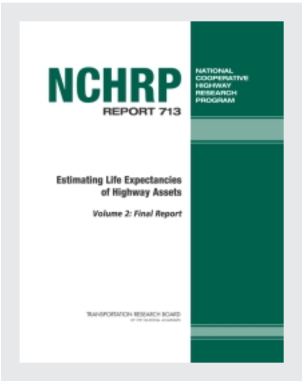

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NATIONAL COOPERATIVE HIGHWAY RESEARCH PROGRAM

NCHRP REPORT 713

Estimating Life Expectancies of Highway Assets

Volume 2: Final Report

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NATIONAL COOPERATIVE HIGHWAY RESEARCH PROGRAM

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The program is developed on the basis of research needs identified by chief administrators of the highway and transportation departments and by committees of AASHTO. Each year, specific areas of research needs to be included in the program are proposed to the National Research Council and the Board by the American Association of State Highway and Transportation Officials. Research projects to fulfill these needs are defined by the Board, and qualified research agencies are selected from those that have submitted proposals. Administration and surveillance of research contracts are the responsibilities of the National Research Council and the Transportation Research Board.

The needs for highway research are many, and the National Cooperative Highway Research Program can make significant contributions to the solution of highway transportation problems of mutual concern to many responsible groups. The program, however, is intended to complement rather than to substitute for or duplicate other highway research programs.

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The members of the technical panel selected to monitor this project and to review this report were chosen for their special competencies and with regard for appropriate balance. The report was reviewed by the technical panel and accepted for publication according to procedures established and overseen by the Transportation Research Board and approved by the Governing Board of the National Research Council.

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COOPERATIVE RESEARCH PROGRAMS

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FOREWORD

By Andrew C. Lemer
Staff Officer
Transportation Research Board

This two-volume report provides a methodology for estimating the life expectancies of major types of highway system assets, in a form useful to state departments of transportation (DOTs) and others, for use in lifecycle cost analyses that support management decision making. Volume 1 is a guidebook for applying the methodology in DOT asset management policies and programs. Volume 2 describes the technical issues and data needs associated with estimating asset life expectancies and the practices used in a number of fields—such as the energy and financial industries—to make such estimates.

The deterioration of highway infrastructure begins as soon as it is put into service. Effective management of highway system assets requires a good understanding of the life expectancy of each asset. Asset life expectancy is the length of time until the asset must be retired, replaced, or removed from service. Determining when an asset reaches the end of its service life generally entails consideration of the cost and effectiveness of repair and maintenance actions that might be taken to further extend the asset's life expectancy. Different types of assets, such as pavements, bridges, signs, and signals, will have very different life expectancies. Asset life expectancy also depends on the materials used; demands actually placed on the asset in use; environmental conditions; and maintenance, preservation, and rehabilitation activities performed.

Effective management of highway system assets requires that agency decision makers design and execute programs that maintain or extend the life of the various types of assets in the system at low cost. Designers use estimates of asset life expectancy in their lifecycle cost analyses to make design decisions, but those estimates depend on assumptions about maintenance practices, materials quality, service conditions, and characteristics of the asset's use. If actual service conditions and maintenance activities subsequently differ from the designer's assumptions, the asset's life is likely to be different from initial estimates. Better information and tools for estimating asset life expectancies are needed to guide in-service asset management programs. Research is needed to determine the life expectancies of assets for at least four potential cases: (1) when maintenance and preservation activities are performed as assumed by the designer in the lifecycle cost analysis, (2) when little or no maintenance is performed over the life of the asset, (3) when more aggressive maintenance and preservation activities are performed to extend the asset's life, and (4) when materials or designs that require no or very little maintenance are used.

The objectives of NCHRP Project 8-71 were to (1) develop a methodology for determining the life expectancies of major types of highway system assets for use in lifecycle cost analyses that support management decision making; (2) demonstrate the methodology's use for at least three asset classes, including pavement or bridges and two others, such as culverts, signs, or signals; and (3) develop a guidebook and resources for use by state DOTs and others for applying the methodology to develop highway maintenance and preservation programs and assess the effect of such programs on system performance.

A research team led by Purdue University, West Lafayette, Indiana, conducted the research. The project entailed a review of current literature and practices within highway agencies and other industries, such as utilities and vehicle- and equipment-fleet management, to describe the methodologies currently used to determine life expectancy for major assets. The research team considered both new and in-service highway assets (such as pavements, bridges, culverts, signs, pavement markings, guardrail, and roadside facilities), and described the factors likely to influence predicted or assumed asset life expectancies. These factors include materials, design criteria, construction quality control, and maintenance policies and practices. Data needs and availability influence analytical ability to estimate and predict asset life expectancies. Geographic location and highway system management policies also influence life expectancies. Considering these factors, the research team described methodologies for estimating the life expectancy of major types of highway system assets, for use in lifecycle cost analyses that support maintenance and preservation management decision making.

The research produced this two-volume report. Volume 1 is a guidebook designed to be used by transportation agency staff wishing to estimate asset life expectancies. The guide will be useful to agency staff and their advisors in developing asset management and maintenance systems, policies, and programs. Volume 2 documents the research project and presents background information and research results that will be useful to other researchers and practitioners wishing to know more about the theories and methods for estimating asset life expectancies.

CONTENTS

Note: Many of the photographs, figures, and tables in this report have been converted from color to grayscale for printing. The electronic version of the report (posted on the Web at www.trb.org) retains the color versions.

SUMMARY

Estimating Life Expectancies of Highway Assets; Volume 2: Final Report

A vital aspect of cost-effective highway asset management is the estimation of asset life expectancies. With reliable estimates of asset life, agencies can, with greater confidence, establish schedules for rehabilitation and replacement; carry out planning, programming, and budgeting; and identify designs best suited to a specific situation or location. This report presents, for purposes of asset life expectancy estimation, a review of the various approaches and methods and a framework that can be implemented using empirical data. The framework includes identification of the influential factors of asset life expectancy and an assessment of the magnitude and direction of these factors. Further, the framework for assessing the sensitivity of asset life expectancy to maintenance is demonstrated. The framework can help agencies predict life expectancy corresponding to different levels of maintenance and preservation activities performed during the asset life or for the utilization of materials or designs that require very little or no maintenance. Also, recognizing that uncertainties surrounding asset life estimates can jeopardize the reliability of planning, the report develops and demonstrates a methodology for incorporating asset life uncertainty into long-term planning tasks such as capital needs assessments. Thus, the overall framework uses sensitivity and risk concepts to demonstrate how the uncertainties in asset life factors could affect the reliability of the estimated life and how, in turn, the uncertainty in the estimated life could affect planning outcomes. The report is accompanied by a Guidebook intended to facilitate the framework implementation by highway agencies. The Guidebook demonstrates how agencies may not only establish the life expectancies of their physical highway assets, but also investigate the sensitivity of these life expectancies to the relevant influential factors of asset life and assess the effects of asset life uncertainty on their asset management processes.

CHAPTER 1

Introduction

1.1 Role of Highway Asset Life Expectancy in Business Processes

As highway agencies grapple with the challenge of ensuring acceptable performance of their highway assets with respect to condition, safety, security, mobility, reliability, and life cycle cost, the preservation of these assets continues to be a critical issue. Highway assets include pavements, bridges, culverts, traffic signals, pavement markings, signals, signs, and flashers. Agencies are increasingly finding it difficult to maintain desired performance levels of these assets. This problem is exacerbated by increasing demand, aging infrastructure, increasing user expectations, and increasingly limited funding availability or certainty.

In light of these trends, highway asset managers, as stewards of the infrastructure, have a fiduciary responsibility to identify and implement cost-effective life cycle management strategies and practices that are in the best interest of taxpayers and highway users. The issue assumes greater importance with the realization that highway assets constitute one of the most valuable public-owned infrastructure systems in the United States. Highway asset managers carry out business processes that include asset valuation, scheduling of preservation actions, and budgeting to meet their asset replacements needs—knowledge of asset life expectancy is a critical input in these processes. Specifically, in order to identify and implement cost-effective life cycle management strategies and practices for highway assets, among other tasks, the asset manager requires reliable estimates of asset life expectancy as well as a proper understanding of the factors that influence asset life.

Several issues are associated with asset life expectancy. First, highway assets deteriorate with age due to the accumulated effects of traffic loadings, climatic conditions, deicing chemicals, and so forth. Thus, for assessing the life of an asset, information about the contribution of these factors to the asset deterioration rate is valuable. Second, the performance of an asset, in response to these deterioration factors, is influenced by the type of predominant asset material and structural design utilized and the application of preservation treatments during the life of the asset. For example, the use of superior materials generally lead to longer asset life; frequent freeze-thaw cycles or temperature extremes tend to shorten asset life; greater frequency and/or intensity of rehabilitation and maintenance activities generally lead to increased asset life. Thus, knowledge of the factors that influence asset life is of interest to asset managers.

Further, where asset life refers to actual life, or the time between successive replacements, the estimation of asset life expectancy is expected to enhance planning practices at agencies that carry out blanket replacements for certain asset types and agencies that use point estimates of asset life for planning purposes. For the latter category of agencies, there is a risk that the fixed-interval policy for asset replacements may lead to hastened or deferred replacements, particularly where the influential factors of asset life (e.g., climate and traffic loading) occur with lower or greater intensity than was expected. In other words, such replacement policies fail to account for the inherent randomness associated with asset life, thus putting agencies at risk for replacing an asset too early, which is not cost-effective, or too late, which can pose a threat to user safety.

Asset life expectancy estimates play several roles in highway management (Figure 1-1). They can help establish the year in which asset replacement will be necessary and thus serve as a basis for establishing short- or long-term physical work programming and budgets. Also, using life expectancy estimation methodologies, agencies can ascertain the efficacy of new designs, new materials, or new preservation practices in terms of the extension of asset life. Thus, life expectancy models can be used to estimate the expected life of a highway asset corresponding to different maintenance treatments or strategies (long-term schedules) and thereby determine the optimal replacement intervals, frequency, timing, and scope of maintenance and annual expenditures; compare design and material alternatives; synchronize work packages, rank projects, allocate funds, establish depreciation rates and carry out asset valuation, and to establish research priorities (Thompson et al., 2011). Examples for these applications are provided in the Guidebook, Volume 1 of *NCHRP Report 713*.

The life expectancy estimation methodologies presented in this report apply to any of the several asset classes and can be used by highway asset managers to establish the life expectancies of their assets. For each asset class, these results can be presented as a simple average value for each combination of factor levels, or as a life expectancy model, which is a function of the various influential factors. The life expectancy factors investigated for this report include material and structural types, climatic conditions, highway functional classes, traffic loadings, soil properties, and past preservation history where available.

Furthermore, this report demonstrates how, after establishing life expectancy models for assets in their jurisdiction, asset managers could investigate the sensitivity of the asset life expectancy in response to changes in the levels of these factors. The report therefore includes a methodology by which agencies can carry out probabilistic assessments of asset life on the basis of the variability of any factor of asset life (in this report, this is illustrated using climatic factors) and the propagation of such uncertainty in terms of its subsequent effect on the descendant business processes (in this report, this is illustrated using long-term physical and fiscal needs assessments under different end-of-life definitions and maintenance strategies). In effect, the report shows

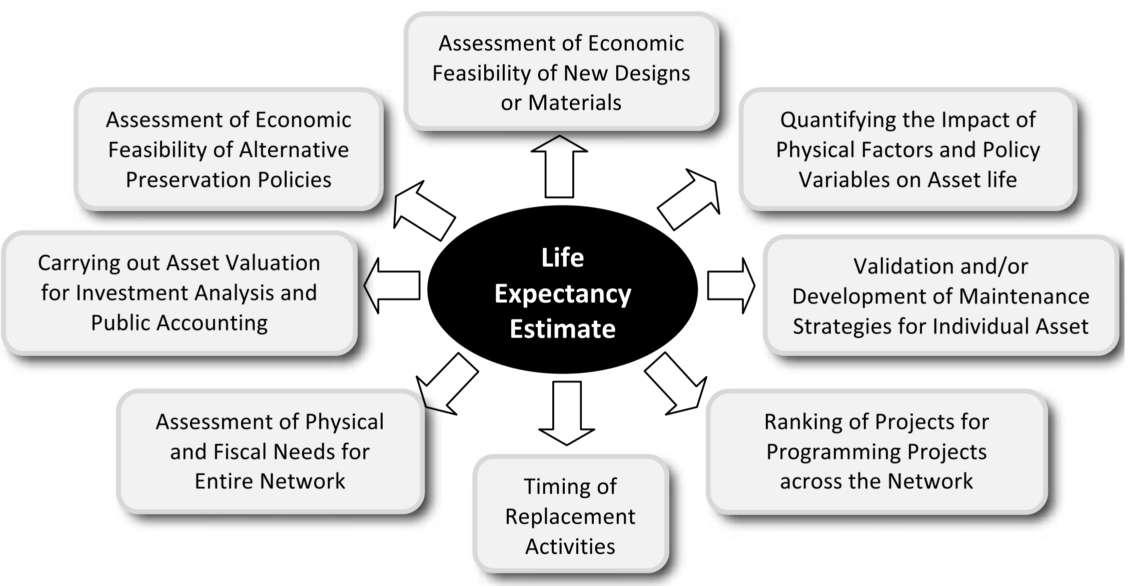


Figure 1-1. Applications of life expectancy in asset management processes.

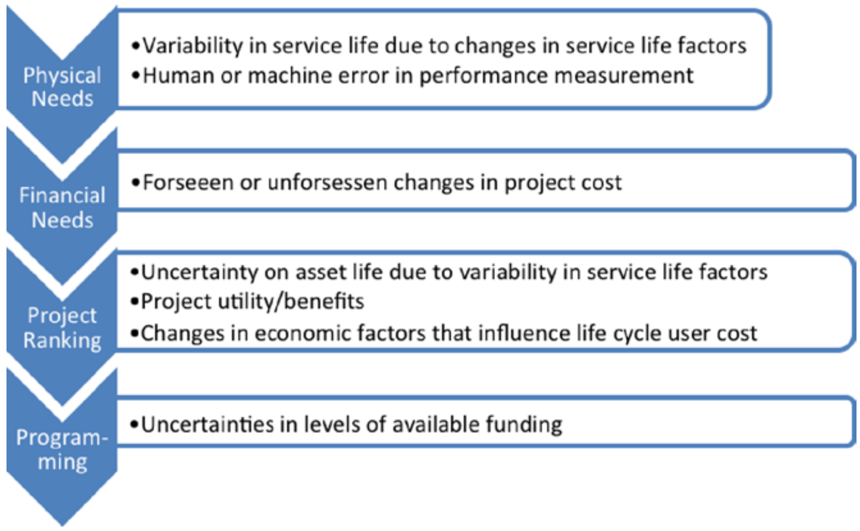


Figure 1-2. Probabilistic considerations for selected tasks associated with asset development.

that by using probabilistic techniques, more robust estimations of asset life could be obtained and used to quantitatively assess the influence of factor level uncertainties on asset life. It is expected that if highway agencies, in the early phases of their project development processes, could obtain robust and more reliable estimates of their asset life expectancy, then the time for carrying out some subsequent action (rehabilitation or replacement) could be ascertained with greater confidence. Thus, they would be better equipped to set aside adequate contingency funds for long-term upkeep of their infrastructure.

It is envisaged that agencies ultimately will move toward planning and programming processes that adequately account for the uncertain nature of asset life, thereby acquiring a better position for assessing the likelihood of the life expectancy outcomes on resulting business practices, formulating a mitigation plan, and communicating their needs more effectively to stakeholders. For example, probabilistic estimates of physical needs (e.g., asset life expectancy and life-extensions of maintenance treatments), fiscal needs (e.g., project costs and life cycle costs), project rankings (e.g., project utility/benefits), and programming (e.g., funding availability) can be used by asset managers to plan for various scenarios and prepare mitigation strategies (Figure 1-2).

1.2 Rationale for Highway Asset Replacement and Retirement

Where asset life is defined as the actual life of the asset (i.e., the time interval between successive replacements), a strong rationale for estimating asset life is the need for agencies to update their highway asset replacement and retirement policies. Agencies seek to replace assets when they reach the end of their actual lives. Therefore, in assessing the life expectancy of highway assets in terms of their actual lives, it is important to consider the primary reasons for which an agency replaces or retires each asset type.

In the National Bridge Inventory (NBI) terminology, assets may be considered at the end of their life when they are no longer structurally adequate or safe or are completely functionally obsolete. Thus, replacement because of structural inadequacy and lack of safety may be driven by the following rationale: the goal to improve an asset's structural performance where repair or rehabilitation is not cost-effective to do so (e.g., a very low NBI substructure condition rating); to eliminate potential vulnerabilities to structural failure due to fatigue or extreme events (e.g., earthquakes); the inability to repair/rehabilitate critical structural components (e.g., corrosion that is inaccessible under gusset plates); or the need to accommodate higher traffic loadings resulting from heavier truck operations (Thompson et al., 2011).

The rationale to replace structures based on their serviceability and functional obsolescence may include an agency's desire to improve an asset's functional performance (e.g., International Roughness Index (IRI) and retroreflectivity) that is beyond cost-effective repair/rehabilitation to keep up with new material, designs, or technologies such as Intelligent Transportation Systems (ITS); accommodate the demands of higher traffic volume (e.g., widen bridge deck due to new economic development); increase bridge vertical clearances due to new truck or ship designs; and to meet regulatory changes that may be caused by poor alignment (Thompson et al., 2011). In terms of replacement due to essentiality for public use, changes in development patterns may render a road or structure no longer needed. Also, the end of an asset's life may be unintended; for instance, a sudden disaster event could cause an asset to fail (Ghosn et al., 2003; Kacin, 2009). Finally, assets may be replaced in order to avoid excessive lifecycle or maintenance costs associated with current design practices or due to expected limitations in long-term funding.

In designing a new asset, agencies strive to account for these factors using the best techniques available at the time of design. However, many of these factors often change during an asset's life span, particularly for long-lived highway assets such as bridges and culverts. For example, a bridge may have been designed to survive 50 years at a time when the Average Daily Traffic (ADT) was half of its current level. At 25 years of age, this bridge may be structurally sufficient; however, due to increased traffic, a wider bridge may be needed. After an asset is put in service, the highway agency attempts to manage risk and deterioration through mitigation actions such as maintenance, repair, and rehabilitation.

Typically, these factors are assessed separately, thus making it imperative for agencies to develop an over-arching methodology to account for the various rationales for replacement or retirement. Any effort to estimate the actual life of a highway asset must be preceded by recognition of the replacement rationales for the asset under investigation. This report presents methods for estimating asset life on the basis of various end-of-life definitions. The historical asset replacement records of many agencies are not always available, and, where they are available, records often lack statements that establish why the asset was reconstructed. Hopefully, in the future, as agency databases become increasingly more reliable, the dominant rationale for asset replacement can be ascertained and actual-life expectancy models can be improved. For example, for assets that do not require capacity expansion over the remainder of their life, records of the asset replacements driven by the need for capacity expansion could be excluded from the analysis. At certain agencies, the rationale for replacement is generally driven by the asset condition. Such agencies typically monitor the asset so they can identify the time when a certain specified threshold condition state is reached and then weigh possible options for replacement or life extension (preservation) interventions. In the applications provided to illustrate the methodologies developed in this report, the actual replacement time was measured on the basis of historical records that encompass all the possible rationales for replacement; and the expected replacement time is measured on the basis of the extrapolated condition of the asset and a certain pre-specified terminal condition state. Thus, the life expectancy of assets in this study refers to the actual life (i.e., the time at which an asset has historically been replaced) and the service life (i.e., the estimated time to reach an undesirable level of service where maintenance activities are no longer financially or technically feasible). The end of service life is not necessarily the same as the end of its actual life. The risk assessment aspect of this study, which is discussed in the next section, considers the end of an asset's life in terms of its actual life or service life as dictated by the influential deterioration factors, rather than sudden asset failure which leads to an abrupt end of asset life, such as bridge collapse, despite the fact that more traditional applications of risk assessment consider abrupt failures [e.g., (Stein & Sedmera, 2006)].

1.3 Uncertainty in Life Expectancy Estimation and Related Business Processes

In asset life expectancy estimation, uncertainties exist that propagate into the subsequent agency applications of the asset life estimates. For instance, consider the uncertainty of asset life surrounding a population of newly installed traffic signs. Based on the median life expectancy for a cohort of signs, a deterministic estimate would indicate that no funding for replacement is needed over a 10-year program. However, when the uncertainty of the sign lives is considered, it is seen that 20% of the cohort will be expected to reach the end of their lives by the end of the 10-year period, implying that funding will, in fact, be needed (Figure 1-3). As demonstrated by this simple example, it seems clear that agencies that apply deterministic estimates of life may be at risk of setting aside insufficient funds to maintain their highway asset network.

In the context of highway asset life expectancy, sources of uncertainty may be classified as follows (Lin, 1995; Maskey, 1999; Val et al., 2000; Biondini et al., 2006; Anoop & Rao, 2007; Williamson et al., 2007; Ertekin et al., 2008):

- **Errors in modeling techniques.** Errors created through the fitting of idealized mathematical models in an attempt to describe complex physical phenomena (e.g., the assumption that the probability of a bridge surviving a period of time is governed by the Weibull distribution may be incorrect).
- **Errors in inputs.** Inherent randomness of structural characteristics (e.g., material properties and strength), future loadings (e.g., traffic volume), environmental conditions (e.g., climatic conditions and soil characteristics), inaccurate inspection data (e.g., visual condition ratings), and structural dimensions (e.g., bridge length).
- **Inaccuracies in parameters.** Inaccurate representation of the contribution of a factor toward asset deterioration processes, particularly due to limited observations or infrequent inspections.
- **Impact of externalities.** Unforeseen causes that may surmount natural deterioration processes (e.g., extreme weather event, design/construction flaw, or malicious attacks).

To capture such uncertainties, agencies can apply relatively objective, probability-based techniques or relatively subjective techniques based on expert opinion regarding the fuzziness, plau-

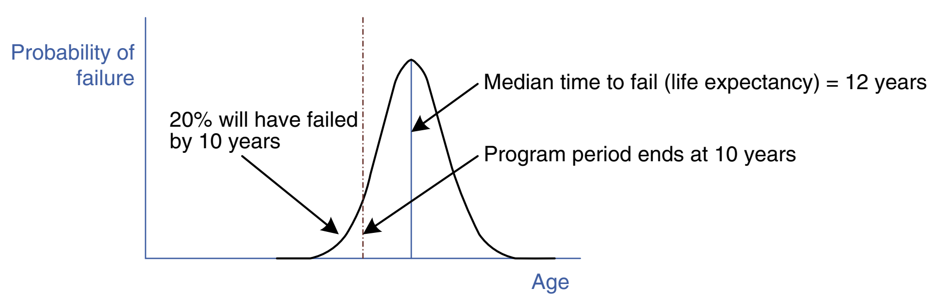


Figure 1-3. Role of uncertainty in long-range planning (Thompson et al., 2011).

sibility, belief, or possibility of different inputs, parameters, or events. This report examines the use of probability-based methods to describe the effect of highly variable inputs such as climatic conditions. From the standpoint of robustness, these techniques represent an improvement over deterministic approaches because they provide a more stable description of asset life while allowing an appreciable level of precision using median estimates. With improved reliability of life expectancy assessments, agencies can adapt to uncertainties more confidently.

With probabilistic models, the uncertainty regarding asset life can be quantified using sensitivity and risk analyses. In this report, both analysis types are presented; however, the use of probabilistic risk assessment (PRA) is emphasized. Case studies of PRA were applied in this report to assess the effects of the uncertainty of life factors on asset life and the subsequent propagation of the uncertainty of asset life on long-term physical and fiscal needs.

1.4 Asset Types (Classes)

A highway asset is any physical structure, on or near the highway, designed to enhance highway operations. The most commonly studied highway assets are pavements and bridges. Nontraditional assets on the highway include guardrails, crash barriers and cushions, culverts, road signs, traffic signals, flashers, pavement markings, road/street lights, and side drains. Other less common assets include gabions, retaining walls, noise barriers, traffic detection/monitoring devices, and emergency telephones.

Plate 1 illustrates some classes of highway assets that were considered in the life expectancy analysis in the study.

1.5 Study Objectives

This report developed a framework for estimating highway asset life expectancies and incorporating such predictions into business-related processes, such as long-range planning, while duly recognizing and quantifying the effect of uncertainty. In addressing the primary objective, the following secondary objectives were realized:

1. Synthesize the available literature on asset life expectancy estimation approaches and the influential factors of asset life.
2. Identify the data collection requirements for highway agencies wishing to model the life expectancy of their assets using local data.
3. Demonstrate the methodologies using data collected at a national or state level.
4. Show how agencies can incorporate asset life expectancy values into lifecycle cost analysis and subsequently for preservation project lifecycle costing, evaluation, programming, network-level needs assessment, and asset valuation.
5. Develop a methodology to quantify the uncertainty surrounding asset life and its subsequent effect on long-term planning decisions.

To facilitate the implementation of the developed techniques, a Guidebook was developed as part of this study. This resource can be used by agencies to address issues related to the primary objective and the specific secondary objectives listed above.

The scope of the NCHRP 08-71 project was to address all highway asset classes. However, data on only a few asset classes are available from state agency databases. As such, the developed methodologies were applied and demonstrated only for a few asset classes—bridges, box and pipe culverts, pavements, pavement markings, traffic signs, roadway lighting, traffic signals, and flashers.

Bridge

Pavement

Road Sign

Flasher

Traffic Signal

Culvert

Gabion

Crash Barrier

Drain Cover

Guardrail

Retaining Walls

Curbs

Pavement Marking/Markers

Plate 1: Highway Assets – Examples

1.6 Organization of this Volume of NCHRP Report 713

Volume 2 of *NCHRP Report 713* first reviews life expectancy modeling techniques and factors in the literature and then synthesizes the existing practices into more generalized methodologies for estimating asset life (Chapter 2). In Chapter 3, the asset and environmental data collected to apply the developed methodologies are reviewed. Chapter 3 further describes the models that were calibrated using the collected data and the developed methodologies. A discussion of the applications of the asset life estimates, with an emphasis on lifecycle costing, is then provided in Chapter 4. A methodology for accounting for uncertainty is discussed in Chapter 5, including a review of past techniques. Chapter 6 shows the sensitivity and risk analysis techniques for the developed models, using case studies for uncertain future climatic conditions and probabilistic needs assessments based on uncertain asset life. A summary of the methodologies, the results of the case studies based on the collected data, and the recommendations for future research are provided in Chapter 7.

CHAPTER 2

Methodologies for Life Expectancy Estimation

2.1 A Review of Existing Techniques for Life Expectancy Estimation

This chapter presents the definitions and measures of asset life expectancy, the highway asset life expectancy values established in past research and practice, the factors that can affect life expectancy, and the statistical and econometric tools that have been used to predict asset life.

2.1.1 Asset Life Definitions and Discussions

Asset life in general refers to the time until an asset must be replaced due to substandard performance, technological obsolescence, regulatory changes, or changes in consumer behavior and values (Lemer, 1996). In assessing the life expectancy of highway assets, the asset manager needs to consider the primary reasons for which the agency replaces or retires the asset. These reasons may include

1. Accommodating demands of higher traffic volume from new economic development.
2. Meeting demands of heavier trucks.
3. Eliminating safety problems (e.g., poor alignment or narrow roadways and bridge decks).
4. Reducing the high maintenance costs associated with current design practices.
5. Changes in development patterns that render a road or structure no longer needed.
6. Eliminating potential vulnerability inherent in the current design (e.g., fatigue damage).
7. Eliminating potential vulnerability to extreme events (e.g., floods, earthquakes, or collision).
8. Addressing deterioration that is beyond cost-effective repair/rehabilitation.

When designing a new road or bridge, agencies try to account for these factors using the best techniques available at the time. However, many of these factors will change during the asset lifespan, especially for long-lived facilities such as bridges. After a facility is in service, the agency tries to manage risk and deterioration through mitigation actions, maintenance, repair, and rehabilitation. There are methods for forecasting these factors (e.g., *NCHRP Report 495* for fatigue life, hydrological and seismic studies for extreme events, and deterioration models).

Ideally, an agency strives to use all such techniques when considering how much longer an asset might last and what additional life might result from agency activity. For deterioration, the agency decision whether to rehabilitate or replace might be based on design details (e.g., access to the deteriorated area). For example, on trusses, the existence of pack rust (corrosion that is inaccessible under gusset plates) might be a reason to replace rather than repair. For pavements, the reason might be subgrade failure. If there is no functional reason to replace a facility, the agency will normally prefer to maintain it forever unless there is irreparable damage. In many cases the motivation to replace a facility is a combination of factors. It is often a matter of benefit/cost analysis in a context of funding constraints and competing projects. An agency might band-aid a facility for many years because of a lack of funding to replace it, when other parts of the network have more urgent needs.

Asset life is an especially useful consideration for assets where the end-of-life factors listed above are not expected to come into play in the foreseeable future. The goal of the agency, then, is to extend service life indefinitely if possible, until one of the higher level considerations takes precedence.

As such, asset life can be viewed from several perspectives as discussed below.

- **Physical life:** The period of time in which the asset is physically standing, with any capability to provide any type of service. The asset may still physically exist at the site: for example an abandoned road, or a covered bridge that can safely carry pedestrians but can no longer carry vehicles, is still within its physical life; however a bridge that has collapsed, but is not yet removed is past its physical life.
- **Functional life:** The period of time in which the asset satisfies all of its functional requirements. Functional life may end due to deterioration, traffic growth, extreme events, or changes in requirements. Life extension activities may restore functional life (e.g., bridge widening) or may restore service life without extending functional life (e.g., structural repairs to a narrow bridge).
- **Service life:** The period of time in which the asset is providing the intended type of service, even if at a degraded level of service. A bridge that is posted but open to traffic or a sign that fails retroreflectivity standards but is still in service are past their functional lives but have not reached the end of their service lives.
- **Economic life:** The period of time in which it is economically optimal to keep the asset in service rather than retiring or replacing it. Economic life is a type of service life that takes into account funding constraints and the cost and effectiveness of life extension activities. In other words, it is sensitive to agency decisions.

Service life is always less than or equal to physical life. Functional life is always less than or equal to service life. Economic life is usually less than or equal to service life, but may be greater if the facility is removed or replaced prematurely.

The above definitions are structured according to the different criteria for end of asset life. Furthermore, the following distinctions are made:

- **Actual life:** The known value of physical, functional, service, or economic life after the asset has actually been retired or replaced.
- **Estimated life:** A forecast of future physical, functional, service, or economic life, which is prepared before the actual life is known.
- **Target life:** A decision about the desired economic life that serves as a basis for planning of design or life extension ac
- **Design life:** A specific type of estimated life and target life that entails a forecast and target for economic life established when the facility is designed.

"Actual" and "estimated" can be adverbs applied to any of the asset life definitions (physical, service, functional, economic).

Also, treatment life can be defined as the amount of life extension given by a specific treatment. This has to be qualified by the type of life (physical, service, functional, economic) and the perspective (actual, estimated, target). For example, the physical life of a pavement may be extended by a structural overlay and the functional life of a narrow bridge can be extended by widening.

In the Guidebook volume of this report, life expectancy is always an estimate or target, because it is derived from a forecasting and decision support tool. In most contexts in the Guide, asset life expectancy is an estimate of future service life, taking into account foreseeable deterioration and life extension activities, but not taking into account traffic growth, changes in functional requirements, unforeseeable extreme events, or funding constraints.

In the literature, there is also a concept of decay life. This is a life expectancy estimate that considers only deterioration and does not consider life extension activities. It is a notional quantity useful as an intermediate result in further life expectancy or lifecycle cost computations. It is most often used in contexts where the analysis period of a lifecycle cost model does not match with the life expectancy of the asset, because the analyst usually will not want to analyze life extension possibilities beyond the end of the analysis period.

Other distinctions that are made in the Guidebook, for specific purposes:

- **Component life** versus **asset life:** components of an asset often have shorter service lives than the asset overall. For example, a bridge deck or pavement wearing surface will have a shorter life compared to the overall bridge or pavement respectively. The Guidebook discusses how to manage component life and life extension activities so as to optimize lifecycle costs for the whole asset.
- **Asset life** versus **cohort life:** policies of blanket replacement or interval replacement are based on a forecast of population distribution of service life, computed over a population of assets (a "cohort"). Service life is more often used at the asset level, while economic life is more often used at the cohort level, when blanket or interval policies are being considered.

In this report, the asset life is referred to in the context of either the physical life or the functional life, depending on which asset type is being investigated and which method is being used (interval approach or condition approach) or the type of data available. Figure 1-4 illustrates the different relationships that could exist between the functional life and physical life definitions. C refers to asset construction, PF refers to physical failure of the asset, FF refers to the functional failure of the asset; in this figure, functional failure means end-of-life and is generally consistent with practices where the asset end-of-life is identified on the basis of functional performance criteria. In other practices, functional failure is not an end-of-life criterion but a criterion for identifying when some repair or expansion intervention is needed.

In Figure 2-1 (a), the asset first reaches a point where it fails functionally; however, the asset is replaced only after several years; if the asset were not replaced in year AY, it is expected that it would suffer physical failure in year PF. This is the most common scenario for most assets at several agencies. However, in certain cases, a proactive agency can predict the year when the functional threshold will be reached and thus replace the asset before it reaches the threshold (see Figure 2-1 (b)) or just as it reaches the threshold (Figure 2-1 (c)). In Figure 2-1 (d), the asset is replaced a considerable length of time after it has failed both functionally and physically and may or may not have been used after these lives were reached. In certain cases, the asset suffers premature physical failure at year PF due to design or construction flaws, natural disaster, or manmade attacks, and thus is reconstructed; in this case, the anticipated physical life is the same as the actual (or observed) life. If the asset did not fail, it would have reached functional failure at the predicted year FF and physical failure at the design year, PF. The scenario in Figure 2-1 (f) is similar to that in Figure 2-1 (a) and (d) except that the asset replacement occurs at the point of physical failure but is similar to the scenario in Figure 2-1(e) because the actual physical life is the same as the anticipated physical life.

For risk analysis for civil infrastructure assets, most existing literature on the subject has focused on physical life solely (Al-Wazeer, 2007). In this report, however, the risk analysis was carried out on the basis of both physical life and functional life because both of these concepts are relevant to asset planning and project programming: identification of the year of asset replacement and rehabilitation, and the subsequent agency tasks of work planning and budgeting are

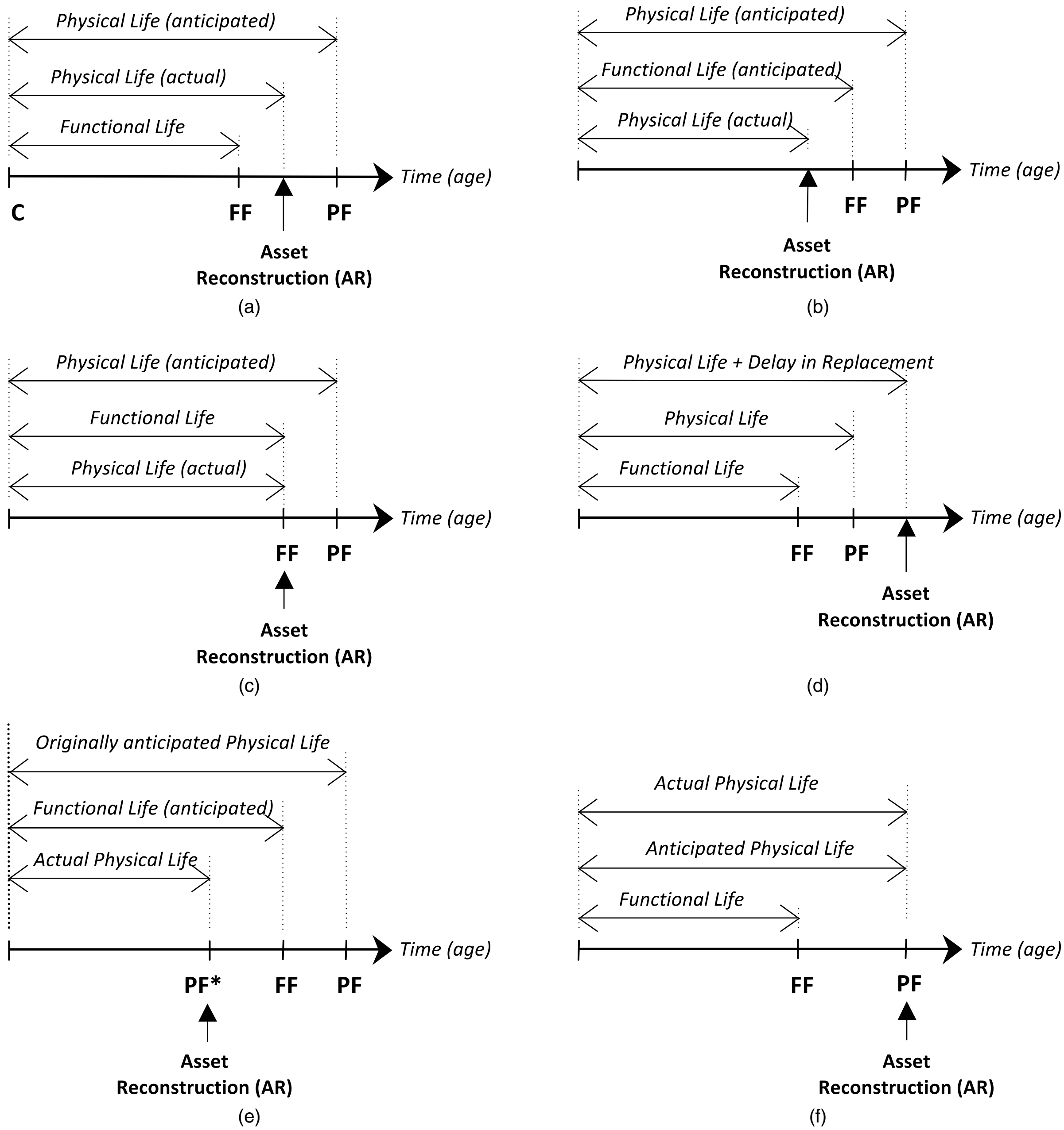


Figure 2-1. Illustration showing different relationships between physical and functional life.

possible only when the actual physical and functional lives are known with a satisfactory degree of confidence.

2.1.2 Measures of Asset Life

A critical consideration in asset life expectancy analysis is the units in which asset life is to be expressed. The most common unit is the asset age in years. However, in recognition that aging is not the only factor of deterioration, asset life can be measured in other units, such as accumulated levels of vehicular use (e.g., ADT or VMT); accumulated traffic loading, which is often used for pavements and pavement markings, bridges, and large culverts; and, for all asset types, the accumulated climatic effects (Shekharan & Ostrom, 2002; McManus & Metcalf, 2003).

Measures of life expectancy that involve the volume of usage or loading or the climatic effects generally allow for a more profound investigation of the effects of these variables on asset longevity. In this report, asset life is expressed in terms of the age (years) of the asset since an agency-specified benchmark such as the initial construction or last reconstruction. This standard is adopted in full recognition that other rationales may exist that have motivated and will continue to motivate the need for carrying out some major action such as replacement/reconstruction or rehabilitation to renew the asset or to restore its functional performance.

2.1.3 Established Life Expectancy Values and Influential Factors

In preparation for the development of asset life expectancy models in this report, a synthesis was carried out for the life values established in the literature for the different highway assets using various modeling methods and techniques. As expected, asset life estimates were found to vary significantly across highway agencies due to the differences in environmental conditions, administrative and cultural practices, maintenance strategies and techniques, and other factors. The following subsections present a review of the published literature on asset life expectancy values, most of which were either predicted using statistical models or subjectively estimated from surveys of experienced asset managers.

The influential factors of asset life can be categorized as follows: asset characteristics (e.g., age, construction/design type, predominant material, and geometrics); site characteristics (e.g., climate, weather, and soil properties); traffic loading characteristics (e.g., traffic volume and percent trucks); and repair history (e.g., maintenance/rehabilitation intensities and frequencies). A review of such factors follows for each asset class.

2.1.3.1 Bridges

Bridge Life Estimates. The actual or functional life expectancy of bridges has been found to vary across countries and across agencies. Some literature focused on the life of the entire bridge while other literature focused on bridge component longevity. In the literature, it is seen that the condition threshold adopted by the agency, as well as the intensity/type/frequency of maintenance and rehabilitation, play a large role in the documented or observed life expectancy of bridge components or bridges.

Estes & Frangopol (2001) compiled bridge life expectancy estimates based on data and expert opinion and concluded that reinforced concrete decks survive between 24 to 48 years or 29 to 58 years if NBI condition rating thresholds of 4 and 3 are applied, respectively; steel railings survive 37 years (NBI rating 3 threshold) to 44 years (NBI rating 4 threshold); and reinforced concrete substructures survive 23 to 42 years (NBI rating 4 threshold) and 27 to 50 years (NBI rating 3 threshold). In Indiana, the life of concrete bridge decks was approximated at 50 years (NBI rating 4 threshold) to 60 years (NBI rating 3 thresholds) (Jiang & Sinha, 1989). In Canada, bridge decks have been found to survive 38 to 45 years (Morcous, 2006). In Florida, concrete decks were estimated to survive a maximum of 146 years; steel decks: 37 years; reinforced concrete superstructures: 80 years (up to 335 years if prestressed); steel superstructures: 46 years; and substructures: 32 to 46 years depending on the painting regimen (Thompson, et al., 2010).

In Massachusetts, a typical bridge life, excluding major maintenance, of 60 years was reported (Massachusetts Infrastructure Investment Coalition, 2005). In Colorado, the median bridge life has been estimated at 56 years (mean life = 76 years) with the deck component surviving 19 years (Hearn & Xi, 2007). Bridges with less common designs may have different life estimates. For example, in Chicago, bascule bridges were found to have an estimated life of 75 to 100 years (Zhang et al., 2008). Bridge decks with stainless steel reinforcement can be expected to last for 75 to 120 years (NX Infrastructure, 2008).

Bridge life is influenced by the maintenance and preservation history of a bridge. In Indiana, it was found that bridge life can vary between 35 and 80 years depending on the maintenance/ preservation activities performed (Cope, 2009; Sinha et al., 2009). For example, if a major repair (e.g., bridge rehabilitation) is carried out every 20 to 25 years, then a bridge life of 70 to 80 years can be expected in Indiana (Sinha et al., 2005). In Massachusetts, bridges were predicted to last 90 years with a preservation activity at year 35, or 110 years if rehabilitated at year 50 (Massachusetts Infrastructure Investment Coalition, 2005). In Indiana, it was estimated that, assuming minor maintenance, concrete and steel bridges would survive 50 and 65 years, respectively (Gion et al., 1993).

International estimates of highway bridge life are generally similar. In Sweden, bridges are expected to survive 40 to 150 years—typically, a minimum of 50 years is assumed (Hallberg, 2005). In the Netherlands, bridges are typically designed to survive 80 to 100 years (van Noortwijk & Klatter, 2004).

Bridge Life Expectancy Factors. Typically, life expectancy and deterioration models have been calibrated separately for each predominant material type (e.g., concrete and steel structures). Of the models calibrated for concrete structures, the life expectancy factors have included the following: climatic conditions including freeze index and cumulative precipitation, geometrics (e.g., span length and number of spans), age (overall and since last treatment), construction technique, wearing surface type, bond strength of overlay with bridge deck, highway functional class, repair history, deck area and percent distressed area (based on spalling or delamination), evaluation methodologies, traffic volume, wheel locations, and accumulated truck loads (Chamberlin & Weyers, 1991; Adams et al., 2002; Testa & Yanev, 2002; Rodriguez et al., 2005; and Chang & Garvin, 2006).

The deterioration of concrete bridges has been linked to corrosion, fatigue, temperature, and/ or collision causing changes in strength and stiffness (Lin, 1995). Primarily, concrete deterioration is caused by corrosion of reinforcement steel, which in turn is a function of the chloride concentration, diffusion coefficient, average depth of bar cover, size and spacing of reinforcement, concrete type, type of curing, amount of air entrainment, carbonation, and water-to-cement ratio (Estes & Frangopol, 2001; Adams et al., 2002; Kirkpatrick et al., 2002; Liang et al., 2002; Melhem & Cheng, 2003; Nowalk & Szerszen, 2004; Sohanghpurwala, 2006; Hearn & Xi, 2007; Oh et al., 2007; Wood & Dean, 2007; Daigle et al., 2008; and Parameswaran et al., 2008). Chlorides reduce the alkalinity of water solutions, leading to rust, which expands and causes a loss in the effective area of reinforcement, which can lead to distresses in the bridge deck. Chloride content is a function of concrete age, roadway functional class, and salt rate from either bodies of water or de-icing chemicals during winter maintenance (Adams et al., 2002). Chloride content is considered "low" at concentrations less than 2.4 kg/m^3, "moderate" when between 2.4 and 4.7 kg/m^3, "high" when between 4.7 and 5.9 kg/m^3, and "severe" when above 5.9 kg/m^3 (Liang et al., 2002). In the case of steel bridges, deterioration and life expectancy have been analyzed on factors including bridge age, volume of truck traffic, truck size distributions, truck axle configuration and weight, cumulative precipitation, freeze index, road classification, type of wearing surface, degradation of individual component, fatigue durability, span length, and high temperatures (Lund & Alampalli, 2004; Lu & de Boer, 2006; Rodriguez et al., 2005; and Lipkus & Brasic, 2007). The main cause of deterioration in masonry arch bridges has been found to be axle loads (Narasinghe et al., 2006).

2.1.3.2 Culverts

Culvert Life Estimates. The design life of culverts and storm drains is typically 50 to 70 years (Wyant, 2002). For these structures, a 50-year life was determined on the basis of laboratory experiments on the corrosion rates of controlled low-strength material (CLSM) fixtures

Table 2-1. Survey results for culvert life expectancy estimates for pipe and box culverts (Markow, 2007).

Pipe Culverts			Box Culverts		
Material	**Number of Responding Agencies**	**Median Life (years)**	**Material**	**Number of Responding Agencies**	**Median Life (years)**
Concrete	13	50	Reinforced concrete	15	50
Corrugated metal	16	35	Timber	3	30
Asphalt-coated corrugated metal	5	50	Precast reinforced concrete	1	50
Small diameter plastic	7	50	Polyvinyl chloride	1	50
High-density polyethylene	1	50	Aluminum alloy	1	50

(Halmen et al., 2008). A 2007 survey of agency estimates for culvert life expectancies indicated slightly lower values, typically ranging from 30 to 50 years for pipe and box culverts (Table 2-1). A 2003 study, however, showed greater variability in culvert life estimates, with predictions ranging from under 40 years to over 100 years, but with most falling between 50 and 80 years (Table 2-2). In comparing state agency estimates of pipe culvert life, it can be inferred that geographically related variations seem to have a significant effect on life. Wyoming DOT expert opinion has estimated the life of pipe culverts in the arid climate of that state at over 75 years (Kidner, 2009). In Florida's wet and warm climatic conditions, metal and reinforced concrete culverts were estimated to survive 91 years and 208 years, respectively (Thompson & Sobanjo, 2010). In Oregon's wet but cold climate, concrete culverts were found to have an expected life of 86 years (Hadiprono et al., 1988). In Missouri, culvert life was estimated at 45 to 50 years (Missouri Highway and Transportation Department, 1990). In New Jersey, culvert life estimates were found to vary greatly by material type: corrugated steel (30 years); concrete, iron, and aluminum (75 years); and brick/clay culverts (150 years) (Meegoda et al., 2008). In New York, steel pipe culvert life was found to range from 13 to 175 years depending on the geographic region, pipe size, and coating (coating life extension—25 to 35 years) (Wyant, 2002).

From these studies, it can be generally inferred that culvert life is highly variable and depends on local conditions. There are relatively few guidelines for predicting culvert life. A survey by Wyant (2002) found that only 7 of 35 DOTs had guidelines for predicting the life of culverts; also, FHWA (2007) reported that several agencies seek models to predict culvert life. As such, the framework provided in later chapters of this report and the accompanying Guidebook are expected to be valuable to agencies that seek to predict culvert life.

Table 2-2. 2003 survey of life expectancy estimates for pipe culverts (Perrin Jr. & Jhaveri, 2004).

	No. of Responding Agencies Indicating Assumed Life Range by Pipe Type				
Life of Pipe Culvert	**RCP**	**NRCP**	**CMP**	**HDPE**	**PVC**
< 40 years			1		
40 – 50 yrs			3		
50 – 60 yrs	2	4	5	3	3
60 – 70 yrs	2				
70 – 80 yrs	8	2	4	3	1
80 – 90 yrs	1			1	1
90 – 100 yrs					
≥ 100 yrs	4	2		2	1
Total	17	8	13	9	6

Culvert Life Expectancy Factors. In past studies, factors found to be significant in influencing culvert life included culvert age, culvert material type, backfill material type, presence of any pipe protection coatings or systems, pipe flow conditions, pH and electrical resistivity of the backfill soil, pH of the flowing water, chloride content, frequency and intensity of culvert inspections or maintenance, presence and type of culvert coating, and topography (flat versus rolling) (Beaton & Stratfull, 1962; Gabriel & Moran, 1998; California Department of Transportation, 1999; Sagues et al., 2001; Wyant, 2002; Halmen et al., 2008). In certain cases, failed culverts are not reconstructed but closed/filled and left in the field, and a new culvert is constructed near the original location. This action is adopted in cases of serious blockages directly influenced by the opening size and flooding potential (Rigby et al., 2002). Mechanistic studies have found that significant life expectancy factors include the amount of fill; level of antioxidants in the soil; soil compaction; condition state of joints, gaskets, and connections; and deflection of the pipe system (Hsuan, 2010; Pluimer, 2010).

2.1.3.3 Traffic Signs

Traffic Sign Life Estimates. In the literature, the life of traffic signs has been carried out from the standpoint of functional performance rather than physical condition and, more specifically, on the basis of the measured retroreflectivity. Often, the life has been established based on different sheeting colors; in Oregon, the ASTM, state, and FHWA standards were used to establish the life of traffic sign sheets (Table 2-3).

A study on traffic sign assets in North Carolina determined that the performance of these assets generally falls below the FHWA performance standards established for that asset type at ages 8 and 15 years (Immaneni et al., 2009).

Considering the high cost of measuring retroreflectivity, some agencies prefer to use assumed point estimates of the life of these assets, which has resulted in blanket cohort replacements at fixed intervals. For instance, the Indiana Department of Transportation (INDOT) has a policy of replacing traffic signs every 10 years, pending no measured violation of the MUTCD retroreflectivity requirements (INDOT, 2008; INDOT). MNDOT replaces signs every 12 years (Nelson, 2011). The Delaware, Kansas, Maine, and North Dakota DOTs assume a life of 10 to 12 years (Wolshon et al., 2002). Also, Indiana, Michigan, and North Carolina are considering moving to a 15-year replacement policy for beaded high-intensity materials (Wolshon et al., 2002).

Traffic Sign Life Expectancy Factors. For traffic sign structures, the life expectancy factors in past research have included the structure type (e.g., single or double mast-arm cantilevers, box-trusses, tri-chord, and monotube), natural wind loading characteristics (e.g., direction and strength of local winds), truck-induced wind gusts, and nature of connections (e.g., welded and threaded). For traffic sign sheeting performance, considerations have included age, sheeting grade and type, sign size, roadway speed limit, color, precipitation, orientation to the sun and traffic, and proximity to the roadway (Black et al., 1991; Black et al., 1992; Paniati & Mace, 1993; Hawkins Jr. et al., 1996; Kirk et al., 2001; Hawkins Jr. & Carlson, 2001; Wolshon et al., 2002; AASHTO, 2003; and Hildebrand, 2003).

Table 2-3. Oregon traffic sign life estimates by sign sheeting and retroreflectivity thresholds (Kirk et al., 2001).

Sheeting Color	Retroreflectivity Threshold ($cd/lx/m^2$)	Life Estimate (years)
White	200 – 250	30 – 70
Yellow	135 – 170	30 – 55
Green	35 – 45	5 – 7
Red	35 – 45	5 – 8

2.1.3.4 Pavement Marking

Pavement Marking Life Estimates. Similar to traffic signs, pavement marking life refers to functional life and not physical life because pavement marking life is often based on retroreflectivity performance. Such performance often varies by material type. At least one study found that paints have a life of 6 to 12 months, and thermoplastics, 3 to 7 years (Abboud & Bowman, 2002). Generally, similar results were found using 100 to 120 mcd/m^2/lux thresholds: 1 to 2 years of life was found for waterborne paints and 4 to 5 years for thermoplastics (Zhang & Wu, 2006).

Pavement Marking Life Expectancy Factors. Pavement marking life expectancy factors were found to include the material type, bead gradations, installation application rates and quality, color, pavement surface type, roadway position (e.g., centerline, edge), climatic conditions (e.g., annual precipitation), frequency of snow plowing, sun exposure, traffic volume and vehicle class distribution, and traffic speed (e.g., life varies between constant sections and acceleration/deceleration sections) (Bowman et al., 1992; Fish, 1996; Harrison & Thamer, 1999; Henry et al., 1999; Migletz et al., 2001; Migletz & Graham, 2002; Parker, 2002; Parker & Meja, 2003; Kopf, 2004; Zhang & Wu, 2006; Jiang, 2008; Lee et al., 2008; Maurer & Bemanian, 2008; and Sathyanarayanan et al., 2008).

2.1.3.5 Pavements

Pavement Life Estimates. Pavement life expectancy generally refers to a functional life when the intended action at the end of life is one that restores the functional adequacy of the pavement and generally refers to actual life when the intended end-of-life action provides a completely new pavement. Pavement life varies by material type: rigid pavements (Portland cement concrete) are generally expected to outlast flexible pavements (asphaltic). From the perspective of functional life, some studies have provided a range of values: an overall assessment of rigid, composite, and flexible pavements produced a range of asset life values from 6 to 20 years (Lee et al., 2002). Rigid pavements in particular have been found to last approximately 16 to 20 years before joint faulting exceeds 0.1 inch, slab cracking exceeds 12% cracked area, and IRI exceeds 160 in/mi (Flom & Darter, 2005); in certain agencies, these thresholds are established to trigger some preservation action. Flexible pavements in Ohio were found to have an average life of 9 years (Yu, 2005) or 12 to 15 years when a PCR threshold of 60 was assumed (Chou, Pulugurta, & Datta, 2008). Flexible pavements in Kansas were estimated to survive up to 8 years, with end of functional life determined by the level of rutting, transverse cracking, and fatigue cracking level (Gedafa et al., 2009).

Pavement Life Expectancy Factors. Pavement life expectancy factors have included surface type (rigid, flexible, and composite) and thickness, construction quality, traffic loading and speeds, structure and overlay age, accumulated climate effects, subgrade moisture conditions, and frequency and intensity of pavement maintenance and rehabilitation (Attoh-Okine & Roddis, 1994; Vepa et al., 1996; Baker et al., 1998; and Gharaibeh & Darter, 2003). For pavements constructed using bituminous asphalt mixes, various factors related to fatigue failure have been identified to be influential to life expectancy (Coetzee & Connor, 1990; Breysse et al., 2005). Environmental effects such as temperature, temperature gradient in the asphalt, and the timing and duration of wet base and subgrade conditions have similarly been found significant for flexible pavement life (Zuo et al., 2007). The life expectancy of pavements constructed using porous asphalt has been found to be influenced by mixture properties (Miradi & Molenaar, 2007). The quality and characteristics of aggregates, level of bonding, layer properties, and degree of compaction have also been found to significantly affect the life of asphaltic pavement (Witczak & Bell, 1978; Noureldin, 1997; and Ziari & Khabiri, 2007). Due to such characteristics, different asphalt mixtures have different life expectancies (e.g., dense-graded conventional asphalt concrete and gap-graded asphalt rubber hot mix); and the quality and thickness of the pavement base material have also been identified as influential (Raad et al., 1993; Romanoschi et al., 1999). Similar factors were found in the study by von Quintus et al. (2007) of hot mix asphalt pavement life. For non-overlaid continuously reinforced concrete pavements, early age crack distribution patterns, coarse aggregate type, and the presence of a swelling subgrade have been found significant for predicting remaining life (Easley & Dossey, 1994; Dossey et al., 1996). Additionally, pavement life has been linked to traffic speed, precipitation, and drainage (Huntington & Ksaibati, 2007).

Pavement studies of asset life expectancy have applied various end-of-life definitions. Common condition/performance measures used to estimate functional life include pavement structural condition (PSC), visual condition index (VCI), distress points/index (particularly rutting, punchouts, transverse, fatigue, and D-cracking distresses), pavement quality indicator (PQI), measures of roughness [e.g., IRI, dynamic load index (DLI), and road quality index (RQI)], effective structural number, and centerline deflection (Fwa, 1991; Attoh-Okine & Roddis, 1994; Henning et al., 1997; Baker et al., 1998; Abdallah et al., 2000; Kuo et al., 2000; Lee et al., 2002; Al-Suleiman & Shiyab, 2003; Gharaibeh & Darter, 2003; Baladi, 2006; Huntington & Ksaibati, 2007; Chou et al., 2008; and Gedafa et al., 2009).

2.1.3.6 Traffic Signals

Traffic Signal Life Estimates. For traffic signals, a life expectancy of approximately 15 years was found from a survey of transportation agencies by Markow (2007) (Table 2-4). Flashers are assumed to have similar life expectancies.

Review of Traffic Signal Life Expectancy Factors. Factors influencing traffic signal head life have been found to include localized wind/gust strength, dominant wind direction with respect to the signal orientation, structure material type, type of structural connections, and climatic and weather factors (South, 1994; Chen et al., 2001; Kloos & Bugas-Schramm, 2005; Lucas & Cousins, 2005; Schrader & Bjorkman, 2006; Markow, 2007).

2.1.3.7 Roadway Lighting

Roadway Lighting Life Estimates. Markow (2007) conducted a survey of agencies on the actual (physical) lives of roadway lighting structures and subsequently established typical estimates that vary between 25 and 30 years (Table 2-5). As stated in a subsequent chapter of this report,

Table 2-4. Survey of life expectancy estimates for traffic signals (Markow, 2007).

	Component	Nr. of Responding Agencies	Median Life (yrs)
Structural System	Tubular steel mast arm	14	20
	Tubular aluminum mast arm	7	20
	Wood pole (and span wire)	9	15
	Concrete pole (and span wire)	2	12.5
	Steel pole (and span wire)	9	20
	Galvanized pole and span arm	1	>100
Controller System	Permanent loop detector	14	7.5
	Non-invasive detector	12	10
	Traffic controller	18	15
	Traffic controller cabinet	17	15
	Twisted copper interconnect cable	11	20
	Fiber optic cable	7	2
Signal Display System	Incandescent lamps	15	1
	Light-emitting diode lamps	18	6.5
	Signal heads	15	20
	Pedestrian displays	1	15

Table 2-5. Survey of life expectancy estimates for roadway lighting (Markow, 2007).

	Component	Nr. of Responding Agencies	Median Life (yrs)
Structural System	Tubular steel	12	25
	Tubular aluminum	9	25
	Cast metal	2	22.5
	Wood posts	2	32.5
	High mast or tower	11	30
Lamps	Incandescent	3	1
	Mercury vapor	6	4
	High-pressure sodium	15	4
	Low-pressure sodium	3	4
	Metal halide	9	3
	Fluorescent	1	5
Other Components	Ballast	9	7.5
	Photocells	11	5
	Control panels	7	20
	Luminaires	2	16.25

higher life estimates were found for roadway lighting structures using historical data. The lower estimate from expert opinion is probably indicative of the need for improved recordkeeping and data analysis to replace expert opinion or to revise expert opinion predictions.

In addition to the surveyed agencies in Markow (2007), New Jersey and Ohio estimate lamp life at 2 to 5 years and 5 to 6 years, respectively (Zwahlen et al., 2003; Szary et al., 2005). In New Jersey, roadway lighting components were estimated to survive 8 to 10 years for batteries and 6 to 24 years for structural systems (Szary et al., 2005).

Roadway Lighting Life Expectancy Factors. Significant factors in roadway lighting life have included the pole/bulb type, temperature extremes, and other environmental factors (Zwahlen et al., 2003; Szary et al., 2005).

2.1.4 Methods for Estimating Life Expectancy

Both empirical (statistical-evidence-based) and mechanistic (physical-based) models have been applied in the literature of life expectancy estimation. This volume of *NCHRP Report 713* focuses on empirical models. However, for the sake of completeness of the information search, mechanistic approaches are summarized below.

2.1.4.1 Mechanistic Methods for Estimating Life Expectancy

Mechanistic methods generally involve the use of field or laboratory tests, which can be destructive or non-destructive, to measure a physical property, such as corrosion, stress, or strain of an asset or component thereof. Theories regarding material behavior are then applied to extrapolate fatigue or physical life information. For concrete structures, for example, mechanistic approaches and applications that have been used in past research for predicting the life of an asset or its structural components are described in Table 2-6.

Of the mechanistic-based methods in Table 2-6, asset life is commonly predicted as a function of corrosion, particularly for assets such as reinforced-concrete box culverts that are susceptible to this mode of deterioration. Corrosion occurs in three stages (Liang et al., 2002):

1. Initiation time—the time for chloride ions to penetrate the concrete surface and onto the passive film surrounding the reinforcement;

Table 2-6. Mechanistic methods for predicting concrete structure life (Liang et al., 2002).

Method	Influence or Application	References in (Liang et al., 2002)
Physical-mathematical model	Predicted time of t_p and t_{cor}	Bazant (1979a,b)
Accelerated durability test method	Prediction of the service life of a structure depended on minimum load-carrying capacity, maximum acceptable deformation, and permeability	Fagerlund (1979)
Evaluation of parameters of deterioration	Use in formulating repair rehabilitation, replacement policy, underestimated value of t_{cor}	Cady & Weyers (1984)
Accelerated test and mathematical model	Prediction of concrete service life	Pommersheim & Clifton (1985)
Probabilistic view	Prediction of service life of building materials and components	Sjostrom (1985)
Failure probability	Design life and durability of concrete structures	Somerville (1986)
Survey data of bridge decks exposed to deicing salt, coastal buildings, and offshore structures	Predicted initiation time	Guirguis (1987)
"Systematic" approach	Service life prediction of building and construction materials	Masters (1987)
Unsteady-state dynamic analysis (using the semi-infinite solid approximation and the Laplace transform. method)	Service life prediction for external vertical walls of RC with external thermal insulations	Fukushima (1987)
Modified version of Bazant's model	Predicted time of t_p	Subramanian & Wheat (1989)
Predictive service life test, aging test, and mathematical model	Service life prediction of building materials and components	Masters & Brandt (1989)
Experimental and field tests	Prediction of corrosion depth in concrete	Tsaur (1989)
Expanded and Bazant model	Prediction of the t_p time, the corrosion cracking time, the breaking time of bond between concrete and steel, and the steel area losing time	Liu & Mian (1990)
Allowable limit and the state of corrosion	Prediction of service lives of RC buildings, but the predicted results are always overestimated	Morinaga (1990)
Predictive service life tests and long term aging, and in-use conditions	Systematic methodology for the prediction of service life of building materials and components	Sjostrom & Brandt (1990)
Mathematical deterioration model expressed the property changing as a function of solar ultraviolet rays, heat, and degradation factors	Service life prediction system of building materials	Tomiita (1990)
Mathematical model consists of the assessment of the annual total damage ratio and the estimation of the service life	To estimate the service life of a bituminous glass-fiber-reinforced multiple waterproof roofing element	Ahoz & Akman (1990)
Probabilistic approach	Service life prediction of ferrocement roof slabs	Quek et al. (1990)
Experience, deduction, accelerated testing, mathematical modeling, reliability, and stochastic concept	Predicting the service life of concrete	Clifton (1990, 1991, 1993)
Measurement of the corrosion rate of reinforcing steel	Prediction of service lives of RC building	Morinaga (1990)
Accelerated corrosion tests and field measurement	Measure the rate of steel corrosion in concrete	Harn et al. (1991)
Gray theory	Predicts remaining service life of harbor structures	Li (1992)
Implementation of Tuntti's model [considers effect of temperature, chloride proportion, & humidity in concrete pores (resistivity)]	Influence of temperature on the service life of rebars	Lopez et al. (1993)

Table 2-6. (Continued).

Method	Influence or Application	References in (Liang et al., 2002)
Time-dependent reliability	Service life assessment of aging concrete structures	Mori & Ellingwood (1993)
Probability method	Service life prediction of existing concrete bridges	Qu (1995)
Reliability approach	Predicts service life of concrete structures exposed to chloride ions	Prezzi et al. (1996)
Fick's second law	Predicts service life of existing concrete exposed to marine environments	Maage et al. (1996)
Testing, structural, and economic models	Service life of existing RC structures	Henriksen (1996)
Generalization of Markov Chains based on time-dependent reliability theory	Prediction of bridge service life	Ng and Moses (1996)
Long-term economic analysis	Service life prediction of concrete road bridges	Brito & Branco 1996)
Calculation of prestressing cable forces from vibro-wire gauges embedded in bridges	Service life prediction of prestressed concrete cantilever bridge	Javor (1996)
Corrosion damage prediction using electrical potential surveys	Service life prediction of concrete bridge deck	Kriviak et al. (1996)
Utilization of measured stress spectra for predicting fatigue accumulation and crack propagation	Service life evaluation of steel or composite bridge; influence of the effective traffic loading on structures	Baumgartner et al. (1996)
Established a computer-integrated knowledge system	Predicting the service life of steel-RC exposed chloride ions	Bentz et al. (1996)
In situ permeability and strength testing	Develop the durability-based design criteria for concrete and assess the remaining life of existing structures	Long & Rankin (1997)
Cumulative damage theory and accelerating the corrosion of rebar in concrete	Service life prediction of rebar-corroded RC structure	Ahmad et al. (1997)
Mathematical model for accelerated testing for concrete structures in chloride laden environments	Predicting the initiation time of concrete structures	Liang et al. (1997, 1999a)
Mathematical model combined Fick's second law with durability coefficient	Predicting the service life of existing RC bridges due to carbonation	Liang et al. (1998, 1999b)
Time-variant reliability method, Monte-Carlo simulation for finding the cumulative-time system failure probability	Service life prediction of deteriorating concrete bridges	Enright & Frangopol (1998)
Fick's second law incorporated surface environment, chloride transport, temperature of surrounding medium, seasonal effects, and construction variability	Predicting the service life of a RC structure in different environments	Amey et al. (1998)
FBECR (fusion-bonded epoxy-coated reinforcing steel) as a physical chloride barrier system	FBECR is not a cost-effective corrosion protection system when compared with bridges built with bare steel in Virginia, because they only provide corrosion protection for 5% of VA's bridge decks	Weyers et al. (1998)
Time-to-cracking model based on elasticity	Corrosion cracking model is dependent on the cover depth, the properties of the concrete and steel/concrete interface, the type of corrosion products, and the size of the reinforcing steel, and is a function of the critical weight of the rust products and corrosion rate	Weyers (1998), Liu & Weyers (1998)

2. Depassivation time—the time for the chlorides, transported to the steel by the alkaline hydrated cement matrix, to locally destroy the passive film, leading to pitting corrosion; and;
3. Propagation or corrosion time—the time when corrosion products form and cracking, spalling, or sufficient structural damage occurs.

Generally, the first two stages are modeled together and can jointly be considered as the initiation time. Attempts to model these time stages are shown in Table 2-7; the asset life is then determined as the sum of the two time periods.

Table 2-7. Prediction of corrosion time stages (Liang, Lin, & Liang, 2002).

Time	Prediction Method	Formula	Reference in (Liang et al., 2002)
Initiation Time, t_p	Weyers	$C(x,t) = S\sqrt{t}\left[1-\mathrm{erf}\left(\frac{x}{2\sqrt{D_c t}}\right)\right]$	Weyers (1998)
	LZCL	$C(x,t) = \left[C_i + (C_s e^{kt} - C_i)\mathrm{erfc}\left(\frac{x}{2\sqrt{D_c t}}\right)\right]^{-kt}$	Liang et al. (2001)
	Hookham	$t = K_c K_e x^2 + K_a x$	Hookham (1992)
	AJMF	$C(x,t) = kt\left\{\left(1+\frac{x^2}{2D_c t}\right)\mathrm{erfc}\left(\frac{x}{2\sqrt{D_c t}}\right) - \left(\frac{x}{\sqrt{\pi D_c t}}\right)e^{-x^2/4D_c t}\right\}$	Amey et al. (1998)
		$C(x,t) = k\sqrt{t}\left\{e^{-x^2/4D_c t} - \left[\frac{x\sqrt{\pi}}{\sqrt{\pi D_c t}}\right]\mathrm{erfc}\left(\frac{x}{2\sqrt{D_c t}}\right)\right\}$	
Propagation time, t_{cor}	Bazant	$t_{cor} = \rho_{cor}\frac{D}{s}\frac{\Delta D^*}{j_r}, \Delta D^* = 2f'_t\frac{L}{D}\delta_{pp}$	Bazant (1979b)
	Modified Bazant	$t_{cor} = \rho_{cor}\frac{D}{s}\frac{\Delta D^*}{j_r}, \Delta D^* = f'_t\left[2\left(\frac{L}{D}\right)+1\right]\delta_{pp}$	Liang et al., 2002
	CW	$t_{cor} = 2\sim5$ years	Cady & Weyers (1984)
	Liu	$t_{cor} = \frac{W_{crit}^2}{2k_p}$ $W_{crit} = \rho_{cor}\left\{\pi\left[\frac{Lf'_t}{E_{ef}}\left(\frac{a^2+b^2}{a^2-b^2} - v_c\right) + d_0\right]D + \frac{W_{st}}{\rho_{st}}\right\}$ $k_p = 0.098\,\frac{1}{\alpha}\pi D i_{corr}, \alpha = 0.57$	Liu (1996)
	Faraday's Law	$t_{cor} = \frac{\delta\rho_{st} ZF}{A i_{corr}}$	Fontana (1987) Mangat & Elgarf (1999)
Initiation Time, t_p	Guirguis	$t = \frac{L}{\lambda D_c}$	Guirguis (1987)
	Bazant	$t = \frac{L}{12D_c}\left(\frac{L}{1-\sqrt{\frac{C^*}{C^S}}}\right)^2$	Bazant (1979b)

NOTES:
$C(x,t)$ = Chlorine content at depth x and time t,; C_i = initial Chlorine content of the concrete; C_s = Chlorine content of the exposed concrete surface; S = Concrete surface concentration coefficient of chloride ions; erf = error function; erfc = complementary error function; k, λ = Constants; D_c = Chloride diffusion coefficient; t_{cor} = corrosion; propagation time; t_1= corrosion initiation time; t = Total service life of RC structures, $t = t_1+t_{cor}$; Z = Valency of the reacting electrode (steel); F = Faraday's Constant; ρ_{st} = Density of material (steel); $\rho_r = \rho_{st}/4$; ρ_{cor} = Density of corrosion product; δ = Material (steel) loss; s = Spacing of bars; A = Atomic weight of iron; L = Concrete cover thickness; λ = Constant; D = Original bar diameter; ΔD^* = Critical value of ΔD that produces inclined cracks; j_r = Rate of rust production per unit area; δ_{pp} = Bar hole flexibility; f'_t = Tensile strength of concrete; i_{corr}= Corrosion current density; d_0 = Thickness of pore band around the steel/concrete interface; C^* = Threshold value of the chloride concentration; C^s = Concentration of chloride ions in pores of concrete at the surface.

The more common techniques for predicting corrosion stage times are Fick's law (Daigle et al., 2008) and Weyers technique [as used in *NCHRP Report 558* (Sohanghpurwala, 2006)]. To slow chloride's ingress into concrete structures, asset managers have used low-permeability concretes, polymer overlays, deck sealers, increased concrete cover depth, and cathodic protection and have investigated alternative reinforcements (Kirkpatrick et al., 2002).

For steel structures, fatigue is more commonly used as a basis for estimating life. Previous experimental studies analyzing fatigue with accelerated loading have included the application of vibration theory, fatigue damage theory, fracture mechanics, the Palmgren-Miner linear damage equation, Miner's hypothesis test, and finite element-based methods (Coetzee & Connor, 1990; South, 1994; Romanoschi et al., 1999; Lund & Alampalli, 2004; Breysse et al., 2005; Lu & de Boer, 2006; Lipkus & Brasic, 2007; Zuo et al., 2007; Samson & Marchand, 2008).

A common method of assessing fatigue involves the use of Miner's Hypothesis (Tanquist, 2002):

$$\sum_{i=1}^{k} \frac{n_i}{N_i} = C$$

where n represents the accumulation of loads over cycle i,
N represents the maximum allowable load cycles, and
C represents the fractional life when C is assumed to be 1.

The fatigue life of steel bridges can also be calculated using the *AASHTO Guide Specifications for Fatigue Evaluation of Existing Steel Bridges* (AASHTO, 1990), which has been used to model the time until an end-of-life criterion occurs (Lund & Alampalli, 2004; Metzger & Huckelbridge Jr., 2006).

Another common technique in bridge life estimation is reliability analysis. This term is generally considered synonymous with the empirical techniques that involve survival analysis. However, in the bridge field, the term reliability pertains to some probabilistic, time-variant index based on the interplay between structural resistance, such as shear and moment strength, reinforcement strength, spacing, and diffusivity, governed by the LRFD (AASHTO, 2010) on one hand, and demand (e.g., traffic volume or truck weights) on the other hand. The life of the asset is taken as the time until the index reaches a pre-specified target level. These indices can be applied to the overall structure or to multiple bridge components. Studies that examined bridge reliability, particularly with the incorporation of probabilistic material strengths, include Lin (1995), Deshmukh & Bernhardt (2000); Lounis (2000), Akgul & Frangopol (2004), Stewart et al. (2004), Biondini et al. (2006), Saber et al. (2006), Oh et al. (2007), and Strauss et al. (2008). Mechanistic models are typically calibrated using laboratory or field experiments under controlled and accelerated conditions that simulate the deterioration of long-lived assets (Roesler et al., 1999). The reliability of these tests, however, is influenced by the extent to which they mimic real-world conditions.

For the purposes of asset management and network-level planning, empirical methodologies, rather than purely theoretical relationships, for life expectancy estimation are considered more appropriate for the practice and consequently is the focus of the analysis in this volume of NCHRP Report 713.

2.1.4.2 Empirical Methods for Estimating Life Expectancy

Empirical modeling techniques for estimating life, either directly or via deterioration levels can be divided into four categories. Studies that have used these categories for estimating asset life are as follows:

- Statistical regression
  - Bridges: Polynomial functional form (Agrawal & Kawaguchi, 2009);
  - Culverts: Linear, log-linear, and exponential functional forms (Hadipronо et al., 1988; Kurdziel & Bealey, 1990; and Halmen et al., 2008);

  - Traffic Signs: Linear, power, exponential, and power functional forms (Kirk et al., 2001; Bischoff & Bullock, 2002; and Immaneni et al., 2009);
  - Pavement Markings: Exponential and smoothing spline functional forms (Abboud & Bowman, 2002; Zhang & Wu, 2006);
  - Pavements: Linear, polynomial, exponential, log-linear, power, and sigmoidal functional forms: (Labi, 2001; Lee et al., 2002; McManus & Metcalf, 2003; Flom & Darter, 2005; Yu, 2005; Chou et al., 2008; and Gedafa et al., 2009);
  - Roadway Lighting: Exponential functional form (Szary et al., 2005).
- Markov chains
  - Bridges: (Jiang & Sinha, 1989; Ng & Moses, 1996; Estes & Frangopol, 2001; Zhang et al., 2003; Hallberg, 2005; Morcous, 2006; Ertekin et al., 2008; and Robelin & Madanat, 2008);
  - Pavements: (Chou et al., 2008).
- Duration models
  - Bridges: Weibull, Exponential, Rayleigh, and Gamma survival models (Ng & Moses, 1996; Klatter & Van Noortwijk, 2003; van Noortwijk & Klatter, 2004; Hearn & Xi, 2007; Nicolai, 2008; Agrawal & Kawaguchi, 2009);
  - Pavement Markings: Weibull survival models (Sathyanarayanan et al., 2008);
  - Pavements: Kaplan-Meier estimate, Cox proportional hazards model, and normal, log-normal, exponential, log-logistic, and Weibull survival distributions (Vepa et al., 1996; Colucci et al., 1997; Eltahan et al., 1999; Romanoschi et al., 1999; Shekharan & Ostrom, 2002; Gharaibeh & Darter, 2003; Bausano et al., 2004; Yu, 2005; Yang, 2007; Yu et al., 2008; Anastasopoulos, 2009; and Irfan et al., 2009);
  - Culverts: Normal and Weibull survival distributions (Halmen et al., 2008; Meegoda et al., 2008);
  - Roadway Lighting: Kaplan-Meier estimate (Zwahlen et al., 2003).
- Machine learning
  - Bridges: k-nearest neighbor inference-based learning, inductive learning, and artificial neural networks (Melhem & Cheng, 2003; Narasinghe et al., 2006);
  - Traffic Signs: Artificial neural network (Swargam, 2004);
  - Pavements: Artificial neural network (Flintsch et al., 1997; Ferregut et al., 1999; and Abdallah et al., 2000).

Generally, it was found that statistical regression is the technique that has been most commonly applied to predict the performance of relatively less-costly assets such as traffic signs, pavement markings, and pipe culverts. Markov chains applications have been limited mainly to pavements and bridges, likely because their calibration requires extensive inspection rating data. Various survival models have been applied to explain pavement life while structural reliability analysis has been more commonly used for predicting bridge life. Of the survival models, the Weibull distribution is widely used across all asset classes. Machine learning has been applied primarily to bridges and pavements, but to a lesser extent than the other approaches, likely because such estimates are perceived as coming from a “black box.” A more extensive treatment of the probabilistic approaches theory is provided in Section 2.2.4.

2.2 Methodology for Estimating Asset Life

In building on the literature, one of the goals of this study was to develop an overarching methodology that could be applied to various asset classes in order to predict highway asset life expectancy. For the methodology used in this study (Figure 2-2), each step is discussed in subsequent subsections.

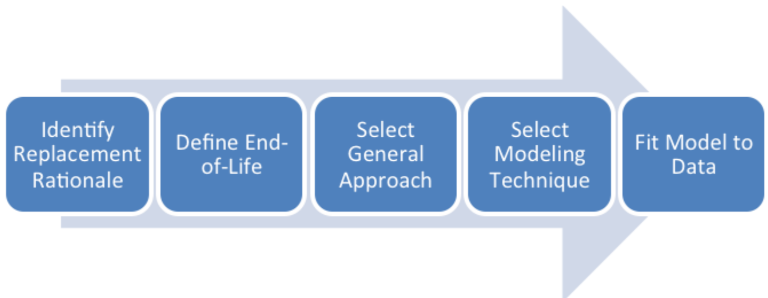


Figure 2-2. General methodology for estimating highway asset life expectancy.

2.2.1 Identify Replacement Rationale

The first step in the developed methodology for predicting asset life expectancy is to identify the rationale for the asset replacement. As discussed in a previous section of this volume of *NCHRP Report 713,* such rationale may generally include structural adequacy and safety, serviceability and functional obsolescence, essentiality for public use, and special reductions. For competing rationales, multiple life estimates can be established for the purposes of comparison.

2.2.2 Define End-of-Life

On the basis of the selected rationale, the next step is to select a representative condition or performance measure pertinent to the asset replacement rationale under consideration. Where end-of-life refers to functional life, an appropriate measure of functional performance and an agency-specified performance threshold are needed. For bridge assets, for example, structural adequacy and safety can be represented by the superstructure, substructure, channel, and scour condition ratings; serviceability and functional obsolescence can be represented by the deck condition rating and deck geometry rating; essentiality for public use can be represented by ADT; and special reductions can be evaluated based on annual maintenance costs. Given a quantitative measure of the rationale, a minimum acceptable threshold, or trigger, is needed. This threshold typically is chosen to reflect the point at which intermediate maintenance actions are no longer cost-effective (Saito & Sinha, 1989).

2.2.3 Select General Approach

The three general life estimation approaches common in the literature are (1) the condition-based approach, (2) the age-based approach, and (3) a hybrid approach. For each of these approaches, the data used could be collected from expert opinion surveys or from data pertaining to in-service assets. Generally, it can be found that for lesser-studied assets, life expectancy is often determined on expert opinion or manufacturer-published values. These values are then commonly used to conduct blanket replacements of all assets in a given age cohort of that asset type. This practice, however, places the agency at risk of foregoing the benefits of remaining service life left in some assets and/or allowing some assets to operate at unacceptable levels of service.

2.2.3.1 Condition-based Approach

The condition-based approach has been commonly used for estimating the functional life of higher valued assets (i.e., bridges and pavements). These assets are periodically monitored/inspected with respect to their condition. As such, deterioration models can be readily developed.

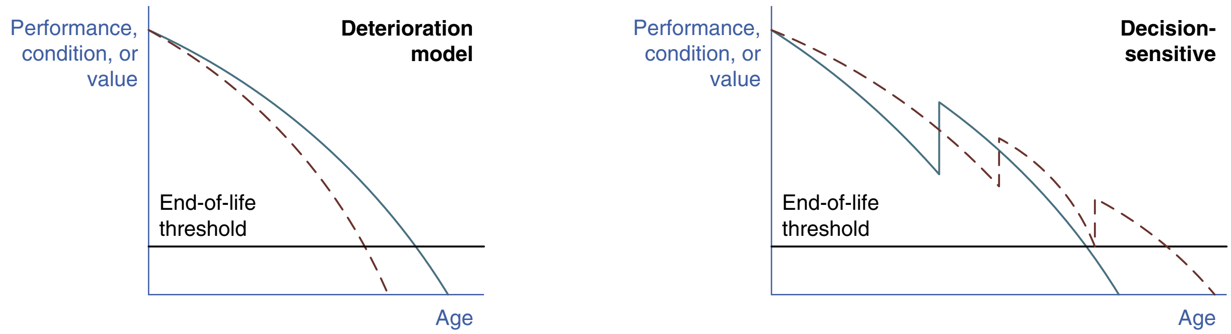


Figure 2-3. Condition-based life expectancy (Conceptual Illustration) (Thompson et al., 2011).

The functional life expectancy is then taken as the time from construction or last reconstruction until one or more performance measures trigger some action intended to restore the functional performance, or in extreme cases of functional inadequacy, replacement. For instance, if an agency sets a minimum performance threshold for a pavement's level of cracking or rutting, then the time when the threshold is first crossed is used (Figure 2-3). Such condition-based life estimates could also be viewed with respect to the occurrence of an extreme event (Sanchez-Silva & Rosowsky, 2008).

In cases where replacement decisions are based on some terminal level of performance, such as road sign reflectivity thresholds, the selection of the specific performance measure is influenced by the rationale for replacement being considered. If replacement is being considered due to structural adequacy and safety, then, for pavements, an agency may wish to predict rutting, PCR, and percent cracks; for bridges, predictions of discrete NBI ratings for decks, substructures, superstructures, structural evaluation, and scour can be made. For other assets, some visual rating of condition can be predicted. If replacement is being considered due to serviceability or functional obsolescence, then pavements can be modeled to predict IRI or PSR; for bridges, the NBI deck geometry or waterway adequacy could be predicted; for culverts, the percent of blockage or channel erosion can be considered; for traffic signs and pavement markings, retroreflectivity can be measured; for traffic signals and roadway lighting, luminescence may be predicted. If "essentiality for public use" requires replacement, then economic development considerations may be used. This could be modeled using traffic forecasts. For special reductions, performance could be based on annual maintenance costs to keep the asset in a serviceable state. Also, multiple rationales could be considered for a given exercise to estimate life expectancy. For example, the NBI sufficiency rating for bridges considers all of the above-mentioned replacement rationale. If one combined factor has not been agreed on by an agency, then the minimum of a series of life values may be taken.

2.2.3.2 Age-based Approach

In the age-based approach, historical replacement records regarding the year of construction and year of demolition/reconstruction are assessed (Figure 2-4). The actual life is best quantified

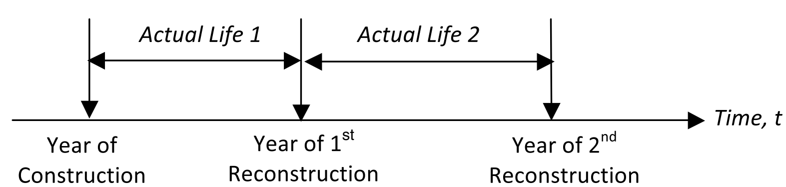


Figure 2-4. Age-based life expectancies (Conceptual Illustration).

using this approach. In this approach, the asset life can be directly predicted and easily incorporated into replacement scheduling decisions.

