Developing Implementation Strategies for Risk Based Inspection (RBI): Back-casting Report

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The goal of this project was to improve asset management through the implementation of Risk-Based Inspection (RBI) practices. This project studied risk-based processes for developing extended inspection interval policies for bridges. Prior tasks in the research included Reliability Assessment Panels from six states developing risk models for bridges with steel and prestressed concrete superstructures. The risk models assess the relative risk of individual bridge components based on attributes that affect the reliability of the component. A back-casting process was applied to a sample population of bridges from the six states. This report describes the back-casting process and results developed through the research. A new data-driven methodology for analyzing the quality and effectiveness of the risk models based on Monte Carlo simulations was developed through the research. This methodology was shown to be effective for analyzing, calibrating, and verifying risk models for bridge components. The conclusions of the research indicate that a substantial number of bridges in good condition could be placed on an extended 72-month inspection interval, allowing inspection resources to be reallocated toward bridges with elevated risk.</td></tr>
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Developing Implementation Strategies for Risk Based Inspection (RBI)

Back-Casting Report

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Disclaimer

The opinions, findings, and conclusions expressed in this document are those of the investigators. They are not necessarily those of the Missouri Department of Transportation, U.S. Department of Transportation, or Federal Highway Administration. This information does not constitute a standard or specification.

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List of Abbreviations and Acronyms

ADT	Average Daily Traffic
ADTT	Average Daily Truck Traffic
CF	Consequence Factor
CP	Corrosion protection level
CR	Condition Rating
CS	Condition State
Delam.	Delamination
DOT	Department of Transportation
FHWA	Federal Highway Administration
LRF	Load Rating Factor
NBI	National Bridge Inventory
NBIS	National Bridge Inspection Standards
NDT	Nondestructive Testing
NSTM	Nonredundant steel tension member
OF	Occurrence Factor
POF	Probability of Failure
PSC	Prestressed Concrete
RAP	Reliability Assessment Panel
RBI	Risk Based Inspection
R/C	Reinforced Concrete
SS.	Superstructure
SNBI	Specification for the National Bridge Inventory
Stl	Steel
Sub	Substructure
vpd	Vehicles per day

Definitions

Attributes: Characteristics that affect the reliability of a bridge or bridge element.

Condition Attributes: Characteristics that relate to the current condition of a bridge or bridge element. These may include element ratings, component ratings, and specific damage modes or mechanisms that have a significant effect on the reliability of an element.

Consequence Factor: Factor describing the expected outcome or result of a failure.

Damage mode: Typical damage affecting the condition of a bridge element (e.g. spalling of concrete, cracking. etc.).

Delphi process: The Delphi process is a method of expert elicitation that involves consulting a panel of experts through a series of systematic feedback rounds to develop consensus opinions on parameters needed for decision-making. Experts are surveyed anonymously and then consensus is formed.

Design Attributes: Characteristics of bridge or bridge element that are part of the element's design. These attributes typically do not change over time except when renovation, rehabilitation or preservation activities occur.

Deterioration mechanism: Process or phenomena resulting in damage to a bridge element (e.g., corrosion, fatigue, etc.).

Element: Identifiable portions of a bridge made of the same material, having similar role in the performance of the bridge, and expected to deteriorate in a similar fashion.

Failure: Termination of the ability of a system, structure or component to perform its intended function (API 2016). For bridges, the condition at which a given bridge element is no longer performing its intended function to safely, and reliably, carry normal loads and maintain serviceability.

Loading Attributes: Loading characteristics that affect the reliability of a bridge or bridge element such as traffic or environment.

Occurrence Factor: Factor describing the likelihood that an element will fail during a specified time interval.

Operational Environment: The operational environment is a combination of the circumstances surrounding and potentially affecting the in-service performance of bridges and bridge elements. These include typical loading patterns, ambient environmental conditions, construction quality and practices, maintenance and management practices, and other factors which may vary between different geographic regions and/or organizational boundaries.

Probability: Extent to which an event is likely to occur during a given time interval (API 2016). This may be based on the frequency of events, such as in the quantitative probability of failure, or on degree of belief or expectation. Degrees of belief about probability can be chosen using qualitative scales, ranks or categories such as "Remote / Low / Moderate / High" or "Remote / Unlikely / Moderate / Likely / Almost Certain."

Reliability: Ability of an item, component, or system to operate safely under designated operating conditions for a designated period of time or number of cycles.

Risk: Combination of the probability of an event and its consequence.

Risk Analysis: Systematic use of information to identify sources and estimate the risk. Information can include historical data, theoretical analysis, informed opinions and engineering judgment.

Risk Model: A collection of attributes, criteria, and weights used to assess the level of risk.

Screening Attribute: Characteristics of a bridge or bridge element that:

- Make the likelihood of serious damage unusually high,
- Make the likelihood of serious damage unusually uncertain,
- Identify a bridge with different anticipated deterioration patterns than other bridges in a group or family.

Executive Summary

The goal of this project was to improve asset management through the implementation of Risk-Based Inspection (RBI) practices. The research was intended to amplify the results of the NCHRP research that produced report NCHRP 782, *Proposed Guidelines for Reliability-Based Inspection Practices* (NCHRP 782) (Washer et al. 2014). The framework described in that report is part of the revised National Bridge Inspection Standards (NBIS) published in 2022. The new rules allow bridge owners to develop extended inspection interval policies that include risk-based intervals of up to 72 months for bridges in good condition.

The project studied this new process for developing extended inspection interval policies for bridges. Prior tasks in the research included Reliability Assessment Panels (RAPs) from six states developing risk models for bridges with steel and prestressed concrete (PSC) superstructures. The risk models assess the relative risk of individual bridge components based on attributes that affect the reliability of the component. A back-casting process described in NCHRP 782 was applied to a sample population of bridges from the six states. This report describes the back-casting process and results developed through the research. A new data-driven methodology for analyzing the quality and effectiveness of the risk models based on Monte Carlo (MC) simulations was developed through the research.

Chapter 1 of the report includes an analysis of the new NBIS requirements and associated FHWA guidance for inspection intervals that provided target ranges for risk models based on the condition rating (CR) of bridge components. These target ranges provide guidance for analyzing risk models and identifying risk levels. This analysis also proposed a modification to the risk matrix initially included in the NCHRP 782 report referenced in the NBIS. This revised matrix allows for bridges assigned a consequence factor (CF) of *high* to be assigned a 72-month inspection interval when the Occurrence Factor (OF) category is *remote*. The proposed change to the risk matrix was supported by the data from 60 sample bridges studied in the research.

Chapter 2 of the report describes the results of back-casting of 60 sample bridges using risk models developed by RAPs in six states. The back-casting process used in this research consisted of examining individual bridge inspection records for a population of randomly selected bridges. Inspection reports from individual states were acquired and analyzed over the time interval of 2004 thru 2021. Risk scores were produced for each inspection year based on the attributes and criteria included in the risk models using a weighted sum scoring process. These data were analyzed to assess the quality and effectiveness of the risk models when applied to typical bridges. Sensitivity studies of the back-casting data were used to analyze methods of weighting attributes in the risk models.

Chapter 3 describes a new data-driven methodology for analyzing the risk models using MC simulations. This methodology uses bridge inventory data to simulate the outcome from risk models when applied to a family of bridges. In this way the risk models can be analyzed, calibrated, and verified using data from bridges. It was shown that this methodology can be used to analyze different scenarios and to adjust attribute weights to meet target ranges.

Chapter 4 includes the conclusions from the back-casting study. The primary conclusions from the study were as follows:

- The analysis of components from the sample bridges showed that the weighted risk models were effective for determining the relative risk of bridge components and identifying bridge components with elevated risk.
- Based on the back-casting results, it was found that 35% of the sample bridges could have an inspection interval of 72 months when the CF was *moderate*. If the CF were *high*, only 8% of the

bridges could qualify for a 72-month inspection interval. These results were based on randomly sampled bridges with component CRs ranging from CR 2 to CR 9 with an average CR of 6.

- A separate analysis of bridges in *good* condition (i.e., CR ≥ 7) showed that 100% of these bridges could have a 72-month interval when the CF was *moderate*. If the CF were *high*, 46% of the bridges in good condition could have an inspection interval of 72 months. These data indicate that implementing a risk-based extended inspection interval policy could place a substantial number of bridges in *good* condition on a 72-month inspection interval. *This will allow for the reallocation of inspection resources toward bridges with elevated risk, which is the primary goal of any risk-based inspection approach.*
- A methodology based on MC simulation was developed for analyzing the risk models and predicting their performance when applied to a family of bridges. It was shown that this methodology can be used to analyze different scenarios and to adjust attribute weights to meet target ranges. Importantly, the research showed that this approach was effective for identifying components in good condition that represent elevated risk when compared with the risk model simulations. *The MC simulation methodology can be used to identify those bridges that present elevated risk and require shorter inspection intervals and those that do not have elevated risk. This is precisely the objective of the risk analysis.*
- It was shown that the methodology developed in the research based on MC simulation was successful in identifying components with elevated risk and could be used to demonstrate the quality of the risk models. This can provide a critical tool for implementation of the RBI approach and gaining approval of extended inspection interval policies.

Chapter 1.
Introduction

The goal of this project was to improve asset management through the implementation of Risk-Based Inspection (RBI) practices. The research was intended to amplify the results of the NCHRP research that produced report NCHRP 782, *Proposed Guidelines for Reliability-Based Inspection Practices* (NCHRP 782) (Washer et al. 2014). The report described a framework for the RBI of bridges that envisioned extended inspection intervals for low-risk bridges. The framework described in that report is part of the revised National Bridge Inspection Standards (NBIS) published in 2022 (USDOT 2022). The new rules allow bridge owners to develop extended inspection policies that include risk-based intervals of up to 72 months for bridges in good condition. Prior to this revision to the NBIS, the maximum allowable routine inspection interval was 48-months for bridges that met certain subjective criteria defined by the Federal Highway Administration (FHWA) (FHWA 1988). The new process allows individual bridge owners to develop risk-based criteria based on analysis by a Reliability Assessment Panel (RAP) formed from key agency staff with knowledge of bridge design, evaluation, inspection, and maintenance practices.

This project studied this new process for developing extended inspection interval policies based on risk. Prior tasks in the research included RAPs from six states developing risk models for bridges with steel and prestressed concrete (PSC) superstructures. The risk models assess the relative risk of individual bridge components based on attributes that affect the reliability of the component. A back-casting process described in NCHRP 782 was applied to a sample population of bridges from the six states. The back-casting process consists of applying the risk models developed by a RAP to historical bridge performance to assess if the risk models were appropriately considering risk factors. The purpose of the back-casting is to verify the effectiveness of the risk models for determining suitable inspection intervals for bridges.

This report describes the back-casting process, developments, and results developed through the research. The back-casting process used in this research included examining individual bridge inspection records for a population of randomly selected bridges. Inspection reports from individual states were acquired and analyzed over the time interval of 2004 thru 2021. The condition rating (CR) of bridge components, element condition state (CS) data (when available), and inspection notes were studied to assess attributes included in the risk models developed by the RAPs. Risk scores were produced for each inspection year based on the attributes and criteria included in the risk models using a weighted sum scoring process. These data were analyzed to assess the quality and effectiveness of the risk models when applied to typical bridges. The risk models were modified over the course of the study based on initial results from back-casting, emerging NBIS requirements, and sensitivity studies conducted as part of the research.

The primary objectives of the back-casting were as follows:

1. Determine if the risk models developed by the RAPs were effective for characterizing the relative risk of individual bridge components.
2. Develop a process for analyzing the risk models to determine appropriate weights for attributes.

This report documents the results of the back-casting and analysis of the risk models. A new methodology for assessing the risk models that will support practical implementation of the technology was developed and is described in this report. This new methodology provides a data-driven process for analyzing the risk models, calibrating the weights of attributes and criteria in the risk models, and assessing the outcome of implementing an extended inspection interval for a family of bridges.

The report provides a review of the overall process for developing RBI intervals for bridges in the background section. An analysis of the new NBIS requirements and how the requirements apply to risk analysis for bridges is provided to set the stage for reporting the results of the back-casting. Chapter 2 describes the back-casting process used in the research and the results from data analysis. Chapter 3 of the report presents the new methodology developed in the research to provide a data-driven approach to analyzing the risk models to support practical implementation of the technology. Chapter 4 includes the conclusions from this task of the research and a discussion of implementation challenges.

1.1. Background

This section provides a brief overview of the RBI process studied through the research. The RBI process discussed in this summary is based on previous research reported in NCHRP Report 782, "*Proposed Guideline for Reliability-based Bridge Inspection Practices.*" (Washer, Connor et al. 2014)

The process of risk-analysis for RBI has two primary components known as the Occurrence Factor (OF) and the Consequence Factor (CF). The OF is an estimate of the likelihood of a serious condition (CR 3) developing in the next 72 months for a particular bridge component (i.e., deck, superstructure, or substructure) considering a particular damage mode (e.g., delamination and spalling). The OF is analogous to a probability of failure (POF). A single bridge component may have multiple OFs based on the damage modes that are likely to affect the component. The CF assesses the potential consequences of a bridge component deteriorating to a serious condition in terms of safety and serviceability (Washer, Connor et al. 2014). Generally, the CF depends on load capacity, Average Daily Traffic (ADT), structural redundancy, and the feature under the bridge.

The OF is estimated based on *attributes* of bridge components, which are characteristics of a bridge component that affect its reliability. Generally, these attributes are characteristics that affect the durability of the component, such as the level of corrosion protection, traffic loading, and current condition. During the initial stages of this project, RAP meetings were held to identify and prioritize attributes for different bridge components and damage modes. Criteria for rating the attributes were also developed. The collection of attributes and associated criteria used to determine the OF is termed a *risk model.* The risk model is used to calculate a *risk score* for each damage mode using a weighted sum model.

The OF and the CF are combined to locate a particular bridge component on a risk matrix as shown in Figure 1.1. Bridge components that tend toward the lower left corner of the matrix have lower risk and require less frequent inspections. Components that tend toward the upper right corner have higher risk and require more frequent inspection. The bridge inspection interval is determined from the component representing the highest risk. Inspection intervals envisioned by the methodology range from 12 to 72 months with the lowest-risk bridges assigned a 72-month interval.

The risk models developed in this project generally conform to the FHWA guidance for RBI intervals published in the National Bridge Inspection Standards in 2022 (USDOT 2022). This update to the NBIS provided new requirements for implementing RBI intervals that were used in the research to assess the risk models and develop processes that will meet the new requirements. The following section analyzes the new requirements and discusses how these requirements were implemented within the research.

1.2. RBI and NBIS Analysis

The update to the NBIS published in 2022 included requirements for implementing risk-based inspection intervals for routine, underwater, and Nonredundant Steel Tension Member (NSTM) inspections (USDOT 2022). The FHWA subsequently issued a memorandum with the subject "National Bridge Inspection Standards Inspection Interval Guidance" to provide additional information and assistance for bridge owners implementing the new NBIS requirements (FHWA 2022). This memo addressed the two methods identified in the NBIS for determining the inspection interval, named Method 1 and Method 2. Method 1 is a simplified risk assessment approach to determine reduced and extended intervals for routine, underwater, and NSTM inspections. Extended intervals of up to 48 months are allowed for bridges meeting certain criteria defined within the NBIS and clarified with the FHWA guidance memo. In general, Method 1 requires that bridge components have a CR of 6 or higher, have a load rating factor (LRF) of 1.0 or greater, minimum vertical clearance of at least 14 ft, and minimal scour vulnerability. Bridge owners must also consider other factors such as material, ADT, design, etc. in developing a Method 1 policy.

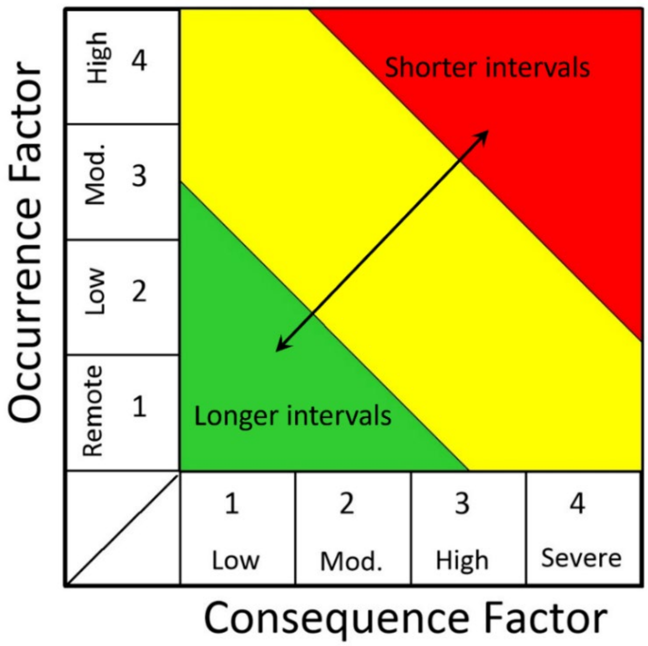


Figure 1.1. Conceptual risk matrix for risk-based bridge inspection.

Method 2 is a more rigorous approach that allows for risk assessment by quantified statistical analysis and / or qualitative expert judgement. The maximum routine inspection interval using Method 2 is 72 months. The risk models formed in this project are the first risk models and processes developed using Method 2 under the new policies. This section of the report summarizes the requirements for the two methodologies to provide context on the needs, criteria, and opportunities within the new risk-based approached to inspection planning. Certain data from the implementation of Method 2 in this research are also presented to illustrate how the new requirements align with research results.

1.2.1. Method 1 Analysis

Method 1 allows for bridges meeting certain criteria to have extended routine inspection intervals of up to 48 months. Table 1.1 summarizes the criteria established in the NBIS and the FHWA memo for an extended 48-month inspection interval. The detailed criteria shown in Table 1.1 refer to items defined in the traditional FHWA Recording and Coding Guide (i.e., the *coding guide*) and the new Specifications for the National Bridge Inventory (SNBI) (FHWA 1995, FHWA 2022). A description of the items indicated by the coding guide and SNBI codes in Table 1.1 are listed below the table for reference.

A key element of Method 1 is that bridges which meet the criteria can be assigned 48-month inspection intervals without FHWA approval when the bridge owner establishes an extended inspection interval policy. The extended interval policy must consider other factors such as structure type, design, materials, etc. determined by the bridge owner. The factors identified by the bridge owner are intended to capture other risks not included in the Method 1 requirements based on engineering judgement and knowledge of their bridge inventory. This allows the bridge owner to assign the 48-month interval for any bridge meeting the identified NBIS criteria and additional factors the owner has included in their extended interval policies. The routine inspection interval is reduced to the traditional 24-month interval when one or more of the Method 1 criteria are not met.

Table 1.1. Summary of FHWA requirements for Method 1 analysis.

Description		Coding Guide	SNBI	Criteria
Deck condition rating		58	B.C.01	≥6
Superstructure Condition Rating		59	B.C.02	≥6
Substructure Condition Rating		60	B.C.03	≥6
Culvert Condition Rating		62	B.C.04	≥6
Channel Condition		61	B.C.09	≥6
Channel Protection Condition		61	B.C.10	≥6
Inventory Load Rating Factor		66	B.LR.05	LF ≥1.0
Routine Permit Loads		-	B.LR.08	A or N[1]
Fatigue Details		-	B.IR.02	N[2]
Highway Minimum Vertical Clearance		53 and 54B	B.H.13	≥ 14.0 ft ≥ 0420 m
Span Material	Coding Guide	43A and 44A	-	2, 3, 4, or 5[3]
Span Material	SNBI	-	B.SP.04	C01-C05 or S01-S05[4]
Span Type	Coding Guide	43B and 44B	-	01, 02, or 05[5]
Span Type	SNBI		B.SP.06	A01, B02-B03, F01-F02, G01-G08, P01-P02, or S01-S02[6]
Scour Vulnerability	Coding Guide	113	-	5, 8, or N[7]
Scour Vulnerability	SNBI	-	Item B.AP.03	A or B[8]
Scour Condition Rating		-	B.C.11	≥6

[1] A) Bridge carries routine permit loads. Load capacity is adequate for all routine permit loads; no routine permit loads are restricted.

[2] N= No E/E' details

[3] Coding Guide Materials: 2. RC continuous, 3. Steel, 4. Steel Continuous, 5. PSC

[4] SNBI Materials**:** C01. Reinforced concrete – cast-in-place, C02. Reinforced concrete – precast, C03. Prestressed concrete – pre-tensioned**,** C04. Prestressed concrete – cast-in-place post-tensioned**,** C05. Prestressed concrete – precast post-tensioned**,** S01. Steel – rolled shapes, S02 Steel – welded shapes. S03 Steel – bolted shapes**,** S04. Steel – riveted shapes**,** S05. Steel – bolted and riveted shapes

[5] Coding guide span types**:** 01. Slab, 02. Stringer/Multi-beam or Girder, 05. Box Beam or Girders – Multiple

[6] SNBI Span types: A01. Arch – under fill without spandrel, B02. Box girder/beam – multiple adjacent, B03. Box girder/beam – multiple spread, F01. Frame – three-sided, F02. Frame – four-sided**,** G01. Girder/beam – I-shaped adjacent**,** G02 Girder/beam – I-shaped spread, G03 Girder/beam – tee-beam, G04. Girder/beam – inverted tee-beam, G05 Girder/beam – double-tee adjacent, G06. Girder/beam – double-tee spread, G07. Girder/beam – channel adjacent, G08. Girder/beam – channel spread, P01. Pipe – Rigid, P02. Pipe – Flexible, S01. Slab – solid, S02. Slab – voided.

[7]Scour Critical Bridges (Coding Guide): 5) Bridge foundations determined to be stable for calculated scour conditions; scour within limits of footing or piles, 8) Bridge foundations determined to be stable for assessed or calculated scour conditions; calculated scour is above top of footing, N) Bridge not over waterway.

[8] SNBI Scour: A. Scour appraisal completed. Bridge determined to be stable for scour, B. Scour appraisal completed. Bridge determined to be stable for scour, dependent upon designed and functioning countermeasures.

The criteria for Method 1 do not consider durability characteristics of a bridge such as corrosion protection, the aggressiveness of the environment, or other factors that could affect the likelihood of future deterioration and damage. It is also notable that there are no criteria related to the Average Daily Traffic (ADT) for a bridge, feature under the bridge, or the degree of redundancy. The Method 1 requirements imply any members that are not defined as NSTMs can be treated equally in terms of redundancy when establishing a 48-month inspection interval, although owners may include redundancy factors in their policies.

The Method 1 criteria may be useful for analyzing a Method 2 assessment to determine if the assessment generally meets FHWA requirements, although there can be differences since the Method 2 analysis involves different criteria and a more rigorous approach to the analysis. A primary difference between Method 1 and Method 2 is that various attributes that affect the likelihood of damage developing in the future are incorporated in Method 2. Method 1 analysis relies entirely on the present condition of the bridge. As a result, a Method 2 analysis may produce different criteria than Method 1. However, the Method 1 criteria provide a general framework for RBI analysis when implementing intervals determined through Method 2 analysis. For example, the Method 1 scour vulnerability criteria are likely to be required under most Method 2 risk models. It should be noted that there is not an explicit requirement that the Method 1 criteria be met when implementing Method 2. For example, one of the Method 1 criteria prohibits bridges with category E or E' details, which have a high susceptibility to fatigue cracking as compared with other steel details, from having an extended interval. If the bridge had minimal loading such that likelihood of fatigue damage was *remote* or an analysis showed infinite fatigue life, a Method 2 analysis could be used to establish an extended routine inspection interval.

1.2.2. Method 2 Analysis

Method 2 is a more rigorous process for risk assessment that allows routine inspection intervals of up to 72 months based on a risk assessment process developed by a RAP. The method requires a set of screening criteria be used to determine how bridges will be considered in the assessment and to establish maximum inspection intervals. Five different requirements for screening criteria are listed as shown in Table 1.2. The first three required screening criteria are to be developed by the RAP and must include flexural and shear cracking in concrete members, fatigue cracking and corrosion in steel members, and criteria for considering details, loadings, conditions, etc. that are likely to affect safety and serviceability of bridges. The final two required screening criteria are specified and indicate the maximum allowable inspection intervals based on general condition ratings (CRs). These requirements indicate that the maximum interval for bridges classified as being in "Fair" condition, i.e., bridges with a lowest component rating of CR 5 or CR 6, is 48-months (FHWA 2022). The maximum interval for bridges classified as being in "Poor" condition, i.e., CR less than or equal to 4, is 24 months.

The required screening criteria indicate that only bridges classified as in "Good" condition, i.e., with CRs of 7 or greater, are eligible for a 72-month interval. Bridges in "Fair" condition have a maximum interval of 48 months, indicating that bridges with CR 5 or 6 could be eligible for a 48-month interval even if the bridges do not meet the Method 1 criteria. For example, a bridge that does not meet one or more of the criteria for an extended intervals under Method 1 may be eligible for an extended interval if Method 2 analysis is completed.

Table 1.2. Required screening criteria for Method 2 analysis.

No.	Requirement
1	Requirements for flexure and shear cracking in concrete primary load members
2	Requirements for fatigue cracking and corrosion in steel primary load members
3	Requirements for other details, loadings, conditions, and inspection finding that are likely to affect the safety or serviceability of the bridge or its members
4	Bridges classified as in poor condition cannot have an inspection interval greater than 24 months;
5	Bridges classified as in fair condition cannot have an inspection interval greater than 48 months

Requirements for attributes and deterioration modes that should be included in a risk model are summarized in Table 1.3. The table rows are numbered 1-5 for reference. Row 1 of the table provides a list of the attribute types that must be included in each analysis, including material properties, loads, safe load capacity, and condition. Several deterioration modes based on the material that forms the bridge are required as shown in rows 2 and 3. The deterioration modes for steel members must include section loss, fatigue, and fracture. For concrete members, the models should include damage modes of flexural cracking, shear cracking, and corrosion of reinforcing steel. There are also component-level requirements described for the bridge superstructure and substructure (rows 4 and 5). Superstructure member deterioration modes must include settlement, impact damage, rotation, and overload. Substructure component deterioration modes must include settlement, rotation, and scour.

Most of the deterioration modes and attributes included in the FHWA guidance documents are addressed by the risk models developed in this project. The FHWA guidance provided a general framework for the analysis of these risk models. Importantly, the guidance provided some target ranges for the analysis that were used to update the risk matrix that defines the inspection intervals for bridges as discussed in the following section.

1.3. Target Ranges for Risk Models

The general framework provided by the FHWA guidance and the updated NBIS requirements provide some expected outcomes from a risk assessment for determining extended inspection intervals. This framework can be used to make judgements on the risk matrix used to determine the inspection intervals for bridges based on the OF and CF determined from a Method 2 risk-based analysis. This section of the report discusses proposed changes to the risk matrix based on a combination of the revisions to the NBIS, the associated guidance provided by FHWA, and results from the back-casting.

Table 1.3. Attributes required for Method 2 analysis.

Row No.	Category	Attributes
1	Attributes for each assessment must include:	Material Properties, Loads, Safe Load Capacity, and Condition
2	Steel members damage modes must include:	Section loss, Fatigue, and Fracture
3	Concrete members damage modes must include:	Flexural Cracking, Shear Cracking, and Steel Corrosion
4	Superstructure members damage modes must include:	Settlement, Vehicle/vessel impact, Rotation, and Overload
5	Substructure members damage modes must include:	Settlement, Rotation, and Scour

The project that produced NCHRP Report 782 was the initial effort to develop a reliability-based bridge inspection practice that could be implemented for highway bridges in the US. The project developed a framework for risk-based inspections that was subsequently adopted in the new NBIS. However, the study did not include broad implementation of the framework developed through the research. Further, the 2022 revisions to the NBIS and associated guidance from the FHWA were not available at the time of the study. Therefore, the framework developed in NCHRP 782 needed to be assessed in terms of the new NBIS requirements to enable the implementation of the new policies into practice.

The NCHRP study proposed a risk matrix for typical bridges as shown in Figure 1.2. The 4 x 4 matrix shows the OF on the ordinate (i.e., vertical axis) and the CF on the abscissa (i.e., horizonal axis). The original risk matrix included inspection intervals ranging from 12 to 96 months based on the OF and CF for a given component and damage mode, as shown in the individual elements of the matrix. The specific elements in the matrix are identified based on their location defined using the nomenclature [$R_{row,column}$], referenced from the bottom left corner of the matrix. For a component damage mode rated as OF 4 (*high*) and a CR of 4 (*severe*) the element [$R_{4,4}$] indicates a 12-month inspection interval. For a component damage mode rated as having an OF 1 (*remote*) and a CF of 1 (*low*), the inspection interval would be 96 months based on the original risk matrix.

The new NBIS requirements can be used to analyze the original risk matrix proposed in NCHRP 782 by comparing the ordinate and abscissa values in the original matrix to the new rules. This analysis provides some general guidance on the appropriate inspection intervals for the different elements of the risk matrix.

Considering the ordinate, the Method 1 guidance and NBIS requirements designate 48 months as a suitable inspection interval for components in CR 6, provided the component is not an NSTM and is located within a structure meeting the other Method 1 criteria. Potential consequences are not considered explicitly. This provides general guidance on how the elements on the ordinate should be defined because CR 6 components can have a 48-month interval regardless of the CF. Since Method 1 considers that any CR 6 component is potentially suitable for a 48-month inspection interval, it will follow that a Method 2 analysis should also identify <u>most</u> CR 6 components suitable for <u>at least</u> a 48-month interval. It should be noted that the weighted sum model used to score the risk models produces results ranging from *remote* to *high*, so not all bridge components of any particular CR will lie in a particular element in the matrix.

Rather, the risk model for a particular component will produce OF scores over a range of values based on the attributes and criteria identified by the RAP and the component being assessed.

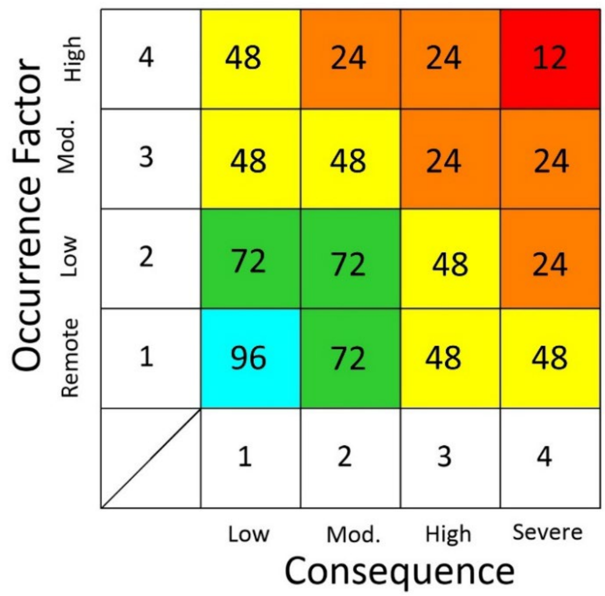


Figure 1.2. Risk matrix proposed in NCHRP Report 782 showing inspection intervals.

Based on engineering judgement, most CR ≥ 7 components are expected to have a lower OF compared to most CR 6 components, and most CR 6 components should have a lower OF than most CR 5 components. Based on the risk matrix with four categories for the OF, most CR ≥ 7 components are expected to score in the range of *remote* to *low*, most CR 6 components would rank in the *low* to *moderate* range, and most components in CR 5 would lie in the *moderate* to *high* range. Figure 1.3 illustrates a risk matrix showing these ranges on the ordinate. These ranges provide a reasonable and rational ordering of the expected OF values for components based on the CR. The ranking for individual components is refined by the risk models developed by the RAP. For example, certain CR 6 components may score lower than certain CR 7 components when the risk factors (i.e., attributes) in the risk models are assessed.

The horizontal axis can also be analyzed based on the new NBIS rules to infer values in the risk matrix. It is assumed in this analysis that the CF is generally defined in terms of the load capacity of the bridge as expressed by a load rating factor (LRF), the degree of redundancy, feature under the bridge, and traffic volumes (e.g., ADT).

