TPF-5(432): Bridge Element Deterioration for Midwest States

(IA, IL, IN, KS, KY, MI, MN, ND, NE, OH, SD, WI)

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16. Abstract

The objective of this research project was to develop element-level deterioration curves for specific bridges using multiple resources and historical data provided by 12 Midwest State Departments of Transportation (DOTs). The research team identified and prioritized a list of elements to be modeled. The three tiers of curves included Tier 1 curves – for reinforced concrete deck (RCD), reinforced concrete slab, National Bridge Inventory items, RCD after major preservation to predict condition improvement; Tier 2 curves – for wearing surface, deck joints, defect development and progression, paint system effectiveness, steel girder corrosion, and substructure elements in harsh environments; and Tier 3 curves – for agency-defined elements, and determining non-destructive evaluation translation.

The scope of work included a literature review to understand the current practices in bridge management and element-level deterioration modeling. The research team spent significant effort in gathering, merging, and cleaning data from all the participating DOTs to create the analysis database. The data gathering process included interviews with State representatives to address any data-related questions. The research team then developed a data screening approach to identify the data items to be gathered for the model estimation dataset for Tier 1 and Tier 2 models, and procedures to filter the data for analysis. In addition, the team developed other information for Tier 3 curves and provided a summary of policy, guidance, and practices.

The deterioration curves are focused, addressing key transition times in bridge lifetimes, which ensure relatively accurate timing of work actions. Moreover, the deterioration models are compatible and complement the effectiveness of various Bridge Management Systems used by the participating agencies.

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COMMON ACRONYMS AND ABBREVIATIONS

AASHTO	American Association of State Highway Transportation Officials
ADE	Agency-Defined Elements
ADT	Average Daily Traffic
ANN	Artificial Neural Network
BME	Bridge Management Element
BMS	Bridge Management System
BPI	Bridge Planning Index
CoRe	Commonly Recognized
CS	Condition State
DAR	Deck Acoustic Response
DOT	Department of Transportation
ER	Emergency Relief
FHWA	Federal Highway Administration
GPR	Ground-Penetrating Radar
GCR	General Condition Rating
GUID	Globally Unique Identifiers
IE	Impact Echo
IR	Infrared
IRT	Infrared Thermography
LPI	Local Bridge Planning Index
MBEI	Manual for Bridge Element Inspection
NBE	National Bridge Element
NBI	National Bridge Inventory
NBIAS	National Bridge Inventory Analysis System

NDE	Non-Destructive Evaluation
NDT	Non-Destructive Testing
NHS	National Highway System
RCD	Reinforced Concrete Deck
SDT	Semi-Destructive Testing
TPF	Transportation Pooled Fund
UIT	Ultrasonic Impact Treatment
UT	Ultrasonic Tomography
WiSAMS	Wisconsin Structures Asset Management System
WisDOT	Wisconsin Department of Transportation
WS	Wearing Surface

EXECUTIVE SUMMARY

INTRODUCTION AND RESEARCH OBJECTIVES

The objective of this research project was to develop element-level deterioration curves for specific bridges using historical data provided by 12 Midwest State Departments of Transportation (DOTs). The research team identified and prioritized a list of elements to be modeled. The three tiers of curves included Tier 1 curves – for reinforced concrete deck (RCD), reinforced concrete slab, National Bridge Inventory items, RCD after major preservation to predict condition improvement; Tier 2 curves – for wearing surface, deck joints, defect development and progression, paint system effectiveness, steel girder corrosion, and substructure elements in harsh environments; and Tier 3 curves – for agency-defined elements, and determining non-destructive evaluation translation.

The scope of work included a literature review to understand the current practices in bridge management and element-level deterioration modeling. The research team gathered, merged, and cleaned data from all the participating DOTs to create the analysis database. The data gathering process included interviews with DOT representatives to address any data-related questions. A data screening approach was developed to identify the data items to be gathered for the model estimation dataset for Tier 1 and Tier 2 models, and procedures to filter the data for analysis. In addition, other information for Tier 3 curves was developed and a summary of policy, guidance, and practices was provided.

The deterioration curves are focused, addressing key transition times in bridge lifetimes, which ensure relatively accurate timing of work actions. Moreover, the deterioration models are compatible and complement the effectiveness of various Bridge Management Systems used by the participating agencies.

RECOMMENDED MODEL TRANSITION TIMES

Table E-1 summarizes the results of Task 6.3, which developed transition times for NBI component ratings. These are based on inspection data gathered since 1990 for all twelve agencies. Each number in the table is the median number of years that bridges remain in the indicated state before transitioning to the next-worse state. Since component ratings do not consider protective systems such as wearing surfaces and coatings, they are not recommended for the planning of preservation needs.

Table E-1. Summary of transition times for NBI component ratings (years)

Component	9	8	7	6	5	4	3	2	1
Deck	1.8	3.8	7.3	8.3	8.8	13.0	24.3	176.8	
Superstructure	2.8	6.1	9.1	9.2	9.9	10.3	16.6	44.7	8.4
Substructure	2.6	6.2	10.0	10.7	11.8	16.5	29.5	43.4	13.3
Culvert	2.3	6.0	14.0	19.4	21.6	19.0	75.2		

Blanks indicate insufficient data available

Table E-2 summarizes the results of the several tasks which developed transition times for element condition states. These are based on inspection data since the date that each of the twelve agencies implemented the 2015 AASHTO Manual for Bridge Element Inspection. Each number is the median number of years for units of each element to transition to the next-worse condition state. For decks and slabs, two sets of results are given. The second set is for bridge management systems, such as AASHTOWare Bridge Management, that explicitly model the effect of wearing surface condition by means of protection factors. Tasks 7.3, 7.4, and 7.5 are experimental models based on defect data. Bridge management systems currently do not model defect progression. Chapters 4 and 5 provide considerably more detail about the results of each task.

Table E-2. Summary of transition times for element condition states (years)

Element Group or Defect	1->2	2->3	3->4
Task 6.1 – RC Deck (for use without protection factor)	43.6	19.7	24.8
Task 6.1 – RC Deck (for use with protection factor)	38.3	24.5	13.8
Task 6.2 – RC Slab (for use without protection factor)	66.8	17.6	49.3
Task 6.2 – RC Slab (for use with protection factor)	43.7	21.5	28.3
Task 6.4 – RC Decks After Major Preservation	38.9	36.5	12.1
Task 7.1 – Wearing Surface	24.6	11.1	13.0
Task 7.2 – Expansion Joints	5.8	5.9	6.0
Task 7.3 – Defect 1080 (Delamination)	328.2	8.7	33.6
Task 7.4 – Defect 3440 (Paint System Effectiveness)	19.2	2.2	2.9
Task 7.5 – Defect 1000 (Steel Corrosion)	25.6	23.2	59.8
Task 7.6 – RC Pier Caps	69.4	12.4	68.0
Task 7.6 – RC Abutments	40.9	16.6	47.6
Task 7.6 – RC Pier Walls	50.3	15.6	25.4
Task 7.6 – RC Columns	23.8	11.3	80.5

SUMMARY OF ADE AND NDE PRACTICE GUIDANCE

The research team reviewed the list of ADEs provided by the State DOTs in the earlier stages of the project to develop an initial list of ADEs. Subsequently, the list of ADEs were updated to capture any changes by the State DOTs during this research project, based on the information provided in agency interviews. The current lists of ADEs used by Midwest DOTs are provided as Appendix V. Agencies have some differences in the way they approach asset inventories and inspections. These differences lead to different sets of ADEs across agencies; however, there are shared purposes for most of the ADEs. The most common purposes for ADEs were recording and tracking additional inventory items, capturing the inventory and performance of different wearing surfaces, additional protective systems, protective coatings, defects and vulnerabilities to track and differentiate performance, and tracking treatments and countermeasures. Communication among Midwest DOTs, particularly for deck condition assessment and related ADEs, may help establish standard definitions and practice. Having similar elements and inspection practices would help with development of future models.

After communication with agencies, the research team observed that most of the information and data related to NDE is on an as-needed basis. Aside from the Wisconsin DOT, there is not yet an agency with an established program or guidelines in collecting and using NDE data. All Midwest states, however, are experimenting with methods or are sometimes using methods for specific structures or purposes. Revising NDE use and practice across Midwest State DOTs in future would be of value.

RESEARCH SUMMARY AND RECOMMENDATIONS

The products of this study include this report, an analytical database compiled from the twelve states, a set of SQL queries to process the data, and a set of spreadsheets to finalize the calculations and customize the results.

Because of the standardization of the data and tools across elements and across agencies, users of these products can combine similar inventories and similar elements as needed, to obtain a sufficiently large dataset to estimate deterioration parameters for any application. This includes the ability to fully populate a bridge management system with reasonable deterioration models.

The study made several recommendations for future research that might improve the analysis and the usefulness of tools that employ these deterioration models. These opportunities include:

- Development of models to relate forecasts of element condition to estimates of the federal performance measures percent-good and percent-poor by deck area.
- Improved understanding of the differences among the twelve agencies in their element deterioration rates.
- Improvements in the quality and consistency of activity data collected by agencies.
- Improvements in the quality and consistency of element condition data collected by agencies.
- Further development of defect data and associated models.
- Improved environment classification.

CHAPTER 1. INTRODUCTION

BACKGROUND

Since the 1970s, State Departments of Transportation (DOTs) have been required to gather a standardized dataset of bridge inventory and biennial inspection data, for submittal to the Federal Highway Administration (FHWA) annually. These are compiled into a National Bridge Inventory (NBI). The NBI includes four data items describing bridge component conditions: deck condition rating (Item 58), superstructure condition rating (Item 59), substructure condition rating (Item 60), and culvert condition rating (Item 62). Each item is recorded using a coding scheme with 9 representing excellent condition and 0 indicating failed condition and beyond corrective action; these are called component condition ratings. Without maintenance intervention, the condition rating of an NBI component will deteriorate over time. The rate of deterioration can be modeled using a discrete Markov chain.

However, the NBI ratings do not provide enough information on the cause of deterioration to forecast future conditions or select appropriate repair schemes, and they do not provide enough information on the impact of some important elements—such as expansion joints and paints—on bridge deterioration. To overcome these limitations, bridge management systems are beginning to use a more extensive condition description organized according to element condition states.

Bridge element condition state inspection has been practiced since 1991 and has been mandatory since 2014. The implementation of the American Association of State Highway Transportation Officials (AASHTO) Manual for Bridge Element Inspection (MBEI) is becoming a common practice across State DOTs. State DOTs are recognizing the benefits of using these detailed condition data to support bridge analysis and decision-making. Part of this benefit is using detailed element inspection data to forecast conditions and apply the resulting information in bridge management decision-making. Even though element-level inspection data can provide more detailed information on bridge deterioration, very few studies have yet been undertaken to develop element-level deterioration models.

This project is part of the Transportation Pooled Fund (TPF) program in which 12 Midwest States (Iowa, Illinois, Indiana, Kansas, Kentucky, Michigan, Minnesota, North Dakota, Nebraska, Ohio, South Dakota, and Wisconsin) pooled their resources to develop specific bridge element-level deterioration models for the participating States (highlighted in green in Figure 1).

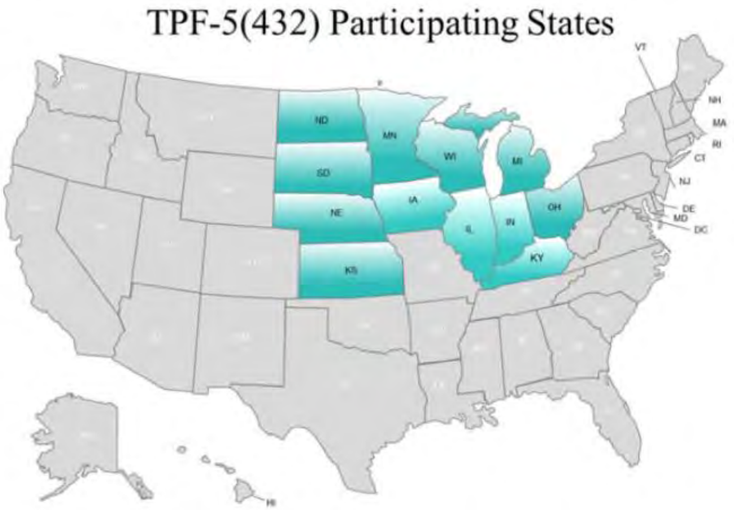

Figure 1. TPF-5(432) participating states

RESEARCH OBJECTIVES

The objective of this research project was to develop element-level deterioration models for specific bridges using multiple resources and historical data provided by 12 Midwest State DOTs. The deterioration curves were developed through data analyses and research that reflect Midwest environments (winter/summer), operations practices (application of deicing chemicals and representative rates of application), maintenance practices, and design/construction details.

The scope of work included a literature review to understand the current practices in bridge management and element-level deterioration modeling. The research team spent significant effort in gathering, merging, and cleaning data from all the participating DOTs to create the analysis database. The data gathering process included interviews with State representatives to address any data-related questions. The research team then developed a data screening approach to identify the data items to be gathered for the model estimation dataset for Tier 1 and Tier 2 models, and procedures to filter the data for analysis. The three tiers of curves included Tier 1 curves, for reinforced concrete deck (RCD), reinforced concrete slab, NBI items, and RCD after major preservation to predict condition improvement; Tier 2 curves, for wearing surface, deck joints, defect development and progression, paint system effectiveness, steel girder corrosion, and substructure elements in harsh environments; and Tier 3 curves, for agency-defined elements and determining non-destructive evaluation (NDE) translation. The team also relied on bridge data from other sources in developing deterioration curves. In addition, the team developed other information for Tier 3 curves, which included identifying agency-defined elements, determining non-destructive evaluation translation, and providing a summary of policy, guidance, and practices.

RESEARCH APPROACH

The critical components of the research approach included data gathering and processing, transition time estimation, model estimation, expert review, and model validation. The subsections that follow describe each of the steps briefly.

- **Literature Review:** The research team reviewed the state of the practice to understand early efforts in bridge management and element-level curve development. Detailed findings from the literature review are provided in Appendix I and incorporated throughout the report when necessary.

- **Data Gathering, Processing, and Screening:** During this process, the research team gathered data from all the participating states and through the FHWA bridge portal to develop the analysis dataset. Using a structured query language, the team processed the data to create a table of inspection pairs.

- **Transition Time Estimation**: The research team developed Markov models with one-year transition probabilities based on the inspection dataset with no consideration for age, past conditions, or any other information. The Markov model expresses the probabilities as a simple matrix indicating the percentage of elements transitioning from one condition state to the next. This model served as the base model, while other models were considered by incorporating past maintenance and preservation activities, the age of the bridge, and other significant variables.

- **Model Estimation**: The research team investigated the benefits and weaknesses of the available modeling approaches and selected a group of methods that addressed the needs of the research questions. During this process, the team estimated models that are representative of the independent variables—administrative regions in which bridges are located as well as other factors such as climate zones, functional class, bridge deck area and material types, and the amount of general traffic and truck traffic volumes. The team also investigated different models, considering important variabilities and uncertainty, to verify if any inconsistencies in the response variables are statistically significant based on the independent variables data available. Furthermore, the team developed adjustment factors for the significant variables based on the bridge location and other attributes. The team examined defect progression as part of this task for each model developed.

- **Expert Review**: To avoid underestimating or overestimating model parameters, the team supplemented the models with assumptions based on expert understandings of actual work completed. The TAC team reviewed all initial models, and the research team gathered comments to refine the models where needed. This process included a series of meetings to achieve consensus on assumptions, model types, independent variables selections, and model forms.

- **Model Validation**: To verify and validate the developed deterioration models, the research team used data and information from the participating DOTs to demonstrate if the models are a good representation of the systems groupings—indicating the flexibility and robustness of the models.

RESEARCH CONTRIBUTIONS

The primary benefit of this project is that the participating States can plug the developed models into their bridge management systems and directly use the data to plan for maintenance. The secondary benefit of this project is the development of the analysis database, designed for the participating States. The database can be updated whenever additional data becomes available to update the models.

ORGANIZATION OF REPORT

The remainder of this report is organized as follows.

- Chapter 2 contains the data gathering procedure and lists the collections of inspection data and maintenance history data. The data cleaning process is also documented in this chapter.
- Chapter 3 discusses data governing policies for the analysis database.
- Chapter 4 and Chapter 5 show the modeling processes and results of Tier 1 and Tier 2 deterioration curves, respectively.
- Chapter 6 documents the findings from the Tier 3 analysis.
- Chapter 7 includes discussion of the results, conclusions, and future work.
- Appendices

CHAPTER 2. DATA GATHERING

DATA GATHERING

The data gathering process was one of the most important and time-intensive tasks of this project. The objective was to gather element condition data and relevant information useful for developing deterioration curves for a selected group of bridge elements. The research team specified nine datasets for the study participants to submit. A two-step approach was used in gathering the data. The first step involved a general data request to the participating State DOTs to upload their data to a shared project folder while the research team downloaded available State data from the FWHA Long-Term Bridge Performance InfoBridge portal. The second step involved a questionnaire, follow-up email communication, and phone interviews with State DOTs to clarify their submissions and address any data gaps. Appendix II contains detail information on data gathering and data processing.

Throughout this process, the research team made the following key observations about the requested data and information:

- Raw Dataset: The data gathered from the DOTs included:
    - 219,383 Bridges
    - 1,778,813 Routine inspections
    - 387,248 Routine inspections with AASHTO Elements
    - 96,954 Routine inspections with AASHTO Element Defects
    - 198,341 Construction Activity entries
    - 9,112 NDE inspections
    - 399 ADEs
- Inspection practices, element definitions, and coding methods: Except for one State DOT, the participating DOTs can be grouped into two main categories in terms of their inspection practices and coding methods. Of the data received, six of the DOTs noted that they use the AASHTO MBEI directly. The other six DOTs, except for one DOT, indicated that they use a modified version of the AASHTO MBEI. The modification usually related to the alteration of element conditions or defect language to suit the agency's needs. In addition to these findings, it was gathered that some challenges might arise in processing/analyzing the inspection data due to the inconsistent coding of element conditions from one inspector to another, or among agencies or districts, or over time. A benefit of pooling data from many agencies is the ability to smooth over such differences, while at the same time the methodology allows for stratification in these ways, to investigate the differences, if there are a sufficient number of data points.
- Component, element-level inspection, and inventory data: Many of the participating State DOTs previously collected data using the AASHTO Guide for Commonly Recognized (CoRe) Structural Elements, beginning as long ago as 1994. At various times, they made the transition to the MBEI. One agency began element data collection as recently as 2016, using only the MBEI. Another is still in the process of beginning element

inspection according to federal requirements. The databases received were limited to the National Highway System (NHS) (both state and locally owned) bridge data.

- Agency-defined elements (ADE): ADEs offer DOTs the flexibility and ability to manage their bridges to meet their specific needs while responding to federal reporting requirements. All but one of the participating DOTs reported their ADEs. However, the research team did not receive historic data for one of the DOTs that reported their ADEs.

- Non-destructive evaluation (NDE): Non-destructive evaluation is mostly considered at the research stage. There was limited evidence of widespread practical application of NDE inspection techniques at the network level among the participating agencies. The research team received NDE data and information from very few DOTs, which have applied various techniques to investigate individual bridges. Examples of techniques the DOTs reported using include ultrasonic impact treatment (UIT), ground penetrating radar (GPR), impact echo, infrared (IR), eddy current, and drone technologies. In general, there was limited evidence of NDE adoption and application on bridges across the network.

- Construction history data: Although most DOTs provided some construction data, they indicated significant challenges, which included the lack of granularity for modeling purposes, unusable data formats, incomplete data, and the inability to link data to specific bridges.

- Construction, preservation, and maintenance policies: Policies translate to actions and if well-documented, they can drive efficient and effective resource allocation. Although bridge preservation is not a new concept, many DOTs have not formally documented their business approach in selecting work types and prioritizing treatments on bridges. Some DOTs have developed preservation manuals based on Federal guidelines, while others documented their processes through other programs such as Transportation Asset Management Plans, capital programs, and scheduled maintenance programs. Others have developed a deck decision matrix to aid decision-making. Although these policies are useful to detect patterns in real bridge work, they remain short in providing usable information such as the actual work done at a given time to inform modeling.

- Deterioration curves: Most of the examples found among the participating agencies were deterioration curves at the bridge component level, used in worst-first prioritization or classification of needs. To improve decision-making, DOTs are finding techniques to predict bridge conditions using the detailed information they gather at the element level. However, it was observed that only a few DOTs have been exploring element-level deterioration curves so far. One of these states was estimating element deterioration rates to indicate the median years the element remains in one condition state, while another was using an age-based approach to forecast element condition over time.

- Element environment: Some of the DOTs classify bridge elements using an environment code based on climate and operational factors at each site that can affect future deterioration rates. It was observed that most of the participating DOTs were not assigning environment codes to different elements, instead placing all elements into a single environment code; predominantly in environment 2 – low or 3 – moderate.

Essentially, these State DOTs assume that bridges or elements in the network will exhibit similar deterioration trends, or the deterioration trends may not be significantly different across the network. However, due to the wide range of environmental conditions across the States, this variable was not considered in the analysis.

- GIS coordinates of bridges: This information enables asset owners to understand location-related issues by easily accessing bridge data and providing better visualization to enable information-sharing and communication with decision-makers. It also facilitates geospatially integrating other external variables in the dataset to explore their impact on deterioration. The dataset gathered contained GIS coordinates of all bridges.

DATA SCREENING

General Form of the Data

Although the primary concern in Tiers 1 and 2 were accuracy and reliability, the research focused on compatibility of models with existing bridge management systems. Hence, the data structure was designed for compatibility with the bridge databases contributed by participating agencies, including the generic NBI data submittal required each year from every state, as well as AASHTOWare™ Bridge Management and agency-customized bridge management systems. The contributed datasets were merged into one analysis database in a MySQL format. Certain changes, discussed below, were needed in order to make this possible. Appendix II contains additional information on the data processing and merging process. In general, no data was deleted from the agency contributions; rather, data was filtered when accessed to set up each model estimation activity and data enhancement methods were considered to link data among agencies. By this means, the analytical process had maximum flexibility to use available relevant data in each model.

Tables Utilized

AASHTOWare™ Bridge Management tables – Only the tables required for deterioration modeling were captured in the integrated database. These were:

- Bridge – main bridge table with one row per bridge
- Roadway – data concerning the roadway on the structure
- Structure_Unit – allows separate element lists by structure unit or span
- Inspevnt – inspection event, including component condition ratings
- Eleminsp – element inspection (old AASHTO CoRe element format)
- Pon_elem_insp – element inspection (new AASHTO MBEI format)
- Elemdefs – element definitions (old AASHTO CoRe element format)
- Pon_elem_defs – element definitions (new AASHTO MBEI format)
- EnvtDefs – environment definitions (old Pontis format)
- Pon_envt_defs – environment definitions (new AASHTOWare™ Bridge Management format)
- Metric_english – element measurement units (only for Pontis or AASHTOWare™ Bridge Management data)

NBI tables – Data that are not in AASHTOWare™ Bridge Management format, such as downloaded NBI files, lack many or most of these tables or attributes. Moreover, the FHWA InfoBridge data consist of roadway and inspection event data joined onto bridge data. Therefore, these datasets were stored in separate tables as follows:

- NBI_bridge, consisting of all the columns provided in the NBI bridge download files.
- NBI_eleminsp, consisting of all the columns provided in the NBI element files.

Additional tables – The team obtained NBI bridge and element data for all participating agencies. Additional bridge management system (BMS) data were obtained from most of the State DOTs, which is in most cases more detailed than the NBI files. For example, the BMS datasets often have element lists subdivided by structure unit, span, and/or environment. The more detailed datasets are preferred where available. Element-level data was used in Tier 2 models. The project team reviewed wearing surface data from the participating States to identify the specific wearing surfaces for the Tier 2 models. This dataset was stored in a separate table as follows:

- Activity – work performed on the structure

Modifications and Additions to the Data

Many of the coded NBI items are defined to have leading zeroes. These can sometimes inadvertently get removed or converted to numeric format when data are manipulated, especially in Excel. The project team ensured these leading zeroes were preserved as specified in the FHWA NBI Coding Guide. In general, these were treated as text data even if they appear numeric. As a part of creation of the integrated analysis database, the research team identified cases where coding conventions differ from the FHWA Coding Guide. These were discussed individually with agencies to decide how best to standardize the data.

The Bridge table in AASHTOWare™ Bridge Management, and both types of NBI downloaded files, include a state code. The same code was added to all the other tables in the database, including definition tables, to accommodate any customizations that individual agencies have made. The database has a separate database table of state codes and state names as given in the NBI Coding Guide, item 1.

AASHTOWare™ Bridge Management tables use Globally Unique Identifiers (GUIDs) as primary and foreign keys in each table. Before merging each agency’s data into the merged database, the project team checked that incoming GUIDs do not duplicate any GUIDs that are already in the merged database. In the case of duplicates, the team generated a new GUID that is unique for the incoming data.

In the NBI tables, the GUIDs are added in the same pattern as the BMS data to uniquely identify the rows and the foreign key relationships. As a part of this activity, the research team constructed an accurate foreign key relationship between the NBI element table and the NBI bridge table. The research team created two columns to clearly identify NHS bridges and state-maintained bridges, respectively. These have the value 1 if true and 0 if false. The method used in this calculation differs among states and was determined in consultation with each state during the process of creating the integrated database.

Some agencies use ADEs as a way of subdividing NBI elements. Where this is the case, the team checked that it received either:

- The agency-defined elements that roll up into NBI elements, which the research team needed to aggregate; or
- NBI elements already in their rolled-up form so that they conform to NBI element requirements.

The element definitions table delivered as a part of the analytical database provides the correspondence between agency-defined elements and AASHTO MBEI elements.

Some agencies use a means of distinguishing different types of wearing surfaces, other than sub-elements of NBE element 510. This was discussed with those agencies to clearly identify the element. For the wearing surface, the most granular data available to the research team was used to conduct the wearing course analysis. The different ways of classifying wearing surfaces are discussed in the first section of Chapter 5, "Element level deterioration curves for wearing surfaces."

In addition to these tables, it was necessary to create a new table of work activities, named Activity, to the extent that participating agencies were able to provide such data, for modeling tasks. This table contains at least a state code, bridge identifier, a bridge GUID that matches the Bridge.bridge_gd column of the bridge table, a bridge GUID that matches NBI_bridge.bridge_gd, a work completion date, and some sort of identification of the type of work as provided by the participating agencies. Activity type is needed to identify whether major preservation was applied to reinforced concrete decks, either alone or in combination with other treatments. The research team consulted separately with each agency to decide how best to code their activity data, since each agency has its own unique system.

Filtering

The project team used guidance from the participating agencies to discern whether the dataset contained element inspections that might be inappropriate for use in modeling. These included records generated using a migration utility (rather than field-collected), or elements that the agency considers especially unreliable, such as test data or training data. A column called "Valid" was added to the bridge, NBI_bridge, inspevnt, eleminsp, pon_elem_insp, and NBI_eleminsp tables to indicate 1 if the record is considered valid and 0 if it is considered invalid according to the information provided by each agency.

Bridge management databases normally enforce referential integrity, but it was necessary to confirm that records are complete. In particular, Eleminsp, Pon_elem_insp, or NBI_eleminsp records were marked invalid (using Valid=0) if any element inspection records lack a matching record in the corresponding Bridge table. In the AASHTOWare™ Bridge Management data, the research team marked invalid any Eleminsp or Pon_elem_insp element inspection records lacking matching data in the corresponding Structure_unit, Inspevnt, Pon_elem_defs, Elemdefs or Envtdefs tables. The research team also marked invalid any Inspevnt records lacking matching data in the Bridge table.

Some agencies using AASHTOWare™ Bridge Management do not use all four environment classes, or have environment classes that are nonstandard. For each agency, the research team evaluated whether environment codes in the Eleminsp or Pon_elem_insp tables should be recoded to a valid value.

The research team marked invalid element inspection records where the quantity by condition state is less than zero, or where the sum over all condition states is zero. In the Eleminsp table, the team marked invalid any record having a non-zero quantity in a condition state greater than Elemdefs.statecnt. CoRe element data had a variable number of condition states per element.

Additionally, the research team checked inspevnt.inspdate for valid inspection dates, and marked invalid as needed. The earliest element inspections were 1995, and NBI inspections could go into the 1980s. Inspection dates were no later than the date the research team received the contributed data. Specific agencies were able to supply a more precise range of dates that are valid.

After participating States reviewed and approved the screening process, the research team developed the analysis dataset, which was a significant milestone in the project.

CHAPTER 3. DATA MANAGEMENT POLICY

A part of this research was to create a data management framework to ensure the analysis database is treated as an asset and secured to maintain its value while being accessible to users. This chapter discusses the formal data management program's components, including governance structure to ensure proper chain of authority, roles and responsibilities to ensure adequate accountability, and primary principles to ensure the policy is implemented.

GUIDING PRINCIPLES FOR DATA MANAGEMENT

Governance Framework

To ensure that the analysis database is adequately updated and rightfully accessed by users, a governance framework was established to include anticipated stakeholders. Two main groups, database owners and database users, were identified. As depicted in Figure 2, the database owners comprise three groups—TAC Panel, Wisconsin Department of Transportation (WisDOT) Data Custodians, and DOT Data Stewards. The database users include both internal and external individuals, groups, or organizations using the data.

In general, the governance framework will ensure proper communication and establish the basis for different access levels to the database. The following section describes the composition and responsibilities of each group in the governance framework.

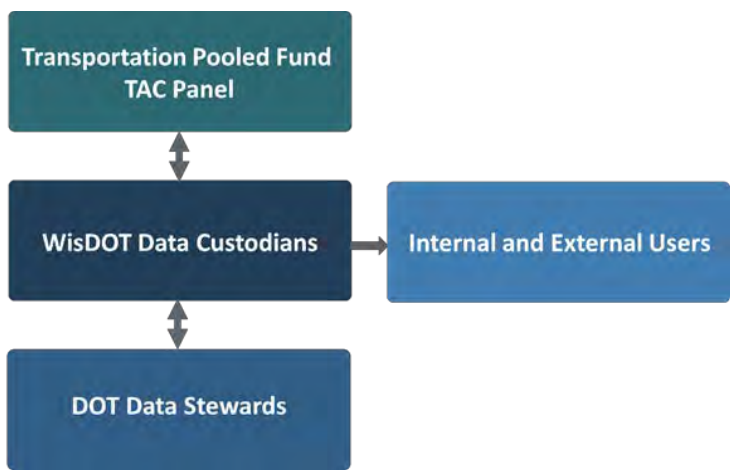

Figure 2. Data Governance Structure

Roles and Responsibilities

The participating DOTs will contribute to compliance with this data management policy. Individuals assigned with key responsibilities will ensure that the outlined data management principles are implemented sufficiently.

Table 1 contains the primary roles and responsibilities and the anticipated composition of each identified role.

Table 1. Governance Roles and Responsibilities

Roles	Who	Primary Responsibilities/Level of Accessibility
Transportation Pooled Fund TAC Panel	One member or designee from participating DOTs	• Ensures the integrity of the database is maintained. • Develops and approves changes to the data management policy. • Oversees the implementation of the policies. • This group will have read rights to the database.
WisDOT Data Custodians	Unit providing web services platform to host the data and individuals providing technical expertise	• Responsible for developing and implementing business rules governing the database. • Responsible for database upload, download, storage, security, and upkeep. • This group will have both read and edit rights to the database with guidance from the data stewards.
Data Stewards	Key contact person(s) from participating DOTs responsible for their bridge data	• Technical experts on bridge data. • Provide bridge data in a usable format to be added to the database. • Ensure data accuracy, completeness, validity, quality, and up-to-date-ness. • This group will have reading and editing rights to their state-specific database but read-only rights to other state databases.
Database Users	This group is made up of DOTs internal users and external users (DOT contractors, researchers, the public, etc.)	• Abide by the data management policy. • Provide insight to how the database can be improved to meet future needs. • This group will have read-only rights to the database and will request and receive data from the WisDOT data custodians.

Guiding Principles for Data Management

Ensuring the quality of the analysis database is critical for State DOTs to ensure the integrity of the database and update models in future efforts. To manage the database effectively, owners and users will demonstrate and comply with a set of data principles. These principles reflect acceptable practice in data management and govern how the database will be modified, updated, accessed, secured, and used. The principles will guide data management decision-making at all levels of governance.

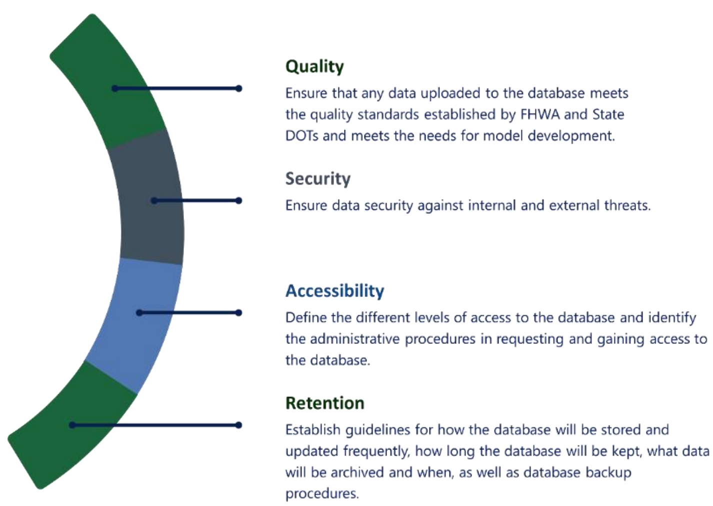

Figure 3. Data Principles

Data Management Policies

The following are the data management policies that will be used to manage this dataset on an ongoing basis after the pooled fund study is completed and the data has been handed over to the managing DOT, WisDOT.

1. Data Repository – The data will be housed at WisDOT. WisDOT will be the Data Custodians. It will be stored on an internal PC specifically designated for this use and managed by the Bureau of Structures. The only person authorized to edit the database is the Chief of the Structures Development Section, or their designee. WisDOT will have overall responsibility for the quality, security, accessibility, and retention of the analysis dataset and models developed from this project. The information to be stored is anticipated to be under one terabyte. It is not anticipated that the project contents described herein will be accessible from outside WisDOT (i.e., live web access).

2. Data Backup – A data backup procedure shall be defined as per WisDOT standard procedures so that the data will not be lost. It is important that WisDOT standard procedures be followed, as a special backup procedure will likely not be followed consistently. At any time, there will be two copies of the database and study results. When/if the data is updated or supplemented with additional data, both copies will be updated. Additional network backup systems also exist.

3. Data to be Stored – The data to be stored includes the following:

    a. Final Report

    b. PowerPoint

    c. Twelve States individual data submittals and information

    d. Data population and validation scripts to pull data from individual states

    e. Raw dataset (combined data from individual states)

    f. Analysis dataset schema and data validation scripts

    g. Analysis dataset (modified data from raw dataset)

    h. Models developed as part of this project

    i. Model development spreadsheets

    j. Data requests

    k. Data feedback forms

4. Data Format – The data will be in the following format:

a. Final Report: The final report will be in Microsoft Word and PDF format. This should also include Word and PDF files associated with all task deliverables.

b. PowerPoint: This should include the PowerPoint developed to serve as a training tool for DOT Bridge Management staff on the project.

c. Twelve States individual datasets and information: Data and individual files for unstructured data (coding practices, documents, etc.) will be in MySQL format. The unstructured data will have a list of the documents and contents for each State.

d. Data population scripts to pull data from individual states: Data population and validation scripts were created in SQL to extract the data from individual States' databases and populate and validate the analysis database. They can be used to extract the data from the State databases that were used for this project. These scripts have the potential to be used for future updates to extract data from individual States' databases if these databases provided under this project do not change. It is important to note that some States' data were in a spreadsheet format and the SQL scripts may not apply.

e. Raw dataset: The format of the raw dataset will be in MySQL format, which will be modified to form the analysis dataset.

f. Analysis dataset: The format of the analysis dataset will be in MySQL format and documented with metadata included within the dataset. MySQL is an open-source database format that can be downloaded and used free of charge. The instructions for downloading and installing MySQL will be included on the data repository in a Word document. This analysis dataset will also include NBI/NBE information downloaded from the FHWA website. The analysis dataset MySQL databases will have a table schema, a data dictionary, and a codes list. It is important that all databases are self-describing so that a proficient database analyst can understand and use the data without the help of the Project Team.

g. Models developed as part of this project: The format of the models will be documented in the spreadsheet.

h. Model development spreadsheets: The Excel spreadsheets used to develop each model will be stored in a locked and read-only format.

i. Data requests: Used to store each data request (see Table 2 below).

j. Data feedback forms: A data feedback process should be in place so that data users can report any discrepancies or inconsistencies in the data, and so they can be tracked to resolution.

5. Data Access – The following are the data access principles:

   a. The WisDOT Data Custodian will be the only agency with read and write access to the datasets.

b. The State DOT Data Stewards will have read-only access to the data.

c. If data is added to the system, it will be provided to WisDOT, and they will upload and update the dataset. This is necessary to ensure that the data is updated in a consistent and comprehensive manner.

d. Any data users will request data from WisDOT and WisDOT will fulfil the request. Data requests should be documented in a spreadsheet with the date, requestor, data requested, and date the request was filled. The data that is provided should be kept in a separate folder so that it can be recreated easily. The transmitting email should also be included. Any permissions (see below) should be included in this folder as well. The folder should be numbered consecutively, and a short description of the request should be a part of the folder name. A data feedback form should be created as explained above.

6. Data Permissions – Data that is to be provided to any source must be approved by the individual DOTs whose data is being accessed. These data permissions should be managed by the WisDOT. This permission should be provided by email and stored in the data request folder.

7. Dataset Integrity – It is very important to preserve this dataset as is. Any modifications to the dataset should be made on a copy and appropriately identified. Also, it should be noted that translating the State-provided datasets into the analysis dataset took a lot of effort and expertise as well as intense coordination with the participating States. In the future, these State-provided datasets may change format as DOTs use new BMSs. Therefore, it is likely that the same methods used to translate the State data into the analysis dataset cannot be replicated and must be conducted from scratch.

Summary of Data Structure

The following contains a summary of the key data items that will be maintained and their corresponding format.

Table 2. Summary of Project Data Structure

Item	Format
Final Report	• Word Doc • PDF
Educational PowerPoint	• PowerPoint Slides
Analysis Dataset	• MYSQL • Word Doc
Data Population Scripts	• MYSQL
Data Validation Scripts	• MYSQL
Models	• MYSQL
Model Development Spreadsheet	• Excel
Participating DOTs Individual Datasets and Information	• MYSQL and unstructured data in resident format in individual State-based folders
Data Requests	• Request and fulfilling email documentation • Include data requested so there is a record and permission to disseminate
Data Feedback Form	• Excel record of data feedback forms and resolution

CHAPTER 4. TIER 1 DETERIORATION CURVES

This chapter discusses the Tier 1 curves that were developed, for RCD, reinforced concrete slab, NBI items, and RCD after major preservation to predict condition improvement. Deterioration models were developed in the form of Markov transition times, which are compatible with common bridge management systems and with previous research. For agencies using the hybrid Markov/Weibull model provided in AASHTOWare™ Bridge Management, the research also developed Weibull shaping parameters, which model the rate of onset of deterioration, and protection factors, which model the ability of wearing surface conditions to affect the rate of substrate deterioration.

As discussed in Appendix I, Markov models are one of the simplest methodologies available for the element and condition state data that each state collects on a periodic basis. Markov model forecasts are expressed as the probability of each possible condition state at a given point in time, given either current condition or the condition resulting from a planned agency action. In any given inspection interval (typically two years), it is assumed that each unit of each element can make just one transition to the next-worse condition state, if no intervening action is taken by the agency. The probability of this transition is expressed in a BMS in the form of a median transition time—the number of years for 50% of a population in a given starting state to make the indicated transition, while the remaining 50% remain in the starting state.

Since each element has four possible condition states, the BMS provides a table and user interface allowing the entry of three transition times for each element. Each condition state implies the potential need for a corrective action, so the deterioration model forecasts the rate at which new needs arise. Combined with a cost model, this enables the planning of the financial needs of a bridge inventory. The primary goal of the present study is to provide a means for selecting appropriate transition times for each agency and its intended planning applications.

A useful property of Markov models as used in common BMSs is that their transition times can be estimated from a database of inspections whose timeframe is far shorter than the typical lifespan of bridge elements. The current AASHTO MBEI has been in use only since 2015, while the average age of existing bridges in the nation is approaching 50 years. A cross-sectional model such as the Markov model does not require information about past conditions or agency actions; it merely forecasts changes in condition year by year.

Another useful property of the Markov models commonly used in BMSs is that their transition times can be estimated algebraically from a database of past inspections. Because statistical fitting methods are not used, there is no fitting error. The algebraic method, described in Appendix IV, provides considerable flexibility to investigate causal variables by means of model stratification. For example, the effect of traffic volume can be investigated by dividing the data set into a small number of traffic volume classes, whose transition times are computed separately.

Although the models lack fitting error, they still require a substantial amount of data for successful estimation. The quality of models is evaluated by observing their stability when computed from different data sets, the existence of intuitive relationships among strata, reasonableness of results, and usefulness for the intended application. Quality is improved by selecting only the minimum number of strata that are necessary for the intended application, so each stratum's population is maximized. Since there can be many possible applications aside from populating a BMS, there can be many possible models in use in a given agency for different planning purposes.

The twelve agencies participating in this study may have very different business needs for their deterioration models, and may also have differing design, material, and operating conditions that affect their deterioration rates. Some may have populations too small for estimation of transition times, unless combined with other similar agencies. To provide the needed flexibility to fit each agency's needs, the deterioration models were delivered in the form of focused inspection pair data sets in Microsoft Excel files, using pivot tables to enable flexible model stratification. Appendix III discusses how to judge the adequate size of a population and how to improve model stability when populations are small.

Each inspection pair in the focused dataset consists of two sets of condition ratings, for inspections spaced two years (± 6 months) apart. The first inspection, denoted **X**, is used as an independent variable to forecast the second inspection, denoted **Y**. The algebraic formulas necessary to compute transition times were packaged as "measures" (in Excel terminology), which can then be presented in the pivot table bodies, sensitive to the settings chosen for filters, rows, and columns. Appendix III discusses the preparation of the inspection pair datasets and the means of customizing the pivot tables to fit each agency and application.

Specific research questions were provided in the research work plan, to be addressed in the models and in this report. These do not encompass all elements required for a BMS, and they also explore modeling applications that current BMSs are not yet able to support. Future researchers can use the data and tools developed in this study to explore other elements and applications. The following sections in this chapter and the next are organized according to the research plan, providing the main results and some of the most interesting variations. The Excel files delivered with this report can be consulted for more detail.