The accuracy of age-based predictions is highly dependent on data availability and integrity. Many agencies lack complete historical records relating to the year the asset was built, maintenance strategies, traffic volumes, and so on. Without sufficient archival information, the credibility of the results may be brought into question. A key piece of information not available in the collected dataset for this study was the rationale or motive behind the replacement of the assets considered. With such data, agencies could organize calibration datasets for only those rationales considered relevant. For instance, if bridge widening is no longer considered necessary, then agencies need only analyze the observed lifespan for an alternative bridge replacement rationale. More generally, the age-based approach assumes that the future will mimic the past, which could be an invalid assumption in light of emerging materials, construction processes, contracting approaches, climate change, and so on.

2.2.3.3 Condition/Age-based Hybrid Approach

Combining the two approaches may also be preferred so as to directly make life predictions based on condition. For instance, the time until an inadequate sufficiency rating is obtained for a bridge can be predicted as opposed to predicting a sufficiency rating by age. Combining historical replacement records and observed times until a condition/performance threshold is reached could serve an alternative approach for asset life estimation.

2.2.4 Select Modeling Technique

In selecting a modeling technique, agencies should consider three dimensions of analysis. The first dimension relates to the basic asset attributes (e.g., asset class and design/material type). The second dimension relates to the nature of the data (e.g., if the data is cross-sectional, time-series or panel; if the dependent variable is discrete or continuous; if sufficient condition-based, age-based, or hybrid model data are available; the geographic representation of the data; and if explanatory variables are available to be analyzed). The third attribute relates to the modeling techniques (e.g., if a deterministic or probabilistic model is preferred; the specific statistical technique that is to be used; and the measure of goodness-of-fit used to validate model results).

On the basis of the selections made at each level, different approaches in the following dimensions may be recommended. For instance, if the asset manager seeks to predict the functional life of a steel box culvert (first level), then a condition-based approach to predict a discrete visual condition rating may be applied to determine the functional life if there is lack of historical replacement data (second level), which would then suggest that a discrete choice model or Markov chain may be the most appropriate (third level).

Asset life expectancy models could be developed using local data; that way, it would be possible to avoid using life expectancies derived using assumptions or expert opinion or transferred from other dissimilar regions that do not reflect local conditions. This would have the additional benefit of identifying influential local factors and assessing their sensitivity on the basis of local changes in conditions. Where the agency is particularly interested in uncertainty considerations when assessing the life of its assets, probabilistic empirical modeling techniques are recommended using local data. However, agencies are generally advised to select an appropriate modeling technique on the basis of the dependent variable and their staff expertise. From the literature review, six modeling techniques were identified for potential application for life expectancy modeling and analysis:

- *Linear and Non-linear Regression Models*—continuous, deterministic model type with direct interpretations of model fit (R^2) and parameter strength.

- *Neural Networks*—continuous, deterministic model type that relies on hidden relationships between sets of variables in order to make forecasts, but is often viewed as a "black box."
- *Discrete Outcome Models*—discrete, probabilistic, and parametric model type that can be applied to ordered data to predict condition states.
- *Markov Chains*—discrete, probabilistic, and non-parametric model type that can predict the probability of being in any discrete state at any point in time.
- *Duration Models*—continuous, probabilistic model type that produces non-, semi-, or fully parametric survival curves and allows for capturing covariate influences.
- *Markov-based Duration Models*—fit a continuous, probabilistic, fully parametric survival curve to a Markov Chain estimate.

In choosing among the modeling techniques, agencies should consider the availability of data. If, for a given asset type, there exist data on intervals between replacements but no performance data, duration modeling could be applied for life expectancy estimation. Duration models can be calibrated to observed historical life. If data on asset condition/performance are discrete in nature and are routinely collected during inspections, Markov-based modeling could be applied. If the asset condition/performance data is continuous in nature on asset condition/performance and generally not routinely collected, a duration model could be applied to determine the asset life on the basis of the observed or expected time at which the performance threshold is reached.

A brief review of these model types is provided in the following subsections.

2.2.4.1 Regression Models

Linear and non-linear regression models are the most commonly applied technique by agencies for asset performance modeling, due to their ease of application and interpretation, simplicity of methodology, clarity of results, and ability to be calibrated with widely available software such as MS Excel. Such models can be applied to (1) predict a continuous performance measure (condition-based) as a function of age and other variables or (2) directly predict asset life as a function of the explanatory variables (age-based). Latent variable and adaptive approaches could also be used to predict condition as a function of past performance and characteristics in a step-by-step fashion. Discrete/continuous modeling could also be applied. With regard to model functional forms and types, the variety of options include

Polynomial

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i x^i$$

If $n = 1$, then Linear
If $n = 2$, then Quadratic
If $n = 3$, then Cubic

Exponential/Logistic

$$Y = \left(\beta_0 + \sum_{i=1}^{n} \alpha_i \beta_i^{x_i} \right)^k \text{ for k} = -1 \text{ or } 1$$

If $k = 1$, then Exponential
If $k = -1$, then Logistic

Gompertz

$$Y = \sum_{i=1}^{n} c_i \alpha_i^{\beta_i^{x_i}}$$

where Y represents a dependent variable

c_i, α_i, and β_i represent estimable parameters and

x_i represents an independent variable

Linear models include various model subtypes (e.g., ordinary, indirect, generalized, two-stage and three-stage least squares, instrumental variables, limited and full information maximum likelihood, and seemingly unrelated regression). The most efficient and consistent of these models are the system equation methods commonly applied for simultaneous equations, as opposed to single equation methods: i.e., ordinary least squares (OLS), indirect least squares (ILS), instrumental variables (IV), two-stage least squares (2SLS), and limited information maximum likelihood (LIML). System-of-equation methods include three-stage least squares (3SLS), seemingly unrelated regression estimation (SURE), and full information maximum likelihood (FIML). Such models are better suited for dealing with serial correlation problems (i.e., lack of independence among explanatory variables), heteroskedasticity (i.e., variables with non-constant standard deviations), and mitigating errors created by endogenous variables (i.e., variables where there is not a unidirectional causal relationship from the independent variable to the dependent variable) (Washington et al., 2003).

In 3SLS, least squares regression is performed in three stages: (1) obtain the 2SLS estimates of the model system, (2) use the 2SLS estimates to compute residuals to determine cross-equation correlations, and (3) use generalized least squares (GLS) to estimate the model parameters as similarly done in SURE (Washington et al., 2003). In other words, 3SLS relies on multiple rounds of OLS to predict instrumental variables (i.e., variables that are "suspected" to be endogenous) which in turn predict the dependent variable. This process results in a more efficient and consistent linear regression model.

Of this set of model subtypes, the 3SLS approach is recommended. Where the data are panel in nature, modeling techniques involving random effects could be incorporated to account for correlation (e.g., multiple inspections for a single structure).

Despite their simplicity in interpretation (particularly for linear regression), there are disadvantages for this general model type. Linear regression methods are only appropriate when the dependent variable has a linear or intrinsically linear relationship with the explanatory variables, which may not necessarily be the case for highway asset performance behavior over time. Furthermore, such models are deterministic and thus yield only a point estimate that may not reflect the true value of the condition or asset life that could be expected. On the other hand, for non-linear models, it is generally far more difficult to develop a set of significant independent variables and, although these models may yield higher coefficients of determination (R^2), they typically lack explanatory power due to their composition of fewer significant variables.

2.2.4.2 Neural Networks

A second approach to consider is that of artificial neural networks. This non-linear adaptive model predicts asset condition on the basis of what it has "learned" (pattern identification) from past data. Statistically, an artificial neural network is a non-linear form of 3SLS, where appropriate "instruments" are used to predict future "events"; in this case, an event is asset life reaching a certain value (Figure 2-5).

To facilitate learning, such models are typically Bayesian-based. This approach updates estimates (i.e., posterior means) by applying weighted averages based on previous estimates (i.e., prior means). Typically, these weights are based on the number of observations. Activation functions within the network have included hyperbolic tangent, log-sigmoid, and bipolar-sigmoid functions. Such approaches have been found to work well with noisy data and are relatively quick; however, such techniques are better suited for smaller databases (Melhem & Cheng, 2003). These models require more sophisticated software to develop (e.g., Palisade's @Risk Neural Tools, NeuroXL) and can sometimes be used as a "black box" (i.e., prediction process unknown but assumed appropriate). However, the ability to "learn" makes these models particularly useful to asset managers.

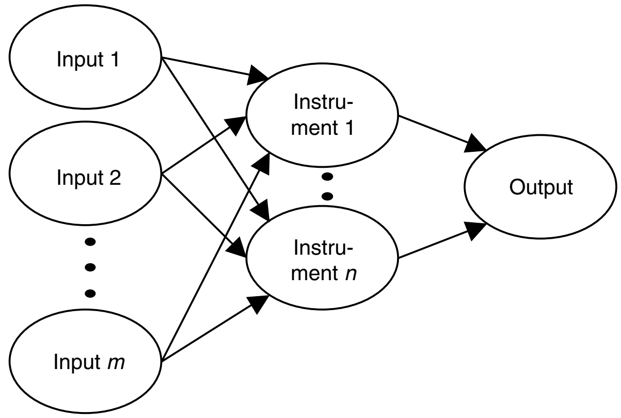


Figure 2-5. Example of an artificial neural network.

2.2.4.3 Ordered Discrete Response Models

Where asset condition/performance data are discrete in nature, it is considered more appropriate to apply discrete-outcome modeling techniques. Based on an assumed distribution, these models can be used to calculate the probability of an asset being in any condition state. For instance, the probability of a bridge being in any condition state on the NBI rating scale (0-worst to 9-best) in any future year can be calculated using these models. Also, such models simplify sensitivity analysis by enabling analysis of marginal effects (i.e., how probability of a condition state changes given a unit change in one of the inputs). These models can be used for panel, ordered, and/or nested data.

Model subtypes are typically of the probit or logit form and can be modified as follows:

- **Ordered** (e.g., NBI condition rating) or **unordered** (e.g., bridge status—functionally obsolete, structurally deficient, satisfactory condition);
- **Nested** (e.g., predict status of all concrete bridges at first level, then predict status of pre-tensioned concrete bridges and post-tensioned concrete bridges at the second nest level); or
- **Mixed, fixed, or random effects** incorporated to account for asset heterogeneity for panel data.

Probit models assume normally distributed variates, whereas logit models assume extreme value distributions. Depending on the data, similar results may be obtained.

Probit

$$P(Y_i) = \Phi\left(\frac{\beta_i x_{in} - \beta_{i+1} x_{(i+1)n}}{\sigma}\right) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\frac{\beta_i x_{in} - \beta_{i+1} x_{(i+1)n}}{\sigma}} EXP\left(-\frac{1}{2} w^2\right) dw$$

Logit

$$P(Y_i) = \frac{EXP(\beta_i x_i)}{\sum_{i=1}^{n} EXP(\beta_i x_i)}$$

For ordered models, the threshold parameters are calibrated to indicate the probability of a condition state. For example, the probability that an asset is in any one of three possible condition states can be computed from an ordered probit model by comparing the model sum ($\Sigma\beta x$) to the threshold parameters (μ) (Figure 2-6). Mathematically, the exact probability of such an

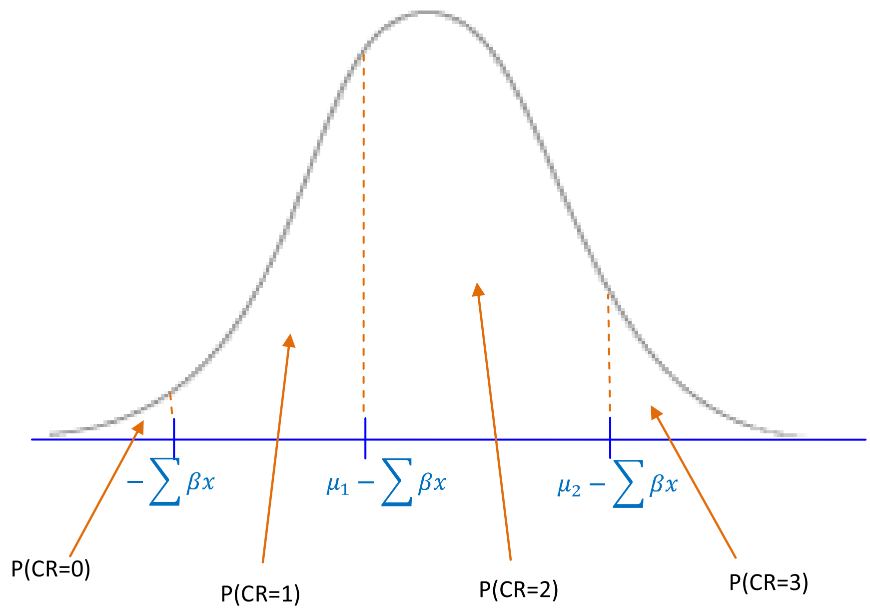


***Figure 2-6. Example illustration of a 3-state ordered probit model* (Washington et al., 2003).**

asset being in any condition state follows the cumulative standard normal distribution with the variable X taking the following forms:

$$P(\textit{Condition State} = 0) = [-\sum \beta x] \sim N(0,1)$$

$$P(\textit{Condition State} = 1) = [\mu_1 - \sum \beta x] \sim N(0,1) - [-\sum \beta x] \sim N(0,1)$$

$$P(\textit{Condition State} = 2) = [\mu_2 - \sum \beta x] \sim N(0,1) - [\mu_1 - \sum \beta x] \sim N(0,1)$$

$$P(\textit{Condition State} = 3) = 1 - [\mu_2 - \sum \beta x] \sim N(0,1)$$

where

x represents the set of independent variables, age, material type, etc.;
β represents the set of parameter estimates;
μ represents the threshold parameters, which in comparison to parameter estimates and variable values, indicate the likelihood of being in a given condition state:

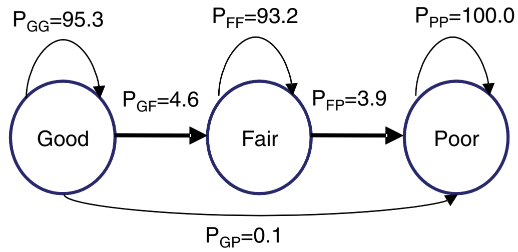
$$\mathrm{X} = [\mu - \sum \beta x] \text{ and } Z = \frac{X\text{-}Mean}{Standard\ Deviation}$$

N(0,1) represents the cumulative standard normal distribution with mean = 0 and standard deviation = 1

These models, however, are only appropriate if the assumed distribution accurately reflects the data. Furthermore, with discrete models, in general, there is a potential for aggregation bias. For example, two culverts may each have a condition rating of say 4 but one may be nearly in a condition state of rating 3 while the other is nearly in a condition state of rating 5. This loss of generality may cause some errors in model calibration.

2.2.4.4 Markov Chains

Markov chains are commonly applied for estimating bridge deterioration curves. A Markov chain is a memoryless (i.e., transition probability based solely on the present state and not on past states), stochastic process with a finite integer number of possible non-negative states, that



Markov Transition Matrix

State Today	State Probability after 1 Year		
	Good (G)	Fair (F)	Poor (P)
Good (G)	95.3	4.6	0.1
Fair (F)	0	93.2	3.9
Poor (P)	0	0	100.0

Figure 2-7. Example Markov chain graph and transition matrix.

is used to predict the probability of being in any state after a period of time. These chains are commonly visualized in terms of a "graph" showing all of the nodes (i.e., condition states) and possible paths (i.e., transitions). Calculations, based on the graph, are carried out using matrix multiplication (Figure 2-7).

The transition matrix corresponds to the probability of transitioning after a period of time (with discrete or continuous time intervals), which can be taken on an annual basis or based on inspection frequencies. In modeling deterioration, transitions to an improved state are considered impossible and are assigned a transition probability of zero; likewise, transitioning to a non-subsequent state (for example, a preceding condition state or two subsequent condition states) may be assigned zero probability by some agencies.

Transition probabilities, represented by, $p_{ij} = \Pr(Y_{k+1} = j | Y_k = i)$, can be found via expert opinion, optimization (Jiang & Sinha, 1989), statistical modeling based on observed frequencies (i.e., the methodology used in this study), or approximated using pairs of inspections (Thompson et al., 2011). To correct for the fact that deterioration rates are not homogenous throughout the life of an asset, multiple transition matrices are typically established for several age ranges (Jiang & Sinha, 1989). Also, Bayesian techniques could be used to update transition probabilities as well. Predictions at various points in time can be derived from the Chapman-Kolmogorov equation (Weisstein) to yield:

$$p(t) = p(t_i)\prod_{i}^{n} p^i$$

where $p(t_i)$ represents the initial state, i, probability vector (e.g., [1, 0, 0] for a new traffic sign on a "good," "fair," or "poor" rating system starting at time 0); P represents the transition matrix; n represents the size of the age group interval.

2.2.4.5 Duration Models

Duration, sometimes labeled as reliability or survival, analysis is a probabilistic approach for predicting the likelihood of a continuous dependent variable passing beyond or "surviving" at any given unit of time. The survival curve is just one representation of probability which can be applied to asset life (Table 2-8).

As shown in Figure 2-8, survival curves can be produced for multiple performance measures or replacement rationales. The leftmost curves are the stochastically dominating functions in a life prediction.

Table 2-8. Representations of probability.

Representation	Relationship	Life Expectancy Interpretation
Density Function	$f(t) = \frac{dF(t)}{dt}$	Area under the curve represents the probability between two life values
Cumulative Function	$F(t) = \sum_{t_i<t} f(t_i)$	'Failure' probability at any point in time
Survival Function	$S(t) = 1 - F(t)$	Probability of surviving beyond any point in time
Hazard Function	$h(t) = \frac{f(t)}{S(t)}$	'Failure' rate which is inversely related to survival

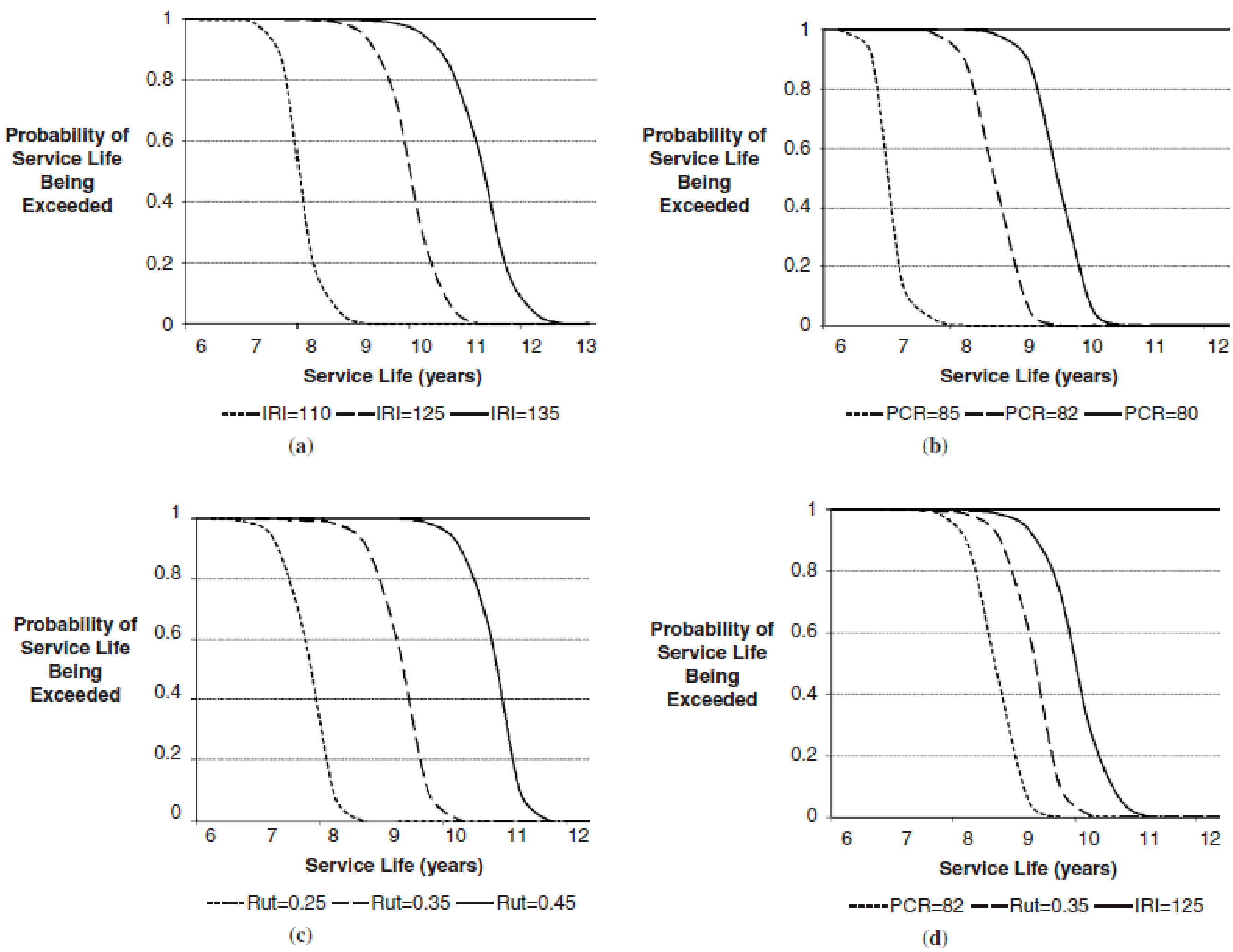


Figure 2-8. Asset survival curves using different performance indicators and performance thresholds (Irfan et al., 2009).

Duration models can be non-parametric, semi-parametric, or fully parametric. Non-parametric methods (e.g., Kaplan-Meier/product-limit estimator or life tables) are less commonly applied in transportation (more common in medical fields) because they do not retain the parametric assumption of the covariate influence; however, they may be appropriate when there is little knowledge of the functional form of the hazard or if a small number of observations is obtained (Washington et al., 2003). The most common non-parametric estimator is the Kaplan-Meier estimate:

$$S(t) = \prod_{t_i < t} \frac{n_i - d_i}{d_i}$$

where n represents the number of assets available at the start of the time period in less censored cases (such as assets that have left the analysis without a conclusive end value); d represents the number of assets 'failed' by the end of the time period.

For the lower (L) and upper (U) bounds of a desired confidence level for a non-parametric model, such as the Kaplan-Meier, the following equations are recommended (Newcombe, 1998):

$$L = \frac{2np + z^2 - 1 - z\sqrt{z^2 - 2 - \frac{1}{n} + 4p(nq+1)}}{2(n+z^2)}$$

$$2np + z^2 + 1 + z\sqrt{z^2 + 2 - \frac{1}{n} + 4p(nq-1)}$$

where n is the number of observations; p is the point estimate of probability (i.e., S(t) for Kaplan-Meier); q is taken as 1-p; z is the Normal distribution test statistic at the desired confidence level.

Semi-parametric models (e.g., Cox proportional-hazards), which account for covariate influence and are appropriate when the underlying distribution of the data is unknown, are considered more flexible without the constraint of a fully parametric form. The Cox model approach takes the following form:

$$S(t) = \ddot{S}(t) * EXP\left(\beta_0 + \sum_{i=1}^{n} \beta_i x_i\right)$$

where $\ddot{S}(t)$ represents a fully parametric survival curve.

Fully parametric models (e.g., gamma, exponential/Markov, Weibull, log-logistic, log-normal, Gompertz) are generally recommended in studies of this nature due to the benefits in model efficiency and in reducing bias, but they are influenced by the extent to which the assigned distribution fits the data. As found in the literature review, the Weibull survival curve is one of the most commonly applied distributions (van Noortwijk & Klatter, 2004):

$$S(t) = EXP\left[-1 * \left(\frac{t-y}{\alpha}\right)^{\beta}\right]$$

where α represents the scaling factor (stretches curve laterally); β represents the shape factor (stretches curve vertically); and γ represents the location factor (shifts curve horizontally by representing value at which 100% survival probability occurs).

The Weibull distribution is a more generalized form of the exponential distribution (β=1) that allows for a more flexible means of capturing duration dependence. Explanatory factors can also be incorporated to develop a fully parametric survival curve with $\alpha = EXP(\beta_0 + \Sigma_{i=1}^{n} \beta_i x_i)$. The hazard function of the Weibull distribution is monotonic, indicating that the hazard never decreases over time (if β>1).

For distributions with non-monotonic hazard functions, log-logistic models can be applied (Washington et al., 2003). The model form for this distribution is

$$S(t) = 1 - \left[1 + \left(\frac{\beta}{t - y}\right)^{\alpha}\right]^{-1}$$

A difficulty arises, however, when the location factor takes different values during the life of an asset. Merely changing the value of the location factor does not account for the changing hazard rate associated with the parametric specification (Ng & Moses, 1996). As such, the survival probability of in-service structures can be updated using conditional probability (Bayesian) theory:

$$S(t|t > T) = \frac{S(t \cap t > T)}{S(T)} = \frac{S(t)}{S(T)}$$

where T represents the age an asset is known to have survived.

To compare distributions, chi-squared test statistics can be computed based on the family of the distribution. The test statistic for functions in the same family can be approximated as follows (Washington et al., 2003):

$$\chi^2 = -2[LL(\beta_A) - LL(\beta_B)]$$

where χ^2 represents the chi-squared test statistic; LL($\beta_{A,B}$) represents the log-likelihood of distributions A and B (e.g., Exponential and Weibull distributions).

In the special case of the Exponential and Weibull distributions, a second technique is to calculate a modified t-statistic which assesses the statistical significance of the difference between the shape factors.

$$Modified\ t - statistic = \frac{\beta - 1}{SE}$$

where β represents the parameter estimate and SE represents the standard error.

If the shape factor is significantly different from 1, then the Weibull distribution may be considered justified; otherwise, the Exponential distribution may be considered a better fit.

When comparing distributions from alternative families, an individual chi-squared test statistic should be calculated for each distribution (Washington et al., 2003):

$$\chi^2 = -2[LL(0) - LL(\beta_c)]$$

where LL(0) represents the restricted log-likelihood function and LL(β_C) represents the log-likelihood function at convergence.

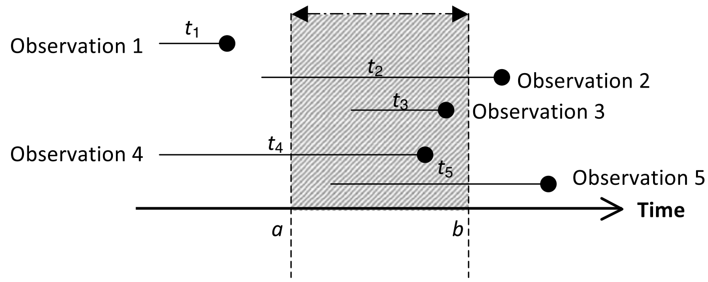


Figure 2-9. Censoring types in duration modeling (Washington et al., 2003).

Using these test statistics, the Gamma, Weibull, Gompertz, Exponential, Log-Logistic, F, and Lognormal parametric duration models were tested in a subsequent section of this report.

Finally, to validate the use of a distribution, the Kaplan-Meier survival curve can be compared to the baseline ancillary survival factors.

A further consideration in calibrating duration models is the inclusion of censored data (Figure 2-9).

Data can be either left-censored, right-censored, both left- and right-censored, not captured, or completely captured over the period of observation. From interpreting Figure 2-12 in terms of asset life expectancies, the censored data types are as follows: the left-censored data (i.e., t_4) indicate that the actual initial construction or reconstruction year is not observed but the time of replacement is; the right-censored data (i.e., t_5) indicate that the asset construction year is known but that it has not been replaced during the time of observation; both types of censoring represent data (i.e., t_2) where neither the construction/reconstruction year and year of replacement are observed; the data not captured (i.e., t_1) are those in which neither construction or replacement data are available; and the completely captured data would represent those assets for which knowledge of both the years of construction and replacement are available (i.e., t_3).

Censored data can be problematic in that it can lead to biased estimates. Yet, it can be helpful in modifying predictions to account for observations that may have dissimilar properties from uncensored data. When more than half of a dataset is censored, the observed average time to failure is no longer predicted by the model and the tail probability estimates are inaccurate (Kim, 1999; Ho & Silva, 2006). To help control bias from censoring, parametric models, or Bayesian inference when the distribution is unknown, are recommended (Kim, 1999). However, when dealing with long-term assets, such as highway infrastructure, right-censored observations are particularly important to account for the data that includes information from more modern designs (Klatter & Van Noortwijk, 2003)—such designs are less likely to have failed within the observational period, resulting in a prediction that does not capture the life expectancies of improved designs. Therefore, in this study, a 50/50 censoring split is assumed appropriate for predicting asset life.

2.2.4.6 Markov-based Duration Models

Markov-based duration models are a technique for fitting a parametric model estimate to a non-homogenous Markov chain with an absorbing state. In doing so, a parametric form, known to better represent life, can be calibrated to readily available inspection data and ease the correlated simulation required in uncertainty analysis. In this sense, the Markovian survival curve is analogous to the Kaplan-Meier estimate with probabilities found via matrix multiplication. Therefore, the Kaplan-Meier estimate is essentially a binary Markov chain with the possible states being "failed" or "survived" (Hosgood, 2002). As such, the goal of fitting a parametric model (or multiple parametric models for intermediate transitions) is to minimize the difference to the nonparametric survival function (Perez-Ocon et al., 2001).

Homogenous Markovian probabilities are inherently exponentially distributed (multiplying by one transition matrix n number of times). However, if the duration in each state is non-exponential and data for a duration model are unavailable, then an alternative is needed. While this may be sufficiently mitigated by the use of multiple transition matrices (i.e., piecewise exponential distributions), another technique would be to fit a parametric survival curve to the Markovian survival curve.

Semi-Markov processes, commonly applied in power system analysis, have been used to convert back and forth between Markov chain models and generalized survival (typically Weibull) functions (Ng & Moses, 1996; van Casteren, 2001; and Thompson et al., 2011). One such technique for this conversion is the equivalent age technique, shown below for a Markov/Weibull model (Thompson et al., 2011):

1. Estimate Markov transition matrix
2. Convert each row of the matrix to a median transition time

$$t_j = \frac{log(0.5)}{log(p_{jj})}$$

3. Allocate a portion of asset life to each condition state, in proportion to transition time, to develop weights

$$w_j = \frac{1}{\Sigma_j t_j} \sum_{k=j}^{N} t_k$$

4. Compute a condition index using Markov predictions and weights, which in turn approximates the Weibull survival probability

$$CI = \sum_j w_j x_j$$

5. Use the inverse of the Weibull survival model to calculate equivalent age

$$t = \alpha * [-\ln(CI)]^{\frac{1}{\beta}}$$

6. Optimize to maximize goodness-of-fit between the actual age corresponding to the Markov prediction and the equivalent age

   Maximize

$$Normal\ Log\ Likelihood = -0.5 * ln(2\pi) - 0.5 * ln[\sigma^2] - 0.5 * \frac{\sum_i^n (Age\ of\ Markov\ Prediction_i - Equivalent\ Age)^2}{\sigma^2}$$

   Subject to

$$Markov\ Median\ Life = Inverse\ Weibull\ Median\ Life$$

$$\beta > 1(assuming\ increasing, monotonic\ hazard)$$

   By changing σ, α, β

This technique, however is more commonly applied when dealing with a time-homogenous Markov chain. For non-homogenous Markov chains, this report recommends an alternative approach that minimizes the root mean square error (RMSE) between the Weibull survival function and Markov chain survival curve by changing the Weibull scaling and shape factors, while maintaining the median life prediction. Markov/Weibull models are particularly useful for infrastructure where deterioration is initially slow and then accelerates with time.

For in-service assets, the same techniques can be applied to calibrate Markov/Beta models. The use of a Beta distribution has been recommended in past research for estimating remaining asset life (Li & Sinha, 2004) due to its flexibility in accounting for various hazard rates (e.g., change in hazard rate due to maintenance activity). The survival function of the Beta distribution is represented by

$$S(t)=1-\frac{\int_0^{\frac{t-\gamma_L}{\gamma_H-\gamma_L}} t^{\alpha_1-1}(1-t)^{\alpha_2-1}\,dt}{\int_0^1 t^{\alpha_1-1}(1-t)^{\alpha_2-1}\,dt},\alpha_1,\alpha_2>0$$

where γ_L represents the lower bound location factor; γ_H represents the upper bound location factor; α_1, α_2 represent non-negative shape factors.

The advantages of Markov-based models include a probabilistic estimate, sole dependence on current conditions (i.e., minimal data needs if transition probabilities known), flexibility in modifying state duration, and efficiency in dealing with larger networks. Their disadvantages include their discrete nature, the deterioration of components is described in visual terms only, there is an assumption of constant inspection periods, no consideration of system condition, and their independence from past data if a first order Markov-chain is used (Morcous, 2006; van Noortwijk & Frangopol, 2004). To overcome the assumption of constant inspection periods, Bayesian techniques can be applied (Morcous, 2006).

2.2.5 Model Selection Recommendations

The best calibrated model can be identified on the basis of the goodness-of-fit measure (e.g., adjusted R^2, McFadden R^2, log-likelihood), the significance of the variables based on t-statistics assuming a minimum 90% confidence level, the intuitiveness of the parameter signs, minimization of the correlation, and the robustness of the estimate. Considering the uncertainties involved in life expectancy estimation, stochastic methods are preferred.

A general procedure by which a highway agency could select the best model is presented in Figure 2-10. It is recommended that the decision be based on the general approach applied, the nature of the dependent variable, the sample size, and the probabilistic/deterministic preference. However, the experience and preferences of agency staff could also be considered in the selection of the best model.

2.2.6 Data Availability Assessment and Grouping of Data

As stated in the discussion of approaches for estimating life, the accuracy of predictions hinges on the availability and quality of agency databases. For the purposes of asset life estimation, it is recommended that agencies maintain archival records of life expectancy factors, condition/performance measures, maintenance activities, year of construction, and the rationale for any replacements or retirements of assets. It may be beneficial to supplement in-house information with data from other agencies. Data from the National Oceanic and Atmospheric Administration

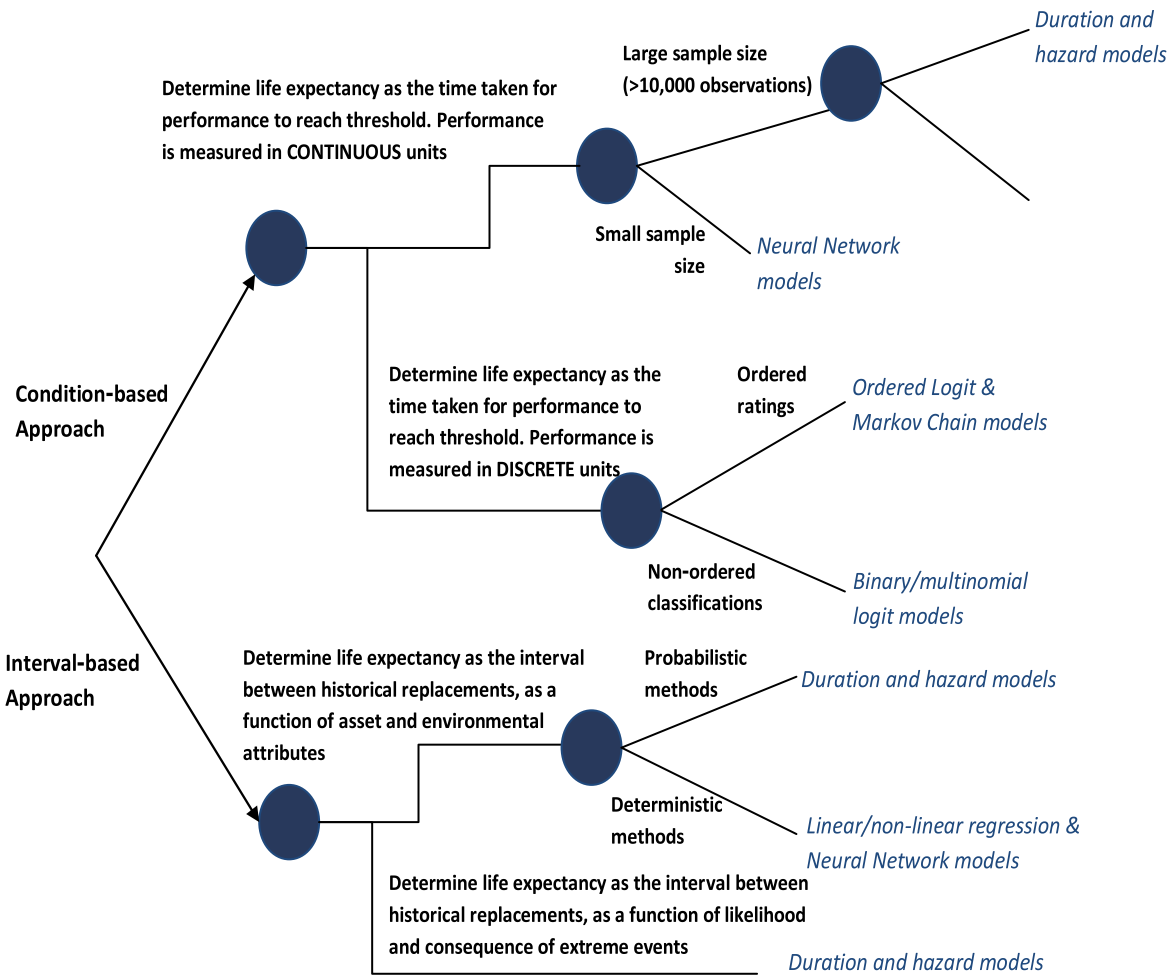


Figure 2-10. General guideline for model selection for life expectancy estimation.

(NOAA) can be used to assess climate factors and National Resources Conservation Service (NRCS) data can be used to assess the influence of soil factors. Such information can be combined with agency databases or overlaid into a geographic information system (GIS) (Chase et al., 2000). For volume of *NCHRP Report 713,* NOAA and NRCS data were collected at the climate division level in order to calibrate parameter estimates.

In analyzing climate data, various groupings of assets should be considered, particularly for any non-covariate approach. If data segmentation is not applied, a biased estimate that is not descriptive of either data segment may be obtained (e.g., life of assets in Group A, 50 years; life of assets in Group B, 90 years. If grouping is not done, the life of all assets in Groups A and B combined, 70 years). Proper groupings of data can lead to more efficient statistical/econometric models and further allow agencies to analyze assets that share similar characteristics (Hanna, 1994). These groupings could be organized by district, climate region, material type, structure type, traffic volume, or repair history. The stratification of data should be arranged so that the heterogeneity within each group is minimized and the heterogeneity between the groups is maximized in order to reduce external effects. For agencies that may seek to establish different groupings, clustering and Delphi techniques can be used. Figure 2-11 shows an example dendogram for statistical groupings of regions of similar climate, developed using SPSS. For this report, SHRP-LTPP climate regions were used.

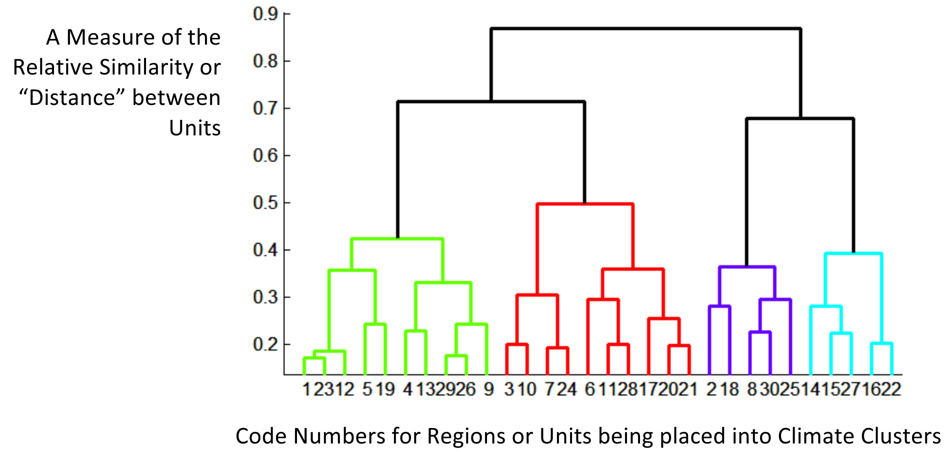


Figure 2-11. Example dendogram developed using cluster analysis.

2.2.7 Incorporating the Impacts of Preservation into Life Expectancy Models

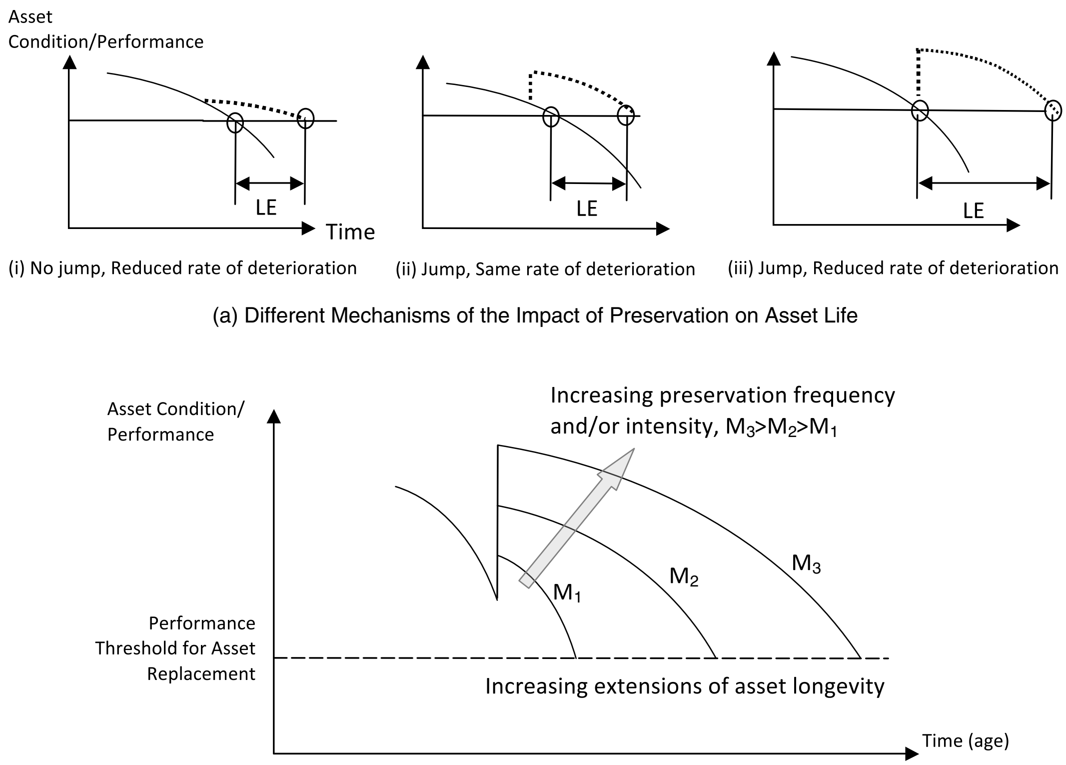
There are at least three key application attributes of preservation over the asset life cycle: occurrence, frequency, and intensity. Occurrence is a binary variable referring to whether the asset receives any preservation over its entire life. Frequency is the number of times the asset receives some preservation activity within a certain time period or the interval between the same or different activities. Intensity is a continuous variable that describes the effort associated with preservation and can be measured in terms of the material quantities used or the average annual expenditure (e.g., added thickness of pavement in a structural overlay, \$/lane-mile or \$ per ft^2 of deck area expended on maintenance of pavements and bridges, respectively). So, it is possible for an asset to receive, for example, low frequency but high intensity or high frequency or low intensity.

There are two contexts of incorporating the effects of preservation into life expectancy models. The first context, addressed in this section (Section 2.2.7), is the determination of the influence of preservation on asset life expectancy. The second context, addressed in Section 4.2.1.7 in Chapter 4, is similar to the first—albeit in the reverse direction: the determination of the effect of superior assets (i.e., those built with long-lived materials, superior designs and innovative construction processes) on preservation application (intensity and frequency) over asset life. For example, the use of stainless steel for deck reinforcement in place of traditional epoxy-coated steel, while more costly, generally leads to longer life expectancies (FHWA, 1988; Yunovich et al., 2002) and has been shown to be more cost-effective in the long term (Cope et al., 2011). Similarly, the construction of French drains under highway pavements has been shown to greatly increase the life of pavement assets (Christopher and McGuffey, 1997). Numerical examples for the second context are provided in Section 4.2.1.7 of Chapter 4. The rest of this section addresses the first context.

As demonstrated in this report, the life expectancy of a highway asset is often influenced by the application of preservation it receives over its lifecycle. From the perspective of preservation frequency and intensity, there could be at least three potential cases: when preservation of the asset over its life cycle is (1) performed at the frequency and intensity as specified or assumed by the designer in the lifecycle cost analysis, (2) performed at a lower frequency and/or intensity than is assumed by the designer, (3) performed at a higher frequency and/or intensity than specified or assumed by the designer in the lifecycle cost analysis.

2.2.7.1 Effect of Different Levels of Preservation on Asset Life: A Conceptual Discussion

For the condition-based approach, performance curves can be developed by agencies for individual or sets of assets. If the effectiveness of a preservation activity is known, it is possible to



(a) Different Mechanisms of the Impact of Preservation on Asset Life

(b) Impacts of Increasing Intensity and Frequency of Preservation on Asset Life

Figure 2-12. Conceptual illustrations of preservation effect on asset longevity (Labi, 2001).

extrapolate how the performance curve will be modified beyond the preservation year and hence the effect on asset life (Lytton, 1987; Markow, 1991; Mamlouk & Zaniewski, 1998). As shown in Figure 2-12(a), for instance, the effectiveness of a preservation activity can be captured in terms of a performance jump for non-increasing performance indicators and/or a reduced rate of deterioration (i.e., change in the slope of the deterioration curve). With knowledge of the jump and/or change in deterioration rate, the life extension can be calculated (i.e., asset life with preservation activity—asset life without preservation activity). Furthermore, the effectiveness can be captured on the basis of the intensity of the activity. As seen in Figure 2-12(b), more intense preservation activities such as asset rehabilitation lead to greater jumps in performance (i.e., greater reductions in deterioration). Also, more intense or more frequent preservation activities lead to more gentle performance curves (i.e., greater reduction in the deterioration rate compared to less intense or less frequent activities).

The timing of the preservation activity then could be scheduled on the basis of the knowledge that the preservation action will "buy" additional time for the asset life. Further discussion of incorporating asset life expectancy into scheduling preservation activities, as well as performing lifecycle cost analysis, are provided in Chapter 4. Prior to such example applications, a demonstration of the best fitting survival models fitted to the data is presented in Chapter 3.

The effect of different levels of preservation received by an asset over its lifecycle on its longevity can be modeled in one of at least two ways:

- Capturing the preservation impacts on asset longevity using preservation occurrence versus frequency/intensity as independent variables
- Capturing the preservation impacts on asset longevity by developing separate post-application performance models for different preservation treatments, intensities, and/or frequencies.

Each of these ways of assessing preservation impacts on asset life are explained in Sections 2.2.7.2 and 2.2.7.3, respectively.

2.2.7.2 Capturing the Preservation Impacts on Asset Longevity Using Preservation Occurrence vs. Frequency/Intensity as Independent Variables

As explained earlier, the life expectancy model could be performance based (where the response variable is an asset performance indicator) or interval based (where the response is a time interval between successive replacements or retirements). If the approach were interval based, then the model would be one that estimates asset life directly as a function of preservation effort and other attributes; in that case, taking the marginal effects of the preservation term would yield the impact of each level of the preservation effort on the asset life expectancy (e.g., 2 additional years of asset life for every inch of pavement overlay or 5 additional years for every $1000 per lane-mile expended on preventive maintenance). The associated non-linearities and scale economies (or diseconomies) could be captured using an appropriate functional form for the model. On the other hand, if the approach were performance based, then the model would be one that estimates asset performance and consequently, on the basis of the threshold performance, can be used to derive asset life; in such a case, the effect of increased maintenance occurrence or frequency/intensity would be to slow the rate of deterioration, thus delaying the time the performance curve reaches the threshold and thus increasing asset life as seen in Figure 2-12.

Preservation Occurrence: The impact of whether preservation occurs or not, over asset life-cycle can be captured by the use of an indicator variable in a statistical asset life expectancy model. Mohamad et al. (1997) developed a model to investigate the effect of maintenance on the level of pavement performance; maintenance was considered a discrete event representing a binary choice of its being performed on a pavement section or not, and pavement performance levels were represented by roughness numbers. Other variables included were pavement thickness, pavement loading, and a regional factor. The researchers also addressed the issue of simultaneity bias that often arises in such solution contexts.

Preservation Intensity/Frequency: Other researchers have modeled the changes in asset performance due to maintenance. For example, Sinha et al., 1988 expressed maintenance effectiveness as the change in pavement roughness, R, as follows: $R = a + b^*\log10M + c^*S + d^*(\log10M^*S)$, where S is a dummy variable representing pavement location, M is the unit routine maintenance expenditure. Used in the appropriate context, these models can be used to derive the expected increase in asset performance (and hence the increase in time to reach performance threshold) due to an expected menu of maintenance actions over several years. Labi (2011) assessed the impact of different levels of maintenance (in terms of $/lane-mile) on the longevity of rehabilitated pavement assets, for each level of truck loading and climatic severity.

2.2.7.3 Capturing the Preservation Impacts on Asset Longevity by Developing Separate Post-application Performance Models for Different Preservation Treatments, Intensities, and/or Frequencies

A post-preservation performance model for the asset specific can be developed for each type, or intensity/frequency level of the preservation treatment, as conceptually illustrated in Figure 2-12. Using data for the different types, intensities, or frequencies of preservation effort, the analyst can develop different asset performance curves, M_1, M_2, and M_3. Generally, higher intensities and frequencies would translate into performance curves that have slower rates of deterioration, and thus, greater life. Methodologies and numerical for determining the asset life from a given asset performance curve are provided in this report and in the Guidebook that accompanies this report.

This section develops a methodology that can be used by an agency to assess the impact of different post-preservation application performance curves on asset life extension.

Figure 2-13 (Labi et al., 2008) presents a blown-up portion of a kink in a typical infrastructure performance curve (the kink reflects the application of an intervention, that is, a preservation treatment). In (a), the figure is shown for the so-called "non-increasing" measures of performance that decrease with asset age, such as Pavement Condition Rating (PCR), Present Serviceability Index (PSI), Sign retroreflectivity, Bridge Sufficiency Rating, mobility index, and safety rating, whose increasing values indicate better performance. In (b), the figure shows typical trends of so-called "non-decreasing" measures of performance that increase with asset age (e.g., surface roughness, faulting index, rut index, bridge vulnerability index, congestion index, crash rating, or some index whose increasing values indicate worsening performance). The functions $f1(t)$ and $f2(t)$ represent the infrastructure performance (or deterioration) model just before preservation and just after preservation, respectively. Typically, $f1(t)$ is steeper than $f2(t)$, but it is not unusual to encounter cases where they have similar slopes.

Symbols used in the figure have the following meanings:

t = accumulation of some temporal attribute such as time, usage, or climate effects. For simplicity, such temporal attributes are collectively referred to as "time" in the rest of this section.

t_a = time at which the preservation treatment was applied to the asset. This typically corresponds to a specific threshold level of service established by the infrastructure agency. Depending on funding availability, actual values of *ta* may not be constant from year to year, but may rather deviate from established thresholds.

t_b = time at which the asset reaches a critical replacement threshold level of service if it had not received the preservation treatment.

t_c = time at which the asset, after preservation treatment, reaches the same level of service at which it received the preservation treatment.

t_e = time at which the asset, after preservation, reaches a critical replacement threshold level of service if it does not receive any other preservation.

t_d = time at which the asset reaches a zero level of service if it had not received the preservation.

t_f = time at which the asset, after the preservation, reaches a zero level of service if does not receive another preservation.

y_m = LOS at which the preservation is carried out (this may or may not be equal to the preservation "trigger" or "threshold" value).

y_c = minimum LOS at which the asset needs replacement or reconstruction, often referred to as the replacement or reconstruction "trigger" or "threshold" value.

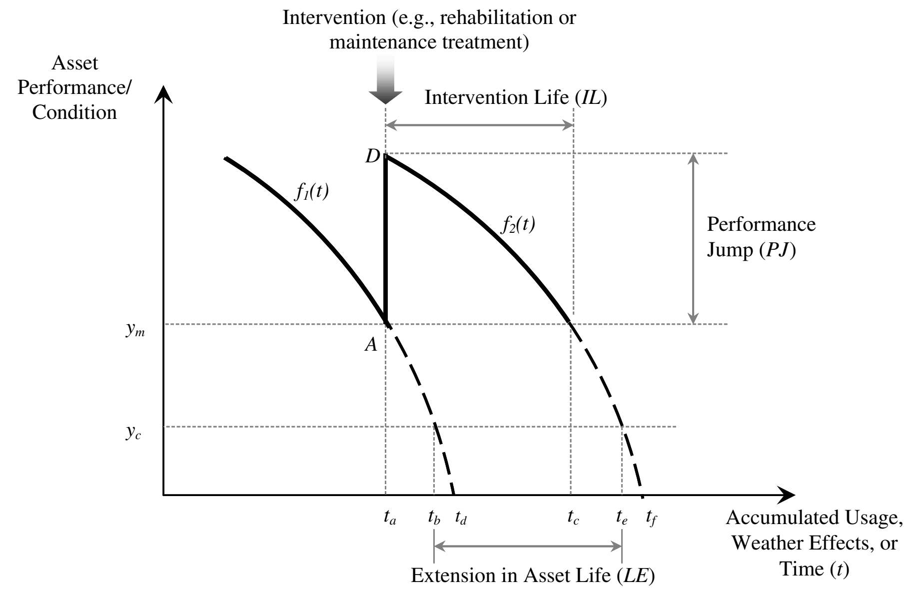
TL = preservation life, i.e., the time that elapses between preservation and when the asset reaches a state that is the same as the state at which it received the preservation.

LE = asset life extension, i.e., the time between the attainment of a critical replacement threshold LOS assuming no preservation and the time between the attainment of a critical replacement threshold LOS assuming no subsequent preservation.

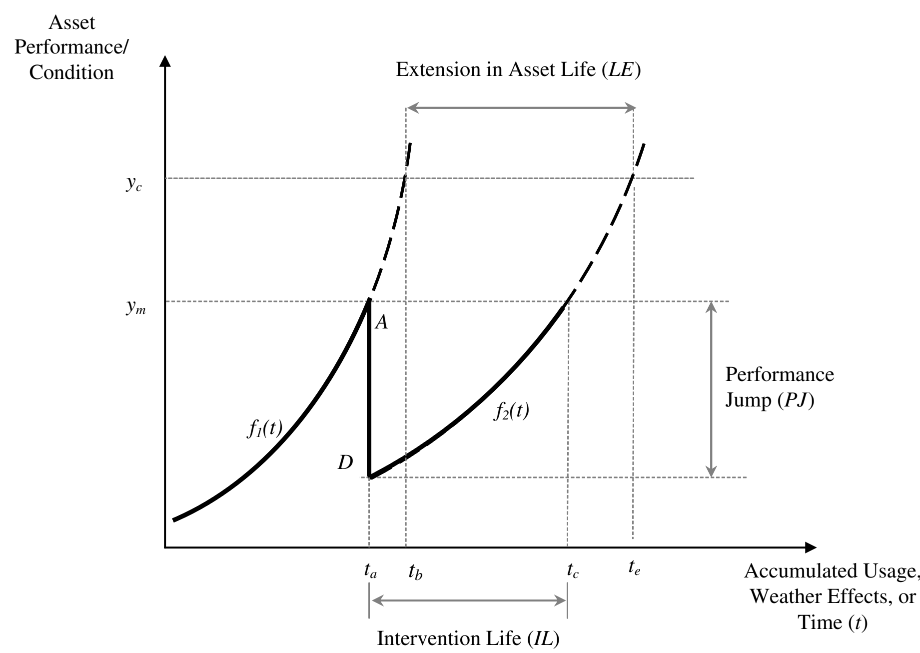
From Figure 2-13, the following basic relationships and assumptions can be established:

1. $LE = t_e - t_b$
2. $f_1(t_b) = y_c = f_2(t_e)$
3. $TL = t_c - t_a$
4. $f_1(t_a) = y_m = f_2(t_c)$
5. TL is solely dependent on the nature of $f_2(t)$ and the numerical values of PJ and y_m
6. LE is dependent on the nature of $f_1(t)$, $f_2(t)$ and the numerical values of y_m and y_c.

On the basis of these basic relationship and assumptions, Labi et al. (2008) showed the following relationships between preservation intensity (represented by the performance jump and the shape of the post-preservation function) and extension in asset life (Table 2-9). Using these relationships, an agency can quantify the impact of asset preservation treatments on the



(a) Non-decreasing Performance Attributes



(b) Non-increasing Performance Attributes

Legend
The Y-axis represents the performance or condition (level of deterioration) of the infrastructure
A - Point of deterioration curve just before preservation
D - Point of deterioration curve just after preservation

Figure 2-13. Relationships between performance jump, preservation treatment life and asset life extension (Labi et al., 2008).

Table 2-9. Estimating the increase in asset life due to preservation actions, for different pre- and post-preservation performance functional forms (Labi et al., 2008).

Mathematical forms of Performance (Pair combinations)		Relationships between Short-term Effectiveness (Preservation-induced Increase in Performance) and Long-term effectiveness (Preservation Life or Extension in Asset Life)
$f_1(t)$ and $f_2(t)$ are linear	$f_1(t)=m_1t+c_1$ $f_1(t)=m_1t+c_1$	$LE=\frac{(y_m-y_c)(m_2-m_1)-PJ*m_1}{m_1m_2}$ $IL=-\frac{PJ}{m_2}$
$f_1(t)$ is linear and $f_2(t)$ is 2nd order polynomial	$f_1(t)=m_1t+c_1$	$LE=\left[\frac{y_m-y_c}{m_1}\right]+\frac{\left(\sqrt{b_2^2-4a_2(c_2-PJ-y_m)}-\sqrt{b_2^2-4a_2(c_2-y_c)}\right)}{2a_2}$ $IL=\frac{\sqrt{b_2^2-4a_2(c_2-y_m-PJ)}-\sqrt{b_2^2-4a_2(c_2-y_m)}}{2a_2}$
$f_1(t)$ is linear and $f_2(t)$ is exponential	$f_1(t)=m_1t+c_1$ $f_2(t)=a_2e^{-b_2t}+c_2$	$LE=\left(\frac{y_m-y_c}{m_1}\right)+\frac{1}{b_2}\ln\left[\frac{PJ+y_m-c_2}{y_c-c_2}\right]$ $IL=\frac{1}{b_2}\ln\left[\frac{PJ+y_m-c_2}{y_m-c_2}\right]$
Both $f_1(t)$ and $f_2(t)$ are exponential	$f_1(t)=a_1e^{-b_1t}+c_1$ $f_2(t)=a_2e^{-b_2t}+c_2$	$LE=\ln\left[\left\{\frac{y_c-c_2}{a_2}\right\}^{\left(\frac{-1}{b_2}\right)}*\left\{\left(\frac{PJ+y_m-c_2}{a_2}\right)^{\left(\frac{b_1}{b_2}\right)}-\left(\frac{y_m-y_c}{a_1}\right)\right\}^{\left(\frac{1}{b_1}\right)}\right]$ $IL=\frac{1}{b_2}\ln\left[\frac{PJ+y_m-c_2}{y_m-c_2}\right]$
$f_1(t)$ is exponential and $f_2(t)$ is linear	$f_1(t)=a_1e^{-b_1t}+c_1$ $f_2(t)=m_2t+c_2$	$LE=\left[\frac{y_c-c_2}{m_2}\right]+\frac{1}{b_1}\ln\left[\left(\frac{y_c-y_m}{a_1}\right)+e^{\frac{-b_1}{m_2}(PJ+y_m-c_2)}\right]$ $IL=-\frac{PJ}{m_2}$
$f_1(t)$ is 2nd order polynomial and $f_2(t)$ is linear	$f_1(t)=a_1t^2+b_1t+c$ $f_2(t)=m_2t+c_2$	$LE=\frac{y_c-c_2}{m_2}+\frac{b_1}{2a_1}+\sqrt{\left(\left\{\frac{b_1}{2a_1}+\frac{PJ+y_m-c_2}{m_2}\right\}^2-\frac{y_m-y_c}{a_1}\right)}$ $IL=-\frac{PJ}{m_2}$
Both $f_1(t)$ and $f_2(t)$ are 2nd order polynomial	$f_1(t)=a_1t^2+b_1t+c_1$ $f_2(t)=a_2t^2+b_2t+c_2$	$LE=-\left[\frac{b_2}{2a_2}-\frac{b_1}{2a_1}\right]-\left[\frac{\sqrt{b_2^2-4a_2(c_2-y_c)}}{2a_2}\right]+\left[\sqrt{\left(\left\{\frac{b_1}{2a_1}-\frac{b_2}{2a_2}-\frac{\sqrt{b_2^2-4a_2(c_2-PJ-y_m)}}{2a_2}\right\}^2-\frac{(y_m-y_c)}{a_1}\right)}\right]$ $IL=\frac{1}{2a_2}\left(\sqrt{b_2^2-4a_2(c_2-PJ-y_m)}-\sqrt{b_2^2-4a_2(c_2-y_m)}\right)$

Abbreviations:
LE = Extension in Asset Life; *IL* = Intervention life or preservation Life; *PJ* = Performance jump (preservation-induced increase in asset performance); *y* = performance indicator.

extension of asset life. This is shown for different pre- and post-preservation performance functional forms. Higher levels of preservation intensity translate into higher performance jumps and more gentle deterioration slopes as represented by the post-preservation functional form $f_2(t)$ and its parameters.

Agencies can apply these relationships to ascertain the increase in asset life due to their different preservation actions. To do this requires the following data: (1) a function that describes the rate of the asset performance deterioration before the preservation, (2) a function that predicts the expected jump in asset performance due to the preservation, and (3) a function that describes the expected rate of performance deterioration after the preservation. If such functions are not available, data could be collected to develop them.

The results are demonstrated using data from approximately 100 flexible pavement sections in Indiana. For purposes of simple illustration, the following performance model was developed: $PSI = 4.4908 - 0.0642\ (AGE)$

A review of the state of practice showed that, on the average, thin overlay preservations had been applied to such pavements at an average condition of 3.1 PSI units (hence $y_m = 3.1$). Also, available pavement condition guides in use in Indiana suggest that interstate pavements are due for replacement when the PSI falls below 2.5 units (therefore $y_c = 2.5$). A recent study in Indiana showed that thin overlay treatments, on the average, offer pavements a 0.87 PSI jump in pavement performance.

From this information, the life of thin overlay treatments in Indiana can be estimated using the relationships presented in Table 2-9. In other words, the time interval that elapses after such preservation until such time that a similar preservation is needed can be estimated. Assuming that both pre- and post-preservation performance functions are linear (at least within the immediate time vicinity of the preservation application), the appropriate equation in Table 2-9 can be used to determine the preservation life given the performance jump of thin overlay treatments, as follows:

$$IL = -\frac{PJ}{m_2} = \frac{-0.87}{-0.0642} = 13.6 \text{ years}$$

From a review of literature on the subject, such a result is consistent with field observations of the actual lives of thin overlays, particularly for pavements with relatively low traffic loading and weather severity. A questionnaire survey of pavement professionals at Indiana districts found that thin overlays have had a 10 to 15 yearly interval between applications for AC pavements (Labi and Sinha, 2002). Raza (1994) stated that thin overlays have had a treatment life of up to 11 years. Also, the Indiana DOT design manual suggests a preservation life of 15 years for thin overlays, for the purposes of lifecycle costing (INDOT, 2002).

The role of thin overlays, like all preventive maintenance activities, is to extend pavement life (O'Brien, 1989; Mamlouk and Zaniewski, 1998) thereby deferring the need for major rehabilitation (Geoffroy, 1996). From the given performance model and threshold data for AC pavements in Indiana, it is also possible to estimate the extension in the pavement asset life due to thin overlay treatments. In other words, it is possible to determine the reduction in pavement life had it not received the thin overlay treatment:

$$LE = \frac{(y_m - y_c)(m_2 - m_1) - PJ * m_1}{m_1 m_2} = \frac{(3.1 - 2.5)(0) - (0.87 * -0.0642)}{0.0642 * 0.0642} = 13.6\ years$$

The extension in asset life, in this example, is equal to the intervention (preservation treatment) life. However, this is not always the case. This result was obtained in this example only because it was assumed that the pattern of deterioration before preservation is the same as that after preservation—both before- and after-preservation functions were assumed to be linear with identical parameters. In reality, it would be realistic to expect that the deterioration slope after preservation is gentler than that before preservation, thereby causing a greater value of asset life.

2.2.7.4 Concluding Remarks for Section 2.2.7

Clearly, it can be beneficial for agencies to model the impacts of preservation occurrence, frequency, and/or intensity on asset longevity. This can be done using preservation occurrence versus frequency/intensity as independent variables or by developing separate post-application performance models for different preservation treatments, intensities, and/or frequencies.

The data needed to carry out this analysis is minimal: annual performance data and contract records that indicate the year of asset construction and the year(s) of subsequent preservation treatment applications. Unfortunately, not many agencies have kept a very good record of their asset preservation histories, particularly, contract records that show year of construction and preservation. There are encouraging signs that agencies have realized the need for doing so and are undertaking such effort in earnest. As data on preservation history becomes increasingly available through increased collection and management of such data, it will be possible for agencies to develop these models that can help them ascertain the impact of different maintenance various to build models.

2.3 Summary

A review of the literature and the developed methodology for estimating highway asset life was presented in this chapter.

From the literature, it was found that references to asset life can be generally broken down as follows: physical, functional, service, treatment, design, residual, and actual (or observed) life. These lifespans are typically quantified by a temporal metric; however, some practitioners prefer the use of a maximum number of accumulated loadings to represent life. It was determined that past researchers had generally estimated the life of highway assets as follows: overall bridge life = 50–60 years, bridge deck life = 25–45 years, culvert life = 30–50 years, traffic sign life = 10–20 years, pavement markings life = 1–5 years, pavement life = 10–20 years, traffic signal life = 15–20 years, and roadway lighting life = 25–30 years. These estimates were found to be highly variable and subject to the end-of-life definition used, climatic conditions, material/design types, and maintenance/preservation intensity. Techniques to model highway asset life have included both mechanistic (e.g., corrosion time models, Miner's hypothesis test, and finite-element models) and empirical (e.g., statistical regression, Markov chains, duration models, and machine learning) methods. The factors used for data segmentation or as inputs to the models generally included asset characteristics (e.g., age, construction/design type, predominant material, and geometrics), site characteristics (e.g., climate, weather, and soil properties), traffic loading characteristics (e.g., traffic volume and percent trucks), and repair history (e.g., maintenance/rehabilitation intensities and frequencies).

On the basis of the findings in the literature, a general methodology is presented in this chapter. The steps include: (1) identify replacement rationale, (2) define end-of-life, (3) select general approach, (4) select modeling technique, and (5) fit model to data. Replacement rationales were noted to possibly include structural adequacy and safety, serviceability and functional obsolescence, essentiality for public use, and special reductions. In defining end-of-life, it was recommended to select a performance measure for the selected replacement rationale and to define life as the time until a particular metric drops below a pre-determined threshold. This threshold could represent a minimum level of service or the time at which preservation activities are no longer financially viable. Three general approaches were recommended on the basis of agency preference and data availability: age-based (life predicted based on historical records of fully observed life), condition-based (condition predicted as a function of time with life inferred from threshold), and hybrid-based (time until condition threshold is reached) approaches. Based on the preference for probabilistic models, two empirical techniques were recommended, which included the calibration of covariate, duration models (e.g., Weibull or Log-logistic functional forms) and non-covariate, Markov-based duration models (e.g., Markov/Weibull or Markov/Beta). Empirical techniques were applied in this study due to the general lack of network-wide data pertaining to mechanistic factors (the paucity of such data, in turn, is likely due to high costs of collecting that kind of data at a network level), exclusiveness to a deterioration-based rationale, and the difficulty of incorporating them into an asset management framework (Yu, 2005). Yet, mechanistic techniques for asset life estimation are considered more appropriate at the level of individual asset (i.e., facility level). The final step in the developed framework deals with model fitting. The best model is considered to be that which maximizes a goodness-of-fit measure, has intuitive parameter signs, and yields results that can be validated with past estimates of life or non-parametric analyses of the data.

Furthermore, this chapter discussed how assets could be placed into clusters for purposes of enhancing the estimation of their lives. Also, considering that asset life is highly dependent on preservation received by the asset, additional details were provided to assist agencies in predicting asset life under various scenarios related to asset preservation frequency and intensity.

CHAPTER 3

Application of the Methodologies for Life Expectancy Estimation

3.1 Introduction

In a bid to demonstrate the methodologies detailed in the previous chapter, data were collected for the various assets. This chapter describes the best fitting model for each asset class based on the collected data. The empirical techniques presented in the previous chapter were applied, including the covariate-based Weibull and Log-logistic duration models and non-covariate-based Markov chain, Markov/Weibull, Markov/Beta, and Kaplan-Meier models. The uncertainties surrounding the selected models are discussed in the next chapter. The results are limited to the accuracy and representative nature of the collected data and are presented purely to show how these models could be applied. More detailed explanations of how these methodologies could be applied are provided in Volume 1 of *NCHRP Report 713*.

3.2 Data Collection

The data sources included state transportation agencies, the NBI database, NOAA for climate data, and NRCS for soil data. The quest for data included sources such as online databases. State highway agencies were requested to provide records of historical asset replacement and/or databases that included the asset age and a measure of condition/performance. Throughout this process, it became apparent that although agencies commonly maintain condition databases for bridges and pavements, condition data for less-costly assets are not generally collected. Instead, mere inventory databases with geographical reference are all that are typically available for assets such as traffic signals, roadway lighting, and crash barriers.

Furthermore, archival databases showing an asset's historical condition are even rarer, as most agencies seem to overwrite the recorded condition of current assets after receiving new condition data each year. For recording the age of longer-lived assets, such as certain pipe culverts, agencies often relied on approximations of age due to a lack of clear historical records. Finally, for assets with historical records, there was inconsistency in terms of what constitutes a lifespan and the rationale(s) for past replacements/removals. Future studies could build on the results of this study by increasing the quantity and improving the quality of data collection for less studied assets. In doing so, agencies can realize potential cost savings in terms of more accurate assessments of asset life and reduced uncertainty which are expected to enhance the planning and programming of asset replacements.

3.2.1 Data Collected and Descriptive Statistics

Two general types of data were collected and collated: asset-specific data and data on the asset environment. For each asset class, the following sections detail the availability of life expectancy factors and a preliminary analysis of fully observed life values for various end-of-life definitions.

Environmental data sources are additionally described with respect to climatic conditions and soil characteristics.

3.2.1.1 Bridge Data

Given the immense capital investment in bridges and their key role in transportation connectivity and security, it is required that bridge data are collected regularly (1968 Federal-Aid Highway Act); therefore, data on bridges, unlike that for other assets, is relatively abundant. The data analyzed in this study is from FHWA's NBI database. However, future analyses may benefit data being made available from the FHWA's current development of the Long-Term Bridge Performance (LTBP) program (FHWA).

The NBI database contains inspection data from all 50 states and Puerto Rico. This data has been available on line since 1992. Inspections are typically conducted biannually, pending special exemptions. Various performance measures exist in the NBI database that can be used in life determination, including Sufficiency Rating, Inventory Rating, Structural Evaluation, Deck Geometry, Bridge Posting, Scour Critical Bridges, Deck, Substructure, or Superstructure (FHWA, 1995).

Various end-of-life criteria were considered in this report to measure bridge life. For the covariate model, bridge life is defined as the age when the NBI Sufficiency Rating first drops to or below 50% on a scale from 100% (entirely sufficient bridge) to 0% (deficient bridge). This threshold represents the maximum qualifying sufficiency rating for federal funds under the Highway Bridge Replacement and Rehabilitation Program (HBRRP) and considers the rationales outlined in the previous section. For the non-covariate models, bridge life was defined as the age when superstructure, substructure, or channel protection rating reaches condition state 4, the deck geometry rating reaches condition state 3, or the scour rating reaches condition state 2. Similarly, bridge deck life was modeled with respect to end-of-life being reached at condition state 5. These condition ratings are on a scale of 0 (must replace) to 9 (like new), except scour ratings, which are on a 0 to 5 condition scale. The sets of models produced similar results.

The life expectancy values presented in this report may vary from actual life values found in practice, due to modeling uncertainties, local conditions, sensitivity of highway asset life to agency decisions [e.g., conservative or liberal preservation policies at agencies), agency-preferred definitions of end-of-life criteria and thresholds, and agency financial positions (e.g., funding availability)]. Further details on bridge Sufficiency Rating calculations are provided in Appendix A.

Historical construction and reconstruction dates are provided in the NBI database. However, some bridge experts do not view such data as completely reliable. Specifically, many agencies consider the Year Reconstructed field to represent the year when the deck was last replaced, while other agencies use the field to track the time at which the entire substructure and superstructure was replaced. As such, the median life of bridges based on all distinct, NBI replacement intervals ("Year Reconstructed" less "Year Built") over the last 17 years of inspections was found to be a mere 34 years. In reality, expert opinion places bridge life closer to at least 50 years. Therefore, this data on historical replacement intervals was excluded in the data analysis.

To demonstrate the asset life expectancy estimation framework by applying it to NBI bridges, 17 years of NBI inspections were sorted by state, structure number, and inspection date. Repeat inspections for each state and structure number were removed for those assets with inspection frequencies longer than 1 year. The age (year of inspection less "Year Reconstructed") at which the Sufficiency Rating dropped to or below 50% was included in the analysis as an observed life. Based on these observed lives, the basic data statistics in Table 3-1 were obtained for various data segmentations.

Generally, concrete bridges relative to steel, NHS bridges relative to non-NHS bridges, and slab bridges relative to beam bridges all have longer lives (+4 years on average). Rural bridges were found to survive an additional 3 years compared to urban bridges. Bridges in areas of freez-

Table 3-1. Data statistics for condition-based bridge life.

Asset Classification	Median Life (years)	Standard Deviation (years)	Number of Observations
Highway System Classification			
NHS	42	22	69,717
Non-NHS	38	17	7,806
Material Type			
Concrete	46	20	22,612
Steel	42	21	37,492
Structural Type			
Beam	40	20	60,204
Slab	44	19	9,651
Geographic Region			
Urban	39	21	12,581
Rural	42	21	65,071
SHRP Climate Region			
Northeast (Wet Freeze)	44	23	37,615
Northwest (Dry Freeze)	45	19	10,735
Southeast (Wet Non-Freeze)	37	17	23,650
Southwest (Dry Non-Freeze)	41	20	5,658
All Bridges	42	21	77,658

ing (generally, the northern areas) were generally estimated to survive longer than their counterparts non-freeze (possibly due to more conservative designs), and bridges in wet climates, regardless of freezing possibility, tended to have shorter life expectancies. Overall, based on the uncensored (completely observed—inspection year and year reconstructed or built known) observations, a national average life of 42 years for bridges, using the NBI database, was determined for all bridges. This is the functional life, that is, the time taken for the bridge to reach the threshold overall condition. These observed cases are based on older designs, maintenance strategies, and construction methods; thus, there is a need to update the prediction with the use of censored observations (van Noortwijk & Klatter, 2004). With the use of both uncensored data (to provide some credence to past estimates and serve as a baseline) and censored data (to update the prediction), more reasonable life values (i.e., 60 years) were obtained in a subsequent section of the report.

Without considering censored observations, however, the interpretation of such results is limited. These censored data are partially observed asset lives, where the year built or the year reconstructed (but not both) is known. These observations generally include newer bridges that have not yet reached the end-of-life threshold. As such, longer life estimates are expected with the inclusion of censoring considerations.

To explain life expectancies after including censored observations, various factors in the NBI database were analyzed in the modeling process. These factors include the following: geometrics (e.g., structure length and deck width), geographic data (e.g., county, state, rural, and urban), highway functional class (e.g., NHS and interstate), material type (e.g., concrete and steel), ownership (e.g., state, federal, and local), structural type (e.g., beam and slab), and traffic loadings (e.g., ADT and percentage truck traffic).

3.2.1.2 Box Culvert Data

The NBI database contains similar information for large box culverts that carry vehicular traffic as it does for bridges.

Due to the general lack of information needed to calculate the Sufficiency Rating, the life expectancy value in this study was taken as a combination of historical replacement intervals and a condition-based approach (where life was defined as the age at which the culvert condition

Table 3-2. Data statistics for interval-based and condition-based estimation of box culvert life.

Asset Classification	Median Life (years)	Standard Deviation (years)	Number of Observations
Highway System Classification			
NHS	29	17	7,421
Non-NHS	32	19	16,611
Material Type			
Concrete	31	18	21,073
Steel	32	20	2,272
Geographic Region			
Urban	28	19	5,029
Rural	32	19	19,021
SHRP Climate Region			
Northeast (Wet Freeze)	33	21	7,024
Northwest (Dry Freeze)	33	19	2,439
Southeast (Wet Non-Freeze)	33	18	5,959
Southwest (Dry Non-Freeze)	28	16	8,634
Measure of Life			
Historical Replacement Intervals	31	18	22,198
Condition-based (CR<4)	39	22	1,858
All Box Culverts	31	19	24,056

rating reaches 4). Historically, box culverts have been replaced on average every 31 years, and the time until the condition-based life threshold is reached was found to be 39 years. This indicates that (1) a different condition-based threshold was applied, (2) rationale besides condition criteria were used in the replacement decisions, or (3) improvements in design or construction processes over the years are yielding longer life of assets.

Table 3-2 suggests that, generally, NHS box culverts have a lower life expectancy by 3 years compared to non-NHS box culverts; steel structures survive 1 year longer than concrete structures; and rural box culverts survive, on average, 4 years longer than their urban counterparts. Life predictions were fairly consistent across the climate regions.

3.2.1.3 Pipe Culvert Data

Data for pipe culverts were found to be less commonly collected compared to other asset types. For this asset type, data was obtained from Pennsylvania DOT. Data on Minnesota and Vermont pipe culverts was also collected; however, these databases generally lacked information pertaining to asset age, resulting in insufficient sample sizes.

Historical replacement and inspection records were unavailable, and the life of pipe culverts, therefore, was taken as the age of these assets with either extensive deterioration (physical condition rating 3 on a scale of 0-best to 3-worst), completely deteriorated, collapsed, or failed (structural condition rating 3 on a scale of 0-best to 3-worst), severe flow restriction (flow condition rating 2 on a scale of 0-best to 3-worst), or a roadway deflection of 1 inch or greater (Pennsylvania DOT, 2008). Complete definitions for the life of pipe culverts can be found in Appendix A.

Based on this definition of life, the information in Table 3-3 was obtained. As expected, larger estimates of asset life were observed for less-restrictive definitions of life. Overall, it can be seen that the dataset has a high degree of uncertainty, resulting in large standard deviations. As such, a greater sample size of observations may be needed to reduce the uncertainty of the life expectancy estimates. The large variability of the data is likely due to the use of different end-of-life conditions. For instance, it was found that structures had a life of 10 to 30 years based on the "flow-restriction" definition of life. Where only physical and structural considerations are considered applicable, life estimates of 50 to 80 years were found to be more typical.

Table 3-3. Data statistics for estimated life of pipe culverts.

Asset Classification	Median Life (years)	Standard Deviation (years)	Number of Observations
Material Type			
Concrete	27	47	5,636
Metal	17	47	4,934
Plastic	6	30	2,219
Structural Type			
Circular	12	46	12,228
Ellipsoid	104	49	480
All Pipe Culverts	12	46	13,115

To explain the life expectancies, various factors in the PennDOT database were analyzed, including the following: geometrics (e.g., height, width, and length), inlet/outlet type (e.g., drop and ditch), material type (e.g., concrete, metal, and plastic), protective coating (e.g., none, asphaltic, epoxy, and polymer), and structural type (e.g., circular, ellipsoid, and arch). Based on preliminary analysis, concrete pipe culverts in Pennsylvania survive an additional 10 years on average compared to metal culverts, and they survive an additional 21 years compared to plastic culverts. The life expectancy of ellipsoidal pipe culverts far exceeds circular pipe culverts on average. Overall, based on assets with the functional end-of-life criteria, the average life was 12 years. As this estimate is lower than most experts would predict, the additional use of censored observations was considered essential for forecasting more realistic life expectancies for this asset type.

3.2.1.4 Pavement Data

Data for pavement life was collected from the FHWA LTPP database, as well as agency data from the Indiana and Washington DOTs. The latter data was of primary use in assessing the life of functional overlay and resurfacing maintenance treatments (Irfan et al. 2009). Data for new asphalt pavements was from the General Pavement Study—1 (GPS-1) of the LTPP database (FHWA 2009). Pavement sections in the GPS-1 experiment include a hot-mix asphalt concrete (HMAC) surface layer with or without other HMAC layers (total HMAC layers thickness ~ 4–8 inches) and placed over a granular base. By using data from GPS-1, the underlying pavement deterioration process (controlled so as not to be influenced by possible preservation treatments), as only seal coats or porous friction courses (not in combination) were allowed on the surface. The service life of flexible pavement rehabilitation treatments was modeled using data from the Specific Performance Study # 5 (SPS-5) of LTPP's western region. SPS-5 has nine test sections in each participating state, and the requisite data was obtained for all the sections in all five states in the SHRP-LTPP western regions. The data included test site location, rehabilitation year, condition (in terms of IRI), climate, and treatment characteristics (e.g., thickness of new layer, level of surface preparation, and mix type). Data from Washington DOT was utilized to model the performance of resurfacing on existing flexible pavements. The reported performance indicator, IRI, was used to categorize the pavements into five groups—"very good" (5) for IRI=<60, "good" (4) for 60<IRI<94, "fair" (3) for 94<IRI<170, "mediocre" (2) for 170<IRI<220, and "poor" for IRI=>220. The end-of-life was defined as the time when IRI = 220.

3.2.1.5 Traffic Sign Data

Inspection data was obtained from in-service traffic sign assets that were analyzed as part of the National Transportation Product Evaluation Program (NTPEP). Data items included sign sheeting retroreflectivity, visual ratings of "good" to "fair" and ultimately "poor," location, and color. The model presented later in this chapter was developed using traffic sign inspection data from Wisconsin. Data collection was primarily concentrated in Ozaukee County, in southeastern Wisconsin.

Table 3-4. Data statistics for roadway lighting life (historical replacement intervals).

Asset Classification	Median Life (years)	Standard Deviation (years)	Number of Observations
Highway Functional Class			
Interstate	74	17	85
Non-Interstate	78	33	30
Mounting Type			
Wooden Pole	74	18	60
All Roadway Lighting	74	23	115

3.2.1.6 Pavement Marking Data

As revealed in the background literature review, the life expectancy of pavement markings is influenced by factors such as color and marking material type. Data for developing the pavement marking life models was collected from existing test decks that were part of NTPEP. Of the several types of pavement marking materials, "1A: 2-year Waterborne yellow markings" were selected to demonstrate the developed framework for asset life expectancy estimation.

3.2.1.7 Roadway Lighting Data

The Missouri DOT has begun maintaining historical records of the installation and replacement dates for roadway lighting fixtures. As such, a small sample size of replacements was used in this report. To calibrate the model, the factors analyzed in the Missouri DOT database include mounting type, highway functional class, height, and material type. For assets of this type that had a fully observed (uncensored) life, the median life was found to be 74 years (Table 3-4). Considering that other states, such as Minnesota, have experienced a life expectancy closer to 30 years, this dataset may require further validation before a model can reasonably be applied.

3.2.1.8 Traffic Signal Data

Historical data for the life expectancy of traffic signal controllers was obtained from three DOTs: Missouri, Pennsylvania, and Oregon. Recorded dates of installation and replacement were collated to obtain actual lives of these assets, and the data analysis yielded an overall median actual (not functional) life of 13 years prior to the consideration of censoring. The data statistics (Table 3-5)

Table 3-5. Data statistics for traffic signal life (historical replacement intervals).

Asset Classification	Median Life (years)	Standard Deviation (years)	Number of Observations
Highway Functional Class			
U.S. Route or Interstate Ramp	10	5	545
State Route	12	13	882
Local Route	20	16	389
Mounting Type			
Mast Arm	12	8	129
Pole	16	11	47
System Control			
Distributed	16	14	100
Isolated	26	17	160
State			
Missouri	9	5	976
Pennsylvania	20	16	840
Oregon	18	11	368
All Traffic Signals	13	13	2,184

Table 3-6. Data statistics for historical flasher life (historical replacement intervals).