NSTMs require a hands-on inspection at a standard interval of 24 months, which can be extended to 48 months if the criteria for Method 1 for NSTMs are met or if an RAP is used to develop a suitable risk model for NSTM inspection. The Method 1 criteria for NSTMs are similar to those for routine inspection but include additional criteria that consider the age of the structure and its fatigue resistance. Historically, the rationale for considering NSTMs differently than redundant steel tension members is an assumed potential for catastrophic collapse resulting from member failure. This is a *severe* consequence, column 4 in the risk matrix as shown in Figure 1.3. Certain other bridges such as some non-redundant concrete members, structures with only three primary members and wide beam spacing, or other situations where the consequence of severe damage presents substantial risk of life may also have a CF characterized as *severe*. Most bridges that do not have NSTMs will generally be described as having *low*, *moderate*, or *high* consequences, based characteristics such as the ADT, feature under the bridge, LRF, etc. The Method 1 policy for routine inspections allows components in CR 6 to have an inspection interval of 48 months regardless of the CF being *low*, *moderate*, or *high*. All elements in the risk matrix shown in Figure 1.2 except column 4 can considered 48-month for CR 6 components under the Method 1 approach.

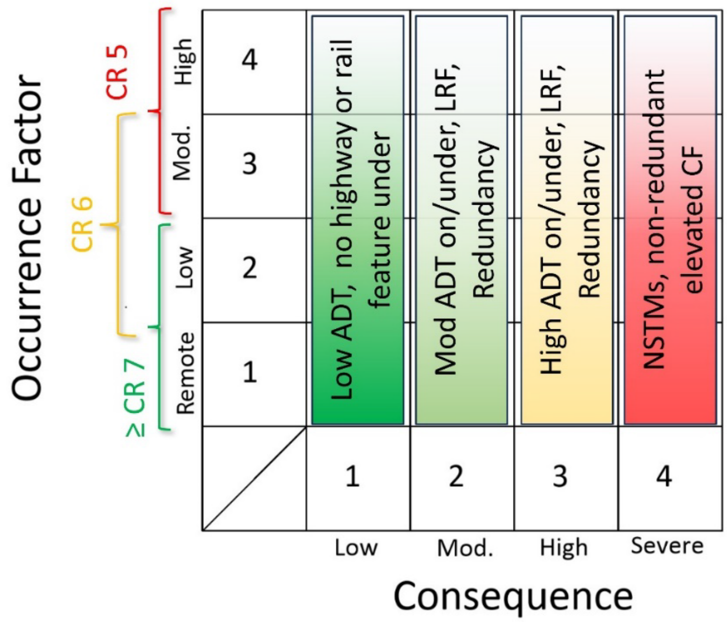


Figure 1.3. Figure showing risk matrix with target ranges for the OF and CF general descriptions.

Most common bridges will have a *moderate* or *high* CF. A bridge with a low CF is assumed to be a bridge with uncommonly low ADT and no highway or rail feature under, as shown in Figure 1.3. It is notable that the Method 1 criteria make no mention of ADT levels on or below a bridge, although it is among the factors bridge owners might consider in their extended interval policy. It is reasonable to expect that high ADT <u>alone</u> does not preclude a bridge from a 72-month interval, since ADT is not required in the Method 1 criteria for extended inspection intervals. Further, most CFs are expected to identify very high ADT as an attribute for components with a *high* CF. Based on these assumptions and understanding of the NBIS requirements, row 1 of the risk matrix shown in Figure 1.2 should be 72 months for any CF that is not *severe*, such that a CR ≥ 7 bridge with *remote* likelihood of failure qualifies for a 72-month interval for CFs of *low*, *moderate*, or *high*.

The distribution of values for components in different CRs shown in Figure 1.3 was substantiated when risk models developed by individual RAPs in this project were applied to real bridges. As will be shown in greater detail later in the report, the target values described that consider CR ≥ 7 components typically having OF in the *remote* or *low* range, and CR 6 components typically having an OF *low* or *moderate*, etc., were close to those produced from the risk models developed by the individual RAPs and applied to the sample bridges. For example, Figure 1.4 shows a cumulative probability distribution for the OF stemming from the deck component of the 60 sample bridges studied in the back-casting. The abscissa shows the OF category ranging from *remote* to *high* at the bottom of the plot and the numerical values for the risk score at the top of the plot. The ordinate shows the probability for a randomly selected bridge deck with a certain risk score based on the attributes and criteria defined by the RAPs in the study. The curve was produced from the original, unweighted risk model developed by the individual RAPs and the risk scores obtained through the back-casting analysis that applied the risk models to components of the 60 sample bridges. The 60 bridge decks from six states were combined and treated as a single sample population to provide the mean and standard deviation needed to form the cumulative probability distribution plot shown in the figure. The figure shows that for decks with CR ≥ 7, 54% of decks scored in the *remote* range, while 46% have scores ranging from the *low* to *moderate* range. Those decks scoring in the *remote* range are decks with CR ≥ 7 that scored 1.0 or less according to a risk model that included attributes such as the CR, CS, rate of chloride application, ADT, corrosion protection level, etc. In other words, these are decks in good condition with good durability characteristics and consequently remote POF (i.e., the likelihood of deteriorating to a CR 3 in the next 72-month interval is *remote*). Decks with CR 6 have increased risk, with only ≈8% of decks expected to score in the *remote* range, ≈61% scoring in the *low* range, and the remaining ≈31% scoring in the *moderate* or *high* range. Decks in CR 5 are scored with ≈32% in the *low* range, ≈44% scoring in the *moderate* range, and ≈18% scoring in the *high* range. The specific percentage values will obviously vary for different components and different risks models, but these results illustrate the general behavior and trends of the risk models developed by the RAPs and applied to actual bridges. Specifically, the plot shows that the attributes and criteria developed through a Method 2 process identified decks in CR ≥ 7 as having relatively lower risk than decks with CR of 6 or 5. Within the group of CR ≥ 7 decks, components were rated as having *remote*, *low*, or *moderate* likelihood, which identifies those low-risk components that may be suitable for a 72-month inspection interval and those components with elevated risk.

Methods to calibrate the individual risk models to improve the quality of the results were developed through the research based on sensitivity studies of the back-casting results. A systematic approach for analyzing and calibrating the risk models using Monte Carlo (MC) simulations was developed and is presented in the report. The initial, raw values shown in Figure 1.4 taken directly from the RAP models developed through the study and applied to real bridges, combined with the FHWA guidance on extended intervals, form the initial expectations for risk categories and risk scores as a function of the CR of a component and provide target ranges for analysis of individual risk models.

1.3.1. Proposed Changes to the Risk Matrix

Changes to the original risk matrix from NCHRP 782 report may be justified considering the analysis of the new NBIS requirements and associated target ranges for components with different CRs. Additionally, a much more robust calibration and validation of risk models has been completed through this project. Figure 1.5A shows the original risk matrix from NCHRP 782 and Figure 1.5B shows the risk matrix being proposed herein, with changes encircled on each risk matrix. As noted above, most CR ≥ 7 components tend to score in the *remote* to *low* range for OF. Since the policy allows a 72-month interval only for bridges with components with CR 7 or greater, it seems rational that the matrix elements [$R_{1,1}$], [$R_{1,2}$], and [$R_{1,3}$] should be 72 months. This allows that CR ≥ 7 components with remote likelihood of failure to have a 72-month interval for any CF other than severe. The matrix element [$R_{2,3}$] is assigned 48-months and provides granularity in the analysis that aligns with the Method 1 approach that a CR 6 bridge with a high CF can have a 48-month interval. In this way bridges with CF of *high* are only eligible for 72-month if the OF is *remote*, and the inspection interval is reduced to a 48-month interval when the likelihood is increased from *remote* to *low* (i.e., OF = *low*).

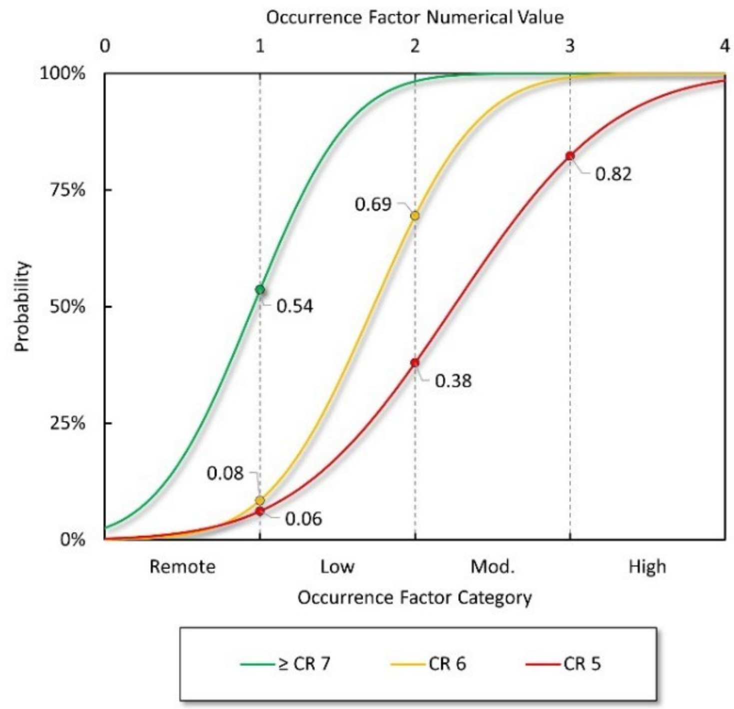


Figure 1.4. Example cumulative probability distribution function for sample bridge decks.

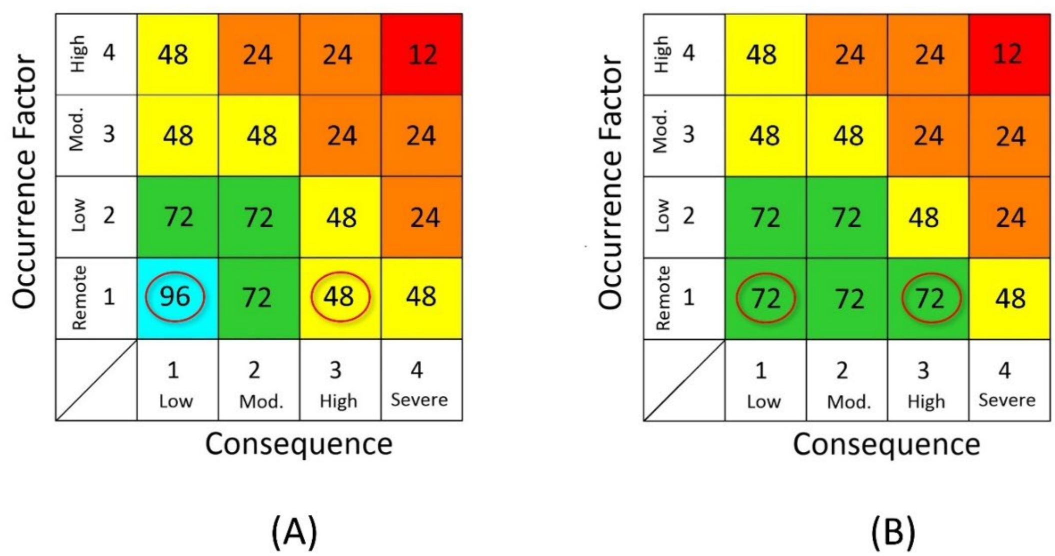


Figure 1.5. Original risk matrix in NCHRP 782 (A) and the proposed risk matrix (B) showing inspection intervals (months).

The risk matrix provides a very rational hierarchy shown in Table 1.4 for components with CF of *high,* meaning a bridge has elevated risk based on the CF attributes. A 72-month interval is only possible for CR ≥ 7 components with *remote* OF for components with a *high* CF. If the OF for a CR ≥ 7 component is *low* then the interval is 48 months. Components in CR 6 are expected to have OFs of *low*, resulting in the 48-month interval which aligns with the Method 1 approach. If the CR 6 component has a OF score of *moderate* then the assigned interval will be 24-months, which is more conservative than the Method 1 approach that does not consider the consequence explicitly. If a CR 6 component OF is *remote*, it seems to qualify for a 72-month interval, although NBIS requirement does not allow a 72-month interval. Regardless, the results from back-casting and MC simulations presented later will demonstrate that there is a relatively low probability of CR 6 components with a risk score of 1.0 or less. For CR 5 components, the interval of 48 months will only apply if the OF is *low* or *remote*, which is expected to be a relatively small proportion of CR 5 components. Most CR 5 components will score in the *moderate* range or *high* range with an assigned interval of 24-months when the CF is *high*.

This analysis of the new NBIS requirements and their intersection with practical application of risk models provides sound rationale for modifying the risk matrix originally proposed in NCHRP 782. The original matrix from the NCHRP report is shown in Figure 1.5A and the proposed matrix to be used considering the new NBIS requirements is shown in Figure 1.5B. The following changes to the original risk matrix are proposed:

- The matrix location [$R_{1,1}$] should be 72 months, since 96-month intervals are not allowable under the NBIS. (It should be noted that should the NBIS be modified in the future, this value could be replaced with 96 months with no negative impacts with respect to the calibration performed herein.)
- The position $R_{1,3}$ was originally indicated as a 48-month interval but is proposed as a 72-month interval to provide appropriate granularity to sort bridges into different "bins" in terms of risk. Assigning a 72-month interval allows that when the likelihood of serious damage is *remote* and the CF is *high*, a 72-month interval is allowable.

Table 1.4. Risk-based inspection intervals for components with CF of *high*.

Condition Rating	OF	Interval (Months)
CR ≥ 7	Remote	72
CR ≥ 7	Low	48
CR 6	Low	48
CR 6	Mod	24
CR 5	Low	48
CR 5	Mod	24
CR 5	High	24

This analysis and proposed risk matrix were used to provide "target ranges" for the analysis of the RAP-developed risk models. Although fixed values were not used explicitly, the target ranges for components were as follows:

- Most components rated in CR ≥ 7 have risk scores in the *remote* range for the OF.
- Most components rated in CR 6 have risk scores in the *low* or *moderate* range for the OF, indicating increased risk as compared with components rated in CR ≥ 7 and less risk than components rated in CR 5.
- Components rated in CR 5 present increased risk as compared with components rated in CR 6 with many having risk scores in *moderate* to *high* category for the OF.

Here we consider "most" as being more than ≈60% of components rated in CR 7 will have a remote likelihood of deteriorating to a CR 3 in the next 72 months. These quantitative proportions are subjective, but conservative, and align with the FHWA policy for Method 1. These target ranges provide approximate, rather than defined, limits to provide a means of weighting risk models.

Another assumption of the research is that bridge components rated in CR 4 or less are screened from the analysis. Components in "poor" condition (i.e., CR ≤ 4) have a maximum interval of 24 months according to the NBIS. Risk analysis can be used to identify bridges in this condition which require inspection intervals of less than 24 months. However, the criteria for attributes in the risk models are generally aimed at prioritizing bridges in fair to good condition. Different criteria and perhaps different attributes are needed to prioritize bridges in CR 4 or lower in terms of risk. For example, most deck models rate a CS attribute as *high* for a deck with more than 5% CS 3 damage. To apply the attribute to bridge components in poor condition the criteria will need to be adjusted. Many CR 4 components may have more that 5% CS 3 damage and rating them all as *high* may not produce any prioritization of the components. The criteria ranges will need to be increased to, for example, CS 3 greater than 15% is *high* relative to other CR 4 components. A separate risk analysis with suitable criteria for components in poor condition is necessary to estimate a rational reduced inspection interval.

Chapter 2.
Back-Casting Results

This section of the report presents results from the back-casting using a population of 60 sample bridges. Back-casting was envisioned as a process of reviewing historical bridge records such as inspection results to determine if the risk assessment produced suitable inspection intervals that captured the deterioration of bridge components. Through the course of the research, it was recognized that the analysis of risk model results for individual bridge components was necessary to analyze the effectiveness of the models and improve results. The following sections summarize the back-casting and the results that were obtained. Much of the data analysis is focused on the assessment of individual components and the damage modes that control the inspection interval for a bridge.

2.1. Example Risk Model

The back-casting was completed using the risk models developed by the individual RAPs in participating states. The models were developed based on input from the RAPs obtained through expert elicitation to determine the most likely damage modes for bridges of a particular family, e.g., bridges with steel superstructures. The expert elicitation consisted of presenting the RAP members with a scenario for a given component and surveying RAP members anonymously to identify the likely damage modes that could have caused that component to be rated in CR 3, Serious Condition. Results of the anonymous survey were presented on a white board and the primary damage modes identified through consensus of the panel. This process of surveying experts anonymously followed by consensus forming is referred to as a Delphi process, a common method for expert elicitation.

The RAP was then surveyed to elicit attributes that affect the likelihood of a specific damage mode developing and resulting in a serious condition. The attributes were ranked according to their impact on the likelihood of a certain damage mode occurring and causing serious damage. For example, for the damage mode of delamination and spalling in a bridge deck, attributes that contribute to the underlying deterioration mechanism of corrosion usually include the level of corrosion protection and the rate of deicing chemical application, and these attributes are assessed to have a *high* impact on the likelihood of serious damage developing. An attribute that has a smaller impact on the likelihood such as the flexibility of the superstructure, which may cause an increased rate of deterioration but has a smaller impact as compared with corrosion protection level or the rate of deicing chemical application, is ranked as *moderate*. This process prioritizes the attributes that contribute to deterioration or damage for a particular damage mode using a qualitative rank of *high, moderate*, or *low*. The ranking of the attribute is used to determine the initial weight of the attribute on a 20-point scale (*high* = 20 points, *moderate* = 15 points, *low* = 10 points). For each attribute, criteria are developed by the RAP to determine how to rate the attribute, again using a qualitative scale of *very high*, *high*, *moderate*, or *low*. For example, the attribute of ADT might have criteria that *high* is greater than 30,000 vehicle per day, *moderate* is 10,000 to 29,999, and *low* is less than 10,000. The combination of attributes, attribute ranks, and criteria form a *risk model* for assessing the relative likelihood of a given damage mode causing the component to deteriorate to a serious condition in the next 72-month period.

Table 2.1 shows an example risk model for a reinforced concrete (R/C) bridge deck. The table includes a code used to describe the attribute, such as C.1, C.2, etc. which identifies the type of attribute (C = condition attribute, L = loading attribute, or D = design attribute), the name of the attribute, and the rank for that attribute identified by the RAP. A complete listing of attributes and codes is included in Appendix A for reference. The criteria for rating an attribute as *very high*, *high*, *moderate*, or *low* are also shown in

Table 2.1. As shown in the table, most attribute criteria include three levels of *high*, *moderate*, or *low.* The only attribute with four levels of criteria is Attribute D.29, Corrosion Protection Level. This attribute was developed in the research to summarize different attributes, such as the concrete cover, reinforcing steel coating, overlays, sealers, etc. that provide corrosion protection, into a single attribute. The criterion for CP 1 is that the element has one layer protection, for example, epoxy-coated rebar (ECR) with low cover. Normal concrete cover and ECR is defined as CP 2, and ECR, normal cover and an overlay is described as CP 3. If the element was constructed with ECR, normal cover, an overlay, and that overlay was sealed on a regular basis, the corrosion protection level will be CP 4.

Risk models were developed for different damage modes for the bridge families as defined by the superstructure material, either steel or PSC concrete. The risk models developed by the RAPs were applied to 10 sample bridges from each state. Methods of calibrating the scoring of the risk models were also developed during the research.

Table 2.1. Example risk model for a R/C deck showing the attribute, attribute rank, and criteria for scoring the attribute.

Code	Attribute	Rank	Criteria	Rating
C.1	Current Condition Rating	High	CR 5 CR 6 CR ≥ 7	High Moderate Low
C.2	Element Condition State	High	CS 3 ≥ 5% or CS 2 ≥ 20% 1%≤ CS3 < 5% or 10% ≤ CS2 < 20% CS 3 < 1% or CS 2 < 10%	High Moderate Low
C.4	Joint Condition	Moderate	DE 2360 ≥ 20% CS 3 DE 2360 1% ≤ CS 3/CS 4 < 20% DE 2360 CS 1 or CS 2, no CS 3	High Moderate Low
C.13	Efflorescence/Staining	Low	DE 1120: CS 3 ≥ 20% or CS 2 ≥ 20% DE 1120: 1% ≤ CS 3 < 20% or 5% ≤ CS 2 < 20%, DE 1120: CS 3 < 1% or CS 2 < 5%	High Moderate Low
L.1A	Average Daily Truck Traffic (ADTT)	Moderate	ADTT ≥ 5000 or ADT ≥ 16,000 1000 ≤ ADTT < 5000 or 7500 ≤ ADT < 16000 ADTT < 1000 or ADT < 7500	High Moderate Low
L.5	Rate of De-icing Chemical application	Low	Interstate / NHS or ADT ≥ 16,000 ADT between 7500 & 16,000 Local, Low ADT ≤ 7500	High Moderate Low
D.29/ C.30	Corrosion Protection Level	Moderate	CP 1 CP 2 CP 3 CP 4	Very High High Moderate Low

2.2. Back-Casting Bridge Population

The bridges used for back-casting were selected randomly from each state's bridge population according to the material of focus for that state. The RAPs considered PSC and steel superstructures, with four states focused on steel bridges and two analyzing PSC bridges as shown in Table 2.2. Ten bridges were selected from each state. The bridges were generally selected at random with two provisions. First, the bridges selected for a particular state were from a certain family of bridges, meaning the bridges had superstructures of a certain material type, either PSC or steel. The bridge family selected for each state matched the risk models developed by the RAPs for that state. Second, bridges were selected to provide geographic distribution across a state. For example, Figure 2.1 shows the geographic distribution of the PSC bridges assessed in the state of Washington.

Table 2.2. Table showing the family of bridges studied in each state.

State	Bridge Family	State	Bridge Family
Connecticut	Steel	Missouri	Steel
Idaho	PSC	Washington	PSC
Illinois	Steel	Wisconsin	Steel

The rationale for randomly selected bridges was to implement the risk models across a cross-section of the bridge population as compared to, for example, only selecting bridges in good condition. It was hoped that such a distribution of bridges could provide insight into the effectiveness of the models for representing the bridge inventory overall and gain insight into how to weight the individual attributes. Additionally, many of the attributes that were identified by the RAPs were likely to be rated as *low* for bridges in good condition, so there would be little opportunity to analyze if these attributes were effective in analyzing the likelihood of deterioration developing to a serious condition in the next 72 months. Finally, the randomly selected bridges can be used to assess if the risk models were durable across a typical bridge inventory in terms of being applicable to all bridges, regardless of the CR for the bridge. Since the risk models assess the relative risk, not the absolute or quantitative risk, bridges of different conditions, ages, and loading were needed to analyze the effectiveness of the models and develop a methodology for weighting the attributes.

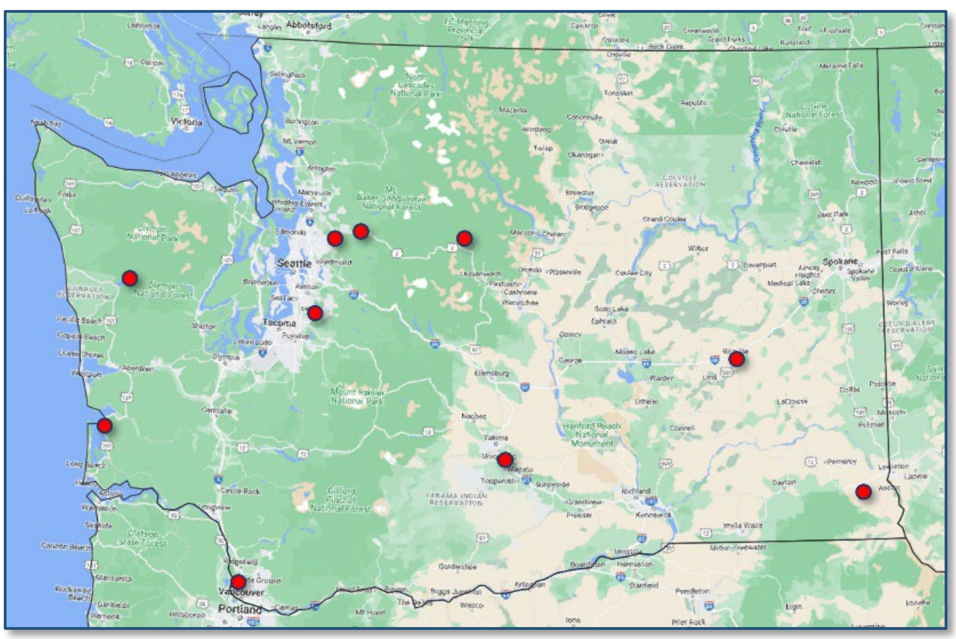


Figure 2.1. Geographic distribution of sample bridges in Washington.

Under the provision of the updated NBIS only bridges in "good" condition are eligible for intervals of 72 months. However, at the time the study was initiated, the NBIS had not yet been finalized, and this limitation was not known. The randomly selected bridges provided a “sample” population of bridges to assess the RAP models and their effectiveness in providing a suitable risk profile of bridges that could be used for inspection planning.

The bridge material types included 40 steel bridges and 20 PSC bridges. One of the steel bridges had PSC approach spans and both the steel and PSC members were analyzed. The distribution of different material types is shown in Figure 2.2.

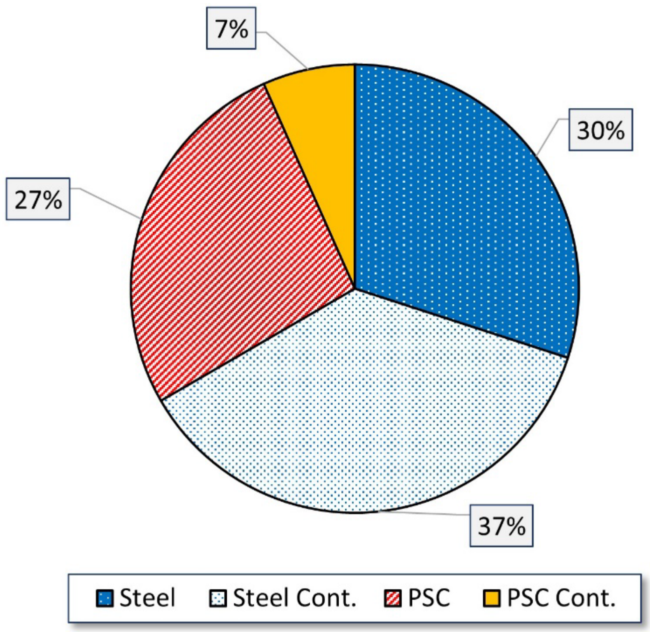


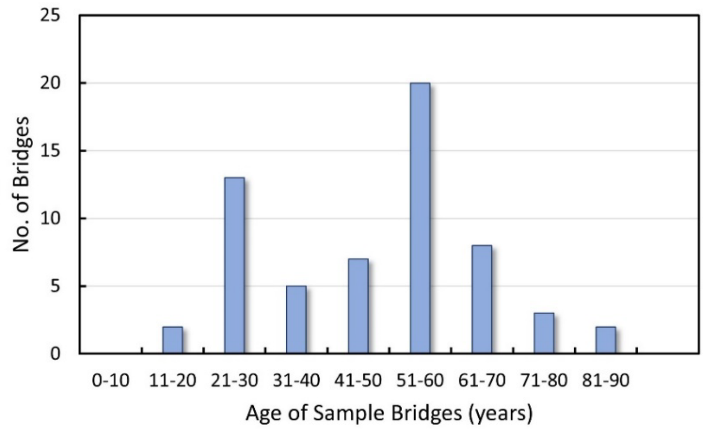
Figure 2.2. Distribution of sample bridge superstructure materials.

Figure 2.3 shows the distribution of the ages of the sample bridges in Figure 2.3A and the ADT characteristics in Figure 2.3B. The average age of the sample bridges in 2020 was 48 years (σ = 17 years), with a minimum of 14 years and a maximum of 88 years.

There was a broad distribution of average daily traffic (ADT) and age of the randomly selected sample bridges. The average ADT was 11,537 vehicles per day (σ = 21,945) with a minimum of 12 vehicles/day and a maximum of 136,800 vehicles per day.

The condition ratings (CR) of the sample bridge components of deck, superstructure, and substructure varied from a low of CR 2 to a maximum of CR 9. The average CR for the sample bridge population was CR 6 (σ = 1). Figure 2.4 shows the frequency plot of the CRs for the sample bridge population for the deck, superstructure, and substructure bridge components based on 2020 National Bridge Inventory (NBI) data. It should be noted that most of the sample bridges had CR that changed over the course of the back-casting period, including bridges that had renovations and repairs.

There were 13 bridges that had a CR in 2020 of at least CR 7 for all three components. Eight of the bridges included in the random selection had a scour CR of 5 or less, indicating these bridges may not qualify for an extended inspection interval. However, the scour ratings were not considered in the analysis because the RAP models do not address scour. The sample population also included five bridges that had a component rated in CR 4 or lower at some time during the back-casting period.

(A)


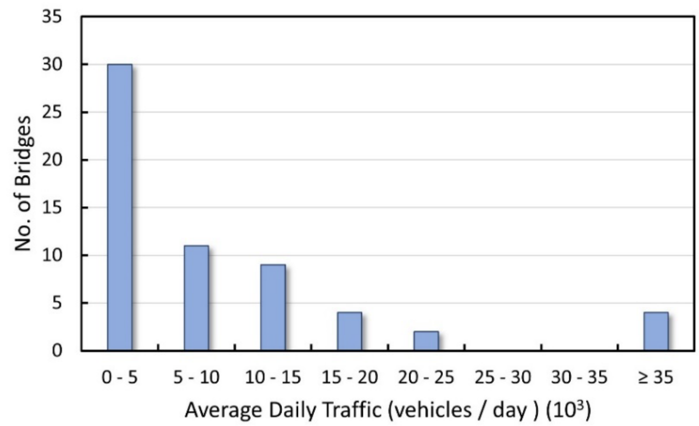
(B)


Figure 2.3. Plots showing age of sample bridges (A) and ADT (B).

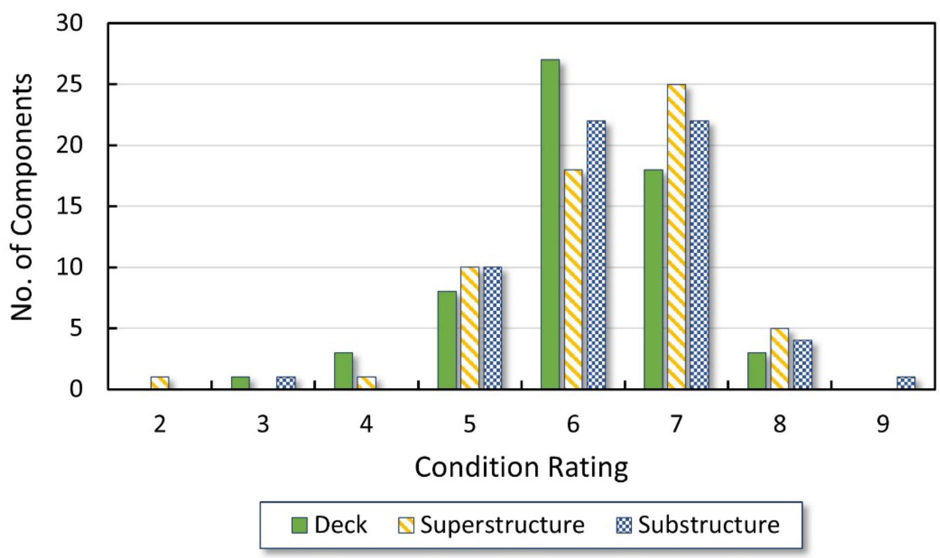


Figure 2.4. Condition ratings for the deck, superstructure, and substructure components of the sample bridges.

