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Development of a Robust Framework for Assessing Bridge Performance using a Multiple Model Approach

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16. Abstract
This project presents a simple approach to multiple model deterioration modeling for bridges by identifying common points between deterioration model approaches and combining the results at these points. Inclusion of other data sources into this framework was explored, and an ontology of these sources and their relationships was developed. The results showed fairly close performance between individual models and combined models when considering a population of bridges in Texas using the National Bridge Inventory data – a resource that Texas would like to make better use of. This performance is a result of the bridges selected via identification of explanatory variables which are assumed through engineering judgment to drive deterioration – a practice that is common in nearly all of the literature. Future work includes exploring more robust ways of identifying explanatory variables.

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The majority of the analysis of deterioration models was completed by Jin Collins as part of her master's degree research. The NBI Query Tool was developed by Christian Lozoya, a master's student at UTEP. The exploration of existing frameworks, and the development of the bridge data ontology were completed by Mariana Benitez, a Ph.D. student at UTEP, and the Weibull analysis was conducted by Mubarak Adesina, another Ph.D. student at UTEP.

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Introduction and Background

Problem Description

In the aftermath of the collapse of the Silver Bridge in December of 1967, the United States Department of Transportation began to maintain a database of bridge information called the National Bridge Inventory or NBI. This database was populated with static information about bridges (i.e., route carried, structural form and materials, etc.) as well as dynamic information (i.e., condition ratings for components, average annual daily traffic, etc). These data and how they are obtained is set forth in the National Bridge Inspection Standards. Every two years each structure is inspected, and dynamic data values are checked and updated if needed by each state department of transportation. The updated data is submitted annually for public consumption through the Federal Highway Administration. One of the more important dynamic data fields is the condition ratings for the major bridge components (e.g., the deck, superstructure, and substructure). For many years, this condition data was the primary source of information for predicting future condition of bridges. Condition ratings factor heavily into decisions regarding funding for repair, rehabilitation, and replacement of structures, despite many changes to the Federal formulas for determining disbursement of Federal funds to the states.

Countless researchers have used NBI data to predict future condition using myriad approaches to deterioration modeling. Each approach has its own benefits and drawbacks, and as with any future prediction, there is no guarantee of accuracy until the future arrives – which negates the need for a prediction. This reframes the accuracy challenge into one of confidence. Given the variations between modeling approaches, there is no consensus 'best' deterioration model. The decision is left to the engineer or agency. Addressing this uncertainty is a primary objective of this research.

Over the past three decades, states began collecting more detailed bridge element information, which goes from, for example, the superstructure level to the girder level. There is an intuitive, hierarchical link between this information and component level condition. The same cannot be said for newer streams of bridge information that have become more popular over the same time period. These new streams of data, for example, may include nondestructive evaluation, vibration testing data, high resolution digital images, structural health monitoring, and finite element models. Currently these data are not well integrated into the bridge management workflow utilized by most departments of transportation. On a bridge to bridge basis, more refined data can be used to inform specific decisions, but there is rarely if ever any effort to tie that into the general bridge knowledge base that is used for modeling future performance of structures.

This deficiency represents a major challenge and threat to quantitative data-driven bridge management of structures because there is risk that when data becomes available it will not be readily integrated into bridge management practice and therefore viewed as irrelevant and unnecessary.

The goal of this research is to establish a robust, flexible framework for integrating data collected from operating structures to provide reliable performance assessments and forecast remaining service life (i.e., descriptive relationships) for structures. We first focus on traditional deterioration modeling using the largest dataset available, the National Bridge Inventory condition ratings. We explore numerous approaches to deterioration modeling, comparing their ability to predict future condition based on training and validation datasets. We also explore novel approaches to combining these methods into a more robust, multiple model deterioration modeling technique. To combat the perceived challenge of integrating new, quantitative data streams, we present several actions. First, we explored existing frameworks in the civil engineering/technology space as options for this challenge. We develop an understanding of what types of data are available and how they relate, a bridge data ontology. Finally, we explore the notion of synthesizing structural health monitoring data for the purpose of develop techniques to integrate that data with standard, qualitative condition information.

Approach

The implemented approach for this research was as follows:

- Literature Survey: A comprehensive review of the literature focused on deterioration modeling of bridges, multiple model approaches to predictions, and frameworks for integrating disparate data sources was conducted and synthesized. Within deterioration modeling, deterministic, probabilistic, mechanistic, reliability and artificial intelligence approaches are explored.

- Exploration of Existing Frameworks for Integrating Bridge Data: Two primary existing frameworks were considered. The first was the loosely titled "Smart City" framework, built on the notion that the Internet of Things and its integration into city services requires an interstitial software layer, much the same as integrating disparate data sources from a bridge into a management service would require. The second framework was Bridge Information Modeling, based on Building Information Modeling. This combines the spatial distribution of bridge elements and components and applies information to them in that context.
- Data Management and Filtering for Deterioration Modeling: The heavy focus on the application of deterioration modeling approaches was using National Bridge Inventory data. This data is notoriously error-prone and inconsistent, simply because of the scale and the number of persons involved in collecting and maintaining it. Several specific NBI data challenges were addressed including developing a robust tool through which the data can be searched and filtered, as well as tying data from year to year (stored and shared in completely unrelated text files) at the bridge level.
- Single Model Deterioration Modeling Approaches: We explore ten approaches to developing deterioration models primarily in the probabilistic category. Each approach develops a transition probability matrix which is used to estimate the probability of a state change, and to determine expected value at any time in the future. The transition probability matrices developed across approaches can vary even with the same supplied data. We explore this and offer some explanation as to why.
- Multiple Model Deterioration Modeling Approaches: The ten approaches for single deterioration modeling share similar crossroads in their development process – mainly the transition probability matrix and the deterioration curve stages. We consider simple and implementable methods for combining these single approaches at those crossroads' points.
- Synthesize the Results and Develop Conclusions and Future Work: This research only begins to address the problem described above. While we were able to start reducing the systemic error associated with arbitrarily selecting a single model form for deterioration modeling, we were not successful in integrating disparate data sources.

The implemented approach of this research varied from the proposed approach substantially. The proposed approach to this project was to quickly establish a proposed framework and focus on refining that approach through the inclusion of additional data obtained through collaboration with the Texas Department of Transportation. A trial population of structures was to be identified as a demonstration testbed for the approach. This population would have varying levels of data, from qualitative component and quantitative element condition data to temporally-varying structural health monitoring data would be available. However, after conferencing with the El Paso District Office – Bridge Division, it became clear that data would not be provided beyond what is publicly available, and that we had over-estimated the market penetration of many of the new data streams into practice. As such we did not develop or adopt a specific framework for integrating disparate data sources, and instead focused on exploring multiple model deterioration modeling primarily using condition ratings from NBI. A primary logistical driver for this was difficulty with retention of graduate students.

Methodology

The section summarizes the methodology that was implemented for this project. We started by exploring traditional approaches for deterioration modeling for bridges in the literature, looking for areas of commonality or overlap. The three primary areas identified were as follows:

- The explanatory variables that define the population of bridges
- The transition probability matrix that is common to so many probabilistic approaches
- The final deterioration curve

For non-probabilistic approaches, there was often something analogous to the transition probability matrix, which defined the relationship between staying in a condition rating and moving.

We focused on probabilistic approaches because of the commonality of the TPM. We explored two primary, and relatively simple approaches to combining the various single model approaches since the TPM was such a strong common point. The first was a combination of the TPM itself. The second was a combination of the deterioration model produced from each process.

In the original scope, we aimed to integrate other sources of data into this calculation. We found this to be difficult for myriad reasons, including:

- The difficulty of finding actual data to use
- The lack of resolution in the data selected
- The challenge in establishing a relationship between data sources that reflects deterioration mechanisms

Given that, and the complete lack of any effort to implement multiple model deterioration modeling without any additional data included, we focused on multiple model approaches to deterioration models.

Organization of this Report

The results of this research are presented in six chapters. Section 2 provides a survey and synthesis of the literature covering three distinct, but interrelated areas:

- Common and Uncommon Sources of Bridge data
- Traditional deterioration modeling for bridges
- Multiple model approaches
- Existing frameworks for integrating disparate data

Section 3 discusses bridge data (existing and novel sources), with a focus on those data streams relevant to deterioration modeling, and how they are managed and filtered. Section 4 presents the application and comparison of ten approaches to deterioration modeling each applied on an individual basis. Section 5 explores multiple model approaches to this challenge, and Section 6 provides conclusions and future work.

Survey of the Existing Literature

This literature review includes several overarching subject areas which all are related to the overarching goal of the project. These areas are:

1. Sources of Bridge Data
2. Deterioration modeling for bridges
3. Multiple model approaches
4. Frameworks for integrating disparate data

One notion that repeatedly comes up in deterioration modeling literature is explanatory variables. These are essentially filter criteria that an engineer assumes drives deterioration behavior in populations of bridges. By selecting historical data for structures with similar values of explanatory variables, it is assumed that the historic deterioration behavior is predictive of future behavior for similar structures. The importance of these variables and the decision of which to consider cannot be overstated. Further discussion is provided in Section 3.

Common Sources of Bridge Data

The three primary common sources of historical bridge data that are the National Bridge Inventory data, National Bridge Element data, and original construction documentation. In addition, some states maintain maintenance records but these are not generally publicly available. The latter two are not publicly available while the former two are, generally.

National Bridge Inventory (NBI)

The NBI database contains the broad information of bridges available on the national level. The Federal Highway Administration (FHWA) bridge inspection program regulations were established by the Federal-Aid Highway Act of 1968. The NBIS was enacted as part of the Federal-Aid Highway Act of 1970. Bridges are one of the important elements in the highway transportation system. These structures are expected to be safe. The safety of bridges was issued by the collapse of the Silver Bridge located at the Ohio River in 1967. The Secretary of Transportation was required to develop and implement the National Bridge Inspection Standards (NBIS) for estimating the deficiencies of existing bridges. The NBIS requires visual inspection biennially. The bridge owners are responsible for the inspections and the collected information is required to report to FHWA for maintaining the data in the National Bridge Inventory (NBI) database (FHWA 2004).

NBI contains 116 items include the followings (Ryan et al. 2012).

- Identification – bridges are identified by location codes and descriptions.
- Structure material and type – bridges are grouped by structural material, the number of spans, and design type.
- Age and service – information includes the built year and functionality of a bridge.
- Geometric data – information includes the structural dimensions of a bridge.
- Inspection – information includes the inspection date and the condition ratings of bridge components.

In the inspection items, condition ratings are determined as compared to the as-built condition and assigned by bridge inspectors using a 0 to 9 rating scale. The inspectors determine the ratings based on engineering expertise and experience (Ryan et al. 2012). The general guideline of condition rating for bridge components are described in the 1995 edition of the FHWA Coding Guide in Table 1 (Ryan et al. 2012).

Table 1. Condition rating codes and descriptions for bridges

Codes	Descriptions
N	Not applicable
9	Excellent condition
8	Very good condition – no problems noted
7	Good condition – some minor problems
6	Satisfactory condition – structural elements show some minor deterioration
5	Fair condition – all primary structural elements are sound but may have minor section loss, cracking, spalling or scour
4	Poor condition – advanced section loss, deterioration, spalling, or scour
3	Serious condition – loss of section, deterioration, spalling, or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present.
2	Critical condition – advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken.
1	"Imminent" Failure condition – major deterioration or section loss present in critical structural components, or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic, but corrective action may put bridge back in light service.
0	Failed condition – out of service; beyond corrective action.

National Bridge Element Data

For standardizing a data system, the FHWA revised the standards including a detail description of elements of a bridge and produced a manual, Commonly Recognized (CoRe) Structural Elements. The manual was accepted as an official American Association of State Highway and Transportation Officials (AASHTO) manual in 1995. Table 2 describes a guideline used in evaluation of element condition rating (Congress 2012). In 2011 The AASHTO Guide Manual for Bridge Element Inspection was published. It included four standardized condition states utilizing a 1-4 rating scale. The AASHTO element-level data are used to determine the condition ratings of bridge components in NBI.

Table 3 describes the condition ratings of bridge elements. These condition states provide severity and extent (i.e. total element quantity) of deterioration of bridge elements (Congress 2012).

Table 2. Condition status and description of bridge

Codes	Descriptions
Good	Element has only minor problems.
Fair	Structural capacity of element is not affected by deficiencies
Poor	Structural capacity of element is affected or jeopardized by deficiencies.

Table 3. Condition state codes and description of bridge elements revised

Code	Description
1	Good – No deterioration to minor deterioration
2	Fair – Minor to Moderate deterioration
3	Poor – Moderate to Severe deterioration
4	Severe – Beyond the limits of 3

The National Bridge Investment Analysis System (NBIAS) introduced in 1999 models the investment needs for bridge maintenance, repair, and rehabilitation incorporated analytical approaches such as a Markovian modeling, optimization, and simulation. Also, the NBIAS model can perform an analysis of bridge conditions using element level data (Ryan et al. 2012). States were required to report element level data of all bridges to FHWA by the Moving Ahead for Progress in the 2lst Century legislation (MAP-21) signed into law in 2012 (Congress 2012).

Plans and Construction Documents and Maintenance Records

State Departments of Transportation maintain records of their structures including as-built drawings, repairs and retrofits, and often regular maintenance records. These records are generally not publicly available

Uncommon Sources of Bridge Data

There are many techniques and technologies for assessing bridge condition quantitatively and qualitatively that are becoming more and more popular. There is a preponderance of literature discussing these applications on specific bridges. However, in the context of over 650,000 bridges nationwide, there are still relatively uncommon.

Finite Element Model Data

Finite element models of bridges are developed primarily for design purposes, or for determining a refined load rating (Golecki and Weidner 2018; White et al. 2012). To construct a model, structural material and geometric properties are imputed parameters separated by bridge component i.e. girders and deck in the FEM application of choice for prediction of deterioration and other values such as deflection, stress, and strain at expected loads. The first step to performing the load rating of a bridge is to conceptualize the structure, which drives the decision on what, if any model, should be used. White provides extensive research on what time of model to use for complex geometries including curved and skewed bridges (White et al. 2016).

FEM provides many benefits including the modeling of bridges with different geometries and material properties in a less time-consuming fashion (Golecki and Weidner 2018). Since deterioration models are dependent on large amounts of data, automation of models would be required to match that scale. This level of modeling at scale for a population of bridges has not occurred yet.

Nondestructive Evaluation

Nondestructive Evaluation (NDE) can be defined as the use of measurements taken using removable transducers and instrumentation to assess structural integrity (Cawley 2018). Based on the different types of inspections originating from the American Association of State Highway and Transportation Officials (AASHTO) bridge inspection manual, one of the five basic bridge inspection types is the special inspection (AASHTO 2019). This inspection is performed to monitor the changing conditions or deficiencies of a bridge once it reaches poor condition rating. NDE is used for reinforced concrete deck deterioration evaluation. With three types of deterioration possible, corrosion, concrete degradation, and delamination, different NDE equipment types can be used for detection (Gucunski and Nazarian 2010; Hooks and Weidner 2016). Some example NDE types with its description and detection details are listed below.

1. Half Cell Corrosion Potential Measurement (HCC)
    a. Description: Detects and quantifies active steel corrosion and measures electric potential between reinforcement and reference electrode w/concrete surface. Not quantitative.
    b. Detection: Regions with a more negative potential indicate prob of corrosion. Values are influenced by concrete cover and corrosion activity. Other factors include moisture, temperature, ion concentrations
2. Electrical Resistivity Measurement (ER)
    a. Description: Evaluates conditions for a corrosive environment
    b. Detection: The higher the electrical resistivity of concrete, the lower the corrosion current passing between the anodic and cathodic areas of RS. Water in concrete is necessary. Damaged or cracked areas increase porosity leading to preferred paths for the fluid and ion flow. Resistivity of less than 5 kohm*cm supports rapid steel corrosion; however, concrete has a high resistance to the current decreasing the corruption rate
3. Ground Penetrating Radar (GPR)
    a. Description: Provides overall assessment of possible concrete degradation; evaluates conditions for a corrosive environment.
    b. Detection: Amplitude will be high when deck is in good condition and weak when delamination and corrosion are present. Moist concrete high in free chloride ions affect GPR signal.
4. Ultrasonic Surface Waves

   a. Description: Concrete degradation; provides information about concrete modulus degradation.
   b. Detection: Uses measurement of velocity of surface waves. Velocity is wavelength dependent; In bridge decks velocity is constant for a limited range of wavelengths. Variation in modulus does not necessarily mean deterioration (present during construction) needs to be periodically measured to identify deterioration.
5. Impact Echo (IE)
   a. Description: Detects and characterizes different stages of delamination. Most commonly used for bottom of the deck and delamination.
   b. Detection: It can detect and assess delamination at various deterioration stages, from initial to progressed and ready to turn into spalls (Gucunski and Nazarian 2010).
6. Linear Polarization Resistance (LPR)
   a. Description: Measures corrosion rate instantaneously and only requires damage to the concrete cover in area of interest to produce an electrical connection with reinforcing steel.
   b. Detection: The relationship between electrochemical potential and electrically charged electrodes generated by the current estimate corrosion rate.
7. Dye Penetrant Testing
   a. Description: Used for examination of metallic materials, nonporous, and both ferrous and nonferrous. Does not require electricity, black lights, or water to perform the test.
   b. Detection: Detects discontinuities, open to the surfaces, such as cracks, laps, laminations, seams, and cold shuts through leaks or gaps.
8. Ultrasonic Testing (UT)
   a. Description: Transmits high-frequency sound energy through material in the form of waves.
   b. Detection: Locates and measures cracks or discontinuities in steel. In the identification of a discontinuity, a portion of the energy is reflected back and transformed into an electric signal, displayed on the equipment screen (Hooks and Weidner 2016).

Each of the NDE technologies mentioned have its own detection area with some complimenting others during the evaluation phase. For example, areas detected by the Ground Penetrating Radar as highly deteriorated are also shown as delaminated in the Impact Echo. Learning the correlation between the different NDE types can reduce the cost of inspection to arrive at a faster rehabilitation decision.

Structural Testing and Structural Health Monitoring

Structural testing and structural health monitoring (SHM) both aim to assess the integrity of a structure non-destructively. Structural testing gives information about a structure at a point in time. An example would be a load test of a bridge to determine lateral load distribution properties. SHM involves attached transducers over a period of time that enables frequent measurements during operation of the structure. Essentially, SHM is a continuous form of structural testing. The signals obtained are often interpreted by comparing them with previous measurements using a process commonly called baseline subtraction. Signal processing and anomaly detection lends itself to automation and machine learning applications (Cawley, 2018).

Load testing is the most common form of structural testing. The performance of structural elements is generally determined by placing strain or deflection-transducer gages at critical locations along the bridge. The bridge is then incrementally loaded to induce maximum effects. The collected data can then be analyzed and used to establish the structural integrity and condition of each component as well as the load distribution. Bridge load testing will allow a satisfactory overall strength evaluation of short span bridges under assessment but would pose a challenge for long span bridges. The information provided will greatly increase the possibility of selective rehabilitation, rather than the current practice of replacing the entire structure (Moussa et al. 1993).

Monitoring of large structures began with attempts to detect local anomaly from a small number of measurements, but is now often referred to as Structural Identification– developing a numerical model of a dynamic system based on its measured response, with emphasis on assessment of the health and performance of the structure, as well as decision making regarding its maintenance and/or rehabilitation. This is applied to large structures such as bridges and is unlikely to be sensitive enough to detect localized anomaly reliably, unless it is extremely severe (Cawley 2018).

This technology is gradually gaining strides in the United States though at a slow rate, but there has been an increase in adoption in Asia (China, Japan, Korea) and some part of Europe. In Switzerland, the Z-24 bridge before complete demolition, was extensively instrumented and tested with the purpose of providing a feasibility benchmark for vibration-based SHM. A long term monitoring program was carried out, from November 11, 1997, until September 10, 1998, to quantify the operational and environmental variability present on the bridge and to detect damage (pier settlement, foundation tilt, spalling of concrete, landslide at abutment, concrete hinge failure, failure of anchor heads, and rupture of tendons) artificially introduced in the last month of operation. Every hour, eight accelerometers captured the vibrations of the bridge as sequences of 65,536 samples (sampling frequency of 100 Hz), and other sensors measured environmental parameters, such as temperature at several locations (Figueiredo et al. 2019; Peeters and De Roeck 2001).

Synthesized SHM Data

SHM systems are either perceived as, or actually are costly, and usually reserved large signature structures where the potential return on investment is easily understood. As the cost of these systems drops, there will be broader implementation. Unfortunately, until that happens, it is difficult to explore how to integrate SHM data into bridge management. One solution would be to use finite element models to generate synthesized SHM data.