DETERIORATION CURVES FOR NBI COMPONENT ITEMS

While most of the requested research questions involved element-level inspection data, one of the tasks was devoted to an older set of component data, using NBI component condition ratings for decks, superstructures, substructures, and culverts (NBI items 58, 59, 60, and 62, respectively). These are classified on a categorical scale of 0 to 9, considering condition, age, functionality, and risk. Only state-maintained bridges are considered in the component-level models.

Component data have strengths and weaknesses for deterioration modeling. The primary strength is that these data have been collected in every state under a reasonably consistent set of definitions, with only minor changes, since 1990. This timeframe is still less than the average age of existing bridges, but does cover a relatively long segment of bridge lifespans, reflecting a long evolution of design, traffic, climate, and operating conditions. Another strength is that federal performance management measures (percent good and poor by deck area) are easily derived from component ratings.

A weakness of component ratings is that they explicitly do not consider many of the factors most significant for bridge preservation, including wearing surfaces, coatings, expansion joint seals, and bearings. In addition to condition, they consider, in a form not easily separable, other characteristics such as age and functionality. Compared to element condition states, component ratings are much less detailed and thus provide less information that might be predictive of future conditions. While certain BMSs support the forecasting of component ratings, they are useful mainly for predicting the growth rate of replacement needs and certain types of rehabilitation, and not for predicting preservation needs. As a result, they are rarely used in common bridge management tools such as life cycle cost analysis and preservation planning.

Table 3 summarizes the Markov transition times for deck component ratings, computed from the data provided for the twelve agency participants in this study, for state-maintained structures. Each row shows the results computed separately for each agency, and the "All" row shows the result when computed for all twelve agencies together. Each number in the body of the table is the median number of years to transition out of the indicated condition state to a worse condition state if no agency action is taken.

Table 3. Transition times for NBI deck component ratings (years)

State	Pop	9	8	7	6	5	4	3	2	1
IA	2,595	2.4	4.7	8.2	9.7	16.8	16.2	999.0	999.0	999.0
IL	5,870	0.9	3.8	6.3	6.5	5.8	9.9	11.7	999.0	999.0
IN	3,988	1.6	3.2	7.3	10.0	14.2	72.5	18.2	8.4	999.0
KS	2,732	999.0	3.6	17.2	8.6	14.6	28.8	999.0		
KY	4,820	0.8	3.8	7.7	10.1	11.3	19.4	44.6	999.0	999.0
MI	3,923	0.8	2.7	4.6	5.9	6.1	8.9	230.4	999.0	
MN	2,437	1.2	3.7	10.6	12.6	11.1	999.0	54.1	999.0	
ND	623	2.1	8.6	13.7	13.5	21.1	999.0	999.0	999.0	
NE	2,030	3.2	6.4	10.2	9.6	23.4	18.6	999.0		
OH	10,338	2.4	4.4	6.3	9.9	7.2	13.7	69.4	999.0	
SD	1,140	0.6	2.3	5.1	7.2	6.2	7.1	15.4	999.0	
WI	4,451	0.7	3.1	6.4	6.0	9.6	14.8	14.7	999.0	
All		1.8	3.8	7.3	8.3	8.8	13.0	24.3	176.8	999.0
Pop	44,946	2,134	8,427	16,784	9,877	3,624	1,307	2,529	256	8

When the Excel spreadsheets report a result of "999.0," this indicates a result greater than or equal to 999 years, which is unlikely to be valid, and/or a population size too small to perform the algebraic computations. Because of the large populations available for NBI component ratings, condition states 9 to 4 are a 10% sample of the population, while states 3 to 1 are a 100% sample. The number of inspection pairs used in the model calculations is reported in the "Pop" column and row in Table 3. Even with a 100% sample, condition states 3, 2, and 1 are very uncommon in many agencies and thus are of questionable validity in the deterioration model. Excessively large values such as "999.9" should not be used in a BMS, and should instead be replaced with expert judgment. Future research with larger populations of inspections may be able to improve on them.

When using models such as Table 3 where some of the condition states are much more common than others, an agency might want to use its own data points for the common conditions such as

7, 6, and 5, and use a combination of all the agencies for the less common ratings such as 9, 4, 3, 2, and 1. It is also valid to use a model computed from a subset of the twelve agencies, perhaps those which share similar operating conditions. The Excel pivot tables provide features to filter the tables to focus on a subset of interest, perhaps a group of agencies, or all state-maintained bridges, or all National Highway System bridges. Appendix III provides instructions on how to select different subsets of elements and bridges for consideration.

Validation

Deterioration models are used for making predictions in planning models, but it must always be remembered that what they actually measure is the change in condition in particular datasets in the past. The operating conditions or maintenance practices that affected deterioration in a past time period, and the inspection practices that governed the collection of a historical dataset, might or might not apply to future bridge conditions in the inventory of interest. The models are most useful for planning if decision-makers agree that future deterioration is likely to be similar enough to past conditions, so that the model is useful for making reasonable distinctions among the outcomes of policy options under consideration. A nominal amount of error is expected when comparing predicted versus actual conditions, and when comparing the results of different models. With this in mind, the spreadsheets delivered in this project provide several different ways of validating the Markov models:

- The computed deterioration model can be applied to each inspection to estimate the condition in the following inspection two years later, as a probability of remaining in the same condition. In the deck component model, the average difference between predicted and actual was 0.6%. As a probabilistic model, a Markov model does not attempt to predict changes in condition of individual bridges, but rather predicts the number of changes in a given inventory in one year.

- The dataset of inspection pairs used in calculating the model is divided randomly into two sets, each estimated separately. The difference in transition time between the two sets can be used as an estimation of the typical amount of random error in the model. In the deck component model, the two datasets differed by 0.2 years for the most common condition states. This difference increased to 1.9 years for state 4, and 4.3 years for state 3, which have much smaller populations in the dataset. Appendix III provides additional guidance on the implications of population size.

- A coefficient of determination, commonly known as “r-squared,” can be computed as a summary indicator of the difference between predicted and actual, where 1.0000 is perfect agreement and 0.0000 is perfect randomness. In the deck component models the coefficient of determination was 0.8894.

- The model can be stratified according to a categorical variable expected to have an intuitive well-defined effect on the rate of deterioration. The stratified results can then be examined to see if the model reflects the intuitively expected behavior. Two examples, construction era (as a range of year-built) and traffic volume class, are discussed below.

- The model results can be compared to alternative published models. Since the alternative models may have been based on different datasets and may have used different methodologies, an exact match cannot be expected. However, if differences between the models can be intuitively explained, this would lend support to the new model.

Because the estimation method is algebraic, it does not have fitting error. Therefore, certain familiar statistical concepts such as confidence interval are less useful for model evaluation. The desired confidence interval is unknown, and the potential sources of uncertainty, such as future changes in operating conditions, funding allocations, and many other factors can be more significant than any arbitrarily chosen confidence level. The main test of model validity is whether the potential amount of error is small enough that the models remain useful for comparing various decision alternatives. In the following sections in this chapter and the next one, validation results in the format described here can be found in the accompanying spreadsheets, and are not discussed in the report unless they are noteworthy.

Model Stratification

Stratification of models can provide additional detail for applications where such detail is needed, and can assist in model validation. The accompanying spreadsheets explore stratification of the deck component model according to several categorical variables, including construction year, traffic volume, functional class, design type and material, and the classification of deck protective systems. NBI data items provide the strata, which in some cases can distinguish roadways on and under a bridge, or can distinguish main spans from approach spans.

NBI data items are highly standardized, but are not equally common within a bridge inventory. Many potential strata failed to produce usable models because they did not have sufficient populations. Choices made by each agency implementing a model, such as the selection of similar agencies to include, the choice whether to include non-state-maintained bridges, and the sampling decision, can affect the usability of each possible stratum. Two illustrative examples will serve to demonstrate the use of stratification.

Table 4 shows the deck component model stratified by construction year, which is grouped into three ranges in order to capture the most important effects, bearing in mind that creation of narrower and more numerous ranges can lead to a problem of insufficient populations to produce useful results.

Table 4. Deck component model stratified by construction era (years)

Era	9	8	7	6	5	4	3	2	1	Avg
<1960	1.5	3.4	5.9	6.8	7.9	10.8	23.1	283.1	999.0	6.7
1960-84	1.7	3.2	6.5	8.9	9.8	18.1	27.6	999.0	999.0	6.3
1985+	1.9	4.7	14.9	18.1	15.2	11.4	34.7	10.4		5.6

It can be seen in Table 4 that newer bridges generally have longer transition times, due to improvements in materials and design features. The pattern is consistent for the most common condition states, and nearly consistent even for some of the less common states. To see the pattern clearly, the pivot table has a “Grand Total” column (labeled such by Excel), labeled “Avg” in Table 4, which shows the average transition time across all condition states, weighted by bridge count. This is computed from the raw data by including all appropriate inspection pairs, so the use of "999" or other large values in the table do not affect the results. This pattern is completely intuitive, lending support to the validity and usefulness of the model and of this stratification.

The three categories of bridge age in Table 4 were selected to roughly approximate the times of large industry-wide changes in bridge design and construction practice, while maintaining a sufficiently large population in each group. As more data are gathered, it may become possible to stratify design methods more finely to investigate the effects of new methods and materials.

Table 5 shows a similar table stratified by traffic volume for the on-roadway of each bridge. It can be used to test the argument that higher traffic volumes might yield faster deterioration rates. Potential counterarguments might be that the effect of traffic is primarily on the wearing surface, which is not considered in NBI deck component ratings, and that the likelihood that bridges which are designed for heavier traffic might be constructed with more durable materials and a higher level of construction inspection.

Table 5. Deck component model stratified by traffic volume on the on-roadway (years)

ADT class	9	8	7	6	5	4	3	2	1	Avg
00-01k	2.1	4.9	8.4	8.1	8.9	10.3	23.5	32.2	999.0	7.0
01-10k	1.8	3.9	7.3	8.2	8.3	12.2	17.7	999.0	999.0	6.2
10k+	1.6	3.2	6.7	8.7	9.7	17.3	73.8	999.0		6.0

Table 5 exhibits an overall pattern of faster deterioration (shorter transition times) with higher traffic volumes, as seen in the "Avg" column. However, the individual condition states are not as consistent as with construction era. In fact, the direction of the traffic volume effect appears to reverse as bridges deteriorate. Probably the combined effects of traffic volume, wearing surface protection, and design considerations are all at work, leading to a muddy relationship that might not be as useful for decision support analysis.

Model Comparison

As part of the validation process, the deck component model in this study was compared graphically to a set of similar models developed earlier for Nebraska (Morcous 2011). Both studies developed Markov models, though Morcous used a different statistical estimation methodology. Figure 4 compares these models, using an arithmetic average of component ratings to provide a relatively simple means of graphical comparison. The Nebraska model divided the state's inventory into three categories to provide a finer distinction of deterioration rates than in the present study.

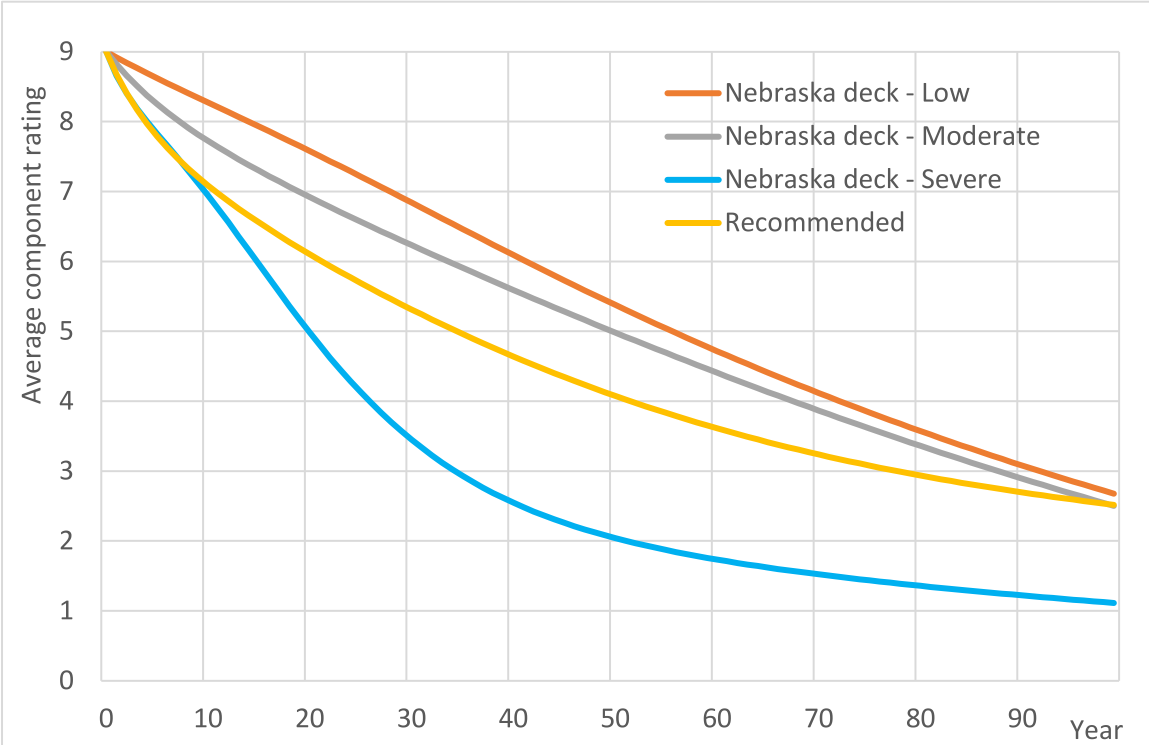

Figure 4. Comparison of the recommended model with the three Nebraska models.

It can be seen that the recommended model projects deterioration at a rate in between the moderate and severe categories of the Nebraska study. This seems intuitive given the state's geographic location within the group of twelve Midwest states participating in this study.

Other NBI Components

Table 6, Table 7, and Table 8 present the recommended models for superstructure, substructure, and culvert component ratings, respectively. In the case of culverts, the number of data points is smaller so condition states 9–4 are represented by a 50% sample. A component condition rating of 1 does not occur in the culvert data set. Stratification and validation considerations are similar to those of the deck component.

Table 6. Transition times for NBI superstructure component ratings (years)

State	Pop	9	8	7	6	5	4	3	2	1
IA	2,579	3.0	10.7	12.8	10.8	22.2	41.4	79.3	5.5	999.0
IL	5,902	1.2	5.8	7.3	6.9	5.8	6.8	9.5	999.0	999.0
IN	3,990	1.8	6.0	10.4	9.9	11.1	15.8	138.5	2.6	999.0
KS	2,715	999.0	9.9	23.8	10.2	8.9	28.8	75.4		
KY	4,816	1.0	5.6	9.5	10.5	14.3	14.3	14.4	3.6	999.0
MI	3,533	1.3	4.7	6.2	6.4	10.7	9.1	42.0	999.0	
MN	2,447	2.2	4.2	10.7	11.9	9.1	72.5	49.2	999.0	
ND	611	5.8	16.6	39.2	24.0	999.0	999.0			
NE	1,938	6.3	12.5	15.0	8.0	27.7	42.4	999.0		
OH	10,165	3.8	6.2	8.1	11.8	8.8	7.3	28.9	10.4	

State	Pop	9	8	7	6	5	4	3	2	1
SD	1,080	1.3	3.8	5.0	13.7	13.2	999.0	999.0	999.0	
WI	4,279	1.3	5.0	6.9	7.3	10.0	11.5	31.0	999.0	
All		2.8	6.1	9.1	9.2	9.9	10.3	16.6	44.7	8.4
Pop	44,054	2,553	11,374	15,333	8,279	3,173	1,039	2,035	262	7

Table 7. Transition times for NBI substructure component ratings (years)

State	Pop	9	8	7	6	5	4	3	2	1
IA	2,552	2.8	7.5	14.1	10.3	25.0	15.9	999.0		999.0
IL	5,041	1.2	7.3	9.1	11.0	11.4	16.4	44.4	999.0	999.0
IN	3,936	1.6	7.0	14.6	15.3	12.5	21.5	999.0	999.0	
KS	2,673	999.0	11.4	24.8	17.3	13.7	999.0	14.3	0.8	999.0
KY	4,741	0.8	4.4	9.5	10.5	16.5	27.9	21.1	8.4	999.0
MI	3,592	0.8	3.3	7.7	7.8	6.7	11.8	19.7	999.0	999.0
MN	2,418	1.8	4.4	12.5	11.6	27.2	39.5	30.8	999.0	
ND	644	3.7	11.4	27.9	36.8	62.8	999.0	999.0		
NE	1,951	6.0	14.7	16.7	16.6	18.1	68.6	999.0	999.0	
OH	10,180	3.4	6.1	7.3	10.6	9.7	12.0	25.7	999.0	
SD	1,056	1.9	2.4	13.6	12.4	18.2	999.0	999.0	999.0	
WI	4,251	1.4	4.8	7.5	8.5	10.3	11.6	31.3	999.0	
All		2.6	6.2	10.0	10.7	11.8	16.5	29.5	43.4	13.3
Pop	43,036	2,151	9,756	17,312	8,782	2,864	768	1,266	127	10

Table 8. Transition times for NBI culvert component ratings (years)

State	Pop	9	8	7	6	5	4	3	2
IA	3,146	1.4	5.0	15.1	47.4	77.7	999.0	8.1	
IL	3,860	1.0	8.5	11.7	19.3	22.5	21.8	999.0	999.0
IN	1,964	1.8	4.3	12.7	12.4	31.2	32.7	999.0	
KS	7,060	999.0	4.7	28.1	18.1	20.0	999.0	999.0	
KY	9,077	0.9	2.7	10.1	19.7	34.2	22.6	999.0	999.0
MI	518	1.0	4.4	8.6	22.4	11.7	2.4	999.0	
MN	3,050	2.4	5.1	9.3	16.9	44.2	90.9	999.0	
ND	1,683	3.1	10.5	35.6	27.1	40.2	14.3	999.0	
NE	5,762	4.1	14.7	48.5	77.2	57.0	59.9	21.1	
OH	3,763	3.3	6.0	6.4	11.4	8.1	10.0	999.0	999.0
SD	778	0.8	4.3	6.9	17.8	13.4	19.6	999.0	
WI	2,935	0.9	4.2	8.9	19.0	20.5	11.8	999.0	
All		2.3	6.0	14.0	19.4	21.6	19.0	75.2	999.0
Pop	43,596	1,812	7,774	19,602	10,671	2,830	683	219	6

ELEMENT-LEVEL DETERIORATION CURVES FOR REINFORCED CONCRETE DECKS

Bridge inspection using elements and condition state distributions has been practiced in the United States since 1992. Various manuals published by FHWA and AASHTO since then have represented an evolution in element and state definitions, and have corresponded to more sophisticated models in BMSs. In 2012, AASHTO published the first element inspection manual that defined all elements as having 4 condition states, and that defined protective system elements whose deterioration could influence substrate deterioration.

In 2014, FHWA made it mandatory that all states gather and report element level inspection data on NHS bridges. During the period from 2012 to 2014, many of the states adopted migration algorithms to convert older element condition state data to be compatible with the new manual in a very approximate way, while at the same time developing training programs and systems to accommodate the new manual. As deterministic algorithms, the migration programs were not compatible with probabilistic deterioration models, so could not be used in the planning tools provided in BMSs.

Based on initial experience using the 2012 and 2013 AASHTO Manuals for Bridge Element Inspection, AASHTO published a revised manual in 2015. The revisions were numerous but more subtle than earlier revisions, differing for example in the exposure of reinforcing steel of concrete elements in condition state 2, the definition of state 4, and the recording of defects. Although further revisions have been published, most of the element and condition state language has been stable since 2015.

During the period from March 2015 to June 2016, the twelve agencies participating in this study completed their implementation of the 2015 manual and retired earlier manuals and migration algorithms. After this point, all twelve states were collecting compatible data for deterioration modeling. The cutoff date identified for each agency is used in the procedures discussed in Appendix III for creating inspection pair datasets focused on each research question, ensuring that earlier data were not used. Early in the study, participating DOTs were polled to provide a cutoff date for implementation of the new manual. These dates were added to the analysis database in the lu_statecode table for use in SQL queries.

For reinforced concrete bridge decks, some of the agencies are subdividing this element into sub-classes as agency-defined elements. These elements distinguish important deck attributes such as the use of epoxy coatings on reinforcing bars, or cathodic protection systems. These agency-defined elements are rolled up into NBI element 12 for FHWA reporting, but analyzed separately in BMSs since they are expected to have different deterioration rates. Agency-defined elements are not standardized, and differ among agencies.

Table 9 reports the final models developed for reinforced concrete bridge deck elements, with all of the agency-defined elements included. The numbers in the table are median transition times, in years, from each condition state to the next-worse state. Significant differences can be seen among the agencies. In some cases, this is likely an artifact of the small populations in some of the agencies, particularly in condition state 4. In other cases, outlier values may reflect changes in bridge inspection procedure, which often occur when a new inspection process is implemented. It is likely that many of these differences will attenuate as agencies gain more experience and amass larger datasets. In the meantime, it is recommended that agencies using these models filter the results to include multiple states having similar operating conditions, which will smooth out the evident variation among agencies. This is easily done in the accompanying Excel spreadsheet files using the pivot table filtering feature described in Appendix III.

Table 9. Transition times for reinforced concrete deck elements (years)

State	Population	1->2	2->3	3->4
IA	4,073	247.2	39.8	61.7
IL	2,129	20.8	20.9	2.3
IN	244	187.7	101.0	999.0
KS	1,462	260.3	51.4	127.7
KY	878	13.4	19.8	33.1
MI	3,411	21.5	19.3	182.5
MN	2,550	41.4	15.3	51.8
ND	1,041	33.1	24.1	42.0
NE	2,236	78.8	14.5	999.0
OH	1,733	49.6	27.6	38.1
SD	1,300	30.8	14.4	132.4
WI	4,706	69.3	19.8	27.6
All	25,764	43.6	19.7	24.8

All element-level models addressed in the research use 100% of the available population of inspection pairs. Appendix IV provides the mathematical methodology for computing these results.

Effect of Agency-Defined Deck Elements

The accompanying Excel spreadsheet provides detailed results for agency-defined elements where these exist. In most cases there were not enough inspection pairs to distinguish among sub-classes of deck elements. The main exceptions were decks with coated steel reinforcing bars in Illinois and Michigan, which each had more than 1000 inspection pairs. In both cases the transition times were longer than the times computed for unprotected decks in those same agencies, suggesting that the coating of reinforcing bars was effective at slowing the rate of deterioration. The distinction was clearest in Michigan, where the transition time from condition state 1 to state 2 was 30.4 years for coated bars, and only 16.4 years for uncoated bars. A similar difference was found for the transition from condition state 2 to state 3, where the transition times were 29.0 and 16.6 years respectively.

Wearing Surface Protection

In certain bridge management tools such as AASHTOWare™ Bridge Management and StruPlan, the deterioration model explicitly changes the rate of deterioration of each deck element based on the condition of an associated wearing surface element, which also deteriorates (Thompson 2021). The forecasting model summarizes wearing surface condition as the predicted fraction in condition state 1, plus two-thirds of the fraction in state 2, plus one-third of the fraction in state 3. This is multiplied by a protection parameter, and then by the concrete deck transition time, to yield a modified transition time for deck deterioration.

The deck transition times entered into these systems are assumed to represent a deck that has no wearing surface protection at all, so the transition time is increased to the extent that a sound wearing surface is present to offer protection. The accompanying spreadsheet has a pivot table that computes deck transition times separately for various levels of wearing surface condition.

Table 10 compares the case where there is no wearing surface at all (or the wearing surface is all in condition state 4), and the case where the wearing surface is present and all in condition state 1. It is apparent that a sound wearing surface offering full protection of the deck slows the rate of deterioration significantly.

Table 10. Deck transition times as affected by presence or absence of wearing surface (years)

Wearing surface	Population	1->2	2->3	3->4
No protection	11,471	38.3	24.5	13.8
Full protection	9,187	67.4	19.1	74.7

Based on the data in Table 10, it is recommended that a value of 67.4 / 38.3 = 1.76 be used as the protection parameter in bridge management models having this feature. More complex methods of deriving the protection parameter were investigated, but did not significantly change the outcome or improve the accuracy of forecasts. In BMSs that model the interaction with wearing surfaces in this way, the deterioration model for reinforced concrete bridge decks should use the unprotected scenario in Table 10.

The Chapter 5 section on wearing surfaces provides more information about the effect of wearing surface protection.

Model Stratification

The accompanying Excel spreadsheet includes pivot tables exploring the potential effects of a variety of independent variables, using the same stratification methodology as discussed above for the NBI component models. Agencies can modify these tables or add more as needed. The same cautionary note is applicable, that a more detailed model is not necessarily a better model, that adding more strata reduces the population of each stratum and may reduce the overall usefulness of the model. Excessive stratification may provide a better fit to a past dataset, but does not necessarily provide a more reliable prediction of future conditions. It is recommended that stratification of the model be used only to the extent that it is necessary to inform relevant policy questions or decision alternatives.

In addition to the stratifications discussed above, the pivot tables investigate agency-defined wearing surfaces, construction era, traffic volume, environmental classification of elements, year of the ending "Y" inspection of each inspection pair, NBI design type and material, and NBI classification of deck and wearing surface protection. Most of these investigations were inconclusive, usually because of insufficient populations of some of the strata. However, the following observations were made:

- As expected, newer bridges in condition states 1 and 2 deteriorated more slowly than older bridges, which is likely due to improvements in design, materials, and quality control over time. Unexpectedly, decks on newer bridges (1985+) in condition state 3 deteriorated to state 4 nearly four times as fast as on old (< 1960) bridges. There is no clear explanation for this, but it might be an artifact of the relatively small quantities in states 3 and 4 in the inventory. In part, it may reflect the fact that decks on bridges more than 60 years old are likely to have been replaced or significantly rehabilitated at some point in their lives.

- The investigated traffic volume strata had more than enough data points for valid models, but still yielded inconclusive results. This is probably for the same reasons as discussed above for NBI deck components, that conflicting factors are at work.

- Most of the twelve partner states do not use the environmental classification of elements as a means of distinguishing design or operating conditions affecting deterioration rates. In the twelve-state dataset, only North Dakota and South Dakota exhibited a visible correlation between environment class and transition times.

- Within the time frame of the available inspection data (2017–2021 for the “Y” inspection of each pair), more recent inspections showed a general trend of slower deterioration. This is likely a result of the continuing adjustment of bridge inspectors to the 2015 AASHTO manual.

Most of the available strata of NBI item 108 (classification of deck protection) were not numerous enough to produce usable models. Nearly half of these data points were empty. However, the data do suggest a possible benefit of low-slump concrete as a wearing surface material, and a benefit of epoxy-coated reinforcing steel. Model accuracy is limited by the large number of missing values, but other research by individual states and by the Strategic Highway Research Program would support the existence of benefits from these materials and in some cases provide quantification of the methods employed in individual agencies.

Onset of Deterioration

Early research using Markov models for bridge deterioration found that these models were unrealistically fast for bridges in like-new condition, suggesting that deterioration rates might have some dependence on bridge age, or age since last major rehabilitation. Unfortunately, the time series of element inspections extends back only to 2015, so there is only limited information available to estimate any sort of time series model that might quantify age-dependency.

An exception to this limitation was identified in the development of AASHTOWare™ Bridge Management, and confirmed in subsequent research. Bridges which were recently built could be safely assumed to have deteriorated steadily, without agency intervention, for at least the first 15 years of their life, and often longer. This assumption would enable the use of a Weibull survival probability model, which does not require a full time series but only requires the ending condition of the series, assuming the element was entirely in condition state 1 at the start of the series.

Weibull survival models are a generalization of the Markov model. The median transition time computed from a Weibull model is exactly the same as the median transition time of a Markov model produced from the same data. The Weibull model adds just one parameter, known as the shaping parameter. Appendix IV provides the mathematical description of this model.

If the shaping parameter is 1.0, the Weibull model produces the same probabilities as the Markov model throughout the life of an element. A shaping parameter greater than 1.0 changes the shape of the deterioration curve so it is initially slower than the Markov model, then speeds up near the median point of the element lifespan. Various research studies have found that the Weibull model proves a closer fit to actual element behavior than the Markov model alone for bridges in like-new condition. For the wide variety of elements that have been investigated, the best-fit shaping parameter has been found to range from 1.0 to 3.0, only rarely outside this range.

As discussed in Appendix IV, there is no closed-form algebraic formula to calculate the shaping parameter from a set of inspection data, so a fitting method is required. The researchers developed a relatively simple fitting procedure using the principles of maximum likelihood estimation, which could be performed in a spreadsheet using data compatible with the Markov model. Part of the simplicity of the method comes from the fact that the Markov transition time is estimated first (as discussed above), and then is used to constrain the solution to the Weibull model. Only relatively new bridges can participate in this process, and the dataset must be screened to exclude outlier elements that may have received agency action, or that may have started in condition states other than state 1.

The spreadsheet that performs this estimation process is delivered with this report. A shaping parameter of 1.58 was found. This is quite close to the value of 1.3 found in Florida research, which used an older element inspection manual.

ELEMENT-LEVEL DETERIORATION CURVES FOR REINFORCED CONCRETE SLABS

The analysis of reinforced concrete slabs followed the same methodology as for decks, with the same relationships to wearing surfaces. Table 11 shows the results. Variations among the twelve agencies are remarkably consistent with the deck models, which not only lends credibility to the analysis but also suggests that there may be systemic differences among historical agency design, construction, and/or operational policies and procedures which might cause the variations observed in the data. For the individual agencies this may suggest potential topics for future research, to better understand the variations and to exchange best practices.

Table 11. Transition times for reinforced concrete slab elements (years)

State	Population	1->2	2->3	3->4
IA	745	107.8	21.3	146.9
IL	168	17.1	17.7	3.9
IN	59	88.8	24.4	999.0
KS	941	251.4	30.4	58.8
KY	76	13.0	4.2	147.3
MI	27	60.4	97.1	314.7
MN	571	64.3	56.1	47.9
ND	51	18.6	20.5	999.0
NE	897	94.3	7.8	999.0
OH	347	24.5	29.7	24.5
SD	1,049	37.2	18.2	56.7
WI	1,801	115.3	23.9	99.5

State	Population	1->2	2->3	3->4
All	6,733	66.8	17.6	49.3

Slab element deterioration was found to be slower than that of bridge deck elements. Figure 5 compares them.

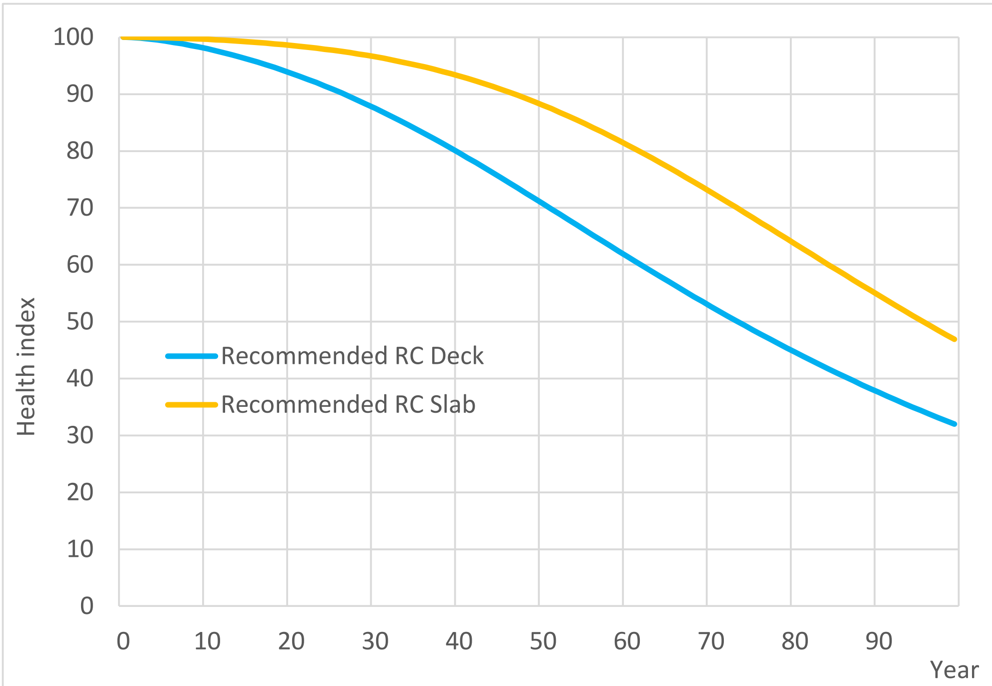

Figure 5. Comparison of the recommended deck and slab models

Table 12 shows the effect of wearing surface protection of slab elements, which is very consistent with bridge decks. The protection parameter was found to be 2.31. In BMSs that model the interaction of slabs with wearing surfaces, such as AASHTOWare™ Bridge Management, the deterioration model for reinforced concrete slabs should use the unprotected scenario in Table 12.

Table 12. Slab transition times as affected by presence or absence of wearing surface (years)

Wearing surface	Population	1->2	2->3	3->4
No protection	1,876	43.7	21.5	28.3
Full protection	2,966	100.9	18.1	252.8

Model stratification for slab elements was investigated in the same way as for deck elements, reaching very similar conclusions. NBI item 108 had a lower proportion of missing values for slabs, compared to decks. The conclusion was the same, that the data suggest significant benefits for low-slump concrete as a wearing surface, and epoxy-coated reinforcing. Other categories of slab protection did not have enough data to draw any conclusions.

The onset of deterioration was modeled for slabs in the same way as for decks. A shaping parameter of 1.81 was found.

ELEMENT-LEVEL DETERIORATION CURVES FOR REINFORCED CONCRETE DECKS AFTER MAJOR PRESERVATION

For the purposes of this study, bridge deck preservation is defined as actions or strategies that prevent, delay, or reduce deterioration of bridge decks; restore the function of the deck; keep the deck in good or fair condition; and extend the deck service life. An action that affects only the wearing surface and not the underlying deck is not classified as major preservation for this study.

The following are examples of major deck preservation if it is normally the case that the wearing surface (if any) is first removed and the substrate is repaired where needed, and/or the condition of the deck element (excluding the wearing surface element) is typically improved by the work.

- Deck overlay/deck resurfacing
- Concrete deck repair (electrochemical extraction, cathodic protection, delaminated area removal and placing repair material)
- Thin polymer epoxy overlay/thin deck overlay
- Asphalt with waterproof membrane overlay
- Rigid overlays
- Deck milling

The following are not examples of major deck preservation:

- Deck patching that affects only the wearing surface
- Deck sealing/concrete sealing/epoxy chip seal
- Drains, cleaning, repair and replace
- Joint seal replacement
- Joint repair/replace/elimination
- Clean/wash bridge deck
- Sealing cracks
- Deck replacement
- Widening

The study investigated the possibility of a residual reduction in the rate of deterioration after a major preservation action is performed. Intervals of up to 30 years were considered between the date of the action and the date of the "X" inspection of each inspection pair. However, most of the agencies provided activity datasets for a much shorter period of time. Also, the detailed investigation of activity datasets, discussed in Appendix IV, showed that most of the datasets were unlikely to be complete. There could be an unknown bias in the model caused by the lack of a complete set of activity data, which might cause the effect of major preservation to be understated. The analysis did not find a clear relationship between the time since major preservation and the rate of deterioration. However, it did find that, in general, a small residual effect in the expected direction does exist. Table 13 compares the transition times after major preservation with the previously discussed deck model (with or without a previous action), both based on the unprotected scenario. Figure 6 compares the scenarios graphically.

Table 13. Residual effect on transition times of recent major preservation (years)

Scenario	Population	1->2	2->3	3->4
Recent major preservation	2,907	38.9	36.5	12.1
All deck elements	25,764	38.3	24.5	13.8

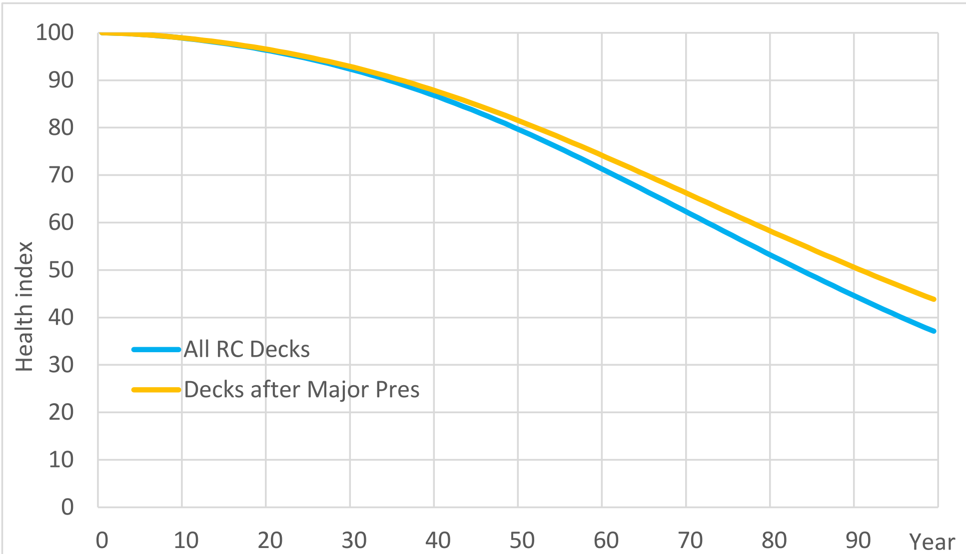

Figure 6. Residual effect on deterioration rate of recent major preservation

PREDICTED IMPROVEMENT IN CONDITION OF REINFORCED CONCRETE DECK AFTER MAJOR PRESERVATION

Using the same definition of major preservation as in the preceding section, the researchers developed a model of the improvement in condition that occurs immediately after a major preservation action. In this case, the action must have taken place between the "X" and "Y" inspections of each inspection pair. The result, shown in Table 14, is in the form of an action effectiveness model, consisting of the transition probabilities from each condition state to the same or improved states.

Table 14. Probabilities of improved conditions following major preservation

	To 1	To 2	To 3	To 4
From 1				
From 2	0.133	0.867		
From 3	0.000	0.127	0.873	
From 4	0.000	0.000	0.219	0.781

In this table, major preservation actions would not be expected to apply to condition state 1, nor would they be expected to result in worse condition states. So those cells in the table are blank.

These results did not show as much improvement as expected. It is likely that this was caused by difficulties the agencies encountered in gathering activity data and classifying projects as major preservation.

CHAPTER 5. TIER 2 DETERIORATION CURVES

This chapter discusses the Tier 2 curves developed under the research, for wearing surface, deck joints, defect development and progression, paint system effectiveness, steel girder corrosion, and substructure elements in harsh environments.

ELEMENT-LEVEL DETERIORATION CURVES FOR WEARING SURFACES

Wearing surfaces received particular attention in the study, because of their outside role in preservation activity, and their effect on the deterioration of bridge decks. A number of participant agencies (South Dakota, Michigan, Nebraska, Wisconsin, Kentucky, and Illinois) are using agency-defined elements to increase the level of detail of wearing surface data, and all of the agencies have use of NBI item 108A as a classification of wearing surfaces. In addition, the researchers developed a somewhat more detailed classification for this study, to attempt to increase the resolution of the deterioration models.

Regardless of the classification scheme, all wearing surfaces are reported to FHWA as element 510. Table 15 shows the transition times that were computed when all such elements are included in the analysis. Nine of the agencies provided wearing surface condition state data suitable for model development.

Table 15. Transition times for wearing surface elements (years)

State	Population	1->2	2->3	3->4
IA	1,069	50.0	24.3	817.8
IN	128	123.3	147.9	525.3
KS	1,512	95.9	13.3	1.6
KY	689	10.0	12.5	10.0
MN	4,320	16.8	8.6	8.0
ND	234	31.7	22.7	11.2
NE	691	55.2	4.2	153.7
SD	1,412	25.8	7.0	8.7
WI	5,699	26.6	15.6	38.7
All	15,753	24.6	11.1	13.0

As was the case for decks and slabs, the data show considerable variation in deterioration rates among the states, in a pattern that is quite similar to the deck and slab models in terms of which agencies had unusually long or short transition times. In general, wearing surface transition times are considerably shorter than those for decks and slabs. The Weibull shape parameter was found to be 2.24.

Classification of Wearing Surfaces

Although three agencies provided agency-defined wearing surface elements, none had sufficient populations to develop deterioration models for these separate elements. NBI item 108A, which classifies wearing surfaces consistently for all states, provided a more useful dataset, combining the conditions reported by all nine agencies. Table 16 compares the strata having populations of at least 500. Monolithic concrete, latex concrete, low slump concrete, and (for state 1) epoxy all provided longer transition times than the combined model reported in Table 15. Bituminous and gravel wearing surfaces performed less well.

Table 16. Wearing surface stratification by NBI item 108A (years)

Type of wearing surface	Population	1->2	2->3	3->4
1 Monolithic Concrete	5,900	35.2	27.6	46.2
3 Latex Concrete or similar	352	27.2	15.4	559.9
4 Low Slump Concrete	4,516	31.2	11.7	107.9
5 Epoxy Overlay	1,091	36.2	6.0	2.4
6 Bituminous	2,810	11.7	7.7	15.0
8 Gravel	562	12.4	4.0	1.9

To increase model resolution, the researchers developed a slightly more detailed classification system, asking the participants to classify their wearing surfaces under a common framework. Using the information from Table 108B and the ADEs, a wearing surface category was assigned to each wearing surface. For all states except Illinois, items 108A, 108B, and 108C from the pon_elm_insp table created a unique code that could be mapped to Table 108B to obtain the corresponding wearing surface category. Illinois has non-standard coding for NBI item 108 and required unique mapping based on table 108C. Because of this, special consideration must be given when using Illinois data for modeling.

Table 17 shows these results, including the categories with insufficient population. The performance of bare sealed decks is especially noteworthy here—their performance closely matches that of the underlying deck elements, which may reflect the way they are defined and inspected. Silica fume overlays, broken out as a separate category, performed especially well.