2.2.1. Basic Back-Casting Procedures

The initial risk models developed by the RAP were used to perform back-casting on ten bridges from each state. Inspection reports for the sample bridges were collected over time intervals ranging as far back as 1996. Inspection report records were reviewed with an emphasis on utilizing inspection notes to determine or infer how the criteria of an individual attribute should be rated for a particular bridge. Consideration was given to attributes that were time dependent such as condition attributes, and those that were typically fixed over the analysis interval such as design attributes. For example, Table 2.3 shows the time-dependent attributes for the superstructure and deck components for a steel bridge analyzed through back-casting. Attribute criteria from the risk model were assessed for each inspection year over the time interval of 2004 – 2021. The attributes shown in the table changed during that back-casting time interval. For example, the CR decreased, and the coating condition was deteriorating over time, according to damage reported in the inspection reports. The deck condition dropped from 7 to 4 during the inspection interval.

Table 2.3. Example listing of time-dependent attributes for a steel bridge.

Attribute Number	Attribute	Characteristic	Characteristic over back-casting period
Deck spalling/delamination damage mode			
C.1	Current condition rating	CR = 5	CR 7, 6, 4, 5, 4
C.2	Current condition state	CS 3 about 2%	Minor to moderate damage
C.13	Efflorescence/staining	Soffit has CS 3 < 1%	CS 1, 2, and 3
L.1	ADT/ADTT	ADT > 20,000	20,190 < ADT < 21,650
L.5	Rate of de-icing chemical application	ADT > 20,000	20,190 < ADT < 21,650
D.4/C.7	Poor Deck Drainage and Ponding	Moderate drainage issue	CS 1, 2, and 3
D.29/C.30	Corrosion protection level	CP 3	Asphalt overlay, sealed in 2017
Steel section loss damage mode			
C.1	Current condition rating	CR = 5	CR 7 to 6 to 5
C.2	Current condition state	CS2 ≥ 20%, CS3 < 10%	Moderate corrosion
C.17	Constructed of Weathering steel / Coating Condition	Paint has CS 3 and 4	CS 3 present all but 2 years
C.4	Joint condition	14% CS 3	CS 1, 2, and 3
D.4 / C.7	Poor Deck Drainage and Ponding	1 drain with CS 2	CS 1, 2, and 3
L.5	Rate of de-icing chemical application	ADT > 20,000	20,190 – 21,650

Design attributes, which typically do not change over the course of time, were also recorded for each year. In some cases, certain design characteristics changed over the course of the assessment interval. For example, a bare R/C deck may have an overlay installed during its service life such that the corrosion protection level increases.

A spreadsheet program was used to document the results of inspection report reviews in a systematic manner and allow for the risk models and attributes to be analyzed for a particular group of sample bridges. The spreadsheet program stored data on the attributes and criteria for each risk model and sample bridge. The program calculated the OF value from the risk model based on the attributes for each component. In this way, the analysis from the inspection report could be stored and used for sensitivity studies on the effect of weighting attributes to improve the quality of the risk models. The resulting inspection interval was determined by considering the CF category of *moderate* or *high*.

The back-casting results presented in Figure 2.5 show the CRs for the components of the deck, superstructure, and substructure from NBI data in Figure 2.5A. The inspection interval based on a CF of *moderate* is superimposed on the figure to illustrate how the inspection interval changed over the course of time. Figure 2.5B shows the results from applying the risk models for the superstructure, substructure, and deck damage modes in each inspection year to determine the OF value. The OF value is shown on the ordinate. For this bridge, the steel superstructure had coating damage, high ADT, leaking joints, deck drainage issues, and the superstructure was subjected to overspray from a roadway below. As a result, the OF values were relatively high even when the bridge was assessed as CR 7 for the steel superstructure damage mode of corrosion damage / section loss.

The deck of the bridge deteriorated over the course of the research, resulting in increased OF values as shown in the figure. The OF also increased for the damage mode of impact because the reported vertical clearance changed from 15.25 ft to 14.78 ft. The criterion for the attribute of vertical clearance was rated *high* when the vertical clearance was less than 15 ft, and *moderate* when the vertical clearance was 15 to 17 ft., and as a result, the small change in vertical clearance changed the OF value.

2.2.1.1. Challenges With Back-Casting

The back-casting proved to be very challenging for several reasons. The two primary issues experienced were that the notes and features of older bridge reports did not provide data consistently over time. For example, damage reported in one bridge inspection may not be present in the next inspection report such that it was difficult to track the progression of damage. This was particularly problematic for bridges that did not have element-level reports. In some cases, inspection policies were evolving over the course of the back-casting time interval, resulting in inconsistent inspection data. For example, element-level inspection data became available or reported elements changed because a state policy changed regarding data requirements for inspection reporting. In addition, some attribute qualities identified by the RAPs were not present in the bridge inspection records, and therefore, required some assumptions or inferences to rate the attributes. The inspection reports sometimes included very little information regarding why a CR changed from one inspection to another. Older bridges with element-level data frequently included inspection notes that did not align with the CS state. For example, a bridge deck may have been described as having widespread cracking or spalling, but 100% of the deck was recorded as in CS 1. Additionally, because the review of the inspection reports often involved assumptions and inferences regarding the appropriate ratings for attribute criteria, the reviews were not repeatable between different reviewers.

2.2.2. Weighted Sum Model

The OF is calculated as a weighted sum model where the initial weights for the model were developed through expert elicitation process with the RAP (Washer, Connor et al. 2014). The initial value weights for a given attribute were set by simply ranking a given attribute as *high*, *moderate*, or *low* in terms of its impact on the POF. Attributes ranked as *high* are expected to have a significant impact or influence of the likelihood and an attribute ranked as *low* are expected have a minor impact. The rankings are subjective but provide a starting point for the weighted sum model, which can be adjusted as necessary to better reflect the actual performance of a family of bridges of similar materials and design and meet target ranges. A method for weighting the attributes was developed through the research and will be described later in the report.

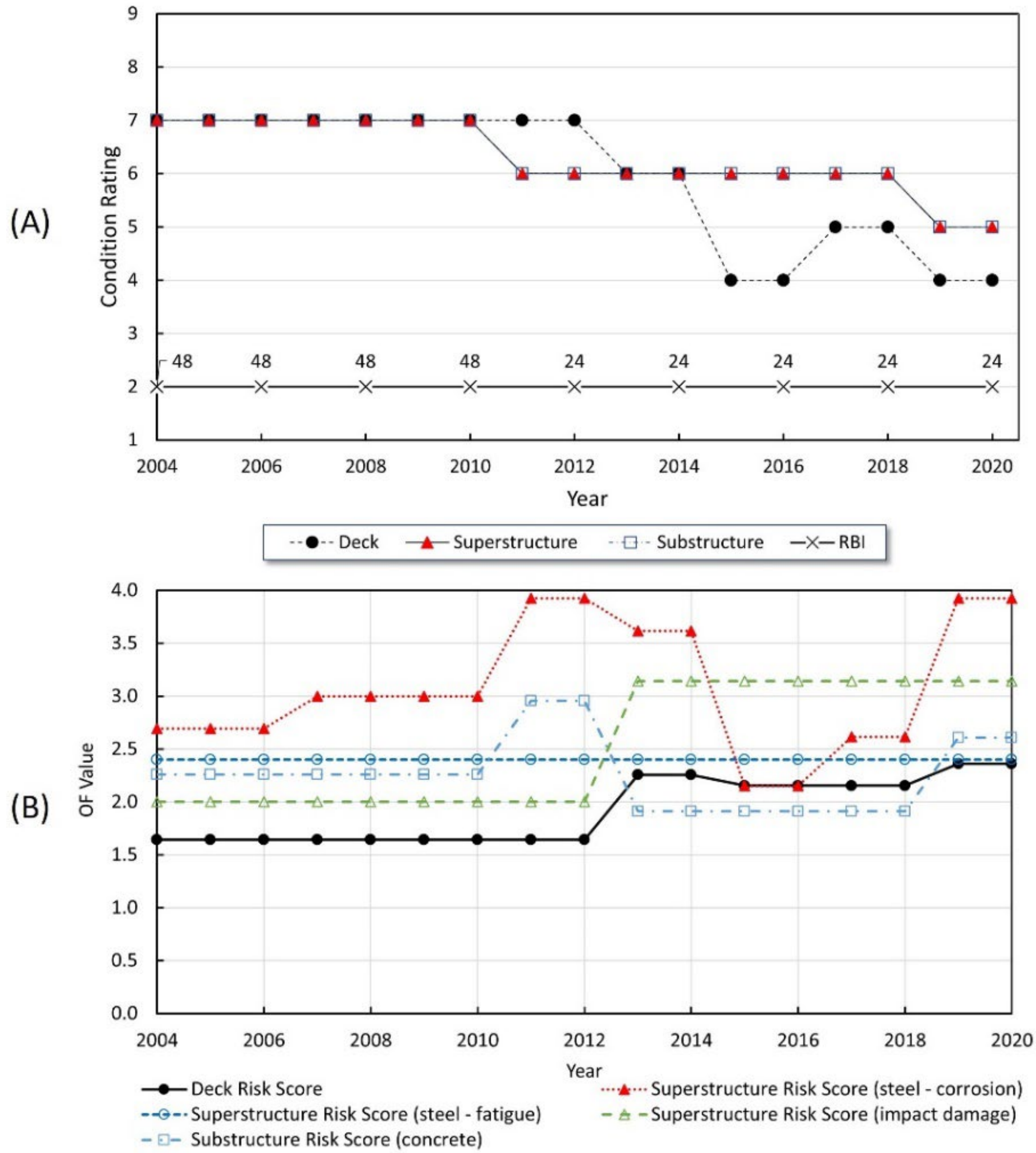


Figure 2.5. Back-casting results for a sample bridge showing the NBI CR and inspection interval (A) and the OF values for each year (B).

Most attributes identified by the RAPs were ranked as *high* indicating a significant impact on the POF. Very few attributes were ranked as *low* by the RAPs. The attributes identified by the RAPs are those that the individual members of the RAP considered most important, so it is normal that many of the attributes were ranked as *moderate* or *high*. Attributes ranked *high* are assigned a maximum value of 20 points, attributes ranked *moderate* are assigned a maximum value of 15 points, and attributes ranked *low* are assigned a maximum value of 10 points.

The criteria for each attribute are used to determine the actual score for an attribute when applied to a bridge component. Three criteria are typically developed to determine if the attribute should be rated *high*, *moderate*, and *low*. If an attribute is rated as *high* based on its criteria, then the attribute is assigned 100% of its weight. If the attribute is rated as *moderate* based on its criteria, then the attribute is assigned 50% of its weight, and if the attribute is rated as *low,* it is assigned 0 points. Attributes can also be described with four levels of *very high*, *high*, *moderate*, and *low,* with assigned point of 100%, 50%, 25% and 0%, respectively. Different point distributions can be used if needed to express the impact of the attribute's qualities on the likelihood of damage developing.

The weighted sum model used for scoring individual damage modes in the initial research is shown by the equation:

$$OF = \sum A_i \Big/ \sum A_{i,\,max} \times 4$$

Where:

A_i = Original score for individual attribute based on its rank

$A_{i,\,max}$ = maximum score for an individual attribute

Equation 2.1. Unweighted Occurrence Factor equation.

This equation uses the weights for each attribute according to the rank provided by the RAP and the result of assessing that attribute's criteria. The scores for each individual attribute are summed to produce the numerator and the maximum scores for each attribute are summed to form the denominator. This is intended to be a simple and rapid process to apply.

Different approaches to weighting attributes were studied to better match the outcome of the risk models with the target ranges when applied to actual bridges and bridge records. The individual attributes were weighted using the equation:

$$OF = \sum w_i A_i \Big/ \sum w_i A_{i,\,max} \times 4$$

Where:

w_i = weight assigned for a given attribute A_i

Equation 2.2. Weighted Occurrence Factor equation.

This equation allows for the attributes initially weighted by the RAP to have their overall weight in the model increased. For example, the score of the CR attribute of a deck was typically 20 points. A multiplier of 1.50 will increase the *high* score to 30, *moderate* score to 15, and *low* remains zero. The maximum score for the model is also increased according to Equation 2.2. In this way increasing the weight of an individual attribute reduces the relative weight of all other attributes in the model, since the denominator is also increased.

The research did not find suitable existing procedures for adjusting the weights of individual attributes in a weighted sum model. Several methods were explored and found to be impractical or not related to engineering decision-making. For example, a method for determining the weights of individual attributes based on its statistical properties provided weights that primarily showed which attributes were most likely to vary over the course of time rather than any engineering rationale. Most of the approaches described in the academic literature for weighting attributes in a weighted sum model did not adequately represent engineering decision-making when implemented on the risk models for bridge components. For this reason, new methods of analyzing risk models for bridges were developed and tested to find suitable weights for attributes.

2.3. Overall Results

This section of the report describes the preliminary results from the original back-casting using the RAP models. Much of the data is analyzed on a component basis to assess the effectiveness of the risk models and provide general results that show how the RAP models performed when applied to actual bridge components. An analysis of the risk scores for all the bridge components in the study is reported.

Some of the original risk models developed from RAP meetings did not include the CR of a component explicitly as an attribute. The RAP meetings focused on attributes and damage modes that indicated an increased relative risk such as corrosion damage, rate of deicing chemical application, joint condition, etc. The damage modes that were identified by the RAP would affect the CR even if the CR were not explicitly mentioned in all cases. When the sample bridges were scored with risk models that did <u>not</u> include the CR explicitly as a separate attribute, it was found from initial back-casting results that the risk scores often did not align with the target ranges for individual sample bridges. For example, a CR 4 component would have a lower risk score than a CR 7 component because bridge condition was not adequately represented in the risk model. These initial results were not very informative and are not included here. Additionally, the risk models without CR attributes did not reflect the rational assessment that most CR 5 components would be more likely to deteriorate to a CR 3 in the next 72 months than a CR 7 component based simply on the fact that the component is already in CR 5. While it may be possible for a CR 7 bridge to deteriorate more rapidly, this would not be a common or expected occurrence. The CR was implemented as an attribute for damage modes that would affect CR, such as corrosion-related damage modes. Damage modes for which the risk is unrelated to the component condition such as the impact damage did not have the CR attribute included because the likelihood of a vehicle impacting a bridge is unrelated to its condition.

Figure 2.6 shows the raw risk scores for corrosion-related damage modes for the deck, superstructure, and substructure based on risk models that include the CR for the subject component and the CS for the element under consideration. The ordinate on the left shows the risk score calculated using Equation 2.1 and the abscissa shows CR for each component. The OF categories are shown next to the ordinate on the right. The data are shown for damage modes of deck delamination and spalling (R/C deck delam. and spalling), steel superstructure corrosion damage (Stl. ss. corrosion), substructure delamination and spalling (R/C sub. delam. and spalling), and delamination and spalling of a PSC superstructure member (PSC ss. delam. and spalling). The data points are slightly offset from the associated CR for clarity, and a trend line in the figure shows the linear regression for all data points combined. These data illustrate that the risk models produced risk scores that trended toward larger values for components with lower CR. The average value for components with CR 5 was 2.54, in the *moderate* range. The average value for components with CR ≥ 7 was found to be 1.11, in the *low* range for the OF. However, Figure 2.6 shows that, in some cases, components with CR ≥ 7 had risk scores greater than components with CR ≤ 5. Most of the components with CR ≥ 7 were rated in the *low* or *moderate* range. These data indicate that the design and loading attributes in the models have weights that are too high as compared with condition attributes. As a result, the models did not produce results that aligned with the target ranges and provided suitable contrast between the calculated OF for components in CR ≥ 7 and components in CR 5 or lower. The assigned values in the risk model need to be adjusted to produce results consistent with the target values and engineering judgement. Several different approaches were pursued to properly weight the attributes in the models to better align results with the target ranges.

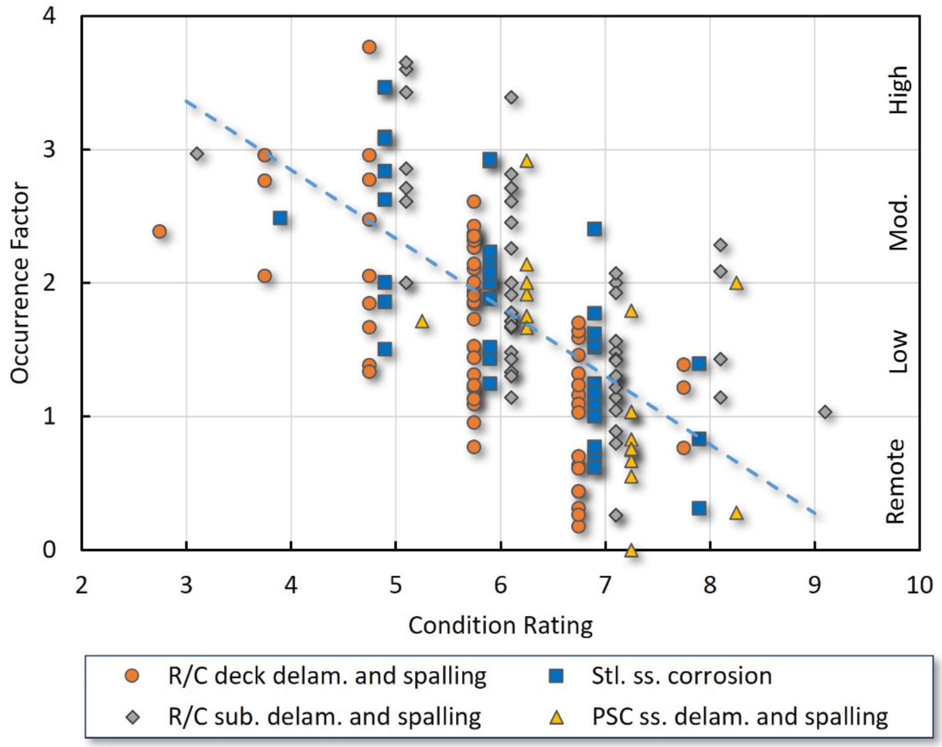


Figure 2.6. Raw OF scores for corrosion-related damage modes for sample bridges.

2.3.1. Assessment of Model Weighting

Based on the results from the initial back-casting process, it was clear that the original risk models were not adequately representing the increased risk as the CR decreases. Sensitivity studies were conducted to assess the impact of different approaches to weighting the attributes on the OF scoring. The objective of the studies was to determine if increasing the weights of certain attributes improves the quality of the risk model when compared with the target ranges and provide insight into how to calibrate the models for implementation.

First, a study was conducted using a procedure that ranked individual attributes based on statistical analysis to assign individual weights. This approach was ineffective and is not reported here. A second study was completed in which attribute weights were adjusted by two methods. The weights for groups of attributes were increased using Equation 2.2, in which the attribute value was increased and the total number of points in the model was also increased. Additionally, individual attributes of the component CR and the element CS, and a group of condition-related attributes, were weighted without increasing the total value of the model. The following section describes the sensitivity study process and results.

2.3.1.1. Sensitivity Study of Attribute Weights

Sensitivity studies were conducted to determine how the risk models developed by the RAPs should be weighted to improve the quality of the models when compared with the target ranges. The risk models include attributes that are categorized in groups as condition, loading, or design attributes. Condition attributes are expected to change over time as a component deteriorates, while design attributes are not expected to change over time. Loading attributes may change over time but are expected to remain relatively constant. For example, ADT is a loading attribute that may change if traffic volumes change significantly over time. The sensitivity study explored if weighting the groups of attributes or weighting individual condition attributes of CR and CS is more effective for improving the overall quality of the models.

Different risk models include different combinations of attributes from the condition, design, or loading groups. For example, Figure 2.7 shows the proportion of the attribute groups for a given set of risk models assessing corrosion-related damage in the superstructure, substructure, and deck. As shown in the figure, the models for corrosion-related damage modes derive ≈50% or more of their total scoring from condition-related attributes. The models include both the CR and CS attributes as well as other condition attributes such as joint condition, efflorescence, or poor deck drainage. In the sensitivity study, the weights of the condition, loading, or design attributes were modified to assess the outcome as compared with target ranges.

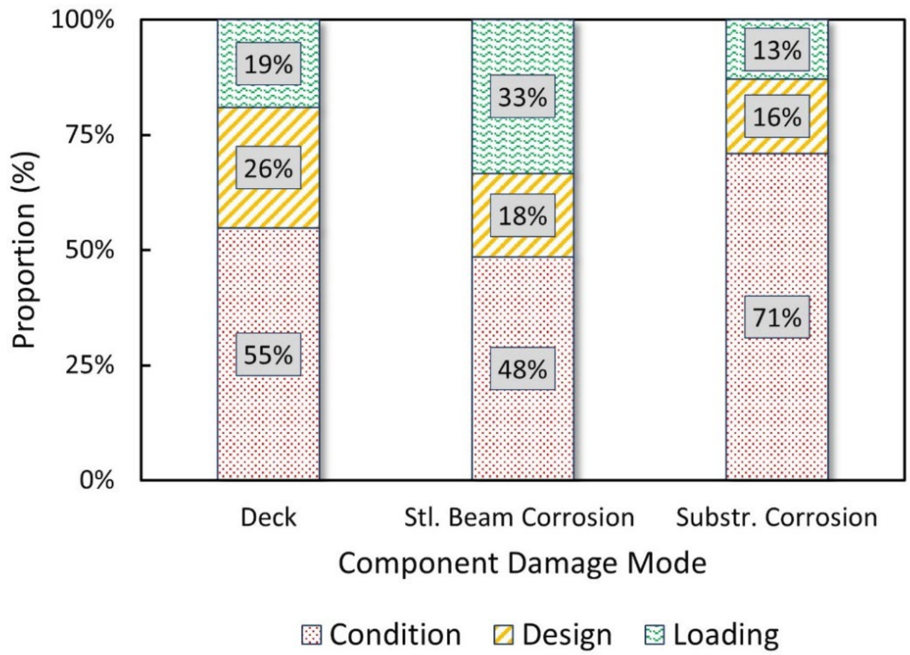


Figure 2.7. Graph showing relative proportions of condition, design, and loading attributes.

An example of the attribute groupings for a bridge deck are shown in Table 2.4. This table shows the attributes that were included in the design, loading, and condition attribute groups. Two attributes were split between different groups. Poor deck drainage could be a design attribute if the bridge was designed with an ineffective drainage system such as deck edge-drains. On the other hand, an initially effective deck drainage system may become clogged or otherwise damaged during service life and become an ineffective drainage system over time. For CP level, a bridge may be constructed with ECR or with an integral overlay making the CP level a design attribute. An overlay or sealing practice may be initiated during the service life of a deck or other component. In this way, these attributes may be reasonably expected to change over time in certain cases, particularly the CP level, since sealing and overlays are increasingly common to provide additional corrosion protection. The sensitivity study examined the OF over the time-period of the back-casting process (2004 – 2021), during which these attributes changed for certain bridges. In fact, several instances of overlays being installed, or deck sealing, occurred during the back-casting period. For this reason, the attributes were split between design and condition to reflect that the scoring for either attribute may change over time, similar to a condition attribute, or may remain constant, similar to a design attribute. Deck drainage was split 50%-50% between design and condition, and the CP level was split 75% condition and 25% design.

The maximum score for the attributes in each group was increased according to Equation 2.2. Weighting a certain group of attributes reduces the relative weights of other attributes in the model as shown in Figure 2.8. The figure shows the weight on the abscissa and the percentage of the risk model on the ordinate to illustrate the trend of applying weights to a risk model for decks. The total number of points in the model is also shown in Figure 2.8 with the markers and line referenced to the ordinate on the right side of the figure. The figure shows the effect of increasing the weight of the condition attributes on the model. The risk model used to produce the figure was a 12-attribute risk model that initially had 210 total points in the model. As shown in the figure, increasing the relative weight (w_i) of a group of attributes decreases the relative weights of other attribute groups. The same process was completed for design and loading groups of attributes separately to gain insight into how the weighting affected the risk scores for the sample bridges. This weighting of the attribute groups according to Equation 2.2 was referred to as the attribute multiplier (AM) approach.

Table 2.4. Example listing of attributes in condition, loading, and design groups.

Code	Attribute
	Condition Attributes
C.1	Current CR
C.2	Current Element CS
C.13	Efflorescence/Staining
D.29/C.30	Corrosion Protection Level (75%)
C.27	Rate of Deterioration
D.4/C.7	Poor Deck Drainage and Ponding (50%)
	Loading Attributes
L.1	Average Daily Traffic
L.5	Rate of De-icing Chemical Application
	Design Attributes
D.24	Superstructure Flexibility
D.8	Concrete Mix Design
D.29/C.30	Corrosion Protection Level (25%)
D.4/C.7	Poor Deck Drainage and Ponding (50%)

The effectiveness of weighting condition-related attributes without increasing the total number of points in the model was also studied. This study examined weighting only the current component CR (C.1) and the current element CS (C.2) or weighting the entire group of condition-related attributes. This was referred to the points-added (PA) approach because points were added to the numerator, but not the denominator as shown in Equation 2.3:

$$OF = \frac{\sum w_i A_i}{\sum A_{i,max}} \times 4$$

Equation 2.3. Equation for point PA method.

The PA sensitivity study focused on increasing the weight of the condition attributes. Condition rating and CS attributes were multiplied by 1.50 without increasing the total number of points in the model. Additionally, all condition attributes were multiplied by 1.50 while keeping the total score the same. Essentially, this produces "add-on" points to specific attributes (or groups of attributes) in the model to present a larger impact on the model score. Using this scoring process, it is possible for a risk model score to exceed 100%, i.e., the OF could be greater than 4, which is undesirable in terms of having a rational model.

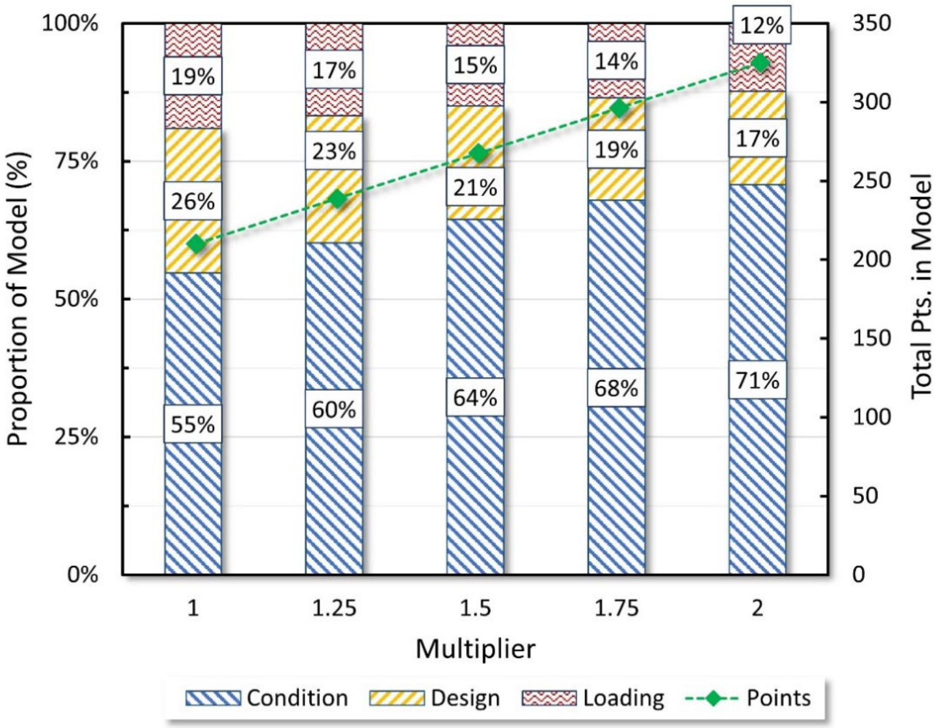


Figure 2.8. Effect of weighting condition attributes using the AM method.

2.3.1.2. Process and Results

Components and damage modes analyzed included delamination and spalling of R/C decks, PSC superstructures, and R/C substructures, and corrosion / section loss and fatigue in steel superstructure members. These models formed a representative group of components and damage modes for the analysis that was common between different RAPs. The process consisted of recording the original unweighted risk model score and progressively increasing the weights of groups of attributes. The OF was calculated using the Equation 2.2. The weights were applied by multiplying a particular group of attributes by w_i = 1.25, 1.5, 1.75, and 2 for the AM study. For the PA study, the OF was calculated by Equation 2.3. The weights were applied by multiplying the condition-related attributes group by w_i = 1.5. The PA study also included weighting the CR and CS (C.1 and C.2) multiplied by w_i = 1.5.

The analysis was conducted on the 60 sample bridges over the back-casting period. Each inspection year was analyzed with the AM and PA approaches. The target values shown in Figure 1.3 were used to analyze the effect of increased weights. The expected OF for a bridge in good condition (CR ≥ 7) was in the *remote* to *low* range, meaning the risk score was nominally between 0 and 2 with a margin of error of 0.1 (i.e., between 0 and 2.1). For bridge with a CR 6, the values of the OF were expected to fall in the *low* to *moderate* range with a 0.1 margin of error (i.e., score between 0.9 and 3.1), and for bridge with CR ≤ 5, results were expected to fall into the range of *Moderate* to *High* (i.e., score between 1.9 and 4). Although the expected outcomes of the risk models will naturally vary for different components in the same CR, the target ranges were applied as ranges over which the results are *expected* to fall. Results were analyzed by determining the number of times the risk model did not match the target ranges; this analysis was completed over the back-casting period of 2004 – 2021.

Table 2.5 summarizes the results of the sensitivity study. The table shows the approach (AM or PA) that yielded the greatest number of results that fell within the target ranges over the back-casing period for each of the risk models. The percentages in the tables represent the percentage of results that fell outside the defined thresholds. For example, a deck rated in CR 5 has a risk score (i.e., OF) of 1.67 in 2012, the risk score does not match the target values. In 2016, the risk score increased to 2.2, so the risk score is within the target range. Each risk model was assessed for each inspection year from 2004 through 2021.

Table 2.5. Results of sensitivity study of weighting for attributes by component.

Component	Original Scoring (%)	Best scoring (%)	Best Scoring Method
R/C Deck, delam. and spalling	7.0	2.0	AM, Condition 1.25
R/C Deck, delam. and spalling	21	13	PA, Condition 1.50
R/C Deck, delam. and spalling	2.0	0	AM, Design 1.25
R/C Deck, delam. and spalling	5.6	0	PA CR & CS 1.50
R/C Deck, delam. and spalling	14	4.0	PA, CR & CS 1.50
R/C Deck, delam. and spalling	0	0	Original
Stl. SS., corrosion	15	11	AM, Condition 2.00
Stl. SS., corrosion	1.1	1.1	Original
Stl. SS., corrosion	10	3.0	AM Design 1.75
Stl. SS., corrosion	17	12	AM, Condition 1.75
Stl. SS., fatigue	0.63	0.63	Original
Stl. SS., fatigue	8.2	1.5	AM, Condition 1.25
Stl. SS., fatigue	18	8.9	AM, Design 1.25
Stl. SS., fatigue	22	15	AM, Condition 1.25
PSC SS, delam. and spalling	8.0	7.0	AM, Design 1.25
PSC SS, delam. and spalling	1.0	1.0	Original
R/C Sub. delam. and spalling	19	12	AM, Condition 1.50
R/C Sub. delam. and spalling	10	2.0	PA, CR & CS 1.50
R/C Sub. delam. and spalling	2.6	2.1	AM, Condition 1.25
R/C Sub. delam. and spalling	2.0	0	AM Condition 2.00
R/C Sub. delam. and spalling	17	13	AM, Condition 1.75
R/C Sub. delam. and spalling	1.0	0	PA, CR & CS 1.50

The results of the study showed that the original risk models produced results that were outside the target ranges an average of 9% (σ = 7.5%) of the inspection cycles. When adjusted by weighting, the average was reduced to 5% (σ = 5.4%). These data indicate that the original models met the target ranges in the majority of inspection cycles during the back-casting period. This was improved when one of the weighting processes was implemented, although no single approach worked in all cases.