This practice is common in papers focused on damage detection. Damage detection efforts typically have a goal to validate an algorithm or sensing approach by creating a structural model, generating output (synthesized or simulated SHM data), and then “damaging the structure” by changing the model. New output is generated and compared, and the damage is located. Figueiredo used a combination of finite element models and machine learning to detect damage, making use of simulated data (Figueiredo et al. 2019). Bridge WIM data was used to develop a loading model which was applied to finite element models to generate simulated SHM data to calculate site-specific dynamic application factors in Alabama (Zhao, Uddin, and Asce 2014). Zhang used partial least square regression on a bridge finite element model to extract virtual inclinometer readings to validate an approach to calculation of deflection for damage detection (Zhang, Sun, and Sun 2016). No references were identified where simulated data was used for the purposes of informing bridge management or deterioration modeling of bridges.

Non-contact Image Approaches

Contrary to structural testing and health monitoring approaches, image approaches provide full field information. Often a full strain field can be detected and measured providing far more information than a traditional strain gage (Webb, Vardanega, and Middleton 2015). The Long-Term Bridge Performance program developed the RABIT Autonomous Bridge Deck Inspection tool which combines numerous forms of Nondestructive evaluation with high resolution imaging which acts as the common contextual thread – along with position information – for all nondestructive techniques.

Recently, numerous researchers have been using unmanned aerial systems (UAS) for bridge inspection and image assessment. The first full application occurred in Minnesota in 2015 (Lovelace 2015). More recently, researchers have been working towards photogrammetric measurement from aerial systems. Ellenberg attempted deflection measurements for the first time using an Xbox Kinect sensor (Ellenberg et al. 2014). Reagan used a two camera, UAS mounted imaging system to conduct digital image correlation measurements of an abutment wall joint (Reagan, Sabato, and Niezrecki 2017). Harris investigated the use of numerous image-based methods on three bridges in Michigan, including multispectral, thermal, LiDAR, and photogrammetry (Harris, Brooks, and Ahlborn 2016).

Efforts to effectively integrate these approaches into bridge management have not been published to date.

Deterioration Modeling

The Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) marked the start of a new era in transportation in the United States. ISTEA required transportation agencies to take a more proactive approach to planning and asset management. This included a requirement for management systems for pavement, bridges, safety, congestion, public transportation, and intermodal systems. For horizontal transportation assets (i.e., bridges and pavement), deterioration modeling was an essential tool (Yanev and Chen 1993). Since ISTEA, Bridge Management Systems (BMS) have been utilized to inform decision-making regarding bridge projects such as maintenance, rehabilitation, and replacement (MR&R) under financial limitations (Agrawal, Kawaguchi, and Chen 2010). The goal of a BMS is to optimize the performance of the bridge networks by implementing the planned MR&R events to the selected bridges. For optimizing the decision of selecting bridge projects, the reliability of the prediction of future condition state of bridges is required. The condition rating of bridges is the most vital variable to predict the future condition of bridges (Yi Jiang 2010). To estimate a future condition rating, a deterioration model is utilized. There are numerous approaches to develop deterioration models which all are defensible but provide different results. Here we consider deterministic, probabilistic, mechanistic, artificial intelligence, and reliability-based approaches to deterioration modeling. In some cases, more than one approach may be included in a single application. An example is a mechanistic approach that generates probability distributions of a variable defined by mechanistic relationships. The grouping herein is based on the primary method for predicting a future state (i.e., mechanistic for the example above).

Deterministic Deterioration Modeling

Deterministic approaches are the simplest method to obtain bridge condition predictions. In deterministic models, the most possible condition rating can be estimated as a function of age and other explanatory variables by a regression process. The same outcome can be obtained if the input variables are the same in deterministic models. Thus, the probabilistic nature of models is not considered (Kotze, Ngo, and Seskis 2015). When an analysis of each bridge does not make an analysis of bridge networks complicated or distorted, a statistical method is suitable to develop an equation of the rate of change in bridge conditions (Hyman and Hughes 1983). Deterioration rates can be developed by a statistical and regression analysis of data in deterministic models (Agrawal and Kawaguchi 2009). In deterministic models the relationship between explanatory variables influencing bridge deterioration and the condition rating are illustrated by a statistical and regression analysis of data. The average duration at each of condition rating states, the average of ratings at different age, and the minimum of ratings of an element are the common deterministic methods to estimate deterioration rates. (Agrawal and Kawaguchi 2009). Yanev and Chen estimated the future condition state of bridge deck in the New York City metropolitan area by linear regression analysis (Yanev and Chen 1993). The rate of change for each condition rating state was obtained and averaged. Also, the average of bridge condition ratings for all bridge ages was calculated. The non-linear regression method was applied to formulate a third order polynomial model to describe the relationship between the condition rating of bridge components and the bridge age in Indiana through statistical and regression analysis by Jiang and Sinha (Y Jiang and Sinha 1989). The basic assumption of deterministic approaches is that the relationship between the future condition of bridges over time is certain. The models neglect the uncertainty and randomness of deterioration processes (Ranjith et al. 2013). Deterministic models have some limitations (Agrawal and Kawaguchi 2009):

- The uncertainty due to intrinsic probabilistic nature of infrastructure deterioration and unobserved explanatory variables is not considered.
- The average condition of a group of bridges without consideration of the current and historical condition of each bridge is calculated.
- Bridge deterioration conditions are predicted by "no maintenance" approach because it is difficult to calculate the impact of MR&R activities.
- The influence of interaction between components is not considered.
- New deterioration rates should be calculated when new data are obtained.

Probabilistic

The condition states of bridge components/elements or the duration at each condition state are treated as random variables in probabilistic or stochastic models. Probability distributions are used to develop deterioration models (Kotze, Ngo, and Seskis 2015). Probabilistic deterioration models can be grouped into two categories: state-based and time-based models. In stated-based models, such as Markov chain, the probability of transition of a facility from one condition state to another in a discrete time is estimated, conditional on a set of explanatory variables. In time-based models, such as Weibull distribution function, the probability of the duration that a facility stays at a condition state is estimated, conditional on the same set of explanatory variables (Mauch and Madanat 2002).

Markov Chain (State-based)

A Markov process named after Andrey Markov, a Russian mathematician is a stochastic process that satisfies the Markov property, "memoryless". A prediction for the future of the process only depends on the present state of a system. Markov used random walk and gambler's ruin as the examples of Markovian processes in his first paper published in 1906. These examples are the Brownian motion process and the Poisson process which are the main processes in the theory of stochastic processes. A Markov chain is one of Markov process that has a discrete state space (Leonard 2011). Markov chains are applied as statistical models to real world. Markovian deterioration models have been utilized in modeling the deterioration of infrastructure facilities such as pavement (A. Butt et al. 1987; Carnahan et al. 1987; DeLisle, Sullo, and Grivas 2003; Golabi, Kulkarni, and Way 1982), storm water pipe (Micevski, Kuczera, and Coombes 2002), sewer pipe (Baik, Jeong, and Abraham 2006), bridge components (Bu et al. 2014; Hatami and Morcous 2015; Yi Jiang 2010; Yi Jiang, Saito, and Sinha 1988), bridge elements (Ranjith et al. 2013; J. O. Sobanjo 2011), and culverts and traffic signs (Thompson et al. 2012). Markovian models are based on the following assumptions (Ranjith et al. 2013).

- The deterioration process is homogenous with constant transition probability in an inspection period.
- A condition state can transit to multi-state. For example, the condition rating can change to any lower condition rating in consecutive inspection period.
- Transition probability matrices are based on stationary transition probabilities.
- The deterioration process is assumed a continuous process within a discrete time interval and constant bridge population.
- The future conditions of bridges are relied only by the present conditions.

A Markov chain is a chain of random variables X_k, X_{k-1}, X_{k-2}, … which are finite with the Markov property. The probability of transition from the current state to the next state is

$$Pr\{X_{k+1} = x_{k+1} | X_k = x_k, \cdots, X_0 = x_0\} = Pr\{X_{k+1} = x_{k+1} | X_k = x_k\} \qquad \text{Eq. 1}$$

If the process is time-independent, the Markov chain can be described as a matrix called the transition probability matrix (TPM). The Markov chain as applied to bridge performance prediction models is used by defining discrete condition ratings and obtaining the probability of transition from one condition rating to another in discrete time. This method is commonly used when prior maintenance records are not available in a BMS database (Yi Jiang, Saito, and Sinha 1988; Morcous and Lounis 2007).

Weibull Distribution (Time-based)

Weibull distribution is commonly used in reliability and lifetime distribution analysis due to its flexibility. It can take on the features of other form of distributions depending on the values of the parameters, shape (β) and scale (α) parameters. The probability density function is

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} e^{-(x/\alpha)^{\beta}} \; for \; x \geq 0. \qquad \text{Eq. 2}$$

Weibull survival models have been utilized in modeling the deterioration of infrastructure facilities such as pipe culverts, roadway lighting fixtures, pavement markings (Thompson et al. 2012), reinforced concrete bridge decks (Mishalani and Madanat 2002), bridge elements (Agrawal and Kawaguchi 2009), bridge decks (J. O. Sobanjo 2011), and bridge components (J. Sobanjo, Mtenga, and Rambo-Roddenberry 2010). Weibull models capture the effects of age and uncertainty more than Markov chain models.

The Weibull survival function is

$$y_g = exp\left(-1.0 \times (g/\alpha)^{\beta}\right) \qquad \text{Eq. 3}$$

where y_g is survival probability at age g; β is the shaping parameter, which determines the initial slowing effect on deterioration; and α is the scaling parameter.

$$\alpha = \frac{T}{(ln\,2)^{1/\beta}} \qquad \text{Eq. 4}$$

where T is the median life expectancy from the Markov model. When β is less than 1, the failure rate (also known as a hazard rate) is decreasing. When β is equal to 1, the failure rate is constant. When β is greater than 1, the failure rate is increasing. Increasing the failure rate indicates that a component/element has been at a condition rating for a long time, so the component/element will transit to a lower condition rating in the next inspection period (Agrawal and Kawaguchi 2009). The shape parameter (β) of 1 is equivalent to a Markov deterioration model, which the transition probability does not change with time. A bigger shape parameter means that the initial deterioration rate is slow, and then the deterioration rate increases faster as the age of a facility increases. Figure 1 shows the effect of the shape parameter on deterioration. The uncertainty of a failure rate decreases as the shape parameter increases (Thompson et al. 2012).

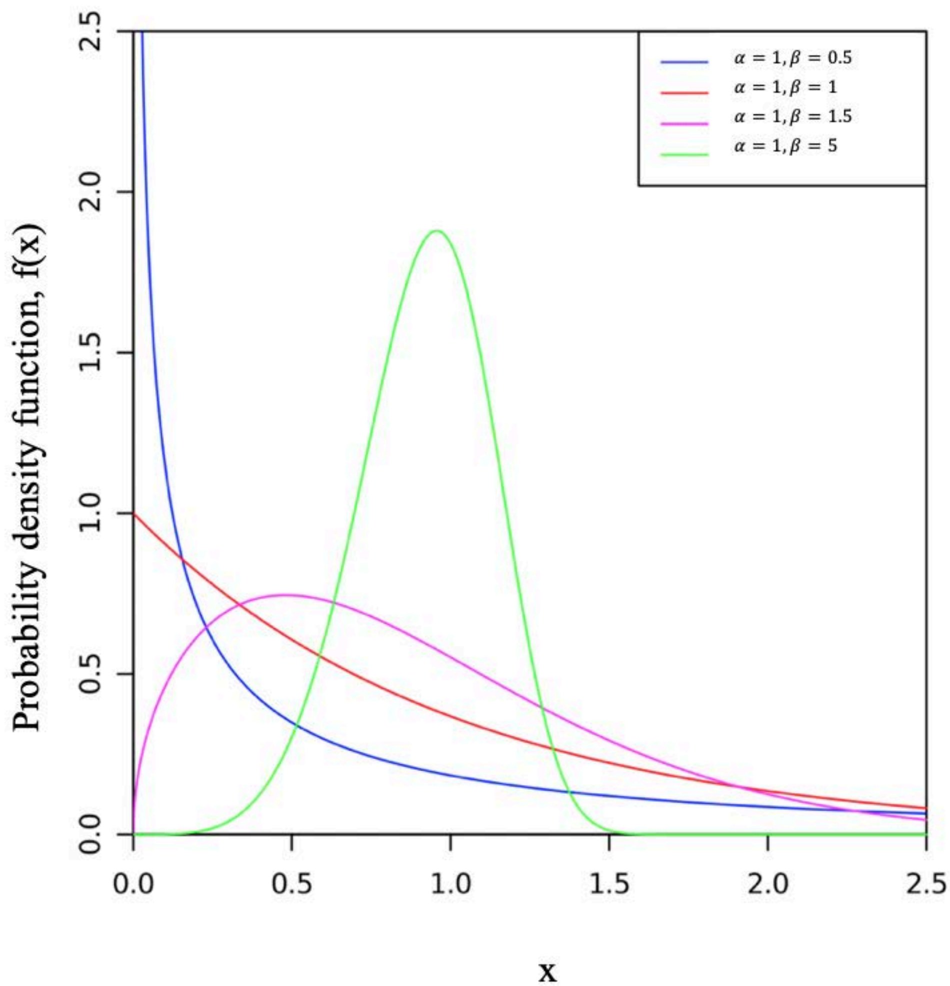

Figure 1. Weibull probability density function with different shape parameters

The average duration that a component/element stays at a condition rating, $E(T_i)$ is

$$E(T_i) = \alpha_i \Gamma\left(1 + \frac{1}{\beta_i}\right) \quad \text{Eq. 5}$$

where Γ is the Gamma function defined as $\Gamma(n) = (n-1)!$; α_i and β_i are scale and shape parameters at condition rating *i* respectively. The average durations for different condition ratings are calculated cumulatively (Agrawal and Kawaguchi 2009).

Some or all of the components or elements in a given condition rating can transit to the next lower condition rating within a discrete interval. The duration or time at which p% of the components/elements will transit to lower condition ratings, t_p is

$$t_p = \alpha[-ln(1-p)]^{1/\beta} \quad \text{Eq. 6}$$

where α and β are the scale and shape parameters (Agrawal and Kawaguchi 2009).

Mechanistic Deterioration Modeling

The deterministic and probabilistic approaches are based on observation of bridge condition states using visual inspection, an inherently subjective process. This method relies on modeling the physical processes of bridge deterioration, focusing on corrosion of rebar in reinforced concrete. The passive film (oxide film) is formed the surface of the reinforcement during concrete hydration and protects the reinforcement from corrosion. The film is destroyed by chloride ions that penetrate into concrete from the surface of the concrete. Corrosion-induced models were applied to predict reinforced concrete bridge deck conditions. Morcous and Lounis applied Fick's second law to estimate the corrosion initiation time and used the Monte Carlos simulation technique to generate the probability density function and cumulative distribution function of the corrosion initiation time (Morcous and Lounis 2007).

$$C(x,t) = C_s\left[1 - erf\left(\frac{x}{2\sqrt{Dt}}\right)\right] \quad \text{Eq. 7}$$

where $C(x,t)$ is the chloride concentration at depth (x) and time (t) C_s is surface chloride concentration, D is diffusion coefficient of chlorides, and erf is error function. Roelfstra divided the deterioration of reinforced concrete due to corrosion into two phases, the initiation phase which chlorides penetrates in the reinforcement from the surface and the propagation phase which the reinforcement corrodes actively (Roelfstra et al. 2004). The deterioration curve generated from the proposed mechanistic model was compared with the curve developed by using Markov chain method. The difference between two curves because the corrosion initiation time was not considered in the Markov chain model. Hu and Nickless divided the corrosion process into three phases, the time of corrosion initiation at the rebar surface, the time to cracking initiation at the interface between concrete and rebar, the time for cracking to propagate to the concrete surface and selected a numerical model for each phase (Hu, Haider, and Jansson 2013; Nickless and Atadero 2017). The Monte Carlos simulation technique was implemented to estimate cumulative deterioration of an entire deck. The damage over the deck was mapped to condition rating scale described by the NBI.

Artificial Intelligence Models for Deterioration Modeling

Artificial intelligence (AI) techniques have been used to model the deterioration of infrastructure facilities such as neural network for storm water pipes (D. H. Tran, Perera, and Ng 2009), artificial neural network (ANN) for water mains, ensemble of neural network (ENN) for bridge elements and components (Bu et al. 2014; Lee et al. 2014; Li and Burgueño 2010), backward prediction models (BPM) for steel bridge structures and bridge elements (Lee et al. 2008; Pandey and Barai 1995), multilayer perceptron (MLP) for abutment walls (Li and Burgueño 2010), and combination of ANN and CBR for the Dickson Bridge (Morcous and Lounis 2005).

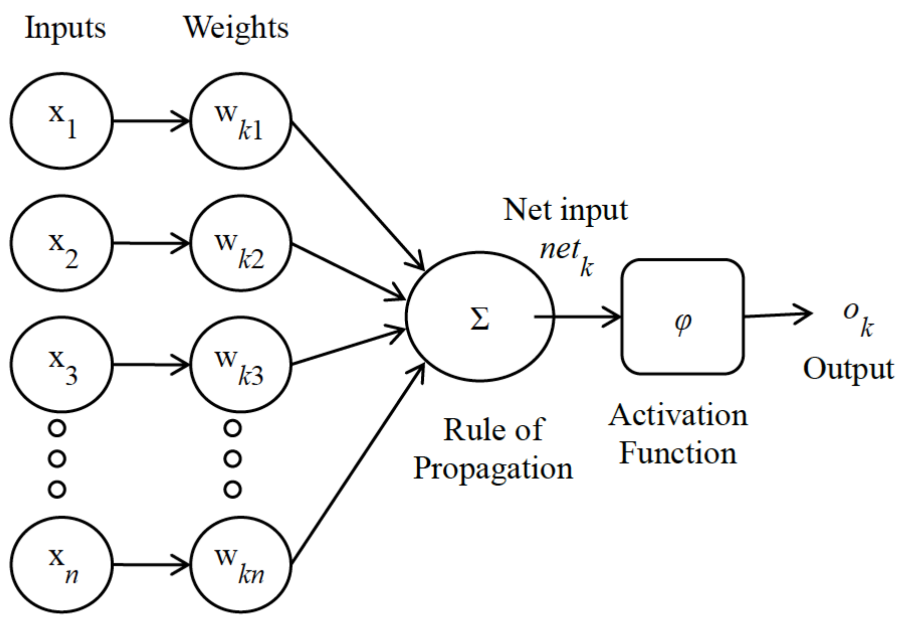

Figure 2. Schematic diagram of ENN process (Winn and Burgueño 2013)

An ANN is a computational model derived from the study of nerve cells or neurons in physiology. An artificial neuron contains receiving sites, receiving connections, a processing element and transmitting connections. Neural network models are stipulated by the net topology, node features, and training or learning processes. A multilayer perceptron has an input layer, an output layer, and a number of hidden layers (Pandey and Barai 1995). An ANN can generate accurate response even though there is noise or uncertainty in training data and evaluate the results of complex matters with a higher order of nonlinear behavior. An ANN learns to map the accurate input-output by an iterative procedure. In the learning process, the weighted connections between neurons are modified, and the error of the model reduced to produce more accurate results. If data are trained only to focus to reduce the errors, the ANN model might not generalize the connection between inputs and outputs. In the process, neurons receive inputs from the previous layer, computes an output through a pre-defined function, and sends the output to neurons on the next layer. An MLP method has one input layer, one output layer, and one or more hidden layers. Figure 2 describes the ENN process. An ENN consists of many individual MLP models and predict the outcomes by combining these models. The net input and output are formulated in Eq. 8 and Eq. 9 (Winn and Burgueño 2013).

$$net_k = \sum_{j=1}^{n} w_{kj} x_j \qquad \text{Eq. 8}$$

$$o_k = \varphi(net_k) \qquad \text{Eq. 9}$$

where $net_k$is the net input; o_k is the output; n refers to the input for which the weight refers, and k refers to the neuron under examination; the input x_n is the output of neurons from the previous layer; w_{kn} is respective weight of x_n (Winn and Burgueño 2013). Lee used an ANN-based BPM to generate unavailable historical bridge condition ratings for using limited bridge inspection data. Figure 3illustrates the process of BPM (Lee et al. 2014). The missing information such as condition ratings can be estimated by using the correlation between explanatory variables and condition states. The correlation can be obtained from the existing historical data by using ANN process (Huang 2010).