Asset Classification	Median Life (years)	Standard Deviation (years)	Number of Observations
Highway Functional Class			
U.S. Route or Interstate Ramp	22	15	117
State Route	15	12	51
Local Route	14	11	35
Mounting Location			
School Zone	12	9	39
Intersection	32	15	81
Barricade	17	12	34
Sign	10	11	29
State			
Missouri	19	14	160
Pennsylvania	14	10	45
All Flashers	16	14	205

generally suggest that signal controllers located on lower functional class highways have longer life expectancies. However, wider ranges in life were observed; signals controlled in isolation have longer lives on average, and more northern states were found to have longer life expectancies.

Factors for analysis in the databases included the number of controllers, signal control method (e.g., pre-timed, semi-actuated, and fully actuated), system control type (e.g., distributed and isolated), highway functional class, and presence of pre-emption technology for emergency vehicles.

3.2.1.9 Flasher Data

Missouri and Pennsylvania maintain historical records for flashers, including information on highway functional class and mounting location. Table 3-6 shows an uncensored median life of 16 years. Flashers mounted at intersections, particularly at U.S. routes or Interstate ramps, were found to have the longest life expectancies, compared to flashers mounted at school zones or barricades.

3.2.1.10 Environmental Data for all Asset Types

Using the data on asset location (county) provided by the state and national asset databases, climate and soil data from the NOAA and NRCS data platforms, respectively, was obtained. From the NOAA database, annual normals (long-term averages) for temperature and precipitation were obtained at the climate divisional level (Figure 3-1). Annual average wind speeds were also collected and assigned to relevant assets based on their proximity to the measurement location. In addition, using daily station normals from the NOAA data platform, the average numbers of freeze-thaw cycles for each climate division were calculated.

The number of cycles is taken as the number of times the temperature moves from below freezing (<32°F) to above freezing and are typically measured in days by comparing the high and low temperatures from one day to the next or within the same day.

From the NRCS database, various soil properties are available at the soil survey area level (each area is approximately represented by a county). Soil properties analyzed in this study include soil pH, liquid limit, plasticity index, soil erodibility, salinity, sodium absorption, cation exchange capacity, percent calcium carbonate, gypsum, sand, silt, clay, potential for frost action, risk of corrosion of steel structures or rebar, and ponding and flooding durations and frequencies. The average soil conditions for each climate division were used for the analysis, because site-specific soil conditions at the exact proximity of each asset were unavailable.

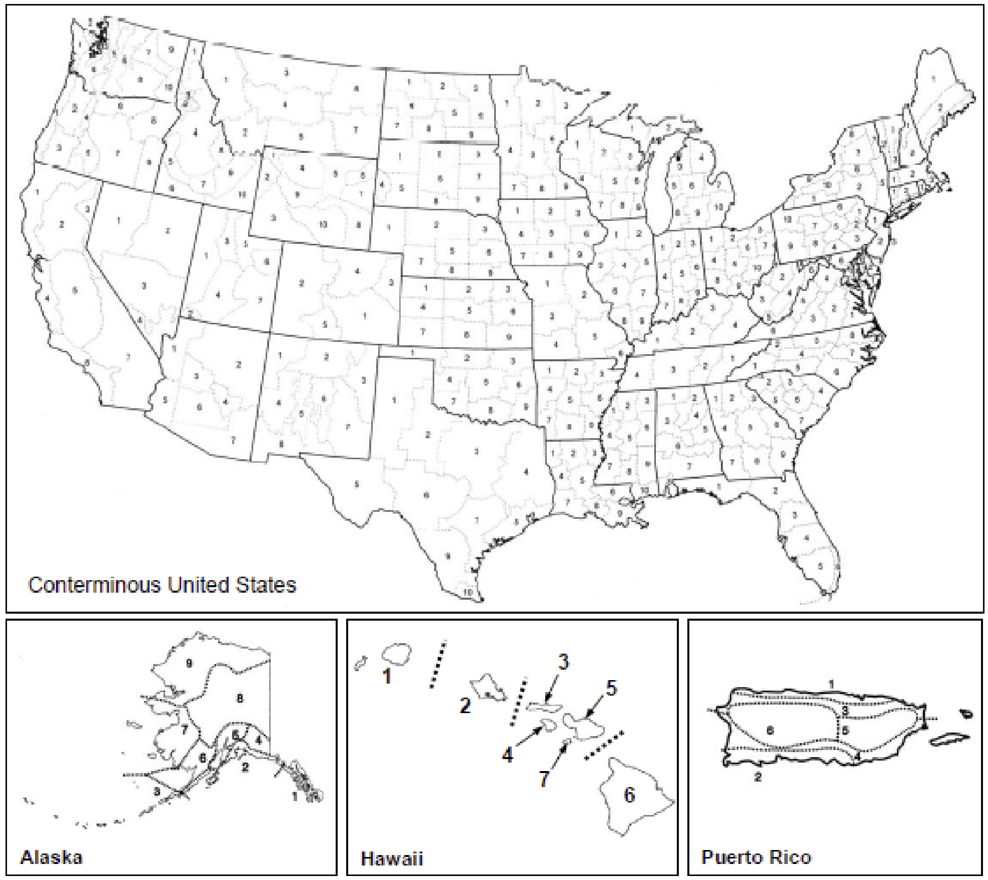


Figure 3-1. U.S. climate divisions (NOAA, 2008).

3.3 Results of the Life Expectancy Models

3.3.1 Bridges

Both covariate and non-covariate models were calibrated for predicting bridge life. The covariate model was used to identify the significant factors that influence bridge life and to predict a composite measure encompassing multiple replacement rationale. The non-covariate technique was applied to predict the life due to multiple rationale or "end-of-life criteria."

The most appropriate covariate model was considered to be the prediction of NBI sufficiency rating using the hybrid condition-based/age-based approach. For this model, the uncensored estimate of bridge life was assumed to be the time at which the sufficiency rating first reaches or drops below 50%. As stated previously, this corresponds to the level at which a bridge may qualify for HBRRP federal funding. Additionally, to incorporate more modern designs, an equivalent number of censored observations were used in the model calibration; and to reduce geographical and climate bias, an equivalent number of observations were included for each SHRP-LTPP region (Figure 3-2).

The use of a Weibull model is justified by past findings in the literature, comparing the model fit statistics of alternative distributions, and for validating the prediction against the non-parametric Kaplan-Meier estimate. A comparison of the Weibull and exponential distributed estimates of the data showed that the Weibull provides a better fit at the 99.99% confidence level. Also, comparison of the exponential distribution to the Weibull distribution showed that the shape parameter estimate is significantly different from 1.00 with over 99.99% confidence. Further, comparison of the log-logistic and Weibull distributions based on the data, shows that the chi-squared test

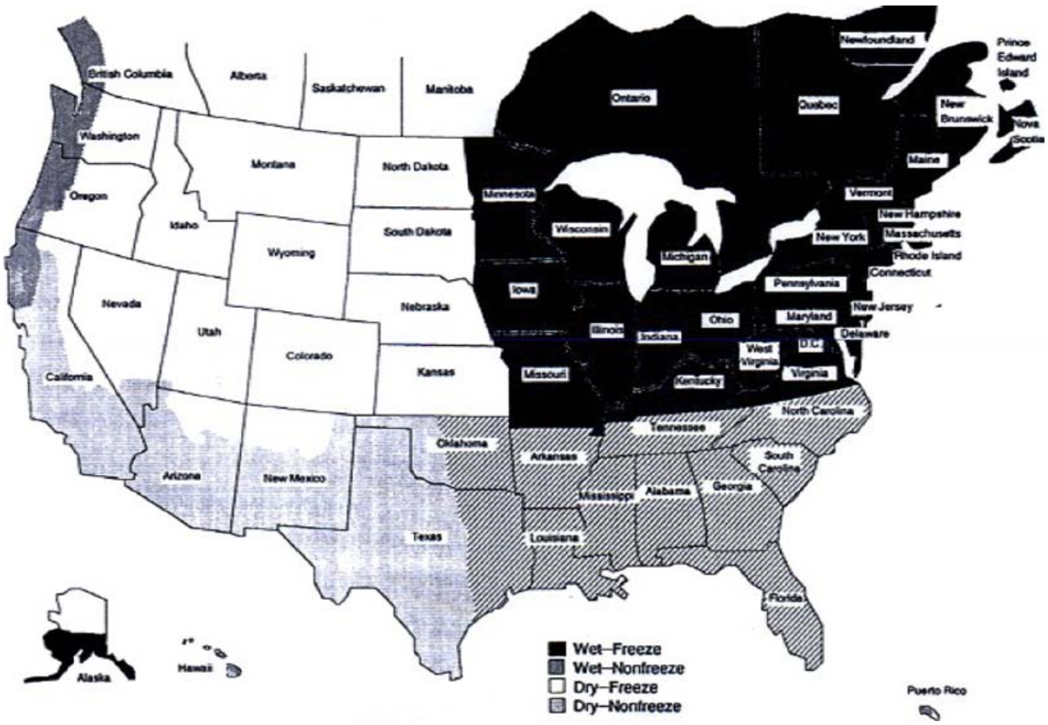


Figure 3-2. SHRP-LTPP climate regions (Hadley, 1994).

statistic from the Weibull distribution is (27,224 > 24,829), indicating a higher level of confidence in the model fit. Using these test statistics, the Gamma, Weibull, Gompertz, Exponential, Log-Logistic, F, and Lognormal parametric duration models were tested. Finally, to validate the use of the Weibull distribution, the Kaplan-Meier survival curve was compared to the baseline ancillary survival factors (Figure 3-3). Visual inspection of the baseline bridge survival curve shows that the non-parametric estimate varies slightly at the tail probabilities with a lower survival probability earlier in the asset life and a higher survival probability later in the asset life. The two survival estimates have a RMSE of 0.034, indicating a very good validation. The chi-squared test statistics indicate a 99.99% confidence level that the Weibull distribution is appropriate.

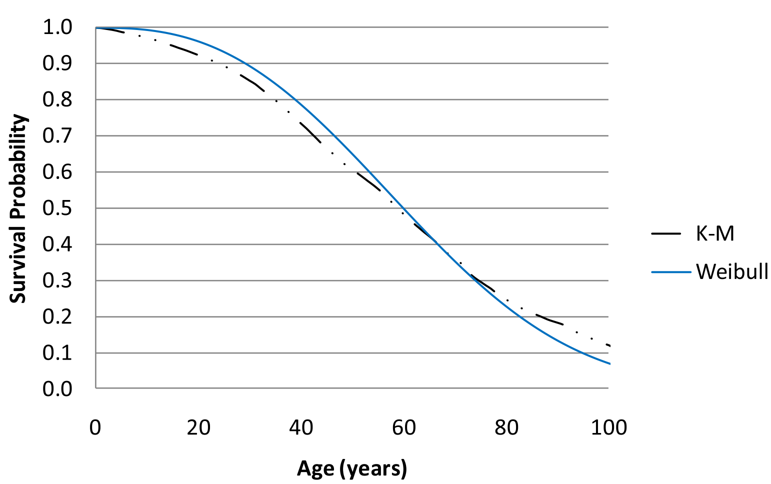


Figure 3-3. Non-parametric validation of Weibull-distributed bridge life covariate model.

Table 3-7. Weibull regression model of bridge life (end-of-life ≡ age when sufficiency rating drops to or below 50%).

Life Expectancy Factor	Parameter Estimate, β	t-Statistic
Constant	4.669	218.699
Normal Annual Temperature (°F)	-0.628E-2	-17.199
Normal Annual Precipitation (in.)	-0.167E-2	-8.674
Geographical classification indicator (1 if rural, 0 otherwise)	0.459E-1	6.474
NHS indicator (1 if on NHS, 0 otherwise)	-0.697E-1	-8.138
Corrosive soil indicator (1 if in area where average soil is classified as highly corrosive to steel or concrete by the NRCS, 0 otherwise)	-0.614E-1	-11.126
Material type indicator (1 if steel, 0 otherwise)	-0.357E-1	-6.549
Structure length in decimeters	-0.765E-5	-6.035
Baseline Ancillary Factors	**Parameter Estimate, β**	**t-Statistic**
Shape Factor, β	2.623	185.168
Scaling Factor, α	68.871	363.000
Model Statistics		
Number of Observations		42,902
Log-likelihood Function at Convergence		-26,785.79
Restricted Log-likelihood Function		-40,397.73

Given the strong fit of the Weibull distribution in describing the likelihood of bridge life, the baseline parameters and covariate influence that were found using maximum likelihood estimation are considered representative. The model (Table 3-7) estimates a baseline median life of 60 years with a 90% confidence interval of [22, 105]. All of the life expectancy factors included in the model were found to be significant at or above the 90% confidence level.

Of the significant covariates, only the indicator for rural bridges was found to have a positive influence on bridge life. The life expectancy factors that were found to have negative influence on bridge life included warmer temperatures, increased precipitation, NHS location, corrosive soil environment, steel material, and longer structure length. The influence of these factors is mostly intuitive as follows:

- Warmer temperatures often lead to greater expansion forces and weaker soil strength, hence lowering asset life.
- Increased precipitation (rain and snowfall) tends to lead to higher intensity of application of deicing chemicals and consequently, higher corrosion rates. Rural structures experience lower traffic loading and congestion (often a replacement rationale due to insufficient bridge width) resulting in longer life.
- NHS structures accommodate higher traffic loadings leading to potential structural problems as well as congestion, which may require roadway widening. However, the data suggests that NHS structures live longer compared to their non-NHS counterpoints, plausibly because the deleterious effects of their higher loadings are offset by the redeeming effects of their higher design standards.
- Corrosive soils generally cause shorter substructure life.
- Steel structures may be more susceptible to climate than concrete if not properly maintained (e.g., painted).
- Longer span structures generally may be associated with greater potential for cracking at span connections.

Further analysis of this model is presented in Chapter 5, specifically in consideration of the sensitivity and risk of uncertain inputs.

In addition to the covariate-based model, non-covariate models were calibrated using the Markov/Weibull and Markov/Beta modeling techniques for multiple replacement rationale or end-of-life criteria. This approach is considered preferable when an agency lacks historical information but maintains inspection records, wishes to update asset life predictions based on an asset's current age and condition rating, or seeks to identify life extension activities that can be tailored to extend asset life by delaying the occurrence of the dominant end-of-life criterion.

Similar to the validation of the baseline survival curve to the Kaplan Meier, this approach compares parametric survival curves to the Markov Chain estimate. Having validated the use of the Weibull distribution, Markov/Weibull models were used to predict the overall life of newly constructed assets. To predict the remaining life, however, the Beta distribution was found to be more flexible and representative. Li & Sinha (2004) similarly found the Beta distribution to best represent remaining life, particularly after a treatment.

Given a time-series of inspections, a frequency-based method was used to estimate the transition probabilities for each end-of-life criterion. All pairs of annual and biannual NBI inspections from 1992 to 2009 were analyzed for the estimation of Markov transition probabilities on a state-by-state basis as well as for all 50 states combined. With the assumption of a one-step deterioration (i.e., only negative unit changes in condition-state per unit time—valid assumption for ~98% of data observations), a discrete-time Markov chain, the annual transition probabilities were calculated for each age range (transition matrices calibrated for each 6 years of life) by

$$P_{ii} = \frac{a_{ii} + \sqrt{b_{ii} * B_i}}{A_i + B_i}$$

where a_{ii} represents the number of annual inspection pairs staying in state i from one year to the next; b_{ii} represents the number of biannual inspection pairs where no condition state change was observed; A_i represents the number of annual inspection pairs starting in state i; B_i represents the number of biannual inspection pairs starting in state i.

This simplified equation represents the weighted transition probabilities based on the number of annual and biannual inspections. The paired transition probability is then $P_{ij} = 1 - P_{ii}$.

Using the transition matrix, the Markov/Weibull and Markov/Beta models were then calibrated by minimizing the RMSE while holding the median life prediction constant and changing the baseline ancillary survival factors. When no observations were available, a 100% transition probability was assumed. The models were fit to the following set of discrete ratings included in the NBI (the full descriptions are provided in Appendix A):

- Deck Condition Rating—represents condition state of the deck on a 0-9 scale;
- Superstructure Condition Rating—represents condition state of superstructure on a 0-9 scale;
- Substructure Condition Rating—represents condition state of the substructure on a 0-9 scale;
- Deck Geometry Rating—represents functional acceptability based on roadway width, traffic volume, and vertical clearance on a 0-9 scale. The Markov transitions for this rating pertain to the change in traffic volume levels;
- Channel Protection Rating—represents condition state of the channel/embankment on a 0-9 scale; and
- Scour Protection Rating—represents condition state of scour-protection features of scour-susceptible structures susceptible to scour on a 0-5 scale (ratings above 5 indicate that a bridge is not susceptible, already repaired, or not investigated).

The results of the analysis are limited to the data quality and number of available observations and can be updated based on the preferred transition probabilities. For instance, far fewer

Table 3-8. Bridge deck transition matrices for all observations.

Age Group (Years)	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6	23.04	11.02	4.65	5.03	3.31	4.69
7 → 12	17.44	10.19	4.94	5.53	4.90	6.22
13 → 18	16.43	9.98	5.33	5.61	5.36	4.84
19 → 24	22.26	11.79	6.18	6.18	5.46	4.79
25 → 30	32.23	13.50	6.97	6.33	5.62	4.49
31 → 36	36.35	15.33	7.49	6.25	5.95	4.50
37 → 42	38.95	15.80	7.74	6.24	5.84	4.24
43 → 48	36.84	17.66	8.14	6.66	5.50	4.76
49 → 54	33.08	18.00	8.92	7.09	5.29	4.57
55 → 60	30.69	17.88	10.64	7.90	5.40	4.66
61 → 66	36.51	18.93	10.41	7.75	5.44	4.31
67 → 72	39.12	18.36	10.84	7.71	5.42	4.36
73 → 78	46.86	20.40	11.37	8.20	5.51	4.54
79 → 84	27.02	21.85	13.49	9.72	6.51	4.86
85 → 90	38.78	25.40	15.75	12.42	7.74	5.17
91 → 96	36.97	22.84	16.23	12.64	7.88	6.12
97 → 102	33.20	19.73	13.42	11.24	8.67	6.90
103 → 108	17.49	16.36	12.45	10.39	6.67	5.73
109 → 114	33.33	29.50	11.97	14.70	9.16	12.61
115 → 120	59.76	24.33	18.29	10.19	8.57	5.52

observations are available for assessing deterioration due to scour than other ratings; therefore, the Weibull parameters and life predictions for this end-of-life criterion are considered less reflective of actual conditions compared to the models that were calibrated using other condition ratings.

Using the previously described approach, the transition matrices from Tables 3-8 through 3-13 were used to calibrate the Weibull parameters and to predict the median life estimates. In order to update future transition probabilities, the number of observations for each model is also provided in Tables 3-14 through 3-19. The Markov/Weibull transition matrices, the number

Table 3-9. Bridge superstructure transition matrices for all observations.

Age Group (Years)	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6	20.08	6.43	4.73	4.58	4.03	4.86
7 → 12	15.55	6.85	4.57	5.19	4.95	6.10
13 → 18	15.36	7.29	4.80	5.56	5.53	6.01
19 → 24	19.59	8.74	5.25	5.82	5.48	5.93
25 → 30	29.61	10.54	5.65	5.80	5.47	5.96
31 → 36	30.73	12.34	6.07	5.77	5.35	5.34
37 → 42	32.96	13.81	6.39	5.79	5.42	4.98
43 → 48	31.82	15.67	7.23	6.10	5.44	5.51
49 → 54	27.81	16.27	8.14	6.72	5.64	5.18
55 → 60	34.31	16.60	9.55	7.15	5.85	4.77
61 → 66	34.61	16.56	9.30	7.35	5.72	4.60
67 → 72	33.87	15.65	9.84	7.43	5.85	4.63
73 → 78	37.74	16.92	9.83	7.55	6.02	4.96
79 → 84	21.51	17.26	10.98	8.89	6.52	5.68
85 → 90	37.04	18.81	12.88	10.65	7.28	6.54
91 → 96	33.39	18.93	14.98	11.39	9.02	7.03
97 → 102	30.14	19.25	12.53	10.56	8.22	7.10
103 → 108	15.94	14.80	11.35	8.78	7.52	6.31
109 → 114	20.00	31.82	12.18	13.25	8.58	4.83
115 → 120	0.00	8.33	16.45	10.77	10.93	7.82

Table 3-10. Bridge substructure transition matrices for all observations.

Age Group (Years)	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6	19.30	8.86	4.35	5.95	6.31	5.20
7 → 12	14.41	8.68	4.61	6.30	6.50	6.50
13 → 18	13.90	8.81	4.84	6.19	6.43	6.15
19 → 24	18.79	10.59	5.48	6.39	6.87	5.88
25 → 30	23.07	12.43	5.84	6.21	6.91	5.77
31 → 36	30.91	14.19	6.33	6.26	6.72	5.76
37 → 42	29.22	14.81	6.76	6.37	6.43	5.39
43 → 48	28.19	16.11	7.43	6.78	6.57	6.11
49 → 54	31.51	16.72	8.23	7.20	6.95	5.54
55 → 60	36.13	16.69	9.75	8.03	6.99	5.28
61 → 66	27.45	17.17	9.66	7.74	6.17	4.78
67 → 72	21.48	17.52	9.61	7.72	5.84	4.69
73 → 78	28.76	18.00	9.98	7.79	5.90	4.56
79 → 84	28.28	16.56	10.52	9.03	6.32	4.84
85 → 90	30.77	18.87	12.58	10.80	7.83	5.76
91 → 96	34.96	18.42	15.29	11.80	9.29	6.38
97 → 102	34.96	15.92	12.92	10.19	8.73	7.32
103 → 108	5.10	12.83	11.71	9.51	8.00	6.80
109 → 114	33.33	25.43	14.07	9.01	7.47	6.61
115 → 120	0.00	7.81	13.52	9.60	9.61	5.80

of observations, and the Weibull predictions and factors for each U.S. state were obtained. The average lifespans, based on all observations for each end-of-life criterion and sorted by threshold, are summarized in Table 3-20.

On average, decks tend to have a functional life varying from 42 to 79 years, depending on the performance threshold used. Given the general lack of inspection pairs beginning at a state equal to or below 5 (only 9.27% of paired observations), a threshold of 5 is considered appropriate. The 42-year life corresponding to this threshold compares well with the life expectancy values in the literature (~25 to 50 year average deck life expectancy). A root mean square error

Table 3-11. Bridge deck geometry transition matrices for all observations.

Age Group (Years)	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6	3.16	6.14	3.57	2.74	2.09	1.43
7 → 12	2.53	6.05	3.53	2.52	1.95	1.32
13 → 18	2.52	5.22	3.46	2.63	1.90	1.34
19 → 24	2.72	4.60	3.20	2.83	2.23	1.56
25 → 30	2.65	4.46	3.06	3.02	2.48	1.79
31 → 36	2.45	4.90	3.32	3.12	2.92	1.97
37 → 42	2.69	4.68	3.73	3.41	2.93	2.00
43 → 48	2.23	4.98	3.94	3.68	2.97	2.32
49 → 54	2.42	5.05	3.55	3.76	2.71	2.16
55 → 60	3.12	4.25	3.15	3.50	2.82	2.49
61 → 66	3.89	3.93	4.38	3.14	2.75	2.59
67 → 72	2.63	4.77	3.83	2.88	2.69	2.36
73 → 78	3.31	5.81	2.95	3.13	2.22	2.26
79 → 84	3.66	4.47	2.99	2.90	2.25	2.42
85 → 90	2.79	4.98	3.12	3.00	2.09	2.13
91 → 96	4.03	5.21	3.09	2.17	2.36	2.01
97 → 102	1.51	2.26	2.72	2.71	1.92	1.85
103 → 108	5.80	3.17	4.98	2.34	1.68	2.32
109 → 114	5.26	9.37	4.17	6.06	2.32	4.77
115 → 120	9.76	3.44	7.04	6.28	6.05	3.70

Table 3-12. Bridge channel protection transition matrices for all observations.

Age Group (Years)	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6	18.76	8.04	6.29	4.23	2.96	2.42
7 → 12	10.87	7.83	6.13	4.33	3.23	1.91
13 → 18	10.88	7.58	5.94	4.14	3.31	1.99
19 → 24	11.41	7.81	6.15	4.03	3.25	1.95
25 → 30	8.96	8.10	6.04	3.99	3.26	1.90
31 → 36	8.72	8.51	6.19	4.11	3.03	2.20
37 → 42	9.59	8.66	6.16	4.08	3.12	1.95
43 → 48	8.73	8.63	6.35	4.14	2.99	1.71
49 → 54	9.89	9.62	7.06	4.37	3.26	1.63
55 → 60	10.62	9.82	7.43	4.72	3.19	1.43
61 → 66	12.17	10.30	7.67	4.88	3.30	1.55
67 → 72	12.45	9.60	7.44	4.96	3.27	1.27
73 → 78	8.68	9.20	7.79	5.20	3.31	1.62
79 → 84	8.31	9.79	8.09	5.34	3.48	1.71
85 → 90	14.10	10.79	9.32	5.81	3.45	2.13
91 → 96	16.59	15.82	12.96	6.60	3.87	3.28
97 → 102	26.10	13.11	10.53	6.73	3.99	3.16
103 → 108	18.47	10.79	10.12	4.74	3.62	2.94
109 → 114	12.50	9.52	8.43	6.66	2.34	2.16
115 → 120	100.00	12.29	8.90	4.82	6.98	1.74

(RMSE) of 0.99 was calculated in comparing the Markov prediction to the Weibull model for the identified threshold.

For superstructures, the average life estimates were found to vary from 48 to 83 years, depending on the threshold. Again with 6.70% of the paired observations having a starting condition rating of below 4, this threshold is considered appropriate. A prediction of 64 years, on average, compares favorably to the literature (~50 to 80 year average superstructure life expectancy). A RMSE value of 0.76 was obtained.

Table 3-13. Bridge scour protection transition matrices for all observations.

Age Group (Years)	Annual Transition Probabilities		
	5 → 4	4 → 3	3 → 2
0 → 6	0.01	0.19	0.04
7 → 12	0.02	0.07	0.01
13 → 18	0.01	0.14	0.03
19 → 24	0.01	0.23	0.01
25 → 30	0.01	0.16	0.01
31 → 36	0.01	0.09	0.01
37 → 42	0.02	0.07	0.01
43 → 48	0.02	0.10	0.01
49 → 54	0.03	0.14	0.01
55 → 60	0.05	0.16	0.04
61 → 66	0.04	0.16	0.02
67 → 72	0.05	0.17	0.01
73 → 78	0.09	0.06	0.02
79 → 84	0.06	0.28	0.13
85 → 90	0.18	0.36	0.04
91 → 96	0.09	0.15	0.09
97 → 102	0.05	0.14	0.11
103 → 108	0.28	1.43	0.11
109 → 114	0.61	3.31	0.06
115 → 120	0.33	0.45	0.60

Table 3-14. Number of observations used in developing bridge deck transition matrices.

Age Group (Years)	No. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6	121,661	201,564	110,832	22,298	8,403	1,425
7 → 12	27,515	159,673	167,842	43,727	13,522	2,600
13 → 18	8,560	119,789	177,808	63,944	20,660	5,080
19 → 24	2,904	90,291	173,056	82,709	30,891	8,831
25 → 30	1,561	71,699	180,695	105,529	43,553	13,887
31 → 36	1,558	55,102	172,016	120,305	53,153	19,944
37 → 42	1,329	37,008	131,923	108,500	51,828	20,424
43 → 48	937	19,775	79,612	76,412	42,148	16,237
49 → 54	594	11,458	47,390	51,545	32,186	13,211
55 → 60	594	10,903	38,395	45,983	33,505	14,512
61 → 66	642	9,475	35,749	47,081	37,651	16,714
67 → 72	495	5,916	24,099	35,663	30,282	14,007
73 → 78	241	3,181	13,781	21,284	19,010	9,814
79 → 84	159	1,747	7,217	11,676	11,479	6,454
85 → 90	145	1,212	4,458	6,808	7,178	4,315
91 → 96	214	1,687	6,466	8,250	6,880	3,575
97 → 102	114	702	3,179	4,658	3,936	1,942
103 → 108	147	496	1,608	2,483	2,460	1,173
109 → 114	6	80	202	302	330	166
115 → 120	6	35	138	164	190	128

Substructures on average were found to survive between 45 and 78 years depending on the threshold. The 59-year prediction corresponding to threshold 4 was found to be within the range of estimates in the literature (~25 to 80 year average substructure life expectancy). A RMSE of 1.21 was calculated for the corresponding threshold.

Asset functional life predictions based on deck geometry rating were found to be significantly higher than those for bridge elements. With average life values over 110 years, this replacement rationale is not considered likely to dominate others. Only 10% of inspection pairs had an initial

Table 3-15. Number of observations used in developing bridge superstructure transition matrices.

Age Group (Years)	No. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6	127,384	219,731	82,220	27,322	10,908	2,354
7 → 12	34,522	201,374	124,644	40,353	14,626	3,633
13 → 18	11,974	163,407	145,728	53,657	20,374	5,689
19 → 24	4,268	130,304	155,052	68,243	27,547	8,796
25 → 30	1,784	106,535	178,305	88,426	37,327	11,713
31 → 36	1,189	77,290	184,565	105,685	46,664	14,984
37 → 42	983	44,393	147,161	100,519	47,991	16,323
43 → 48	553	20,119	88,651	74,915	40,476	14,275
49 → 54	370	10,428	49,375	52,355	33,255	13,064
55 → 60	329	9,351	39,180	47,624	33,692	16,373
61 → 66	338	7,933	34,358	49,798	38,742	19,317
67 → 72	273	4,733	21,995	36,823	32,565	16,860
73 → 78	152	2,182	11,575	21,588	22,080	12,301
79 → 84	69	921	5,521	11,351	13,757	8,902
85 → 90	50	520	3,009	6,148	8,803	6,330
91 → 96	104	981	4,935	6,897	7,638	5,785
97 → 102	52	404	2,352	3,991	4,135	2,934
103 → 108	82	286	1,177	2,191	2,517	1,775
109 → 114	5	22	114	226	363	314
115 → 120	1	12	75	144	255	189

Table 3-16. Number of observations used in developing bridge substructure transition matrices.

Age Group (Years)	Nr. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6	118,520	195,493	107,586	32,259	11,468	3,536
7 → 12	31,980	163,190	151,838	48,108	16,922	5,482
13 → 18	10,199	124,922	165,045	63,563	25,093	9,300
19 → 24	2,742	95,230	168,463	77,428	34,032	13,533
25 → 30	857	75,219	184,559	97,955	44,138	17,934
31 → 36	583	53,564	182,002	114,674	53,057	22,181
37 → 42	422	30,932	136,503	106,793	53,821	23,876
43 → 48	322	14,018	78,413	76,376	44,939	20,819
49 → 54	203	7,729	44,105	50,713	35,104	17,465
55 → 60	135	7,573	35,236	46,356	34,778	19,242
61 → 66	133	6,982	32,206	49,287	38,592	21,123
67 → 72	165	3,827	21,852	37,629	32,184	16,831
73 → 78	102	1,906	12,205	22,537	21,495	11,671
79 → 84	58	918	6,392	12,120	13,302	8,392
85 → 90	41	606	3,604	6,915	8,665	6,053
91 → 96	93	1,097	4,806	8,117	8,040	5,502
97 → 102	32	440	2,217	4,238	4,582	3,085
103 → 108	50	337	1,116	2,400	2,525	1,837
109 → 114	3	28	178	405	441	244
115 → 120	1	15	99	273	252	186

value below a condition state of 3, depending on the threshold and a threshold of 3 therefore was assumed.

Observed transition probabilities for the channel ratings suggest an average life varying from 53 to 120 years. With only 3.69% of the inspection pairs beginning at a condition state of 4 or lower, a threshold of 4 was considered appropriate. This threshold corresponds to a life prediction of 81 years on average, with a RMSE of 0.85.

Table 3-17. Number of observations used in developing bridge deck geometry transition matrices.

Age Group (Years)	Nr. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6	53,845	11,777	73,200	120,338	99,648	61,720
7 → 12	43,370	10,335	63,071	105,624	91,381	60,518
13 → 18	38,400	10,969	61,565	97,925	89,819	60,326
19 → 24	36,735	12,551	61,739	93,550	90,517	62,756
25 → 30	33,279	11,054	55,479	95,193	103,970	82,337
31 → 36	26,622	7,629	40,616	83,310	109,059	104,943
37 → 42	15,368	4,185	20,585	55,527	91,064	104,206
43 → 48	8,511	2,560	9,293	27,964	59,643	74,827
49 → 54	3,702	1,333	5,733	15,638	37,757	49,587
55 → 60	2,337	1,504	7,031	14,625	31,377	44,424
61 → 66	2,276	2,840	6,828	14,693	30,080	42,580
67 → 72	1,696	2,332	5,277	9,571	20,718	30,689
73 → 78	955	1,388	3,627	5,478	11,799	17,385
79 → 84	492	1,280	3,115	3,597	6,579	8,437
85 → 90	297	1,356	2,363	2,736	4,372	4,711
91 → 96	257	1,195	2,602	3,318	5,551	5,367
97 → 102	146	942	1,011	1,644	2,940	3,082
103 → 108	88	459	488	909	1,738	1,853
109 → 114	19	28	38	93	139	200
115 → 120	6	16	18	42	67	122

Table 3-18. Number of observations used in developing bridge channel protection transition matrices.

Age Group (Years)	No. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6	51,391	158,989	97,624	41,327	10,725	2,305
7 → 12	15,693	120,078	109,857	55,537	15,719	3,730
13 → 18	7,366	97,674	109,966	65,519	20,596	5,272
19 → 24	4,122	83,035	104,530	69,587	24,046	6,681
25 → 30	3,484	79,840	107,015	75,216	26,764	7,407
31 → 36	3,580	75,240	109,946	80,298	30,006	8,257
37 → 42	2,854	60,928	97,378	75,868	29,507	8,243
43 → 48	1,882	38,335	69,749	60,928	25,277	7,006
49 → 54	1,080	25,631	48,046	45,833	20,428	6,102
55 → 60	841	23,844	42,954	44,270	22,425	7,788
61 → 66	739	23,453	42,494	47,636	24,376	8,424
67 → 72	597	16,214	30,682	36,903	20,353	6,888
73 → 78	352	9,301	18,485	23,592	13,699	4,728
79 → 84	217	5,537	10,558	13,816	8,895	3,219
85 → 90	128	3,386	6,553	8,601	5,980	2,220
91 → 96	169	3,441	8,577	9,388	5,127	1,778
97 → 102	98	1,418	3,988	5,456	3,276	912
103 → 108	84	897	2,032	3,145	1,921	631
109 → 114	8	225	417	445	218	97
115 → 120	1	121	266	304	139	60

Similar to the deck geometry ratings situation, life predictions based on scour were found to be well above the predictions based on the element condition ratings. With the limited number of observations, relative to the other ratings, average life was estimated at over 120 years. A threshold of 2 was assumed given that only 9.47% of inspection pairs start in an equal or worse condition state.

Combining all the possible replacement rationale and identified thresholds, it can be seen that decks, on average, survive 42 years, while the entire bridge structure has a life of 59 years based

Table 3-19. Number of observations used in developing bridge scour protection transition matrices.

Age Group (Years)	No. of Annual and Biannual Inspection Pairs by Starting Condition State		
	5	4	3
0 → 6	31,935	5,263	2,931
7 → 12	32,094	5,594	4,250
13 → 18	33,380	5,894	6,184
19 → 24	33,642	5,516	7,289
25 → 30	34,946	5,744	8,461
31 → 36	36,688	6,185	9,142
37 → 42	32,855	5,930	10,801
43 → 48	24,053	5,253	10,014
49 → 54	15,083	4,058	6,584
55 → 60	10,663	4,188	4,296
61 → 66	12,236	5,271	5,583
67 → 72	11,821	4,514	6,001
73 → 78	8,882	2,791	3,973
79 → 84	5,332	1,470	2,024
85 → 90	3,864	915	1,231
91 → 96	3,669	896	836
97 → 102	3,458	543	564
103 → 108	2,095	327	263
109 → 114	149	43	81
115 → 120	77	34	63

Table 3-20. Markov/Weibull model predictions of bridge life by end-of-life criterion for all observations.

End-of-life criterion	End-of-Life Threshold	Average Life (years)	90% Confidence Interval	Weibull Scaling Factor, α	Weibull Shape Factor, β
Deck Condition Rating	5	42	[15,75]	48.62	2.50
	4	58	[22,100]	66.44	2.70
	3	79	[36,123]	88.33	3.28
Superstructure Condition Rating	5	48	[18,83]	55.03	2.68
	4	64	[27,104]	72.26	3.02
	3	83	[40,125]	91.97	3.57
Substructure Condition Rating	5	45	[16,79]	51.84	2.59
	4	59	[23,100]	67.36	2.77
	3	78	[34,124]	87.62	3.15
Deck Geometry Rating	5	>120*	N/A	N/A	N/A
	4	>120*	N/A	N/A	N/A
	3	110	[35,209]	129.24	2.27
Channel Protection Rating	5	53	[17,100]	62.20	2.29
	4	81	[31,139]	92.77	2.70
	3	120	[56,183]	133.43	3.45
Scour Protection Rating	4	>120*	N/A	N/A	N/A
	3	>120*	N/A	N/A	N/A
	2	>120*	N/A	N/A	N/A
*Insufficient observations for predictions of Asset Life beyond 120 years					

on the dominating substructure rating. This estimate is almost identical to that of the covariate model, which predicted an overall, average bridge life of 60 years.

A comparison of predictions by climatic region was similarly completed using the identified thresholds (Table 3-21). Insufficient observations were available for estimating life based on scour at this geographic level. Overall, it was found that bridges in the Northeast region had a median life of 56 years; Northwest region bridges had a median life of 70 years; bridges in the

Table 3-21. Markov/Weibull model predictions of bridge life by end-of-life criterion and SHRP-LTPP region.

End-of-life criterion and Threshold	SHRP-LTPP Region	Average Life (years)	90% Confidence Interval	Weibull Scaling Factor, α	Weibull Shape Factor, β
Deck Condition Rating = 5	NE	37	[13,66]	42.73	2.54
	NW	49	[19,84]	56.02	2.74
	SE	50	[20,85]	57.04	2.78
	SW	39	[10,83]	47.06	1.95
Superstructure Condition Rating = 4	NE	57	[23,95]	64.76	2.87
	NW	80	[42,115]	87.66	4.01
	SE	69	[33,105]	76.71	3.46
	SW	78	[37,120]	86.80	3.43
Substructure Condition Rating = 4	NE	56	[22,95]	63.90	2.78
	NW	70	[31,110]	78.42	3.23
	SE	58	[23,97]	65.90	2.87
	SW	65	[21,123]	76.32	2.28
Deck Geometry Condition Rating = 3	NE	>120	N/A	N/A	N/A
	NW	>120	N/A	N/A	N/A
	SE	112	[97,122]	114.33	17.80
	SW	>120	N/A	N/A	N/A
Channel Protection Condition Rating = 4	NE	65	[23,118]	75.46	2.46
	NW	108	[54,159]	118/93	3.80
	SE	109	[47,175]	122.66	3.10
	SW	94	[33,169]	108.82	2.50
Scour Protection Condition Rating = 2	NE	>120	N/A	N/A	N/A
	NW	>120	N/A	N/A	N/A
	SE	>100	N/A	N/A	N/A
	SW	>100	N/A	N/A	N/A

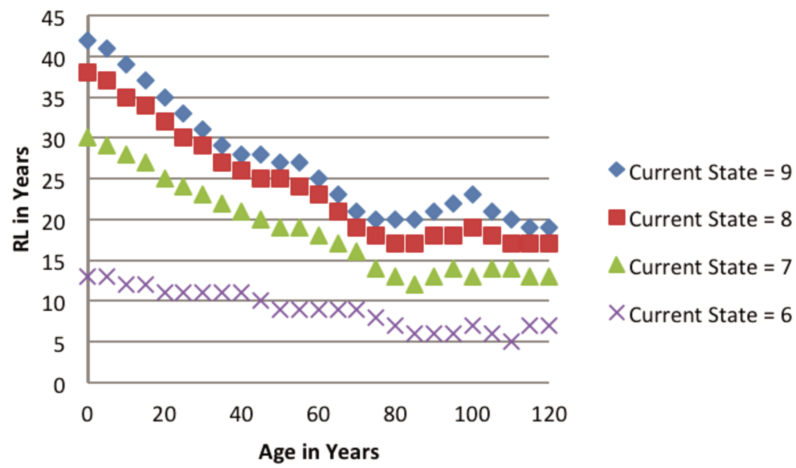


Figure 3-4. Bridge deck median RL by age and current rating.

Southeast region had an average life of 58 years; and the median life of bridges in the Southwest region was found to be 65 years. These findings suggest that eastern bridges, which are generally associated with wetter climates, have a shorter overall life by approximately 7 to 14 years than their northern and southern counterparts. Minor differences in life were found between the northern and southern geographic splits, suggesting that the role played by freezing climatic conditions in bridge asset life is less significant compared to that of precipitation.

The dominant condition rating for bridges in each climatic region was found to be the substructure rating, which would suggest that life extension activities for the substructure would likely be needed for longer lived superstructures (e.g., stainless steel reinforcement). The bridges in the Northeast region had the lowest substructure life, which was consistent with the case for all other condition ratings except deck geometry. The longest-lived substructures and superstructures, on average, were found in the Northwest region; and the longest-lived decks and channels were found in the Southeast region.

One of the benefits of the Markov technique is the ability to adjust life predictions based on the current asset age and condition state. If the assumption of new construction in condition state 9 (or 5 for scour protection) is relaxed, then the median life predictions for the identified thresholds and for each end-of-life criterion using all observations are obtained (Figures 3-4 through 3-9). Individual beta distributions could be developed for each combination of condition states and ages.

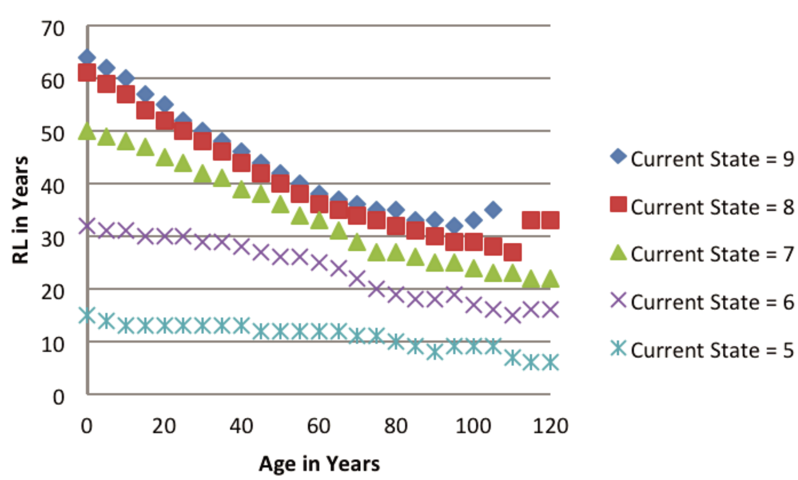


Figure 3-5. Bridge superstructure median RL by age and current rating.

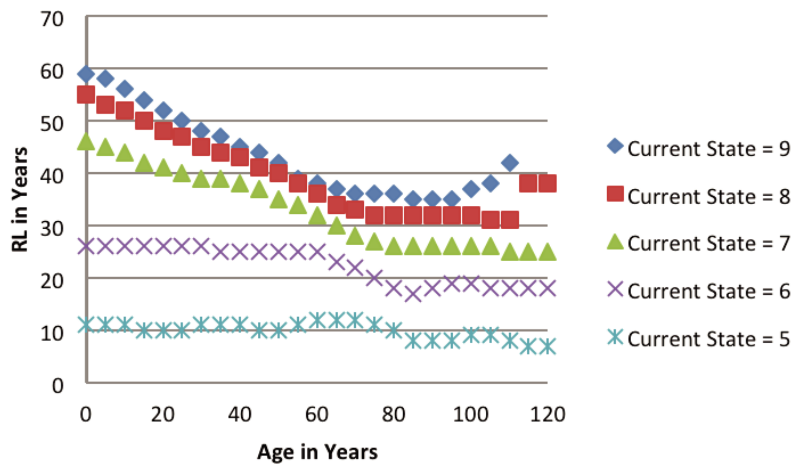


Figure 3-6. Bridge substructure median RL by age and current rating.

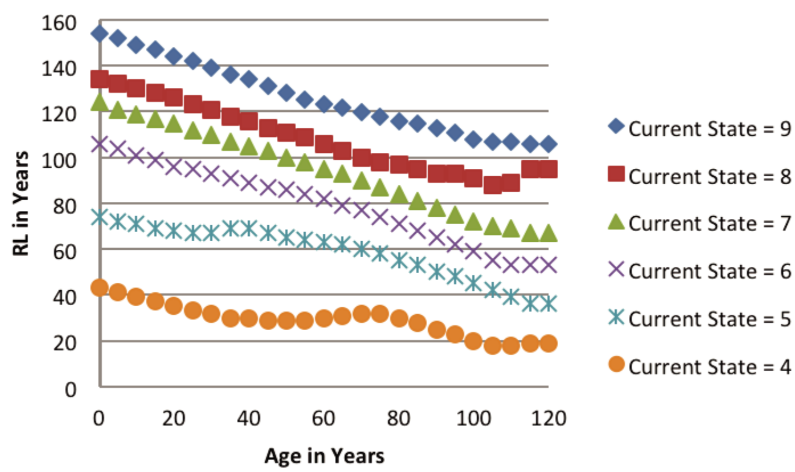


Figure 3-7. Bridge deck geometry median RL by age and current rating.

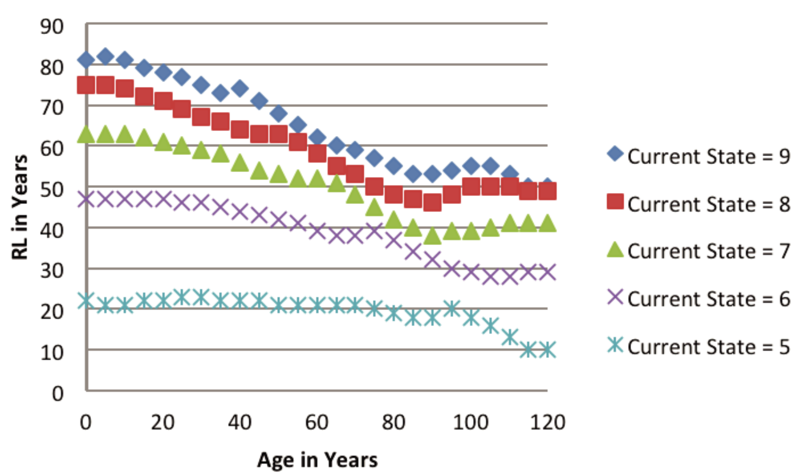


Figure 3-8. Bridge channel protection median RL by age and current rating.

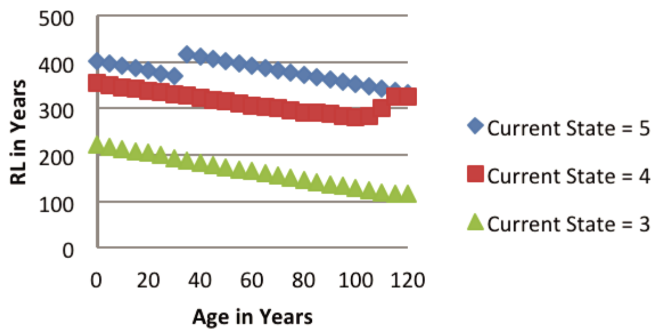


Figure 3-9. Bridge scour protection median RL by age and current rating.

Minor discrepancies such as sudden kinks, are observed at certain ages of the RSL versus age curves in Figures 3-4 to 3-9. This is because for the age-condition data pairs at those ages, the lack of adequate observations yields such "non-representative" or unintuitive transition probabilities. In other words, the increase at remaining life at advanced ages of the asset, from the Markovian prediction, arises from the absence or inadequacy of observations in those age groups. Therefore, expert opinion or an alternative approach such as optimization could be used to bridge the data gap that would eliminate such anomalies in the curve.

Using the developed figures, the remaining life of an asset or its component can be predicted. For example, a 60-year-old bridge (that has received no component replacement since construction) with current deck rating of 6, superstructure rating of 6, substructure rating of 5, deck geometry rating of 6, channel protection rating of 6, and not susceptible to scour would be estimated to have the following median remaining lives: deck, 9 years; superstructure, 25 years; substructure, 12 years; deck geometry, 82 years; channel protection, 39 years. Similar applications will be discussed in the following chapter in more detail.

3.3.2 Box Culverts

For analysis purposes, culvert data were grouped as follows: (1) large culverts (exceeding 20-ft. span), typically concrete material and box-shape—these assets are found in the NBI database; and (2) small culverts, typically plastic or metal pipes—these are found in DOT in-house databases. Similar to the analysis of bridges, covariate and non-covariate models were calibrated for the prediction of box culvert life using the NBI database. The covariate model was used to identify significant life expectancy factors and to predict the structural life of box culverts. The non-covariate technique was applied to predict the life due to multiple rationale or "end-of-life criteria."

For box culverts, there was insufficient data on deck geometry for calculating the NBI sufficiency rating; as such, the box culvert condition rating was estimated using the hybrid condition-based/age-based method. For this model, the uncensored estimates of culvert life were assumed to be (1) historical replacement record ("year of reconstruction" NBI data field—"year built" NBI data field) and (2) the time at which the culvert condition rating first reaches or drops below condition state 3. When modeling highway asset life expectancy, special care was taken in analyzing a representative sample set. An equivalent number of uncensored and censored observations were included in the model calibration set; this approach allows for an equal weighting between historical observations and observations based on more modern designs, construction techniques, and maintenance strategies. Furthermore, the data analyzed in this report allowed for an equivalent number of observations from each of the LTTP-SHRP regions, so as to mitigate any geographical bias in the results. Model checks similar to those described in the previous section were carried out; the results indicated that the Weibull distribution is the most appropriate model form for

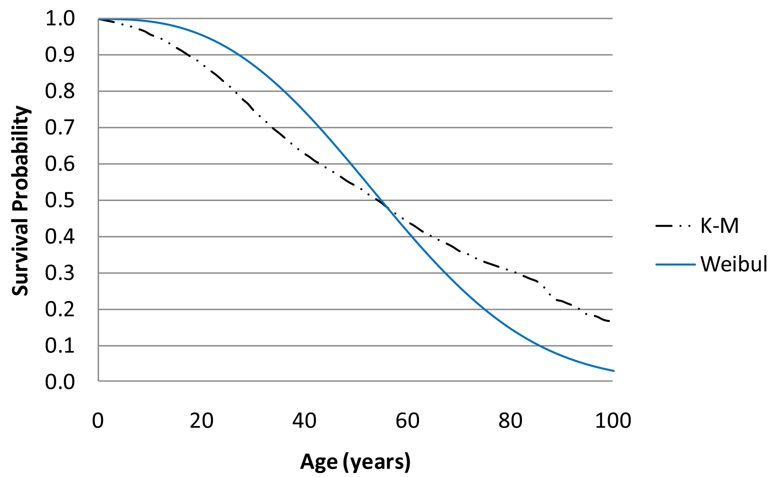


Figure 3-10. Non-parametric validation of Weibull-distributed box culvert life covariate model.

the data (>99.99% confidence). With a RMSE of 0.096, the fit of the model is slightly lower than for bridges (Figure 3-10). The covariate model (Table 3-22), calculated with maximum likelihood methods, indicates a median life of 55 years with a 90% confidence interval of [21, 94].

Factors with a significant, positive effect on life were found to include precipitation, rural geographic setting, concrete material type, state maintenance responsibility, and structure length. Factors with a negative effect included temperature, NHS status, Interstate classification, and soil acidity. The intuitiveness of these factors was relatively strong and consistent with the covariate bridge life model. The most surprising result was the positive influence of precipitation on culvert life, which is opposite that observed for bridges. Considering that culverts are inherently hydraulic structures, the negative consequences normally associated with precipitation may be mitigated by improved removal of harmful runoff. Otherwise, the finding that box culverts with lower

Table 3-22. Weibull regression model of box culvert life.

Life Expectancy Factor	Parameter Estimate, β	t-Statistic
Constant	4.016	286.844
Normal Annual Temperature (°F)	-0.323E-2	-9.760
Normal Annual Precipitation (in.)	0.322E-2	9.672
Geographical classification indicator (1 if rural, 0 otherwise)	0.843E-1	9.032
NHS indicator (1 if on NHS, 0 otherwise)	-0.168E-2	-1.647
Functional class indicator (1 if on interstate, 0 otherwise)	-0.250	-14.691
Maintenance responsibility indicator (1 if state responsible, 0 otherwise)	0.333E-1	4.000
Corrosive soil indicator (1 if in area where average soil is classified as highly corrosive to steel or concrete by the NRCS, 0 otherwise)	-0.853E-1	-10.944
Acidic soil indicator (1 if in area with average soil of pH < 6.5 according to NCRS, 0 otherwise)	-0.723E-1	-8.517
Material type indicator (1 if concrete, 0 otherwise)	0.270	29.887
Structure length in decimeters	0.140E-4	2.086
Baseline Ancillary Factors	**Parameter Estimate, β**	**t-Statistic**
Shape Factor, β	2.728	133.200
Scaling Factor, α	63.211	263.833
Model Statistics		
Number of Observations		19,512
Log-likelihood Function at Convergence		-10,384.79
Restricted Log-likelihood Function		-19,790.65

(End-of-life ≡ Historical Replacement Interval and Age when Culvert Condition Rating drops to or below 3)

Table 3-23. Box culvert condition transition matrices for all observations.

Age Group (Years)	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6	18.85	9.29	3.64	3.06	4.22	5.94
7 → 12	13.53	8.15	3.58	2.99	4.57	2.83
13 → 18	14.18	7.49	3.82	3.11	4.34	5.29
19 → 24	16.18	8.85	4.55	3.34	4.25	5.47
25 → 30	20.58	10.16	4.92	3.71	4.43	4.31
31 → 36	23.29	11.07	5.16	3.52	4.18	3.89
37 → 42	25.98	11.09	5.06	2.93	3.56	4.22
43 → 48	31.09	10.43	5.09	2.88	3.44	4.65
49 → 54	37.07	10.40	5.25	3.31	3.31	4.65
55 → 60	35.25	13.63	5.99	3.62	3.29	3.06
61 → 66	34.79	11.50	5.89	3.69	3.50	2.79
67 → 72	31.49	10.87	5.26	3.03	3.25	3.10
73 → 78	71.92	10.72	5.26	3.98	3.37	2.73
79 → 84	39.64	12.83	8.51	6.88	5.58	4.53
85 → 90	50.00	10.87	11.34	6.96	7.60	5.75
91 → 96	62.16	18.21	6.92	7.73	5.00	4.55
97 → 102	14.42	12.60	5.03	5.93	5.12	5.19
103 → 108	0.00	10.40	5.68	5.89	4.77	1.87
109 → 114	100.00	0.00	100.00	0.00	100.00	11.11
115 → 120	100.00	0.00	0.00	9.69	25.00	0.00

traffic volume (associated with rural, non-NHS, and non-Interstate) have longer life estimates is not surprising, nor the negative effect of soil acidity. Concrete structures (the predominant box culvert material type) have a higher capacity for heat retention and buckling, in part caused by the lack of soil moisture—this is likely the reason that a negative effect for temperature was found (Committee on Climate Change and U.S. Transportation, National Research Council, 2008).

Markov/Weibull and Markov/Beta models were fit to the box culvert data. Due to the lack of observations for deck geometry and scour, the models for the culvert condition rating and the channel protection rating were analyzed. The transition matrices for the culvert condition rating and channel protection rating are provided in Tables 3-23 and 3-24, respectively; to further

Table 3-24. Box culvert channel protection transition matrices for all observations.

Age Group (Years)	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6	20.62	9.71	6.35	4.20	3.05	2.47
7 → 12	11.00	8.87	5.90	3.79	2.73	1.04
13 → 18	9.36	8.62	5.59	3.69	2.25	1.16
19 → 24	9.70	8.84	6.06	3.83	2.68	1.12
25 → 30	6.88	10.04	5.87	4.05	2.83	1.54
31 → 36	5.90	10.48	6.18	3.75	2.76	1.35
37 → 42	8.71	10.85	5.97	3.66	2.55	1.57
43 → 48	9.90	10.02	5.55	3.35	2.25	1.10
49 → 54	12.17	10.62	5.53	3.44	2.31	1.29
55 → 60	19.45	11.22	6.36	3.72	2.45	1.67
61 → 66	18.42	10.05	6.11	3.58	2.40	1.42
67 → 72	15.03	8.53	5.31	3.25	2.61	1.38
73 → 78	12.81	8.43	5.63	3.17	2.09	2.07
79 → 84	15.15	10.57	7.10	4.18	2.00	1.64
85 → 90	36.23	11.57	8.20	4.85	6.62	2.03
91 → 96	23.61	14.86	9.25	4.89	2.57	2.23
97 → 102	7.93	8.67	7.09	3.14	3.37	2.07
103 → 108	0.00	5.71	4.73	4.32	0.20	1.97
109 → 114	100.00	0.00	0.00	0.00	0.00	0.00
115 → 120	100.00	0.00	0.00	0.00	0.00	100.00

Table 3-25. Nr. of observations used in developing box culvert condition transition matrices.

Age Group (Years)	Nr. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6	32,774	48,836	27,139	5,671	923	217
7 → 12	7,759	40,176	39,666	10,679	1,864	527
13 → 18	2,660	32,304	42,715	15,332	3,234	994
19 → 24	822	23,075	39,656	17,721	4,410	1,375
25 → 30	340	18,188	39,218	20,798	5,704	1,757
31 → 36	186	14,583	41,783	24,657	6,991	2,067
37 → 42	109	11,127	38,955	25,350	7,132	2,079
43 → 48	80	7,075	28,702	21,033	6,218	1,649
49 → 54	43	4,885	18,717	14,388	4,638	1,304
55 → 60	54	3,964	14,399	11,335	4,265	1,342
61 → 66	41	3,646	13,096	11,463	4,536	1,518
67 → 72	34	1,947	8,121	8,639	3,413	1,175
73 → 78	13	781	3,322	4,181	1,909	742
79 → 84	4	235	844	1,103	746	435
85 → 90	6	114	333	377	349	203
91 → 96	22	253	793	727	477	214
97 → 102	11	86	461	497	376	146
103 → 108	1	65	334	365	272	108
109 → 114	0	1	0	14	0	9
115 → 120	0	1	1	16	8	6

update the transition matrices, the number of observations in each age group was ascertained (Table 3-25 and Table 3-26).

The median life predictions from the transition matrices for new construction or reconstruction were found to vary from 61 to 103 years with respect to the culvert condition rating, and the channel life varied from 55 to 115 years (Table 3-27). The covariate median life estimate of 55 years falls at the lower end of this range and both are within the range of expert opinion (i.e., 50 to 80 years).

Table 3-26. Nr. of observations used in developing box culvert channel protection transition matrices.

Age Group (Years)	Nr. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6	18,845	49,036	30,227	10,840	2,310	443
7 → 12	4,418	33,887	34,675	17,876	4,844	1,089
13 → 18	2,053	26,798	34,760	21,379	6,660	1,520
19 → 24	1,115	20,803	31,439	21,457	7,097	1,664
25 → 30	1,007	18,754	30,997	22,540	7,513	1,864
31 → 36	889	17,208	33,211	24,427	8,720	2,165
37 → 42	769	14,493	31,687	24,341	8,484	2,181
43 → 48	498	9,848	24,546	19,431	7,010	1,796
49 → 54	220	6,780	16,224	13,325	4,924	1,407
55 → 60	138	5,515	12,681	11,195	4,311	1,272
61 → 66	100	4,713	11,993	11,076	4,447	1,418
67 → 72	90	2,901	7,981	7,637	3,182	991
73 → 78	30	1,336	3,569	3,767	1,648	417
79 → 84	14	498	1,092	1,128	536	159
85 → 90	7	242	376	405	238	101
91 → 96	30	354	727	753	411	120
97 → 102	20	154	446	545	331	75
103 → 108	10	116	302	411	245	52
109 → 114	0	5	5	10	1	1
115 → 120	0	4	10	17	2	0

Table 3-27. Markov/Weibull model predictions of box culvert life by end-of-life criterion for all observations.

End-of-life criterion	End-of-Life Threshold	Average Life (years)	90% Confidence Interval	Weibull Scaling Factor, α	Weibull Shape Factor, β
Culvert Condition Rating	5	61	[22,109]	70.62	2.50
	4	85	[43,125]	93.69	3.77
	3	103	[56,146]	112.35	4.22
Channel Protection Rating	5	55	[15,116]	66.28	1.96
	4	88	[30,161]	102.40	2.42
	3	115	[72,150]	122.95	5.48

The culvert condition threshold of 3 used in the calibration of the covariate model had a median life of 61 years after excluding historical records and accounting for censored observations. This estimate is far less than the 103 years predicted by the Markov/Weibull technique. Considering that only 1,858 observations of a culvert condition rating of 3 were observed in the NBI database, additional observations are needed to select between the two techniques. Therefore, the condition state 4 threshold was considered more appropriate in representing the life expectancy values of box culverts using the Markov/Weibull technique. Life predictions based on the channel protection rating were found similar to the predictions for bridge structures. Channel life was found to vary from 55 to 115 years, depending on the threshold. In combining the possible end-of-life rationale, it was found that box culverts can be expected to have a median life of 85 years with the culvert condition rating dominating by 3 years (culvert rating = 4 life vs. channel rating = 4 life).

As with the bridge data, further analysis was carried out on the basis of the geographic setting of the data. The overall life predictions were 71 years in the Northeast region, 109 years in the Northwest region, 104 years in the Southeast region, and 97 years in the Southwest region (Table 3-28). The channel rating was found to be a dominant factor in the Northeast region, while the culvert condition rating was found dominant in the Southeast region. The other regions were found to have similar life predictions for both end-of-life criteria. As was the case for bridge assets, the lowest culvert life was observed in the Northeast region. There seemed to be no significant distinction between eastern and western box culverts or southern and northern box culverts. The Markov/Weibull predictions for box culverts for each state are presented in Appendix C.

In a final analysis of box culvert life, the remaining life using the Markov predictions was carried out (Figures 3-11 and 3-12). In analyzing the box culvert channel protection rating, it was found that there were inadequate observations for older structures. By continuing to monitor this rating over time, more accurate transition probabilities can be obtained for the later stages of box culvert life.

Table 3-28. Markov/Weibull model predictions of box culvert life by end-of-life criterion and climatic region.

End-of-life criterion and Threshold	SHRP Region	Average Life (years)	90% Confidence Interval	Weibull Scaling Factor, α	Weibull Shape Factor, β
Culvert Condition Rating = 4	NE	74	[32,119]	83.27	3.77
	NW	109	[42,186]	124.61	2.74
	SE	104	[48,161]	116.11	3.33
	SW	97	[35,173]	112.04	2.54
Channel Protection Condition Rating = 4	NE	71	[30,161]	81.83	2.58
	NW	109	[26,125]	119.08	4.14
	SE	>120	N/A	N/A	N/A
	SW	97	[28,194]	115.35	2.12

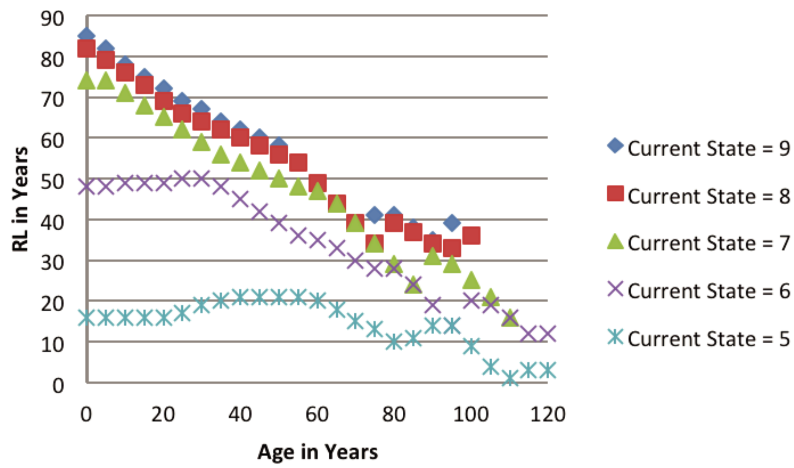


Figure 3-11. Box culvert condition median RL by age and current rating.

3.3.3 Pipe Culverts

In the latter case where the archives of annual or biannual inspections were available, only a cross-sectional database of Pennsylvania cross-pipes was available for pipe culverts. Therefore, Markovian approaches were deemed inappropriate and duration modeling was carried out instead, under the assumption that assets were replaced as soon as the end-of-life thresholds were reached (i.e., the cross-section of assets in a "failed" state are considered uncensored and all others are censored observations). As a result, the estimates are expected to represent an underestimation of the true life of pipe culverts.

The end-of-life conditions for the modeling included

- Extensive deterioration [physical condition rating 3 on a scale of 0 (best)—3 (worst)];
- Completely deteriorated, collapsed, or failed [structural condition rating 3 on a scale of 0 (best)—3 (worst)];
- Severe flow restriction [flow condition rating 2 on a scale of 0 (best)—2 (worst)]; or
- Deflection of the roadway just above the culvert of 1 inch or greater.

Two cohorts were clear in the analysis, which obviously were due to the application of blanket replacements: 63% of the uncensored asset life below 30 years and 33% of uncensored asset life over

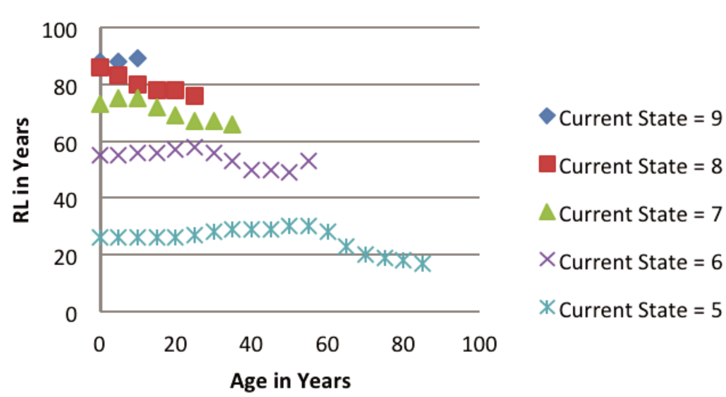


Figure 3-12. Box culvert channel rating median RL by age and current rating.

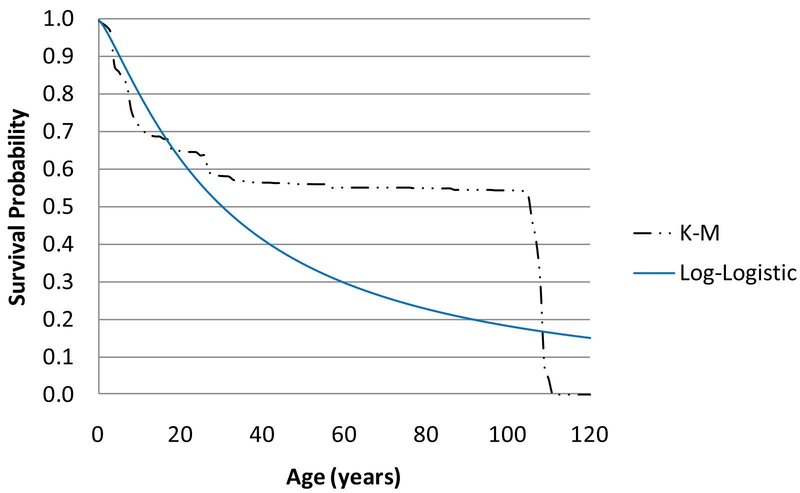


Figure 3-13. Non-parametric validation of log-logistic-distributed pipe culvert life model.

100 years. Therefore, the results of this analysis could be greatly improved with additional deterioration data in the missing age range. Nevertheless, a covariate duration model was calibrated.

The use of log-logistic regression was justified after calculating the log-likelihood statistics to assess the influence of the covariates. In fitting the baseline log-logistic survival curve to the Kaplan-Meier estimate, however, a poor fit was observed (RMSE=0.234) (Figure 3-13). The average model estimate of the pipe culvert life was found to be 30 years (Table 3-29). This estimate is slightly lower than the estimate from the most recent survey of expert opinion discussed in the previous chapter. As such, an alternative end-of-life criterion was used to provide a more practical representation of culvert life.

Factors with a significant influence on asset life were found to be the soil, material, structural, climate, and geometric properties. Of these, it was found that pipe culverts in warmer temperatures, consisting of metal material, or having a protective coating generally exhibited

Table 3-29. Log-logistic regression model of pipe culvert life.

Life Expectancy Factor	Parameter Estimate, β	t-Statistic
Constant	1.346	3.424
Normal Annual Temperature (°F)	0.273	46.854
Normal Annual Precipitation (in.)	-0.160	-25.041
Normal Annual Freeze-Thaw Cycles (days)	-0.276E-1	-38.311
Material indicator (1 if plastic, 0 otherwise)	-0.958	-37.029
Material indicator (1 if metal, 0 otherwise)	0.288	11.097
Coating indicator (1 if coating applied, 0 otherwise)	0.150	4.338
Approximate area opening [height (in.) * width (in.)]	-0.363E-3	-22.221
Plasticity Index of average soil in NRCS survey area	-0.138	-45.694
Baseline Ancillary Factors	**Parameter Estimate, β**	**t-Statistic**
Shape Factor, β	1.256	139.766
Scaling Factor, α	30.414	93.943
Model Statistics		
Number of Observations		26,230
Log-likelihood Function at Convergence		-29,736.22
Restricted Log-likelihood Function		-47,715.90

(End-of-life ≡ Age of Assets with Physical or Structural Condition Rating of 3, Flow rating of 2, or Roadway Deflection > 1")

longer life. Conversely, culverts with large openings, made of plastic, or in soils with a high plasticity index had a lower asset life.

The intuitiveness and parameter estimates corresponding to these factors is limited by the left-censored nature of the dependent variable, the assumption of immediate replacement, the lack of mid-life observations, and the fact that the dataset was limited in its scope (data were from Pennsylvania only). As such, the climatic effects were found to be contrary to that of box culverts. Also, the implication that metal culverts have a longer lifespan is rather unintuitive, as expert opinion suggests that metal culverts have shorter life.

3.3.4 Traffic Signals

Traffic signal condition data are rarely collected and were not available for this analysis. Instead, signals are commonly replaced due to blanket replacement policies, technological improvements, or fatigue. As such, only historical replacement intervals data were made available for this study from Missouri, Oregon, and Pennsylvania. Thus, the asset lives estimated for this asset are actual lives and not functional lives.

The Log-logistic distribution was found to be the more appropriate model form compared to the non-parametric Kaplan-Meier estimate, with 99.99% confidence and a RMSE of 0.046 (Figure 3-14). The model estimates an average life of 19 years (Table 3-30), which is consistent with the typical life range of 15 to 20 years estimated by experts.

Significant factors were found to include climate and the functional class of the road at which the signal is located. The traffic control signals in warmer climates were found to have a shorter life. Also, those in higher precipitation areas were found to have longer life. The climate factors may indicate correlation with different administrative practices across the states, which is an area that requires further study. Furthermore, it was found that signals that serve less-travelled minor arterials are likely to have longer lives, likely because such "lives" actually are a reflection of actual lives and not the lives associated with functional obsolescence typically seen or tolerated at roads of lower classes.

3.3.5 Flashers

It is expected to find a slightly longer lifespan for flashers because advances in flasher technologies are relatively rare. The historical life data collected from Oregon and Missouri were found

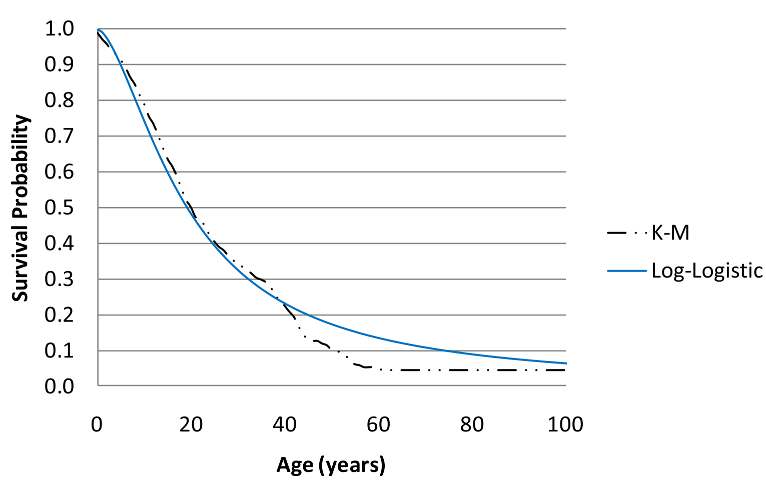


Figure 3-14. Non-parametric validation of log-logistic-distributed traffic signal life model.

Table 3-30. Log-logistic regression model of traffic signal life (end-of-life ≡ historical replacement interval).

Life Expectancy Factor	Parameter Estimate, β	t-Statistic
Constant	2.877	76.249
Normal Annual Temperature (°F)	-0.149E-1	-5.299
Normal Annual Precipitation (in.)	0.155E-1	5.468
Functional class indicator (1 if controlling city or county roads, 0 otherwise)	0.377	8.121
Baseline Ancillary Factors	**Parameter Estimate, β**	**t-Statistic**
Shape Factor, β	1.633	42.721
Scaling Factor, α	19.179	39.500
Model Statistics		
Number of Observations		2,207
Log-likelihood Function at Convergence		-2,291.08
Restricted Log-likelihood Function		-3,189.00

to be the best fit by the Weibull distribution with 99.99% confidence, and the next best model form was the log-logistic survival distribution. In comparison to the Kaplan-Meier, an RMSE of 0.134 was found (Figure 3-15). The baseline covariate model indicated a median flasher life of 28 years, which indeed exceeds that of traffic signals by +9 years (Table 3-31).

Similar to traffic signals, flasher life was found to be significantly affected by climate and the mounting location. Flashers serving intersection traffic (i.e., blinking red stop light) were found to have a longer life. Climatic conditions, such as temperature, precipitation, and wind speed, had a negative relationship with actual life. Also of significance was the finding that flashers over school zones were more frequently replaced, which may be reflective of the criticality and sensitivity of the service area and hence a higher replacement priority.

3.3.6 Roadway Lighting

Of all the assets studied, roadway lighting had the fewest observations available. Subsequently, more data is needed to justify the parametric form used to describe the asset life. The only data available included historical replacement intervals and basic information regarding the material type and location for Missouri assets. Thus, the actual life, and not the functional life, was estimated for the data type.

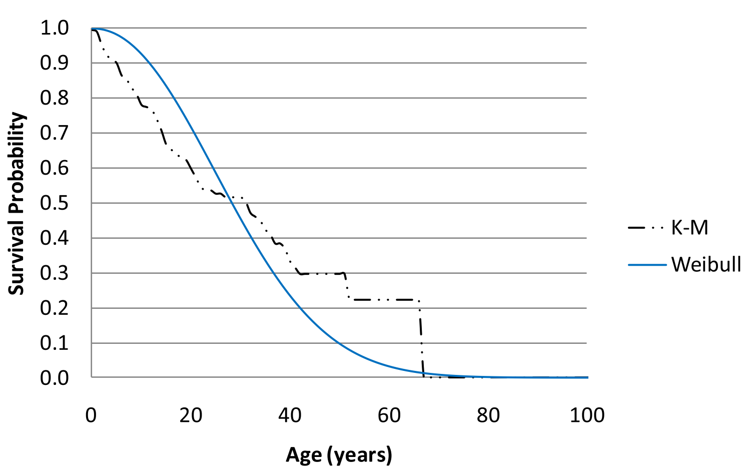


Figure 3-15. Non-parametric validation of Weibull-distributed flasher life model.

Table 3-31. Weibull regression model of flasher life.

Life Expectancy Factor	Parameter Estimate, β	t-Statistic
Constant	9.574	6.896
Normal Annual Temperature (°F)	-0.490E-1	-2.562
Normal Annual Precipitation (in.)	-0.605E-1	-2.685
Mounting location indicator (1 if over intersection, 0 otherwise)	0.819	4.607
School zone indicator (1 if controlling school zone, 0 otherwise)	-0.177	-1.337
Average wind speed in miles per hour	-0.114	-1.419
Baseline Ancillary Factors	**Parameter Estimate, β**	**t-Statistic**
Shape Factor, β	2.126	11.870
Scaling Factor, α	33.591	16.005
Model Statistics		
Number of Observations	180	
Log-likelihood Function at Convergence	-115.79	
Restricted Log-likelihood Function	-242.05	

End-of-life is the end of the Historical Replacement Interval

With the limited data collected, the Weibull distribution was found to be appropriate with 99.99% confidence. The fit to the Kaplan-Meier estimate indicated a RMSE of 0.168 (Figure 3-16), largely due to an abundance of observations over age 75. With expert opinion placing its end of life at closer to 30 years, the integrity of the dataset needs to be enhanced in the future.

The best fitting Weibull regression model, estimated with the maximum likelihood technique, indicates an average life of 100 years (Table 3-32). This estimate far exceeds that of life estimates in the literature, suggesting that additional observations are needed for modeling the life of this asset.

Life expectancy factors found to be statistically significant include climate, material type, functional class of roadway, mounting type, and fixture height. Factor levels found to be associated with a longer life for this asset class include warmer climates, sign mounting, and interstate service. Tall roadway lighting assets and metal poles tended to have a shorter life.

3.3.7 Traffic Signs

The functional performance of traffic signs can be modeled using an appropriate performance indicator, such as the retroreflectivity of the sign sheeting materials (a continuous variable). In

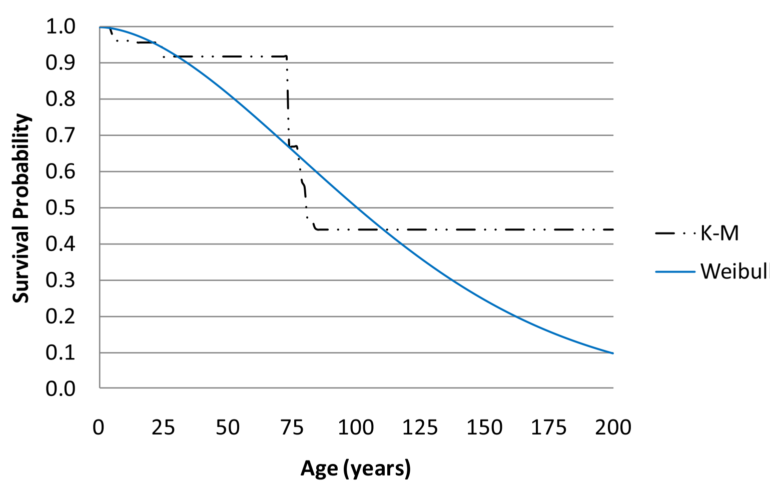


Figure 3-16. Non-parametric validation of Weibull-distributed roadway lighting life model.

Table 3-32. Weibull regression model of roadway lighting life (end-of-life ≡ historical replacement interval).

Life Expectancy Factor	Parameter Estimate, β	t-Statistic
Constant	-4.674	-1.479
Normal Annual Temperature (°F)	0.172	2.933
Material type indicator (1 if metal pole, 0 otherwise)	-1.023	-7.964
Mounting location indicator (1 if on sign, 0 otherwise)	1.069	3.113
Functional class indicator (1 if on interstate, 0 otherwise)	0.437	3.440
Fixture height indicator (1 if less than 30 feet, 0 otherwise)	-0.350	-1.391
Baseline Ancillary Factors	**Parameter Estimate, β**	**t-Statistic**
Shape Factor, β	1.764	14.201
Scaling Factor, α	123.609	10.372
Model Statistics		
Number of Observations		229
Log-likelihood Function at Convergence		-177.88
Restricted Log-likelihood Function		-328.68

addition, a Markov chain can be calibrated to estimate the transition probability of traffic sign performance, progressing from a subjective rating of "good" to "fair" and ultimately "poor." The Markov model in Table 3-33 considers the "poor" stage as the end-of-life condition, while the "good" stage is the initial condition.

The transition matrix for this asset class was calibrated by optimizing the Markov chain to a non-linear representation of the average deterioration curve, based on a regression of asset age against condition state. The survival curve in Figure 3-17 suggests that the average life of the traffic signs is about 12 years and that similar signs are unlikely to last beyond 30 years.

3.3.8 Pavement Markings

From the literature, it is well established that the life expectancy of pavement markings varies with respect to such factors as color and marking material type. The following example illustrates the Weibull-distributed survival probability model developed on the basis of "1A: 2-year Waterborne yellow markings" data from existing test decks conducted by NTPEP.

$$S(t) = \exp\left(-1.0 \times (t/\alpha)^{\beta}\right)$$

where $t \equiv$ the age at which the survival probability is sought, in months.
$\beta =$ shape parameter, 3.87, and the scaling parameter is given by

$\alpha = \exp(1.1 - 0.58 * \text{Orientation (1 if longitudinal, 0 if transverse)} - 0.01 * \text{Initial Retroreflectivity value} - 0.29 * \text{Road surface type (1 if asphalt, 0 if concrete)})$

Table 3-33. Example transition matrix: simple Markov model for traffic signs.

To condition state: From condition state	Good	Fair	Poor
Good	0.8949	0.1051	0
Fair	0	0.8277	0.1723
Poor	0	0	1.0000

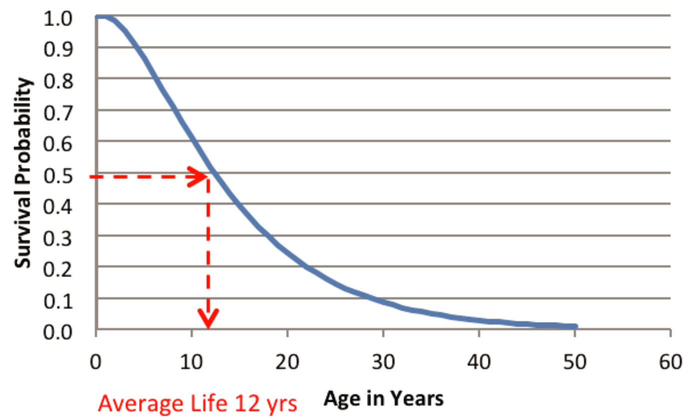


Figure 3-17. Example life expectancy estimate of traffic signs.

The skip-retroreflectivity value of 65 mcd/sq.m/lux was taken as the end-of-life performance threshold. The percentiles of survival distribution can be plotted to give an indication of life expectancy. In this case, the plot suggests that 25% of the markings have a life of approximately 45 months or more, while 75% of the markings have a life of at least 18 months. On average, the calibrated model indicates an average life of 26 months (Figure 3-18).

The marking performance can also be rated using a discrete subjective rating process which may enable the modeler to apply alternative estimation methods such as Markov chains or ordered probit models. A rating scale may be more appropriate than the current continuous rating based on retroreflectivity only since markings can deteriorate due to abrasion, lack of durability, and lack of contrast.

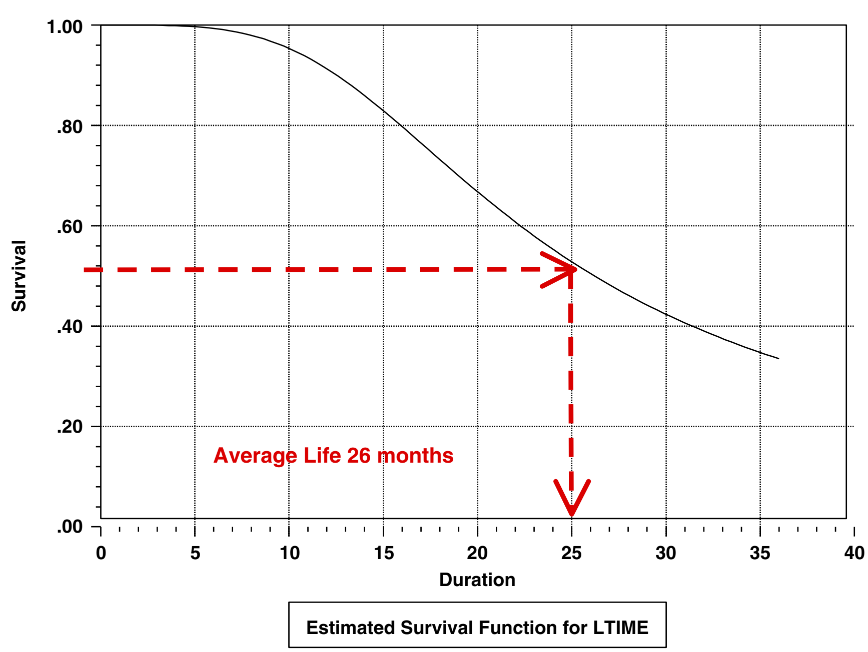


Figure 3-18. Example life expectancy estimate of 1A: 2-yr water-based yellow pavement marking.