Considering the different processes used for weighting the attributes, the results of this sensitivity study indicated that increasing the weights of the condition-related attributes improved the quality of the risk models in 14 of the 22 cases shown in Table 2.5, with five cases of PA providing the best results and nine cases of AM providing the best results. The original, unweighted model provided the best results in 4 of the cases.

It was also noted that the largest variations from the target values were for the damage mode of fatigue cracking for steel superstructures. The likelihood of fatigue cracking is theoretically not related to the CR of the superstructure. However, CRs generally decline as a bridge ages and corrosion damage increases. The number of stress cycles the component is exposed to increases as the bridge ages, and corrosion damage can act as initiation points for cracking. As a result, there is a relationship between the likelihood of fatigue cracking and the condition of the bridge. However, the target ranges did not align well with results of the fatigue risk models.

The conclusions from this sensitivity study were as follows:

1. Increasing the weights of the condition-related attributes, either using the AM or PA method, improved the quality of the risk models when compared with the target ranges. While not true for every case, the trend indicated that the approach most likely to improve the quality of the models was to weight the CR and CS in the models.
2. The PA method was not sufficiently more effective as compared with the AM method to justify its use moving forward, considering that the approach can produce results that do not conform to the overall model of rating risk for components on a scale of 0 to 4.
3. Risk models for fatigue cracking produced the largest variation from the target ranges.

From the sensitivity study, it was also concluded that a more systematic method of weighting the attributes was needed to effectively calibrate the risk model to meet the target ranges. The population of sample bridges produced different results for the different weighting scenarios studied. The number of condition, loading, and design attributes varies for different models, and the sample of 60 bridges each had unique characteristics and deterioration patterns. Additionally, the historical data obtained from inspection reports was cumbersome to work with and difficult to repeat. While this sensitivity study produced some insight into the behavior of the risk models as compared with actual bridges, it is not practical to apply this method to calibrate the models generally. A more effective methodology was needed and the MC simulations that will be described provide a more durable and implementable approach.

Based on these results, additional studies were conducted with the CR and CS attributes weighted by a factor of 2 as described below.

2.3.1.3. CR and CS Weighting

The risk models were implemented with increased weights for the primary condition attributes based on the results of the initial analysis of the back-casting results and the sensitivity study. The models were weighted by increasing the value of the CR and CS attributes (C.1 and C.2) by a factor of 2 (w_i = 2). Increasing the weights of these attributes decreases the weights of all other attributes as previously discussed and shown in Equation 2.2. This produced results for weighted models that could be compared with results for the unweighted models.

The results for the primary corrosion-related *unweighted* risk models were previously shown in Figure 2.6. As shown in that figure, there was a general trend that lower CR components have increased values of. However, there are cases where CR ≥ 7 components have OF values that are greater than some CR 5 components. Many CR ≥ 7 components exceeded the value of 1 for the OF and were rated with OF = *low*. If the CF is *high* and the OF is *low*, the inspection interval will be 48 months, based on the proposed risk matrix. Therefore, it was desirable to increase the contrast between components in CR ≥ 7, which practically would be expected to have *remote* likelihood in most cases based on engineering judgement, and components in CR 5, which would not qualify for extended intervals using Method 1 according to the current NBIS requirements. Additionally, the sensitivity study described in the previous section showed that weighting the risk models by increasing the relative value of the condition-related attributes improved the quality of the risk models when compared with the target ranges. To provide additional contrast in the risk values that would better align with expected values, the results from the back-casting were modified by multiplying the CR and CS by 2 using Equation 2.2.

Weighting the models in this way has the effect of reducing the risk values for components with CR ≥ 7 when attribute C.2, Element Condition State, is also rated as *low*. The risk values are reduced because the attribute C.1, Current Condition Rating, is rated a *low* for a component in CR ≥ 7, and therefore, scores 0 points regardless of what weighting factors are applied to the models. The weighted attribute's maximum score is added to the denominator, resulting in a reduced risk score overall. For components with CR 6 and lower, points are added to both the numerator and the denominator, resulting in an increased risk score. Additionally, it is much more likely for a component rated in CR 6 or CR 5 to have element CSs that rate as either *moderate* or *high* for attribute C.2 as compared with a component in CR ≥ 7. As a result, the risk scores are reduced for components in good condition and increased for components in fair condition or poor condition.

The overall results of using the weighted risks models are shown Figure 2.9. The figure includes a linear regression line based on all the data shown. It can be observed that the slope of the regression line is increased as compared with the regression line shown in Figure 2.6. Notable in the figure is that all the components in CR ≥ 7 now score in the *remote* or *low* range. Components in CR 6 are primarily in the *low* or *moderate* range. Components in CR ≤ 5 generally score in the *moderate* to *high* range. These results illustrate greater contrast in the risk scores for components with different CRs, with components in good condition having lower risk scores and components in fair and poor condition having increased risk scores as compared with the unweighted risk models. The results from the weighted models align more closely with the target ranges described earlier.

The weighting of the CR and CS attributes has a relatively small overall effect on the average value of the risk score for components in different CRs as shown in Figure 2.10. This figure depicts the average of the risk scores calculated from the risk models. The average risk scores for the unweighted and weighted models are shown. Error bars show the standard deviation of the results. The figure illustrates that the average OF value does not change by a large amount, but the change is significant because the average for CR ≥ 7 components drops from 1.11, in the *low* range, to 0.9, in the *remote* range. When compared with the proposed risk matrix shown in Figure 1.5B, components in CR ≥ 7 with a *remote* OF will qualify for extended intervals even if the CF was *high*. As discussed earlier in the report, the target range for components rated in CR ≥ 7 is in the *low* to *remote* range*,* based on the rationale that bridges in good condition rarely, if ever, deteriorate to a CR of 3 in a 72-month interval.

Based on these data from the sensitivity studies, the back-casting results were analyzed for scenarios where the CR and CS are weighted by a factor of 2 and compared with the original, unweighted risk models. This data was used to estimate the resulting inspection interval that would apply based on the risk scores. A method for analyzing individual weights and calibrating individual risk models was also developed that allows a bridge owner to predict the outcome of applying the risk model to their bridge inventory.

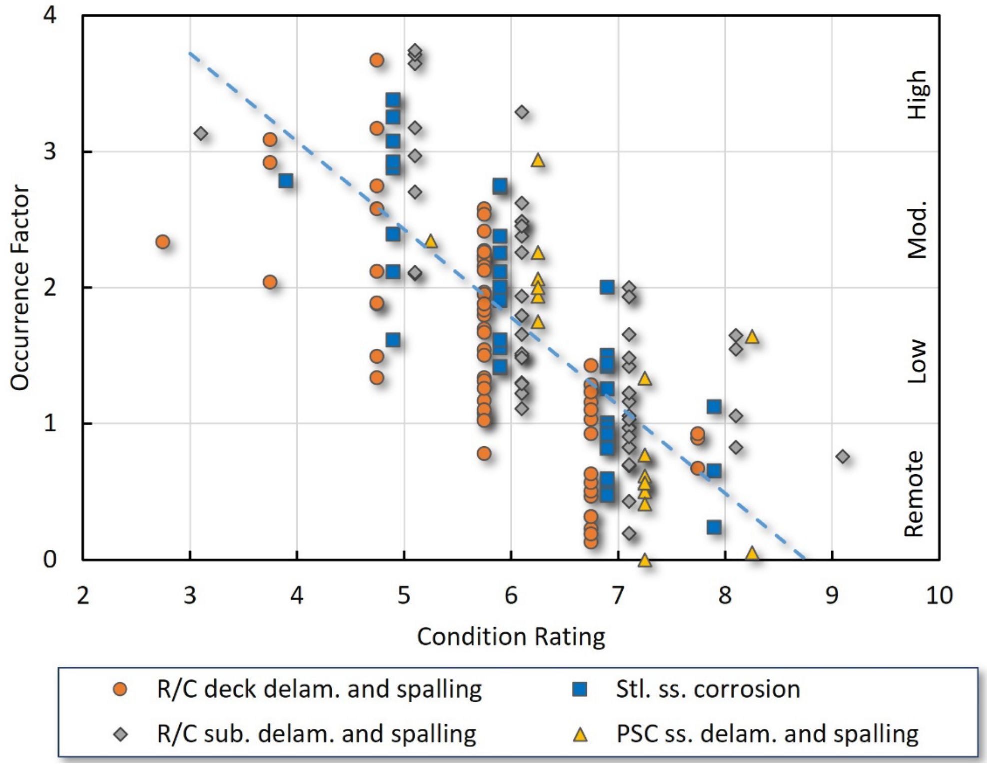


Figure 2.9. OF results for components of 60 sample bridges with weighted CR and CS.

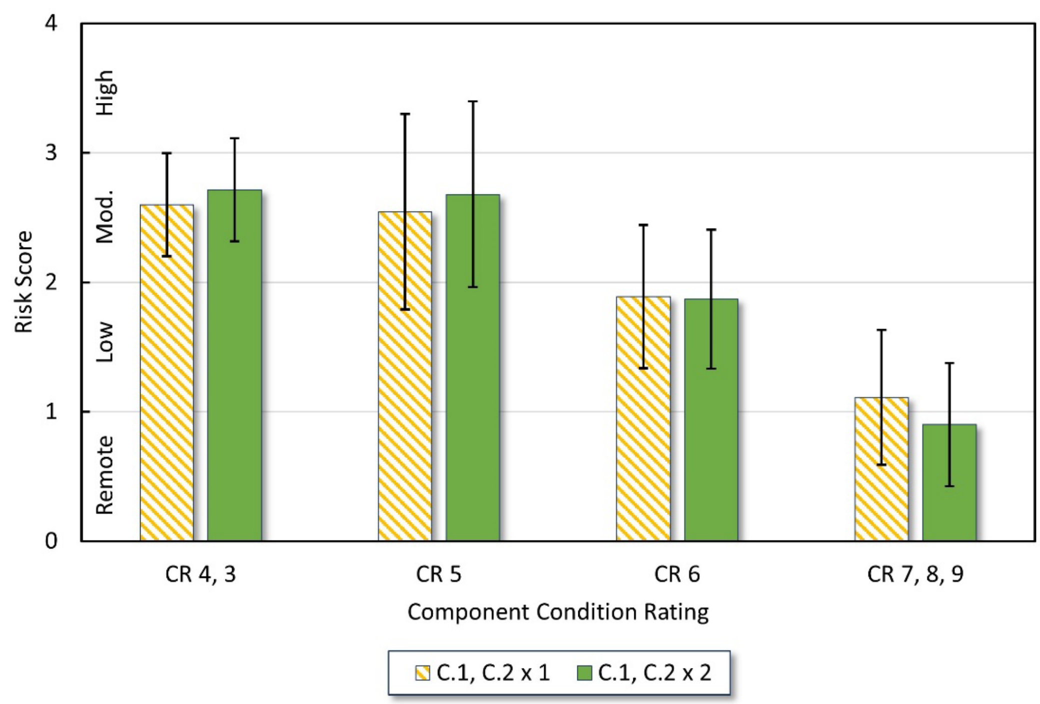


Figure 2.10. Bar chart showing the average OF for sample bridge components for weighted and unweighted models.

2.4. Risk-Based Intervals

This section discusses the overall trends in the data formed from the back-casting process. The inspection intervals were determined for two different CF values, CF = 2, *moderate*, and CF = 3, *high*. The CF = 4, *severe*, was not included in the analysis because this CF generally applies to bridges that lack redundancy such as NSTMs. The CF factor of *low* has the same intervals as the CF of *moderate* except for bridge components with a *high* OF according to the risk matrix shown Figure 1.5. As shown in the back-casting data, an OF *high* typically occurs for bridge components with a CR of 5 or less. As a result, there is not relevant information contained in an analysis of a *low* CF.

The inspection interval for a bridge is controlled by the highest risk score for any component of the bridge. As such, the controlling component with the highest risk score was used to assess the sample bridges and determine the risk-based inspection interval.

2.4.1. Inspection Intervals Based on Component Ratings

This section shows results for applicable inspection intervals considering the risk scores for the controlling component and damage mode for each of the sample bridges. Results are presented with different CFs to illustrate potential outcome of the analysis in a general way considering that different owners may have somewhat different parameters for the CF. The CF of *low* (CF = 2), the CF of *high (*CF = 3) were used to determine the inspection intervals based on the unweighted and weighted risk scores using the risk matrix included in the NCHRP 782 report. In addition, the inspection intervals were determined with the proposed risk matrix, discussed earlier in the report, in which a component with a remote OF and the high CF is assigned an interval of 72 months. This scenario is listed as “CF 3P.” The results presented in this section consider the CR for components in the year 2020 as compared with the results from the risk analysis. Results for weighted and unweighted models are presented. The data was analyzed based on the controlling component risk score for each bridge. The NBIS requirement that only bridges in “good” condition are eligible for extended intervals of 72 months was not considered in the analysis. An analysis of the bridges in the sample set that had all three components rated as CR ≥ 7, i.e., bridges in good condition, is provided later in the report.

The results showed a distribution of inspection intervals that were slightly different if the weighted models were used as compared with the unweighted model. Table 2.6 shows the overall results for the weighted and unweighted models. It was found that for the CF of *low*, 42% of the sample bridges could be assigned an inspection interval of 72 months. For CF = 3, there were no bridges in the sample population that qualified for a 72-month interval using the risk matrix from NCHRP 782. If the proposed risk matrix were used, 5% of the sample bridges could have an interval of 72 months.

If the weighted models were used, there was a small difference in the number of bridges that could have a 72-month interval, increasing from 5% (3 bridges) to 8% (5 bridges) as shown in Table 2.6. The small increase in the number of bridges that have a 72-month interval does not seem that significant; however, the number of bridges in the sample population with all component CR ≥ 7 was relatively small, only 13 of the 60 bridges. Additionally, for CF = 2, the percentage of bridges eligible for a 72-month interval goes down when the weighted model is used. This occurs because some of the components eligible for a 72-month interval in the weighted model are controlled by components in CR 6. As a result, the risk score for these components is increased when the model is weighted resulting in a reduced inspection interval. It is notable that the percentage of bridges with a 24-month interval increases when the condition factors (CR and CS) are weighted as compared with the unweighted model.

Table 2.6. Inspection intervals determined from controlling damage mode for unweighted and weighted models.

Consequence Factor	24 Months (%)	48 Months (%)	72 Months (%)
CF 2, Unweighted	18	40	42
CF 3, Unweighted	58	42	0
CF 3P, Unweighted	58	37	5
CF 2, Weighted	23	42	35
CF 3, Weighted	65	35	0
CF 3P Weighted	65	27	8

Analyzing these results according to the CR of the bridge components provides some insight into how the weighted and unweighted models compare for the sample bridges. The bridges considered in this analysis were those that did not have an impact damage mode controlling the inspection interval. There were 11 sample bridges that had the controlling damage mode of impact for either the superstructure or substructure. Components from the remaining 49 bridges were analyzed to assess the effect of weighting. The proposed risk matrix was used to determine the inspection interval based on the risk score and the resulting OF category. Figure 2.11 presents the results of the analysis showing the calculated inspection interval for the components of 49 sample bridges considered, based on the controlling component and damage mode for each bridge. The CF was assumed to be CF = 3P in the analysis.

There was an increase in the number of components in good condition that could have a 72-month inspection interval when the weighted models were used as shown in Figure 2.11. Primarily, components that had been assigned a 48-month interval changed to 72-month interval when the model was weighted. The increased weight of the condition attributes of CR and CS results in a reduction in the risk score for these components, and consequently a change in the assigned interval. There was also a decrease in the number of CR 5 components that could be assigned an interval of 48 months, with those components typically changing from a 48-month interval to a 24-month interval. Additional analysis of those bridges with CR ≥ 7 for all components is shown in section 2.4.2.1.

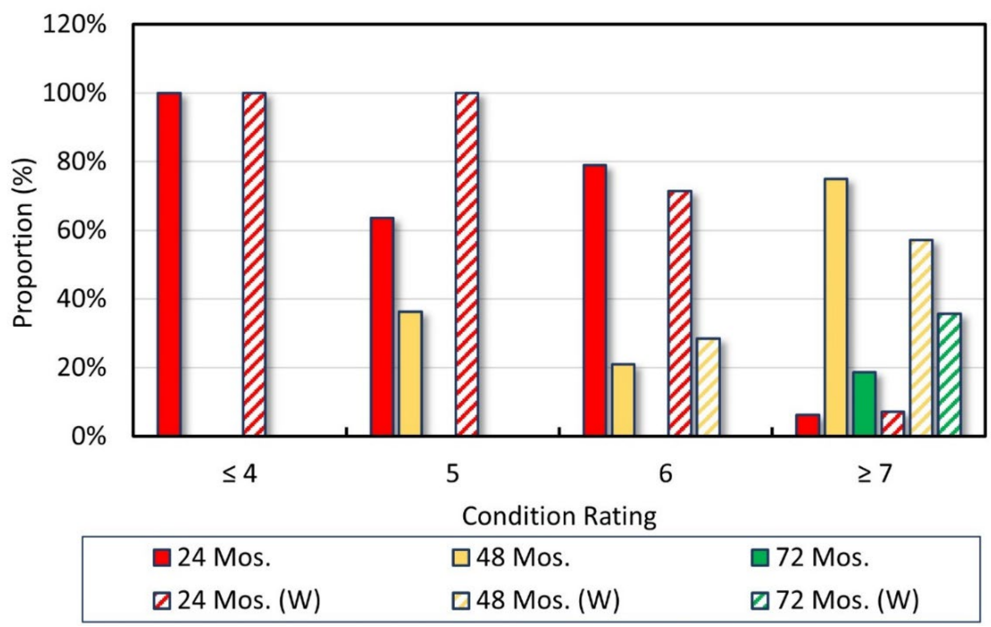
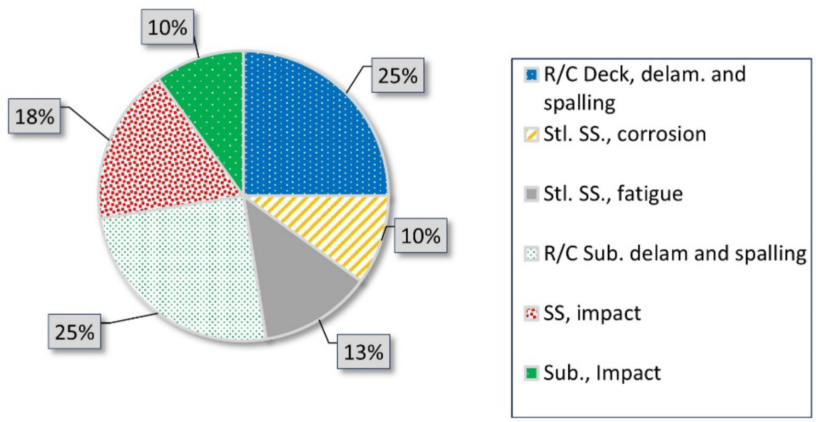


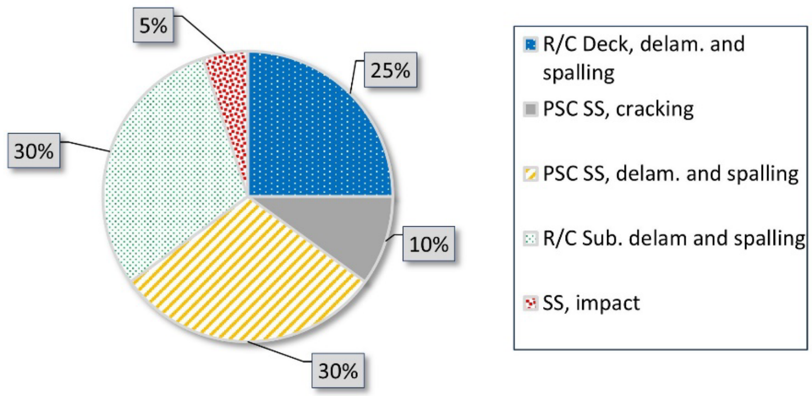
Figure 2.11. Inspection intervals determined from weighted and unweighted risk models with CF = 3P.

2.4.2. Damage Modes

Data from the 60 sample bridges were analyzed to determine the predominant damage modes that controlled the inspection interval for a given bridge. The data presented here is for the weighted model, with CR and CS multiplied by a factor of 2, and other damage modes remaining the same weights as defined by the RAP. The results are shown in Figure 2.12 which presents two pie charts showing the proportion of bridges that controlled the inspection interval according to the different damage modes. The predominant damage modes for steel bridges (Figure 2.12A) were deck delamination and spalling and substructure delamination and spalling. A significant portion of the bridges (18%) were controlled by the likelihood of impact damage due to low vertical clearance of the bridges from the roadways below. It was notable that 13% of the bridges were controlled by the fatigue cracking damage mode, while only 10% of the bridges were controlled by superstructure corrosion damage, i.e., likelihood of section loss. For PSC bridges (Figure 2.12B), about 1/3 of the bridges were controlled by superstructure and substructure delamination and spalling. The deck delamination and spalling modes controlled another 25% of these bridges.



(A)



(B)

Figure 2.12. Distribution of damage modes for sample bridges showing steel (A) and PSC (B) bridges.

It was notable that the analysis showed no single dominant damage mode for the randomly selected population of 60 bridges. In fact, the damage modes were fairly evenly distributed among the superstructure, substructure, and deck. There was a significant proportion of the bridges that had their inspection intervals based on the likelihood of impact damage due to either low clearance, in the case superstructure impact, or location close to the roadway, for substructure impact damage. Overall, almost 20% of the bridges were controlled by either superstructure or substructure impact.

The NBIS and associated FHWA guidance allows only bridges in good condition to be considered for intervals of up to 72 months for inspection. The 13 sample bridges that were in good condition in 2020 were analyzed separately to assess those bridges that could be eligible for extended inspection intervals and the results are presented in the following section.

2.4.2.1. Bridges in Good Condition

There were 13 sample bridges that had a CR ≥ 7 for the components of superstructure, substructure, and deck. There were seven steel bridges and six PSC bridges in this group. Three of the bridges had controlling damage modes of superstructure or substructure impact. The most common controlling damage mode was PSC delamination and spalling, which controlled for three out of the six bridges with PSC superstructures. Overall, there was a fairly even and broad distribution of damage modes, with eight different damage modes controlling for sample bridges in good condition. This included R/C deck delamination and spalling, steel superstructure fatigue cracking, and superstructure impact with two bridges each, and steel superstructure corrosion, PSC superstructure cracking, R/C substructure delamination and spalling, and substructure impact with one bridge each.

Bridges in good condition with a controlling risk score of impact damage were re-analyzed without considering the impact damage mode. The highest weighted risk score <u>other</u> than impact damage was used in the analysis. This resulted in the controlling damage mode being one of the condition-related damage modes such as delamination and spalling of a component. For example, it was assumed that one bridge was controlled by deck delamination and spalling, a second bridge was controlled by fatigue cracking, and the third bridge was controlled by substructure delamination and spalling.

The resulting damage modes were proportioned as shown in Figure 2.13. The figure shows the proportion of bridges in good condition controlled by each damage mode. The data showed that the predominant damage modes were deck delamination and spalling, PSC superstructure delamination and spalling, and steel superstructure fatigue. Delamination and spalling of the substructure also played a significant role. Overall, the results demonstrated that among randomly selected bridges in good condition, there was a distribution of the controlling damage modes divided somewhat equally between the deck, superstructure, and substructure components.

The percentage of bridges in good condition eligible for a 72-month inspection interval is shown in Table 2.7. The results show that considering the proposed risk matrix, almost 50% of the sample bridges that are in good condition qualify for an extended inspection interval when the CF = *high*. If the CF were *moderate* (i.e., CF = 2), all the bridges in good condition would qualify for the extended interval.

Table 2.7. Proportion of bridges in good condition eligible for 72-month inspection interval.

Model	CF 2	CF 3	CF 3P
Unweighted	100%	0%	23%
Weighted	100%	0%	46%

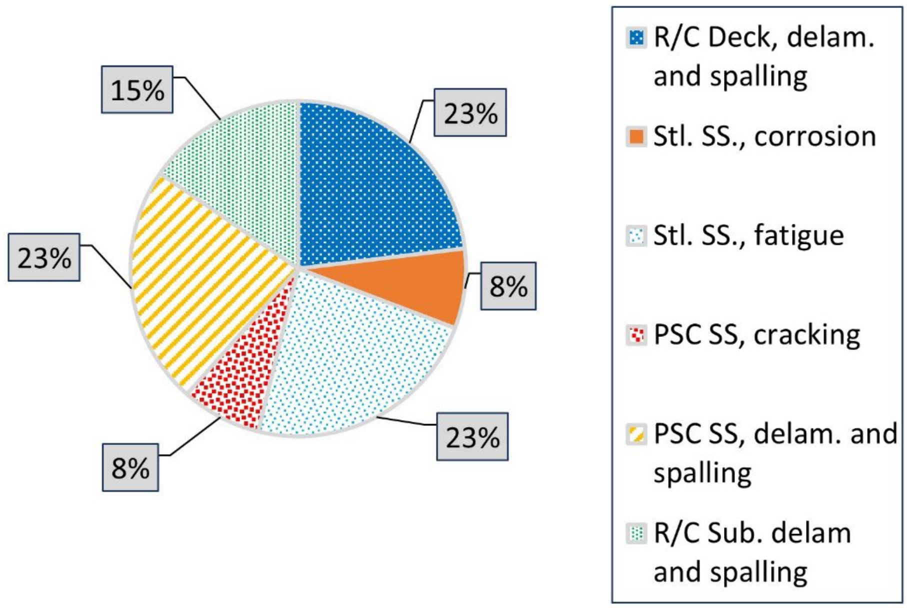


Figure 2.13. Distribution of controlling damage modes for CR ≥ 7 bridges without considering the impact damage mode.

2.5. Statistical Analysis of Component Risk Scores

The results from the back-casting process were analyzed statistically to assess the model performance as compared to the target ranges and the effect of weighting attributes. The analysis focused on the time-dependent damage modes, i.e., those related to corrosion damage. These models were selected for the analysis for three reasons. First, the primary deterioration mechanism for highway bridges is corrosion, which affects all bridges in the inventory to varying degrees. Second, the corrosion risk models include the largest number attributes making their calibration the most challenging. Finally, risk models for damage modes such as impact damage and fatigue cracking are dependent primarily on characteristics such as ADT, vertical clearance, or era of construction. These models are typically consistent over time for a given bridge and rely primarily on engineering decision-making regarding the attributes that control the risk. For example, the likelihood of impact damage is independent of the CR for the superstructure of a bridge. Damage modes associated with corrosion are time dependent and would be expected to have increased risk scores as the CR for the component declines and the bridge ages. The analysis was conducted with the objective of analyzing if the risk scores were consistent with the target ranges for bridge components with CRs of 5, 6, or ≥ 7.

The analysis was conducted on a component level examining components in CR ≥ 7, CR 6, and CR 5 separately. Components in CR 4 or CR 3 were neglected from most of the analysis because these components are screened from an RBI analysis. The risk scores for these components with CR ≤ 4 can be seen in Figure 2.6 and Figure 2.9 which show that the risk scores for these components were similar to CR 5 components.

2.5.1. Back-Casting Results – All Components

The combined results for the components of deck, superstructure, and substructure were analyzed for corrosion-related damage mode of delamination and spalling for R/C decks, R/C substructures, and PSC superstructures, and for corrosion damage / section loss for steel superstructure components. The data analyzed consisted of the risk scores determined from the individual risk models developed from the six different RAPs.

The results were analyzed to determine the overall distribution of results and quantify the impact of weighting components. This method of analyzing the results provides insight into the expected results for a larger population of bridges. It was assumed in the analysis that the risk scores were normally distributed. In the analysis, the risk scores were sorted into bins with a range of 0.25. For example, risk scores of 1.10, 1.15, and 1.20 were counted in a bin with the range ($1.00 < x \leq 1.25$). Risk scores were sorted according to the CR for the subject component. These data were analyzed for unweighted and weighted risk models.

The mean and sample standard deviation of the risk scores assigned to each CR were used to produce normal distribution plots to illustrate the distribution of the risk scores. Cumulative normal distribution curves are presented to demonstrate the proportion of a bridge inventory that would be expected to have risk scores that fall within the OF ranges for *remote*, *low*, *moderate*, or *high*. Components in "Good" condition (i.e., CR ≥ 7) were grouped together and components in "Poor" condition (i.e., CR ≤ 4) were neglected from the analysis.

The results for all of the components considered in the analysis are shown in Figure 2.14A and Figure 2.14B. Figure 2.14A shows the results from the unweighted risk models. Results for CR 5, CR 6, and CR ≥ 7 are shown separately. The bar chart presents the number of risk scores (i.e., count) falling into each bin on the left ordinate. The right ordinate shows the frequency or proportion of components from a normal distribution based on the mean and sample standard deviation of the data for each CR. This axis is unscaled because the data are normalized such that the integral of each normal curve is equal to 1. The horizontal axis on the bottom shows the OF category, and the horizontal axis on the top of the plot shows the numerical values of the risk scores.

It can be observed in these results that the mean value for CR ≥ 7 bridges (the apex of the normal distribution curve) is larger than 1.0, and these data appear normally distributed. For CR 6 components, the mean value is close to 2.0, and for CR 5 bridges, the mean value is in the range of ≈ 2.5. Overall, it can be observed that the trend of these data correlate with the CR, i.e., CR 7 components have lower risk scores as compare with CR 6 components, and CR 6 components have lower risk scores than CR 5 components.

Figure 2.14B illustrates the effect of weighting the CR and CS attributes (C.1 and C.2) for the different components. Qualitatively, it can be observed that the risk scores for CR ≥ 7 bridges are decreased as compared with Figure 2.14A, and the risk scores for CR 5 components are increased. This illustrates that the overall effect of the weighting was to provide greater discrimination in the risk scores for CR 5, 6, and ≥ 7 bridges. It can also be observed in Figure 2.14A that the mean values for components with CR ≥ 7 and CR 6 are in the *low* range and mean value for components with CR 5 is in the *moderate* range. When the model is weighted, the mean value for components with CR ≥ 7 is reduced to being in the *remote* range. It can also be observed that the mean value for components in CR 5 has increased to being closer to the numerical value of 3.0.

The cumulative probability distribution shown in Figure 2.15 quantifies the percentage of the components expected to fall within each OF category. The cumulative probability graph shows the probability of a randomly selected component being ranked as *remote*, *low*, *moderate*, or *high*. The figure shows the results from the unweighted and weighted models as different line types. The weighting causes those components with CRs ≥ 7 to tend toward a lower category, from *low* to *remote*. For components in CR 5, the weighting causes the curve to shift to the <u>right</u>, which increases the probability that a given CR 5 component will be categorized as *high* and reduces the likelihood of a CR 5 component will be categorized as *low* or *Remote*.