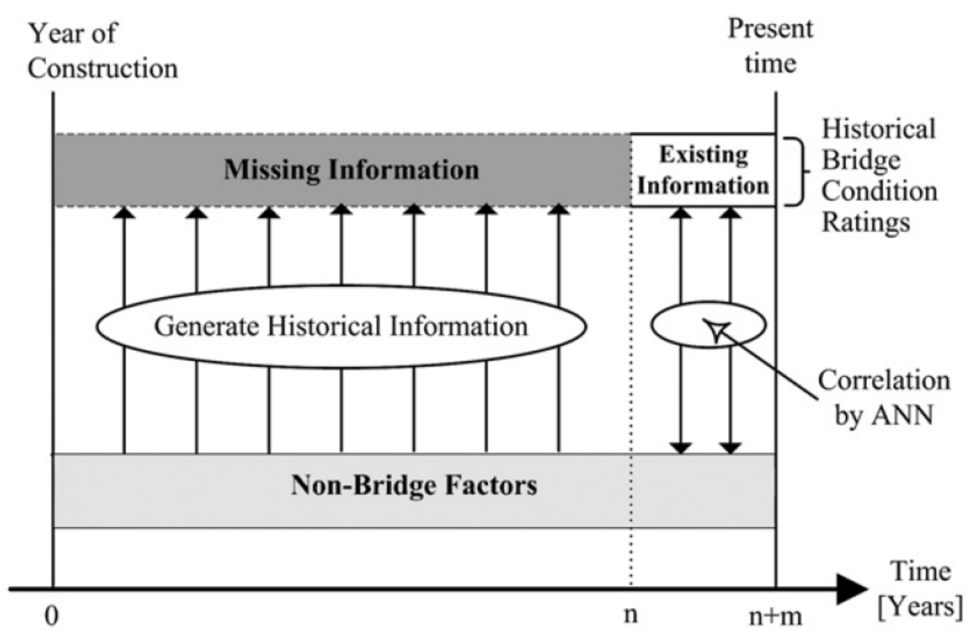

Figure 3. Sketch of the BPM process (Huang 2010)

Reliability-based Deterioration Models

Bridge design is reliability-based procedure, but most approaches to predict bridge condition do not consider the reliability of performances of elements, components, or a system of a bridge. The safety of bridges can be measured by using the reliability index, β. A bridge is in excellent condition where $\beta \geq 9.0$, in very good condition where $9.0 > \beta \geq 8.0$, in good condition where $8.0 > \beta \geq 6.0$, in fair condition where $6.0 > \beta \geq 4.6$, and in unacceptable condition where $\beta < 4.6$ (B. D. M. Frangopol, Kong, and Gharaibeh 2003). The performance function, $g(t)$ for a given failure mode, the probability of failure of a system with several failure modes, $P_{sys}(t)$, and the reliability index, $\beta(t)$ associated with the failure state of the system are

$$g(t) = r(t) - q(t) \quad \text{Eq. 10}$$

$$P_{sys}(t) = P[any\ g_i(t) < 0], for\ all\ t > 0 \quad \text{Eq. 11}$$

$$\beta(t) = \Phi^{-1}\left(1 - P_{sys}(t)\right) \quad \text{Eq. 12}$$

where $r(t)$ and $q(t)$ are the instantaneous resistance and load effect at the time instant t, respectively, $g_i(t)$is the performance function associated with the ith system failure mode, and Φ is the standard normal cumulative distribution function (Barone and Frangopol 2014). There are three methods to approximate the failure probability, the mean value first-order second-moment method, the first order reliability method, and the Monte Carlos simulation method (Akgül and Frangopol 2004). The time-dependent bi-linear and nonlinear reliability index models, $\beta(t)$ without maintenance are as follows:

$$\beta(t) = \begin{cases} \beta_0, for\ 0 \leq t \leq t_I \\ \beta_0 - \alpha_1(t - t_I), for\ t > t_I \end{cases} \quad \text{Eq. 13}$$

$$\beta(t) = \begin{cases} \beta_0, for\ 0 \leq t \leq t_I\ , \\ \beta_0 - \alpha_2(t - t_I) - \alpha_3(t - t_I)^p, for\ t > t_I\ , \end{cases} \quad \text{Eq. 14}$$

where $\alpha_1, \alpha_2, \alpha_3$ are reliability index deterioration rates, t_I is the deterioration initiation time, and p is a parameter related to the nonlinear effect in terms of a power law in time. An increase in p results in an increase in the rate of reliability index deterioration. The time-dependent condition index model, $C(t)$ at time $t \geq 0$ is following:

$$C(t) = \begin{cases} C_0, for\ 0 \leq t \leq t_{IC} \\ C_0 - \alpha_C(t - t_{IC}), for\ t > t_{IC} \end{cases} \qquad \text{Eq. 15}$$

$$C(t) = \begin{cases} C_0, for\ 0 \leq t \leq t_{IC} \\ C_0 - \alpha_C(t - t_{IC}), for\ t > t_{IC} \end{cases} \qquad \text{Eq. 16}$$

where C_0 is the initial condition, α_C is the condition deterioration rate, t_{IC} is the condition index which is considered constant for a period equal to the time of damage initiation, and $C(t)$ is the condition at time t which is assumed to decrease with time. The reliability-based model with maintenance is as follows:

$$\beta_j(t) = \beta_{j,0}(t) + \sum_{i=1}^{n_j} \Delta\beta_{j,i}(t), \qquad \text{Eq. 17}$$

where n_j is the number of maintenance actions associated with reliability index profile j, $\beta_{j,0}(t)$ is the reliability index profile without maintenance, and $\Delta\beta_{j,i}(t)$ is the additional reliability index profile associated with the *i*th maintenance action. The reliability index profile of the system is obtained by combining the reliability index profiles of all individual elements and limit states considered (D. M. Frangopol, Kallen, and Noortwijk 2004).

Multiple Model Approaches

There is a documented non-uniqueness issue with any given model solution to an experimental problem because the model is more detailed than the experimental data (Janter and Sas 1990). Further, any single model solution is prone to errors in modeling assumptions and measurement issues (Smith and Saitta 2008). While this is especially problematic in the bridge realm when it comes to model-experiment correlation, the same issues arise with deterioration modeling and any prediction of future performance.

Multiple model approaches address these issues by providing multiple feasible solutions to a given problem (Smith and Saitta 2008). Beck presented a probabilistic approach to identifying model solutions using a Markov Chain Monte Carlo sampling approach to explore the model parameter space (Beck and Au 2002). Though not explicitly designed to produce multiple models, the MCMC sampling generates a new model each iteration. Smith specifically produces models that exceed a threshold value based on the perceived error sources in the measurement and model (Smith and Saitta 2008). Zarate and Caicedo developed alternative solutions, or local minima, and allowed the selection between those solutions to be done through heuristics (Zárate and Caicedo 2008). Dubbs employed a MCMC approach but retained all models and weighed them based on their ability to predict measured responses (Dubbs and Moon 2015). All of these applications adopt a single model form and vary parameters to create differing models. Reversible Jump MCMC (RJMCMC) allows for transition between model forms during parameter sampling, given a consistent set of parameters (Weidner 2012).

In the deterioration modeling space, none of the approaches described above were applied. However, Thomas and Sobanjo implement a semi-Markov approach which utilizes both a Markov approach (state-based) and a Weibull approach (time-based) during different points in the deterioration curve (Thomas and Sobanjo 2016).

Frameworks for Integrating Disparate Data Sources

In order to integrate novel sources of bridge data into bridge management through deterioration modeling and future condition predicting, a framework which establishes rules for integration is required. We considered two existing frameworks. The Smart City framework integrates distributed, heterogeneous sensing into city services. In our application, this would not explicitly establish a physical, spatial or temporal relationship between data sources. The second approach as the Bridge Information Modeling framework which would explicitly establish a relationship between data streams.

Smart Cities

The phrase "smart city" has been used interchangeably to describe a city that is digital through its managerial services and infrastructure monitoring. The main goal of a "smart" city is to create a strategy focused on mitigating problems generated by urbanization and population growth. The problems faced by cities not only include social and organizational such as diverse stakeholders and political complexity, but also include technical, physical and material problems. These technical, physical and material problems include resource scarcity, health concerns, air pollution, traffic congestion, and aging infrastructure (Chourabi et al. 2012).

The Institute of Electrical and Electronics Engineers (IEEE) as well as the European smart cities classification standard define a smart city to include economy, people, living, governance, environment, and mobility (Zubizarreta, Seravalli, and Arrizabalaga 2016). The driving force of these pillars are a city's citizens. A flourishing economy produced by includes productivity, entrepreneurship, market, and labor. Through communication between its citizens, changes that benefit the city can be made that affect the economy, government, and environment positively. The new, post-industrialized city is then considered a linked system with an effective combination of digital telecommunication networks, embedded intelligence, and software (Chourabi et al. 2012).

Two layers that have commonly been present in cities are the services and the infrastructure layer. An additional layer critical to the classification of a smart city is the data layer or digitalization (Iglus 2017). This new layer works hand in hand with the other layers by complementing and completing them with data that is useful to serve society. This data can be acquired through the use of sensors, smart phones, and other means that utilize the internet. The linking of the three layers produce a phenomenon known as the Internet of Things (IoT) (Iglus 2017). Through the utilization of the IoT, citizen involvement in the government and services can be improved through the analyzing of user data.

An evaluation of a handful of cities around the world representative of smart cities was performed by Anthopoulos with a comparison of each for further understanding of what makes a city "smart" (Anthopoulos 2017). Ten cities of varying population sizes including Seoul, South Korea, and Washington, D.C., USA were part of the study. The chosen city indicators were those with an open data website, smart services, and smart infrastructure. Interviews with officials in each city were also performed to understand the purpose of the active projects. After the evaluation and comparison of the cities, the four objectives presented in each cities' projects were scale, definition, sustainability, and the fringes. Scale summarized project scope and viewed the scope beyond urban innovation or climate change initiatives. Definition redefined the commonly used definitions of a smart city tailored to each city. Sustainability aimed to identify sustainable, environmental efforts. Lastly, the fringes objective summarized future improvements i.e. innovation growth (Anthopoulos 2017).

Evidence towards the development of the smart city of Seoul, South Korea began in the year 2014. The catalyst is argued to be one of two actions, the partnership between the local government and the local Information and Communication Technologies (ICT) industry or the implementation of green projects, electronic government service, and the "Owl Bus" bus service driven by data analytics (Anthopoulos 2017). An outline of Anthopoulos objectives specific for Seoul is condensed below.

- Scale – Seoul's steady development emphasized the importance of long-term planning as smart technology embedding in a city can extend to a decade. On the other hand, fast improvements can be implemented through mobility such as lanes specifically for pedestrian or buses.
- Definition – Technology-based innovations and ecological friendly environments were the most prevalent descriptors from the smart cities definitions. Shortcomings from both aspects were the slow implementation of digitalization and the limited open space due to traffic and old buildings.
- Sustainability – The adoption of technology was evident throughout the city's residents as well as the shifting to ecofriendly choices such as recycling and walking. However, new construction was a preference instead of reusing existing buildings, negatively affecting green urban planning.
- Fringes – Although the smart technology has been implemented in Seoul, poverty and technology is still ubiquitous. As competition between other cities is arising, the technological divide should decline.

While Seoul represents the common smart city case in other cities studies such as Hong Kong, other cities follow a Washington, DC. path. Though there is a divide between social classes, there are mainly middle class and upper class. Smart services, open space, and smart mobility options are prevailing along with slow local government involvement. In summary, cities that combine local government and ICT industry for improvements in infrastructure, services and mobility are in the path to improving the quality of life of its users known as a smart city.

Bridge Information Modeling (BrIM)

Bridge Information Modeling or BrIM has emerged after the widely used tool of Building Information Modeling (BIM). BrIM is a modeling approach to deliver quality design projects through the planning, construction, and lifespan of a bridge through the sharing of accurate information and documentation. During the planning phase, the range of stakeholders can access the project for easier access to changes. Throughout the course of construction, the pre-fabrication phase as well as real-time deliveries of materials can be monitored. After the completion of the project, the as-built physical representation of the bridge can be accessed by different levels of collaborators and integrate bridge finite element analysis, wireless monitoring, and sharable cloud data. This modeling application is a holistic digital representation of the complete characteristics of bridges that encourages the sharing of information throughout the bridges' life critical decisions (Chipman et al. 2016).

The Federal Highway Administration explored the existing BrIM models available in the market (Chipman et al. 2016). Each of the applications were rated based on market interest, certification of application in widely used engineering software, testing tools and files availability, and import/export data options. The three BrIM applications reviewed were LandXML, OpenBrIM, and Industry Foundation Classes (IFC). To evaluate the ease of use of the applications two bridges were used as part of the case study. The following description of the bridges is taken directly from Chipman (Chipman et al. 2016).

- *The first bridge evaluated is Pennsylvania Turnpike - Ramp 1195N over SR 51. This bridge follows a horizontal alignment consisting of circular and straight sections at a constant vertical grade, with varying super-elevation and varying cross-section. It consists of steel framing, with reinforced concrete abutments, piers, and decking.*
- *The second bridge evaluated is the Van White Memorial Overpass in Minneapolis, MN. This bridge follows a horizontal alignment consisting of circular and straight sections with a parabolic vertical curve, with varying super-elevation and constant cross section. It consists*

of a reinforced concrete box girder, abutments, and piers. As this bridge is situated in an urban area, it consists of decorative railings, walkways, and lighting, and makes use of geometry consisting of curved surfaces that cannot be described by polygons alone but requires B-Spline surfaces and Constructive Solid Geometry (CSG).

The first step to evaluate was the modeling process in the applications. The difficulty of use as well as the time taken to model the bridges were the main focus in the step. It is common for models to be more time-consuming in the last details, however the layout of the bridge components i.e. girders and deck took several days to model. Another finding was the more complex a bridge, the more tedious of a task. Large model files were also a disadvantage, foreshadowing an elongated processing time in the next steps. After modeling from scratch, it was found that some BrIM applications such as IFC and OpenBrIM had example bridge models, which facilitated the modeling of new bridges with similar characteristics.

The second step was the importing of the application file into existing software such as Autodesk Revit. The importance factor in this step was the acceptance of the type of file created in the BrIM application of choice for easy import.

IFC was the best overall as it is the most accepted by vendors software developers followed by LandXML and OpenBrIM, respectively. IFC's open file format and vendor validation and certification influenced the results. It started by modeling building details during its design, construction, and maintenance phase (Chipman et al. 2016). However, it may be used for bridge modeling as well, according to the FHWA. The only limitation viewed in using IFC was lack of positioning physical elements relative to alignment curves (Chipman et al. 2016). The two example bridges modeled from the case study, a steel and a concrete box girder bridge, can be viewed in the IFC's Building Smart Alliance website. A continuing effort of expanding the interoperability throughout software vendors and the transportation community is in process.

Data Management and Preparation

This chapter presents issues surrounding the organization, management, and manipulation of bridge data in support of the development of a robust framework for bridge management. An ontology of bridge data is developed in order to map out and understand the opportunities for integrating different sources of information into bridge management practice. A tool was developed for organizing and querying the NBI data which ties together data at the bridge level across all years of data availability. Finally, a discussion of the treatment and importance of explanatory variables is provided.

Development of an Ontology of Bridge Data

An ontology is a conceptual mapping of the relationships between concepts in a specific domain. In order to facilitate inclusion of uncommon and novel data sources in bridge management, it is critical to understand what types of data exist, the characteristics of that data, and how it is related to other data. Based on a review of the literature, the following data sources were identified and discussed in Chapter 2:

- National Bridge Inventory
- National Bridge Element
- Plans and Construction Documents
- Maintenance Records
- Finite Element Models
- Nondestructive Testing
- Structural Testing
- Structural Health Monitoring
- High Resolution Images
- Crowdsourced Data

Several critical characteristics of bridge data are proposed. These characteristics are as follows:

- Qualitative versus quantitative: Is the data based on a subjective opinion or a measurement of some kind?
- Discrete versus continuous – temporal: Does the data describe the bridge at a single point in time, or is the data continuous over time?
- Discrete versus continuous - spatial: Does the data describe large portions of the or the entire structure, or single points on the structure?
- Static versus dynamic: Does the data vary with time, or does it describe a time invariant characteristic?
- Real versus synthetic: Is the data generated using a model or other synthetic approach, or is it measured/taken based on the real structure?

The ontology is presented in a series of tables which map the sources to their key characteristics and establish relationships between data sources. Table 4 shows the categories of data versus the key characteristics listed above. Table 5 shows a mapping of the data sources identifying relationships between disparate sources. From the ontology it is readily apparent that the National Bridge Inventory data is critical to collecting other streams of data. It is the foundational layer of information on which all of the data sources in the ontology are built.

Table 4 - Bridge Data Ontology: Key Characteristics

Data Source	Data Type: Qualitative or Quantitative?	Temporal Condition: Discrete or Continuous?	Spatial Distribution: Partial or Complete?	Consistency: Static or Dynamic?	Provenance: Real or Synthetic?
National Bridge Inventory	Both; Condition data is qualitative	Discrete, but updated every year	Complete at bridge level	Both	Real
National Bridge Element	Both; Qualitative assessments are quantified	Discrete, but updated every year	Complete at element level	Both	Real
Plans and Construction Documents	Quantitative	Discrete	Complete	Static	Real
Maintenance Records	Both	Discrete	Complete	Static, but grows over time	Real
Finite Element Models	Quantitative	Discrete, but can represent different points in time	Complete	Dynamic	Synthetic
Nondestructive Testing	Quantitative	Discrete	Partial	Static, but will change between applications	Real
Structural Testing	Quantitative	Discrete	Partial	Static, but will change between applications	Real
Structural Health Monitoring	Quantitative	Continuous	Partial	Static unless system configuration is changed	Real
High Resolution Images	Quantitative	Discrete	Both	Static, but will change between applications	Real
Crowdsourced Data	Qualitative	Discrete	Partial	Dynamic	Both

Table 5 - Bridge Data Ontology: Relationships Between Data

National Bridge Inventory										
National Bridge Element	FHWA formula for relating components to elements									
Plans and Construction Documents	Static data in NBI from plans	Static data in NBE from plans								
Maintenance Records	Condition rating increases can be explained by mtaintenance	NBE drives mainteance actions	Plans used to guide maintenance							
Finite Element Models	Can be used to inform model construction but much information is missing	Can be used to inform model construction but some information is missing	Critical for Model Construction	Maintenance can be critical for support condition modeling						
Nondestructive Testing	NBI can help identify structures for NDE	NBE can help identify structures for NDE	Plans are crtiical for interpreting NDE	Maintenance can be critical interpreting NDE data	FE is critical for interpreting data					
Structural Testing	NBI can help identify structures for testing	NBE can help identify structures for testing	Plans are critical for designing a test	Maintenance can provide context to changes between structural tests	FE is critical for interpreting data	NDE often explains testing observations				
Structural Health Monitoring	NBI can help identify structures for SHM	NBE can help identify structures for SHM	Plans are critical for designing an SHM system	Records can provide context to observed changes in baseline	FE is critical for interpreting data	NDE often explains monitoring observations	SHM is structural testing over time			
High Resolution Images	NA	Some researchers are quantifying deterioration with images	Plans provide context for images	NA	Photos provide excellent reference for modeling decisions	With advanced processing techniques, images are a type of NDE	Images are important for post-processing of data	Images are important for post-processing of data		
Crowdsourced Data	Often used for news stories	NA	NA	NA	NA	NA	NA	NA	NA	
Data Source	National Bridge Inventory	National Bridge Element	Plans and Construction Documents	Maintenance Records	Finite Element Models	Nondestructive Testing	Structural Testing	Structural Health Monitoring	High Resolution Images	Crowdsourced Data

NBI Query Tool

The Federal Highway Administration hosts the NBI data on their website (FHWA 2019). The NBI data is available from 1992 through 2018 in ASCII format. Each year is broken down by state. In recent years, files were available as delimited or non-delimited, though this practice began in the past ten years. In order to operate on the full available of historical NBI data for the United States, a few key challenges must be overcome.

1. Managing the 1404 individual text files in which the data is contained
2. Non-unique bridge identification numbers across states
3. Manually connecting bridges across years accurately
4. Adding and removing bridges from the database as they come into or go out of service
5. Flexibility required for searching bridges.

The solution created was a script developed in Python (Python 2019) that segments the NBI data by property. The NBI data contains up to 120 items in 445 characters per bridge. These properties can all be used to search and filter the bridges. Some typical search capabilities built into the query tool are:

- Latitude and Longitude of bridges are used in a radial search based on a specific coordinate
- Inequalities and intervals can be searched for numeric quantities
- Classifications like bridge material, age, etc.

The query algorithm begins by iterating over every file. The items of each bridge in each file are compared to the query criteria. The bridge is considered a match if all of the items for which criteria is specified match at least one of the specified criteria. Matching bridges are appended to a 3-dimensional tensor, whose coordinates can be denoted as x, y, and z. Each x of the tensor represents a bridge, and each y represents an item. The z coordinate represents time and navigating along this coordinate is representative of inspecting the time history of a bridge. When a structure number matches across different files, each year's data for that bridge is placed chronologically along the z coordinate of the tensor. This creates a time history for each bridge.

