontis BMS. Today, this tool is the predominant BMS used in the United States, used by 44 state agencies [4]. The norm in BMS element definitions and inspections in the United States is the American Association of State Highway and Transportation Officials' (AASHTO's) Commonly Recognized (CoRe) Structural Elements Guide. The guide is intended for national consistency in defining and inspecting BMS elements. However, it provides some flexibility to the states to adapt the guide and element definitions to their needs and add additional agency elements. The major BMS elements are structural elements that are sub-elements of the three NBI elements (deck, superstructure, and substructure). They provide more detailed condition information than the NBI condition ratings.

For each CoRe element there are several condition states that represent different stages of deterioration, and the maximum number of condition states can be 3, 4, or 5, depending on the particular element. Condition state 1 represents the best possible condition, while condition states 3, 4, or 5 represent the worst. BMS element-level inspection data are assigned as percentages of the total element quantities in these condition states. Agencies can also define environments that indicate the severity of the external condition for an element. Deterioration of the structures is partially affected by environmental conditions and other operational factors such as traffic and loading conditions [5]. The environments enable deterioration modeling specific to environmental conditions for the BMS elements. Four standard environmental classifications designated as benign, low, moderate, and severe have been defined to capture these effects. The deterioration models reflect more rapid deterioration for more severe environments (e.g., a pile element in a stream or a deck element subject to high average daily traffic). A number of structural units can also be defined for larger multiple-span structures. Therefore, the element condition data for one BMS element can be fragmented across several structural units and environments. BMS elements also include a set of special elements called smart flags, which allow tracking of distress conditions such as pack rust and deck cracking [5]. They indicate different patterns of deterioration other than typical CoRe element deteriorations.

Table 4-2 gives an example Pontis inspection (modified from real data for illustrative purposes) for a bridge where there are two deck, one superstructure (in two environments), and six substructure elements. This structure has only one structural unit. BMS element condition data represents the percentage of that element in that specific condition. For example, for element 275 (a reinforced concrete backwall) in Table 4-2, 72 % of that element is in condition state 1 (which is the best condition), 25 % of the element is in condition state 2, and 3 % of the element is in condition state 3. The number of possible condition states is 4, where condition state 4 represents the worst condition. The NBI condition ratings for this structure from the same field inspection are 6 (satisfactory) for the deck and 5 (fair) for both superstructure and substructure.

Table 4-2: An example Pontis bridge inspection data

#	Env	Element Name	States	Subsystem (Use)	% in 1	% in 2	% in 3	% in 4	% in 5
22	1	P Conc Deck/Rigid Ov	5	Deck	0	100	0	0	0
359	1	Botm Deck Smart Flag	5	Deck	0	100	0	0	0
109	1	P/S Conc Beam	4	Superstructure	100	0	0	0	
109	2	P/S Conc Beam	4	Superstructure	97	3	0	0	
202	1	Pntd Stl H-Pile	5	Substructure	94	0	0	6	0
234	1	R/C Pier Cap	4	Substructure	99	1	0	0	
234	2	R/C Pier Cap	4	Substructure	70	30	0	0	
271	1	R/Conc Stub Abutment	4	Substructure	97	3	0	0	
275	1	R/C Backwall w/Stub	4	Substructure	72	25	3	0	
279	1	R/Conc Column	4	Substructure	62.5	37.5	0	0	
300	1	Strip Seal Exp Joint	4	NA	70	30	0	0	
301	1	Pourable Joint Seal	3	NA	0	100	0	0	
310	1	Elastomeric Bearing	3	NA	100	0	0		
313	1	Fixed Bearing	3	NA	0	100	0		
321	1	R/Conc Approach Slab	4	NA	100	0	0	0	
331	1	Conc Bridge Railing	4	NA	90	10	0	0	

BMSNBI (NBI Translator)

Although the level of implementation varies among agencies and not many state transportation agencies can use Pontis BMS to support decision making at the moment, all Pontis licensees collect BMS element condition data and use the inspection module of Pontis. Consequently, a majority of Pontis licensee states collect and manage bridge condition data for both rating systems. Since BMS element condition data contain more detailed information on the general NBI elements, state agencies, experts in the field, and the FHWA questioned the redundancy of collecting NBI condition ratings. As a response to this interest, Hearn *et al.* developed [6] the BMSNBI (also known as the NBI Translator) software that maps BMS element condition data to NBI condition ratings, with the collaboration of the Colorado Department of Transportation, for the FHWA. The tool was calibrated with data from 11 states.

BMSNBI generates NBI condition ratings by a four-step process [7]. First, elements are grouped under matching NBI elements. Second, NBI ratings are assigned for each element. This assignment is done according to the mapping process as shown in Table 4-3 and repeated for each BMS element under each NBI element. Here, P_i represents the percentage of element quantity in condition state *i*, and $M_{i,j}$ is the mapping constant (quantity requirement for the total quantity in percentages for the first *i* condition states. as shown in the left hand side). For a BMS element to be assigned a specific NBI rating (such as a 9 or an 8, as we see in Table 4-3) all the percentage requirements represented by the inequalities on the left hand side should hold. So, for an element to be assigned an NBI rating of 8, the percentage of element quantity in condition state 1 (P_1) should be equal to or greater than $M_{1,8}$, the total of percentages in the first two condition states (P_1+P_2) should be equal to or greater than $M_{2,8}$, and so on.

Table 4-3: NBI generation [7]

Requirements on Element Quantities			NBI Rating
P_1	$\geq$	$M_{1,9}$	
$P_1 + P_2$	$\geq$	$M_{2,9}$	9
$P_1 + P_2 + P_3$	$\geq$	$M_{3,9}$	
$P_1 + P_2 + P_3 + P_4$	$\geq$	$M_{4,9}$	
P_1	$\geq$	$M_{1,8}$	
$P_1 + P_2$	$\geq$	$M_{2,8}$	8
$P_1 + P_2 + P_3$	$\geq$	$M_{3,8}$	
$P_1 + P_2 + P_3 + P_4$	$\geq$	$M_{4,8}$	

After the NBI rating assignment for each BMS element is done, NBI ratings are computed for each NBI element by a weighed combination of element ratings. Users can choose from two options for the weights used in this calculation: equal weights for all elements or weights based on relative quantities of elements. Finally, if there are any smart flags, NBI ratings are modified accordingly, and because smart flags are used for describing special defects in miscellaneous bridge elements, this modification is a reduction in NBI rating.

The BMSNBI has been available as a built-in module within Pontis BMS since 1994, and FHWA accepts translated NBI ratings instead of field NBI rating, for the annual NBI submissions. However, only three states use BMSNBI for their NBI data submissions. In 2007, Hale *et al.* reported general skepticism among the states regarding the accuracy of the BMSNBI algorithm [7]. The study involved 17 state departments of transportation (DOTs), and the states reported that they are not comfortable using BMSNBI results for their NBI submissions. Among these 17 states, Oklahoma has been using generated ratings for submissions. However, they were in the process of stopping this process at the time of the study due to the variance between generated and field ratings. In another comparison study between generated and field ratings done by the data from Kansas bridges [8], the Kansas DOT decided that the generated ratings were statistically insufficient and inconsistent, considering the coefficient of determination between generated and field ratings was only 25% in the best case.

A recent comparison of the field and translated ratings was done for Iowa bridges [9]. When the number of bridges in different NBI rating categories was compared, the overall condition of the network for the same NBI rating categories was different for actual and generated ratings. Figure 4-1 is a graph from this study that shows this comparison for the superstructure ratings. The BMSNBI is conservative in assigning NBI ratings and thus tends to assign lower ratings. The translated ratings were not representative of the bridge network condition based on the actual ratings, and the results supported the concerns about the efficiency of the algorithm that have been previously reported.

A recent national survey conducted by Iowa State University to assess the impact of BMS implementation on decision making both at the state and national level also confirms the limited use of the BMSNBI algorithm by the states. At present, only three states report translated ratings to the FHWA for the annual NBI data submissions, and they stopped collecting NBI condition ratings.

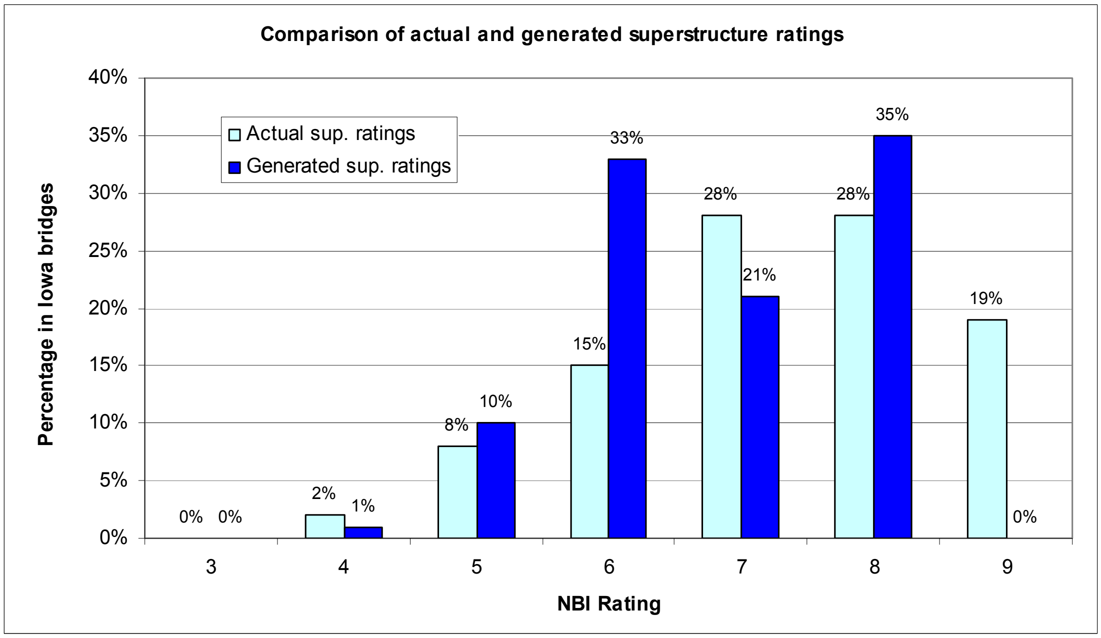

Figure 4-1: Comparison of actual and generated (translated) superstructure ratings

BMSNBI algorithm is not only used for NBI submissions; it has two other major uses. The first is within Pontis BMS modeling framework (Pontis 4.x). The algorithm is used to develop performance measures for forecasted future conditions, so the translated ratings affect the simulation results [10]. Therefore, even though the majority of states do not use the BMSNBI to submit NBI ratings, they are indirectly using its results as part of Pontis program simulation. The second major use is within the National Bridge Investment Analysis (NBIAS) software tool, which is used by FHWA to forecast bridge needs for the “Condition and Performance” reports prepared for Congress [11]. Therefore, the problems in the algorithm affect not only the NBI submissions, but also Pontis BMS simulations and forecasted bridge needs reported to Congress.

Alternative Algorithms for NBI Condition Rating Prediction

The noted problems and lack of confidence in the BMSNBI algorithm induced research to develop alternative tools. Two recent studies from the literature dated 2007 and 2008 proposed alternative translators. The first alternative translator was an Artificial Neural Networks (ANN) model [12]. This study utilized data from the states of Wisconsin and Maryland. In the analyses, when the training data for the ANN model and the data used for predictions were from the same state, the ANN model was reported to perform better than the

BMSNBI. The comparison was done by looking at the percentages of predictions for four classes based on the differences between the predicted and actual NBI ratings. This study achieved some improvement in prediction accuracy with respect to the BMSNBI for the sample data set. The authors, however, noted that with data from only two states their results could not be generalized and concluded to be better than the BMSNBI results. In this ANN model, the single input vector contained all element-level data, and the target output was the set of three NBI ratings. This modeling approach does not provide an understanding of or explore the analytical relationship between an NBI element and matching BMS elements [13].

The second study from the literature was published in 2008 [13] and proposed another alternative tool called the NewTranslator. The modeling methodology for the NewTranslator is pretty similar to that of Bridge Health Index[7]. The tool is a proposed index calculation and not an estimator. The first step in the calculation is computing condition indices on a zero to one scale for individual BMS elements. Then an NBI rating is assigned to these elements assuming an index value of zero is equal to an NBI rating of 3 and an index value of 1 is equal to an NBI rating of 9. The relationship in between is assumed to be linear. NBI ratings for an NBI element are calculated based on the individually assigned NBI ratings of elements and element weights based on expert opinion. Statistical analysis showed that the ratings from the BMSNBI and the NewTranslator are not precisely the same, and the NewTranslator is more accurate in assigning NBI ratings in the higher range. However, it was also reported that the NewTranslator tends to indicate high NBI ratings for bridges with poor element condition data.

Sobanjo *et al.* provided graphs to show the variation in the accuracy of the translated ratings by their method [13]. The average of absolute error (NewTranslator rating-field rating) was plotted vs. field NBI rating classes. The average of absolute error for decks (as read from the graph) was close to 0.8 for NBI rating classes 7 and 8, approximately 0.5 for NBI rating class 9, and above 1 for all other NBI rating classes. For superstructures, the

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[7] The Bridge Health Index is a single number (from 0-100) which reflects the condition distribution for the different elements on a structure [5]. This index reflects a weighted condition distribution of elements and the weights for elements are either expert assignments or element failure costs.

average of absolute error was smaller than 1 when only the field NBI superstructure rating was 9. For substructures, the average of absolute error was smaller than 1 when field ratings were 8 and 9, close to 0.9 for NBI rating class 8, and almost zero for NBI rating class 9.

Sobanjo *et al.* [13] reported that the method was a potential new method due to the improved accuracy in the higher range of NBI ratings, since this is a weakness of the BMSNBI. However, the fact that the method assigns higher NBI ratings in the low NBI range for bridges with bad element condition data was also noted as a problem. The poor conditions in especially old structures are critical, and such information is too valuable to be overlooked. Also, since the study is a computational index, the statistical relationship between specific BMS elements and field NBI condition ratings is not addressed.

To address the general issues with NBI ratings, in 2010 the AASHTO Subcommittee on Bridges and Structures approved a new element-level bridge inspection manual. The new AASHTO Bridge Element Inspection Manual [14] replaces the AASHTO Guide to Commonly Recognized Structural Elements. This new manual provides two sets of bridge elements: the National Bridge Elements (NBE) and the Bridge Management Elements (BME). The NBEs represent the primary structural components of bridges and are proposed as a refinement of the deck, superstructure, substructure, and culvert condition ratings defined in the FHWA's Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges [14]. The intention with the introduction of the NBEs is to eventually replace the NBI condition inspections with NBE condition inspections to provide a more detailed and objective condition assessment of the nation's bridges. However, the time for such a possible transition is not certain yet. Continuing use of the two different bridge condition inspections still indicates a potential need to accurately predict NBI condition ratings from BMS element condition data.

OBJECTIVE

The objective of this study is to develop a statistical model to predict NBI deck, superstructure, and substructure condition ratings based on BMS element condition data.

METHODOLOGY

Classification and Regression Trees

Classification and Regression Trees (CART) is a statistical technique used for predicting continuous dependent variables or categorical variables (classes) from one or more continuous and/or categorical predictor variables [15]. The analysis essentially builds a tree of logical conditions based on the predictor variables and is also commonly known as recursive partitioning.

The prediction models in CART are obtained by recursively partitioning (splitting) the data space by one predictor variable at a time and fitting a simple model to each partition. While the classification trees are designed for categorical dependent (response) variables that take a finite number of discrete values, regression trees are for continuous dependent variables [16]. The trees are designed to minimize the expected error between the observations and predictions for the dependent variables. Figure 4-2 presents an example classification tree from the study.

For the CART analyses in this paper, SAS JMP Statistical Software Partition Platform was used. In the SAS JMP platform, the splits are determined by maximizing a LogWorth statistic that is related to the likelihood ratio chi-square statistic (reported as “G^2” in the platform), which involves the ratios between the observed and expected frequencies [15] of the dependent variable. When the response variable is categorical (e.g., field NBI condition rating), the response rates become the fitted value. The most significant split (along the ranges of continuous independent variables) can be determined by the largest likelihood ratio chi-squared statistic. The split is chosen to maximize the difference in the responses between the two groups after the split. For the CART models in this study; the categorical dependent variables are the field NBI condition ratings, while the independent (predictor) variables are the BMS element quantities in different condition states, presented by a percentage of the total quantity (e.g., XPCTSTATE#).

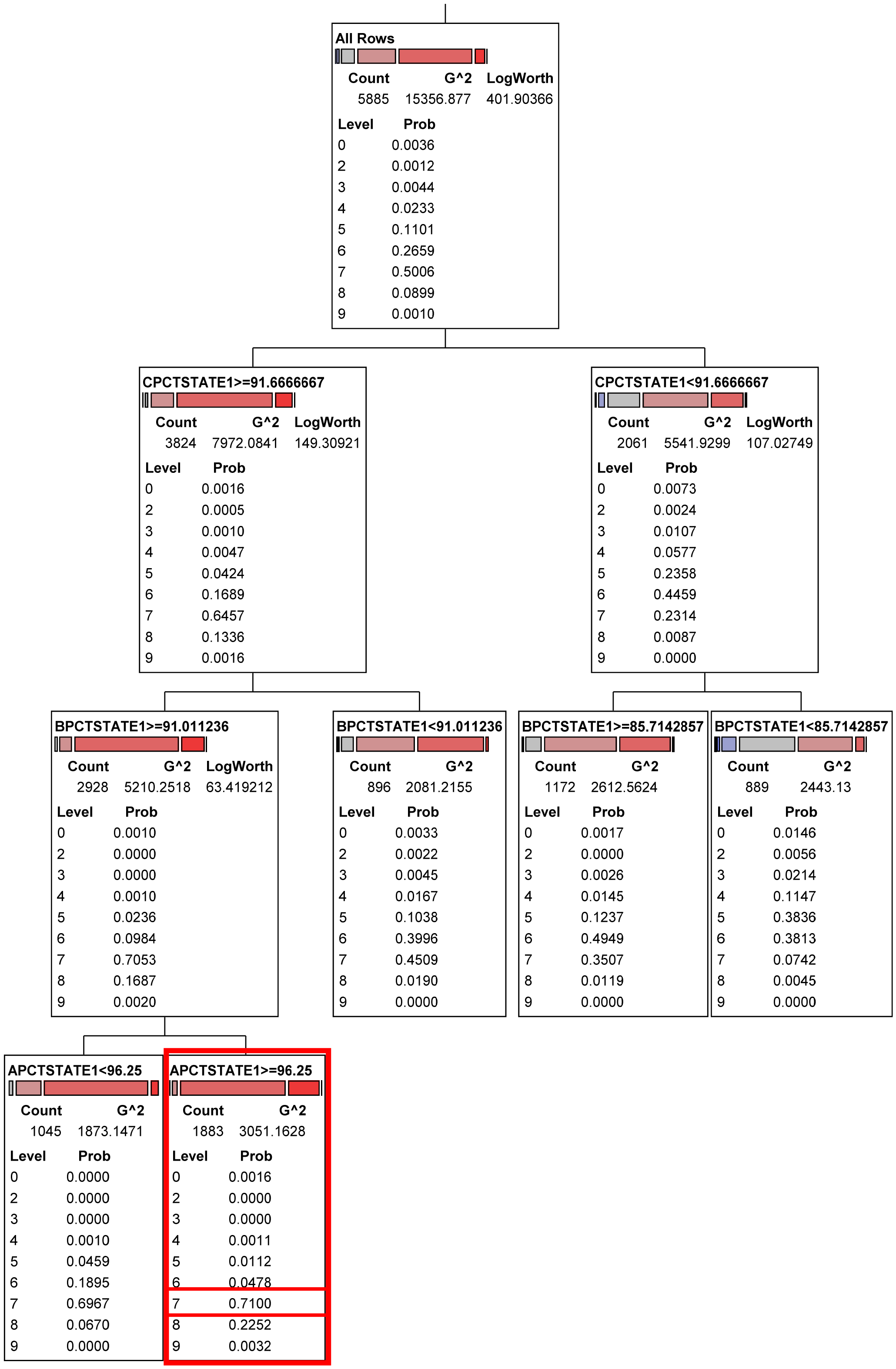

Figure 4-2: An example classification tree

The initial letters A, B, or C before the PCTSTATE# denote different types of BMS elements (e.g., in a substructure, element A can be a column, element B can be an abutment, and element C can be an abutment cap).

Splitting can continue until little predictive ability is gained by further splitting [17] by comparing column contributions or coefficient of determination (R^2) values, and where to end the splitting is a user decision. Recursive splits along the range of the same independent variable indicate a trend rather than a different clustering within the data.

The initial cluster in Figure 4-2 has 5,885 observations, and the first split is based on the first condition state of element C. The initial best split where CPCTSTATE = 91.67 splits the observation set into two clusters. The marked cluster with 1,883 observations as shown in Figure 4-3 is one of the five ending clusters after four splits. For each end cluster (leaf), the predicted probabilities for the observations to be in a specific dependent variable class are reported. The largest predicted probability designates the class (dependent variable) prediction for a specific cluster. The predicted probabilities for this cluster suggest that NBI condition rating 7 is the most likely class prediction.

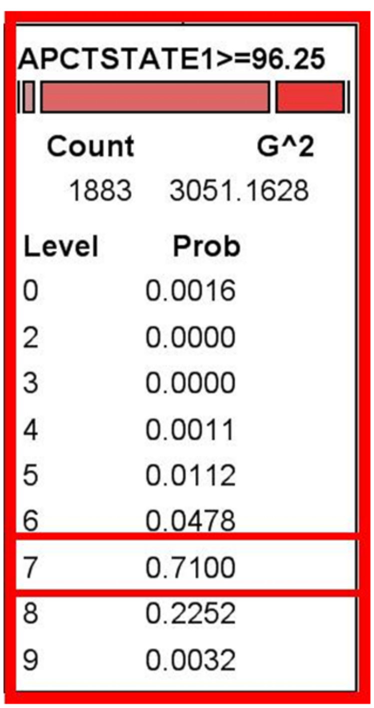

Figure 4-3: An example end leaf and predicted probabilities for a classification tree

Description of the Data Set

Sample BMS element condition data and NBI condition ratings from three state DOTs (Montana, Iowa, and Kansas) were used for the CART analyses in this study. Deck condition data could be acquired for only two state DOTs, while superstructure and substructure condition data were available for all three. The results of the analyses are not identified by the states. These states are notated as State DOT A, B, and C anonymously within this paper.

None of these three DOTs uses translated ratings for agency purposes or reports them to the FHWA. However, for State DOTs A and B, the "Elements.prn" [7] file, which is necessary to use the BMSNBI algorithm, was updated, and translated ratings were obtained for a smaller set of observations for comparison purposes.

The BMS implementation in State DOT A is at its earlier stages. State DOT A does not use BMS element condition data for condition assessment, and neither does it use the BMS recommendations to determine bridge work candidates at present. State DOT A does not have a quality assurance (QA) process for the BMS element condition data. Minimal in-house training for bridge inspectors is offered by the state.

State DOTs B and C are at similar stages of BMS implementation. Both states use BMS element condition data for assessing their bridge conditions, and they make use of BMS decision support capabilities while they select bridge work candidates. They have QA reviews for BMS element condition data. State DOT B provides in-house training for bridge inspectors each year, while State DOT C provides similar training every two years.

State DOTs B and C have concurrent NBI and BMS condition data, while State DOT A has only recently started doing concurrent inspections. Therefore, the data subsets for State DOT A for simultaneous BMS element-level and NBI condition inspections were combined from different data sources.

Modeling Approach

For the CART models in this study, the NBI condition rating classes from zero to nine were defined as the dependent categorical variables. The independent variables were assigned as the percentages of the related BMS element quantities in the condition states. These percentages of total quantities in a condition state are notated as PCTSTATE# in the analyses, where # designates the specific condition state. The number of possible condition states for BMS elements varies and can be 3, 4, or 5, depending on the type of element. The quantity of the BMS elements was included in the analyses as another predictor variable. Different combinations and numbers of BMS elements represent the NBI deck, substructure, and superstructure elements, depending on the structure design.

Deck

NBI deck elements are typically represented by single BMS deck or slab elements, which can be in one of the five condition states as a whole. Bridge railings and deck joints are also a field for BMS data inventory but are not to be considered in the overall NBI deck evaluation [3] and were thus not included in the analyses. Therefore, the predictor variables for decks in the data set are represented by five cases, a 100% in one of the condition states from 1 to 5.

Superstructure

Depending on the design and length of the bridges, NBI superstructure elements were represented by up to 10 BMS elements in the data sets from State DOTs A, B, and C; however, a majority of the observations had up to three major BMS elements. The number of inspections and the number of BMS superstructure elements in these observations are given in Table 4-4.

Table 4-4: Number of BMS elements in the sample superstructure observations by State DOT

		State DOT A		**State DOT B**		**State DOT C**	
		# inspections	% of inspections	# inspections	% of inspections	# inspections	% of inspections
Number of BMS elements in the superstructure	1	5121	**94.41%***	2241	**46.26%***	7334	**81.46%***
	2	190	3.51%	1179	**24.34%***	848	**9.42%***
	3	113	2.08%	1139	**23.51%***	235	2.61%
	4			150	3.10%	274	3.04%
	5			99	2.04%	214	2.38%
	6			24	0.50%	86	0.96%
	7			8	0.17%	12	0.13%
	8			0	0.00%		
	9			0	0.00%		
	10			4	0.08%		
	Total	5424		4844		9003	

**Used for the CART models*

A majority of the observations from State DOT A had one BMS element in the superstructure, either a girder or a beam. In addition to a single beam or girder, State DOTs B and C had a number of observations where a bearing element complemented the girder or beam element. Condition of bearings is not to be considered for assigning NBI condition ratings other than extreme conditions. Regardless, bearing condition was kept as a predictor variable in the analysis when available, to see whether it has any significant statistical effect on NBI superstructure ratings.