3.3.9 Pavements

3.3.9.1 Life of New Asphalt Pavements

A non-parametric survival analysis (Kaplan-Meier method) was conducted to estimate the actual probability of survival of a pavement section in relation to pavement age. For illustrative purposes, a pavement section is considered to be functionally inadequate when IRI>150. Having chosen this threshold value, the estimated life represents the age at which a new pavement section will need rehabilitation for the first time. The survival curve of the GPS-1 pavement sections is shown in Figure 3-19. It can be seen that the average life of a new asphalt pavement is approximately 25 years.

3.3.9.2 Life of Rehabilitation Treatments

An age-based model was developed to determine the lives of different rehabilitation techniques as found in the LTPP SPS-5 study. The number of observations is 493 and the resulting model is

$$\ln(IRI) = 0.035 + 0.049 * (AGE) - 0.12 * (LTHICK) - 0.19 * (SPREP);\ R^2 = 0.52$$

where $\ln(IRI)$ = the natural log of IRI of a treated pavement section in given year in m/km;
AGE = Time elapsed since rehab treatments, in years;
$LTHICK$ = Indicator variable for thickness of rehabilitation treatment (1 if 5 inches and 0 if 2 inches); and
$SPREP$ = indicator variable for surface preparation of rehabilitation treatment (1 if intensive and 0 if minimal).

3.3.9.3 Life of Functional AC Overlay

Functional AC overlay is a common rehabilitation treatment for AC pavements. The following model was developed using data from interstates in a mid-western state in the United States. The regression model found to best describe functional AC overlay performance is

$$IRI = e^{-1.37 + 2.18 \times \log(PRE\_IRI) + 0.3 \times 10^{-5} \times AGE \times TRAADT + 0.03 \times PRECIP}, \qquad R^2 = 0.59$$

where PRE_IRI = IRI before the implementation of the treatment; AGE = Treatment age; TRAADT = Truck annual average daily traffic; and PRECIP = Annual average precipitation

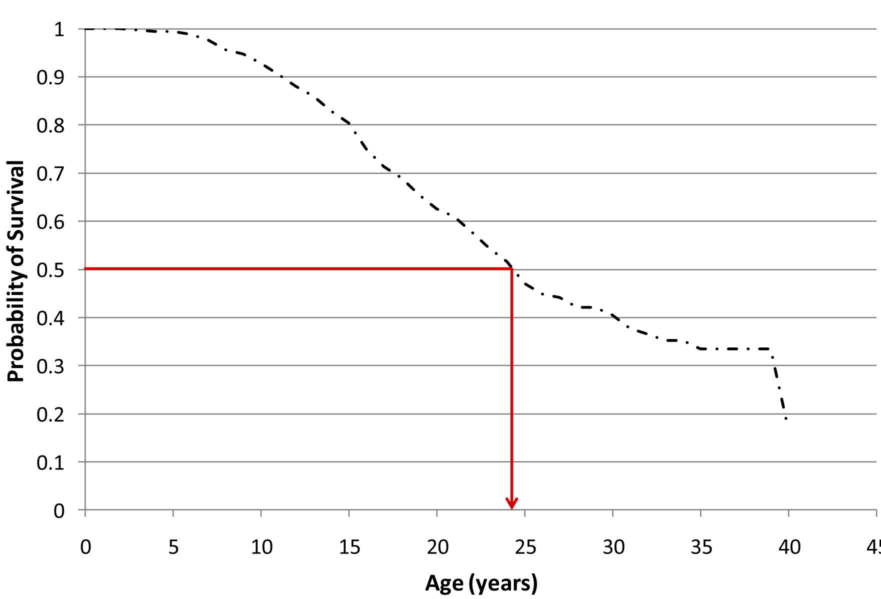


Figure 3-19. Survival curve (Kaplan-Meier method) for hot-mix asphalt concrete pavements.

Table 3-34. Markov model of pavement resurfacing.

To condition state: From condition state	5	4	3	2	1
5	0.8176	0.1824	0	0	0
4	0	0.7408	0.2592	0	0
3	0	0	0.6230	0.3770	0
2	0	0	0	0.4361	0.5639
1	0	0	0	0	1.0000

Making AGE the subject of the equation, and assuming that when IRI reaches the threshold value, treatment age can be found that is equal to the treatment life, t_L.

$$t_{SL} = \frac{\ln\left(IRI_{Threshold}\right) + 1.37 - 2.18 \times Avg\left[\log\left(PRE_{IRI}\right)\right] - 0.03 \times Avg\left(PRECIP\right)}{0.3 \times 10^{-5} \times Avg\left(TRAADT\right)}$$

The functional AC overlay average life can be estimated in years. For instance, using the average values in the model the following result was obtained:

$$t_L = \frac{\ln\left(IRI_{Threshold}\right) + 1.37 - 2.18 \times Avg\left[\log\left(PRE\_IRI\right)\right] - 0.03 \times Avg\left(PRECIP\right)}{0.3 \times 10^{-5} \times Avg\left(TRAADT\right)} = 15.5$$

The functional AC overlay average life was estimated at 15.5 years. As can be seen in the above equation, the average values of the independent variables are used in order to estimate the average life.

3.3.9.4 Life of Resurfacing Treatment on Flexible Pavement

Data from Washington State was used to model the performance of resurfacing treatments on flexible pavements. The performance indicator of IRI was used to categorize the pavements into 5 groups—"very good" (5) for IRI=<60, "good" (4) for 60<IRI<94, "fair" (3) for 94<IRI<170, "mediocre" (2) for 170<IRI<220, and "poor" for IRI=>220. The end-of-life criterion was considered to be the state when IRI equals 220. A simple Markov chain model was developed, with a transition matrix as shown in Table 3-34. It was calibrated according to the average deterioration curve, which is a quadratic curve of the average ages in each condition state.

The resulting survival curve in Figure 3-20 suggests that the resurfaced pavements have a median life of 12 years.

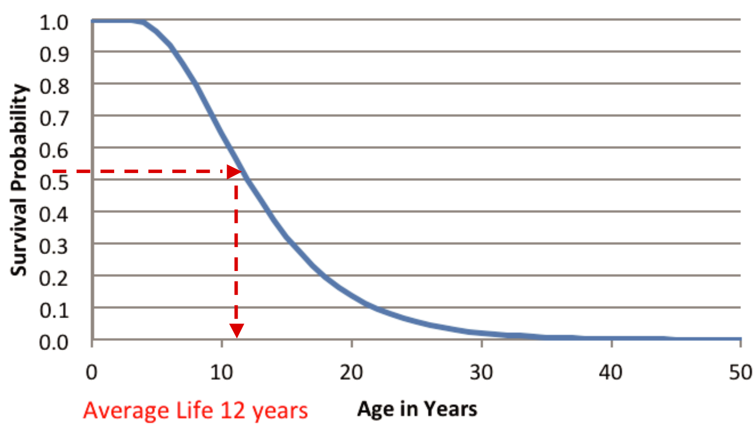


Figure 3-20. Example life expectancy estimate of pavements treated with resurfacing.

3.4 Summary

In demonstrating the methodologies presented in the previous chapter, numerical examples for predicting life were provided by defining end-of-life; selecting an age-based, condition-based, or hybrid-based approach; and applying an appropriate modeling technique. The end-of-life definitions used in this chapter varied between the actual observed life and the time until a threshold was triggered for some measure of performance or condition. The approach used to estimate life coincided with the end-of-life definition. When only historical replacement interval data was available, the age-based approach was used; and when condition data was available, a hybrid-based approach (Weibull or Log-logistic regression) and a condition-based approach (Markov/Weibull or Markov/Beta) were both used. Of the modeling techniques, emphasis was placed on probabilistic estimates produced from Weibull or Log-logistic regression and Markov/Weibull or Markov/Beta models. The use of such techniques were justified through a study of past research, comparing model fit statistics, and assessing the error between the estimated model and non-parametric estimates. The covariate, Weibull, and Log-logistic regression approach allowed for the identification of significant life expectancy factors and the ability to further refine life predictions based on disaggregate data. The non-covariate, Weibull/Markov and Weibull/Beta approaches allowed for the comparison of multiple "end-of-life criteria" and the flexibility of comparing different end-of-life thresholds and updating predictions based on current conditions.

To summarize the predictions, the baseline, average lives, and 90% confidence levels from the developed models are presented in Table 3-35. The model factors and statistics are summarized in Table 3-36. Given the calibration of a Markov/Beta model for each age-condition pair for each rating (e.g., for bridges, unique models for every combination of 20 age groups, 9 condition states, and 5 condition/performance ratings), the corresponding parameters obtained are too numerous to be presented in this report. However, the model results for new constructed bridge components are summarized in the appendix. From the model calibrations, several significant factors were identified, which generally include the climatic conditions, soil properties, asset geometrics, functional class characteristics, and maintenance responsibility. In comparing

Table 3-35. Summary of asset life model predictions.

Asset Class	End-of-Life Definition	Median Life (years)	90% C.I.
Bridges	Sufficiency Rating ≤ 50%	60	[22, 105]
	Deck Rating ≤ 5	42	[15,75]
	Superstructure Rating ≤ 4	64	[27,104]
	Substructure Rating ≤ 4	59	[23,100]
	Deck Geometry Rating ≤ 3	>120	N/A
	Channel Protection Rating ≤ 4	81	[31,139]
	Scour Protection Rating ≤ 2	>120	N/A
Box Culverts	Historical Replacement Interval or Culvert Rating ≤ 3	55	[21,94]
	Culvert Condition Rating ≤ 4	85	[43,125]
	Channel Protection Rating ≤ 4	88	[30,161]
Pipe Culverts	Physical or Structural Rating = 3, Flow Rating = 2, or Roadway Deflection ≥ 1 inch	30	[3,317]
Traffic Signals	Historical Replacement Interval	19	[3,116]
Flashers	Historical Replacement Interval	28	[8,56]
Roadway Lighting	Historical Replacement Interval	100	[23,230]
Traffic Signs	Condition Rating = "Poor"	12	N/A
Pavement Markings (1A: 2-yr water based yellow)	Retroreflectivity < 65 mcd/sq.m/lux	2.17	N/A
Pavement (New construction)	IRI $_{Threshold}$ = 150 in/mile	24	N/A
Pavement (AC Overlay)	IRI $_{Threshold}$ = 100 in/mile	15.5	N/A

Table 3-36. Summary of asset life model statistics.

Asset Class	End-of-Life Definition	RMSE*	Model Type	Survival Factors
Bridges	Sufficiency Rating ≤ 50%	0.034	Weibull	α = 68.87 β = 2.62
	Deck Rating ≤ 5	0.986	Markov/ Weibull	α = 48.62 β = 2.50
	Superstructure Rating ≤ 4	0.757	Markov/ Weibull	α = 72.26 β = 3.02
	Substructure Rating ≤ 4	1.211	Markov/ Weibull	α = 67.36 β = 2.77
	Channel Protection Rating ≤ 4	0.847	Markov/ Weibull	α = 92.77 β = 2.70
Box Culverts	Historical Replacement Interval or Culvert Rating ≤ 3	0.096	Weibull	α = 63.21 β = 2.73
	Culvert Condition Rating ≤ 4	3.683	Markov/ Weibull	α = 93.69 β = 3.77
	Channel Protection Rating ≤ 4	3.204	Markov/ Weibull	α = 102.40 β = 2.42
Pipe Culverts	Physical or Structural Rating = 3, Flow Rating = 2, or Deflection ≥ 1"	0.234	Log-Logistic	α = 30.41 β = 1.26
Traffic Signals	Historical Replacement Interval	0.046	Log-Logistic	α = 19.18 β = 1.63
Flashers	Historical Replacement Interval	0.134	Weibull	α = 33.59 β = 2.13
Roadway Lighting	Historical Replacement Interval	0.168	Weibull	α = 123.61 β = 1.76
*RMSE refers to relative fit to Kaplan-Meier estimates for Survival Regression Models and to Markov estimates for Markov/Weibull Models				

this list to the literature, additional factors that were unavailable at the time of analysis but that should be assessed include the repair history (frequency and intensity), construction quality, and frequency/intensity of deicing chemical applications. In comparing "end-of-life criteria," it was seen that element condition ratings generally are the predominant criteria for rehabilitation or replacement; other criteria include extreme events.

By following the methodologies and applying the techniques described in the previous chapter, similar analyses can be carried out by agencies to predict, more reliably, the expected functional or actual lives of their assets. As a prelude to a discussion of uncertainty in life expectancy models, the next chapter discusses how life expectancy predictions could be applied in common business practices of an agency. Primarily, the estimation of life is useful for assessing lifecycle costs which can be used to evaluate various policies and design selections.

CHAPTER 4

Incorporating Life Expectancy Estimates into Asset Management Functions

4.1 Fundamental Life Expectancy Applications

Life expectancy estimates are important for evaluating, ranking, valuing, and budgeting asset replacement and life-extending maintenance/preservation activities. This chapter discusses the issues associated with such decisions and presents examples to show how the life expectancy estimates could be applied in practice. The Guidebook that accompanies this report describes the context of the related asset management decision-making process of highway agencies and provides an extended range of demonstrations on how asset life expectancy estimates could be incorporated into asset management functions.

4.1.1 Evaluating Replacement and Life-Extension Activities Using LCCA

Life Cycle Cost Analysis (LCCA) allows for the economic-based evaluation of competing alternatives over an analysis period, in consideration of monetized benefits and costs (AASHTO, 1993). For LCCA to be appropriate to a given problem at hand, the analysis period is typically equivalent to the life expectancy of the asset. In the asset management task of preservation treatment or strategy (policy) identification, the optimal treatment or strategy does one of the following: minimizes the lifecycle costs over the asset lifecycle at a specified level of benefits, maximizes the lifecycle benefits under given cost constraints, or maximizes some function of the lifecycle benefits and costs under benefit and/or cost constraints.

4.1.1.1 Brief History of LCCA

FHWA has championed the use of LCCA in analyzing major investment decisions where such analyses are likely to increase the efficiency and effectiveness of investment decisions (FHWA, 1994; FHWA, 1996; FHWA, 2002). As such, recent legislation has required the use of lifecycle costing in highway design, engineering, and management (FHWA, 1998):

- 1991 Intermodal Surface Transportation Efficiency Act (ISTEA 1991)—required the consideration of lifecycle costing in highway design and engineering;
- 1995 National Highway System Designation Act (NHS Act of 1995)—required states to conduct LCCA and Value Engineering Analysis on NHS projects whose costs exceeded a certain threshold; and
- 1998 Transportation Equity Act for the 21st Century (TEA-21)—removed LCCA requirements established in the NHS Act of 1995 but required the development of LCCA procedures on NHS projects.

To aid in managing infrastructure assets, the Governmental Accounting Standards Board (GASB) released a statement, GASB 34, which established new financial reporting requirements so as to ensure the appropriate use of public resources and allow for increased operational accountability (GASB, 1999). Furthermore, both domestic and international studies have found that cost-effective long-term investment decisions in highway asset management could be made at lower costs if LCCA were adopted properly (Al-Mansour & Sinha, 1994).

The following subsections detail lifecycle techniques with an emphasis on the benefits and applications of increased knowledge concerning asset life expectancy. Using LCCA for new and in-service assets is discussed. Examples of how to incorporate life expectancies into LCCA to enhance operational, tactical, and strategic management functions are provided in subsection 4.2.1.

4.1.1.2 LCCA Analysis Period and Asset Life Expectancy Relationship

Research has shown that the validity of economic decisions hinges on a sufficient length of the selected analysis period (Walls III & Smith, 1998). Although incremental changes beyond a sufficient length have been found inconsequential (Walls III & Smith, 1998), the life expectancy estimate allows for a proper basis for the period selection.

The analysis period (also known as the planning horizon, planning period, or payment period) is the timeframe over which economic costs and benefits are analyzed. This length is typically expressed in years and varies depending on whether an agency is considering an existing or proposed asset and can be either less than, equal to, or more than the asset life. For a new or proposed asset, the analysis period is often considered with respect to the overall life expectancy of the asset; for an existing asset, the analysis period is often considered as the remaining life (Figure 4-1). The LCCA is then classified as a full-life LCCA for the former case and a partial-life or remaining-life LCCA for the latter.

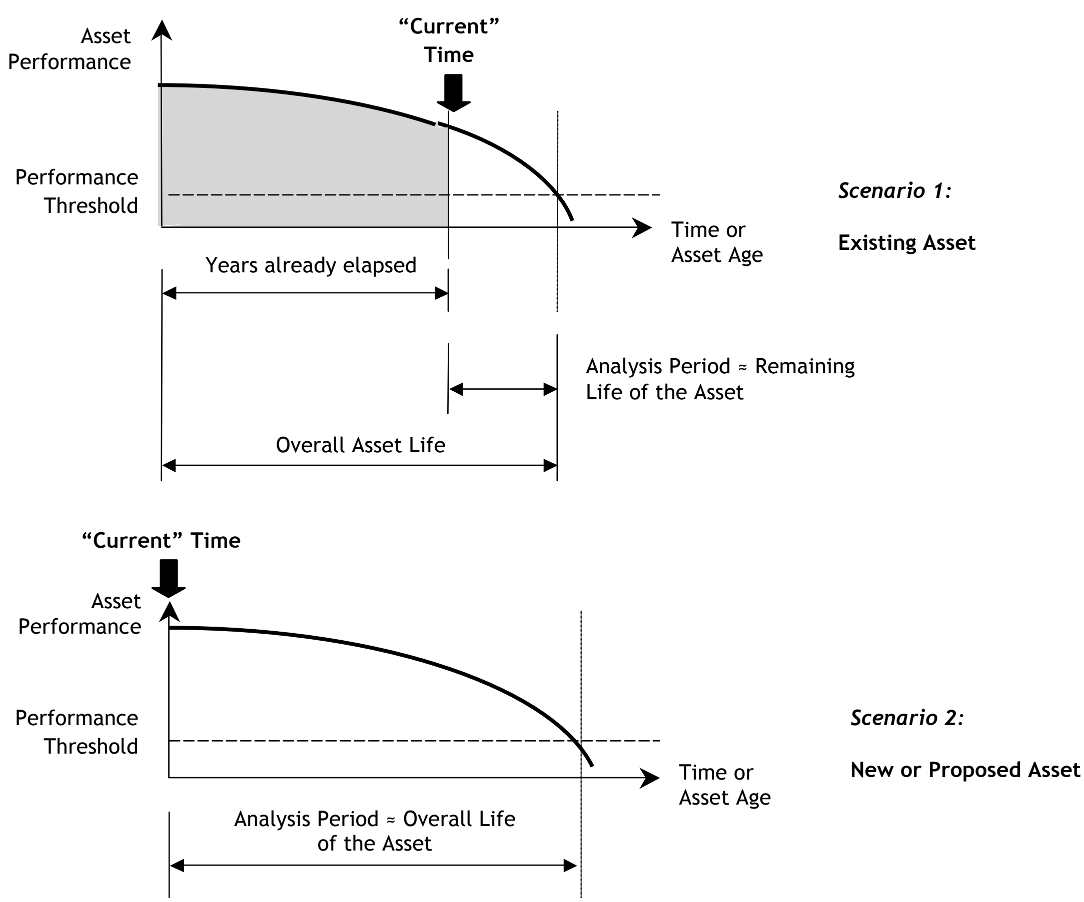


Figure 4-1. Analysis period for existing and new assets, w.r.t. functional life.

The analysis period for LCCA can be set as less than, equal to, or more than the life expectancy estimate (Figures 4-2 and 4-3). The former case (Analysis period < life expectancy) is used for evaluation of the short-term or medium-term impacts of some intervention. A more valid comparison would be to compare the economic costs and benefits over the entire life expectancy so as to weigh both the construction and replacement costs. For agencies that do not replace the asset at the culmination of life, a residual period can be included in the analysis period.

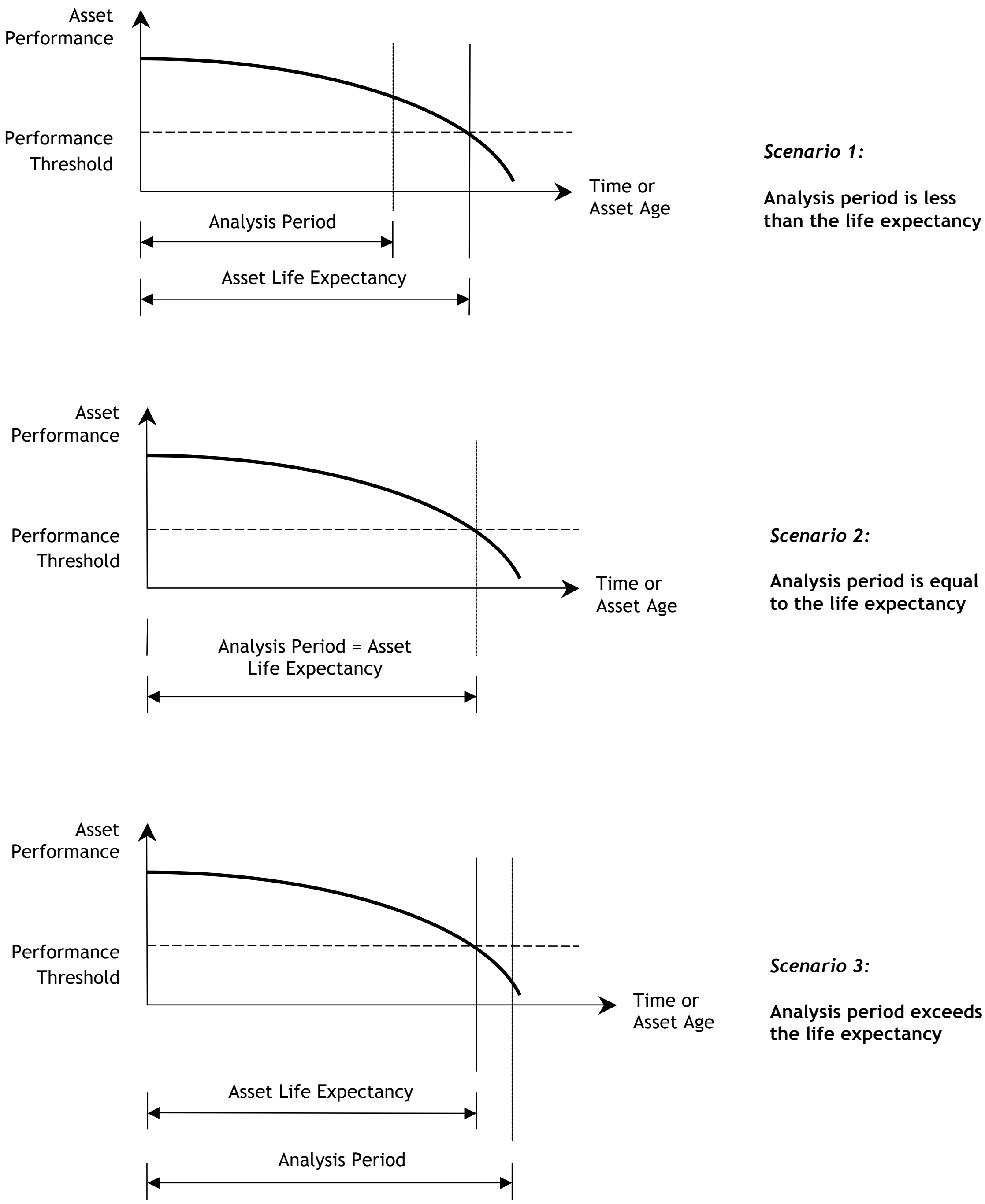


Figure 4-2. Scenarios for analysis period length relative to overall life, new assets, w.r.t. functional life.

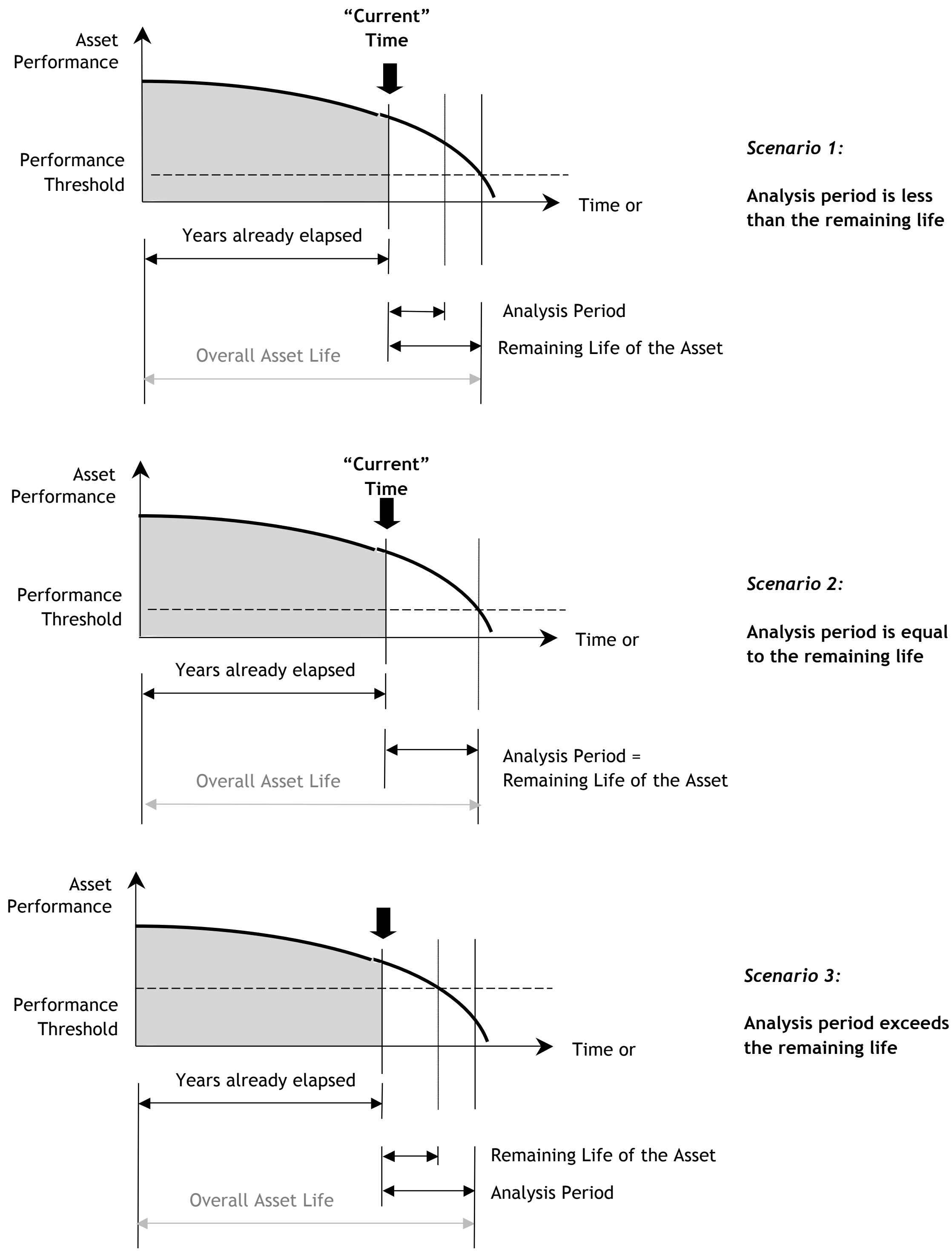


Figure 4-3. Scenarios for analysis period length relative to remaining life, existing assets, w.r.t. functional life.

In the subsequent sections and chapters of this report, the term analysis period is used synonymously with asset life, unless otherwise indicated.

4.1.1.3 Basic LCCA Concepts

The fundamental interest formulae (also known as equivalence equations) that drive LCCA are used to transform amounts or series of amounts of money from one time period to another in due cognizance of the time value of money. Five variables are related in these formulae (Appendix D): an "initial" amount, a "future" amount, a "periodic" (typically annual) amount, an effective interest rate, and an analysis period. As discussed in the previous subsection, the life expectancy estimate can be used as an effective analysis period. To compare alternatives, seven methods using the interest formulae are used as follows.

(a) Present Worth of Costs (PWC)

This method is used when comparing alternative preservation options with equivalent life (or lowest common multiple of life) and benefits. The approach converts all costs into an equivalent single cost assumed to occur at the beginning of the analysis period.

(b) Net Present Value (NPV)

To account for the present worth of benefits, the NPV method is used. NPV represents the present worth of benefits less the present worth of costs. As with PWC, NPV reflects the value of the asset preservation option at the time of the base year of the analysis and can be used to compare alternatives with equivalent analysis periods. Of competing highway asset preservation alternatives, the alternative with the highest NPV is considered the most economically efficient one.

(c) Equivalent Uniform Annual Cost (EUAC)

The EUAC method converts all initial and lifecycle costs into an equivalent annual cost over the analysis period. As such, this method is useful for comparing asset preservation options with different lives but the same levels of benefits.

(d) Equivalent Uniform Annual Return (EUAR)

Similar to NPV, the EUAR method combines all costs and benefits or returns associated with a highway asset preservation option into a single annual value of return (benefits less costs) over a given analysis period. This method can be used when the alternatives have different lives.

(e) Internal Rate of Return (IRR)

Another measure commonly used to analyze investment feasibility is IRR. This method compares the net rate of return (interest rate at NPV equilibration point where NPV = 0 due to PWB = PWC) against the minimum attractive rate of return (MARR). If the IRR exceeds the MARR, then a sufficient net profit is anticipated by the end of the analysis period.

(f) Benefit-Cost Ratio Method (BCR)

The benefit-cost ratio (BCR) is the ratio of the NPV or EUAR of all benefits to that of all costs incurred over the analysis period. A preservation option with a BCR exceeding 1 is considered to be economically feasible, and the alternative with the highest BCR value is considered the best alternative.

(g) Incremental Benefit-Cost Ratio Method

Similar to the BCR method, the incremental approach relies on a pairwise comparison between alternatives. Therefore, if the following ratio is greater than 0, then alternative x is preferred; otherwise, alternative y is preferred.

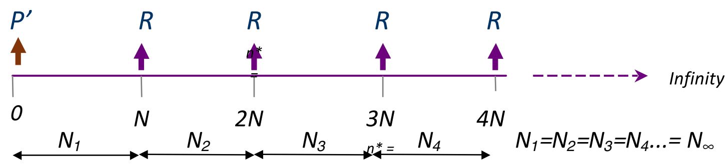


Figure 4-4. Perpetual lifecycle profile for a typical highway asset.

$$\frac{B_X - B_Y}{C_X - C_Y}$$

Any of the LCCA methods can be used to evaluate the economic efficiency of alternatives.

Another concept in LCCA is the consideration of highway infrastructure that is reconstructed as soon as a replacement rationale has been triggered. For such assets, lifecycle costs can be evaluated in perpetuity. For example, the present worth in perpetuity can be evaluated through a single compounded amount R based on a recurring life of N using the following formula (Sinha & Labi, 2007):

$$PW_{R,\infty} = P' + \frac{R}{(1+i)^N} + \frac{R}{(1+i)^{2N}} + \frac{R}{(1+i)^{3N}} + \cdots = P' + \frac{R}{(1+i)^N - 1}$$

The perpetual lifecycle, however, assumes a recurring life period (Figure 4-4). In reality, the life can be variable due to inherent randomness in life expectancy as well as changing environments in terms of climate, design advances, technological developments, and so forth.

4.1.1.4 Life Expectancy Applications in LCCA

The applications of life expectancy estimates in lifecycle cost analysis can be categorized as operational, tactical, or strategic, with increasing degrees of sophistication. Operational applications refer to the use of an asset life expectancy value to carry out fundamental calculations via the interest formula; for instance, the calculation of equivalent annual costs of new or in-service assets. Tactical applications, which draw on the results of operational applications, refer to the use of asset life expectancy values to establish lifecycle profiles at the project level for comparing various strategies. Strategic decisions can then be made based on such applications; examples include

- Lifecycle Scheduling, Programming, and Budgeting
  - Trade-off analysis between user cost and asset life versus agency expenditure (Wu & Flintsch, 2009).
- Lifecycle Assessment of Innovations in Asset Management
  - Lifecycle analysis of the longevity and cost-effectiveness of bridge decks constructed using stainless steel, FRP, etc. (Xi et al., 2004; Cope, 2009);
  - Cost-effectiveness of warranty contracts on the basis of product life (Shober et al., 1996; Singh et al., 2007).
- Timing of Specific Treatments for Asset Preservation
  - Quantifying the consequences of delayed or hastened asset preservation actions (Sharaf et al., 1988; Bilal et al., 2010).
- Lifecycle Impacts of Rehabilitation and Maintenance Treatments
  - Assessing the life of asset preservation treatments (Lemer, 1996; Migletz et al., 2001; Gharaibeh & Darter, 2003; Labi & Sinha, 2003; Lamptey et al., 2005; Labi et al., 2006; and Ong et al., 2010);
  - Ratio of effectiveness (life) to cost, for individual alternative preservation treatments (Morian et al., 2003; Irfan et al., 2009);

- Establishing the effectiveness of the asset in terms of the average performance over its life or the area bounded by the asset's performance curve (Labi et al., 2006). Both of these measures of effectiveness are derived on the basis of the increase in asset life expectancy due to the preservation intervention; and
- Quantifying the effectiveness (and given the cost model, the cost-effectiveness) of a preservation intervention that the asset receives.

Other examples of strategic applications include

- Establishing the optimal application threshold for individual asset preservation treatments (Bilal et al., 2010; Pasupathy et al., 2007);
- Determining the feasibility of a given preservation treatment, material type, and so forth;
- Identifying the most cost-effective treatment to apply to the asset at a given time;
- Identifying optimal rehabilitation and maintenance treatment types and timings over asset lifecycle (Abaza, 2002; Markow & Balta, 1985; and Tsunokawa & Schofer, 1994);
- Ranking/prioritizing the selection of assets that are most deserving of some preservation action at a given year and within budgetary constraints.

In addition to assigning an economic worth to alternatives, life expectancy estimates can be used for financial accounting.

4.1.2 Asset Valuation Using Estimates of Asset Life Expectancy

Transportation asset valuation is an area of financial accounting that takes into account the depreciating worth of a deteriorating asset with a finite lifespan (Johnson, 2003; Baladi, 2006; and Dojutrek, 2011). Techniques commonly applied to estimating the book value of an asset include straight-line and sum-of-years depreciation. These techniques take into account the life of the asset along with a cost value [construction cost, replacement cost, worth-as-is, and discounted (willing-to-pay)]:

$$Straight-line\ Depreciation = \frac{Asset\ Cost - Salvage\ Value}{Service\ Life}$$

$$Sum-of-years\ Depreciation = \frac{(Asset\ Cost - Salvage\ Value) * Remaining\ Service\ Life}{\sum_{i=1}^{Service\ Life} Age_i}$$

Considering that assets may survive beyond their estimated asset lives, an alternative valuation technique may be applied. For instance, by using the survival curve, the asset value can be evaluated using:

$$Asset\ Value = Asset\ Cost * S(t)$$

Such values can be updated based on the programming of asset maintenance, preservation, or replacement projects.

4.1.3 Ranking Replacement and Life Extension Activities Using Utility Theory

In dealing with multiple attributes, and particularly non-monetary performance measures, the application of utility functions is one technique for ranking investment priorities. Utility is typically defined as a unitless measure of "desirability" or "satisfaction." Past studies have sought to develop utility curves for such measures as the general areas of agency cost, user cost, mobility, safety, environment, condition, and remaining life (Li & Sinha, 2004; Sinha et al., 2009). Of

$$U = 1.1659 * [1 - EXP(-0.0195 * RSL^2)]$$

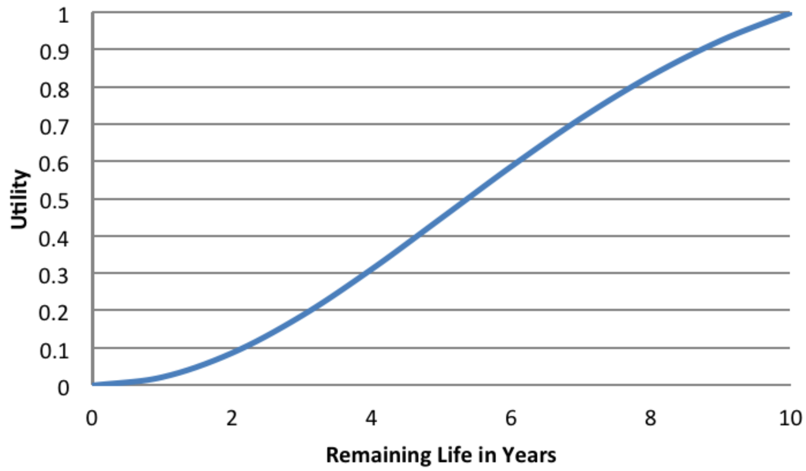


Figure 4-5. General utility curve for remaining life (Li & Sinha, 2004).

interest in this study is the utility of the remaining life, which has been developed using expert opinion for all assets (Figure 4-5) as well as for bridges (Figure 4-6).

From the two utility curves presented, it can be seen that utility has been assigned a generally linear relationship to remaining life (RL), with a lack of concern over structures with a RL over 15 years (beyond most programming horizons). As such, assets with a low predicted RL will have the highest priority when it comes to replacement projects. However, as discussed in the next chapter, if the RL is uncertain, then the utility and ranking consequently will be uncertain as well. The selection of ranked projects, however, is constrained to the available budget which is related to life expectancy.

$$if\ RSL < 5, U = 0$$

$$if\ 5 \leq RSL \leq 15, U = 0.1 * RSL - 0.5,$$

$$else, \qquad U = 1$$

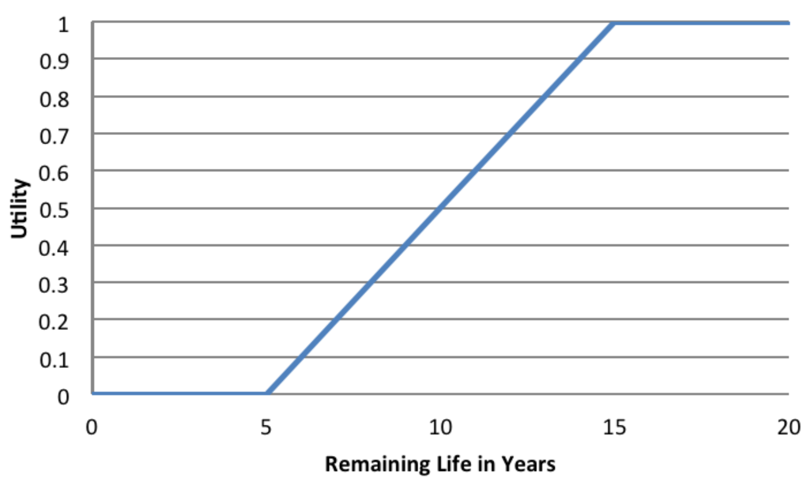


Figure 4-6. Utility curve for bridge remaining life (Sinha et al., 2009).

4.1.4 Budgeting for Asset Replacement

In budgeting, agencies seek to compare anticipated financial needs over a planning horizon against projected funds. The length of the planning horizon can vary based on the length of the improvement plan (typically 3, 5, or 10 years) or incorporated into a more long-term plan (spanning 25 years typically). Although many agencies still practice "worst-first" activity planning, long-term life expectancy forecasts can be used to minimize the lifecycle costs of assets and identify needs prior to any potential shortage of funds. If replacement is the most viable option for an asset within the planning horizon, then the replacement cost directly adds to the budget needs. The total replacement costs for all deserving assets are then summed up to assess the needed budget for replacement projects.

To demonstrate the use of life expectancy in the various business applications, the following section provides sample calculations.

4.2 Example Calculations Involving Asset Life Expectancy

Numerical examples of lifecycle cost analysis, ranking projects by utility, and budgeting over various planning horizons in business applications are presented in the following subsections.

4.2.1 LCCA Calculations Involving Asset Life Expectancy

The basic concepts of economic analysis, as discussed in preceding sections, form a basis for carrying out LCCA-based evaluation of alternative actions to preserve existing or new highway assets. In this subsection, various applications that may benefit highway agencies are presented from basic calculations of LCCA measures to compare alternative preservation activities, justify routine preventive maintenance, identify the optimal replacement interval, compare design alternatives, compare life extension alternatives, price design and preservation activities, synchronize replacements, and assess the value of life expectancy information. The LCCA examples presented here were adapted from the Guidebook that accompanies this report.

4.2.1.1 Example Calculations of Basic LCCA Measures

Standard economic textbooks provide formulae (Appendix D) for basic calculations in engineering economics that serve as the basis for lifecycle cost analysis. In engineering economic analysis, six essential cases can be assessed (note inflation is assumed to be accounted for):

Case 1: Finding the future amount (F) corresponding to a certain initial amount (P) at the end of a given analysis period.

For example, assume it has been estimated from life expectancy models that the remaining life of a certain traffic signal is 5 years. The current price is $20,000. The equivalent cost of replacement when that activity is due can be calculated using the SPCAF, $(1+i)^N$, where N is the analysis period (in this case, the remaining life = 5 years). Assume a 5% interest rate, $F = P\,[(1+i)^N] = 20{,}000[(1+0.05)^5] = 25{,}526$. The cost of replacement 5 years from now is then $25,526.

Case 2: Finding the initial amount (P) that would yield a future amount (F) at the end of a given period.

For example, 5 years from now (December 2010), a certain highway agency has determined that a certain box culvert will reach the end of its life and will need to be replaced at an estimated cost of $50,000 at that year. How much should the firm put away now in order to be able to pay for the culvert replacement in December 2015? Using the Single Payment Present Worth Factor (SPPWF) and assuming a 5% interest rate, $P = F/(1+i)^N = 50{,}000/(1+0.05)^5 = 39{,}176$.

Therefore, the firm should set aside \$39,176 now in order to be able to construct the box culvert 5 years from now (in 2015).

Case 3: Finding the amount of uniform annual payments (A) that would yield a certain future amount (F) at the end of a given period.

Assume, as shown in Case 2, that the highway agency is setting aside uniform amounts every year to construct the box culvert when it is due for construction in 2015 at a cost of \$50,000 at that year. The amount that needs to be set aside annually can be calculated using the Sinking Fund Deposit Factor (SFDF). In other words, we seek *A* given *F*. Assuming a 5% interest rate, $A = F\{i/[(1+i)^N - 1]\} = 50{,}000\{0.05/[(1+0.05)^5 - 1]\} = 9{,}049$. Therefore, the agency should set aside \$9,049 each year from now (2010) in order to be able to finance the construction of the culvert in 2016.

Case 4: Finding the final compounded amount (F) at the end of a given period due to uniform annual payments (A).

The results of life expectancy modeling suggest that the street light system on a certain city's main street is due for replacement 8 years from now. The city engineer's office has in place a revenue generation scheme that provides \$9,000 per year. The engineer's office seeks to ascertain the amount to be generated when the street lights are due for replacement. This is a Uniform Series Compounded Amount Factor (USCAF) problem: we seek *F* given *A*. Assume a 5% interest rate, $F = A\{[(1+i)^N - 1]/i\} = 9{,}000\{[(1+0.05)^8 - 1]/0.05\} = 85{,}942$. Therefore, at the end of the life of the street lights, the local agency would have raised \$85,942.

Case 5: Finding the initial amount (P) that is equivalent to specified uniform future amounts (A) over a given analysis period.

For example, a certain highway agency seeks how much to set aside at the current time (say, year 2010), that would be equivalent to annual amounts of \$2,100 for routine maintenance of its road flasher assets over the remaining 12 years of the asset life. Assume that all the flashers in question were installed in the same year. This is a Uniform Series Present Worth Factor (USPWF) problem: we seek *P* given *A*. Assume 4% interest rate. $P = A\{[(1+i)^N - 1]/[i(1+i)^N]\} = 2{,}100\{[(1+0.04)^{12} - 1]/[0.04(1+0.04)^{12}]\} = 19{,}709$. Therefore, \$19,709 needs to be procured at the current time to yield the required annual maintenance amount over the remaining life of the road flasher assets.

Case 6: Finding the amount of uniform annual payments (A) over a given period that is equivalent to an initial amount (P).

A state highway agency seeks to finance the replacement of its aging road signs that were constructed in the early 1970s. In December 2010, the agency receives a loan of \$200,000 to carry out the project, to be repaid over a 10-year period. From life expectancy models, the expected life of the new assets is 15 years. How much will the agency need to pay back to the bank every year (starting December 2011) until December 2021? It may be noted in this example, as a matter of interest, that the analysis period is less than the life expectancy of the new asset. This is a Uniform Series Capital Recovery Factor (USCRF) problem. In other words, we seek *A* given *P*. Assume 3% interest rate, $A = P\{[i(1+i)^N]/[(1+i)^N - 1]\} = 200{,}000\{[0.03(1+0.03)^{10}]/[(1+0.03)^{10} - 1]\} = 23{,}446$. Therefore, \$23,446 needs to be paid back every year.

4.2.1.2 Example LCCA Calculations for Comparing Alternative Preservation Activities

As described previously, seven methods of evaluating lifecycle costs can be applied. Examples of each relating to asset life expectancy are provided.

(a) Present Worth of Costs (PWC)

Consider a bridge replacement proposed by an agency. The initial cost of design type A is $50,000,000; average annual maintenance cost is $250,000; and the bridge has a salvage value of $8,000,000. For design type B, the initial cost is $30,000,000; the average annual maintenance cost is $750,000; and the salvage value is $2,000,000. From a life expectancy model, it was determined that both designs have a useful life of 75 years.

The present worth of design A, PWC_A (in millions) = $50 + 0.25 \times USPWF(7\%, 75) - 8 \times SPPWF(7\%, 75)$ = $53.50M.

PWC_B (in millions) = $30 + 0.75 \times USPWF(7\%, 75) - 2 \times SPPWF(7\%, 75)$ = $40.63M.

Thus, design B is more economically attractive from a lifecycle viewpoint.

(b) Net Present Value (NPV)

An agency seeks to identify the more cost-effective material to replace an aging guardrail for a long stretch of highway passing through a valley. Design type A is all steel while design type B is partial timber and partial steel. The benefits of each design are a reflection of the number of fatalities/injuries avoided if that design were used and the cost per fatality or injury. Design type A has an initial project cost of $200,000; asset life of 7 years; salvage value of $22,000; annual maintenance/operating costs of $80,000; and annual benefits of $750,000. Design type B has an initial project cost $175,000; asset life of 5 years; salvage value of $15,000; annual maintenance/operating costs of $90,000; and annual benefits of $650,000.

Using the NPV, concept, identify the superior alternative. Assume a 4% interest rate.

Solution. The NPV concept is generally not used to compare two alternatives with different analysis periods (in this case, asset lives). However, the lowest common multiple (LCM) of the two life values could be used with the assumption that the asset is replaced repeatedly until the LCM of the lives is reached. Thus, in this problem, we use a total life of 35 years for each alternative—this means that design A will be reconstructed 5 times while design B will be reconstructed 7 times over the analysis period. USPWF and SPPWF mean uniform series present worth factor and single payment present worth factor, respectively (see Appendix D).

NPV_A = – 200 – 80*USPWF(4%,7) + 750*USPWF(4%,7) + 22*SPPWF(4%,7) +
[–200 – 80*USPWF(4%,7) + 750*USPWF(4%,7) + 22*SPPWF(4%,7)]*SPPWF(4%,7)+
[–200 – 80*USPWF(4%,7) + 750*USPWF(4%,7) + 22*SPPWF(4%,7)]*SPPWF(4%,14)+
[–200 – 80*USPWF(4%,7) + 750*USPWF(4%,7) + 22*SPPWF(4%,7)]*SPPWF(4%,21) +
[–200–80*USPWF(4%,7)+750*USPWF(4%,7)+22*SPPWF(4%,7)]*SPPWF(4%,28)=3838
+3838*SPPWF(4%,7) +3838*SPPWF(4%,14) + 3838*SPPWF(4%,21) +3838*SPPWF(4%,28)
= 17,769 (thousand $)

NPV_B = – 175 – 90*USPWF(4%, 5) + 650*USPWF(4%, 5) + 15*SPPWF(4%,5s) =
[–175 – 90*USPWF(4%,5) + 650*USPWF(4%,5) + 15*SPPWF(4%,5)]*SPPWF(4%,5)+
[–175 – 90*USPWF(4%,5) + 650*USPWF(4%,5) + 15*SPPWF(4%,5)]*SPPWF(4%,10)+
[–175 – 90*USPWF(4%,5) + 650*USPWF(4%,5) + 15*SPPWF(4%,5)]*SPPWF(4%,15)+
[–175 – 90*USPWF(4%,5) + 650*USPWF(4%,5) + 15*SPPWF(4%,5)]*SPPWF(4%,20)+
[–175 – 90*USPWF(4%,5) + 650*USPWF(4%,5) + 15*SPPWF(4%,5)]*SPPWF(4%,25)+
[–175 – 90*USPWF(4%,5) + 650*USPWF(4%,5) + 15*SPPWF(4%,5)]*SPPWF(4%,30)+
=2330+2330*SPPWF(4%,5)+2330*SPPWF(4%,10)+2330*SPPWF(4%,15)+2330*SPPWF
(4%,20) +2330*SPPWF(4%,25) +2330*SPPWF(4%,30)
= 14,546 (thousand $)

Thus, design A is more desirable.

(c) Equivalent Uniform Annual Cost (EUAC)

Consider a case where road lighting can be provided satisfactorily using either one of two alternative pole types, A and B, that differ in both material and design configuration. Type A has an initial cost of $10,000; annual maintenance and operating costs of $800; and $2,000 salvage value. Type B has an initial cost of $7,500; annual maintenance and operating costs of $1,200; and $1,000 salvage value. From life expectancy modeling, the estimated remaining lives of pole types A and B are 16 and 12 years, respectively. Assume a 6% interest rate.

The EUAC of each alternative is calculated as follows:

EUAC of type A = 10,000 × *USCRF*(6%, 16) + 800 – 2,000 × *SFDF*(6%, 16) = $1,710
EUAC for type B = 7,500 × *CRF*(6%, 12) + 1,200 – 1,000 × *SFDF*(6%, 12) = $2,040

Clearly, type A is more desirable, from the lifecycle cost viewpoint.

(d) Equivalent Uniform Annual Return (EUAR)

Two alternative materials are being considered for road pavement markings at Interstate Highway 999. Alternative A involves an initial project cost of $2,000,000; an estimated design life of 5 years; annual maintenance costs of $80,000; and $70,000 worth of annual benefits in terms of monetized savings due to enhanced safety. Assume that both alternatives will yield similar levels of performance and have no salvage value. Alternative B has an initial project cost of $1,750,000; an estimated life of 3.5 years; annual maintenance and operating costs of $90,000; and $50,000 worth of annual benefits in terms of safety enhancement. Assume a 4% interest rate The agency can identify the superior alternative as follows:

$EUAR_A$ (in millions) = 0.07 – [2 **USCRF* (4%,5) + 0.08] = –$0.46M
$EUAR_B$ (in millions) = 0.05 – [1.75**USCRF* (4%,3.5) + 0.05] = –$0.66M

Thus, pavement marking material type A is more desirable, from a lifecycle perspective.

(e) Internal Rate of Return (IRR)

A county road agency is considering the construction of a culvert to provide all-weather accessibility to a remote area of the county. The $30,000 culvert will reduce travel time by eliminating the need for lengthy detours. However, given the acidity of the soil, the estimated life of the culvert is only 40 years, after which time the value of the culvert will be $15,000. The expected travel time savings is $5,000 per year, and the average annual maintenance cost is $2,000. Is the project economically desirable or should the agency just do nothing? The minimum attractive rate of return is 5%.

Equating the net cash flow on both sides yields

$$5{,}000 \times USPWF(i\%,40) + 15{,}000 \times SPPWF(i\%,40) = 30{,}000 + 2000 \times USPWF(i\%,40)$$

Solving this equation by trial and error yields: $i = 9.88\% > 5\%$ so it is economically more efficient to undertake the project than the do-nothing alternative.

(f) Benefit-Cost Ratio Method (BCR)

For the problem in (b), determine the benefit-cost ratio for each alternative and identify which alternative is superior.

For Alternative A: Benefits (in millions) = $0.07M
Cost (in millions) = 2 × *USCRF* (4%, 5) + 0.08 = $0.53M; BCR_A = 0.07/0.53 = 0.13
For Alternative B: Benefits (in millions) = $0.05M; Costs (in millions) = 1.75 × *USCRF* (4%, 3.5) + 0.09 = $0.71M; BCR_B = 0.05/0.71 = 0.07
$BCR_A > BCR_B$. Thus, Alternative A is more desirable.

(g) Incremental Benefit-Cost Ratio Method

Consider a new subset of alternatives with the following benefits and costs:

Alternative X: Benefits = \$2M, Cost = \$0.8M;
Alternative Y: Benefits = \$3M, Cost = \$1.5M;
Alternative Z: Benefits = \$9M, Cost = \$4M;

Determine the best alternative using the incremental benefit-cost ratio method.

First, solution: compare Alternatives X and Y:

$$\frac{B_X - B_Y}{C_X - C_Y} = \frac{\$2M - \$3M}{\$0.8M - \$1.5M} = 1.43 \rightarrow \textit{Alternative X is superior to Alternative Y}$$

Next, compare Alternatives X and Z:

$$\frac{B_X - B_Z}{C_X - C_Z} = \frac{\$2M - \$9M}{\$0.8M - \$4M} = 2.19 \rightarrow \textit{Alternative X is superior to Alternative Z}$$

The best alternative, therefore, is Alternative X.

(h) Perpetuity Considerations

In addition to evaluating projects with a finite analysis period, agencies can also assess lifecycle costs in perpetuity. Consider the following case for a large reinforced box culvert that is slated for reconstruction.

Assume that the reconstruction cost is \$600,000. During each replacement cycle, the culvert will require two rehabilitations, each at a cost of \$200,000, at the 20th and 40th year; the average annual cost of maintenance is \$5,000. From life expectancy models, the estimated life is 60 years. At the end of the replacement cycle, the bridge will again be reconstructed and the entire cycle is assumed to repeat in perpetuity. Find the capitalized costs to perpetuity. Assume a 5% interest rate. Assume P' (the starting non-recurring cost = 0).

The compounded lifecycle cost, R, is determined as follows: 600,000* SPCAF(5%, 60) + 200,000*SPCAF(5%, 40) + 200,000*SPCAF(5%, 20) + 5,000*USCAF(5%, 60) = \$14,914,087.

Then the present worth of R, taken to perpetuity, is

$$PW\infty = \frac{R}{(1+i)^N - 1} = \frac{\$14{,}914{,}087}{(1+0.05)^{60} - 1} = \$843{,}596$$

4.2.1.3 Example LCCA Calculations for Justifying Routine Preventive Maintenance

Common examples of routine treatments include sealing of pavement cracks; washing of bridges, signs, pavements, and guiderails; spot painting of steel structures; and concrete patching. To evaluate the merit of such strategies, consider the following example which compares a preventive maintenance scenario against the do-nothing scenario. A highway asset under the two scenarios will likely have different lives. For comparing asset alternatives that have different lives, there are at least three methods: (1) convert all costs and benefits into EUAC, (2) compute lifecycle cost over a life that is a lowest common denominator of the separate life expectancy estimates, or (3) find the present worth of periodic payments to perpetuity.

Table 4-1. Example comparison of lifecycle activity profiles in evaluating the benefit or disbenefits of conducting routine preventive maintenance.

	Cost per lane-mile by policy	
Year	"Routine Preventative Maintenance" Strategy	Do-Nothing Policy
4	$400	
8	$400	
12	$400	
16	$400	
20	$400	$30,000
24	$30,000	

Consider, for example, the use of the EUAC approach for comparing the two preservation policies in a pavement management system (Table 4-1). For the routine preventive preservation policy, assume crack sealing is performed every 4 years at $400 per lane-mile resulting in an overall life extension of 4 years; and for the do-nothing option, assume only reconstruction is performed at a cost of $30,000 per lane-mile for both alternatives. Assume an interest rate of 4%.

The EUAC of the two alternatives can be compared as follows:

$$PV_{Routine\ Preventive\ Maintenance} = \$400\left[\frac{1}{(1+0.04)^4}+\frac{1}{(1+0.04)^8}+\cdots\frac{1}{(1+0.04)^{20}}\right]+\$20,000\left[\frac{1}{(1+0.04)^{24}}\right]$$
$$= \$12,984\,/\,\text{lane-mile}$$

$$EUAC_{Routine\ Preventive\ Maintenance} = \$12,984\left[\frac{0.04(1+0.04)^{24}}{(1+0.04)^{24}-1}\right] = \$852/\text{lane-mile}$$

$$EUAC_{Do-Nothing} = \$30,000\left[\frac{0.04}{(1+0.04)^{20}-1}\right] = \$1,007/\text{lane-mile}$$

With these assumptions, the agency could reduce annual costs by $156 per lane-mile if routine preventive maintenance is carried out.

4.2.1.4 Example LCCA Calculations for Identifying the Optimal Replacement Interval

Certain types of assets have various alternatives for preservation over their lifecycles, depending on different maintenance/preservation policies. The optimal lifecycle activity profile is one that minimizes lifecycle cost.

For example, consider the alternative profiles in Table 4-2 for a highway bridge serving a railway. Assuming an interest rate of 5%, the present worth of all bridge agency costs to perpetuity are to be compared across the alternative profiles. The profile will be the one that minimizes the present value of costs to perpetuity.

Option 1 (Rehabilitate at years 25 and 40 $\rightarrow$ Asset Life = 50 years)

$$PW_{Option1} = \$600k\left[\frac{1}{(1+0.05)^{50}}\right]+\$200k\left[\frac{1}{(1+0.05)^{25}}+\frac{1}{(1+0.05)^{40}}\right]+\$5k\left[\frac{(1+0.05)^{50}-1}{0.05*(1+0.05)^{50}}\right]$$
$$= \$231,072$$

$$PW\infty_{Option1} = \frac{\$231,072}{(1+0.05)^{50}-1} = \$22,075$$

Table 4-2. Example data for optimizing replacement and maintenance activity intervals.

	Profile 1	Profile 2	Profile 3	Profile 4
Replacement Cost	$600k	$600k	$600k	$600k
Rehabilitation Cost	$200k	$200k	$200k	$200k
Annual Maintenance Cost	$5k	$5k	$5k	$5k
Estimated Life (years)	50	60	70	80
Rehabilitation Year 1	25	25	25	20
Rehabilitation Year 2	40	45	45	40
Rehabilitation Year 3	--	--	55	60

Option 2 (Rehabilitate at years 25 and 45 $\rightarrow$ Asset Life = 60 years)

$$PW_{Option\,2} = \$600k\left[\frac{1}{(1+0.05)^{60}}\right] + \$200k\left[\frac{1}{(1+0.05)^{25}} + \frac{1}{(1+0.05)^{45}}\right] + \$5k\left[\frac{(1+0.05)^{60}-1}{0.05*(1+0.05)^{60}}\right]$$
$$= \$208,088$$

$$PW\infty_{Option\,2} = \frac{\$208,088}{(1+0.05)^{60}-1} = \$11,770$$

Option 3 (Rehabilitate at years 25, 45 and 55 $\rightarrow$ Asset Life = 70 years)

$$PW_{Option\,3} = \$600k\left[\frac{1}{(1+0.05)^{70}}\right] + \$200k\left[\frac{1}{(1+0.05)^{25}} + \frac{1}{(1+0.05)^{45}} + \frac{1}{(1+0.05)^{55}}\right]$$
$$+ 5k\left[\frac{(1+0.05)^{70}-1}{0.05*(1+0.05)^{70}}\right]$$
$$= \$197,753$$

$$PW\infty_{Option\,3} = \frac{\$197,753}{(1+0.05)^{70}-1} = \$6,720$$

Option 4 (Rehabilitate at years 20, 40, and 60 $\rightarrow$ Asset Life = 80 years)

$$PW_{Option\,4} = \$600k\left[\frac{1}{(1+0.05)^{80}}\right] + \$200k\left[\frac{1}{(1+0.05)^{20}} + \frac{1}{(1+0.05)^{40}} + \frac{1}{(1+0.05)^{60}}\right]$$
$$+ 5k\left[\frac{(1+0.05)^{80}-1}{0.05k(1+0.05)^{80}}\right]$$
$$= \$213,876$$

$$PW\infty_{Option\,4} = \frac{\$213,876}{(1+0.05)^{80}-1} = \$4,404$$

Using the assumed costs, Option 4 was found to minimize lifecycle cost in perpetuity. Therefore, it is recommended to pursue rehabilitation activities in years 20, 40, and 60 and then replace the structure in year 80.

4.2.1.5 Example LCCA Calculations for Comparing Design Alternatives

Asset managers constantly must choose between competing designs and material types, each with a unique life expectancy. To decide between designs, lifecycle costs can be evaluated. For example, consider the decision of applying a protective coating to a pipe culvert.

Suppose that without the coating, the pipe culvert is expected to survive 50 years with a construction cost of $1,000. With the coating, the pipe culvert is expected to survive 56 years with a construction cost of $1,200. Three possible ways of making this comparison would be (1) an annual cost basis using EUAC, (2) a least common multiple analysis period consisting of multiple replacement cycles, or (3) replacement cycles to perpetuity. For this example, a perpetuity is assumed, with a 4% interest rate. The present values of the two options, to perpetuity are

$$PV\infty_{no\ coating} = \$1,000 \times \left(1 + \frac{1}{(1+0.04)^{50} - 1}\right) = \$1,164$$

$$PV\infty_{coating} = \$1,200 \times \left(1 + \frac{1}{(1+0.04)^{56} - 1}\right) = \$1,350$$

Therefore, in this illustration, the uncoated design option is preferred.

4.2.1.6 Example LCCA Calculations for Comparing Life Extension Alternatives

Another life expectancy application faced by asset managers is the need to compare two or more life extension alternatives with different costs and levels of effectiveness. Consider the set of alternatives presented in Table 4-3, for a bridge having a life of 50 years (before maintenance); a replacement cost of $500,000; and an interest rate of 4%.

In a bridge management system, these types of strategies are typically compared on a net present value basis, and more than one of them may be selected. For the current example, EUAC is used as the selection criterion.

EUAC of Deck Overlay

$$= \left[\$15k * \left(\frac{1}{(1+0.04)^{20}} + \frac{1}{(1+0.04)^{40}}\right) + \$500k * \left(\frac{1}{(1+0.04)^{50+7}}\right)\right] * \frac{0.04(1+0.04)^{50+7}}{(1+0.04)^{50+7} - 1} = \$2.84k$$

$$\text{EUAC of Deck Patching} = \$500 + \left[\$500k * \left(\frac{1}{(1+0.04)^{50+3}}\right)\right] * \frac{0.04(1+0.04)^{50+3}}{(1+0.04)^{50+3} - 1} = \$3.36k$$

$$\text{EUAC of Joint Replacement} = \$300 + \left[\$500k * \left(\frac{1}{(1+0.04)^{50+2}}\right)\right] * \frac{0.04(1+0.04)^{50+2}}{(1+0.04)^{50+2} - 1} = \$3.29k$$

Table 4-3. Example bridge life extension alternatives.

Activity	Frequency	Life Extension of Activity at Applied Frequency	Activity Cost
Deck overlay	Every 20 years	7	$15k
Deck patching	Every year	3	$500
Joint replacement	Every year	2	$300
Deck overlay & joint replacement	Overlay every 20 years & joint replacement every yr	9	$15k for overlay and $100 for joint replacement
Deck patching & joint replacement	Every year	5	$700
Deck rehabilitation	Once at year 35	30	$200k

EUAC of Deck Overlay and Joint Replacement

$$= \$100 + \left[\$15k * \left(\frac{1}{(1+0.04)^{20}} + \frac{1}{(1+0.04)^{40}} \right) + \$500k * \left(\frac{1}{(1+0.04)^{50+9}} \right) \right] * \frac{0.04(1+0.04)^{50+9}}{(1+0.04)^{50+9} - 1}$$
$$= \$2.74k$$

EUAC of Deck Patching and Joint Replacement

$$= \$700 + \left[\$500k * \left(\frac{1}{(1+0.04)^{50+5}} \right) \right] * \frac{0.04(1+0.04)^{50+5}}{(1+0.04)^{50+5} - 1} = \$3.32k$$

$$\text{EUAC of Deck Rehabilitation} = \left[\$200k * \left(\frac{1}{(1+0.04)^{35}} \right) + \$500k * \left(\frac{1}{(1+0.04)^{50+30}} \right) \right] * \frac{0.04(1+0.04)^{50+30}}{(1+0.04)^{50+30} - 1} = \$3.32k$$

$$\text{EUAC of Do Nothing} = \$500k * \left(\frac{0.04}{(1+0.04)^{50} - 1} \right) = \$3.28k$$

From this array of activity options, the improvement policy that minimizes the cost under these assumptions is annual deck overlay and joint replacement. It can also be seen that the life extensions from patching, joint replacement, and rehabilitation under these assumptions are not cost-effective (relative to the do-nothing option).

4.2.1.7 Example LCCA Calculations for Pricing Design and Preservation Alternatives

Many agencies invest in research and development programs in an attempt to produce practical, cost-effective designs and materials. The primary concern with innovations, however, relates to reliability, life extension benefits, and cost of application. To facilitate decisions on whether or not to apply a new design, agencies often assess break-even points (i.e., the levels at which alternative designs become less costly than the traditional design).

Example. For a bridge planned for construction, an agency wishes to assess the feasibility of using solid stainless steel reinforcement bars in place of traditional carbon steel. The bridge length and total deck width (ft) are 148.66 and 49.33, respectively; traffic volume is 8,527 AADT; weight of deck reinforcement is 62,963 pounds; and during the construction, rehabilitation, and deck replacements, workzone traffic is diverted to a 1.3-mile 30-mph detour. If the lives of two bridges are 75 years and 100 years, respectively, with the activity profiles shown in Figure 4-7A, at what price is the stainless steel alternative preferred? The costs of initial con-

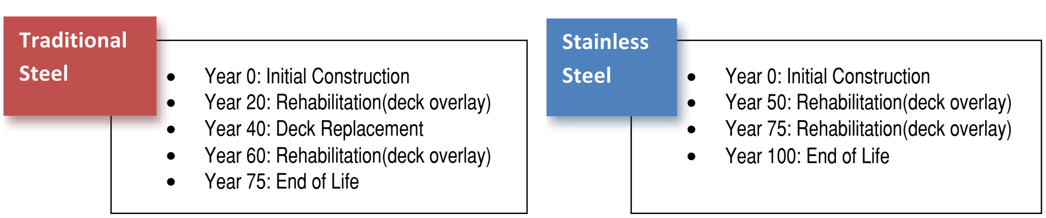


Figure 4-7A. Example activity profiles for carbon steel and stainless steel options (Cope, 2009).

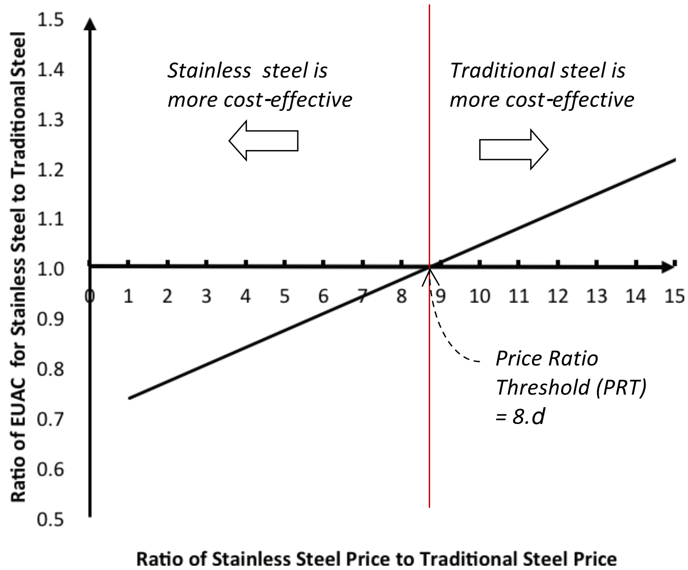


Figure 4-7B. Sensitivity of relative long-term cost-effectiveness of longer-life innovative material to the innovative-traditional price ratio.

struction, deck replacement, and deck rehabilitation are provided in Appendix E. The project durations for initial construction, deck replacement, and deck rehabilitation are 120, 60, and 21, respectively.

Values of other analysis variables are as follows: discount rate = 4%; Vehicle occupancy = 1.8; minimum hourly wage = $13.43; average fuel economy = 23 mpg; cost of fuel = 3.75/gal; traditional carbon steel price = 1.15$/lb; carbon steel service life = 40 yrs; stainless steel service life = 100 yrs.

Results. The result of the analysis is shown in Figure 4-7B. This depicts the values of the ratio of the lifecycle cost of the stainless steel option relative to the traditional steel option, at various ratios of the price of stainless steel relative to traditional steel. The differences in the lifecycle costs of stainless and traditional steel arise from their different lifecycle profiles which in turn are due to the differences in the deck life (stainless steel decks have been found to have greater longevity (Cope (2009)). The chart shows that the stainless steel alternative is the superior alternative as long as the stainless steel price is less than 8.7 times the price of traditional steel. This is referred to as the price threshold ratio (PRT) for stainless steel desirability. The higher the PRT, the more favorable is the use of stainless steel. Higher values of the discount rate, vehicle occupancy, minimum hourly wage, fuel cost, and stainless steel service life, and lower values of average fuel economy would cause the Price Ratio function to shift to the right and thus, a higher PRT and consequently, a greater domain of cost-effectiveness for the stainless steel option.

4.2.1.8 Example LCCA Calculations for Synchronizing Replacements

Maintenance interventions can be costly and disruptive, and agencies often wish to synchronize work within a corridor to minimize the disruption. Therefore, knowledge of the remaining life of all assets in a corridor would assist the manager in timing replacement and/or maintenance activities. For example, consider a small system of assets located along the same roadway (Table 4-4). If the location costs (i.e., mobilization, traffic control, and user costs) are estimated to be $7,000 per construction set-up, then what are the optimal replacement times so as to minimize the present value of costs to perpetuity? Assume the assets are to be replaced no later than their remaining life.

Table 4-4. Example data for synchronizing replacement intervals.

Asset	Life of Newly Constructed Asset	Remaining Life	Replacement Cost
Pavement Markings	5	3	$200
Traffic Sign	10	4	$300
Traffic Signal	15	5	$500

The objective of this problem is to minimize the total lifecycle cost, computed as follows:

$$PV = \sum_{n=1}^{Analysis\ Period} Annual\ Replacement\ Cost * \left(\frac{1}{1+i}\right)^n$$

where *Annual Replacement Cost* = Location Cost * $\Sigma^{3}_{asset=1}$ x_{asset} Replacement $Cost_{asset}$;

x = binary decision variable indicating replacement, 1 = replace, 0 = do-nothing;
n = year of potential replacement.

The only constraint is that the remaining life must exceed zero, $RL \geq 0 \; \forall$ n.

This optimization problem can be solved using a Microsoft Excel solver software package, although the example is simple enough to solve by inspection: an agency would ideally like to coordinate replacements so as to minimize cost and that the new construction life estimates have a common multiple of 5 years. Therefore, the optimal solution is to

- Replace all assets in year 3.
- Replace pavement markings every 5 years thereafter (i.e., years 8, 13, 18, 23, 28, 33).
- Replace traffic signs every 10 years thereafter (i.e., years 13, 23, 33).
- Replace traffic signals every 15 years thereafter (i.e., years 18, 33).

This produces the same lifecycle profile every 30 years with a present value of $26,000.

Alternatively, if an agency did not coordinate replacement schedules, and thus replaced assets at the time each asset's full life is reached

- Replace pavement markings in year 3 and every 5 years thereafter (i.e., years 3, 8, . . . 33).
- Replace traffic signs in year 4 and every 10 years thereafter (i.e., years 4, 14, 24, 34).
- Replace traffic signals in year 5 and every 15 years thereafter (i.e., years 5, 20, 35).

Then, a common lifecycle profile of every 30 years with a present value of $80,000 is obtained.

This example shows that the policy of sacrificing 1 year of traffic sign life and 2 years of traffic signal life initially, so as to synchronize replacements, ultimately lowers the present value of costs by $54,000 ($80,000–$26,000).

4.2.1.9 Example LCCA Calculations for Assessing the Value of Life Expectancy Information

To justify the development of asset management systems for less-studied asset types (i.e., assets other than bridges or pavements), a comparison of expert opinion to statistically based life expectancy estimates can be used to evaluate the benefits of additional data collection used in model development. For example, suppose a life expectancy model predicts a box culvert life of 60 years. If an asset is 45 years old and expert opinion places the life at 50 years, then a replacement project is likely to be programmed within 5 years. However, statistical evidence would suggest this project should not be programmed for another 15 years. The consequences of this can be quantified using lifecycle analysis. Assume that the cost of replacement is $100,000 at an interest rate of 4%.

Remaining EUAC of replacement, as scheduled by expert opinion:

$$\$100k * \frac{0.04}{(1+0.04)^5 - 1} = \$18.46k$$

Remaining EUAC of replacement, as scheduled by life expectancy modeling:

$$\$100k * \frac{0.04}{(1+0.04)^{15} - 1} = \$4.99k$$

Based on this analysis, reliance on expert opinion instead of data-based modeling may cost an additional $13,470 over the asset's life, depending on the accuracy of the life expectancy model. Reliable life estimates can benefit agencies in setting financial needs and effectively spending taxpayer funds.

4.2.2 Asset Valuation Based on Asset Life Expectancy

To demonstrate the application of asset valuation techniques, assume that an urban concrete box culvert is to be constructed on a non-NHS non-interstate roadway, maintained by a state agency, with the following characteristics and environmental conditions (opening width = 19.2m, structure length = 11.5m, opening area = 5.33m; normal annual temperature = 50.4°F, normal annual precipitation = 39.4 inches) and a soil classified as highly corrosive with a pH above 6.5. Given these conditions, assumption of a cost of $3,770 per lineal square foot given the opening area (Sinha et al., 2009), and the covariate model in a previous section, the asset value as a function of time can be projected (Figure 4-8).

Standard straight-line depreciation techniques can be seen to underestimate asset value relative to the survival-based depreciation (by $72,000 at median life estimate). This demonstrates the risk of underestimating asset life and that the current infrastructure system may be more valuable than as predicted, considering that half of the assets will survive longer than the time estimated using a deterministic approach.

4.2.3 Project Selection Decisions Involving Asset Life Expectancy

Project selection is often based on the ranking of various alternatives using utility theory. The set of projects that maximizes utility while constrained to a budget is then programmed. The

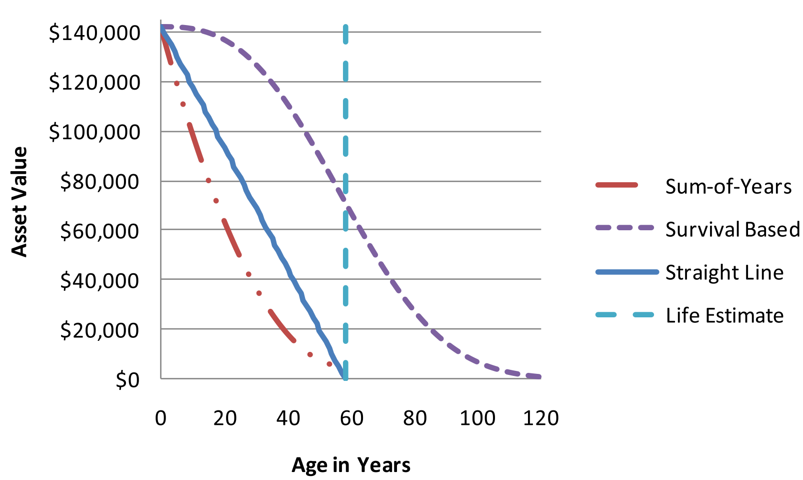


Figure 4-8. Example asset valuation using highway asset life expectancy.

Table 4-5. Example ranked projects with associated utility and cost.

Activity	Utility	Cost
Bridge A replacement	100	$2400k
Bridge B rehabilitation	75	$250k
Box Culvert A replacement	55	$100k
Pipe Culvert A replacement	35	$5k
Bridge C deck patching	32	$20k

utility of projects is often in part based on remaining life estimates, with a higher utility value associated with longer life. For example, assume an agency has calculated the utility for a set of projects with respect to life expectancy, deterioration, lifecycle cost, and estimated project cost (Table 4-5). k represents 1000's of dollars. Assume a budget of $2,750,000.

To select a set of projects, optimization techniques can be applied to the problem:

$$Maximize\ Program\ Utility = \sum_{i}^{m} x_i Utility_i$$

$$Subject\ to\ Program\ Cost \leq \sum_{i}^{m} x_i Cost_i$$

where x ≡ binary decision variable with 1 = program, 0 = do not program; m ≡ number of potential projects.

This simple example can be readily solved in Excel for a small sample size. In this case, the optimal solution would be to replace bridge A, rehabilitate bridge B, replace pipe culvert A, and patch bridge C, thereby yielding a total utility of 242 at a cost of $2,675,000. The remaining $75,000 could be carried over to the next programming cycle.

4.2.4 Budget Calculations Involving Asset Life Expectancy

The calculation of budget needs is irrespective of utility. For instance, with the data in Table 4-6, a budget of $20,000 is needed for a 5-year horizon (Bridge C project); $120,000 is needed for a 10-year planning horizon (Box Culvert A and Bridge C projects); and $2,520,000 for a 15-year planning horizon (Bridges A and C and Box Culvert A projects).

4.3 Summary

Life expectancy estimates are critical for the evaluation of alternatives via lifecycle costing, programming of projects via utility, and assessing budget needs. Building on the life expectancy prediction and the business applications, the following chapter will focus on incorporating uncertainty. Primarily, the risk of making less than optimal business decisions based on uncertain asset life is examined.

Table 4-6. Example needs assessment data.

Activity	RL	Cost
Bridge A replacement	15	$2400k
Bridge B replacement	30	$250k
Box Culvert A replacement	9	$100k
Pipe Culvert A replacement	21	$5k
Bridge C deck replacement	5	$20k

CHAPTER 5

Methods to Account for Asset Life Uncertainty in Asset Replacement Decisions

5.1 Rationale for Incorporating Risk Into Long-Term Planning

Although asset life estimates are critical for cost-effective asset management, asset life is an uncertain quantity and its variability could lead to less-than-optimal decisions. An inaccurate life estimate puts an agency at risk of errant project prioritization. Risk-informed decisions can allow agencies to compare levels of confidence against costs.

The uncertainty of the estimate of asset life can be a result of (Lin, 1995; Maskey, 1999):

- Modeling Techniques—error created through idealized mathematical modeling attempting to describe complex physical phenomena (e.g., assumed normality of errors);
- Inputs—inherent randomness of structural characteristics (e.g., material properties and strength), future loadings (e.g., traffic volume), environmental conditions (e.g., climatic conditions and soil characteristics), and inaccurate inspection data (e.g., visual condition ratings);
- Parameters—inaccurate representation of the contribution of a factor toward asset deterioration processes; and
- Externalities—unforeseen factors that may surmount natural deterioration processes (e.g., extreme weather event, design/construction flaw, and terrorist attack).

In this chapter, two types of propagating uncertainties are examined. First, using the developed covariate models, the uncertainty surrounding future climatic conditions is assessed. In dealing with climate change, researchers have focused on either mitigation or adaptation. The latter is examined with respect to adapting to new asset life expectancies given the uncertain future climate. The uncertainty surrounding temperature, precipitation, and freeze-thaw cycles have been found to be significant factors of asset life expectancy; therefore, the uncertainty surrounding the values of these factors is expected to compound the uncertainty of asset life and the consequent planning decisions.

Second, using the non-covariate models, the uncertainty surrounding the "end-of-life criterion" and the overall life of an asset is quantified. As a result, the methodology presented will be of use for asset managers to assign confidence levels to typical planning decisions and to prepare mitigation strategies.

Techniques for quantifying such uncertainties are detailed in the following section, after which a comprehensive review of risk analysis in transportation is presented. To build on this literature, a methodology and case study assessments of risk are provided.

5.2 Overview of Uncertainty Analysis

The two basic methods of assessing uncertainty can be classified as sensitivity (deterministic) analysis or risk (stochastic) assessment, a part of the larger concept of risk analysis. More detailed methodologies of these analysis types are detailed in Sections 5.2.8 and 5.2.9, respectively.

Sensitivity, or, "what if?" analysis generally refers to the analysis of how output varies given a systematic (typically the unit) change in inputs and/or parameters across their respective sets. This analysis is typically carried out for one input at a time; however, a multivariate sensitivity analysis is possible if the correlation between inputs is relatively known. Another dimension of sensitivity analysis addresses the extent to which an input variable (in the context of this study, a life expectancy factor) may vary without affecting the output variable (asset life expectancy).

Instead of evaluating the impact of systematic changes, a risk assessment could track changes in the output in response to a random sampling of input and/or parameter values from a distribution. This approach is more commonly applied for random variables that have a known distribution and for dealing with multiple random variables.

Prior to conducting sensitivity analysis or risk assessment, it is critical to understand the set of potential values being varied or sampled.

5.2.1 Describing Values with Set Theory

Sets (i.e., all possible values for a given input, parameter, or output) are typically described using (Isukapalli, 1999; Ayyub & Klir, 2006)

- Classical (Crisp) Set Theory—Set of mutually exclusive values.
  - e.g., set $A = \{x_1, x_2, x_3\}$
- Fuzzy Set Theory (Zadeh, 1965)—Set of vague/imprecise values that can have partial membership in various subsets.
  - e.g., set $A = \{x_1/M(x_1), x_2/M(x_2), x_3/M(x_3)\}$
- Rough Set Theory (Pawlak, 1982)—A coarse interval set of values defined by approximated lower and upper bounds that can be crisp or fuzzy.
  - e.g., set $A = \{[\underline{R}(x_1),\quad (x_1)], [\underline{R}(x_2), \overline{R}(x_2)], [\underline{R}(x_3),\quad (x_3)]\}$

Figure 5-1 illustrates classical (crisp), fuzzy, and rough values. For example, if a bridge condition rating is said to be either in one state or another, then the set of condition ratings is classical. If the bridge condition rating is said to be partially in more than one state, then the set is fuzzy. If

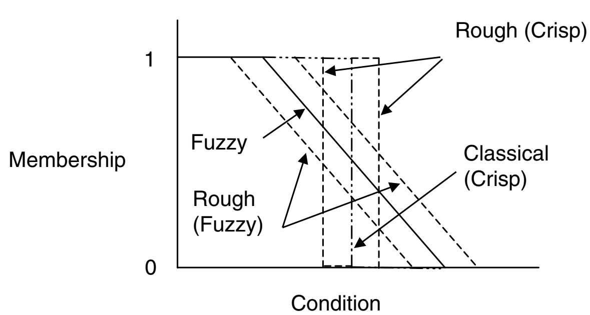


Figure 5-1. Example of classical (crisp), fuzzy, and rough values.

the bridge condition rating is definitely (crisp) or partially (fuzzy) between one state and another within some range, then a rough set is used.

5.2.2 Uncertainty Types

The selection of a set depends on the type of uncertainty. Generally, uncertainty can be classified as either aleatory or epistemic (Ayyub & Klir, 2006). Aleatory uncertainty applies to measures with inherently random properties that can be modeled using stochastic approaches over crisp sets (e.g., likelihood of an extreme event). Epistemic uncertainty applies to measures that are subjective or vague, typically assessed over fuzzy sets (e.g., likelihood of an individual describing the temperature as hot, warm, or cool).