Coordinate algorithm:

The coordinate algorithm searches for bridges within a certain radius of a specified coordinate using spherical distance. This is the only search criteria which is not based on specific data already included in the NBI data files and requires a subsequent calculation, detailed below:

$$distance = a \times r \qquad \text{Eq. } 18$$

where:

$r = Earth's\, radius$

$a = cos^{-1}(sin\varphi_1) \cdot sin\varphi_2 \cdot cos(\theta_1 - \theta_2) + cos\varphi_1 \cdot cos\varphi_2$

$\varphi_1 = 90 - epicenter_x$

$\varphi_2 = 90 - point_x$

$\theta_1 = epicenter_y$

$\theta_2 = point_y$

The NBI query tool is available for use and improvement on GitHub at https://github.com/PASS-Lab/MMDM/blob/master/QueryNBI.py.

Importance of Explanatory Variables

The bridge deterioration modeling processes explored in Chapter 2 were all dependent on identification of what is known as explanatory variables. These variables are characteristics of a population of bridges which are hypothesized to tie the performance of those bridges together, and allow one make assumptions about past data at the population level in order to make future predictions. Bridges are classified with explanatory variables in order to develop deterioration models.

Morcous classified concrete bridge decks in Quebec, Canada with explanatory variables including functionality, location, average daily traffic, percentage of truck traffic, and environments (Morcous, Lounis, and Mirza 2003). Wellalage grouped railway bridges in Australia by explanatory variables including structure material, number of tacks, average ton passed per week, element type, environments, and span length (Wellalage, Zhang, and Dwight 2014). Agrawal classified bridge elements in New York State, U.S.A. based on explanatory variables including design type, location, structure material, ownership, annual average daily truck traffic, deicing salt usage, snow accumulation, environments, and functionality (Agrawal and Kawaguchi 2009). Huang identified 11 explanatory variables statistically relevant to concrete bridge deck deterioration in Wisconsin by using the ANN approach, a pattern classification problem (Huang 2010). The explanatory variables included maintenance history, age, previous condition, district, design load, structure length, deck dimension, average daily traffic, skew, number of spans, and environments. Table 6 summarizes explanatory variables based on application.

Table 6. Explanatory variables applied on bridge deterioration modeling

Application	**Explanatory variables**
Bridge elements	• Design type, • Location, • Structure material, • Ownership, • Annual average daily truck traffic, • Deicing salt usage, • Snow accumulation, • Environments, and • Functionality
Bridge components	• Functionality, • Location, • Average daily traffic, • Percentage of truck traffic, • Maintenance history, • Age, • Previous condition, • District, • Design load, • Structure length, • Deck dimension, • Skew, • Number of spans, and • Environments
Railway bridge components	• Structure material, • Number of tacks, • Average ton passed per week, • Element type,

	• Environments, and • Span length

In each case, there was no explicit analysis that led to decision to pick explanatory variables beyond engineering judgment and experience. However, the Federal Highway Administration Long-Term Bridge Performance program explicitly noted that bridge decoupling performance and identifying causal relationships was one of the primary challenges to improving bridge performance. The following is taken from the FHWA LTBP Bridge Performance Primer (Hooks and Frangopol 2013):

> *Experience has shown the performance of any specific bridge is dependent on complex interactions of multiple factors, many of which are closely linked and include the following:*
>
> - *Original design parameters and specifications, such as bridge type, materials of construction, geometry, and load capacity.*
> - *Initial quality of materials and of the as-built construction.*
> - *Varying environmental conditions of climate and air quality, marine environment, or even surrounding soil.*
> - *Incidence of corrosion or other deterioration processes.*
> - *Traffic volumes and frequency and weight of truck traffic carried by the structure.*
> - *Types, frequency, and effectiveness of bridge preservation, preventive maintenance, rehabilitation, and/or replacement actions.*
>
> *All of these factors combine to affect the condition and operational capacities of the bridge and its various structural elements at any given point in the life of the bridge. Measures such as those mentioned above can be used to evaluate the overall performance of a bridge or a group of bridges under different service*

conditions. Researchers hope to show the qualitative or quantitative impact of a parameter or set of parameters on some specific aspect of bridge performance.

Of the factors listed above, original design parameters, environmental conditions, and traffic effects are often included in explanatory variables for deterioration modeling. And yet, these factors are clearly influencing deterioration (as one major aspect of bridge performance) in indistinguishable manners. Disambiguating these factors to establish causal relationships was an overarching goal of this project that was not achieved.

For the purposes of studying deterioration models, a set of explanatory variables was selected with the implicit acceptance that one or more variables may have been missed, or bridges that would provide value for deterioration predictions may have not been included.

Section 6 presents future work suggestions including a strong need to investigate better approaches to determining explanatory variables.

Single Model Deterioration Modeling Approaches

Data Review and Filtration

Data describing Texas bridges spanning 2000 to 2010 year were collected from the National Bridge Inventory (NBI) database and reviewed. There were over 50,000 bridges in Texas from 2000 to 2010 (Figure 4). In this research, the bridges were grouped by following characteristics.

- Structure material - concrete
- Design type – stringer/multi-beam or girder

Figure 5 shows an example of bridges categorized by structure material. There were 27,154 concrete bridges in 2010. The explanatory variables and data sets were randomly selected, and the environment was assumed to be similar throughout the state. The data were paired with two consecutive inspection periods, set A (2000 and 2002 year), set B (2004 and 2006 year), and set C (2008 and 2010 year). There were two reasons for pairing data. The first reason was to check whether a bridge was subject to the MR&R activities. If there is an increase of condition rating, the component might be repaired. All models applied to estimate a TPM are based on "do nothing" condition, which there are no MR&R activities on bridges. The second reason was that some models required bridges to be divided by condition rating groups. According to the Markovian property, the 2002, 2006, and 2010 data were considered as the present data and using the 2000, 2004, and 2008 data, the bridges were grouped in this research. Figure 6 shows an example of bridge decks according to condition rating groups. There are 624 and 2,780 out of 3,887 decks in condition rating 8 and 7 respectively in 2008. The three data sets were used to check the consistencies of transition probability matrices and deterioration curves between different data sets. The reconstructed bridges were filtered if their condition ratings were not 9. These bridges were considered to be subject to the MR&R activities, not considered as new bridges. The bridges more than 60 years were eliminated. Their condition ratings were 7 or 8, so they could be maintained or repaired. After this bridge level filtering, the data were filtered in component level to check each component to be subject to the MR&R activities. The bridge components were eliminated if they showed any in condition rating within two consecutive inspection periods. Figure 7 shows total number of bridges before filtering and number of bridge components after filtering.

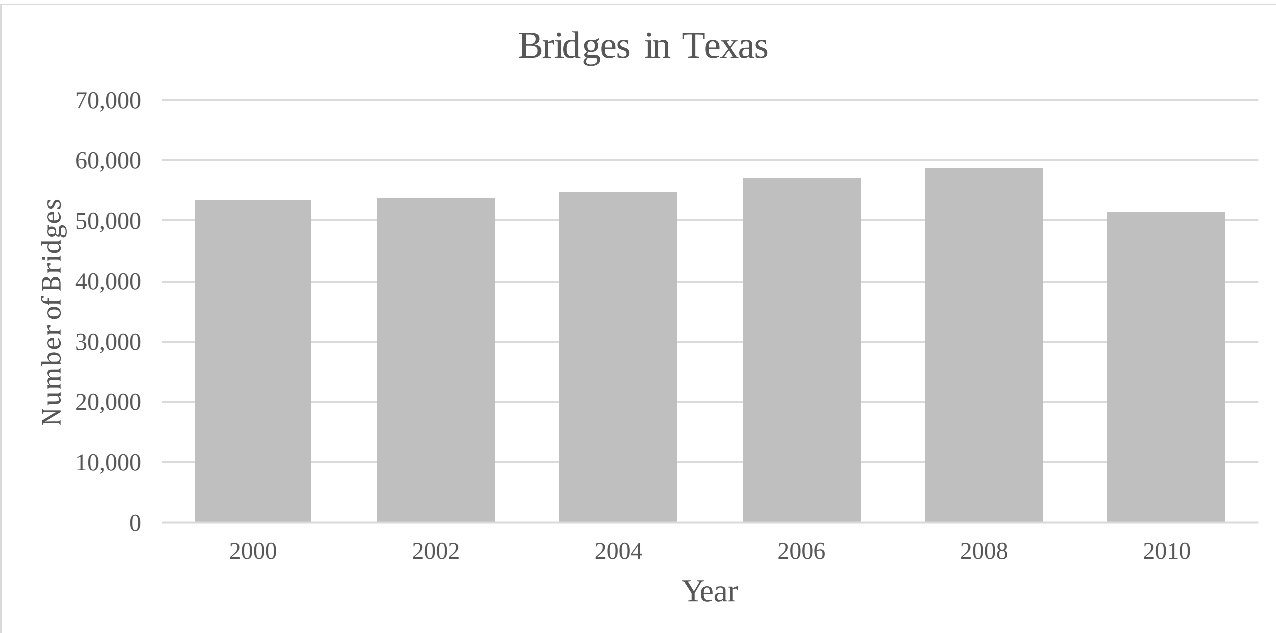

Figure 4. Total number of bridges in Texas from 2000 to 2010

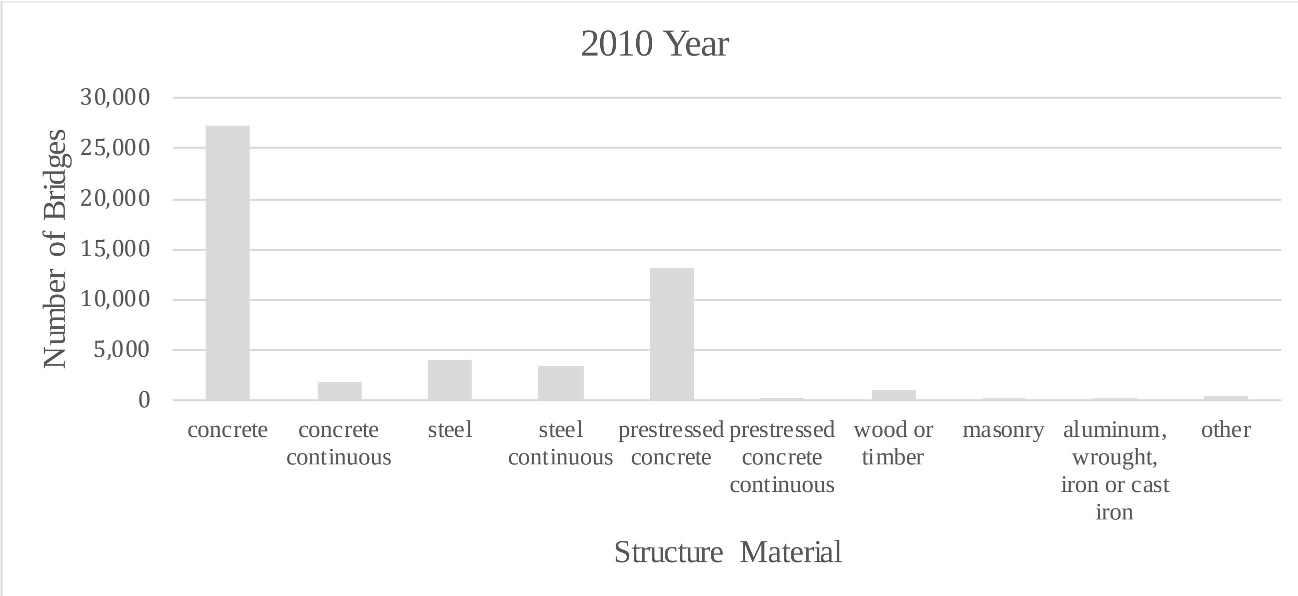

Figure 5. Number of bridges according to structure material

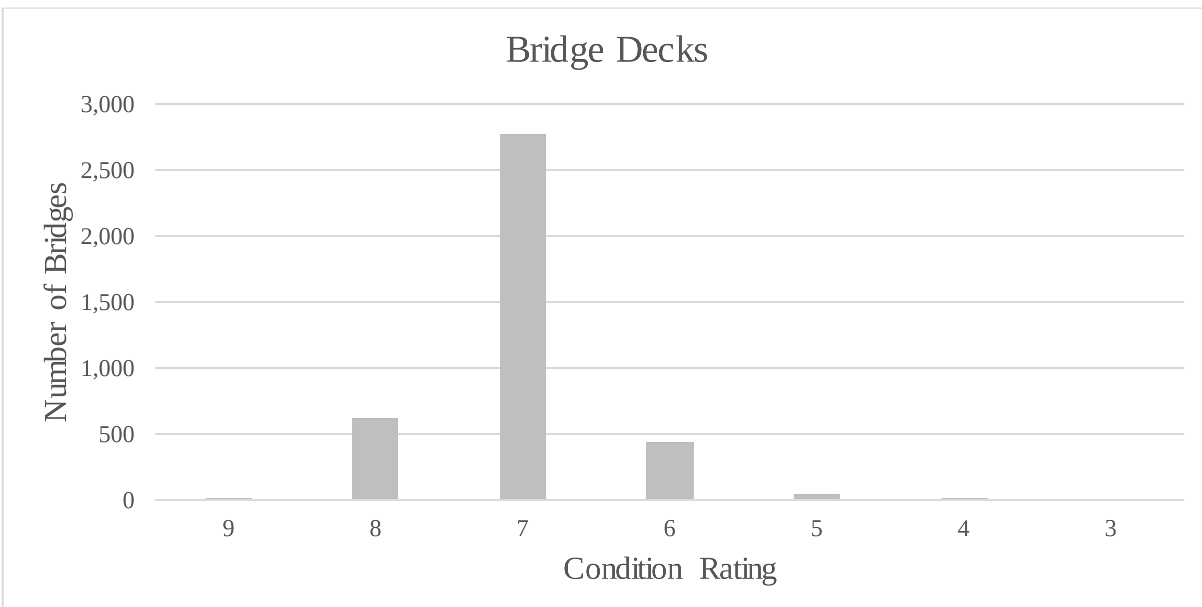

Figure 6. Number of bridge decks in 2008 by condition rating groups

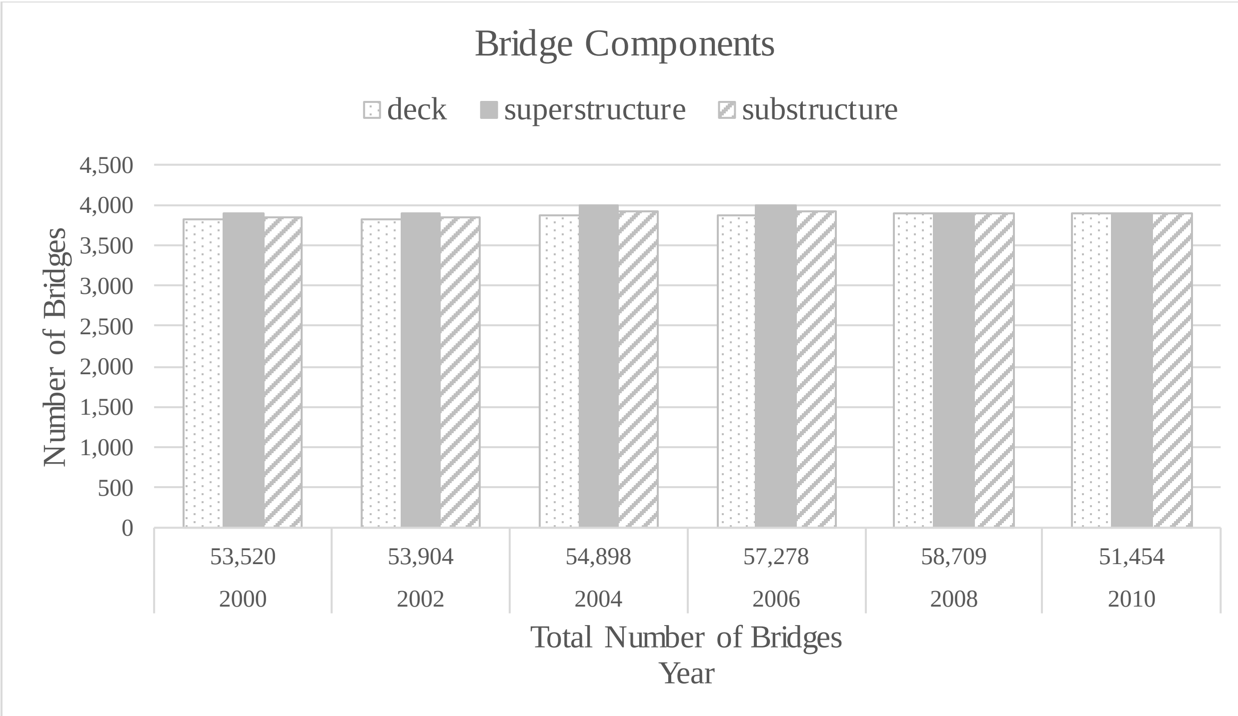

Figure 7. Number of bridge components after filtering

Regression Nonlinear Optimization (RNO)

In RNO method, a transition probability matrix can be estimated by minimizing the absolute difference between the averaged actual condition rating at age, *t* and the estimated condition rating for the corresponding age obtained by the Markovian process. $S(t)$ is a third order polynomial which is the best fit to actual data. The formula of objective function is (Jiang et al. 1988):

$$min \sum_{t=1}^{T} |S(t) - E(t,P)| \qquad \text{Eq. 19}$$

$$S(t) = A + Bt + Ct^2 + Dt^3 \qquad \text{Eq. 20}$$

$$E(t,P) = Q_0 \times P^t \times R \qquad \text{Eq. 21}$$

where:

T = the largest age of the bridge in a data set;

$S(t)$ = the average condition rating at time, t;

$E(t,P)$ = the expected value;

Q_0 = the initial condition state, [1 0 0 0 0 0 0];

P^t = TPM at any time, t;

R = the condition rating, [9 8 7 6 5 4 3].

The coefficients were obtained by using curve fitting tool in Matlab with 2010 data shown in Table 7. These values were substituted Eq. 20 and it was used to estimate transition probabilities. Table 8 presents the estimated TPMs of bridge components. The transition probability of staying the same in condition rating 5 is 0.49. It is lower than the values for the superstructure and substructure, 0.95 and 0.94 respectively. In Figure 8, the condition rating of bridge components computed by Eq. 21 were plotted as a function of age. The plot shows three lines. Each line depicts a deterioration rate of bride deck (solid line), superstructure (dash line), and substructure (dot line). The deterioration rates of all three components are similar up to about 30 years. The substructure deteriorates faster after 30 years.