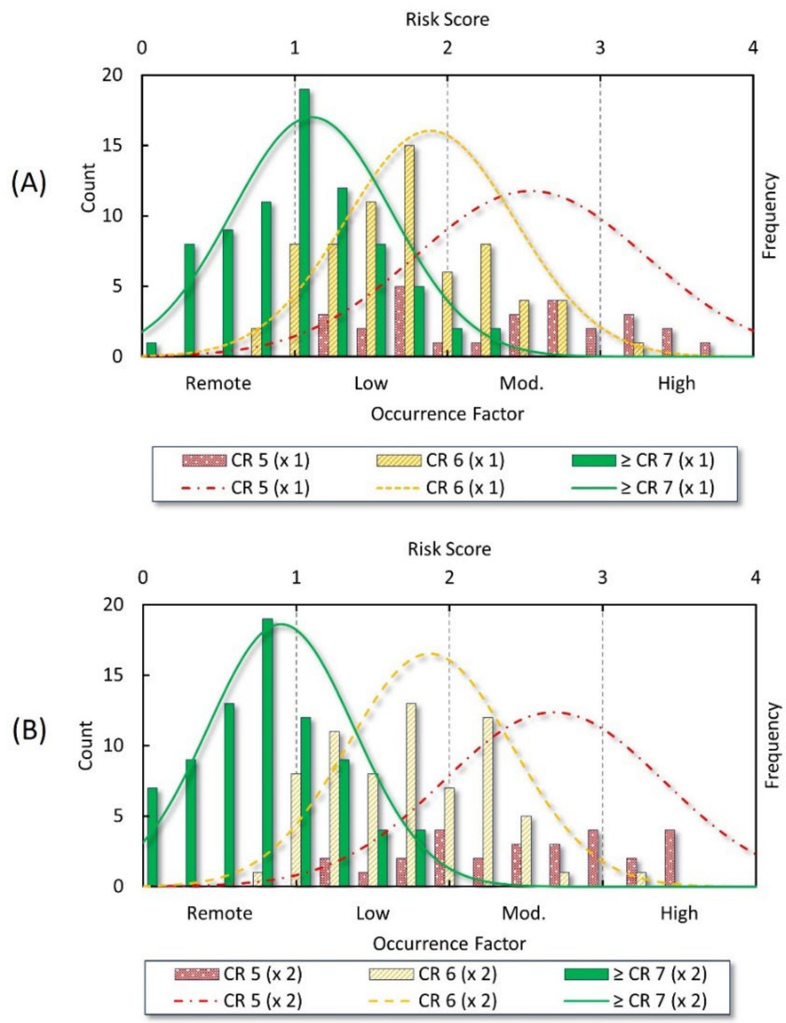


Figure 2.14. Combined results for all components showing risk scores (OF) for sample bridge components in unweighted (A) and weighted (B) models.

These results illustrate several important points. First, components that are rated CR ≥ 7 generally score much lower than components rated in CR 5. This is not surprising since the CR accounts for a large portion of the scoring, so two components with the same attributes in the risk model but different CRs will always score differently. But more importantly, components rated in CR ≥ 7 do not all score in the "*remote*" category, only 58% of components will score in that range based on the mean and sample standard deviation of these data. As shown in the figure, 42% of the components in CR ≥ 7 will be in the *low* or *moderate* category. These components are those with increased risk factors as identified by the individual RAPs, meaning that the models are sensitive to loading and design attributes, as well as other condition attributes such as joint condition. For example, if most of the attributes in the risk model were rated as *high*, the risk score will be in the *low* or even *moderate* range. In this way, the models are shown to be sensitive to changes in the attributes identified by the RAPs when applied to real bridges.

Considering the results quantitatively shows some important results from weighting the attributes C.1 and C.2. Based on the statistics from the sample bridges, the weighting increased the proportion of CR ≥ 7 components rated as *remote* from 41% to 58%, meaning most CR ≥ 7 components will be rated in the *remote* range, based on the statistical analysis. Recalling the risk matrix shown in Figure 1.5B, components with a *remote* OF have a 72-month interval if the CF was rated as *high*. For components in CR 5, the weighting had the effect of reducing the proportion of components rated as *low* from 24% to 17%, meaning that 50% of components in CR 5 will be rated in the *moderate* category and 33% will be rated in *high* category.

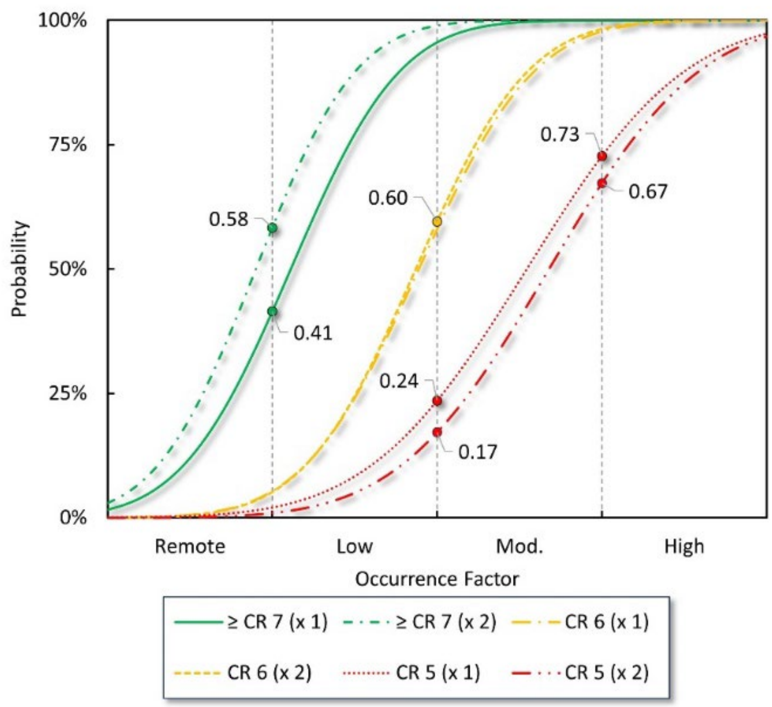


Figure 2.15. Cumulative probability distribution for all components showing results for the weighted and unweighted models.

Components that have CR 6 were essentially unchanged by the weighting. These data shown in Figure 2.15 indicate that 60% of randomly selected components will have risk scores in the *remote* or *low* range. This is consistent with the Method 1 policy that a bridge with components in CR 6 may be eligible for a 48-month inspection interval. In fact, those CR 6 components rated as *remote* could be eligible for interval of 72-months regardless of the CF and those rated as *low* could qualify for a 72-month interval if the CF was *moderate*, as shown in Figure 1.5B.

The results indicate the quality of the risk models was improved toward target ranges by increasing the weight of the primary condition attributes by a factor of 2 relative to the other attributes in the model. The data were analyzed in a similar manner for R/C decks and steel superstructures; these data are presented below. Similar results were found for PSC superstructures and R/C substructure components. Quantitative values for the mean and standard deviation for all components combined, and for deck, superstructure, and substructure components individually, are shown in a summary table at the end of the section.

2.5.2. Back-Casting Results – R/C Decks

The analysis of R/C deck risk scores was completed using data from all 60 bridges in the sample bridge population. The results of the risk scoring were analyzed to assess if the weighting process used with individual components such as the deck, superstructure, or substructure produced results that were consistent with the results from all components in the study combined that was presented in the previous section.

Figure 2.16A shows the results for unweighted R/C deck risk models with the risk scores presented as a bar chart and the normal distribution presented as a line plot. The results showed that analyzing components in good condition generally resulted in risk scores of less than 2.0, while risk scores for components in fair condition were greater than 1.0 and less than 3.0. The normal distribution curves illustrate that the mean value for CR ≥ 7 decks was in the range of *remote* (i.e., ≤ 1.0), CR 6 components were rated in the *Low* range, and CR 5 components were rated as *Moderate* in terms of the OF for the decks.

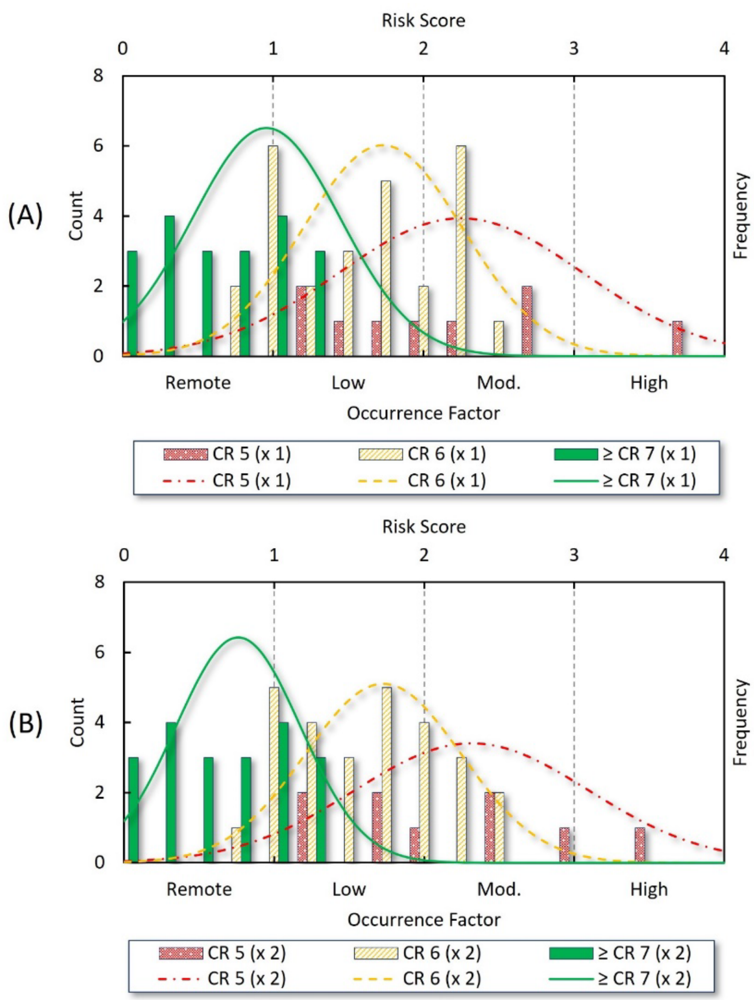


Figure 2.16. Back-casting results for deck components based on unweighted (A) and weighted (B) risk models.

The results from the weighted models are shown in Figure 2.16B. The effect of weighting was to increase the number of CR ≥ 7 deck components rated in the *remote* to *low* range and increase the number of CR 5 components rated in the *moderate* to *high* range for the OF.

The significance of weighting the risk models can be quantified by examining the cumulative distribution function based on the normal distributions shown in Figure 2.16. This cumulative distribution is shown in Figure 2.17. The effect of weighting the condition attributes in this manner was to increase the probability that a CR ≥ 7 component will be categorized as *remote* in term of the relative risk. For example, the unweighted model showed a 54% probability of a CR ≥ 7 component being rated in the *remote* OF category. Using the weighted model, the probability of being categorized as *remote* is increased to 72%. In other words, almost ¾ of deck components in good condition will be rated in the *remote* category. This is consistent with engineering judgement that most CR 7 decks are very unlikely to suddenly become CR 3 decks. Twenty-eight percent of the decks in CR ≥ 7 will be categorized as having a *low* likelihood of deteriorating to a CR of 3 in the next 72-month time interval.

On the other hand, deck components in CR 5 will have an increased risk of deteriorating to a CR 3 in the next 72-month interval, and this is shown in the data. About 19% of decks in CR 5 will be categorized as *high* for relative risk of deteriorating to a CR 3 in the next 72-month interval. Only 34% of CR 5 decks will be rated as having a *low* or *remote* OF.

The results are based on a relatively small number of data points – only 60 decks; however, they illustrate that the RAP models were effective in ranking bridges relatively and identifying those components with elevated risk. More precise "tuning" of the weights could be used to further delineate the relative risk levels. A methodology for analyzing bridges within a state inventory will be discussed in Chapter 3.

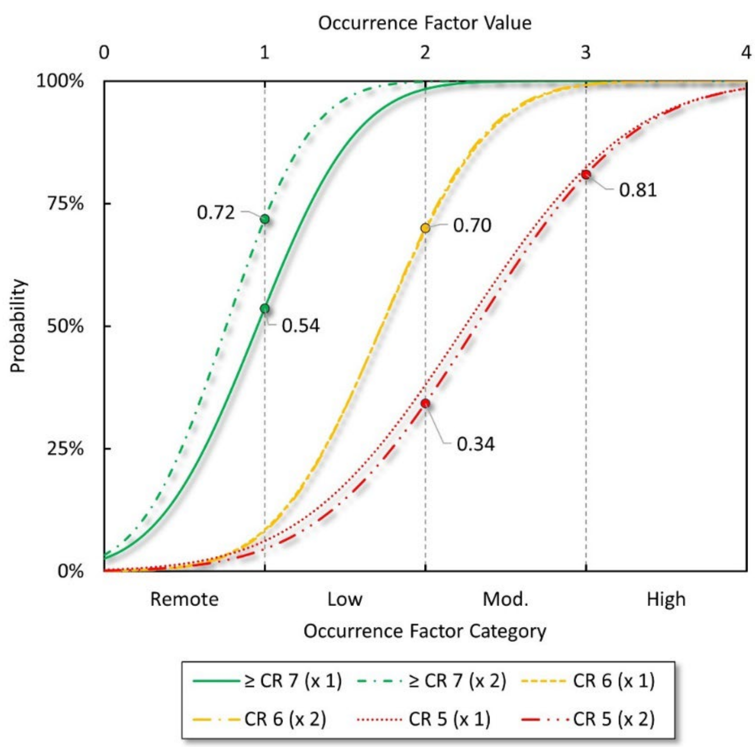


Figure 2.17. Cumulative probability distribution function for weighted and unweighted risk models for deck components.

2.5.3. Back-Casting Results – Steel Superstructure Corrosion Damage

The results for the damage mode of corrosion damage / section loss for steel superstructures were analyzed for the population of 40 steel bridges in the study. The results for the unweighted risk models are shown in Figure 2.18A and the weighted model results are shown in Figure 2.18B. Results for the steel superstructure corrosion / section loss model were similar to the results for decks and all components combined. The mean OF value for CR ≥ 7 steel superstructures in the unweighted models was in the *low* range. The mean value was reduced to the *remote* range when the risk models were weighted. The mean value for CR 6 steel superstructures was not significantly affected by the weighting, while the mean value for CR 5 steel superstructures was slightly increased.

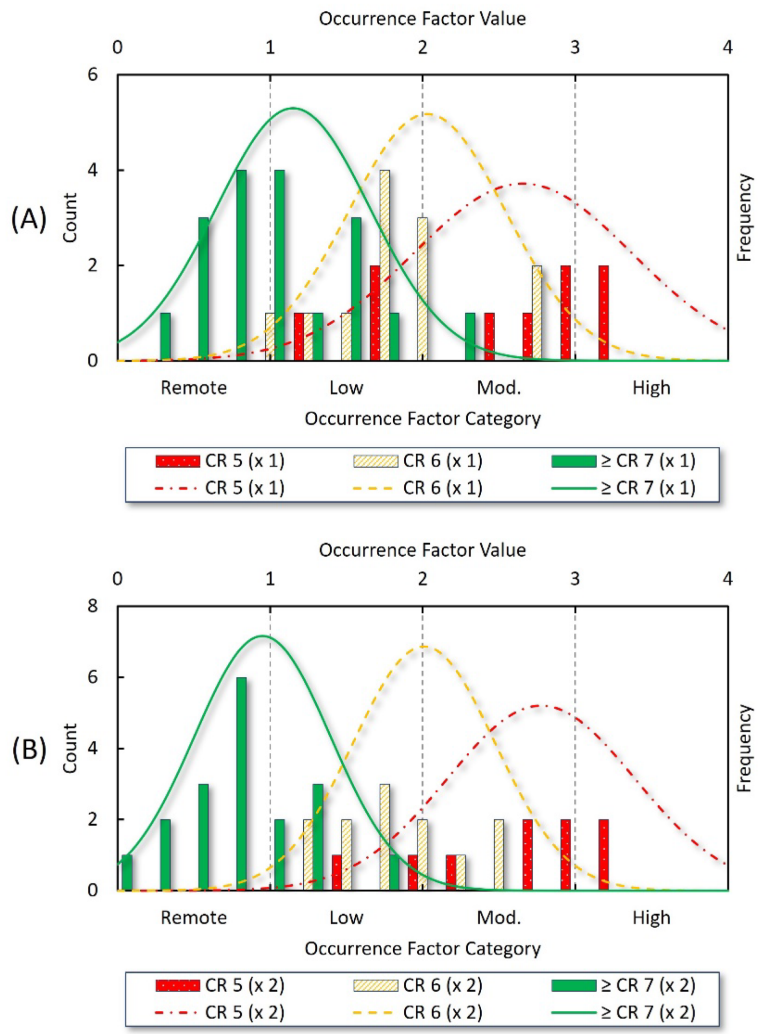


Figure 2.18. Back-casting results for steel superstructure components based on unweighted (A) and weighted (B) risk models.

The quantitative results are shown in Figure 2.19 with data labels showing key transitions between different OF categories. As shown in the figure, the weighting of the risk models increases the likelihood that a randomly selected CR ≥ 7 steel superstructure will be rated as *remote* from 38% to 54%. The weighting also has significant impact on CR 5 steel superstructures. In the unweighted model, the likelihood of a randomly selected steel superstructure being rated as either *moderate* or *high* is 82%, while in the weighted model that likelihood is increased to 90%.

The mean and standard deviation values from the analyses are shown in Table 2.8 for all of the components combined into one group and for R/C decks. Table 2.9 shows the results for steel superstructures, PSC superstructures, and R/C substructures. The results are presented with the mean value above the sample standard deviation (shown in parenthesis) for CR ≥ 7 components. Results from the unweighted models are shown in the first row of data and results from the weighted models are shown in the second row of data. The trends illustrated in the figures above are shown in the quantitative data in the table. For example, the mean values for CR ≥ 7 components were reduced by the weighting of the condition attributes of CR (C.1) and the CS (C.2), and the mean value for CR 5 components was increased. The sample standard deviations generally tended to be reduced for the weighted models as compared with the unweighted models.

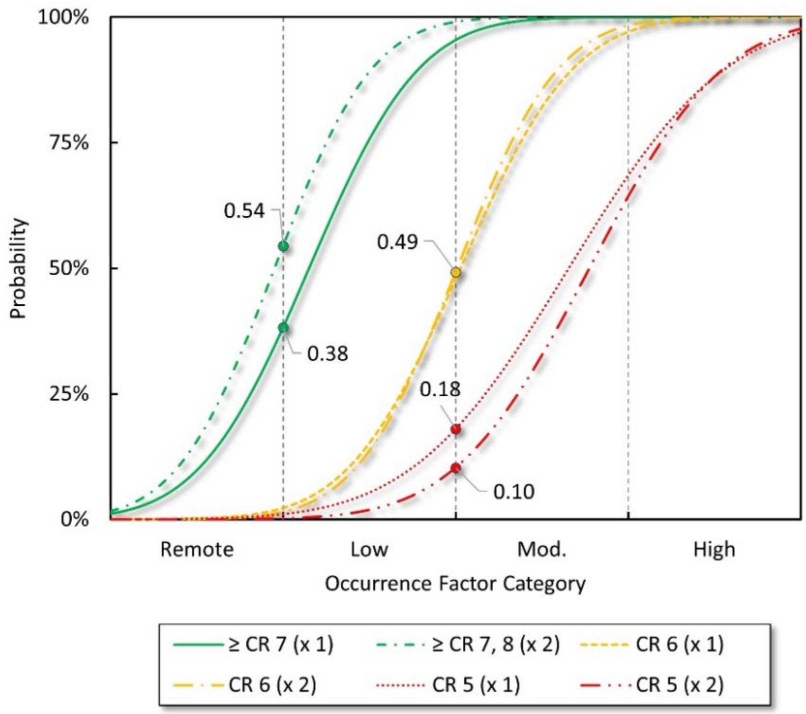


Figure 2.19. Cumulative distribution function for steel superstructure corrosion damage mode showing weighted and unweighted results.

For PSC superstructures, there was only a single CR 5 component in the sample bridge population, so statistics are not presented for CR 5 PSC superstructures. It is also notable that the PSC superstructure models indicate that most PSC superstructures will be in the *remote* OF rank even in the unweighted models, based on the statistical analysis.

The back-casting study provided data-driven analysis of the risk models developed by the RAPs applied to a population of 60 sample in-service bridges. However, the methodology of analyzing historical inspection records to analyze the effectiveness of the models was time consuming and arduous. Additionally, the unique nature of individual bridges requires a significant number of bridges to be analyzed to produce generalized conclusions; validating the accuracy of that conclusion is challenging. In order to calibrate risk models to meet the target values, a more efficient process was sought that provides a systematic methodology to test the risk models, assess the effects of changing the weight or number of attributes in the model, or assess the impact of different criteria used to rate the individual attributes. A systematic, data-driven method was developed to predict the outcomes from the risk models and support implementation of the RBI process.

Table 2.8. Table showing mean and standard deviation data for all components combined and R/C deck delamination and spalling damage mode.

Model	All comp CR ≥ 7	All comp CR 6	All comp CR5	Decks CR ≥ 7	Decks CR 6	Decks CR5
Unweighted Mean (Std. Dev.)	1.11 (0.52)	1.89 (0.55)	2.54 (0.75)	0.96 (0.49)	1.73 (0.53)	2.25 (0.81)
Weighted Mean (Std. Dev.)	0.90 (0.48)	1.87 (0.54)	2.68 (0.72)	0.76 (0.41)	1.73 (0.52)	2.32 (0.78)

Table 2.9. Table showing mean and standard deviation data steel superstructure, PSC superstructure, and R/C substructure delamination and spalling.

Model	Stl. Cor CR ≥ 7	Stl. Cor CR 6	Stl. Corr CR 5	PSC SS CR ≥ 7	PSC SS CR 6	Sub corr. CR ≥ 7	Sub corr. CR 6	Sub corr. CR5
Unweighted Mean (Std. Dev.)	1.15 (0.45)	2.03 (0.51)	2.66 (0.72)	0.88 (0.54)	2.06 (0.45)	1.31 (0.49)	1.96 (0.61)	2.86 (0.66)
Weighted Mean (Std. Dev.)	0.95 (0.45)	2.01 (0.46)	2.78 (0.61)	0.66 (0.45)	2.16 (0.42)	1.09 (0.49)	1.89 (0.60)	3.02 (0.68)

Chapter 3.
The Monte Carlo Approach

Monte Carlo simulation is a common method of analyzing multi-variable processes when there is uncertainty in the variables that form the input. The method uses probabilistic theories to combine the results from different input variables and provide a variety of outputs that are possible outcomes, given the probabilistic characteristics of the input. The method is frequently used in risk assessment when there is uncertainty in the parameters affecting the level of risk. This approach was used to develop a methodology for analyzing the potential outcomes of the risk models developed by the RAPs. The methodology allows the user to assess the criteria used in a risk model, assess the effect of applying the risk model to families of bridges with similar characteristics, and calibrate a risk model to produce results consistent with the target ranges described earlier in the report.

The structure of the MC simulations used in this research is illustrated if Figure 3.1. The process begins with a RAP developing a risk model that includes attributes and criteria for each attribute, shown as the RAP model in the figure. Probability distributions are then determined or estimated for each attribute to describe the likelihood of a given attribute being rated *very high, high*, *moderate*, or *low* according to the criteria from the RAP model. These data provide the input for the MC simulation.

The MC simulation produces values of 1 (*low*), 2 (*moderate*), 3 (*high*), or 4 (*very high*) that are distributed according to the probabilities inputted for each attribute. The simulation produces 30,000 different risk scores (i.e., OF values) based on these probabilities. This results in 10,000 separate risk scores for each CR (i.e., CR ≥ 7, CR 6, and CR 5). The output of the MC simulation describes the <u>likely</u> outcomes from implementing the risk models on a family of bridges. The steps to performing the MC simulations are relatively straightforward:

1. The RAP develops a risk model for a component that identifies attributes that have an impact on the POF, i.e., damage evolving to a point where a component is rated in serious condition (CR 3) during the next 72 months.
2. Criteria for each attribute are identified by the RAP based on engineering judgement. The criteria characterize the attribute's rating as *very high*, *high*, *moderate*, or *low* in terms of the attribute's impact on the POF.
3. The probability of each attribute being rated as *very high*, *high*, *moderate*, or *low* based on its criteria is calculated or estimated for the subject family of bridges being analyzed. The likelihood estimate can be made based on available bridge inventory data, estimates by an engineer or analyst, or by the RAP members through a Delphi process using questionnaires.
    a. If data is available from element-level inspection results, information in the bridge file, past inspection reports, or SNBI items, the conditional probability can be determined based on frequency. The probabilities should consider the CR of the component. For example, a deck rated in CR ≥ 7 has a different likelihood of having CS 3 quantities greater than 5% as compared with a deck rated in CR 5.
    b. If data is not available for the given attribute, probabilities can be determined based on point estimates. For example, a bridge owner is unlikely to have data recording the concrete cover of bridge decks. However, engineers familiar with the bridge inventory and the evolution of construction specifications in a state can estimate what <u>proportion</u> of inventory is <u>likely</u> to have low cover. Precision is not required, although obviously the higher quality the input data, the higher quality the output data. If the attribute

probabilities are deemed critical, a Delphi process can be used to elicit expert opinion from the RAP panel or other experts in a systematic way.

4. Perform MC simulations using the risk models and the attribute probabilities to determine the mean and standard deviation of the resulting data. The MC simulations use the probability data developed in step 3 for each attribute.
5. Based on the MC simulations, construct cumulative distribution curves to present the MC outputs graphically. These curves can be used to analyze the likely outcome from the applying the risk model to the subject family of bridges.

RAP model

Attribute	Rank	Criteria	Rating
Current Condition Rating	High	CR 5	High
		CR 6	Moderate
		CR 7	Low
Element Condition State	High	CS 3 ≥ 5% or CS 2 ≥ 20%	High
		1%≤ CS3 < 5% or 10% ≤ CS2 < 20%	Moderate
		CS 3 < 1% or CS 2 < 10%	Low
Joint condition	Moderate	DE 2360 ≥ 20% CS 3 / CS 4	High
		DE 2360 1% ≤ CS 3/CS 4 < 20%	Moderate
		DE 2360 CS 1 or CS 2, no CS 3	Low
Efflorescence/Staining	Low	DE 1120: CS 3 ≥ 20% or CS 2 ≥ 20%	High
		DE 1120: 1% ≤ CS 3 < 20% or 5% ≤ CS 2 < 20%,	Moderate
		DE 1120: CS 3 < 1% or CS 2 < 5%	Low
Average Daily Truck Traffic (ADTT)	Moderate	ADTT ≥ 5000 or ADT≥16,000	High
		1000 ≤ ADTT < 5000 or 7500 ≤ ADT < 16000	Moderate
		ADTT < 1000 or ADT < 7500	Low
Rate of De-icing Chemical application	Low	Interstate / NHS or ADT ≥ 16,000	High
		ADT between 7500 & 16,000	Moderate
		Local, Low ADT ≤ 7500	Low
Corrosion Protection Level	Moderate	CP1	Very High
		CP2	High
		CP3	Moderate
		CP4	Low

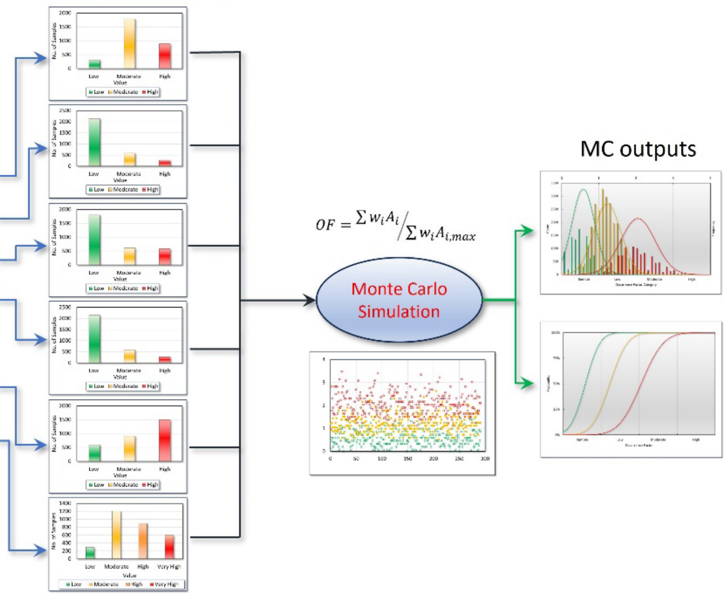


Figure 3.1. Schematic of the MC simulation process applied to a risk model.

The results produced from the MC simulation were found to be a powerful tool that enables several different critical tasks for developing effective risk models:

1. Calibration of the risk models to determine the appropriate weights for individual attributes to meet target ranges.
2. Comparing risk model results for components of different CRs.
3. Conducting sensitivity studies to assess the thresholds used for the criteria for each attribute.
4. Analyzing the outcome of applying the risk models to bridge families or portions of bridge families with similar characteristics.
5. Predict the impact of an extended inspection interval policy on a bridge inventory.

For example, MC simulations can be used to show the effect of weighting the condition attributes of CR and CS as compared with weighting attributes like ADT or Rate of Deicing Chemical Application. The MC simulations also provide simple illustrations of how bridge components with different CRs compare one to another.

The outcome from applying risk models to bridges of the same family, but with different characteristics, can also be assessed using the MC simulation approach. For example, MC simulations can be used to compare how the RAP model will rate a population of bridges with high ADT as compared to a population of bridges with low ADT. The following section provides an example of MC simulation results for a bridge deck to illustrate the process and the analysis that can be conducted using this approach.

3.1.1. Example Bridge Deck MC Simulation

The process illustrated in Figure 3.1 was used to analyze a model for R/C decks to illustrate how the overall process works. Table 3.1 shows a risk model developed by a RAP for delamination and spalling in a typical R/C deck on a steel superstructure in Wisconsin. There are nine attributes identified by the RAP, including CR, CS, joint condition, etc. For each attribute, the RAP identified criteria that describe a quantity or condition that would indicate an increased impact on the POF. For example, for attribute C.2, Current Element CS, if a deck had a wearing surface (Element 510) with > 10% CS 3 damage OR a deck (Element 12) with > 5% CS 3, it would have *high* impact on the POF.

Table 3.1. Example deck risk model with 9 attributes.

Attribute	Rank	Criteria	Rating
C.1, Current condition rating	High	CR 5 CR 6 CR ≥ 7	High Mod. Low
C.2, Current Element CS or Plow damage	High	Deck Surface (El. 510) CS3 > 10%, or El. 12 > 5% Deck Surface (El. 510) CS3 1 – 10%, CS2 ≥ 15%, or 1% ≤ El. 12 ≤ 5% Deck Surface (510) CS 1 or CS2 < 15%, CS 3 < 1%, El. 12<1%	High Mod. Low
C.13, Efflorescence/Staining Deck Soffit	High	Deck Element Soffit > 5% Deck Element Soffit 1% ≤ CS3 ≤ 5% Deck Element Soffit < 1%	High Mod. Low
L. 1A Average Daily Traffic	High	ADT ≥ 20,000 ADT 10,000 – 19,999 ADT < 10,000	High Mod. Low
L.5 Rate of Deicing Chemical application	High	Interstate / Urban or ADT > 10,000 Rural, Non-Interstate, 2,000 < ADT < 10,000 Rural, Non- Interstate, ADT < 2000	High Mod. Low
L.2, Dynamic Loading from riding Surface	Mod.	Dynamic forces increase rate of deterioration (ADE 9324 CS4) Dynamic forces not a significant consideration	High Low
D.4/C.7 Poor Deck Drainage and Ponding /Quality of Deck Drainage	High	Element 9004 Deck Drainage: CS 3 or open rails Element 9004 Deck drainage: CS 2 Element 9004 Deck drainage: CS 1	High Mod. Low
D.29/C.30, Corrosion Protection Level	High	CP1 CP2 CP3 CP4	V. High High Mod. Low
C.29 NDE Applied	High	Non- NDT The bridge is subject to NDT	High Low

For each attribute in the model, an estimate of the likelihood of that attribute being rated as *high*, *moderate*, or *low* was produced from either bridge inventory data or engineering judgement. Most attributes were estimated from bridge inventory data. For example, considering the attribute C.2, Element CS, data for NHS bridges in the subject state were analyzed to determine the probability of a CR ≥ 7 deck on a steel bridge meeting the *high* criteria, meaning that the wearing surface element (Element 510) has more than 10% CS 3 or the deck element (Element 12) has more than 5% CS 3. Probabilities were determined for the *high*, *moderate*, and *low* criteria for deck components in CR ≥ 7, CR 6, and CR 5 as shown in Table 3.2. Calculated probabilities were obtained from a simple frequency analysis – i.e., counting the number of decks on steel bridges in CR ≥ 7 that met the *high* criteria and dividing by the total number of CR ≥ 7 decks on steel bridges. The probabilities are different for CR ≥ 7, CR 6, and CR 5 decks as would be expected. As shown in Table 3.2, CR ≥ 7 decks have a zero or near – zero probability of meeting the high criteria based on historical data. Deck components rated in CR 6 have a 2% likelihood meeting the criteria while deck components rated in CR 5 have a 14% chance.