5.2.3 Likelihood Representations

To describe the likelihood of a value, the following objective and subjective approaches have traditionally been applied and are listed in order of increasing generalization (Ayyub & Klir, 2006):

- Classical Probability Theory—describes the likelihood in terms of the probability of an input, parameter, and/or output being randomly sampled from a classical (crisp) set.
  - Samples are drawn from statistical distributions (e.g., common life expectancy distribution forms include Weibull, Loglogistic, and Exponential).
- Probability Theory based on Fuzzy Events—describes the likelihood in terms of the probability of an input, parameter, and/or output being randomly sampled from a fuzzy set.
  - Samples are drawn from membership functions.
- Classical Possibility Theory—describes the likelihood in terms of the possibility of an input, parameter, and/or output being sampled from classical (crisp) sets.
  - Samples are drawn from a pair of possibility and necessity functions using probability sampling techniques.
- Theory of Graded Possibilities—describes the likelihood in terms of the possibility of being sampled from fuzzy sets.
  - Samples are drawn from a pair of possibility and necessity functions using fuzzy sampling techniques.
- Dempster-Shafer Theory of Evidence (DSTE)—describes the likelihood in terms of a higher and lower approximation of belief, drawing input, parameter, and/or output samples from classical (crisp) sets.
  - Samples are drawn from a pair of belief and plausibility functions using probability sampling techniques.
- Fuzzified DSTE—describes the likelihood in terms of a higher and lower approximation of belief, drawing input, parameter, and/or output samples from fuzzy sets.
  - Samples are drawn from a pair of belief and plausibility functions using fuzzy sampling techniques.
- Theory based on Feasible Interval-Valued Probability Distributions (FIPD)—describes the likelihood in terms of a range of probabilities randomly sampled from rough (crisp) sets.
  - Samples are drawn from interval probability distributions using probability sampling techniques.
- Fuzzified FIPD—describes the likelihood in terms of a range of probabilities randomly sampled from rough (fuzzy) sets.
  - Samples are drawn from interval membership functions using fuzzy sampling techniques.
- Other Theories include the use of λ measures, probability boxes, decomposable fuzzy measures, and ρ-additive measures

5.2.4 Distribution Fitting

To build a probability distribution for an uncertain asset life variable of interest, statistical analysis and/or expert opinion may be used. In statistical analysis, distributions with parameters optimized to match a set of actual data or simulated data [based, for example, on resampling methods such as the jackknife, bootstrap, permutation test, and cross-validation techniques (Efron, 1982)] are compared using goodness-of-fit measures such as the Anderson-Darling, Kolmogorov-Smirnov, and Chi-Squared tests.

Where data are unavailable, expert opinion can be used to construct a distribution. Such techniques have included the use of the Extended Pearson Tukey Method, Four-Point Bracket Method, reference lotteries, and paired comparisons of situations (Clemen & Reilly, 2001). Caution must be taken to remove biases in the estimates.

5.2.5 Sampling Distributions

To sample from the distributions for a risk assessment exercise, the following techniques could be used (Isukapalli, 1999; Abebe et al., 2000):

- Conventional Probability Sampling Techniques—Monte Carlo Simulation (slower convergence but flexible for joint probability sampling) or Latin Hypercube Sampling (faster convergence but not suited for joint probability sampling),
- Unconventional Probability Sampling Techniques—Fourier Amplitude Sensitivity Test (FAST), Reliability-Based Methods (FORM and SORM) and Response Surface Methods, and
- Fuzzy Sampling Techniques—α-cuts based on the fuzzy extension principle.

The main difficulty in simulation arises when dealing with multiple correlated covariates. Techniques for simulating correlated normally distributed covariates are well documented and have been commonly applied in the literature. Such techniques typically involve the use of a Cholesky decomposition of the covariance matrix, which is then multiplied to a sample of individually simulated variables.

For dealing with correlated covariates that are not normally distributed, more advanced techniques are needed. It may be possible to theoretically derive the joint distribution function; however, the complexity quickly becomes unmanageable when dealing with multiple random variables such as complex derivation of the joint distribution function for a bivariate Weibull (Yacoub et al., 2005). A second technique is to simulate the correlation using the rank order correlation technique (Azam, 2011). In this technique, the correlation matrix is built around the relative ranking of each observation in its respective distribution. This approach maintains the independent distributions of the random variables—the correlation matrix is deterministic. A third approach is to simulate one random variable and use the value as an independent variable to predict another random such as the envelope method (Kokkaew & Chiara, 2010) or via lookup tables and/or Boolean logic developed by expert opinion. Yet another technique that has been applied extensively in the financial and insurance risk fields is that of modifying random values using statistical copulas.

A copula is a joint probability distribution that accounts for correlations by converting various probabilistic dependency structures into uniform random variables while not modifying the individual marginal distributions. These uniform random values are then utilized in the simulation of the individual marginal distributions, which may be of different functional forms. The existence of a copula is often proven using Sklar's Theorem (Sklar, 1959), which has been translated by (Weisstein):

> "Let H be a two-dimensional distribution function with marginal distribution functions F and G. Then there exists a copula, C, such that:
>
> $$H(x,y) = C[F(x),G(y)]$$

Conversely, for any univariate distribution functions F and G and any copula C, the function H is a two-dimensional distribution function with marginals F and G. Furthermore, if F and G are continuous, then C is unique."

This theorem can similarly be expanded for a multivariate copula.

Two general families of copulas exist: Archimedean and Elliptical (Figure 5-2). Archimedean copulas are of a closed form, which eases the incorporation of multivariate random variables (Sener et al., 2010). Archimedean copulas include the Clayton, Gumbel, and Frank functional forms:

Clayton—stronger correlation at low-end values

Copula: $C_\alpha(x, y) = max[(x^{-\alpha} + y^{-\alpha} - 1)^{-1/\alpha}, 0]$

With $\alpha = \dfrac{2\tau}{1-\tau}$; $\alpha \in (-1, \infty)$ where τ is the Kendall's tau

Generating Function: $\varphi_\alpha(t) = \dfrac{1}{\alpha}(t^{-\alpha} - 1)$

Gumbel—asymmetric strong correlation at extrema with tightest fit at the maxima tail

Copula: $C_\alpha(x, y) = exp\{-[(-ln\, x)^\alpha + (-ln\, y)^\alpha]^{1/\alpha}\}$

With $\alpha = \dfrac{1}{1-\tau}$; $\alpha \in (1, \infty)$

Generating Function: $\varphi_\alpha(t) = (-\ln t)^\alpha$

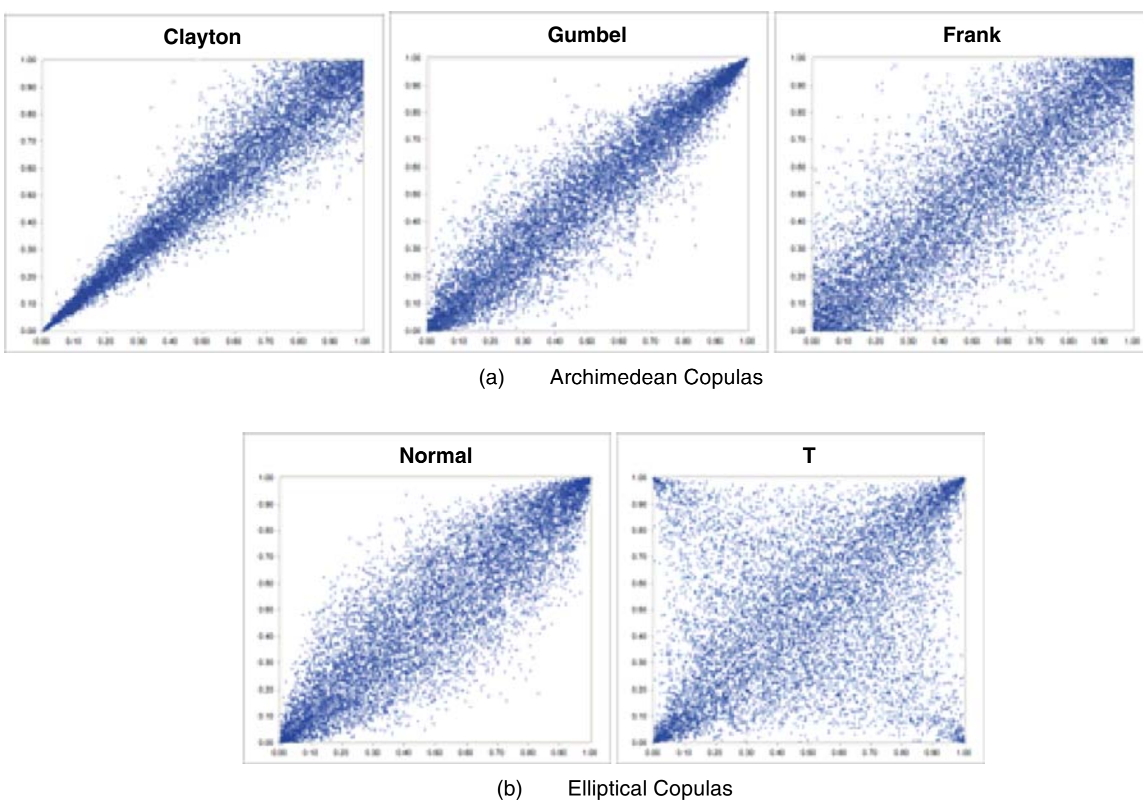


Figure 5-2. Statistical copula correlation patterns (Vose Software, 2007).

Frank—symmetric weak correlation from tail to tail

$$\text{Copula: } C_\alpha(x,y) = -\frac{1}{\alpha} ln\left(1 + \frac{(e^{-\alpha x}-1)(e^{-\alpha y}-1)}{e^{-\alpha}-1}\right)$$

$$\text{With } \frac{D_1(\alpha)-1}{\alpha} = \frac{1-\tau}{4}; \alpha \in (-\infty,\infty) \text{ where } D_1(\alpha) = \frac{1}{\alpha}\int_0^\alpha \frac{t}{e^t-1}dt$$

$$\text{Generating Function: } \varphi_\alpha(t) = -ln\left(\frac{exp(-\alpha t)-1}{exp(-\alpha)-1}\right)$$

Elliptical copulas include the Normal (Gaussian) and T-distribution functional forms:

Normal (Gaussian)—Elliptical-shaped correlation with strong correlation at tails

$$\text{Copula: } C_\rho(x,y) = \int_{-\infty}^{\Phi^{-1}(x)}\int_{-\infty}^{\Phi^{-1}(y)} \frac{1}{2\pi(1-\rho^2)^{1/2}} exp\left(-\frac{x^2-2\rho xy+y^2}{2(1-\rho^2)}\right)dxdy$$

With $\rho(x,y) = sin\left(\frac{\pi}{2}\tau\right)$ where ρ is the Pearson's product moment correlation coefficient

T-distribution—Star-shaped correlation that approximates the Normal copula at high values of nu (ν<30)

$$\text{Copula: } C_{\rho,\nu}(x,y) = \int_{-\infty}^{t_\nu^{-1}(x)}\int_{-\infty}^{t_\nu^{-1}(y)} \frac{1}{2\pi(1-\rho^2)^{1/2}}\left(1+\frac{x^2-2\rho xy+y^2}{\nu(1-\rho^2)}\right)^{-(\nu+2)/2} dxdy$$

With $\rho(x,y) = sin\left(\frac{\pi}{2}\tau\right)$ where ρ is the Pearson's product moment correlation coefficient.

The selection of a copula can be made based on various information criteria, with the general goal of minimizing some value. These include

Schwarz Information Criterion (SIC) or Bayesian Information Criterion (BIC)

$$SIC = ln(n)k - 2ln(L_{max})$$

Akaike Information Criterion (AIC)

$$AIC = \left(\frac{2n}{n-k-1}\right)k - 2ln(L_{max})$$

Hannan-Quinn Information Criterion (HQIC)

$$HQIC = 2ln[ln(n)]k - 2ln(L_{max})$$

where n represents the number of observations; k represents the number of parameters to be estimated; and L_{max} represents the maximum log-likelihood function value.

5.2.6 Representing Output Uncertainty

The output, in the context of this study, is the resulting asset life that has been predicted on the basis of the uncertain factors. To evaluate the resulting range of outputs, various representations are used in order to apply decision rules. Generic representations include

- Sensitivity Analysis
  - Tornado diagrams
  - Elasticity plots
  - Spider diagrams
- Risk Analysis
  - Risk matrices
  - Decision trees
  - Influence diagrams

5.2.7 Decision Making Under Uncertainty

From these representations of uncertainty, decisions can be made through the application of various theories:

- Expert Opinion—simple approach for assigning strategies based on the risk value;
- Expected Utility Theory—traditional approach that places an average level of "satisfaction/happiness" with pursuing a certain action based on a probabilistic outcome;
- Prospect Theory—alternative approach to EUT that consists of (1) framing/editing—a concave function for gains, convex function for losses (with the loss function being steeper than the gain function) (Figure 5-3); and (2) valuation—a non-linear transformation of the probability scale, making small probabilities larger and moderate to large probabilities smaller (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992);
- Regret (Rejoice) Theory—alternative that assesses the emotional difference between the actual payoff from the policy chosen and the expected payoff from an alternative policy (Loomes & Sugden, 1982); and
- Salience Theory—similar to prospect theory but does not assume the curvature of the functions and replaces true probabilities with probabilistic weights (Bordalo et al., 2010).

The selection between strategies ultimately comes down to the risk attitude of the decision-maker. This attitude can be inferred from the shape (i.e., convexity or concavity) of the value or utility curve associated with an outcome. For instance, a convex value function indicates a risk-taker persona because more satisfaction is obtained at increasingly higher stakes. Likewise, a risk-averse persona makes decisions based on a concave value function, indicating that less satisfaction is obtained with increasing stakes (See Figure 5-4).

In this study, to assess uncertainty of asset life, both sensitivity and risk analyses were conducted based on the nature of the uncertainty; specifically, discrete indicator variables with

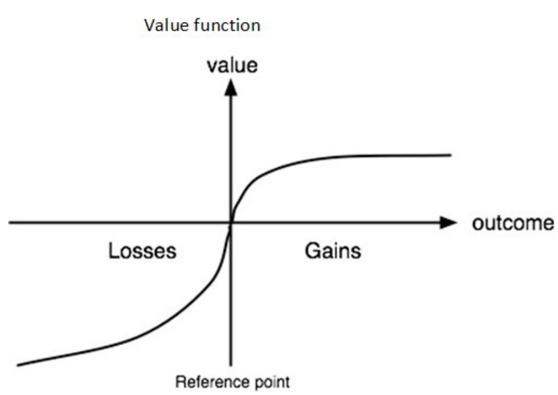


Figure 5-3. Value function using prospect theory (Kahneman & Tversky, 1979).

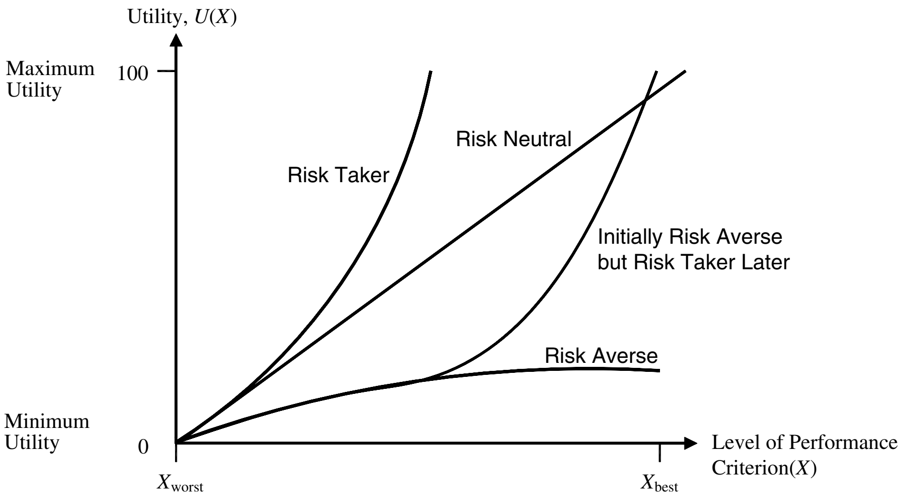


Figure 5-4. Defining risk value with utility curves (Sinha & Labi, 2007).

known crisp sets were assessed using sensitivity analysis, and continuous variables with aleatory uncertainty described by probability theory were assessed using risk analysis. These techniques are reviewed in the following subsections.

5.2.8 Review of Sensitivity Analysis

In this study, different kinds of sensitivity analysis were carried out, depending on the nature of the model. For covariate models, a one-way sensitivity analysis was conducted with the life expectancy factors systematically varied within a classical (crisp) set from the minimum value to the maximum value. For non-covariate methods, varied groupings of data were applied, and the changes in predicted value of the asset life were analyzed.

Interpretations of sensitivity vary, depending on the type of the selected model for asset life. For covariate models, the parameter estimate indicates the sensitivity of the factors. For linear regression models, the sensitivity of the life expectancy factors can be interpreted directly on the basis of the estimated parameter (coefficient). In this case, with every unit change in the input (e.g., traffic loading), the output (asset life expectancy) can vary by the magnitude of the coefficient (β). For survival models, the output varies based on an acceleration parameter [exp(β)], where the survival curve shifts according to $t_{i+\Delta} = t_i * exp(\beta)^{\Delta}$. For covariate, ordered, discrete models, this change is commonly represented by the marginal effect (i.e., the change in the probability that the predicted asset life will fall in a certain specific discrete range of values given some unit change in an explanatory variable).

The sensitivity of non-covariate models is assessed by the modeling of different groupings of data. For example, to assess the sensitivity of the life of bridges to NHS status, a survival curve for NHS bridges could be compared to that for non-NHS bridges.

Results of sensitivity analysis are typically represented by two general types of sensitivity plots: tornado diagrams (Figure 5-5) and spider diagrams (Figure 5-6), which are similar to elasticity plots.

Tornado and spider diagrams are typically constructed using one-way sensitivity analysis (i.e., vary one input and assess the change in the output when all other inputs are set at their respective average or other values). The tornado diagram, in particular, further identifies the factors that have either a positive or negative effect on the outcome. The independent variables with

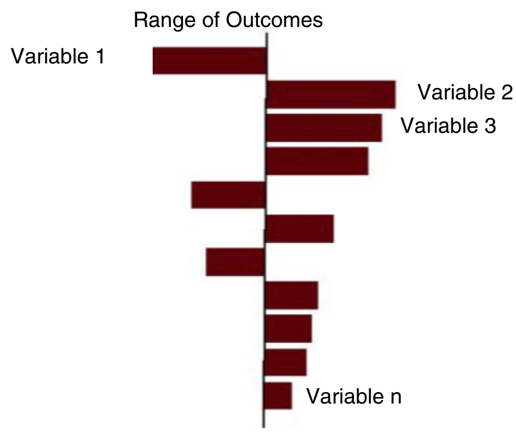


Figure 5-5. Example of a tornado diagram (Molenaar et al., 2006).

the largest range of outputs are considered as those to which the response variable (asset life) is most sensitive.

5.2.9 Review of Risk Analysis

The probabilistic statistical techniques applied in this study were recommended, in part, to account for inherent uncertainties in asset life expectancy. The calibrated survival curves describe the probability of an asset reaching a given age while maintaining an acceptable level of performance.

Using the developed models, a probabilistic risk analysis therefore can be incorporated into asset management through four steps (Ford, 2009; Governmental Accountability Office, 2009; and Molenaar et al., 2010):

1. Risk Identification—describe the consequences and the conditions that may influence the likelihood of the risk (e.g., risk of non-representative needs assessment due to uncertain levels of traffic loading or climate).
2. Risk Assessment—quantify the likelihood and consequences of the risk (e.g., consequence = shortage in funds and likelihood = probability of needing a certain level of funding).

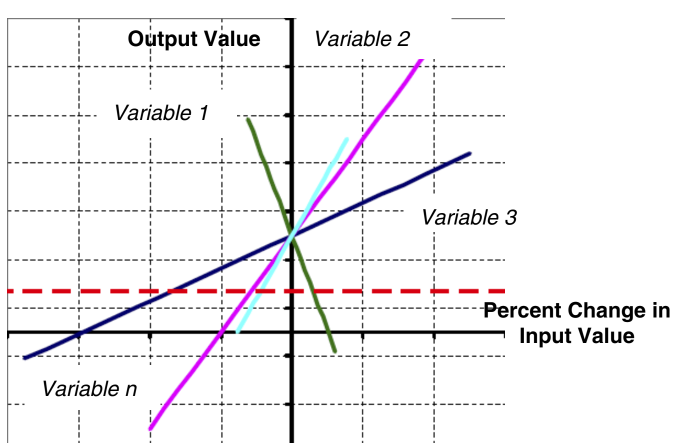


Figure 5-6. Example of a spider diagram (van Dorp, 2009).

3. Risk Management—decide on a mitigation strategy based on the likelihood and consequence of the risk (e.g., request legislative for additional funding).
4. Risk Monitoring—measure the effectiveness of the mitigation strategy (e.g., sufficient funds allocated?).

To identify risks, these techniques generally rely on expert opinion of future events or past experience. The assessment of risk is then completed using qualitative (e.g., fault tree analysis) or quantitative techniques (e.g., probabilistic risk analysis) means (Table 5-1).

For this study, emphasis was placed on conducting a probabilistic risk assessment (PRA) based on the ability to fit probabilistic distributions to uncertainties associated with the asset life expectancy factors.

This approach involves two statistical techniques: distribution fitting and Monte Carlo simulation (see Figure 5-7) (Molenaar et al., 2006). Distributions can be fit using software (e.g., Mathwave Technologies, 2004; Vose Software, 2007) or by manually conducting various goodness-of-fit tests (e.g., Kolmogorov-Smirnov, Anderson Darling, Chi-squared). Knowing the input distributions, it is then possible, using simulation techniques, to generate random combinations of the

Table 5-1. Risk assessment methods (Ayyub, 2003).

Method	Scope
Safety/Review Audit	Identifies equipment conditions or operating procedures that could lead to a casualty or result in property damage or environmental impacts.
Checklist	Ensures that organizations are complying with standard practices.
What If/Then	Identifies hazards, hazardous situations, or specific accident events that could result in undesirable consequences.
Hazard and Operability Study (HAZOP)	Identifies system deviations and their causes that can lead to undesirable consequences and determine recommended actions to reduce the frequency and/or consequences of the deviations.
Preliminary Hazard Analysis (PrHA)	Identifies and prioritizes hazards leading to undesirable consequences early in the life of a system. It determines recommended actions to reduce the frequency and / or consequences of the prioritized hazards. This is an inductive modeling approach.
Probabilistic Risk Analysis/ Assessment (PRA)	Assesses risk with a quantitative risk assessment method developed by the nuclear engineering community for risk assessment. This comprehensive process may use a combination of risk assessment methods.
Failure Modes and Effects Analysis (FMEA)	Identifies the component (equipment) failure modes and the impacts on the surrounding components and the system. This is an inductive modeling approach.
Fault-Tree Analysis (FTA)	Identifies combinations of equipment failures and human errors that can result in an accident. This is a deductive modeling approach.
Event-Tree Analysis (ETA)	Identifies various sequences of events, both failures and successes that can lead to an accident. This is an inductive modeling approach.
Delphi Technique	Assists in reaching the consensus of experts on a subject such as project risk while maintaining anonymity by soliciting ideas about the important project risks, which are collected and circulated to the experts for further comment. Consensus on the main project risks may be reached in a few rounds of this process.
Interviewing	Identifies risk events based on experienced project managers or subject-matter experts. The interviewees identify risk events based on their experience and project information.
Experience-Based Identification	Identifies risk events based on experience, including implicit assumptions.
Brainstorming	Identifies risk events using facilitated sessions with stakeholders, project team members, and infrastructure support staff.

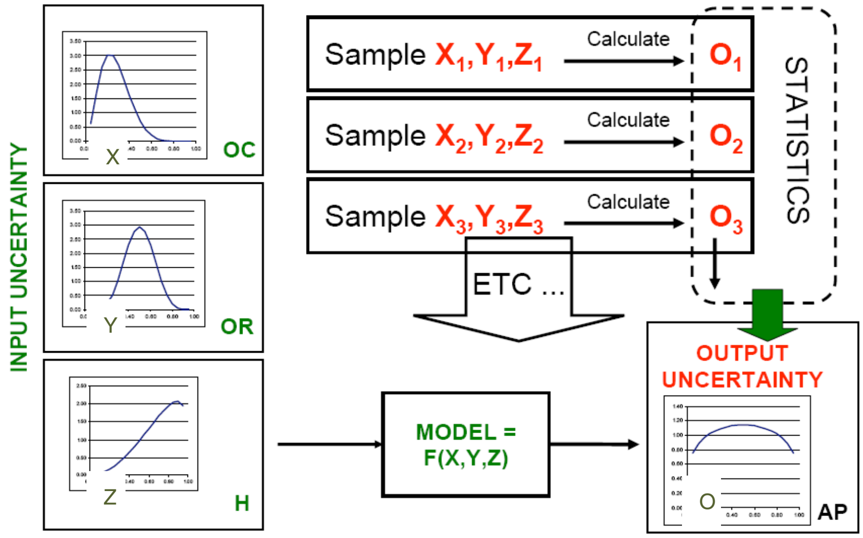


Figure 5-7. Monte Carlo simulation process (van Dorp, 2009).

input factors on the basis of their probability distribution functions and dependency structures, to determine the nature of the output. As such, the risk of obtaining an input with varying degrees of confidence can be assessed.

The risk of obtaining an input with varying degrees of confidence can be assessed. The selection of a strategy to mitigate risk depends on the risk tolerance of the agency. At the risk management step, four strategies are commonly pursued (Ford, 2009):

1. Avoid (generally applied for risks with high consequence and high likelihood)—Do not pursue an alternative with inherent risk(s);
2. Reduce (generally applied for risks with low consequence and high likelihood)—Pursue an alternative while taking steps to reduce the likelihood or consequence of the risk;
3. Retain (generally applied for risks with low consequence and low likelihood)—Accept the outcome if the risk is realized or not;
4. Transfer (generally applied to risks with high consequence and low likelihood)—Pursue an alternative, granted that an insurance policy can be purchased so as to reduce individual agency consequences.

The effectiveness of the mitigation strategy can be documented as part of ex-poste evaluation studies (Bhargava et al., 2009).

5.3 Literature Review of Risk Studies in Transportation Engineering

Risk analysis is a burgeoning study area in the field of transportation. To date, however, project-level and consequence-side risk studies have dominated the literature in this field (Table 5-2).

This chapter of Volume 2 of *NCHRP Report 713* focuses on the gap in the literature with regard to the more likely, but less consequential, network-level risks. Past work by the author in this area has included assessments of the risk of inaccurate congestion-relief programming due to uncertain socio-economic characteristics used in travel demand modeling (Ford, 2009). In this study, the risk of an inaccurate needs assessment based on uncertain life estimates is assessed.

Table 5-2. Classification of past risk analyses.

	Likelihood-side Risk Studies	Consequence-side Risk Studies
Project-Level	Cost overrun, inaccurate benefit/cost analysis, and schedule slippage [e.g., (Risk Management Tool for Managing the Planning / Environmental Phases of Prospective Major Projects; Li & Madanu, 2009; Olumide Jr., 2009; Bhargava et al., 2009; Molenaar et al., 2010)]	Structural failure and reliability and crash risk and liability [e.g., (Gifford, 2004; Stein & Sedmera, 2006; Agent, 2010)]]
Network-Level	Errant needs assessment and project programming [e.g., (Ford, 2009)]	Network resiliency to extreme events [e.g.,(Sanchez-Silva & Rosowsky, 2008)].

The underlying concept is that the propagation of uncertainty may be mitigated by managing the risk earlier in the decision-making process (Figure 5-8).

Considering the classical definition of risk (*Risk* = Likelihood * Consequence), high-consequence hazards can be considered just as serious as high-likelihood hazards (i.e., the likelihood of a structural failure or environmental disaster may be low, but the consequences in terms of economic and human losses are high). Alternatively, the likelihood of inaccurate cost estimates or needs assessment is high, but the consequences in terms of economic losses may be relatively low. Assuming similarly inverse proportions, then similar risk values are obtained for each of these two hypothetical situations.

Generally, these two situations are typically not assigned the same level of risk. That is, people tend to be more risk-averse when dealing with high-consequence hazards and more risk-neutral when dealing with high-likelihood hazards. For instance, consider public opinion surrounding transportation safety: people tend to be far more fearful of airplane crashes (a high-consequence hazard—not likely to occur, but often deadly when it occurs) compared to automobile crashes (a high-likelihood hazard—more likely to occur, but often not deadly when it occurs). Consequently, management techniques and research have skewed towards consequence-side hazards.

High-likelihood hazards are being given increasing attention in the literature at the project-level. However, a substantial gap exists at the network-level. This may in part be due to a possible disconnect between transportation asset managers and long-term planners. Asset managers, traditionally, are primarily concerned with programming the most "deserving" projects given a budget. Yet, this budget is often influenced by the long-term planning needs assessment submitted to elected officials. Often, there is no guarantee that full funding will be made available to cover all the needs. For full-funding requests to be heeded, a clear quantitative assessment of risk is needed. Budget requests can be strengthened by providing elected officials with probabilistic assessments of the average network performance/condition, the lifecycle costs, and an enumeration of the assets that will be forced to persist beyond their life expectancy. Furthermore, to make the most of a limited budget, agencies may need to assess the cost and performance risks associated with alternative network-level programming policies.

Risk-informed decisions can then be made to mitigate the risk. For instance, past risk-based mitigation strategies have included contingency setting for project cost overrun (Olumide, 2009), evacuation planning for extreme events (Wolshon, 2002; Kalafatas, 2005), and stochastic optimization of maintenance decisions to preserve reliability for structural failure or serviceability (Lounis, 2006). Such decisions are best made in an uncertainty-based asset management framework where "what if?" analyses and tradeoffs could be incorporated (Dicdican et al., 2004; Krugler, et al., 2007; Bai et al., 2008; and Bai & Labi, 2009).

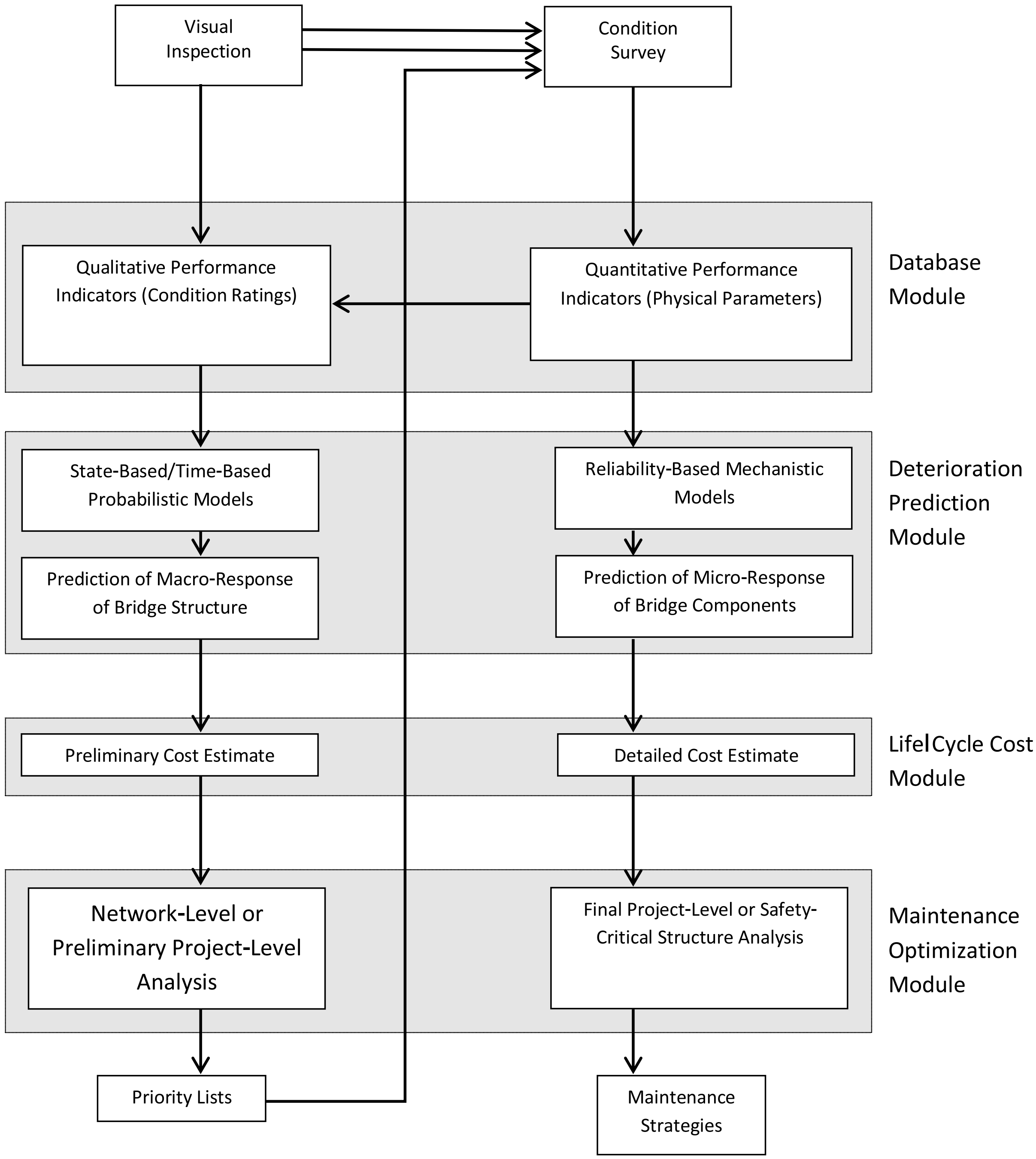


Figure 5-8. Example framework for management system (Morcous et al., 2010).

Other general uncertainty assessments in the literature have included fuzzy assessments of parameter uncertainty (Abebe et al., 2000), bridge condition ratings (Pan, 2007), inspection timing (Li & Burgueño, 2010), and bridge costs and work packages (Sadeghi et al., 2010).

To describe the simultaneous occurrence of two or more uncertain events, copula dependence modeling has been used in transportation engineering applications. These include the use of copulas for spatial correlation in studies that have modeled travel activity (Bhat & Sener, 2009), vehicle ownership prediction (Rashidi & Mohammadian, 2011), routing decisions based on travel time estimation (Wan & Kornhauser, 2010), estimating vehicle type choice and miles travelled (Spissu et al., 2009), collision type and crash severity (Rana et al., 2010), commuter mode choice and number of non-work stops (Portoghese et al., 2011), and live load estimation due to uncertain axle weights (Srinivas et al., 2006).

5.4 Methodology for Assessing the Risk of Uncertain Life Estimates in Long-Term Planning Decisions

Probabilistic risk assessment (PRA) techniques are used in this chapter to quantify the variability in asset remaining life due to uncertain climatic conditions of the several factors that influence asset life. Climatic conditions are used for purpose of illustration. The effect of the resulting variability in asset remaining life, in turn, on agency processes such as capital needs assessments and asset replacement/rehabilitation programs.

The methodology is summarized in Figure 5-9. The first step in any uncertainty assessment is to identify what is uncertain. In this case, the uncertainty being investigated is highway asset life expectancy and the factors used to produce that estimate. A description of the likelihood of the uncertainty is needed. Given the nature of the inherent randomness of the uncertainty, probabilistic distributions can be fit to describe the uncertainty of an event. Using these distributions, the uncertainty can be simulated with respect to the dependency structure. In this study, this is represented by the best-fitting copula. Then, the uncertain values are inserted into the model to predict the outcome. For uncertain factors of life expectancy, such as climate, this model is the life expectancy model; for uncertain inputs of lifecycle cost analysis, such as asset life, this model is lifecycle cost formulae. Finally, confidence can be placed on the outcomes, allowing agencies to make risk-informed decisions.

5.4.1 Risk Identification

The first step in any risk analysis is to identify potential problems before they become manifest. Asset managers should first focus on what factors are used in the decision-making process. Next, the level of uncertainty regarding these factors and any variables used in the estimation process should be noted. At this point, expert opinion can be used to approximate the impact of the uncertainty. If, from expert opinion, the impact is expected to be significant, then a formal risk assessment is recommended.

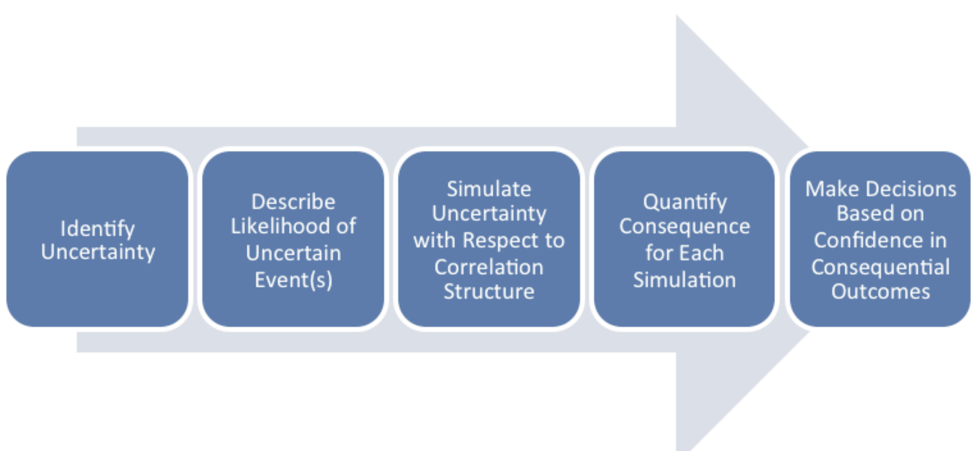


Figure 5-9. General methodology for assessing uncertainty.

For example, following this approach, it was noted that life expectancy estimates are often used as part of the decision-making process. The uncertainty surrounding the estimate and the life expectancy factors (e.g., climate) can be significant. Considering that life estimates are critical in lifecycle cost analysis, budgeting for replacement projects, and prioritizing projects, the impact is deemed worthy of a formal risk assessment. To demonstrate this risk assessment process, this study will focus on the risk of uncertain future climate at the project-level, which propagates into the risk of an inaccurate needs assessment at the network-level.

5.4.1.1 Risk of Uncertain Future Climate

Climate factors, such as temperature, precipitation, and freeze-thaw cycles, have a significant effect on asset life. The future climatic conditions are highly uncertain with experts estimating anywhere from 0 to 5 degree Fahrenheit increases in annual temperature and annual precipitation, going up or down by up to 15 to 20% in the short-term (next 30 years) (ICF International, 2009). Estimates over a 50-year period can produce even more variability as shown in Figure 5-10.

Such temperature changes can affect the soil and material behavior and, consequently, a reduction in the remaining lives of existing highway assets (Mills & Andrey, 2002; Walters, 2009; Long and Labi, 2010). In addition to changing annual averages, climate scientists expect sea level rises, longer heatwaves, reduced freshwater availability, increased storm intensity, and stronger hurricanes (Backus et al., 2009; Schwartz, 2010). Adaptive risk analyses therefore have been widely recommended to quantify the climate uncertainty and its effects on infrastructure (Committee on Climate Change and U.S. Transportation, National Research Council, 2008; Lowe et al., 2009; Lindquist, 2010; and Yohe, 2010). The quantification of climate change impacts on asset longevity, however, are lacking, thereby resulting in a major gap in the literature. In this study, empirical evidence is used to assess the risk of uncertain climate averages on life estimates. Then the impact of uncertain life on agency preservation policies is also assessed. To assess this risk, correlated simulation techniques of distributions built on expert opinion can be applied to the developed life expectancy models. The simulated estimates of life expectancy in turn are used to assess the impacts on asset preservation needs assessment.

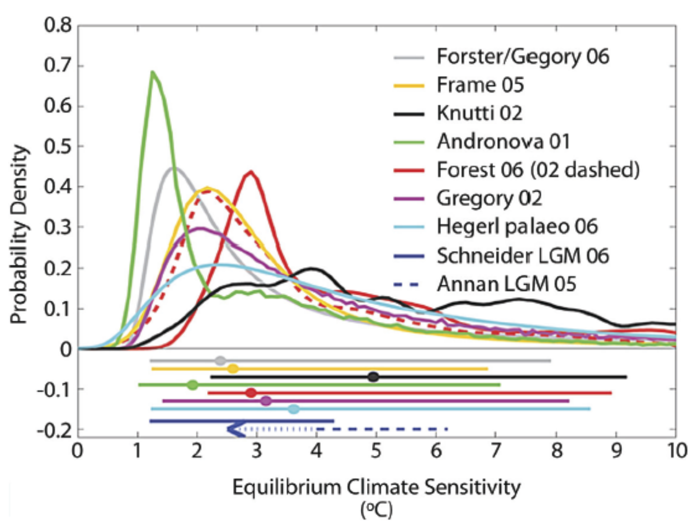


Figure 5-10. Multiple 2050 temperature change projections relative to current climate (Solomon, et al., 2007).

5.4.1.2 Risk of Inaccurate Needs Assessment

Due to the propagation of asset life uncertainty throughout the agency business processes, it can be argued that the agency's long-term financial need is inherently random. To assess this need, an age-based approach could be used (Sinha et al., 2005). In this approach, a point estimate of life is compared to the current asset's age. If the remaining life of the asset is within the planning horizon, then the current value of the replacement cost is included within the financial needs for that horizon. For an indefinite horizon, the funding amount needed to maintain the system perpetually can likewise be analyzed (Sinha et al., 2009). Agencies often will apply blanket replacement at the point estimate of life, particularly for less costly assets such as traffic signs.

The life estimate used in this analysis is typically assumed to be the design life or the material manufacturer's estimate; some of these are based on decades-old nomographs (e.g., pipe culvert life prediction) (Wyant, 2002). More sophisticated management systems utilize models to predict life, some of which are probabilistic in nature. Yet, even probabilistic models are often used deterministically (van Noortwijk & Klatter, 2004; Abaza & Murad, 2010) because all planning decisions are based on the median or the expected value. The true uncertainty of decisions is subsequently lost. Therefore, it is recommended that agencies take full advantage of the information available from probabilistic models that can be developed from their data and to use these models for stochastic risk-based needs assessment.

Network-level stochastic needs assessments have been more commonly applied by transit agencies (Lord, 1977; Molenaar et al., 2010) and in the utility industry (Long Island Power Authority, 2009). Their general concept is that a probability distribution can be fit to uncertain needs, allowing the agency to assign a level of confidence with various levels of resource availability. A point estimate of median life, based on a model, only corresponds to the 50% confidence level. Therefore, to avoid the risk of an agency not having sufficient funds, this section assesses the likelihood of such an event and the consequence with respect to various point estimates.

5.4.2 Risk Assessment

The risk-based needs assessments in this study were carried out on the basis of the following life expectancy estimation methods: (1) the covariate hybrid-based approach and (2) the non-covariate condition-based approach. The approaches were used to demonstrate the incorporation of risk in needs assessment.

5.4.2.1 Predicting Life Expectancy Based on Uncertain Inputs

For the covariate models, the propagating risk of uncertain inputs can be assessed using the following steps:

1. Fit probability distributions to uncertain inputs (e.g., temperature and precipitation) using expert opinion or by maximizing goodness-of-fit measure. The assumption is that past uncertainty is considered indicative of future uncertainty;
2. Test correlation between observed values of uncertain input sample (e.g., Pearson Moment-Correlation Coefficient);

   a. $$\rho_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

3. If there is significant correlation ($\sim\rho x,y > |0.3|$), fit statistical copula by the minimization of –AIC, –SAIC, and –HQIC, or simulate independently;

4. Use Monte Carlo Simulation with uncertainty parameter(s) derived from copula for correlated covariates or without parameters for independent covariates; and
5. Insert randomly sampled inputs into the life expectancy survival model to develop a random survival curve.

At the project-level, changes in life estimates can be evaluated at this point by randomly sampling from the curve under various sets of inputs.

5.4.2.2 Predicting Budget Needs Based on Uncertain Life Expectancy Estimates

At the network-level, the propagation of this uncertainty across the network can be assessed by continuing with a fiscal needs assessment:

1. Simulate life of stock: if an active asset is no longer serviceable, then the RL = 0; otherwise, randomly sample life value from curve for new assets or from conditional survival curve for in-service assets. Note: samples should be shifted to the year of analysis in the case of non-annual inspections or a planning gap and according to current age;
2. For assets with a RL within the planning horizon, simulate multiple new life values to estimate the replacement needs in the off chance of multiple replacements being needed at a location within the planning horizon;
3. Calculate the present dollar value of funding needs and the number of bridge locations requiring replacement. For assets with a RL outside the planning horizon, assume no funds needed for replacement; otherwise, apply present dollar value formula with n = RL and a planning-level cost estimate; and
4. Fit probability distribution to the set of random outputs to assess confidence levels or base confidence on percentile analysis of dataset. Contingency values can be assigned based on preferred confidence level relative to the median value.

For the non-covariate models, a slightly different approach is required due to the competing nature of the risks. Competing risk models can be classified as unconditional or conditional (Figure 5-11).

The unconditional competing risk model is applied for independent risks at which the minimum random life value is assumed to dominate. For the conditional model, a correlated random life estimate can be sampled from the survival models. However, when dealing with correlated multivariate duration models, a generalized approach may be more appropriate (Bhat, 1996). For non-covariate duration models, copulas have been used, primarily in medical statistics, to model the correlation between competing risks (Georges, et al., 2001; Escarela & Carriere, 2003; Shemyakin & Youn, 2006; and Simon et al., 2010).

With respect to the competing risks of asset failure and assuming no maintenance actions over the remaining life, slight modifications to the previously outlined approach are needed:

- Step 1: Correlation should be tested with respect to median remaining life estimates given the current age and observed condition state;
- Step 5: This step could be removed as the model does not utilize covariates; and
- Step 6: Models are already calibrated conditionally to current serviceability; therefore, the distribution can be sampled directly with the copula.

To assess the RL under the assumption that maintenance actions are carried out according to agency policy, then

- Step 6: Simulated duration values are no longer RL, but instead the time until a strategic action is implemented. RL can then be simulated based on a distribution fit to the updated Markov estimate (e.g., same age but improved condition state).

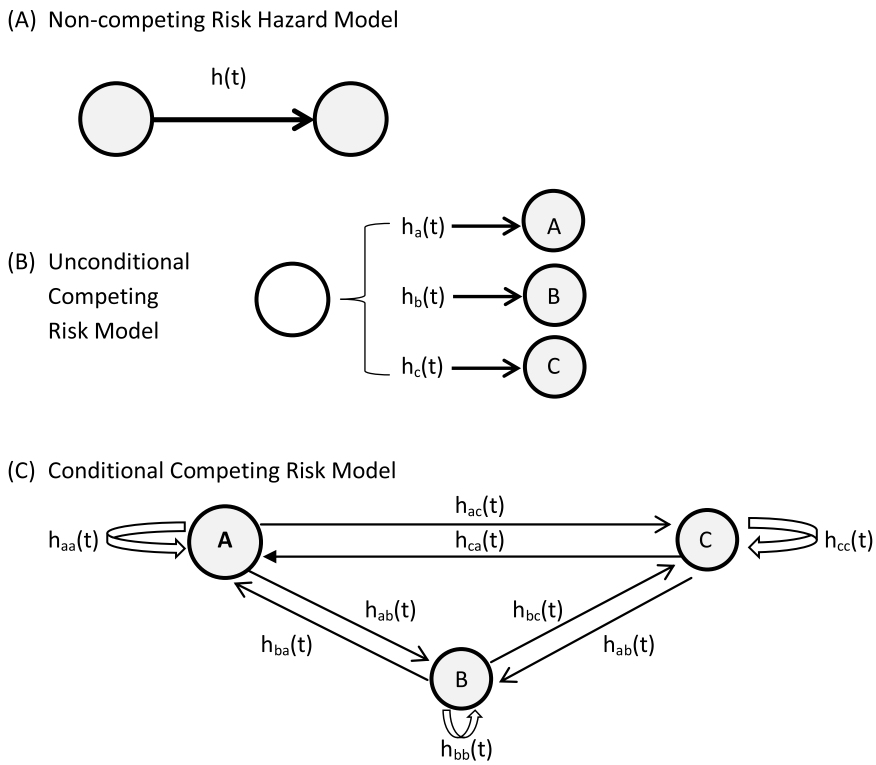


Figure 5-11. Competing risk models (Peter et al., 2002).

By following the non-covariate competing risk approach, the current dollar value of needs over the planning horizon can be compared to other policies such as the do-nothing policy. However, comparisons to the covariate estimate are limited because the previous approach only estimated budget needs for replacement projects under the current preservation policy.

5.4.2.3 Comparing Replacement Policies

To assess the needs-related risk associated with the current replacement policies, the probabilistic needs assessments can be compared to deterministic estimates. In this study, comparison is made on the basis of the assumption that assets are replaced at a specific point in time.

5.4.3 Risk Management

For the risks described in this framework, two mitigation strategies are recommended: reduce and transfer. These are described in the sections below.

5.4.3.1 Mitigation Strategies

To reduce the risk, either the likelihood or consequence can be lowered. The likelihood can be lowered by collecting and maintaining historical condition and replacement data and refining the life expectancy estimates. To lower the consequence of climate impacts, improved designs or structural retrofitting can be performed; to lower the consequences in terms of fiscal risk, contingency funds can be set aside (Olumid, 2009). To transfer the risk of inadequate funding availability, public private partnerships of replacement projects can be sought.

5.4.3.2 Setting Risk Tolerance

To select between mitigation strategies or levels of mitigation (e.g., contingency setting), an agency should decide on a risk tolerance level. A common technique for doing so is developing utility curves via subjective techniques (e.g., swinging value lotteries) (Clemen & Reilly, 2001). For instance, if the risk is deemed too high, then risk reduction strategies are recommended.

5.4.4 Risk Monitoring

Improvements to risk mitigation strategy selections can be accomplished using ex-poste evaluation (Bhargava et al, 2009). By measuring the effectiveness of the risk mitigation strategy, risk tolerance levels can be refined.

5.5 Summary

In this chapter, an overview of uncertainty assessments was provided by detailing the sensitivity and risk analysis techniques. A framework for assessing, managing, and monitoring the risks of inaccurate life estimates due to uncertain climate and inaccurate needs assessment was presented. These are based on the use of covariate or non-covariate modeling techniques. To demonstrate the uses of uncertainty assessments, the next chapter presents a sensitivity analysis and risk assessment of uncertain climate at the project-level, as well as a thorough network-level probabilistic needs assessment based on uncertain life estimates.

CHAPTER 6

Demonstration of Uncertainty Assessment Techniques in Asset Life Estimation and in Asset Replacement Decisions

6.1 Overview of Uncertainty Assessments on Developed Models

To demonstrate the uncertainty in life expectancy estimation, this chapter presents a sensitivity analysis and probabilistic risk assessment of each developed model. In the sensitivity analysis section, ranges of possible life expectancy factor values were examined with respect to the life expectancy estimate for each developed model. In the risk assessment section, probabilistic estimates of life due to climate uncertainty and long-term fiscal needs due to uncertain life were evaluated. Furthermore, in assessing risk, probabilistic estimates were used to compare estimates to standard practices and alternative maintenance policies to set contingency amounts for different levels of confidence.

6.2 Sensitivity Analysis of Developed Models

Sensitivity analysis is a technique for quantifying uncertainty. Sensitivity analyses are faster to produce than risk assessments and are of particular use when little is known about the probability distributions of the input factors. Using this technique, agencies can identify which input factor or "what-if?" scenario represents the greatest influence on the output. Furthermore, the validity of the developed model can be assessed on the basis of the reasonableness of the range of outputs. To demonstrate the technique, sensitivity analyses of the developed models are presented for each asset class in the following sections.

6.2.1 Sensitivity of Bridge Life Prediction

A sensitivity analysis of the developed bridge covariate model was developed over the assumed ranges for each life expectancy factor (Table 6-1).

The resulting tornado diagram (Figure 6-1) represents a one-way sensitivity analysis. The diagram suggests that, other things being equal, an NHS bridge would, on average, have 4.05 years lower life compared to a non-NHS bridge; a bridge in corrosive soil would, on average, have a shorter life of 3.34 years compared to one in non-corrosive soil. In the same conditions, steel structures would generally survive 2.04 years less compared to concrete structures; bridges in areas of higher precipitation generally have life estimates that are 1.22 years lower; bridges in areas with higher temperature generally have 1.04 years lower life; the longevity of short-span bridges generally exceed that of longer bridges by 3 days only; and rural bridges generally outlast their urban counterparts by 2.64 years. The most influential negative and overall factor was found to be the NHS status; the most influential positive factor was found to be the rural status.

Table 6-1. Range of bridge life values for covariate model sensitivity analysis.

Life Expectancy Factor	Minimum Value	Assumed Value	Maximum Value
Normal Annual Temperature (°F)	50	51	53
Normal Annual Precipitation (in.)	38	43	51
Geographical classification indicator (1 if rural, 0 otherwise)	0	0	1
NHS indicator (1 if on NHS, 0 otherwise)	0	1	1
Corrosive soil indicator (1 if in area where average soil is classified as highly corrosive to steel or concrete by the NRCS, 0 otherwise)	0	0	1
Material type indicator (1 if steel, 0 otherwise)	0	1	1
Structure length in decimeters	490	500	510

Sensitivity analyses of the non-covariate Indiana bridge models were conducted for different data segments. Scour was excluded from analysis, given the relative lack of scour criticality for Indiana bridges. The following information was determined from the data presented in Table 6-2:

- NHS status is generally associated with shorter life by 3 years for Indiana bridge decks and longer life by 7 to 22 years longer life for Indiana superstructures, substructures, and channels.
- Concrete structures were generally found to have a longer life in Indiana by 3 to 7 years compared to steel structures.
- Beam bridge median life was generally 2 years shorter compared to slab bridges.
- The lives of decks, substructures, and superstructures for urban bridges were found to be generally less than those of their rural counterparts by 1 to 10 years; for bridge channel protection, however, urban structures were higher by 8 years compared to their rural counterparts.

The changes in the non-homogenous Markov survival curves for the various data segmentations are presented in Figures 6-2 through 6-5, for each bridge element.

6.2.2 Sensitivity of Box Culvert Life Prediction

For the covariate box culvert life model, the most influential factor was the Interstate indicator, which had a negative effect of 14 years (Table 6-3 and Figure 6-6). The most influential positive factor was found to be the use of concrete, which extended life by 12 years. For the uncertainty surrounding climate, likely temperature changes will produce a range of median life estimates varying up to 1 year and precipitation up to 2 years.

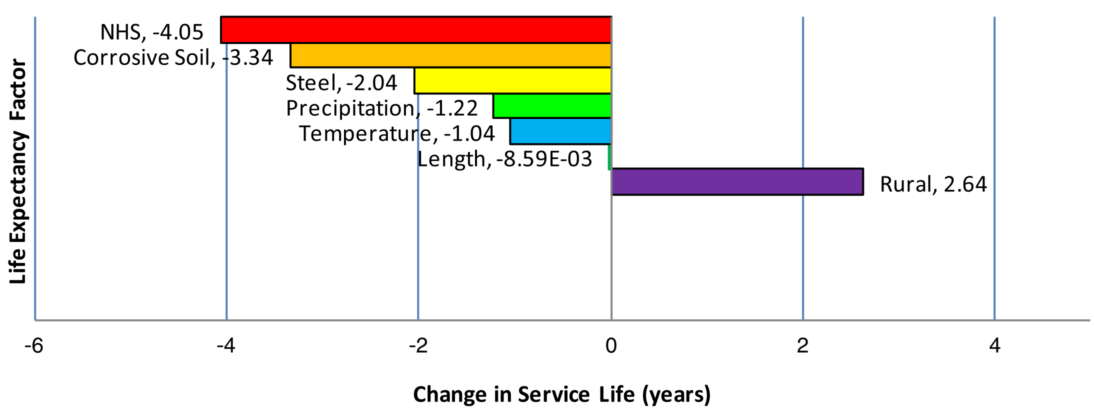
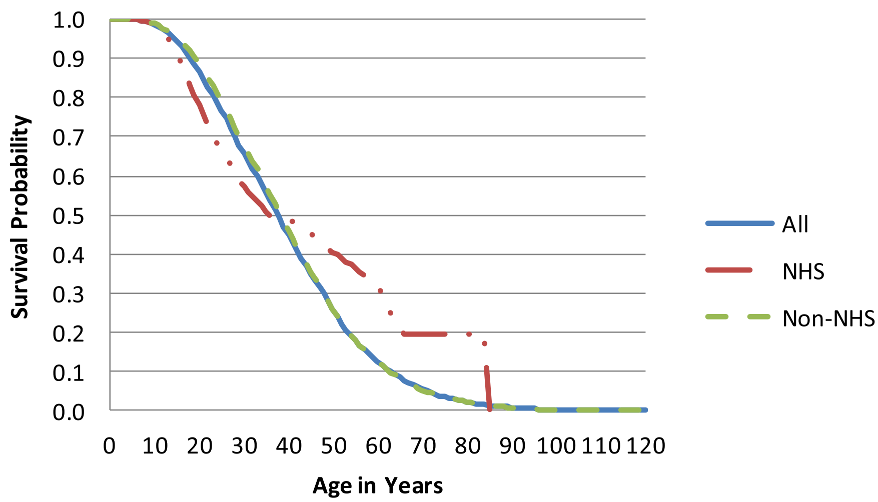


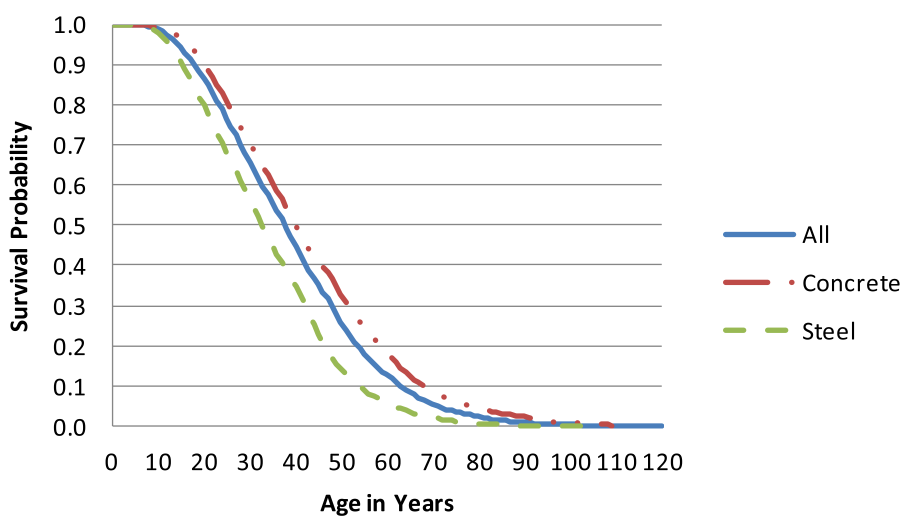
Figure 6-1. Tornado diagram for the covariate bridge life model.

Table 6-2. Bridge median life predictions by end-of-life definition and data segmentation.

	Deck Rating ≤ 5	Superstructure Rating ≤ 4	Substructure Rating ≤ 4	Channel Protection Rating ≤ 4
NHS	36 yrs	69	80	85
Non-NHS	39	62	64	63
Concrete	40	64	68	64
Steel	33	59	61	61
Beam	38	60	62	61
Slab	40	66	73	69
Urban	30	54	64	71
Rural	40	63	65	63
All IN Bridges	38	62	65	63



(a) NHS Status



(b) Material Type

Figure 6-2. Sensitivity of non-covariate Indiana bridge deck life models.

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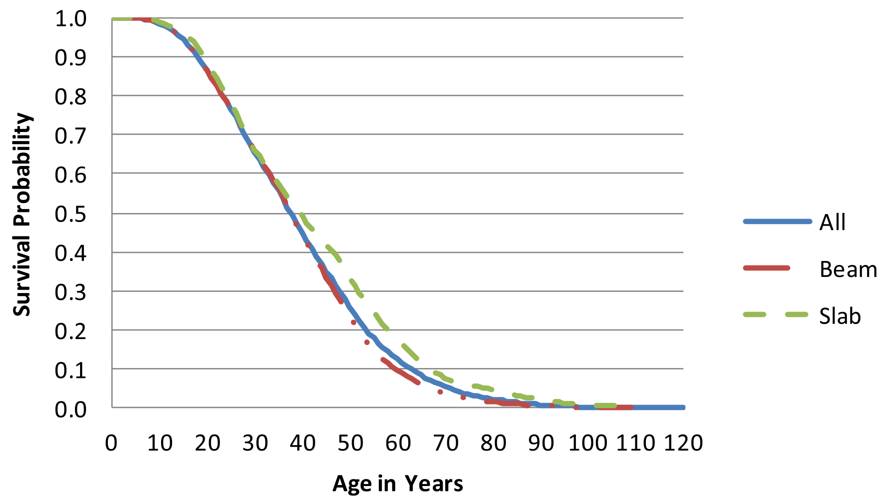
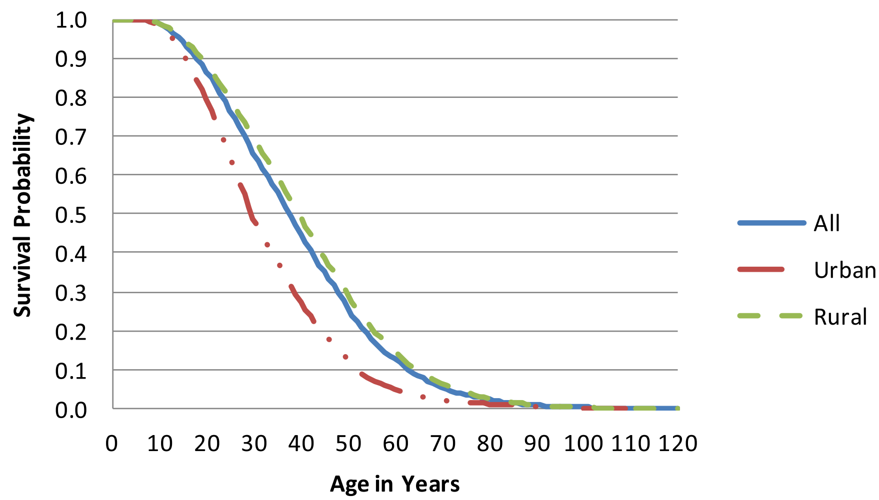
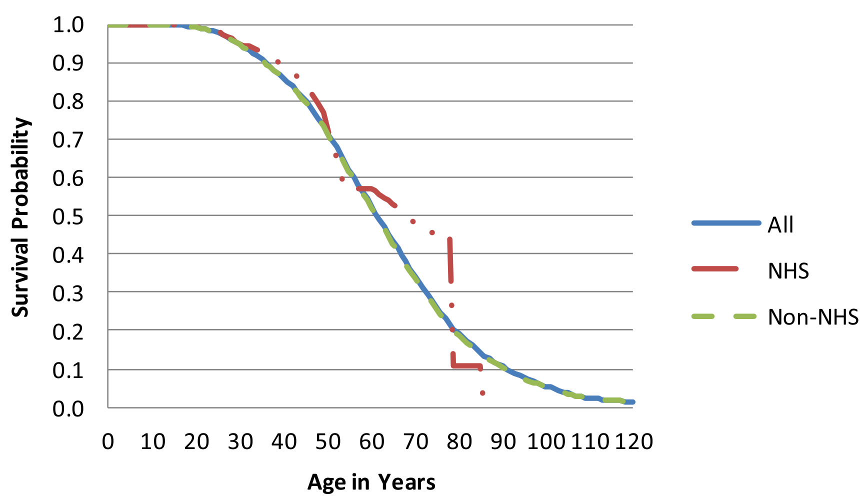


(c) Structural Type



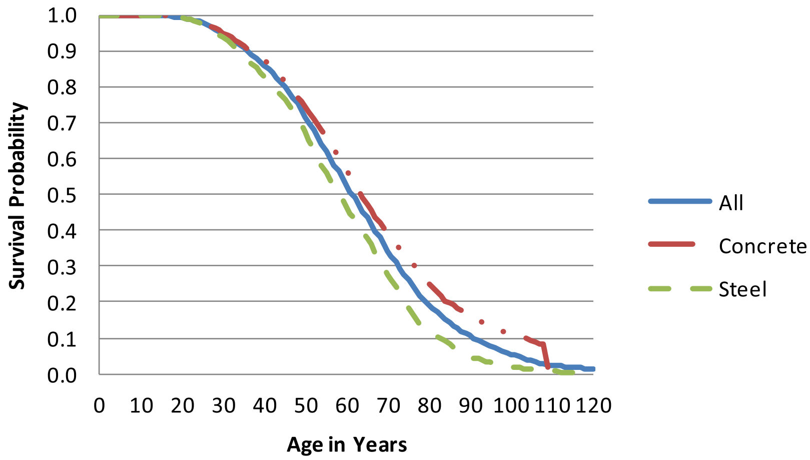
(d) Geographic Region

Figure 6-2. (Continued).

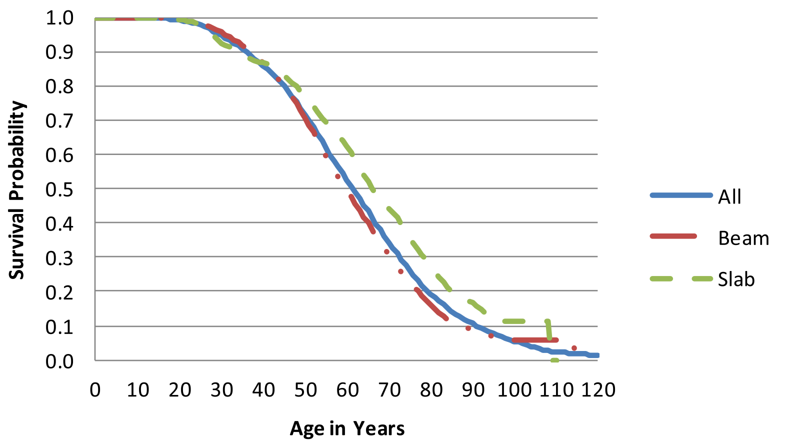


(a) NHS Status

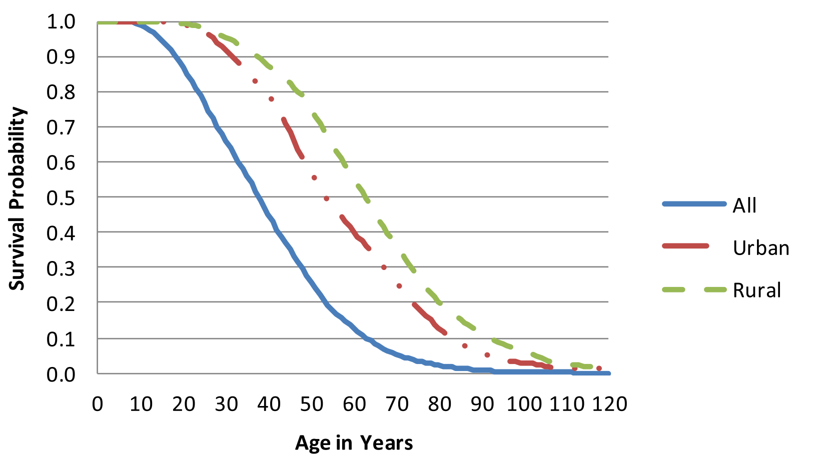
Figure 6-3. Sensitivity of non-covariate Indiana bridge superstructure life models.



(b) Material Type



(c) Structural Type



(d) Geographic Region

Figure 6-3. (Continued).

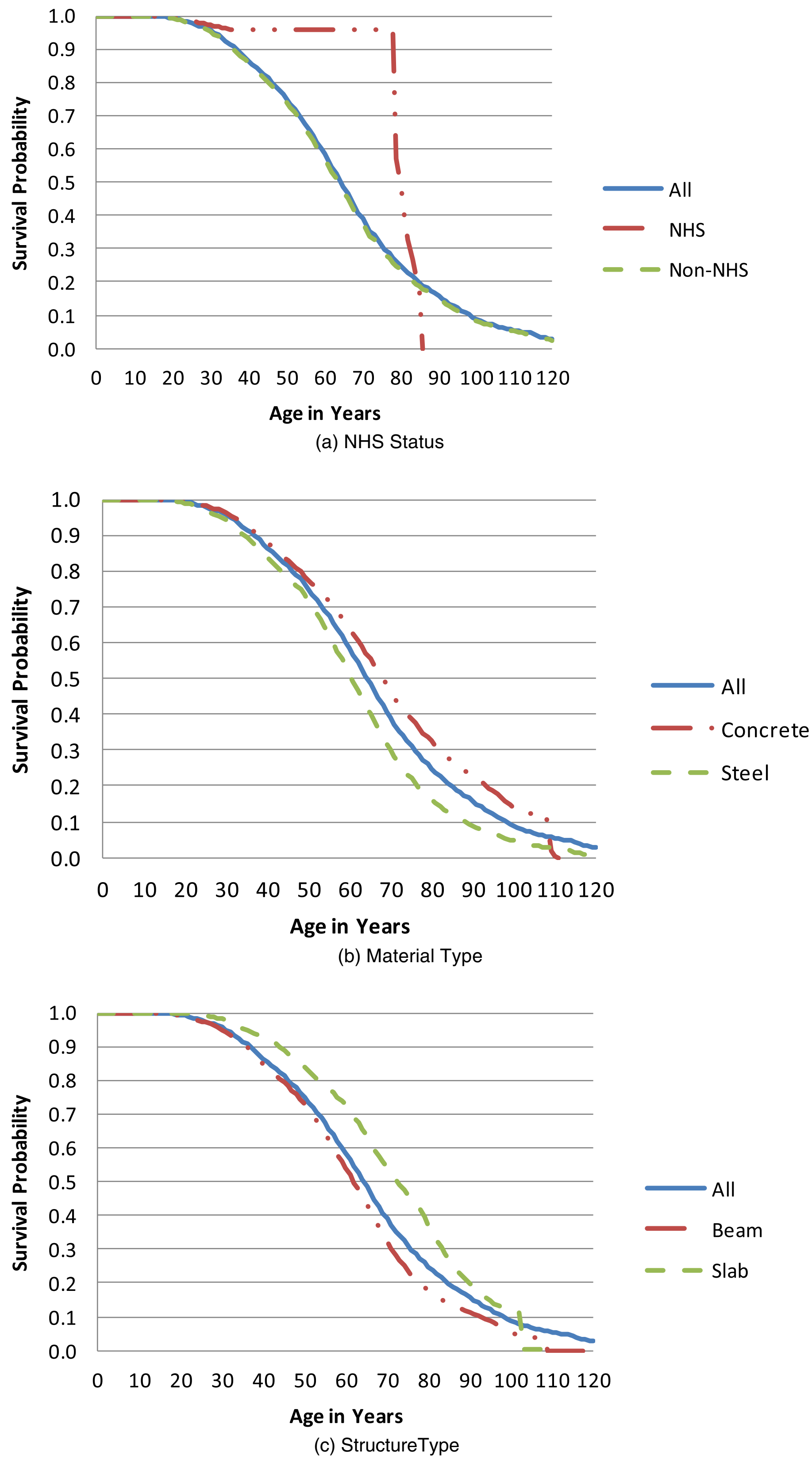
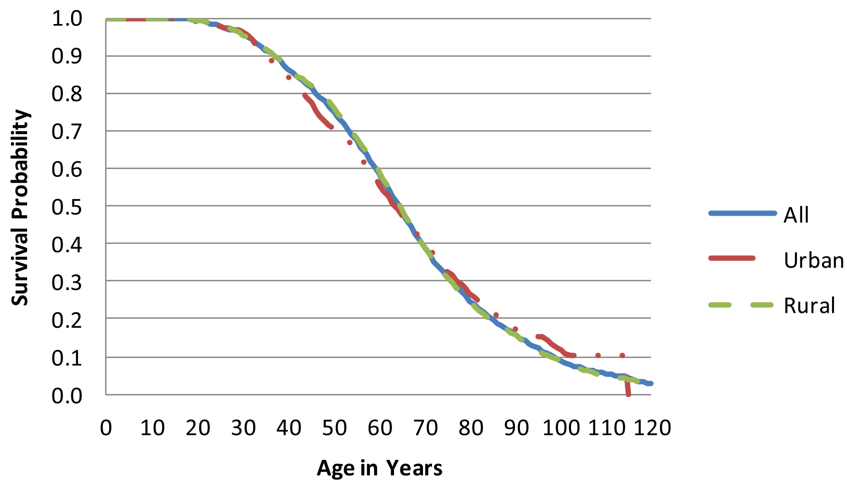
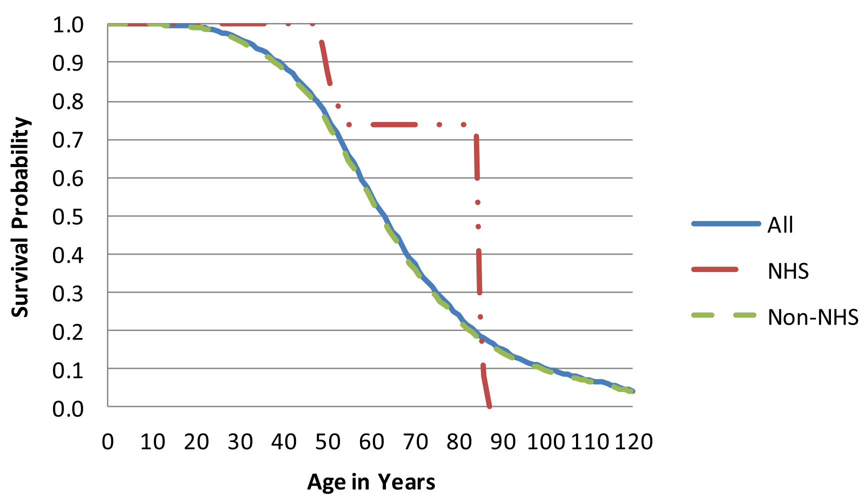


Figure 6-4. Sensitivity of non-covariate Indiana bridge substructure life models.

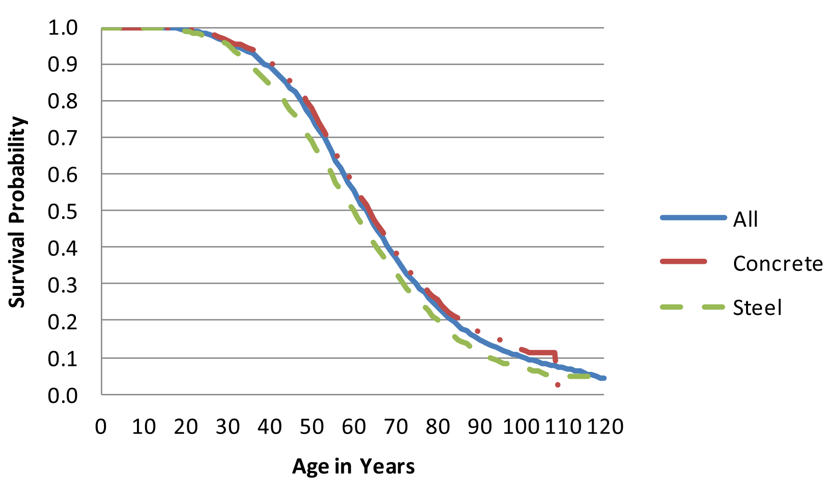


(d) Geographic Region

Figure 6-4. (Continued).



(a) NHS Status



(b) Material Type

Figure 6-5. Sensitivity of non-covariate models for Indiana bridge channel protection facility life.

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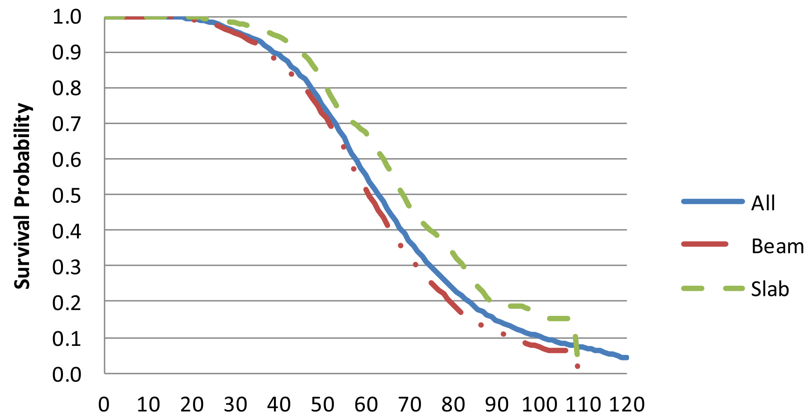
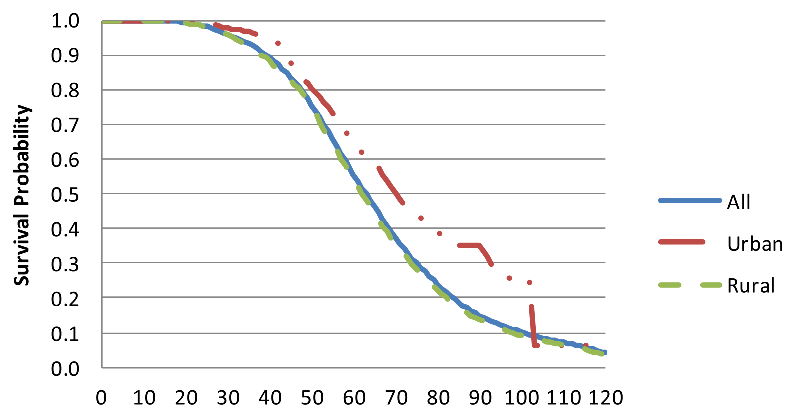


(c) Structure Type



(d) Geographic Region

Figure 6-5. (Continued).

Table 6-3. Range of box culvert life values for covariate model sensitivity analysis.

Life Expectancy Factor	Minimum Value	Assumed Value	Maximum Value
Normal Annual Temperature (°F)	50	51	53
Normal Annual Precipitation (in.)	38	43	51
Geographical classification indicator (1 if rural, 0 otherwise)	0	0	1
NHS indicator (1 if on NHS, 0 otherwise)	0	1	1
Functional class indicator (1 if on interstate, 0 otherwise)	0	1	1
Maintenance responsibility indicator (1 if state responsible, 0 otherwise)	0	1	1
Corrosive soil indicator (1 if in area where average soil is classified as highly corrosive to steel or concrete by the NRCS, 0 otherwise)	0	0	1
Acidic soil indicator (1 if in area with average soil of pH < 6.5 according to NCRS, 0 otherwise)	0	0	1
Material type indicator (1 if concrete, 0 otherwise)	0	1	1
Structure length in decimeters	140	150	160

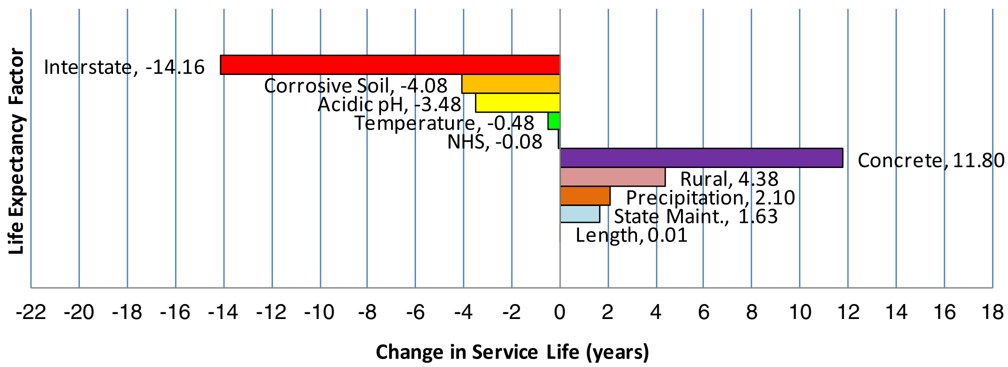


Figure 6-6. Tornado diagram for the covariate box culvert life model.

The sensitivity analysis for the non-covariate box culvert life model produced the following results (Table 6-4):

- Compared to their non-NHS counterparts, NHS box culverts generally indicate a 5-year longer life where the end-of life criteria is the culvert condition rating;
- Concrete structures had median life estimates ranging from 27 to 32 years in life extensions as compared to steel.
- The life of urban structures was generally found to be 6 to 11 years longer than rural structures.

The non-homogenous Markov chains for the Indiana box culvert are shown in Figures 6-7 and 6-8.

6.2.3 Sensitivity of Pipe Culvert Life Prediction

An assessment of the pipe culvert model sensitivity to the characteristics is presented in Table 6-5. From these results, it is clear that further enhancements to the prediction are required. Climate uncertainty (i.e., temperature, precipitation, and freeze-thaw cycles) accounted for a 7- to 60-year range in median life predictions, indicating that the parameter estimates were likely errant (Figure 6-9). Collecting additional data is recommended to mitigate the heterogeneity associated with these parameters. Other factors found to significantly affect life included 8 additional years of life for metal culverts compared to plastic, an additional 3 years when coating protection is applied, and a loss of 3 years due to the soil plasticity.

Table 6-4. Box culvert median life predictions by end-of-life definition and data segmentation.

	Culvert Rating ≤ 4	Channel Protection Rating ≤ 4
NHS	78	75
Non-NHS	73	82
Concrete	83	88
Steel	51	61
Urban	80	91
Rural	78	80
All IN Bridges	75	84

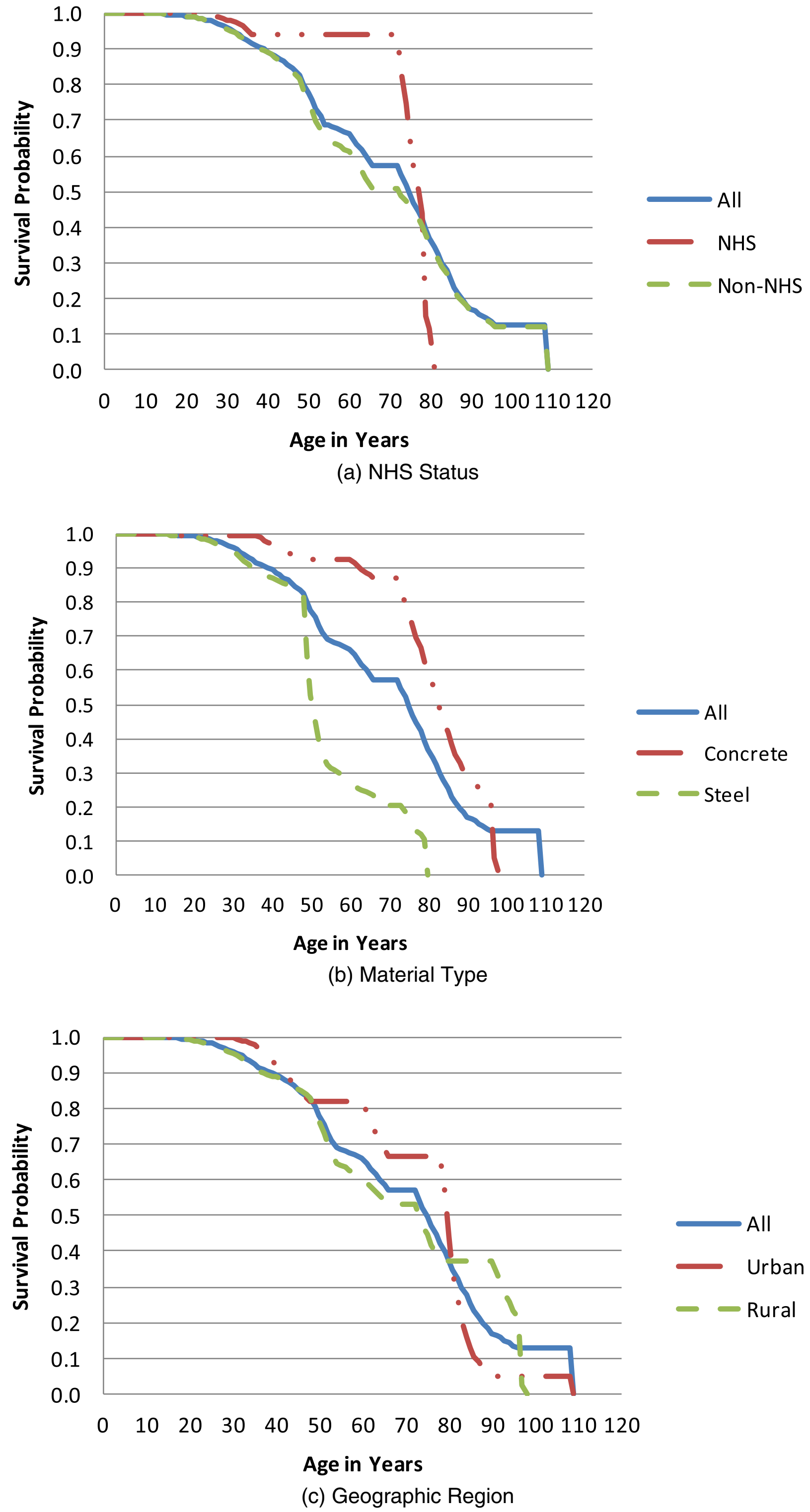
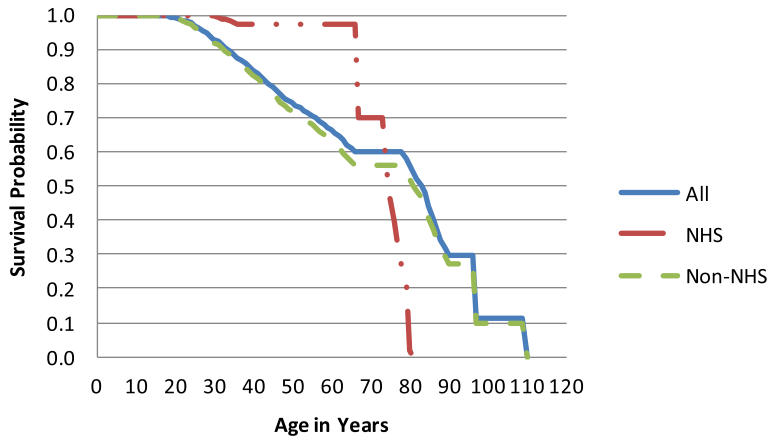
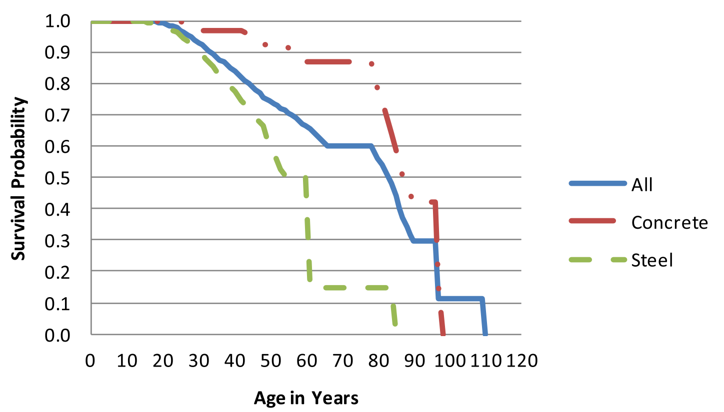


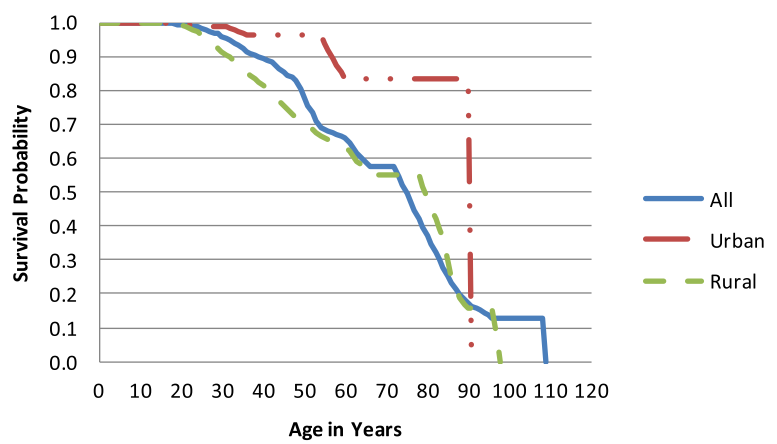
Figure 6-7. Sensitivity of the non-covariate Indiana box culvert condition life models.