Table 7. Coefficients of third order polynomials of bridge components with 2010 data

Components	A	B	C	D
Deck	9	-0.1860	0.005189	-0.00004650
Superstructure	9	-0.2065	0.006108	-0.00005857
Substructure	9	-0.1999	0.005767	-0.00005714

Table 8. Transition probability matrices of bridge components using RNO

Deck	$P = \begin{bmatrix} 0.84 & 0.16 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.78 & 0.22 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.49 & 0.51 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.56 & 0.44 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Superstructure	$P = \begin{bmatrix} 0.82 & 0.18 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.75 & 0.25 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.99 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.95 & 0.05 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.90 & 0.10 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Substructure	$P = \begin{bmatrix} 0.83 & 0.17 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.77 & 0.23 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.97 & 0.03 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.94 & 0.06 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.88 & 0.12 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

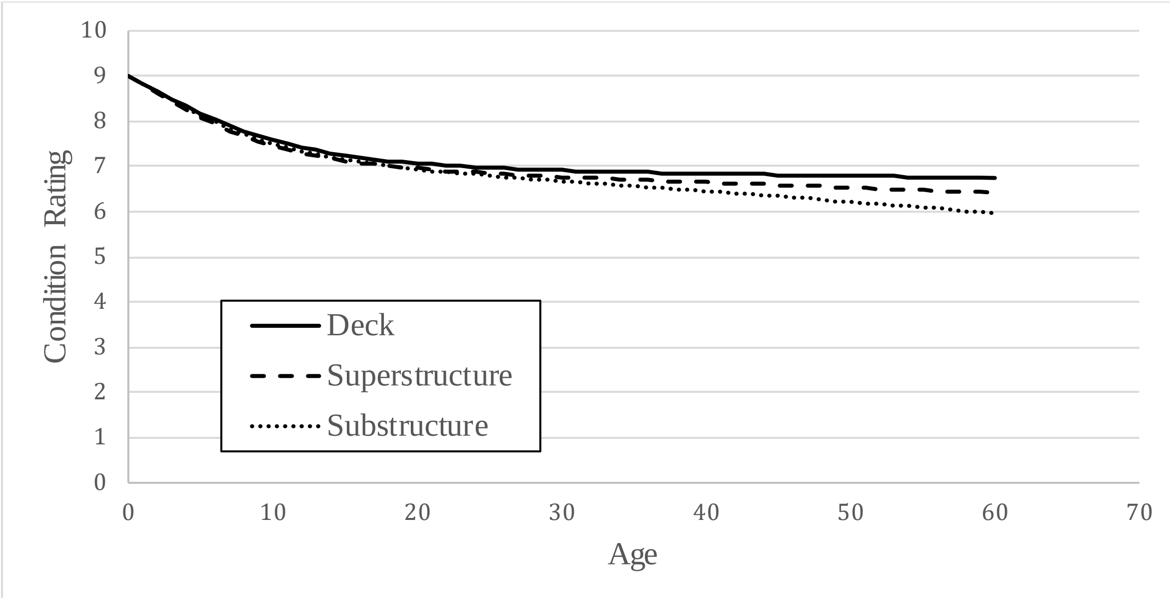

Figure 8. Deterioration rate curves estimated using RNO with 2010 data

Bayesian Maximum Likelihood (BML)

From Bayesian theorem the conditional distribution of θ (an unknown variable set) given by Y (a known data set of bridge condition ratings) is following

$$P(\theta|Y) \propto P(\theta)L(Y|\theta) \qquad \text{Eq. 22}$$

where $P(\theta|Y)$, $P(\theta)$, and $L(Y|\theta)$ are called a target distribution, prior distribution, and likelihood distribution respectively. From Bayes-Laplace "principle of insufficient reason" prior distribution, $P(\theta)$ can be assumed to be a uniform distribution. Therefore, the target distribution can be proportional to the likelihood distribution (Wellalage, Zhang, and Dwight 2014). From the joint probability theory, the likelihood distribution can be expressed (H. D. Tran 2007).

$$L(Y|\theta) = \prod_{t=1}^{T} \prod_{i=1}^{9} (C_{it})^{N_i^t} \qquad \text{Eq. 23}$$

For easy computation the distribution function can be transformed into logarithm likelihood function as follows:

$$log[L(Y|\theta)] = \sum_{t=1}^{T} \sum_{i=1}^{9} N_i^t \, log(C_{it}) \qquad \text{Eq. 24}$$

where T is the largest age in the data set, N_i^t is the number of bridge components in condition state i at year t, and C_{it} is the probability of condition state i at year t. Since only transition probabilities, C_{it} are random variables, a vector of transition probabilities, C_{it} can be obtained by maximizing log likelihood function, $log[L(Y|\theta)]$.

$$C_{it} = [C_{9t} \; C_{8t} \; C_{7t} \; C_{6t} \; C_{5t} \; C_{4t}] \qquad \text{Eq. 25}$$

Table 9 presents the transition probability matrices of bridge deck, superstructure, and substructure. Figure 9 describes the deterioration rate curves of bridge deck (solid line), superstructure (dash line), and substructure (dot line) estimated by using Eq. 10. Up to 20 years the superstructure deteriorates faster than other components and after 20 years the substructure deteriorates faster than other components.

Table 9. Transition probability matrices of bridge components using BML

Deck	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.93 & 0.07 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.99 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Superstructure	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.80 & 0.20 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.99 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Substructure	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.90 & 0.10 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.98 & 0.02 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.99 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.99 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.99 & 0.01 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

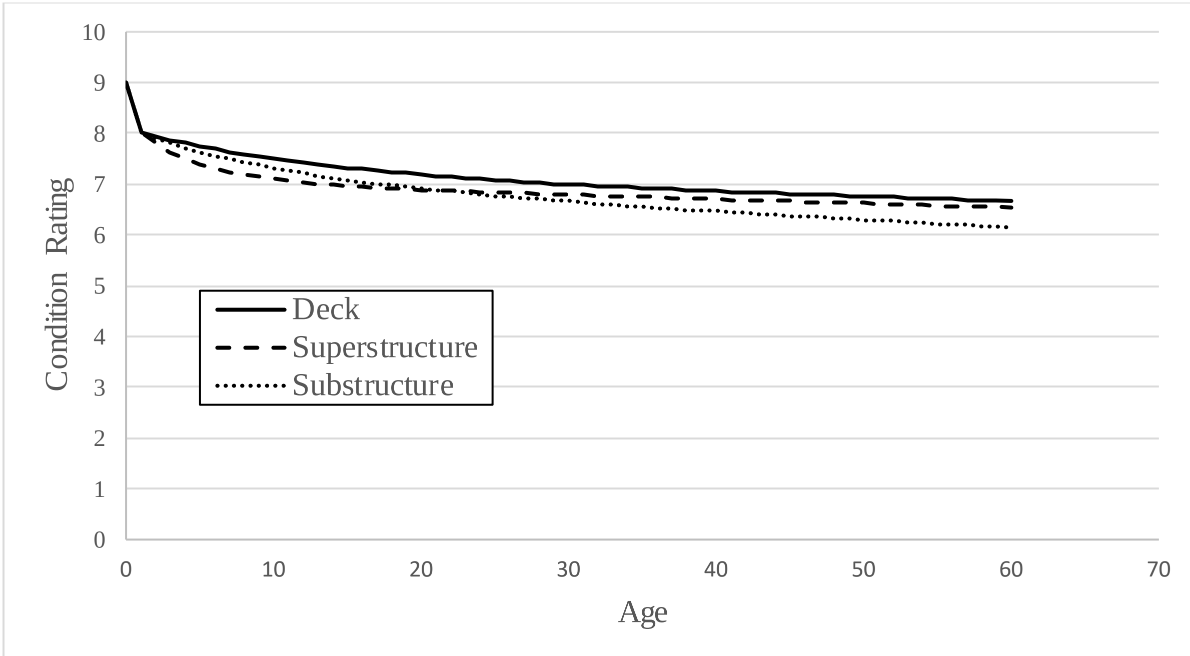

Figure 9. Deterioration rate curves estimated using BML with 2010 data

Ordered Probit Model (OPM)

The ordered probit model is used to model unobservable features of the population in social sciences. The facility deterioration is unobservable. However, the model can encapsulate it based on the assumption of being a constant unobservable variable. An incremental deterioration model can be generated from the observed condition rating as an "indicator" of the unobserved deterioration. The variable, Z_n is the number of transitions of condition state of bridge n between two successive inspection periods. It is assumed that the deterioration is constant within the same condition rating group, and each group has different deterioration mechanism. Therefore, a different deterioration model is needed for each condition rating group. Madanat categorized the deterioration process of bridge decks into two steps (Madanat and Ibrahim 2002). The transitions from condition rating 9 to 7 were determined by the change of the electrical potential intensity and the chloride content amount. The transition from condition rating 6 to 5 is determined by the amount of spall of concrete. Based on the deterioration process of reinforced concrete defined by Hu and Nickless, the first step is related to the phase from corrosion initiation to cracking initiation

(Hu, Haider, and Jansson 2013; Nickless and Atadero 2017). The second step is related to the phase of cracking propagation to the surface. The unobserved deterioration of bridge, n in given condition state, i, U_{in} can be expressed as a function of explanatory variable, X_n.

$$log(U_{in}) = \beta_i' X_n + \varepsilon_{in} \qquad \text{Eq. 26}$$

where β_i' is a set of parameters in condition state i, X_n is a set of explanatory variables for bridge n; ε_{in} is an error term (Madanat and Ibrahim 2002). Figure 10 illustrates the ordered probit model that Trans applied this model to estimate TPM of storm water pipe deterioration in Australia (H. D. Tran 2007). The deterioration is plotted as function of time. The deterioration curve, Z_i consists of two parts, deterministic ($\beta_i' X_n$) and random (ε_{in}) parts. θ_1 and θ_2 are thresholds and 1, 2, and 3 indicate condition states (1 is corresponding to condition rating 9 in NBI).

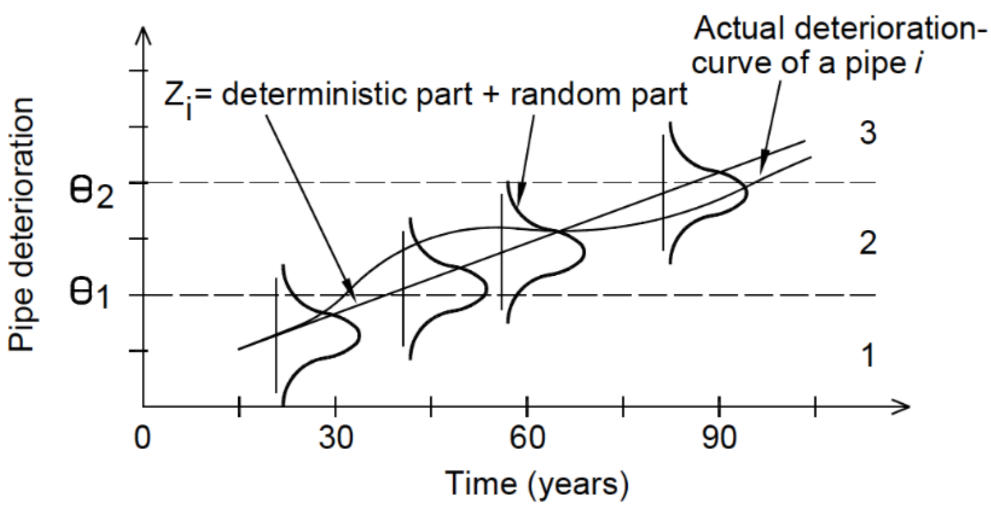

Figure 10. Schematic illustrating the Ordered Probit Model (H. D. Tran 2007)

Since U_{in} is unobservable, the relationship can be expressed by using Z_{in} and between two thresholds, γ_{ij} and $\gamma_{i(j+1)}$ as follows (Madanat, Mishalani, and Ibrahim 2002):

$$Z_{in} = j \; if \; \gamma_{ij} \leq U_{in} < \gamma_{i(j+1)};$$ Eq. 27

$$Z_{in} = j \; if \; \; log\,\gamma_{ij} - \beta_i' X_n \leq \varepsilon_{in} < log\,\gamma_{i(j+1)} - \beta_i' X_n;$$ Eq. 28

for j = 0, …, i. Based on the assumption that ε_{in} is a normal cumulative distribution, $F(\varepsilon_{in})$, the transition probability from condition state i to condition state i-j for a bridge in an inspection period can be written as follows (Madanat, Mishalani, and Ibrahim 2002):

$$p(Z_{in} = j) = F\left(\delta_{i(j+1)} - \beta_i X_n\right) - F(\delta_{ij} - \beta_i X_n)$$ Eq. 29

where $\delta_{ij} = log\gamma_{ij}$. The parameter β_i and thresholds $\gamma_{i1}, \gamma_{i2}, \ldots, \gamma_{ii}$ can be obtained by optimizing the logarithm objective function as follows (Madanat, Mishalani, and Ibrahim 2002):

$$L_i^* = \prod_{n=1}^{N_i} \prod_{j=0}^{i-1} p(Z_{in} = j)^{d_{nj}}$$ Eq. 30

$$log(L_i^*) = \sum_{n=1}^{N_i} \sum_{j=0}^{i-1} d_{nj} log[p(Z_{in} = j)]$$ Eq. 31

where:

L_i^* is the likelihood function of the ordered probit model for condition state i

N_i is total number of bridges in condition state i in the data set

d_{nj} is equal to 1 if $Z_{in} = j$, and 0 otherwise.

After the parameter and thresholds are obtained, the transition probabilities, $\hat{p}(j|X_n, i)$ for each bridge can be computed as follows (Madanat, Mishalani, and Ibrahim 2002):

$$\hat{p}(j=0|X_n,i) = F(\delta_{i1} - \hat{\beta}_i' X_n)$$
$$\hat{p}(j=1|X_n,i) = F(\delta_{i2} - \hat{\beta}_i' X_n) - F(\delta_{i1} - \hat{\beta}_i' X_n)$$
$$\hat{p}(j=2|X_n,i) = F(\delta_{i3} - \hat{\beta}_i' X_n) - F(\delta_{i2} - \hat{\beta}_i' X_n)$$
$$\vdots$$
$$\hat{p}(j=i|X_n,i) = 1 - F(\delta_{ii} - \hat{\beta}_i' X_n) \qquad \text{Eq. 32}$$

for j = 0, 1, 2, …, i. Then the probabilities of each bridge are grouped to estimate the mean value of transition probabilities, $\hat{p}^g_{i(i-j)}$ as follows (Madanat, Mishalani, and Ibrahim 2002):

$$\hat{p}^g_{i(i-j)} = \frac{1}{N_g}\sum_{n=1}^{N_g} \hat{p}(j|X_n,i)\,;\, j = 0,\dots,i;\, g = 1,\dots,G \qquad \text{Eq. 33}$$

where N_g is the total number of bridges in group g and G is the total number of groups (Madanat, Mishalani, and Ibrahim 2002).

The parameters, δ and β of bridge components with 2008-2010 data according to condition rating groups were obtained by optimizing the log likelihood function. Table 10 shows the values of parameters of bridge deck Table 11 presents estimated transition probability matrices of deck, superstructure, and substructure and Figure 11 shows the deterioration rate curves of deck (solid line), superstructure (dash line), and substructure (dot line) with 2008-2010 data. The substructure deteriorates slower than other components up to 20 years, and then it deteriorates faster than other components.

Table 10. Parameters, δ and β of bridge deck with 2008-2010 data

Condition Rating Group	β	δ_1	δ_2	δ_3
$i = 9$	-1.41E-06	-5.88E+00	-2.37E-06	5.46E+00
$i = 8$	1.25E-02	6.77E-01	2.73E+00	7.44E+00
$i = 7$	9.21E-03	1.99E+00	3.25E+00	6.84E+00
$i = 6$	-6.93E-03	1.35E+00	7.03E+00	3.00E+00
$i = 5$	4.84E-02	4.23E+00	9.32E+00	3.00E+00
$i = 4$	-2.40E+03	4.91E+01	2.00E+00	3.00E+00

Table 11. Transition probability matrices of bridge components using OPM

Deck	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.71 & 0.29 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Superstructure	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.53 & 0.47 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Substructure	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.85 & 0.15 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

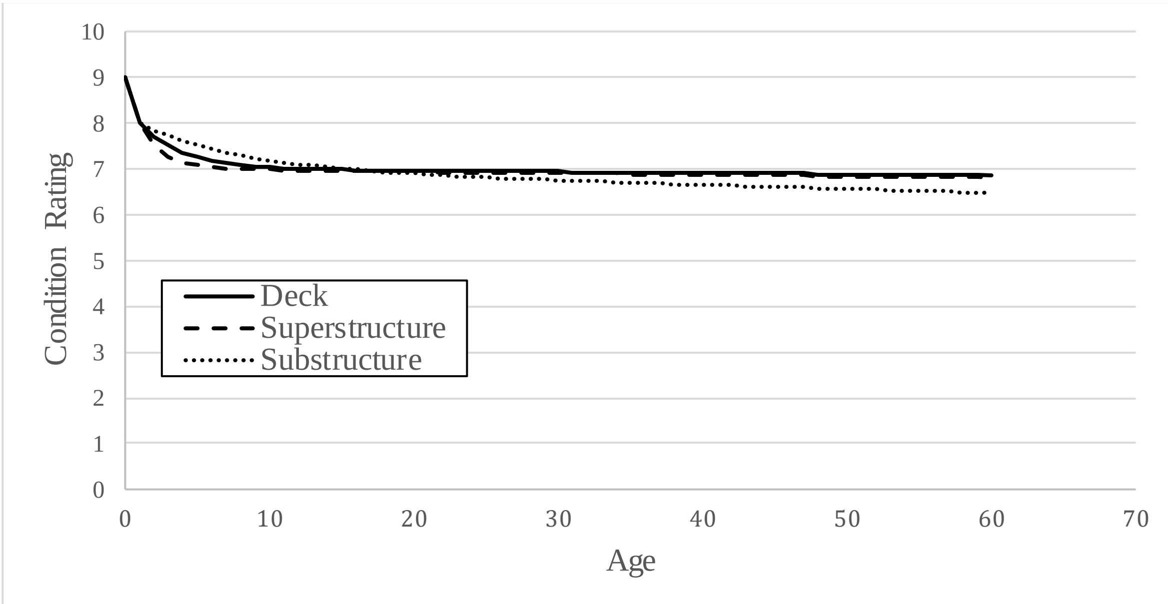

Figure 11. Deterioration rate curves estimated using OPM with 2008-2010 data

Poisson Regression (PR)

The Poisson regression model describes events that occur randomly and independently overtime. Incremental bridge deterioration can be modeled as a function of the number of transitions in an inspection period by using the Poisson Regression method. From the model, transition probabilities of a data set of bridge components/elements can be obtained. Different deterioration models are needed for each condition state because mechanistic deterioration procedures are different. The model estimates the deterioration of a bridge in an inspection period using the change in the condition states between two successive inspections. In a continuous-time Markov process, a deterioration rate is a negative exponential distribution, so the Poisson distribution is applicable for the deterioration model. The Poisson mass function is as follows (Madanat, Mishalani, and Ibrahim 2002):

$$p(Z_{in} = j) = \frac{e^{\lambda_{in}} \lambda_{in}^{j}}{j!}, j = 0,1,2, \dots, i; i = 1,2, \dots, k-1 \qquad \text{Eq. 34}$$

where λ_{in} is a deterioration rate in condition state i; j is the number of transitions in condition state in an inspection period; k is the highest condition state. The deterioration rate, λ_{in} as a function of explanatory variables is as follows (Madanat, Mishalani, and Ibrahim 2002):

$$\lambda_{in} = e^{(\beta X_n)} \qquad \text{Eq. 35}$$

where β is a set of parameters and X_n is a set of explanatory variables for a bridge, n. By optimizing the object function (log of the likelihood distribution), the β_i can be obtained. The likelihood distribution and log of the likelihood are as follows (Madanat, Mishalani, and Ibrahim 2002):

$$L_i^* = \prod_{n=1}^{N_i} \frac{e^{-\lambda_{in}} \lambda_{in}^{Z_{in}}}{Z_{in}!} \qquad \text{Eq. 36}$$

$$log(L_i^*) = \sum_{n=1}^{N_i} -\lambda_{in} + Z_{in}\, log(\lambda_{in}) \qquad \text{Eq. 37}$$

Substitute Eq. 35, then

$$log(L_i^*) = \sum_{n=1}^{N_i} Z_{in}(\beta X_n) - e^{(\beta X_n)} \qquad \text{Eq. 38}$$

Z_{in} is the number of transitions of condition states in an inspection period. It is assumed the maximum value of Z_{in} is equal to i. The transition probabilities for each bridge, n is as follows (Madanat, Mishalani, and Ibrahim 2002):

$$p(Z_{in} = j | X_n, i) = \frac{e^{-\lambda_{in}} \lambda_{in}^{j}}{j!}, j = 0,1,2, \ldots, i \qquad \text{Eq. 39}$$

For network-level, bridges in a data set are grouped into condition states. The average transition probability for each group is computed as follows:

$$p^{g}_{i(i-j)} = \frac{1}{N_g}\sum_{n=1}^{N_g} p(Z_{in} = j|X_n, i)\ , j = 0,1, \dots , i; g = 1, \dots , G \qquad \text{Eq. 40}$$

where N_g is the total number of bridges in group g and G is the total number of facility groups (Madanat, Mishalani, and Ibrahim 2002).

The parameters according to condition rating groups of bridge components were obtained by optimizing the log likelihood function and shown in Table 12. The transition probability matrices for deck, superstructure, and substructure are shown in

Table 13. The deterioration rate curves in Figure 12 show the same pattern with ones estimated by using OPM.