Table 17. Stratification using a more detailed grouping of wearing surfaces (years)

Type of wearing surface	Population	1->2	2->3	3->4
Asphalt Overlay (No Membrane)	2,585	11.6	7.8	14.1
Asphalt Overlay (with Membrane)	367	17.4	5.7	143.1
Bare Deck/Sealed Concrete	5,605	38.4	31.5	71.0
Concrete Overlay (Latex Modified)	348	28.3	15.1	559.0
Concrete Overlay (Low Slump)	3,847	22.7	11.7	130.9
Concrete Overlay (Silica Fume)	1,157	89.6	20.2	264.3
Gravel Overlay	546	12.2	3.8	1.9
Polyester Polymer Overlay (PPC)	365	56.8	2.0	0.5
Thin Polymer Overlay (2 Layer Epoxy)	838	30.5	6.6	3.2
Timber	44	33.0	51.7	8.2

Model Stratification

Table 18 shows that bridges built since 1985 have considerably more durable wearing surfaces than those built previously. This is true even though it is highly likely that the wearing surfaces have been replaced since 1985 on those older bridges. Table 19 shows, perhaps counter-intuitively, that wearing surfaces with higher traffic volumes have been performing better than those with lower volumes, for condition states 1 and 2. This may be because bridges intended for higher volumes may have been constructed with a higher quality of materials and construction quality assurance.

Table 18. Effect of construction year on wearing surface deterioration (years)

Construction era	Population	1->2	2->3	3->4
<1960	3,349	17.6	10.9	10.2
1960-84	7,044	21.5	9.6	16.2
1985+	5,360	39.5	19.7	12.4

Table 19. Effect of traffic volume on wearing surface deterioration (years)

ADT class	Population	1->2	2->3	3->4
1 (<1k)	6,490	19.2	10.5	12.3
2 (<10k)	6,124	28.9	11.2	15.8
3 (>=10k)	3,137	32.8	13.5	9.8

Overall Influence of Wearing Surfaces

Combining the effects of the wearing surface and deck models, Figure 7 shows that wearing surfaces deteriorate considerably faster than deck elements. In spite of that, when a deck is protected by a wearing surface its performance is considerably improved.

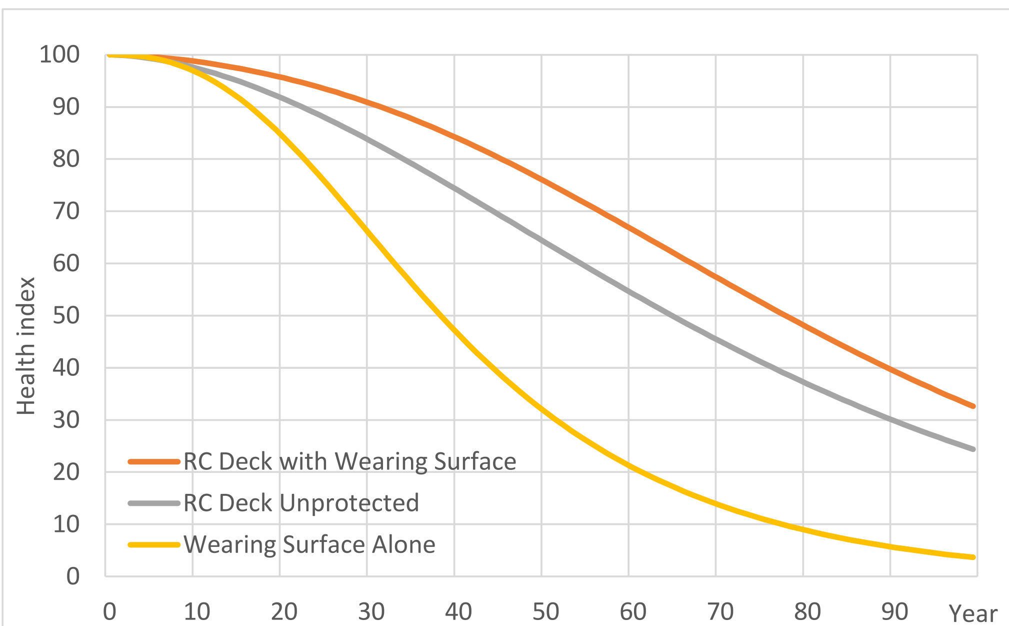

Figure 7. Effect of wearing surfaces on deck element deterioration

ELEMENT-LEVEL DETERIORATION CURVES FOR DECK JOINTS

The seven different types of expansion joints were modeled together and separately, to provide insight into their deterioration. Table 20 shows the variation by agency when they are modeled together, and Table 21 shows the separate types of joints, with all agencies combined.

Table 20. Transition times for expansion joints (years) by agency

State	Population	1->2	2->3	3->4
IA	4,924	5.8	7.2	21.9
IL	1,924	4.8	6.2	4.0
IN	271	13.5	3.7	10.6
KS	846	20.5	5.2	2.0
KY	746	4.1	3.7	2.5
MI	6,335	3.3	6.2	4.7
MN	3,024	6.7	3.3	6.2
ND	240	6.5	3.7	3.6
NE	1,961	14.6	1.9	4.9
OH	1,483	6.2	5.1	3.9
SD	1,091	7.9	21.4	11.0
WI	1,931	6.0	8.6	6.1
All	24,778	5.8	5.9	6.0

Table 21. Transition times for expansion joints (years) by element type

Joint type	Population	1->2	2->3	3->4
300 Strip Seal Expansion Joint	9,896	4.8	11.5	4.8
301 Pourable Joint Seal	8,797	5.2	3.4	6.7
302 Compression Joint Seal	3,250	10.2	4.3	5.3
303 Assembly Joint With Seal	565	8.5	6.9	6.8
304 Open Expansion Joint	949	8.3	10.6	8.3
305 Assembly Joint Without Seal	859	9.4	5.7	4.9
306 Other Joint	462	15.6	5.2	4.4
All	24,778	5.8	5.9	6.0

A variety of problems can occur on expansion joints as they age, but the most serious and common one is leakage. The rapid transition times in most of the agencies probably means that their inspectors are focusing on leakage in making their assessments of condition state. The Weibull shaping parameter estimate was inconclusive, due to the relatively short median transition times. In accordance with earlier research, a shaping parameter of 1.0 is recommended, to agree with an unmodified Markov model.

Table 22 quantifies the effect of bridge construction year on joint performance. The effect is consistent but small, as expected, since joint seals are replaced frequently, and the entire joint has likely been replaced on many of the older structures.

The effect of traffic volume in Table 23 is mostly consistent, and reflects the combined influence of traffic impact and higher construction standards on bridges intended for heavier traffic.

Table 22. Effect of construction year on expansion joint deterioration (years)

Construction era	Population	1->2	2->3	3->4
<1960	4,293	5.5	6.1	5.9
1960-84	13,309	5.3	6.2	5.9
1985+	7,176	6.8	5.2	6.2

Table 23. Effect of traffic volume on expansion joint deterioration (years)

ADT class	Population	1->2	2->3	3->4
1 (<1k)	3,083	6.5	6.8	6.5
2 (<10k)	11,831	5.8	6.0	7.4
3 (>=10k)	9,811	5.6	5.5	4.6

DETERIORATION CURVES FOR DEFECT DEVELOPMENT AND PROGRESSION

In the AASHTO MBEI, bridge inspectors are asked to consider a well-defined set of defects when assigning condition states to each element. Defects represent common causes and processes of deterioration, such as corrosion and cracking, defined in four condition states in the same format as element states. Many agencies ask their inspectors to record defects in their BMSs. In some cases the inspectors record all defects, while in other cases they record only the ones that reduce the element condition state, or only the most significant. When a defect is absent on a bridge, some inspectors record it as condition state 1, while others omit the defect record entirely.

In bridge inspection data, each defect is linked to the element in which it was found, but the specific locations of defects and deteriorated condition states within an element or bridge are not identified or linked.

Defects are not intended to be modeled. Currently there are no BMSs that attempt to forecast defect progression. However, in this study, as an experiment, the researchers gathered the defect data entered in inspection reports and investigated whether patterns in the data might support future modeling. Six of the twelve agency participants were able to provide such data.

Three sets of research questions focused on defects, the first concerning bridge deck and slab delamination, recorded as AASHTO defect 1080 (concrete delamination/spall/patched area) applied to NBI elements 12 (reinforced concrete deck) and 38 (reinforced concrete slab). Applying the same methodology as was used for bridge decks, the transition times for defect 1080 were found to be as shown in Table 24 and

Table **25.**

Table 24. Transition times for defect 1080 on decks and slabs, by agency (years)

State	Population	1->2	2->3	3->4
IA	4,885	787.1	20.7	170.3
KY	905	160.6	3.2	354.9
ND	1,100	132.0	4.4	27.7
NE	2,862	487.0	6.0	114.4
SD	2,315	314.2	30.8	25.4
WI	6,109	276.9	5.8	29.4
All	18,176	328.2	8.7	33.6

Table 25. Transition times for defect 1080 on decks and slabs, by element (years)

Element	Population	1->2	2->3	3->4
12 R/C Decks	13,724	331.6	9.3	29.1
38 R/C Slabs	4,452	318.3	7.5	54.4
All	18,176	328.2	8.7	33.6

In these tables, if a defect record is absent, it is treated as 100% in state 1. It was found that the vast majority of decks and slabs were in state 1 (lacking any sign of delamination) and remained there. This yielded a large transition time for defect state 1.

A related research question concerned the relationship between defect 1080 and defect 1130 (concrete cracking). It was asked whether a correlation could be found between the status of defect 1130 and the rate of deterioration of defect 1080. This might suggest (but does not prove) a cause-and-effect relationship, that cracking contributes to the progression of delamination on decks and slabs.

Table 26 shows the results of this analysis, limited to decks that have a defect 1080 record. In this table the status of defect 1130 is represented in a health index format, the fraction in state 1 plus two-thirds of the fraction in state 2, plus one-third of the fraction in state 3. As an example of the row categories, "Up to 0.80" indicates values up to and including 0.8, while "up to 0.98" indicates values above 0.8, up to and including 0.98. The table indicates that the expected relationship exists in state 1, but is reversed in states 2 and 3 of defect 1080. This result is likely clouded by the fact that when two types of defects are present at a specific location on a deck, the inspector in some cases may have noticed or recorded only one of them.

Table 26. Transition times for defect 1080, as affected by the status of defect 1130 (years)

Defect 1130	Population	1->2	2->3	3->4
Up to 0.80	545	12.3	35.8	80.2
Up to 0.98	2,509	15.1	29.4	66.9
Up to 1.00	5,425	30.9	16.5	52.6
No defect record	1,498	17.1	17.0	35.1
All	9,980	25.6	23.2	59.8

DETERIORATION CURVES FOR PAINT SYSTEM EFFECTIVENESS

A set of research questions was posed regarding defects 3410 (chalking), 3420 (peeling, bubbling, and cracking), and 3440 (effectiveness) of steel protective coatings. In BMS data, these defect records are each associated with a steel coating record, which in turn is associated with a steel element.

Table 27, Table 28, Table 29, and Table 30 show the effect of steel coatings and each type of defect record on the rate of deterioration of the steel substrate. In these tables, the transition times are for the underlying steel elements, of which all superstructure types are combined and all element records are equally weighted. The rows in the table are ranges of the indicated protective coating or defect, their states combined in a health index format (fraction in state 1, plus two-thirds of the fraction in state 2, plus one-third of the fraction in state 3) as explained in the previous section.

Table 27. Transition times for steel superstructure elements, by range of coating condition (years)

Coating condition index	Population	1->2	2->3	3->4
0.00	592	6.8	19.9	53.5
up to 0.80	3,355	15.6	26.7	98.7
up to 0.98	1,864	24.2	21.6	23.0
up to 1.00	4,169	33.8	17.4	49.2
All	9,980	25.6	23.2	59.8

Table 28. Transition times for steel superstructure elements, by range of defect 3410 (years)

Defect 3410 index	Population	1->2	2->3	3->4
up to 0.80	841	29.3	68.1	999.0
up to 0.98	468	35.6	33.2	999.0
up to 1.00	2,969	35.3	14.1	191.8
No defect record	5,701	20.1	23.0	39.7
All	9,980	25.6	23.2	59.8

Table 29. Transition times for steel superstructure elements, by range of defect 3420 (years)

Defect 3420 index	Population	1->2	2->3	3->4
up to 0.80	450	28.0	31.9	138.4
up to 0.98	1,181	39.3	41.5	62.7
up to 1.00	3,571	36.0	16.1	161.5
No defect record	4,776	17.3	23.1	46.8
All	9,980	25.6	23.2	59.8

Table 30. Transition times for steel superstructure elements, by range of defect 3440 (years)

Defect 3440 index	Population	1->2	2->3	3->4
0.00	451	6.4	28.7	72.0
up to 0.80	1,739	16.9	27.0	106.6
up to 0.98	979	20.4	24.8	42.2
up to 1.00	3,939	33.5	22.7	999.0
No defect record	2,871	23.3	19.4	23.2
All	9,980	25.6	23.2	59.8

Table 27 shows that paint condition has a clear effect on the deterioration of steel substrates from state 1 to state 2, but has less effect on subsequent progression of the deterioration of the steel. Table 28 and Table 29 are inconclusive about the effects of defects 3410 and 3420 on steel deterioration. Table 30 shows a clear correlation between defect 3440 and steel deterioration, in a pattern consistent with the coating effect, as expected.

Considering defect 3420 by itself, Table 31 shows the rate of progression for bridges having that defect record. Only five of the agencies are using this defect. In all five states, coatings having this defect in state 1 rarely leave state 1. Table 32 shows the progression of defect 3440, which exhibits an inconsistent pattern among states.

Table 31. Transition times for defect 3420 (years)

State	Population	1->2	2->3	3->4
IA	4,058	77.8	11.0	124.9
KY	782	940.9	4.8	2.5
ND	1,076	95.9	1.2	1.8
NE	938	121.7	2.5	5.4
SD	1,076	77.1	1.2	1.1
All	7,930	93.1	5.7	7.8

Table 32. Transition times for defect 3440 (years)

State	Population	1->2	2->3	3->4
IA	4,022	92.2	1.6	41.5
KY	804	24.0	0.9	0.6
ND	1,182	4.2	0.3	0.6
NE	896	549.7	6.6	7.8
SD	1,137	7.0	6.9	8.3
WI	1,694	13.1	5.9	3.4
All	9,736	19.2	2.2	2.9

DEFECT DETERIORATION CURVES FOR STEEL GIRDER CORROSION

This research question concerns defect 1000 (steel corrosion) applied to any coated steel superstructure element. All steel superstructure element records are equally weighted. Table 33 shows the transition times for the steel substrate elements, as affected by the level of corrosion recorded. The rows in the table are ranges of defect 1000, its states combined in a health index format (fraction in state 1, plus two-thirds of the fraction in state 2, plus one-third of the fraction in state 3).

Table 33. Transition times for steel superstructure elements, by range of defect 1000 (years)

Defect 1000	Population	1->2	2->3	3->4
up to 0.80	545	12.3	35.8	80.2
up to 0.98	2,509	15.1	29.4	66.9
up to 1.00	5,425	30.9	16.5	52.6
No defect record	1,498	17.1	17.0	35.1
All	9,980	25.6	23.2	59.8

Table 34 shows the progression of defect 1000 considered by itself. The pattern is very inconsistent among agencies, probably reflecting inconsistencies among inspectors in how these defects are recorded in the BMS. This is not surprising, considering that few inspectors would have expected the data to be used in a model development exercise. The results might be very different if there existed a common expectation for how the data would be used. The conclusion to be reached is that these defect data are not suitable for model development at this time.

Table 34. Transition times for defect 1000 (years)

State	Population	1->2	2->3	3->4
IA	4,087	428.0	16.5	999.0
KY	875	24.7	2.2	5.8
ND	1,136	4.7	4.6	14.3
NE	979	456.1	17.6	24.4
SD	1,064	292.8	84.5	194.2
WI	1,703	187.9	20.4	45.7
All	9,843	48.2	6.8	18.3

ELEMENT-LEVEL DETERIORATION CURVES FOR REINFORCED CONCRETE SUBSTRUCTURE ELEMENTS

A set of deterioration models was developed for several classes of concrete substructure elements, using the same methodology as for joints and decks. Separate models were developed for abutments, pier caps, columns, and pier walls. The populations of all these elements were large, and the patterns were consistent across these elements. Detailed results are reported here for pier caps, and summary results for all four element types. The accompanying spreadsheets provide details for all the models.

Table 35 shows the agency breakdown of the pier cap deterioration model. Most of the agencies found very long transition times as expected, especially from state 1 to state 2. The differences among states could result from concrete quality, expansion joint designs, corrosive factors in the operating environment, inspection procedures, or other factors.

Table 35. Transition times for reinforced concrete pier caps (years)

State	Population	1->2	2->3	3->4
IA	4,768	247.5	63.2	999.0
IL	2,052	38.2	7.0	26.1
IN	181	352.8	6.0	999.0
KS	1,377	225.1	55.0	187.0
KY	853	21.9	6.6	64.4
MI	2,522	33.5	9.3	97.3
MN	2,547	32.2	9.2	61.7
ND	377	100.4	48.9	999.0
NE	4,156	200.0	8.2	109.1
OH	2,007	96.6	42.9	302.1
SD	1,627	58.7	46.0	46.6
WI	2,854	83.4	12.6	478.3
All	25,320	69.4	12.4	68.0

Age of the bridges may also be a significant factor in deterioration rates. Table 36 shows a fairly consistent pattern where newer pier caps deteriorate more slowly, very likely due to improvements in design, materials, and construction quality assurance.

Table 36. Effect of construction year on reinforced concrete pier cap deterioration (years)

Construction era	Population	1->2	2->3	3->4
<1960	4,317	37.4	12.7	53.2
1960-84	12,685	66.5	11.8	81.6
1985+	8,318	121.3	14.4	252.9

Another useful stratification is by traffic volume under the bridge. When deicing chemicals are in use, traffic passing under a bridge sprays corrosive liquids on substructure elements, accelerating corrosion. In Table 37 this effect is easy to see.

Table 37. Effect of traffic volume under the bridge on concrete pier cap deterioration (years)

ADT under	Population	1->2	2->3	3->4
No road under	16,939	92.8	15.7	72.3
1 (<1k)	1,032	86.3	9.1	71.9
2 (<10k)	2,225	67.4	10.4	89.4
3 (>=10k)	5,125	37.1	7.8	52.4

Similar observations are visible for all the substructure elements. The accompanying spreadsheets provide the details. Table 38 summarizes the results for all four element types analyzed.

Table 38. Summary transition times for reinforced concrete substructure element types (years)

Element type	Population	1->2	2->3	3->4
Pier caps	25,320	69.4	12.4	68.0
Abutments	33,799	40.9	16.6	47.6
Pier walls	8,172	50.3	15.6	25.4
Columns	19,334	23.8	11.3	80.5

The result for columns in Table 38 is interesting, as there is little intuitive reason to expect the deterioration rate for columns to differ substantially from that for pier walls. It is possible that the difference may arise as a result of inspection procedure. Unlike other substructure elements, columns are inspected in units of each, rather than linear feet. Further research may help to clarify the differences in inspector perception as they decide how to assess column conditions.

A maximum likelihood estimation model was developed, applicable to any of the concrete substructure elements, to estimate the shaping parameter of a Weibull model for the onset of deterioration. The recommended shaping parameter is 2.64.

CHAPTER 6. TIER 3 INPUTS

This chapter discusses the Tier 3 inputs for ADEs developed under the research. These inputs include the identification of ADEs relevant for the Midwest DOTs, determination of how NDE is applied in bridge inspection, and the provision of guidance to relate NDE results to defect reporting.

IDENTIFICATION OF AGENCY-DEFINED ELEMENTS

Initially for this task, a database with agency ADEs as identified in Task 2 was reviewed. This database was updated to note any changes, following the agency interviews and the review of agency inspection manuals. Agencies have some differences in the way they approach asset inventories and inspections. These differences lead to different sets of ADEs across agencies; however, there are shared purposes for most of the ADEs.

Interviews for this task were conducted for nine agencies (Iowa, Kansas, Kentucky, Michigan, Minnesota, North Dakota, Nebraska, South Dakota, and Wisconsin). Ohio and Indiana currently do not have any ADEs. This section includes a summary of agency approaches to ADEs and important notes from each agency interview, a classification of shared purposes for ADEs, and suggestions on ADEs that would be of use for other Midwest DOTs to consider adopting will be shared. The lists of ADEs by agency are presented in Appendix V.

Agency Interviews

Iowa

The Iowa DOT has a refined set of ADEs for tracking and making maintenance decisions (epoxy coating, black rebars in deck) so that they can look at performance of structures with specific ADEs in the future to make informed decisions. All elements in the list have a clear purpose and have been useful to track a specific thing not available in the Bridge Management Elements (BMEs) or the National Bridge Elements (NBEs). For example, sliding steel joints are tracked as ADEs and are replaced as needed.

The Iowa DOT also uses environments. For decks, environments are defined based on traffic counts. For steel open girders, they use three different environments: beam ends (environment 4), exterior girders (environment 3), and interior girders (environment 2). They track condition in different environments to identify repair needs. Iowa DOT also uses element-level defects. They note that using defects help them identify which defect is causing condition state (CS) 2, CS3, or CS4 designations and believe that if they do not have the granularity, they cannot identify the real need and required work.

Currently, the Iowa DOT is happy with their list of ADEs. In future, they may consider ADEs for different overlays.

Kentucky

The Kentucky Transportation Cabinet recently revised their inspection manual and added ADEs for different wearing surfaces (WS). They have five ADEs for wearing surfaces (latex, PCC, AC with membrane, AC, and epoxy WS). They also have ADEs for additional inventory items such as wingwalls, drainage systems, and secondary elements, as well as ADEs that track vulnerabilities or defects such as longitudinal shear key and embankment erosion.

South Dakota

The South Dakota DOT has added ADEs for WSs, protective coatings, protective systems, and tracking repair needs. They created ADEs for different materials to model different deterioration in future. They wanted to track these differences and prove from data what was happening. For some of the data elements they hope to see the value in future. So far, ADEs for precast concrete culverts and different types of overlays and protective coatings give them the ability to track and model needs.

Michigan

The Michigan DOT has over eighty ADEs, some of which track needs or condition for other assets (e.g., seventeen ADEs for signs). Their deck and slab elements are mostly ADEs that vary by protective systems, and they also have ADEs for different WSs. They also have a top surface (810) and bottom surface (811) for concrete decks, complementary to deck/slab items with no WS, which they find to be the most critical ADEs to track top/bottom deck condition, validate and assess deck General Condition Rating (GCR) and decide and justify deck actions. For instance, the Michigan Deck Preservation Matrix uses bottom of deck (percent of deck underside area that is spalled, delaminated or map cracked) to select repair options. They have nine ADEs for scour countermeasures and additional defects as ADEs (e.g., 826, beam end deterioration).

In their current BMS, defects are not leveraged much yet. They plan to use defects more comprehensively after they transition to AASHTOWare™ Bridge Management (they have been working on customization for the DOT and will add ancillary management). With ADEs, they separate concrete deck elements to validate and support inventory items and would like to be able to have separate deterioration profiles if applicable. The ADEs on scour inventory items are tracked and may lead to a structure to become a priority for scour countermeasure.

They are currently considering adding approximately forty new items. The list includes foundation types, construction details, work history, rebar types, protective coatings, high load hits, proposed drainage area, and an Emergency Relief (ER) fund flag to track when ER funds are used once along with a second flag to indicate that they are used again.

Kansas

The Kansas DOT has recently revised their bridge element inspection manual and have a draft available. The list of ADEs presented in Appendix V captures the revised elements. They find the culvert wing, hinge, and girder end ADEs very helpful. They also break bridges into units and do full inspection on each unit. They have ADEs for deterioration at concrete girder ends, deck cracking, and scour. For decks and slabs, they collect on each unit how many delamination and spalls there are, deck cracking based on density and size, top and bottom. They also accumulate spalls and cumulative defects reported for the deck. Currently inspectors do on-paper notes at the field and put them into AASHTOWare™ Bridge Management at the office. They are in the process of transitioning to electronic data collection for the field.

Minnesota

The Minnesota DOT has thirty ADEs, and quite a few of them are unique to the agency. They have an ADE for protected species (birds and bats), which is utilized by environmentalist staff and helps with mitigation efforts. They do not collect element-level defects but have a list of ADEs that are reminiscent of AASHTO CoRe smart flags for a series of defects, such as impact damage, concrete shear cracking, scour, and steel section loss, to name a few. They also track concrete deck cracking and sealing by an ADE (810 Concrete Wearing Surface, Cracking & Sealing) to track defects by lineal feet to plan seal work for crews. The DOT is also looking at crack densities for scoping and preservation planning, to better define the work. Tiled surface, decorative facade, and slope protection are among other ADEs they have that are not common across other agencies. Defect-related ADEs are used in risk assessment in their Bridge Planning Index (BPI) and Local Bridge Planning Index (LPI). For deck inspections, they evaluate 510 as top and deck/slab bottom as the structural deck element (all bridges have 510).

The Minnesota DOT has a list of ADEs under development/consideration for research and product assessment. They are considering an element to track structures that have research, design, construction, or maintenance trials (Figure 8). A trial is defined as a test performed to assess the suitability or performance of a new detail, technique, product, treatment, etc. They are considering map cracking and are open to defects in future if agencies find significant value.

ADE for Bridge Trials – Draft Concept

Once a trial is implemented on a state-owned bridge, a Bridge Office representative (likely in the Bridge Preservation Unit) will add the ADE through an update report at the end of the inspection cycle to avoid conflicts. The District will also be contacted.

#901: Bridge Trials (1 Each)				
This element is intended to track structures that have research, design, construction, or maintenance trials. A trial is defined as a test performed to assess the suitability or performance of a new detail, technique, product, treatment, etc. *The element will initially be entered with a quantity of 1. If additional trials are performed on the same bridge, the total quantity will be increased to reflect the number of trials. Each trial should be rated under the appropriate condition state and documented in the element notes.*				
Defect or Item	**Condition States**			
	1 Good	**2 Fair**	**3 Poor**	**4 Severe**
Bridge Trial	Trial was effective. Monitoring is no longer in progress.	New trial that has not been inspected yet.	Monitoring in progress.	Trial was ineffective. Do not use in the future.

The element notes need to include sufficient direction to the inspector regarding the evaluation process so that we receive documentation to support future decisions. The notes will include the associated element, type of trial, the goal of the trial, what to compare to (control), and instructions to the inspector on how to evaluate. The official evaluation notes will be included in the element that is affected by the trial, not this ADE.

Example Element Notes:
Do not delete this element or the element notes.
Trial # 1 Element: 331, west barrier **Category**: Reinforcement **Trial**: Added 4 larger longitudinal reinforcement bars (#6) to the west barrier. **Goal**: To help control cracking. **Evaluation**: Compare number of cracks and average crack width on both barriers. Document evaluation in Element 331. **Year Trial Started**: 2017

Figure 8. The Minnesota DOT Draft ADE for Bridge Trials

Nebraska

The Nebraska DOT has a comprehensive list of ADEs that distinguish bridge elements by material, add elements that are not part of BMEs or NBEs (headwall, wingwall), and collect data for scour mitigation treatments (riprap, A-Jack, gabions etc.). They have unique elements such as deck chlorides (tracks chloride testing results), fix barrier terminal section, and crash cushions terminal section (traffic safety features on bridge). The DOT has a list of WSs, but they are planning to add more overlay types to capture (e.g., polyester overlays) and record differences and model differences and to assess performance. They are interested in doing top/bottom deck inspections starting next year.

North Dakota

The North Dakota DOT has five ADEs that track headwalls, wings, slope protection, and precast concrete box culverts. Headwall and wing ADEs were added to separate defects from abutments. Before they added the headwall and wing ADEs, they were getting culvert rehab recommendations but would essentially need to track and treat cracking. The DOT is considering adding joints in culverts as ADEs, and are collecting defects. Within their inventory, they do not have many structures with complex elements. They model state highways and do not recommend anything other than concrete overlays, so there is currently no need to have multiple wearing surface of elements.

Illinois

The Illinois DOT has approximately a hundred ADEs. They have twenty-one ADEs for deck and slab elements, which vary by the type of wearing surface and protective systems. For steel elements, they also vary ADEs by protective coating (unpainted, non-lead painted, lead painted). They do not collect data on element-level defects but have a series of ADEs (e.g., culvert settlement, abutment scour) that are used for tracking defects.

Wisconsin

The Wisconsin DOT has twenty-one ADEs for WSs, protective coatings (e.g., duplex systems, galvanization), protective systems, additional inventory items, and miscellaneous items such as FRP strengthening and external post tensioning. Wearing surface ADEs are used for all wearing surface types even on the original deck surface. When no overlay exists, WS ADE 8000 Bare Wearing Surface is used to distinguish the top of deck condition from the bottom of deck condition (e.g., recorded under NBE 12). This distinction between the top and bottom of the deck/slab is required for Wisconsin's automated BMS. They note that material variability impacts their planning and therefore the list of ADEs and the associated defects is designed to capture data needed for planning efforts. They are considering adding girder ends to capture deterioration there and recording defects in space (3D model of defects). Wearing surface types and defects have particularly been useful for bridge management.

Classification of ADEs

Additional Inventory Items

This category can also be perceived as the general category that covers all ADEs, since ADEs are inherently additional inventory items. Here, we focus on the ADEs that are tracked as additional items but do not fit into some of the below categories with a specific purpose.

These items can be a part of an NBE or BME that the agency would like to isolate and track. Some common examples include wingwalls (Kentucky, Wisconsin, Nebraska, Michigan, Illinois, Kansas, and Iowa), hinges (Kansas and Minnesota), headwalls (Kentucky, North Dakota, Michigan, and Nebraska at abutments or culverts), and aprons (Nebraska and Iowa).

Some ADEs in this category may also be a feature on or close to the bridge that is not necessarily a structural element, but that the agency prefers to keep and track within the bridge inventory. Recording and tracking maintenance and treatment needs that may be done by bridge crews appear to be a motivation for these ADEs. Some examples include curbs or sidewalks, approaches by material, debris around structure, channel drift, vegetation, drainage system, utilities, signs, and guardrails with other materials.

ADEs in this category also include NBEs or BMEs with new or other materials, such as High-Performance Concrete Deck and High-Performance Concrete Slab (South Dakota). Different types of joints were also noted in the lists.

Additional Wearing Surfaces

WS ADEs that track different materials are very common across the agencies. Below, unique materials that were noted from the lists in Appendix V are noted.

- Wearing Surface (Bare)
- Latex Wearing Surface
- PCC Wearing Surface
- AC Wearing Surf w/ Membrane
- AC Wearing Surface
- Epoxy Wearing Surface, Epoxy/Polymer Chip Seal Overlay
- Gravel Wearing Surface
- Low Slump Dense Concrete Overlay
- Latex Modified Concrete Overlay
- Polyester Concrete Overlay
- Timber Running Planks
- Asphalt Overlay with Preformed Fabric Membrane
- Asphalt Overlay with Cold Liquid Applied Membrane
- Asphalt Overlay with Hot Liquid Applied Membrane
- Rubberized Asphalt Chip Seal (RACs) Overlay
- Fiber Reinforced Concrete Overlay
- A40/A45 Concrete Overlay

It should be noted that the Illinois DOT preferred to have deck and slab elements that are categorized by the combination of wearing surfaces of different materials and protective systems. So, while they collect data on the variability of WSs, the data framework is different.

Additional Protective Systems

Additional protective systems (an extension of BME 520) are also tracked by Midwest DOTs.

- Concrete reinforcing steel mixed protection system
- Epoxy Resteel
- Stainless Resteel, Stainless Steel Reinforcing
- Zinc and Epoxy Resteel
- Coated Reinforcing
- Non-Metallic Reinforcing

Additional Protective Coatings

Agencies have also defined different protective coatings (extension of BMEs 515 and 521) for varied materials. While there are some differences in the terminology, the below list includes the unique systems noted from the ADE lists.

- Weathering steel
- Concrete as protective coating
- Healer sealer
- Steel patina
- Fiber reinforced polymer
- Lead Based Coating
- Non-Lead Based Coating
- Metalized/Galvanized Coating
- Silanes/Siloxanes
- Methacrylates
- Silicates
- Galvanization
- Duplex Systems

Additional Defects/Vulnerabilities

While some DOTs collect element-level defects (

Table 39), other agencies do not and have opted to include defects as ADEs. These ADEs are like the AASHTO CoRe Elements' Smart Flags. Some agencies defined these ADEs for data continuation of the previous smart flags.

Table 39. Collection of Element-Level Defect Data

Element-Level Defect Data	No Element-Level Defect Data
• Iowa • Kentucky • Wisconsin • Nebraska • South Dakota	• Indiana • Illinois • Kansas • Michigan (not yet) • Minnesota • North Dakota • Ohio

Additional defect or vulnerabilities noted in the ADE lists are:

- Concrete girder ends
- Shear cracking
- Longitudinal shear key
- Embankment erosion
- Channel Drift
- Channel Alignment
- Erosion Control/Protection
- Pier Settlement
- Culvert Settlement
- Culvert Scour
- Scour

Treatments/Countermeasures

Agencies also track specific treatments and countermeasures (particularly for scour mitigation) by ADEs.

- Plain Riprap
- Heavy Riprap
- Channel Armoring
- Articulating Conc Block
- Gabion
- Grout Filled Bags
- Sheet Piling
- Other Scour Protect
- Scour Monitoring
- Slopes & Slope Protection (concrete, other)
- A-Jack

Miscellaneous

In this category, ADEs that did not fit into the other categories are listed.

- Secondary elements, transverse tensioning rod
- FRP Strengthening
- Jacketing
- Culvert Liner
- External Post Tensioning, Steel Tension Rods/Post-Tensioned Cables
- Deck chlorides
- Electric potential
- Protected species

Recommendations

While the list of ADEs defined by an agency is specific to the asset management practice, needs, and restrictions of that agency, this research also inquired whether there is opportunity to move towards consistency across agencies to provide better or more consistent data for similar future efforts. The participating agencies can consider continuing to meet to unify element and defect definitions. There could also be value to consistent numbering among MWBPP agencies. Since the agencies will focus on planning potential changes for the Specifications for the National Bridge Inventory (SNBI) soon, the timing also may provide opportunities for this parallel effort. After reviewing the ADE lists by agencies and follow-up interviews, below recommendations are presented for the consideration of Midwest states:

- Deck condition and deck treatments are a major component of any bridge management program in the United States. The ADEs presented found discrepancies in the agency data frameworks and the way WS and structural deck/slab condition are captured. Agencies also collect defect information differently. Having a uniform way of assessing deck condition across the Midwest would improve future modeling efforts like this pooled fund study. Unifying terminology and numbering could improve communication across agencies as well.

  Quite a few agencies are either capturing bottom of deck condition or are planning to. Unifying deck condition assessment framework could be a worthy first step for the participating DOTs. It should however be noted that continuation of data items (e.g., elements and defects) is also integral to better models. The recommendations here are for consideration and need further discussion among the TAC members.

- Also critical for future efforts for modeling deck performance over time is capturing deck treatment/work history. Data that can be queried and easily linked to element data will help analysts to produce improved models.

- ADEs such as the Minnesota DOT's Protected Species ADE may provide valuable information over time and can help with project development and scheduling.

- ADEs such as wingwalls, headwalls, hinges, and aprons are common. Review of these lists may help agencies discover ADEs that they would like to add or refine.

- Some agencies are also tracking maintenance needs through ADEs such as sidewalks, curbs, debris around structure, channel drift, vegetation, drainage system, utilities, and signs. Including the inspection of these assets within bridge inspections and coordinating the maintenance efforts for these assets under bridge crews are good options. These are also agency-specific decisions and bound by the way inspection and maintenance are organized.

- Defining and tracking WSs, protective systems, and protective coatings for new materials or different materials existing in the inventory will enable agencies to contract performance and cost for life cycle planning. Many Midwest agencies are cognizant of this and have created ADEs for these purposes. Modeling preservation is a challenge for most states, and having these data items over time will improve efforts toward modeling and programming preservation treatments.

- The deterioration at the concrete girder ends has been recognized for its difference and adopted as an ADE by four Midwest DOTs (Kansas, Illinois, Michigan, and Iowa (as environment)). This ADE helps agencies to create projects and track the severity of deterioration at these locations.

- Collecting data on element-level defects is a big commitment but has potential for improving future models, identifying treatments based on defect data, and improving overall element condition data.

- Tracking specific treatments and countermeasures is great asset management practice. Depending on the agency data management, these could be captured under maintenance systems as well. For bridge management purposes, it is necessary that the data is easily accessible to the bridge staff and can be queried.

DETERMINATION OF NDE TRANSLATION

The original scope for this task was to determine what type of inspection information related to NDE Midwest DOTs have and how it is used that translates into information on element-level defects (GPR, Infrared Thermography (IRT), or other). There was interest to determine which NDE technologies to advance further, and to provide detailed instructions for other DOTs on how to collect the data, the data to be captured, and the format of the data. After communication with agencies, we have seen that most of the information related to NDE is on an as-needed basis. Aside from the Wisconsin DOT, there is not yet an agency with an established program or guidelines in collecting and using NDE data. All Midwest states, however, are experimenting with methods or are sometimes using methods for specific structures or purposes. It would be of value to revisit this subtask within a few years. It would also be of value to create a group within either TSP2 Midwest Bridge Preservation Partnership or within this project that meets on a schedule to share the status of NDE use at the agencies. Here, comments from agencies on their NDE use are noted as a reference for Midwest DOTs.

NDE Usage by Agency

Iowa

The Iowa DOT does target NDE when needed. They do not yet enter quantities for elements. The DOT uses NDE to verify potential deterioration. They sound decks for overlays in order to determine repair quantities for the following year. For this they use an ABI acoustic sounding system, which is relatively fast (100 times faster than hand), safer than manual sounding, and generally works well and has been useful. The DOT currently does not have policies or a guidance document for NDE. For weathering steel bridges, they do a tape test to see how much of the patina comes off to see how well the patina is adhering. Pictures are uploaded to their Structure Inventory and Inspection Management System, but there is no coding yet.

Indiana

The Indiana DOT has so far used GPR, Impact Echo (IE), and IRT (truck-mounted). These methods have been used on approximately 250 bridges out of the approximately 6,000 that the DOT owns and maintains. They currently have a research project with Purdue University that is assessing different technologies with multiple vendors on the same structures. With this study, they would like to build a toolbox and identify which method to use for which purpose.

Illinois

The Illinois DOT hasn't used NDE Data for routine bridge inspections—typically NDE is only used prior to a major rehabilitation, for the purposes of plan preparation. They have used steel section loss measurements for load rating inspections.

Kentucky

The Kentucky Transportation Cabinet is using drones, growing their drone program, and intend to measure condition quantities in future.

South Dakota

The South Dakota DOT does magnetic particle and dye penetrant for steel decks. If needed, they contract Ultrasonic Tomography (UT) testing. They have a limited number of pins for ultrasonic testing. They have no formal program or documentation currently.

Michigan

The Michigan DOT does not have substantial NDE data. They tried thermography imaging of decks on a research/trial basis. They are working to find high accuracy/minimal impact to public technologies.

Kansas

The Kansas DOT does UT for pin and hangers. They also do a straight beam and shoot at a 25-degree angle (for grooves). They use it to identify cracks and grooving. The DOT got some IE for post-tensioning boxes done by consultants (rebar) and found it to be very expensive. They have a couple of structures with strain gages, for university research. They are using drones, IRT on decks, and LIDAR for vertical underclearances.

Minnesota

The Minnesota DOT has been experimenting with NDE methods but do not have an established program yet. They have used GPR for deck repair quantities and tracked the results but have not gotten good correlation to actual quantities. They have also used IE, IRT, and Deck Acoustic Response (DAR) for a limited number of bridges.

Nebraska

The Nebraska DOT has manual chaining for every project for quantities, when programmed. They are looking at infrared scanning for large structures with high traffic and to use input from infrared scanning for border decisions moving forward. Manual chaining and infrared scanning are the DOT's most utilized technologies. Some automated chain dragging was done, and they have a report available. So far, these are structure- and/or decision-specific input. Translation of NDE data into condition assessment is needed. They also have a report on ultrasonic wave propagation, continuous Long-Term Health Monitoring using Ultrasonic Wave Propagation, and Integrated 3D Bridge-Condition Visualization to facilitate element-based bridge condition rating.

North Dakota

The North Dakota DOT has no routine NDE use aside from deck chaining. They do deck chaining to determine project repair quantities. They have also done a research project with Infrasense to scan 80 structures with IRT, in order to correlate IRT with chain drag and come up with delaminations. The DOT has a handheld IR camera but no routine procedures to use the camera aside from research projects. Inspectors have dye penetrant kits that they utilize as suitable. Some consultants might have Magnetic Particle tests with them. For anything further, the DOT would hire consultants for specific concerns. They have no specific guidelines yet but are working on them.

Wisconsin

WisDOT has a deck scanning program and a deck scanning policy that is Appendix A of their Structure Inspection Manual. The deck scanning policy applies to state-owned bridges, offering guidance on the use of non-destructive testing (NDT), semi-destructive testing (SDT), and NDE. The policy document states that the guidelines are necessary to determine accurate scope of deliverable projects, certify structure work concepts for various funding programs, and refine deterioration models used in the Wisconsin Structures Asset Management System (WiSAMS).

All NDE results are recorded under WS ADEs in WiSAMS. The Highway Structures Information System takes the NDE results and converts them to CS for the next inspector, displayed as recommended values. However, it is under the inspectors' discretion to use the recommended values. The dates of the NDE data are set between regular bridge inspections. Entry changes region to region, so they do not see a need for exploring how the NDE data may have translated into condition state data. The deck scanning policy includes guidelines for IRT, Chloride Ion Testing, GPR, and IE. They are trying to scan decks every five years, but the policy document has thresholds and requirements for when decks should be scanned.

SUMMARY OF POLICY, GUIDANCE, AND PRACTICES

The objective here was to provide a summary of policy, guidance, and practices that Midwest DOTs could employ to relate NDE results to defect reporting (to describe delamination and deterioration) and how DOTs use NDE to make quantifiable inspection and actionable work actions for concrete bridge decks. Due to the status of NDE use as noted earlier, this task was not investigated further. Continuing communication among Midwest DOTs on policy and guidance for NDE would be of value. As discussed previously, WisDOT captures NDE data within their BMS. Here, the data items are summarized as a reference.

Table 40. Wisconsin DOT NDE Data Items for Deck Evaluation

NDE Method	NDE Defect Quantities*	NDE to Element Condition Mapping
Visual	Spall	Defect 3210, CS3
	Asphalt Patching	Defect 3210, CS3
	Concrete Patching	Defect 3210, CS2
IR or Sounding	Delamination	Defect 3210, CS2
IR or Sounding	Debonding	Defect 3210, CS2
GPR	Contamination/Deterioration	NA**
Chloride Ion Testing	Avg Chloride Concentration (Per weight of concrete) at rebar level	Defect 8905***

*Additional NDE data is recorded in the WI Highway Structures Information System (HSIS) according to the Deck Scanning Policy located in Appendix A of the WI Structures Inspection Manual.
**GPR results have no direct correlation to AASHTO element defects. WI is evaluating results for predictive ability of future defects.
***Even though defect 8905 is available for use in the Field Inspection Manual, it is not actively being used and not typically recorded. Chloride ion test results are stored in HSIS by other means.