More than 23% of the State DOT B superstructure observations had three superstructure BMS elements, typically a beam or a girder accompanied by two different bearing elements. Different classification trees were fit for each of these groups, since the contributing BMS elements (the predictor variables) were different.

All superstructure elements were in four condition states, with the exception of painted steel elements. The AASHTO CoRe element condition state definitions for painted steel elements were used in all three states. Since the definitions of condition states 2 and 3 together represent a close definition of typical condition state 2 for unpainted steel elements, the percentages for painted steel elements were adjusted as shown in Figure 4-4.

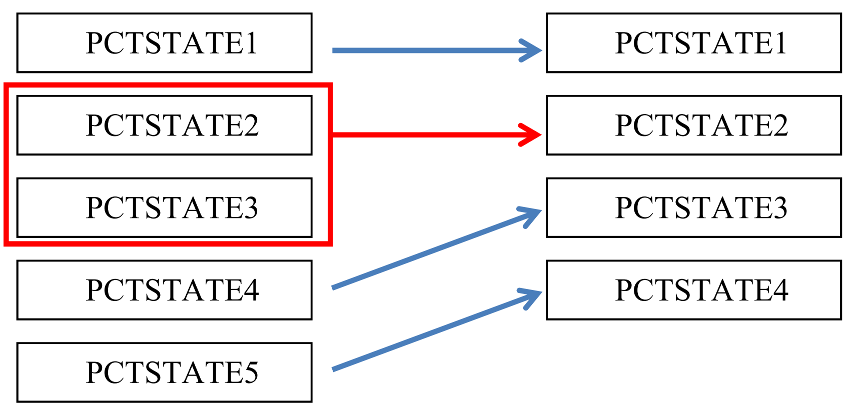

Figure 4-4: Adjustment of condition state quantities for painted steel elements

Substructure

The combination of BMS element types that represented the NBI substructure elements across the three State DOTs also varied. Three typical combinations that represented NBI substructures were as follows:

- A single abutment element
- A combination of one span support element (e.g., a wall, column, pier, or pile) with an abutment element

- A cap element, to complement one span support element and an abutment

The number of inspections and the number of BMS substructure elements in these observations are given in Table 4-5.

Table 4-5: Number of BMS elements in the sample substructure observations by state

		State DOT A		State DOT B		State DOT C	
		# inspections	% of inspections	# inspections	% of inspections	# inspections	% of inspections
Number of BMS elements	1	300	7.56%*	338	4.26%*	2162	21.91%*
	2	162	4.08%*	4169	52.59%*	962	9.75%*
	3	1992	50.20%*	3123	39.40%*	5887	59.66%*
	4	1514	38.16%*	273	3.44%	661	6.70%
	5			19	0.24%	165	1.67%
	6			5	0.06%	25	0.25%
	7					5	0.05%
	Total	3968		7927		9867	

**Used for the CART models*

RESULTS AND DISCUSSION

This section reports the results using a series of tables and figures. The notations used for these tables and figures are as follows:

- Field deck, field super, or field sub: NBI condition ratings assigned by bridge inspectors in the field for deck, superstructure, or substructure
- CART deck, CART super, or CART sub: Predicted NBI condition ratings for deck, superstructure, or substructure by the CART model
- Error (CART deck/ CART super/ CART sub): Error in prediction calculated by subtracting the field NBI condition ratings from predicted values (e.g., for decks: (CART deck-field deck))
- BMSNBI deck, BMSNBI super, or BMSNBI sub: Predicted NBI condition ratings by the BMSNBI (Available for subsets of the data, for State DOTs A and B)
- Error (BMSNBI deck/super/sub): Error in prediction by the BMSNBI calculated by subtracting the field NBI condition ratings from the BMSNBI predictions (e.g., (CART deck-field deck))

Deck

NBI deck elements are represented by only one BMS element. Deck BMS elements can be in one of the five condition states as a whole element. Therefore, the element condition observations for decks can be any of the five cases where the PCTSTATE# is 100%. Given five possible types of observations, the deck observations can be partitioned into at most five clusters (leaves).

State DOT A

Table 4-6 gives the count and percentage of the errors in predicting NBI deck ratings by error class for State DOT A. Approximately 40 % of the predicted NBI condition ratings matched the field NBI condition ratings. 92.5% of the predictions were within one error term; 25% of the predictions were one NBI class above, and almost 28% of the predictions were one NBI class below. Deck BMS element observations in condition states 4 and 5 were partitioned to one leaf and predicted as NBI condition rating 4. Deck BMS element observations in condition state 3 were assigned NBI condition rating 5. Deck BMS element observations in condition state 2 were predicted as NBI condition rating 6. However, the predicted probabilities for NBI condition rating 6 or 7 were pretty close: 0.384 and 0.372, respectively. The predicted probabilities for NBI condition ratings 7 (0.370) and 8 (0.374) were even closer for deck BMS element observations in condition state 2.

Table 4-6: Accuracy of predictions by the distribution of error terms (Deck, DOT A)

Error (CART deck)	count	%		
-3	7	0.22%		
-2	89	2.77%		
-1	894	27.78%		
0	1277	**39.68%**	**98.94%**	**92.51%**
1	806	25.05%		
2	118	3.67%		
3	21	0.65%		
4	6	0.19%		
	3218			

Figure 4-5 compares the field and predicted NBI ratings by NBI condition class. Since the deck BMS element observations could only be partitioned into four NBI rating classes, the distributions of the field and predicted NBI ratings by class for State DOT A deck data are not similar. Since deck BMS element observations in condition states 4 and 5 were partitioned to one leaf and predicted as NBI condition rating 4, the remaining observations that are deck elements in condition states 1, 2, and 3 could be matched only to three NBI condition rating classes (5, 6, and 8).

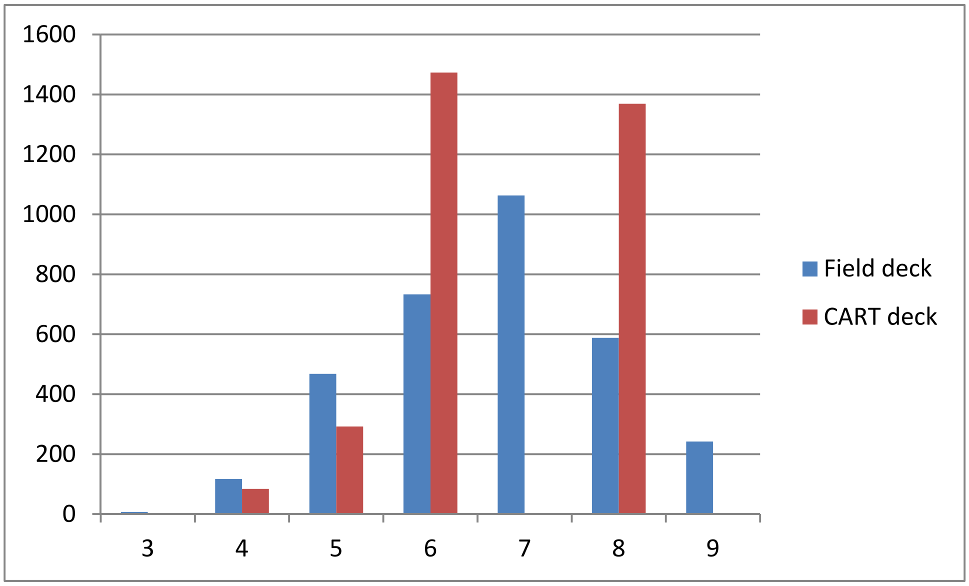

Figure 4-5: Comparison of field and CART ratings by NBI condition class (Deck, DOT A)

Table 4-7 compares the errors in predictions from RP and BMSNBI for a smaller available set of observations, while Figure 4-6 gives the distribution of observations by method and NBI class. Exact predictions and predictions within one error term are both better for CART results. However, CART assigns all observations to NBI condition rating 8 and BMSNBI to NBI condition rating 7; hence, both methods do not provide a good overall picture of the NBI deck field ratings.

Table 4-7: Comparison of the predictions by two methods (Deck, DOT A)

	Error (CART deck)	Error (BMSNBI deck)	CART		BMSNBI	
-2	0	118	0.00%		25.88%	
-1	118	187	25.88%		41.01%	
0	187	135	**41.01%**	**96.49%**	**29.61%**	**73.90%**
1	135	15	29.61%		3.29%	
2	15	1	3.29%		0.22%	
3	1	0	0.22%		0.00%	
	456	456				

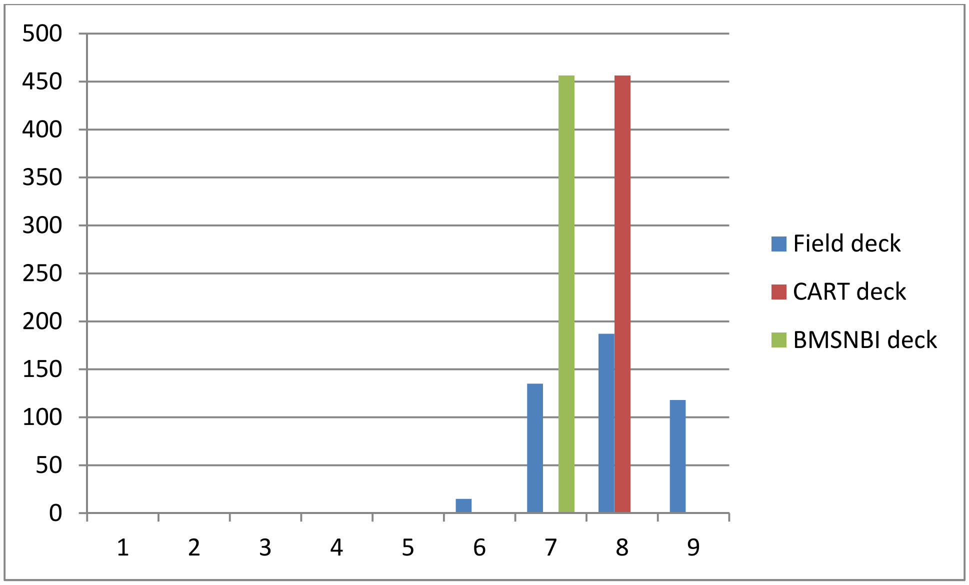

Figure 4-6: Comparison of field, CART and BMSNBI ratings by NBI condition class (Deck, DOT A)

The same set of figures and tables with similar content are given in this section for State DOT B deck analysis and then for both superstructure and substructure rating analyses of the three states. Several SAS JMP partition reports (a view of the classification tree, number of splits, coefficient of determination [R^2], and column contributions) are provided in Appendix B.

State DOT B

The CART deck predictions for State DOT B had overall better accuracies than for State DOT A. 63% of the predictions were exact matches, and almost all observations were predicted within one error term (Table 4-8).

Table 4-8: Accuracy of predictions by the distribution of error terms (Deck, DOT B)

Error (CART deck)	count	%	
-3	3	0.04%	
-2	3	0.04%	
-1	2496	32.97%	
0	4765	**62.95%**	**99.67%**
1	284	3.75%	
2	12	0.16%	
3	6	0.08%	
4	1	0.01%	
	7570		

As with State DOT A deck observations, deck BMS element observations were clustered into four leaves. Only 21 of the 7,570 observations were in condition state 5 and were predicted as NBI condition rating 3. BMS element condition states 4 and 3 were predicted as NBI condition ratings 5 and 6, respectively. Condition states 1 and 2 were clustered into one leaf and the predicted NBI condition rating class for both condition states was 7. Figure 4-7 gives the distributions of field and predicted NBI ratings by NBI condition class. CART analysis cannot make a distinction between NBI rating 7 and 8, but the number of predictions for NBI condition classes 5 and 6 are closer to the number of field ratings in the same classes.

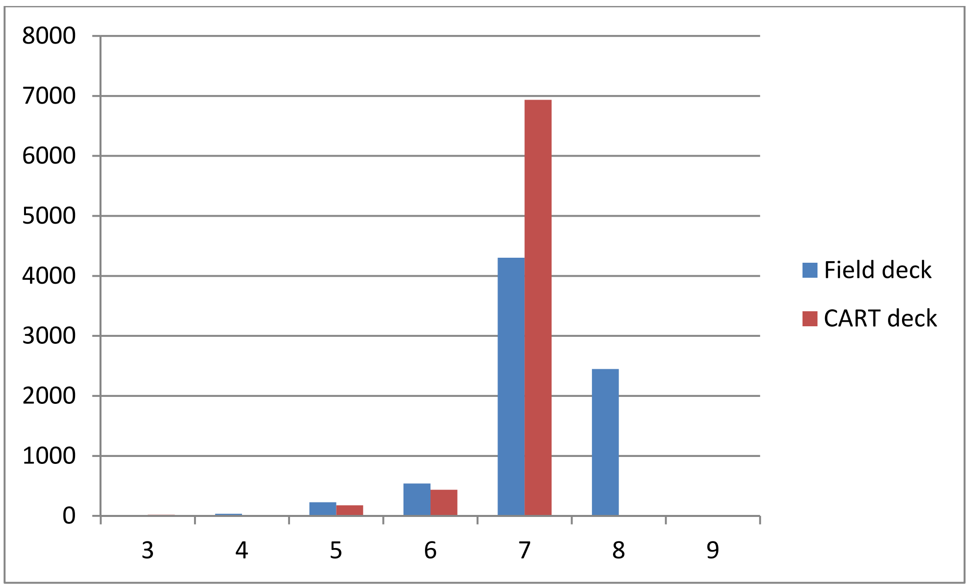

Figure 4-7: Comparison of field and CART ratings by NBI condition class (Deck, DOT B)

For 85% of the observations in the previous analysis, BMSNBI predictions were also available. Table 4-9 compares the errors from both methods in predicting NBI condition ratings. Exact matches are higher for CART predictions by 16%.

The BMSNBI overestimates the number of bridges with NBI condition ratings 5 and 6 (Figure 4-8), while CART underestimates it. However, for NBI condition rating class 7, CART predictions are higher in number than both BMSNBI predictions and field ratings. Neither of the algorithms predicts NBI condition class 8, which is the second largest cluster in the field ratings.

Table 4-9: Comparison of the predictions by two methods (Deck, DOT B)

	Error (CART deck)	Error (BMSNBI deck)	RP		NBI Translator	
-5	0	1	0.00%		0.02%	
-4	0	6	0.00%		0.09%	
-3	3	70	0.05%		1.08%	
-2	3	175	0.05%		2.70%	
-1	2169	2884	33.51%		44.56%	
0	4059	3042	**62.72%**	**99.77%**	**47.00%**	**94.65%**
1	229	200	3.54%		3.09%	
2	9	78	0.14%		1.21%	
3	0	13	0.00%		0.20%	
4	0	3	0.00%		0.05%	
	6472	6472				

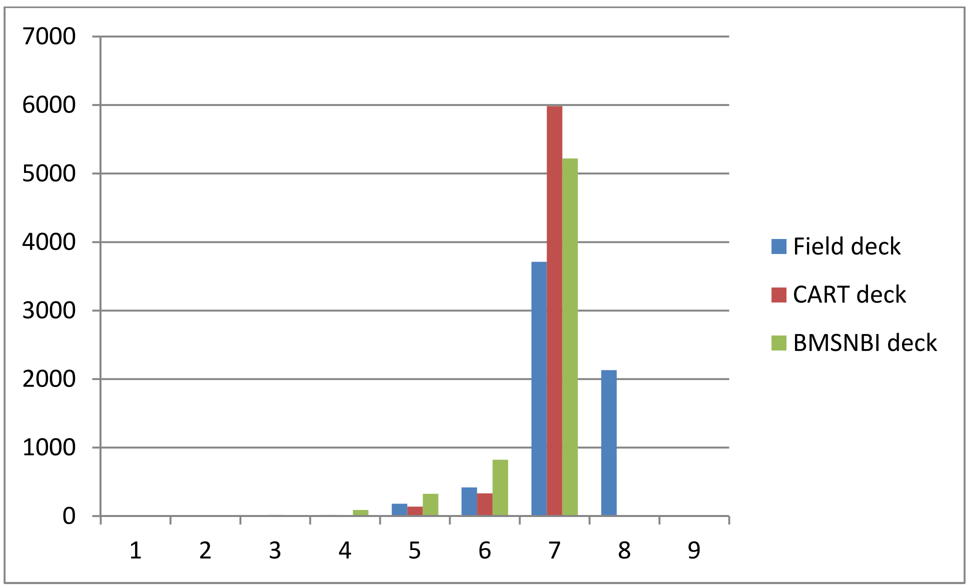

Figure 4-8: Comparison of field, CART and BMSNBI ratings by NBI condition class (Deck, DOT B)

Superstructure

State DOT A

Since superstructures of the majority of the bridges in State DOT A were represented by one BMS element (a beam or a girder), CART analyses were done for the 2,533 single BMS element condition observations with matching NBI condition inspections. Unlike deck BMS elements, superstructure BMS elements can be in several condition states. Therefore, the

PCTSTATE# variables can be equal or smaller than 100% and are numeric continuous variables.

The predictions from CART matched the same NBI rating class for 48% of the observations, and 91% of all predictions were within one error term (Table 4-10). Predicted NBI rating classes were 5, 6, 7, and 8, and the predictions for NBI rating 5 were only for 7 observations. While there is a significant number of field NBI rating observations for class 9 (Figure 4-9), no predictions were observed.

Table 4-10: Accuracy of predictions by the distribution of error terms (Superstructure, DOT A)

Error (CART super)	count	%	
-2	8	0.32%	
-1	587	23.17%	
0	1207	**47.65%**	**%90.76**
1	505	19.94%	
2	190	7.50%	
3	31	1.22%	
4	4	0.16%	
5	1	0.04%	
	2533	100.00%	

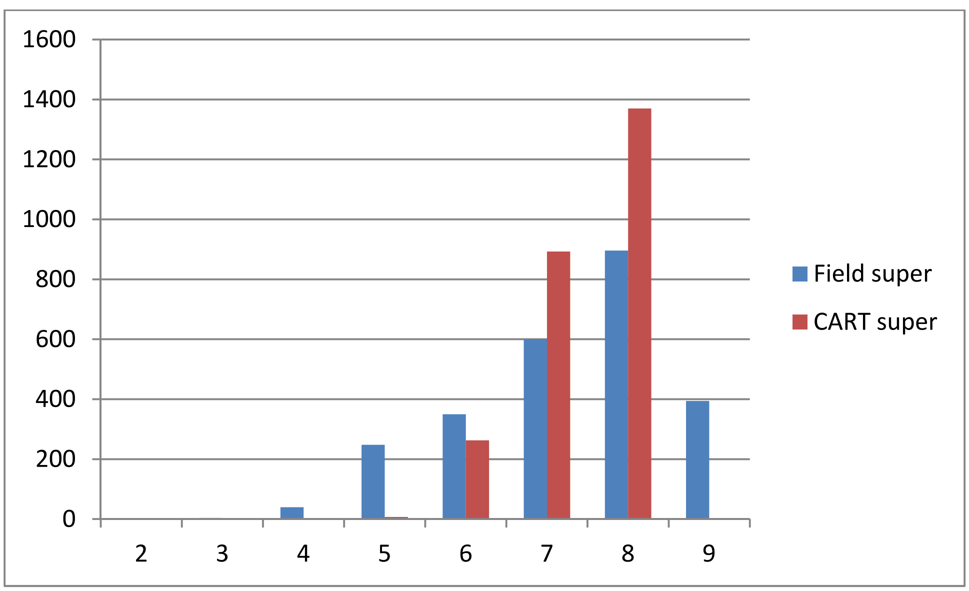

Figure 4-9: Comparison of field and CART ratings by NBI condition class (Superstructure, DOT A)

For a smaller set of 1,179 observations, the predictions from CART and BMSNBI were compared (Table 4-11). The exact matches and predictions within one error term were pretty close for both methods but slightly better for RP. The BMSNBI was more accurate for lower NBI rating classes of 4 and 5 (Figure 4-10). BMSNBI overestimated NBI rating class 6, while CART underestimated the same class; the reverse situation was observed for NBI rating class 7, and both methods overestimated NBI class 8. Neither method predicted NBI rating class 9, although more than 200 observations were in the data set.

Table 4-11: Comparison of the predictions by two methods (Superstructure, DOT A)

	Error (CART super)	Error (BMSNBI super)	CART		BMSNBI	
-4	0	1	0.00%		0.08%	
-3	0	18	0.00%		1.53%	
-2	2	59	0.17%		5.00%	
-1	321	370	27.23%		31.38%	
0	539	532	**45.72%**	**92.54%**	**45.12%**	**90.75%**
1	231	168	19.59%		14.25%	
2	73	29	6.19%		2.46%	
3	13	2	1.10%		0.17%	
	1179	1179				

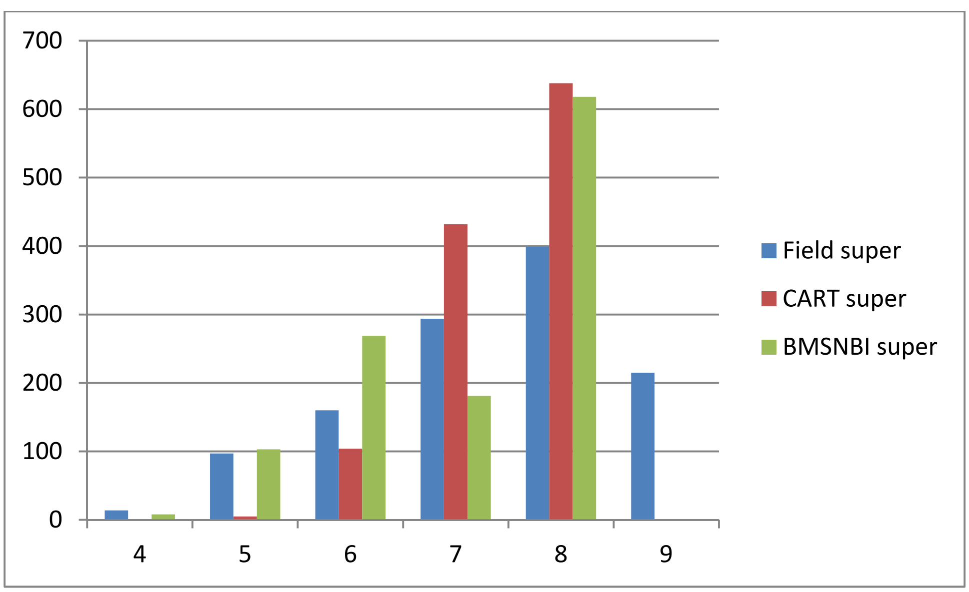

Figure 4-10: Comparison of field, CART and BMSNBI ratings by NBI class (Superstructure, DOT A)

State DOT B

Half of the observations for State DOT B were single BMS elements (a beam or a girder) (Table 4-4), and for the rest of the observations the beam or girder element was accompanied by either one or two additional bearing elements. While the first condition state of the beam/girder elements was the major contributor to the splitting in the algorithm, bearing elements also contributed. The exact matches in predictions were much higher in percentage than State DOT A. Almost 80% of the predictions were exact matches, while most (98%) of the predictions were within one error term (Table 4-12). Higher NBI ratings of 7 and 8 were slightly overestimated, while lower ratings were slightly underestimated. However, overall distributions of field and predicted ratings by rating class were quite similar (Figure 4-11).

Table 4-12: Accuracy of predictions by the distribution of error terms (Superstructure, State DOT B)

Error (CART super)	count	%	
-4	2	0.04%	
-3	3	0.07%	
-2	1	0.02%	
-1	226	4.96%	
0	3639	**79.82%**	**97.70%**
1	589	12.92%	
2	73	1.60%	
3	26	0.57%	
	4559		

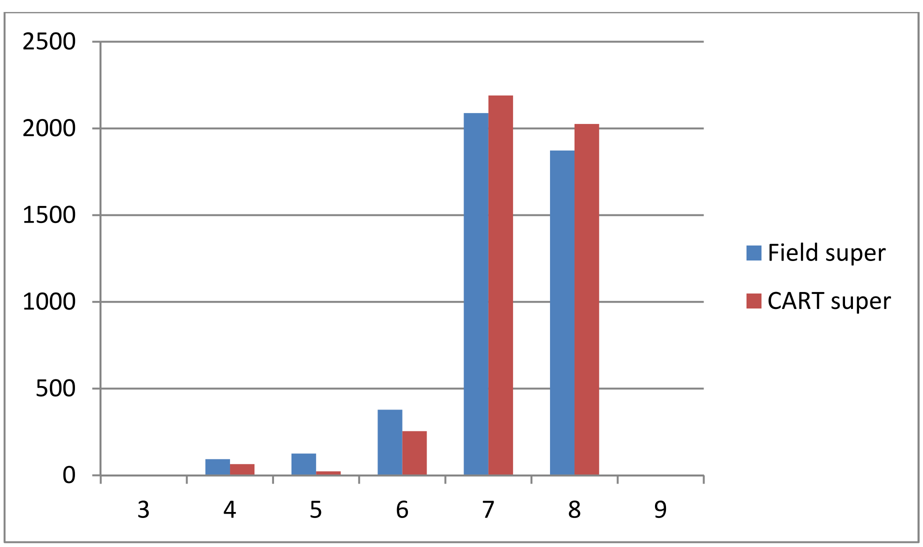

Figure 4-11: Comparison of field and CART ratings by NBI condition class (Superstructure, DOT B)

For 1,715 observations, field and predicted ratings by both methods were compared (Table 4-13). The percentage of exact matches from the CART algorithm were 82%, similar to the results from the main data set. However, exact matches from the BMSNBI were only 27%. Predictions from the CART algorithm had higher accuracies within one error term (98% to 78%).