(a) NHS Status



(b) Material Type



(c) Geographic Region

Figure 6-8. Sensitivity of the non-covariate Indiana box culvert channel protection life models.

Table 6-5. Range of pipe culvert life values for covariate model sensitivity analysis.

Life Expectancy Factor	Minimum Value	Assumed Value	Maximum Value
Normal Annual Temperature (°F)	46	47	49
Normal Annual Precipitation (in.)	40	46	54
Normal Annual Freeze-Thaw Cycles (days)	95	100	105
Material indicator (1 if plastic, 0 otherwise)	0	1	1
Material indicator (1 if metal, 0 otherwise)	0	0	1
Coating indicator (1 if coating applied, 0 otherwise)	0	1	1
Approximate area opening [height (in.) * width (in.)]	143	144	145
Plasticity Index of average soil in NRCS survey area	0	0	1

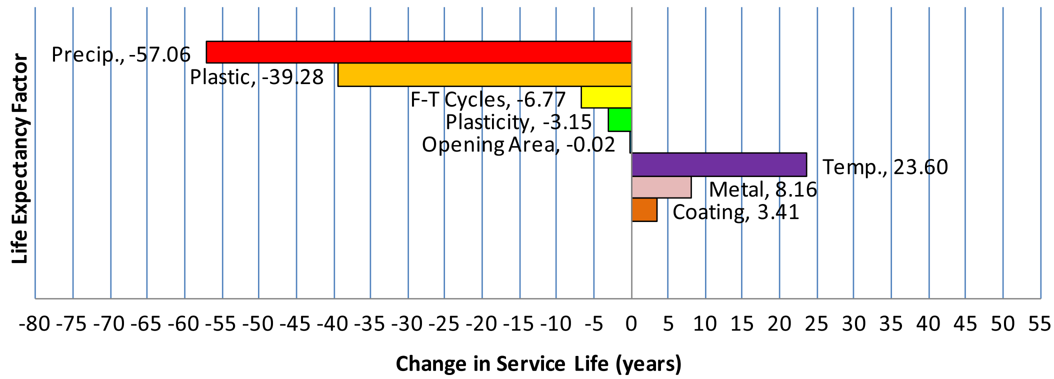


Figure 6-9. Tornado diagram for the covariate pipe culvert life model.

6.2.4 Sensitivity of Traffic Signal Life Prediction

The results of the traffic signal sensitivity analysis suggest that the functional or area classification of the road (city/county road versus major arterial/interstate road) has the most profound effect on the life of a traffic signal, followed by precipitation and temperature (see Table 6-6 and Figure 6-10).

6.2.5 Sensitivity of Flasher Life Prediction

A sensitivity analysis of the flashers life model with the attributes shown in Table 6-7 indicate that flashers that control intersections seem to have longer life expectancies compared to those not installed at those locations; climate factors produce median life estimates over a range of 3 to 16 years (Figure 6-11).

Table 6-6. Range of traffic signal life values for covariate model sensitivity analysis.

Life Expectancy Factor	Minimum Value	Assumed Value	Maximum Value
Normal Annual Temperature (°F)	46	47	49
Normal Annual Precipitation (in.)	40	46	54
Functional class indicator (1 if controlling city or county roads, 0 otherwise)	0	1	1

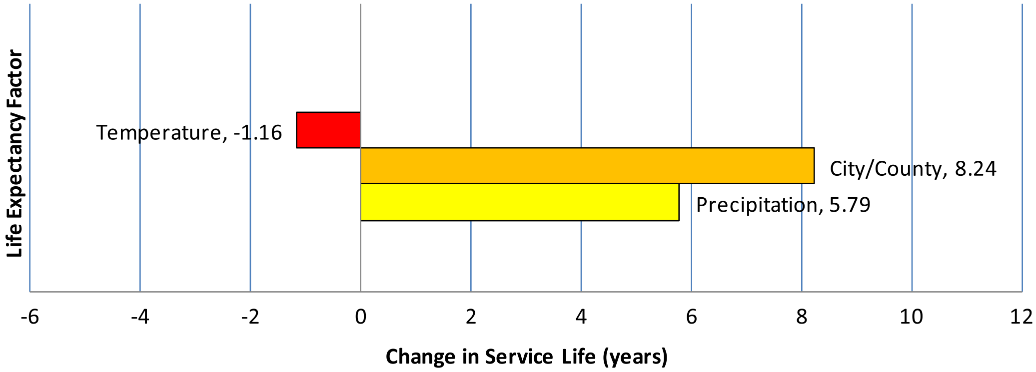


Figure 6-10. Tornado diagram for the covariate traffic signal life model.

6.2.6 Sensitivity of Roadway Lighting Life Prediction

Roadway lighting life was found to be most sensitive to the material type and mounting location (Table 6-8 and Figure 6-12). It was found that metal poles generally exhibit significantly shorter life compared to those fabricated using non-metals. Also, lights mounted on signs were found to be associated with longer life compared to those mounted on poles.

6.2.7 Summary of Sensitivity Analyses

The following conclusions were reached after analyzing the sensitivity of the developed covariate models to various ranges of the life expectancy factors: bridge life was most affected by

Table 6-7. Range of flasher life values for covariate model sensitivity analysis.

Life Expectancy Factor	Minimum Value	Assumed Value	Maximum Value
Normal Annual Temperature (°F)	48	49	51
Normal Annual Precipitation (in.)	38	43	51
Mounting location indicator (1 if over intersection, 0 otherwise)	0	0	1
School zone indicator (1 if controlling school zone, 0 otherwise)	0	1	1
Average wind speed in miles per hour	9	10	11

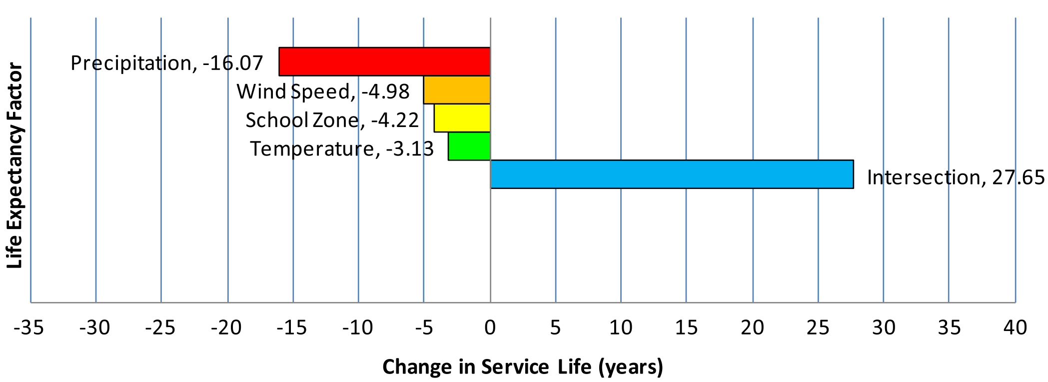


Figure 6-11. Tornado diagram for the covariate flasher life model.

Table 6-8. Range of roadway lighting life values for covariate model sensitivity analysis.

Life Expectancy Factor	Minimum Value	Assumed Value	Maximum Value
Normal Annual Temperature (°F)	48	49	51
Material type indicator (1 if metal pole, 0 otherwise)	0	1	1
Mounting location indicator (1 if on sign, 0 otherwise)	0	0	1
Functional class indicator (1 if on interstate, 0 otherwise)	0	1	1
Fixture height indicator (1 if less than 30 feet, 0 otherwise)	0	0	1

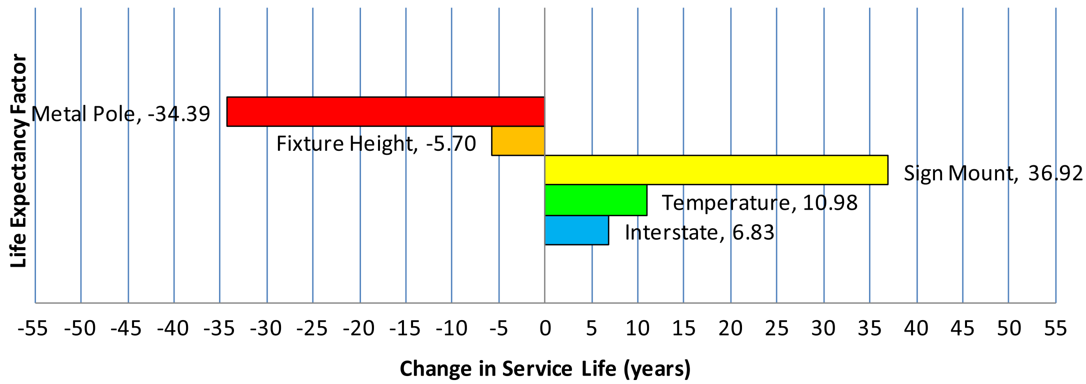


Figure 6-12. Tornado diagram for the covariate roadway lighting life model.

NHS status; box culvert life was most influenced by Interstate status; pipe culvert life was heavily dependent on precipitation levels; traffic signal life was influenced most by roadway functional class; flasher life was affected primarily by mounting location; and roadway lighting life was most significantly influenced by mounting type.

On the basis of Indiana box culvert data, the sensitivity analysis results for the non-covariate models were similar to those obtained for the covariate models. It was found that Indiana bridge life was most sensitive to NHS status (a reflection of the balance between traffic loading and design features); for box culverts, longevity was found to be most influenced by the material type.

Furthermore, it was found that the collected data empirically suggests that a temperature range of 3 degrees can affect bridge life by −1 year, box culvert life by −6 months, pipe culvert life by +24 years, traffic signal life by −1 year, flasher life by −3 years, and roadway lighting life by +11 years. A range of annual precipitation values varying by roughly −12% to +15% was found to influence bridge life by −1 year, box culvert life by +2 years, pipe culvert life by −57 years, traffic signal life by +6 years, and flasher life by −16 years. Roadway lighting was found to not be significantly influenced by precipitation. While the extent of the influence of climate requires further study, particularly for pipe culverts, it is readily apparent that climate factors significantly affect the life of infrastructure and, given the uncertainty, can be analyzed further by risk assessments.

6.3 Risk Assessments of Highway Asset Replacement Decisions

In the remaining sections of this chapter, emphasis is placed on assessing the risk of highway asset replacement decisions. First, the risk posed by uncertain climate is assessed at the project level with respect to life predictions and annual lifecycle costs. Secondly, by repeating the first step for all assets in the net worth, the risk of uncertain life is assessed at the network-level. This latter analysis focuses on (1) propagating the uncertain climate effects found to significantly affect the covariate model life predictions and (2) assessing the risk posed by correlated competing "end-of-life criteria" utilizing the non-covariate models. Both methods are demonstrated using data from the Indiana NBI bridge database, however, similar studies can be carried out for assets in other agencies' databases.

6.3.1 Risk of Uncertain Future Climate

As shown in the sensitivity analyses, uncertain climate translates into uncertainty of infrastructure life. To assess the likelihood of asset life predictions, expert opinion of probabilistic estimates of future climatic conditions were obtained for two scenarios: (1) low-emissions—assuming significant action taken to reduce greenhouse gases and (2) moderately high-emissions—assuming no action taken (Figures 6-13 and 6-14). Normal distributions were assumed, and the

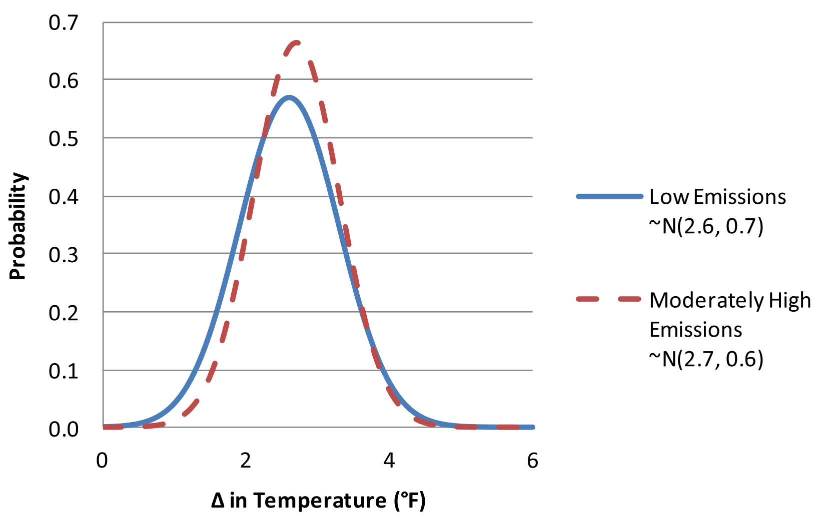


Figure 6-13. Probabilistic forecast of midwest annual temperature change for 2010–2040 normals (ICF International, 2009).

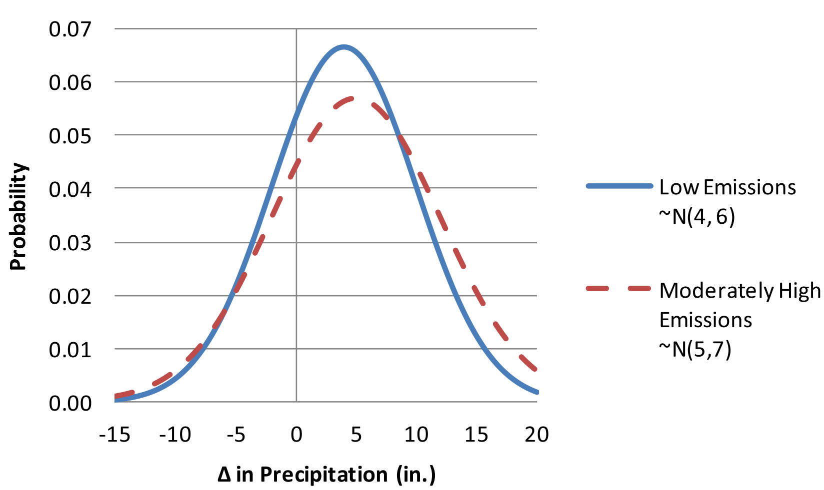


Figure 6-14. Probabilistic forecast of midwest annual precipitation change for 2010–2040 normals (ICF International, 2009).

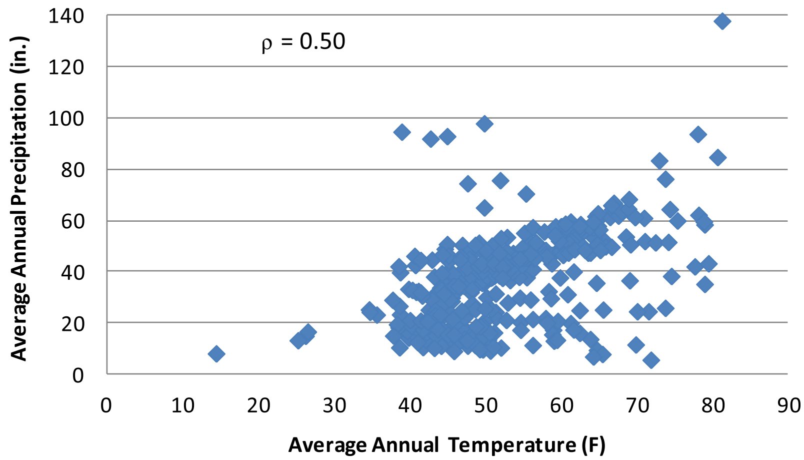


Figure 6-15. Correlation pattern of average annual temperature and precipitation over all U.S. climate divisions based on current normals.

standard deviation was taken as the range of values that experts thought were likely. In ICF International (2009), emission policies had a marginal effect on short-term climate, with the moderately high-emissions scenario corresponding to slightly lower uncertainty and slightly higher estimates. Agencies wishing to replicate the analysis could use any distribution appropriate in the place of those provided.

To model the dependency structure, the correlation between the random variables was evaluated over the normal annual values for every climate division in the United States for the last 30 years. With this sample, a Pearson product-moment correlation coefficient of 0.50 was found, indicating the need for correlated simulation. Overall, a positive relationship was found that is consistent with the higher moisture capacity of warmer air (Figure 6-15).

To simulate this correlation pattern, a statistical copula was fit to the data. The best fitting copula was found to be the normal copula with covariance = 0.5643, which corresponded to –SIC of 96.96; AIC of 100.86; and HQIC of 99.31, using maximum likelihood estimation.

In the case of pipe culverts, additional correlation tests were conducted with respect to freeze-thaw cycles. A negative but insignificant Pearson product moment correlation factor was found, suggesting that freeze-thaw cycles could be modeled independently. To approximate future freeze-thaw cycles, a probability distribution was fit to the values obtained by randomly sampling seasonal temperature distributions for each emissions scenario (ICF International, 2009). The resulting distribution was found to be normal with a standard deviation of 1.66 surrounding the deterministic estimate.

Ten thousand trials were conducted for each asset class, assuming the characteristics presented in the sensitivity analysis section. The changes in median life values, survival curves, equivalent annual cost, and utility associated with replacing the structure for various ages were quantified.

6.3.1.1 Risk Assessment of Uncertain Future Climate on Bridge Life

From the correlated simulation of temperature and precipitation and subsequent incorporation into the covariate life expectancy model, the probability of life predictions was quantified with respect to the median estimate and the overall survival curve.

In terms of the median estimate, the low-emissions scenario produced a median value of 55.77 years with a 90% confidence interval of [55.06, 56.50] and the moderately high-emissions

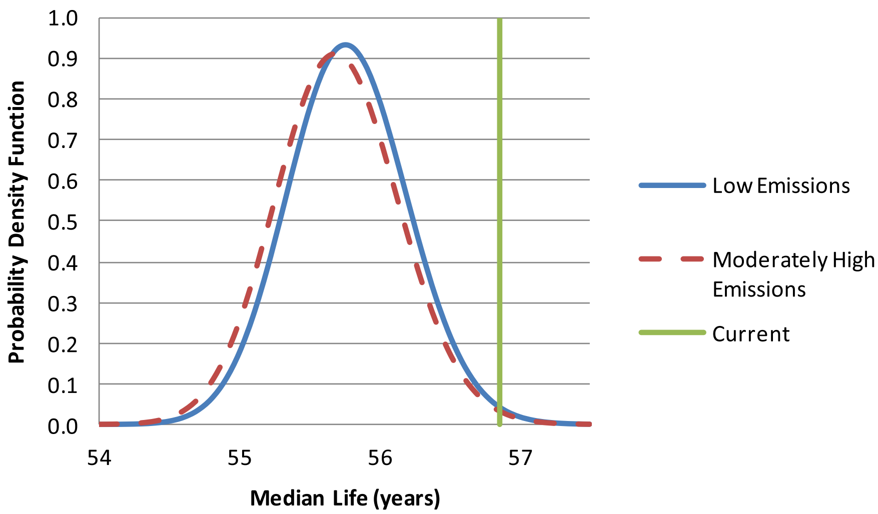


Figure 6-16. Risk-based median bridge life prediction due to climate uncertainty.

scenarios produced a median value of 55.70 years with a 90% confidence interval of [55.00, 56.40] (Figure 6-16). Under the current climatic conditions (annual average temperature = 49°F and annual average precipitation = 43 in.), an estimate of 56.86 years was predicted. As such, it was concluded that lower bridge lives of 1.09 years and 1.16 years for the two scenarios, respectively, are most probable. On the basis of the developed model, the likelihoods that bridge life will be lower are 99.31% and 99.47% for the two scenarios, respectively.

With respect to the overall survival curve for bridges in the sample dataset (Figure 6-17), it is readily observed that there is very little variability.

6.3.1.2 Risk Assessment of Uncertain Future Climate on Box Culvert Life

With the box culvert covariate model, empirical evidence suggested that culverts in warmer climates generally have a significantly shorter life, while those in wet climates generally have a significantly longer life. This was unlike the result for bridges in the given dataset, where it was observed that increases in temperature and precipitation both reduce life.

In a correlated simulation of future climatic conditions with the characteristics presented previously, the effects on median life (Figure 6-18) and overall survival probabilities (Figure 6-19) were assessed.

From the analysis, it was found that the median estimate in the low-emissions scenario produced a value of 50.03 years with a 90% confidence interval of [49.42, 50.64], and the moderately high-emissions scenarios yielded a value of 50.09 years with a 90% confidence interval of [49.39, 50.81] (Figure 6-18). Under the current climatic conditions (annual average temperature = 49°F and annual average precipitation = 43 in.), an estimate of 50.18 years was predicted. As such, it can be concluded that lower lives of 1.80 months and 1.08 months for the two scenarios, respectively, are most probable. From the model, the likelihoods that box culvert life will be lower are 65.57% and 58.71% for the two scenarios, respectively.

6.3.1.3 Risk Assessment of Uncertain Future Climate on Pipe Culvert Life

In the analysis of pipe culverts, it was found that temperature had a positive impact on asset life, while precipitation values and freeze-thaw cycles had a negative effect. With the wide

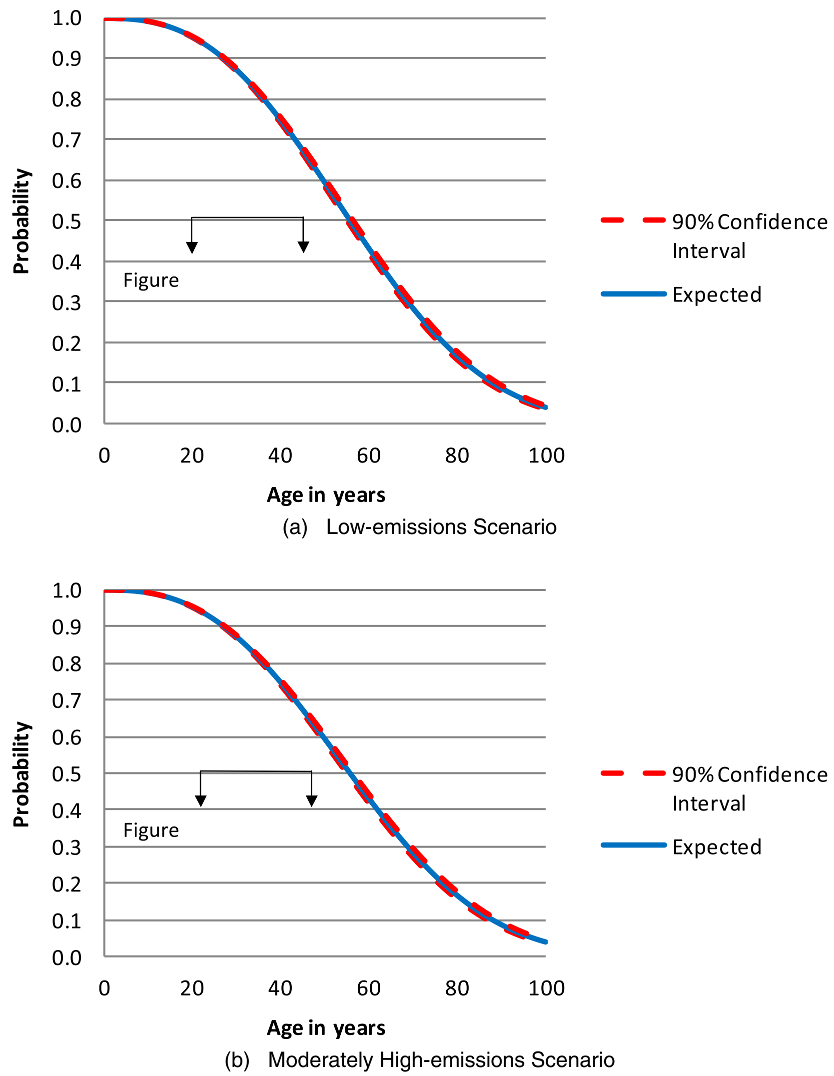


Figure 6-17. Risk-based bridge survival curve due to climate uncertainty.

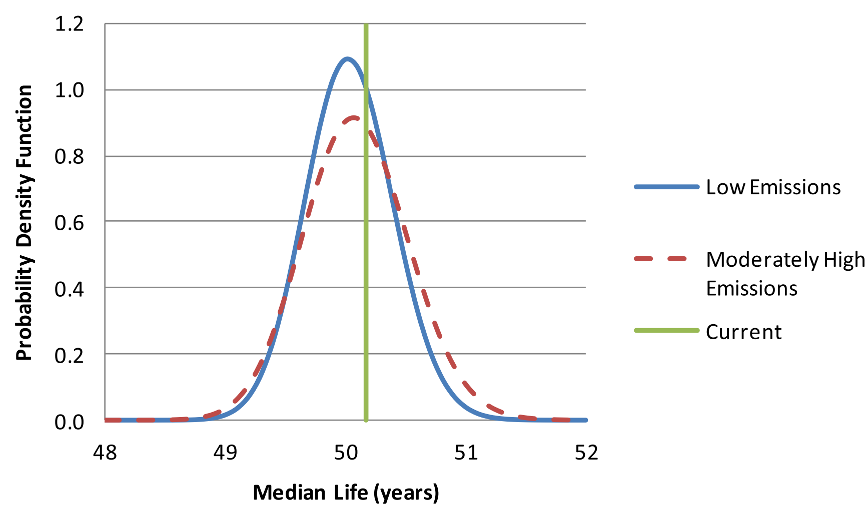
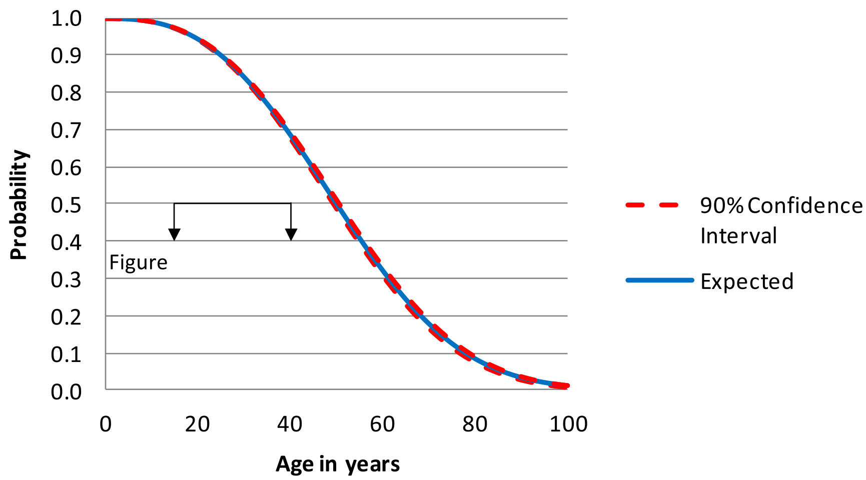
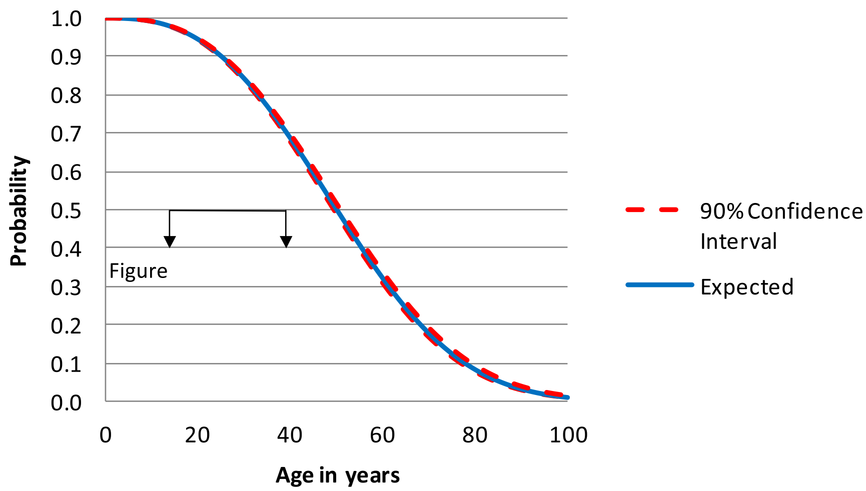


Figure 6-18. Risk-based median box culvert life prediction due to climate uncertainty.



(a) Low-emissions Scenario



(b) Moderately High-emissions Scenario

Figure 6-19. Risk-based box culvert survival curve due to climate uncertainty.

variability in precipitation and the greater influence of temperature on asset life than freeze-thaw cycles, it was found that the uncertain climate likely leads to longer culvert life. Median life estimates were found to vary from 35.58 years (90% C.I. = [16.11, 78.45]) in the low-emissions scenario, 34.48 years (90% C.I. = [14.25, 84.14]) in the moderately high-emissions scenario, and 18.26 years under the current climatic conditions (annual temperature = 47°F, annual precipitation = 46 in.) (Figure 6-20). In the low-emissions scenario, a longer life of 17.32 years was found, compared to a 16.22-year life extension in the moderately high-emissions scenario. Based on the risk assessment, there was 8.30% chance of a reduced median life in the low-emissions scenario and an 11.88% chance of reduced life in the moderately high-emissions scenario. The wide variability in life predictions can further be seen in Figure 6-21, indicating that an improved model could be more beneficial.

6.3.1.4 Risk Assessment of Uncertain Future Climate on Traffic Signal Life

A probabilistic risk assessment of traffic signal life due to uncertain climate produced the range of median life estimates in Figure 6-22. Temperature and precipitation found to be positively associated with asset longevity of a traffic signal, it was found that the future

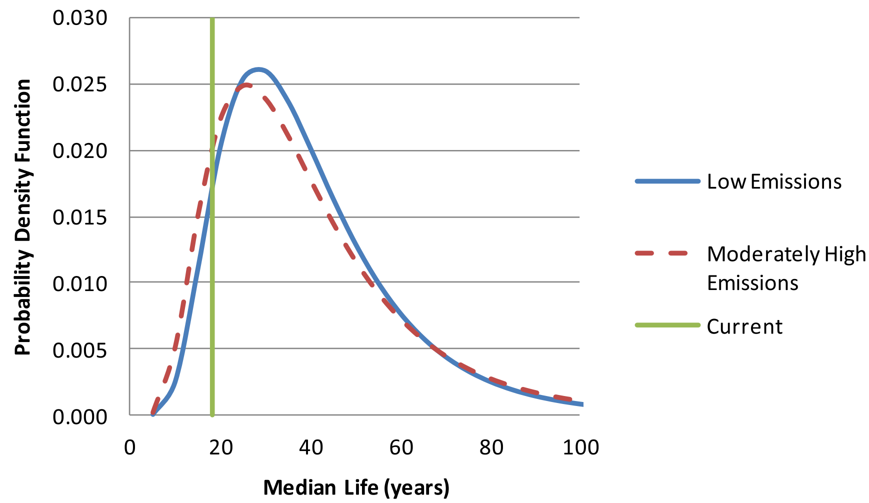


Figure 6-20. Risk-based prediction of pipe culvert median life due to climate uncertainty.

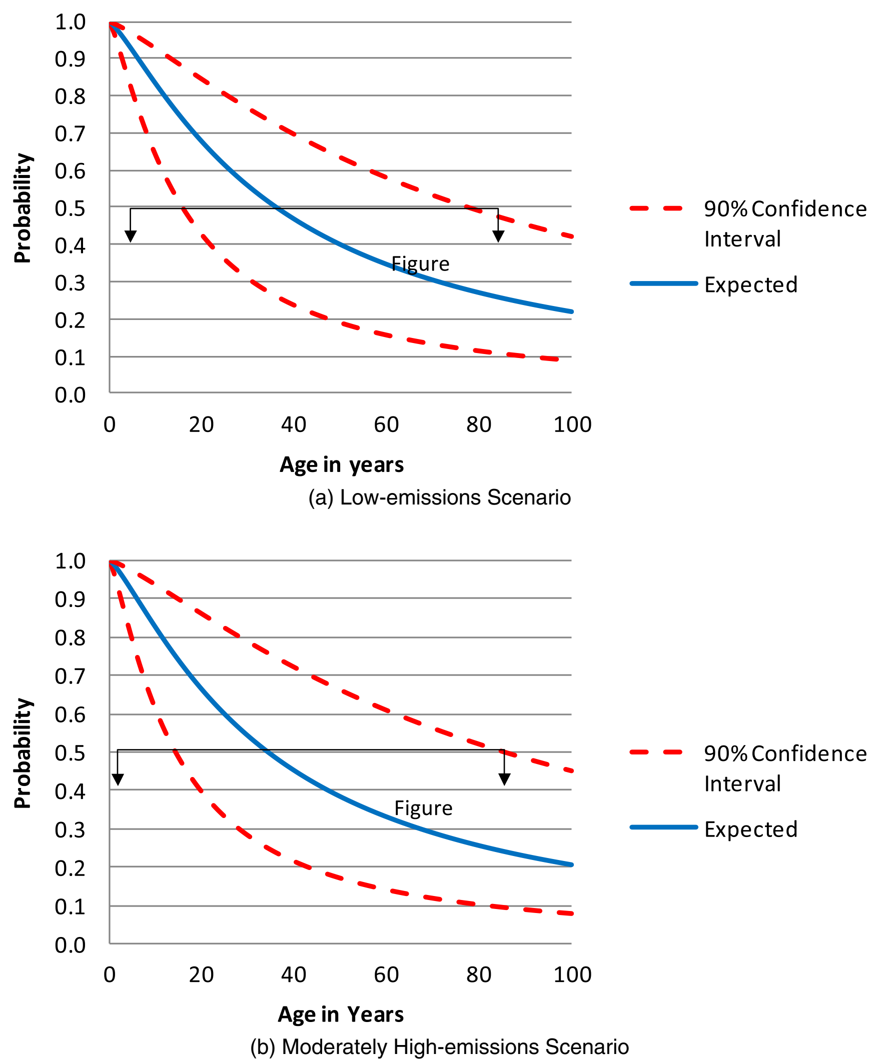


Figure 6-21. Risk-based pipe culvert survival curve due to climate uncertainty.

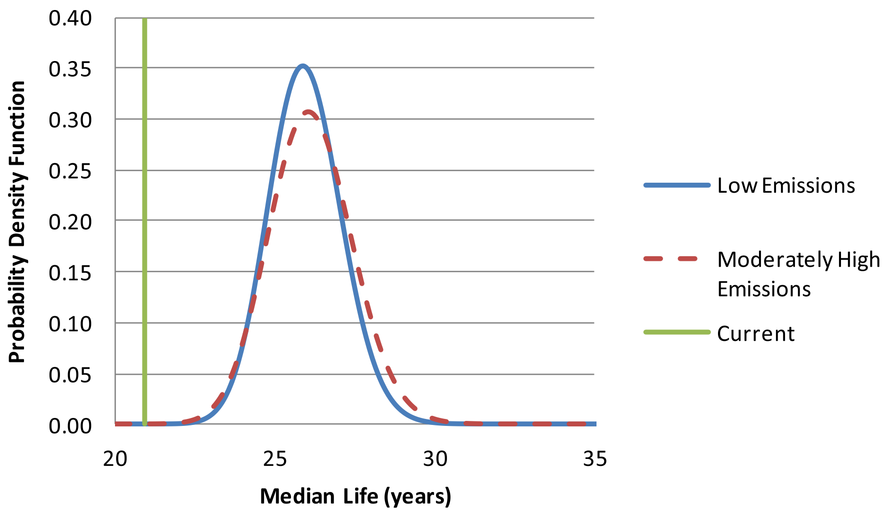


Figure 6-22. Risk-based prediction of traffic signal median life due to climate uncertainty.

median life estimate can be extended with over 99.99% confidence by 4.98 years for the low-emissions scenario and 5.14 years for the moderately high-emissions scenario. The current median life prediction (annual temperature = 47°F, annual precipitation = 46 in.) was found to be 20.95 years, 25.93 years (90% C.I. = [24.14, 27.86]) for the low-emissions scenario, and 26.09 years (90% C.I. = [24.03, 28.30]) for the moderately high-emissions scenario.

It was found that the traffic signal survival curves exhibit the greatest uncertainty at the 26 to 31 years age range (Figure 6-23).

6.3.1.5 Risk Assessment of Uncertain Future Climate on Flasher Life

Flasher life was found to be negatively associated with both temperature and precipitation. However, given the uncertainty in future precipitation, there was a 9.94% chance of a longer median life under the low-emissions scenario and 9.68% chance of a longer life under the moderately high-emissions scenario. The median predictions, for the characteristics defined in the sensitivity analysis, were found to be 21.80 years with current climatic conditions (annual temperature = 49°F, annual precipitation = 43 in.), 17.30 years (90% C.I. = [12.99, 23.24]) with the low-emissions scenario, and 16.77 years with the moderately high-emissions scenario (90% C.I. = [12.35, 23.31]) (Figure 6-24). These findings equate to an average life shortened by 4.50 and 5.03 years, respectively.

In assessing the survival curves, greater uncertainty occurs as the asset ages (Figure 6-25).

6.3.1.6 Risk Assessment of Uncertain Future Climate on Roadway Lighting Life

In the risk assessment of roadway lighting life, based on the characteristics described in the sensitivity analysis, longer lifespans were found, which corresponds to the finding that lighting in warmer climates has significantly longer life. With precipitation not found to have a significant effect on life, a non-correlated Monte Carlo simulation was conducted. From the analysis, it was found that the median life prediction varied from 30.19 years (90% C.I. = [24.97, 36.6]) to 30.71 years (90% C.I. = [25.86, 36.43]) in the two emissions scenarios (Figure 6-26). These estimates were found to be 10.89 and 11.41 years longer than the 19.3 years of median life under the current climate scenario (annual temperature = 49°F).

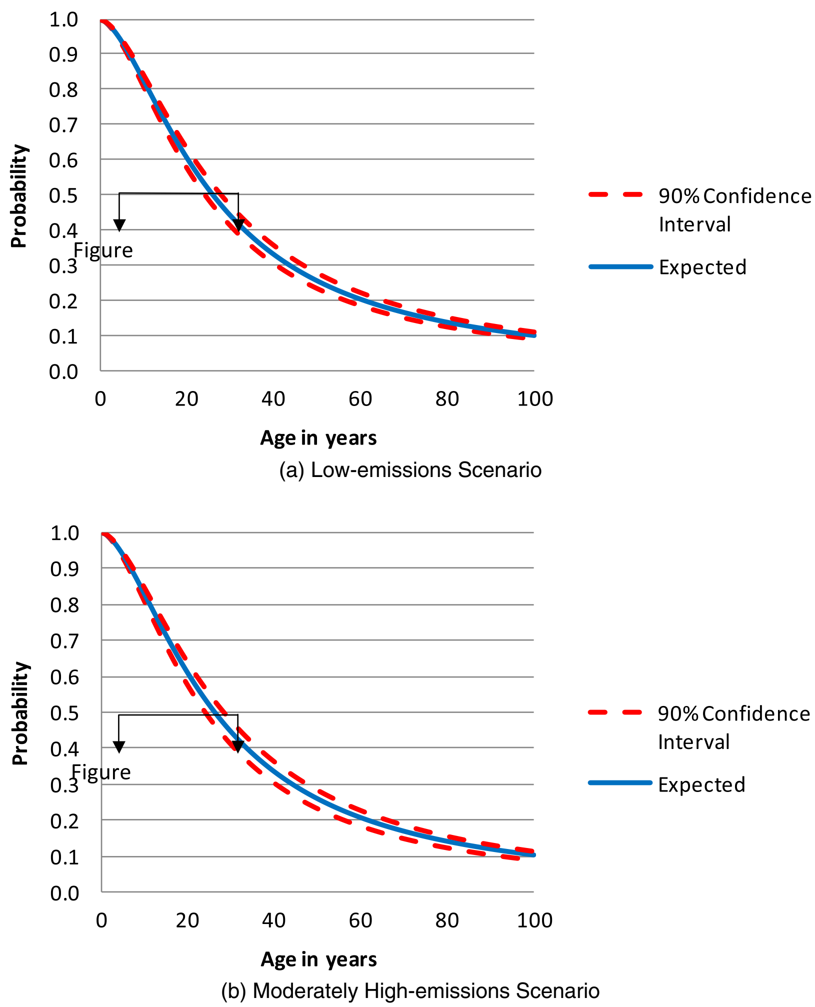


Figure 6-23. Risk-based traffic signal survival curve due to climate uncertainty.

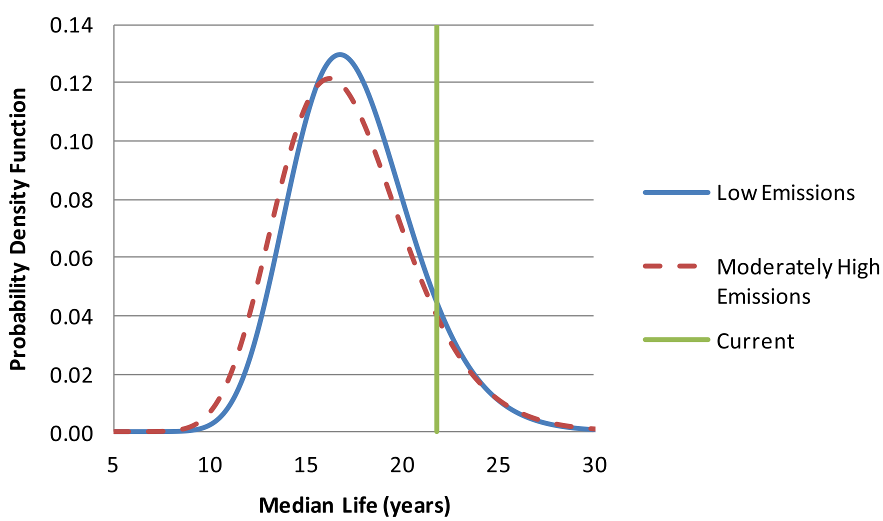


Figure 6-24. Risk-based prediction of flasher median life due to climate uncertainty.

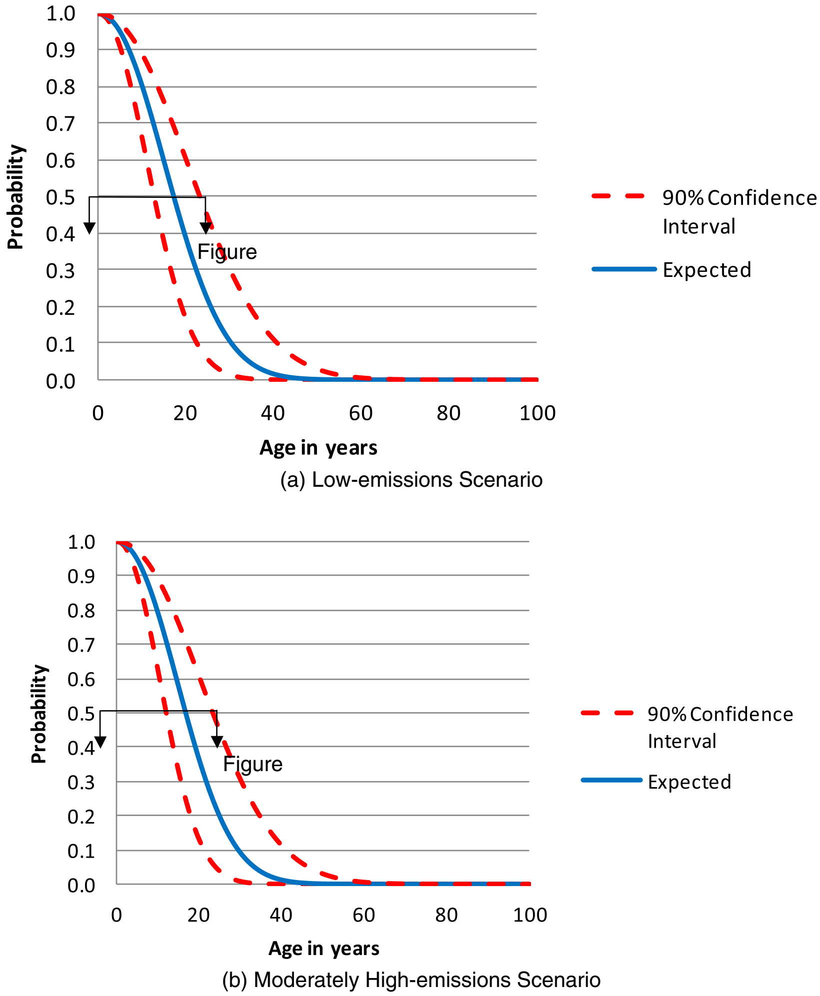


Figure 6-25. Risk-based flasher survival curve due to climate uncertainty.

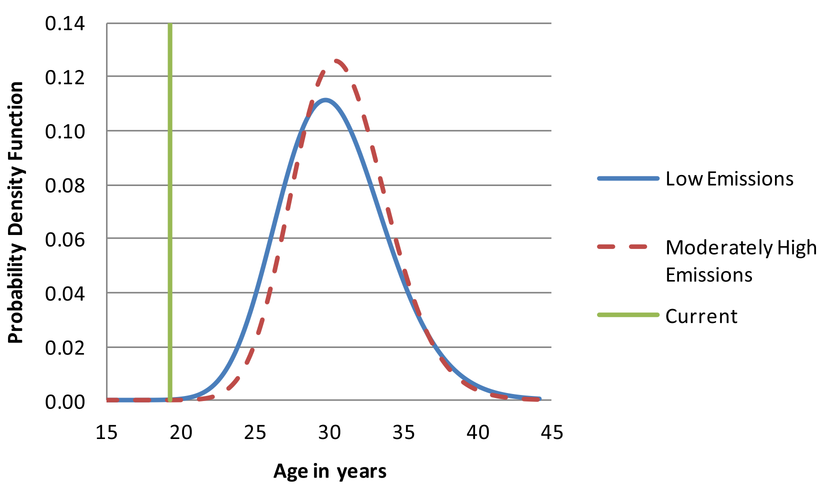


Figure 6-26. Risk-based prediction of roadway lighting median life due to climate uncertainty.

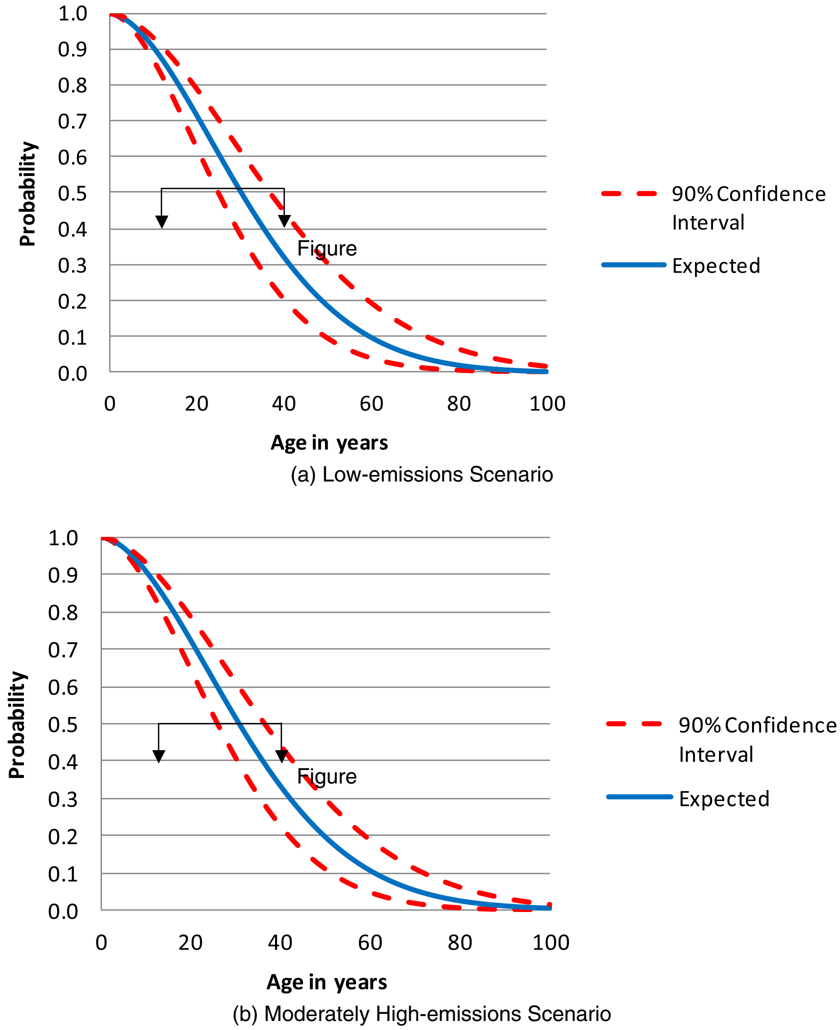


Figure 6-27. Risk-based roadway lighting survival curve due to climate uncertainty.

As with the flashers, upon analyzing the survival curves, the uncertainty of roadway lighting life was found to propagate with age (Figure 6-27).

6.3.2 Risk-based Needs Assessment

Due to the uncertainty of asset life, the fiscal and physical long-term needs of an agency are inherently uncertain. To demonstrate how to quantify this uncertainty, probabilistic risk assessments of various scenarios were examined and compared using the Indiana NBI data. Three general categories of risk-based needs assessments were analyzed over a 15-year planning horizon:

1. Hybrid age/condition-based probabilistic assessment of replacement needs given recently observed climatic conditions and uncertain future climatic conditions;
2. Condition-based probabilistic assessment of replacement needs for varying maintenance/preservation policies; and
3. Deterministic assessments of replacement needs for varying estimates of life and modeling techniques.

The first scenario utilizes the developed covariate model to assess the risk of uncertain climate on budget needs. Scenario 2 compares the uncertain budget needs based on varying definitions of what constitutes a serviceable bridge (e.g., Substructure Rating ≥ 4, Substructure and Super-

Table 6-9. Bridge replacement costs used for the analysis.

Cost Component	Bridge Type	$Cost = a * L^b * W^c$
Superstructure Replacement	Reinforced Concrete Slab	a = 0.0488; b =0.899; c = 1
	Concrete Beam/Girder	a = 0.0513; b = 0.979; c = 0.828
	Steel Beam/Girder	a = 0.123; b = 1; c = 0.519
	Other	a = 0.0885; b = 0.906; c = 0.747
Substructure Replacement	Reinforced Concrete Slab	a = 0.120; b = 0.727; c = 0.602
	Other	a = 0.028; b = 0.936; c = 0.983
Approach (L=500)		a = 0.769; b = 0.823; c = 0
Other		a = 0.721; b = 0.696; c = 0.932

structure rating ≥ 4, Substructure, Superstructure, and Channel rating ≥ 4 and Deck Geometry rating ≥ 3) and what maintenance/preservation policies are pursued during the remainder of the life estimate (e.g., rehab superstructure at rating = 5 and substructure at rating = 5, do nothing). To examine the consequences of deterministic assessments of highway asset preservation needs, the results obtained on the basis of Scenario 3 can be compared with those of other scenarios.

The cost of replacement for each bridge was assumed to be the sum of the Cobb-Douglas bridge element replacement cost functions in Table 6-9 (Sinha et al., 2009). These were applied over the entire Indiana bridge stock in 2009 (Figure 6-28) to estimate the overall cost of replacement at each year.

For each scenario, the total budget needs in 2009 current dollars over a 15-year planning horizon were analyzed. Likewise, the number and percentage of assets expected to need one or more replacements within the planning horizon were noted.

6.3.2.1 Hybrid (Age/Condition-based) Probabilistic Needs Assessment

In Scenario 1, three risk analyses were conducted on the covariate bridge life model that predicted the time until the NBI sufficiency rating dropped to or below 50%, in order to assess the current (2009) dollar value of replacement needs from 2009–2023:

A. Simulation of bridge life using current climate inputs;
B. Simulation of bridge life using uncertain future climate inputs under the low-emissions scenario; and
C. Simulation of bridge life using uncertain future climate inputs under the moderately high-emissions scenario.

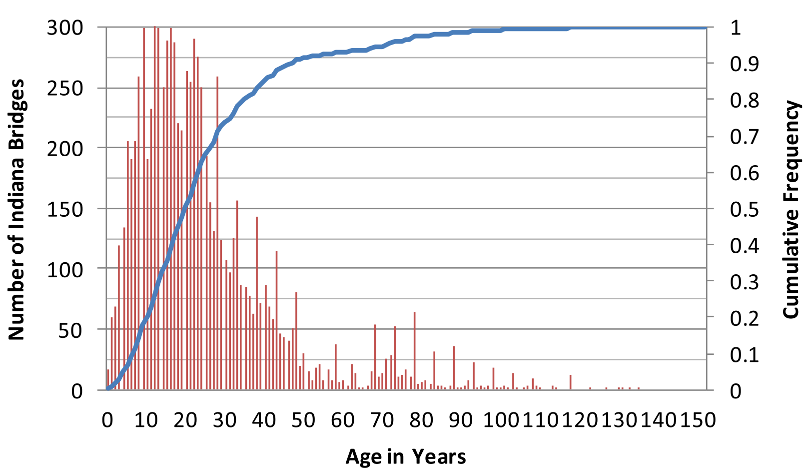


Figure 6-28. Histogram of bridge age for Indiana NBI stock as of 2009.

In Scenario 1A, a Weibull-distributed random variable was sampled from the conditional survival probability curve for all assets that had a sufficiency rating above 50% (which indicates that these assets had some remaining life). The year 2009 served as a reference point; that is, the remaining life of all assets was analyzed relative to 2009. Thus, for assets not inspected in 2009, the difference between their most recent inspection year and 2009 was subtracted from the random life value; for example, for a bridge inspected in 2008 and found to have a 25-year remaining life, the remaining life relative to 2009 is 25 − (2009 − 2008) = 24 years; where this operation yielded a negative value, a minimum remaining life of zero was used. Likewise, a planning gap (in years) can be subtracted from the random value based on agency preferences (e.g., probabilistic delay in replacement applied in using renewal theory (van Noortwijk & Klatter, 2004)). For structures that had a remaining life within the planning horizon, a second life prediction was simulated using the unconditional survival model. Likewise, in the unlikely event that an asset fails more than twice within the planning horizon, five life predictions were contingently estimated. However, in the simulations, only 0.2% of the active structures required more than one replacement. If the remaining life extended beyond the planning horizon, then no costs were added to the assessed needs, otherwise, the current dollar value of the replacement cost was added to the fiscal needs amount. Each structure was assumed to have an independent life estimate. In future studies on this subject, it may be possible to assess potential spatial correlation effects. Over 10,000 trials of this simulation were carried out.

In following this approach for the current climate, it was found that, on average, 3,620 bridges (22.5% of total Indiana NBI stock) need to be replaced in 2009 (i.e., physical need), and this corresponds to a fiscal need of \$1.749 billion. From the trials, it was found that, for 90% confidence, a minimum of \$1.800 billion is needed for replacing 3,554 (22.0%) to 3,686 (22.9%) bridges. Therefore, to improve confidence from 50% to 90%, an additional (contingency) fund of \$51 million should have been set aside in 2009. For 99.99% confidence, an additional (contingency) \$123 million is needed.

In Scenarios 1B and 1C, the analysis was repeated with the addition of random temperature and precipitation values, with dependencies drawn from the copula described in a previous section.

The probabilistic needs assessment was then conducted over 10,000 trials with the correlated simulation of temperature and precipitation input into the life expectancy model for each emissions scenario. The random simulation of the uncertain life was then conducted as in Scenario 1A. The resulting probabilistic needs assessment indicated an average value of \$1.798 billion for replacing 3,712 (23.0%) "failed" structures under the low-emissions scenario; and \$1.801 billion for replacing 3,720 (23.1%) "failed" structures under the moderately high-emissions scenario. At 90% confidence, it was found that a minimum value of \$1.855 billion for replacing 3,784 (23.5%) "failed" structures was needed for the low-emissions scenario; and \$1.859 billion for replacing 3,790 (23.5%) "failed" structures for the moderately high-emissions scenario. These results suggest that if the agency seeks to increase the confidence of its needs assessment to 90%, a contingency amount of \$57 million is needed under the low-emissions scenario and \$58 million is needed under the moderately high-emissions scenario. For 99.99% confidence, \$176 million and \$178 million are needed for the low- and moderately high-emission scenarios, respectively.

In comparing the estimates, it was found that, on average, the uncertain climate will result in additional needs of \$49 million and \$52 million over the next 15 years for bridge replacement projects given the low- and moderately high-emissions scenarios, respectively (Figure 6-29).

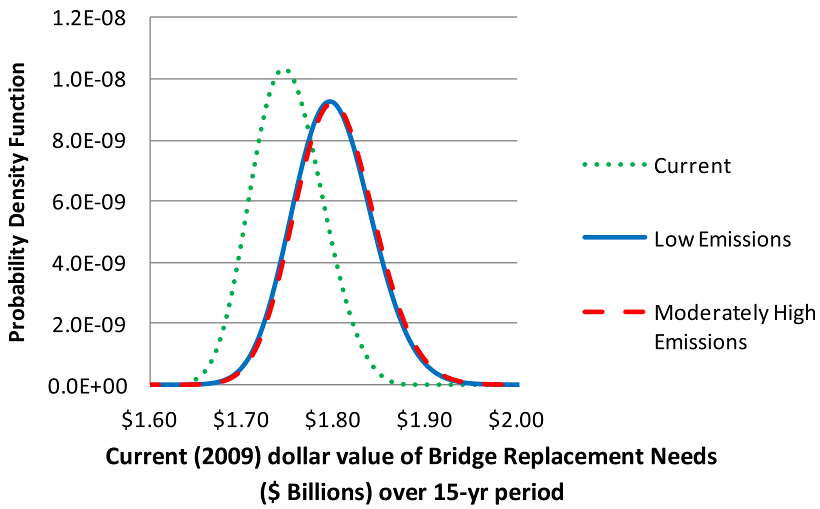


Figure 6-29. Uncertainty in the assessed need for bridge replacement over 15-year period, for different emissions scenarios (Climate Conditions).

In terms of the number of structures needing replacement, it was found that, on average, an additional 92 to 100 replacements (0.6% of the stock) were required (Figure 6-30).

The needs amount corresponding to different confidence levels are reflective of the stochastic dominance of the moderately high-emissions scenario over the low-emissions scenario and the current (or "no-change") emissions scenario (Figure 6-31).

6.3.2.2 Condition-based Probabilistic Needs Assessment

Although age-based models are more commonly used for fiscal analysis, a condition-based needs prediction was also assessed for the remaining life of the current asset stock in order to accommodate possible variations in maintenance activity decisions. Two risk assessments

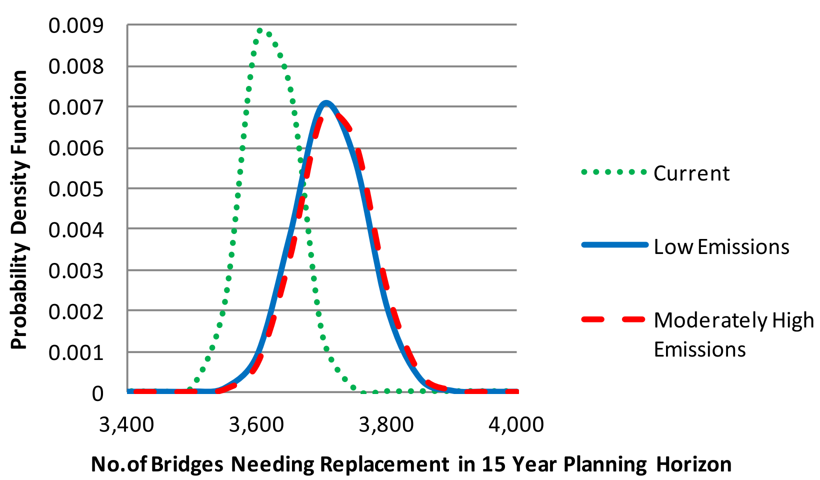


Figure 6-30. Uncertainty in the number of bridges needing replacement within planning horizon, for different emissions scenarios (Climate Conditions).

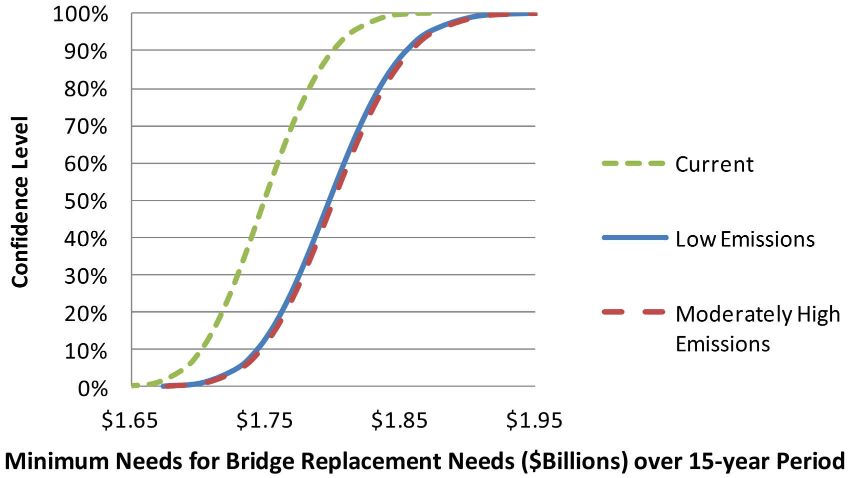


Figure 6-31. Bridge replacement needs in current (2009) dollars, within planning horizon, for different confidence levels and climate conditions.

were carried out with varying definitions of life and varying maintenance/preservation policies:

A. Simulation of bridge life, with respect to superstructure and substructure condition, assuming no remaining major maintenance activities other than deck replacements; and
B. Simulation of bridge life, with respect to superstructure and substructure condition, assuming superstructure and substructure rehabilitation activities (assume life extensions beyond remaining time within planning horizon) at the time of deck replacement.

Condition-based probabilistic needs assessments are particularly beneficial where the agency seeks to assess asset life corresponding to different end-of-life thresholds, evaluate different condition-based maintenance or preservation policies or strategies, or investigate the relative impacts of different end-of-life criteria on asset life and/or identify the dominant criterion. For instance, if agency experts expect the substructure rating criterion to dominate all other criteria in bridge life assessment, then the most beneficial action, in terms of extending the life of the entire bridge, would be one that enhances substructure condition or life. The main disadvantages of this approach are the inability to adjust directly for climate covariates, unless sufficient data are available to model transition probabilities as a function of such independent factors. However, the acceleration parameters found for the covariate models can be used to scale the condition-based survival curves.

To predict the remaining life of the bridge models, a Beta distribution was fit to the remaining life according to the Markov chain with an initial state vector corresponding to the current age and respective condition state. To simulate multiple correlated life estimates based on each "end-of-life criterion," a copula was fit based on the current median life predictions of the current Indiana NBI stock.

The correlation matrix (Table 6-10) between the remaining deck, superstructure, and substructure life showed a strong correlation between the remaining life of the bridge elements.

To probabilistically model this dependence, a multivariate copula was fit to represent the correlation between deck life, superstructure life, and substructure life. The best fitting copula was found to be of the Clayton form ($\alpha = 3.758$) with $-$SIC = 16,272.87, $-$AIC = 16,280.67, and $-$HQIC = 16,278.11.

Table 6-10. Correlation matrix of remaining Indiana deck, superstructure, and substructure life.

	Deck RL	Superstructure RL	Substructure RL
Deck RL	1	0.74	0.70
Superstructure RL	0.74	1	0.81
Substructure RL	0.70	0.81	1

By randomly sampling the dependency from the copula and the remaining life for decks, superstructures, and substructures from the Beta distributions for every asset in the active Indiana bridge stock, the total current (2009) dollar value of the replacement needs was quantified.

In Scenario 2A, it was found that in 2009, the current dollar value of median fiscal replacement needs was $1.962 billion with 3,884 bridges (24.12% of stock) requiring total replacement (Figures 6-32 and 6-33) and $850 million (Figure 6-34) for 5,466 deck replacements (Figure 6-35). These results correspond to an overall fiscal need, excluding minor maintenance/preservation activities, of $2.811 billion (Figure 6-36). For 90% confidence, it was found that a minimum of $2.865 billion would be needed (Figure 6-37); over 3,821 (24% of stock) to 3,944 (25% of stock) structures would need total bridge replacement; and 5,386 (33% of stock) to 5,545 (34% of stock) would need deck replacement. Therefore, to improve confidence from 50% to 90%, an overall additional (contingency) fund of $54 million should be set aside in 2009. For 99.99% confidence, an additional (contingency) of $175 million is needed.

In Scenario 2B, with the same copula dependency and Beta distributions, a correlated Monte Carlo simulation was performed. If the remaining superstructure or substructure life dominated the remaining deck life and end of life occurred within the next 15 years, then the full replacement cost was added to the assessed needs. If the remaining deck life dominated and end of life occurred within the next 15 years, then the sum of the costs in Table 6-11 was added to the assessed needs.

The life extension of the rehabilitation activities was assumed to extend beyond the remaining time within the planning horizon. This is considered reasonable with life extension estimates of 25 years for superstructure life and 20 years for substructure life (Sinha et al., 2009). Probabilistic estimates of the treatment life can be incorporated in future research.

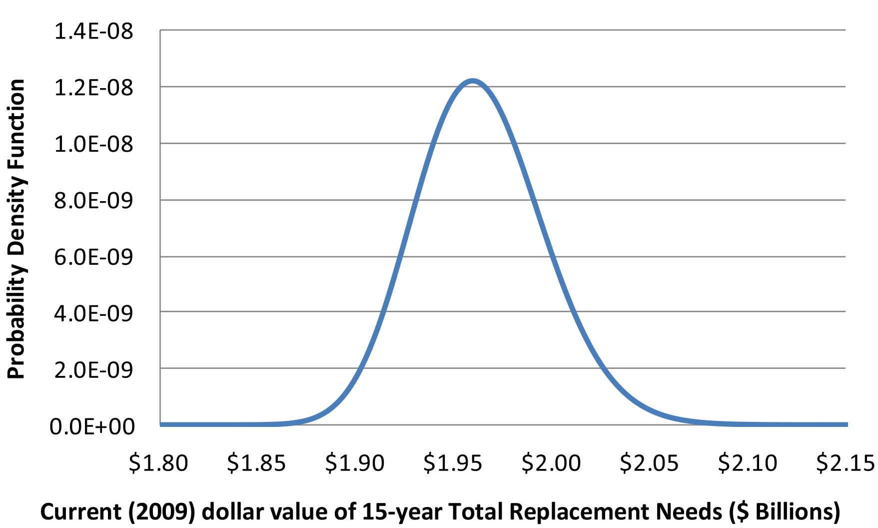


Figure 6-32. Uncertainty in the needs for total bridge replacement over 15-year period assuming replacement-only policy.

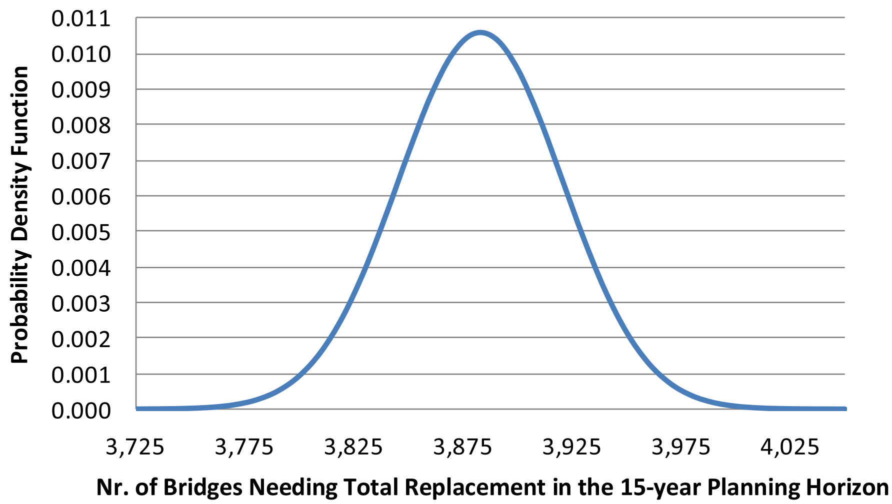


Figure 6-33. Uncertainty in number of bridges needing total replacement assuming replacement-only policy.

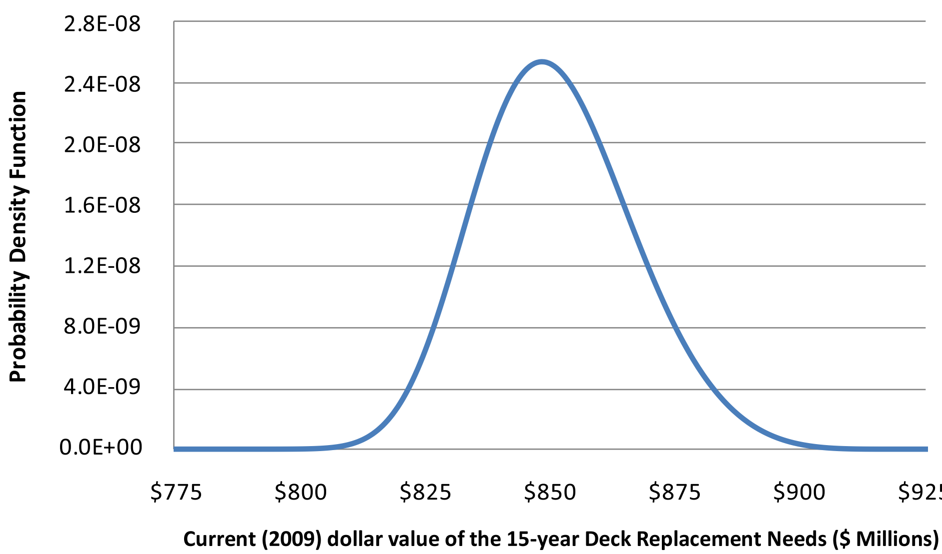


Figure 6-34. Uncertainty in the assessed need for bridge deck replacement over 15-year period assuming replacement-only policy.

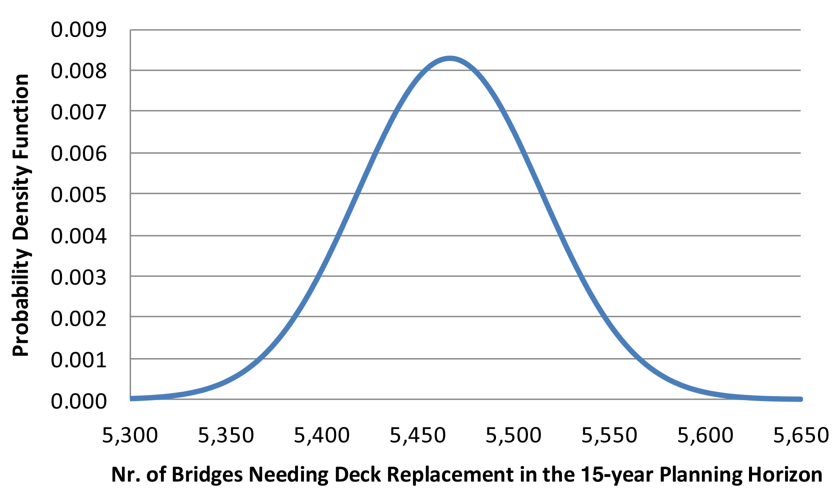


Figure 6-35. Uncertainty in the number of bridge deck replacements.

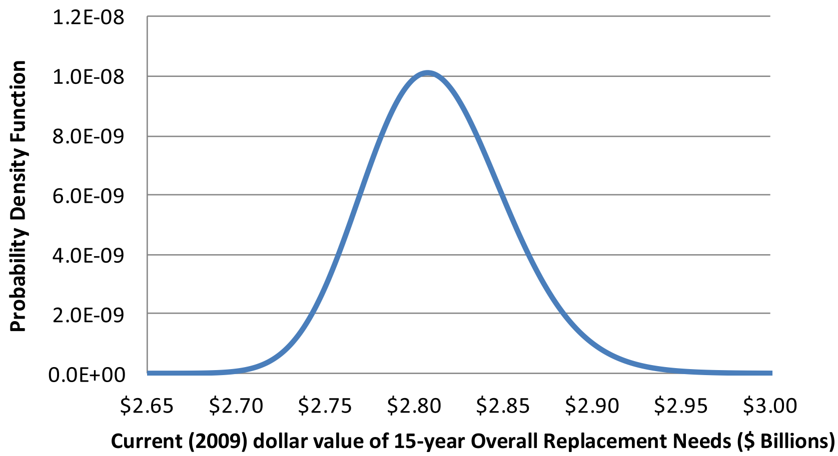


Figure 6-36. Uncertainty in the assessed need for total bridge replacement needs over 15-year period; assuming replacement-only policy.

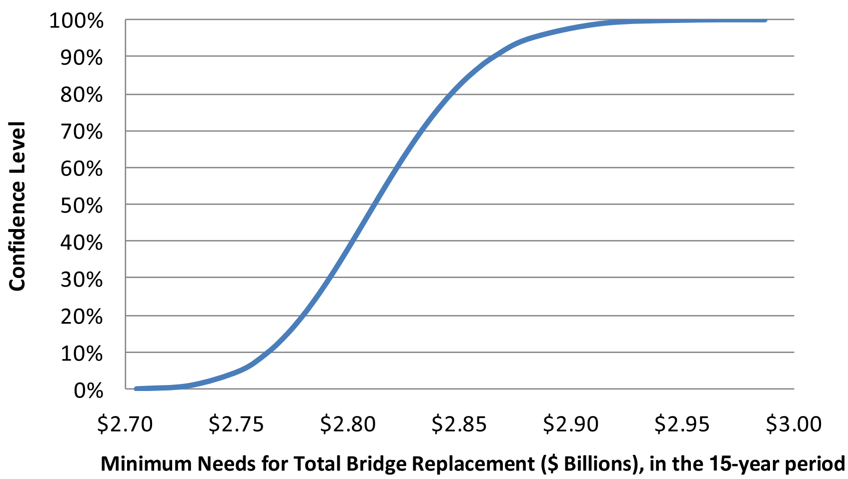


Figure 6-37. Minimum needs for total bridge replacement within planning horizon, for replacement-only policy, at different confidence levels.

Table 6-11. Deck replacement, superstructure rehabilitation, and substructure rehabilitation costs (Sinha et al., 2009).

Cost Item	$Cost = a * L^b * W^c$
Deck Replacement	a = 0.035; b =1; c = 1
Superstructure Rehabilitation	a = 0.0035; b = 1; c = 1
Substructure Rehabilitation	a = 0.010; b = 1; c = 1

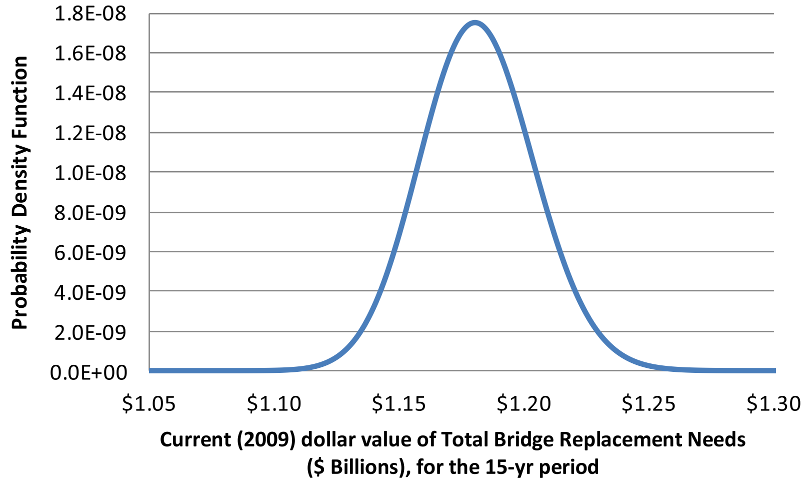


Figure 6-38. Uncertainty in assessed need for total bridge replacement needs over 15-year period assuming replacement & rehabilitation policy.

Following this approach, it was found that, on average, $1.181 billion would be needed for bridge replacement (Figure 6-38) and $1.143 billion for deck replacement, superstructure rehabilitation, and substructure rehabilitation (Figure 6-39). In applying this preservation policy, 2,149 bridges (90% C.I. = [2,115, 2,185]) required total replacement (Figure 6-40). Overall, this need corresponds to $2.324 billion in current dollar value of fiscal needs (Figure 6-41). For 90% confidence, it was found that at least $2.363 billion was needed for overall replacement needs. These findings would suggest that contingency funds, relative to the median, for 90% confidence should be $38 million and $122 million for 99.99% confidence.

In comparing the needs associated with the replacement-only and the replacement + rehabilitation policies, it was determined that an overall average of $487 million could be saved (in the form of reduced need) if the latter policy were adopted. This corresponds to a $781 reduction in the overall cost of total bridge replacement and a $293 million increase in deck replacement/rehabilitation cost, relative to the replacement-only policy.

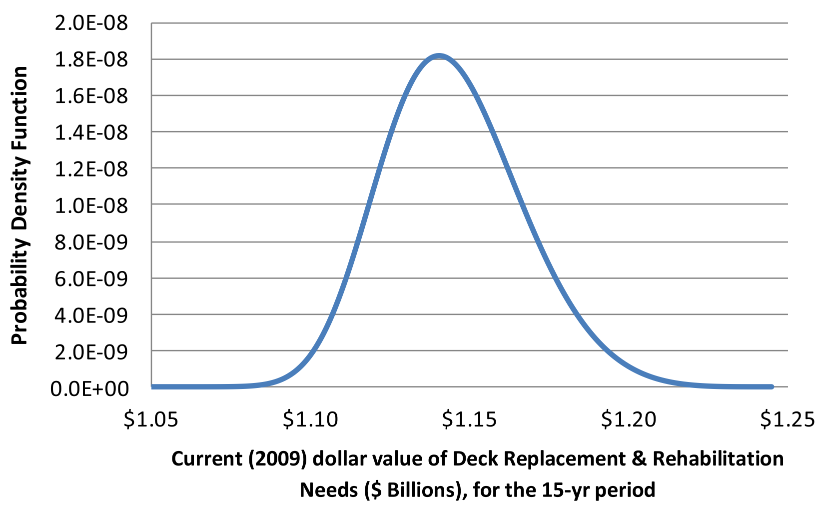


Figure 6-39. Uncertainty in the assessed need for Indiana NBI bridge deck replacement needs over 15-year period; assuming replacement+rehabilitation policy.

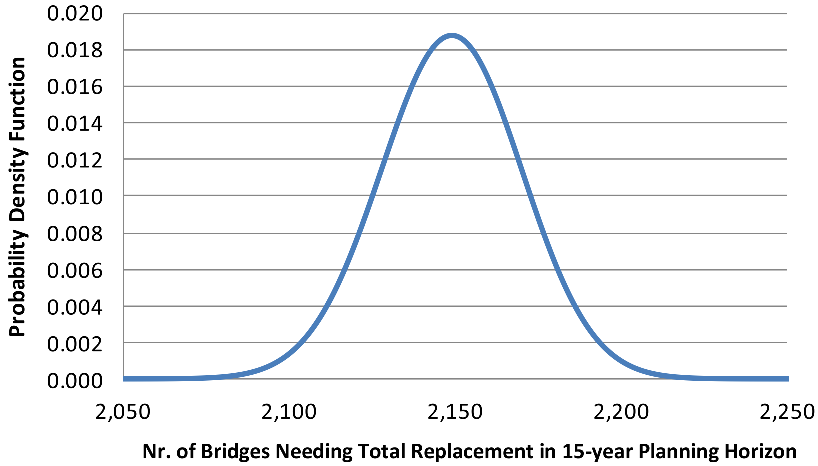


Figure 6-40. Uncertainty in the number of Indiana NBI bridges needing total replacement over 15-year period; for the replacement+rehabilitation policy.

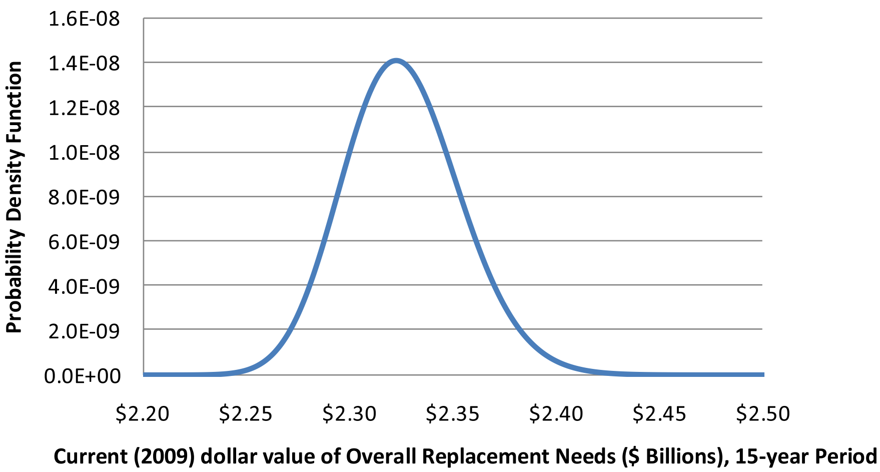


Figure 6-41. Uncertainty in the assessed need for overall bridge replacement over 15-year period assuming replacement & rehabilitation policy.

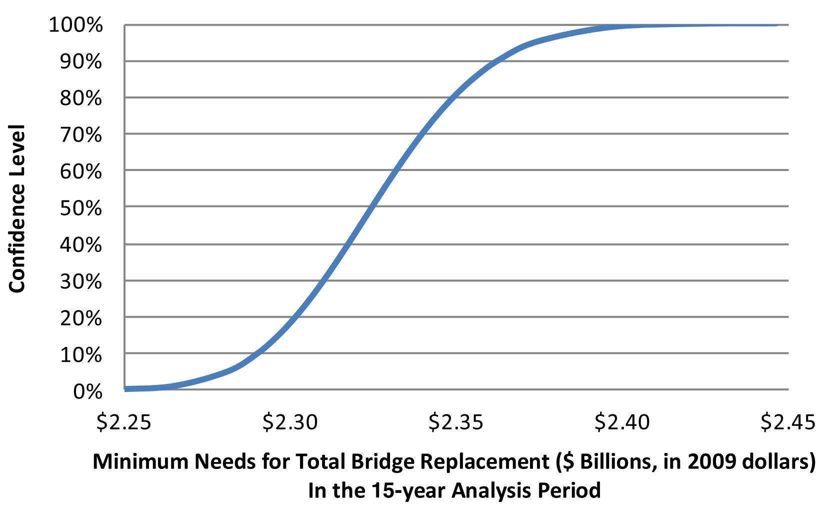


Figure 6-42. Minimum needs for total bridge replacement within planning horizon for the replacement+rehabilitation policy, at different confidence levels.