WisDOT has the condition states assigned based on current AASHTO guidance. However, they do not agree with the current guidance and note that both Concrete Patching and Delamination/Debonding cannot be captured under the same defect and element condition state. They also note that the AASHTO guidance needs to be revised at a national level to improve the use of the data from the defects and element condition states in automated BMSs. Ideally, they would like to see Concrete Patching in CS1, Debonding in CS2, and Delamination in CS3. They believe this stratification better aligns with the severity of each defect, which in turn allows an automated BMS to assign an eligible treatment to correct the condition.

CHAPTER 7. IMPLEMENTATION AND CONCLUSIONS

This research study gathered bridge inspection and activity data from twelve Midwest State DOTs, and developed a robust methodology to calculate bridge deterioration models. The methodology was applied to respond to a set of research questions, some oriented toward populating bridge management systems, and some intended to address other decision support needs that require forecasts of bridge condition. The products of the study include this report, an analytical database compiled from the twelve states, a set of SQL queries to process the data, and a set of spreadsheets to finalize the calculations and customize the results. The deliverables are suitable for many purposes, including:

- Developing a reasonable set of deterioration parameters at the element and component levels for BMSs in any of the twelve states, or for other bridge inventories experiencing similar design, construction, and operating conditions. The study computed these results for some of the most common elements, but the same data and tools can readily be used in the same way for any sufficiently large set of element data.

- Developing deterioration models focused on specific decision support questions for design, construction, or operations decisions at the project or network levels. Agencies often use custom-developed spreadsheets for these applications.

- Long-range financial planning and needs analysis for specific types of bridge work at the network level, where it is necessary to estimate the rate at which new needs arise under normal conditions of bridge aging and deterioration.

- Investigating the sensitivity of bridge deterioration and corrective action needs, as affected by relevant variables such as construction year, traffic volume, climate conditions and changes, and preservation strategies.

- Comparing deterioration rates among agencies, as a means to identify potential areas of improvement in design, operations, maintenance, or inspection policies and methods.

- Communicating to decision-makers the consequences of inadequate preservation of the highway infrastructure.

Because of the standardization of the data and tools across elements and across agencies, users of these products can combine similar inventories and similar elements as needed, to obtain a sufficiently large dataset to estimate deterioration parameters for any application. This includes the ability to fully populate a BMS with reasonable deterioration models.

The analytical database contains a variety of data that may be helpful, in a given application, to stratify the deterioration model to enable comparisons among subsets of a bridge inventory relevant to management decisions. The Excel spreadsheets produced in the study contain pivot tables exploring many of these variables. It is possible to create a highly stratified model that closely matches the analytical dataset, but caution is advised. A close match to a past dataset does not guarantee a close fit to future conditions; in fact, it may reduce model accuracy for forecasting purposes because of the smaller population contributing to each stratum. It is recommended that model stratification be used only when necessary to distinguish among decision alternatives.

The usefulness of a deterioration model depends, in part, on the degree to which decision-makers are confident that the model provides a reasonable forecast of future conditions. The greatest limitation of the current dataset is the short time frame of the data, 2015–2021, in which the operating conditions may or may not be typical in all of the locations covered by the data. The algebraic method used in preparing these models ensures reasonable fidelity to recent data, but there can be no guarantee that future operating conditions will be the same.

The current research was timely because of the immediate need of agencies to have a useful BMS. However, repeating the study in 10 years or so will improve the degree to which the model is reflective of conditions that are more variable in the long term. The appendices of this report describe all the data processing steps used in preparing the database and models, which should help future researchers to update the analysis. Of course, future innovations in data and analysis methods may be able to improve the methodology as well.

The study has identified several categories of future research that might improve the analysis and the usefulness of tools that employ these deterioration models. These opportunities include:

- Development of models to relate forecasts of element condition to estimates of the federal performance measures percent-good and percent-poor by deck area. Many agencies continue to use NBI component condition ratings in part because of the need to forecast the federal measures, even though element-level data provide superior deterioration models and more detailed guidance for treatment selection and cost estimation. The StruPlan model has shown that such a relationship can be developed with reasonable statistical confidence, even though it is highly non-linear (Thompson 2021). Other, better methods may be found with suitable research.

- Improved understanding of the differences among the twelve agencies in their element deterioration rates. Some of the observed differences may relate to the adjustment of inspectors to new inspection methods, but other differences may relate to more longstanding design, construction, maintenance, or inspection practices. The variation among agencies is wider than expected, so credibility of these models may be improved by finding ways to make long-term deterioration rates more consistent across the region.

- Improvements in the quality and consistency of activity data collected by agencies. Deterioration model estimation methods rely on the ability to identify which inspection pairs in a dataset have been influenced by agency action that may have changed the condition of the element or the deterioration rate. BMSs also rely on the ability to identify the type of work performed, and the quantity and cost of the work. Agencies are found to be highly uneven in this capability. The field would benefit from further standardization of treatment identification, improvements in the state of the practice of work accomplishment data capture including automated assistance, and cost allocation methods.

- Improvements in the quality and consistency of element condition data collected by agencies. While ADEs are specific to DOTs' asset management practice, needs, and restrictions of that agency, there is an opportunity to move towards consistency across agencies to provide better or more consistent data for similar future efforts. The TAC team can consider continuing to meet to unify element and defect definitions. There could also be value to consistent numbering among MWBPP agencies, since the agencies will focus on planning potential changes for the Specifications for the National Bridge Inventory soon.

- Further development of defect data and associated models. The research showed some potential for the use of deterioration models for defect data. However, inspectors thus far have not been expecting such data to be used for this purpose, so quality is inconsistent. Because the consistent collection of such data could prove time-consuming, researchers may want to consider establishing scientifically-selected samples of bridges where thorough and consistent gathering of such data can be assured over an extended number of years.

- Improved environment classification. BMSs support the ability to classify elements according to operating conditions that could affect deterioration rates. The use of deicing chemicals is believed to be especially influential, in conjunction with traffic volume and protective features of the bridge such as protection of expansion joint areas and separation of structural elements from splash zones. The stratification features of the models delivered here may identify other significant variables. Agencies can use this information to rationalize their system of environment classification to make it more useful for deterioration modeling.

This study required a significant amount of work on the part of the twelve agency participants, including two complete rounds of data gathering, significant effort to classify elements and activities, and review of some very detailed analyses. The researchers are very appreciative of their time and effort.

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APPENDIX I – LITERATURE REVIEW

TYPES OF FORECASTING MODELS

Early Efforts

Bridge deterioration models have served important roles in structural asset management since as far back as the 1960s. Early models often adopted the same forms as pavement models but attempted to work with NBI condition ratings. These were sometimes used successfully for very coarse estimates of network bridge needs, but their predictive power was found to be very limited for most purposes. Literature reviews in the late 1980s found a large number of models that had been developed, but almost none were implemented for production use on state bridge inventories, since they did not stand up to validation (O'Connor and Hyman 1989).

In this early period, it was common to use deterministic deterioration models based on time series regression analysis. One of the earliest examples was developed for pavement management by the AASHO Road Test in 1958-60 and elaborated in subsequent studies (Patterson 1987). The models developed in these studies popularized a widely-recognized shape for infrastructure deterioration models (Hong and Prozzi 2005). This type of model has relatively few parameters, so it is easy to quantify from experimental data, provided that a sufficiently long time series is available. A typical shape for a 0–100 scale and 100-year life is shown in Figure 9.

$$p_t = p_0 - (p_0 - p_f)\left(\frac{t}{\rho}\right)^{\alpha}$$

where: p_t = performance at time t
p_0 = initial performance
p_f = terminal performance
t = year of forecast
ρ = lifespan
α = shaping parameter

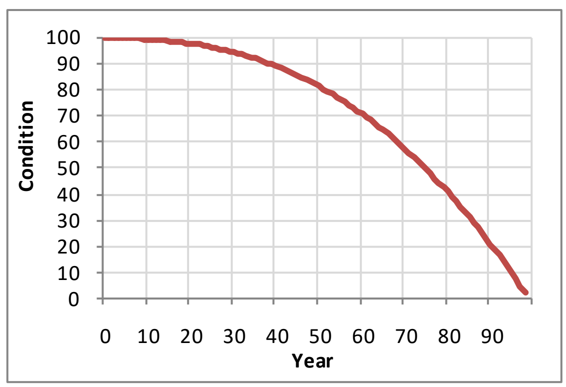

Figure 9. AASHO Road Test deterioration model

The shaping parameter in Figure 9 determines how quickly the initial deterioration progresses, a common feature of most types of deterioration models. In the earliest applications of deterioration models to bridges, variations on the AASHO curve were common. Typically, researchers would use National Bridge Inventory condition ratings to characterize performance. NCHRP Report 300 (Hudson et al. 1987) is a good example of the approach commonly taken in the 1980s.

As agencies began to work with these models, they found a variety of problems. A big problem was with the NBI condition scale, which did not provide the kind of information necessary for reliable prediction of future conditions. By failing to separate the severity of deterioration from its extent, the data made it impossible to reliably select treatments and estimate quantities. This concern led directly to the development of the AASHTO CoRe Element Guide in the early 1990s.

Another problem was that time series linear or non-linear regression analysis was not an appropriate method for working with categorical data such as NBI ratings. Deterioration was not a smooth curve as depicted in Figure 9, but was actually a step function. Approximating condition as a continuous variable led to plainly incorrect regression models that did not accurately reflect the data. The movement to AASHTO condition states made it even more obvious that conventional linear regression could not be used to develop deterioration models for bridges.

An additional problem was that the progression of condition over time is highly inconsistent from one bridge to the next. This is due to a variety of factors, especially an inability to measure the construction quality, material properties, and environmental characteristics that make a big difference in deterioration. The uncertainty is a major factor in effective forecasting; ignoring this uncertainty causes large statistical biases and incorrect decision-making.

So even though engineers had long been comfortable with the general shape of the AASHO curve, they were forced to abandon it because of the need to gain a more accurate description of bridge condition and its uncertainty.

Role of Uncertainty

Early attempts to use deterministic models in bridge management were especially problematic when using the models to estimate bridge needs on a medium time scale, such as 10 years, which is often needed for capital programming.

Estimation of bridge preservation needs on that time scale is like any other financial planning exercise in that it entails significant uncertainty. The uncertainty takes two different forms: normal variability of outcomes, which can be tracked and measured as events come to pass ("known unknowns"); and exceptional variability of outcomes, which is very difficult to predict ("unknown unknowns"). Examples of the latter would be the timing of the next big earthquake or the advent of a disruptive new technology. Since billions of dollars are at stake in bridge preservation decisions, expectations are high to reduce uncertainty as much as possible and to account for any reasonable variability that remains.

Figure 10 shows an example of the effects of uncertainty. The graph shows the uncertainty in lifespan of a group of bridge decks that are currently in Fair condition. Some of these decks may reach Poor condition within just two years, while others might last two decades or longer. The median remaining life might be 12 years, yet a significant fraction will deteriorate to Poor condition within 10 years. In a 10-year estimate of needs it would be important to make allowance for this "premature deterioration," even though none have yet reached Poor condition.

In current best practice, bridge management systems account for known uncertainties in deterioration rates by using probabilistic deterioration models, and account for known uncertainties in costs and funding by using sensitivity analysis. Exceptional uncertainties are not analyzed; sometimes they can be accommodated using expert judgment, but usually such unexpected events resist credible judgment.

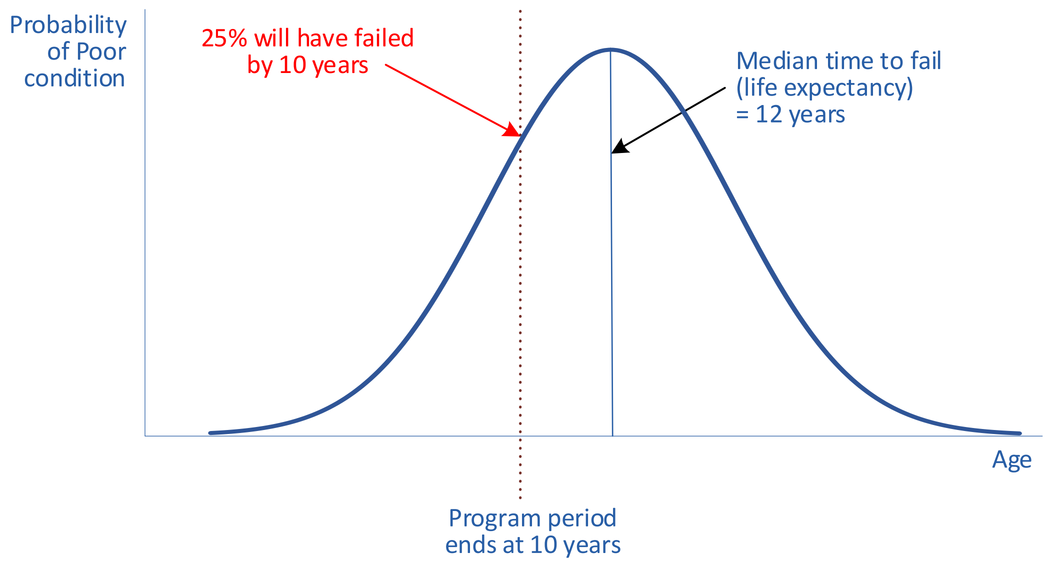

Figure 10. Premature deterioration as a result of uncertainty

Markov Models

Most bridge management systems worldwide use what is formally known as a discrete-time, discrete-state Markov model, which is arguably the simplest possible model that is compatible with element-level inspection and incorporates uncertainty (Mirzaei et al. 2014, Thompson et al. 2012). The discrete-time aspect stems from the convention that deterioration forecasts are made at uniform one-year intervals, conforming to common agency practice of inspections at multiples of one year and planning/programming cycles of one year. Discrete-time models are simpler and more flexible than continuous-time models, which can forecast over any time interval including fractional years.

The discrete-state aspect of the models comes from the AASHTO Manual for Bridge Element Inspection. This bridge inspection standard, used by every state, describes the condition of each structural element of a bridge by classification of defects into a small number of categories, distributing the total quantity of the element over the available categories. National Bridge Inventory component condition ratings are also discrete states, and can be modeled in the same way, as is done in AASHTOWare™ Bridge Management.

Under the discrete-time, discrete-state assumptions, Markov models can be expressed as transition probability matrices, as in the left side of Figure 11. The example has a uniform time unit of one year and a universe of four condition states. The change in condition is described as the probability that a unit of element (e.g., a lineal foot of girder) will make the transition from one state to another in one year.

Markov models in this form are easy to work with, because forecasts for any number of periods in the future can be made using matrix multiplication. The middle of Figure 11 shows the initial years of such a forecast, and the right side of Figure 11 shows the forecast as a graph, expressed in terms of a health index (Shepard 1999). The health index presentation of the model can be used in the way a deterministic model normally would be used.

		Probability one year later			
		State1	State2	State3	State4
Today	State 1	0.980	0.020	0.000	0.000
	State 2		0.955	0.045	0.000
	State 3			0.871	0.129
	State 4				1.000

Annual forecast conditions					
Year	State1	State2	State3	State4	Health
0	1.000	0.000	0.000	0.000	100.0
1	0.980	0.020	0.000	0.000	99.3
2	0.961	0.038	0.001	0.000	98.7
3	0.942	0.055	0.002	0.000	98.0
4	0.924	0.071	0.005	0.000	97.3
5	0.906	0.086	0.007	0.001	96.5
6	0.888	0.100	0.010	0.002	95.8
7	0.871	0.113	0.013	0.003	95.0
8	0.853	0.125	0.017	0.005	94.2
9	0.837	0.136	0.020	0.007	93.4
10	0.820	0.146	0.024	0.010	92.6
11	0.804	0.156	0.027	0.013	91.7

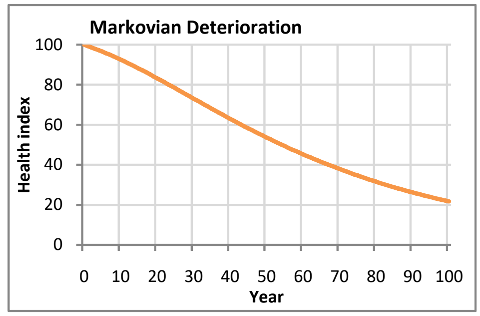

Figure 11. Markov model

Another convenient property of a Markov model is the ability to express each row of the transition probability matrix as a single number, the median number of years to transition. An expert elicitation model based on this feature would use questions of the form:

> Suppose 100 units of this element are in condition state S. After how many years will 50 units have deteriorated to state S+1, with 50 units remaining in state S, if no action is taken?

If it takes T years for 50% of a population of elements to transition from one state to the next, then the probability in a 1-year period of staying in the starting condition state can be calculated from:

$$P = 0.5^{(1/T)}$$

The probability of making a transition to a worse state is then (1-P).

In its first release, AASHTOWare Pontis used a transition period of 2 years to match the most common inspection cycle. In a 2-year period it is not uncommon for rapidly deteriorating elements, such as expansion joints, to transition through two condition states. So even though Pontis deterioration models were derived from median transition time, they were stored as the full transition probability matrix, allowing users to manually supply a non-zero probability of a two-state transition.

Release 3 of Pontis changed the transition period to 1 year, but maintained storage of the full transition probability matrix. Agencies only rarely took advantage of the two-state transition possibility. In AASHTOWare™ Bridge Management, the decision was made to store only the median transition times. Pontis provided a built-in regression tool to estimate transition probabilities from historical inspection data. AASHTOWare™ Bridge Management does not have such a tool, due to concerns that not enough data would be available under the newly-published AASHTO Manual for Bridge Element Inspection. AASHTOWare™ Bridge Management does provide a graphical interface which can be used to facilitate expert judgment elicitation of median transition times.

Table 41 shows an example of a deterioration model developed for the FHWA's National Bridge Investment Analysis System (NBIAS), which is used by the FHWA Office of Policy for periodic Reports to the Congress on national bridge needs (Thompson 2018). This was developed using statistical analysis of element inspection data gathered from a panel of 15 states. The table shows the model for a cool, wet climate. NBIAS has nine climate zones to approximate any county in the USA.

Table 41. FHWA's NBIAS deterioration model for cool, wet climate zone (median years to transition from each condition state to the next-worse state, by element)

Element group		Median years from state to state		
		1 to 2	2 to 3	3 to 4
A1	Concrete deck	7	14	14
A2	Concrete slab	5	17	10
A4	Steel deck	8	4	5
A5	Timber deck/slab	6	6	12
B1	Strip seal expansion joint	16	6	6
B2	Pourable joint seal	7	4	4
B3	Compression joint seal	7	6	6
B4	Assembly joint/seal	14	9	9
B5	Open expansion joint	13	9	9
C1	Uncoated metal rail	10	16	32
C2	Coated metal rail	18	13	12
C3	Reinforced concrete railing	26	21	16
C4	Timber railing	18	5	5
C5	Other railing	21	7	7
D1	Unpainted steel super/substructure	13	23	23
D2	Painted steel superstructure	14	20	7
D6	Prestressed concrete superstructure	39	23	9
D7	Reinforced concrete superstructure	14	23	14
D8	Timber superstructure	24	14	8
E1	Elastomeric bearings	54	11	11
E2	Metal bearings	16	19	19
F1	Painted steel substructure	11	17	6
F3	Concrete column/pile	22	20	21
F5	Concrete abutment	29	33	17
F6	Concrete cap	40	42	20
F8	Timber substructure	10	18	9
G1	Reinforced concrete culverts	21	24	30
G2	Metal and other culverts	7	10	18
P1	Deck wearing surface	6	19	11
P2	Protective coating	10	7	5

Onset of Deterioration

A problem noted in Florida research (Sobanjo and Thompson 2011), as well as research by California (Thompson and Johnson 2005) and by the National Cooperative Highway Research Program (Patidar et al. 2007), is that the Markovian models used in most BMS have fairly rapid initial deterioration. This creates a serious problem for multi-year programming models, because it is difficult to configure such models to maintain a realistically high network condition level. Bridge engineers have long believed that transition probabilities are time-dependent, that the probability of transition is low for a new element and increases with age.

A model using a Weibull curve has been proposed as an alternative that could ameliorate this problem (Agrawal and Kawaguchi 2009). Weibull distributions are very common in survival functions for reliability theory, where they are often used to model the probability of failure. However, they are useful for any change in state. Such a model is easily made age-based.

The Agrawal study in New York State used a Weibull model with a long time series of condition ratings in the style used in the National Bridge Inventory. In this type of rating system, unlike the CoRe Element system, the inspector rates the entire element using a single number, rather than dividing the total quantity of the element among condition states. In New York, each element receives a rating on a scale of 1 to 7. With a long time series of data, it is possible to determine the duration of an element in each condition state, so all state transitions can be quantified using age-based models.

With AASHTO element inspection data, a given unit of an element is not followed from one inspection to the next, so it is not possible to know the duration in most condition states. The age of the bridge does at least provide the duration in state 1, if no previous maintenance action has been taken. Therefore, it is possible to use a survival function to model the probability of remaining in condition state 1, as a function of age. Subsequent transitions below state 2 would still be modeled using Markov models.

A Markov model has a constant probability of transitioning from state 1 to state 2, so the survival function is used as an enhancement, to make the transition probability variable. A new bridge will have a very high probability, approaching 1.0, of remaining in state 1 from year to year. As the bridge ages, the probability decreases. Once a portion of an element deteriorates to condition state 2, Markovian deterioration takes over for the remainder of the process.

The Weibull curve has the following functional form:

$$y_{1g} = \exp\left(-\left(g / \alpha\right)^{\beta}\right)$$

where y_{1g} is the state probability of condition state 1 at age (year) g, if no intervening maintenance action is taken between year 0 and year g; β is the shaping parameter, which determines the initial slowing effect on deterioration; and α is the scaling parameter, calculated as:

$$\alpha = \frac{t}{(\ln 2)^{1/\beta}}$$

where t is the median transition time from state 1 to state 2, from the Markov model.

Figure 12 shows the form of the Weibull curve, for four different values of the shaping parameter β, with t=20. A shaping parameter of 1 is mathematically equivalent to a Markov model, featuring the problematic rapid onset of deterioration. A shaping parameter of 2 introduces a delay, and higher values postpone significant deterioration even longer.

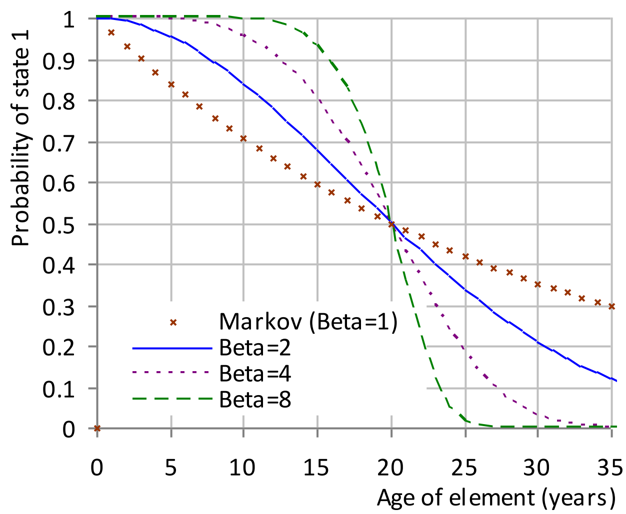

Figure 12. Comparison of shaping parameters

Note that all the curves in Figure 12 intersect in 20 years at a probability of 0.5, since the Markov median transition time is the same in all cases in the example.

Florida DOT developed a complete set of hybrid Markov/Weibull models for its bridge elements in 2010. These are shown in Figure 13. Subsequently similar models have been implemented as a part of AASHTOWare Bridge Management.

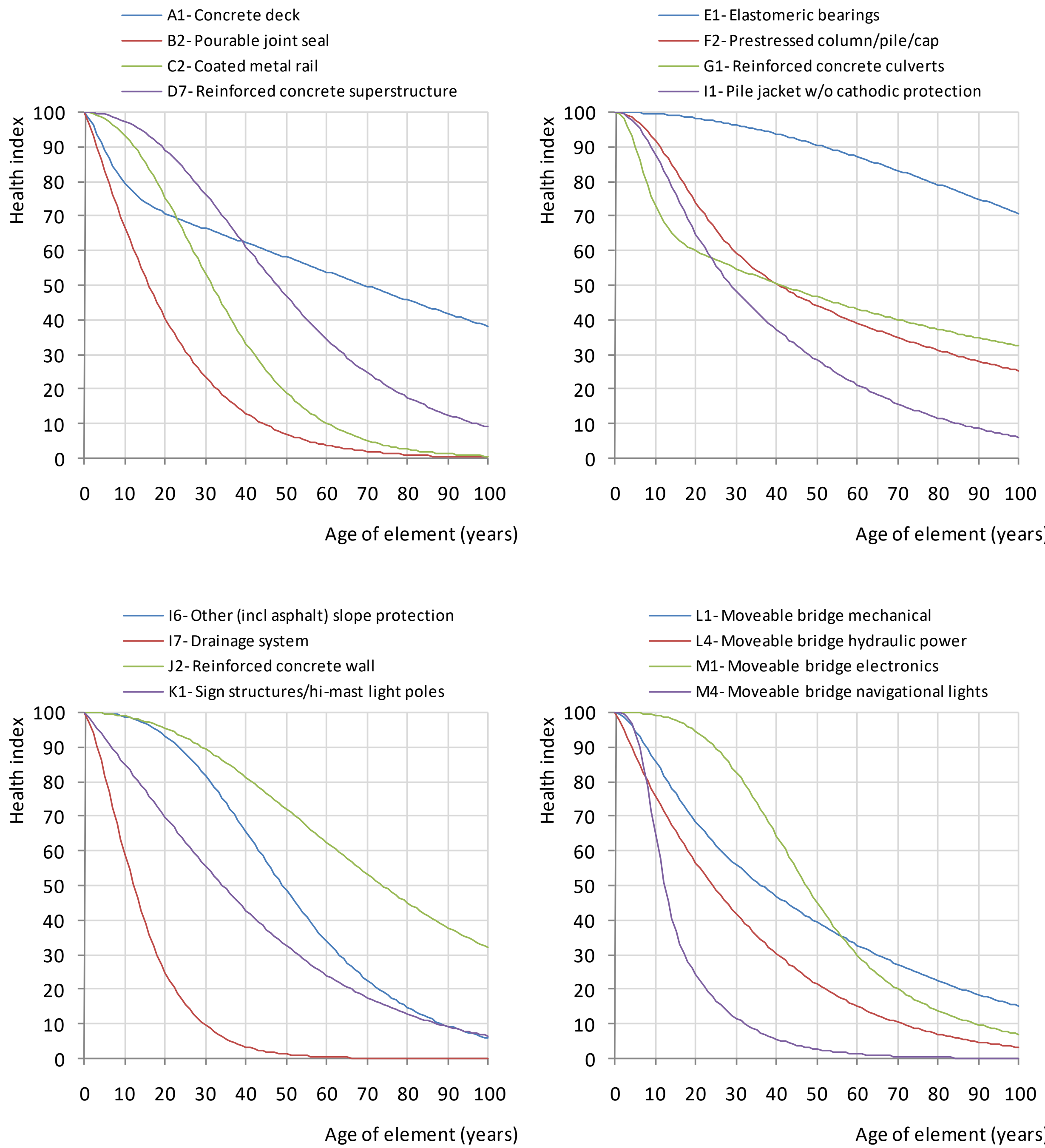

Figure 13. Comparisons of deterioration models among element types

Modeling the Effect of Protective Systems

The AASHTO Manual for Bridge Element Inspection provides special elements for recording the condition of common types of protective systems, specifically deck wearing surfaces, steel coatings, concrete coatings, and other concrete protective systems. Each of these has four condition states, which would interact with the four condition states of the substrate elements that they protect.

One way of modeling the interaction of two elements is the use of a two-dimensional Markov model. If the substrate and the protective element each have four condition states, the combination of the two elements will have 16 condition states in total, each representing a combination of one state from each element. This approach was first adopted in pavement management systems in Arizona and Kansas (Golabi et al, 1982). Later it was used in pavement and bridge management systems in Finland (Vesikari 1990). Such a system would be difficult to use under the AASHTO Manual for Bridge Element Inspection, because it would be necessary for the inspector to record the quantity in each of the 16 combination condition states of, for example, a protected bridge deck or a painted steel element.

The developers of AASHTOWare™ Bridge Management simplified the model by taking advantage of the decision to avoid two-state transitions and present the Markov deterioration model as merely a median transition time. They defined a new quantity called the protection factor, which summarizes the full effect of all possible element interactions that affect a given element at a given point in time. This protection factor may increase the median years to transition, thus slowing deterioration. It is applied like this:

$$M_i' = M_i \times PF$$

Where:

M_i' = Adjusted median years to transition from state i to state i+1

M_i = Default median years to transition from state i to state i+1

PF = Protection factor for the element

When there is one protecting element, denoted P, the protection factor PF is calculated as follows:

$$PF = \sum_s \left(PP_{Ps} \times F_{Ps} \right)$$

Where:

PP_{Ps} = Protection parameter for protecting element P, state s (PP_{Ps} >=1.0)

F_{Ps} = Fraction of element P in state s, $\sum_s F_{Ps} = 1.0$

PP_{Ps} is a parameter indicating how much of its full protection element P gives when it is in condition state s. It is evident that the protection factor is normally greater than 1.0.

Under the conventions used in AASHTOWare™ Bridge Management, Markov median transition times are always estimated under the assumption that protective systems are absent or, if present, that they are fully deteriorated. A calculation similar to the health index is used as a way to summarize the condition of protecting elements, and this is multiplied by a single protection parameter for each protecting element to yield the protection factor, which then increases the median transition time.

Research conducted for Florida DOT developed a set of computational methods to use protection factors in Markov and Weibull models, suitable for spreadsheet analysis (Sobanjo and Thompson

2011). Taking advantage of the Solver tool in Microsoft Excel, these methods enable maximum likelihood estimation of protection parameters, essentially the same methodology that the Florida research also used for Weibull shaping parameters.

Environment Factors

The concept of protection factors applied to median transition times, as used in AASHTOWare™ Bridge Management, came from earlier work on element environments for Florida DOT in the development of its Project Level Analysis Tool (Sobanjo and Thompson 2004) and in NCHRP Report 590 (Patidar et al. 2007). The Florida research found that it was reasonable, within the margin of error of deterioration models, to represent element environments by a single environmental factor applied to median transition times, rather than separately estimating the effect of environmental and operating conditions on each element individually. This discovery significantly simplified the modeling that had previously been done for AASHTO's Pontis software.

By adopting this perspective, AASHTO reduced the model size in AASHTOWare™ Bridge Management by storing median transition times undifferentiated by environment, and then providing a separate table with four environment factors to represent each of the four allowed environment classifications for elements. (Most states do not use all four environments.) Subsequent Florida research found that these environment factors could be estimated reliably from inspection data (Sobanjo and Thompson 2011).

In the development of the most recent version of the NBIAS, the researchers classified each bridge in the 15-state data set of Pontis inspections, according to the associated county as reported in the National Bridge Inventory. Using the Highway Performance Monitoring System, each county was then associated with one of nine nationwide climate zones based on moisture and temperature. Environment factors were then developed for each climate zone (Thompson 2018).

Forecasting of Federal Performance Measures

As noted earlier, past efforts to model deterioration of National Bridge Inventory component condition ratings have often been unsuccessful because of the difficulty of separating the severity of defects from their extent. As a result, application of such models was limited to business processes that did not require bridge-level treatment selection or cost estimation, such as coarse long-range needs estimates. This realization is what led to the development of the AASHTO CoRe Elements in the early 1990s.

In the time since the publication of the CoRe Elements, most bridge management systems worldwide have employed element-level deterioration models, which have broader applicability to all business processes served by BMS. However, in 2017 FHWA promulgated new federal performance measures based on NBI component conditions (FHWA 2017) and transportation asset management rules that imply the need for forecasting of these measures over a ten-year period (FHWA 2016).

AASHTOWare™ Bridge Management provides a Markov model that can be used to forecast NBI component ratings from earlier component ratings, which can then be converted to transportation performance management measures. Michigan DOT (Kelley 2016) developed a method to compute these transition probabilities from NBI component inspection data. These models still require an additional step to make them sensitive to element level data.

One possible approach is the use of an algorithm, known as a "translator" or "converter," to estimate NBI component conditions from element data, which can be forecast more reliably. One such program was developed for use in AASHTO's Pontis software and was also offered as a stand-alone program by FHWA (Hearn et al. 1993). Investigations by various states found that the outputs of the program often did not closely track NBI ratings determined by inspectors (Aldemir-Bektas and Smadi 2007). A few agencies, such as Florida DOT, developed their own translators (Sobanjo and Thompson 2011), but most continued the earlier practice of determining NBI condition ratings in the field, and did not attempt to forecast future ratings. Anecdotal experience with the most recent converter within AASHTOWare™ Bridge Management indicates that that model still needs further development and validation.

An alternative approach is to develop a statistical model that directly relates element conditions to the federal percent good and percent poor measures, without first translating to NBI condition ratings. If the problem is framed in this way, it presents an opportunity to use very simple binary-choice models, similar to what are often used in reliability (pass/fail) analysis and travel demand (mode choice) modeling, that are compatible with the exponentially-distributed data gathered in bridge inspections and produced by bridge element deterioration models. For example, Figure 14 shows a Weibull model developed by one of the authors (unpublished research in progress) that correlates an estimate of percent good against the fraction of elements forecast to be in condition state 1 using a Markov model.

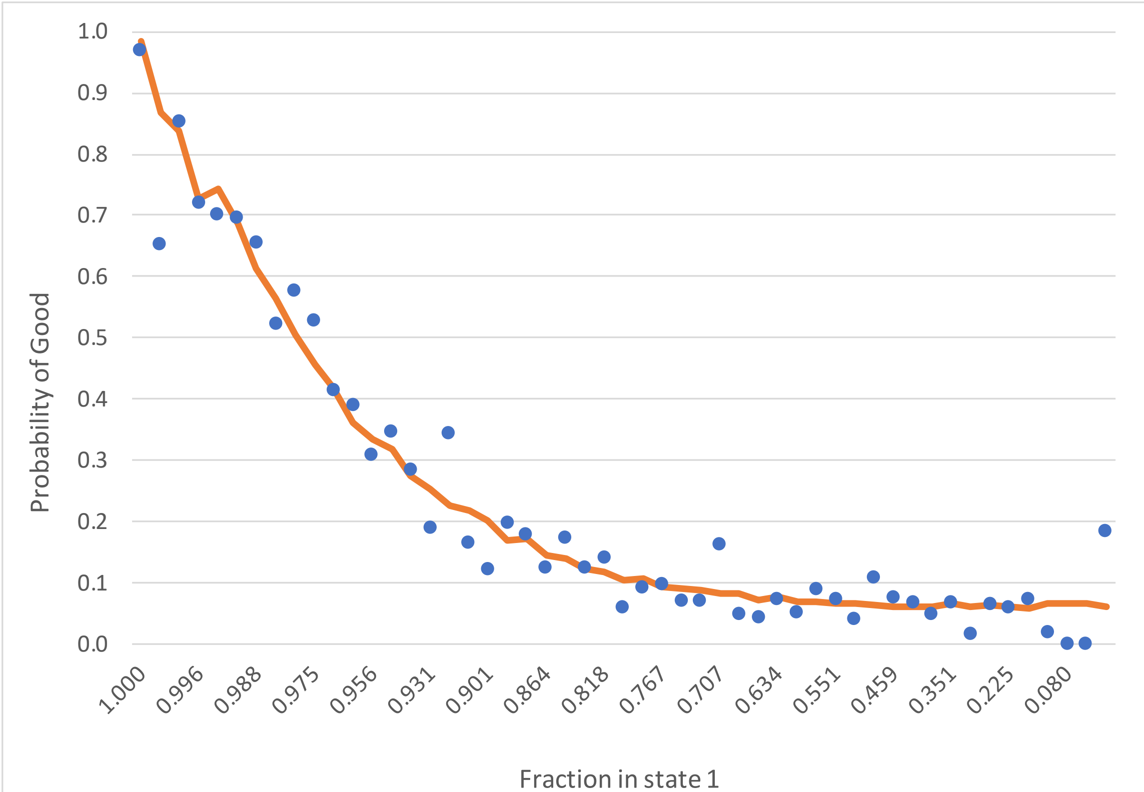

Figure 14. Weibull model of percent good vs. fraction in condition state 1

Other Forecasting Models

Researchers have developed many alternative forms of deterioration models, although only the Markov and Weibull models have been implemented and validated in production-level bridge management systems. When investigating new model forms, it is important to match the choice of model to the statistical characteristics of the data. For example, bridge element data are strongly exponentially distributed, as exemplified in Figure 15. Model families such as Weibull, lognormal, or logit can readily be made compatible with such data, while other families such as linear, normal, or probit models are not compatible. Similarly, NBI component conditions are categorical data, not scalar, so they require discrete choice models or step functions. An inappropriate choice of model can lead to results that appear to have strong coefficients of determination but which in fact are systematically biased, giving inaccurate forecasts.

A general survey and more detailed technical discussion of models of deterioration and life expectancy of infrastructure assets can be found in NCHRP Report 713 (Thompson et al. 2012). Some additional model forms that were investigated in this report, but have not been put into practice, include ordered probit, the Cox survival probability model, semi-Markov models, and various machine learning systems.

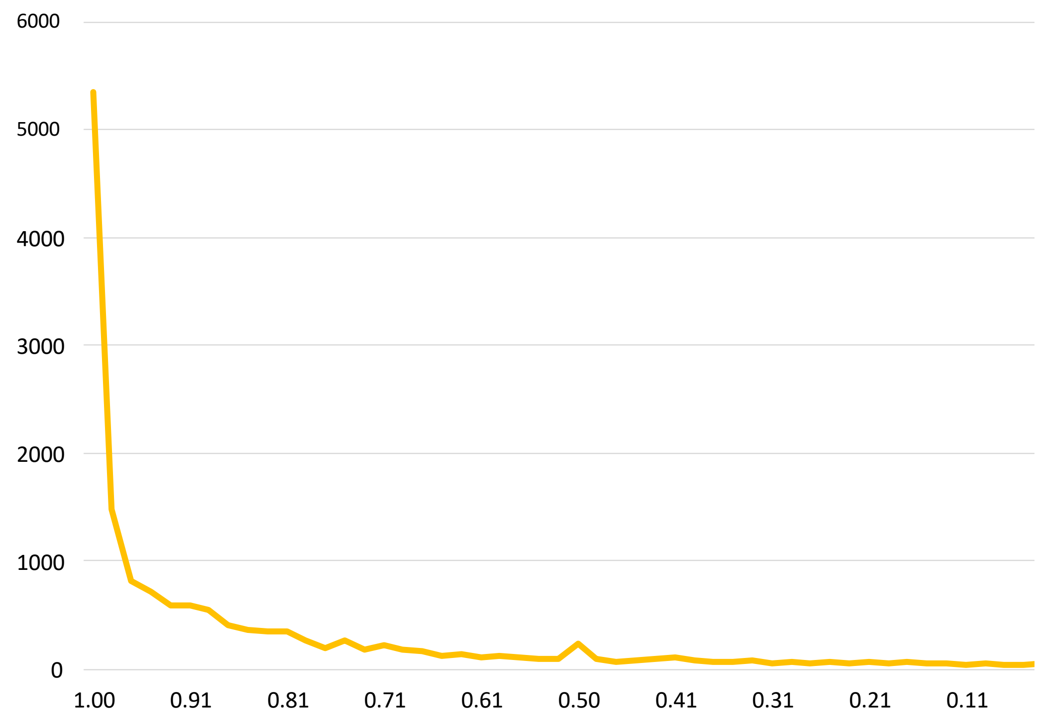

Figure 15. Example frequency distribution of percent in condition state 1 (Kentucky element inspections, 2019)

MODEL ESTIMATION METHODS

All methods for estimating deterioration models must cope with the limitations of the bridge inspection process as it currently exists. With only a very limited amount of continuous monitoring or non-destructive evaluation, the data sets in most agencies are limited to snapshots of visual observations, in most cases spaced two years apart. From one inspection to the next, the condition of each element on each bridge may change. However, specific units or locations on each element are not tracked; only total quantities are recorded. Condition is made worse by time, weather, traffic, pollution, and operating conditions such as the use of deicing chemicals. These factors promote physical and chemical processes that may increase the severity of material defects, or increase the extent of defects at any given severity level.

To counteract this normal deterioration and its impacts, the agency applies preservation actions intended to either improve condition, or at least slow the rate of deterioration. While deterioration can be observed every year, preservation actions occur infrequently, often at intervals of 10–30 years or more.

In order to estimate statistical models of deterioration, it is necessary to separate the effect of deterioration from the effect of agency actions. These effects are not directly measured, but must be deduced from a limited amount of information in two snapshots of condition spaced 2 years apart, plus any available evidence of agency actions that may have been performed in between the two snapshots. Figure 16 shows the problem schematically. If an agency action occurred on the element between 2013 and 2015, then the percent of the element observed to be in state 3 in 2015 may be due to a combination of normal deterioration from states 1, 2, or 3 and the effect of agency action in improving parts of the element which may previously have been in states 3 or 4. Estimation of the deterioration model is a matter of quantifying the flows along the blue paths.