Table 4-13: Comparison of the predictions by two methods (Superstructure, State DOT B)

	Error (CART super)	Error (BMSNBI super)	CART		BMSNBI	
-4	1	0	0.06%		0.00%	
-3	2	1	0.12%		0.06%	
-2	0	359	0.00%		20.93%	
-1	77	807	4.49%		47.06%	
0	1406	471	**81.98%**	**98.08%**	**27.46%**	**78.48%**
1	199	68	11.60%		3.97%	
2	24	8	1.40%		0.47%	
3	6	1	0.35%		0.06%	
	1715	1715				

When the predictions from both methods are compared with field ratings by NBI rating class (Figure 4-12), predictions from the CART algorithm have like distributions for the data set. BMSNBI overestimates NBI rating classes 5 and 6 and underestimates 7 and 8 by marked differences compared to the CART algorithm.

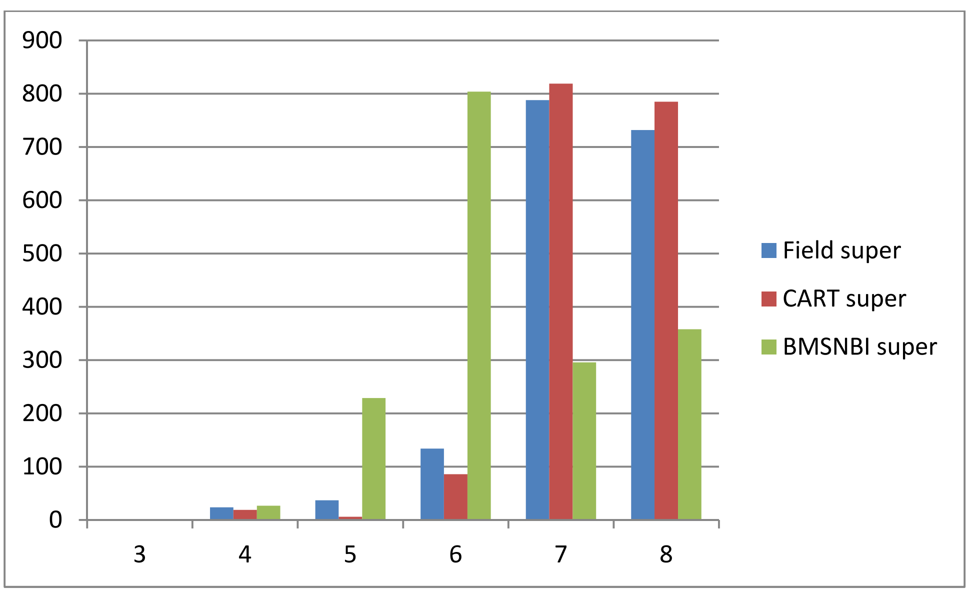

Figure 4-12: Comparison of field, CART and BMSNBI ratings by NBI class (Superstructure, DOT B)

State DOT C

81% of the observations from State DOT C were single BMS elements, and 9% of the observations had an additional bearing element. 59% of the predictions by the CART algorithm were exact matches, and 98% of the observations were predicted within one error term (Table 4-14).

Table 4-14: Accuracy of predictions by the distribution of error terms (Superstructure, State DOT C)

Error (CART super)	count	%	
-3	1	0.01%	
-2	54	0.66%	
-1	2144	26.26%	
0	4818	**59.00%**	**98.07%**
1	1046	12.81%	
2	63	0.77%	
3	12	0.15%	
4	10	0.12%	
5	7	0.09%	
6	6	0.07%	
7	5	0.06%	
	8166	100.00%	

The predictions for NBI classes 4 and 6 were closer in number to the field ratings in these classes (Figure 4-13). However, NBI class 5 was underestimated and class 7 was overestimated. There were 1,640 field ratings for NBI class 8, but no predictions.

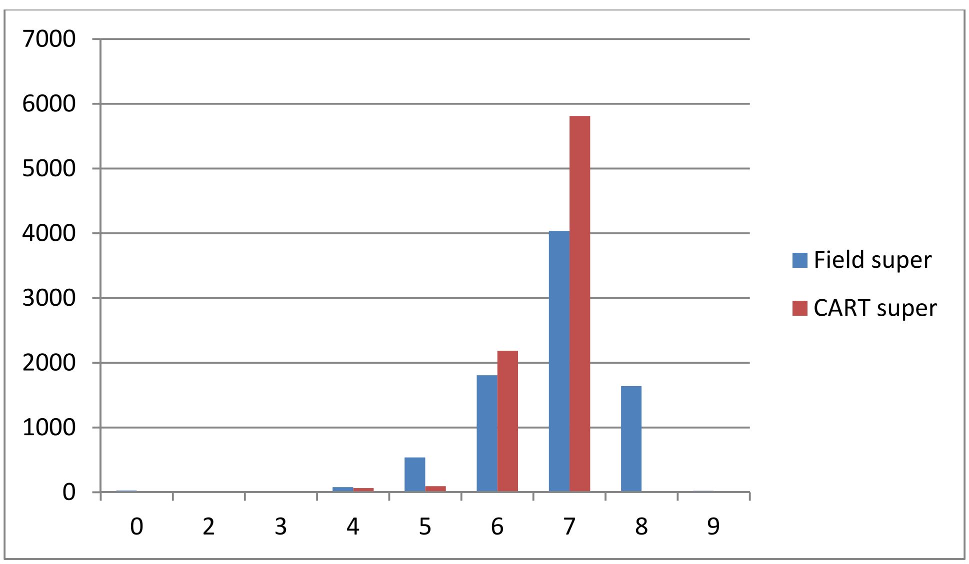

Figure 4-13: Comparison of field and CART ratings by NBI condition class (Superstructure, DOT C)

Substructure

State DOT A

There were three BMS elements per substructure for 50% and four BMS elements for 38% of the observations (Table 4-5). CART analysis was done separately for all subsets of substructures having 1, 2, 3, or 4 for BMS elements. 55% of the predictions were exact matches, and 94% of the predictions were within one error term (Table 4-15).

Table 4-15: Accuracy of predictions by the distribution of error terms (Substructure, State DOT A)

Error (CART sub)	count	%	
-3	4	0.10%	
-2	20	0.50%	
-1	703	17.72%	
0	2170	**54.70%**	**94.18%**
1	863	21.75%	
2	161	4.06%	
3	40	1.01%	
4	5	0.13%	
7	1	0.03%	
	3967	100.00%	

CART analysis predicted NBI rating classes 5, 6, 7, 8, and 9 only (Figure 4-14). The predictions for classes 6 and 9 were less than the field ratings, while there were more predictions than the field ratings for classes 7 and 8.

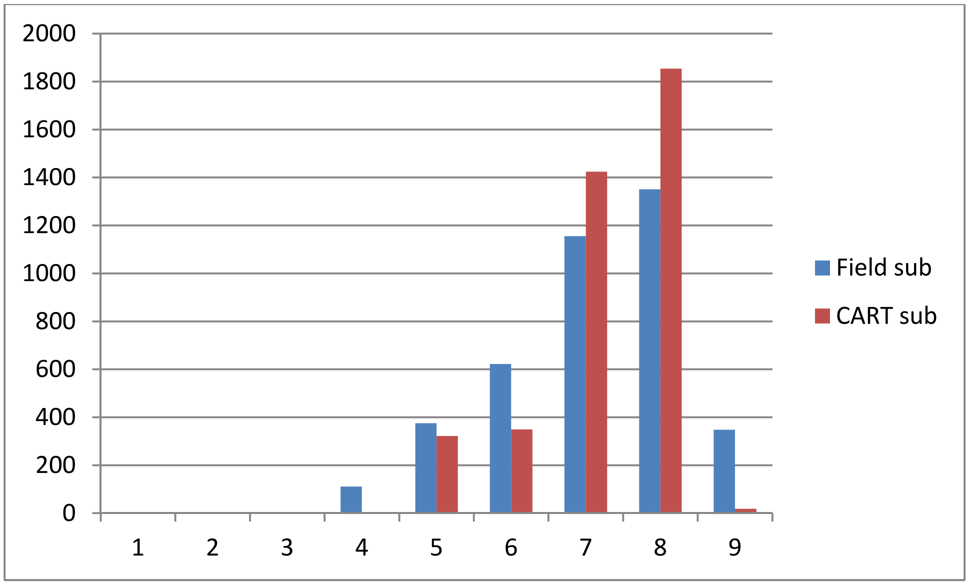

Figure 4-14: Comparison of field and CART ratings by NBI condition class (Substructure, DOT A)

For the available 1,939 observations, predictions from the BMSNBI and CART algorithms were compared (Table 4-16). CART predictions were higher in number for both exact matches (54% to 29%), and the predictions were within on error term (95% to 83%).

Table 4-16: Comparison of the predictions by two methods (Substructure, State DOT A)

	Error (CART sub)	Error (BMSNBI sub)	CART		BMSNBI	
-4	0	1	0.00%		0.05%	
-3	2	20	0.10%		1.03%	
-2	10	263	0.52%		13.56%	
-1	378	830	19.49%		42.81%	
0	1042	561	**53.74%**	**95.15%**	**28.93%**	**82.67%**
1	425	212	21.92%		10.93%	
2	56	46	2.89%		2.37%	
3	21	5	1.08%		0.26%	
4	4	0	0.21%		0.00%	
5	0	1	0.00%		0.05%	
7	1	0	0.05%		0.00%	
Total	1939	1939				

The number of predictions from BMSNBI was close to the number of field ratings for the low rating classes of 4, 5, and 6; however, the algorithm overestimated class 7 and did not predict NBI class 8, which has the highest number of observations among the classes (Figure

4-15). The distribution of CART predictions among NBI classes resembled more of the field ratings.

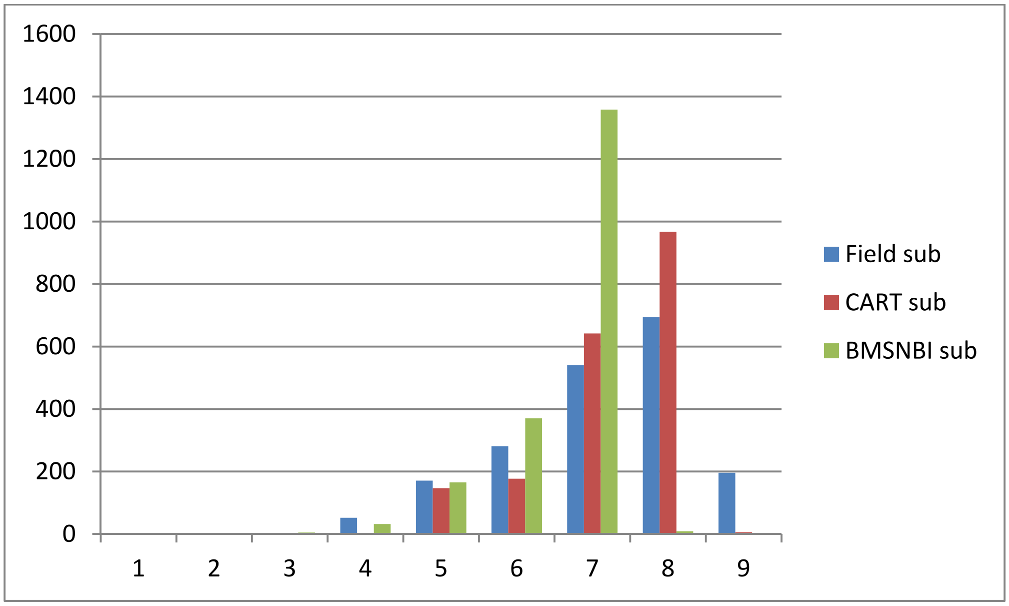

Figure 4-15: Comparison of field, CART and BMSNBI ratings by NBI class (Substructure, DOT A)

State DOT B

Two BMS elements represented the substructure for more than half of the observations from State DOT B (Table 4-5). Three separate CART analyses were done for substructures with one, two, and three BMS elements. 77.3% of the predictions were exact matches, and 98% of the predictions were within one error term (Table 4-17).

Table 4-17: Accuracy of predictions by the distribution of error terms (Substructure, State DOT B)

Error (CART sub)	count	%	
-2	20	0.26%	
-1	657	8.61%	
0	5899	**77.31%**	**98.35%**
1	948	12.42%	
2	88	1.15%	
3	14	0.18%	
4	4	0.05%	
	7630		

The distribution of the CART predictions was quite similar to that of the field ratings (Figure 4-16).

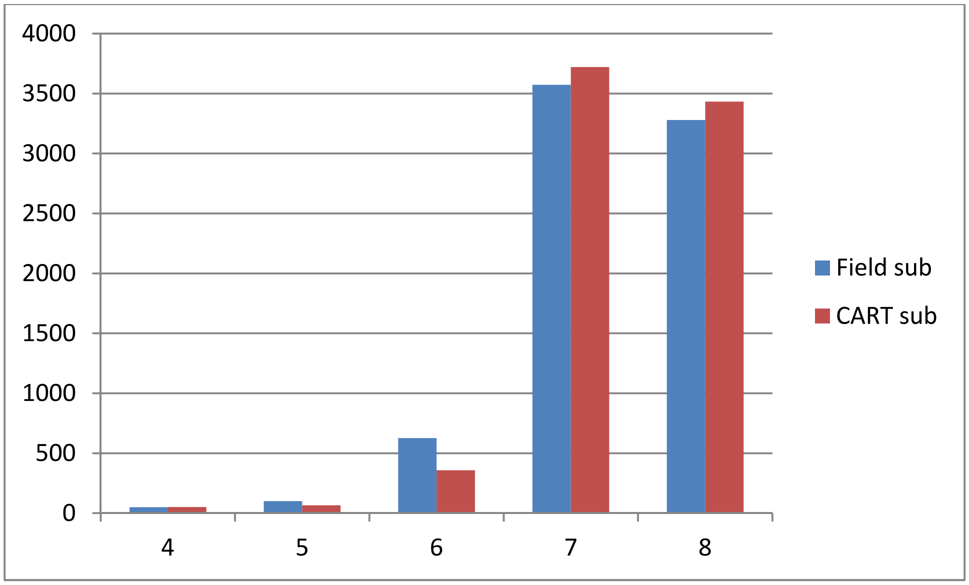

Figure 4-16: Comparison of field and CART ratings by NBI condition class (Substructure, DOT B)

The predictions were compared for a smaller data set of 2,878 observations (Table 4-18). The percentage of exact matches by CART algorithm was 78%, compared to 41% by the BMSNBI.

Table 4-18: Comparison of the predictions by two methods (Substructure, State DOT B)

	Error (CART sub)	Error (BMSNBI sub)	CART		BMSNBI	
-4	0	3	0.00%		0.10%	
-3	0	5	0.00%		0.17%	
-2	4	54	0.14%		1.88%	
-1	288	1573	10.01%		54.66%	
0	**2246**	**1170**	**78.04%**	**99.13%**	**40.65%**	**97.74%**
1	319	70	11.08%		2.43%	
2	19	2	0.66%		0.07%	
3	1	1	0.03%		0.03%	
4	1	0	0.03%		0.00%	
	2878	2878				

Since the BMSNBI does not predict NBI class 8, the number of predictions by the algorithm for NBI class 7 was much higher than the field and predicted ratings by the CART algorithm (Figure 4-17). CART predictions resembled a similar distribution to that of field ratings.

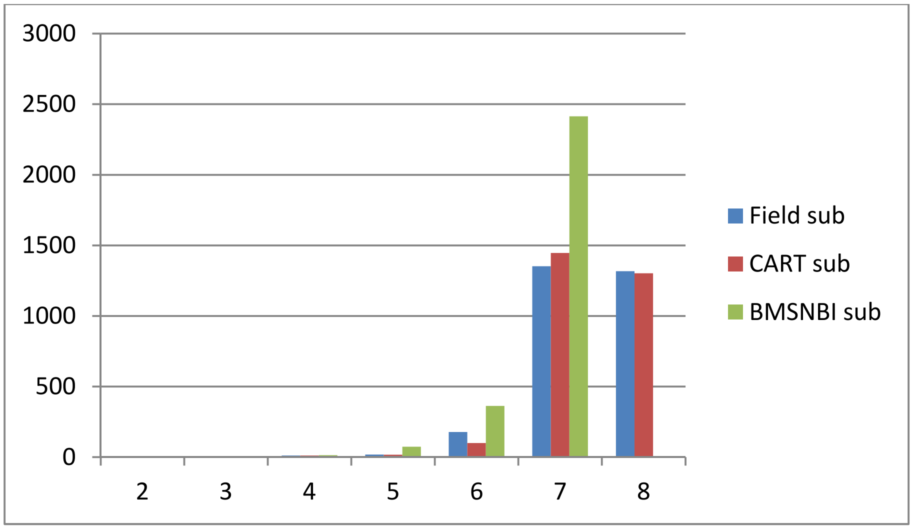

Figure 4-17: Comparison of field, CART and BMSNBI ratings by NBI condition class (Substructure, State DOT B)

State DOT C

Substructure observations from State DOT C were typically composed of three BMS elements (60%), and the remaining observations were in general composed of one (22%) or two (10%) BMS elements (Table 4-5). 64% of the predictions from the CART analysis were exact matches (Table 4-19).

Table 4-19: Accuracy of predictions by the distribution of error terms (Substructure, State DOT C)

Error (CART sub)	count	%	
-3	4	0.04%	
-2	69	0.77%	
-1	1661	18.44%	
0	5779	**64.15%**	**96.50%**
1	1253	13.91%	
2	197	2.19%	
3	17	0.19%	
4	10	0.11%	
5	6	0.07%	
6	7	0.08%	
7	5	0.06%	
	9008		

The CART algorithm did not predict NBI class 8. Therefore, the predictions for NBI class 7 were higher in number when compared to the field ratings. However, overall distributions, apart from NBI class 7, were quite similar.

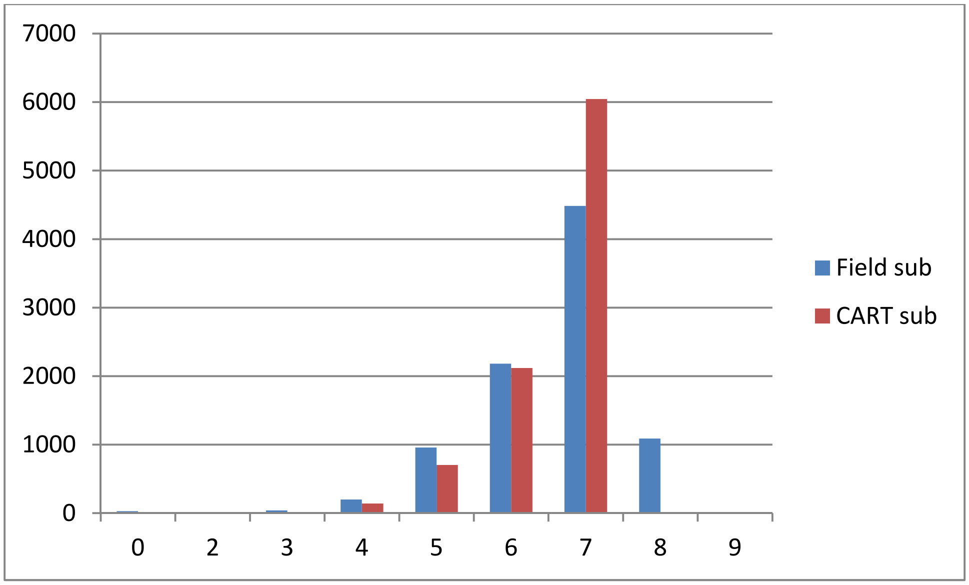

Figure 4-18: Comparison of field and CART ratings by NBI condition class (Substructure, DOT C)

Summary of Results

The accuracy of CART predictions represented by absolute errors for all three states is summarized in Table 4-20. For all rating types, the percentage of exact matches was the highest for State DOT B and the lowest for State DOT A. The percentage of predictions within one error term was higher than 90% for all NBI condition classes.

Table 4-20: CART Predictions

	State DOT A		State DOT B		State DOT C	
	CART Error=0	|CART Error|=1	CART Error=0	|CART Error|=1	CART Error=0	|CART Error|=1
Deck	40%	98%	63%	99.7%		
Superstructure	48%	91%	80%	98%	59%	98%
Substructure	55%	94%	77%	98%	64%	97%

Comparison of absolute errors in predictions between the CART algorithm and the BMSNBI algorithm for State DOTs A and B is given in Table 4-21. For all rating types, the percentage of exact matches was higher for the CART algorithm. For State DOT B, the percentages of exact matches for superstructure and substructure ratings were higher than the BMSNBI predictions by 37% and 54.5%, respectively.

Table 4-21: CART and BMSNBI Comparison

	Deck		Superstructure		Substructure	
	State DOT A	State DOT B	State DOT A	State DOT B	State DOT A	State DOT B
CART Error = 0	41%	63%	46%	82%	54%	78%
BMSNBI Error=0	30%	47%	45%	27%	29%	41%
|CART Error|=1	96%	99.8%	93%	98%	95%	99%
|BMSNBI Error|=1	74%	95%	91%	78%	83%	98%

Comparison with Other Proposed Methods

Percentages of exact predictions and predictions within one absolute error term from the ANN model as reported by Al-Wazeer *et al.* [12] are included in Table 4-22. The table includes the best results from the study for both states and all rating types. The sample bridge data used in the ANN study come from two state DOTs and are different than State DOTs A, B, and C mentioned in this paper. Since the sample data sets used by the ANN model and the CART algorithm are different, a true comparison of the accuracy of these methods is not possible. However, it should be noted that the highest percentage of exact predictions by the ANN model is 48%, while it is almost 80% for the CART algorithm. Except CART deck predictions for State DOT A, the percentages of exact predictions and predictions within one error term achieved by the CART algorithm are higher than corresponding ANN prediction percentages.

Table 4-22: ANN study (Best results)[12]

	Deck		Superstructure		Substructure	
	DOT M	DOT W	DOT M	DOT W	DOT M	DOT W
ANN Error=0	43%	41%	43%	44%	48%	39%
|ANN Error|=1	88%	83%	85%	86%	93%	85%

NewTranslator is another proposed methodology for translating BMS element condition data to NBI condition ratings [13]. Sobanjo *et al.* presents the variation in accuracy of translated ratings by plotting the average of absolute errors for each NBI rating class [13]. The average of absolute errors is higher than 0.8 for all NBI rating classes except class 9. The comparable averages of absolute errors by the CART algorithm are given in Table 4-23. The highest average absolute error in this study is 0.7. For State DOT B and C predictions, the averages of absolute errors are always below 0.5. Since the data sets used for the two methods are different, a true comparison of accuracy is not possible, but the achieved averages of absolute errors for the CART algorithm are significantly lower than the reported values by the NewTranslator.

Table 4-23: Average Absolute Error of CART predictions

	Average Absolute Error		
	State DOT A	State DOT B	State DOT C
Deck	0.69	0.38	
Superstructure	0.63	0.23	0.44
Substructure	0.53	0.25	0.40

CONCLUSIONS

The statistical results from the CART method in this paper propose a potentially more accurate method of predicting NBI condition ratings than the previous algorithms in the literature. Direct comparisons of the predictions from the CART algorithm and the BMSNBI indicated better accuracy for the CART algorithm. While a true comparison with the other two proposed methods in the literature was not possible, the CART algorithm achieved higher accuracies than these earlier methods when similar accuracy measures were compared.

This methodology does not make assumptions about the impacts (weights) of specific BMS elements on the related NBI condition ratings. On the contrary, due to the way the predictor variables were defined, the column contributions from the CART results suggest the statistical impact of a specific BMS element type (e.g., abutment, column, girder) and condition state in the prediction. Analyses of such information can be useful to state transportation agencies for exploring how the condition of different BMS elements contributes to the assignment of NBI condition ratings.

The statistical results from this study and the classification trees from the CART algorithm are specific to the states in this study and cannot be generalized. Yet, the study provides a prediction methodology based on simple logical conditions that can be used to create easy to understand business rules for state transportation agencies.

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CHAPTER 5. GENERAL CONCLUSION

CONCLUSIONS

This dissertation includes three complementary papers on bridge management practice, policy, and condition data in the United States.

Chapter 2, "An Independent Look at Federal Bridge Programs: Findings from a National Survey," presented findings from a national survey on bridge management and an overview of the federal bridge programs in the United States. Survey results indicated the dominant impact of federal funding eligibility on state-level bridge management decisions. Ninety percent of responding states do not believe that federally required NBI data items cover their data needs for bridge management. States collect an extensive amount of data on their bridge network, including two types of condition inspections (NBI and BMS). However, systematic use of the data to support cost-effective bridge management decisions is limited. While the majority of reporting state departments of transportation have implemented a BMS, the level of implementation is varied and the overall input from BMSs to network-level decisions remains minimal. State transportation agencies need federal guidance on areas such as using decision support tools, implementing BMSs, and improving data quality.