Table 12. Parameter, β of bridge components with 2008-2010 data

Condition Rating Group	Deck	Superstructure	Substructure
$i = 9$	0.240	0.129	0.147
$i = 8$	-0.022	-0.013	-0.037
$i = 7$	-0.087	-0.084	-0.061
$i = 6$	-0.073	-0.075	-0.075
$i = 5$	-0.088	-0.098	-0.107
$i = 4$	-105.126	-250.745	-1026.686

Table 13. Transition probability matrices of bridge components using PR

Deck	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.76 & 0.24 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Superstructure	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.56 & 0.44 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Substructure	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.84 & 0.16 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

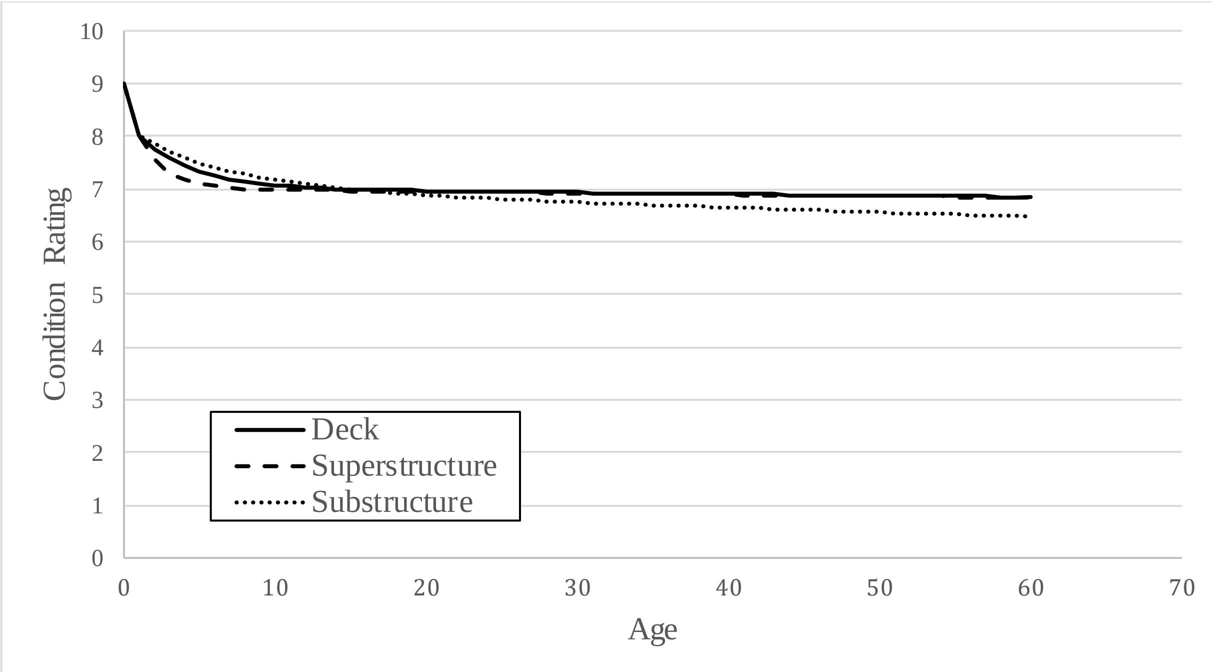

Figure 12. Deterioration rate curves estimated using PR with 2010 data

Negative Binomial Regression (NBR)

In Negative Binomial Regression models, a disturbance term in the parameter of the Poisson distribution was introduced "overdispersion" situation that the variance of data was larger than the mean (Madanat, Mishalani, and Ibrahim 2002). λ^*_{in} is a random variable as a function of explanatory variables:

$$\lambda^*_{in} = e^{(\beta X_n + \varepsilon_n)} \qquad \text{Eq. 41}$$

where ε_n is a random error term. A negative binomial probability distribution is as follows:

$$p(Z_{in} = j) = \frac{\Gamma\left(\frac{1}{\alpha_i} + j\right)}{\Gamma\left(\frac{1}{\alpha_i}\right) j!} \left(\frac{1}{1 + \alpha_1 \lambda^*_{in}}\right)^{1/\alpha_i} \left(1 - \frac{1}{1 + \alpha_i \lambda^*_{in}}\right)^{j} \qquad \text{Eq. 42}$$

where $\Gamma(\ )$ is gamma function, α_i is rate of “overdispersion,” and Z_{in} is the number of transitions of condition states in an inspection period. The likelihood distribution function of the negative binomial for condition state is as follows:

$$L_i^* = \prod_{n=1}^{N_i} \frac{\Gamma\left(\frac{1}{\alpha_i} + Z_{in}\right)}{\Gamma\left(\frac{1}{\alpha_i}\right) Z_{in}!} \left(\frac{1}{1+\alpha_i \lambda_{in}^*}\right)^{1/\alpha_i} \left(1 - \frac{1}{1+\alpha_i \lambda_{in}^*}\right)^{Z_{in}} \qquad \text{Eq. 43}$$

By optimizing the log of the object function, λ_{in}^* and α_i can be estimated.

$$log(L_{in}^*) = \sum_{n=1}^{N_i} log\left(\Gamma\left(\frac{1}{\alpha_i} + Z_{in}\right)\right) - log\left(\Gamma\left(\frac{1}{\alpha_i}\right)\right) - log(Z_{in}!) + \frac{1}{\alpha_i} log\left(\frac{1}{1+\alpha_i \lambda_{in}^*}\right) + Z_{in} log\left(1 - \frac{1}{1+\alpha_i \lambda_{in}^*}\right) \qquad \text{Eq. 44}$$

Transition probabilities of condition states for each bridge can be estimated by applying the obtained parameter to the negative binomial probability distribution function, and a transition probability matrix can be obtained by the same process in the Poisson regression method (Madanat, Mishalani, and Ibrahim 2002).

The parameters according to condition rating groups of bridge components were obtained by optimizing the log likelihood function and shown in Table 14. The transition probability matrices for deck, superstructure, and substructure are shown in Table 15. The deterioration rate curves in Figure 13 show the same pattern with ones estimated by using OPM and PR.

Table 14. Parameters, α and β, of bridge components with 2008-2010 data

Condition Rating Group	α (Deck)	β (Deck)	α (Superstructure)	β (Superstructure)	α (Substructure)	β (Substructure)
$i = 9$	0.01	0.40	0.01	0.13	0.01	0.16
$i = 8$	0.01	-0.02	0.01	-0.01	0.68	-0.03
$i = 7$	15.86	-0.07	18.84	-0.07	6.31	-0.05
$i = 6$	0.91	-0.07	0.07	-0.59	7.16	-0.07
$i = 5$	1.14	-0.62	1.15	-0.62	1.14	-0.62
$i = 4$	1.15	-0.62	1.15	-0.62	1.15	-0.62

Table 15. Transition probability matrices of bridge components using NBR

Deck	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.76 & 0.24 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Superstructure	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.56 & 0.44 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

Substructure	$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.87 & 0.13 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

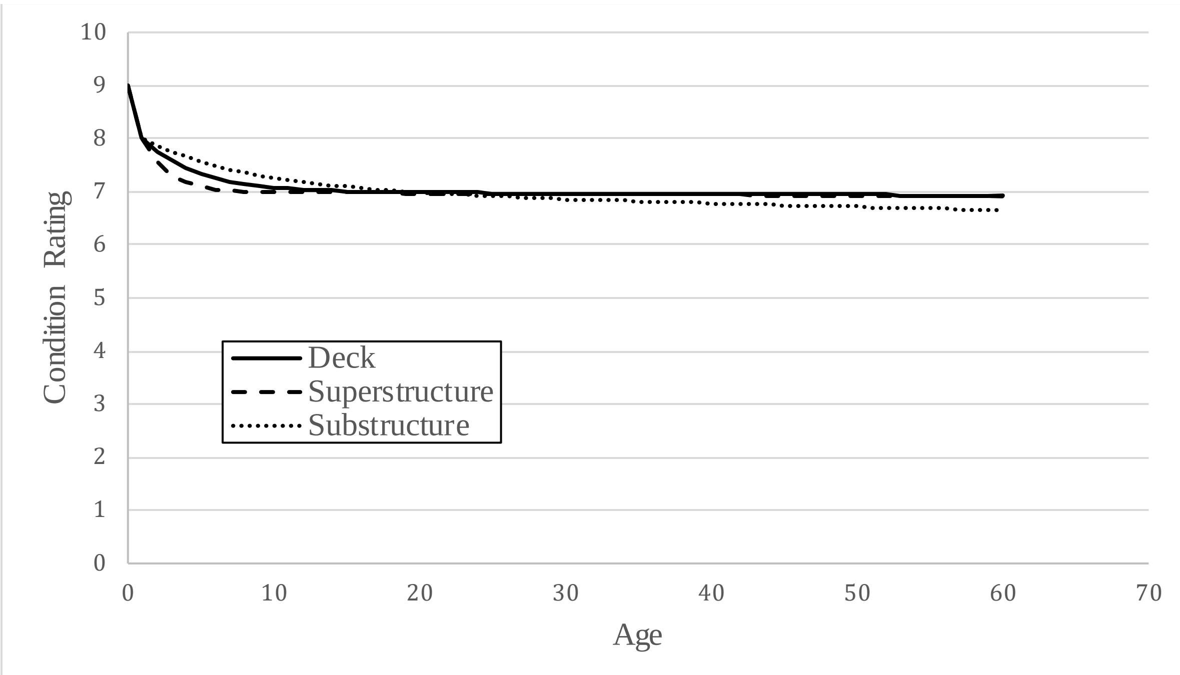

Figure 13. Deterioration rate curves estimated using NBR with 2010 data

Proportional Hazard Model (PHM)

In the proportional hazard model, the effects of explanatory variables can be explicitly expressed as hazard ratio in a transition probability matrix. The example format of a transition probability matrix is following (Cavalline et al. 2015).

$$P = \begin{bmatrix} p_{99}^{HR_9} & 1-p_{99}^{HR_9} & 0 & 0 & 0 & 0 & 0 \\ 0 & p_{88}^{HR_8} & 1-p_{88}^{HR_8} & 0 & 0 & 0 & 0 \\ 0 & 0 & p_{77}^{HR_7} & 1-p_{77}^{HR_7} & 0 & 0 & 0 \\ 0 & 0 & 0 & p_{66}^{HR_6} & 1-p_{66}^{HR_6} & 0 & 0 \\ 0 & 0 & 0 & 0 & p_{55}^{HR_5} & 1-p_{55}^{HR_5} & 0 \\ 0 & 0 & 0 & 0 & 0 & p_{44}^{HR_4} & 1-p_{44}^{HR_4} \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad \text{Eq. 45}$$

where $p_{99}, p_{88}, \ldots, p_{44}$ are transition probabilities and $HR_9, HR_8, \ldots, HR_4$ are hazard ratios.

In the model, the transition probability matrix consists of two parts:

- Transition probabilities that obtained by the simplified Kaplan-Meier method
- Hazard ratios associated with explanatory variables

Transition probabilities and hazard ratios are estimated for each condition state. If a hazard ratio is less than 1, the deterioration process is slower. If a hazard ratio is greater than 1, the deterioration process accelerates.

Hazard Ratio

Hazard rate is the instantaneous rate from a condition state to another condition state. It can be expressed as a function of explanatory variables as follows:

$$h(t,\vec{z}) = h_0(t)e^{\vec{z}\vec{\beta}} = h_0(t)e^{(z_1\beta_1+z_2\beta_2+\cdots+z_n\beta_n)} \quad \text{Eq. 46}$$

$$h(t,\vec{z}) = h_0(t)e^{z_1\beta} \quad \text{Eq. 47}$$

where β is the regression coefficient associated with the hazard rate, z and $h_0(t)$ is the baseline hazard function. Hazard ratio is the ratio of the hazard rates, the relative risk of failure $\big(h(t,1)\big)$ to the value of baseline hazard function $\big(h(t,0)\big)$.

$$HR = \frac{h(t,1)}{h(t,0)} = e^{\beta(1-0)} = e^{\beta} \qquad \text{Eq. 48}$$

Kaplan-Meier Estimator

Kaplan and Meier (KM) method is used to estimate non-parametric cumulative transition probability corresponding to transition times and events, $TP(t_x)$ assumed one-step transition as follows (Archilla, DeStefano, and Grivas 2002):

$$TP(t_x) = 1 - \hat{R}(t_x) \qquad \text{Eq. 49}$$

$$\hat{R}(t_x) = [(r_x - 1)/r_x] \times R_{x-1} \qquad \text{Eq. 50}$$

where $\hat{R}(t_x)$ is the reliability at t_x equal to TT_{ijk}, r_x is order of times observed in a set of data. TT_{ijk} is the time associated with one-step transition of bridge i and component j to condition rating k.

$$TT_{ijk} = \frac{\left[\left(FCR_k - LCR_{k''}\right) + \left(LCR_{k'} - FCR_{k'}\right)\right]_{ij}}{2} \qquad \text{Eq. 51}$$

where $LCR_{k''}$ is last date a component was observed in a prior condition rating k''. $FCR_k/LCR_{k'}$ is first/last date a component was observed in initial condition rating k' (Archilla, DeStefano, and Grivas 2002).

HR ratios of bridge components according to condition rating group show in Table 16. The value less than 1 means that the deterioration rate is smaller than its baseline probability which obtained by Kaplan-Meier estimation. The value equal to 1 means that the probability is the same as its baseline probability. The value greater than 1 means that the deterioration accelerates.

Table 17 presents the estimated TPMs for bridge components. The deterioration rate curves for bridge deck (solid line), superstructure (dash line), and substructure (dot line) are plotted in Figure 14. The superstructure deteriorates faster than other components.

Table 16. Parameter, HR of bridge components with 2008-2010 data

Condition Rating Group	Deck	Superstructure	Substructure
$i = 9$	1.00	0.67	0.50
$i = 8$	1.32	2.01	1.53
$i = 7$	1.13	1.52	1.38
$i = 6$	1.10	1.37	1.03
$i = 5$	0.93	0.61	1.38
$i = 4$	1.00	1.00	1.00

Table 17. Transition probability matrices of bridge components using PHM

Deck	$P = \begin{bmatrix} 0.50 & 0.50 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.97 & 0.03 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.97 & 0.03 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.93 & 0.07 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Superstructure	$P = \begin{bmatrix} 0.63 & 0.37 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.91 & 0.09 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.96 & 0.04 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.90 & 0.10 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.80 & 0.20 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

Substructure	$P = \begin{bmatrix} 0.71 & 0.29 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.96 & 0.04 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.97 & 0.03 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.96 & 0.04 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.95 & 0.05 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

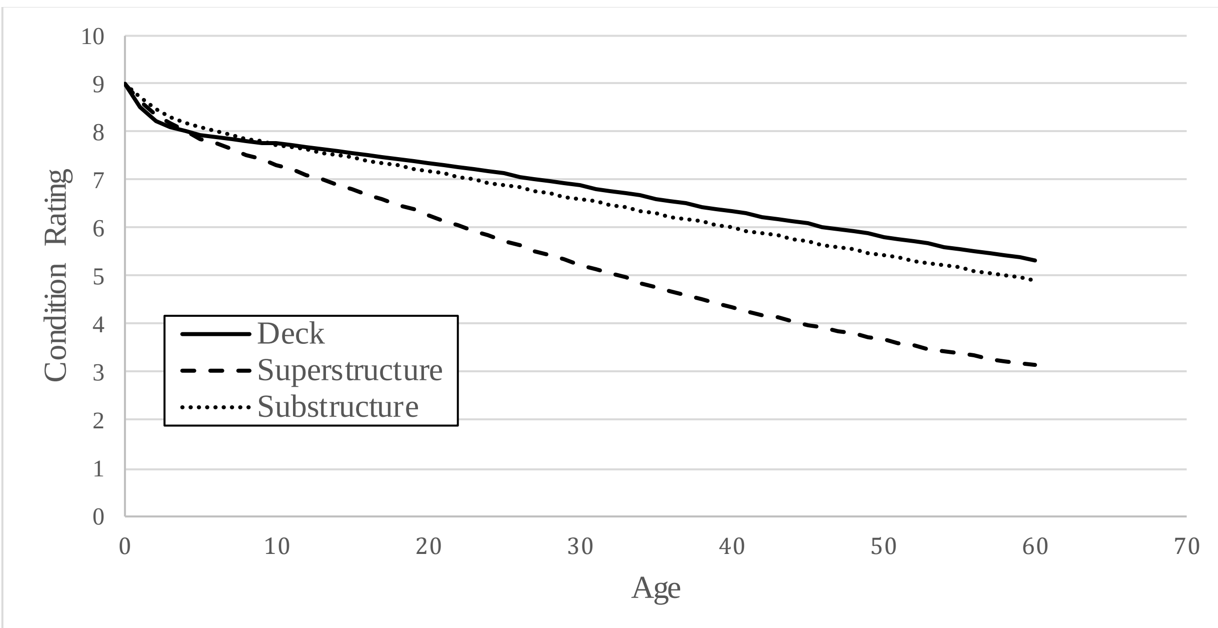

Figure 14. Deterioration rate curves estimated using PHM with 2010 data

Semi-Markov Model

A semi-Markov model of the bridge deterioration is different than other models mentioned above. In the other models, time is not explicitly expressed in computation of transition probabilities. However, in a semi-Markov model, transition probability function is a function of time. In this research, a semi-Markov process followed a model formulated and developed by J. O. Sobanjo, (2011).

At any time t, the transition probability $p_{ik}(t,\Delta)$ out of a state i into any lower condition state, k within a period Δ after time t, is following.

$$p_{ik}(t,\Delta) = \frac{F_i(t+\Delta) - F_i(t)}{S_i(t)} \qquad \text{Eq. 52}$$

where $\mathrm{F_i}(\mathrm{t})$ is the cumulative distribution function of a probability distribution function, $f_i(t)$ in state i and $\mathrm{S_i}(\mathrm{t})$ is the survivor function in state i. Therefore,

$$p_{ik}(t,\Delta) = 1 - \frac{S_i(t+\Delta)}{S_i(t)} \qquad \text{Eq. 53}$$

The probability of staying the same condition state i is following

$$p_{ii}(t,\Delta) = 1 - p_{ik}(t,\Delta) = \frac{S_i(t+\Delta)}{S_i(t)} \qquad \text{Eq. 54}$$

The following assumptions are made to simplify the computation in bridge deterioration process.

- The initial time is zeros in the initial state i. In other words, the age of a bridge is not considered in the initial state i.
- There are no MR&R activities on bridges.
- The condition rating of a bridge cannot be decreased more than two ratings in an inspection period.

Then the semi-Markov process can be formulated as:

$$P_{ij}(t) = S_i(t), i = j, \qquad \text{Eq. 55}$$

$$P_{ij}(t) = \sum_k \sum_{x=1}^{t} f_{ik}(x) P_{kj}(t-x)\,, i \neq j \qquad \text{Eq. 56}$$

where k is an state between states i and j. A transition probability can be computed within time Δ after time t in state k. $\mathrm{P_{kj}}(\mathrm{t}-\mathrm{x})$ can be rewritten as a function of the cumulative distribution function.

$$P_{ij}(t) = \sum_{k}\sum_{x=1}^{t} f_{ik}(x)\left[\frac{F_{kj}(t-x)-F_{kj}(0)}{1-F_{kj}(0)}\right], j = k+1 \qquad \text{Eq. 57}$$

Therefore, $P_{ik}(t)$ can be obtained by following equation

$$P_{ik}(t) = 1-(P_{ii}(t)+P_{ij}(t)) \qquad \text{Eq. 58}$$

In this report, the Weibull survival function was used, and the shape and scale parameters were obtained and shown in Table 18. The value of β in condition rating 4 is infinite, so the transition probability of staying the same in condition rating 4 is assumed to be as 1. Transition probability matrices were estimated for every year (Table 19). Transition probabilities of staying the same condition rating is decreasing as time is increasing. For example, the probability of staying in condition rating 8 at 1-year is 1 and it drops 0.06 at 60-year. Figure 15 shows deterioration rate curves of deck (solid line), superstructure (dash line), and substructure (dot line) estimated with 2008-2010 data. Their deterioration rates are similar up to 10 years and after 50 years.