For the age-based approach, over the next 15 years, the replacement costs associated with the replacement-only policy were found to be 12% higher compared with the replacement+rehabilitation policy (see Figure 6-42). These results suggest that sufficiency ratings are a less restrictive measure than the applied condition-based definition of life and that the preservation policy is an improvement over those that lead to sufficiency-based survival durations.

6.3.2.3 Deterministic Needs Assessments

Expert opinion is often used for fiscal needs assessments, particularly where it is assumed that all assets of a certain type will survive to a certain point estimate of life and thus blanket replacements of all assets in a specific age cohort will be carried out at a certain point in time. The risk of assuming any point estimate of life therefore can be assessed in comparison to probabilistic estimates of needs. To demonstrate this approach, a deterministic needs assessment was conducted under six scenarios:

A. Single point estimate of asset life;
B. Deterministic application of Scenario 1A;
C. Deterministic application of Scenario 1B;
D. Deterministic application of Scenario 1C;
E. Deterministic application of Scenario 2A;
F. Deterministic application of Scenario 2B.

In Scenario 3A, a needs assessment was conducted under the assumption that various point estimates of life will be realized by each asset (Figures 6-43 and 6-44). For instance, if the life is assumed to be 60 years, then $760 million, covering 2,303 bridge replacements (14.3% of stock), is needed. However, as demonstrated in the previous sections, this estimate significantly underestimates fiscal needs. If that is the case, the use of a 60-year point estimate would place the agency at risk, on average, of underestimating the needs by $421 million to $1.202 billion in fiscal needs and underestimating total physical replacement needs by 1,581 structures to overestimating needs by 154 structures (Table 6-12).

For the remaining subscenarios, the deterministic application of the developed models was assessed. This approach, considered to be the most commonly applied, along with historical projections based on previous expenditures (Sinha et al., 2005), assumes that all structures will survive to their median life estimate. Intuitively, this technique makes sense on a project-level; however, the odds of an entire network converging to the respective median value is highly improbable. In reality, the full survival curve should be considered.

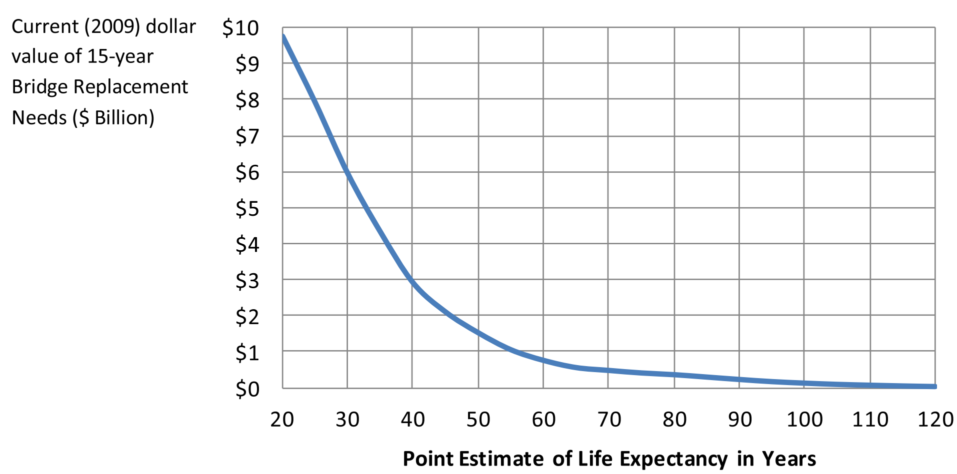


Figure 6-43. Deterministic fiscal needs assessment for bridge replacements for different life expectancy estimates, over 15-yr period.

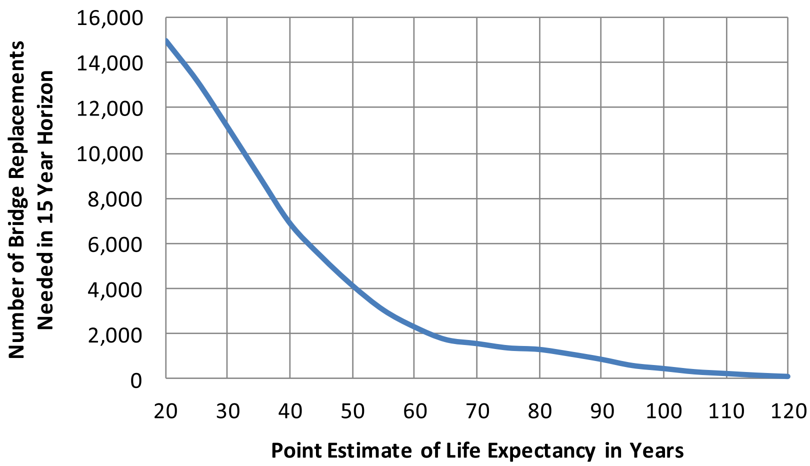


Figure 6-44. Deterministic physical needs assessment for bridge replacements for different life expectancy estimates, over 15-yr period.

Consider, for example, a set of 10 bridge assets, each predicted to have a survival probability of 60% over the next 15-year period and a replacement cost of $500,000. Under the deterministic approach, no funds would be required. Probabilistically, however, it is reasonable to consider that 40% (100%-60%) of these assets will need replacement. The mathematical expectation is then 0.40*10=4 bridges will need replacement which, at a replacement cost of $500k, equates to $2 million (4*$500k). Inversely, consider the same set of bridges had a survival probability of 40%. Under the deterministic approach, all would require replacement at a cost of $5 million (10*$500k). Probabilistically, it would be expected that 0.60*10=6 bridges will need replacement, equating to $3 million (6*$500k). In this case, the deterministic approach overestimates the needs by $2 million. Therefore, the deterministic approach only becomes a balanced measure for estimating needs when there is an equivalent number of assets below and above the median life estimate (Figure 6-45). Considering that agencies keep a minimal number of assets beyond the life estimate (see Figure 6-48), it can be seen that agencies will tend to significantly underestimate needs.

Over a larger stock (e.g., Indiana NBI bridge stock = 16,100), it can thus be inferred that there is a significant risk of underestimating long-term fiscal needs. To demonstrate how to quantify this risk, needs assessments of the previously presented scenarios were conducted. Also, to quantify the extent of underestimation of needs using the deterministic approach, assessments under each of the previously presented scenarios were conducted.

In Scenario 1, the age-based approach was used to estimate the needs based on the conditional time until a bridge reaches a sufficiency rating of 50%. As part of Scenario 1A, the deterministic needs, assuming the current climatic conditions, were found to be $794 million and 1,950

Table 6-12. Risk of underestimating long-term fiscal needs by scenario, assuming a 60-yr life for all bridge structures.

Scenario	Fiscal Need Under(Over)-estimated, Relative to Median Value	Physical Need Under(Over)-estimated, Relative to Median Value
1A	$989 million	1,317 structures
1B	$1.038 billion	1,409 structures
1C	$1.041 billion	1,417 structures
2A	$1.202 billion	1,581 structures
2B	$421 million	(154) structures

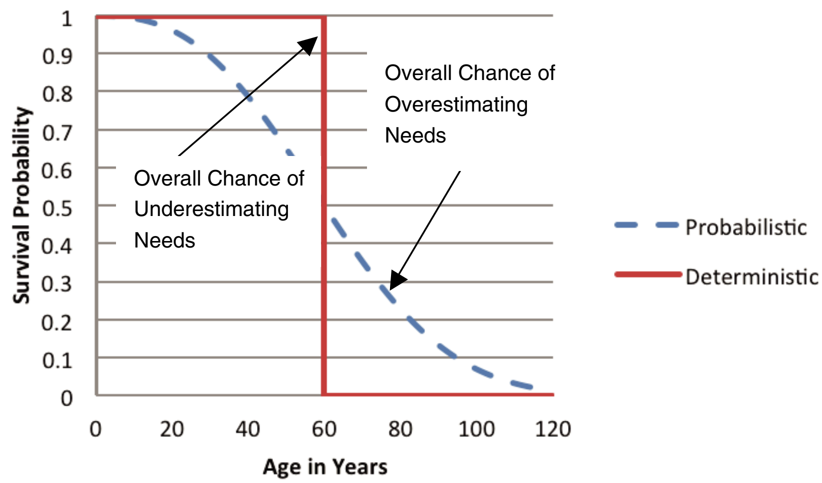


Figure 6-45. Example showing possible extent of need under- or over-estimation by assuming deterministic estimates of asset life.

replacements (12.11% of stock). This is found through a derivation of the conditional Weibull survival function:

$$\$\text{ Needs} = \sum_{j=1}^{16,100} \text{Repl. Cost}_j * \frac{1}{(1+i)^{RL_j}}, \forall \text{ RL} < 15$$

$$\text{if Suff. Rating}_j \leq 50\%, \text{RL}_j = 0$$

$$\text{else,} \qquad \text{RL}_j = \beta_j \sqrt[a]{-ln\left(0.5 * e^{\left(\frac{Age_j}{\beta_j}\right)^a}\right)} - Age_j$$

Where conditional survival was not considered, it was found that the needs would have been estimated at $1.154 billion and 2,803 replacements (17.41% of stock), which demonstrates the importance of updating survival probabilities. Thus, the deterministic, conditional survival estimate would put an agency at risk for underestimating fiscal needs by $955 million and physical needs by 1,670 replacements.

For Scenarios 1B and 1C, the same calculation was performed using the estimated future climatic conditions for the two emission scenarios, resulting in new β_j values. Under Scenario 1B, with an expected temperature change of 2.6 and precipitation change of +4%, the deterministic fiscal needs were evaluated at $803 million and 1,999 replacements (12.42% of stock) for the low-emissions scenario. Under Scenario 1C, with an expected temperature change of 2.7 and precipitation change of +5%, identical deterministic estimates of fiscal and physical needs were found for the moderately high-emissions scenario due to insignificant changes in expected climatic conditions between the emissions scenarios.

Finally, a deterministic application of remaining life, using the condition-based approaches under different maintenance/preservation policies, was assessed. In the case of replacement-only policies, i.e., no-rehabilitation activities, a deterministic fiscal and physical estimate of $1.566 billion and 3,526 of the active bridges requiring total replacement (21.90% of stock with 76.34% "failing" due to the superstructure end-of-life measure) were obtained, respectively. This corresponds to an additional $775 million and 5,644 bridge decks (35.06% of stock) requiring replacement throughout the total structure life, resulting in an overall fiscal need of $2.342 billion. As a result, an agency would be at risk for underestimating fiscal needs by $469 million and physical needs by 358 active bridges requiring replacement, as well as an overestimation of 178 active decks requiring replacement.

When the designated preservation policy was applied, fiscal needs were found to be $450 million for bridge replacement and $1.267 billion for rehabilitation and deck replacement activities and physical needs were found to be 985 replacements (6.12% of stock) and 6,615 maintenance activities (41.09% of stock). The overall fiscal need determined using this approach is $1.717 billion, representing a savings of $625 million compared to the replacement-only policy. The resulting risk associated with using a purely deterministic approach was found to underestimate fiscal needs by $731 million and physical needs by 1,164 active bridge requiring total replacement and a 1,153 overestimation of active decks requiring replacement, compared to the replacement-only policy.

As demonstrated in this section, agencies that do not consider the uncertainty in life estimates are at great risk for underestimating, and sometimes overestimating, fiscal and physical needs. A deterministic estimate of life across a network does not translate into an appropriate estimate of needs. Instead, it is recommended to conduct probabilistic risk assessments of life, or, at the very least, to calculate the sum of expected needs across the network (van Noortwijk & Klatter, 2004). This approximation can be obtained by using the conditional survival curve:

$$E\left[Fiscal\ \ Needs\right] = \sum\nolimits_{j=1}^{n} Cost_j * \bar{S}\left(t_j + Planning\ \ Horizon\right)$$

6.4 Summary

In this chapter, uncertainty assessments were conducted to quantify the effects of uncertain climate on asset life and also of the propagating risk of uncertain asset life on fiscal and physical needs assessments.

Sensitivity analysis techniques were demonstrated at the project level, assuming typical characteristics for various asset classes. Findings included

- Bridge life is significantly influenced by NHS status (an indication of the balance between the effort of higher load and/or superior design features).
- Box culvert life is most influenced by Interstate status, followed closely by material type.
- Pipe culvert life is heavily dependent on precipitation levels.
- Traffic signal life is influenced most by roadway functional class of traffic sign location.
- Flasher life is affected primarily by the mounting location.
- Roadway lighting life is most significantly influenced by the mounting type.

In terms of one-way sensitivity to uncertain annual temperature and precipitation values, the life extensions and reductions for a range of 3°F and a range of −12% to +15% change in precipitation (in.) were assessed (Table 6-13). It was found that climate will have a significant effect on life. It was observed that precipitation has no significant effect on roadway lighting life. These findings, like all others in the case studies in this report, are based on the data used for the study. As such, further studies by agencies using their local data are recommended. In this report, the possible effects of correlated climate variables on asset life were investigated using simulation.

Project-level risk assessments were conducted to further evaluate the joint effects of uncertain climate under two emissions scenarios (Table 6-14). Given the parameter estimates for the climate variables and the set of project-level characteristics used in the sensitivity analysis, it was found that bridges, box culverts, and flashers were likely to have a shorter life as a result of uncertain climate. Pipe culverts, traffic signals, and roadway lighting were found to have increased life in the future climate conditions due to the predicted levels of temperature and precipitation that appear to be more favorable to asset longevity.

Table 6-13. Summary of one-way sensitivity analysis of climate conditions for typical project-level characteristics.

Asset Class	Range of Median Life Estimates Based on Uncertain Temperature	Range of Median Life Estimates Based on Uncertain Precipitation
Bridges	-1 year	-1 year
Box Culverts	-6 months	+2 yrs
Pipe Culverts	+24 yrs	-57 yrs
Traffic Signals	-1 yr	+6 yrs
Flashers	-3 yrs	-16 yrs
Roadway Lighting	+11 yrs	--

After demonstrating the project-level risk assessments, this chapter also conducted network-level risk assessments on the basis of the individual project-level assessment to quantify the influence of uncertain life on long-term system-wide fiscal and physical needs. Multiple scenarios were examined using the Indiana NBI bridge data as an illustration. The covariate and non-covariate models developed earlier were used to simulate the bridge lives (Table 6-15):

- Scenario 1A: Age-based probabilistic assessment of replacement needs assuming no change in climatic conditions;
- Scenario 1B: Age-based probabilistic assessment of replacement needs assuming uncertain climatic conditions under the low-emissions case;
- Scenario 1C: Age-based probabilistic assessment of replacement needs assuming uncertain climatic conditions under the moderately high-emissions case;
- Scenario 2A: Condition-based probabilistic assessment of replacement needs assuming no remaining major maintenance activities;
- Scenario 2B: Condition-based probabilistic assessment of replacement needs assuming a policy of rehabilitating the superstructure and substructure at the time of deck replacements;
- Scenario 3A: Expert-opinion-based deterministic assessment of replacement needs based on a single point estimate of life for all bridges;
- Scenario 3B: Deterministic assessment of replacement needs based on a median value from Scenario 1A;

Table 6-14. Summary of probabilistic risk analysis of climate conditions for typical project-level characteristics.

(a) Low-emissions Scenario

Asset Class	Average Change in Median Life Estimate	Probability of Lower Future Median Life
Bridges	-1.09 years	99.31%
Box Culverts	-1.80 months	65.57%
Pipe Culverts	+17.32 yrs	8.30%
Traffic Signals	+4.98 yrs	<0.01%
Flashers	-4.50 yrs	90.06%
Roadway Lighting	+10.89 yrs	<0.01%

(b) Moderately High-emissions Scenario

Asset Class	Average Change in Median Life Estimate	Probability of Lower Future Median Life
Bridges	-1.16 years	99.47%
Box Culverts	-1.08 months	58.71%
Pipe Culverts	+16.22 yrs	11.88%
Traffic Signals	+5.14 yrs	<0.01%
Flashers	-5.03 yrs	90.32%
Roadway Lighting	+11.41 yrs	<0.01%

Table 6-15. Comparison of risk-based vs. deterministic needs assessments for Indiana NBI bridges, 2009–2023.

Scenario	Median Funding Needs for Total Replacement ($ billion)	Additional (Contingency) Need at 90% Confidence ($billion)*	Median Physical Needs Nr of Bridges Requiring Replacement)	Physical Needs 90% Confidence Interval ($ billion)
1A	1.749	0.051	3,620	[3,554, 3,686]
1B	1.798	0.057	3,712	[3,622, 3,805]
1C	1.801	0.058	3,720	[3,628, 3,811]
2A	1.962	0.044	3,884	[3,821, 3,944]
2B	1.181	0.030	2,149	[2,115, 2,185]
3A (Assumed 60 yr life)	0.760	--	2,303	--
3B	0.794	--	1,950	--
3C	0.803	--	1,999	--
3D	0.803	--	1,999	--
3E	1.566	--	3,526	--
3F	0.45 0	--	985	--

*Relative to the deterministic scenario; Column 3 = assessed need at 90% confidence less median value in column 2.

- Scenario 3C: Deterministic assessment of replacement needs based on a median value from Scenario 1B;
- Scenario 3D: Deterministic assessment of replacement needs based on a median value from Scenario 1C;
- Scenario 3E: Deterministic assessment of replacement needs based on a median value from Scenario 2A; and
- Scenario 3F: Deterministic assessment of replacement needs based on a median value from Scenario 2B.

In comparing the hybrid condition/age-based needs assessments, it was found that the uncertain climate will likely cause an increase in 15-year bridge replacement fiscal needs by $49 to $52 million, corresponding to physical needs of 92 to 100 bridge replacement, depending on emission levels.

In comparing the condition-based needs assessments, it was found that by pursuing the policy of rehabilitating the superstructure and substructure at the time of deck replacements, the overall fiscal replacement needs could be lowered by $487 million, corresponding to a reduction of total physical replacement needs by 1,735 structures.

It is observed that the use of deterministic life estimates places the agency at a greater risk of underestimating its long-term needs. For example, for the case study considered in this report, a deterministic bridge life of 60 years would result in an underestimation of physical needs of as much as 1,581 replacements, translating into $1.202B, depending on the definition of end-of-life, emissions scenario (i.e., climatic conditions), and maintenance/preservation policy. Where median life estimates for respective individual bridges were used instead of a fixed value of life, physical needs were underestimated by as much as 1,721 structures (translating into fiscal needs underestimation of as much as $998 million).

After demonstrating the risk consequence associated with uncertain asset life expectancy estimates, it is recommended in this chapter to (1) eschew deterministic estimation of asset life and asset preservation needs and (2) to appropriate estimate to contingency funds For funding needs to cover fluctuations in asset longevity due to uncertainty of asset life factors.

In demonstrating the methodologies for uncertainty assessments, the sensitivity of the life expectancy factors and the subsequent risk to life and needs assessments were quantified. Agencies can use this framework to improve decision-making and mitigate potential risks through probabilistic estimates.

CHAPTER 7

Summary and Conclusions

7.1 Study Overview

This report documents the research that developed a methodology for determining the life expectancies of major types of highway system assets for use in lifecycle cost analyses supporting management decision making. The study demonstrated the application of the methodology for different asset types. Finally, the study developed a guidebook and resources that can be used by highway agencies and other organizations for applying the methodology to develop highway maintenance and preservation programs and, ultimately, to assess the impact of such programs on system performance.

In accomplishing these project objectives, the research carried out tasks that include a review of current literature and practices within highway agencies and other industries, of the methodologies they currently use to determine life expectancy for major assets; data description and an assessment of the availability of data for estimating and predicting asset life expectancies, development of a methodology for estimating the life expectancy of major types of highway system assets, for use in lifecycle cost analyses supporting maintenance and preservation management decision making; analysis of the sensitivity of asset life expectancies to maintenance and preservation program activities; application of the methodology for estimating life expectancies of new and in-service assets for assets and demonstration of the methodology's capability to show the influence of such factors as design parameters, materials quality, construction quality, service usage, environmental factors, and maintenance practices; development of a Guidebook and other resources that will assist highway agencies to implement the methodology. Also, a workshop was organized to further enhance the Guidebook.

Recognizing that many agencies incorporate deterministic estimates (often from expert opinion) of asset life in their lifecycle investment evaluations and planning decisions, this study carried out the described tasks and ultimately presented an array of probabilistic statistical techniques for life expectancy estimation that could be incorporated into asset management systems. The study also proposed a method for quantifying the effects of the uncertainty of asset life factors on asset life, as well as the uncertainty of asset life on planning decisions. To demonstrate the proposed methods, statistical models were developed for various asset types, and sensitivity analysis was conducted for each model to illustrate the impact of each asset life factor. Furthermore, to demonstrate the risk associated with long-term planning decisions, a probabilistic risk analysis of the longevity of a given class of assets in a certain state was demonstrated and it was shown how the uncertainty associated with one of the influential factors (climatic conditions) leads to risk propagation by causing uncertainty of estimates of fiscal needs for highway asset preservation.

The sections below summarize each aspect of the study and the finding from the case study, including the life expectancy modeling, use of life expectancies in highway asset management decisions, and accounting for uncertainties in asset replacement decisions. The chapter concludes by identifying areas for future research.

7.2 Life Expectancy Modeling

To provide a statistical basis for highway asset life expectancy estimates, the following general methodology was proposed: (1) identify replacement rationale, (2) define end-of-life, (3) select general approach (i.e., age-based, condition-based, or hybrid-based), (4) select modeling technique (i.e., duration model, Markov-based duration models), and (5) fit model to data.

In demonstrating the methodology on the collected dataset, the following median life estimates were obtained for the given end-of-life definition: 60 years for bridges, 55 to 90 years for box culverts, 30 years for pipe culverts, 19 years for traffic signals, 28 years for flashers, and 100 years for roadway lighting.

7.3 Use of Life Expectancies in Highway Asset Management Decisions

Applications of life estimates at an operational, tactical, and strategic level of management were provided, with an emphasis on lifecycle cost analysis, project prioritization, and needs assessment. Numerical examples included the basic calculations of LCCA measures to compare alternative preservation activities, justify routine preventive maintenance, identify the optimal replacement interval, compare design alternatives, compare life extension alternatives, price design and preservation activities, synchronize replacements, and assess the value of life expectancy information. Also, examples of project ranking on the basis of the utility of remaining life and budgeting of long-term needs were presented.

7.4 Accounting for Uncertainties in Asset Replacement Decisions

Given such wide applications of life estimates in planning practices and the inherent uncertainties in asset life, a methodology was proposed and demonstrated for quantifying the effect of the uncertainty via sensitivity and risk analysis. The proposed methodology was to

1. Identify uncertainty (e.g., uncertainty in climatic conditions and uncertainty in asset life due to uncertain life expectancy factors such as climatic variations);
2. Describe the likelihood of uncertain event(s) (i.e., expert opinion or fit probability distributions to uncertainty);
3. Simulate uncertainty with respect to correlation structure (e.g., probabilistic copula dependency structures)
4. Quantify the consequences for each simulation (e.g., change in asset life prediction, change in long-term fiscal and physical needs predictions); and
5. Make decisions based on confidence in consequential outcomes (e.g., set contingency or reduce risk by data collection and/or model improvements).

This methodology was demonstrated by applying sensitivity analysis and project-level probabilistic risk analysis to the developed models and by presenting a case study for conducting a network-level probabilistic risk analysis on the developed bridge life models.

Through sensitivity analysis, it was found that bridge life was most affected by NHS status; box culvert life was most influenced by Interstate status, closely followed by material type; pipe culvert life was heavily dependent on precipitation levels; traffic signal life was influenced mostly by roadway functional class; flasher life was affected primarily by mounting location; and roadway lighting life was most significantly influenced by mounting type.

In addition, it was found that climate effects could significantly impact asset life, resulting in the need for probabilistic risk analysis techniques. A project-level risk analysis of climate by emissions scenario for the asset classes showed median life estimates to vary by −1.09 to −1.16 years for bridges, −1.80 to −1.08 months for box culverts, +17.32 to +16.22 years for pipe culverts, +4.98 to +5.14 years for traffic signals, −4.50 to −5.03 years for flashers, and +10.89 to +11.41 years for roadway lighting.

At the network level, various end-of-life definitions, climatic conditions, modeling techniques, and preservation policy scenarios were examined to assess the risk of uncertain life on long-term fiscal and physical needs for the Indiana bridge stock. Through the analysis scenarios, it was found that

- Uncertain climatic conditions, on average, are expected to place the example agency at risk for an additional \$49 to \$52 million, corresponding to 92 to 100 bridge replacements over a 15-year planning horizon.
- For 90% confidence in total bridge replacement needs, a contingency fund of \$30 to \$58 million is needed, depending on the climatic conditions estimate, preservation policy, and end-of-life definition.
- A preservation policy of rehabilitating superstructures and substructures at the time of deck replacements was found to save, on average, \$487 million, relative to the replacement-only policy.
- If expert opinion places bridge life at 60 years and this value is used deterministically for needs assessment, then fiscal needs would be underestimated by \$421 million to \$1.202 billion, corresponding to a physical needs assessment ranging from 1,581 replacement underestimations to 154 replacement overestimations depending on the definition of life, climatic conditions, and maintenance/preservation policies.
- A deterministic application of the developed models was found to underestimate physical needs by 358 to 1,721 structures corresponding to underestimation of fiscal needs by \$396 million to \$998 million.

To ensure that agencies have sufficient funds for keeping assets in service, the probabilistic risk analyses conducted herein can be incorporated in asset management practices. Overall, these results demonstrate the need for reliable estimation of highway asset life and the use of these estimates in a probabilistic manner in order to quantify the uncertainty associated with agency processes that utilize asset life values.

7.5 Areas of Future Research

It is recommended that future research in this area address the impact evaluation of asset life factors on asset longevity, evaluation of innovative materials and construction processes, and preservation strategies that promise longer asset life, and the impact evaluation of asset longevity on agency business processes such as lifecycle-based planning and budgeting, needs assessment.

Also, future research can take a closer look at the consequences of carrying out agency business processes from a purely deterministic viewpoint. As demonstrated in this study, there is significant benefit in embracing probabilistic analyses and risk-based decision-making processes. Agencies stand to benefit from the ability to make decisions based on varying levels of confidence and the ability to capture more realistic dependencies. Thus, there is a clear and present need to continue research in areas that will support such analyses. There is considerable past and ongoing research that are contributing, in diverse ways, to this drive toward probabilistic analysis. These include probabilistic assessments of asset performance, preservation treatment effectiveness, inspection timings, planning gaps, treatment costs, and the likelihood and consequence of extreme natural or anthropogenic events.

A few areas of further research, therefore, include probabilistic quantification of maintenance activity effectiveness on asset life; assigning confidence to design and programming decisions via comparison of probabilistic lifecycle costs given the uncertainty of asset life; further analysis of climate effects on asset life; and quantifying the impacts of having improved data collection procedures with respect to model development and overall planning decisions.

Summing up, it is anticipated that enhancements in asset life estimation would help agencies identify factors that favor asset longevity and thus adopt policies and strategies aimed at increasing asset life and making the most use of taxpayer dollars. Also, more reliable estimation of asset life would lend more confidence in agency planning, programming, and budgeting processes.

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Appendices

APPENDIX A

Definitions of Life Expectancy Condition/Performance Measures

Bridges

NBI Sufficiency Rating Formula (FHWA, 1995):

1. Structural Adequacy and Safety (55% maximum)
   a. Only the lowest rating code of Item 59, 60 or 62 applies.
      If Item 59 (Superstructure Rating) or
      Item 60 (Substructure Rating) is ≤ 2 then A = 55%
      = 3 A = 40%
      = 4 A = 25%
      = 5 A = 10%
      If Item 59 and Item 60 = N and
      Item 62 (Culvert Rating) is ≤ 2 then A = 55%
      = 3 A = 40%
      = 4 A = 25%
      = 5 A = 10%
   b. Reduction for Load Capacity:
      Calculate using the following formulas where
      IR is the Inventory Rating (MS Loading) in tons or use Figure 2:
      $B = (32.4 - IR)^{1.5} \times 0.3254$
      Or
      If $(32.4 - IR) \leq 0$, then B = 0
      "B" shall not be less than 0% or greater than 55%
      $S_1 = 55 - (A + B)$
      S_1 shall not be less than 0% nor greater than 55%.
2. Serviceability and Functional Obsolescence (30% maximum)
   a. Rating Reductions (13% maximum)
      If #58 (Deck Condition) is ≤ 3 then A = 5%
      = 4 A = 3%
      = 5 A = 1%
      If #67 (Structural Evaluation) is ≤ 3 then B = 4%
      = 4 B = 2%
      = 5 B = 1%

If #68 (Deck Geometry) is	≤ 3	then	$C = 4\%$
	$= 4$		$C = 2\%$
	$= 5$		$C = 1\%$
If #69 (Underclearances) is	≤ 3	then	$D = 4\%$
			$D = 2\%$
			$D = 1\%$
If #71 (Waterway Adequacy) is	≤ 3	then	$E = 4\%$
	$= 4$		$E = 2\%$
	$= 5$		$E = 1\%$
If #72 (Approach Road Alignment) is	≤ 3	then	$F = 4\%$
	$= 4$		$F = 2\%$
	$= 5$		$F = 1\%$

$J = (A + B + C + D + E + F)$

J shall not be less than 0% nor greater than 13%.

b. Width of Roadway Insufficiency (15% maximum)
Use the sections that apply:
(1) applies to all bridges:
(2) applies to 1-lane bridges only:
(3) applies to 2 or more lane bridges:
(4) applies to all except 1-lane bridges.

Also determine X and Y:

$$X(\text{ADT/Lane}) = \frac{\text{Item 29 (ADT)}}{\text{First 2 digits of \#28 (Lanes)}}$$

$$Y(\text{Width/Lane})^* = \frac{\text{Item 51 (Bridge Rdwy Width)}}{\text{First 2 digits of \#28 (Lanes)}}$$

*A value of 10.9 meters will be substituted when item 51 is coded 0000 or not numeric.

(1) Use when the last 2 digits of #43 (Structure Type) are not equal to 19 (Culvert):

If (#51 + 0.6 meters) < #32 (Approach Roadway Width) $G = 5\%$

(2) For 1-lane bridges only, use Figure 3 or the following:

If the first 2 digits of #28 (Lanes) are equal to 01 and

$Y < 4.3$	then	$H = 15\%$
$Y \geq 4.3 < 5.5$		$H = 15\left[\frac{5.5 - Y}{1.2}\right]\%$
$Y \geq 5.5$		$H = 0\%$

(3) For 2 or more land bridges. If these limits apply.

Do not continue on to (4) as no lane width reductions are allowed.

If the first 2 digits of #28 = 02 and $Y \geq 4.9$	$H = 0\%$
If the first 2 digits of #28 = 03 and $Y \geq 4.6$	$H = 0\%$
If the first 2 digits of #28 = 04 and $Y \geq 4.3$	$H = 0\%$
If the first 2 digits of #28 $\geq$ 05 and $Y \geq 3.7$	$H = 0\%$

(4) For all <u>except</u> 1-lane bridges, use Figure 3 or the following:

If $Y < 2.7$ and $X > 50$		then	$H = 15\%$
$Y < 2.7$ and $X \leq 50$			$H = 7.5\%$
$Y \geq 2.7$ and $X \leq 50$			$H = 0\%$
If $X > 50$ but ≤ 125 and			
	$Y < 3.0$	then	$H = 15\%$
	$Y \geq 3.0 < 4.0$		$H = 15(4\text{-}Y)\%$
	$Y \geq 4.0$		$H = 0\%$
If $X > 125$ but ≤ 375 and			
	$Y < 3.4$	then	$H = 15\%$
	$Y \geq 3.4 < 4.3$		$H = 15(4.3\text{-}Y)\%$
	$Y \geq 4.3$		$H = 0\%$
If $X > 375$ but ≤ 1350 and			
	$Y < 3.7$	then	$H = 15\%$
	$Y \geq 3.7 < 4.9$		$H = 15\left[\frac{4.9 - Y}{1.2}\right]\%$
	$Y \geq 4.9$		$H = 0\%$
If $X > 1350$ and			
	$Y < 4.6$	then	$H = 15\%$
	$Y \geq 4.6 < 4.9$		$H = 15\left[\frac{4.9 - Y}{1.2}\right]\%$
	$Y \geq 4.9$		$H = 0\%$

$G + H$ shall not be less than 0% nor greater than 15%.

c. Vertical Clearance Insufficiency – (2% maximum)

If #100 (STRAHNET Highway Designation) > 0 and

#53 (VC over Deck) $\geq$ 4.87	then	I = 0%
#53 < 4.87		I = 2%

If #100 = 0 and

#53 $\geq$ 4.26	then	I = 0%
#53 < 4.26		I = 2%

$S_2 = 30 - [J + (G + H) + I]$

S_2 shall not be less than 0% nor greater than 30%

3. Essentiality for Public Use (15% maximum)
   a. Determine:
      $K = (S_1 + S_2)/85$
   b. Calculate:
      A = 15{[#29(ADT)#19(DetourLength)]/[320,000K]}
      "A" shall not be less than 0% nor greater than 15%
   c. STRAHNET Highway Designation:

If #100 is > 0	then B = 2%
If #100 = 0	then B = 0%

$S_3 = 15 - (A + B)$

S_3 shall not be less than 0% nor greater than 15%

4. Special Reductions (Use only when $S_1 + S_2 + S_3 \geq 50$)
   a. Detour Length Reduction, use Figure 4 or the following:
      $A = (\#19)^4 \times (7.9 \times 10^{-9})$
      "A" shall not be less than 0% nor greater than 5%.
   b. If the 2nd and 3rd digits of #43 (Structure Type Main) are equal to 10, 12, 13, 14, 15, 16, or 17; then
      B = 5%
   c. If 2 digits of #36 (Traffic Safety Features) = 0 C = 1%,
      If 3 digits of #36 = 0 C = 2%,
      If 4 digits of #36 = 0 C = 3%,

$S_4 = A + B + C$

S_4 shall not be less than 0% nor greater than 13%.

Sufficiency Rating = $\mathbf{S_1 + S_2 + S_3 - S_4}$

The Rating shall not be less than 0% nor greater than 100%

NBI Deck, Superstructure, and Substructure Ratings (FHWA, 1995):

Code	*Description*
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 back in light service.
0	FAILED CONDITION—out of service—beyond corrective action.

NBI Channel/Channel Protection Rating (FHWA, 1995):

Code	*Description*
N	Not applicable. Use when bridge is not over a waterway (channel).
9	There are no noticeable or noteworthy deficiencies which affect the condition of the channel.
8	Banks are protected or well vegetated. River control devices such as spur dikes and embankment protection are not required or are in a stable condition.
7	Bank protection is in need of minor repairs. River control devices and embankment protection have a little minor damage. Banks and/or channel have minor amounts of drift.
6	Bank is beginning to slump. River control devices and embankment protection have widespread minor damage. There is minor stream bed movement evident. Debris is restricting the channel slightly.
5	Bank protection is being eroded. River control devices and/or embankment have major damage. Trees and brush restrict the channel.
4	Bank and embankment protection is severely undermined. River control devices have severe damage. Large deposits of debris are in the channel.
3	Bank protection has failed. River control devices have been destroyed. Stream bed aggradation, degradation or lateral movement has changed the channel to now threaten the bridge and/or approach roadway.
2	The channel has changed to the extent the bridge is near a state of collapse.
1	Bridge closed because of channel failure. Corrective action may put back in light service.
0	Bridge closed because of channel failure. Replacement necessary.

NBI Deck Geometry Rating (FHWA, 1995):

Rating taken as minimum of Table A-1 through Table A-3.

Table A-1. Deck geometry rating by comparison of adt to bridge roadway width, curb-to-curb.

Code	Bridge Roadway Width 2 Lanes: 2 Way Traffic						Bridge Roadway Width 1 Lane: 2-way Traffic	
	ADT (both directions)						ADT (both directions)	
	0-100	101-400	401-1000	1001-2000	2001-5000	>5000	0-100	>100
9	>9.8	>11.0	>12.2	>13.4	>13.4	>13.4	--	--
8	9.8	11.0	12.2	13.4	13.4	13.4	>4.9	--
7	8.5	9.8	11.0	12.2	13.4	13.4	4.6	--
6	7.3	8.5	9.1	10.4	12.2	13.4	4.3	--
5	6.1	7.3	7.9	8.5	10.4	11.6	4.0	--
4	5.5	6.1	6.7	7.3	8.5	9.8 (8.5)*	3.7	--
3	4.9	5.5	6.1	6.7	7.9	9.1 (7.9)*	3.4	<4.9
2	Any width less than required for a rating code of 3 and structure is open							
0	Bridge closed							
*Use value in parenthesis for bridges longer than 60 meters								

Table A-2. Deck geometry rating by comparison of number of lanes to bridge roadway width, curb-to-curb.

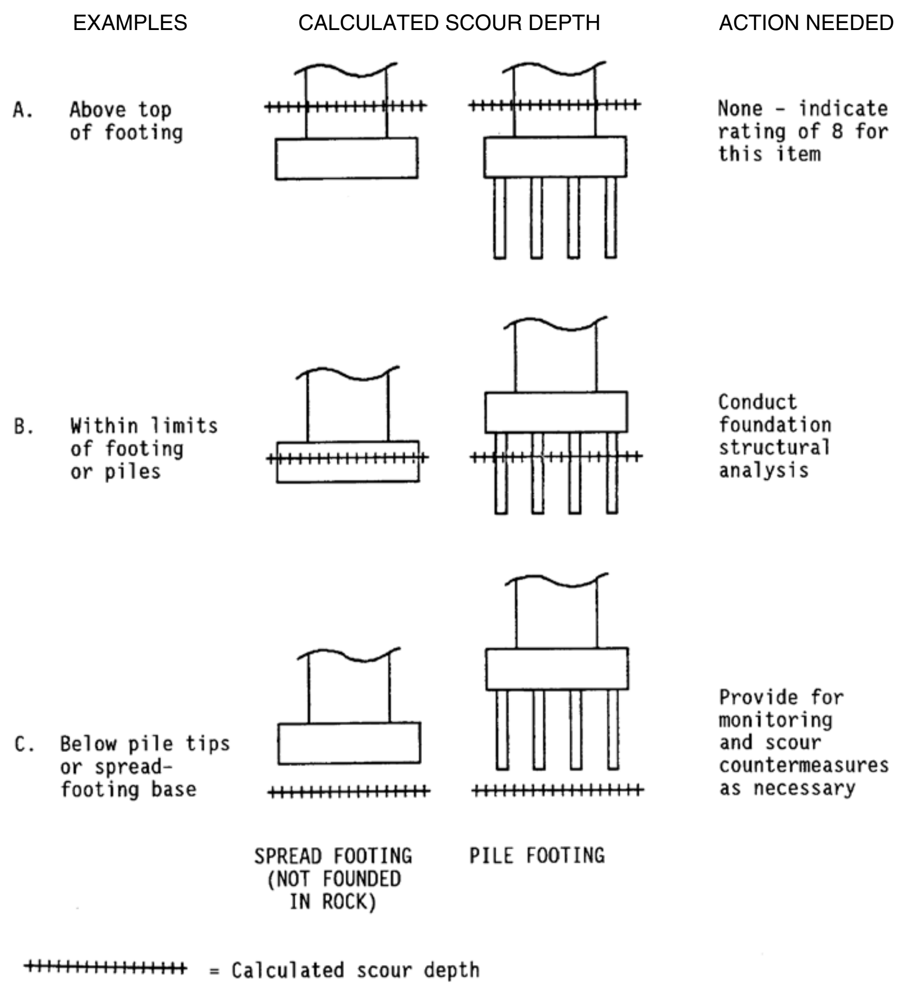
Code	Bridge Roadway Width 2 or More Lanes				Bridge Roadway Width 1-way Traffic	
	Interstate and Other Divided Freeways		Other Multilane Divided Facilities		Ramps Only	
	2 Lanes 1-way	3 or more Lanes	2 Lanes 1-way	3 or more Lanes	1 Lane	2 or more Lanes
9	>12.8	>3.7N+7.3	>12.8	>3.7N+5.5	>7.9	>3.7N+3.7
8	12.8	3.7N+7.3	12.8	3.7N+5.5	7.9	3.7N+3.7
7	12.2	3.7N+6.1	11.6	3.7N+4.6	7.3	3.7N+3.0
6	11.6	3.7N+4.9	11.0	3.7N+3.7	6.7	3.7N+2.4
5	11.0	3.7N+4.3	10.1	3.4N+3.0	6.1	3.7N+1.8
4	10.4 (8.8)*	3.4N+3.7 (3.4N+2.1)*	9.1	3.4N+1.8	5.5	3.7N+1.2
3	10.1 (8.5)*	3.4N+3.4 (3.4N+1.8)*	8.2	3.4N+1.5	4.9	3.7N+0.6
2	Any width less than required for a rating code of 3 and structure is open					
0	Bridge closed					
*Use value in parenthesis for bridges longer than 60 meters N = Total number of lanes of traffic on the structure.						

Table A-3. Deck geometry rating by comparison of functional class to bridge roadway width, curb-to-curb.

Code	Minimum Vertical Clearance		
	Functional Class		
	Interstate and Other Freeway	Other Principal and Minor Arterial	Major and Minor Collectors and Locals
9	>5.18	>5.02	>5.02
8	5.18	5.02	5.02
7	5.10	4.72	4.72
6	5.02	4.41	4.41
5	4.80	4.34	4.34
4	4.57	4.26	4.26
3	Vertical clearance less than value in rating code of 4 and requiring corrective action.		
2	Vertical clearance less than value in rating code of 4 and requiring replacement.		
0	Bridge closed.		

NBI Scour Protection Rating (FHWA, 1995):

Code	*Description*
N	Bridge not over waterway.
U	Bridge with "unknown" foundation that has not been evaluated for scour. Since risk cannot be determined, flag for monitoring during flood events and, if appropriate, closure.
T	Bridge over "tidal" waters that has not been evaluated for scour, but considered low risk. Bridge will be monitored with regular inspection cycle and with appropriate underwater inspections. ("Unknown" foundations in "tidal" waters should be coded U.)
9	Bridge foundations (including piles) on dry land well above flood water elevations.
8	Bridge foundations determined to be stable for assessed or calculated scour conditions; calculated scour is above top of footing. (Example A)
7	Countermeasures have been installed to correct a previously existing problem with scour. Bridge is no longer scour critical.
6	Scour calculation/evaluation has not been made. (Use only to describe case where bridge has not yet been evaluated for scour potential.)
5	Bridge foundations determined to be stable for calculated scour conditions; scour within limits of footing or piles. (Example B)
4	Bridge foundations determined to be stable for calculated scour conditions; field review indicates action is required to protect exposed foundations from effects of additional erosion and corrosion.
3	Bridge is scour critical; bridge foundations determined to be unstable for calculated scour conditions: —Scour within limits of footing or piles. (Example B) —Scour below spread-footing base or pile tips. (Example C)
2	Bridge is scour critical; field review indicates that extensive scour has occurred at bridge foundations. Immediate action is required to provide scour countermeasures.
1	Bridge is scour critical; field review indicates that failure of piers/abutments is imminent. Bridge is closed to traffic.
0	Bridge is scour critical. Bridge has failed and is closed to traffic.


EXAMPLES
CALCULATED SCOUR DEPTH
ACTION NEEDED
A. Above top of footing
None - indicate rating of 8 for this item
B. Within limits of footing or piles
Conduct foundation structural analysis
C. Below pile tips or spread-footing base
Provide for monitoring and scour countermeasures as necessary
SPREAD FOOTING (NOT FOUNDED IN ROCK)
PILE FOOTING
= Calculated scour depth

Box Culverts

NBI Culvert Rating (FHWA, 1995):

Code	*Description*
N	Not applicable. Use if structure is not a culvert.
9	No deficiencies.
8	No noticeable or noteworthy deficiencies which affect the condition of the culvert. Insignificant scrape marks caused by drift.
7	Shrinkage cracks, light scaling, and insignificant spalling which does not expose reinforcing steel. Insignificant damage caused by drift with no misalignment and not requiring corrective action. Some minor scouring has occurred near curtain walls, wingwalls, or pipes. Metal culverts have a smooth symmetrical curvature with superficial corrosion and no pitting.
6	Deterioration or initial disintegration, minor chloride contamination, cracking with some leaching, or spalls on concrete or masonry walls and slabs. Local minor scouring at curtain walls, wingwalls, or pipes. Metal culverts have a smooth curvature, non-symmetrical shape, significant corrosion or moderate pitting.
5	Moderate to major deterioration or disintegration, extensive cracking and leaching, or spalls on concrete or masonry walls and slabs. Minor settlement or misalignment. Noticeable scouring or erosion at curtain walls, wingwalls, or pipes. Metal culverts have significant distortion and deflection in one section, significant corrosion or deep pitting.
4	Large spalls, heavy scaling, wide cracks, considerable efflorescence, or opened construction joint permitting loss of backfill. Considerable settlement or misalignment. Considerable scouring or erosion at curtain walls, wingwalls or pipes. Metal culverts have significant distortion and deflection throughout, extensive corrosion or deep pitting.
3	Any condition described in Code 4 but which is excessive in scope. Severe movement or differential settlement of the segments, or loss of fill. Holes may exist in walls or slabs. Integral wingwalls nearly severed from culvert. Severe scour or erosion at curtain walls, wingwalls or pipes. Metal culverts have extreme distortion and deflection in one section, extensive corrosion, or deep pitting with scattered perforations.
2	Integral wingwalls collapsed, severe settlement of roadway due to loss of fill. Section of culvert may have failed and can no longer support embankment. Complete undermining at curtain walls and pipes. Corrective action required to maintain traffic. Metal culverts have extreme distortion and deflection throughout with extensive perforations due to corrosion.
1	Culvert closed. Corrective action may put back in light service.
0	Culvert closed. Replacement necessary.

NBI Channel/Channel Protection Rating (FHWA, 1995):

Code	*Description*
N	Not applicable. Use when box culvert is not over a waterway (channel).
9	There are no noticeable or noteworthy deficiencies which affect the condition of the channel.
8	Banks are protected or well vegetated. River control devices such as spur dikes and embankment protection are not required or are in a stable condition.
7	Bank protection is in need of minor repairs. River control devices and embankment protection have a little minor damage. Banks and/or channel have minor amounts of drift.
6	Bank is beginning to slump. River control devices and embankment protection have widespread minor damage. There is minor stream bed movement evident. Debris is restricting the channel slightly.
5	Bank protection is being eroded. River control devices and/or embankment have major damage. Trees and brush restrict the channel.
4	Bank and embankment protection is severely undermined. River control devices have severe damage. Large deposits of debris are in the channel.
3	Bank protection has failed. River control devices have been destroyed. Stream bed aggradation, degradation or lateral movement has changed the channel to now threaten the box culvert and/or approach roadway.
2	The channel has changed to the extent the box culvert is near a state of collapse.
1	Box culvert closed because of channel failure. Corrective action may put back in light service.
0	Box culvert closed because of channel failure. Replacement necessary.

Pipe Culverts

Pennsylvania DOT Pipe Culvert Physical Rating:

Code	*Description*
0	Approaching original condition—like new, no defects
1	Discoloration, slight spalling of mortar, minor surface rust or scale which could include minor pitting, slight loss of interior protection.
2	Moderate spalling and loss of mortar and/or aggregate, moderate to heavy rust and pitting, significant loss of interior protection, weathered joints.
3	Extensive deterioration, rotted, perforated to completely deteriorated bottom, loss of invert.

Pennsylvania DOT Pipe Culvert Structural Rating:

Code	*Description*
0	No displacement, as installed, good condition.
1	Pipe sag or structural components displaced <20°.
2	Pipe sag or structural components displaced ≥20° joint separation, scouring.
3	Completely deteriorated, collapsed or failed.

Pennsylvania DOT Pipe Culvert Structural Rating:

Code	*Description*
0	Open, no restriction of flow.
1	Minor flow restriction. Pipes or other structures are less than half clogged. Ditches have minor siltation or clogging with stones or debris to less than half the cross-section.
2	Severe flow restriction. Pipes or structures are more than half to completely clogged. Ditches are 50% or more filled with dirt, stones, debris or any other condition which causes the ditch to be non-functional due to inadequate slope.
3	Undetermined. Flow condition of pipe, structure or ditch cannot be determined due to excess vegetation.
4	Undetermined. Flow condition of pipe, structure or ditch cannot be determined due to inaccessibility.
5	Same as condition 0 with possible illicit discharge.
6	Same as condition 1 with possible illicit discharge.
7	Same as condition 2 with possible illicit discharge.
8	Same as condition 3 with possible illicit discharge.
9	Same as condition 4 with possible illicit discharge.

APPENDIX B

Bridge Markov/Weibull Results by Element, Region, and 'End-of-Life Criterion'

Table B-1. Bridge deck element Markov/Weibull results (end-of-life threshold: deck condition rating = 3).

Region	Weibull Scaling Factor, α	Weibull Shape Factor, β	Median Service Life	90% Confidence Interval	RMSE
Alabama	89.97	3.12	80	[35, 128]	6.40
Alaska	72.62	4.55	67	[38, 92]	10.20
Arizona	83.08	2.83	73	[29, 122]	5.55
Arkansas	100.46	10.46	97	[76, 112]	9.86
California	85.38	2.83	75	[30, 126]	4.43
Colorado	115.13	3.29	103	[47, 161]	10.02
Connecticut	97.59	5.24	91	[55, 120]	4.54
Delaware	60.81	5.67	57	[36, 74]	3.25
Florida	87.01	15.68	85	[72, 93]	7.97
Georgia	131.29	2.96	116	[48, 190]	5.82
Hawaii	110.47	27.27	109	[99, 115]	8.67
Idaho	92.49	5.04	86	[51, 115]	6.83
Illinois	109.67	2.98	97	[41, 158]	1.84
Indiana	88.95	3.46	80	[38, 122]	1.95
Iowa	89.75	3.57	81	[39, 122]	2.62
Kansas	104.13	5.17	97	[59, 129]	1.85
Kentucky	67.77	3.01	60	[25, 98]	3.31
Louisiana	104.20	5.12	97	[58, 129]	8.03
Maine	76.88	3.39	69	[32, 106]	2.38
Maryland	85.10	14.67	83	[70, 92]	21.15
Massachusetts	67.34	3.17	60	[26, 95]	3.29
Michigan	73.32	3.04	65	[28, 105]	1.56
Minnesota	80.97	14.88	79	[66, 87]	16.24
Mississippi	109.57	4.01	100	[52, 144]	7.51
Missouri	91.07	2.83	80	[32, 134]	3.77
Montana	96.11	3.68	87	[43, 129]	5.15
Nebraska	109.05	7.73	104	[74, 126]	2.35
Nevada	75.66	5.77	71	[45, 92]	5.41
New Hampshire	83.70	2.98	74	[31, 121]	5.31
New Jersey	113.43	9.21	109	[82, 128]	11.01
New Mexico	86.05	3.73	78	[39, 115]	5.73
New York	81.57	3.30	73	[33, 114]	0.89
North Carolina	93.09	31.02	92	[85, 96]	7.49
North Dakota	N/A	N/A	>120	N/A	N/A
Ohio	57.75	2.95	51	[21, 84]	1.15
Oklahoma	54.86	3.24	49	[22, 77]	3.29
Oregon	80.97	14.88	79	[66, 87]	14.75
Pennsylvania	84.68	3.39	76	[35, 117]	1.96
Rhode Island	77.76	2.73	68	[26, 116]	3.33
South Carolina	100.16	4.31	92	[50, 129]	7.24
South Dakota	69.64	3.15	62	[27, 99]	3.20
Tennessee	109.07	19.17	107	[93, 115]	4.61
Texas	105.19	2.97	93	[39, 152]	5.97
Utah	77.96	14.36	76	[63, 84]	20.14
Vermont	65.67	2.95	58	[24, 95]	1.75
Virginia	108.53	3.99	99	[52, 143]	5.30
Washington	114.18	3.56	103	[50, 155]	7.21
West Virginia	86.67	3.10	77	[33, 124]	2.69
Wisconsin	72.66	2.89	64	[26, 106]	4.46
Wyoming	61.12	2.96	54	[22, 89]	1.99
Entire U.S.	88.33	3.28	79	[36, 123]	0.89
Northeast U.S.	81.22	3.04	72	[31, 117]	1.09
Northwest U.S.	102.86	4.61	95	[54, 130]	3.29
Southeast U.S.	92.60	4.28	85	[46, 120]	3.01
Southwest U.S.	93.37	3.47	84	[40, 128]	4.98

Table B-2. Bridge deck element Markov/Weibull results (end-of-life threshold: deck condition rating = 4).

Region	*Weibull Scaling Factor, α*	*Weibull Shaping Factor, β*	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	70.00	2.66	61	[23, 106]	2.93
Alaska	64.09	2.71	56	[21, 96]	5.73
Arizona	67.08	2.03	56	[16, 115]	7.29
Arkansas	90.41	3.34	81	[37, 126]	5.93
California	54.22	1.75	44	[10, 101]	5.35
Colorado	82.14	2.10	69	[20, 138]	4.40
Connecticut	83.01	2.85	73	[29, 122]	2.12
Delaware	49.37	3.18	44	[19, 70]	3.23
Florida	80.91	4.10	74	[39, 106]	2.93
Georgia	139.91	1.87	115	[29, 252]	5.85
Hawaii	96.05	6.79	91	[62, 113]	4.46
Idaho	73.79	3.28	66	[30, 103]	2.86
Illinois	79.07	2.43	68	[23, 124]	2.93
Indiana	67.24	2.80	59	[23, 99]	0.75
Iowa	68.63	3.61	62	[30, 93]	1.70
Kansas	85.87	3.81	78	[39, 114]	2.54
Kentucky	54.25	2.99	48	[20, 78]	1.42
Louisiana	88.62	5.59	83	[52, 108]	10.66
Maine	57.82	2.92	51	[21, 84]	2.07
Maryland	56.83	2.86	50	[20, 83]	2.65
Massachusetts	60.42	2.80	53	[21, 89]	2.19
Michigan	55.58	2.50	48	[17, 86]	2.45
Minnesota	62.34	3.42	56	[26, 86]	1.61
Mississippi	95.03	3.67	86	[42, 128]	8.03
Missouri	72.18	2.70	63	[24, 108]	2.81
Montana	75.10	2.54	65	[23, 116]	1.81
Nebraska	92.06	4.00	84	[44, 121]	2.27
Nevada	64.98	3.79	59	[30, 87]	4.47
New Hampshire	71.00	2.70	62	[24, 107]	1.71
New Jersey	91.92	3.59	83	[40, 125]	3.68
New Mexico	59.34	2.42	51	[17, 93]	5.10
New York	56.05	2.73	49	[19, 84]	1.47
North Carolina	104.48	2.65	91	[34, 158]	15.50
North Dakota	N/A	N/A	>120	N/A	N/A
Ohio	42.60	2.60	37	[14, 65]	1.61
Oklahoma	43.91	3.09	39	[17, 63]	2.87
Oregon	70.41	3.30	63	[29, 98]	1.75
Pennsylvania	61.12	2.57	53	[19, 94]	1.05
Rhode Island	54.37	2.52	47	[17, 84]	2.13
South Carolina	82.09	14.19	80	[67, 89]	22.13
South Dakota	55.11	2.65	48	[18, 83]	3.56
Tennessee	117.78	3.48	106	[50, 161]	6.45
Texas	78.59	2.82	69	[27, 116]	2.21
Utah	69.81	2.42	60	[20, 110]	2.74
Vermont	53.42	2.86	47	[19, 78]	0.99
Virginia	64.03	2.73	56	[22, 96]	1.97
Washington	72.76	9.47	70	[53, 82]	19.22
West Virginia	63.24	2.32	54	[18, 101]	4.19
Wisconsin	52.44	2.80	46	[18, 78]	2.46
Wyoming	47.34	2.18	40	[12, 78]	3.76
Entire U.S.	66.44	2.70	58	[22, 100]	1.17
Northeast U.S.	58.61	2.63	51	[19, 89]	1.58
Northwest U.S.	82.79	3.27	74	[33, 116]	1.70
Southeast U.S.	75.69	3.42	68	[32, 104]	1.46
Southwest U.S.	68.58	2.19	58	[18, 113]	2.81

Table B-3. Bridge deck element Markov/Weibull results (end-of-life threshold: deck condition rating = 5).

Region	*Weibull Scaling Factor, α*	*Weibull Shaping Factor, β*	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	47.52	2.48	41	[14, 74]	1.18
Alaska	28.30	2.22	24	[7, 46]	3.72
Arizona	50.49	2.28	43	[14, 82]	1.75
Arkansas	64.42	1.88	53	[13, 116]	3.17
California	37.71	1.87	31	[8, 68]	3.45
Colorado	57.22	2.09	48	[14, 97]	1.91
Connecticut	62.74	2.17	53	[16, 104]	4.13
Delaware	39.95	2.77	35	[14, 59]	2.74
Florida	74.58	2.66	65	[24, 113]	3.98
Georgia	82.66	2.03	69	[19, 142]	4.63
Hawaii	75.23	3.16	67	[29, 106]	2.91
Idaho	58.60	2.64	51	[19, 89]	2.78
Illinois	60.75	2.36	52	[17, 97]	2.09
Indiana	44.29	2.39	38	[13, 70]	0.74
Iowa	49.00	3.41	44	[20, 68]	1.24
Kansas	59.17	2.84	52	[21, 87]	1.05
Kentucky	43.33	2.79	38	[15, 64]	1.66
Louisiana	71.72	3.22	64	[29, 101]	2.58
Maine	45.55	2.82	40	[16, 67]	1.01
Maryland	42.55	2.62	37	[14, 65]	1.07
Massachusetts	44.34	2.37	38	[13, 70]	1.74
Michigan	40.78	2.40	35	[12, 64]	2.75
Minnesota	48.30	3.16	43	[19, 68]	0.98
Mississippi	72.01	2.74	63	[24, 107]	2.51
Missouri	53.62	2.78	47	[18, 80]	2.64
Montana	53.24	2.18	45	[14, 88]	1.33
Nebraska	60.43	3.26	54	[24, 85]	1.18
Nevada	55.19	3.08	49	[21, 79]	8.92
New Hampshire	53.04	2.23	45	[14, 87]	2.16
New Jersey	60.99	2.30	52	[17, 98]	2.29
New Mexico	42.51	2.64	37	[14, 64]	1.74
New York	39.84	2.31	34	[11, 64]	2.16
North Carolina	58.71	2.03	49	[14, 101]	3.71
North Dakota	102.66	3.04	91	[39, 147]	3.98
Ohio	32.74	2.34	28	[9, 52]	1.88
Oklahoma	31.64	3.00	28	[12, 46]	1.33
Oregon	53.62	2.78	47	[18, 80]	1.22
Pennsylvania	39.62	2.40	34	[11, 63]	1.72
Rhode Island	40.09	2.70	35	[13, 60]	1.93
South Carolina	54.42	2.92	48	[20, 79]	2.52
South Dakota	39.97	2.76	35	[14, 59]	1.47
Tennessee	86.64	2.14	73	[22, 145]	4.00
Texas	57.16	2.38	49	[16, 91]	1.85
Utah	51.43	2.05	43	[12, 88]	2.81
Vermont	40.44	2.54	35	[13, 62]	0.54
Virginia	37.25	2.41	32	[11, 59]	1.22
Washington	64.69	2.26	55	[17, 105]	2.93
West Virginia	46.22	2.53	40	[14, 71]	2.52
Wisconsin	37.94	2.63	33	[12, 58]	1.82
Wyoming	28.71	2.05	24	[7, 49]	2.98
Entire U.S.	48.62	2.50	42	[15, 75]	0.99
Northeast U.S.	42.73	2.54	37	[13, 66]	1.17
Northwest U.S.	56.02	2.74	49	[19, 84]	0.77
Southeast U.S.	57.04	2.78	50	[20, 85]	0.72
Southwest U.S.	47.06	1.95	39	[10, 83]	2.23

Table B-4. Bridge superstructure element Markov/Weibull results (end-of-life threshold: superstructure condition rating = 3).

Region	*Weibull Scaling Factor, α*	*Weibull Shaping Factor, β*	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	86.10	14.84	84	[70, 93]	20.66
Alaska	63.50	9.12	61	[46, 72]	14.96
Arizona	80.97	14.88	79	[66, 87]	11.85
Arkansas	97.18	8.33	93	[68, 111]	5.39
California	112.94	10.31	109	[85, 126]	6.78
Colorado	102.36	11.00	99	[78, 113]	7.29
Connecticut	105.80	4.22	97	[52, 137]	4.02
Delaware	57.36	8.72	55	[41, 65]	13.96
Florida	88.21	9.88	85	[65, 99]	8.34
Georgia	126.68	4.16	116	[62, 165]	5.21
Hawaii	97.14	6.74	92	[63, 114]	4.59
Idaho	91.03	6.44	86	[57, 108]	7.39
Illinois	113.46	3.15	101	[44, 161]	0.79
Indiana	89.70	3.59	81	[39, 122]	1.37
Iowa	90.23	14.65	88	[74, 97]	14.71
Kansas	102.75	7.75	98	[70, 118]	2.36
Kentucky	82.45	3.39	74	[34, 114]	2.76
Louisiana	116.13	5.79	109	[70, 140]	9.23
Maine	87.33	3.66	79	[39, 118]	3.14
Maryland	88.57	3.60	80	[39, 120]	3.68
Massachusetts	72.92	2.51	63	[22, 113]	3.88
Michigan	75.36	3.56	68	[33, 103]	2.07
Minnesota	82.66	3.77	75	[38, 111]	1.51
Mississippi	118.83	3.21	106	[47, 167]	7.57
Missouri	110.87	4.40	102	[56, 142]	4.79
Montana	119.94	8.71	115	[85, 136]	9.80
Nebraska	112.18	7.75	107	[76, 129]	3.86
Nevada	78.20	5.33	73	[45, 96]	6.59
New Hampshire	106.28	3.27	95	[43, 149]	5.13
New Jersey	122.32	5.94	115	[74, 147]	6.51
New Mexico	88.08	3.81	80	[40, 118]	3.07
New York	73.69	3.33	66	[30, 102]	1.53
North Carolina	100.11	11.62	97	[78, 110]	9.27
North Dakota	N/A	N/A	>120	N/A	N/A
Ohio	58.98	2.91	52	[21, 86]	0.83
Oklahoma	57.29	3.78	52	[26, 77]	2.15
Oregon	125.40	1.86	103	[25, 226]	8.63
Pennsylvania	89.87	3.53	81	[39, 123]	2.45
Rhode Island	72.45	2.35	62	[20, 116]	3.75
South Carolina	118.87	4.23	109	[59, 154]	9.30
South Dakota	84.72	3.38	76	[35, 117]	2.50
Tennessee	109.38	106.58	109	[106, 111]	8.57
Texas	94.67	3.81	86	[43, 126]	3.08
Utah	121.56	3.36	109	[50, 169]	7.02
Vermont	78.41	3.23	70	[31, 110]	1.39
Virginia	102.03	2.92	90	[37, 149]	2.30
Washington	108.76	4.95	101	[60, 136]	6.35
West Virginia	100.91	2.92	89	[36, 147]	2.19
Wisconsin	78.67	3.57	71	[34, 107]	2.52
Wyoming	78.97	14.53	77	[64, 85]	18.59
Entire U.S.	91.97	3.57	83	[40, 125]	1.08
Northeast U.S.	85.19	3.21	76	[34, 120]	0.97
Northwest U.S.	104.81	6.43	99	[66, 124]	2.46
Southeast U.S.	88.15	4.33	81	[44, 114]	1.55
Southwest U.S.	103.27	3.50	93	[44, 141]	3.44

Table B-5. Bridge superstructure element Markov/Weibull results (end-of-life threshold: superstructure condition rating = 4).

Region	Weibull Scaling Factor, α	Weibull Shaping Factor, β	Median Service Life	90% Confidence Interval	RMSE
Alabama	73.14	2.46	63	[22, 114]	3.28
Alaska	59.59	8.25	57	[42, 68]	16.01
Arizona	68.63	9.36	66	[50, 77]	16.04
Arkansas	88.90	4.54	82	[46, 113]	6.12
California	104.54	4.30	96	[52, 135]	2.40
Colorado	78.97	14.53	77	[64, 85]	16.62
Connecticut	90.45	2.98	80	[33, 131]	1.84
Delaware	42.87	3.04	38	[16, 62]	2.47
Florida	80.53	5.15	75	[45, 100]	4.63
Georgia	135.44	2.24	115	[36, 221]	5.70
Hawaii	83.23	3.52	75	[36, 114]	6.26
Idaho	76.61	3.50	69	[33, 105]	2.38
Illinois	84.72	2.71	74	[28, 127]	3.10
Indiana	69.29	3.30	62	[28, 97]	1.10
Iowa	78.83	3.51	71	[34, 108]	2.11
Kansas	89.52	4.85	83	[49, 112]	2.56
Kentucky	63.31	2.99	56	[23, 91]	1.28
Louisiana	95.00	3.30	85	[39, 133]	6.28
Maine	72.93	3.18	65	[29, 103]	2.00
Maryland	65.69	2.95	58	[24, 95]	1.61
Massachusetts	62.29	2.57	54	[20, 96]	2.25
Michigan	61.96	3.08	55	[24, 89]	1.49
Minnesota	60.10	3.42	54	[25, 83]	2.39
Mississippi	93.46	3.86	85	[43, 124]	7.10
Missouri	92.17	3.13	82	[36, 131]	2.22
Montana	103.50	3.11	92	[40, 147]	3.11
Nebraska	97.96	5.84	92	[59, 118]	2.72
Nevada	65.89	3.91	60	[31, 87]	7.23
New Hampshire	91.92	2.90	81	[33, 134]	3.47
New Jersey	102.43	3.80	93	[47, 137]	2.00
New Mexico	72.46	2.35	62	[20, 116]	4.77
New York	57.75	2.95	51	[21, 84]	1.66
North Carolina	78.97	14.53	77	[64, 85]	18.67
North Dakota	113.99	10.29	110	[85, 127]	5.58
Ohio	48.93	2.84	43	[17, 72]	0.98
Oklahoma	48.18	3.22	43	[19, 68]	1.98
Oregon	71.61	2.86	63	[25, 105]	1.86
Pennsylvania	64.77	2.87	57	[23, 95]	1.11
Rhode Island	44.85	2.21	38	[12, 74]	2.01
South Carolina	71.97	2.75	63	[24, 107]	6.81
South Dakota	68.21	2.86	60	[24, 100]	1.69
Tennessee	108.31	4.59	100	[57, 138]	8.06
Texas	77.36	3.21	69	[31, 109]	1.28
Utah	82.37	3.04	73	[31, 118]	2.45
Vermont	61.90	3.10	55	[24, 88]	2.10
Virginia	59.48	3.18	53	[23, 84]	1.63
Washington	78.97	14.53	77	[64, 85]	19.08
West Virginia	79.18	2.66	69	[26, 120]	1.80
Wisconsin	61.68	3.20	55	[24, 87]	1.73
Wyoming	67.85	3.44	61	[29, 93]	2.32
Entire U.S.	72.26	3.02	64	[27, 104]	0.76
Northeast U.S.	64.76	2.87	57	[23, 95]	1.25
Northwest U.S.	87.66	4.01	80	[42, 115]	1.72
Southeast U.S.	76.71	3.46	69	[33, 105]	0.85
Southwest U.S.	86.80	3.43	78	[37, 120]	2.10

Table B-6. Bridge superstructure element Markov/Weibull results (end-of-life threshold: superstructure condition rating = 5).

Region	Weibull Scaling Factor, α	Weibull Shaping Factor, β	Median Service Life	90% Confidence Interval	RMSE
Alabama	51.19	2.42	44	[15, 81]	1.43
Alaska	29.45	2.24	25	[8, 48]	2.30
Arizona	58.82	2.57	51	[19, 90]	3.17
Arkansas	69.04	1.91	57	[15, 122]	2.05
California	77.95	2.68	68	[26, 117]	3.06
Colorado	61.99	2.34	53	[17, 99]	2.19
Connecticut	68.69	2.41	59	[20, 108]	1.20
Delaware	33.60	2.49	29	[10, 52]	1.21
Florida	69.57	3.18	62	[27, 98]	3.06
Georgia	75.68	2.41	65	[22, 119]	4.79
Hawaii	71.42	2.92	63	[26, 104]	5.52
Idaho	60.16	2.89	53	[22, 88]	1.61
Illinois	64.94	2.47	56	[20, 101]	1.80
Indiana	52.14	2.93	46	[19, 76]	0.79
Iowa	58.12	3.29	52	[24, 81]	0.78
Kansas	67.14	3.26	60	[27, 94]	1.47
Kentucky	52.34	2.84	46	[18, 77]	1.28
Louisiana	73.26	3.06	65	[28, 105]	2.45
Maine	59.44	3.20	53	[23, 84]	2.01
Maryland	42.78	2.53	37	[13, 66]	1.15
Massachusetts	47.04	2.26	40	[13, 76]	1.07
Michigan	46.10	2.58	40	[15, 71]	1.50
Minnesota	48.33	3.14	43	[19, 69]	0.83
Mississippi	68.56	2.75	60	[23, 102]	2.30
Missouri	69.11	2.94	61	[25, 100]	1.19
Montana	72.66	2.57	63	[23, 111]	2.42
Nebraska	78.46	3.67	71	[35, 106]	1.94
Nevada	59.45	3.81	54	[27, 79]	4.40
New Hampshire	71.09	2.40	61	[21, 112]	1.23
New Jersey	71.01	3.06	63	[27, 102]	1.47
New Mexico	48.69	2.48	42	[15, 76]	1.94
New York	45.00	2.56	39	[14, 69]	1.78
North Carolina	63.26	2.32	54	[18, 102]	5.30
North Dakota	120.19	3.75	109	[54, 161]	5.34
Ohio	38.45	2.40	33	[11, 61]	1.15
Oklahoma	35.33	2.80	31	[12, 52]	0.92
Oregon	54.03	2.63	47	[17, 82]	1.16
Pennsylvania	44.61	2.73	39	[15, 67]	1.07
Rhode Island	28.11	2.32	24	[8, 45]	1.48
South Carolina	53.41	3.43	48	[22, 74]	2.32
South Dakota	47.95	2.77	42	[16, 71]	1.05
Tennessee	81.98	2.55	71	[26, 126]	3.28
Texas	58.14	2.43	50	[17, 91]	0.65
Utah	65.29	2.39	56	[19, 103]	2.38
Vermont	46.85	2.75	41	[16, 70]	1.39
Virginia	40.99	2.82	36	[14, 60]	0.93
Washington	64.31	2.65	56	[21, 97]	1.53
West Virginia	58.96	2.22	50	[15, 97]	1.97
Wisconsin	46.25	3.04	41	[17, 66]	0.98
Wyoming	49.00	2.38	42	[14, 78]	2.29
Entire U.S.	55.03	2.68	48	[18, 83]	0.67
Northeast U.S.	48.33	2.61	42	[16, 74]	0.99
Northwest U.S.	64.53	2.95	57	[24, 94]	0.88
Southeast U.S.	59.34	2.78	52	[20, 88]	0.81
Southwest U.S.	62.45	2.52	54	[19, 96]	0.71

Table B-7. Bridge substructure element Markov/Weibull results (end-of-life threshold: substructure condition rating = 3).

Region	Weibull Scaling Factor, α	Weibull Shaping Factor, β	Median Service Life	90% Confidence Interval	RMSE
Alabama	87.51	2.19	74	[22, 145]	4.67
Alaska	71.39	5.77	67	[43, 86]	10.77
Arizona	80.97	14.88	79	[66, 87]	15.52
Arkansas	100.38	5.58	94	[59, 122]	9.95
California	113.51	9.04	109	[82, 128]	6.54
Colorado	101.99	4.49	94	[53, 130]	6.91
Connecticut	123.96	2.85	109	[44, 182]	11.60
Delaware	68.08	4.73	63	[36, 86]	4.99
Florida	90.65	6.96	86	[59, 106]	8.00
Georgia	114.65	3.42	103	[48, 158]	14.86
Hawaii	104.91	19.90	103	[90, 111]	7.53
Idaho	80.97	14.88	79	[66, 87]	17.19
Illinois	118.45	3.30	106	[48, 165]	1.28
Indiana	90.96	3.54	82	[39, 124]	1.37
Iowa	71.60	3.27	64	[29, 100]	3.50
Kansas	101.22	4.33	93	[51, 130]	1.42
Kentucky	84.44	3.09	75	[32, 120]	3.01
Louisiana	95.77	5.00	89	[53, 119]	4.73
Maine	80.20	3.01	71	[30, 116]	2.85
Maryland	99.84	3.96	91	[47, 132]	7.96
Massachusetts	79.58	3.21	71	[32, 112]	4.02
Michigan	86.30	3.21	77	[34, 121]	2.33
Minnesota	75.30	3.14	67	[29, 107]	2.69
Mississippi	112.49	2.17	95	[29, 187]	7.40
Missouri	108.44	4.52	100	[56, 138]	7.38
Montana	144.23	1.62	115	[23, 284]	10.21
Nebraska	108.50	8.65	104	[77, 123]	3.31
Nevada	77.18	6.58	73	[49, 91]	7.34
New Hampshire	120.44	3.67	109	[54, 162]	4.72
New Jersey	116.90	22.42	115	[102, 123]	7.27
New Mexico	80.89	4.12	74	[39, 106]	6.89
New York	71.21	2.99	63	[26, 103]	1.36
North Carolina	101.67	7.79	97	[69, 117]	8.42
North Dakota	117.75	15.53	115	[97, 126]	6.80
Ohio	64.94	3.24	58	[26, 91]	0.84
Oklahoma	45.71	3.37	41	[19, 63]	1.92
Oregon	65.84	8.31	63	[46, 75]	16.12
Pennsylvania	92.05	3.54	83	[40, 125]	0.86
Rhode Island	76.27	3.20	68	[30, 108]	5.31
South Carolina	105.88	2.61	92	[34, 161]	6.13
South Dakota	67.10	3.28	60	[27, 94]	1.67
Tennessee	113.40	9.27	109	[82, 128]	7.24
Texas	77.67	3.10	69	[30, 111]	1.38
Utah	100.91	4.49	93	[52, 129]	6.09
Vermont	78.71	2.51	68	[24, 122]	3.48
Virginia	N/A	N/A	>120	N/A	N/A
Washington	124.27	2.80	109	[43, 184]	10.10
West Virginia	119.57	3.04	106	[45, 172]	1.79
Wisconsin	83.66	3.35	75	[35, 116]	3.60
Wyoming	82.18	3.09	73	[31, 117]	5.33
Entire U.S.	87.62	3.15	78	[34, 124]	0.91
Northeast U.S.	85.35	3.16	76	[33, 121]	1.14
Northwest U.S.	100.40	3.73	91	[45, 135]	1.06
Southeast U.S.	82.28	3.46	74	[35, 113]	1.66
Southwest U.S.	94.83	3.02	84	[35, 136]	2.11

Table B-8. Bridge substructure element Markov/Weibull results (end-of-life threshold: substructure condition rating = 4).

Region	Weibull Scaling Factor, α	Weibull Shaping Factor, β	Median Service Life	90% Confidence Interval	RMSE
Alabama	63.28	2.07	53	[15, 108]	3.34
Alaska	60.23	2.87	53	[21, 88]	6.11
Arizona	69.75	9.11	67	[50, 79]	18.65
Arkansas	79.97	14.71	78	[65, 86]	25.19
California	111.90	4.42	103	[57, 143]	6.95
Colorado	81.80	2.35	70	[23, 130]	3.02
Connecticut	86.53	3.14	77	[34, 123]	1.48
Delaware	48.82	2.89	43	[17, 71]	2.50
Florida	97.21	2.73	85	[33, 145]	9.75
Georgia	100.51	3.01	89	[37, 145]	11.71
Hawaii	104.20	4.47	96	[54, 133]	5.72
Idaho	68.06	3.35	61	[28, 94]	3.44
Illinois	79.97	14.71	78	[65, 86]	19.85
Indiana	73.10	3.12	65	[28, 104]	1.58
Iowa	57.67	3.54	52	[25, 79]	3.06
Kansas	83.62	3.84	76	[39, 111]	1.95
Kentucky	65.16	2.74	57	[22, 97]	1.20
Louisiana	87.95	3.05	78	[33, 126]	6.67
Maine	65.15	2.74	57	[22, 97]	1.54
Maryland	69.12	2.32	59	[19, 111]	3.76
Massachusetts	62.98	2.38	54	[18, 100]	2.25
Michigan	69.86	2.70	61	[23, 105]	1.23
Minnesota	60.11	3.42	54	[25, 83]	1.29
Mississippi	82.06	2.53	71	[25, 127]	5.94
Missouri	82.68	3.31	74	[34, 115]	1.86
Montana	78.78	2.49	68	[24, 122]	3.40
Nebraska	99.30	4.20	91	[49, 129]	2.60
Nevada	66.16	3.20	59	[26, 93]	4.03
New Hampshire	99.86	2.45	86	[30, 156]	3.20
New Jersey	105.78	2.85	93	[37, 156]	1.31
New Mexico	60.10	2.92	53	[22, 88]	1.11
New York	48.83	2.43	42	[14, 77]	2.15
North Carolina	79.50	2.59	69	[25, 122]	4.76
North Dakota	117.04	5.15	109	[66, 145]	5.25
Ohio	50.94	2.95	45	[19, 74]	1.09
Oklahoma	36.44	2.82	32	[13, 54]	1.16
Oregon	57.68	2.56	50	[18, 88]	2.93
Pennsylvania	65.11	2.75	57	[22, 97]	0.72
Rhode Island	45.86	2.68	40	[15, 69]	3.74
South Carolina	52.33	8.03	50	[36, 60]	14.63
South Dakota	54.51	2.88	48	[19, 80]	1.32
Tennessee	115.10	3.03	102	[43, 165]	5.53
Texas	63.38	2.58	55	[20, 97]	0.92
Utah	99.27	2.19	84	[26, 164]	5.27
Vermont	54.87	2.37	47	[16, 87]	2.96
Virginia	75.91	2.36	65	[22, 121]	3.52
Washington	78.89	2.74	69	[27, 118]	3.39
West Virginia	95.17	2.46	82	[28, 149]	1.96
Wisconsin	64.35	3.53	58	[28, 88]	3.77
Wyoming	63.73	2.49	55	[19, 99]	2.21
Entire U.S.	67.36	2.77	59	[23, 100]	1.21
Northeast U.S.	63.90	2.78	56	[22, 95]	1.68
Northwest U.S.	78.42	3.23	70	[31, 110]	0.84
Southeast U.S.	65.90	2.87	58	[23, 97]	1.08
Southwest U.S.	76.32	2.28	65	[21, 123]	2.65

Table B-9. Bridge substructure element Markov/Weibull results (end-of-life threshold: substructure condition rating = 5).

Region	*Weibull Scaling Factor, α*	*Weibull Shaping Factor, β*	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	49.41	2.26	42	[13, 80]	1.54
Alaska	29.60	2.17	25	[8, 49]	1.03
Arizona	65.59	2.61	57	[21, 100]	2.56
Arkansas	63.23	1.70	51	[11, 120]	3.92
California	79.97	14.71	78	[65, 86]	18.46
Colorado	59.53	1.88	49	[12, 107]	2.95
Connecticut	64.56	2.29	55	[18, 104]	1.10
Delaware	34.30	2.74	30	[12, 51]	1.90
Florida	71.01	2.41	61	[21, 112]	2.85
Georgia	63.57	2.25	54	[17, 104]	3.26
Hawaii	74.22	3.58	67	[32, 101]	2.54
Idaho	52.45	2.79	46	[18, 78]	1.46
Illinois	66.04	2.49	57	[20, 103]	1.89
Indiana	54.92	2.72	48	[18, 82]	0.57
Iowa	47.67	3.56	43	[21, 65]	1.25
Kansas	62.82	3.19	56	[25, 89]	0.78
Kentucky	50.87	2.53	44	[16, 79]	0.47
Louisiana	70.21	2.61	61	[22, 107]	2.84
Maine	50.60	2.62	44	[16, 77]	0.95
Maryland	45.66	2.33	39	[13, 73]	1.06
Massachusetts	40.56	2.08	34	[10, 69]	2.55
Michigan	50.69	2.23	43	[13, 83]	2.28
Minnesota	49.09	3.35	44	[20, 68]	0.84
Mississippi	67.75	2.12	57	[17, 114]	3.19
Missouri	62.15	3.00	55	[23, 90]	1.43
Montana	56.13	2.34	48	[16, 90]	1.01
Nebraska	76.34	3.62	69	[34, 103]	1.86
Nevada	64.22	2.68	56	[21, 97]	3.55
New Hampshire	74.16	2.05	62	[17, 127]	2.47
New Jersey	66.65	2.64	58	[22, 101]	1.58
New Mexico	39.33	2.52	34	[12, 61]	1.35
New York	37.61	2.27	32	[10, 61]	2.23
North Carolina	57.71	1.99	48	[13, 100]	5.56
North Dakota	99.18	4.26	91	[49, 128]	5.81
Ohio	39.49	2.45	34	[12, 62]	0.96
Oklahoma	28.20	2.27	24	[8, 46]	1.27
Oregon	46.16	2.56	40	[14, 71]	1.34
Pennsylvania	41.27	2.22	35	[11, 68]	1.01
Rhode Island	29.68	2.13	25	[7, 50]	2.83
South Carolina	44.58	3.38	40	[19, 62]	3.22
South Dakota	40.95	2.33	35	[11, 66]	1.88
Tennessee	84.29	2.33	72	[23, 135]	2.86
Texas	47.12	2.24	40	[12, 77]	1.33
Utah	67.79	2.11	57	[17, 114]	3.00
Vermont	39.21	2.57	34	[12, 60]	1.59
Virginia	42.44	2.23	36	[11, 69]	1.97
Washington	60.96	2.62	53	[20, 93]	1.63
West Virginia	64.68	1.84	53	[13, 117]	4.20
Wisconsin	51.57	3.21	46	[20, 73]	1.03
Wyoming	45.50	2.03	38	[11, 78]	1.30
Entire U.S.	51.84	2.59	45	[16, 79]	0.77
Northeast U.S.	48.24	2.65	42	[16, 73]	0.81
Northwest U.S.	60.08	2.92	53	[22, 87]	0.66
Southeast U.S.	53.16	2.53	46	[16, 82]	0.71
Southwest U.S.	55.93	2.11	47	[14, 94]	1.01

Table B-10. Bridge channel/embankment protection Markov/Weibull results (end-of-life threshold: channel condition rating = 3).

Region	Weibull Scaling Factor, α	Weibull Shaping Factor, β	Median Service Life	90% Confidence Interval	RMSE
Alabama	113.24	3.87	103	[53, 150]	9.15
Alaska	76.17	12.70	74	[60, 83]	8.41
Arizona	80.97	14.88	79	[66, 87]	14.11
Arkansas	106.22	17.36	104	[90, 113]	10.17
California	N/A	N/A	>120	N/A	N/A
Colorado	101.38	15.46	99	[84, 109]	8.05
Connecticut	120.15	3.76	109	[55, 161]	4.75
Delaware	60.38	9.13	58	[44, 68]	10.93
Florida	92.48	22.78	91	[81, 97]	8.18
Georgia	100.69	53.02	100	[95, 103]	4.71
Hawaii	105.25	30.62	104	[96, 109]	5.18
Idaho	93.01	16.78	91	[78, 99]	9.73
Illinois	N/A	N/A	>120	N/A	N/A
Indiana	106.86	3.12	95	[41, 152]	4.13
Iowa	N/A	N/A	>120	N/A	N/A
Kansas	114.88	6.98	109	[75, 134]	3.84
Kentucky	102.28	3.14	91	[40, 145]	12.94
Louisiana	100.22	11.22	97	[77, 111]	8.50
Maine	98.08	4.89	91	[53, 123]	9.50
Maryland	100.11	11.62	97	[78, 110]	12.00
Massachusetts	107.17	12.21	104	[84, 117]	8.25
Michigan	113.46	6.25	107	[71, 135]	3.22
Minnesota	99.18	4.26	91	[49, 128]	3.66
Mississippi	113.98	8.20	109	[79, 130]	7.56
Missouri	110.70	57.98	110	[105, 113]	7.17
Montana	106.44	11.17	103	[82, 117]	11.98
Nebraska	N/A	N/A	>120	N/A	N/A
Nevada	67.24	7.42	64	[45, 78]	5.26
New Hampshire	115.17	9.94	111	[85, 129]	3.90
New Jersey	N/A	N/A	>120	N/A	N/A
New Mexico	87.10	15.00	85	[71, 94]	8.48
New York	87.27	2.22	74	[23, 143]	3.12
North Carolina	101.44	10.63	98	[77, 112]	6.32
North Dakota	111.16	34.91	110	[102, 115]	4.06
Ohio	83.66	2.99	74	[31, 121]	3.51
Oklahoma	113.83	8.45	109	[80, 130]	7.32
Oregon	91.13	7.89	87	[63, 105]	6.47
Pennsylvania	112.15	3.20	100	[44, 158]	0.88
Rhode Island	63.61	8.74	61	[45, 72]	19.49
South Carolina	116.39	7.74	111	[79, 134]	9.26
South Dakota	112.64	15.46	110	[93, 121]	7.24
Tennessee	106.22	17.32	104	[89, 113]	5.01
Texas	87.10	15.00	85	[71, 94]	17.68
Utah	117.00	6.96	111	[76, 137]	6.12
Vermont	89.93	3.97	82	[43, 119]	4.94
Virginia	111.16	18.69	109	[95, 118]	9.58
Washington	101.44	10.63	98	[77, 112]	11.82
West Virginia	N/A	N/A	>120	N/A	N/A
Wisconsin	99.11	17.01	97	[83, 106]	6.03
Wyoming	98.14	249.56	98	[97, 99]	4.02
Entire U.S.	133.43	3.45	120	[56, 183]	1.55
Northeast U.S.	115.94	3.37	104	[48, 161]	1.12
Northwest U.S.	N/A	N/A	>120	N/A	N/A
Southeast U.S.	110.99	41.06	110	[103, 114]	8.74
Southwest U.S.	113.44	7.45	108	[76, 131]	6.76

Table B-11. Bridge channel/embankment protection Markov/Weibull results (end-of-life threshold: channel condition rating = 4).