In Chapter 3, "A Discussion on the Efficiency of NBI Translator Algorithm," a statistical comparison of field NBI condition ratings and ratings generated by FHWA's NBI Translator (BMSNBI) algorithm for Iowa bridges was presented. Statistical analysis indicated that the ratings generated by the NBI Translator algorithm are not representative of actual NBI ratings. Results from the research raised questions about the effectiveness of the algorithm.

Chapter 4, "CART Algorithm for Predicting NBI Condition Ratings," presented a new methodology to predict National Bridge Inventory (NBI) condition ratings from bridge management system (BMS) element condition data, based on Classification and Regression Trees (CART). Analyses were conducted with bridge condition data from Iowa, Kansas, and Montana for the years 2006 to 2010. The proposed methodology achieved significantly better accuracies than other methodologies reported in the literature. CART predicted exact matches of many field ratings 80% of the time and typically more than 60%. In the best case, CART predicted exact matches 55% more often than BMSNBI and typically predicted exact matches at least 10% more frequently than BMSNBI. The CART prediction methodology uses simple and logical conditions of BMS element condition data to predict NBI condition ratings and has potential use for federal and state transportation agencies summarizing bridge condition data.

RECOMMENDATIONS FOR FUTURE RESEARCH

Advancing implementation of BMSs in support of decision making at the national level has many challenges. A modeling approach that is consistent with states' expectations and verified by data and experience is yet to be achieved. Current models are complex and require continuous updates to verify assumptions and model inputs. Simplified network-level tools and methodologies are needed that summarize available data into objective information to guide bridge management decisions. Such tools that also consider economic analysis can support cost-effective, network-level decisions for both state and federal governments.

Future work on the CART algorithm to predict NBI condition ratings can utilize bridge condition data from other states to explore the potential of the algorithm to summarize BMS element condition data at the national level. An improved methodology can be used by state departments of transportation for their reporting requirements and for assessment of the national network and future needs at the federal level. Unified classification trees can also provide insight on the relative impacts of BMS elements on the NBI condition ratings.

The quest for better tools and methodologies that help the bridge management community is an ongoing effort. Tools and methodologies, however, require sustaining implementation to be useful. Questions remain and further research is needed on technical, institutional, and managerial aspects.

APPENDIX A. SURVEY RESULTS

A Survey on Bridge Management in the US: States' Perspective

SurveyMonkey

1. Please enter your contact information and the date of survey

	Response Percent	Response Count
Name	100.0%	40
Agency	100.0%	40
Email	100.0%	40
Phone Number	100.0%	40
Date	97.5%	39
	answered question	40
	skipped question	0

2. Do you believe that NBI data items cover all of your data needs for bridge management?

	Response Percent	Response Count
Yes	10.0%	4
No	90.0%	36
	answered question	40
	skipped question	0

3. What additional data items do you think are necessary for bridge management?	Response Percent	Response Count
AASHTO CoRe (original or modified by the state) Element condition data	**88.9%**	**32**
Condition information on deck joints	69.4%	25
Condition information on wearing surfaces	69.4%	25
Condition information on paint / protective coatings	72.2%	26
Condition information on bearings	55.6%	20
	Other (please specify)	15
	answered question	**36**
	skipped question	**4**

4. Please check all that apply for the data items you collect in bridge inspections	Response Percent	Response Count
NBI data items	**95.0%**	**38**
AASHTO CoRe (original or modified by the state) element condition data	82.5%	33
Agency specific items	92.5%	37
	If you have agency specific items please specify below (You can provide a state inspection manual instead of listing the agency specific items when you have a long list. You can send the manual by email to basak@iastate.edu)	27
	answered question	**40**
	skipped question	**0**

5. Which software are you using to store, manage and use the AASHTO CoRe (original or modified by the state) element level condition data that you are collecting?

	Response Percent	Response Count
Pontis	**82.4%**	**28**
State developed system	29.4%	10
Other	2.9%	1
	Other (please specify)	6
	answered question	**34**
	skipped question	**6**

6. When did you start collecting element level condition data?

	Response Count
	34
answered question	**34**
skipped question	**6**

7. Did you add agency-specific elements to AASHTO CoRe elements?

	Response Percent	Response Count
Yes	**79.4%**	**27**
No	20.6%	7
	answered question	**34**
	skipped question	**6**

8. Did you modify any of the AASHTO CoRe elements?

	Response Percent	Response Count
Yes	44.1%	15
No	55.9%	19
answered question		34
skipped question		6

9. Which one of the below do you prefer in assessing your bridge conditions as an agency?

	Response Percent	Response Count
Only NBI condition ratings	15.0%	6
Only element level condition data	12.5%	5
Both	72.5%	29
answered question		40
skipped question		0

10. Do you translate element level condition data to NBI condition ratings?

	Response Percent	Response Count
Yes	15.0%	6
No	85.0%	34
answered question		40
skipped question		0

11. If you translate element level condition data to NBI condition ratings, please check below for all that applies:	Response Percent	Response Count
We use translated NBI condition ratings for internal purposes within the agency	50.0%	3
We report translated NBI condition ratings to the FHWA	50.0%	3
answered question		6
skipped question		34

12. Do your inspectors input inspection data into multiple systems (databases)?	Response Percent	Response Count
Yes	10.0%	4
No	90.0%	36
answered question		40
skipped question		0

13. Is this a duplication of effort (Recording is done separately for each system/database)?	Response Percent	Response Count
Yes	25.0%	1
No	75.0%	3
answered question		4
skipped question		36

14. Are there programmatic uses of that data by any other office (the data is used for agency needs beyond archiving)?		
	Response Percent	Response Count
Yes	50.0%	2
No	50.0%	2
	answered question	4
	skipped question	36

15. Do you have a process for data quality control?		
	Response Percent	Response Count
Yes	92.5%	37
No	7.5%	3
	answered question	40
	skipped question	0

16. We document:	Response Percent	Response Count
QC roles and responsibilities	**94.4%**	**34**
Process for tracking how qualifications (such as years and type of experience, training completed, certifications) are met	77.8%	28
Special needs/requirements for specific types of inspections	63.9%	23
Procedures for review and validation of inspection reports and data	88.9%	32
Procedures for identification and resolution of data errors, omissions and/or changes	77.8%	28
	answered question	**36**
	skipped question	**4**

17. Do you have in-house routine training for bridge inspectors?	Response Percent	Response Count
Yes	**62.2%**	**23**
No	37.8%	14
	If yes, what is the frequency?	23
	answered question	**37**
	skipped question	**3**

18. Do you have in-house routine training for team leaders?	Response Percent	Response Count
Yes	40.5%	15
No	**59.5%**	**22**
If yes, what is the frequency?		17
answered question		**37**
skipped question		**3**

19. Which National Highway Institute Courses do you require/utilize?	Response Percent	Response Count
None	11.1%	4
130053 - Bridge Inspection Refresher Training	**75.0%**	**27**
130054 - Engineering Concepts for Bridge Inspectors	47.2%	17
Other	27.8%	10
Other (please specify)		18
answered question		**36**
skipped question		**4**

20. Do you have a process for data quality assurance?	Response Percent	Response Count
Yes	**90.0%**	**36**
No	10.0%	4
answered question		**40**
skipped question		**0**

21. We have a quality assurance process for:

	Response Percent	Response Count
NBI data other than condition ratings	82.9%	29
NBI condition ratings	**88.6%**	**31**
AASHTO CoRe element condition data	60.0%	21
Other	20.0%	7
Other (please specify)		7
answered question		**35**
skipped question		**5**

22. Office QA reviews:

	Response Percent	Response Count
We do not have office QA reviews	11.1%	4
We have office QA reviews for all inspections	41.7%	15
We have office QA reviews for random inspections	**55.6%**	**20**
What percentage of all inspections are the random inspections (please note an estimate)?		15
answered question		**36**
skipped question		**4**

23. Field QA reviews:	Response Percent	Response Count
We do not have field QA reviews	11.1%	4
We have field QA reviews for all inspections	16.7%	6
We have field QA reviews for random inspections	**77.8%**	**28**
What percentage of all inspections are the random inspections (please note an estimate)?		23
	answered question	**36**
	skipped question	**4**

24. Review team	Response Percent	Response Count
We have a reviewing engineer	**55.6%**	**20**
We have a team of reviewing engineers	44.4%	16
	answered question	**36**
	skipped question	**4**

25. We document:	Response Percent	Response Count
QA roles and responsibilities	**96.7%**	**29**
Procedures for conducting QA reviews	76.7%	23
Disqualification procedures for team leaders and consultant inspection firms with a continued record of poor performance	26.7%	8
Re-qualification procedures for previously disqualified team leaders and consultant inspection firms	23.3%	7
Procedures to validate QC procedures	40.0%	12
	Other (please specify)	2
	answered question	**30**
	skipped question	**10**

26. Do you involve local agencies in the development of your bridge programs?	Response Percent	Response Count
Yes	47.5%	19
No	**52.5%**	**21**
	If yes, please explain briefly how?	17
	answered question	**40**
	skipped question	**0**

27. Do you have a set of criteria for prioritizing your bridge projects?	Response Percent	Response Count
Yes	**82.5%**	**33**
No	17.5%	7
If yes, please list briefly (e.g. traffic volume, benefit-cost ratio, NBI condition ratings)?		27
answered question		**40**
skipped question		**0**

28. Are you using a Bridge Management Software (Pontis or other) to develop your bridge program (the list of selected bridge projects in the state transportation improvement program (STIP))?	Response Percent	Response Count
Yes	45.0%	18
No	**55.0%**	**22**
answered question		**40**
skipped question		**0**

29. What percentage of the projects in your annual program comes from the recommendations of the Bridge Management Software (a general estimate)?	Response Count
	18
answered question	**18**
skipped question	**22**

30. Please list the realized benefits from the Bridge Management Software so far.	
	Response Count
	18
answered question	18
skipped question	22

31. What general improvements you think are necessary to make the Bridge Management Software you are using more effective?	
	Response Count
	18
answered question	18
skipped question	22

32. Major difficulties you have faced while implementing the Bridge Management Software?	
	Response Count
	18
answered question	18
skipped question	22

33. How do you develop your bridge program? Please explain briefly.	
	Response Count
	40
answered question	40
skipped question	0

34. Why are you not using a Bridge Management Software for developing your bridge program?

	Response Count
	40
answered question	40
skipped question	0

35. Are you planning to use a Bridge Management Software for this purpose in the future?

	Response Percent	Response Count
Yes	80.0%	32
No	20.0%	8
answered question		40
skipped question		0

36. Do you make use of any other tools (such as an in-house developed program) in the development of your bridge programs?

	Response Percent	Response Count
Yes	65.0%	26
No	35.0%	14
If yes, please list:		24
answered question		40
skipped question		0

37. Do you address risks (such as scour, seismic safety) while developing your bridge programs?		Response Percent	Response Count
Yes		**80.0%**	**32**
No		20.0%	8
		answered question	**40**
		skipped question	**0**

38. When evaluating project alternatives does your agency utilize life cycle cost analysis?		Response Percent	Response Count
Yes		37.5%	15
No		**62.5%**	**25**
		answered question	**40**
		skipped question	**0**

39. How does the National Bridge Inspection Program (NBIP) and related policies/requirements affect the way you develop your bridge program? Please comment briefly:	Response Count
	40
answered question	**40**
skipped question	**0**

40. How does the Highway Bridge Program (HBP) and related policies/requirements affect the way you develop your bridge program? Please comment briefly:

	Response Count
	40
answered question	**40**
skipped question	**0**

41. Do you think that the flexibility provided to the States in using Federal bridge funds is adequate?

	Response Percent	Response Count
Yes	**67.5%**	**27**
No	32.5%	13
If no, please comment briefly why:		22
answered question		**40**
skipped question		**0**

42. How much is your agency spending to preserve, rehabilitate and replace bridges annually?

	Response Count
	40
answered question	**40**
skipped question	**0**

43. How much is your agency spending to address vulnerabilities such as scour, seismic or collision risks annually?	
	Response Count
	40
answered question	**40**
skipped question	**0**

44. Considering all available transportation funds in your jurisdiction, what percentage of the total is being allocated to bridges annually?	
	Response Count
	40
answered question	**40**
skipped question	**0**

45. What kind of difficulties do you have in preparing and submitting your NBI data files?	
	Response Count
	40
answered question	**40**
skipped question	**0**

46. Are you familiar with how the FHWA uses NBI data in allocating Federal bridge funds (apportionment factors for States depend on the rehabilitation and replacement needs of eligible deficient structures identified by NBI condition ratings)?

	Response Percent	Response Count
Yes	77.5%	31
No	22.5%	9
answered question		40
skipped question		0

47. Are you familiar with how the FHWA uses NBI data in preparing biennial Conditions & Performance Reports, report to Congress (condition reports and future investment / impact scenarios based on NBI data)?

	Response Percent	Response Count
Yes	57.5%	23
No	42.5%	17
answered question		40
skipped question		0

48. How do you evaluate FHWA's use of NBI data in allocating Federal bridge funds and preparing biennial congressional reports?

	Response Count
	40
answered question	40
skipped question	0

49. In your opinion, is NBI data sufficient for allocating Federal bridge funds and preparing the Conditions & Performance Reports?		
	Response Percent	Response Count
Yes	27.5%	11
No	**72.5%**	**29**
	answered question	**40**
	skipped question	**0**

50. Do you think AASHTO CoRe (original or modified by the state) Element condition data should also be used for allocating Federal bridge funds and preparing the Conditions & Performance Reports?		
	Response Percent	Response Count
Yes	**67.5%**	**27**
No	32.5%	13
	answered question	**40**
	skipped question	**0**

51. Do you have any suggestions to improve allocation of Federal bridge funds and preparation of the Conditions & Performance Reports?	
	Response Count
	40
answered question	**40**
skipped question	**0**

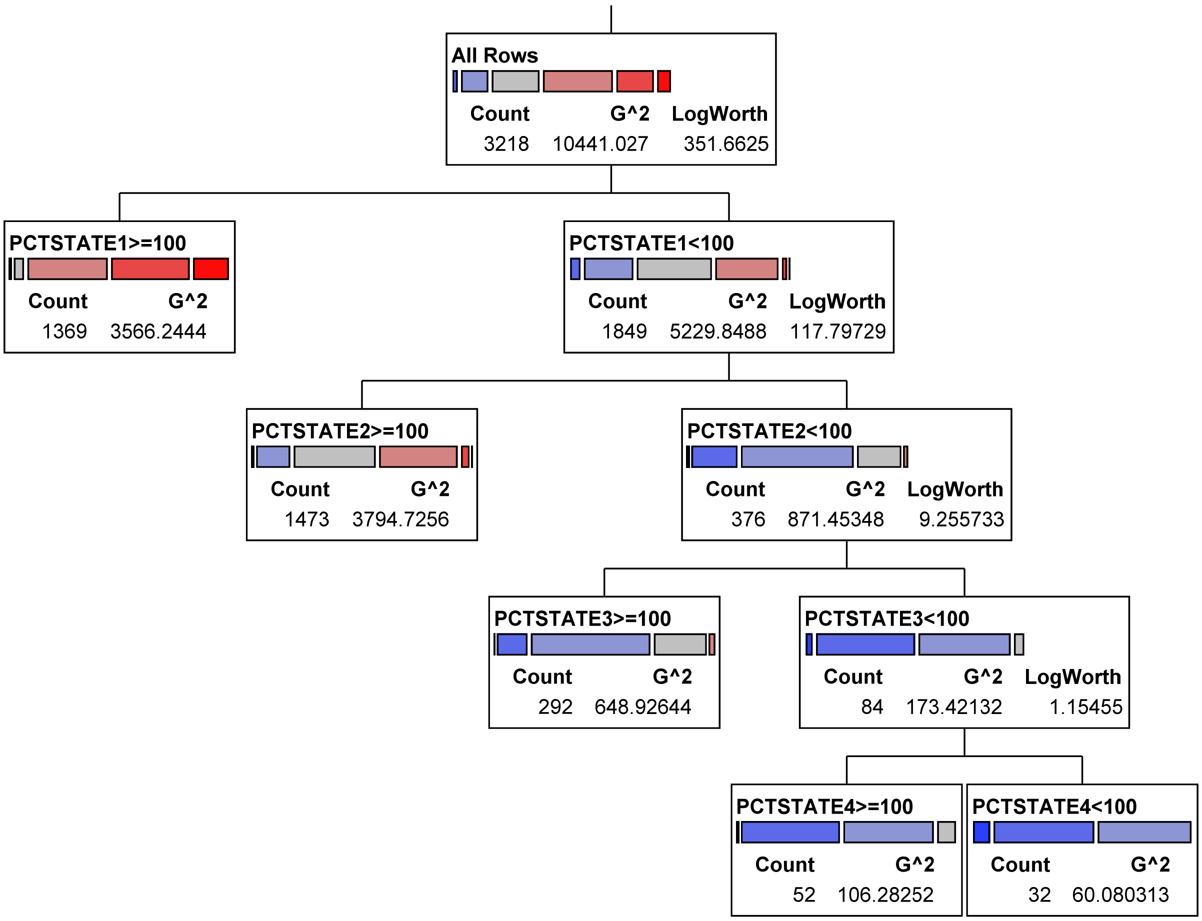
52. Do you believe additional support or guidance is needed for the following topics (please check all that apply)?		
	Response Percent	Response Count
Qualifications required for bridge inspection personnel	9.7%	3
Inspection workload	19.4%	6
Bridge inspection QC/QA Programs	41.9%	13
Data management	25.8%	8
Data quality	35.5%	11
Reporting requirements	25.8%	8
Funding restrictions	51.6%	16
Bridge management implementation	64.5%	20
Using decision support tools for supporting bridge program development	**67.7%**	**21**
	answered question	**31**
	skipped question	**9**

53. Please provide any general comments/concerns about this survey or anything else you would like to mention.	
	Response Count
	15
answered question	**15**
skipped question	**25**

APPENDIX B. CART ANALYSES REPORTS

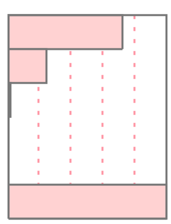
State A - Deck

RSquare=0.217
Number of observations=3218
Number of splits=4



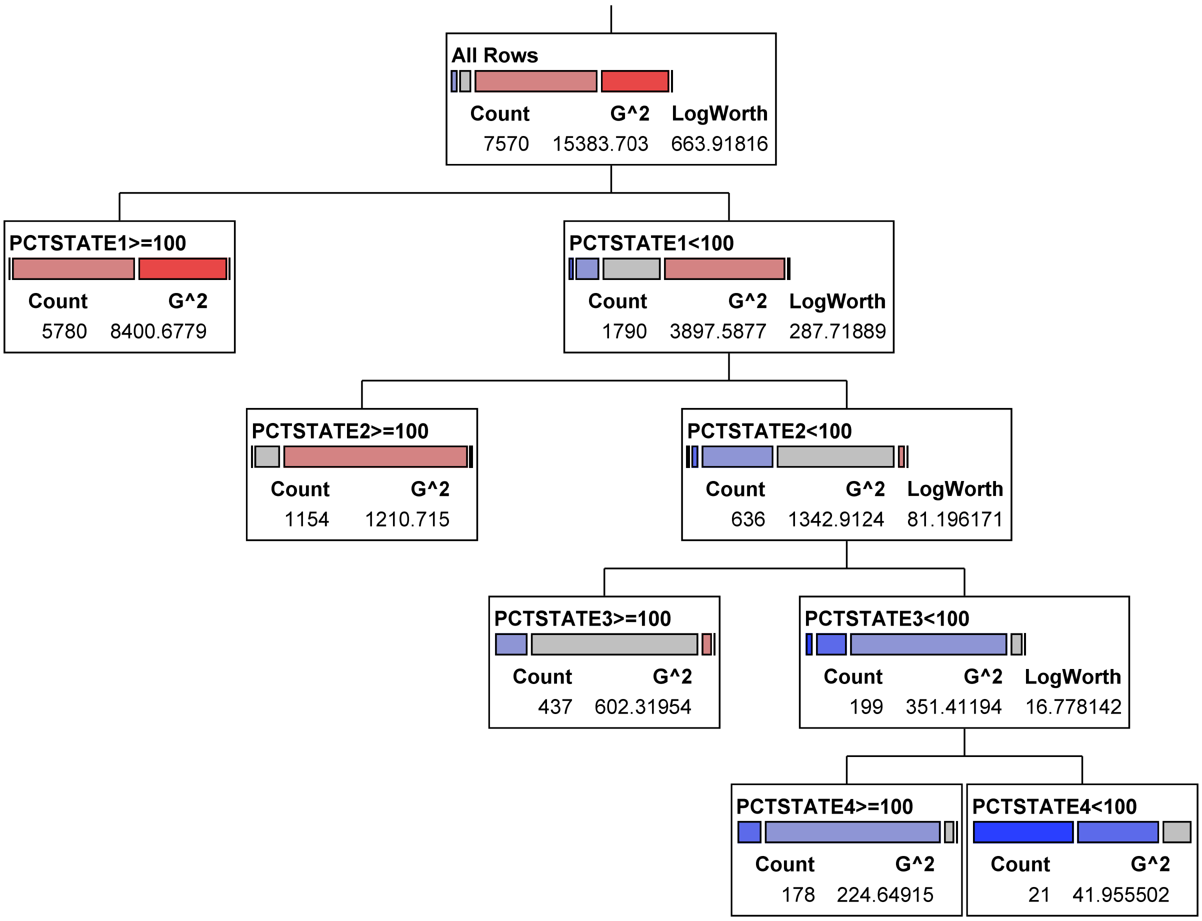
Column Contributions

Term	Number of Splits	G^2
PCTSTATE1	1	1644.93347
PCTSTATE2	1	563.669735
PCTSTATE3	1	49.1057245
PCTSTATE4	1	7.05848764
PCTSTATE5	0	0
Total	4	2264.76742



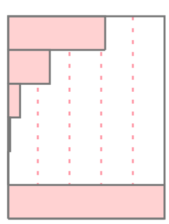
State B - Deck

RSquare=0.319
Number of observations=7570
Number of splits=4



Column Contributions

Term	Number of Splits	G^2
PCTSTATE1	1	3085.43762
PCTSTATE2	1	1343.96023
PCTSTATE3	1	389.18091
PCTSTATE4	1	84.8072882
PCTSTATE5	0	0
Total	4	4903.38604

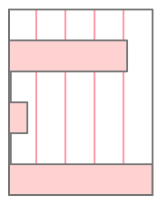


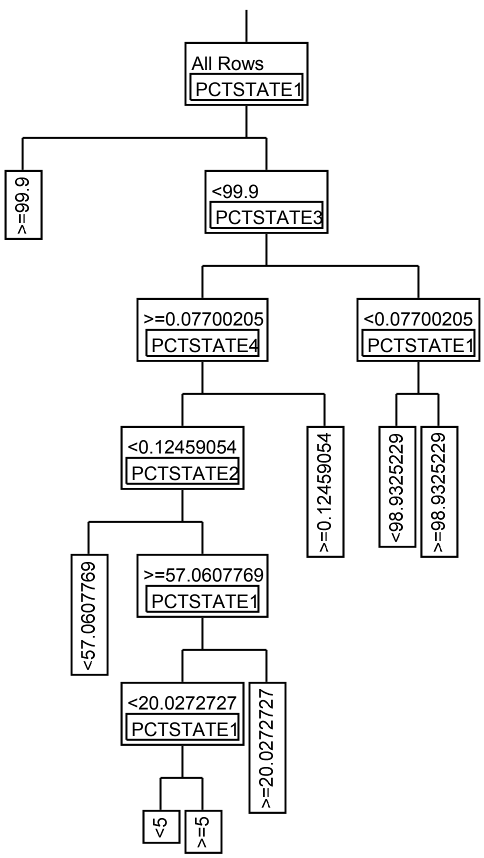
State A – Superstructure
1 BMS Element (Beam/Girder)