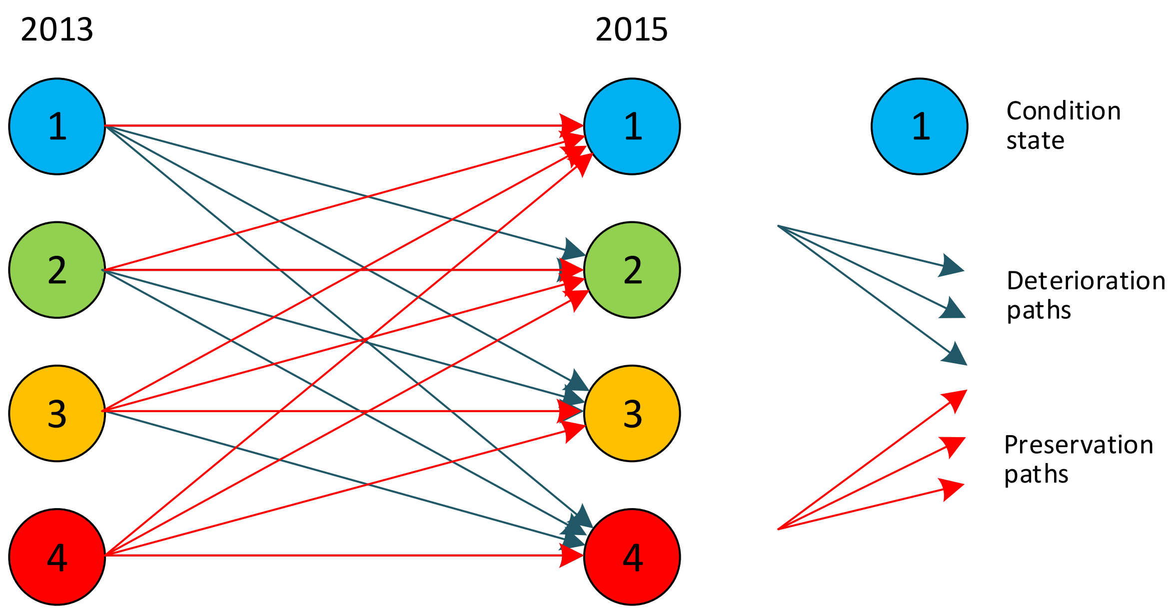

Figure 16. Changes in condition between two element inspections

Expert Judgment Elicitation

Historically the most common method for developing Markov deterioration models for bridge management systems has been expert judgment elicitation (Thompson 2007). In this methodology, a structured series of questions are asked of a panel of experienced inspectors and engineers, in the following form:

> Suppose 100 units of this element are in condition state S. After how many years will 50 units have deteriorated to at least state S+1, with 50 units remaining in state S, if no action is taken?

The answers to these questions are processed in order to derive median transition times, which can then be converted to transition probabilities as discussed above (Golabi et al. 1992). Often the elicitation process uses some form of the Delphi method, where the panelists are asked to answer each question independently, and then are convened to discuss and possibly modify their responses. The average of all final responses is then used as the final median transition time (Sobanjo and Thompson 2001).

AASHTOWare's bridge management software has a graphical presentation of the deterioration model which is intended to support the elicitation of expert judgment for median transition times (Figure 17). The calculations used for these graphics are the same as those presented above in Figure 11. This tool does not directly support the Delphi method. It has in some cases been used as a visual aid in Delphi sessions, but more often is reflective of the judgment of just one person in each agency.

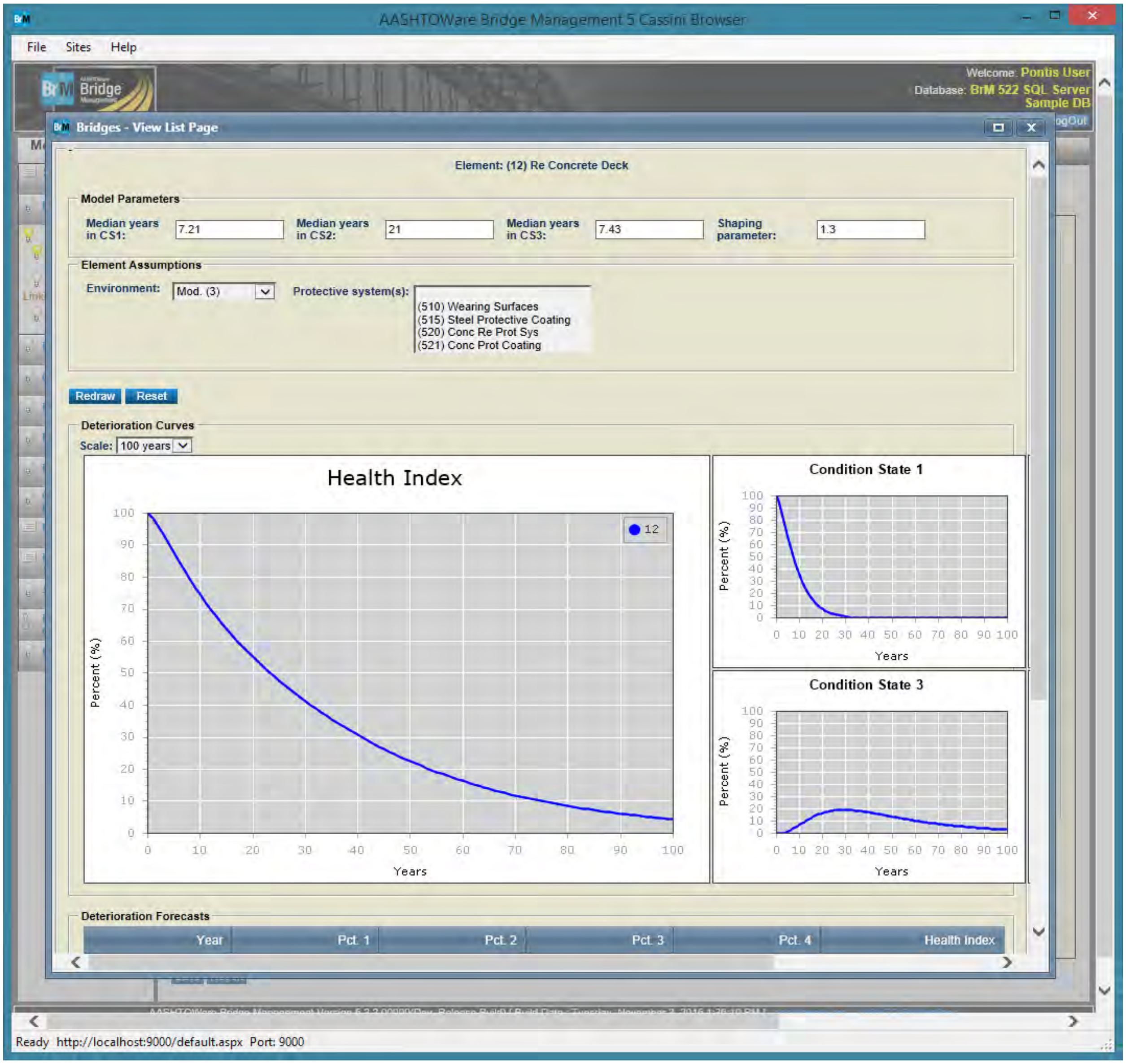

Figure 17. Deterioration model in AASHTOWare™ Bridge Management

Linear Regression

AASHTO's Pontis bridge management system contained a utility to estimate transition probabilities from past element inspection data, using linear regression (Golabi et al. 1992, Sobanjo and Thompson 2011). Unlike the deterministic time-series models discussed earlier, the Pontis regression was a cross-sectional model where the linear parameters to be estimated were transition probabilities. The following computations were performed.

Conditions at the beginning of the period:

$$[X] = \{x_1^i, x_2^i, x_3^i, x_4^i, x_5^i\} \text{ for all inspection pairs i}$$

Conditions at the end of the period:

$$[Y] = \{y_1^i, y_2^i, y_3^i, y_4^i, y_5^i\} \text{ for all inspection pairs i}$$

These are the known values in the estimation equation. The prediction equation is:

$$[Y] = [P][X]$$

where [P] is the transition probability matrix. The unknown transition probabilities can be estimated:

$$[\overline{P}] = [XX]^{-1}[XY]$$

Matrix of XX sums:

$$[XX] = \sum_i x_j^i x_k^i \text{ for all combinations of j and k}$$

Matrix of XY sums:

$$[XY] = \sum_i x_j^i y_k^i \text{ for all combinations of j and k}$$

The exponent on [*XX*]-1 indicates matrix inversion. Following the regression computation, the resulting matrix is normalized to ensure that it satisfies the rules of a well-formed transition probability matrix. Any values to the left of the diagonal are set to zero. If any diagonal elements are less than 0.01, they are changed to 0.01. Negative values to the right of the diagonal are set to zero. Then each row is adjusted to sum to 1.0:

$$p'_{jk} = \frac{p_{jk}}{s_j} \qquad s_j = \sum_k p_{jk}$$

Since the inspection pairs all have an interval of two years, the result must be transformed to show the probabilities in one year, by algebraically finding the square root of the transition probability matrix.

Many of the agencies using Pontis applied the regression procedure at one time or another to update their deterioration models. South Carolina DOT was one agency that used the procedure almost every year (Thompson 2007).

Florida One-Step Method

One conclusion that was common to all early research on Markov models was that the probability of a two-state transition—for instance, from state 1 to 3, or 2 to 4—in a single year was very small, even for fast-deteriorating elements such as expansion joints. As a result, AASHTO decided to limit transitions to one step at a time, allowing it to store deterioration models in the form of median transition times rather than transition probability matrices. This made the models simpler to manage and document.

If p_{13} and all other elements non-adjacent to the diagonal of the transition probability matrix are assumed to be zero, as in Figure 3 above, then it is a *one-step* transition matrix.

To set up the estimation of a one-step matrix, the prediction equation is defined as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & 0 & 0 \\ & p_{22} & p_{23} & 0 \\ & & p_{33} & p_{34} \\ & & & p_{44} \end{bmatrix}^2 \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

The element inspection vectors [*Y*] and [*X*] are spaced two years apart, but the transition probability matrix [*P*] is expressed for a one-year transition. Hence, it is applied twice. Writing out the individual equations necessary to calculate [*Y*] results in:

$$\begin{gathered} y_1 = x_1 p_{11} p_{11} \\ y_2 = x_1 p_{11} p_{12} + x_1 p_{12} p_{22} + x_2 p_{22} p_{22} \\ y_3 = x_1 p_{12} p_{23} + x_2 p_{22} p_{23} + x_2 p_{23} p_{33} + x_3 p_{33} p_{33} \\ y_4 = x_2 p_{23} p_{34} + x_3 p_{33} p_{34} + x_3 p_{34} p_{44} + x_4 p_{44} p_{44} \end{gathered}$$

Since the sum of each row in [*P*] must be 1.0, the following additional equations apply:

$$p_{12} = 1 - p_{11} \quad p_{23} = 1 - p_{22} \quad p_{34} = 1 - p_{33}$$

The vectors [*X*] and [*Y*] can be computed from the database of inspection pairs to describe the combined condition of the element before and after. So these quantities are known. Thus the system of seven equations and seven unknowns can be solved algebraically for the elements of [*P*]. A complication arises because the equations are second-order polynomials in p_{ii}, so it is necessary to use the quadratic equation to find the roots.

Florida DOT developed spreadsheet models using both the linear regression method and the one-step method, and compared the results (Sobanjo and Thompson 2011). It found a very close correspondence between the two methods for common elements, and nearly identical statistical performance in terms of coefficients of variation. The one-step method was able to produce reasonable models with smaller data sets, and encountered fewer numerical problems (such as division by zero) because it does not require matrix inversion. The research developed a general rule-of-thumb that about 500 element inspection pairs are sufficient to produce a statistically valid deterioration model for a given element.

Maximum Likelihood Estimation

Markov models lend themselves to relatively simple methods of estimation, such as those described in the preceding sections. Certain models used in bridge management, however, are more complex. For example, there is no simple algebraic method to estimate protection factors or Weibull model shaping parameters. For these tasks, a more general tool known as maximum likelihood estimation can be used.

The general framework for maximum likelihood estimation can be described in the following steps:

8. Prepare a table containing one row per element inspection pair or per observation, containing all the explanatory variables and the observed outcomes.
9. Add to each row of the table a computation to forecast the outcomes using the unknown model parameters to be estimated.
10. Provide an initial guess of the unknown model parameters. In each row of the table compare the observed outcome against the forecast outcome, using a formula known as a log likelihood function.
11. Iteratively adjust the unknown model parameters until the total log likelihood function is maximized.

The table in step 1 can be a spreadsheet, as was used in the Florida DOT research when estimating Weibull shaping parameters (Sobanjo and Thompson 2011). For a Markov model, the explanatory variables are the conditions observed in the first inspection of each inspection pair, where an inspection pair consists of two past inspections (percent by condition state) spaced two years apart on the same element of the same bridge. In general, any explanatory variables of interest could be included, such as age, traffic volume, etc. The observed outcomes are the conditions observed in the second inspection of each inspection pair. The object of the exercise is to find the set of unknown model parameters that is most likely to explain the outcomes that were observed.

The forecast computation in step 2 can be any reasonable functional form that makes intuitive or theoretical sense in explaining the observed outcomes. As noted above, the functional form must be compatible with the data: for example, a Weibull, logit, or lognormal model to fit exponentially-distributed data such as element condition states; or a discrete choice model to fit categorical data such as NBI condition ratings.

In step 3, the log likelihood function is a measure of the relative deviation of each observation between the forecast and the observed outcome. It is expressed as a negative number, so maximizing it is a process of finding parameters that move the total log likelihood closer to zero. A body of statistical theory exists for using the log likelihood function to evaluate the explanatory power of a model and to compare two or more alternative models.

In step 4, the iterative search for the maximum likelihood model parameters is often conducted using statistical packages such as "R," or can be conducted using generalized search algorithms such as Excel's Solver.

Bayesian Updating

It is possible to combine multiple deterioration models developed using different methods, even using expert judgment. The statistical principle that makes this possible is called Bayes Rule, and the procedure for combining models is known as Bayesian updating. Pontis, for example, contained an automated procedure that could update a model using expert judgment, by combining it with a model based on past inspections. Each model is weighted according to the number of bridges that contribute to the model, resulting in a weighted average of transition probabilities (Golabi et al. 1992). The combined model could be further combined with new models as additional inspection data were gathered.

Limitations of Expert Judgment

Agencies that lack historical bridge inspection data typically develop interim models using an expert judgment elicitation process, but the literature suggests that a high priority should be placed on moving to statistically valid models as quickly as possible.

Florida DOT compared its expert judgment models, gathered in 2000 (Sobanjo and Thompson 2001) with statistical models developed 10 years later, which were based on a total of 14 years of inspections (Sobanjo and Thompson 2011). Table 42 compares median transition times for the new models to the median transition times in the earlier expert elicitation models. It shows a significant pattern of differences. Historical data-based median transition times were, on average, 1.97 times what the expert panelists had estimated.

Table 42. Ratio of new median transition times to old expert judgment models

By element category*		By element material*	
Joints	3.2	Unpainted steel	1.8
Railing	1.6	Painted steel	1.9
Superstructure	1.7	Prestressed concrete	1.7
Bearings	2.2	Reinforced concrete	2.1
Substructure	2.0	Timber	1.8
Movable bridge equip	1.8	Other material	2.1
Channel	1.4	Decks	1.9
Other elements	1.4	Slabs	3.3
By condition state**		**By environment****	
From state 1 to 2	1.8	Benign	2.2
From state 2 to 3	2.6	Low	2.6
From state 3 to 4	3.8	Moderate	2.7
From state 4 to 5	6.1	Severe	2.9

Unweighted averages over the elements in each category, considering only usable models
* Based on median years from best to worst condition state
** Based on state-to-state median transition times

PRACTICAL ISSUES IDENTIFIED IN PAST STUDIES

Alabama

Alabama's Markov deterioration models were developed using inspections gathered since 2013 under the AASHTO Manual for Bridge Element Inspection. In this project (Thompson 2018), after creating the inspection pairs and filtering out the improved condition due to potential maintenance actions, it was observed that most of the elements do not have a sufficient population of data (at least 500 element inspection pairs) to estimate a reliable statistical model. Therefore, elements were grouped based on material and component categories (Table 6 of the report). After processing the data, the one-step method was applied to elements and NBI inspection data to produce Markov transition probabilities as the deterioration models to be used in AASHTOWare™ Bridge Management (Table 18 of the report). Developed models were reviewed by experts, validated, and compared with the Florida models. It was seen that median transition times in Alabama are 28% shorter than Florida due to the harsher environment. It was observed that the environmental factor does not have a significant impact on median element life expectancy, except for the concrete substructures. No modification for Weibull shaping parameters and protection parameters were implemented.

Relevancy:

- Data processing and challenges.
- Element level deterioration model (Markov model, one-step method).

Challenges or shortcomings:

- Lack of preservation work accomplished data. It was recommended to record the mentioned data to identify the deterioration trends more accurately.

Because of a lack of historical preservation data, the assumption was made that bridges whose condition improved in any way had received some sort of preservation work, and all others had not. The report discusses the potential biases that could result from this assumption.

Colorado

In this project (Hearn 2012), mechanistic models were used to describe the physical and chemical mechanism that causes deterioration. The mechanistic models were selected from the literature. RC bridge decks were selected as the element of the study and cracking was predicted through the models. Moreover, the effect of epoxy coated rebar, waterproofing membranes, asphalt overlays, joint deterioration, and maintenance action (membrane, asphalt, and joint replacement) on the deck deterioration process was investigated.

Relevancy:

- If DOTs decide to implement mechanistic models, this study will be useful.

Challenge or shortcoming:

- Lack of data (experimental or field) for the model inputs.
- Lack of maintenance history.

In a separate study (Nickless and Atadero 2017), Colorado DOT reviewed deterioration models and action costs from other US Departments of Transportation to develop element-level transition probabilities and action costs in Pontis. In this study, grouping bridge elements by bridge component and construction material yields eighteen and twenty deterioration models, respectively. Considering all the bridge components, construction material and protection yields fifty-nine deterioration models (Table 45 of the report). Deterioration models were developed for the defined groups based on percentage method and corresponding median life in each condition state was calculated.

Relevancy:

- A list of Pontis results for element-level transition probabilities and cost was provided that may be useful.

Florida

In this study (Sobanjo and Thompson 2011), several models were investigated and developed to enhance implementation of Pontis in the Florida bridge management system, such as a) a project- and network-level analysis tool, b) an improved version of the NBI translator, c) a deterioration and action effectiveness model, and d) a user cost model. Three sets of data were used in the analysis including inspection reports, maintenance activities record, and contract work activity. Separate Markov models were estimated for the 72 elements (after grouping or clustering) under study, considering four environments, plus one more set that combined all four environments. Assuming that bridges deteriorate slowly, the one-step method was used to estimate the Markov transition probabilities (Table 4.19 of the report). Weibull parameters were estimated through iterative maximum likelihood using an Excel solver module. As for the effectiveness model, information regarding the historical activity and condition data was gathered to modify the Markov transition matrix. The comparison of the data-driven model with the expert judgment one shows a large difference. Finally, several existing user cost models were reviewed and new accident models were developed based on crash data.

Relevancy:

- Data processing.
- Element level deterioration model (Markov model, in which transition probabilities were calculated by one-step method Weibull model).
- Maintenance effectiveness model.

The Florida research was updated in 2015 to convert it to use the new AASHTO Manual for Bridge Element Inspection, which has four condition states defined for every element (Sobanjo and Thompson 2016). This was accomplished using a probabilistic migration probability matrix, developed from expert judgment based on differences in element and condition state definitions between the 2013 AASHTO manual and the earlier CoRe Element guide.

Indiana

Deterioration models were developed for bridges located on the state highway system. The identified bridges were grouped based on the material type, climate condition, and functional class. Modeling consisted of finding the best formula that described a bridge component as a function of bridge age considering the influential variables. It was found that exponential or polynomial of the second or third order were the best models. For each of the deck and substructure, six deterioration models were built, and 42 models were developed for the superstructure. According to the study, the influential variables that played a role in the deterioration process were age, being on the interstate, the angle of skew, length, service under the bridge, the number of spans, frozen index, the number of freeze-thaw cycles, truck traffic, and deck protection (Moomen et al 2016).

Relevancy:

- Deterministic curves for the NBI bridge components as a function of significant parameters playing a role in the deterioration process.
- Some of the environmental variables were considered in the modeling.

Kansas

Kansas DOT used Florida's one-step method to develop bridge deterioration models from element data in the new AASHTO four-state format that has been used in Kansas since 2015 (Thompson 2018). The dataset was relatively small because of the short time frame of the inspections considered, and because only state-maintained and NHS bridges were included. Nonetheless, the research produced reasonable and useful deterioration models for the most common elements, which were also applied to similar but less common elements in order to achieve full coverage of the bridge database.

Similar to the situation found in Alabama and Virginia models, the Kansas research was affected by a lack of historical maintenance data, which made it necessary to assume that only bridges whose condition had improved had received preservation work. This is likely to have caused a bias in the result, whose direction and magnitude could not be determined from the available data. In addition, the Kansas data contained very few instances of condition state 4, making median transition times unrealistically long in a few cases.

Michigan

Through this project (Kelley 2016), deterioration rates of NBI components were evaluated at regular intervals. To this end, for four years' time interval of inspection data, probability of survival at each condition rating was computed (percentage method) and correspondingly the median transition years were calculated. From the comparison of deterioration curves of NBI components, it was concluded that they have a similar deterioration curve, but that in the absence of maintenance activities, deterioration rates of decks and superstructures would be faster than substructures and culverts.

Relevancy:

- Deterioration curves for NBI components.

In this study (Winn and Burgueno 2013), the deterioration process of bridge decks in Michigan was modeled by artificial neural network (ANN) methods using the national bridge inventory data. The developed models were capable of predicting the bridge deck deterioration at the bridge, project, and network level. It was shown that the developed models overcame the error and complexity in the dataset better than the currently used Markov models, consequently providing better results. However, in comparison to the mechanistic model, the ANN models cannot provide the detailed information that a mechanistic model can.

Relevancy:

- Deterioration curves for NBI components, concrete deck.

This study (Hu et al. 2013) developed a probabilistic-based framework based on mechanistic models available in the literature to predict the service condition of reinforced concrete bridge decks. Chloride-induced corrosion followed by carbonation was recognized as the major cause of deterioration of reinforced concrete deck components. Using the developed probabilistic-based framework and mechanistic models, deck damage severity can be predicted by contour plots of time to cracking and crack width. The severity of the damage was then mapped to the NBI rating scale to determine the condition of the deck.

Relevancy:

- Deterioration curves for NBI components, concrete deck.

Minnesota

This study (Nelson 2014) processes and analyzes inventory and inspection bridge data to determine how many years on average a bridge deck remains at the various NBI conditions. To this end, deterioration tables were created in which the number of years remaining in each NBI condition rating and the age of the deck when the NBI rate was reached were reported. Moreover, the influential factors that affect the deterioration process of a bridge deck were determined. It was shown that the presence of epoxy coated bar, the location of the bridge (whether it was inside or outside Metro District), and concrete cover were recognized as the most significant parameters in the deterioration process of bridge decks. Bridges with epoxy coated bars and increased cover perform better than bridges without epoxy coated bars. Bridges located within the Metro District drop to an NBI condition code of 7 faster than other districts, which could be due to infrequent sealing maintenance activity and more frequent application of deicing salt. Although ADT and the presence of a concrete overlay play a role in the deterioration process of bridge decks, the effect is not significant enough to create separate deterioration tables.

Relevancy:

- Effect of rebar coating on the deterioration process of a bridge deck.

The goal of another project (Zimmerman 2007) was to recommend cost-efficient maintenance strategies for a particular type of bridge deck, decks that were overlaid with low-slump concrete between 1974 and 1981. To achieve this goal, it was required to develop deterioration models to predict the future condition of bridges. Therefore, inventory and historic inspection data was gathered from FHWA and MnDOT. Then the data was categorized into three different groups with similar deterioration characteristics. The criteria of data classification were material type of the superstructure, maximum span length of the superstructure, and the average daily traffic (ADT), which were recognized as the most significant variables affecting the deterioration rates of the bridges under consideration. For each class of data, deterioration curves were developed and the average number of years for a drop in rating to occur as well as slope for the drop in rating were estimated. Due to the limited number of data in some condition states, some assumptions were considered in this project; for example, the slope of the deterioration curve from condition rating 9 to 8 was assumed the same as the slope from 8 to 7.

Relevancy:

- Deterioration curves for bridge decks with low slump overlay.

Nebraska

In this project (Hatami and Morcous 2011, 2013), two approaches of deterministic and stochastic were used to calculate bridge deterioration rates. Through the deterministic model, the relationship between the age and condition of bridge components was formulated. To this end, NBI condition rating data were extracted from 1998 to 2010 for Nebraska bridges. Bridges were classified based on agency district, material, deck and structure type, functional classification, structure authority, wearing surface and deck protection, type of service on bridges, and traffic load to get a homogenous and consistent data. Different deterministic models were generated for the defined grouped bridges. In addition to the deterministic deterioration models, stochastic models (Markov transition probability matrices) were developed using the available inventory and condition data to be implemented in Pontis. Transition probabilities were calculated by the percentage prediction method. In this method, the probabilities are defined as the ratio of the number of transitions from state i to j within a given time period to the total number of bridges in state i before the transition. Three environmental categories (low, moderate, and severe) were defined as a function of average daily traffic and average daily truck traffic, and three transition matrices were calculated for the defined environments.

Relevancy:

- Deterministic deterioration curve.
- Impact of some of the deterioration parameters such as wearing surface and reinforcement coating on the process were investigated.
- Stochastic deterioration model for NBI components.
- Effect of environmental factors (traffic load) was studied.

New York

Bridges were classified based on some internal and external parameters to develop models for a group of bridges with similar characteristics and rate of deterioration. Both Markov and Weibull models were used in this project to express the deterioration process. The transition matrix of the Markov model is calculated by formulating nonlinear programming optimization. The main drawback of nonlinear optimization is convergence. To resolve this issue, a second-level Markov process was used in this project. The Weibull model is expressed the time duration an element stays in a particle condition rating. A computer program has been developed in C++ to classify bridges and calculate deterioration rates by Markov Chain and Weibull-based approaches. Moreover, the program is capable of developing a polynomial regression as the deterministic approach to predict the prediction process. From the comparison of Markov and Weibull prediction of deterioration rates, it has been found that the Weibull model is more reliable for the prediction of bridge deterioration rates. This conclusion was driven from comparison of deterioration rates predicted by Markov and Weibull models for plate girder, deck with coated and uncoated rebar, pier cap, abutment bearings, and abutment joints (Agrawal et al. 2009).

Relevancy:

- Markov and Weibull-based deterioration models.
- Filtering data and classification of bridges.
- Case study for wearing surface deterioration modeling.
- Case study for the deck deterioration with coated and uncoated reinforcement.
- Case study for slab deterioration.
- Case study for abutment joint and bearing deterioration.

North Carolina

In this project (Cavalline et al. 2015), deterministic and probabilistic deterioration models were updated for NBI components to be used in the bridge management software. To update the deterministic models, bridge components and culverts were grouped into families using a priori classifications. Material type, design type, geographic location, and daily traffic were some of the factors used for classification of components. Probabilistic models were developed using survival analysis and proportional hazard techniques to account for the effects of bridge parameters such as age, design, geographic, and functional characteristics on deterioration rates.

In addition to the deterioration models, user cost calculation was updated to address ADT growth rates, vehicle operating cost, vehicle distribution, vehicle weight distribution, vehicle height distribution, accident injury severity, accident cost, and annual bridge-related crashes. Preliminary work was performed to evaluate the impact of maintenance actions on condition ratings of components. To this end, maintenance management system data between 2003 and 2014 was used to generate new transition probabilities that account for typical maintenance actions applied between condition 4 through 7.

Relevancy:

- Deterministic models for NBI components.

- Probabilistic models using survival analysis and proportional hazard techniques capable to capture the effect of bridge characteristics and environmental parameters.

Ohio

A stochastic Markov model was developed to study the effect of geographical location, bridge material type, and age on the degradation rate of over 45,000 bridges within the interval of 1995 to 2004. It was observed that degradation rates were different for bridges located in northern and southern districts and bridges with concrete and steel material. In addition to the location and material, rate of deterioration was sensitive to the age of bridges; three age groups of new-, middle-, and old-aged bridges exhibited different degradation rates. The degradation rate is high for new bridges, slows down for middle age bridges, and then the old age bridges show maintenances (Zambre 2004).

Relevancy:

- Markov transition probabilities calculated based on the percentage method.
- Age, material, and geographical location were identified as significant parameters in determining the rate of deterioration.

Pennsylvania

In this study (Manafpour et al. 2018), a semi-Markov process (based on accelerated failure time) was used to develop bridge deck deterioration models to predict the performance of Pennsylvania bridge decks and provide the best and most cost-efficient remediation practices for deck cracking. A summary of 30 years of historical inspection data for more than 22000 concrete bridges was collected on the extent of cracking for decks with different concrete types and protective systems. The estimated Sojourn times (i.e., the average time a deck lasts in a particular condition rate) from the semi-Markov process was related to various explanatory factors such as rebar type, single vs multiple span, bridge length, interstate vs non-interstate bridge, and District number. It was observed that a) Sojourn time is longer for coated rebar, b) Sojourn time is longer for shorter, simple-span, and non-interstate bridges, and c) location was recognized as a statistically significant variable that could be due to traffic variations, maintenance practices, and climate condition.

Relevancy:

- Semi-Markov model for decks with crack defect (crack development and progression).

Rhode Island

This is a master thesis (Eden 2018) in which deterioration models were developed for NBI components (deck, superstructure, and substructure) which are representative of the state of Rhode Island. Dynamic Bayesian network was used to develop a prediction model for the deterioration process of bridges.

Relevancy:

- If DOTs want to use a model which can be adjusted by the new inspection dataset, Bayesian method could be a good option, but it is not compatible with AASHTOWare™ Bridge Management.

Challenges:

- Presence of inconsistencies and errors in the dataset.
- Limited data for design load, material, and structure type.

Virginia

This dissertation (Reardon 2015) provided an investigation of the interaction between bridge elements, particularly subordinate deterioration. Subordinate deterioration occurs when deterioration of a specific element is dependent on the deterioration of other elements. Element-level inspection data from Virginia's database were gathered to study the interaction of two bridge elements; for example, the impact of bridge joints on the condition of bearing (as one of the subordinate elements). The Markov model was adjusted to incorporate subordinate deterioration. The results revealed that bearing elements in the bridges without joints or well-performing joints have a better condition as expected.

Relevancy:

- Deterioration model of a joint and its impact on the other elements.

A separate Virginia study followed Florida's one-step methodology to develop Markov deterioration models for all Pontis elements (Thompson 2012). In a paper comparing the Virginia and Florida results, the Virginia results were found to have consistently longer median transition times, which was likely due to significantly higher traffic volumes on the Florida bridges. The Virginia research also confirmed the Florida finding that median transition times derived from the statistical analysis of inspection data were more than twice as long as the corresponding median transition times derived from expert judgment.

A significant problem found in the Virginia research was the very small number of elements recorded as being in the worst defined condition state. It was reported that inspectors were reluctant to code elements as being in states 4 or 5 because it represented, to them, a recommendation that the load rating of the bridge should be reconsidered. As a result, median transition times to the worst-defined condition state were found to be unrealistically long.

Washington

In this study (O'Leary and Walsh 2018), a statistical deterioration model was developed for concrete columns (elements 205 and 227) for Eastern and Western Washington climates. Transition probabilities were calculated for dry and submerged elements using the percentage method. Transition from condition state 1 (CS1) to 2 has a higher probability for a dry element, but there is a higher probability of transition from CS3 to CS4 for a submerged element. It was shown that the location or climate of columns in Eastern and Western Washington do not have any effect on the deterioration process.

Relevancy:

- Deterioration of substructure elements.

Wyoming

Both deterministic and stochastic deterioration models were developed for the deck, superstructure, and substructure components of Wyoming bridges. Through the deterministic model, the best-fitted curve was found to relate to the condition rating of bridge components and the mean of bridge age for each class of bridges. Classification of bridges based on the explanatory variables can improve the accuracy in the model. Least Absolute Shrinkage and Selection Operator (LASSO) is a well-known version of penalized regression that was used for bridge classification and the explanatory variable selection process. Based on the LASSO results, wearing surface, structure length, functional classification, and average daily traffic were significant parameters for the deterioration of deck elements. Deck structure type, bridge roadway width (curb to curb), functional classification, and length of maximum span were the most important parameters for superstructure. While for the substructure, type of wearing surface, design load, bridge roadway width (curb to curb), and functional classification were the significant parameters.

Two sets of Markov models were used as the stochastic model to express the deterioration process for bridges with less than 30 years and with greater than 30 years. The transition probabilities of the Markov model were estimated using percentage prediction method, which counts the numbers corresponding to the element of transition probability matrix (Cortez and Maguire 2014).

Relevancy:

- Deterministic and stochastic deterioration models for NBI components.
- Significant explanatory variables playing role in deterioration process of NBI components were recognized.

Statewide Performance Function for Steel Bridge Protection Systems

In this study (Zayed et al. 2002), using regression analysis and Markov Chains techniques, deterioration models were developed to predict the performance of steel bridge paint over time. The regression model was used to estimate the extent of condition improvement as a function of paint age and other variables; however, Markov model was beneficial for condition prediction. Climate, age, traffic loads, and environmental conditions were the factors under study. It was found that age was the most significant variable, while traffic load and environmental conditions were statistically insignificant. The models were developed for two highway classes (interstates and non-interstates) as well as two paint types (lead-based and zinc/vinyl-based) and applied on the data collected from the Michigan DOT to analyze the paint system.

Relevancy:

- Deterioration model for paint system (protective steel).

Lifecycle Decision Framework for Steel Bridge Painting

This paper (Agbelie et al. 2017) developed a decision tree for the maintenance strategy and scheduling of the painting system. To this end, two separate log-linear regression models were established for two highway classes of NHS and non-NHS. It has shown that an increase in the paint condition rating decreases exponentially with the painting age. Moreover, it was found that temperature is one of the significant parameters that affects the deterioration rate of the paint system.

Relevancy:

- Deterioration model for paint system (protective steel).

Reliability of Corroded Steel Girder Bridges

This study (Kayser and Nowak 1989) quantified the reduction in safety for deteriorating steel girder bridges by developing a corrosion model. The effect of environmental parameters on the corrosion process were investigated, and it was concluded that bridges exposed to seawater or deicing salt use are more prone to corrosion, followed by bridges located in an urban environment with automobile and industrial pollutants, and finally bridges with exposure to pure water. Moreover, it was observed that the rate of corrosion is higher at a) locations along the bottom flange's top surface due to the accumulation of traffic spray and b) over the entire web with pronounced corrosion close to the supports due to the leakage of deicing salts through the deck.

Relevancy:

- Deterioration model for paint system (protective steel).

Modeling Bridge Deterioration Using Case-Based Reasoning

A new case-based reasoning approach has been used to describe the deterioration of bridges. The advantages of this method compared to the Markov chain process are a) capturing interactive effects between deterioration mechanisms of bridge components, and b) updating by the new inspection data (Morcous et al. 2002).

Relevancy:

- Bridge-deterioration model that addresses the limitation of Markov modeling, such as historical data being disregarded, interactive effects, and not being easily updated using new inspection data.

Artificial Neural Network Model of Bridge Deterioration

This study (Huang 2010) developed an artificial neural network model to predict the deterioration of bridges. To this end, significant parameters in this process were recognized by statistical analysis and by using historical maintenance and inspection data from Wisconsin DOT. The model developed provided predictions of bridge condition with good accuracy.

Relevancy:

- Deterioration modeling of bridge decks.
- Significant factors influencing the deterioration.

Challenges:

- Most agencies do not keep maintenance records adequately.

Development of an Integrated Method for Probabilistic Bridge-Deterioration Modeling

In these studies (Bu et al. 2014, 2015), the backward prediction model is incorporated to generate the missing historical condition ratings in case the historical records are insufficient for a reliable performance prediction. The performance modeling in this study is a Markov-based method incorporating both the state-based and time-based models. The K-M method is used for the time-based model and the expected-value is used for the state-based model to generate the transition probabilities. The proposed approach also includes the categorization of bridges based on material types, traffic volume, and the construction era to identifying similar deterioration patterns.

Relevancy:

- Using the backward prediction model could be an option if sufficient condition data is not available.
- The proposed strategy integrating the state-based and time-based model could be useful for the project.
- Classification criteria for categorizing bridges with similar deterioration trends could be beneficial.

Estimating Bridge Deterioration for Small Data Sets Using Regression and Markov Models

This study (Munoz et al. 2016) presented a change to the traditional approach by using the small data method to estimate transition probabilities. The proposed small data method provided more conservative results, which mean earlier maintenance actions than the estimation of traditional methods.

Relevancy:

- The proposed approach could be used in the project when small sample sizes are available.

System-Level Deterioration Model for Reinforced Concrete Bridge Decks

Through this study (Ghodoosi et al. 2015), a reliability-based approach is proposed to estimate the deterioration process of bridge elements. In the proposed approach, the predicted element-level structural conditions are applied in the nonlinear finite-element model of bridge superstructure to estimate the system reliability indexes at different time intervals. This approach estimates the reliability of bridges considering the structural parameters, load redistribution, redundancy of the structure, and correlation between structural elements. It was found that considering the interaction between the structural component leads to a lower probability of failure, therefore element-level assessment of a bridge deck is a conservative approach.

Relevancy:

- If the interaction between the structural elements is required to be considered in this project, the proposed approach could be advantageous.

Deterioration Forecasting Model with Multistage Weibull Hazard Functions

In this study (Kobayashi et al. 2010), a time-dependent deterioration model (multistage Markovian hazard model) is developed in which a multistage Weibull hazard model is used. The parameters of the model are estimated by employing the maximum likelihood method. As a result, the proposed methodology estimates the transition probability of condition state for any arbitrary time intervals.

Relevancy:

- If the time-dependent approach is required, the proposed approach is a good option; however, it has a main challenge.

Challenges or shortcomings:

- A complex numerical approach is required to estimate the parameters of the model. Local optimum and initial value of parameters are challenges within the maximum likelihood method.

Integrating Semiparametric and Parametric Models in Survival Analysis of Bridge Element Deterioration

This study (Yang et al. 2013) presented a Cox model to support multivariate analysis (considering several explanatory variables) with no assumption for the baseline hazard function in advance. It has found that the mixed Weibull distribution can be used in modeling the lifetimes of the units with more than one failure cause. The developed method was applied to three types of expansion joints for bridges located in Hong Kong.

Relevancy:

- Application of the Cox proportional hazard model.
- Case study for three type of expansion joints.

CONCLUSIONS

The first priority of the present study is to produce models compatible with bridge management systems such as AASHTOWare™ Bridge Management. For this purpose, the study will produce Markov models as in section 1.3, Weibull models as in section 1.4, protection factors as in section 1.5, and environment factors as in section 1.6 for the bridge elements and NBI components listed in Tiers 1 and 2 of the work plan.

For development of Markov models, the one-step method described in Section 2.3 was found to be most effective for developing statistically valid models with a limited population of data. For all other models, the maximum likelihood method in Section 2.4 will be needed. These methods are consistent with what was used in the Alabama, Florida, Kansas, and Virginia projects.

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APPENDIX II – DATA GATEHRING, PROCESSING AND DATABASE SCHEMA

DATA GATHERING

This section describes the processes used in gathering the data, assesses the information gathered, and details key findings.

A two-step approach was used in gathering data and information for this project:

- **Step 1** – Focused on requesting a list of data items from all participating DOTs.
- **Step 2** – Focused on collecting additional data and information using a targeted follow-up questionnaire, email correspondence, and phone interviews.

The research team issued a data request to the participating State DOTs. The request included directions for each agency to upload available data and information to a shared project folder, which was unique for each State to control data accessibility.

Requested Data

- The following data and information were requested from each State DOT:
- Inspection practices and coding methods of the DOTs related to element inspection and recording. This included historical inspection practices and coding methods, if available.
- State definitions of elements and coding practices for consistency and applicability.
- All available component and element-level inspection and inventory/attribute data and information for all bridges maintained by the DOT. This request also included historic CoRe element data and information, as available.
- Any agency defined element.
- Nondestructive evaluation data and information for all bridges.
- Construction history data as related to the analysis needs.
- Relevant DOT policies and practices related to bridge construction, preservation, and maintenance, as appropriate.
- Current deterioration curves that the State has generated along with the documented assumptions used to generate the curves (e.g., as excel, access, or word file).
- GIS coordinates of all bridges.
- Element environment[1].

The team reviewed the received information and developed a targeted follow-up questionnaire for each participating DOT. The questionnaire intended to clarify any gaps in the data and information each state provided. Upon receipt and review of the responses and additional documents submitted, the research team determined which one, or a combination of these actions, were required to take:

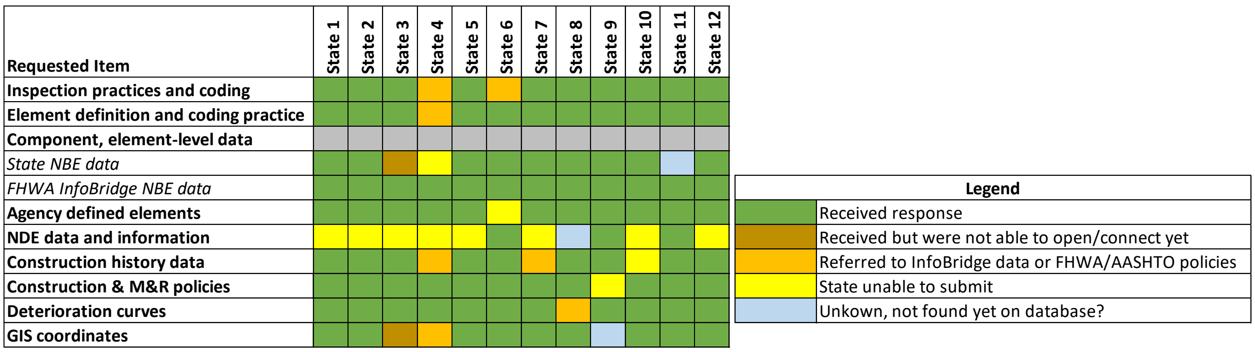
- No action needed – Responses and information gathered were satisfactory;
- Email follow up – Further minor clarification required; or

[1] This was not included in the initial data request, but the research team included it in the follow-up interviews.

- Phone interview (upon DOT request or research team recommendation) – Discussion required.

Received Data Status

Following the data request, questionnaire issuance, and follow-up correspondence and phone interviews, the research team gathered various useful information for this task and the research in general. In addition to the data received from each DOT, the research team also downloaded bridge data for each State from the Federal Highway Administration (FHWA) Long-Term Bridge Preservation (LTBP) InfoBridge database and from FHWA's Bridge Inspection website.



Data Assessment

To better understand the practices of the participating State DOTs, and to provide a better background for developing the project and subsequent analysis databases, the research team assessed the data received and the responses gathered. The following subsections provide brief descriptions of each data item.

Inspection Practices, Element Definitions, and Coding Methods

Of the responses received, half noted that they use the AASHTO MBEI directly. The other half of the responses, except for one DOT, indicated that they use a modified version of the AASHTO MBEI. These modifications are mostly related to language variation in clarifying condition states to suit the State's needs. For example, one State's definition of a bridge may include structures with a minimum size of 10ft instead of the federal 20ft requirement. Another example is using wearing surface when inspectors are unable to see the bottom surface of the deck. One DOT indicated that they use a State-specific inspection manual with major differences from the AASHTO inspection manual. However, this DOT also revealed that they will be transitioning to the federal elements beginning in 2020.