Table 18. Parameters, α and β of bridge components: Deck with 2008 data

Condition Rating Group	Scale, α	Shape, β
$i = 9$	3.72	8.34
$i = 8$	38.36	2.34
$i = 7$	40.91	3.25
$i = 6$	47.18	6.22
$i = 5$	48.74	7.33
$i = 4$	52.00	Inf

Table 19. TPM at various years

$P(0) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$P(1) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
$P(10) = \begin{bmatrix} 0 & 0.98 & 0.02 & 0 & 0 & 0 & 0 \\ 0 & 0.96 & 0.04 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$P(20) = \begin{bmatrix} 0 & 0.87 & 0.13 & 0 & 0 & 0 & 0 \\ 0 & 0.80 & 0.19 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.91 & 0.09 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
$P(30) = \begin{bmatrix} 0 & 0.65 & 0.35 & 0 & 0 & 0 & 0 \\ 0 & 0.57 & 0.42 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0.69 & 0.31 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.94 & 0.06 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.97 & 0.03 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$P(40) = \begin{bmatrix} 0 & 0.40 & 0.60 & 0 & 0 & 0 & 0 \\ 0 & 0.33 & 0.62 & 0.05 & 0 & 0 & 0 \\ 0 & 0 & 0.39 & 0.60 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.70 & 0.30 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.79 & 0.21 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
$P(50) = \begin{bmatrix} 0 & 0.19 & 0.81 & 0 & 0 & 0 & 0 \\ 0 & 0.16 & 0.69 & 0.15 & 0 & 0 & 0 \\ 0 & 0 & 0.15 & 0.83 & 0.02 & 0 & 0 \\ 0 & 0 & 0 & 0.24 & 0.76 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.30 & 0.70 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$P(60) = \begin{bmatrix} 0 & 0.06 & 0.94 & 0 & 0 & 0 & 0 \\ 0 & 0.06 & 0.63 & 0.31 & 0 & 0 & 0 \\ 0 & 0 & 0.03 & 0.88 & 0.09 & 0 & 0 \\ 0 & 0 & 0 & 0.01 & 0.98 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0.01 & 0.99 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

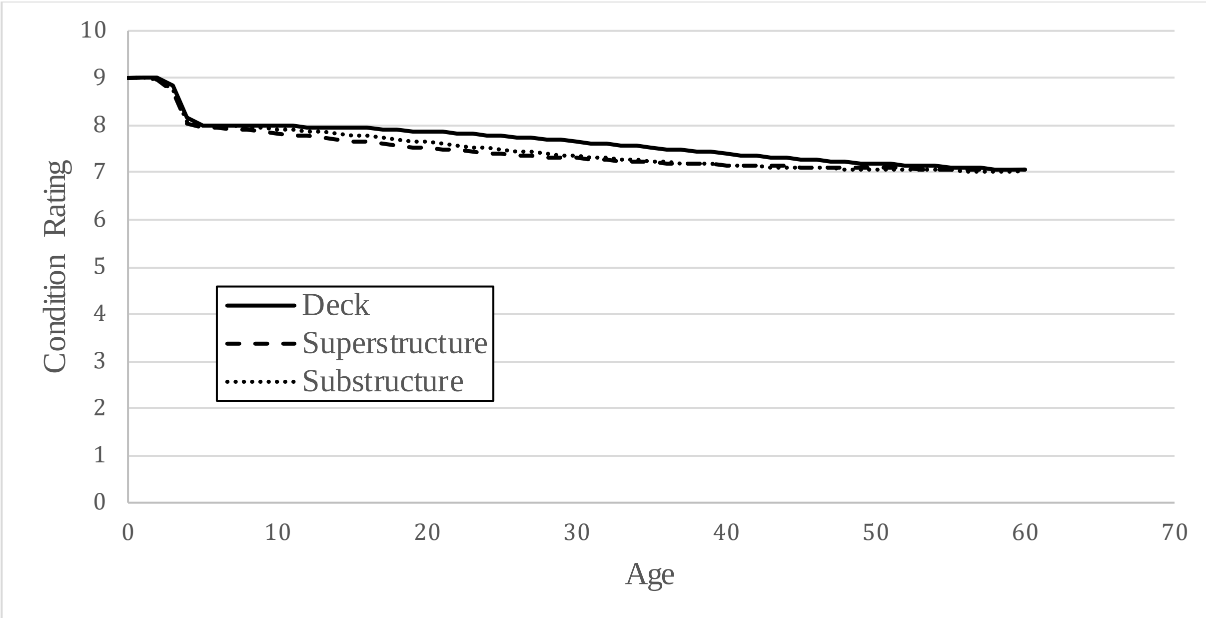

Figure 15. Deterioration rate curves estimated using semi-Markov with 2010 data

Weibull Distribution Based Approach

The data obtained from the National Bridge Inventory (NBI) shows a record of over 50,000 highway bridges in the state of Texas from the year 1992 to 2017. Weibull distribution approach was used to model the deterioration rate of concrete decks with multi span girders over a ten-year period (2006 – 2016). The bridges were filtered with respect to deck condition ratings and further classified by age.

In order to develop a Weibull based deterioration curve, the shape and scale parameters for each condition rating need to be determined. The frequency distribution chart Figure 17 presents the distribution of bridges for various condition rating (9 to 4) with respect to age of bridge. There are several things to note. First, the number of bridges in each condition rating in the data set varies substantially. Most bridges are rated between 8-6, and these distributions show a clear bimodal tendency with peaks at approximately 25 and 50 years. These shapes of distribution do not allow for clean calculation of the shape and scale parameters as discussed in Chapter 2 and depicted in Figure 1. Table 20 shows the tabulation of these parameters for this dataset.

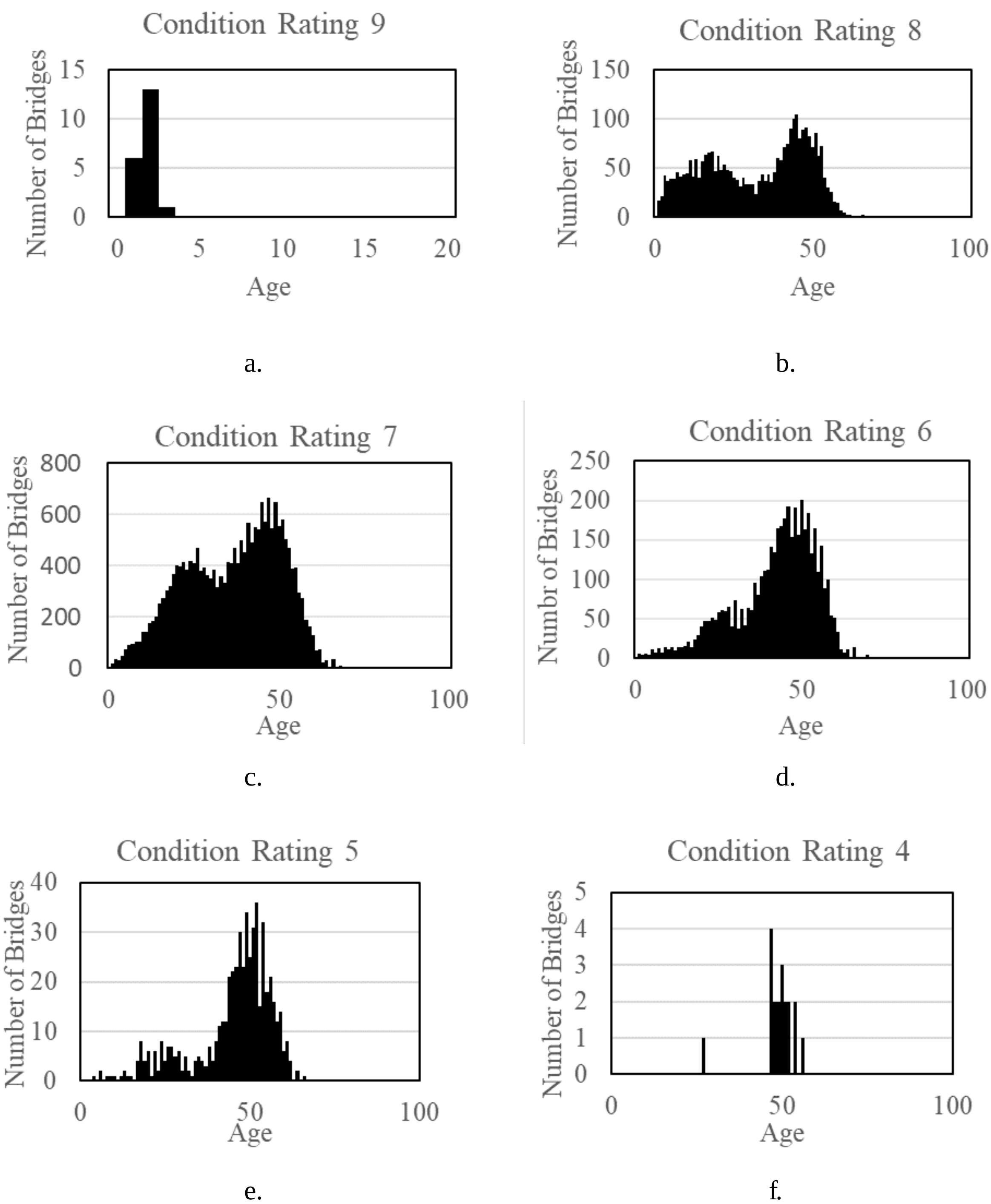

Figure 16 – Frequency Distributions of Age at Each Condition Rating

Note the marked jump in the scale parameter between condition rating 9 and 8. This is both a function of the small number of structures with a condition rating of 9 and the tendency in this dataset for bridges to dwell at condition rating 8. The mean age of these structures was 35 years old. The resulting polynomial best fit, shown in Figure 17, provides an impossible solution.

Table 20: Weibull Distribution Parameters for Condition Rating

Condition Rating	Scale Parameter	Shape Parameter
9	1.95	3.81
8	35.86	1.99
7	40.85	2.87
6	46.64	4.03
5	49.40	5.0
4	51.27	13.20

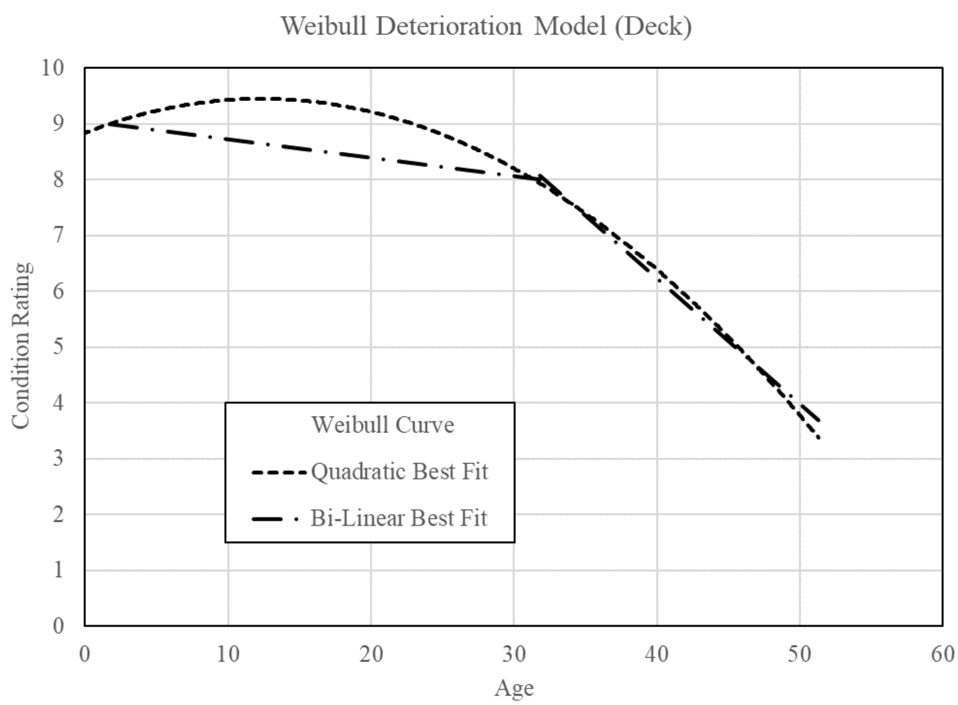

Figure 17 - Weibull Deterioration Model

The deterioration curve shown from the Weibull prediction extends above a condition rating of 9 which is both illogical and physically impossible in a relative sense. A bilinear approximation is shown to highlight the difference.

Evaluation of Results

Obtained TPMs and deterioration curves using RNO, BML, OPM, PR, NBR, PHM, and the mean value of these TPMs with the three data sets were compared with actual data by using the chi-squared goodness-of-fit test to find which model estimates closer probability distribution to the actual value and measured the consistence between them by using the modal assurance criterion test to find whether TPMs and deterioration curves obtained by using different data sets are consistent.

Chi-square goodness-of-fit Test

The closeness of the predicted condition states and probability distributions were measured. Condition state distributions of the 2010 year were estimated with the initial condition distribution, Q_0 obtained from the 2008-year data set by the Markovian process. The initial condition state distribution of bridge deck is

$$Q_0 = [0.001\ 0.161\ 0.715\ 0.112\ 0.011\ 0.001\ 0] \quad \text{Eq. 59}$$

The expected value of condition state distribution, $P(2)$ at time, t=2 is computed as follows:

$$P(2) = Q_0 \times P^2 \quad \text{Eq. 60}$$

The chi-square is

$$\chi^2 = \sum_{i=1}^{k} \frac{(R_i - E_i)^2}{E_i} \quad \text{Eq. 61}$$

where k is number of observations; R_i is actual condition state of the ith observation; and E_i is expected value of the ith observation. The smaller chi squared value means the estimated value is closer to actual value. Table 21 shows the results. The values of the chi-square test of bridge deck, superstructure, and substructure are 0.05 or less than 0.05 obtained from different models, except the value of bridge deck in PHM model. In other words, the estimated probability distribution is fitted over 95 % to the actual probability distribution. However, the probability distribution estimated using PHM for bridge deck is not fitted well to the actual distribution.

Table 21. The values of chi-square of bridge components using different models

Models	Deck	Super structure	Sub structure
RNO	0.02	0.01	0.10
BML	0.01	0.01	0.02
OPM	0.02	0.01	0.01
PR	0.01	0.01	0.01
NBR	0.02	0.01	0.01
PHM	0.39	0.05	0.05

Modal Assurance Criterion

Modal Assurance Criterion (MAC) is used as a statistical indicator to compare of modes quantitatively in modal analysis. The MAC value represents the consistence of modes of two structures, which are mathematically represented as matrices. A MAC value is similar to coherence. This concept was applied to compute the consistence of TPMs and deterioration curves between the three data sets, set A, set B, and set C in this research. The value of the MAC is between 0 and 1. A value larger than 0.9 represents that the modes are consistent and a value closer to 0 represents that the modes are less consistent (Pastor et al. 2012).

$$MAC(A,X) = \frac{\left|\sum_{j=1}^{n}\{\varphi_A\}_j\{\varphi_X\}_j\right|^2}{\left(\sum_{j=1}^{n}\{\varphi_A\}_j^2\right)\left(\sum_{j=1}^{n}\{\varphi_X\}_j^2\right)} \qquad \text{Eq. 62}$$

where $\{\varphi_A\}$ and $\{\varphi_X\}$ are the two sets of vectors. The results are shown in

Set A	$P = \begin{bmatrix} 0.77 & 0.23 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.98 & 0.02 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.96 & 0.04 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.81 & 0.19 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.98 & 0.02 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.98 & 0.02 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Set B	$P = \begin{bmatrix} 0.24 & 0.76 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.98 & 0.02 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.97 & 0.03 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.75 & 0.25 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.33 & 0.67 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Set C	$P = \begin{bmatrix} 0.50 & 0.50 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.97 & 0.03 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.97 & 0.03 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.93 & 0.07 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

Table 23, Table 24 and Table 25. Some MAC values for TPMs are less than 0.9, but all MAC values for deterioration curves are 1, and are not shown. The values in RNO, BML, OPM, PR, and NBR are about 0.9 or more than 0.9. This means estimated transition probabilities using these models with different data sets are similar. Some MAC values in PHM are lower than 0.9. In deck, the values of A&B and A&C are 0.73 and 0.67 respectively. In Table 22, the probabilities obtained with different data set are different. However, the deterioration rates using these TPMs are similar (Figure 18). From these results a consistent deterioration rate can be estimated using a model mentioned in this research with any random data set if the same classifications of bridge components are applied. can be similar.

Table 22. Transition probability matrices of decks using PHM with different data sets

Set A	$P = \begin{bmatrix} 0.77 & 0.23 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.98 & 0.02 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.96 & 0.04 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.81 & 0.19 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.98 & 0.02 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.98 & 0.02 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Set B	$P = \begin{bmatrix} 0.24 & 0.76 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.98 & 0.02 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.97 & 0.03 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.75 & 0.25 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.33 & 0.67 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Set C	$P = \begin{bmatrix} 0.50 & 0.50 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.97 & 0.03 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.97 & 0.03 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.93 & 0.07 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

Table 23. Modal Assurance Criterion Results for TPM of bridge deck

Models	A&B	A&C	B&C
RNO	0.97	0.96	1.00
BML	1.00	0.98	0.98
OPM	0.97	0.97	0.91
PR	0.99	0.97	0.94
NBR	0.99	0.97	0.92
PHM	0.73	0.67	0.95

Table 24. Modal Assurance Criterion for TPM of bridge superstructure

Models	A&B	A&C	B&C
RNO	0.99	1.00	0.98
BML	1.00	0.98	0.98
OPM	0.95	0.98	0.89
PR	0.97	0.97	0.92
NBR	0.96	0.97	0.89
PHM	0.97	0.88	0.91

Table 25. Modal Assurance Criterion for TPM of bridge substructure

Models	A&B	A&C	B&C
RNO	1.00	1.00	1.00
BML	1.00	0.99	0.98
OPM	0.94	0.99	0.92
PR	0.98	0.99	0.95
NBR	0.98	0.99	0.95
PHM	0.97	0.84	0.83

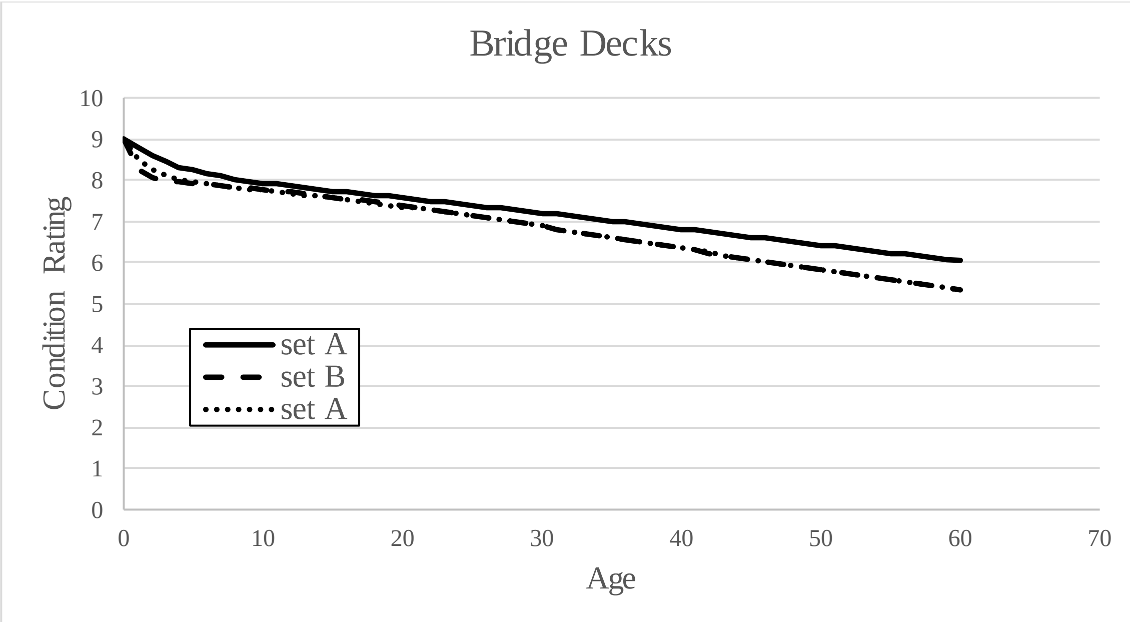

Figure 18. Deterioration rate curves of decks estimated using PHM with different data sets

Multiple Model Deterioration Modeling Approaches

This chapter presents two approaches to multiple model deterioration modeling. The first approach utilizes the deterioration modeling approaches that involve a transition probability matrix – state-based approaches – to create a single combined TPM. The second takes a similar approach at the deterioration curve stage.

Multiple Approach with Markovian process

To generate a reliable deterioration rate curve by the Markovian process the individual models included regression nonlinear optimization (RNO), Bayesian maximum likelihood (BML), ordered probit model (OPM), Poisson regression (PR), negative binomial regression (NBR), and proportional hazard model (PHM) were combined. Figure 19 describes the procedure of multiple model approach. The following steps are included:

- The mean values of transition probabilities were computed by averaging the sum of each transition probability obtained from each model.
- Using Eq. 10 with the transition probability matrix, a deterioration rate curve was generated.
- The upper and lower boundary envelopes were estimated by (1) checking the goodness-of-fit for each curve (2) selecting the third order polynomial for all curves based on the value of R^2, closer to 1 (3) applying the polynomial to each curve and obtaining the lower and upper boundary with 95% confidential interval (4) comparing the boundary values of each curve and (5) determining the lowest and highest values at any time. If the value showed lower than zero, the lower limit was zero. If the value increased, the upper limit was the value before increasing.

Table 26 show the transition probability matrices for bridge deck, superstructure, and substructure respectively. Figure 20, Figure 21, and Figure 22 depict deterioration rate curves of bridge components. The graphs show three curved lines. Mean (solid line) is the deterioration curve obtained from averaging models mentioned above, LB (dot line) is the lower boundary, and UB is the upper boundary. The estimated future condition rating can be within the boundaries in 95% certainty. For example, the condition rating of a bridge deck at 40 years can be 4, 5, 6, 7, or 8.