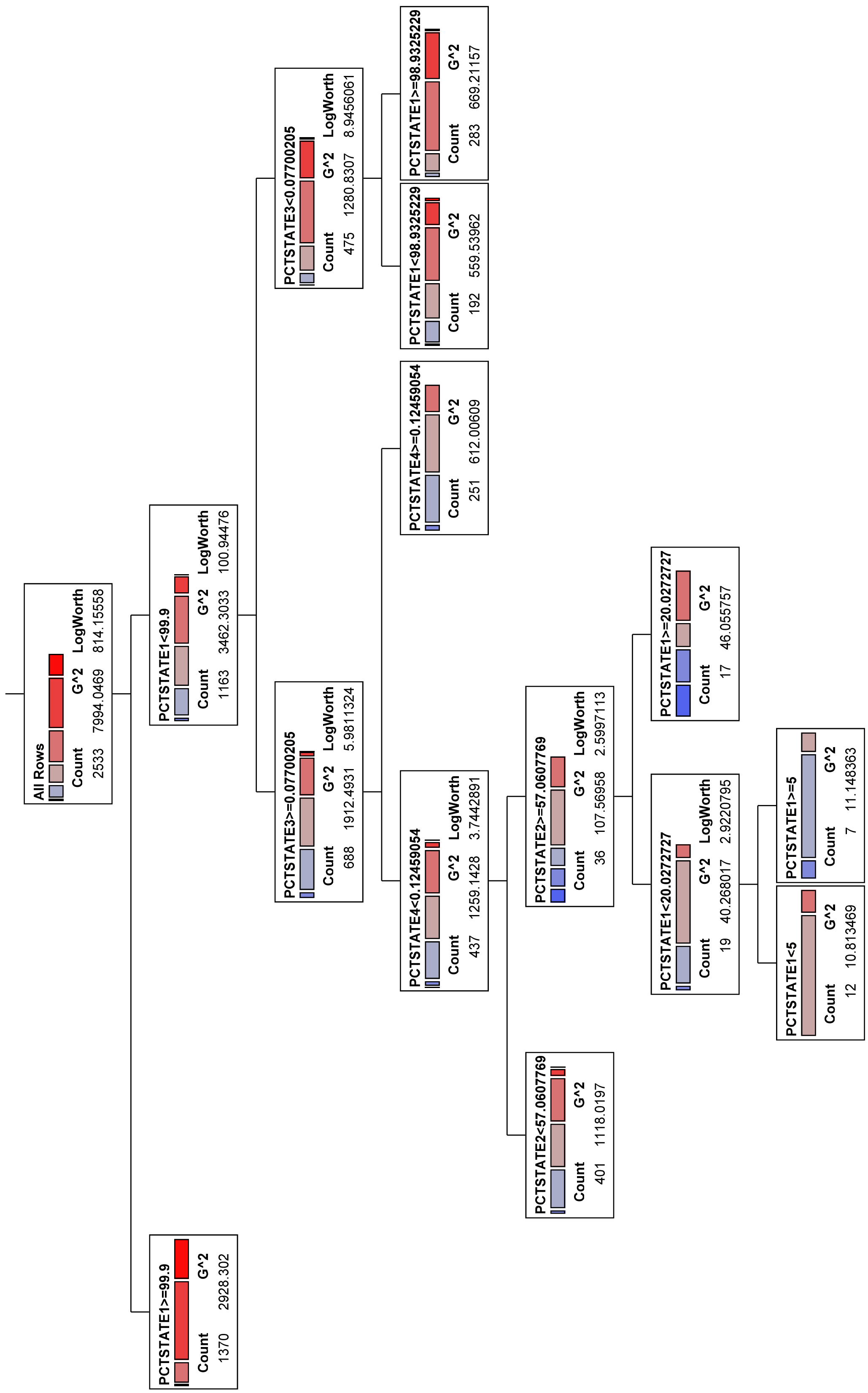
RSquare=0.255
Number of observations=2533
(Matching inspected ratings for 5121 total observations)
Number of splits=7

Column Contributions

Term	Number of Splits	G^2
quantity	0	0
PCTSTATE1	4	1695.07316
PCTSTATE2	1	33.5535357
PCTSTATE3	1	268.979469
PCTSTATE4	1	41.3441341
Total	7	2038.9503





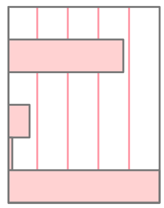

All Rows
Count 2533 G^2 7994.0469 LogWorth 814.15558
PCTSTATE1>=99.9
Count 1370 G^2 2928.302
PCTSTATE1<99.9
Count 1163 G^2 3462.3033 LogWorth 100.94476
PCTSTATE3>=0.07700205
Count 688 G^2 1912.4931 LogWorth 5.9811324
PCTSTATE3<0.07700205
Count 475 G^2 1280.8307 LogWorth 8.9456061
PCTSTATE1<98.9325229
Count 192 G^2 559.53962
PCTSTATE1>=98.9325229
Count 283 G^2 669.21157
PCTSTATE4<0.12459054
Count 437 G^2 1259.1428 LogWorth 3.7442891
PCTSTATE4>=0.12459054
Count 251 G^2 612.00609
PCTSTATE2<57.0607769
Count 401 G^2 1118.0197
PCTSTATE2>=57.0607769
Count 36 G^2 107.56958 LogWorth 2.5997113
PCTSTATE1<20.0272727
Count 19 G^2 40.268017 LogWorth 2.9220795
PCTSTATE1>=20.0272727
Count 17 G^2 46.055757
PCTSTATE1<5
Count 12 G^2 10.813469
PCTSTATE1>=5
Count 7 G^2 11.148363

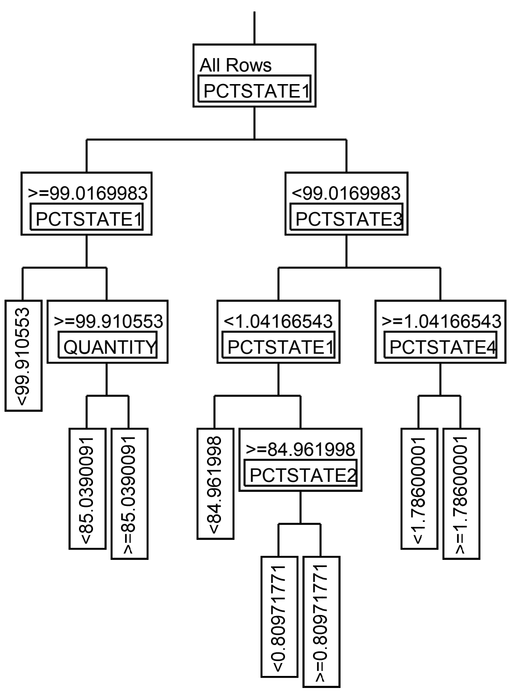
State B – Superstructure
1 BMS Element (Beam/Girder)

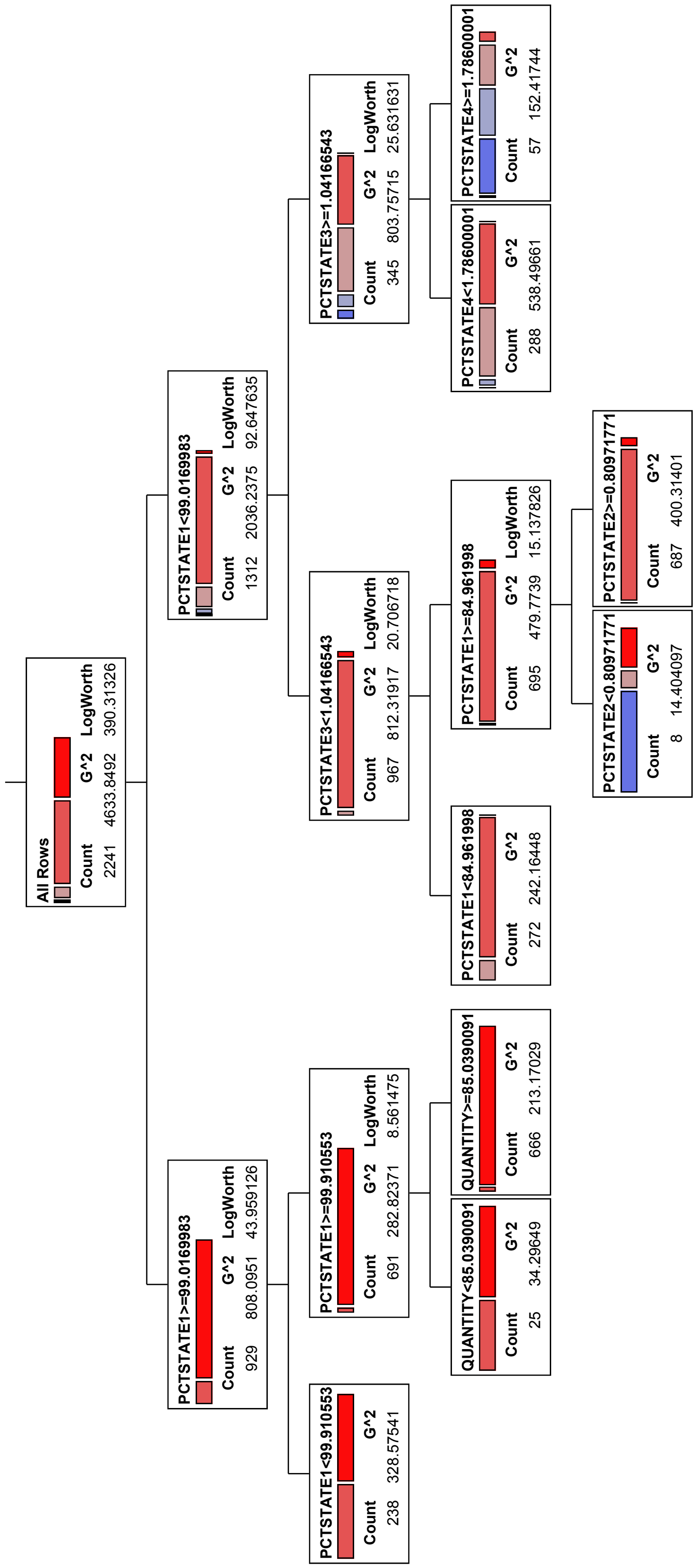
RSquare=0.585
Number of observations=2241
Number of splits=7

Column Contributions

Term	Number of Splits	G^2
QUANTITY	1	35.356938
PCTSTATE1	3	2076.59336
PCTSTATE2	1	65.0557929
PCTSTATE3	1	420.161174
PCTSTATE4	1	112.843095
Total	7	2710.01036





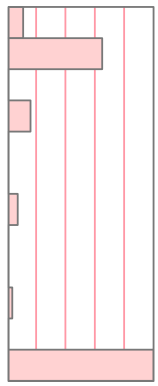

All Rows
Count 2241 G^2 4633.8492 LogWorth 390.31326
PCTSTATE1>=99.0169983
Count 929 G^2 808.0951 LogWorth 43.959126
PCTSTATE1<99.0169983
Count 1312 G^2 2036.2375 LogWorth 92.647635
PCTSTATE1<99.910553
Count 238 G^2 328.57541
PCTSTATE1>=99.910553
Count 691 G^2 282.82371 LogWorth 8.561475
QUANTITY<85.0390091
Count 25 G^2 34.29649
QUANTITY>=85.0390091
Count 666 G^2 213.17029
PCTSTATE3<1.04166543
Count 967 G^2 812.31917 LogWorth 20.706718
PCTSTATE3>=1.04166543
Count 345 G^2 803.75715 LogWorth 25.631631
PCTSTATE1<84.961998
Count 272 G^2 242.16448
PCTSTATE1>=84.961998
Count 695 G^2 479.7739 LogWorth 15.137826
PCTSTATE2<0.80971771
Count 8 G^2 14.404097
PCTSTATE2>=0.80971771
Count 687 G^2 400.31401
PCTSTATE4<1.78600001
Count 288 G^2 538.49661
PCTSTATE4>=1.78600001
Count 57 G^2 152.41744

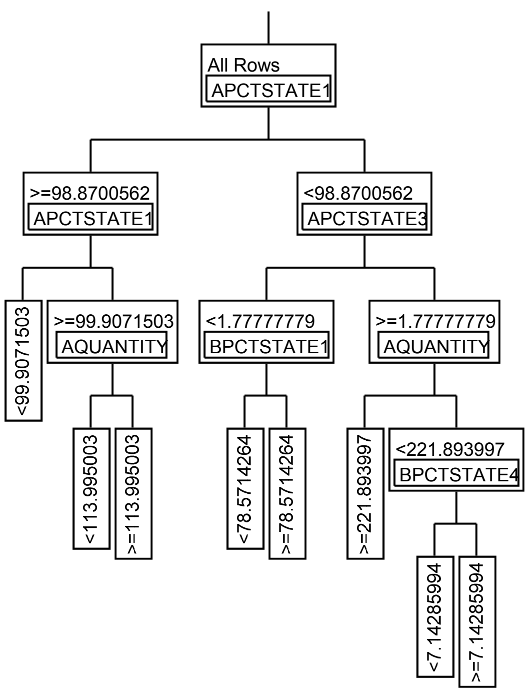
State B – Superstructure
2 BMS Elements (Beam/Girder + Bearing)

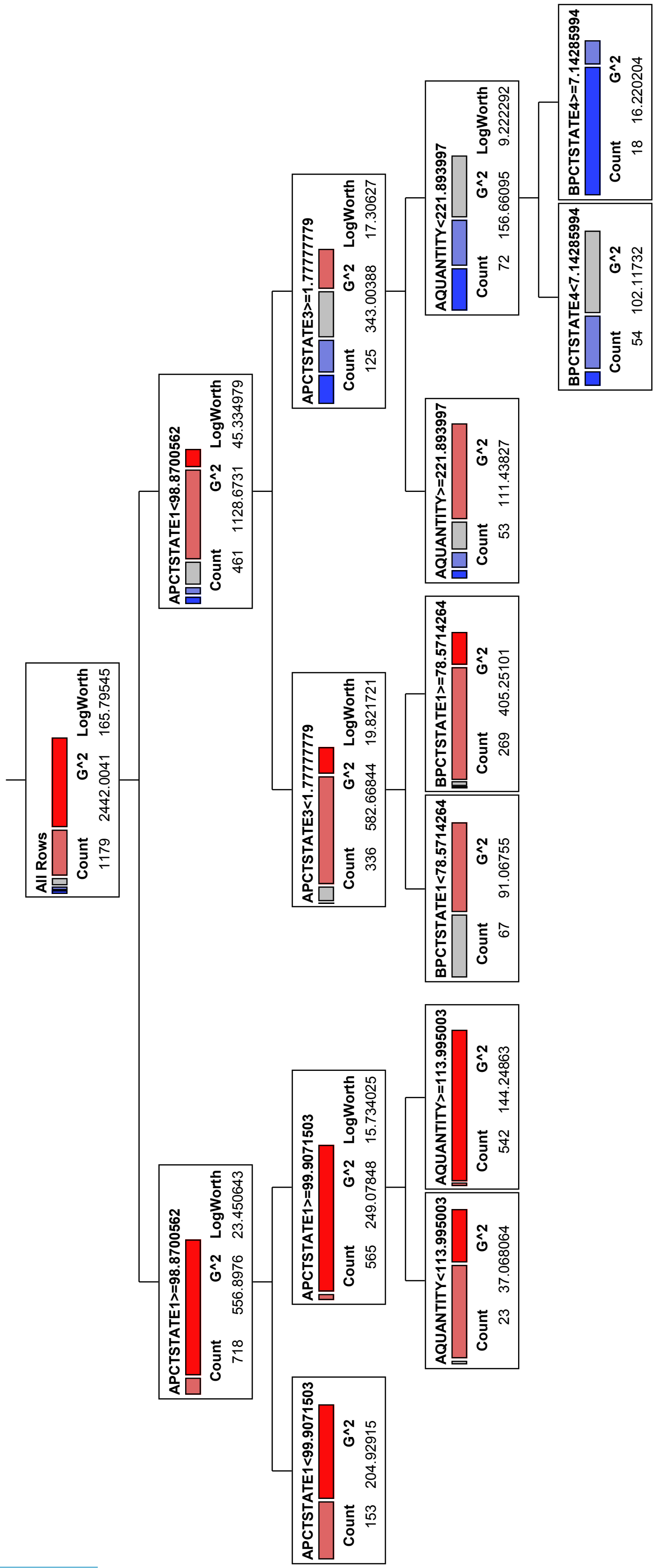
RSquare=0.544
Number of observations=1179
Number of splits=7

Column Contributions

Term	Number of Splits	G^2
AQUANTITY	2	142.66644
APCTSTATE1	2	859.3234
APCTSTATE2	0	0
APCTSTATE3	1	203.000768
APCTSTATE4	0	0
APCTSTATE5	0	0
BPCTSTATE1	1	86.3498831
BPCTSTATE2	0	0
BPCTSTATE3	0	0
BPCTSTATE4	1	38.3234251
BPCTSTATE5	0	0
Total	7	1329.66392






All Rows
Count 1179 G^2 2442.0041 LogWorth 165.79545
APCTSTATE1>=98.8700562
Count 718 G^2 556.8976 LogWorth 23.450643
APCTSTATE1<98.8700562
Count 461 G^2 1128.6731 LogWorth 45.334979
APCTSTATE1<99.9071503
Count 153 G^2 204.92915
APCTSTATE1>=99.9071503
Count 565 G^2 249.07848 LogWorth 15.734025
AQUANTITY<113.995003
Count 23 G^2 37.068064
AQUANTITY>=113.995003
Count 542 G^2 144.24863
APCTSTATE3<1.77777779
Count 336 G^2 582.66844 LogWorth 19.821721
BPCTSTATE1<78.5714264
Count 67 G^2 91.06755
BPCTSTATE1>=78.5714264
Count 269 G^2 405.25101
APCTSTATE3>=1.77777779
Count 125 G^2 343.00388 LogWorth 17.30627
AQUANTITY>=221.893997
Count 53 G^2 111.43827
AQUANTITY<221.893997
Count 72 G^2 156.66095 LogWorth 9.222292
BPCTSTATE4<7.14285994
Count 54 G^2 102.11732
BPCTSTATE4>=7.14285994
Count 18 G^2 16.220204

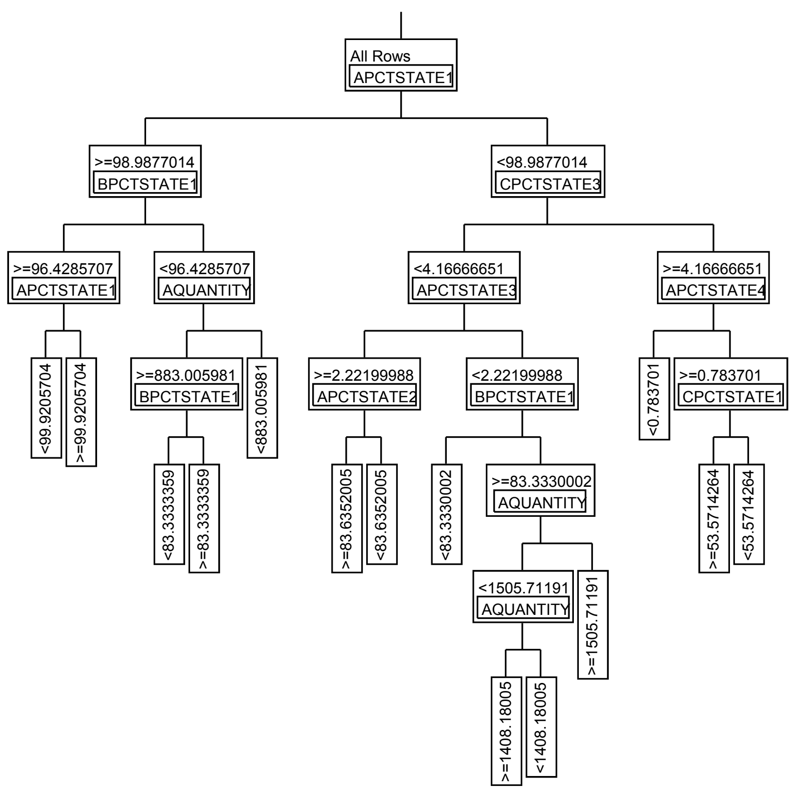
State B – Superstructure

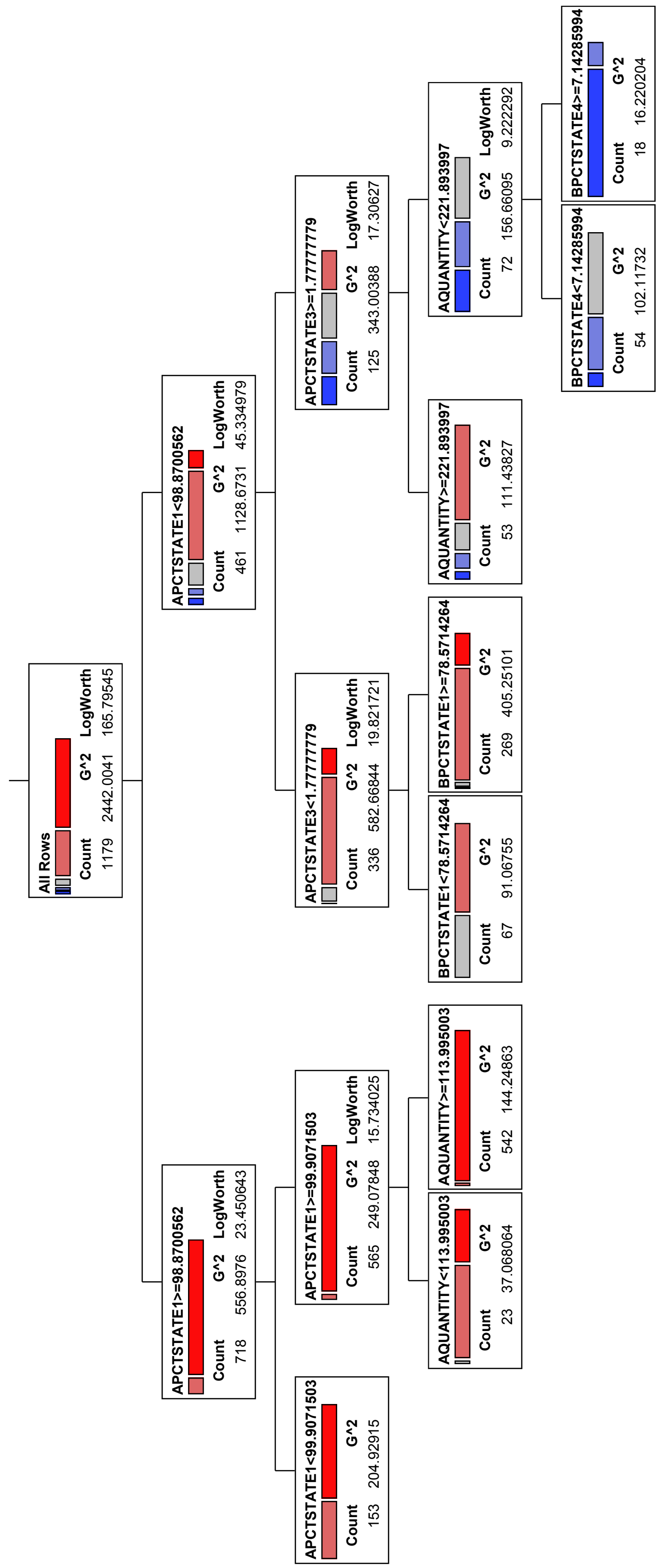
3 BMS Elements (Beam/Girder + Bearing1 + Bearing2)

RSquare=0.419
Number of observations=1139
Number of splits=13

Column Contributions

Term	Number of Splits	G^2
AQUANTITY	3	100.930909
APCTSTATE1	2	581.664411
APCTSTATE2	1	26.9180658
APCTSTATE3	1	68.4517662
APCTSTATE4	1	45.9368756
APCTSTATE5	0	0
BPCTSTATE1	3	121.442587
BPCTSTATE2	0	0
BPCTSTATE3	0	0
BPCTSTATE4	0	0
BPCTSTATE5	0	0
CPCTSTATE1	1	27.3336803
CPCTSTATE2	0	0
CPCTSTATE3	1	184.653214
CPCTSTATE4	0	0
CPCTSTATE5	0	0
Total	13	1157.33151



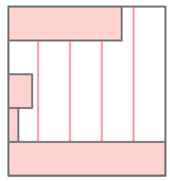

All Rows
Count G^2 LogWorth
1179 2442.0041 165.79545
APCTSTATE1>=98.8700562
Count G^2 LogWorth
718 556.8976 23.450643
APCTSTATE1<98.8700562
Count G^2 LogWorth
461 1128.6731 45.334979
APCTSTATE1<99.9071503
Count G^2
153 204.92915
APCTSTATE1>=99.9071503
Count G^2 LogWorth
565 249.07848 15.734025
AQUANTITY<113.995003
Count G^2
23 37.068064
AQUANTITY>=113.995003
Count G^2
542 144.24863
APCTSTATE3<1.77777779
Count G^2 LogWorth
336 582.66844 19.821721
APCTSTATE3>=1.77777779
Count G^2 LogWorth
125 343.00388 17.30627
BPCTSTATE1<78.5714264
Count G^2
67 91.06755
BPCTSTATE1>=78.5714264
Count G^2
269 405.25101
AQUANTITY>=221.893997
Count G^2
53 111.43827
AQUANTITY<221.893997
Count G^2 LogWorth
72 156.66095 9.222292
BPCTSTATE4<7.14285994
Count G^2
54 102.11732
BPCTSTATE4>=7.14285994
Count G^2
18 16.220204