During the interviews, one agency mentioned that inconsistent coding of element conditions has been a concern due to the subjective nature of various inspectors' interpretation of the element condition states. They continue to provide enough support to their inspectors to ensure consistent and accurate data is recorded.

In addition to the National Bridge Elements (NBE) and Bridge Management Elements (BME), participating DOTs have specific ADEs and other items in their systems for decision-making.

For further discussion on the ADEs findings, please refer to the subsection "Agency Defined Elements."

Component, Element-level Inspection, and Inventory Data

The research team received data from different sources such as Pontis, AASHTOWare™ Bridge Management, BMS, and other management systems and in different formats including DMP, BAK, Microsoft Access, and Microsoft Excel files. It is important to note that two States did not upload their data directly to the shared folder but referred the research team to download the State data from FHWA LTBP InfoBridge. The research team downloaded the State NBE data through InfoBridge beginning in 2015. This data is a combination of migrated CoRe data and field inspected NBE data. This data was combined to form the project database.

On the other hand, not all State DOTs submitted CoRe element data from older element inspection for several reasons. Some of the reasons include a concern expressed by the agency about insufficient data quality, lack of availability, or additional effort being needed to process data. It was observed that some DOTs have migrated several years of their CoRe data using the AASHTO migrator or a State-developed algorithm. Notably, most of the DOTs transitioned into field collection of NBE data between 2015 and 2016 using the original translation as a guide to correct element quantities. Some States indicated that correcting elements quantities from the migrated data is still a work in progress. The research team identified any inconsistencies in the database and worked with the States to eliminate or accommodate them during the data processing and modeling process. The strength identified here is that most of the States are now gathering NBE data directly from the field, while the remaining DOTs mentioned they will transition for their 2020 submission.

Agency Defined Elements

The number of ADEs ranged from a couple of elements to all the elements in the State DOT inspection manual. Only one responding DOT indicated that they do not utilize ADEs in their bridge management system. Another DOT also mentioned using a substantial number of ADEs but could not provide inspection history for these elements.

Non-destructive Evaluation (NDE) Data and Information

It was observed that very few participating DOTs apply these techniques, and it is performed in a limited manner across their system. For example, one DOT mentioned using GPR on two concrete decks to determine the amount of deterioration. Another DOT also indicated using techniques like GPR, impact echo, and IR to investigate less than five percent of its bridge inventory.

Only three DOTs provided information on NDE data and information. Specifically, these DOTs revealed using various NDE techniques on selected bridges on the State network. Some examples of techniques DOTs are applying include UIT, GPR, impact echo, IR, eddy current, and drone technologies. It is important to mention that some DOTs indicated they are investigating NDE application at the research stage, which has not yet been implemented to support analysis.

Construction History Data

In practice, construction history data has not been gathered, processed, shared, and stored in the most usable format for bridge performance analysis. Although most of the participating DOTs provided some of these data, it was apparent that their use in the modeling process was going to be challenging. The key challenges that limited their use included:

- The lack of granularity in the data – In many cases, there was not enough detail on the actual work activity that was done on a bridge.
- Data coverage – Partial availability of work history. DOTs have not recorded the full extent of work completed on individual bridges.
- Time work was done – Most datasets lack accurate dates for when the work was completed.
- Data integration – Some DOTs track construction work in a different database and were unable to link construction history to a given bridge due to the absence of a unique ID linking data items from different database systems.

The research team worked with the individual DOTs during the data processing stage to develop cautious approaches to make the available information useful to the project and future decision analysis. The team worked with the participating DOTs and the Technical Advisory Committee to find practical means of addressing the data and information gap.

Construction, Preservation, and Maintenance Policies

Most of the participating agencies indicated they are taking action to more formally document preservation policies. These manuals contain agency goals, objectives, and relevant preservation actions the agency employs in their bridge management systems. While others do not have a formal manual, they have developed and documented logical processes in selecting treatments for bridge management. Some of these processes were documented in the State DOT Transportation Asset Management Plans (TAMPs) and capital or scheduled maintenance programs. It was observed that existing bridge preservation manuals were based on the Federal Highway Administration (FHWA) preservation guide providing definitions and a basis for consistent decision-making by identifying and prioritizing bridge preservation and improvement needs. These documents contain certain threshold requirements and minimum design criteria applicable to major preservation and rehabilitation projects.

Deterioration Curves

This piece of information was requested from the States to enable the research team to understand practice maturity across States. The information gathered indicated that some participating State DOTs have tackled deterioration modeling in some form. The team observed that most DOTs have established a forecasting approach to estimate the performance and condition of at least one of the bridge components (i.e., superstructure, substructure, deck, or wearing surface). These forecasting approaches range from expert trend analysis using a basic spreadsheet to rigorous regression analysis. Although the former approach has major limitations, the latter approach offers practitioners the ability to better analyze the relationship between influential variables such as the regional location of the bridge, construction details, and other factors. For example, one State DOT provided a research report detailing two models using deterministic and stochastic analysis. This DOT continues to investigate how best to transition from using national average parameters to adopting state-specific models that consider bridge-specific characteristics.

Two State DOTs provided element-level deterioration models. One of these two models estimates deterioration rates in the form of median years an element is expected to remain in one condition state. The other DOT uses an age-based approach that does not consider the impact of work done on the bridge. The lack of maintenance data is expected to be a limitation as DOTs are investigating better ways to document and to link detailed, useful information regarding bridge work history to bridge inventory and condition data to inform performance prediction.

Element Environment

It was observed that agencies were not assigning environment codes to different elements but placed all elements into a single environment code; predominantly in environment 2 – low or 3 – moderate. Essentially, these State DOTs assume that bridges or elements in the network will exhibit similar deterioration trends or the deterioration trends may not be significantly different across the network.

For those agencies that do use environment codes, the policy ranges from simple geographic location to a very comprehensive assessment of bridge and element exposure to functional class, traffic levels, de-icing agents, scour potential, number of load paths, exposure to water seepage, etc. A detailed assessment of the agency's inspection manuals revealed that in addition to the four AASHTO environment codes, one of the State DOTs defines a fifth value of EnvKey in inspecting bridges. This additional environmental code captures elements that have never been exposed or were exposed but now covered.

DATA PROCESSING AND DATABASE SCHEMA

This section contains the listing of bridge database columns used in the estimation of deterioration models. This list changed as the analysis proceeded. The participating agencies are using several different BMSs with different database schemas, each with different strengths and weaknesses for deterioration modeling. As a result, there is no one-size-fits-all data structure. This appendix is meant to represent a superset of attributes that best fit the research needs while making it possible to import and combine essential data from each participating agency.

In the following tables each row is a data attribute provided in the integrated analysis database, organized by table and column. The NBI column indicates the corresponding item name that is provided in NBI submittal files, which are downloadable for any state from FHWA's InfoBridge website. These were assumed to be compatible with any agency's bridge database and are the minimum items needed for deterioration model development. Items that are not shown with an NBI column name are optional but investigated for use in the deterioration models to the extent that the participating agencies were able to provide them.

In addition to the items listed, each table in the integrated database has a column to indicate the NBI state code, a column to indicate whether the record is valid, and a column to indicate the reason for an invalid code. For space reasons, AASHTOWare™ Bridge Management is abbreviated as BrM in the following tables.

Table 43. Bridge – Main bridge table

Table	Column	NBI column	Description
Bridge	BRIDGE_ID	STRUCTURE_NUMBER_008	Bridge identifier 008
Bridge	DISTRICT	HIGHWAY_DISTRICT_002	District 002
Bridge	FACILITY	FACILITY_CARRIED_007	Facility carried 007
Bridge	CUSTODIAN	MAINTENANCE_021	Custodian 021
Bridge	OWNER	OWNER_022	Owner 022
Bridge	YEARBUILT	YEAR_BUILT_027	Year built 027
Bridge	SERVTYPON	SERVICE_ON_042A	Service type on 042A
Bridge	SERVTYPUND	SERVICE_UND_042B	Service type under 042B
Bridge	MATERIALMAIN	STRUCTURE_KIND_043A	Material main 043A
Bridge	DESIGNMAIN	STRUCTURE_TYPE_043B	Design main 043B
Bridge	MATERIALAPPR	APPR_KIND_044A	Material approach 044A
Bridge	DESIGNAPPR	APPR_TYPE_044B	Design approach 044B
Bridge	NHS_IND	HIGHWAY_SYSTEM_104	NHS status 104
Bridge	YEARRECON	YEAR_RECONSTRUCTED_106	Year reconstructed 106
Bridge	NBISLEN	BRIDGE_LEN_IND_112	NBIS length 112
Bridge	ON_OFF_SYS		SHS status (Pontis or BrM only)
Bridge	BRIDGE_GD		Primary key (BrM 5.2+)
Bridge	BRKEY		Primary key (Pontis or BrM 5.1.x)

The items in Table 44 appear as part of the bridge table in NBI submittal files. Only data for the on-bridge record are needed for deterioration modeling.

Table 44. Roadway – Roadways on and under the bridge

Table	Column	NBI column	Description
Roadway	FUNCCLASS	FUNCTIONAL_CLASS_026	Functional class 026
Roadway	ADTTOTAL	ADT_029	ADT 029
Roadway	TRUCKPCT	PERCENT_ADT_TRUCK_109	Truck percent 109
Roadway	ROADWAY_GD		Primary key (BrM 5.2+)
Roadway	BRIDGE_GD		Foreign key to Bridge (BrM 5.2+)
Roadway	BRKEY		FK to Bridge (Pontis or BrM 5.1.x)
Roadway	ON_UNDER	RECORD_TYPE_005A	Route on or under 5A

In certain BMS databases the data from table detailed in Table 45 provides the ability to record multiple lists of elements on each bridge, organized by structure unit or span. That level of detail is useful, and will be used if provided, but is not mandatory. This information does not occur in NBI files.

Table 45. Structure_Unit – Grouping of elements into spans or structure units

Table	Column	Description
Structure_Unit	STRUCTURE_UNIT_GD	Primary key (BrM 5.2+)
Structure_Unit	BRIDGE_GD	Foreign key to Bridge (BrM 5.2+)
Structure_Unit	BRKEY	Foreign key to Bridge (Pontis or BrM 5.1.x)

Table	Column	Description
Structure_Unit	STRUNITKEY	Part of primary key (Pontis or BrM 5.1.x)

NBI submittal files provide only one inspection per bridge per year. However, all BMS databases provide storage for all inspections that have been conducted, which can be more than one per year on certain structures. This is shown in the table detailed in Table 46.

Table 46. InspEvnt – Inspection event

Table	Column	NBI column	Description
InspEvnt	OPPOSTCL	OPEN_CLOSED_POSTED_041	Open or closed 041
InspEvnt	DKRATING	DECK_COND_058	Deck rating 058
InspEvnt	SUPRATING	SUPERSTRUCTURE_COND_059	Superstructure rating 059
InspEvnt	SUBRATING	SUBSTRUCTURE_COND_060	Substructure rating 060
InspEvnt	CULVRATING	CULVERT_COND_062	Culvert rating 062
InspEvnt	INSPDATE	DATE_OF_INSPECT_090	Inspection date 090
InspEvnt	INSPEVNT_GD		Primary key (BrM 5.2+)
InspEvnt	BRIDGE_GD		Foreign key to Bridge (BrM 5.2+)
InspEvnt	BRKEY		FK to Bridge (Pontis or BrM 5.1.x)
InspEvnt	INSPKEY		Part of primary key (Pontis or BrM 5.1.x)

Element inspections were stored in the format shown in Table 47 in older databases under Pontis and versions of AASHTOWare™ Bridge Management up to 5.1.x, and may occur in agency-custom databases designed to be compatible with Pontis. It does not need to be populated for agencies that are not using the older format.

Table 47. ElemInsp – Element inspection for CoRe elements (Pontis or BrM 5.1.x)

Table	Column	NBI column	Description
ElemInsp	BRKEY	STRUCNUM	Part of primary key. FK to Bridge.
ElemInsp	INSPKEY		Part of primary key. FK to InspEvnt.
ElemInsp	ELEMKEY	EN	Part of primary key. FK to ElemDefs.
ElemInsp	ENVKEY		Part of primary key. FK to EnvtDefs.
ElemInsp	STRUNITKEY		Part of primary key. FK to Structure_Unit.
ElemInsp	QTYSTATE1	CS1	Quantity in condition state 1
ElemInsp	QTYSTATE2	CS2	Quantity in condition state 2
ElemInsp	QTYSTATE3	CS3	Quantity in condition state 3
ElemInsp	QTYSTATE4	CS4	Quantity in condition state 4
ElemInsp	QTYSTATE5		Quantity in condition state 5
ElemInsp	ELCONDEST		Flag indicating condition is an estimate

Many of the Tier 1 and Tier 2 models are specified to be element-level models, and therefore require data that is compatible with the AASHTO MBEI and NBI submittal rules. The table detailed in Table 48 is the most common format for such data, and is the preferred format for agencies that are able to provide it.

Table 48. Pon_Elem_Insp – Element inspection for AASHTO MBEI elements (BrM 5.2+)

Table	Column	NBI column	Description
Pon_Elem_Insp	BRKEY	STRUCNUM	Legacy foreign key to Bridge.
Pon_Elem_Insp	INSPKEY		Legacy foreign key to InspEvnt.
Pon_Elem_Insp	ELEM_KEY	EN	Legacy foreign key to ElemDefs.
Pon_Elem_Insp	ELEM_PARENT_KEY	EPN	Legacy foreign key to Pon_Elem_Insp.
Pon_Elem_Insp	ENVKEY		Legacy foreign key to EnvtDefs.
Pon_Elem_Insp	STRUNITKEY		Legacy foreign key to Structure_Unit.
Pon_Elem_Insp	ELEM_QTYSTATE1	CS1	Quantity in condition state 1
Pon_Elem_Insp	ELEM_QTYSTATE2	CS2	Quantity in condition state 2
Pon_Elem_Insp	ELEM_QTYSTATE3	CS3	Quantity in condition state 3
Pon_Elem_Insp	ELEM_QTYSTATE4	CS4	Quantity in condition state 4
Pon_Elem_Insp	PON_ELEM_INSP_GD		Primary key
Pon_Elem_Insp	PON_ELEM_DEFS_GD		Foreign key to Pon_Elem_Defs
Pon_Elem_Insp	PON_ENVT_DEFS_GD		Foreign key to Pon_Envt_Defs
Pon_Elem_Insp	INSPEVNT_GD		Foreign key to InspEvnt
Pon_Elem_Insp	STRUCTURE_UNIT_GD		Foreign key to Structure_Unit
Pon_Elem_Insp	PARENT_PON_ELEM_INSP_GD		Foreign key to parent in Pon_Elem_Insp
Pon_Elem_Insp	BRIDGE_GD		Foreign key to Bridge

The table detailed in Table 49 is needed only for agencies using the older data format of Pontis or AASHTOWare™ Bridge Management 5.1.x.

Table 49. ElemDefs – Element definitions for CoRe elements (Pontis or BrM 5.1.x)

Table	Column	Description
ElemDefs	ELEMKEY	Primary key
ElemDefs	PAIRCODE	Foreign key to Metric_English
ElemDefs	ELEMNUM	Element identifier
ElemDefs	COREFLAG	Flag indicating CoRe element
ElemDefs	SMARTFLAG	Flag indicating smart flag
ElemDefs	PARENT	FK to ElemDefs (sub-element roll-up)
ElemDefs	ELEMSHORT	Short name
ElemDefs	ELEMLONG	Long name
ElemDefs	STATECNT	Number of condition states
ElemDefs	EACHFLAG	Flag indicating unitary inspection

The table detailed in Table 50 is needed for agencies using AASHTOWare™ Bridge Management 5.2+. It will be necessary to generate a set of records based on the AASHTO MBEI for data sources generated from NBI submittal files. If agency-defined elements are provided by any agency, it is necessary to at least have an element number and name for each such element.

Table 50. Pon_Elem_Defs – Element definitions for AASHTO MBEI elements (BrM 5.2+)

Table	Column	Description
Pon_Elem_Defs	ELEM_KEY	Legacy primary key
Pon_Elem_Defs	ELEM_NBE_STAT	Flag indicating National Bridge Element
Pon_Elem_Defs	ELEM_PROTECT_SYS	Flag indicating protective system

Table	Column	Description
Pon_Elem_Defs	ELEM_SMART_FLAG	Flag indicating smart flag
Pon_Elem_Defs	ELEM_PAIRCODE	Legacy foreign key to Metric_English
Pon_Elem_Defs	ELEM_MODEL	Flag indicating whether to model
Pon_Elem_Defs	ELEM_SHORTNAME	Short name
Pon_Elem_Defs	ELEM_LONGNAME	Long name
Pon_Elem_Defs	PON_ELEM_DEFS_GD	Primary key
Pon_Elem_Defs	METRIC_ENGLISH_GD	Foreign key to Metric_English

The table detailed in Table 51 is needed only for agencies using the older data format of Pontis or AASHTOWare™ Bridge Management 5.1.x.

Table 51. EnvtDefs – Environment definitions (Pontis or BrM 5.1.x)

Table	Column	Description
EnvtDefs	ENVKEY	Primary key
EnvtDefs	ENVTNUM	Environment identifier
EnvtDefs	ENVTSHORT	Short name

The table detailed in Table 52 is needed for agencies using AASHTOWare™ Bridge Management 5.2+. It will be necessary to generate a set of records based on the AASHTO Manual for Bridge Element Inspection for data sources generated from NBI submittal files.

Table 52. Pon_Envt_Defs – Environment definitions (BrM 5.2+)

Table	Column	Description
Pon_Envt_Defs	ENVKEY	Legacy primary key (BrM 5.1.x)
Pon_Envt_Defs	ENVTNUM	Environment identifier
Pon_Envt_Defs	ENVTSHORT	Short name
Pon_Envt_Defs	PON_ENVT_DEFS_GD	Primary key (BrM 5.2+)

The table detailed in Table 53 is used for the interpretation of element units in files generated from Pontis or AASHTOWare™ Bridge Management. It is not needed for other data sources.

Table 53. Metric_English – Units of measure

Table	Column	Description
Metric_English	PAIRCODE	Legacy primary key (BrM 5.1.x)
Metric_English	METRICUNIT	Metric unit abbreviation
Metric_English	ENGLISHUNIT	US Customary unit abbreviation
Metric_English	FACTOR	Conversion factor
Metric_English	METRIC_ENGLISH_GD	Primary key (BrM 5.2+)

APPENDIX III – MODEL CUSTOMIZATION

This appendix describes the model development work performed in the study, starting with the analytical database detailed in the preceding appendix. Agencies and researchers wishing to develop deterioration models for specific applications can use this information to modify or customize the work performed in the study to fit the needs of specific tools and systems for specific purposes. The discussion is presented step-by-step in the logical order in which the data processing steps were performed, using a set of SQL and Excel files delivered with this report as products of the study. The sequence can be entered at any step, depending on the kinds of modifications to be made. The major steps, presented as sections of this appendix, are as follows:

Pre-processing of the analytical database. The steps in this section were performed as part of the study to supplement the analytical database, described in Appendix II, to add information required for modeling. It is unlikely that future researchers or agency users would need to repeat these exact steps, as they are specific to the data sources available at the time of the study, and would likely be different for future updates of the source data and for changing requirements of future modeling applications.

Generation of inspection pairs. This step, which is essential for the model estimation methodology, matches inspections that are spaced approximately two years apart to create two tables of inspection pairs, one at the component level and one at the element level. All subsequent analysis relies on these two tables. Any agency or researcher wishing to provide a new set of data to the analysis would need to perform this step. Much of the SQL code is concerned with overcoming differences among the twelve participating agencies in how they organize and code their bridge management data. Thus, the SQL may need to be modified if the source databases change.

Generation of focused datasets. The steps in this section correspond to the specific tasks in the analysis work plan, extracting records from the inspection pair tables to fit the needs of specific research questions. Agencies or researchers wishing to explore different research questions, such as the development of models for elements not addressed in the present study, would need to set up new SQL queries to extract the necessary data. The datasets produced by these queries are meant to be copied and pasted into the analysis spreadsheets delivered in the study, on the Pairs worksheet provided in each Excel file.

Using the spreadsheet models. Using Excel pivot tables, the spreadsheets delivered in the study support the most common customizations that agencies may wish to use, such as selecting which states' data to consider and what model stratifications to investigate. Agencies wishing to implement the study results directly, without making any changes or additions to the analytical database and without investigating additional elements, may be able to meet all their needs with the spreadsheets without having to repeat any of the preceding steps.

In general, each Excel analysis spreadsheet delivered in the study has a matching SQL file to produce the focused dataset it requires. A researcher wanting to address a new research question, such as a deterioration model for a group of elements not addressed in the study, would in most cases make a copy of one of the Markov spreadsheets and its corresponding SQL file, and modify these to accommodate the elements of interest. The files that were delivered for expansion joints and substructure elements are the simplest and might be the best choice to copy and adapt to new elements.

As a rule of thumb, the focused dataset should contain at least 500 inspection pairs. It is advisable to combine similar elements to achieve at least this population, and to investigate further aggregation, to 1000 or more, to ensure that the resulting model is stable. In most cases condition state 4 (for element data) and NBI ratings 0 thru 4 (for component data) are the least populous and most likely to exhibit instability if the population size is too small.

In conducting the study, the researchers used Microsoft SQL Server Express for all SQL-based data processing work. The SQL files were translated to MySQL for delivery, entailing some minor changes in syntax. All Excel work was performed using Microsoft Office 365.

PRE-PROCESSING OF THE ANALYTICAL DATABASE

To support the later analysis steps, certain data items were appended or updated in the analytical database. This was done using Excel files to automate the generation of SQL statements, which were then copy/pasted into the database manager's SQL query window for execution. These files can easily be modified and re-run if a researcher wishes to make changes in this information.

LU_State_Code Table

Most of the twelve agencies had been gathering element data well before implementation of the 2015 AASHTO MBEI. Earlier data may have been generated using a migrator program or field-gathered under an earlier manual, all of which would be incompatible with later data for modeling purposes. The research team discussed with each agency to indicate a starting date that would reasonably assure compatible data. As mentioned, states reported different data; however, May 1, 2015 was used as the default for all states.

A date field named StartDate was added to the LU_State_Code table. This was then populated using SQL statements generated in the Excel file "LU_STATE_CODE_supplement.xlsx".

Pon_Elem_Defs Table

Most of the research questions applied to groups of elements, usually one or more AASHTO-defined elements plus sets of agency-defined elements. To improve the ease and consistency of element grouping, a set of columns were added to the pon_elem_defs table. The following columns were added:

- Name – varchar(100), element name for reporting, in most cases provided by the agency in its data submittal, but in other cases gleaned from agency inspection manuals.
- Cat – varchar(7), element category.
- Type – varchar(7), element type.
- Matl – varchar(7), element material.
- RC_Deck – smalllint, 0 or 1 to mark reinforced concrete decks for Tasks 6.1, 6.4, 6.5.
- RC_Slab – smallint, 0 or 1 to mark reinforced concrete slabs for Task 6.2.

- Wearing – smallint, 0 or 1 to mark wearing surfaces for Task 7.1.
- Joint – smallint, 0 or 1 to mark expansion joints for Task 7.2.
- Defect – smallint, 0 or 1 to mark defects for Task 7.3.
- Paint – smallint, 0 or 1 to mark coating elements for Task 7.4.
- Painted – smallint, 0 or 1 to mark substrate elements for Task 7.4.
- Corrosion – smallint, 0 or 1 to mark corrosion defects for Task 7.5.
- Substr – smallint, 0 or 1 to mark substructure elements for Task 7.6.

The Excel file "Pon_Elem_Defs_supplement.xlsx" was used to generate a set of SQL statements to enter these data in the database. This script was also used to populate the ELEM_KEY_AASHTO column to group agency-defined elements as would be done for federal reporting.

Activities Table

This table in the analytical database identified the 198,341 records using long textual descriptions unsuitable for automated processing. So it was necessary to classify them. The following steps were used.

The researchers added the following columns to the table:

- AnyAct – smallint, 0 or 1 to indicate any type of usable record.
- CndAct – smalling, 0 or 1 to indicate an activity of a type that would be expected to improve condition.
- MajAct – smallint, 0 or 1, to indicate major preservation activities for Tasks 6.4 and 6.5.

A small number of agencies provided numerous activity records involving activities such as bridge washing, clearing of vegetation, and renumbering of structures. Such records would have AnyAct=1 but CndAct=0.

The researchers ran these queries to initialize the new columns:

- update ACTIVITIES set AnyAct=0,MajAct=0 (don't initialize CndAct);
- update ACTIVITIES set AnyAct=1 where WORK_YEAR>=1990 and WORK_YEAR<=2021 (115,494 records);

The researchers executed the script generated by "Activities supplement.xlsx" to provide the activity classifications, which were generated manually by examination of the textual descriptions.

The researchers ran the following queries to ensure that the new items are fully populated:

- Update ACTIVITIES set CndAct=0 where AnyAct=1 and CndAct is null and type_of_work is null;
- Update ACTIVITIES set CndAct=1 where AnyAct=1 and (major_preservation='1' or CndAct is null);
- Update ACTIVITIES set CndAct=0 where AnyAct=0;
- Update ACTIVITIES set MajAct=1 where AnyAct=1 and major_preservation='1';

The final activities table has 81,117 records that are CndAct=1, of which 12,518 are MajAct=1.

Ohio Supplements

Ohio provided all of its data in the NBI submittal format rather than offering a separate bridge management format as the other eleven agencies had done. It therefore required some special processing to generate the necessary data.

Three of the tables, metric_english, pon_envt_defs, and pon_elem_defs, were populated using a set of SQL queries generated in the file "Ohio supplement.xlsx". The remaining tables were populated using a set of SQL queries which extracted the necessary data from the provided NBI files:

- Create Ohio bridge records.sql
- Create Ohio structure_unit records.sql
- Create Ohio inspevnt records.sql
- Create Ohio pon_elem_insp records.sql

GENERATION OF INSPECTION PAIRS

The mathematical methodology for estimation of deterioration models, discussed in Appendix IV, starts with a table of paired inspections, spaced 2 years (± 6 months) apart. The first inspection is denoted "X", and the second is "Y". Conditions in the Y inspection are predicted based on information about the X inspection and about the bridge. Two tables of inspection pairs are generated: NBIPair for component-level inspections, and ElemPair for element level inspections.

For both types of inspection pairs, the queries first prepare subqueries for the X and Y inspections separately, then join them together along with relevant bridge-level data. Each of the queries must access supporting data from additional tables and perform various calculations to make the data ready for use in modeling. For example, some of the research questions require information about the roadways under a bridge, so additional subqueries are necessary to obtain these data. The twelve submitted databases differed significantly in the organization and coding of data items, especially in the use of missing data codes and agency-customized coding. Much of the SQL code was devoted to standardizing these items so they could be used in a consistent way across agencies.

To support sampling and validation, each inspection pair was assigned a random number, used later to define random subsets of the inventory. This is stored in the table to ensure that the focused datasets drawn for individual research questions are consistent with each other, and that validation results in the Markov spreadsheets are stable.

Component Inspection Pairs

The SQL query file "Create NBIPair.sql" performs all the manipulations and calculations required to generate component inspection pairs. All NBI records are used if they have a roadway-on that serves highway traffic, and an inspection from 1990 to 2021 inclusive. Inspection pairs are accepted if their dates are 2 years ± 6 months apart, have condition codes from 0 to 9, did not improve in condition, and did not change in their deck and wearing surface classifications (which might indicate a deck or wearing surface replacement).

A complication with NBI data is that a record is provided for every bridge for every year, even if no new inspection was conducted in every year. The file therefore contains duplicate inspections, which must be suppressed in the query. In all, 2,266,020 component inspection pairs were generated.

Element Inspection Pairs

The SQL query file "Create ElemPair.sql" performs all the manipulations and calculations required to generate element inspection pairs. Bridges must have a roadway-on that carries highway traffic. Inspections must be within the date range specified by the agency to have usable inspection data. Agencies were asked to identify any additional criteria which might render an inspection invalid for modeling purposes, such as underwater inspections or special investigations. Inspection pairs are accepted if their dates are 2 years ± 6 months apart, if they agree on bridge, structure unit, element, environment, and total quantity, and if they did not change their deck and wearing surface classifications.

Element inspections are joined with their corresponding protective elements, if any. They are also joined with information about any associated activities that might affect their condition or deterioration rate. In all, 1,181,415 element inspection pairs were generated.

Generation of Focused Datasets

Each of the spreadsheets that perform the final model estimation calculations has a Pairs worksheet containing a list of inspection pairs, filtered to contain the elements relevant to that spreadsheet. Each spreadsheet has a corresponding SQL file which extracts the relevant inspection pairs. The researchers used copy/paste to place the SQL query result into the Pairs worksheet. The SQL files are:

- Task 6.1 RC Decks.sql
- Task 6.1 RC Decks – Weibull.sql
- Task 6.2 RC Slabs.sql
- Task 6.2 RC Slabs – Weibull.sql
- Task 6.3 NBI Deck.sql
- Task 6.3 NBI Superstructure.sql
- Task 6.3 NBI Substructure.sql
- Task 6.3 NBI Culvert.sql
- Task 6.4 RC Decks after Major Preservation.sql
- Task 6.5 Improv after Major Pres.sql
- Task 7.1 Wearing Surfaces.sql
- Task 7.1 Wearing Surfaces – Weibull.sql
- Task 7.2 Joints.sql
- Task 7.2 Joints – Weibull.sql
- Task 7.3 Defect Development.sql

- Task 7.4 Paint system defects – steel model.sql
- Task 7.4 Paint system defects – 3420 model.sql
- Task 7.4 Paint system defects – 3440 model.sql
- Task 7.5 Steel girder corrosion – steel model.sql
- Task 7.5 Steel girder corrosion – corrosion defect model.sql
- Task 7.6 RC Abutments.sql
- Task 7.6 RC Pier caps.sql
- Task 7.6 RC Columns.sql
- Task 7.6 RC Pier walls.sql
- Task 7.6 RC Substructures – Weibull.sql

Any of these queries can be modified by a new researcher to change the selection of inspection pairs to be considered in the corresponding spreadsheet.

USING THE SPREADSHEET MODELS

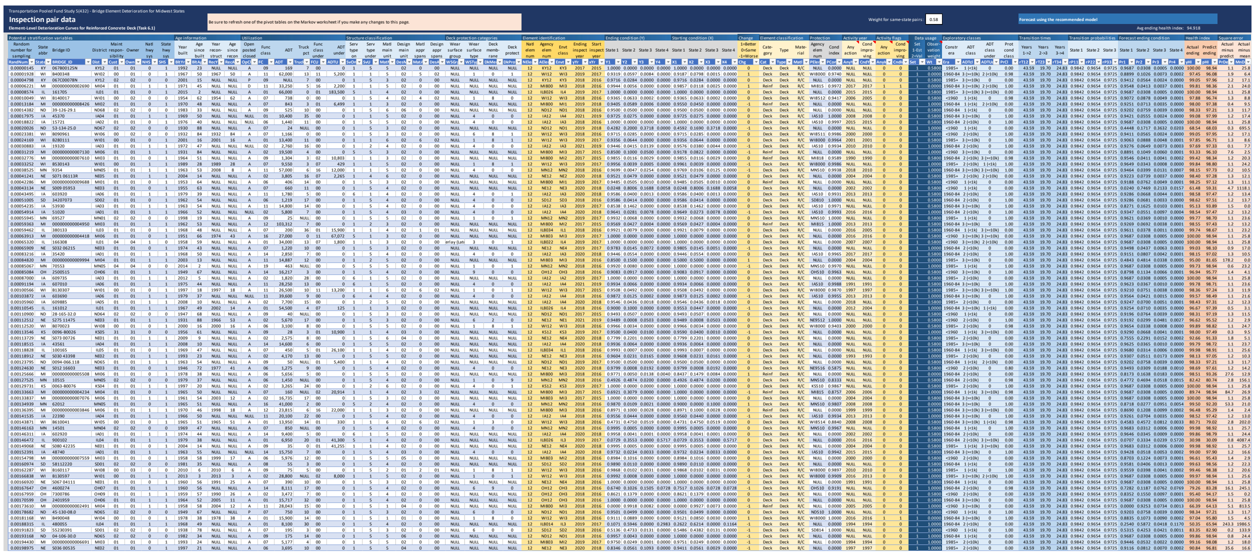
All of the analytical calculations discussed in Appendix IV are conducted within the framework of Excel pivot tables in spreadsheet models. There is at least one Markov spreadsheet file for each task, named for the task. The files contain no macros and are not locked in any way. The spreadsheet files are:

- Task 6.1 RC Decks.xlsx
- Task 6.1 RC Decks – Weibull.xlsx
- Task 6.2 RC Slabs.xlsx
- Task 6.2 RC Slabs – Weibull.xlsx
- Task 6.3 NBI Deck.xlsx
- Task 6.3 NBI Superstructure.xlsx
- Task 6.3 NBI Substructure.xlsx
- Task 6.3 NBI Culvert.xlsx
- Task 6.4 RC Decks after Major Preservation.xlsx
- Task 6.5 Improv after Major Pres.xlsx
- Task 7.1 Wearing Surfaces.xlsx
- Task 7.1 Wearing Surfaces – Weibull.xlsx
- Task 7.2 Joints.xlsx
- Task 7.2 Joints – Weibull.xlsx
- Task 7.3 Defect Development.xlsx
- Task 7.4 Paint system defects – steel model.xlsx
- Task 7.4 Paint system defects – 3420 model.xlsx
- Task 7.4 Paint system defects – 3440 model.xlsx
- Task 7.5 Steel girder corrosion – steel model.xlsx
- Task 7.5 Steel girder corrosion – corrosion defect model.xlsx
- Task 7.6 RC Abutments.xlsx
- Task 7.6 RC Pier caps.xlsx
- Task 7.6 RC Columns.xlsx
- Task 7.6 RC Pier walls.xlsx

- Task 7.6 RC Substructures – Weibull.xlsx

Each of the Markov spreadsheet files contains four or five worksheets, as discussed in the following sections.

Inspection Pair Data



This worksheet contains raw data pasted in from the analysis database. It also includes a few calculations to support the analysis, especially exploratory clustering of ordinal variables, and forecasts using the recommended model for validation purposes. Each Excel file has a different set of inspection pairs appropriate for the scope of its task. For element-level models, this worksheet contains 100% of the population from the analysis database, as many as 50,000 data points. For NBI components, the worksheet contains a stratified sample to keep the total size manageable.

Each Excel file is self-contained with all the available data it needs, so there is no need to connect to a database or import data.

Of particular note in the Pairs worksheet is a group of cells in the top center, which control the manner in which activity data are considered. By default, all inspection pairs that improve in condition are omitted, and all that declined in condition are fully included in the model. All inspection pairs that remain in the same condition between the X and Y inspections are weighted to account for the probability that an activity took place. The methodology is explained in Appendix IV. The weight can be changed at the top of the worksheet to reflect conditions specific to a given agency and the data subset it chooses to use.

Weight for same-state pairs: 0.58

Activity year		Activity flags		Data usage	
Any action	Cond impro-ving	Any action	Cond impro-ving	Set 1-Est 2=Val	Obser-vation weight
AnyY	CndY	AnyI	CndI	Set	Wt
NULL	NULL	0	0	1	0.5800
NULL	NULL	0	0	1	0.0000
NULL	NULL	0	0	1	0.5800
2017	2017	1	1	1	0.0000
2015	2015	0	0	1	0.5800
NULL	NULL	0	0	1	0.5800
NULL	NULL	0	0	1	0.5800
NULL	NULL	0	0	1	0.5800
NULL	NULL	0	0	1	0.5800
2019	2018	0	1	1	0.5800
2019	2019	1	1	1	0.0000
2009	2009	0	0	1	1.0000
NULL	NULL	0	0	1	0.0000

As an alternative, an agency may wish to consider activity records explicitly, if it is certain that the available data offer full coverage of all activities conducted on all the bridges considered in the Pairs worksheet. The AnyIn column has the value 1 if any type of activity record was recorded in the year between inspections or in the year of the second inspection of each pair. The CndIn column has a 1 in the more limited case of an activity record that is considered likely to affect condition. Every row with a 1 in CndIn also has a 1 in AnyIn, but the reverse is not true. The AnyIn column includes activities such as deck washing, brush clearing, and renumbering of bridges, which normally would not be expected to affect condition. The methodology used in calculating weights considers only the CndIn column.

To change the methodology used for considering activities, modify the formula in the Wt column to reflect the needs of the application. The default formula is

=IF([@Chg]=1,0,IF([@Chg]=0,SameWeight,1))

This formula gives 0 if the Y inspection has better condition than the X inspection; SameWeight (the number entered at the top of the worksheet) if X and Y are the same condition; and 1 if the Y inspection has worse condition than X. As an example of one alternative, an agency may wish to change this to

=IF(CndIn=0,1,0)

This will omit inspection pairs where an activity was recorded, regardless of the change in condition and ignoring the same-condition weight. This version uses the activity flag that only considers activities likely to change condition. Another alternative is to use ActIn rather than CndIn to consider any activity record. If the activity flags are to be used, it is very important to limit the scope of inspection pairs in the Pairs worksheet to include only bridges and inspections where activity data are likely to be available. This may mean omitting subsets such as:

- States that do not have activity data;
- Non-state-maintained structures;
- Districts that are not diligent in recording maintenance activity;

- Bridges subject to contract maintenance where work is not reliably reported; and
- Time periods during which the activity recording systems do not have complete data.

These considerations will naturally vary from one agency to another.

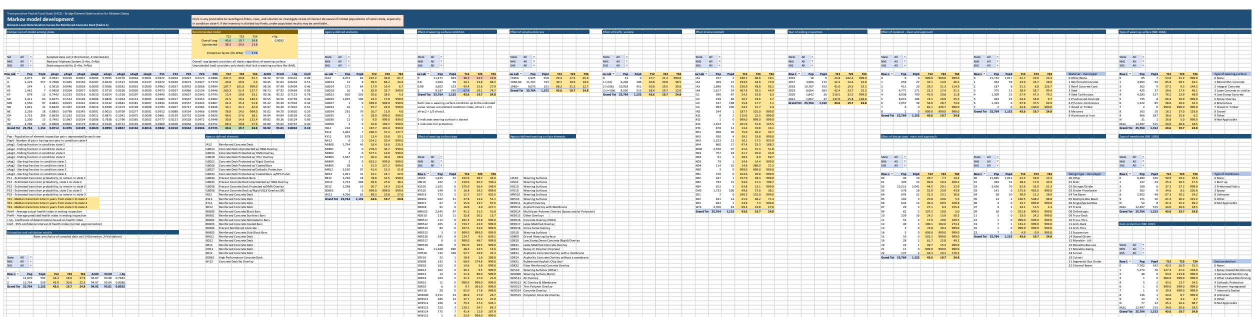
If any changes are made in the Pairs worksheet, it is necessary to visit the Markov worksheet, right-click any cell in any one of the pivot tables, and choose Refresh. This will cause all of the pivot tables in the file to be updated to reflect the change in the data.

There are many other possibilities for using this feature for specialized investigations. For example, a model might be developed to consider only pairs having non-condition-improving activities using a formula like:

=IF(AND(AnyIn=1,CndIn=0),1,0)

In theory any column in the Pairs worksheet can participate in this formula for an application that requires it. It is emphasized however that agencies wishing only to populate their BMSs, and who do not have specialized analysis objectives, should not change the default model in this way.

Markov Model Development



This is the main worksheet for model development. It contains a collection of Excel pivot tables configured to address a variety of research questions. The pivot tables draw on the table of inspection pairs and perform a set of closed-form calculations of Markov transition probabilities and median transition times. The pivot table functionality enables stratification of the model in any manner of interest to investigate how different variables may affect deterioration rates.

At the top of each Markov worksheet is a recommended model derived from the pivot table analysis. Typically there are three transition times, meant to be entered directly into the deterioration model page of AASHTOWare™ Bridge Management or any other BMS using this type of model. For Tasks 6.1 and 6.2 there are two sets of transition times:

- Overall average, ignoring the effect of a wearing surface, if any.
- Unprotected, meant to be used in conjunction with a wearing surface protection factor in AASHTOWare™ Bridge Management.

Green, red, and blue shading are used to make it easier to find the source of each recommended model in the pivot tables.

Recommended model				
	T12	T23	T34	r-Sq
Overall avg:	43.6	19.7	24.8	0.8032
Uprotected:	38.3	24.5	13.8	
Protection factor (for BrM):		1.76		
Overall avg (green) considers all decks regardless of wearing surface.				
Unprotected (red) considers only decks that lack a wearing surface (for BrM).				

The upper left pivot table in the worksheet shows the breakdown of the model for each of the 12 states that are participating in the study. Some of the states have relatively small populations of usable inspection pairs and might not be reliable. However, the combined effect of multiple states is statistically reliable. By default all the tables make use of data from all 12 states, but each table can be filtered to include any subset of the states. Each table can also be subset by NHS or state-maintained status if desired.