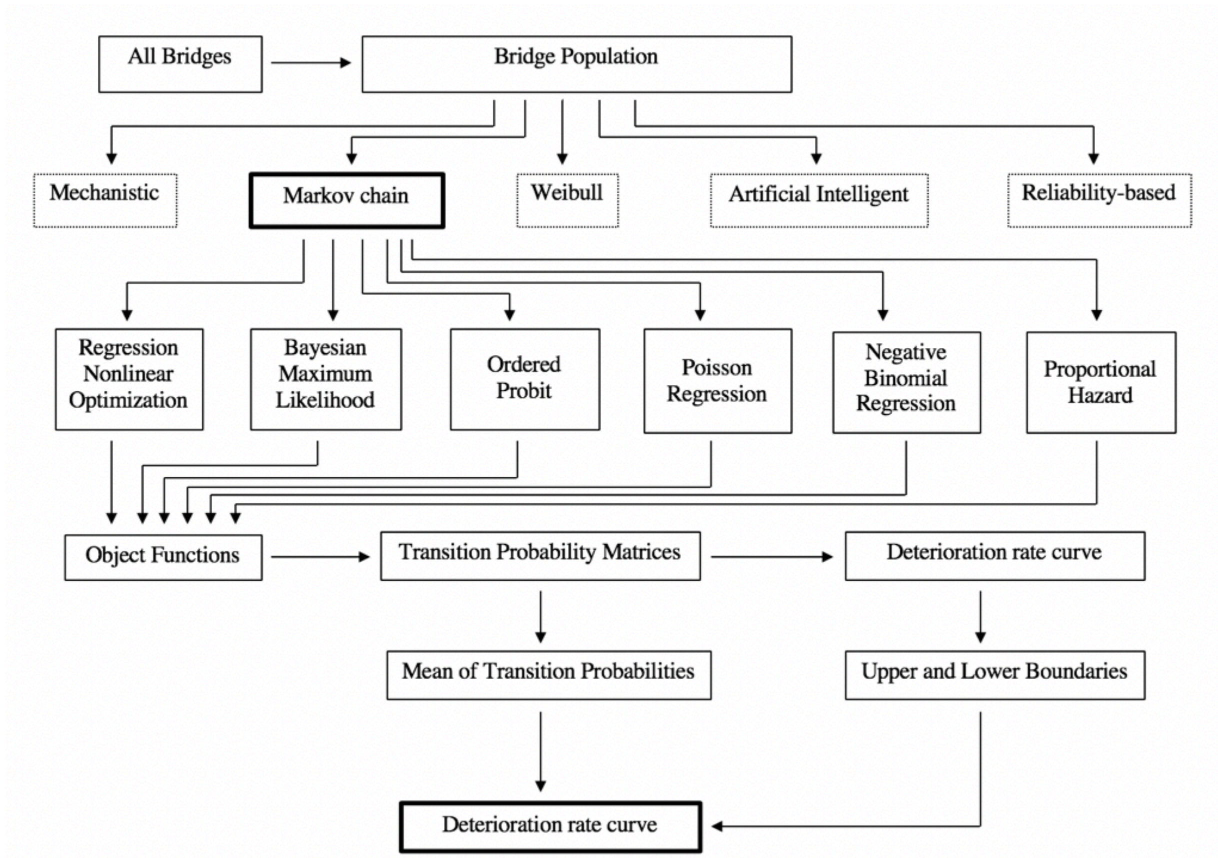

Figure 19. Multiple model approach work flow chart

Table 26. Mean transition probability matrices of bridge components

Deck	$P = \begin{bmatrix} 0.22 & 0.78 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.82 & 0.18 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.99 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.75 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.76 & 0.24 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Superstructure	$P = \begin{bmatrix} 0.24 & 0.76 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.69 & 0.31 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.98 & 0.02 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.82 & 0.18 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.95 & 0.05 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Substructure	$P = \begin{bmatrix} 0.26 & 0.74 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.87 & 0.13 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.98 & 0.02 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.99 & 0.01 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.82 & 0.18 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.97 & 0.03 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

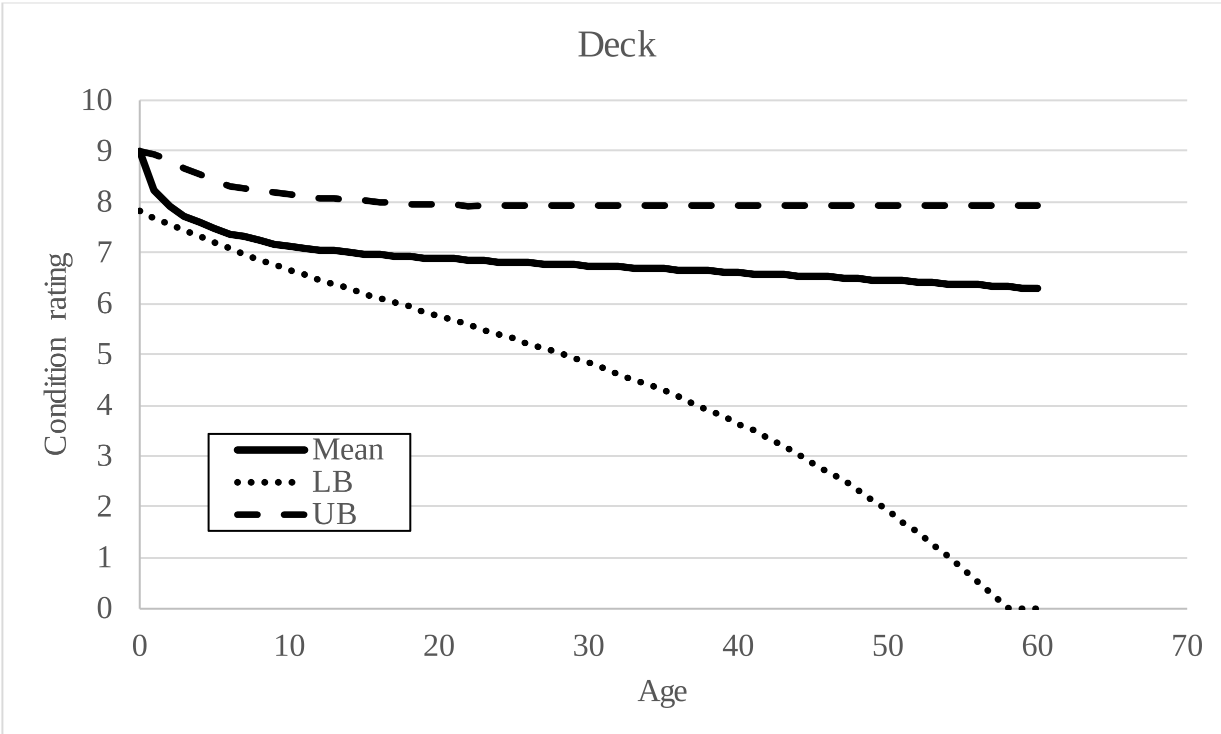

Figure 20. Deterioration curve of deck using multiple approach with 2010 data

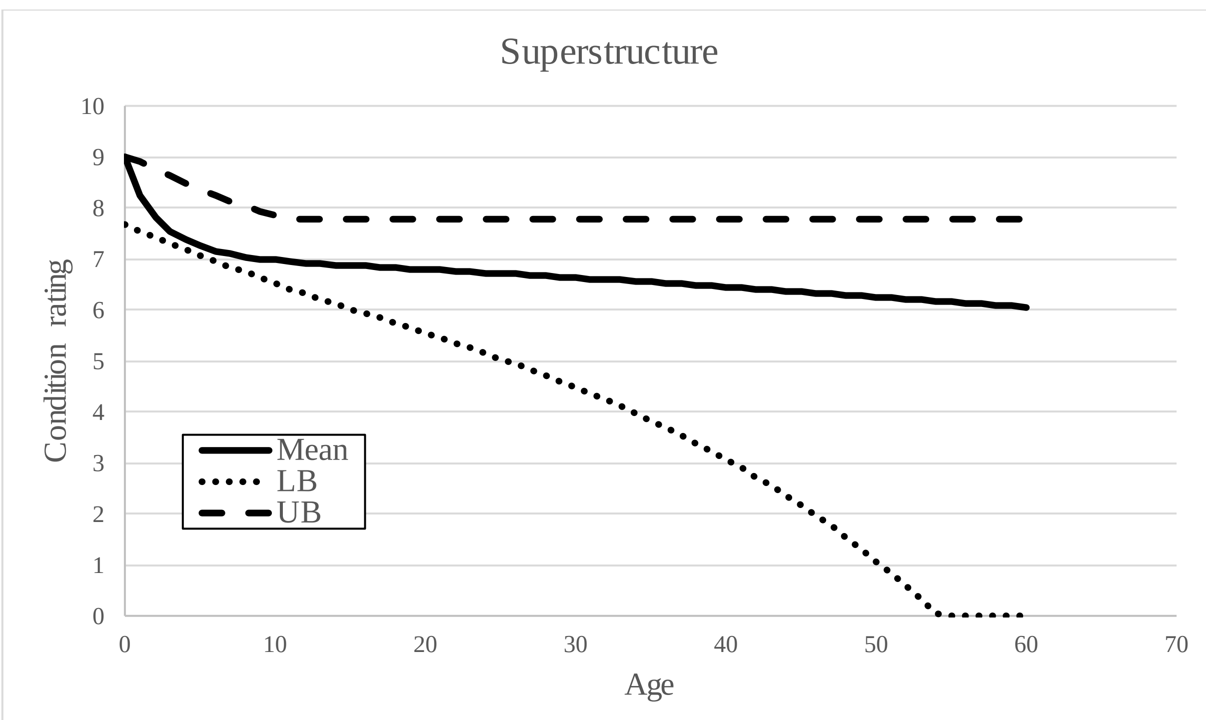

Figure 21. Deterioration curve of superstructure using multiple approach with 2010 data

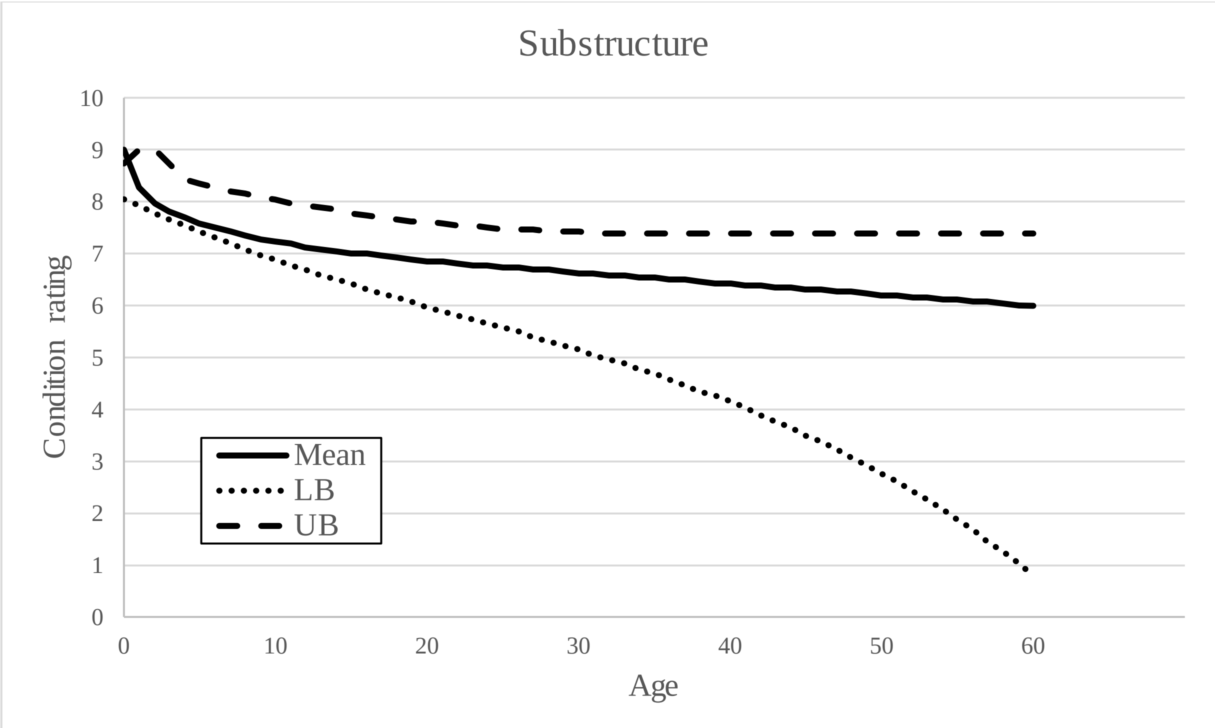

Figure 22. Deterioration curve of substructure using multiple approach with 2010 data

Discussion of Multiple Model Approaches

The Markovian approach to multiple model deterioration modeling results in a single, bounded deterioration curve. However, the bounds for the curve expand so broadly that they do not provide valuable information after the first 20 years. When one considers deterioration modeling for bridge components and all of the uncertainty and related variables, this makes more sense. From a bridge management standpoint, this is not a desirable answer. At least this approach is clear that while it is likely that a concrete bridge in Texas will be at a condition rating near 6 at age 50, it is also possible that bridge will need to be replaced well before age 50. Averaging multiple models together provides confidence in the mean deterioration curve because it reflects the expect value of several models combined. At the same time, the bounds provide insight into the less likely but still possible outcomes which are often lost when using a single model. While this approach is simplistic, it provides substantially more value than any single model.

Conclusions and Future Work

Summary

This report describes a research effort focused on developing a robust, flexible framework for providing reliable performance assessments and forecasting remaining service life for structures. The intention per the proposal was to integrate quantitative data into the framework, but the focus shifted to exploring a more robust approach to deterioration modeling that incorporated multiple models. This has more immediate impact on practice as it was discovered that the market penetration of uncommon data sources like structural health monitoring is not great enough to support exploration of the topic, nor are those entities using the technology readily sharing the data.

There were serval deliverables for this project. An ontology of bridge data sources was developed. An open-source python tool for querying NBI data was created and is available on GitHub in perpetuity. Finally, several approaches to multiple model deterioration modeling are presented. In depth conclusions and future work needs are presented herein.

Bridge Data Ontology

An ontology of bridge data sources was developed. The ontology serves as a starting point which can be built upon as the future of bridge engineering comes to fruition. The ontology is presented through some key characteristics reflecting the type of data, time factor, form factor, and other characteristics that serve to define and distinguish these data sources. The second portion of the ontology is the relationships between the data sources, which are hierarchical predominately. Those relationships are key to integrating these data streams in the future.

Smart Cities

The smart cities ideology is centered on the connectivity of a city's services and infrastructure through digital telecommunications. This same concept can be integrated in the bridge community for tracking the condition and design changes in bridges. Through a comprehensive literature search, it was determined that the concept of smart cities was better suited to serve as a guiding principle than an implementable framework for this application. The key tenets of smart cities are

People, Living, Economy, Environment, Governance and Mobility with technology as a consistent thread throughout. There is a symmetry between these and structural performance. However, the broad definition of structural performance required to include these six tenets is not congruent with the definition of performance associated with deterioration modeling. To adopt this framework would be to introduce complexity unnecessarily.

Bridge Information Modeling

Bridge Information Modeling can be used as the documentation of bridge design plans where data can be tied to components, regions, or even specific points in the spatially accurate model. This data can be used to inform the development of bridge finite element models and can house results from those models. Experimental data from point in time experiments could be included as well. Existing CAD files and other software certified by the BrIM application of choice can be imported in the system for a less time-consuming modeling task. Multiple stakeholders can have access to the bridge BrIM project and easily share updates and changes.

The challenges with BrIM as a framework for data integration in this context are twofold. First any data that varies with time adds an extra dimension to BrIM that appears to be less of a consideration. Second, simply tying data to a point in space on a bridge does not establish the relationships required to utilize that data together. There would have to be an effort to understand how data relates to one another mechanistic, probabilistically or hierarchically, which does not lend itself to automation or general application.

Single Model Approaches

Ten approaches for developing deterioration curves were implemented for a subset of Texas bridges using component level deterioration information from the National Bridge Inventory database. The results were fairly consistent across approaches. The Proportional Hazard Method tended to produce the most conservative results, likely because it does not rely only on past data, but also on a regression analysis of the explanatory variables which are used to define the dataset. This analysis served to accentuate the importance of the supplied data, as opposed to the selected model. In this case, the model predictions would all be similar to examining Figure 23 and simply guessing that the condition rating would likely be a 7 or a 6 at age 50. Given the long outlook and large amount of uncertainty surrounding deterioration modeling, it could be argued that this is the more appropriate action. All of this serves to highlight the importance of the new bridge data sources discussed in the bridge ontology, and how they might serve to improve this process.

Multiple Model Approaches

A predicted future condition state with single model approach might not be reliable. The approach provides a single average value at each age. However, all bridges at the same age are not the same condition rating. For example, a concrete bridge deck at 50 years old, the estimated condition rating is 7 from PR, OPM, BML, RNO, NBR, and 6 from PHM. The average of the actual condition rating of the deck at 50 years old in 2010 data is 7. However, Figure 23 shows the number of bridge decks at each condition rating at 50 years old. A range of the condition rating is from 8 to 4. The range is within the boundaries obtained from the multiple model approach method.

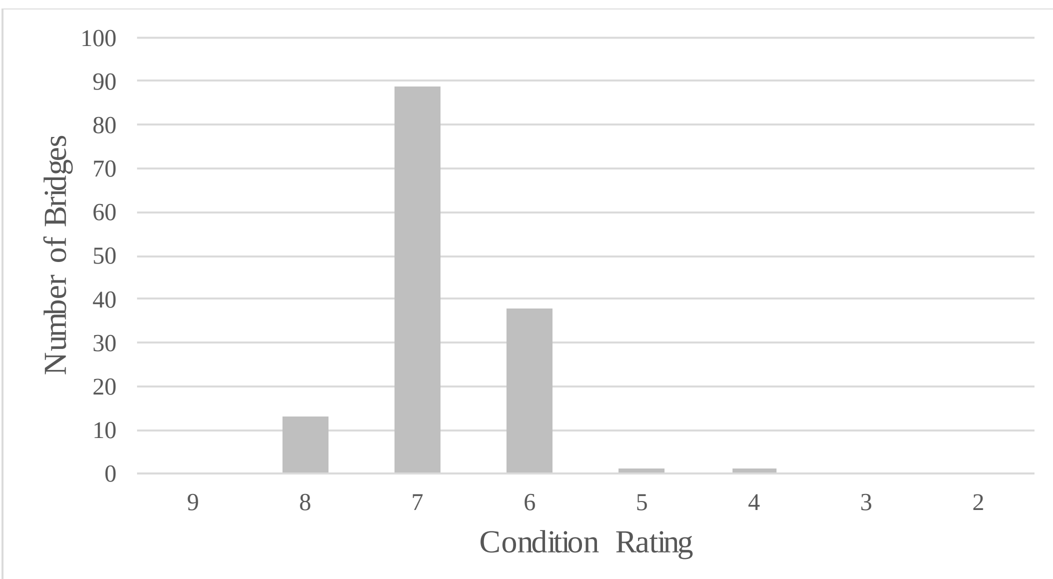

Figure 23. Number of bridge decks at 50 years by condition rating groups with 2010 data

Some future work was identified during this research to improve reliability of prediction condition states of bridges. The recommendation for future work is included:

- The relationships between explanatory variables and bridge deterioration should be investigated in depth. This step is treated in a very cursory manner in most deterioration modeling applications. Expert judgment is used to identify explanatory variables and little to no thought is given to the implications of that decision. This crucial preliminary step has influenced nearly all of the bridge deterioration literature. In this research, the choice of bridges clearly affected the results as most of the bridges clustered between 8 and 6 and did not provide strong data on which to make predictions.
- Integrating many single model approaches within a given model type (i.e., probabilistic models) does not provide a substantial increase in the value of the prediction because of the broad range of outcomes that actually gets wider with each additional model including in the approach. There is a need to include different model families, like mechanistic models, to improve the results. This research focused on including different models within a family.
- The primary challenges to this are identifying approaches that include both the temporal and spatial differences in the data to be included, as well as identifying the relationships between data sources that define their mathematical or categorical relationships.
- Ensemble approaches provide promising results, but also have the potential to mask the deficiencies in the original data through overfitting. It is easy to end up with a model that overfits data and provides high accuracy without any indication of the potential variability in responses. These approaches should be explored in greater detail.

All results from this project, and future on-going work, will be housed on GitHub at https://github.com/PASS-Lab/MMDM, and is available under the MIT Open Source License. See the repository for details.

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