Table 3.2. Example probability table for attribute C.2, Current element condition state.

Criteria	Rating	CR ≥ 7	CR 6	CR 5
Deck Surface (El. 510) CS3 > 10%, or El. 12 > 5%	High	0%	2%	14%
Deck Surface (EL. 510) CS3 1 – 10%, CS2 ≥ 15%, or 1% ≤ El. 12 ≤ 5%	Mod.	10%	23%	42%
Deck Surface (510) CS 1 or CS2 < 15%, CS 3 < 1%, El. 12<1%	Low	90%	75%	44%

It should be noted that this probability analysis was completed using Microsoft Excel and existing data from the NBI (https://infobridge.fhwa.dot.gov/) and the FHWA NHS element-level data (https://www.fhwa.dot.gov/bridge/nbi/element.cfm). Most bridge owners will have internal databases used for asset management that contain these data.

For data that were not available from inventory or element-level data, point estimates were used. For example, data for attribute C.13, Efflorescence / Staining of the deck soffit was not available, so the probabilities were estimated based on engineering judgement. Most CR ≥ 7 decks are unlikely to have significant soffit damage while a significant proportion of CR 5 decks may have soffit damage. A conservative point estimate was made of the probability of a bridge deck meeting the *high*, *moderate*, or *low* criteria as shown in Table 3.3. It was estimated that 3% of decks rated in CR ≥ 7, 5% of CR 6 decks, and 20% of CR 5 decks may be rated as *high*.

Table 3.3. Probability estimate used to describe C.13, Efflorescence/staining for bridge decks.

CR ≥ 7 (%) [H / M / L]	CR 6 (%) [H / M / L]	CR 5 (%) [H / M / L]
[3 / 7 / 90]	[5 / 10 / 85]	[20 / 20 / 60]

Estimates for each attribute were developed from inventory data or by engineering estimate. The probability values provided the input data for the MC simulations.

Example results for the MC simulation are shown in Figure 3.2A and Figure 3.2B. Figure 3.2A shows the probability distribution from the MC simulation based on the risk model shown in Table 3.1. The bar chart illustrates the number of MC simulations resulting in the value represented by each column or bar. The line plot shows the probability distribution function based on the mean and standard deviation of the data represented in the bar chart. As shown in the figure, the MC simulations produce normally distributed results represented by the bar chart and modeled by the line plot. From these data, the cumulative probability distribution was determined as indicated by the arrow in the figure.

Figure 3.2B shows three cumulative distribution curves produced from the data shown in Figure 3.2A. The cumulative probability distribution curve quantifies the probability of a randomly selected deck being rated as having *remote*, *low*, *moderate*, or *high* OF based on the simulation. For example, the data shows that about 76% of CR ≥ 7 decks will be assessed as having *remote* likelihood and ≈24% will be assessed as *low*. Approximately 31% of deck components rated as CR 6 will be rated as *remote* with most others rated as *low*. Deck components in CR 5 will be assessed as *low* or *moderate*. In this way the MC results shown in Figure 3.2B quantify the likely outcomes from the risk model being applied to a population of actual bridges with characteristics typical of the bridge population on which the analysis is based.

Components that present uncommonly high POF as compared with typical bridges are not captured by the MC simulations because their attributes do not match the typical values used to form the model. For example, a deck rated in CR 7 with more than 5% CS 3 damage would be unusual and would have an increased risk as compared with typical CR 7 decks. The damaged deck is captured by the risk model but is not included in the MC simulation, as will be discussed in the following section.

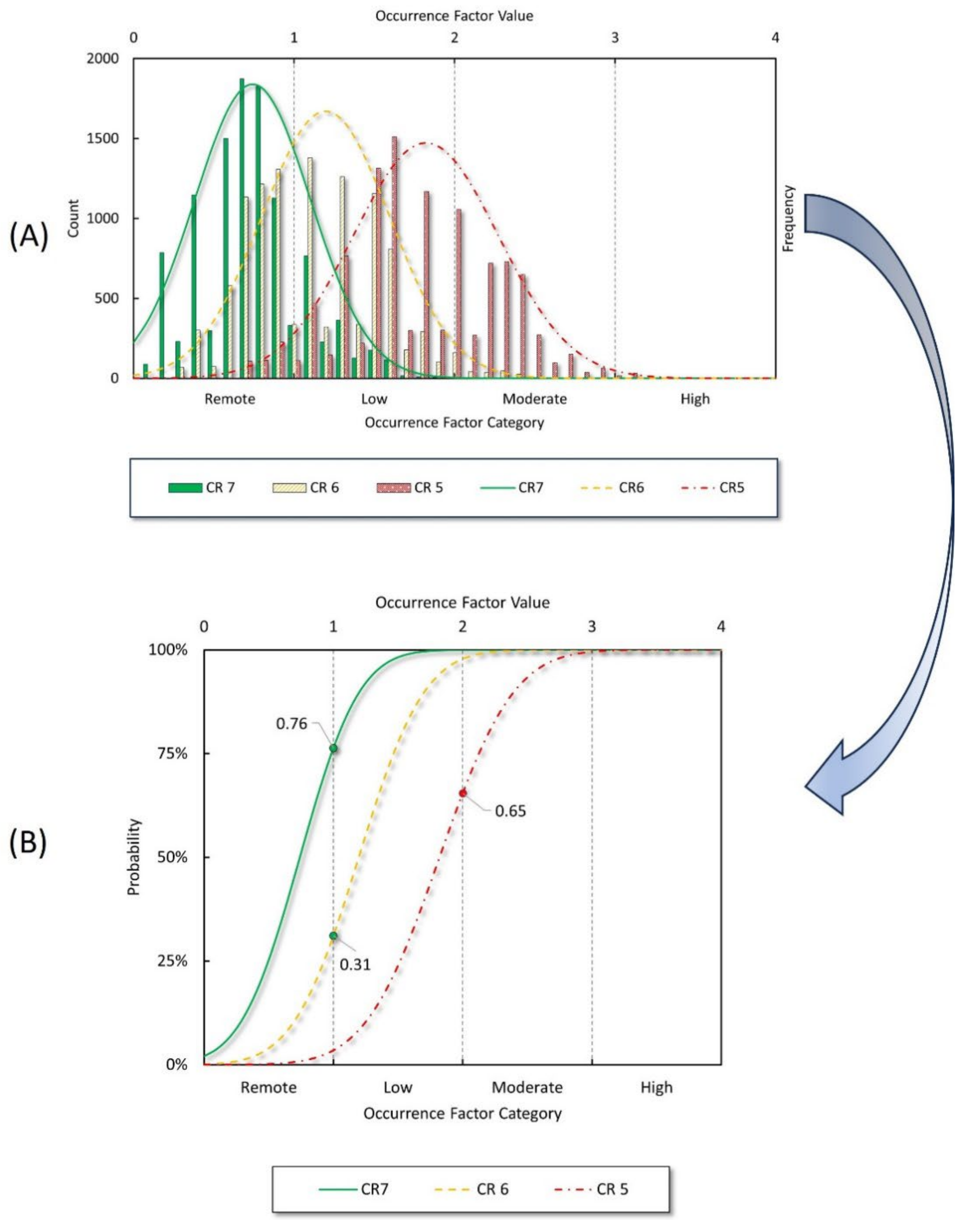


Figure 3.2. Example MC simulation results for CR ≥ 7, CR 6, and CR 5 bridge decks showing probability distribution (A) and the cumulative probability distribution (B).

3.2. Identifying Components with Elevated Risk

The foundation of the MC simulation uses the typical attributes found in the bridge inventory and the associated probabilities such that the MC outcome reveals typical results. In this way the bridge owner can assess what the typical results will be for a given family of bridges, but *not the specific results for an individual bridge*. For example, it is unlikely that a bridge deck with CR 7 will have more than 5% CS 3 damage, as previously mentioned. But if that were the case, then the score may be higher than any values predicted by the MC simulation.

For example, consider a bridge deck with different levels of actual damage or potential for damage using the risk model shown in Table 3.1. The damage in the deck is described by the condition attributes C.1, Current Condition Rating, C.2, Element Condition State, and C.13 Efflorescence/Staining. The <u>potential</u> for damage is described by the loading and design attributes such as ADT, Rate of Deicing Chemical Application, Poor Deck Drainage, etc. Three different scenarios are shown in Table 3.4.

Scenario 1 presents a deck with current damage and relatively low potential for future damage. Scenario 1 is a deck with more than 5% CS 3 damage in the deck element, damage in the soffit of the deck, low ADT, a low rate of deicing chemical application, typical corrosion protection (i.e., ECR with normal cover, CP 2), good deck drainage, and NDT testing applied to the deck.

Scenario 2 is a deck without current damage in the deck or soffit, but with other attributes that indicate the potential for damage is increased as compared with other decks. For this case, the CS attribute C.2 is rated as low, there is no damage in the soffit of the deck, but the deck is exposed to high ADT, high rate of deicing chemical application, poor deck drainage, and no NDT testing.

Scenario 3 illustrates a deck with <u>*both*</u> current damage to the deck and high potential for damage. Scenario 3 includes CS 3 damage of greater than 5% in both the deck and the soffit, high ADT, high rate of deciding chemical application, and poor deck drainage.

The resulting OF values calculated from the risk model for each scenario are listed in Table 3.4 and shown graphically in Figure 3.3. As these data show, a deck in CR 7 with damage in the deck scores in the *low* OF range (1.33). For scenario 2, where the potential for damage is high but damage has not yet occurred, OF values are also rated in the *low* range (1.96), but any damage in the deck pushes that result from *low* to *moderate*. For deck components with both current damage in the deck AND attributes that indicate a high potential for deterioration, a CR 7 component scores in the *high* range. These values are increased for a CR 6 and CR 5 decks.

Table 3.4. Example scenarios for decks with damage and the resulting OF values.

Scenario No.	Scenario Description	CR ≥ 7 (OF)	CR 6 (OF)	CR 5 (OF)
1	Deck with CS 3 > 5% damage in deck and soffit, no efflorescence or staining, low ADT, low rate of deicing chemical application, good deck drainage, no dynamic loading, and NDT applied.	1.33	1.69	2.04
2	Deck without deck or soffit damage, high ADT, high rate of de-icing chemical application, poor deck drainage, dynamic loading on deck, and no NDT applied	1.96	2.31	3.38
3	Bridge deck with CS 3 > 5% damage in deck, soffit damage, High ADT, high rate of deicing chemical application, dynamic loading on deck, poor deck drainage, and no NDT	3.02	3.38	3.73

Figure 3.3 shows the cumulative probability distribution curves based on the conditional probabilities for each attribute for a deck in CR ≥ 7, CR 6, and CR 5. The results for the three different scenarios are shown as individual points on the figure with the ordinant values chosen arbitrarily to provide clarity in the figure. The points are color-coded to indicate the CR of the deck as CR 7 (green), CR 6 (yellow), or CR 5 (red).

Values for decks in CR 7 are shown with data labels. As shown in the figure, the original MC simulation that produced the curves did not predict any CR 7 bridges would score in the *moderate* or *high* range, with most CR 7 decks being assessed in the *remote* range. This is because the likelihood of a CR 7 deck having a significant amount of CS 3 damage is small given the typical probabilities for the overall inventory of bridges. However, were the deck to be atypical and have significant damage (i.e., scenario 1), the OF value is increased.

If the potential for damage is high (i.e., scenario 2), the OF value is also increased. For scenario 2, the OF value for the CR 7 deck is 1.96, a value greater that any predicted by the MC simulation. This is due to the low likelihood that all attributes associated with the potential for damage would be rated as *high* for an individual deck. Regardless of the likelihood of this situation, the risk model assesses the elevated risk associated with the high potential for damage.

The highest OF scores are obtained when the deck has both damage and high potential for damage (i.e., scenario 3). For scenario 3, the OF for the CR ≥ 7 deck is elevated to 3.02, indicating a *high* relative likelihood of failure. For all three scenarios, the OF values for decks rated in CR 6 and CR 5 are also elevated as would be expected.

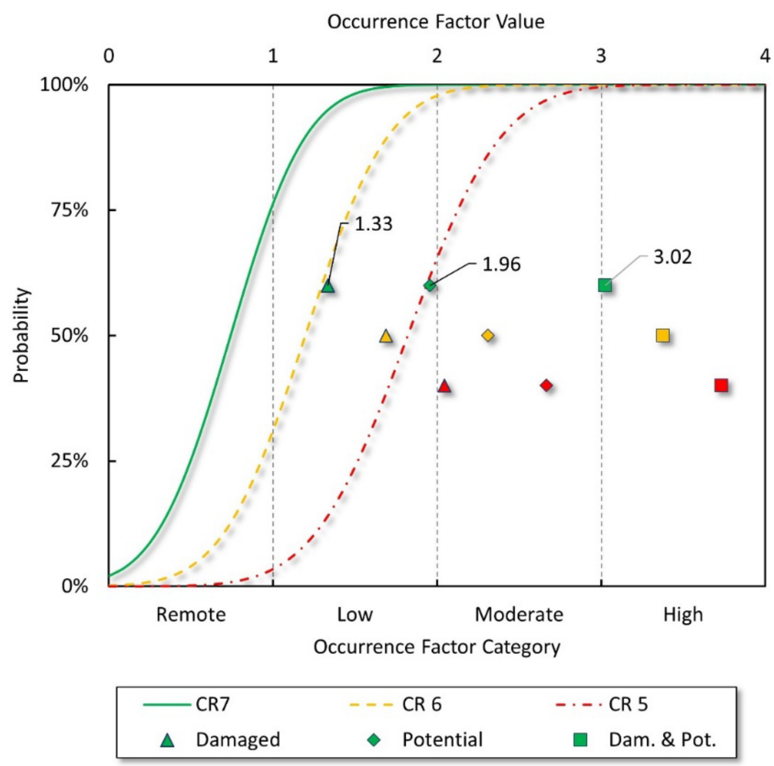


Figure 3.3. Results for different damage scenarios plotted with MC simulation results.

This example illustrates the objective of the risk model to identify the increased risk that may be present if there is atypical damage (scenario 1), atypical potential for damage (scenario 2), or both (scenario 3). In this way, the example illustrates the approach of using a MC simulation to produce expected or typical results for a family of bridges. The atypical component with unusually high damage or potential for damage can be identified because its risk score is greater than would be expected for the typical bridge represented by the MC simulation. When applied to actual bridges where a CR ≥ 7 deck is expected to have a *remote* OF, a bridge with atypical characteristics is appropriately assessed as having increased risk as indicated by the OF being categorized by *low*, *moderate*, or *high*. The example illustrates how the MC simulation can be used to identify those bridges that present *elevated risk and require shorter inspection intervals* and those that *do not have elevated risk. This is precisely the objective of the risk analysis.*

Different scenarios can be studied probabilistically using the MC simulations by setting certain probabilities at 100%. To illustrate this feature, five scenarios were considered as shown in Table 3.5. The analysis considers the original MC model with typical probabilities for attributes. Three scenarios consider increasing levels of damage with the deck element having CS 3 > 5%, both the deck and the deck soffit having CS 3 > 5%, finally the deck and soffit having CS 3 > 5% and high ADT. Finally, a scenario is considered in which the attributes other than condition are rated *high*.

Table 3.5. Scenarios for probabilistic analysis of a risk model for decks.

Scenario No.	Scenario Description
1	CR ≥ 7 deck with original probabilities for attributes, deck CS 1, typical ADT
2	CR ≥ 7 deck with deck element (El. 12) CS 3 > 5%, soffit CS 1, typical ADT
3	CR ≥ 7 deck with deck element (El. 12) CS 3 > 5%, soffit damage CS 3 > 5%, typical ADT
4	CR ≥ 7 deck with deck element (El. 12) CS 3 > 5%, soffit damage CS 3 > 5%, and high ADT
5	CR ≥ 7 deck with deck element (El. 12) CS 1, soffit CS 1, high ADT, high deicing, high ponding, dynamic loading and no NDT

The results of this analysis are shown in Figure 3.4. The figure shows only results for CR 7 decks for clarity. As the damage in the deck increases, the distribution curve is shifted to the right such that when CS 3 damage is present at a level of greater than 5% in the deck, only about 12% of decks will be rated in the *remote* range. If there is damage in both the deck and the soffit, most CR 7 decks will be rated as *low* with ≈33% being rated in the *moderate* range. Finally, if the deck was also exposed to high ADT, most of the CR 7 decks will be rated in the *moderate* range (≈67%). The figure also shows the results of having CS 1 in the deck and soffit, but attributes that address the potential for damage are rated *high*. This scenario considers a deck with high ADT, high deicing chemical application, poor deck drainage, dynamic loading on the deck, and no NDT applied. This scenario is labeled as “High potential for damage” in the figure. Most decks with these precursors to damage will be rated in the *low* category (67%).

These examples illustrate how the MC simulations based on conditional probabilities for the attributes identified by the RAP form a model that can be used to analyze the results of applying risk models to a population of bridges. However, risk models can have different numbers of attributes, and the attributes can have different relative weights. To make the MC simulation procedure described above practically implementable, an understanding of the sensitivity of the process is needed so engineers can analyze the way in which the number of attributes in the model affect the outcome. The following section presents a parametric study of the effect of the number of attributes has on the outcome of the MC simulation process.

3.3. Example MC Simulation for R/C Decks

This section presents the application of the MC simulation process to the example risk model developed for bridge decks shown in Table 3.1. The section describes the different steps in producing the MC simulation in terms of obtaining probabilities to describe the attributes and examples of how the MC simulation can be used to analyze different scenarios such as comparing how the risk model will assess high ADT bridges as compared with low ADT bridges.

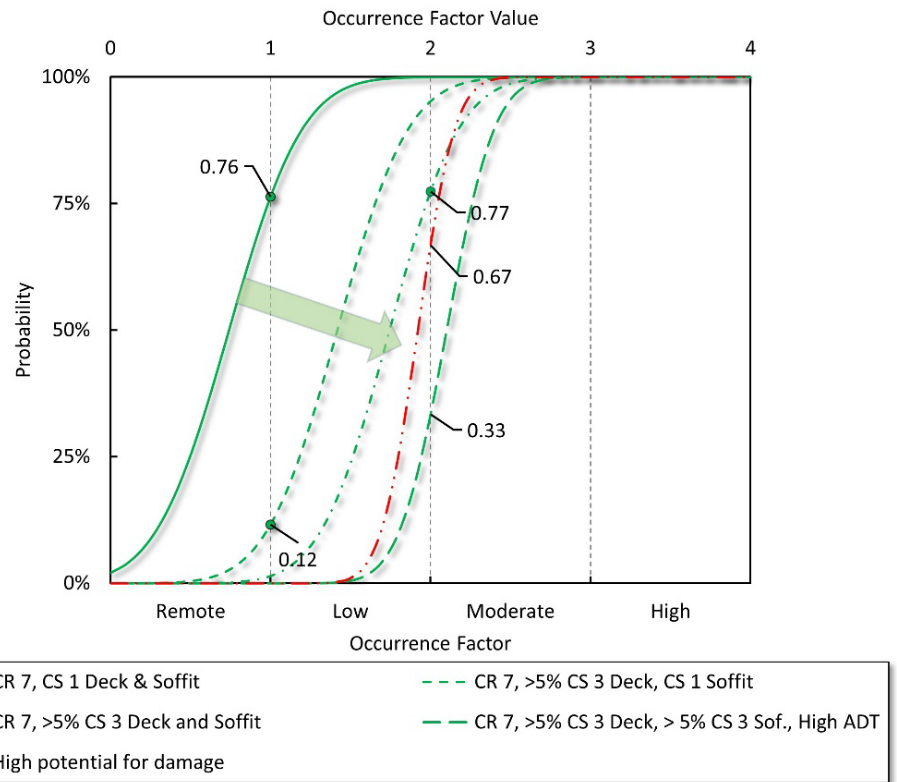


Figure 3.4. MC simulation results for decks with increasing levels of damage as shown in Table 3.5.

The different deck risk models developed by the RAPs under the project shared many common attributes such as the CR and CS, rate of deicing chemical application, and ADT. The Wisconsin model was unique in having an attribute to consider the reduced risk from performing nondestructive testing (NDT) as part of the condition assessment of the deck. Performing NDT on the deck provides additional insight on the condition of the deck by detecting subsurface damage not observable in a routine visual inspection. The attribute in the risk model represents this effect by reducing the overall risk score, and the MC simulation was used to assess how including this attribute in the risk model affects the likelihood of a CR 7 deck being rated in the *remote, low, moderate, or high* OF category.

3.3.1. Assessment of Probabilities

As previously mentioned, bridge inventory data and element level inspection results can be used for many of the attributes listed in the risk models to determine the probabilities for each attribute. For situations where there is no available data for a given attribute, engineering judgement can be used. In addition, the interaction or coupling of different attributes must be considered when estimating the probabilities for different criteria. For example, if ADT values are used for more than one attribute in a model, these attributes may be coupled. If ADT is part of the criteria for rating the increased deterioration rate that may result from high traffic volumes, and ADT is part of the criteria for rating the application of deicing chemicals, the attributes are coupled because ADT levels will affect the rating for both attributes. The algorithms within the MC simulation need to be appropriately adjusted to consider the coupling of the ADT attribute and the Rate of Deicing Chemical Application attribute. For example, when bridges with ADT > 10,000 vehicles per day (vpd) are rated as *moderate* for the attribute L.1, ADT, then the Rate of Deicing Chemical Application is also rated as *high.* The MC models must consider this interaction to produce a reliable result.

3.3.2. RC Bridge Deck Attribute Probabilities

An analysis of RC bridge decks was conducted based on the Wisconsin risk model shown previously in Table 3.1. The risk model included nine attributes. Most of the attributes were rated on a *low*, *moderate*, and *high* rating scale. There were two attributes what were rated on a high-low basis. Bridge decks subjected to dynamic loads resulting from the "bump at the end of the bridge" were rated as either high or low. Additionally, there was an attribute to assess the reduction in risk from performing NDT of the deck as part of the condition assessment.

The element-level data for NHS bridges were analyzed to estimate probabilities for attributes in the risk model. The attribute C.2, Element Condition State included both the deck element (Element 12) and the wearing surface (Element 510). The data for NHS bridges were used to provide estimates of the probabilities of a randomly selected deck being rated as *high*, *moderate*, or *low*. The analysis utilized criteria for the deck element (Element 12) and the wearing surface element (Element 510) as shown in Table 3.2. For the rating of *high*, the deck element had a threshold of greater than 5% in CS 3, while the wearing surface element had a threshold of 10%.

3.3.2.1. Average Daily Traffic Analysis

The ADT values for the state of Wisconsin were determined from an analysis of the 2022 NBI data. The analysis considered state-owned bridges to provide a conservative estimate of traffic levels, since state – owned bridges will typically have the greatest number of vehicles as compared with locally owned bridges. The NBI data for Wisconsin were analyzed for bridges with steel superstructures specifically. To conduct the analysis, the NBI data was reduced to only those bridges with steel superstructures and basic configurations (stringer, stringer and floor beams, and box beams). For bridge decks, there were two attributes that considered the ADT levels in the analysis. Loading attribute L.1, ADT, considered bridges with ADT of 20,000 vehicles or more as *high*, and vehicles with 10,000 – 19,999 as *moderate*. This attribute represents the increased rate of damage accumulation that tends to accompany high ADT levels. The attribute L.5, Rate of Deicing Chemical Application, considers the ADT level and if the bridge is located in an urban area or on an Interstate. Bridges with ADT > 10,000 vpd or located on Interstates or in urban areas are ranked as *high*, non-interstate bridges with ADT of between 2,000 and 10,000 vpd are rated as *moderate*, and less than 2,000 are rated as *low*.

These attribute criteria are not independent, and therefore, the relationship between the attribute criteria needed to be considered for the MC simulation. If a bridges' ADT levels were identified as *high* or *moderate* for L.1, that same bridge would have to be defined as *high* for L.5. Therefore, the only variability for attribute L.5 was at the *moderate* or *low* ranks, and as such the appropriate probabilities were calculated based on the total number of bridges with less than 10,000 ADT. The probability values used for bridges with an ADT of less than 10,000 vpd are shown in bold in Table 3.6.

To address the requirement for L.5 that any interstate or urban roadway should be rated as *high* and any bridge with >10,000 vpd should also be rated *high*, a more detailed study of the ADT values was completed. To estimate the number of bridges that could be characterized as an interstate or urban bridge, the NBI Item 26, Functional Classification of Inventory Route, was analyzed. The values of NBI Item 26 were considered to determine those bridges associated with "Principal Arterial – Interstate, Principal Arterial-Other" for both urban and rural areas, as well as "Other Principal Arterial" and "Minor Arterial" indicated as "Urban."

Table 3.6 lists the probabilities based on ADT data to assess if a given bridge should be rated according to L.1 and L.5 for the MC Simulation. A simple "if" statement was used to define L.5 based on L.1, meaning that L.5 was *high* if L1 was defined as *moderate* or *high.* Among the remaining bridges, it was determined that the likelihood of a given bridge being less than 10,000 ADT and being an interstate/urban bridge meeting the definition of L.5 *high* rating was 39%, and the likelihood of the rating of *moderate* and *low* was 24% and 37%, respectively.

Table 3.6. Values for ADT used for bridge deck analysis for WI.

ADT Level	Rank	Probability (%)	L.5 -L.1 (%)
ADT≥20,000	High	20	-
ADT 10,000 – 19,999	Moderate	22	-
ADT <10,000	Low	58	-
Interstate / Urban or ADT>10,000	High	65	**39**
Rural, Non-Interstate, 2,000<ADT<10,000	Moderate	16	**24**
Rural, Non- Interstate, ADT<2,000	Low	22	**37**

3.3.2.2. Point Estimates

Probabilities to describe the criteria of the attributes can be determined from existing bridge inventory data in many cases, but there are other cases where the data may not be available. For these cases, an engineering estimate is needed to determine the probabilities. This section describes some of the estimates made in analyzing the deck risk model to illustrate estimating probabilities based on engineering judgement.

There were several attributes in the risk model that did not have data available in the NHS bridge element database. This included C.13, Efflorescence / Staining, C.7, Quality of Deck Drainage System, D.29/C.30, Corrosion Protection Level, L.2, Dynamic Loading from Riding Surface, and C.28, NDE Applied to Component. For these attributes, engineering estimates were used to provide input data for the MC simulations.

A point estimate based on engineering judgement was used for the attribute of efflorescence and rust staining. The Manual for Bridge Element Inspection (MBEI) describes efflorescence with rust as CS 3, and consequently this definition was applied here. It was assumed that the likelihood (i.e., probability) of efflorescence with rust staining on the deck soffit will vary based on the CR of the deck component. It was deemed unlikely that a deck rated in CR 7 will have efflorescence with rust staining. The attribute criteria indicated that the rating of *high* for this attribute was defined as having greater than 5% of the deck soffit assigned CS 3 (CS 3 > 5%). The rating of *moderate* was defined as 1% to 5% of the deck soffit (1% ≤ CS 3 ≤ 5). Since it is unlikely that a CR 7 deck will have a significant amount of rust-stained efflorescence on the deck soffit, it was estimated that not more than 3% of CR 7 decks were likely to meet the criteria to be rated *high* and not more that 7% were likely to be rated as *moderate.* The resulting probability vector was [3, 7, 90]. The estimated values are represented by a bar chart shown in Figure 3.5A. Efflorescence with rust staining is more likely for CR 6 bridges, but still relatively uncommon, and it was estimated that not more than 10% of CR 6 decks had a significant amount of CS 3 efflorescence with rust staining. It was estimated that 5% of the population of CR 6 components would be rated as *high* and 10% would be rated *moderate*, and the resulting probability vector was [5, 10, 85]. For CR 5 deck components, it was assumed that up to 40% of this population might have some efflorescence in CS 3, but no more than 20% were likely to be affected at the *high* level and no more than 20% at the *moderate* level.

For corrosion protection level, it was assessed that only a small portion of the existing inventory of bridges would have low cover or bare reinforcing steel and no overlay or other corrosion protection. It was assumed that 5% of the inventory might be CP 1. A significant portion of the inventory is likely to have either normal cover with ECR and be rated as CP 2, or normal cover, ECR, and an overlay, and be rated CP

3. There would only be a small portion of the inventory that had ECR, normal cover, an overlay, and a sealer applied (i.e., CP4). It was assumed that the CP level was not a function of the CR for the component. Therefore, the distribution of [5, 40,45,10] shown in Figure 3.5B was assumed for this attribute for CR 7, 6, and 5 deck components.

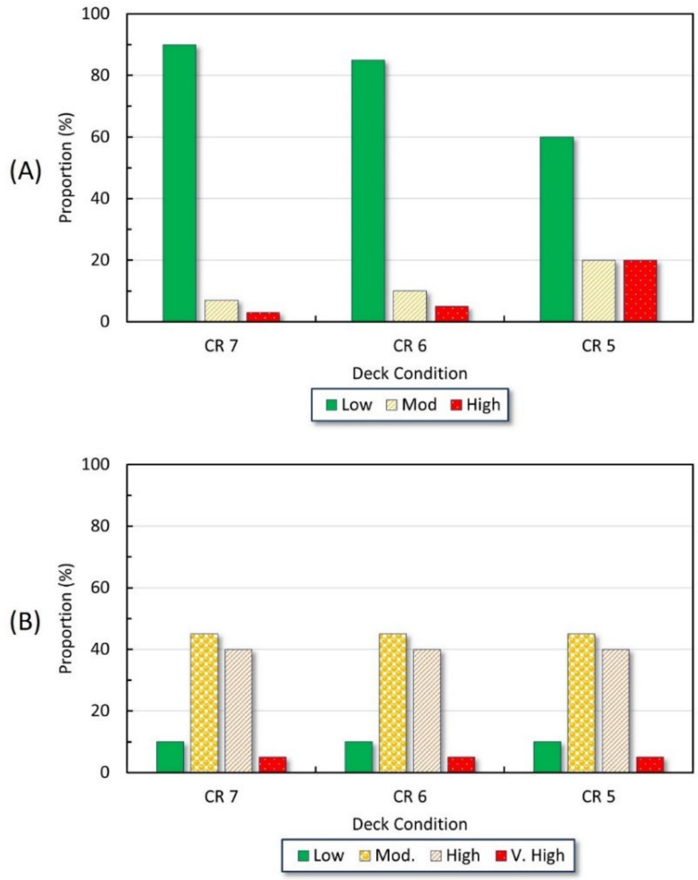


Figure 3.5. Probability distribution estimates for the attributes of efflorescence and staining (A) and corrosion protection level (B).

Similar estimates were made for C.7., Quality of Deck Drainage System, L.2, Dynamic Loading from Riding Surface, and C.29, NDE Applied to Component. Table 3.7 lists the probability values used for the analysis of the bridge deck risk model for Wisconsin. The MC simulations were conducted separately for CR 7, CR 6, and CR 5 components.

The probabilities shown in Table 3.7 were used to perform MC simulations to determine the effect of weighting the condition attributes. Considering that the MC simulation is run for CR 7, CR 6, and CR 5 bridges separately, with 10,000 models for each condition rating, the effect of weighting the condition attributes differently was studied using different potential weighting schemes and the effect on the resulting average value derived from the simulations. The condition attributes were the focus of the study for two reasons. First, the results from the back-casting illustrated that different weights for the condition attributes generally improved the quality of models based on the assumption that risk will increase as the CR for a given component decreases. Second, from a practical standpoint, it would be expected that actual damage represented by the condition attributes will have a more significant effect on the relative risk as compared with a loading attribute or a design attribute, each of which may contribute to rate of deterioration.

Table 3.7. Table showing probability values for MC Simulation for bridge decks in WI.