Set	All	Sampled data set (1=Estimation, 2=Validation)
NHS	All	National Highway System (1=Yes, 0=No)
SHS	All	State responsibility (1=Yes, 0=No)

ow Lab	Pop	Pop4	yAvg1	yAvg2	yAvg3	yAvg4	xAvg1	xAvg2	xAvg3	xAvg4	P11	P12	P22	P23	P33	T12	T23	T34	ActHI	PreHI	r-Sq	Conf
IA	4,073	82	0.9541	0.0410	0.0047	0.0002	0.9595	0.0370	0.0034	0.0001	0.9972	0.0028	0.9827	0.0173	0.9888	247.2	39.8	61.7	98.30	97.50	0.9316	0.08
IL	2,129	557	0.7698	0.1945	0.0150	0.0207	0.8229	0.1521	0.0104	0.0147	0.9672	0.0328	0.9673	0.0327	0.7370	20.8	20.9	2.3	90.45	91.63	0.8242	0.51
IN	244	1	0.9516	0.0446	0.0038	0.0000	0.9586	0.0381	0.0033	0.0000	0.9963	0.0037	0.9932	0.0068	0.9994	187.7	101.0	999.0	98.26	97.49	0.9404	0.46
KS	1,462	7	0.9658	0.0304	0.0037	0.0001	0.9710	0.0260	0.0030	0.0000	0.9973	0.0027	0.9866	0.0134	0.9946	260.3	51.4	127.7	98.73	97.92	0.9464	0.09
KY	878	12	0.7442	0.2232	0.0316	0.0010	0.8254	0.1538	0.0207	0.0000	0.9495	0.0505	0.9657	0.0343	0.9793	13.4	19.8	33.1	90.36	92.32	0.7123	0.78
MI	3,411	63	0.8275	0.1523	0.0196	0.0006	0.8826	0.1054	0.0114	0.0005	0.9683	0.0317	0.9647	0.0353	0.9962	21.5	19.3	182.5	93.55	94.56	0.6739	0.30
MN	2,550	97	0.8831	0.0915	0.0241	0.0012	0.9132	0.0681	0.0181	0.0007	0.9834	0.0166	0.9557	0.0443	0.9867	41.4	15.3	51.8	95.22	95.39	0.7932	0.34
ND	1,041	31	0.8420	0.1367	0.0199	0.0014	0.8780	0.1073	0.0139	0.0009	0.9793	0.0207	0.9717	0.0283	0.9836	33.1	24.1	42.0	93.97	94.30	0.7810	0.51
NE	2,236	18	0.8855	0.0798	0.0345	0.0001	0.9013	0.0709	0.0277	0.0001	0.9912	0.0088	0.9534	0.0466	0.9996	78.8	14.5	999.0	95.02	94.70	0.9020	0.29
OH	1,733	206	0.8630	0.1232	0.0126	0.0011	0.8875	0.1041	0.0075	0.0008	0.9861	0.0139	0.9752	0.0248	0.9820	49.6	27.6	38.1	94.94	94.84	0.8539	0.30
SD	1,300	15	0.7492	0.1967	0.0534	0.0006	0.7838	0.1796	0.0365	0.0002	0.9777	0.0223	0.9528	0.0472	0.9948	30.8	14.4	132.4	89.82	90.36	0.8124	0.66
WI	4,706	63	0.8968	0.0842	0.0179	0.0012	0.9149	0.0712	0.0135	0.0005	0.9900	0.0100	0.9656	0.0344	0.9752	69.3	19.8	27.6	95.89	95.62	0.8767	0.20
Grand Tot	**25,764**	**1,152**	**0.8712**	**0.1076**	**0.0189**	**0.0024**	**0.8993**	**0.0857**	**0.0134**	**0.0016**	**0.9842**	**0.0158**	**0.9654**	**0.0346**	**0.9725**	**43.6**	**19.7**	**24.8**	**94.92**	**95.01**	**0.8032**	**0.10**

Pop - Population of element inspection pairs represented by each row
Pop4 - Number of pairs having non-zero in condition state 4
yAvg1 - Ending fraction in condition state 1
yAvg2 - Ending fraction in condition state 2
yAvg3 - Ending fraction in condition state 3
yAvg4 - Ending fraction in condition state 4
xAvg1 - Starting fraction in condition state 1
xAvg2 - Starting fraction in condition state 2
xAvg3 - Starting fraction in condition state 3
xAvg4 - Starting fraction in condition state 4
P11 - Estimated transition probability, to remain in state 1
P12 - Estimated transition probability, state 1 to state 2
P22 - Estimated transition probability, to remain in state 2
P23 - Estimated transition probability, state 2 to state 3
P33 - Estimated transition probability, to remain in state 3
T12 - Median transition time in years from state 1 to state 2
T23 - Median transition time in years from state 2 to state 3
T34 - Median transition time in years from state 3 to state 4
ActHI - Average actual health index in ending inspection
PreHI - Average predicted health index in ending inspection
r-Sq - Coefficient of determination based on health index
Conf - 95% confidence interval of health index (normal approximation)

This table includes intermediate results of the calculations that make up the closed-form model estimation process. These calculations are implemented as Power Pivot “Measures”. All of the pivot tables perform all of the calculations, but to avoid clutter the intermediate results are hidden in most of the tables. The table in the lower left of each Markov worksheet randomly divides the dataset into two sets and compares them. This gives an idea of the amount of variation that can be expected from random error. Usually the results are very close together, but the differences may be greater if the population is small. Because the model uses closed-form algebraic calculations, solutions are exact and not fitted. This makes statistical measures of goodness-of-fit less relevant, although r-squared is provided. The most significant criterion is reasonableness of the effects of explanatory variables.

State	All							
NHS	All							
SHS	All							
Row L	**Pop**	**Pop4**	**T12**	**T23**	**T34**	**ActHI**	**PreHI**	**r-Sq**
1	12,970	593	43.2	18.9	27.9	94.87	94.98	0.7981
2	12,794	559	43.9	20.6	22.3	94.97	95.04	0.8086
Grand Tot	**25,764**	**1,152**	**43.6**	**19.7**	**24.8**	**94.92**	**95.01**	**0.8032**

A later section of this appendix provides more detail on how to customize the pivot tables or add more.

Population Summaries

Transportation Pooled Fund Study 5(432) - Bridge Element Deterioration for Midwest States

Population summaries

Element-Level Deterioration Curves for Reinforced Concrete Deck (Task 6.1)

All populations reported here are weighted to reflect inspection pairs which have not experienced work activity.

Population by year of ending inspection

NHS All; SHS All

Pop / ow Lab	2016	2017	2018	2019	2020	2021	and Total
IA		34	1,165	1,084	1,245	544	4,073
IL	1	449	831	849			2,129
IN		37	208				244
KS		359	598	505			1,462
KY	2	163	550	162			878
MI	13	1,091	1,129	1,172	6		3,411
MN		2	1,220	1,329			2,550
ND		176	346	511	8		1,041
NE	1	225	454	492	542	522	2,236
OH		16	1,678	39			1,733
SD	1	302	546	444	8		1,300
WI		1,132	2,063	1,477	34		4,706
Grand Tot	**18**	**3,986**	**10,787**	**8,064**	**1,842**	**1,067**	**25,764**

Population by NHS status

SHS All

Pop / ow Lab	0	1	and Total
IA	1,432	2,641	4,073
IL	758	1,372	2,129
IN	17	228	244
KS	596	867	1,462
KY	616	262	878
MI	1,292	2,119	3,411
MN	1,907	643	2,550
ND	787	254	1,041
NE	1,176	1,060	2,236
OH	112	1,621	1,733
SD	983	317	1,300
WI	3,436	1,270	4,706
Grand Tot	**13,110**	**12,654**	**25,764**

Population by state responsibility

NHS All

Pop / ow Lab	0	1	and Total
IA		4,073	4,073
IL	59	2,070	2,129
IN	1	243	244
KS	198	1,264	1,462
KY	314	564	878
MI	5	3,405	3,411
MN	1,287	1,264	2,550
ND	559	482	1,041
NE	121	2,115	2,236
OH	28	1,704	1,733
SD	675	626	1,300
WI	1,638	3,068	4,706
Grand Tot	**4,885**	**20,879**	**25,764**

Population by construction era

NHS All; SHS All

Pop / ow Lab	<1960	1960-84	1985+	and Total
IA	522	1,908	1,643	4,073
IL	414	1,297	417	2,129
IN	26	125	94	244
KS	372	430	661	1,462
KY	125	313	440	878
MI	689	2,010	711	3,411
MN	492	985	1,074	2,550
ND	290	430	321	1,041
NE	458	894	883	2,236
OH	180	1,034	519	1,733
SD	449	520	332	1,300
WI	909	1,820	1,977	4,706
Grand Tot	**4,925**	**11,767**	**9,073**	**25,764**

Population by open/posted/closed status

NHS All; SHS All

Pop / ow Lab	A	B	D	E	G	K	NULL	P	R	and Total
IA	1,771				9		2,289	4		4,073
IL	2,086		24			3		17		2,129
IN	244									244
KS	1,368							7	88	1,462
KY	679	17		1		2		180		878
MI	3,364		38			1		8		3,411
MN	2,216	4	1			4		321	4	2,550
ND	948				1	12		81	0	1,041
NE	2,131	37				6		61		2,236
OH	1,732					1				1,733
SD	1,038	3				1		258		1,300
WI	4,583					5		119		4,706
Grand Tot	**22,160**	**61**	**63**	**1**	**9**	**35**	**2,289**	**1,055**	**92**	**25,764**

Open/posted/closed status

A Open, no restriction
B Posting Recommended
D Open, temp shored
E Open, temp struct
G New-Not Yet Open
K Closed to all traffic
P Posted for load
R Posted for Non-Load

Population by service type on

NHS All; SHS All

Pop / ow Lab	1	5	6	7	8	and Total
IA	2,966	155	948	2	1	4,073
IL	1,659	454	16			2,129
IN	234	10	1			244
KS	1,450	1		12		1,462
KY	871	6	1	1		878
MI	2,820	532	29	27	4	3,411
MN	1,981	569				2,550
ND	896	15	130			1,041
NE	1,865	75	293	2		2,236
OH	1,522	81	121	8	1	1,733
SD	1,243	55	1	1		1,300
WI	4,104	581	11	9		4,706
Grand Tot	**21,612**	**2,534**	**1,551**	**62**	**5**	**25,764**

Population by service type under

NHS All; SHS All

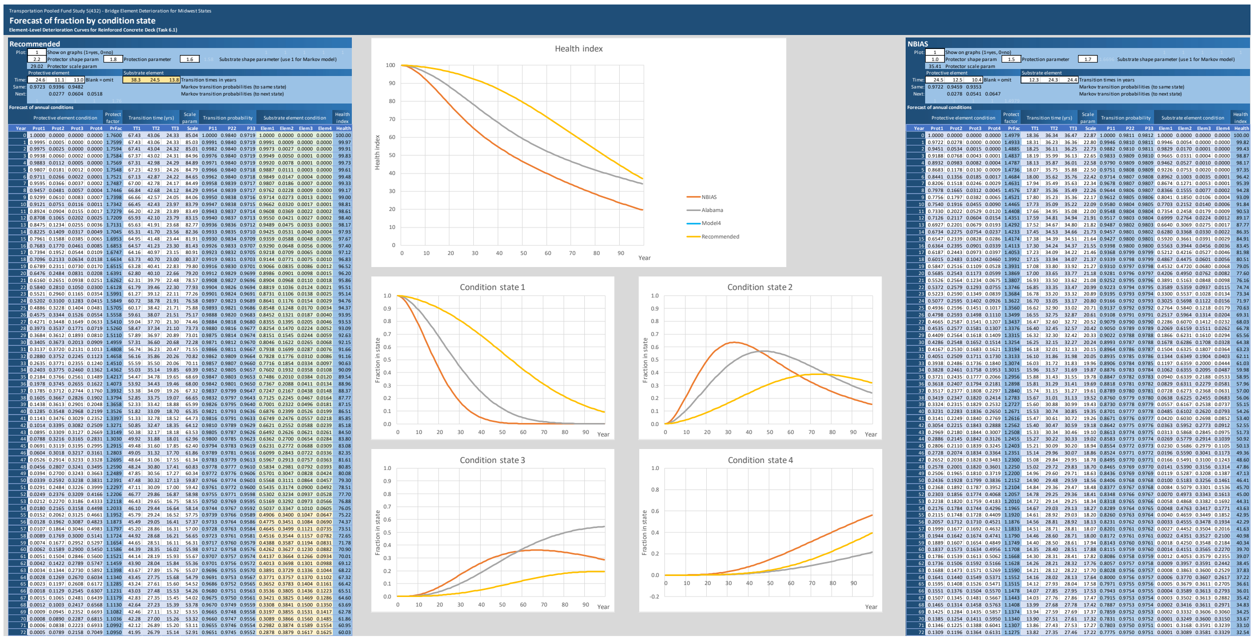
Pop / ow Lab	0	1	2	3	4	5	6	7	8	9	and Total
IA	38	1,685	288	19	86	1,797	62	39	53	5	4,073
IL	3	1,123	203	5	142	546	30	19	23	37	2,129
IN	4	96	29		13	89	11		3		244
KS	3	567	90	1	100	499	52	19	131		1,462
KY	4	181	36	1	13	614	18	3	6	2	878
MI	32	2,038	192	16	50	1,022	36	20	4		3,411
MN	34	658	204	46	73	1,472	34	13	13	3	2,550
ND	2	202	47		16	760	5	4	2	4	1,041
NE	4	573	139		103	1,346	27	31	13		2,236
OH	7	888	182	2	72	418	77	34	31	21	1,733
SD		273	54		13	942	9	6	1	3	1,300
WI	59	1,628	291	7	90	2,527	41	31	31		4,706
Grand Tot	**192**	**9,913**	**1,755**	**98**	**770**	**12,031**	**402**	**219**	**310**	**75**	**25,764**

Type of service

1 Highway
2 Railroad
3 Pedestrian-bicyle
4 Highway-railroad
5 Highway-pedestrian
6 2d level interchg
7 3d level interchg
8 4th level interchg
9 Building or plaza
0 Other

This worksheet contains additional pivot tables that summarize the number of inspection pairs contributing to each model. These population statistics are weighted to account for unreported activities, which allows all of the states' contributions to be used even if they did not provide a full set of activity data. The tables help an analyst to understand the contents of the dataset to evaluate the potential value of various stratification options.

Forecast Graphs



This worksheet displays graphs of the recommended model and any other Markov/Weibull models of interest. The graphs show health index at the top, followed by each of the four condition states individually. Each model is a complete Markov/Weibull calculation that includes the effect of wearing surface protection. The shape parameter can be set to 1 to remove the Weibull effect (i.e., show a purely Markov model), and the wearing surface model can be omitted if desired.

Up to four sets of calculations and graph lines are provided, but more can be added by copy/pasting additional tables to the right. Any of the tables and their corresponding graph lines can be turned off or hidden if not needed.

Settings

This worksheet provides the headings for all of the worksheets in the file.

Customizing the Pivot Tables

The model estimation methodology relies on Excel pivot tables to provide flexibility for agencies to stratify the Markov deterioration model in any way needed for a specific application. Example applications include:

- Limiting the model to a selection of states most similar to one's own.
- Limiting the model to NHS or state-maintained bridges.

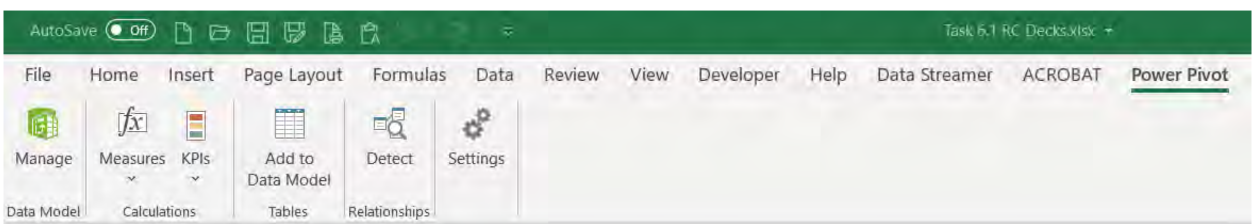
- Customizing the assignment of element environments to reflect traffic volume, construction era, or other variables for which policy sensitivity may be desired.

- Providing additional protection factors in the form of formula factors, a feature supported in AASHTOWare™ Bridge Management for advanced users.

- Developing custom applications for forecasting, needs analysis, life cycle planning, or investment planning, which could be implemented in spreadsheets, database scripts, or report writers. Such applications might be limited to selected portions of the inventory or might desire policy sensitivity that differs from what is provided in the agency's BMS.

Important note on customization: It is very easy, with the information provided in the Markov pivot tables, to configure a very detailed deterioration model in a BMS. It is recommended that this temptation be resisted. Although Markov models are very robust, complex models can produce forecasts that are hard for stakeholders to understand, or even counterintuitive. Excessive stratification also weakens the statistical reliability of models, increasing the risk of bias—that they reflect idiosyncrasies of a specific dataset rather than stable long-term structure behavior. There is no statistical test to prove or disprove a biased model; it is a matter of understanding the data and its limitations.

In order to create or customize pivot tables, ensure that Excel's Power Pivot add-on is active. This add-on is normally installed with Microsoft Office, but in some cases might be disabled. This can be ascertained by looking for a Power Pivot tab in the Excel ribbon.



If the Power Pivot tab is not visible, please consult this Microsoft support article for instructions:

https://support.microsoft.com/en-us/office/start-the-power-pivot-add-in-for-excel-a891a66d-36e3-43fc-81e8-fc4798f39ea8

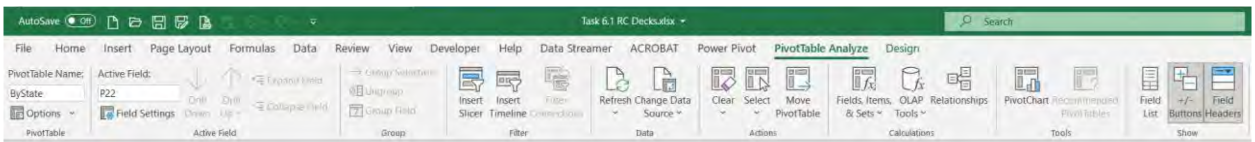
Please see this article if unsure whether a specific version of Office supports Power Pivot:

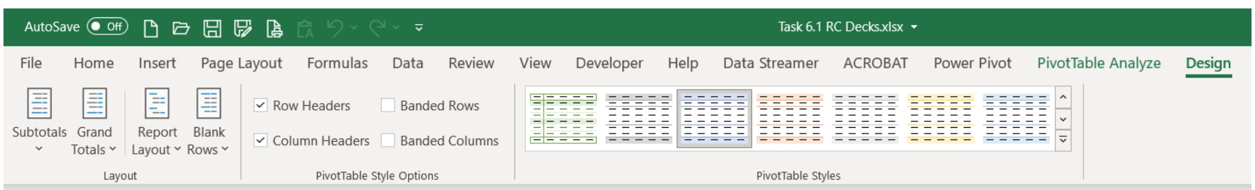
https://support.microsoft.com/en-us/office/where-is-power-pivot-aa64e217-4b6e-410b-8337-20b87e1c2a4b

The spreadsheets used in this study were created using Office 365, which is essentially the same as Office 2019. The pivot table functionality used in these models employs two sets of Excel functionality:

- Power Pivot "Measures" (also sometimes called "calculated fields"), which contain the closed-form calculations of Markov transition probabilities and median transition times. These are stored once with the workbook, and then available for use by any or all of the pivot tables in the file. Each Measure specifies a data table to be the source of data used by the Measure. The files used in this study have only one data table, called "Pairs." Features to create and manage Measures are found on the Power Pivot ribbon of Excel.

- Individual pivot tables, where the data and results can be displayed. A file can have as many pivot tables as needed, on as many worksheets as needed. Each pivot table specifies the data table from which the data are to be obtained (again, "Pairs"), and can make use of any of the columns in that table as well as any Power Pivot measures that are associated with that table. The Insert tab of Excel has the command to Insert Pivot Table. After clicking in any existing pivot table, the Pivot Table Analyze and Design tabs have the features to configure and customize the pivot table that was selected.

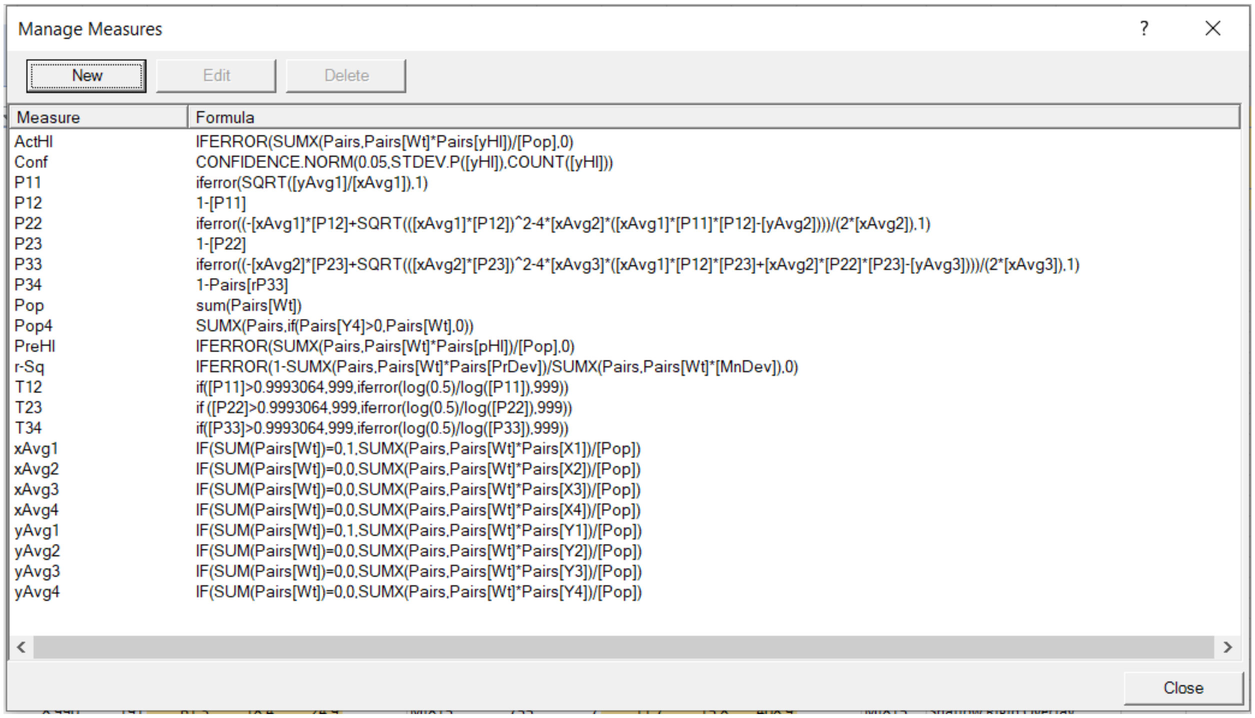




Excel has many useful features to set up data models and pivot tables, and do an enormous number of calculations with the data. This study keeps the application simple and does not use most of this functionality. This document describes the features the study is using. For more elaborate needs, there are several good books about advanced features, such as Jelen and Alexander 2018.

Creating and Managing Measures

To create or manage measures, use the Measures button on the Power Pivot tab. The dialog which will appear looks like this:



Manage Measures

New Edit Delete

Measure	Formula
ActHI	IFERROR(SUMX(Pairs,Pairs[Wt]*Pairs[yHI])/[Pop],0)
Conf	CONFIDENCE.NORM(0.05,STDEV.P([yHI]),COUNT([yHI]))
P11	iferror(SQRT([yAvg1]/[xAvg1]),1)
P12	1-[P11]
P22	iferror((-[xAvg1]*[P12]+SQRT(([xAvg1]*[P12])^2-4*[xAvg2]*([xAvg1]*[P11]*[P12]-[yAvg2])))/(2*[xAvg2]),1)
P23	1-[P22]
P33	iferror((-[xAvg2]*[P23]+SQRT(([xAvg2]*[P23])^2-4*[xAvg3]*([xAvg1]*[P12]*[P23]+[xAvg2]*[P22]*[P23]-[yAvg3])))/(2*[xAvg3]),1)
P34	1-Pairs[rP33]
Pop	sum(Pairs[Wt])
Pop4	SUMX(Pairs,if(Pairs[Y4]>0,Pairs[Wt],0))
PreHI	IFERROR(SUMX(Pairs,Pairs[Wt]*Pairs[pHI])/[Pop],0)
r-Sq	IFERROR(1-SUMX(Pairs,Pairs[Wt]*Pairs[PrDev])/SUMX(Pairs,Pairs[Wt]*[MnDev]),0)
T12	if([P11]>0.9993064,999,iferror(log(0.5)/log([P11]),999))
T23	if ([P22]>0.9993064,999,iferror(log(0.5)/log([P22]),999))
T34	if([P33]>0.9993064,999,iferror(log(0.5)/log([P33]),999))
xAvg1	IF(SUM(Pairs[Wt])=0,1,SUMX(Pairs,Pairs[Wt]*Pairs[X1])/[Pop])
xAvg2	IF(SUM(Pairs[Wt])=0,0,SUMX(Pairs,Pairs[Wt]*Pairs[X2])/[Pop])
xAvg3	IF(SUM(Pairs[Wt])=0,0,SUMX(Pairs,Pairs[Wt]*Pairs[X3])/[Pop])
xAvg4	IF(SUM(Pairs[Wt])=0,0,SUMX(Pairs,Pairs[Wt]*Pairs[X4])/[Pop])
yAvg1	IF(SUM(Pairs[Wt])=0,1,SUMX(Pairs,Pairs[Wt]*Pairs[Y1])/[Pop])
yAvg2	IF(SUM(Pairs[Wt])=0,0,SUMX(Pairs,Pairs[Wt]*Pairs[Y2])/[Pop])
yAvg3	IF(SUM(Pairs[Wt])=0,0,SUMX(Pairs,Pairs[Wt]*Pairs[Y3])/[Pop])
yAvg4	IF(SUM(Pairs[Wt])=0,0,SUMX(Pairs,Pairs[Wt]*Pairs[Y4])/[Pop])

Close

The mathematical basis for these calculations is discussed in Appendix IV. The variables calculated here are:

- Pop – Population of inspection pairs, weighted to reflect a uniform allowance for unreported activities applied to inspection pairs whose condition did not change.

- Pop4 – Population having a non-zero quantity in condition state 4. If this number is very small (say, less than 30) it calls into question the statistical reliability of the transition time from state 3 to state 4. It was found that the states are not uniform in the extent to which they use state 4, and some use it very rarely.

- xAvg fields – The fraction in each condition state in the first inspection (denoted X1..X4) of the pairs.

- yAvg fields – The fraction in each condition state in the second inspection (denoted Y1..Y4) of the pairs.

- Pxy fields – The calculated transition probability from condition state x to condition state y, in one year. Note that inspection pairs are 2 years apart, but transition probabilities are 1 year. The calculation incorporates these conventions. Although this is a one-step Markov model for estimation, a unit of element can move by two states during the 2-year interval between inspections for forecasting.

- Txy fields – Median transition time, in years, from condition state x to condition state y. This is the main result of the model and the value that will eventually be entered into a BMS.

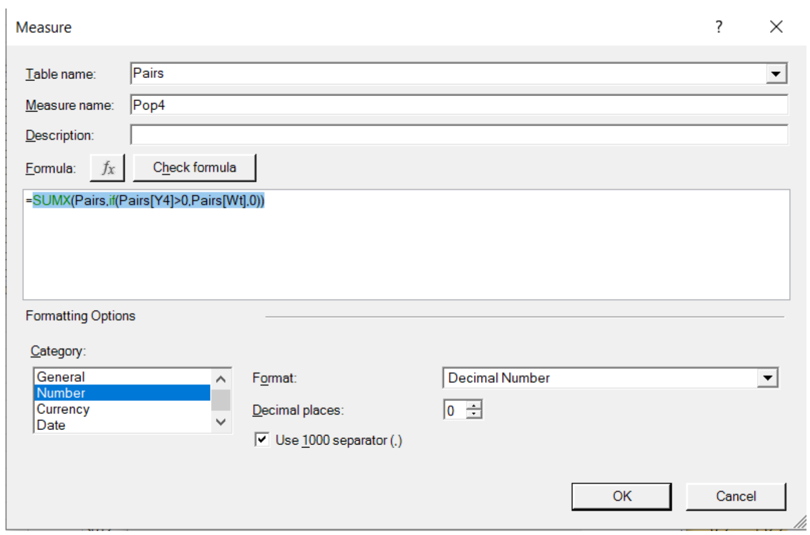
- ActHI – Actual health index calculated from Y1..Y4, which is calculated by a formula on the Pairs worksheet.

- PreHI – Predicted health index calculated from X1..X4 using the recommended model, which is calculated by a formula on the Pairs worksheet.

- r-Sq – Coefficient of determination, a common tool for representing the fraction of variation in the data which is explained by the model.

- Conf – The width of the 95% confidence interval in health index. This is a rough approximation using a normal distribution.

The buttons at the top of the Manage Measures dialog can be used to add measures or even change the ones that are already there. Here is the dialog to add or edit a measure:



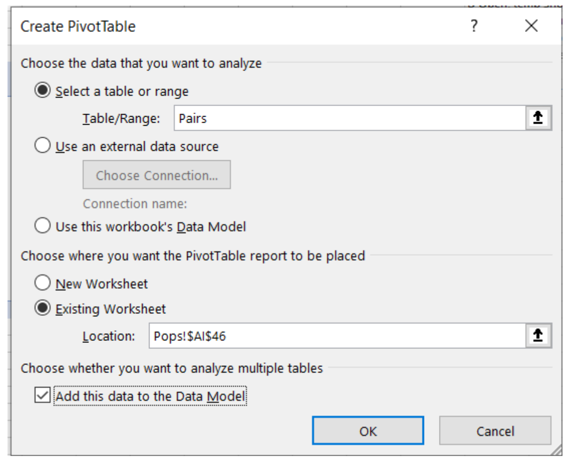
Technically the formula language used in measures is called DAX. It is very similar to Excel worksheet formulas but adds some features (such as aggregation) that are particularly useful in pivot tables. It is a good idea to specify the number formatting options because then Excel will automatically use them whenever using the measure in a new pivot table.

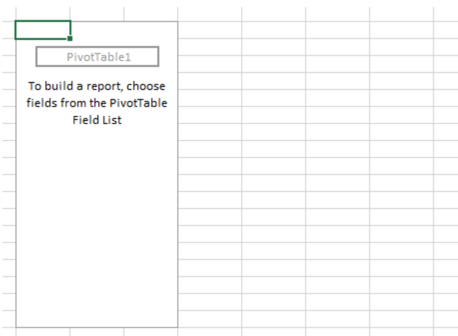
The basic functionality of a pivot table is to divide up the data source into strata according to row and column variables a user can specify. The measures are calculated separately for each stratum automatically any time the pivot table is changed. So if a pivot table has a separate row for each functional class (for example), then Excel performs the calculation separately for each functional class using only the rows belonging to that functional class. Also, the “grand total” (a misnomer) is calculated separately using all the rows, not a literal summation.

Creating and Managing Pivot Tables

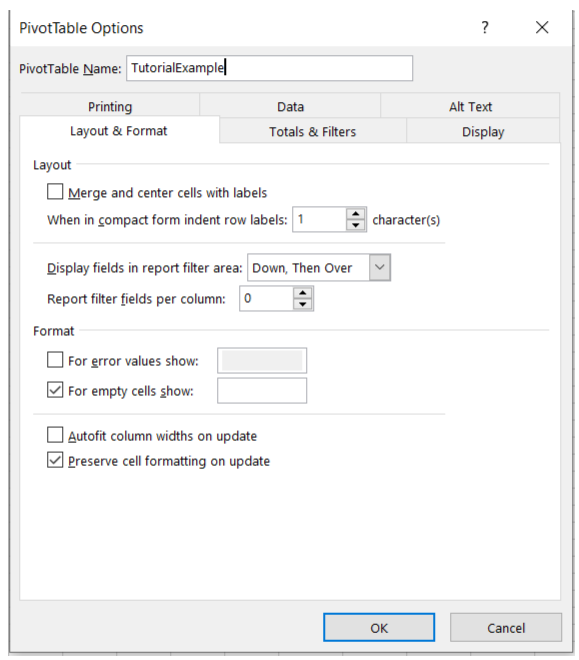
To create a new pivot table, just click the worksheet cell where the table is to be placed, then click Pivot Table on the Insert ribbon. The cell selected will be the upper left cell of the main body of the table, with the body of the table below and the filter controls above it. Make sure there is enough blank space above, below, and to the right for the new table. Use a new worksheet if unsure how much space will be needed. Excel notices if there is already data in the way, and will ask whether to over-write it. The following dialog will appear:

For this application, appropriate options are shown in the example at right, specifying Pairs as the table to analyze, and checking the box labeled “Add this data to the Data Model”. (Power Pivot won’t work if this box is not checked.) After clicking OK, the new table will look like this:

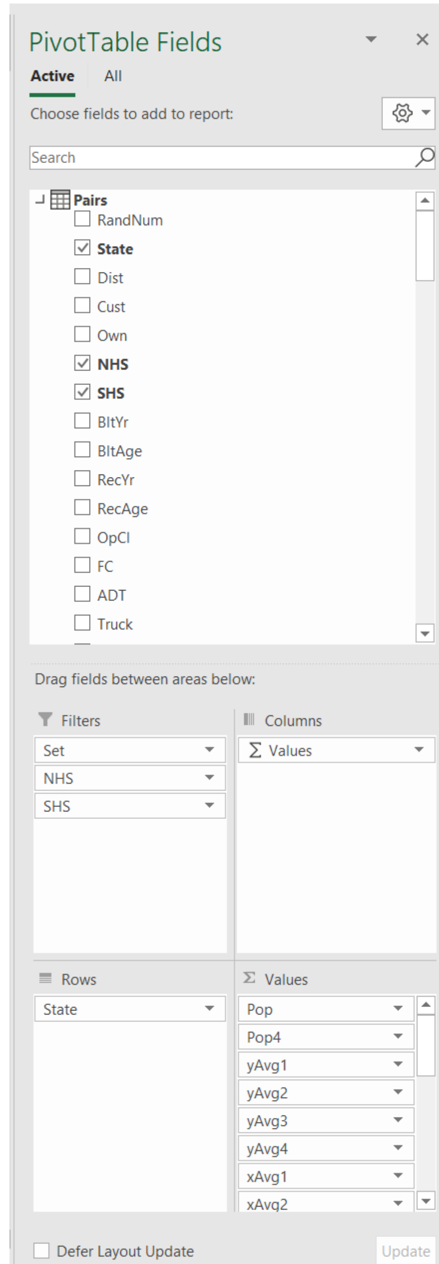




Right-click in the table and choose Pivot Table Options, to see the dialog at right. The table name is optional. Most importantly, uncheck the box labeled “Autofit column widths on update” to ensure that the worksheet column widths remain stable.



After creating a new pivot table, or any time later, it is possible to click anywhere in the table to select it for editing. The Pivot Table Fields pane should appear on the right side of the Excel window. If it is not visible, go to the Pivot Table Analyze ribbon and click the Field List button, which is usually on the right side of the ribbon in the Show section.



The top half of the pane lists all the fields and measures that are available for the table selected, the Pairs table. The following things can be done with the fields and measures:

- Drag a field or measure to the Filters area to create a filter control for the table. This will then limit the calculations in the table to just a subset of the Pairs table.
- Drag to the Rows area to have the pivot table show a separate row for each unique value of the field or measure.
- Drag to the Values area to display a measure or an aggregation of a field, that the pivot table will show in a column.

It is possible to drag to the Columns area so separate results are shown for each unique value of the field or measure, but arranged in columns rather than rows. This is typically done when a 2-dimensional cross-tabulation is desired.

It is not necessary to show all the calculated measures in the table. Excel keeps track of inter-dependencies among formulas and recalculates whatever it needs in order to display the results selected.

Usually Excel automatically recalculates the pivot table any time there is a change in it. Usually this is fast, but not always. Sometimes it takes up to 20 seconds in these models, and can in certain cases be much longer, especially if the Pairs table has more than about 60,000 rows. (Excel can hold more than 1 million.) Automatic recalculation can be disabled using the “Defer layout update” checkbox at the bottom of the Pivot Table Fields pane.

If additional filtering capability is needed, or if multiple pivot tables are to be controlled using the same filter, consider using the Slicer feature on the PivotTable Analyze ribbon.

Once all desired changes are completed, right-click any of the pivot tables and choose Refresh. This will cause Excel to recalculate all of the pivot tables in the file, which sometimes takes a few minutes.

Ordinal and Categorical Variables

The pivot table approach to data analysis is especially suitable for categorical data: each bridge element is assigned to a category, such as (geographic) state or environment, and receives a transition time computed for its category. For the most part, this is how Markov models are meant to be used.

There are a few ordinal variables, such as ADT and age, that are conceived as a continuous scale of numbers. There may be temptation to use one or more of these as row variables in the pivot table, then run a linear or non-linear regression on it. While this is possible, it is not strictly correct from a statistical perspective and may create an unintended bias in the model. The reason is heteroskedasticity. Ordinary least squares regression assumes that the variance of the data is uniform along the regression line (homoskedasticity), and that the explanatory variables are independent of each other. This is not the case with ADT, particularly because there are relatively few high-volume bridges and large chunks of that population share design, construction, maintenance, and operational characteristics very different from the rest of the inventory. It is even less true with age, because of the time dependency of construction quality, the drop-off in population of older bridges, a tendency to favor replacement of certain types, and the use of age already in the Weibull model.

Because of heteroskedasticity, one end of the regression line may be unduly and sometimes dramatically shifted by outliers or population clusters in the data. In addition to the problem with bias itself, the regression methodology hides the bias and makes it difficult to discover and correct. The model may look great graphically, have a high r-squared value, but still be highly inaccurate.

To avoid this problem, it is better to discretize ordinal data items to make them into categorical variables, and define the categories so they are as consistent as possible in their populations and few in number. This has been done in the Markov spreadsheets by creating in the Pairs table the columns Era (construction era, a range of year-built), ADTcl (traffic volume class), and PrCl (protective element condition class). Transition times computed for categorical data in this way are unbiased from a statistical perspective. Also, because they are computed using a closed-form methodology, there is no fitting error, making interpretation simpler. If a category contains a low population or idiosyncratic data, this characteristic becomes more visible (not foolproof, but better) and is more easily corrected, usually by aggregating with adjacent categories having larger populations. If too many categories are created, each one can be dominated by a cluster of bridges with something in common that is not measured but not random; for example, same contractor, same material supplier, past weather or market events (or lack thereof) that might or might not repeat in the future, or some combination of factors. Unless policy sensitivity is required for some business purpose, it is better to use fewer, bigger, categories that aggregate and smooth over these factors.

An exception to this general principle is the shape parameter used to produce age-dependency in the Weibull model. The designers of AASHTOWare™ Bridge Management chose to model this variable as ordinal because the ranking significance of it is important in preservation decision-making. In this case the independent variable continues to be handled as ordinal, but the model estimation method is maximum likelihood rather than ordinary least squares. This ordinal variable has a high level of heteroskedasticity, but the maximum likelihood method is not as biased by it. For agencies that are not using AASHTOWare™ Bridge Management, the categorical handling of this variable is produced in the pivot tables and can be used in alternative model formulations.

For analysts interested in building more elaborate deterioration models, a good practical book on the pitfalls and limitations of statistical algorithms, accessible to non-statisticians, is Christian 2020.

APPENDIX IV – MATHEMATICAL MODELS USED FOR TIER 1 AND TIER 2 CURVES

This appendix describes the mathematics used in the model estimation spreadsheets. It is intended for researchers who may wish to modify the spreadsheet calculations or explore the basis of the calculations.

MARKOV MODELS

Most BMSs worldwide use what is formally known as a discrete-time, discrete-state Markov model, which is arguably the simplest possible model that is compatible with element-level inspection and incorporates uncertainty (Mirzaei et al. 2014, Thompson et al. 2012). The discrete-time aspect stems from the convention that deterioration forecasts are made at uniform one-year intervals, conforming to common agency practice of inspections at multiples of one year and planning/programming cycles of one year. Discrete-time models are simpler and more flexible than continuous-time models, which can forecast over any time interval including fractional years.

The discrete-state aspect of the models comes from the AASHTO MBEI. This bridge inspection standard, used by every state, describes the condition of each structural element of a bridge by classification of defects into a small number of categories, distributing the total quantity of the element over the available categories. NBI component condition ratings are also discrete states, and can be modeled in the same way, as is done in AASHTOWare™ Bridge Management.

Under the discrete-time, discrete-state assumptions, Markov models can be expressed as transition probability matrices, as in the left side of Figure 18. The example has a uniform time unit of one year and a universe of four condition states. The change in condition is described as the probability that a unit of element (e.g., a lineal foot of girder) will make the transition from one state to another in one year.

Markov models in this form are easy to work with, because forecasts for any number of periods in the future can be made using matrix multiplication. For any condition state j, its probability is:

$$y_j = \sum_i x_i p_{ij} \quad or \ [Y] = [P][X]$$

Where:

x_i = the probability of state i one year earlier.
$[X]$ = a vector of x_i for all i.
p_{ij} = the probability of state j given state i one year earlier.
$[P]$ = the matrix of transition probabilities.

The middle of Figure 18 shows the initial years of such a forecast, and the right side of Figure 18 shows the forecast as a graph, expressed in terms of a health index (Shepard 1999). The health index presentation of the model can be used in the way a deterministic model normally would be used.

Today	Probability one year later			
	State1	State2	State3	State4
State 1	0.980	0.020	0.000	0.000
State 2		0.955	0.045	0.000
State 3			0.871	0.129
State 4				1.000

Annual forecast conditions					
Year	State1	State2	State3	State4	Health
0	1.000	0.000	0.000	0.000	100.0
1	0.980	0.020	0.000	0.000	99.3
2	0.961	0.038	0.001	0.000	98.7
3	0.942	0.055	0.002	0.000	98.0
4	0.924	0.071	0.005	0.000	97.3
5	0.906	0.086	0.007	0.001	96.5
6	0.888	0.100	0.010	0.002	95.8
7	0.871	0.113	0.013	0.003	95.0
8	0.853	0.125	0.017	0.005	94.2
9	0.837	0.136	0.020	0.007	93.4
10	0.820	0.146	0.024	0.010	92.6
11	0.804	0.156	0.027	0.013	91.7

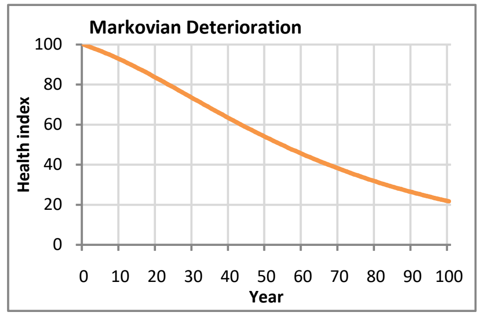


Figure 18. Markov model

Another convenient property of a Markov model is the ability to express each row of the transition probability matrix as a single number, the median number of years to transition. An expert elicitation model based on this feature would use questions of the form:

Suppose 100 units of this element are in condition state S. After how many years will 50 units have deteriorated to state S+1, with 50 units remaining in state S, if no action is taken?

If it takes T years for 50% of a population of elements to transition from one state to the next, then the probability in a 1-year period of staying in the starting condition state can be calculated from:

$$P = 0.5^{\left(\frac{1}{T}\right)}$$

The probability of making a transition to a worse state is then $(1 - P)$.