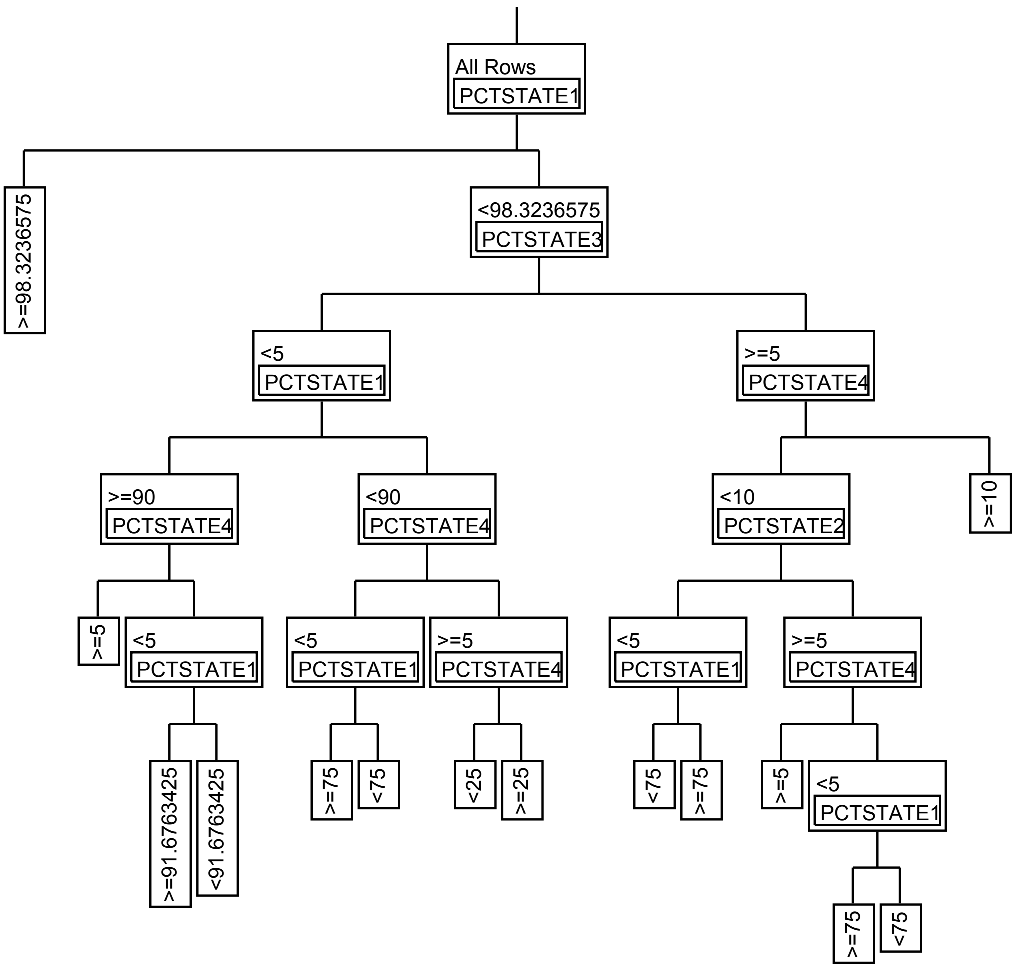
State C – Superstructure
1 BMS Element (Beam/Girder)

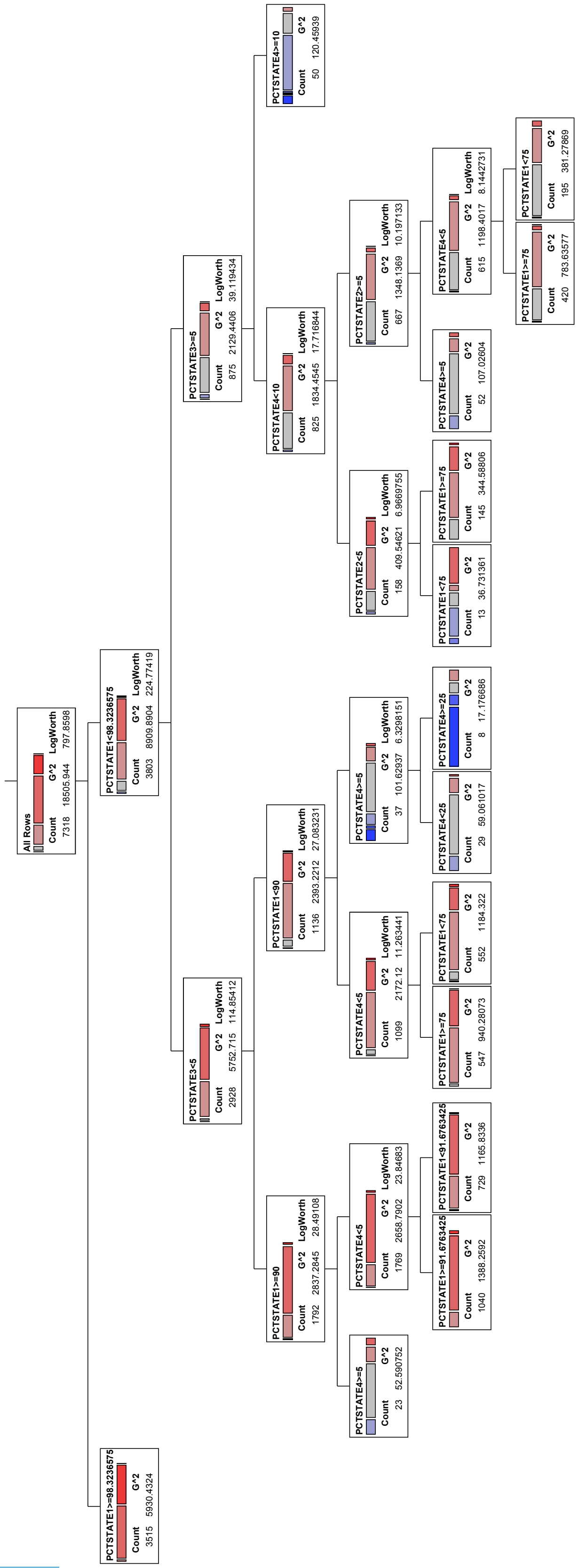
RSquare=0.324
Number of observations=7318
Number of splits=13

Column Contributions

Term	Number of Splits	G^2
PCTSTATE1	6	4401.25328
PCTSTATE2	1	76.7714123
PCTSTATE3	1	1026.89686
PCTSTATE4	5	487.957598
Total	13	5992.87915





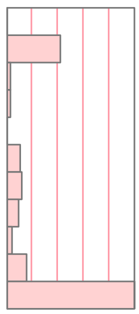

All Rows
Count 7318 G^2 18505.944 LogWorth 797.8598
PCTSTATE1>=98.3236575
Count 3515 G^2 5930.4324
PCTSTATE1<98.3236575
Count 3803 G^2 8909.8904 LogWorth 224.77419
PCTSTATE3<5
Count 2928 G^2 5752.715 LogWorth 114.85412
PCTSTATE3>=5
Count 875 G^2 2129.4406 LogWorth 39.119434
PCTSTATE1>=90
Count 1792 G^2 2837.2845 LogWorth 28.49108
PCTSTATE1<90
Count 1136 G^2 2393.2212 LogWorth 27.083231
PCTSTATE4<10
Count 825 G^2 1834.4545 LogWorth 17.716844
PCTSTATE4>=10
Count 50 G^2 120.45939
PCTSTATE4>=5
Count 23 G^2 52.590752
PCTSTATE4<5
Count 1769 G^2 2658.7902 LogWorth 23.84683
PCTSTATE4<5
Count 1099 G^2 2172.12 LogWorth 11.263441
PCTSTATE4>=5
Count 37 G^2 101.62937 LogWorth 6.3298151
PCTSTATE2<5
Count 158 G^2 409.54621 LogWorth 6.9669755
PCTSTATE2>=5
Count 667 G^2 1348.1369 LogWorth 10.197133
PCTSTATE1>=91.6763425
Count 1040 G^2 1388.2592
PCTSTATE1<91.6763425
Count 729 G^2 1165.8336
PCTSTATE1>=75
Count 547 G^2 940.28073
PCTSTATE1<75
Count 552 G^2 1184.322
PCTSTATE4<25
Count 29 G^2 59.061017
PCTSTATE4>=25
Count 8 G^2 17.176686
PCTSTATE1<75
Count 13 G^2 36.731361
PCTSTATE1>=75
Count 145 G^2 344.58806
PCTSTATE4>=5
Count 52 G^2 107.02604
PCTSTATE4<5
Count 615 G^2 1198.4017 LogWorth 8.1442731
PCTSTATE1>=75
Count 420 G^2 783.63577
PCTSTATE1<75
Count 195 G^2 381.27869

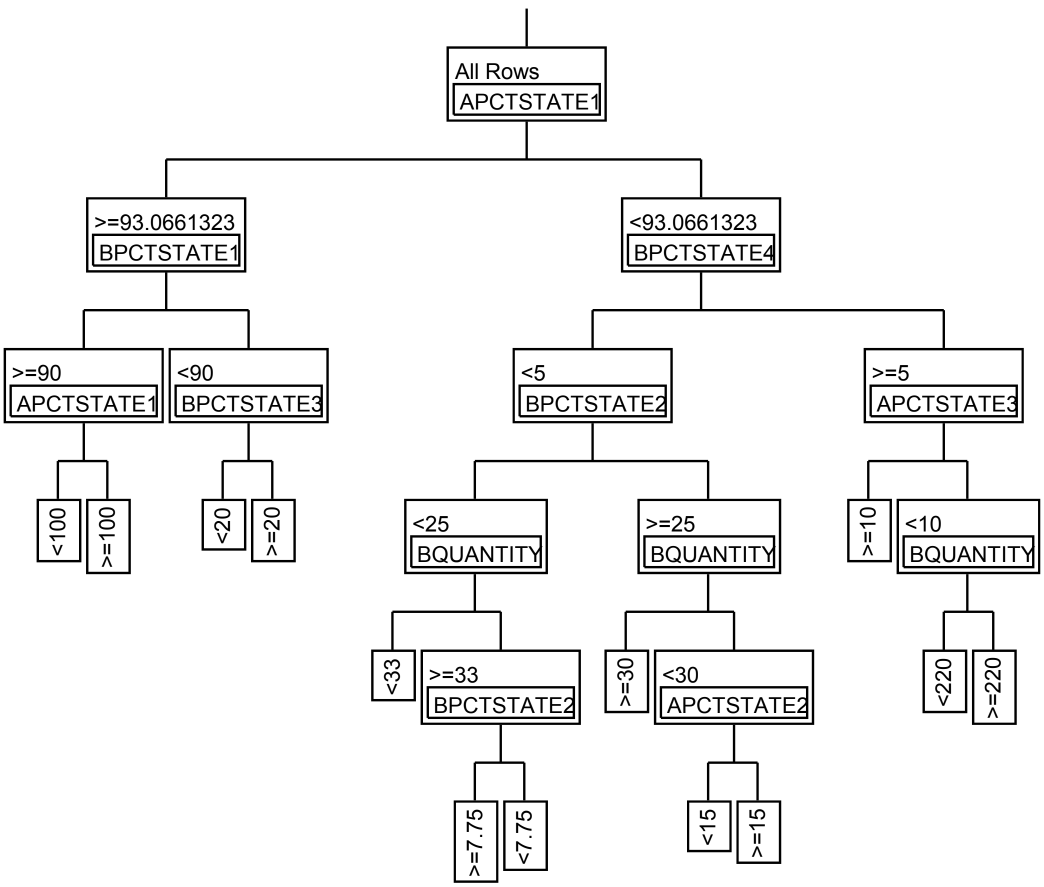
State C – Superstructure
2 BMS Element (Beam/Girder + Bearing)

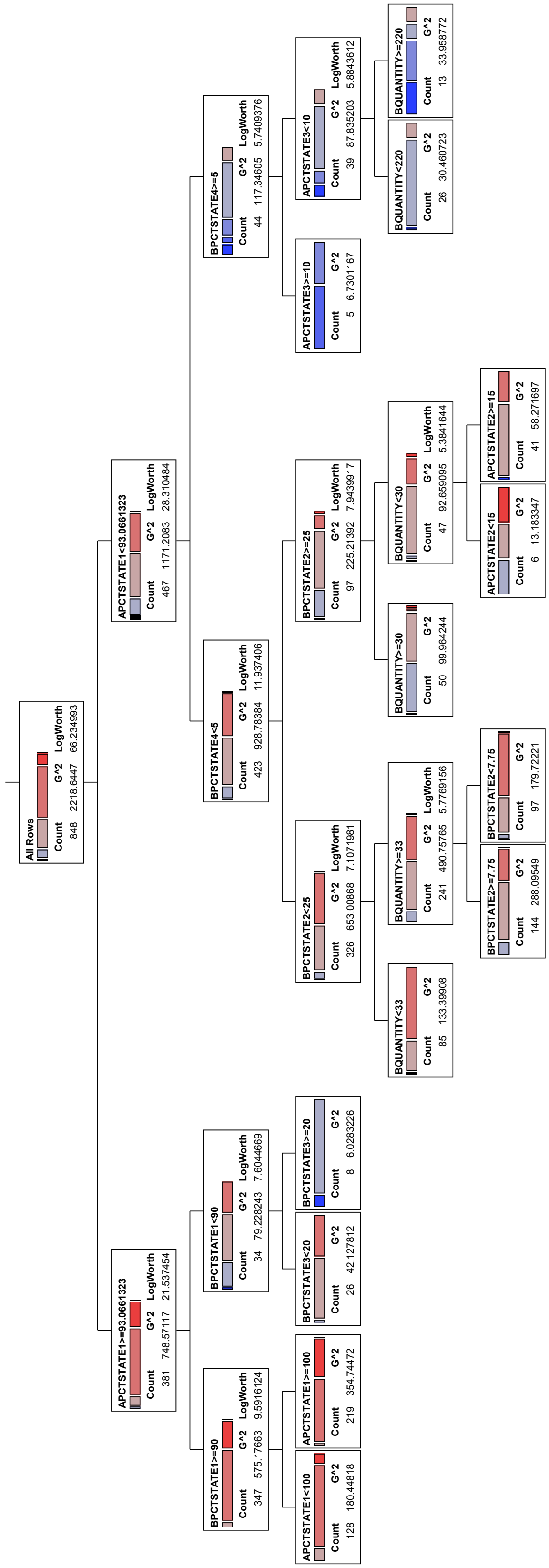
RSquare=0.357
Number of observations=848
Number of splits=12

Column Contributions

Term	Number of Splits	G^2
AQUANTITY	0	0
APCTSTATE1	2	340.217147
APCTSTATE2	1	21.2040499
APCTSTATE3	1	22.780726
APCTSTATE4	0	0
BQUANTITY	3	85.1514928
BPCTSTATE1	1	94.2676856
BPCTSTATE2	2	72.4753529
BPCTSTATE3	1	31.0721084
BPCTSTATE4	1	124.880254
Total	12	792.048817





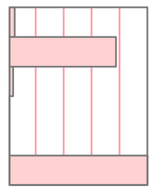

All Rows Count 848 G^2 2218.6447 LogWorth 66.234993
APCTSTATE1<93.0661323 Count 467 G^2 1171.2083 LogWorth 28.310484
APCTSTATE1>=93.0661323 Count 381 G^2 748.57117 LogWorth 21.537454
BPCTSTATE4>=5 Count 44 G^2 117.34605 LogWorth 5.7409376
BPCTSTATE4<5 Count 423 G^2 928.78384 LogWorth 11.937406
APCTSTATE3>=10 Count 5 G^2 6.7301167
APCTSTATE3<10 Count 39 G^2 87.835203 LogWorth 5.8843612
BQUANTITY<220 Count 26 G^2 30.460723
BQUANTITY>=220 Count 13 G^2 33.958772
BPCTSTATE2>=25 Count 97 G^2 225.21392 LogWorth 7.9439917
BPCTSTATE2<25 Count 326 G^2 653.00868 LogWorth 7.1071981
BQUANTITY>=30 Count 50 G^2 99.964244
BQUANTITY<30 Count 47 G^2 92.659095 LogWorth 5.3841644
APCTSTATE2<15 Count 6 G^2 13.183347
APCTSTATE2>=15 Count 41 G^2 58.271697
BQUANTITY<33 Count 85 G^2 133.39908
BQUANTITY>=33 Count 241 G^2 490.75765 LogWorth 5.7769156
BPCTSTATE2>=7.75 Count 144 G^2 288.09549
BPCTSTATE2<7.75 Count 97 G^2 179.72221
BPCTSTATE1>=90 Count 347 G^2 575.17663 LogWorth 9.5916124
BPCTSTATE1<90 Count 34 G^2 79.228243 LogWorth 7.6044669
APCTSTATE1<100 Count 128 G^2 180.44818
APCTSTATE1>=100 Count 219 G^2 354.74472
BPCTSTATE3<20 Count 26 G^2 42.127812
BPCTSTATE3>=20 Count 8 G^2 6.0283226

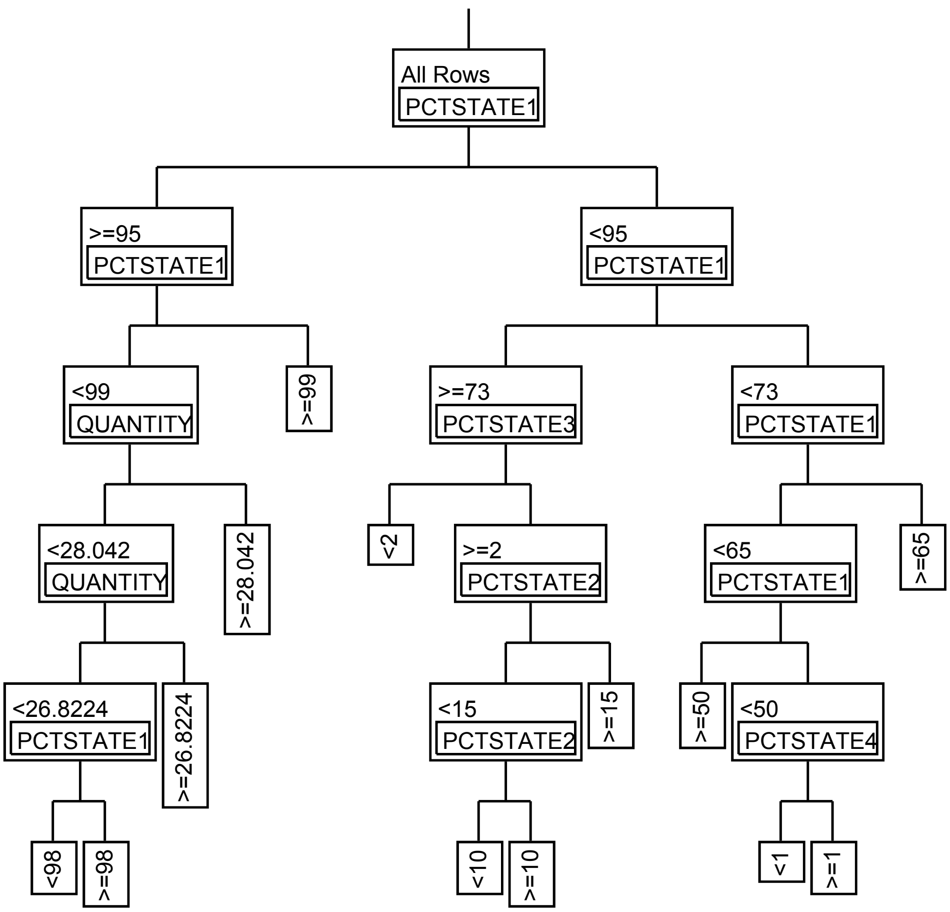
State A – Substructure
1 BMS Element (Abutment)

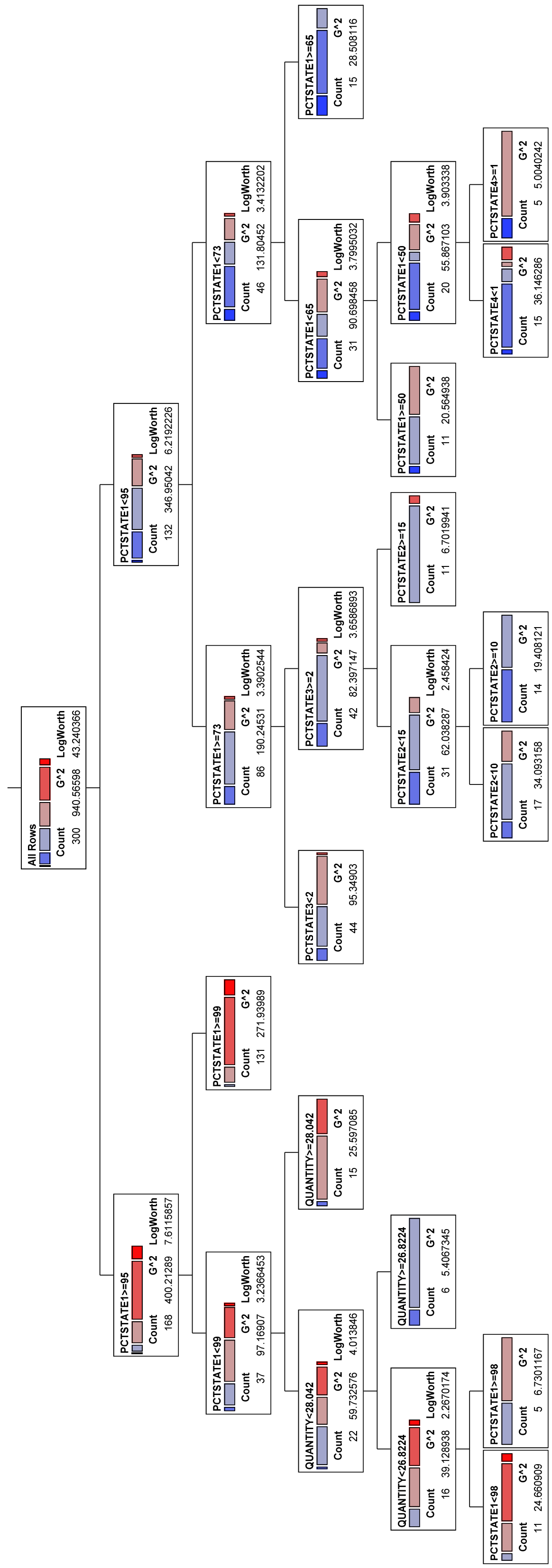
RSquare=0.383
Number of observations=300
Number of splits=12

Column Contributions

Term	Number of Splits	G^2
QUANTITY	2	27.036313
PCTSTATE1	6	284.009469
PCTSTATE2	2	22.1938733
PCTSTATE3	1	12.4991294
PCTSTATE4	1	14.7167928
Total	12	360.455578





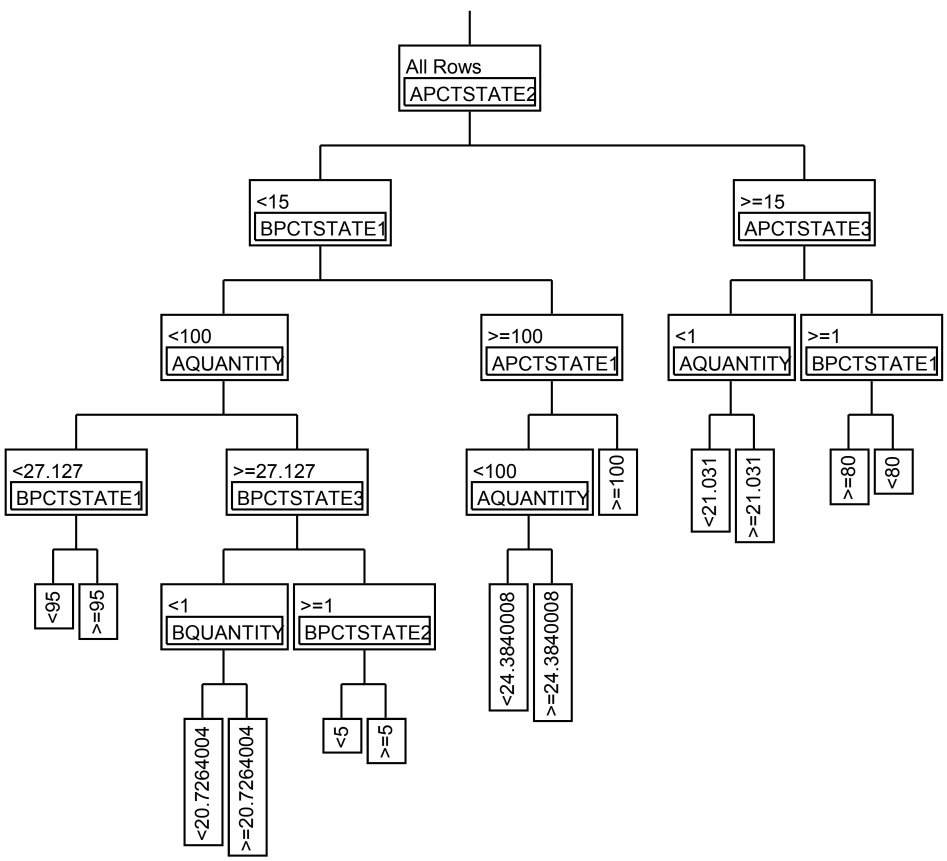

All Rows
Count 300 G^2 940.56598 LogWorth 43.240366
PCTSTATE1<95
Count 132 G^2 346.95042 LogWorth 6.2192226
PCTSTATE1>=95
Count 168 G^2 400.21289 LogWorth 7.6115857
PCTSTATE1<73
Count 46 G^2 131.80452 LogWorth 3.4132202
PCTSTATE1>=73
Count 86 G^2 190.24531 LogWorth 3.3902544
PCTSTATE1>=65
Count 15 G^2 28.508116
PCTSTATE1<65
Count 31 G^2 90.698458 LogWorth 3.7995032
PCTSTATE1>=50
Count 11 G^2 20.564938
PCTSTATE1<50
Count 20 G^2 55.867103 LogWorth 3.903338
PCTSTATE4<1
Count 15 G^2 36.146286
PCTSTATE4>=1
Count 5 G^2 5.0040242
PCTSTATE3<2
Count 44 G^2 95.34903
PCTSTATE3>=2
Count 42 G^2 82.397147 LogWorth 3.6586893
PCTSTATE2<15
Count 31 G^2 62.038287 LogWorth 2.458424
PCTSTATE2>=15
Count 11 G^2 6.7019941
PCTSTATE2<10
Count 17 G^2 34.093158
PCTSTATE2>=10
Count 14 G^2 19.408121
PCTSTATE1<99
Count 37 G^2 97.16907 LogWorth 3.2366453
PCTSTATE1>=99
Count 131 G^2 271.93989
QUANTITY<28.042
Count 22 G^2 59.732576 LogWorth 4.013846
QUANTITY>=28.042
Count 15 G^2 25.597085
QUANTITY<26.8224
Count 16 G^2 39.128938 LogWorth 2.2870174
QUANTITY>=26.8224
Count 6 G^2 5.4067345
PCTSTATE1<98
Count 11 G^2 24.660909
PCTSTATE1>=98
Count 5 G^2 6.7301167