Att. No.	Att. Name	CR ≥ 7 (%) [H/M/L]	CR 6 (%) [H/M/L]	CR 5 (%) [H/M/L]
C.1	Current Condition Rating (fixed)	[0/0/100]	[0/100/0]	[100/0/0]
C.2	Current Element CS or plow damage	[0/10/90]	[2/23/75]	[14/42/44]
C.13	Efflorescence / Rust Staining	[3/7/90]	[5/10/85]	[20/20/60]
L.1	ADT	[20/22/58]	[20/22/58]	[20/22/58]
L.5	Rate of Deicing Chemical Application	[65/16/22][1] [39/24/37]	[65/16/22][1] [39/24/37]	[65/16/22][1] [39/24/37]
C.7	Quality of Deck Drainage System	[1/9/90]	[5/15/80]	[10/30/60]
C.29/ D.30	Corrosion Protection	[5/40/45/10]	[5/40/45/10]	[5/40/45/10]
L.2	Dynamic Loading	[10/90]	[10/90]	[10/90]
C.29	NDT Applied to Component	[30/70]	[30/70]	[30/70]

[1] Depends on L.1, see section 3.3.2.1.

The MC results for the original risk model for decks in WI are shown in Figure 3.6. The figure shows two plots. A column or bar plot shows the distribution of results from MC simulations for CR 7, CR 6, and CR 5 decks. The ordinate (i.e., y-axis) on the left shows the count from the simulation for each 0.1-width bin of data represented by the columns. The second plot shown with curves is the normal distribution for the data from the MC models based on the mean and sample standard distribution. It can be observed in the figure that the mean OF values increase as the CR decreases. It can also be observed from the column plot that the MC results appear normally distributed. It should be noted the results from the weighted sum model are not continuous because only certain values of the OF are possible when the attribute scores are summed. As a result, the appearance of the column plot depends on the width of the bins assigned to the data and how the bin width interacts with the OF values. For example, a gap appears in the *low* OF category because there are values that cannot be produced by the weighted sum model.

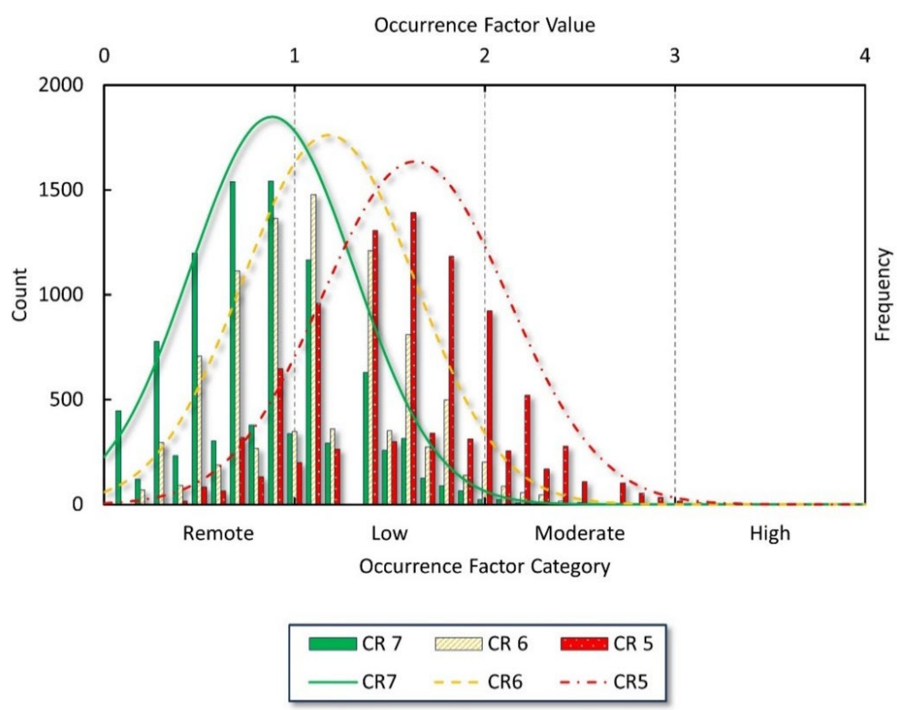


Figure 3.6. Results of MC simulations for decks with CR 7, CR 6, and CR 5.

The cumulative distribution functions from the MC simulations are shown in Figure 3.7. The figure shows the distribution function for the unweighted risk model and a model that is weighted by multiplying the CR and CS by a factor of 2. For decks with CR 7, the unweighted model estimates about 61% of CR 7 decks will fall in the *remote* category for the OF. When the model is weighted, the likelihood of a CR 7 deck being rated in the *remote* category was increased to 76%.

When the model is weighted, it has the effect of shifting the CR 7 data to the left and the CR 5 data to the right as shown in Figure 3.7. When the attributes C.1 and C.2 are increased from 20 points to 40 points, the total number of points in the model is increased by 40 points. Since components in CR 7 score 0 points for the CR attribute, the proportion of the available points scored by a CR 7 component is reduced. Since the proportion of the CR attribute is increased in the weighted sum model, CR 5 components scored higher, and therefore, the cumulative distribution curve shifts to the right. This is significant because it provides a means of calibration of the model that applies not only to the CR and CS attributes, but to any other attribute as well.

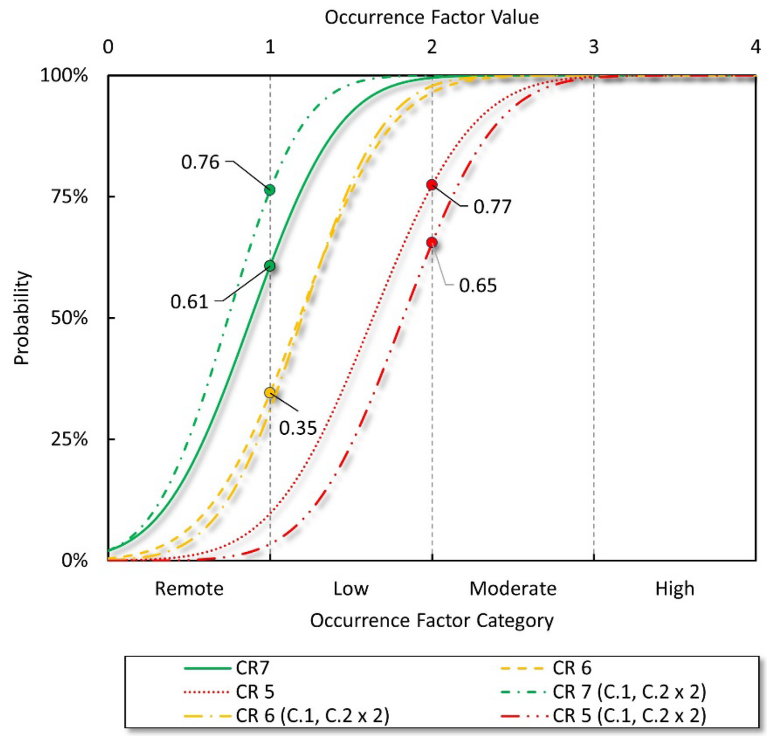


Figure 3.7. Cumulative distribution function based on MC simulations for unweighted and weighted models.

To illustrate the effect of increasing the weights of individual condition attributes on the overall results of the risk model, different weightings of CR and CS attributes were considered. Although any of the attributes in the model can be weighted in a certain way to better represent engineering judgement and to meet the target ranges, the condition-related attributes link the risk models to the standard methods of condition assessment, and the sensitivity studies of the back-casting data indicated weighting these attributes improved the quality of the model. To test the effect of weighting CR and CS, the MC simulation model was prepared with different weighting scenarios. The weighting scenarios included the original, unweighted model and models with the attributes C.1, CR, and C.2, CS multiplied by 1.5, 2.0, 2.5, 3.0, 3.5, and 4. The results are shown in Figure 3.8 which illustrates how increasing the multiplier for C.1 and C.2 affects the mean value of the MC simulations for deck components based on the risk model.

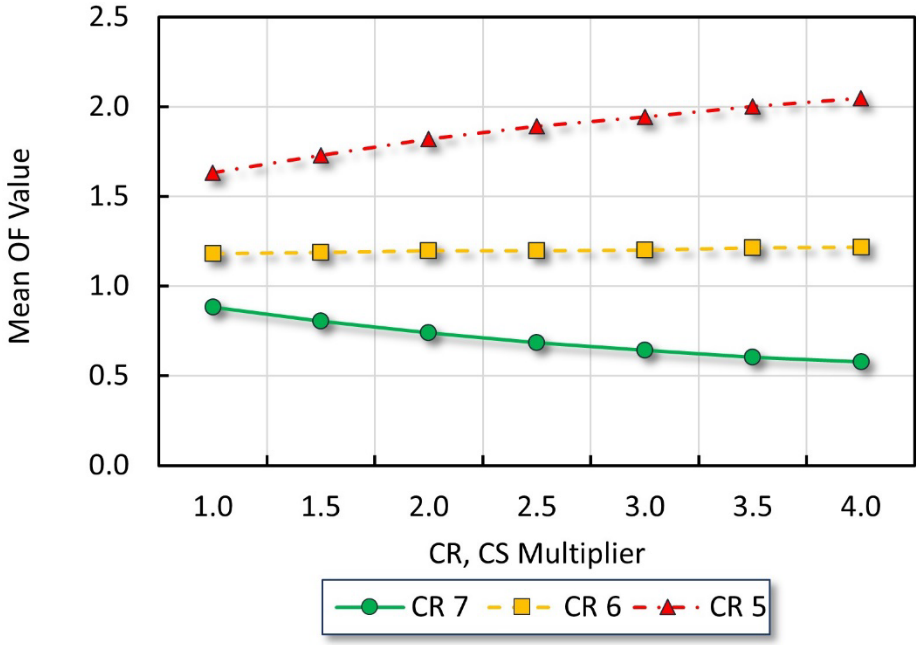


Figure 3.8. Effect of weighting on the mean values of the OF for CR 5, CR 6, and CR 7 deck components.

These data demonstrate how increasing the weight of the condition-related attributes reduces the mean value of the risk model for bridge components in good condition and increases the mean value for components in CR 5. Components in CR 6 change only a small amount. These data, along with parametric studies of the MC simulation process presented later in the report, can provide guidance to users on how to calibrate the risk models to be consistent with engineering judgement.

3.3.3. Effect of ADT on Example R/C Deck Model

An important question for most engineers would be how high ADT bridges compare with low ADT bridges when the risk model is applied. This obviously depends on if the risk model includes an ADT attribute, an attribute with criteria that depends on ADT, or an attribute that is correlated with ADT. The WI deck model has an ADT (L.1) attribute and an attribute with criteria that depend on ADT, L.5, Rate of De-Icing Chemical Application, as previously described.

To analyze the effect of high ADT, MC simulations were completed assuming that all the bridges had an ADT of greater than 20,000 vpd, and all the bridges have ADT of less than 10,000 vpd. In this way, the effect of high ADT on model results can be quantified. The results are shown in Figure 3.9, which shows the cumulative probability distribution for decks with high ADT and low ADT.

As the data shows, for high ADT bridges, only 36% of CR 7 deck components will be rated as having *remote* likelihood, while for low ADT bridges, 99% will be rated as having a *remote* likelihood. Recall that based on the proposed risk matrix, components rated as *remote* may be eligible for a 72-month interval when the CF is *moderate* or *high* (CF 2 or CF 3). Components rated with a *low* OF are only eligible for a 72-month interval if the CF is *moderate* or *low* (CF 1 or CF 2). Most CR 6 decks will be rated as having a *low* OF, meaning that if the CF was high, the assigned inspection interval will be 48-months. This fits with the NBIS requirements for Method 1 that states that components in CR 6 can have a 48 interval regardless of the ADT level on the bridge. High ADT reduces the likelihood of the deck being rated as *remote*, meaning that when other attributes are increased (for example, the deck has poor drainage or soffit damage) the OF will be *low* rather than *remote*. Importantly, the model shows that simply having high ADT will not prevent a deck from being rated as *remote*, in fact, almost 40% of decks will still be rated as *remote,* considering both CR 7 and CR 6 decks.

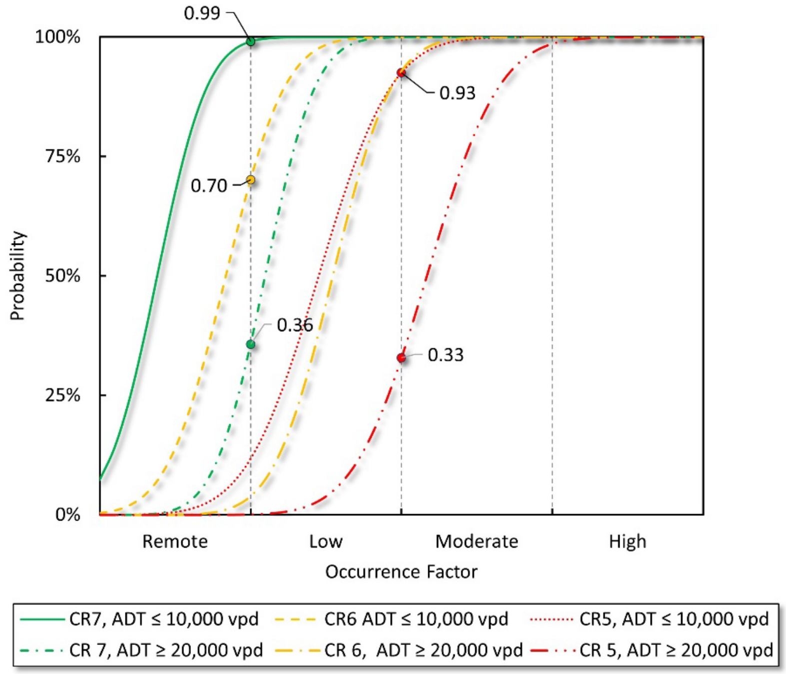


Figure 3.9. Cumulative distribution of results from MC simulations for low and high ADT bridges.

This result indicates that the risk model is sensitive to the effect of increased ADT on the deterioration pattern of decks with increased ADT reducing the likelihood for a particular deck to be rated as *remote* as compared with the overall population of decks.

3.3.4. Application of NDE

The application of NDT technologies for RBI has the assumed effect of reducing the uncertainty in the condition assessment for a given component. Practically speaking, NDE technologies are primarily applied to decks of bridges. While other components are sometimes subjected to NDT, such as steel members with section loss or a potential for cracking, these applications are not widespread. Bridge decks are most commonly tested with technologies such as infrared thermography (IRT) or ground penetrating radar used to assess the condition and potential for future damage, respectively.

The WI deck model included an attribute to consider if a given bridge had been subjected to NDT. Wisconsin currently has a policy to assess bridge decks with IRT. It was assumed for the previous analysis that 70% of bridge decks in the inventory had been assessed with NDT. The rank of the attribute was *high*, meaning 20 points are assigned to any bridge that was <u>not</u> assessed with NDT, raising its relative risk as compared with a component that had undergone NDT. This parameter for NDT was analyzed for two purposes. First, to assess how the inclusion of NDT affects the model in terms of overall results, and second, how the ranking of an attribute affects the outcome of the risk model. For example, if the weight of the NDT attribute was 10 points instead of 20 points.

To illustrate the impact of having an NDT attribute, the MC simulation was conducted with the weighted model (CR, CS x 2) assuming 90% of the decks in the inventory were assessed with NDT. A second simulation was conducted assuming only 10% of the decks were assessed with NDT. The overall results are represented in Figure 3.10 that shows the cumulative probability distribution for the two scenarios. The figure shows only data for CR 7 and CR 6 for clarity. The difference in the overall results is significant in the sense that many more CR 7 decks will be considered to have *remote* likelihood if NDT is applied as compared with decks without NDT. When very few decks (10%) have been assessed with NDT, only 55% of the decks will be ranked as *remote,* while if 90% of the decks had NDT, the overall results will place 83% of the decks in the *remote* category. On the other hand, decks in CR 7 fall primarily in the *low* to *remote* range regardless of whether NDT is applied, aligning with the target ranges.

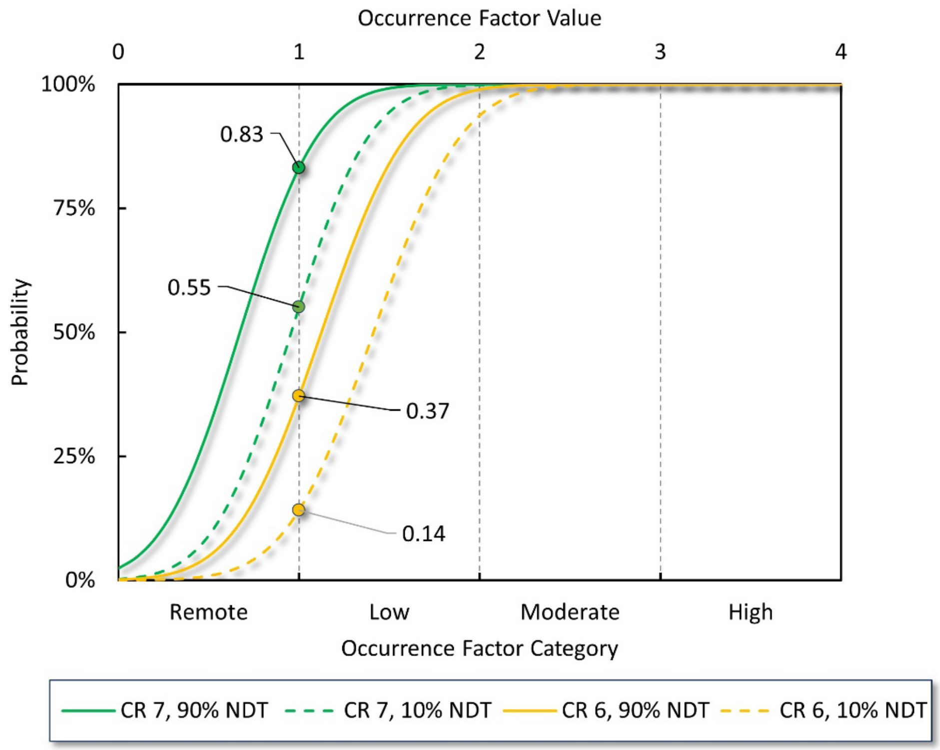


Figure 3.10. MC simulation results showing effect of NDT on OF values.

The second question is how the weight of the NDT attribute affects the results of the overall model. For example, if the RAP had ranked the effect of NDT to be *low*, then that attribute would only be assigned 10 points, and therefore have less of an overall effect on the model. The results of the analysis with the NDT attribute ranked *low* are shown in Figure 3.11. As shown in the figure, the proportion of the CR 7 bridges categorized as *remote* will be 69% if only a few bridges (10%) were subjected to NDT and 82% when most of the decks (90%) were assessed with NDT. Comparing the results shown in Figure 3.10 and Figure 3.11 illustrates the effect on the mean risk score of a particular attribute being ranked *low* rather than *high* by the RAP.

3.3.5. Comparison of MC Simulation and Back-Casting Results

The MC simulation process provides a methodology for analyzing the risk models developed by a RAP in a data-driven process based on available bridge inventory data and engineering estimates of the attribute probability values. An important question is how the MC simulation compares with results from the back-casting process. The back-casting data provides real results from in-service bridges based on the risk models developed by the RAP and review of inspection records. The MC simulation predicts results based on probability theories and bridge inventory data. To validate the MC simulation procedure developed through the research, the statistical results from the back-casting and the MC simulation outputs were compared.

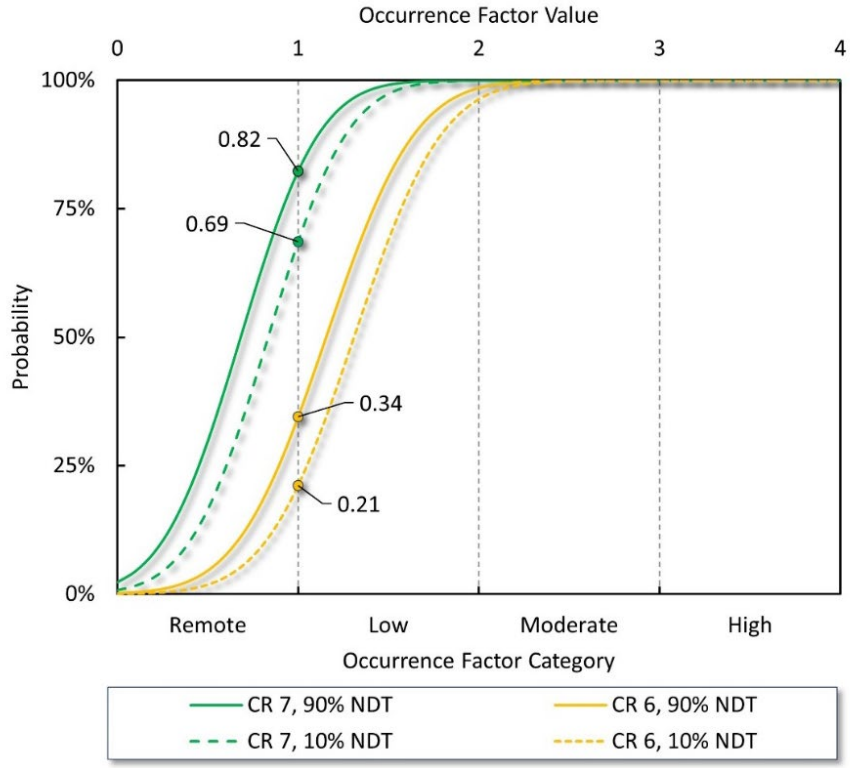


Figure 3.11. MC results for 90% NDT and 10% NDT with NDT at 10 points.

The back-casting data combines the results from different RAP models applied to bridge components in the sample bridges. As a result, it would not be expected that the results from an MC simulation would match exactly the back-casting results, but the trends should be similar. To compare the results from the MC simulation and the back-casting results, two risk models developed by RAPs were compared with the back-casting results. The risk model for decks in Missouri and the risk model for steel superstructures developed in Connecticut were compared with the deck and steel superstructure data from the back-casting.

Figure 3.12 shows the results from the MC simulations of these two models and the back-casting results, with the back-casting results noted as "BC," and the MC simulation results formed from the Missouri deck and the Connecticut steel superstructure risk models marked as "MO" and "CT," respectively. Figure 3.12A shows the statistical results from the analysis of 60 bridge decks from sample bridges and the MC simulation of the risk model for bridge decks in MO. The results of the back-casting and the MC simulation are remarkably similar for R/C deck components in CR 7. In fact, the likelihood of the OF being *remote* are the same, 72%. The results for CR 6 and CR 5 decks do not match as closely but are similar. As mentioned, it would not be expected that the MC simulation and the back-casting would be the same since the back-casting results are from six different, albeit similar, risk models. Additionally, the back-casting results are from six different states across the county, whereas the MO results are based on statistics from the MO bridge inventory and point estimates based on engineering judgement. If the point estimate were chosen differently, or statistics from a different bridge inventory were used, the data may not align as closely.

Figure 3.12B shows the results for the steel superstructure corrosion damage mode. This figure compares the results from the 40 steel superstructures in the back-casting study and the risk model from the state of Connecticut. Here, the results do not match as closely for steel superstructure components in CR 7, but the results are similar.

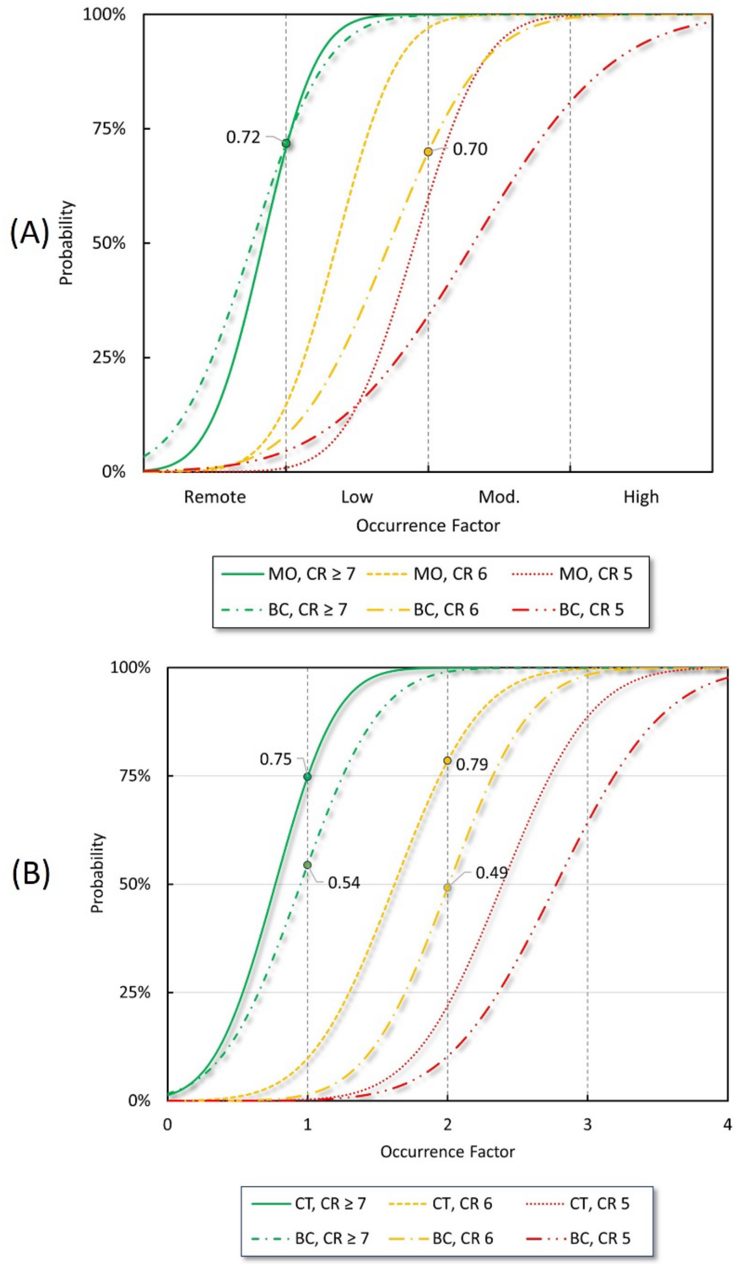


Figure 3.12. Comparison of the back-casting results and MC simulation for A) R/C decks and B) steel superstructure corrosion damage.

The attributes and attribute criteria could be adjusted to make the results from the MC simulation and the back-casting results align more closely. A particular owner could use this method to verify the risk models applied to their own inventory, following the procedure of sampling bridges, applying the risk model to actual components, and comparing the results to the MC simulation based on the inventory data. In this way, the risk model can be calibrated and then verified for a given bridge inventory.

3.4. Parametric Study of the MC Simulation process

The MC simulations provide an effective methodology for analyzing the risk models to estimate appropriate weights and assess the likely outcome of the models when applied to a family of bridges. The risk models commonly have a different number of attributes, generally ranging from a low of four attributes to a high of 12 attributes in this study. The number of attributes in the model will affect the outcome because each attribute constitutes a smaller portion of the model as the number of attributes is increased. Combined with the almost infinite combination of probabilities for the individual attributes, it can be difficult to assess the effect of the number of attributes in the model, and how any one of the attributes being rated as *high* might affect the outcome of the model.

To provide some insight on how the number of attributes in the model and their respective probabilities affect a weighted-sum risk model, a parametric study was conducted. The purpose of the study was to illustrate general trends of the MC simulation of the risk models to observe several effects:

1. How does the number of attributes affect the outcome of the risk models?
2. How does the estimated attribute probabilities effect the outcome of the risk models?
3. What is the impact from a single attribute being rated as high, while all others are rated according to their individual likelihoods?

The parametric study considered a generic risk model with 14 attributes and probabilities ranging from the low end, i.e., a low likelihood of a particular attribute being rated as *high*, through the relatively high end, where the likelihood of a given attribute being rated *high* is increased. The specific probabilities were as shown in Table 3.8 for five different cases. For each case, all attributes were assigned the same probabilities to provide results illustrating the behavior of models with generally low probabilities as compared with models with generally high probabilities and illustrate the trends of the data.

The low probability models (Case A) considered probabilities for each attribute of [5/10/85]. The likelihood of a given attribute being rated *high* was doubled to produce the resulting probabilities shown in Table 3.8 for each case. Case E considers the model without probabilities, such that all attributes are initially rated as *low.* For case E, the MC simulations were not used because this scenario modeled a linear analysis of simply changing an individual attribute's rating from *low,* with 0 points assigned for that attribute, to *high*, with 20 points assigned for that attribute.

Table 3.8. Listing of probabilities for parametric study models.

Case A [H/M/L]	Case B [H/M/L]	Case C [H/M/L]	Case D [H/M/L]	Case E [H/M/L]
[5/10/85]	[10/20/70]	[20/40/40]	[40/40/20]	[100/0/0]

The MC simulations were performed for models with 14, 12, 10, 8, 6, 5, and 4 attributes. For each model, the results of having one, two, three, or four attributes rated as *high* were determined from MC simulations. Results are presented as the mean value of the MC results for a component in CR 7, meaning that one of the attributes (C.1, Current Condition Rating) is always rated as *low*. Results are shown in several figures. First, considering the raw risk score itself, Figure 3.13A and Figure 3.13B show the results for different numbers of attributes in the model and the effect of one, two, three, or four attributes rated as *high*. The results for case A with probabilities of [5/10/85] are shown in Figure 3.13A, and results for case C with probabilities of [20/40/40] are shown in Figure 3.13B as examples. The figure shows the mean risk score (i.e., OF value) on the ordinate and the number of attributes rated as *high* on the abscissa. It can be observed in the figure that the basic model without any attributes rated *high* is greater for case C as compared with case A. Since the MC simulation is selecting values (i.e., ratings) for each attribute randomly according to the defined probability distribution, the rating of *high* and *moderate* are selected much more frequently for case C as compared with case A, resulting in a greater mean value of the risk score. For case A, the average mean risk score was found to be 0.31 and for case C, the mean risk score was 1.26. The mean risk values increase as the number of attributes rated *high* increase as would be expected.

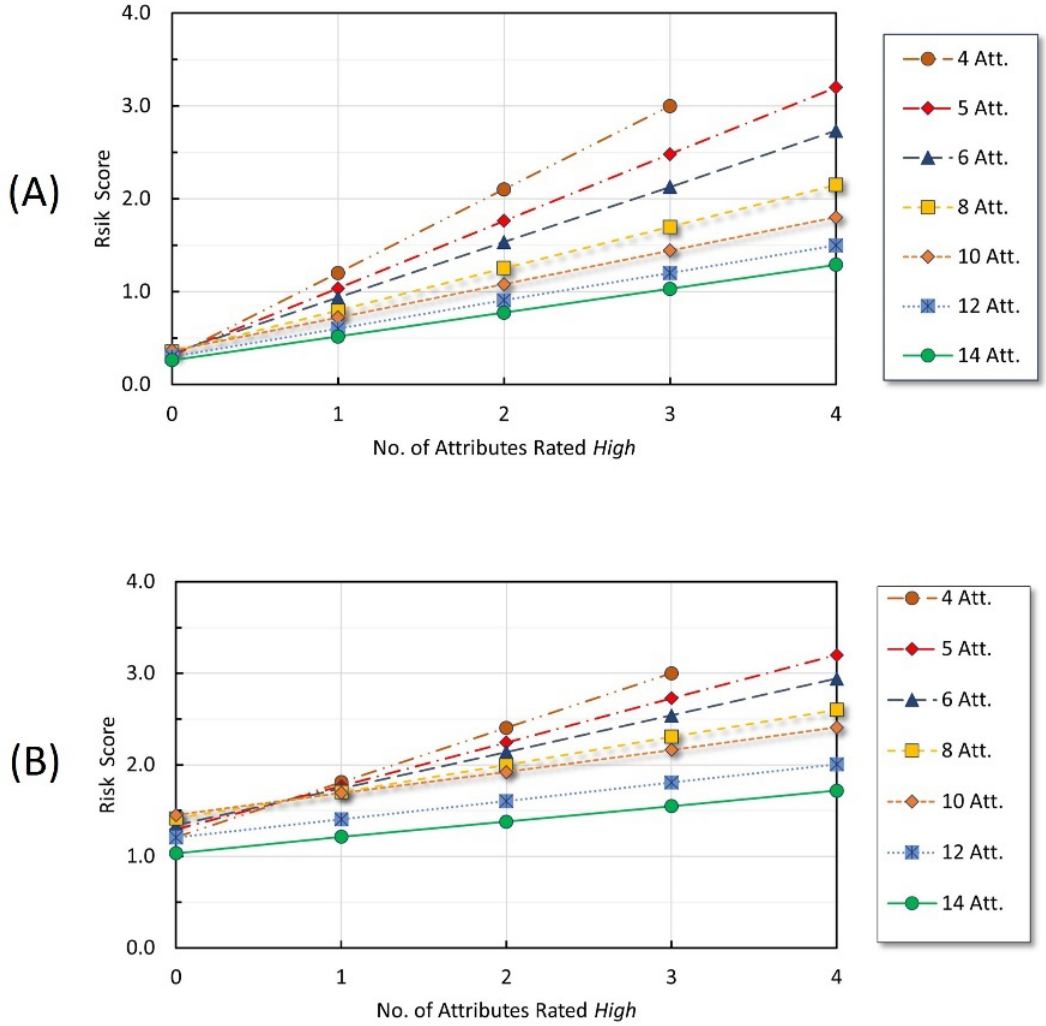


Figure 3.13. Risk scores for case A (A) and case C (B) for different numbers of attributes rated as high.