The inverse of this equation is also useful. If the transition probability P is known, the median transition time can be calculated from:

$$T = \frac{\log{(0.5)}}{\log{(P)}}$$

ONSET OF DETERIORATION

A problem noted in Florida research (Sobanjo and Thompson 2011), as well as research by California (Thompson and Johnson 2005) and by the National Cooperative Highway Research Program (Patidar et al. 2007), is that the Markovian models used in most BMSs have fairly rapid initial deterioration. This creates a serious problem for multi-year programming models, because it is difficult to configure such models to maintain a realistically high network condition level. Bridge engineers have long believed that transition probabilities are time-dependent—that the probability of transition is low for a new element and increases with age.

With AASHTO element inspection data, a given unit of an element is not followed from one inspection to the next, so it is not possible to know the duration in most condition states. The age of the bridge does at least provide the duration in state 1, if no previous maintenance action has been taken. Therefore, it is possible to use a survival function to model the probability of remaining in condition state 1 as a function of age. Subsequent transitions below state 2 would still be modeled using Markov models.

A Markov model has a constant probability of transitioning from state 1 to state 2, so the survival function is used as an enhancement, to make the transition probability variable. A new bridge will have a very high probability—approaching 1.0—of remaining in state 1 from year to year. As the bridge ages, the probability decreases. Once a portion of an element deteriorates to condition state 2, Markovian deterioration takes over for the remainder of the process.

The Weibull curve has the following functional form:

$$y_{1g} = \exp\left(-(g/\alpha)^{\beta}\right)$$

Where:

- y_{1g} = the state probability of condition state 1 at age (year) g, if no intervening maintenance action is taken between year 0 and year g.
- β = the shaping parameter, which determines the initial slowing effect on deterioration.
- α = the scaling parameter, calculated as:

$$\frac{T}{(\ln(2))^{1/\beta}}$$

Where:

- T = the median transition time from state 1 to state 2, from the Markov model.

These formulas for the state probability of condition state 1 are used in the Markov spreadsheets in any situation where median transition times remain constant over time. This includes the deterioration of protective elements on the Graph worksheets, and the maximum likelihood worksheets for estimating the shaping parameter. In these cases, the state probability of state 2 is

$$y_{2g} = y_{1(g-1)} - y_{1g} + y_{2(g-1)}P_{22}$$

The amount that does not remain in state 1 after one year is modeled to transition to state 2, where it joins the amount already in state 2. All remaining transitions use the Markov model.

For substrate elements where the transition times might change due to deterioration of a protective element, see the following section.

Figure 19 shows the form of the Weibull curve, for four different values of the shaping parameter β, with T=20. A shaping parameter of 1 is mathematically equivalent to a Markov model, featuring the problematic rapid onset of deterioration. A shaping parameter of 2 introduces a delay, and higher values postpone significant deterioration even longer.

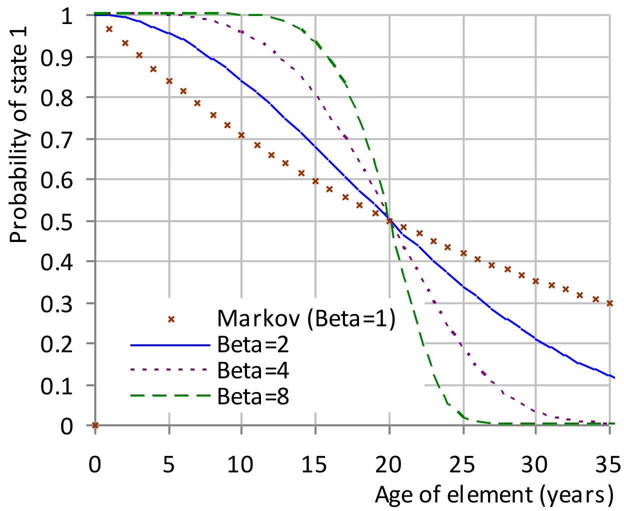


Figure 19. Comparison of shaping parameters

Note that all the curves in Figure 19 intersect in 20 years at a probability of 0.5, since the Markov median transition time is the same in all cases in the example.

MODELING THE EFFECT OF PROTECTIVE SYSTEMS

The AASHTO MBEI provides special elements for recording the condition of common types of protective systems, specifically deck wearing surfaces, steel coatings, concrete coatings, and other concrete protective systems. Partner agencies have defined many additional elements for specific types of protective systems. Each of these has four condition states, which would interact with the four condition states of the substrate elements that they protect.

The developers of AASHTOWare™ Bridge Management took advantage of the decision to avoid two-state transitions and presented the Markov deterioration model as merely a median transition time. They defined a new quantity called the protection factor, which summarizes the full effect of all possible element interactions that affect a given element at a given point in time. This protection factor may increase the median years to transition, thus slowing deterioration. It is applied like this:

$$\acute{M_i} = M_i \times PF$$

Where:

$\acute{M_i}$ = Adjusted median years to transition from state i to state $i+1$
M_i = Default median years to transition from state i to state $i+1$
PF = Protection factor for the element

For protecting element P, the protection factor PF is calculated as follows:

$$PF = PP_P \times (F_{P1} + 2/3 \times F_{P2} + 1/3 \times F_{P3})$$

Where:

PP_P = Protection parameter for protecting element P

F_{Ps} = Fraction of element P in state s

PP_P is a parameter indicating how much of its full protection element P gives when it is in a given condition. The protection factor is normally greater than 1.0.

Under the conventions used in AASHTOWare™ Bridge Management, Markov median transition times are always estimated under the assumption that protective systems are absent or, if present, that they are fully deteriorated. A calculation similar to the health index is used as a way to summarize the condition of protecting elements, and this is multiplied by a single protection parameter for each protecting element to yield the protection factor, which then increases the median transition time.

The protection afforded by a protecting element causes a year-to-year change in the transition probabilities affecting the substrate. For example, as a wearing surface deteriorates, the rate of deterioration of the substrate deck increases. For the Markov model, a new set of transition probabilities is computed for each year of age, based on the forecast condition of the protecting element. For the Weibull model, the transition probability from state 1 to state 1 for each year is computed as follows:

$$P_{11} = \exp(-(\mathrm{g} \,/\, \alpha)^{\beta} + ((\mathrm{g} - 1) \,/\, \alpha)^{\beta})$$

Where g is the age and all other symbols are the same as above for the Weibull model. Then the transition probability from state 1 to state 2 is $p_{12} = 1 - p_{11}$

ENVIRONMENT FACTORS

AASHTOWare™ Bridge Management stores median transition times undifferentiated by environment, and then provides a separate table with four environment factors to represent each of the four allowed environment classifications for elements. Environment factors affect transition times in the same way as protection factors *PF* in the equations above. It is possible to have multiple environment factors representing separate independent variables that influence the rate of deterioration. These separate factors are multiplied together to yield a total protection factor to be used in computing an adjusted transition time.

In the Markov spreadsheet models, potential environment variables are computed in separate pivot tables as transition times for subsets of a model. The corresponding environment factor can be computed from these by dividing each transition time by the base transition time (selected by the agency) for the model. This makes it possible for the agency to consider multiple independent variables if it chooses to do so. In AASHTOWare™ Bridge Management, this more complex model can be computed using deterioration formulas.

ESTIMATION OF TRANSITION PROBABILITIES

To set up the estimation of a transition probability matrix, the prediction equation is defined as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & 0 & 0 \\ & p_{22} & p_{23} & 0 \\ & & p_{33} & p_{34} \\ & & & p_{44} \end{bmatrix}^2 \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

The element inspection vectors [Y] and [X] are spaced two years apart (plus or minus 6 months), but the transition probability matrix [P] is expressed for a one-year transition. Hence, it is applied twice using the exponent "2" on the transition probability matrix above. Writing out the individual equations necessary to calculate [Y] results in:

$$y_1 = x_1 p_{11} p_{11}$$

$$y_2 = x_1 p_{11} p_{12} + x_1 p_{12} p_{22} + x_2 p_{22} p_{22}$$

$$y_3 = x_1 p_{12} p_{23} + x_2 p_{22} p_{23} + x_2 p_{23} p_{33} + x_3 p_{33} p_{33}$$

$$y_4 = x_2 p_{23} p_{34} + x_3 p_{33} p_{34} + x_3 p_{34} p_{44} + x_4 p_{44} p_{44}$$

Since the sum of each row in [P] must be 1.0, the following additional equations apply:

$$p_{12} = 1 - p_{11} \qquad p_{23} = 1 - p_{22} \qquad p_{23} = 1 - p_{22}$$

The vectors [X] and [Y] can be computed from the database of inspection pairs to describe the combined condition of the element before and after. So these quantities are known. Thus the system of seven equations and seven unknowns can be solved algebraically for the elements of [P].

A complication arises because the equations are second-order polynomials in p_{ii}, so it is necessary to use the quadratic equation to find the roots. For example, the equation for p_{33} is:

$$p_{33} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

$$a = x_3 \qquad b = x_2 p_{23} \qquad c = x_1 p_{12} p_{23} + x_2 p_{22} p_{23} - y_3$$

Each same-state transition probability p_{ii} is constrained to be in the range from 0 to 1 exclusive. Even though the quadratic equation finds two roots, in practice only zero or one root are in the necessary range. The final equations for the same-state probabilities are:

$$p_{11} = \sqrt{y_1 / x_1}$$

$$p_{12} = 1 - p_{11}$$

$$p_{22} = \frac{-x_1 p_{12} + \sqrt{(x_1 p_{12})^2 - 4 \times x_2 \times (x_1 p_{11} p_{12} - y_2)}}{2 \times x_2}$$

$$p_{23} = 1 - p_{22}$$

$$p_{33} = \frac{-x_2 p_{23} + \sqrt{(x_2 p_{23})^2 - 4 \times x_3 \times (x_1 p_{12} p_{23} + x_2 p_{22} p_{23} - y_3)}}{2 \times x_3}$$

$$p_{34} = 1 - p_{33}$$

$$p_{44} = 1$$

These equations are implemented in the spreadsheet models as pivot table measures.

MAXIMUM LIKELIHOOD ESTIMATION

Markov models lend themselves to relatively simple methods of estimation, such as those described in the preceding section. Certain models used in bridge management, however, are more complex. For example, there is no closed-form algebraic method to estimate Weibull model shaping parameters. For these tasks, a more general tool known as maximum likelihood estimation can be used.

The general framework for maximum likelihood estimation can be described in the following steps:

55. Prepare a table containing one row per element inspection pair or per observation, containing all the explanatory variables and the observed outcomes.
56. Add to each row of the table a computation to forecast the outcomes using the unknown model parameters to be estimated.
57. Provide an initial guess of the unknown model parameters. In each row of the table compare the observed outcome against the forecast outcome, using a formula known as a log likelihood function.
58. Iteratively adjust the unknown model parameters until the total log likelihood function is maximized.

For a Markov model, the explanatory variables are the conditions observed in the first inspection of each inspection pair. The outcomes are the conditions observed in the second inspection of each inspection pair. The object of the exercise is to find the set of unknown model parameters that is most likely to explain the outcomes that were observed.

The forecast computation in step 2 is the Markov and/or Weibull models described above.

In step 3, the log likelihood function is a measure of the relative deviation of each observation between the forecast and the observed outcome. It is expressed as a negative number, so maximizing it is a process of finding parameters that move the total log likelihood closer to zero. A body of statistical theory exists for using the log likelihood function to evaluate the explanatory power of a model and to compare two or more alternative models.

In step 4, the iterative search for the maximum likelihood model parameters is conducted using the generalized search algorithm in Excel's Solver.

The Weibull model is a time-series model, requiring, in principle, a long series of inspections where it is known that no action was taken on the bridge. In practice, the only situations where this is possible is with new bridges, which rarely receive actions during the first 15–20 years of their lives. Thus maximum likelihood estimation of the shaping parameter is necessarily limited to the earliest years of the deterioration curve. There is undoubtedly a bias associated with this, but only a controlled experiment of long-term bridge monitoring would be able to gather necessary data to quantify and/or correct the bias.

FILTERING FOR ACTIVITIES

The dataset used for model estimation includes all element inspections provided to the research team by the partner agencies and gathered according to the 2015 or later AASHTO MBEI. In most cases this means inspections that occurred on or after May 1, 2015, but in some cases a later date was used if an agency provided it. To ensure uniformity among the 12 states, only bridges having a roadway-on and qualifying for the NBI were included. For each task, the dataset was further reduced to just the elements appropriate for that task. For example, Task 6.1 (RC decks) included only RC deck elements, whether defined by the MBEI or as agency-defined elements.

Most of the tasks require development of deterioration models, intended for use in bridge management models to forecast conditions when no action is programmed. It is necessary therefore to remove inspection pairs where a programmed activity took place. An effort to quantify this can start by examining the inspection pairs where condition improved. The left side of Table 54 shows, for each partner state, an analysis of the correlation between improvements in condition and reported activities that occurred within the time interval of the inspection pair for reinforced concrete decks. Four of the states—Indiana, Michigan, Minnesota, and Wisconsin—have a high correlation, while the others are much lower. The same pattern is observed when considering inspection pairs where condition did not change, reported on the right side of Table 54.

It is often difficult for agencies to fully capture records of bridge work, due to inconsistent reporting by crews in the field and by contractors. It is unlikely that the differences among states are due to differences in actual work accomplishment; it is more likely to be differences in reporting. When considering the differences between the left side and right side of Table 54, it is also evident that a significant percentage of unchanged inspection pairs have activities associated with them. The activities are not coded with an identification of the affected element, so it is unknown whether the reported activities concern bridge decks, or whether they concern other elements of each bridge.

Using the Markov model spreadsheets, the effect of filtering models by activity was investigated. It was observed that the differences in reporting led to large differences in computed transition times, sometimes by as much as a factor of 2. In half of the agencies, relying solely on activity records would over-estimate their transition times to an unacceptable degree, because so few activities were reported. Further, it is desirable to include non-state-maintained bridges in model estimation to maximize the precision of the analysis, but activity records are typically reliable only for state-maintained structures.

Table 54. Correlation between change in condition and reported activities (reinforced concrete deck elements)

State	Count of inspection pairs	Pairs with improved condition	Improved pairs with activity	Percent of improved pairs with activity	Pairs with unchanged condition	Unchanged pairs with activity	Percent of unchanged pairs with activity
IA	6883	849	51	6.0	4669	150	3.2
IL	2803	198	10	5.1	1274	79	6.2
IN	400	19	3	15.8	328	25	7.6
KS	2108	106	0	0.0	1756	0	0.0
KY	868	159	1	0.6	345	5	1.4
MI	5171	621	62	10.0	2726	114	4.2
MN	2216	699	234	33.5	603	165	27.4
ND	814	172	6	3.5	381	2	0.5
NE	3186	201	0	0.0	2072	0	0.0
OH	2914	661	0	0.0	1306	0	0.0
SD	964	106	0	0.0	553	0	0.0
WI	4662	557	90	16.2	2469	226	9.2

Given the magnitude of this potential bias, an alternative way was sought to represent the effect of work activity. It is relatively safe, and common in published research, to assume that inspection pairs that improved in condition had an activity associated with them, and to omit them from estimation datasets for deterioration models. It is also common to assume that inspection pairs which deteriorated in condition had no action taken. The challenge is in how to handle inspection pairs that did not change in condition.

One way to handle this is to focus on the four states that evidently had the most complete reporting of work activity. Together these states had reported work activity for 20.52% of the cases where condition improved. The other 79.48% are an unknown combination of unreported activities or random (or unexplained) variation in the data, but most likely unreported activity. For bridges that stayed unchanged in deck element condition, 8.65% are associated with activities in these states. If we assume the same error rate for unchanged condition as for improved condition, then 8.65%/20.52% = 42% of unchanged inspection pairs are associated with activities on average.

Since most of the states appear to under-report activities, or report none at all, it is necessary to make some sort of assumptions that treat all the data in a reasonable uniform way. It could be assumed that 42% of inspections that stayed the same did so because of some sort of activity. It is not known which specific bridges are affected in this way, so an alternative approach is to weight each unchanged observation to reflect the reduced probability that it should be included in the model. In the Pairs worksheet, this is reflected using the column called Wt which is 0 if the element condition improved, 0.58 if element condition stayed the same, and 1 if condition deteriorated. In the pivot tables all conditions and population statistics use this weight. This significantly improved the reasonableness of the models and the similarity to earlier models from other studies.

The weight can be modified by each agency if desired to reflect the agency's own knowledge of its work reporting processes, accounting for the fact that certain agencies, and certain parts of each agency's inventory (such as non-state-maintained bridges) might not have complete reporting of work accomplishments.

A similar analysis was performed for Task 6.3 using component conditions rather than element conditions. Deck, superstructure, and substructure weights using this calculation all had weights of about 70%, considering only state-maintained bridges. Only a very small fraction of culverts had any reported work, so this calculation was judged unreliable for culverts. It was decided to use the same weight, 70%, as for the other component ratings.

APPENDIX V. LIST OF ADES BY AGENCY

Table 55. Iowa ADEs (state code 19)

ADE	AASHTO	Task 8 Notes
819 – Concrete reinforcing steel mixed protection system		additional protective system
821- Reinforced concrete stub abutment backwall	215	additional inventory item
825- Reinforced concrete wingwall		additional inventory item
831- Sliding steel plate joint	305	additional inventory item
851- Weathering steel protective coating	515 (D-M)	additional protective coating
855- Concrete used as a protective coating		additional protective coating
827-Concrete apron on a culvert		additional inventory item

Table 56. Kentucky ADEs (state code 21)

ADE	AASHTO	Task 8 Notes
800 - Reinforced Concrete Culvert Wingwall		additional inventory item
801 - Reinforced Concrete Culvert Headwall		additional inventory item
802 - Drainage System		tracking, repair needs
803 - Reinforced Concrete Curb		tracking, repair needs
804 - Reinforced Concrete Sidewalk		tracking, repair needs
806 - Steel Closed Web/Box Cross Girder	102	additional inventory item
807 - Steel Cross Girder/Beam	107	additional inventory item
805 - Transverse Tensioning Rod		additional inventory item
808 - Tunnel		additional inventory item
809 - Cable Anchorage		additional inventory item
850 - Secondary Element		additional inventory item
851 - Transitions		additional inventory item
852 - Drains		additional inventory item
853 - Utilities		additional inventory item
854 - Longitudinal Shear Key		additional defect
855 - Debris on and Around Superstructure		tracking, repair needs
856 - Channel Drift		tracking needs, also scour analysis
857 - Embankment Erosion		tracking needs, also scour analysis
858 - Channel Alignment		extension of NBI item, tracking at element level, also scour
859 - Vegetation		maintenance related, also scour
860 - Erosion Control/Protection		tracking needs, also scour analysis
899 - Shear Cracking		tracking, vulnerability/risk

ADE	AASHTO	Task 8 Notes
811 - Latex Wearing Surface		additional wearing surface
812 - PCC Wearing Surface		additional wearing surface
813 - AC Wearing Surf w/ Membrane		additional wearing surface
814 - AC Wearing Surface		additional wearing surface
815 - Epoxy Wearing Surface		additional wearing surface

Table 57. South Dakota ADEs (state code 46)

ADE	AASHTO	Description	Task 8 Notes
809	510	Gravel Wearing Surface	additional wearing surface
810	510	Low Slump Dense Concrete Overlay	additional wearing surface
811	510	Latex Modified Concrete Overlay	additional wearing surface
812	510	Epoxy/Polymer Chip Seal Overlay	additional wearing surface
813	510	Asphalt w/ Membrane Overlay	additional wearing surface
814	510	Asphalt w/o membrane Overlay	additional wearing surface
815	515	Weathering Steel Coating	additional protective coating
816	515	Lead Based Coating	additional protective coating
817	515	Non-Lead Based Coating	additional protective coating
818	515	Metalized/Galvanized Coating	additional protective coating
820	520	Epoxy Resteel	additional protective system
821	520	Stainless Resteel	additional protective system
822	520	Zinc and Epoxy Resteel	additional protective system
825	521	Silanes/Siloxanes	additional protective coating
826	521	Methacrylates	additional protective coating
827	521	Silicates	additional protective coating
830	510	Timber Running Planks	additional wearing surface
831	510	Rubberized Asphalt Chip Seal (RACs) Overlay	additional wearing surface
832	510	Fiber Reinforced Concrete Overlay	additional wearing surface
833	510	A40/A45 Concrete Overlay	additional wearing surface
841	241	Culvert-Precast Concrete	additional inventory item
865	12	High Performance Concrete Deck	additional inventory item
866	38	High Performance Concrete Slab	additional inventory item
870		Asphalt Concrete Approaches	tracking, repair needs
871		Roadway over Culvert	tracking, repair needs
872		Gravel Approaches	tracking, repair needs
873		Sidewalk Approaches	tracking, repair needs
880		Utilities	tracking, repair needs

Table 58. Michigan ADEs (state code 26)

ADE	AASHTO	Task 8 Notes
800 - Conc Deck - Black Bars	12	additional inventory item
801 - Conc Deck - Stainless Bars	12	additional inventory item

ADE	AASHTO	Task 8 Notes
802 - Conc Deck - Nonmetal Bars	12	additional inventory item
803 - Conc Deck - Coated Bars	12	additional inventory item
804 - Precast Reinforced Conc Deck	13	additional inventory item
805 - Conc Slab - Black Bars	38	additional inventory item
806 - Conc Slab - Stainless Bars	38	additional inventory item
807 - Conc Slab - Nonmetal Bars	38	additional inventory item
808 - Conc Slab - Coated Bars	38	additional inventory item
809 - Precast Slab		additional inventory item
810 - Conc Deck - Top Surface		complementary to deck/slab items when no wearing surface
811 - Conc Deck - Btm Surface		complementary to deck/slab items when no wearing surface
812 - Reinf Conc Fascia		additional inventory item
813 - Conc Deck - Slag Aggregate	12	additional inventory item
815 - Rigid Overlay	510	additional wearing surface
816 - Epoxy Overlay	510	additional wearing surface
817 - Ashpalt Ovl w/ Membrane	510	additional wearing surface
818 - Asphalt Ovl w/o Membrane	510	additional wearing surface
819 - Timber Running Planks	510	additional wearing surface
820 - False Decking - Timber		additional inventory item
821 - Maintenance Sheeting - Steel		additional inventory item
822 - Stay in Place Forms (SIP)		additional inventory item
823 - P/S Concrete Box Beams	104	additional inventory item
824 - Steel Truss/Arch Tension Mem		additional inventory item
825 - Steel Diaphram/Cross Frame		additional inventory item
826 - Beam End Deterioration		additional defect
828 - Pressure Relief Joint (PRJ)		additional inventory item
829 - Field Stone		additional inventory item
830 - Plain Riprap		additional inventory item, scour
831 - Heavy Riprap		additional inventory item, scour
832 - Channel Armoring		additional inventory item, scour
833 - Articulating Conc Block		additional inventory item, scour
834 - Gabion		additional inventory item, scour
835 - Grout Filled Bags		additional inventory item, scour
836 - Sheet Piling		additional inventory item, scour

ADE	AASHTO	Task 8 Notes
837 - Other Scour Protect		additional inventory item, scour
838 - Scour Monitoring		additional inventory item, scour
840 - Reinf Conc Sidewalk		tracking, repair needs
841 - Conc Filled Steel Grid Sidewalk		tracking, repair needs
842 - Open Steel Grid Sidewalk		tracking, repair needs
843 - Steel Plate Sidewalk		tracking, repair needs
844 - Beam End Contact		additional defect
845 - Beam End Temp Supp (SH)		additional defect
846 - Beam End Temp Supp (FH)		additional defect
847 - Steel Lateral Bracing		additional inventory item
849 - A588 Steel Patina	515	additional protective coating
850 - Healer Sealer	521	additional protective coating
851 - Reinf Conc Culvert 3-Sided	241	additional inventory item
852 - Reinf Concrete Wingwall	215	additional inventory item
853 - Steel Wingwall	219	additional inventory item
854 - Timber Wingwall	216	additional inventory item
855 - Masonry Wingwall	217	additional inventory item
856 - Other Wingwall	218	additional inventory item
857 - Culvert Joint		additional inventory item
858 - Pedestrian Approach (Conc)		additional inventory item
859 - Pedestrian Approach (Steel)		additional inventory item
860 - MSE Abutment		additional inventory item
861 - Culvert Wingwall		additional inventory item
862 - Culvert Footing		additional inventory item
863 - Culvert Headwall		additional inventory item
880 - Vertical Adhesive Anchors		additional inventory item
881 - Sign Conn, Type A1, A2 & B		additional inventory item
882 - Sign Conn, Conc, Type C,D,& E		additional inventory item
883 - Sign Conn, Conc, Type K, L, & M		additional inventory item
884 - Sing Conn, Conc, Type O, P, & Q		additional inventory item
885 - Sign Conn, Conc, Type R, S, & T		additional inventory item

ADE	AASHTO	Task 8 Notes
886 - Sign Conn, Conc, Type U,V, & W		additional inventory item
887 - Sign Conn, Steel, Type F Mod & G		additional inventory item
888 - Sign Conn, Steel, Type H, I, & J		additional inventory item
889 - Sign Conn, Steel, Old Type C & D		additional inventory item
890 - Sign Conn, Steel, Type C & D		additional inventory item
891 - Sign Conn, Steel, Old Type E & F		additional inventory item
892 - Sign Conn, Steel, Type E & F		additional inventory item
893 - Sign, Column		additional inventory item
894 - Sign, Mounted		additional inventory item
895 - Sign, Steel Bolted Conn		additional inventory item
896 - Sign, Conc Anchored Conn		additional inventory item
897 - Sign Bolts & Anchors		additional inventory item
899 -Fiber Reinforced Polymer		additional protective coating

Table 59. Kansas ADEs (state code 20)

Kansas (20)		
ADE	AASHTO	Task 8 Notes
844 - Culvert Wing, Reinforced Concrete		additional inventory item
345 - Hinge, Concrete		additional inventory item
844 - Reinforced Concrete Wing on Culvert		additional inventory item
845 - Concrete Hinge		additional inventory item
846 - Concrete Girder Ends		additional defect
850 - Steel Hinge		additional inventory item
858 - Deck Cracking		additional defect
861 - Scour		additional defect

Table 60. Minnesota ADEs (state code 27)

ADE	AASHTO	Task 8 Notes
850 Steel Hinge Assembly		additional inventory item
851 Concrete Hinge Assembly		additional inventory item
800 Critical Findings or Safety Hazards		additional inventory item
805 Prestressed Concrete Slab		additional inventory item
810 Concrete Wearing Surface - Cracking & Sealing	510	tracking repair needs, defect
815 Plow Fingers		additional inventory item

ADE	AASHTO	Task 8 Notes
816 Approach Relief Joint		additional inventory item
822 Bituminous Approach Roadway		additional inventory item
823 Gravel Approach Roadway		additional inventory item
855 Secondary Members (Superstructure)		additional inventory item
856 Secondary Members (Substructure)		additional inventory item and continuation
861 Non-Integral Retaining Wall		additional inventory item and continuation
862 Tiled Surface		maintenance, tracking
863 Decorative Facade		maintenance, tracking
870 Culvert End Treatment		additional inventory item
871 Roadway Over Culvert		additional inventory item
880 Impact Damage		risk assessment, in BPI, LPI for locals
881 Steel Section Loss		risk assessment, in BPI, LPI
882 Steel Cracking		risk assessment, in BPI, LPI
883 Concrete Shear Cracking		risk assessment, in BPI, LPI
884 Substructure Settlement & Movement		risk assessment, in BPI, LPI
885 Scour		risk assessment, in BPI, LPI
890 Load Posting and Vertical Clearance Signing		risk assessment, in BPI, LPI
891 Other Bridge Signing		to separate severity
892 Slopes & Slope Protection		risk assessment, in BPI, LPI
893 Guardrail		maintenance and tracking
894 Deck & Approach Drainage		tracking and maintenance but could also lead to issues if left untreated
895 Sidewalk, Curb, & Median		tracking and maintenance
899 Miscellaneous Items		additional inventory item
900 Protected Species		birds and bats, appreciated by environmentalist staff and helps with mitigation efforts

Table 61. Nebraska ADEs (state code 31)

ADE	AASHTO	Task 8 Notes
9038 - R/C Slab - Void	38	additional inventory item
9101 - Stl Opn Grd W/Cover Plt	107	additional inventory item
9102 - HP Stl Cld Web/Box Grd	102	additional inventory item
9104 - PS Inverted T Girder	109	additional inventory item
9106 - PS NU Girder	109	additional inventory item
9107 - HP Stl Open Grd		additional inventory item
9109 - PS Double T Girder	109	additional inventory item
9152 - X-Frame		additional inventory item
9202 - Sub Stl Column	202	additional inventory item

ADE	AASHTO	Task 8 Notes
9203 - Sub Other Column	203	additional inventory item
9204 - Sub Pre Conc Column	204	additional inventory item
9205 - Sub R/C Column	205	additional inventory item
9206 - Sub Timber Column	206	additional inventory item
9207 - Sub Stl Tower		additional inventory item
9208 - Sub Timber Trestle		additional inventory item
9210 - Sub R/C Pier Wall	210	additional inventory item
9211 - Sub Other Pier Wall	211	additional inventory item
9212 - Sub Timber Pier Wall	212	additional inventory item
9213 - Sub Masonry Pier Wall	213	additional inventory item
9215 - Sub R/C Abutment	215	additional inventory item
9216 - Sub Timber Abutment	216	additional inventory item
9217 - Sub Masonry Abutment	217	additional inventory item
9218 - Sub Other Abutments	218	additional inventory item
9219 - Sub Stl Abutment	219	additional inventory item
9220 - Sub R/C Footing/Cap	220	additional inventory item
9225 - Sub Stl Pile	225	additional inventory item
9226 - Sub PS Pile	226	additional inventory item
9227 - Sub R/C Pile		additional inventory item
9228 - Sub Timber Pile	228	additional inventory item
9229 - Sub Other Pile	229	additional inventory item
9230 - R/C Grade Beam Cap		additional inventory item
9231 - Stl Grade Beam Pile		additional inventory item
9232 - PS Grade Beam Pile		additional inventory item
9234 - R/C Grade Beam Pile		additional inventory item
9235 - Timber Grade Beam Pile		additional inventory item
9236 - Other Grade Beam Pile		additional inventory item
9237 - Stl Wing Wall	219	additional inventory item
9238 - R/C Wing Wall	215	additional inventory item
9240 - Timber Wing Wall	216	additional inventory item
9241 - Masonry Wing Wall		additional inventory item
9242 - Other Wing Wall	218	additional inventory item
9243 - Stl Head Wall		additional inventory item
9244 - R/C Head Wall		additional inventory item
9245 - Timber Head Wall		additional inventory item
9246 - Mason Head Wall		additional inventory item
9247 - Other Head Wall		additional inventory item
9248 - Stl Grade Beam Cap	231	additional inventory item
9250 - Riprap		scour mitigation
9251 - A-Jack		scour mitigation
9252 - Spur Dike		scour mitigation
9253 - Gabions		scour mitigation
9254 - Articulating Block		scour mitigation
9255 - Conc Slope Protection		scour mitigation

ADE	AASHTO	Task 8 Notes
9256 - Other Slope Protection		scour mitigation
9261 - Rtngle MSE Abutment	215	additional inventory item
9262 - Cruciform MSE Abutment	217	additional inventory item
9263 - Blck MSE Abutment	219	additional inventory item
9270 - Stl Apron		additional inventory item
9271 - R/C Apron		additional inventory item
9272 - Timber Apron		additional inventory item
9273 - Masonary Apron		additional inventory item
9274 - Other Apron		additional inventory item
9303 - Fix Pinned Bearing		additional inventory item
9304 - Fix Plate Bearing		additional inventory item
9311 - Rocker W/Pin Bearing		additional inventory item
9312 - Roller Bearing		additional inventory item
9313 - Slide Plate Bearing		additional inventory item
9331 - R/C Open Brdg Rail		additional inventory item
9332 - Timber Appr Rail		additional inventory item
9333 - Mtl Appr Rail		additional inventory item
9334 - R/C Closed Appr Rail		additional inventory item
9335 - R/C Open Appr Rail		additional inventory item
9336 - R/C Appr Rail Wing Wall		additional inventory item
9337 - Oth Appr Rail		additional inventory item
9338 - Mtl Trans Rail		additional inventory item
9339 - R/C Closed Trans Rail		additional inventory item
9340 - R/C Open Trans Rail		additional inventory item
9341 - Timber Trans Rail		additional inventory item
9342 - Oth Trans Rail		additional inventory item
9343 - Flx Barrier Terminal Section		additional inventory item
9344 - Crash Cushions Terminal Section		additional inventory item
9345 - Mason Appr Rail		additional inventory item
9401 - Preformed Silicone Joint	302	additional inventory item
9403 - Asphalt Plug Joint	306	additional inventory item
9511 - Asphalt Overlay		additional wearing surface
9512 - Asphalt Overlay with Membrane		additional wearing surface
9513 - Asphalt Overlay with Preformed Fabric Membrane		additional wearing surface
9514 - Asphalt Overlay with Cold Liquid Applied Membrane		additional wearing surface
9515 - Asphalt Overlay with Hot Liquid Applied Membrane		additional wearing surface
9550 - Deck Chlorides		miscellaneous
9551 - Elec Potential		miscellaneous
9552 - Debris Block Flow		miscellaneous
9553 - Silt in Culv Barrel		miscellaneous

Table 62. North Dakota ADEs (state code 38)

ADE	AASHTO	Task 8 Notes
841 – Precast concrete box culverts	109	additional inventory item
8398 – Slope protections		additional inventory item
8399 –Slope protection, RC		additional inventory item
8402 –Headwalls		additional inventory item
8401 – Wings		additional inventory item

Table 63. Illinois ADEs (state code 17)

ADE	AASHTO	Task 8
8013 - Concrete Deck Unprotected w/ HMA Overlay	12	additional deck + WS +PS
8014 - Concrete Deck Protected w/ HMA Overlay	12	additional deck + WS +PS
8018 - Concrete Deck Protected w/ Thin Overlay	12	additional deck + WS +PS
8022 - Concrete Deck Protected w/ Rigid Overlay	12	additional deck + WS +PS
8026 - Concrete Deck Protected w/ Coated Bars	12	additional deck + WS +PS
8027 - Concrete Deck Protected w/Cathodic Protection	12	additional deck + WS +PS
8032 - Timber Deck with HMA Overlay		additional deck + WS +PS
8033 - Concrete Deck Protected w/ Coated Bars w/PPC Panel	12	additional deck + WS +PS
8034 - Precast Concrete Deck Bare	12	additional deck + WS +PS
8035 - Precast Concrete Deck Unprotected w/ HMA Overlay	12	additional deck + WS +PS
8036 - Precast Concrete Deck Protected w/HMA Overlay	12	additional deck + WS +PS
8038 - Concrete Slab Bare	12	additional deck + WS +PS
8039 - Concrete Slab Unprotected w/HMA Overlay	38	additional deck + WS +PS
8040 - Concrete Slab Protected w/HMA Overlay	38	additional deck + WS +PS
8044 - Concrete Slab Protected w/ Thin Overlay	38	additional deck + WS +PS
8048 - Concrete Slab Protected w/ Rigid Overlay	38	additional deck + WS +PS
8052 - Concrete Slab Protected w/ Coated Bars	38	additional deck + WS +PS
8053 - Concrete Slab Protected w/Cathodic Protection (SF)	2015 Manual	additional deck + WS +PS
8055 - Timber Slab with HMA Overlay (SF)	2015 Manual	additional deck + WS +PS
8056 - Precast Concrete Deck w/Rigid Overlay (SF)	12	additional deck + WS +PS
8057 - Steel Deck Concrete Filled Grid w/HMA Overlay (SF)	29	additional deck + WS +PS
8058 - Sidewalk (SF)		additional inventory item
8101 - Unpainted Steel Closed Web/Box Girder	102	additional inventory item
8103 - Non-Lead Painted Steel Closed Web/Box Girder	102	additional inventory item
8106 - Unpainted Steel Open Girder	107	additional inventory item

ADE	AASHTO	Task 8
8108 - Keyway		additional inventory item
8112 - Unpainted Steel Stringer	113	additional inventory item
8118 - Non-Lead Painted Steel Open Girder	107	additional inventory item
8119 - Non-Lead Painted Steel Stringer	113	additional inventory item
8121 - Lead Painted Steel Bottom Chord Through Truss		additional inventory item
8122 - Non-Lead Painted Steel Bottom Chord Through Truss		additional inventory item
8123 - Non-Lead Painted Steel Thru Truss Excluding Bottom		additional inventory item
8124 - Non-Lead Painted Steel Deck Truss		additional inventory item
8125 - Unpainted Steel Thru Truss Excluding Bottom Chord		additional inventory item
8126 - Lead Painted Steel Thru Truss Excluding Bottom Cho		additional inventory item
8128 - Non-Lead Painted Steel Arch/Arch Tie		additional inventory item
8129 - Non-Lead Painted Steel Floor Beam	152	additional inventory item
8130 - Unpainted Steel Deck Truss		additional inventory item
8131 - Lead Painted Steel Deck Truss		additional inventory item
8140 - Unpainted Steel Arch/Arch Tie (SF)	2015 Manual	additional inventory item
8142 - Post tension Segmental Box Girders	109	additional inventory item
8151 - Unpainted Steel Floor Beam	152	additional inventory item
8160 - Unpainted Steel Pin and/or Pin and Hanger		additional inventory item
8162 - Non-Lead Painted Steel Pin and Hanger		additional inventory item
8163 - Non-Lead Painted Gusset Plate		additional inventory item
8171 - Unpainted Steel Closed Web/Box Girder Ends Includi	102	additional inventory item
8172 - Lead Painted Steel Closed Web/Box Girder Ends Incl	102	additional inventory item
8173 - Non-Lead Painted Steel Closed Web/Box Girder Ends	102	additional inventory item
8174 - Unpainted Steel Open Girder Ends Including Diaphra		additional inventory item
8175 - Lead Painted Steel Open Girder Ends Including Diap		additional inventory item
8176 - Non-Lead Steel Open Girder Ends Including Diaphrag		additional inventory item
8177 - Upainted Steel Stringer Ends Including Diaphragms		additional inventory item
8178 - Lead Painted Steel Stringer Ends Including Diaphra		additional inventory item
8179 - Non-Lead Steel Stringer Ends Including Diaphragms		additional inventory item

ADE	AASHTO	Task 8
8180 - Unpainted Steel Deck Truss Below Deck Joints		additional inventory item
8181 - Lead Painted Steel Deck Truss Below Deck Joints		additional inventory item
8182 - Non-Lead Painted Steel Deck Truss Below Deck Joint		additional inventory item
8190 - Unpainted Steel Floor Beam Below Deck Joints	152	additional inventory item
8191 - Lead Painted Steel Floor Beam Below Deck Joints	152	additional inventory item
8192 - Non-Lead Painted Steel Floor Beam Below Deck Joint	152	additional inventory item
8200 - Non-Lead Painted Steel Column or Pile Extension	202	additional inventory item
8201 - Unpainted Steel Column or Pile Extension	202	additional inventory item
8209 - MSE Abutment and Wingwall		additional inventory item
8220 - Non-Lead Painted Steel Abutment and Wingwall	231	additional inventory item
8221 - Lead Painted Steel Abutment and Wingwall	231	additional inventory item
8222 - Unpainted Steel Abutment & Wing Wall	231	additional inventory item
8224 - Unpainted Steel Pile	225	additional inventory item
8230 - Unpainted Steel Pier or Abutment Cap not Below Dec	231	additional inventory item
8236 - Non-Lead Painted Steel Pier or Abutment Cap	231	additional inventory item
8237 - P/S Conc Beam Ends Incl Diaphrams Under Deck Joint		additional inventory item
8238 - Concrete Beam Ends Including Diaphrams Under Deck		additional inventory item
8239 - Timber Deck Runners		additional inventory item
8246 - Non-Lead Steel Pile	225	additional inventory item
8270 - Unpainted Steel Pier or Abutment Cap Below Deck Jo	231	additional inventory item
8271 - Lead Painted Steel Pier or Abutment Cap Below Deck	231	additional inventory item
8272 - Non-Lead Painted Steel Pier or Abutment Cap Below	231	additional inventory item
8306 - Finger Joints With Trough	305	additional inventory item
8307 - Neoprene Expansion Joint	306	additional inventory item
8308 - Continuous Seal Neoprene Expansion Joint	306	additional inventory item
8316 - Moveable Steel Bearings below continuous decks		additional inventory item
8322 - Concrete Approach Beam		additional inventory item
8323 - Approach Pavement		additional inventory item

ADE	AASHTO	Task 8
8360 - Abutment Settlement		additional defect
8361 - Abutment Scour		additional defect
8362 - Pier Settlement (EA)	2015 Manual	additional defect
8363 - Pier Scour		additional defect
8401 - Steel Closed Web/Box Girder	102	additional inventory item
8402 - Steel Bottom Chord Through Truss		additional inventory item
8403 - Steel Through Truss Excluding Bottom Chord		additional inventory item
8404 - Steel Deck Truss		additional inventory item
8406 - Steel Open Girder	107	additional inventory item
8407 - Steel Arch		additional inventory item
8408 - Steel Floor Beam	152	additional inventory item
8409 - Steel Column or Pile Extension	202	additional inventory item
8410 - Steel Pier or Abutment Cap	231	additional inventory item
8411 - Steel Pin and Hanger		additional inventory item
8412 - Steel Stringer	113	additional inventory item
8413 - Steel Gusset Plate		additional inventory item
8414 - Steel Pile (LF)	2015 Manual	additional inventory item
8460 - Culvert Settlement		additional defect
8461 - Culvert Scour		additional defect

Table 64. Wisconsin ADEs (state code 55)

ADE	Description	AASHTO	Task 8 Notes
8000	Wearing Surface (Bare)	510	additional wearing surface
8511	AC Overlay	510	additional wearing surface
8512	AC Overlay w/ Membrane	510	additional wearing surface
8513	Thin Polymer Overlay	510	additional wearing surface
8514	Concrete Overlay	510	additional wearing surface
8515	Polyester Concrete Overlay	510	additional wearing surface
8516	Painted Steel	515	additional protective coating
8517	Weathering Steel	515	additional protective coating
8518	Galvanization	515	additional protective coating
8519	Duplex Systems	515	additional protective coating
8522	Coated Reinforcing	520	additional protective system
8523	Stainless Steel Reinforcing	520	additional protective system
8524	Non-Metallic Reinforcing	520	additional protective system
8800	FRP Strengthening		miscellanous
8801	Jacketing		miscellanous
8802	Culvert Liner		miscellanous
8803	External Post Tensioning		miscellanous
8165	Steel Tension Rods/Post-Tensioned Cables		additional inventory item

ADE	Description	AASHTO	Task 8 Notes
8166	Timber Spreader Beam		additional inventory item
8170	Other Primary Structural Members		additional inventory item
8400	Integral Wingwall		additional inventory item