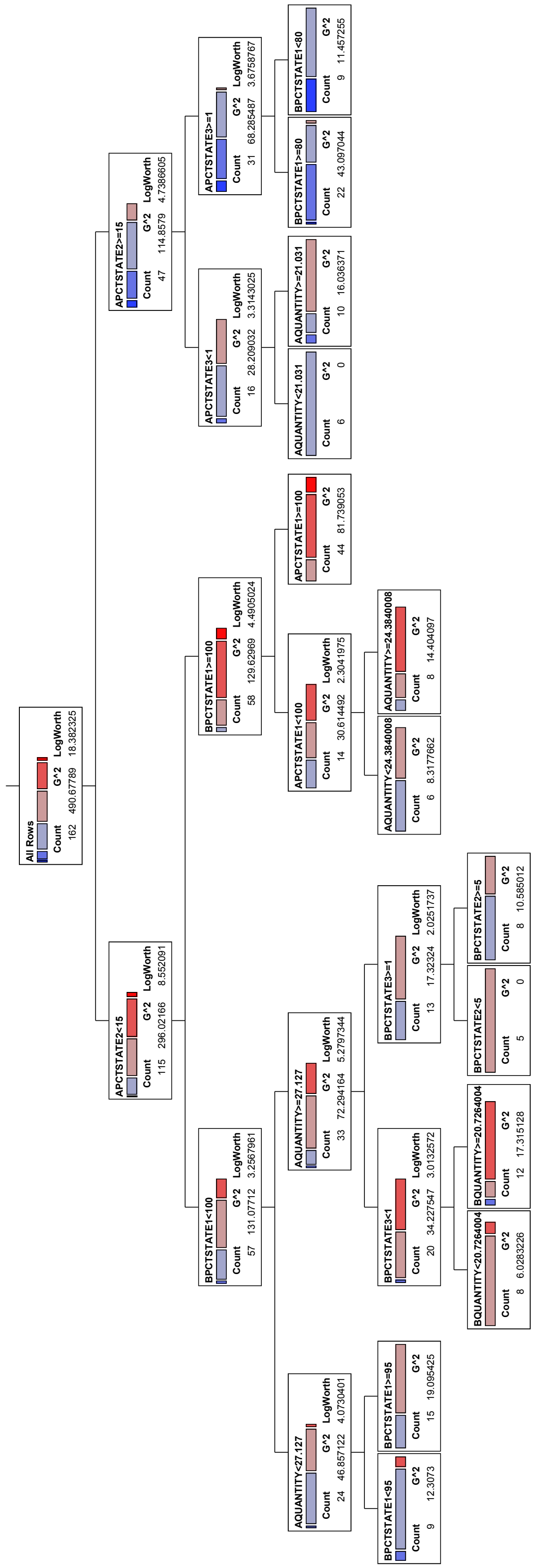
State A – Substructure
2 BMS Elements (Abutment + Column/Pile/Backwall)

RSquare=0.510
Number of observations=162
Number of splits=12

Column Contributions

Term	Number of Splits	G^2
AQUANTITY	3	31.991119
APCTSTATE1	1	17.2761433
APCTSTATE2	1	79.798327
APCTSTATE3	1	18.3633844
APCTSTATE4	0	0
BQUANTITY	1	10.8840956
BPCTSTATE1	3	64.50044
BPCTSTATE2	1	6.73822769
BPCTSTATE3	1	20.7433782
BPCTSTATE4	0	0
Total	12	250.295115




All Rows
Count 162 G^2 490.67789 LogWorth 18.382325
APCTSTATE2<15
Count 115 G^2 296.02166 LogWorth 8.552091
APCTSTATE2>=15
Count 47 G^2 114.8579 LogWorth 4.7386605
BPCTSTATE1<100
Count 57 G^2 131.07712 LogWorth 3.2567961
BPCTSTATE1>=100
Count 58 G^2 129.62969 LogWorth 4.4905024
APCTSTATE3<1
Count 16 G^2 28.209032 LogWorth 3.3143025
APCTSTATE3>=1
Count 31 G^2 68.285487 LogWorth 3.6758767
AQUANTITY<27.127
Count 24 G^2 46.857122 LogWorth 4.0730401
AQUANTITY>=27.127
Count 33 G^2 72.294164 LogWorth 5.2797344
APCTSTATE1<100
Count 14 G^2 30.614492 LogWorth 2.3041975
APCTSTATE1>=100
Count 44 G^2 81.739053
AQUANTITY<21.031
Count 6 G^2 0
AQUANTITY>=21.031
Count 10 G^2 16.036371
BPCTSTATE1>=80
Count 22 G^2 43.097044
BPCTSTATE1<80
Count 9 G^2 11.457255
BPCTSTATE1<95
Count 9 G^2 12.3073
BPCTSTATE1>=95
Count 15 G^2 19.095425
BPCTSTATE3<1
Count 20 G^2 34.227547 LogWorth 3.0132572
BPCTSTATE3>=1
Count 13 G^2 17.32324 LogWorth 2.0251737
AQUANTITY<24.3840008
Count 6 G^2 8.3177662
AQUANTITY>=24.3840008
Count 8 G^2 14.404097
BQUANTITY<20.7264004
Count 8 G^2 6.0283226
BQUANTITY>=20.7264004
Count 12 G^2 17.315128
BPCTSTATE2<5
Count 5 G^2 0
BPCTSTATE2>=5
Count 8 G^2 10.585012

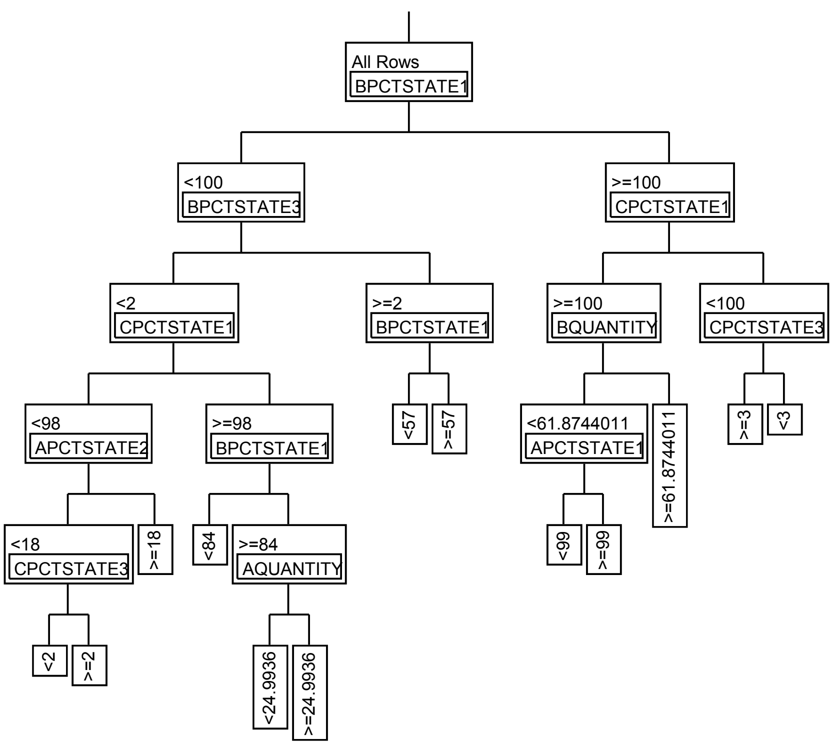
State A – Substructure

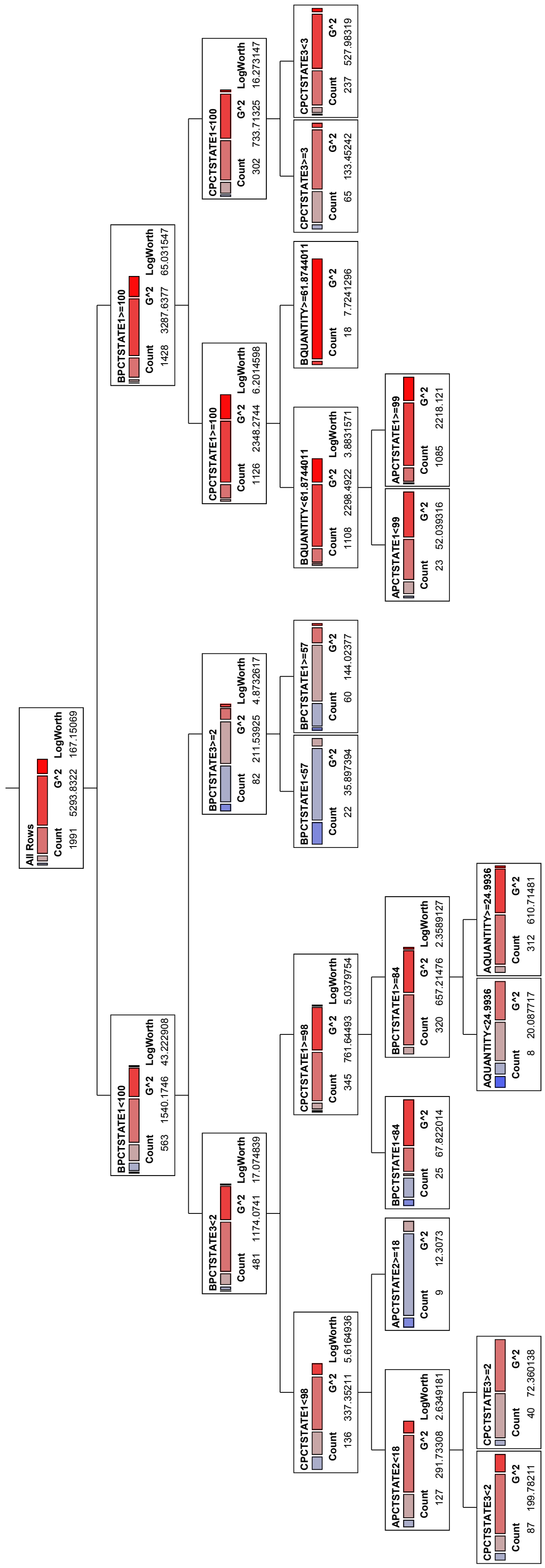
3 BMS Elements (Cap + Abutment + Column/Pile/Backwall)

RSquare=0.225
Number of observations=1991
Number of splits=12

Column Contributions

Term	Number of Splits	G^2
AQUANTITY	1	26.4122332
APCTSTATE1	1	28.3318648
APCTSTATE2	1	33.3117303
APCTSTATE3	0	0
APCTSTATE4	0	0
BQUANTITY	1	42.058024
BPCTSTATE1	3	534.246131
BPCTSTATE2	0	0
BPCTSTATE3	1	154.561269
BPCTSTATE4	0	0
CQUANTITY	0	0
CPCTSTATE1	2	280.727141
CPCTSTATE2	0	0
CPCTSTATE3	2	91.8684755
CPCTSTATE4	0	0
Total	12	1191.51687





All Rows
Count 1991 G^2 5293.8322 LogWorth 167.15069
BPCTSTATE1<100
Count 563 G^2 1540.1746 LogWorth 43.222908
BPCTSTATE1>=100
Count 1428 G^2 3287.6377 LogWorth 65.031547
BPCTSTATE3<2
Count 481 G^2 1174.0741 LogWorth 17.074839
BPCTSTATE3>=2
Count 82 G^2 211.53925 LogWorth 4.8732617
CPCTSTATE1>=100
Count 1126 G^2 2348.2744 LogWorth 6.2014598
CPCTSTATE1<100
Count 302 G^2 733.71325 LogWorth 16.273147
CPCTSTATE1<98
Count 136 G^2 337.35211 LogWorth 5.6164936
CPCTSTATE1>=98
Count 345 G^2 761.64493 LogWorth 5.0379754
BPCTSTATE1<57
Count 22 G^2 35.897394
BPCTSTATE1>=57
Count 60 G^2 144.02377
BQUANTITY<61.8744011
Count 1108 G^2 2298.4922 LogWorth 3.8831571
BQUANTITY>=61.8744011
Count 18 G^2 7.7241296
CPCTSTATE3>=3
Count 65 G^2 133.45242
CPCTSTATE3<3
Count 237 G^2 527.98319
APCTSTATE2<18
Count 127 G^2 291.73308 LogWorth 2.6349181
APCTSTATE2>=18
Count 9 G^2 12.3073
BPCTSTATE1<84
Count 25 G^2 67.822014
BPCTSTATE1>=84
Count 320 G^2 657.21476 LogWorth 2.3589127
APCTSTATE1<99
Count 23 G^2 52.039316
APCTSTATE1>=99
Count 1085 G^2 2218.121
CPCTSTATE3<2
Count 87 G^2 199.78211
CPCTSTATE3>=2
Count 40 G^2 72.360138
AQUANTITY<24.9936
Count 8 G^2 20.087717
AQUANTITY>=24.9936
Count 312 G^2 610.71481

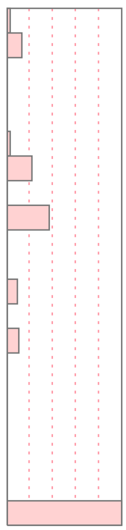
State A – Substructure

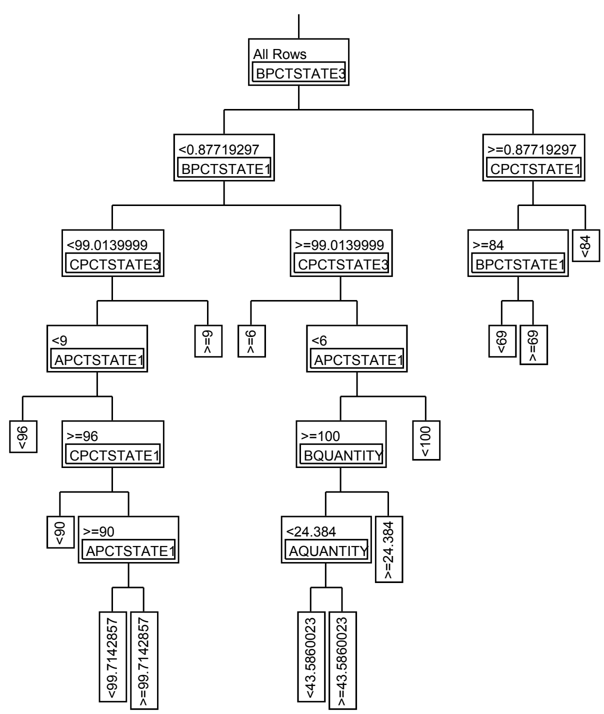
4 BMS Elements (Cap + Abutment + Backwall/PierWall + Column)
(All reinforced concrete bridges and elements)

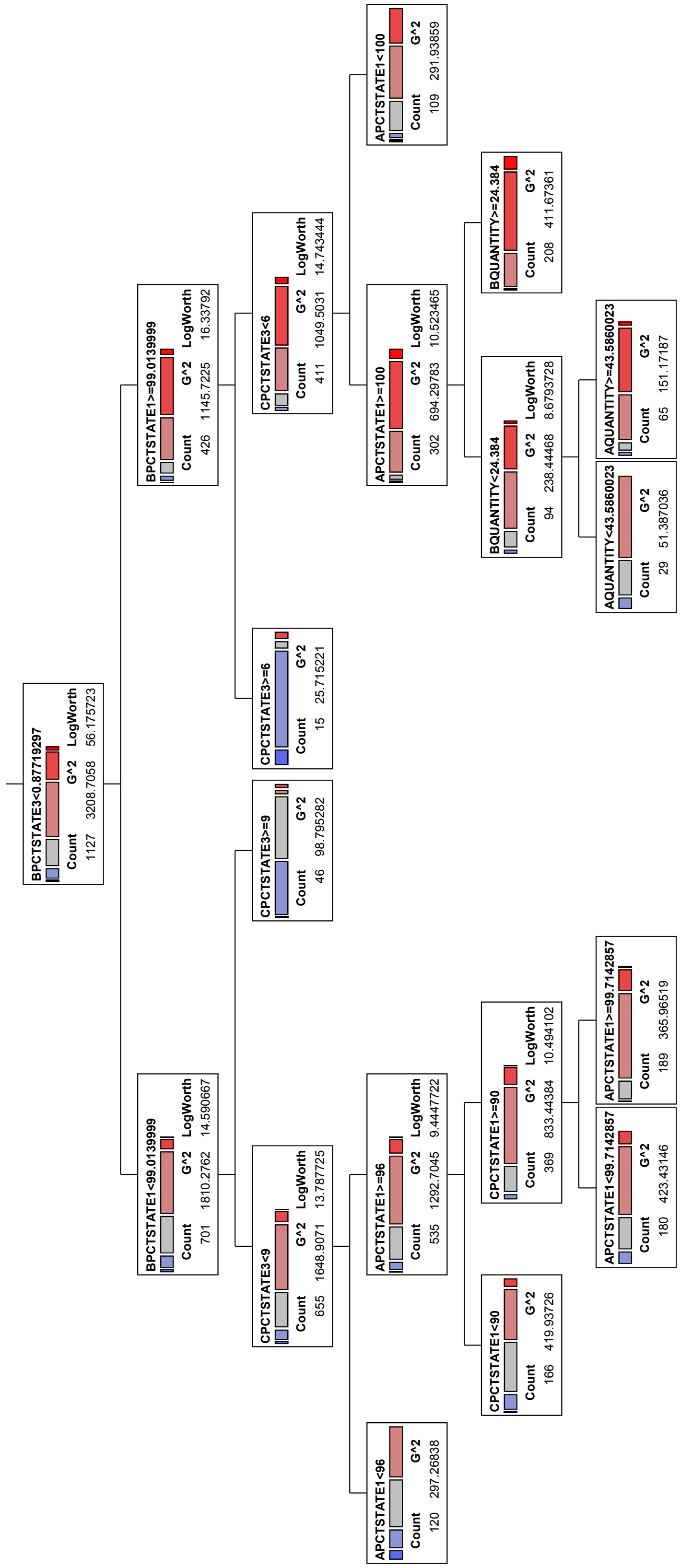
RSquare=0.269
Number of observations=1514
Number of splits=12

Column Contributions

Term	Number of Splits	G^2
AQUANTITY	1	35.8857674
APCTSTATE1	3	166.24809
APCTSTATE2	0	0
APCTSTATE3	0	0
APCTSTATE4	0	0
BQUANTITY	1	44.1795476
BPCTSTATE1	2	288.647503
BPCTSTATE2	0	0
BPCTSTATE3	1	484.438746
BPCTSTATE4	0	0
CQUANTITY	0	0
CPCTSTATE1	2	124.585784
CPCTSTATE2	0	0
CPCTSTATE3	2	133.078021
CPCTSTATE4	0	0
DQUANTITY	0	0
DPCTSTATE1	0	0
DPCTSTATE2	0	0
DPCTSTATE3	0	0
DPCTSTATE4	0	0
Total	12	1277.06346





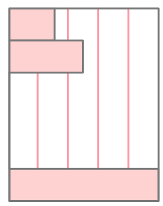

BPCTSTATE3<0.87719297
Count G^2 LogWorth
1127 3208.7058 56.175723
BPCTSTATE1<99.0139999
Count G^2 LogWorth
701 1810.2762 14.590667
BPCTSTATE1>=99.0139999
Count G^2 LogWorth
426 1145.7225 16.33792
CPCTSTATE3<9
Count G^2 LogWorth
655 1648.9071 13.787725
CPCTSTATE3>=9
Count G^2
46 98.795282
CPCTSTATE3>=6
Count G^2
15 25.715221
CPCTSTATE3<6
Count G^2 LogWorth
411 1049.5031 14.743444
APCTSTATE1<96
Count G^2
120 297.26838
APCTSTATE1>=96
Count G^2 LogWorth
535 1292.7045 9.4447722
APCTSTATE1>=100
Count G^2 LogWorth
302 694.29783 10.523465
APCTSTATE1<100
Count G^2
109 291.93859
CPCTSTATE1<90
Count G^2
166 419.93726
CPCTSTATE1>=90
Count G^2 LogWorth
369 833.44384 10.494102
BQUANTITY<24.384
Count G^2 LogWorth
94 238.44468 8.6793728
BQUANTITY>=24.384
Count G^2
208 411.67361
APCTSTATE1<99.7142857
Count G^2
180 423.43146
APCTSTATE1>=99.7142857
Count G^2
189 365.96519
AQUANTITY<43.5860023
Count G^2
29 51.387036
AQUANTITY>=43.5860023
Count G^2
65 151.17187

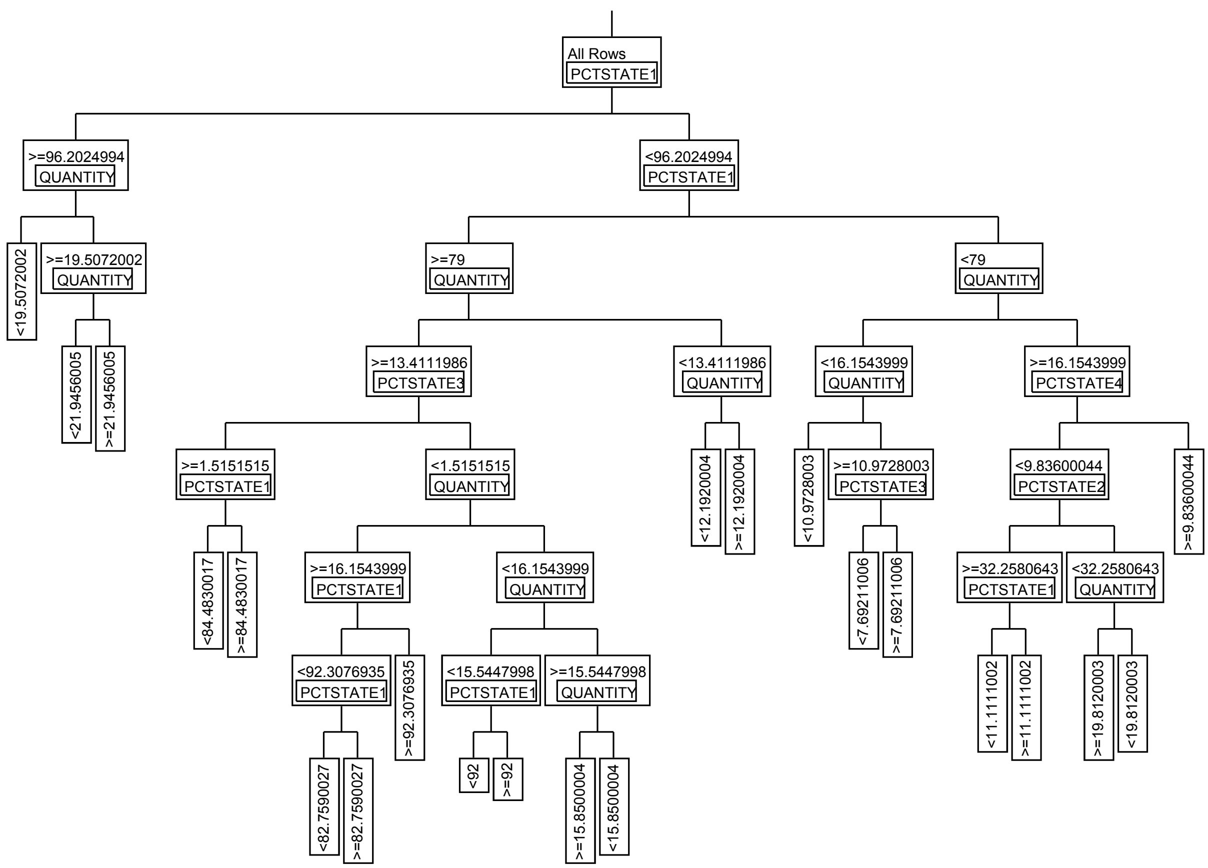
State B – Substructure
1 BMS Element (Abutment)