Region	Weibull Scaling Factor, α	Weibull Shaping Factor, β	Median Service Life	90% Confidence Interval	RMSE
Alabama	80.66	2.35	69	[23, 129]	2.74
Alaska	80.60	3.70	73	[36, 108]	10.26
Arizona	78.99	2.45	68	[23, 124]	4.62
Arkansas	108.67	6.84	103	[70, 128]	15.51
California	N/A	N/A	>120	N/A	N/A
Colorado	100.62	13.89	98	[81, 109]	8.35
Connecticut	122.87	2.08	103	[29, 208]	4.07
Delaware	59.59	8.25	57	[42, 68]	11.31
Florida	89.97	6.45	85	[57, 107]	5.69
Georgia	99.69	52.50	99	[94, 102]	4.96
Hawaii	105.30	16.57	103	[88, 113]	7.74
Idaho	91.66	8.99	88	[66, 104]	4.20
Illinois	N/A	N/A	>120	N/A	N/A
Indiana	71.04	3.05	63	[27, 102]	3.11
Iowa	107.18	2.58	93	[34, 164]	1.41
Kansas	91.23	14.80	89	[75, 98]	18.39
Kentucky	68.67	2.17	58	[17, 114]	2.76
Louisiana	87.10	15.00	85	[71, 94]	12.00
Maine	69.10	2.32	59	[19, 111]	5.18
Maryland	90.23	14.65	88	[74, 97]	22.27
Massachusetts	85.19	2.88	75	[30, 125]	3.00
Michigan	85.10	14.67	83	[70, 92]	16.23
Minnesota	77.85	3.04	69	[29, 112]	2.07
Mississippi	107.93	3.43	97	[45, 149]	5.43
Missouri	124.78	2.71	109	[42, 187]	10.76
Montana	93.24	15.10	91	[77, 100]	14.78
Nebraska	112.47	11.68	109	[87, 124]	7.72
Nevada	60.84	3.63	55	[27, 82]	9.70
New Hampshire	117.21	5.77	110	[70, 142]	4.99
New Jersey	N/A	N/A	>120	N/A	N/A
New Mexico	87.53	6.90	83	[57, 103]	3.97
New York	46.58	2.41	40	[14, 73]	1.80
North Carolina	112.29	2.50	97	[34, 174]	8.29
North Dakota	110.93	20.89	109	[96, 117]	6.01
Ohio	51.47	2.34	44	[14, 82]	1.51
Oklahoma	113.87	2.82	100	[40, 168]	6.42
Oregon	88.92	3.93	81	[42, 118]	6.76
Pennsylvania	55.97	2.75	49	[19, 83]	1.46
Rhode Island	62.82	7.97	60	[43, 72]	18.57
South Carolina	115.43	7.61	110	[78, 133]	9.30
South Dakota	117.64	4.81	109	[63, 148]	8.83
Tennessee	105.77	13.80	103	[85, 115]	5.72
Texas	70.94	2.43	61	[21, 111]	1.89
Utah	119.03	4.65	110	[63, 151]	6.41
Vermont	69.97	2.38	60	[20, 111]	2.47
Virginia	121.49	2.22	103	[32, 199]	6.56
Washington	100.80	9.55	97	[74, 113]	11.57
West Virginia	N/A	N/A	>120	N/A	N/A
Wisconsin	92.58	4.29	85	[46, 120]	3.93
Wyoming	97.14	247.81	97	[96, 98]	4.36
Entire U.S.	92.77	2.70	81	[31, 139]	0.85
Northeast U.S.	75.46	2.46	65	[23, 118]	2.51
Northwest U.S.	118.93	3.80	108	[54, 159]	2.91
Southeast U.S.	122.66	3.10	109	[47, 175]	13.84
Southwest U.S.	108.82	2.50	94	[33, 169]	5.97

Table B-12. Bridge channel/embankment protection Markov/Weibull results (end-of-life threshold: channel condition rating = 5).

Region	Weibull Scaling Factor, α	Weibull Shaping Factor, β	Median Service Life	90% Confidence Interval	RMSE
Alabama	48.37	2.22	41	[13, 79]	2.55
Alaska	71.91	2.77	63	[25, 107]	6.60
Arizona	68.94	1.93	57	[15, 122]	3.19
Arkansas	75.44	2.23	64	[20, 123]	4.51
California	N/A	N/A	>120	N/A	N/A
Colorado	114.08	2.26	97	[31, 185]	15.61
Connecticut	69.54	2.23	59	[18, 114]	2.66
Delaware	36.75	2.65	32	[12, 56]	1.86
Florida	81.05	2.77	71	[28, 120]	4.64
Georgia	101.10	11.75	98	[79, 111]	8.26
Hawaii	72.76	9.47	70	[53, 82]	18.14
Idaho	88.22	3.75	80	[40, 118]	5.98
Illinois	86.37	2.18	73	[22, 143]	2.25
Indiana	49.50	2.60	43	[16, 75]	1.18
Iowa	63.07	2.36	54	[18, 100]	1.47
Kansas	61.88	2.37	53	[18, 98]	0.59
Kentucky	49.35	1.98	41	[11, 86]	2.31
Louisiana	78.47	2.32	67	[22, 126]	2.46
Maine	48.31	1.94	40	[10, 85]	3.21
Maryland	62.14	2.61	54	[20, 95]	3.00
Massachusetts	61.07	2.28	52	[17, 99]	2.96
Michigan	64.46	2.61	56	[21, 98]	1.34
Minnesota	56.67	2.52	49	[17, 88]	0.80
Mississippi	97.45	1.86	80	[20, 176]	5.13
Missouri	69.40	2.52	60	[21, 107]	2.61
Montana	91.23	14.80	89	[75, 98]	21.65
Nebraska	113.70	4.60	105	[60, 144]	2.66
Nevada	43.07	2.41	37	[13, 68]	2.70
New Hampshire	133.04	1.84	109	[26, 242]	7.11
New Jersey	96.35	2.27	82	[26, 156]	2.10
New Mexico	69.63	2.46	60	[21, 109]	2.60
New York	29.32	2.30	25	[8, 47]	1.86
North Carolina	71.76	1.72	58	[13, 136]	4.84
North Dakota	110.95	4.93	103	[61, 139]	7.12
Ohio	39.20	2.13	33	[10, 66]	1.05
Oklahoma	65.55	2.09	55	[16, 111]	3.30
Oregon	55.51	2.20	47	[14, 91]	2.29
Pennsylvania	37.18	2.44	32	[11, 58]	0.78
Rhode Island	52.33	8.03	50	[36, 60]	11.30
South Carolina	123.34	2.96	109	[45, 179]	10.65
South Dakota	80.97	14.88	79	[66, 87]	18.53
Tennessee	76.96	14.19	75	[62, 83]	23.36
Texas	40.19	1.86	33	[8, 72]	1.44
Utah	135.32	1.69	109	[23, 259]	6.04
Vermont	34.09	2.27	29	[9, 55]	1.04
Virginia	60.20	1.97	50	[13, 105]	2.81
Washington	102.29	3.85	93	[47, 136]	5.27
West Virginia	84.10	14.51	82	[69, 91]	22.23
Wisconsin	76.26	2.29	65	[21, 123]	2.33
Wyoming	83.10	3.16	74	[32, 118]	5.40
Entire U.S.	62.20	2.29	53	[17, 100]	0.71
Northeast U.S.	51.49	2.33	44	[14, 82]	1.03
Northwest U.S.	84.27	3.14	75	[33, 119]	1.49
Southeast U.S.	79.24	2.40	68	[23, 125]	3.35
Southwest U.S.	66.71	1.47	52	[9, 141]	3.14

Table B-13. Bridge deck geometry Markov/Weibull results (end-of-life threshold: deck geometry rating = 3).

Region	*Weibull Scaling Factor, α*	*Weibull Shaping Factor, β*	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	101.54	68.88	101	[97, 103]	2.10
Alaska	69.93	6.34	66	[44, 83]	6.49
Arizona	117.94	4.65	109	[62, 149]	8.21
Arkansas	116.21	6.67	110	[74, 137]	8.54
California	N/A	N/A	>120	N/A	N/A
Colorado	103.50	75.03	103	[99, 105]	6.12
Connecticut	N/A	N/A	>120	N/A	N/A
Delaware	86.68	6.60	82	[55, 102]	4.98
Florida	100.02	3.88	91	[47, 133]	5.43
Georgia	87.52	4.73	81	[47, 110]	4.78
Hawaii	109.05	853.86	109	[109, 109]	6.02
Idaho	100.92	19.10	99	[86, 107]	6.33
Illinois	N/A	N/A	>120	N/A	N/A
Indiana	98.13	4.24	90	[49, 127]	3.05
Iowa	N/A	N/A	>120	N/A	N/A
Kansas	N/A	N/A	>120	N/A	N/A
Kentucky	103.35	8.53	99	[73, 118]	4.81
Louisiana	92.90	37.64	92	[86, 96]	4.96
Maine	97.48	4.59	90	[51, 124]	3.25
Maryland	110.22	18.04	108	[93, 117]	5.09
Massachusetts	109.29	6.18	103	[68, 131]	1.40
Michigan	115.22	189.07	115	[113, 116]	6.22
Minnesota	117.67	25.57	116	[105, 123]	6.31
Mississippi	111.46	16.39	109	[93, 119]	6.85
Missouri	115.11	390.97	115	[114, 115]	4.90
Montana	115.61	68.92	115	[111, 117]	4.66
Nebraska	115.78	23.61	114	[102, 121]	5.73
Nevada	85.16	199.97	85	[84, 86]	5.91
New Hampshire	117.79	4.72	109	[63, 149]	3.87
New Jersey	N/A	N/A	>120	N/A	N/A
New Mexico	92.66	20.27	91	[80, 98]	9.79
New York	100.81	2.94	89	[37, 146]	3.07
North Carolina	120.87	3.55	109	[52, 165]	7.97
North Dakota	111.11	381.18	111	[110, 111]	4.93
Ohio	N/A	N/A	>120	N/A	N/A
Oklahoma	110.57	70.86	110	[106, 112]	5.83
Oregon	109.17	235.91	109	[108, 110]	5.79
Pennsylvania	N/A	N/A	>120	N/A	N/A
Rhode Island	N/A	N/A	>120	N/A	N/A
South Carolina	86.10	14.84	84	[70, 93]	11.77
South Dakota	112.50	81.70	112	[108, 114]	5.32
Tennessee	110.24	168.27	110	[108, 111]	4.27
Texas	114.85	4.57	106	[60, 146]	7.90
Utah	105.34	113.27	105	[103, 106]	5.24
Vermont	109.57	15.42	107	[90, 118]	6.48
Virginia	N/A	N/A	>120	N/A	N/A
Washington	111.89	21.49	110	[97, 118]	7.56
West Virginia	116.50	84.97	116	[112, 118]	4.89
Wisconsin	118.22	35.47	117	[109, 122]	5.54
Wyoming	98.37	26.21	97	[88, 103]	5.42
Entire U.S.	N/A	N/A	>120	N/A	N/A
Northeast U.S.	N/A	N/A	>120	N/A	N/A
Northwest U.S.	N/A	N/A	>120	N/A	N/A
Southeast U.S.	114.33	17.80	112	[97, 122]	6.31
Southwest U.S.	128.78	5.88	121	[78, 155]	2.70

Table B-14. Bridge deck geometry Markov/Weibull results (end-of-life threshold: deck geometry rating = 4).

Region	*Weibull Scaling Factor, α*	*Weibull Shaping Factor, β*	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	99.56	65.07	99	[95, 101]	5.56
Alaska	49.28	4.03	45	[24, 65]	4.28
Arizona	87.10	15.00	85	[71, 94]	15.59
Arkansas	120.09	2.55	104	[37, 185]	5.89
California	N/A	N/A	>120	N/A	N/A
Colorado	106.73	3.83	97	[49, 142]	8.10
Connecticut	127.14	3.65	115	[56, 172]	7.61
Delaware	76.36	6.23	72	[47, 91]	4.87
Florida	84.52	3.07	75	[32, 121]	4.95
Georgia	72.37	4.75	67	[39, 91]	6.28
Hawaii	97.06	602.58	97	[97, 97]	6.57
Idaho	102.50	8.17	98	[71, 117]	6.97
Illinois	N/A	N/A	>120	N/A	N/A
Indiana	78.97	14.53	77	[64, 85]	16.50
Iowa	N/A	N/A	>120	N/A	N/A
Kansas	N/A	N/A	>120	N/A	N/A
Kentucky	98.43	3.64	89	[44, 133]	5.96
Louisiana	93.86	11.86	91	[73, 103]	7.36
Maine	76.71	2.71	67	[26, 115]	4.36
Maryland	99.60	13.87	97	[80, 108]	4.83
Massachusetts	96.97	4.91	90	[53, 121]	2.84
Michigan	106.67	10.48	103	[80, 118]	4.82
Minnesota	122.75	5.62	115	[72, 149]	7.98
Mississippi	103.39	6.84	98	[67, 121]	4.96
Missouri	112.59	70.34	112	[108, 114]	5.90
Montana	112.34	17.38	110	[95, 120]	5.95
Nebraska	115.06	20.31	113	[99, 121]	6.33
Nevada	79.16	186.01	79	[78, 80]	6.32
New Hampshire	120.25	2.37	103	[34, 191]	6.53
New Jersey	113.00	13.63	110	[91, 122]	8.80
New Mexico	91.12	5.27	85	[52, 112]	10.00
New York	74.51	2.68	65	[25, 112]	3.50
North Carolina	107.47	2.20	91	[28, 177]	6.97
North Dakota	110.11	377.69	110	[109, 110]	4.93
Ohio	N/A	N/A	>120	N/A	N/A
Oklahoma	121.53	3.37	109	[50, 168]	8.05
Oregon	107.09	9.40	103	[78, 120]	7.33
Pennsylvania	N/A	N/A	>120	N/A	N/A
Rhode Island	92.09	6.45	87	[58, 109]	2.56
South Carolina	76.92	3.89	70	[36, 102]	3.92
South Dakota	111.51	80.45	111	[107, 113]	5.29
Tennessee	112.32	12.20	109	[88, 123]	8.70
Texas	101.32	3.80	92	[46, 135]	6.24
Utah	105.85	20.81	104	[92, 112]	7.68
Vermont	99.64	7.69	95	[68, 115]	6.35
Virginia	112.28	31.94	111	[102, 116]	7.34
Washington	117.41	4.93	109	[64, 147]	8.64
West Virginia	121.01	7.19	115	[80, 141]	7.85
Wisconsin	117.36	31.34	116	[107, 122]	6.32
Wyoming	94.03	11.20	91	[72, 104]	5.84
Entire U.S.	N/A	N/A	>120	N/A	N/A
Northeast U.S.	N/A	N/A	>120	N/A	N/A
Northwest U.S.	N/A	N/A	>120	N/A	N/A
Southeast U.S.	119.37	4.03	109	[57, 157]	7.35
Southwest U.S.	137.50	2.87	121	[49, 202]	1.50

Table B-15. Bridge deck geometry Markov/Weibull results (end-of-life threshold: deck geometry rating = 5).

Region	*Weibull Scaling Factor, α*	*Weibull Shaping Factor, β*	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	100.70	13.50	98	[81, 109]	7.63
Alaska	41.71	3.06	37	[16, 60]	3.25
Arizona	80.97	14.88	79	[66, 87]	18.96
Arkansas	133.14	1.43	103	[17, 287]	5.70
California	115.68	7.27	110	[77, 135]	7.16
Colorado	79.97	14.71	78	[65, 86]	19.02
Connecticut	98.41	4.68	91	[52, 124]	8.37
Delaware	65.50	3.51	59	[28, 90]	6.76
Florida	68.84	3.50	62	[29, 94]	7.91
Georgia	61.56	6.15	58	[38, 74]	4.21
Hawaii	95.74	7.22	91	[63, 111]	7.18
Idaho	108.10	3.38	97	[45, 149]	7.78
Illinois	127.44	3.57	115	[55, 173]	4.95
Indiana	68.96	2.63	60	[22, 105]	2.65
Iowa	135.85	2.20	115	[35, 224]	3.65
Kansas	N/A	N/A	>120	N/A	N/A
Kentucky	80.03	2.74	70	[27, 120]	6.05
Louisiana	91.47	5.00	85	[50, 114]	5.74
Maine	54.66	2.43	47	[16, 86]	3.60
Maryland	93.14	6.45	88	[59, 110]	4.62
Massachusetts	88.00	3.85	80	[41, 117]	3.01
Michigan	106.77	3.82	97	[49, 142]	5.94
Minnesota	130.03	2.08	109	[31, 221]	5.22
Mississippi	72.76	9.47	70	[53, 82]	19.24
Missouri	111.85	48.00	111	[105, 114]	7.96
Montana	114.43	7.54	109	[77, 132]	6.07
Nebraska	114.46	16.85	112	[96, 122]	5.93
Nevada	74.26	104.35	74	[72, 75]	6.29
New Hampshire	85.57	2.52	74	[26, 132]	6.22
New Jersey	125.45	2.61	109	[40, 191]	8.21
New Mexico	76.21	4.31	70	[38, 98]	8.58
New York	58.50	2.67	51	[19, 88]	2.33
North Carolina	76.34	1.91	63	[16, 136]	5.56
North Dakota	109.11	374.07	109	[108, 109]	5.03
Ohio	N/A	N/A	>120	N/A	N/A
Oklahoma	90.23	14.65	88	[74, 97]	27.96
Oregon	107.25	3.65	97	[48, 145]	5.36
Pennsylvania	92.23	14.95	90	[76, 99]	18.92
Rhode Island	70.36	3.32	63	[29, 98]	7.44
South Carolina	59.43	2.40	51	[17, 94]	3.69
South Dakota	110.62	65.06	110	[106, 113]	6.15
Tennessee	101.85	9.52	98	[75, 114]	7.73
Texas	78.12	2.95	69	[29, 113]	2.26
Utah	106.38	11.34	103	[82, 117]	9.67
Vermont	86.58	5.50	81	[50, 106]	3.05
Virginia	119.46	4.00	109	[57, 157]	5.23
Washington	120.50	2.49	104	[37, 187]	9.24
West Virginia	121.55	3.36	109	[50, 168]	7.50
Wisconsin	124.41	4.66	115	[66, 157]	9.97
Wyoming	94.16	6.50	89	[60, 111]	5.46
Entire U.S.	129.24	2.27	110	[35, 209]	1.60
Northeast U.S.	127.64	2.32	109	[36, 205]	2.13
Northwest U.S.	N/A	N/A	>120	N/A	N/A
Southeast U.S.	128.21	1.75	104	[24, 240]	6.44
Southwest U.S.	94.83	3.02	84	[35, 136]	3.76

Table B-16. Bridge scour protection Markov/Weibull results (end-of-life threshold: scour protection rating = 2).

Region	Weibull Scaling Factor, α	Weibull Shaping Factor, β	Median Service Life	90% Confidence Interval	RMSE
Alabama	87.52	61.99	87	[83, 89]	7.49
Alaska	67.53	46.13	67	[63, 69]	9.85
Arizona	109.11	349.72	109	[108, 109]	5.70
Arkansas	87.14	230.90	87	[86, 88]	6.49
California	117.56	6.38	111	[74, 140]	7.03
Colorado	111.65	15.24	109	[92, 120]	6.49
Connecticut	N/A	N/A	>120	N/A	N/A
Delaware	103.14	278.06	103	[102, 104]	6.97
Florida	97.09	416.66	97	[96, 97]	5.54
Georgia	97.72	49.68	97	[92, 100]	9.21
Hawaii	85.64	49.17	85	[81, 88]	9.43
Idaho	93.74	46.49	93	[88, 96]	7.00
Illinois	N/A	N/A	>120	N/A	N/A
Indiana	126.10	2.52	109	[39, 195]	3.18
Iowa	118.99	21.74	117	[104, 125]	5.53
Kansas	118.22	19.30	116	[101, 125]	4.58
Kentucky	54.88	2.37	47	[16, 87]	2.74
Louisiana	125.38	1.86	103	[25, 226]	6.03
Maine	103.72	52.73	103	[98, 106]	9.13
Maryland	N/A	N/A	>120	N/A	N/A
Massachusetts	103.72	52.73	103	[98, 106]	9.13
Michigan	120.71	11.76	117	[94, 133]	6.76
Minnesota	N/A	N/A	>120	N/A	N/A
Mississippi	101.15	11.58	98	[78, 111]	6.87
Missouri	109.29	138.08	109	[107, 110]	5.34
Montana	94.25	15.17	92	[77, 101]	9.81
Nebraska	109.15	262.31	109	[108, 110]	6.09
Nevada	73.32	83.12	73	[71, 74]	4.76
New Hampshire	49.10	8.38	47	[34, 56]	13.14
New Jersey	110.64	24.49	109	[98, 116]	9.09
New Mexico	86.91	16.51	85	[73, 93]	10.10
New York	118.24	3.09	105	[45, 169]	3.24
North Carolina	94.05	32.76	93	[86, 97]	8.48
North Dakota	85.64	49.17	85	[81, 88]	9.43
Ohio	N/A	N/A	>120	N/A	N/A
Oklahoma	113.99	3.62	103	[50, 154]	5.12
Oregon	97.46	77.84	97	[94, 99]	4.41
Pennsylvania	N/A	N/A	>120	N/A	N/A
Rhode Island	115.74	56.97	115	[110, 118]	8.98
South Carolina	75.89	9.44	73	[55, 85]	20.59
South Dakota	3.06	18.75	3	[3, 3]	28.87
Tennessee	101.04	11.98	98	[79, 111]	6.78
Texas	87.23	140.06	87	[85, 88]	6.69
Utah	105.40	15.89	103	[87, 113]	7.94
Vermont	N/A	N/A	>120	N/A	N/A
Virginia	N/A	N/A	>120	N/A	N/A
Washington	108.99	3.81	99	[50, 145]	4.13
West Virginia	N/A	N/A	>120	N/A	N/A
Wisconsin	94.25	15.17	92	[77, 101]	11.02
Wyoming	19.56	12.59	19	[15, 21]	13.95
Entire U.S.	N/A	N/A	>120	N/A	N/A
Northeast U.S.	N/A	N/A	>120	N/A	N/A
Northwest U.S.	N/A	N/A	>120	N/A	N/A
Southeast U.S.	110.09	426.37	110	[109, 110]	0.99
Southwest U.S.	111.54	75.57	111	[107, 113]	5.01

Table B-17. Bridge scour protection Markov/Weibull results (end-of-life threshold: scour protection rating = 3).

Region	*Weibull Scaling Factor, α*	*Weibull Shaping Factor, β*	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	87.50	21.22	86	[76, 92]	8.52
Alaska	40.98	1.96	34	[9, 72]	7.65
Arizona	43.62	1.47	34	[6, 92]	4.55
Arkansas	86.14	228.92	86	[85, 87]	6.84
California	125.35	2.81	110	[43, 185]	6.02
Colorado	117.97	2.70	103	[39, 177]	9.65
Connecticut	N/A	N/A	>120	N/A	N/A
Delaware	18.68	3.90	17	[9, 25]	26.54
Florida	94.25	15.17	92	[77, 101]	9.43
Georgia	94.25	15.17	92	[77, 101]	11.07
Hawaii	2.07	10.57	2	[2, 2]	35.36
Idaho	103.13	3.21	92	[41, 145]	6.79
Illinois	N/A	N/A	>120	N/A	N/A
Indiana	86.04	2.67	75	[28, 130]	1.42
Iowa	126.60	4.19	116	[62, 165]	7.95
Kansas	121.60	6.57	115	[77, 144]	7.38
Kentucky	39.32	1.78	32	[7, 73]	2.35
Louisiana	18.43	4.55	17	[10, 23]	4.63
Maine	85.32	96.97	85	[83, 86]	8.32
Maryland	56.10	215.36	56	[55, 56]	7.20
Massachusetts	86.68	46.87	86	[81, 89]	8.24
Michigan	135.48	2.36	116	[39, 216]	6.10
Minnesota	N/A	N/A	>120	N/A	N/A
Mississippi	102.72	6.39	97	[65, 122]	6.76
Missouri	115.23	2.59	100	[37, 176]	8.78
Montana	107.64	2.18	91	[28, 178]	8.26
Nebraska	121.23	2.25	103	[32, 197]	7.07
Nevada	41.45	6.00	39	[25, 50]	16.35
New Hampshire	52.90	1.11	38	[4, 142]	12.58
New Jersey	45.03	2.16	38	[11, 75]	3.52
New Mexico	82.63	5.19	77	[47, 102]	5.76
New York	78.05	2.00	65	[18, 135]	4.59
North Carolina	94.25	15.17	92	[77, 101]	9.77
North Dakota	80.66	44.83	80	[75, 83]	9.28
Ohio	N/A	N/A	>120	N/A	N/A
Oklahoma	117.36	1.58	93	[18, 235]	4.38
Oregon	108.62	1.43	84	[14, 234]	5.31
Pennsylvania	67.06	2.26	57	[18, 109]	2.63
Rhode Island	59.59	2.09	50	[14, 101]	14.36
South Carolina	69.97	8.45	67	[49, 80]	26.19
South Dakota	2.07	10.57	2	[2, 2]	35.36
Tennessee	108.54	3.26	97	[44, 152]	8.82
Texas	86.23	137.79	86	[84, 87]	6.70
Utah	95.32	7.91	91	[65, 110]	11.59
Vermont	86.61	51.71	86	[82, 88]	9.42
Virginia	N/A	N/A	>120	N/A	N/A
Washington	89.32	1.42	69	[11, 193]	4.48
West Virginia	125.89	2.54	109	[39, 194]	5.34
Wisconsin	93.21	15.24	91	[77, 100]	10.69
Wyoming	5.49	1.16	4	[0, 14]	8.74
Entire U.S.	N/A	N/A	>120	N/A	N/A
Northeast U.S.	N/A	N/A	>120	N/A	N/A
Northwest U.S.	N/A	N/A	>120	N/A	N/A
Southeast U.S.	109.09	422.29	109	[108, 109]	1.08
Southwest U.S.	114.21	9.77	110	[84, 128]	5.96

Table B-18. Bridge scour protection Markov/Weibull results (end-of-life threshold: scour protection rating = 4).

Region	*Weibull Scaling Factor, α*	*Weibull Shaping Factor, β*	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	112.29	1.32	85	[12, 258]	6.74
Alaska	35.20	5.69	33	[21, 43]	17.14
Arizona	41.02	1.31	31	[4, 95]	4.99
Arkansas	85.14	225.93	85	[84, 86]	6.09
California	135.35	1.69	109	[23, 259]	6.33
Colorado	120.78	1.08	86	[8, 334]	5.65
Connecticut	N/A	N/A	>120	N/A	N/A
Delaware	17.57	3.91	16	[8, 23]	27.83
Florida	93.21	15.24	91	[77, 100]	10.60
Georgia	93.21	15.24	91	[77, 100]	11.07
Hawaii	1.22	1.82	1	[0, 2]	50.00
Idaho	131.29	1.00	91	[7, 393]	9.65
Illinois	N/A	N/A	>120	N/A	N/A
Indiana	64.68	1.68	52	[11, 124]	3.44
Iowa	156.96	1.18	115	[13, 398]	4.99
Kansas	94.00	1.45	73	[12, 200]	1.50
Kentucky	23.88	1.30	18	[2, 56]	2.38
Louisiana	11.45	2.71	10	[4, 17]	5.55
Maine	57.68	30.77	57	[52, 60]	5.48
Maryland	55.10	211.10	55	[54, 55]	6.87
Massachusetts	90.83	5.53	85	[53, 111]	8.74
Michigan	153.97	1.26	115	[14, 369]	5.97
Minnesota	N/A	N/A	>120	N/A	N/A
Mississippi	98.65	2.46	85	[30, 154]	9.42
Missouri	48.53	1.35	37	[5, 109]	2.82
Montana	43.86	8.47	42	[31, 50]	25.60
Nebraska	73.96	2.08	62	[18, 125]	2.80
Nevada	53.09	1.10	38	[4, 144]	7.01
New Hampshire	53.38	1.00	37	[3, 160]	11.67
New Jersey	23.27	1.17	17	[2, 60]	2.46
New Mexico	81.64	5.12	76	[46, 101]	5.84
New York	39.39	1.07	28	[2, 109]	2.60
North Carolina	93.21	15.24	91	[77, 100]	10.15
North Dakota	79.10	300.86	79	[78, 79]	6.55
Ohio	N/A	N/A	>120	N/A	N/A
Oklahoma	34.61	1.00	24	[2, 104]	4.91
Oregon	76.96	14.19	75	[62, 83]	26.96
Pennsylvania	32.03	1.27	24	[3, 76]	2.47
Rhode Island	58.67	2.03	49	[14, 101]	14.56
South Carolina	60.38	9.13	58	[44, 68]	26.01
South Dakota	1.22	1.82	1	[0, 2]	50.00
Tennessee	115.84	1.67	93	[20, 224]	10.44
Texas	86.56	20.17	85	[75, 91]	10.27
Utah	78.92	1.63	63	[13, 155]	6.23
Vermont	85.64	49.17	85	[81, 88]	9.43
Virginia	N/A	N/A	>120	N/A	N/A
Washington	65.59	1.10	47	[4, 178]	2.35
West Virginia	80.97	14.88	79	[66, 87]	25.55
Wisconsin	85.12	262.67	85	[84, 85]	5.86
Wyoming	3.98	1.30	3	[0, 9]	6.66
Entire U.S.	N/A	N/A	>120	N/A	N/A
Northeast U.S.	N/A	N/A	>120	N/A	N/A
Northwest U.S.	N/A	N/A	>120	N/A	N/A
Southeast U.S.	97.23	6.63	92	[62, 115]	7.93
Southwest U.S.	113.38	9.30	109	[82, 128]	5.99

Table B-19. Indiana bridge deck transition matrices.

Age Group	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6 years	36.02	12.07	5.02	4.07	2.36	8.71
7 → 12 yrs	42.41	14.15	6.18	4.96	3.94	5.03
13 → 18 yrs	38.17	14.00	6.45	5.48	4.96	3.19
19 → 24 yrs	57.36	16.18	7.06	5.67	4.73	2.62
25 → 30 yrs	66.67	21.02	7.37	5.70	3.95	2.50
31 → 36 yrs	24.41	22.69	9.04	5.10	4.46	2.78
37 → 42 yrs	42.26	24.02	10.34	5.98	3.11	2.53
43 → 48 yrs	55.28	15.48	10.37	6.14	4.11	2.99
49 → 54 yrs	55.28	26.72	9.91	8.23	4.34	1.87
55 → 60 yrs	29.29	26.62	12.81	7.43	4.81	3.53
61 → 66 yrs	46.55	29.29	14.81	8.55	5.37	4.72
67 → 72 yrs	36.75	22.04	13.75	8.88	4.94	4.72
73 → 78 yrs	100.00	22.30	14.97	8.35	5.07	5.25
79 → 84 yrs	100.00	37.98	16.84	9.34	6.46	4.12
85 → 90 yrs	N/A	22.54	13.99	10.09	5.75	4.31
91 → 96 yrs	22.54	30.99	14.37	12.02	6.96	7.05
97 → 102 yrs	0.00	22.54	17.04	10.05	8.18	5.41
103 → 108 yrs	100.00	32.58	14.72	9.86	9.86	4.88
109 → 114 yrs	N/A	8.71	10.20	8.09	2.47	7.42
115 → 120 yrs	N/A	5.72	21.83	5.72	7.65	0.00

Table B-20. Indiana bridge superstructure transition matrices.

Age Group	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6 years	31.53	6.68	2.78	3.34	4.77	2.67
7 → 12 yrs	34.77	7.99	3.80	4.38	5.64	5.72
13 → 18 yrs	32.84	9.24	4.61	4.27	4.60	4.35
19 → 24 yrs	100.00	10.46	5.06	4.94	4.54	4.48
25 → 30 yrs	18.35	12.11	5.10	4.27	5.92	2.67
31 → 36 yrs	29.29	15.47	5.88	5.90	5.53	3.79
37 → 42 yrs	29.29	19.44	7.49	6.10	4.45	5.21
43 → 48 yrs	100.00	14.16	8.00	6.99	4.89	6.61
49 → 54 yrs	18.35	23.07	8.62	7.63	5.98	6.03
55 → 60 yrs	18.35	24.04	10.20	7.67	5.87	3.28
61 → 66 yrs	29.29	18.94	10.27	9.68	6.17	4.06
67 → 72 yrs	29.29	25.17	14.66	10.14	6.70	5.30
73 → 78 yrs	100.00	29.29	15.78	8.50	7.68	4.38
79 → 84 yrs	N/A	18.35	12.96	8.96	7.43	5.87
85 → 90 yrs	N/A	22.54	9.11	7.42	6.77	5.64
91 → 96 yrs	N/A	22.54	15.48	13.21	7.76	5.85
97 → 102 yrs	N/A	N/A	11.65	15.73	6.65	7.50
103 → 108 yrs	N/A	100.00	25.46	6.75	9.99	6.19
109 → 114 yrs	N/A	N/A	4.26	9.55	6.14	1.44
115 → 120 yrs	N/A	0.00	50.00	1.68	4.96	7.80

Table B-21. Indiana bridge substructure transition matrices.

Age Group	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6 years	31.44	5.70	2.28	3.36	3.39	1.57
7 → 12 yrs	33.10	7.57	3.41	4.41	4.64	5.42
13 → 18 yrs	24.72	8.14	4.42	4.58	4.25	3.72
19 → 24 yrs	50.00	9.88	4.84	5.18	5.53	3.45
25 → 30 yrs	29.29	11.68	4.66	5.50	4.41	3.38
31 → 36 yrs	100.00	13.77	5.18	5.61	5.39	4.61
37 → 42 yrs	29.29	14.17	6.99	5.52	5.26	4.32
43 → 48 yrs	100.00	7.34	7.20	5.70	4.18	7.01
49 → 54 yrs	100.00	17.16	7.46	6.03	4.98	3.68
55 → 60 yrs	29.29	23.62	9.30	6.55	5.89	5.26
61 → 66 yrs	N/A	22.54	11.10	8.13	6.72	4.96
67 → 72 yrs	N/A	35.11	12.48	8.47	7.38	5.33
73 → 78 yrs	N/A	13.40	10.21	9.46	6.20	5.17
79 → 84 yrs	N/A	10.56	11.81	9.24	6.06	5.25
85 → 90 yrs	N/A	14.72	11.88	7.70	5.23	5.74
91 → 96 yrs	N/A	22.54	13.98	10.00	6.37	8.04
97 → 102 yrs	N/A	100.00	16.79	6.66	6.78	7.07
103 → 108 yrs	N/A	N/A	15.76	6.32	5.47	6.07
109 → 114 yrs	N/A	N/A	21.83	7.53	4.19	6.07
115 → 120 yrs	N/A	29.29	25.46	9.42	9.55	3.18

Table B-22. Indiana bridge channel protection transition matrices.

Age Group	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6 years	35.31	8.27	4.30	3.18	1.82	0.43
7 → 12 yrs	13.67	10.05	5.33	3.50	3.34	1.84
13 → 18 yrs	13.60	10.16	5.33	3.48	2.80	1.57
19 → 24 yrs	29.29	11.83	6.85	3.73	2.91	1.67
25 → 30 yrs	7.42	13.72	7.70	4.69	3.17	1.47
31 → 36 yrs	13.40	13.43	8.08	5.04	2.57	1.80
37 → 42 yrs	14.72	12.58	7.91	5.41	2.92	2.17
43 → 48 yrs	29.29	6.62	8.62	5.65	3.42	3.09
49 → 54 yrs	0.00	12.47	10.00	5.96	5.00	1.42
55 → 60 yrs	29.29	22.35	10.90	7.32	5.50	2.42
61 → 66 yrs	29.29	15.79	11.25	8.30	5.52	2.87
67 → 72 yrs	13.40	23.30	11.16	8.64	5.86	2.23
73 → 78 yrs	10.56	13.40	10.43	9.41	5.21	3.35
79 → 84 yrs	18.35	10.94	11.11	7.49	5.88	3.91
85 → 90 yrs	0.00	6.75	9.59	5.75	5.01	2.45
91 → 96 yrs	N/A	7.42	12.26	7.60	4.53	1.94
97 → 102 yrs	100.00	10.56	7.42	4.65	3.95	5.05
103 → 108 yrs	100.00	5.72	11.99	5.55	3.98	0.00
109 → 114 yrs	N/A	0.00	4.83	5.64	3.64	0.00
115 → 120 yrs	N/A	29.29	8.71	0.00	7.07	0.00

Table B-23. Indiana bridge deck geometry transition matrices.

Age Group	Annual Transition Probabilities					
	9 → 8	8 → 7	7 → 6	6 → 5	5 → 4	4 → 3
0 → 6 years	2.06	10.18	3.66	4.20	2.85	1.64
7 → 12 yrs	2.74	10.04	4.81	3.88	2.85	1.36
13 → 18 yrs	2.87	7.65	4.46	5.04	3.60	1.68
19 → 24 yrs	5.14	6.42	6.25	5.48	3.97	1.68
25 → 30 yrs	3.72	12.48	8.75	6.50	4.41	1.82
31 → 36 yrs	1.85	10.08	7.65	6.13	4.13	2.18
37 → 42 yrs	4.03	11.61	7.49	5.48	3.48	2.21
43 → 48 yrs	2.77	20.94	9.75	6.33	4.76	2.57
49 → 54 yrs	2.11	12.90	4.15	7.42	6.12	2.53
55 → 60 yrs	2.22	15.98	9.37	11.59	5.59	4.15
61 → 66 yrs	3.03	18.76	14.78	8.18	5.15	4.52
67 → 72 yrs	5.51	20.12	13.23	9.14	6.67	5.46
73 → 78 yrs	5.72	21.83	9.04	7.73	5.60	6.32
79 → 84 yrs	5.72	21.29	15.23	10.48	8.53	6.51
85 → 90 yrs	0.00	22.38	11.08	9.71	4.10	10.21
91 → 96 yrs	N/A	18.66	12.10	7.18	6.39	7.62
97 → 102 yrs	N/A	7.07	10.81	6.63	7.00	10.25
103 → 108 yrs	N/A	29.29	16.11	5.72	2.11	9.03
109 → 114 yrs	N/A	13.40	0.00	8.01	24.41	17.08
115 → 120 yrs	N/A	18.35	42.26	3.92	13.40	0.00

Table B-24. Indiana bridge scour protection transition matrices.

Age Group	Annual Transition Probabilities	
	5 → 4	4 → 3
0 → 6 years	0.94	1.82
7 → 12 yrs	1.12	3.50
13 → 18 yrs	1.19	3.47
19 → 24 yrs	1.15	1.72
25 → 30 yrs	1.21	1.66
31 → 36 yrs	1.45	2.03
37 → 42 yrs	1.56	1.95
43 → 48 yrs	1.10	3.52
49 → 54 yrs	2.75	2.76
55 → 60 yrs	2.29	5.05
61 → 66 yrs	3.02	6.05
67 → 72 yrs	3.18	3.81
73 → 78 yrs	3.97	4.98
79 → 84 yrs	2.96	4.65
85 → 90 yrs	4.12	3.92
91 → 96 yrs	4.47	8.44
97 → 102 yrs	3.61	7.26
103 → 108 yrs	1.38	12.29
109 → 114 yrs	1.32	10.56
115 → 120 yrs	0.00	0.00

Table B-25. Number of observations used in developing Indiana bridge deck transition matrices.

Age Group	No. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6 years	3,545	12,149	8,073	1,404	257	30
7 → 12 yrs	205	6,748	12,106	3,825	712	102
13 → 18 yrs	34	3,191	10,832	5,165	1,210	207
19 → 24 yrs	11	1,362	7,867	4,549	1,365	271
25 → 30 yrs	9	715	5,547	4,001	1,252	263
31 → 36 yrs	7	343	3,550	3,329	1,226	255
37 → 42 yrs	9	194	1,840	2,268	932	200
43 → 48 yrs	5	77	768	1,118	721	170
49 → 54 yrs	5	54	520	868	577	189
55 → 60 yrs	8	52	609	1,174	724	202
61 → 66 yrs	7	58	700	1,314	919	304
67 → 72 yrs	5	51	488	1,143	871	336
73 → 78 yrs	2	53	260	756	719	323
79 → 84 yrs	1	39	188	595	472	223
85 → 90 yrs	0	20	123	427	349	166
91 → 96 yrs	5	21	90	208	253	125
97 → 102 yrs	1	5	77	110	102	57
103 → 108 yrs	2	11	55	96	48	21
109 → 114 yrs	0	6	31	58	41	14
115 → 120 yrs	0	9	18	18	34	10

Table B-26. Number of observations used in developing Indiana bridge superstructure transition matrices.

Age Group	No. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6 years	3,679	11,436	8,240	1,506	365	76
7 → 12 yrs	322	9,306	10,957	2,486	566	180
13 → 18 yrs	51	5,963	11,125	3,240	734	223
19 → 24 yrs	6	3,328	8,411	3,085	867	217
25 → 30 yrs	3	1,938	6,347	2,848	958	266
31 → 36 yrs	2	890	4,356	2,462	967	350
37 → 42 yrs	4	282	2,482	1,758	804	286
43 → 48 yrs	1	95	1,016	949	671	219
49 → 54 yrs	3	49	564	811	603	231
55 → 60 yrs	6	26	630	1,023	833	372
61 → 66 yrs	6	35	657	1,080	1,070	566
67 → 72 yrs	4	25	427	930	1,027	649
73 → 78 yrs	1	10	203	645	785	537
79 → 84 yrs	0	3	99	450	552	430
85 → 90 yrs	0	5	69	273	382	283
91 → 96 yrs	0	10	42	150	248	185
97 → 102 yrs	0	0	41	69	140	90
103 → 108 yrs	0	1	27	69	79	50
109 → 114 yrs	0	0	12	55	42	35
115 → 120 yrs	0	1	4	30	31	20

Table B-27. Number of observations used in developing Indiana bridge substructure transition matrices.

Age Group	No. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6 years	3,342	10,897	8,979	1,679	420	96
7 → 12 yrs	286	8,942	10,927	2,831	817	218
13 → 18 yrs	30	5,294	10,614	3,856	1,251	329
19 → 24 yrs	8	2,743	7,732	3,558	1,450	443
25 → 30 yrs	6	1,650	5,626	3,093	1,346	467
31 → 36 yrs	1	854	4,013	2,395	1,191	477
37 → 42 yrs	2	319	2,268	1,787	859	343
43 → 48 yrs	1	99	944	1,020	648	207
49 → 54 yrs	1	51	564	787	566	263
55 → 60 yrs	2	60	581	1,058	708	420
61 → 66 yrs	0	35	596	1,173	963	558
67 → 72 yrs	0	19	440	937	922	646
73 → 78 yrs	0	8	222	616	732	536
79 → 84 yrs	0	10	144	414	604	391
85 → 90 yrs	0	11	94	297	432	242
91 → 96 yrs	0	5	50	200	292	162
97 → 102 yrs	0	1	39	101	145	88
103 → 108 yrs	0	0	31	98	94	34
109 → 114 yrs	0	0	18	69	61	17
115 → 120 yrs	0	2	9	39	22	16

Table B-28. Number of observations used in developing Indiana bridge channel protection transition matrices.

Age Group	No. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6 years	1,257	8,409	6,795	2,521	667	116
7 → 12 yrs	161	5,205	8,247	4,032	1,051	274
13 → 18 yrs	71	2,985	7,871	4,817	1,447	384
19 → 24 yrs	36	1,491	5,831	4,663	1,656	514
25 → 30 yrs	14	798	4,073	4,018	1,745	550
31 → 36 yrs	16	455	2,593	3,000	1,598	504
37 → 42 yrs	11	263	1,428	1,911	1,114	350
43 → 48 yrs	4	125	697	1,065	700	230
49 → 54 yrs	1	77	500	813	554	249
55 → 60 yrs	4	68	660	971	682	419
61 → 66 yrs	2	55	692	1,157	904	547
67 → 72 yrs	4	51	536	980	888	567
73 → 78 yrs	5	20	349	669	670	516
79 → 84 yrs	3	29	243	527	464	326
85 → 90 yrs	2	23	208	340	307	248
91 → 96 yrs	0	21	126	253	226	130
97 → 102 yrs	1	10	91	121	142	61
103 → 108 yrs	1	9	71	102	77	21
109 → 114 yrs	0	4	53	73	42	11
115 → 120 yrs	0	2	30	40	22	11

Table B-29. Number of observations used in developing Indiana bridge deck geometry transition matrices.

Age Group	No. of Annual and Biannual Inspection Pairs by Starting Condition State					
	9	8	7	6	5	4
0 → 6 years	2,989	238	3,354	6,501	6,880	3,840
7 → 12 yrs	2,052	278	2,835	5,854	6,702	4,548
13 → 18 yrs	1,167	265	2,075	4,940	6,542	4,515
19 → 24 yrs	539	193	1,197	3,461	5,610	3,783
25 → 30 yrs	274	94	478	2,346	4,750	3,359
31 → 36 yrs	109	47	204	1,321	3,400	2,947
37 → 42 yrs	76	32	111	563	1,990	2,034
43 → 48 yrs	110	32	97	269	839	1,065
49 → 54 yrs	96	29	123	189	514	721
55 → 60 yrs	91	51	168	229	571	910
61 → 66 yrs	67	100	168	204	568	1,031
67 → 72 yrs	28	105	170	172	434	809
73 → 78 yrs	18	108	139	148	248	474
79 → 84 yrs	9	92	167	141	153	238
85 → 90 yrs	2	83	129	92	137	129
91 → 96 yrs	0	65	88	65	97	75
97 → 102 yrs	0	22	44	39	37	36
103 → 108 yrs	0	12	27	27	24	29
109 → 114 yrs	0	4	11	26	7	16
115 → 120 yrs	0	3	3	13	4	8

Table B-30. Number of observations used in developing Indiana bridge scour protection transition matrices.

Age Group	No. of Annual and Biannual Inspection Pairs by Starting Condition State		
	5	4	3
0 → 6 years	2,659	166	85
7 → 12 yrs	3,275	305	151
13 → 18 yrs	3,459	352	200
19 → 24 yrs	3,150	468	153
25 → 30 yrs	2,869	486	179
31 → 36 yrs	2,325	399	162
37 → 42 yrs	1,582	336	119
43 → 48 yrs	959	159	45
49 → 54 yrs	534	92	56
55 → 60 yrs	442	122	89
61 → 66 yrs	572	162	150
67 → 72 yrs	608	241	173
73 → 78 yrs	501	206	167
79 → 84 yrs	360	110	121
85 → 90 yrs	310	78	74
91 → 96 yrs	206	68	51
97 → 102 yrs	127	50	45
103 → 108 yrs	73	13	30
109 → 114 yrs	38	5	30
115 → 120 yrs	18	1	8

APPENDIX C

Box Culvert Markov/Weibull Results by State and 'End-of-Life Criterion'

Table C-1. Box culvert condition Markov/Weibull results (end-of-life threshold: culvert condition rating = 3).

Region	Weibull Scaling Factor, α	Weibull Shape Factor, β	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	113.79	10.83	110	[86, 126]	8.07
Alaska	51.41	13.17	50	[41, 56]	11.71
Arizona	73.58	5.70	69	[44, 89]	8.05
Arkansas	87.33	97.35	87	[85, 88]	5.16
California	99.39	93.99	99	[96, 101]	6.11
Colorado	99.31	15.59	97	[82, 107]	10.88
Connecticut	84.23	7.12	80	[55, 98]	7.06
Delaware	57.30	2.34	49	[16, 92]	8.17
Florida	90.46	7.25	86	[60, 105]	6.19
Georgia	107.21	12.06	104	[84, 117]	7.47
Hawaii	72.75	6.93	69	[47, 85]	9.69
Idaho	104.79	5.47	98	[61, 128]	9.31
Illinois	117.79	4.72	109	[63, 149]	8.88
Indiana	104.57	4.88	97	[57, 131]	7.27
Iowa	118.30	4.48	109	[61, 151]	8.60
Kansas	117.16	5.82	110	[70, 141]	7.86
Kentucky	104.39	4.99	97	[58, 130]	9.86
Louisiana	87.35	90.43	87	[85, 88]	6.08
Maine	57.65	2.26	49	[15, 94]	4.60
Maryland	86.43	4.08	79	[42, 113]	9.61
Massachusetts	85.78	4.45	79	[44, 110]	14.87
Michigan	67.92	3.41	61	[28, 94]	5.64
Minnesota	97.09	3.34	87	[40, 135]	2.15
Mississippi	100.31	117.73	100	[98, 101]	5.25
Missouri	109.21	190.11	109	[108, 110]	4.75
Montana	76.89	9.56	74	[56, 86]	14.63
Nebraska	105.14	268.16	105	[104, 106]	6.17
Nevada	70.83	6.59	67	[45, 84]	13.96
New Hampshire	119.30	2.49	103	[36, 185]	6.90
New Jersey	108.26	7.36	103	[72, 126]	8.25
New Mexico	84.18	7.20	80	[56, 98]	8.39
New York	81.70	2.17	69	[21, 135]	4.92
North Carolina	107.09	9.40	103	[78, 120]	7.82
North Dakota	85.09	344.13	85	[84, 85]	6.20
Ohio	69.93	3.04	62	[26, 100]	4.09
Oklahoma	87.48	3.60	79	[38, 119]	5.79
Oregon	74.02	4.32	68	[37, 95]	11.33
Pennsylvania	110.24	5.40	103	[64, 135]	6.37
Rhode Island	20.72	4.23	19	[10, 27]	17.65
South Dakota	84.24	4.77	78	[45, 106]	3.89
Tennessee	114.08	13.41	111	[91, 124]	6.09
Texas	110.64	5.12	103	[62, 137]	5.57
Utah	76.00	13.75	74	[61, 82]	10.36
Vermont	105.42	2.49	91	[32, 164]	15.03
Virginia	79.34	85.81	79	[77, 80]	5.12
Washington	73.09	6.36	69	[46, 87]	5.09
West Virginia	92.38	89.92	92	[89, 94]	6.33
Wisconsin	113.41	2.35	97	[32, 181]	8.74
Wyoming	79.42	69.62	79	[76, 81]	9.44
Entire U.S.	112.35	4.22	103	[56, 146]	1.81
Northeast U.S.	103.33	3.48	93	[44, 142]	1.99
Northwest U.S.	118.44	4.96	110	[65, 148]	7.46
Southeast U.S.	110.54	7.13	105	[73, 129]	7.14
Southwest U.S.	108.62	6.90	103	[71, 127]	6.84

Table C-2. Box culvert condition Markov/Weibull results (end-of-life threshold: culvert condition rating = 4).

Region	Weibull Scaling Factor, α	Weibull Shape Factor, β	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	116.98	5.19	109	[66, 145]	10.71
Alaska	50.57	11.59	49	[39, 56]	11.76
Arizona	72.59	5.61	68	[43, 88]	8.11
Arkansas	86.33	96.16	86	[84, 87]	6.50
California	98.42	85.69	98	[95, 100]	7.64
Colorado	95.33	3.56	86	[41, 130]	9.39
Connecticut	85.73	4.48	79	[44, 110]	6.36
Delaware	50.76	2.21	43	[13, 83]	9.84
Florida	90.99	5.38	85	[52, 112]	7.36
Georgia	121.06	2.27	103	[33, 196]	6.59
Hawaii	71.78	6.77	68	[46, 84]	9.77
Idaho	104.83	4.72	97	[56, 132]	9.78
Illinois	116.62	3.20	104	[46, 164]	7.93
Indiana	83.51	3.41	75	[35, 115]	5.03
Iowa	85.70	3.89	78	[40, 114]	2.20
Kansas	121.30	3.43	109	[51, 167]	6.68
Kentucky	93.47	3.86	85	[43, 124]	8.41
Louisiana	86.35	89.34	86	[84, 87]	6.11
Maine	43.51	1.93	36	[9, 77]	7.46
Maryland	74.46	2.70	65	[25, 112]	5.15
Massachusetts	81.74	3.68	74	[36, 110]	13.77
Michigan	63.35	2.97	56	[23, 92]	4.22
Minnesota	71.22	2.99	63	[26, 103]	1.84
Mississippi	99.31	116.69	99	[97, 100]	5.10
Missouri	97.15	5.61	91	[57, 118]	4.26
Montana	75.89	9.44	73	[55, 85]	14.89
Nebraska	104.14	265.30	104	[103, 105]	5.60
Nevada	57.36	8.72	55	[41, 65]	19.35
New Hampshire	111.23	2.18	94	[28, 184]	6.10
New Jersey	97.24	5.52	91	[57, 119]	5.72
New Mexico	92.15	2.38	79	[26, 146]	7.82
New York	53.00	1.97	44	[12, 93]	3.60
North Carolina	99.64	5.31	93	[57, 122]	6.71
North Dakota	80.35	84.18	80	[78, 81]	4.51
Ohio	48.59	2.52	42	[15, 75]	3.64
Oklahoma	64.95	2.81	57	[23, 96]	1.81
Oregon	71.93	5.16	67	[40, 89]	10.45
Pennsylvania	90.47	2.70	79	[30, 136]	3.74
Rhode Island	17.65	3.73	16	[8, 24]	16.68
South Dakota	66.72	4.09	61	[32, 87]	3.13
Tennessee	113.41	11.99	110	[89, 124]	6.58
Texas	88.12	6.12	83	[54, 105]	7.88
Utah	76.49	7.86	73	[52, 88]	6.87
Vermont	88.85	3.49	80	[38, 122]	15.25
Virginia	88.66	2.60	77	[28, 135]	13.49
Washington	72.23	6.08	68	[44, 87]	5.65
West Virginia	93.21	15.24	91	[77, 100]	9.68
Wisconsin	73.57	3.37	66	[31, 102]	5.02
Wyoming	80.16	3.92	73	[38, 106]	11.24
Entire U.S.	93.69	3.77	85	[43, 125]	3.68
Northeast U.S.	83.27	3.10	74	[32, 119]	3.29
Northwest U.S.	124.61	2.74	109	[42, 186]	7.50
Southeast U.S.	116.11	3.33	104	[48, 161]	6.10
Southwest U.S.	112.04	2.54	97	[35, 173]	8.31

Table C-3. Box culvert condition Markov/Weibull results (end-of-life threshold: culvert condition rating = 5).

Region	Weibull Scaling Factor, α	Weibull Shape Factor, β	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	80.86	1.95	67	[18, 142]	3.85
Alaska	47.22	5.18	44	[27, 58]	7.55
Arizona	71.83	5.26	67	[41, 88]	8.72
Arkansas	97.57	2.66	85	[32, 147]	9.58
California	118.75	1.81	97	[23, 218]	8.24
Colorado	63.83	1.79	52	[12, 118]	4.38
Connecticut	74.01	2.07	62	[18, 126]	3.99
Delaware	26.69	1.53	21	[4, 55]	4.66
Florida	77.09	2.36	66	[22, 123]	4.03
Georgia	75.47	1.39	58	[9, 166]	6.21
Hawaii	74.02	3.68	67	[33, 100]	11.26
Idaho	63.12	10.73	61	[48, 70]	8.34
Illinois	78.40	3.24	70	[31, 110]	1.57
Indiana	59.14	2.18	50	[15, 98]	2.26
Iowa	63.14	3.05	56	[24, 90]	1.21
Kansas	87.68	2.56	76	[28, 135]	3.43
Kentucky	65.12	2.17	55	[17, 108]	1.80
Louisiana	85.35	88.23	85	[83, 86]	8.61
Maine	33.41	2.08	28	[8, 57]	3.64
Maryland	60.64	2.12	51	[15, 102]	3.54
Massachusetts	56.94	2.82	50	[20, 84]	3.81
Michigan	47.31	2.18	40	[12, 78]	3.47
Minnesota	54.78	2.77	48	[19, 81]	2.54
Mississippi	98.31	115.40	98	[96, 99]	4.98
Missouri	74.76	2.62	65	[24, 114]	3.97
Montana	63.61	8.74	61	[45, 72]	14.85
Nebraska	103.14	263.01	103	[102, 104]	5.79
Nevada	54.74	2.11	46	[13, 92]	6.01
New Hampshire	101.21	1.48	79	[14, 212]	6.79
New Jersey	76.14	5.24	71	[43, 94]	5.71
New Mexico	49.24	2.00	41	[11, 85]	1.92
New York	39.58	1.72	32	[7, 75]	4.28
North Carolina	77.32	2.11	65	[19, 130]	2.36
North Dakota	82.65	8.12	79	[57, 95]	6.71
Ohio	38.10	2.55	33	[12, 59]	2.35
Oklahoma	44.57	1.97	37	[10, 78]	1.96
Oregon	68.33	2.50	59	[21, 106]	8.33
Pennsylvania	60.44	2.16	51	[15, 100]	1.85
Rhode Island	20.89	1.11	15	[1, 56]	7.54
South Dakota	51.79	3.09	46	[20, 74]	0.99
Tennessee	126.44	2.47	109	[38, 197]	5.27
Texas	64.43	2.32	55	[18, 103]	3.09
Utah	79.76	3.15	71	[31, 113]	4.58
Vermont	37.14	2.46	32	[11, 58]	4.56
Virginia	54.09	1.78	44	[10, 100]	4.75
Washington	75.52	3.06	67	[29, 108]	11.93
West Virginia	80.01	2.74	70	[27, 119]	6.27
Wisconsin	60.96	2.62	53	[20, 93]	1.15
Wyoming	61.10	5.28	57	[35, 75]	8.40
Entire U.S.	70.62	2.50	61	[22, 109]	1.19
Northeast U.S.	60.61	2.39	52	[18, 96]	1.14
Northwest U.S.	87.03	2.71	76	[29, 131]	2.66
Southeast U.S.	87.35	2.21	74	[23, 144]	2.86
Southwest U.S.	65.25	2.14	55	[16, 109]	1.81

Table C-4. Box culvert channel/embankment protection Markov/Weibull results (end-of-life threshold: channel condition rating = 3).

Region	Weibull Scaling Factor, α	Weibull Shape Factor, β	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	116.46	6.42	110	[73, 138]	8.22
Alaska	59.69	7.94	57	[41, 69]	10.13
Arizona	69.21	123.49	69	[68, 70]	8.03
Arkansas	89.26	9.85	86	[66, 100]	8.81
California	101.67	55.83	101	[96, 104]	8.16
Colorado	100.34	15.52	98	[83, 108]	11.45
Connecticut	73.69	39.05	73	[68, 76]	8.08
Delaware	79.34	4.40	73	[40, 102]	12.10
Florida	106.25	4.53	98	[55, 135]	8.90
Georgia	102.41	15.39	100	[84, 110]	6.27
Hawaii	74.62	44.21	74	[70, 76]	9.30
Idaho	76.96	14.19	75	[62, 83]	16.05
Illinois	110.46	88.08	110	[107, 112]	5.88
Indiana	103.22	8.79	99	[74, 117]	8.57
Iowa	109.57	70.71	109	[105, 111]	7.20
Kansas	119.43	4.45	110	[61, 153]	8.78
Kentucky	90.56	5.79	85	[54, 109]	7.19
Louisiana	88.50	12.79	86	[70, 96]	5.46
Maine	71.22	4.01	65	[34, 94]	5.71
Maryland	118.46	4.95	110	[65, 148]	8.99
Massachusetts	64.51	9.25	62	[47, 73]	14.19
Michigan	93.21	15.24	91	[77, 100]	12.41
Minnesota	97.24	6.62	92	[62, 115]	2.82
Mississippi	100.60	61.13	100	[96, 102]	6.07
Missouri	109.06	630.24	109	[109, 109]	1.76
Montana	79.33	8.56	76	[56, 90]	11.92
Nebraska	108.55	25.49	107	[97, 113]	7.06
Nevada	53.96	3.13	48	[21, 77]	11.60
New Hampshire	86.20	160.16	86	[85, 87]	6.44
New Jersey	83.10	14.35	81	[68, 90]	8.89
New Mexico	82.64	11.29	80	[64, 91]	9.31
New York	63.96	2.76	56	[22, 95]	6.85
North Carolina	88.23	14.34	86	[72, 95]	8.01
North Dakota	88.37	23.52	87	[78, 93]	7.26
Ohio	76.93	3.88	70	[36, 102]	11.48
Oklahoma	98.28	28.03	97	[88, 102]	6.58
Oregon	86.14	233.30	86	[85, 87]	6.73
Pennsylvania	110.26	5.38	103	[64, 135]	15.11
Rhode Island	16.55	3.73	15	[7, 22]	27.30
South Dakota	94.52	13.58	92	[76, 102]	7.58
Tennessee	109.56	72.02	109	[105, 111]	6.35
Texas	92.48	22.67	91	[81, 97]	10.58
Utah	84.24	9.34	81	[61, 95]	8.93
Vermont	43.33	48.57	43	[41, 44]	5.59
Virginia	80.46	64.42	80	[77, 82]	8.25
Washington	75.40	69.50	75	[72, 77]	8.19
West Virginia	101.00	12.17	98	[79, 111]	7.24
Wisconsin	81.92	10.08	79	[61, 91]	11.50
Wyoming	86.09	332.46	86	[85, 86]	6.49
Entire U.S.	122.95	5.48	115	[72, 150]	4.34
Northeast U.S.	131.17	2.79	115	[45, 194]	10.17
Northwest U.S.	110.37	109.97	110	[107, 111]	6.50
Southeast U.S.	N/A	N/A	>120	N/A	N/A
Southwest U.S.	100.71	13.44	98	[81, 109]	7.90

Table C-5. Box culvert channel/embankment protection Markov/Weibull results (end-of-life threshold: channel condition rating = 4).

Region	Weibull Scaling Factor, α	Weibull Shape Factor, β	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	124.19	2.81	109	[43, 184]	9.69
Alaska	58.70	7.78	56	[40, 68]	10.21
Arizona	68.21	121.63	68	[67, 69]	8.46
Arkansas	91.15	5.25	85	[52, 112]	10.40
California	100.25	149.77	100	[98, 101]	5.98
Colorado	98.87	19.19	97	[85, 105]	11.26
Connecticut	72.84	5.33	68	[42, 89]	4.83
Delaware	73.65	5.62	69	[43, 90]	10.51
Florida	108.92	3.16	97	[43, 154]	9.51
Georgia	101.34	15.66	99	[84, 109]	6.16
Hawaii	73.14	187.16	73	[72, 74]	7.33
Idaho	78.46	6.26	74	[49, 93]	15.86
Illinois	122.46	3.15	109	[48, 174]	8.57
Indiana	96.11	2.72	84	[32, 144]	9.26
Iowa	95.41	3.97	87	[45, 126]	3.80
Kansas	127.90	2.29	109	[35, 206]	7.92
Kentucky	72.61	2.32	62	[20, 117]	3.85
Louisiana	88.58	8.88	85	[63, 100]	7.31
Maine	50.00	3.00	44	[19, 72]	6.26
Maryland	128.44	2.23	109	[34, 210]	8.93
Massachusetts	63.50	9.12	61	[46, 72]	13.77
Michigan	72.44	3.38	65	[30, 100]	5.94
Minnesota	82.69	2.94	73	[30, 120]	2.96
Mississippi	99.60	60.48	99	[95, 101]	5.45
Missouri	91.23	14.80	89	[75, 98]	12.38
Montana	78.27	8.58	75	[55, 89]	11.99
Nebraska	114.64	4.68	106	[61, 145]	8.69
Nevada	50.15	2.38	43	[14, 79]	6.62
New Hampshire	85.20	158.20	85	[84, 86]	6.80
New Jersey	81.47	20.08	80	[70, 86]	5.30
New Mexico	90.22	2.76	79	[31, 134]	8.73
New York	36.91	2.10	31	[9, 62]	2.98
North Carolina	92.46	4.35	85	[47, 119]	12.07
North Dakota	87.94	16.42	86	[73, 94]	7.43
Ohio	42.06	2.35	36	[12, 67]	2.81
Oklahoma	99.39	4.15	91	[49, 129]	7.57
Oregon	85.14	230.62	85	[84, 86]	6.69
Pennsylvania	56.30	2.30	48	[15, 91]	1.39
Rhode Island	15.44	3.73	14	[7, 21]	26.74
South Dakota	93.86	11.86	91	[73, 103]	8.41
Tennessee	101.08	8.89	97	[72, 114]	8.75
Texas	81.96	2.83	72	[29, 121]	8.88
Utah	83.27	9.14	80	[60, 94]	8.98
Vermont	43.47	6.26	41	[27, 52]	7.47
Virginia	89.50	2.94	79	[33, 130]	14.55
Washington	74.59	45.89	74	[70, 76]	8.54
West Virginia	110.77	2.76	97	[38, 165]	8.36
Wisconsin	67.30	3.73	61	[30, 90]	5.87
Wyoming	85.09	328.76	85	[84, 85]	5.69
Entire U.S.	102.40	2.42	88	[30, 161]	3.20
Northeast U.S.	81.83	2.58	71	[26, 125]	2.75
Northwest U.S.	119.08	4.14	109	[58, 155]	9.41
Southeast U.S.	N/A	N/A	>120	N/A	N/A
Southwest U.S.	115.35	2.12	97	[28, 194]	12.35

Table C-6. Box culvert channel/embankment protection Markov/Weibull results (end-of-life threshold: channel condition rating = 5).

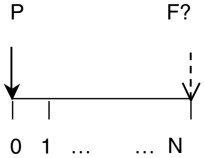
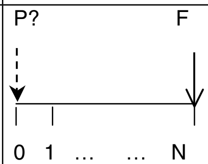
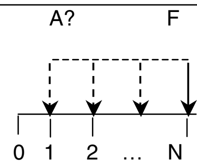
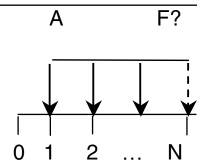
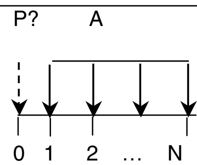
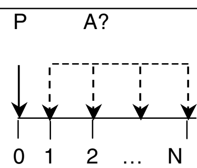
Region	Weibull Scaling Factor, α	Weibull Shape Factor, β	*Median Service Life*	*90% Confidence Interval*	*RMSE*
Alabama	65.01	1.97	54	[14, 113]	3.29
Alaska	59.19	4.99	55	[33, 74]	10.01
Arizona	67.21	119.74	67	[66, 68]	8.66
Arkansas	77.57	2.27	66	[21, 126]	4.56
California	99.25	148.08	99	[97, 100]	5.36
Colorado	89.68	8.76	86	[64, 102]	9.87
Connecticut	55.63	2.18	47	[14, 92]	5.03
Delaware	26.49	1.97	22	[6, 46]	4.18
Florida	68.88	1.77	56	[13, 128]	4.48
Georgia	100.64	13.79	98	[81, 109]	6.55
Hawaii	60.92	7.47	58	[41, 71]	7.05
Idaho	77.47	6.17	73	[48, 93]	15.93
Illinois	78.19	1.83	64	[15, 142]	3.32
Indiana	54.46	1.41	42	[7, 119]	4.68
Iowa	75.34	2.48	65	[23, 117]	2.98
Kansas	72.28	2.16	61	[18, 120]	3.17
Kentucky	52.02	1.71	42	[9, 99]	3.99
Louisiana	92.54	1.74	75	[17, 174]	4.27
Maine	37.12	1.72	30	[7, 70]	2.75
Maryland	59.46	1.71	48	[10, 113]	3.80
Massachusetts	57.35	1.66	46	[10, 111]	7.14
Michigan	46.40	2.47	40	[14, 72]	1.19
Minnesota	53.64	2.39	46	[15, 85]	1.60
Mississippi	102.19	8.76	98	[73, 116]	7.36
Missouri	74.16	2.25	63	[20, 121]	3.29
Montana	77.22	8.61	74	[55, 88]	12.07
Nebraska	113.79	4.56	105	[59, 145]	8.59
Nevada	36.64	3.51	33	[16, 50]	10.36
New Hampshire	84.59	5.36	79	[49, 104]	7.27
New Jersey	76.33	5.06	71	[42, 95]	9.10
New Mexico	50.98	1.89	42	[11, 91]	2.41
New York	22.36	2.25	19	[6, 36]	1.70
North Carolina	56.41	1.80	46	[11, 104]	2.59
North Dakota	86.94	16.28	85	[72, 93]	8.59
Ohio	31.60	2.33	27	[9, 51]	1.37
Oklahoma	77.12	2.14	65	[19, 129]	3.39
Oregon	55.41	2.98	49	[20, 80]	4.92
Pennsylvania	32.32	2.04	27	[8, 55]	1.95
Rhode Island	14.42	3.54	13	[6, 20]	27.00
South Dakota	84.21	2.34	72	[24, 135]	7.66
Tennessee	89.86	1.89	74	[19, 161]	3.26
Texas	42.07	1.72	34	[7, 80]	1.81
Utah	84.21	5.73	79	[50, 102]	9.71
Vermont	31.88	2.82	28	[11, 47]	1.35
Virginia	39.44	1.75	32	[7, 74]	3.16
Washington	73.05	549.84	73	[73, 73]	5.26
West Virginia	69.41	1.71	56	[12, 132]	4.25
Wisconsin	48.49	2.18	41	[12, 80]	1.39
Wyoming	77.83	5.72	73	[46, 94]	8.62
Entire U.S.	66.28	1.96	55	[15, 116]	1.54
Northeast U.S.	50.95	1.90	42	[11, 91]	2.36
Northwest U.S.	85.19	2.60	74	[27, 130]	4.10
Southeast U.S.	87.99	2.12	74	[22, 148]	3.59
Southwest U.S.	56.64	1.59	45	[9, 113]	2.88

APPENDIX D

Interest Formulae for LCCA

Table D-1. Interest formulae for LCCA (Sinha & Labi, 2007).

Note: N represents the analysis period

Description	Cash Flow Diagram	Computational Formula	Factor Computation[1]
Finding the future compounded amount (F) at the end of a specified analysis period, given the initial amount (P) and interest rate.		F = P * SPCAF The Single Payment Compound Amount Factor, SPCAF (i%, N) may be read off from standard economic analysis tables, or may be computed as shown.	$SPCAF = (1+i)^N$ $SPCAF = e^{N*i}$
Finding the initial amount (P) that would yield a given future amount (F) at the end of a specified analysis period, given the interest rate.		P = F * SPPWF The Single Payment Present Worth Factor, SPPWF (i%, N) may be read off from standard economic analysis tables, or may be computed as shown.	$SPPWF = \frac{1}{(1+i)^N}$ $SPPWF = \frac{1}{e^{N*i}}$
Finding the uniform yearly amount (A) that would yield a given future amount (F) at the end of a specified analysis period, given the interest rate.		A = F * SFDF The Sinking Fund Deposit Factor, SFDF (i%, N) may be read off standard economic analysis tables, or may be computed as shown.	$SFDF = \frac{i}{(1+i)^N - 1}$ $SFDF = \frac{e^i - 1}{e^{N*i} - 1}$
Finding the future compounded amount (F) at the end of a specified analysis period due to annual payments (A), given the interest rate.		F = A * USCAF The Uniform Series Compounded Amount Factor, USCAF (i%, N) may be read off from standard economic analysis tables, or may be computed as shown.	$USCAF = \frac{(1+i)^N - 1}{i}$ $USCAF = \frac{e^{N*i} - 1}{e^i - 1}$
Finding the initial amount (P) that is equivalent to a series of uniform annual payments (A), given the interest rate and a specified analysis period.		P = A * USPWF The Uniform Series Present Worth Factor, USPWF (i%, N) may be read off from standard economic analysis tables, or may be computed as shown.	$USPWF = \frac{(1+i)^N - 1}{i*(1+i)^N}$ $USPWF = \frac{1 - e^{-N*i}}{e^i - 1}$
Finding the amount of uniform yearly payments (A) that would completely recover an initial amount (P) at the end of a specified analysis period, given the interest rate.		A = P * USCRF The Uniform Series capital Recovery Factor, USCRF (i%, N) may be read off from standard economic analysis tables, or may be computed as shown.	$USCRF = \frac{i*(1+i)^N}{(1+i)^N - 1}$ $USCRF = \frac{e^i - 1}{1 - e^{-N*i}}$

Note: 1) In column 4, upper and lower formulae are for discrete and continuous compounding, respectively.
2) For fixed discrete compounding yearly, i = nominal interest rate and N represents years.
3) When there is more than one compounding period per year, the formulae and tables can be used as long as there is a cash flow at the end of each interest period. i represents the interest rate per period and N is the number of periods.
4) When the compounding is more frequent than a year, but the cash flows are annual, the formulae can be used with N as number of years and i as the effective annual interest rate.

APPENDIX E

Cost Models for Bridge Preservation

Bridge construction/replacement cost estimation models (Saito et al. 1990):

$$BRTC = 0.155(BL)^{0.903}(DW)^{0.964} \tag{E1}$$

Where
$BRTC$ = total bridge construction/replacement cost, in \$1000;
BL = bridge length, in ft;
DW = bridge deck width (out-to-out), in ft.

Equation (E1) can be used to calculate the initial bridge construction/replacement cost for the bridge using traditional steel.

For the bridge using stainless steel, the cost difference between the traditional carbon steel and the stainless bridge is added to the result from Equation (E1) to get the initial construction costs.

$$AC_{initial}^{StainlessSteel} = BRTC + (P_{stainless} - P_{traditional}) * W_D \tag{E2}$$

Where
$AC_{initial}^{StainlessSteel}$ is bridge construction/replacement cost for stainless steel deck bridge;
$P_{traditional}$ is the unit price of traditional steel;
$P_{stainless}$ is the unit price of stainless steel;
W_D is the weight of the bridge deck reinforcement.

Deck replacement or rehabilitation cost models (Saito et al. 1990):

$$AC_{deck-replacement}^{TraditionalSteel} = BL * DW * C_{DP} \tag{E3a}$$

$$AC_{deck-replacement}^{StainlessSteel} = BL * DW * C_{DP} + (P_{stainless} - P_{traditional}) * W_D \tag{E3b}$$

$$AC_{deck-rehab} = BL * DW * C_{DR} \tag{E4}$$

Where
$AC_{deck-replacement}^{TraditionalSteel}$ is deck replacement cost for traditional steel deck;
$AC_{deck-replacement}^{StainlessSteel}$ is deck replacement cost for stainless steel deck;
C_{DP} is the unit cost of deck replacement, in \$/ft^2;
C_{DR} is the unit cost of deck rehabilitation, in \$/ft^2.

APPENDIX F

Inventory and Decision Support Systems for Non-Traditional Assets

A number of state highway agencies have established inventory databases for non-traditional highway assets such as roadway signs, traffic signals and lighting, pavement markings, and guardrails. As more and more of these systems evolve towards decision preservation investment support systems for these assets and for assessing their preservation program fiscal needs, there is greater need for reliable assessment of the lives of the assets. Reliable estimates of asset life help establish the future year of replacement and thus are useful for replacement planning, programming and budget development. This section describes efforts at a sample of states where inventory databases or decision support systems at various stages of development, have been established for non-traditional highway assets.

Georgia's Highway Sign Management System (HSMS) includes a database for all highway signs in the state (Roberts, 2002). The data include sign location (milepost, coordinates), position (right/overhead/left), type and purpose, dimensions (height and width), material type, and dates of fabrication and installation. It is envisaged that the system will evolve to one with a decision-making capability. For that to happen, data on costs and lives for the road signs, on the basis of their attributes, will be needed.

North Dakota's Roadway Sign Asset Management System (RSAMS) is an inventory and decision support system that generates a priority list of signs to be replaced or reviewed (Kruse and Simmer, 2003). The sign attribute data is collected or updated using a handheld computer and GPS technology. Thus, the use of road sign life is implicit in the system. The system is intended to be integrated with management systems of other assets in the state highway inventory.

Oregon DOT Region 2, over a decade ago, developed a Sign Management System (SMS) to track the inventory, location, and other attributes of road signs in Oregon (FHWA, 2005). The system provides a platform for planning, scheduling, executing, and management of individual maintenance programs for these assets, and to determine their maintenance budget on the basis of their expected life. The system also helps in protecting the agency against tort liability.

Wisconsin's Sign Inventory Management System (SIMS) revolves around a database on road sign location, jurisdiction, route, milepost, roadway position, sign direction, post type and length, sign code, size, base material, face material, age of sign, date of manufacture and installation, sign number and physical condition. The system facilitates sign replacement planning on the basis of the life of these assets (Wisconsin DOT, 2003). This is geared toward the optimal timing of the sign replacements by avoiding unduly delayed (deferred) or hastened (premature) replacements. SIMS is a useful tool for project contract preparation: by providing a list of signs slated for replacement, the system helps contractor to provide realistic bids. SIMS also assesses sign replacement needs and thus facilitates development of annual program.

Virginia's Sign Inventory Management System (SIMS) stores data on road sign location, position and direction, post length type, sign code. The Web-based system facilitates planning for replacing signs and for developing program funding needs on an annual basis. There are six modules: random condition assessment, needs-based budget request module, planning and scheduling module, work order and accomplishment module, inventory module and analysis tools module (Larson and Skrypczuk, 2004). Estimations of the lives of these assets are critical in the planning and scheduling module.

Minnesota's Automated Facilities Management System (AFMS) for traffic signal and lighting tracks the electrical services section's maintenance activities and coordinates requests for materials and work produced by the Minnesota DOT Metro Division and the eight districts traffic offices overseen by Minnesota DOT (FHWA, 2004). The system utilizes predictions of the asset lives of the electrical components in order to develop the maintenance schedules.

Oregon's Traffic Signal Information System (TSIS) includes data such as highway route and location, street name, direction of traffic flow, intersecting street name, nearest city, name of county, name of district, region number, name of company supplying power, meter number for location, mile point, date of activation, recent date of repair, months of inspection and maintenance, comments, and signal priority. Through its asset inventory, maintenance budget development, and established service life of each the asset categories, the system facilitates maintenance and inventory tracking and thus enhances planning, scheduling, executing, and managing individual maintenance programs. The system is fully integrated throughout the DOT's intranet (FHWA, 2004).

Virginia's Traffic Signal System Inventory (TSSI) system tracks and manages the signal infrastructure (Larson and Skrypczuk, 2004). The system is intended to ultimately contain asset-related and project-related data that will enhance decision-support for investments geared toward traffic signal repairs, rehabilitation, and replacement.

Maryland State Highway Administration's Traffic Structure Inventory Inspection and Maintenance (TSIIM) system tracks maintenance and inspection activities (FHWA, 2005). The TSIIM is intended to provide historical data review, track the condition and performance of these assets, ascertain the future years at which they will need repair or replacement, establish annual funding needs for repair or replacement, and develop optimal funding allocations.

Arizona's Pavement Marking Management System (PMMS) includes a database of all signs and pavement markings, a method for tracking lifetime product performance and thus to determine the asset life, and procedures and processes for monitoring, maintaining, and replacing these products (Arizona DOT, 2002).

Iowa's Pavement Marking Management System (PMMS) consists of two primary components: retroreflectivity-based performance curves for the pavement marking material and an application matrix tailored to the pavement marking products and roadway and environmental conditions in Iowa (Hawkins et al., 2006). The system is integrated into the agency's pavement and safety management systems.

Missouri DOT's Pavement Marking Management System (PMMS) provides an automated system that is an inventory of pavement markings and also provides a tool for managing these assets on the basis of their performance, costs, and longevity. A major component of the system is the measurement of the life of these assets (Davidson, 2003).

Virginia's Marking Management System (MMS) was designed to identify years of marking replacement, develop annual physical and fiscal needs, and facilitate development of annual budget estimates for these assets (Cottrell and Hanson, 2001). The data items in the database include the marking color, type, product manufacturer, reflectivity, spotting distance, and roadway surface type.

Idaho Transportation Department's Geographic Roadway Application for Information Location (GRAIL) System stores data on GPS location, curvature and other attributes of guardrails and other highway assets on the state highway system (ITD, 2002).

Kansas DOT's integrated preventive maintenance program tracks all pavement markings according to the year of installation expected life of pavement, type of marking material used, and performance guarantees of the pavement markings, and thus predicts the life of the pavement marking. The pavement marking investment decision-making process includes a Brightness Benefit Factor (BBF), a benefit-to-cost ratio based on the material's retroreflectivity, durability, and installed cost. The analysis takes account of traffic, expected life of the asset, and motorist delay (McGinnis, 2001). In the spring, maintenance crews are sent out to visually inspect specific pavement markings at night for retroreflectivity compliance. Information from the inspections is sent to the engineering department to update the list of roads that require new markings and/or warranty repairs. In addition, the list takes into consideration all planned maintenance activities, so that in selecting the optimal marking material to be used, the service life of the marking is evaluated relative to the interval until the next pavement maintenance activity (Kansas DOT, 1999).

North Dakota's pavement marking investment decision-making process selects pavement markings on the basis of the pavement surface material, predicted pavement surface condition, the anticipated level of traffic, and marking position (e.g., center or edge) (Kruse and Simmer, 2003). The expected life of each material type is an implicit factor in the decision process. The pavement marking materials considered include conventional paint; inlaid, patterned, and preformed plastic; and grooved, patterned, and preformed plastic. The process includes a guide to determine the best pavement marking practices under a given set of field conditions.

Abbreviations and acronyms used without definitions in TRB publications:

AAAE	American Association of Airport Executives
AASHO	American Association of State Highway Officials
AASHTO	American Association of State Highway and Transportation Officials
ACI–NA	Airports Council International–North America
ACRP	Airport Cooperative Research Program
ADA	Americans with Disabilities Act
APTA	American Public Transportation Association
ASCE	American Society of Civil Engineers
ASME	American Society of Mechanical Engineers
ASTM	American Society for Testing and Materials
ATA	American Trucking Associations
CTAA	Community Transportation Association of America
CTBSSP	Commercial Truck and Bus Safety Synthesis Program
DHS	Department of Homeland Security
DOE	Department of Energy
EPA	Environmental Protection Agency
FAA	Federal Aviation Administration
FHWA	Federal Highway Administration
FMCSA	Federal Motor Carrier Safety Administration
FRA	Federal Railroad Administration
FTA	Federal Transit Administration
HMCRP	Hazardous Materials Cooperative Research Program
IEEE	Institute of Electrical and Electronics Engineers
ISTEA	Intermodal Surface Transportation Efficiency Act of 1991
ITE	Institute of Transportation Engineers
NASA	National Aeronautics and Space Administration
NASAO	National Association of State Aviation Officials
NCFRP	National Cooperative Freight Research Program
NCHRP	National Cooperative Highway Research Program
NHTSA	National Highway Traffic Safety Administration
NTSB	National Transportation Safety Board
PHMSA	Pipeline and Hazardous Materials Safety Administration
RITA	Research and Innovative Technology Administration
SAE	Society of Automotive Engineers
SAFETEA-LU	Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (2005)
TCRP	Transit Cooperative Research Program
TEA-21	Transportation Equity Act for the 21st Century (1998)
TRB	Transportation Research Board
TSA	Transportation Security Administration
U.S.DOT	United States Department of Transportation