Notably, it can be observed in the figure that the relationship between the number of attributes rated as *high* and the risk score is linear, and the rate of increase is greater for case A than for case C. Since any given attribute is four times as likely to be rated as *high* in case C as compared with case A due to the probabilities listed in Table 3.8, the effect of having one or more of the attributes being rated high is smaller. This illustrates the trend in the model that could be useful for estimating, for example, how the risk model will change if analyzed for only the portion of bridges with high ADT in relation to how many attributes are in the mode and the associated probabilities. If one individual attribute such as ADT is always rated as *high,* the effect is larger if the other attributes generally have low probabilities of being rated as *high*, and the effect will be more pronounced with fewer attributes in the model. However, overall score will be smaller when the probabilities are lower.

The results can be summarized by assessing the change in the risk score for any single attribute being rated as *high*. Figure 3.14 shows the results from analyzing the change in risk scores as the number of attributes is increased. Figure 3.14A shows the number of attributes on the abscissa. The primary ordinate shows the change in the risk score, and the secondary ordinate shows the change in the risk score as a proportion of the overall scale of 0 to 4 points. The figure shows that the change in risk score is greater when the overall probabilities are relatively low, as previously discussed. For example, the 14 attribute model changes 0.29 points (≈7%) for the case E (linear model) and only 0.11 points (≈3%) for case D ([40/40/20]) for a 14-parameter risk model. The relationship between the change in risk score and the number of attributes in the model is parabolic as shown in Figure 3.14A.

The relationship is linear when considering the proportion of the model formed by each attribute as shown in Figure 3.14B. In other words, the change in the OF value is proportional to the percentage of the model derived from any one attribute. For a model with relatively high probabilities for individual attributes, the change in risk model when a single attribute is rated as *high* is smallest, while the change is largest for a model with relatively low probabilities. The linear model produces the largest change, and if the model has only four parameters, a single attribute rated as *high* changes the model by one OF category, e.g., from *low* to *moderate*.

The parametric study does not provide specific values but illustrates the tendencies of the risk models when analyzed using the MC simulation approach developed through the research. In terms the effects on the model, the study showed the following:

1. How does the number of attributes affect the outcome of the risk models?

   The smaller the number of attributes, the larger the contribution of each attribute to the final OF value. This means that the change in the OF value resulting from any attribute being rated *high* will increase as the number of attributes decreases. This is an obvious result for the linear model, but also holds true with the MC simulations. It was also shown that the change in the OF value is proportional to the percentage of the model of each attribute.

2. How do the estimated attribute probabilities affect the outcome of the risk models?

   The mean value of the OF resulting from the MC simulation is smaller when the probability of *high* or *moderate* ratings is lower. As these probabilities increase, the mean value of the OF calculated from the MC simulation increases. This means that when the probability of attributes being rated *high* is increased, the cumulative distribution function such as that shown in Figure 3.12 will *move to the right*.

3. What is the impact from a single attribute being rated as high, while all others are rated according to their individual likelihoods?

The change in the OF values resulting from any one attribute being rated *high* is greater when the probability of *high* and *moderate* is smaller. However, the mean risk score is smaller. The effect of an individual attribute being rated *high* is reduced as the number of attributes increases.

These results show that the effect of any individual attribute having increased probabilities will have a smaller when other attributes have relatively high probabilities, and larger when other attributes have low probabilities. It should be noted that the MC simulation results shown are for cases where *every* attribute in the model has either high probabilities or low probabilities. Most real models will have a mixture of relatively high and relatively low probabilities.

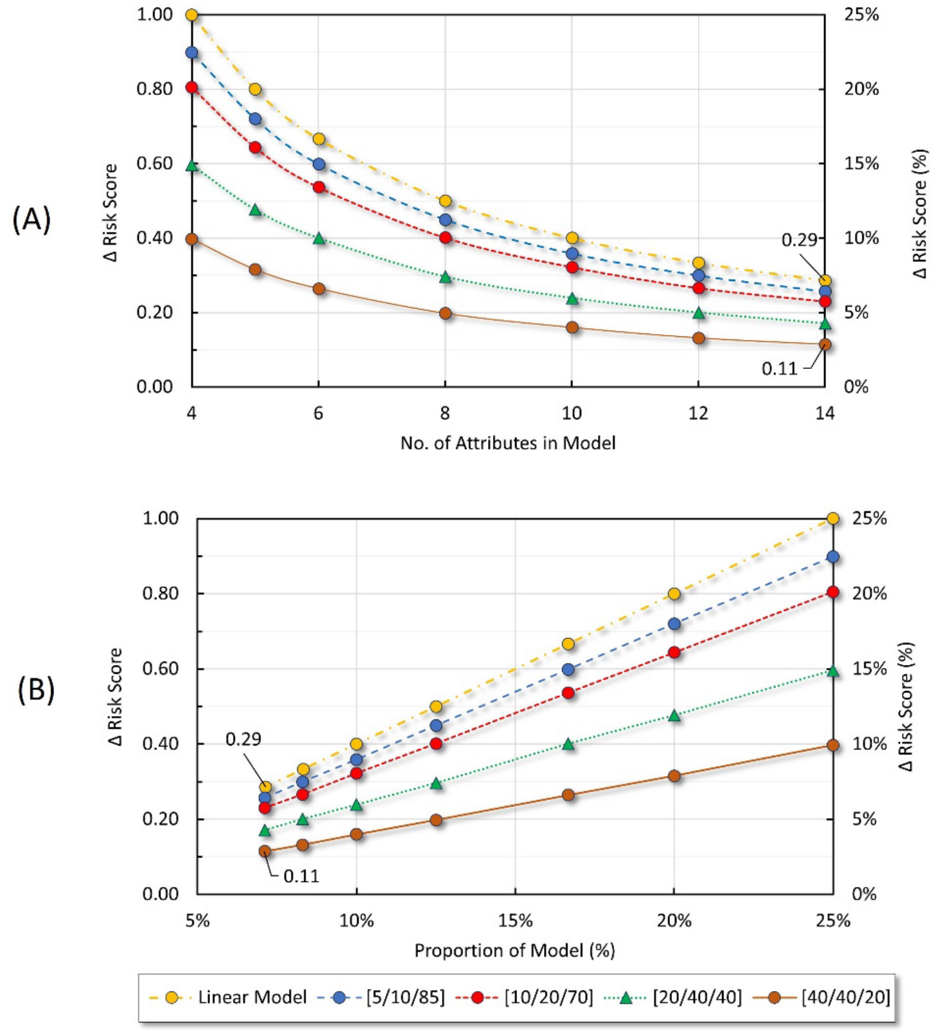


Figure 3.14. Plot showing change in risk scores as a function of the number of attributes in the model.

3.4.1. Application to a Real Model

A parametric study was completed for an actual RAP model from the study. The purpose was to gain insight into how the number of attributes affected the model outcomes, the effect of having one attribute rated as uniformly high, and the effect of the probability distributions. A 10-parameter deck model from the state of Missouri was used for the study. The number of attributes in the model was reduced by removing attributes from the MC simulation.

The attributes and probabilities used for the model are shown in Table 3.9. The table lists 10 different attributes, each with assigned probabilities of being rated as *very high*, *high*, *moderate*, or *low*. The point values are different for different attributes based on the rank assigned by the RAP. The condition attributes C.1 and C.2 are weighted to be worth 40 points each. Most of the other attributes are scored on a 20-point scale, with two exceptions. The attribute D.29/C.30, Corrosion Protection, was assigned 30 points and Attribute D.24, Superstructure Flexibility, was ranked as moderate by the RAP and only assigned 15 points.

As shown in the table, a typical risk model has a mix of points assigned and probabilities. Understanding how the likelihood for each attribute and the number of attributes in the model affect the outcome is challenging since there are an infinite number of combinations, though the tendencies were described in the previous section. To study this specific model, different numbers of attributes were used to compare the mean value from the MC simulation (based on the probabilities shown in Table 3.9) to the mean value when a single attribute was rated *high*. Two studies were completed. Study 1 compared a base model using the original probabilities to results when the attribute C.13, Efflorescence / Staining, was selected to be uniformly rated as *high*. This attribute has a low likelihood of being rated as *high* or *moderate* based on the probabilities applied. The probabilities were based on an engineering estimate and reflect the fact that a CR 5 deck is more likely to be affected by efflorescence on the deck soffit as compared with a deck in CR 7. The five attributes that were included in all models in Study 1 are shown in bold in Table 3.9, and attribute C.13 is italicized to indicate the attribute that was set to *high*.

Table 3.9. Probabilities for parameter study with weighted models.

Attribute	Probability CR ≥ 7 (H/M/L, %)	Probability CR 6 (H/M/L, %)	Probability CR 5 (H/M/L, %)	Total Points Study 1	Total Points Study 2
C.1 Current CR	[0/0/100]	[0/100/0]	[100/0/0]	**40**	**40**
C.2 Current CS	[0/20/80]	[5/60/35]	[20/40/40]	**40**	**40**
C.13 Efflorescence/Staining	[0/5/95]	[5/5/90]	[10/20/70]	***20***	20
L.1 Average Daily Traffic	[40/40/20]	[40/40/20]	[40/40/20]	20	20
L.5 Rate of De-icing Chemical application	[25/25/50]	[25/25/50]	[25/25/50]	20	***20***
C.7 Quality of Deck Drainage	[5/5/90]	[10/10/80]	[10/10/80]	20	20
D.29/C.30 Corrosion Protection	[5/45/45/5]	[5/45/45/5]	[5/45/45/5]	**30**	**30**
C.27 Rate of Deterioration	[5/5/90]	[5/5/90]	[5/5/90]	20	20
D.24 Superstructure Flexibility	[5/95]	[5/95]	[5/95]	**15**	**15**
D.8 Concrete Mix Design	[10/60/30]	[10/60/30]	[10/70/20]	20	20
			Total	245	245

Study 2 used the same model probabilities as Study 1, but the attribute that was rated *high* was L.5, Rate of Deicing Chemical Application. The probability estimates used for this attribute were relatively high [25/25/50]. The five attributes that were included in all the models are shown in bold in the table and L.5 is shown in italic to indicate it was the attribute rated high.

Figure 3.15A and Figure 3.15B show the mean OF values determined from the MC simulations. Figure 3.15 (A) shows the mean value results from Study 1 and Figure 3.15B shows the mean value results from Study 2. The data shows the OF results for CR 7, CR 6, and CR 5 decks. The figures show the number of attributes in the model on the abscissa and the resulting risk score on the ordinate. It can be observed in these data that as the number of attributes goes down, the OF values generally increase for between 7 and 10 attributes, but level off or decline for models with 6 attributes. For models with five attributes, in some cases the risk score is increased relative to models with 6 attributes, and in some cases, it is reduced. There is a lack of a consistent trend because the individual attributes have different probability distributions. If the attribute has a relatively high likelihood of being rated as *high*, removing the attribute from the model can result in the risk score declining when it is removed. For example, the models with five attributes in study 1 does not have attributes L.1, ADT, and L.5, Rate of Deicing Chemical Application. Each of these attributes have relatively high likelihoods of being rated as *high* and when these are removed, the overall risk value decreased in Study 1. For Study 2 the attribute L.5 was not removed for the five-attribute model and the risk score increased relative to the six-attribute model.

The change in the risk model when a specific attribute was rated as *high* was analyzed and compared with the parametric study of the generic 14 attribute model described in the previous section. Figure 3.16 shows the results from Study 1 and Study 2 superimposed on results from the 14 parameter model discussed in the previous section. For study 1, the attribute that was changed to *high* was C.13, which had a relatively low probability of being rated as *high*. Consequently, when this attribute is changed to be rated as *high*, the impact on the risk is close to the linear model. For study 2 the attribute that was uniformly set to *high* was L.5, Rate of Deicing Chemical Application. This attribute had relatively high probabilities [25/25/50] based on an engineer’s estimate. Consquently, when it is changed from having its original probilities to being uniformly rated as *high*, the change in the mean values resulting from the MC simulations is smaller, close to the lowest values found from the 14 parameter study, as shown in Figure 3.16.

These data illustrate the tendencies of the weighted sum risk models that can be used by engineers implementing RBI practices. Insight regarding the effect of weighting individual attributes, the number of attributes in the model, and the probability distributions can be used in decision-making when RAP results are formed into risk models. These data also show that the sensitivity of the MC simulations to the probabilities assigned to individual attributes is limited. As the number attributes in the model increased, the sensitivity to the probability distribution is reduced, as shown in Figure 3.14. These data suggest point estimates used to determine probabilities using engineering judgement do not require high precision, although obviously the accuracy has some impact on the overall model results.

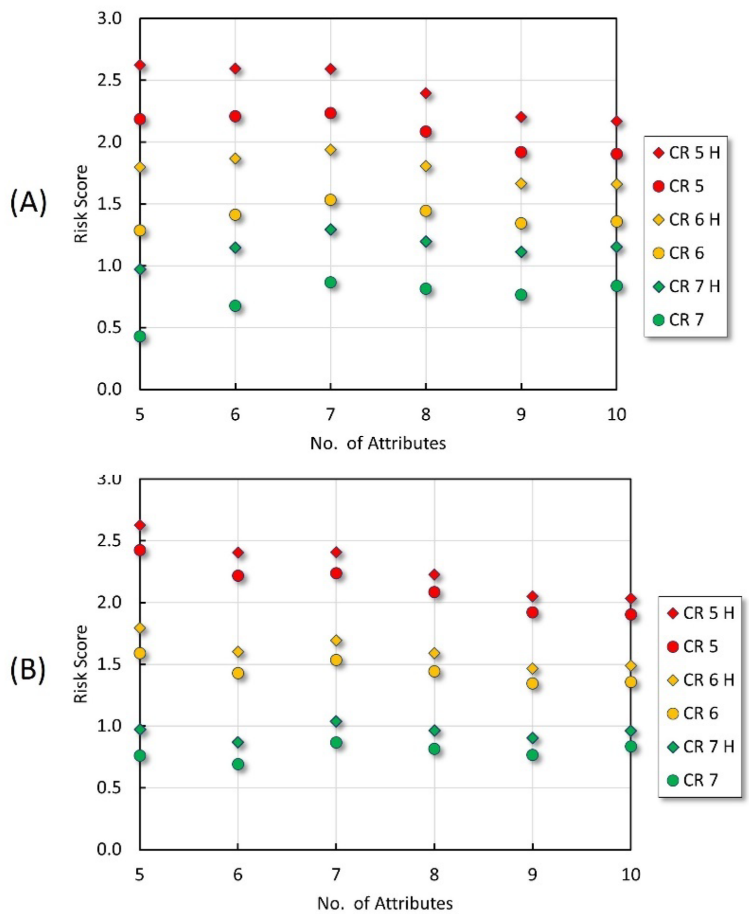


Figure 3.15. Risk scores from deck model with CP system and other attributes from original MO deck model.

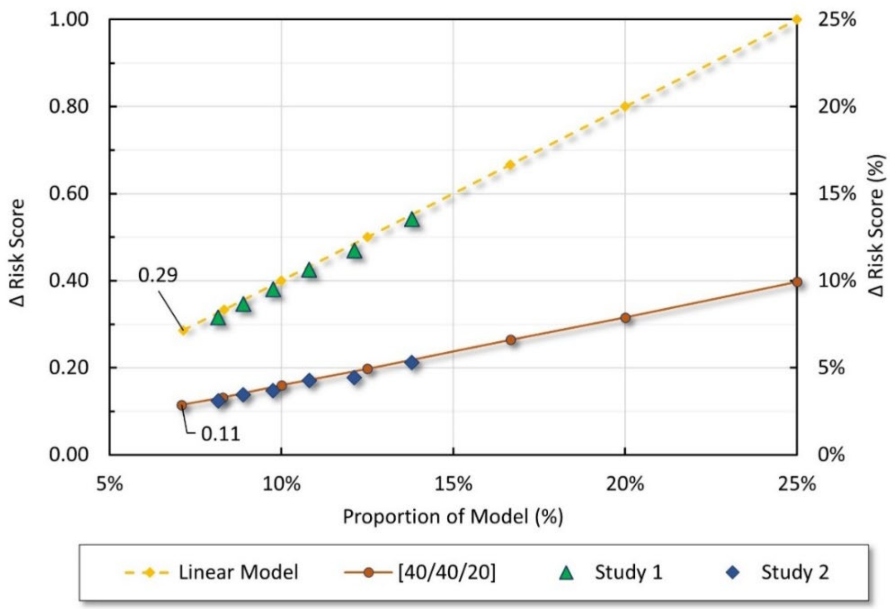


Figure 3.16. Plot showing change in risk scores for Study 1 and Study 2.

Chapter 4.
Conclusions and Discussion

4.1. Conclusions

This report describes the results of back-casting of 60 sample bridges using risk models developed by RAPs in six states. The results of the back-casting were analyzed in terms of the risk scores for individual components and inspection intervals determined by risk analysis. Sensitivity studies of the back-casting data were used to analyze potential methods of weighting attributes in the risk models. Based on the back-casting results, a new data-driven methodology for analyzing the risk models using MC simulations was developed and tested. This methodology uses probability and data from an owner's bridge inventory to simulate the outcome from risk models developed by RAPs. In this way, the risk models can be analyzed, calibrated, and verified using data from bridges.

An analysis of the new NBIS and associated FHWA guidance for inspection intervals was completed that provided target ranges for risk models based on the CR of bridge components. The target ranges provide guidance for analyzing risk models and identifying risk levels for bridge components. This analysis also resulted in a proposed a modification to the risk matrix initially included in the NCHRP 782 report. This revised matrix allows for bridges assigned a *high* CF to be assigned a 72-month inspection interval when the OF category is *remote*. The proposed change to the risk matrix was supported by the data from 60 sample bridges that showed only CR ≥ 7 components with good reliability characteristics (i.e., attributes) were categorized in the *remote* OF range, while others were categorized in the *low* or *moderate* OF range.

Back-casting was conducted on 60 sample bridges in six states. The sample bridges were randomly selected from the bridge inventory and included bridges with CRs ranging from CR 2 to CR 9, with an average CR of 6. Risk models developed by the RAP were used to determine the risk score and categorize the OF as *remote*, *low*, *moderate*, or *high.*

Sensitivity studies of data from the back-casting showed that the weighting of certain attributes improved the quality of the risk models as compared with the target ranges. The results of back-casting analyzed with both weighted risk models and unweighted risk models showed that weighting the CR and CS attributes improved the quality of results.

The sample bridge components of deck, superstructure, and substructure were analyzed using the risk models developed by the six RAPs. The analysis showed that the weighted risk models were effective for determining the relative risk of bridge components. The risk models reflected the target ranges developed in the research and generally rated components in CR ≥ 7 in the *remote* or *low* OF categories, CR 6 components in the *low* to *moderate* range, and CR 5 components in the *moderate* to *high* range. However, the risk models also identified bridge components that did not match the target ranges. For example, when components in good condition (i.e., CR ≥ 7) were analyzed individually using the weighted risk models, 7% of the components were rated as having a *moderate* OF, 57% were rated in *low* category, and 36% were rated as having a *remote* OF (see Figure 2.11). These data show that the risk models were able to identify components with elevated risk when the general CR indicated the component was in good condition. This is significant because it illustrates that the risk models developed by the RAPs were able to sort bridge components based on risk using the attributes and criteria in the risk models.

The inspection interval was determined for the CF factor of *moderate* and *high* based on the controlling component and damage mode for each bridge. When weighted risk models were applied, it was found that 35% of the sample bridges could have an inspection interval of 72 months when the CF was *moderate*.

If the CF was *high*, only 8% of the bridges could qualify for a 72-month inspection interval. These results were based on randomly sampled bridges, many of which were not in good condition (i.e., CR ≥ 7).

A separate analysis of bridges in good condition showed that 100% of the bridges could have a 72-month interval if the CF were *moderate*. If the CF were *high*, 46% of the bridges in good condition could have an inspection interval of 72 months. These data indicate that implementing an extended inspection interval policy including Method 2 analysis will place a substantial number of bridges in good condition on a 72-month inspection interval. *This allows for the reallocation of inspection resources toward bridges with elevated risk, which is the primary goal of the RBI approach.*

A methodology based on MC simulation was developed for analyzing the risk models and predicting the performance of the models when applied to a family of bridges. It was shown that this methodology can be used to analyze different scenarios and to adjust attribute weights to meet target ranges. Importantly, the research showed that this approach was effective for identifying components in good condition that represent elevated risk when compared with the risk model simulations. The MC simulation methodology can be used to identify those bridges that present *elevated risk and require shorter inspection intervals* and those that *do not have elevated risk. This is precisely the objective of the risk analysis.* It was shown that the methodology was successful in identifying components with elevated risk and could be used to *demonstrate the quality* of the risk models. This provides a critical tool for implementation of the RBI approach and gaining approval of extended inspection interval policies.

Summarizing the conclusions of this phase of the research in terms of the objectives were as follows:

1. Determine if the risk models developed by the RAPs were effective for characterizing the relative risk of individual bridge components.

The back-casting showed that the quality of the initial risk models developed by the RAPs was improved by weighting the risk models. The weighted models were effective for characterizing the risk of individual components when compared with the target ranges.

2. Develop a process for analyzing the risk models to determine appropriate weights for attributes.

A methodology was developed based on MC simulations that was able to model the outcome of the risk models for a family of bridges. It was shown that this model could be used to calibrate the risk models to match the target ranges by weighting attributes. The methodology for modeling the outcome of applying the risk models to bridge components performed well when compared with actual data from the sample bridges.

4.1.1. Discussion

This report describes results from the back-casting process and documents methods for implementing an RBI interval within the constraints of the NBIS. This included developing a new process that provides a methodology for analyzing risk models developed by RAPs and completing key task such as weighting the attributes and assessing the quality of the risk models by either comparing results from the MC simulation to actual results from sample bridges or calculating projected risk scores and comparing those scores to the MC simulation. The methodology also provides a mechanism for bridge owners to predict how many bridges in their inventory may be eligible for extended inspection intervals.

Most of the analysis completed utilized element-level inspection data to determine the ratings for individual attributes and to determine probabilities to be inputted to the MC Simulation. A practical question is whether bridges that are not subject to element-level inspections can be analyzed using these approaches. For Method 1, there is clearly no provision requiring element-level inspection because the criteria for Method 1 only refer to component CRs, not element-level CSs. The NBIS does not require that a bridge <u>must</u> have element-level data to be eligible for extended inspection intervals using Method 2. However, it does require that the extended inspection interval policy include "inspection procedures and data collection that are aligned with the level of inspection required to obtain the data to apply the criteria." One way to meet this requirement is through element-level inspection, and the attributes in the risk models have been developed with criteria that match element-level inspection results in many cases.

However, bridges that do not have complete element-level inspections could be included in an extended interval policy if the data necessary to rate the criteria were collected during an inspection. This data could be collected through alternate inspection procedures that require the specific items included in the risk models to be documented during an inspection. This may be a subtle point, since much of the data collected during an element-level inspection will still need to be collected, but only for bridges included in the extended inspection policy, and only for relevant criteria from the risk model. Bridges that are not included in the policy will not require element-level inspection data. So, for example, an owner could require element-level data matching the risk models to be collected for bridges in good condition and utilize Method 1 for bridges in fair condition.

The methodology developed for analyzing the risk models using MC simulation also relies on element-level inspection data. In this project, the element-level data for NHS bridges was used to provide probabilities to be inputted to the MC simulation. For states that conduct element-level inspection on a larger portion of their bridge inventories, the analysis could be based on that larger population of bridges. The probabilities MC simulations utilize probability estimates that express general trends which show, for example, the proportion of joints that are likely to be rated *high* according to the risk model criteria. As a practical matter those estimates could be extended to portions of the inventory that do not currently have element-level inspection results to analyze the likely results from implementing RBI for those bridges. This assumes that the population of bridges that are not subject to element-level inspections have similar deterioration patterns to those bridges that are subject to element-level inspections. For example, state-owned bridges that are not on the NHS system but receive similar levels of maintenance as the NHS bridges. For local bridges, the RAP could identify transfer mechanisms to relate the existing element-level data statistics to locally owned bridges in a conservative way.

4.1.2. Implementation of MC Simulations

The MC simulations used in the research are relatively simple to implement. The data used to form probabilities for rating attributes is generally available from existing inventory data. For data that are not available, engineering judgement can be used to form point estimates of the probability of a given attribute being rated *high*, *moderate*, or *low*. As shown in the parametric studies, the sensitivity of the MC simulations to the probabilities assigned to individual attributes is limited and is reduced as the number of attributes in the model increases. As a result, high precision is not required for the point estimates, although obviously the quality of the input affects the quality of the output.

The MC simulation process in general is well-known and widely used, particularly in the finance industry to predict future performance based on past trends. It is also common in the risk analysis field, though generally structured differently than the models used in this research. Because MC simulation is common in many industries, there are myriad software available for performing MC simulations. For this research, the MC simulations were performed using Microsoft Excel spreadsheets. A single data table was used to produce 30,000 simulations. Therefore, the MC simulation process can be implemented by either purchasing software designed for that purpose or developing relatively simple algorithms in Microsoft Excel.

References

API (2016). API Recomended Practice 580, Risk-Based Inspection, 3rd edition. Washinton, D.C., American Petroleum Institute. **1:** 94.

FHWA (1988). Technical Advisory: Revisions to the National Bridge Inspection Standards (NBIS). D. o. Transportation. Washington, D.C.

FHWA (1995). Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges. U.S.D.O.T. Washington, D.C. **:** 78.

FHWA (2022). National Bridge Inspection Standards Inspection Interval Guidance. FHWA. Washington, D.C. , FHWA 13.

FHWA (2022). Specifications for the National Bridge Inventory. FHWA. Washington, D.C. , Federal Highway Administration Washington, DC, USA**:** 335.

USDOT, F. (2022). National Bridge Inspection Standards. 23 CFR 650. FHWA. Washington, D.C., Federal Registrar. **87 FR 27396:** 42.

Washer, G., R. Connor, A. Ciolko, R. Kogler, P. Fish, D. Forsyth, C. Applebury and M. Nasrollahi (2014). "Proposed Guideline for Reliability-Based Bridge Inspection Practices." NCHRP Report 782(Washington, D.C.).

APPENDIX A:
LISTING OF ATTRIBUTES

APPENDIX A Listing of Attributes for RBI

This appendix includes the listing of attribute and codes used for risk models included in the report. Attributes from the NCHRP report are shown in plain text. Attributes identified through the present study are shown in bold text. Attributes in italics were included in the original NCRHP report but modified for the present study.

Table A-1. Listing of screening and loading attributes for RBI.

No.	Title	No.	Title
S.1	Current Condition Rating	*L.1A*	*Average Daily Traffic ADT*
S.2	Fire Damage	*L.1B*	*Average Daily Truck Traffic ADTT*
S.3	Susceptible to Collision	L.2	Dynamic Loading from Riding Surface
S.4	Flexural Cracking	L.3	Exposure Environment
S.5	Shear Cracking	L.4	Likelihood of Overload
S.6	Longitudinal Cracking in Prestressed Elements	L.5	Rate of De-Icing Chemical Application
S.7	Active Fatigue Cracks Due to Primary Stress Ranges	L.6	Subjected to Overspray
S.8	Details Susceptible to Constraint Induced Fracture (CIF)	L.7	Remaining Fatigue Life
S.9	Significant Level of Active Corrosion or Section Loss	L.8	Overtopping / High Water
S.10	Design Features	-	-
S.11	**Rate of Deterioration**	-	-
S.12	**Fabrication Defects and / or Connection Damage**	-	-
S.13	**E Or E' Details**	-	-
S.14	**Scour Rating**	-	-
S.15	**Waterway Adequacy**	-	-
S.16	**Current Element Condition State**	-	-
S.17	**Construction Quality**	-	-
S.18	**Exposed Strand (PSC)**	-	-
S.19	**Load Rating Factor**	-	-
S.20	**Scour Rating**	-	-
S.21	**Settlement Or Rotation**	-	-

Table A-2. Listing of design attributes used for RBI.

No.	Title	No.	Title
D.1	Joint Type	D.15	Constructed of Weathering Steel
D.2	Load Posting	D.16	Element Connection Type
D.3	Minimum Vertical Clearance	D.17	Worst Fatigue Detail Category
D.4	Poor Deck Drainage and Ponding	D.18	Skew
D.5	Use of Open Decking	D.19	Presence of Cold Joints
D.6	Year of Construction	D.20	Construction Techniques and Specifications
D.7	Application of Protective Systems	D.21	Footing Type
D.8[1]	Concrete Mix Design	D.22	Subsurface Soil Condition
D.9	Deck Form Type	**D.23**	**Age of Component**
D.10	Deck Overlays	**D.24**	**Superstructure Flexibility**
D.11	Minimum Concrete Cover	**D.25**	**Embedded Girder Ends**
D.12	Reinforcement Type	**D.26**	**Structure Type**
D.13	Built-up Member	**D.27**	**Feature Under**
D.14	Constructed of High-performance Steel	**D.29**	**Corrosion Protection Level**

Table A-3. Listing of condition attributes for RBI.

No.	Title	No.	Title
C.1	Current Condition Rating	C.16	Longitudinal Cracking In Prestressed Elements
C.2	Current Element Condition State	C.17	Coating Condition
C.3	Evidence of Rotation or Settlement	C.18	Condition of Fatigue Cracks
C.4	Joint Condition	C.19	Presence of Fatigue Cracks Due to Secondary or Out of Plane Stress
C.5	Maintenance Cycle	C.20	Non-Fatigue Related Cracks or Defects
C.6	Previously Impacted	C.21	Presence of Active Corrosion
		C.22	Presence of Debris
C.7	Quality Of Deck Drainage System	**C.23**	**Wear / Abrasion or Rutting**
C.8	Corrosion-Induced Cracking	**C.24**	**Bearing Condition**
C.9	General Cracking	**C.25**	**Construction Quality**
C.10	Delamination	**C.26**	**Debris Damage**
C.11	Presence of Repaired Areas	**C.27**	**Rate of Deterioration**
C.12	Presence of Spalling	**C.28**	**Presence of Repair Areas**
C.13	Efflorescence / Staining	**C.29**	**NDT Applied to Component**
C.14	Flexural Cracking	**C.30**	**Corrosion Protection Level**
C.15	Shear Cracking	**C.31**	**Bearing Condition**