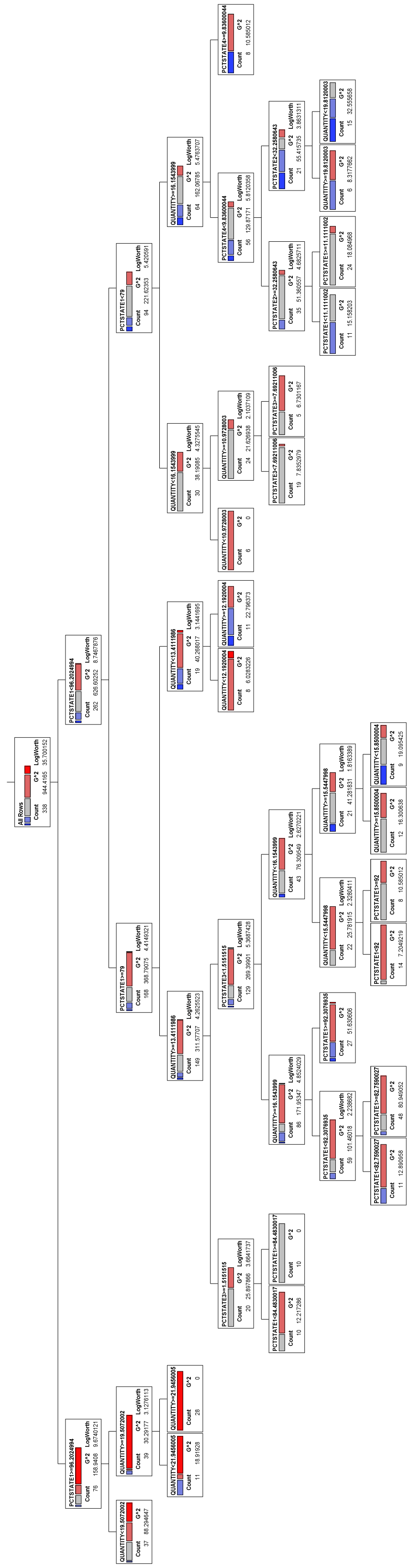
RSquare=0.528
Number of observations=338
Number of splits=21

Column Contributions

Term	Number of Splits	G^2
QUANTITY	10	168.854467
PCTSTATE1	7	261.334229
PCTSTATE2	1	23.0954215
PCTSTATE3	2	23.3417154
PCTSTATE4	1	21.6111224
Total	21	498.236955







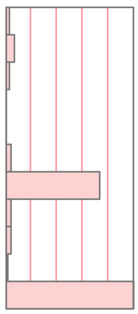
State B – Substructure

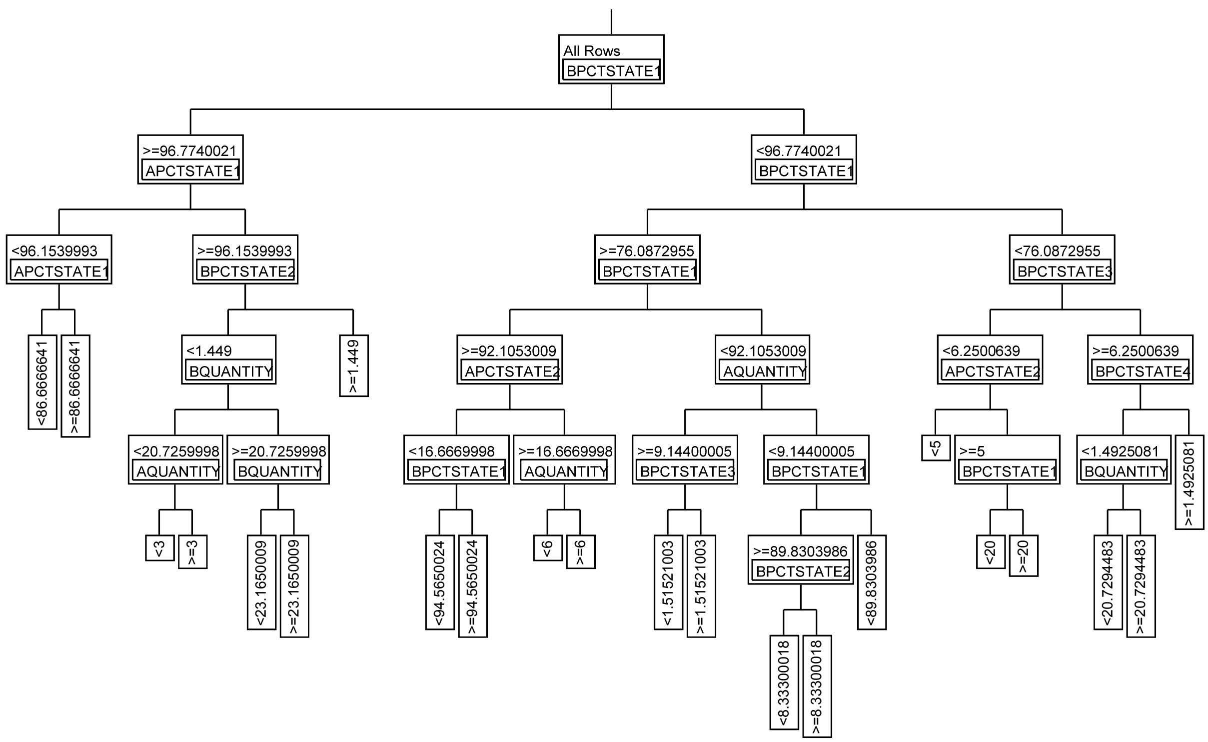
2 BMS Elements (Column/Pile + Abutment)

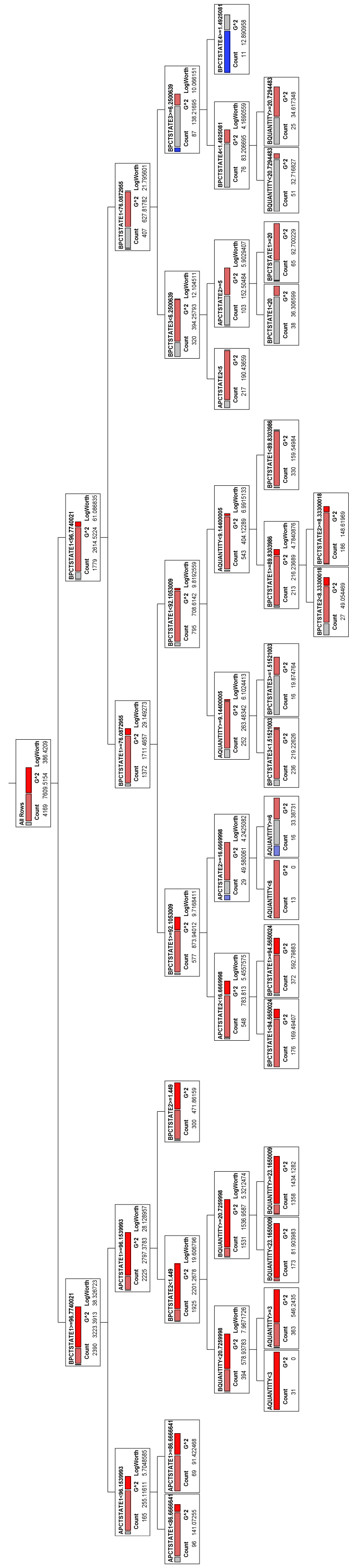
RSquare=0.401
Number of observations=4169
Number of splits=21

Column Contributions

Term	Number of Splits	G^2
AQUANTITY	3	89.8949668
APCTSTATE1	2	193.517993
APCTSTATE2	2	91.8635644
APCTSTATE3	0	0
APCTSTATE4	0	0
BQUANTITY	3	122.170241
BPCTSTATE1	6	2249.10621
BPCTSTATE2	2	142.811703
BPCTSTATE3	2	119.725323
BPCTSTATE4	1	42.1193004
Total	21	3051.2093





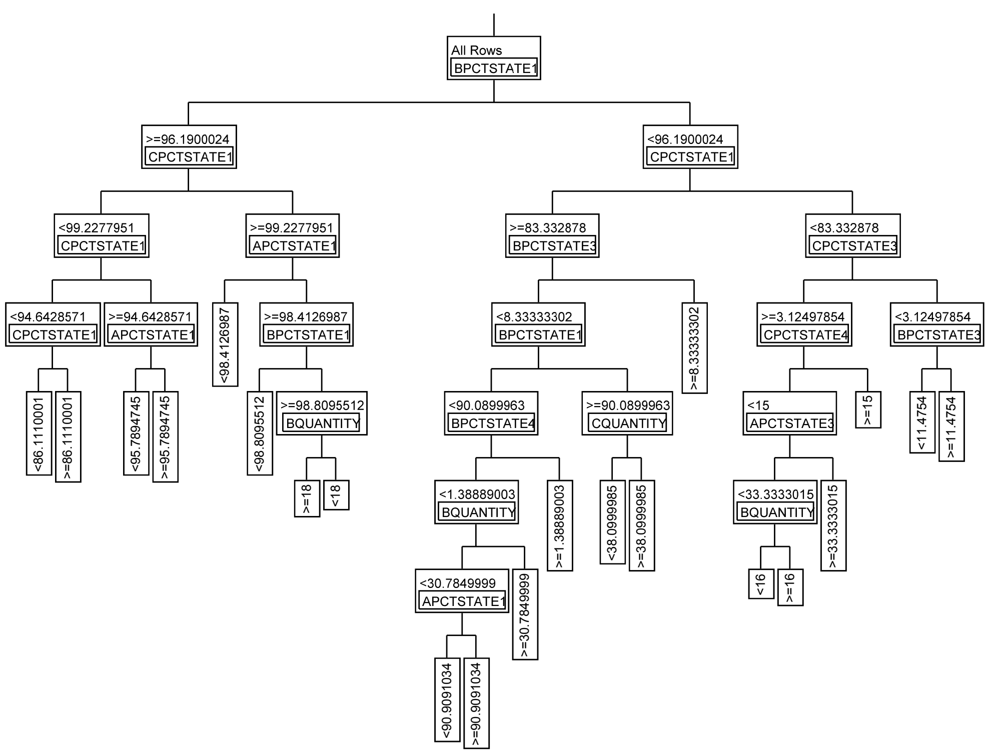


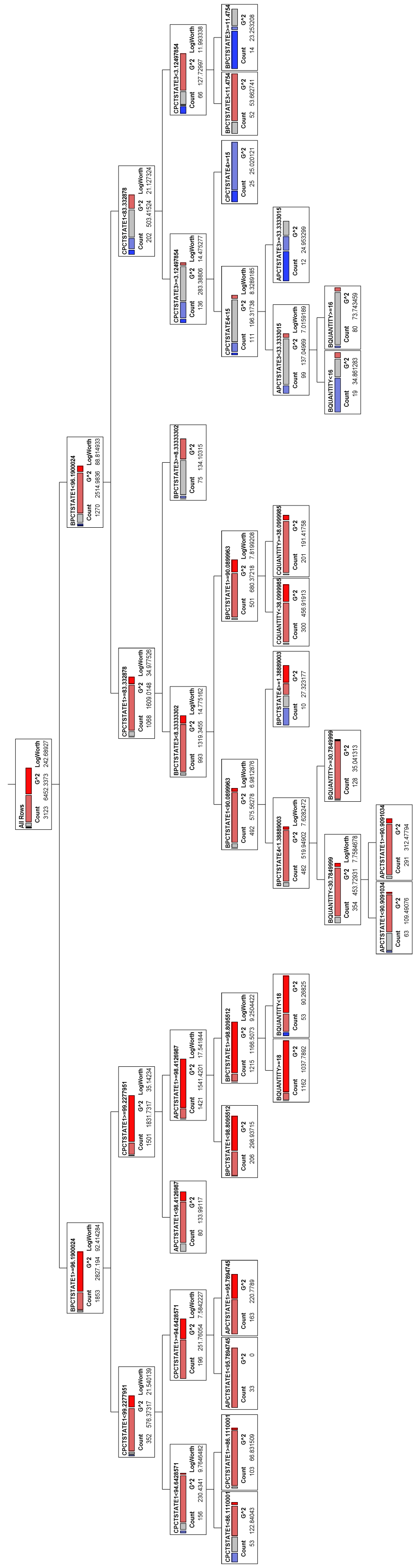
State B – Substructure
3 BMS Elements (Column/Pile + Abutment + Cap)

RSquare=0.462
Number of observations=3123
Number of splits=20

Column Contributions

Term	Number of Splits	G^2
AQUANTITY	0	0
APCTSTATE1	3	222.343631
APCTSTATE2	0	0
APCTSTATE3	1	34.314392
APCTSTATE4	0	0
BQUANTITY	3	98.097465
BPCTSTATE1	3	1249.63916
BPCTSTATE2	0	0
BPCTSTATE3	2	206.380168
BPCTSTATE4	1	28.290579
CQUANTITY	1	32.035462
CPCTSTATE1	4	956.583323
CPCTSTATE2	0	0
CPCTSTATE3	1	92.2972147
CPCTSTATE4	1	62.0505558
Total	20	2982.03195



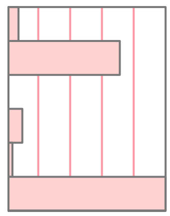


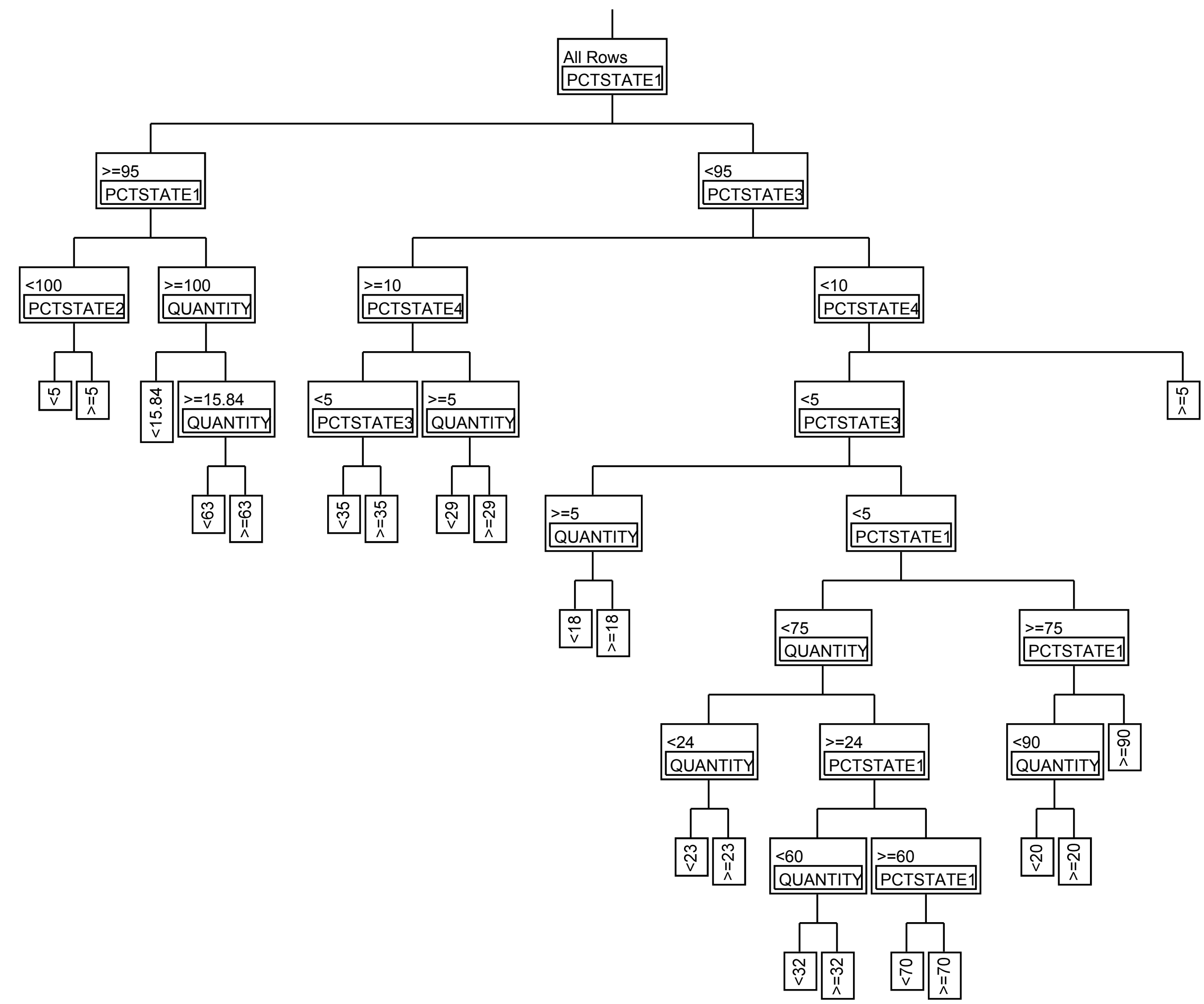
State C – Substructure
1 BMS Element (Abutment)

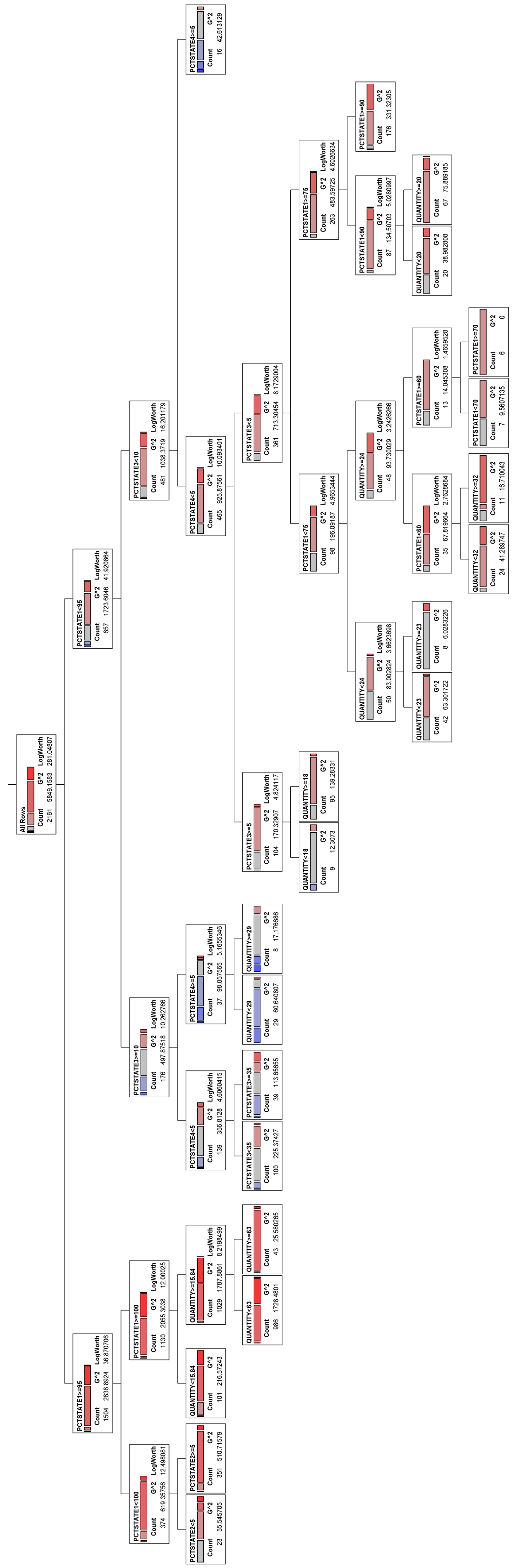
RSquare=0.362
Number of observations=2161
Number of splits=20

Column Contributions

Term	Number of Splits	G^2
QUANTITY	8	186.136204
PCTSTATE1	6	1518.62454
PCTSTATE2	1	53.0960633
PCTSTATE3	3	247.38156
PCTSTATE4	2	112.887934
Total	20	2118.1263





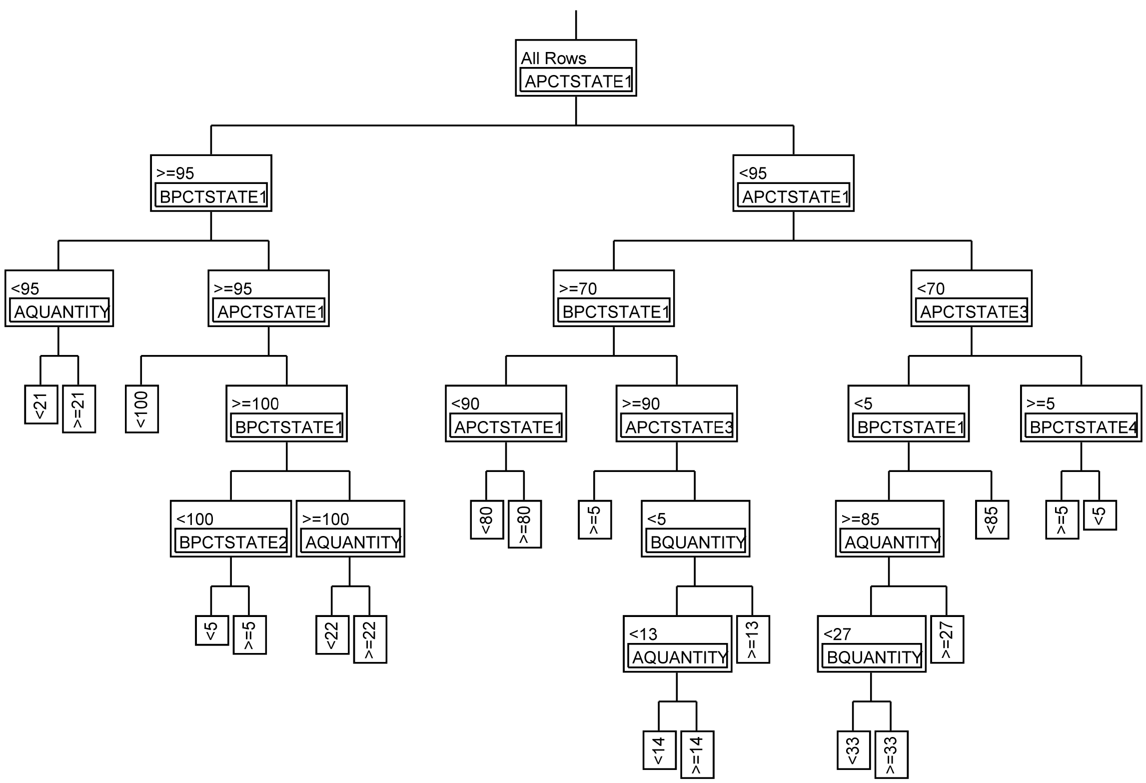


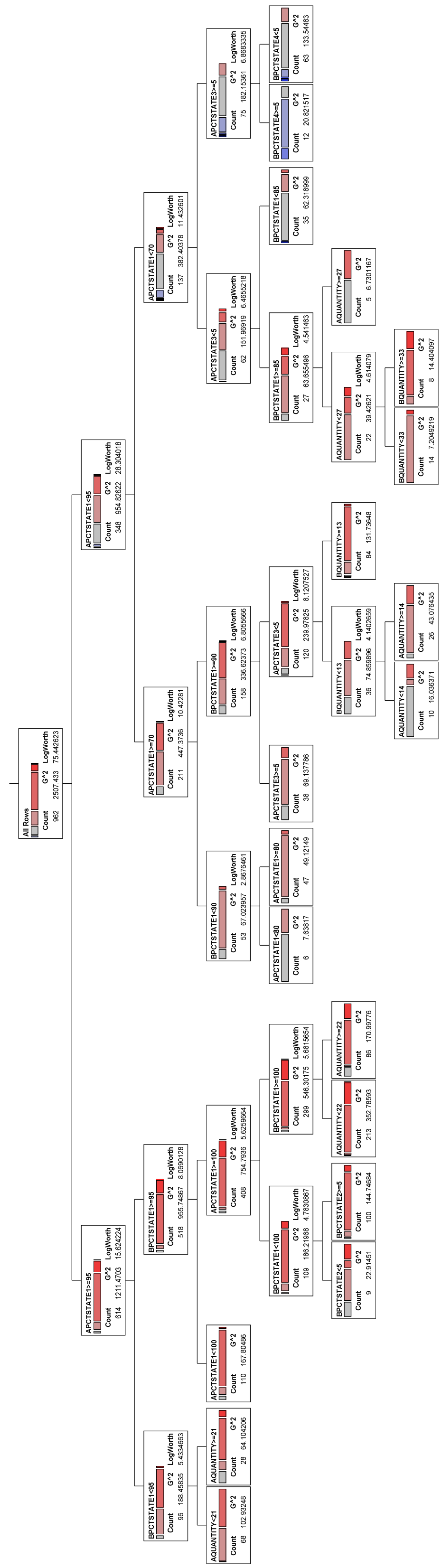
State C – Substructure
2 BMS Elements (Column/Pile + Abutment)

RSquare=0.367
Number of observations=962
Number of splits=18

Column Contributions

Term	Number of Splits	G^2
AQUANTITY	4	77.1859829
APCTSTATE1	4	509.599776
APCTSTATE2	0	0
APCTSTATE3	2	75.7886735
APCTSTATE4	0	0
BQUANTITY	2	51.1990672
BPCTSTATE1	4	159.256098
BPCTSTATE2	1	18.5583322
BPCTSTATE3	0	0
BPCTSTATE4	1	27.7872598
Total	18	919.37519





State C – Substructure

3 BMS Elements (Column/Pile + Abutment + Cap)

RSquare=0.305
Number of observations=5885
Number of splits=20

Column Contributions

Term	Number of Splits	G^2
AQUANTITY	0	0
APCTSTATE1	4	561.829206
APCTSTATE2	0	0
APCTSTATE3	2	281.341445
APCTSTATE4	1	50.7372446
BQUANTITY	0	0
BPCTSTATE1	5	1382.01782
BPCTSTATE2	0	0
BPCTSTATE3	1	75.8682568
BPCTSTATE4	1	99.2861114
CQUANTITY	0	0
CPCTSTATE1	2	1982.95039
CPCTSTATE2	0	0
CPCTSTATE3	3	181.095778
CPCTSTATE4	1	73.5930845
Total	20	4688.71933