A RISK- AND PERFORMANCE-BASED

INFRASTRUCTURE ASSET MANAGEMENT FRAMEWORK

A Dissertation

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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August 2015

Major Subject: Civil Engineering

ABSTRACT

Asset managers who maintain the infrastructure can improve the efficiency of their practices by making use of decision-support frameworks. These models use performance data to help maximize the outcomes of maintenance strategies and financial allocations. In this research a new decision-support framework for asset managers was developed and tested. This framework improves upon existing models in two respects: (a) it provides an effective and practical method of accounting for uncertainty/risk, and (b) it includes a method for predicting asset performance over time in situations where there is limited historical data.

Outcome-based scenario analysis was chosen as the most effective approach to model risk in asset management. The proposed framework presents managers with “best-case,” “most-likely case,” and “worst-case” scenarios, which are defined by applying quantile regression analysis to the asset-performance data. For situations in which there is a lack of adequate historical performance data, an elicitation model was developed based on the Delphi technique. This approach provides a rigorous method for estimating asset performance using information solicited from a panel of experts. The elicited data was aggregated by a Bayesian hierarchical model and the Markov Chain Monte Carlo algorithm.

A case study was conducted to demonstrate the applicability of the decision-support model. While the proposed framework is generic and could be used for any type of asset, this study involved pavement condition on the city streets of Bryan, Texas. The results indicated that using a traditional deterministic model (rather than a scenario-based approach) could lead to significant over- or under-estimation of the budgets required to achieve certain asset-performance results. This demonstrates the urgent need for asset managers to use a practical model that can provide them with information about uncertainty and risk in asset-performance assessments. The case study also demonstrated the effectiveness of the data-elicitation technique, as the results of this approach were shown to be commensurate with historical information about pavement performance collected by the city of Bryan. The success of this approach in approximating historical performance trends provides evidence for its usefulness in situations where such historical data is unavailable.

DEDICATION

To my parents,

Shahin Abrishami and Hossein Hessami,

who taught me how to reach my goals

and to all my teachers

who helped me to become a better soul.

ACKNOWLEDGEMENTS

I am thankful to many for their support and encouragement in this journey. I would especially like to thank my mentor and committee chair, Dr. Stuart Anderson, for his enthusiasm and support during my doctoral study and for pushing me to become a better scholar. I am also grateful to Dr. Roger Smith, for without his mentorship, encouragement, calmness, and insights fulfilling this research would have been all but impossible. I was lucky to meet you at the right time. I would like to thank my other committee members, Dr. John Walewski and Dr. Josias Zietsman, for their guidance and support throughout the course of this research.

Thanks are also due to the faculty, staff, and researchers at Texas A&M University's Zachary Department of Civil Engineering and the Texas A&M Transportation Institute for providing a productive environment to implement my research and for making my time at Texas A&M University a great experience. I would also like to extend my gratitude to the pavement experts who participated in the data-elicitation portion of this study. Their input was vital to the robustness of this research.

I was extremely lucky to have several dear friends who were always by my side and supported me in difficult times during my graduate studies. Your encouragement was crucial in helping me to reach this end-point. I will always treasure these friendships, and I look forward to future adventures together.

I thank my entire family, especially my mother, Shahin, my father, Hossein, and my brothers, Ali and Reza, for their love, care, patience, and understanding during this onerous process. I love you all very much, and I hope to see you more frequently now that this task is completed.

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CHAPTER I

INTRODUCTION

1.1 Background and Motivation of the Research

Public infrastructure assets are the physical structures, facilities, and networks that provide for basic social and economic needs. Roads and other transportation networks, energy production and distribution infrastructure, communication networks, schools and other public buildings, and waste management facilities are all included under this heading. The prosperity of a nation's economy is closely tied to the quality of its infrastructure assets and how well they facilitate trade and other basic human functions (Fulmer, 2009; Grigg, 1996; Hudson et al., 1997).

Infrastructure asset management is the process of managing the operation, maintenance, and recycling/disposal of infrastructure assets. In a broad sense, the purpose of this endeavor is to achieve the managing organization's goals during the assets' life cycle (regardless of whether the goal is defined as a for-profit agency, or as a service to society). In practice this definition can be scaled down to a more functional concept, which is managing the maintenance of infrastructure assets at an acceptable level of performance, and the decision-making process to allocate available resources for this purpose. Infrastructure assets deteriorate as they age. They need to be regularly maintained or replaced if they are to continue to contribute to the well-being of their users. For planning at a broad network level, asset managers need to gauge what types of maintenance and rehabilitation should be performed on infrastructure assets each year. They need to be able to identify efficient operating practices and to calculate the funds that are needed to maintain specific levels of infrastructure functionality.

A significant concern for asset managers is that the effects of investment in infrastructure maintenance and rehabilitation play out over the long term, often measured in decades. In today's high-turnover society, both public and private decision-makers, with a lack of sufficient financial resources, are often loathe to invest in projects whose effects are not immediately apparent and whose benefits may not even be traced back to the decision-makers' tenure. The result is an overall decreasing level of funding for infrastructure maintenance, which in the U.S. has led to conditions of degraded infrastructure and declining performance (American Society of Civil Engineers, 2013).

The troubling deterioration of public infrastructure in the U.S. has been known for several decades. Under the Public Works Improvement Act of 1984, a temporary advisory council was established from the ranks of the Army Corps of Engineers to evaluate the condition of the country's infrastructure. The council's report, submitted to Congress in 1988 after several years of study, was titled *Fragile Foundations*. In this report the engineers found convincing evidence that the U.S.'s spending on public infrastructure had declined to levels that were inadequate to sustain economic progress and social wellbeing over the long run (National Council on Public Works Improvement, 1988).

Reduced spending for the maintenance and rehabilitation of public infrastructure does not necessarily result in the failure of each individual asset over a short period of time. However, insufficient investment in infrastructure gradually erodes the economic productivity of the nation. The future costs associated with rebuilding infrastructure that has been left to decline are generally much higher than are the costs entailed in adequate ongoing upkeep. Furthermore, if infrastructure is left to decline, then it is likely that the costs of future rebuilding will have to be assessed at a time of deteriorating economic capacity (National Council on Public Works Improvement, 1988).

To better maintain the nation’s infrastructure, the public-works council suggested both an increase in overall spending levels and a more efficient allocation of funds. Performance enhancements, rational budgeting processes, the adoption of new technologies, and enhancing accountability were recommended as some of the most important managerial improvements. A summary list of the council’s recommendations is provided in Figure 1-1.

- A national commitment to invest more (a doubling of current investment levels)
- Accelerated spending of federal trust funds
- Clarification of federal, state, and local roles
- Flexible administration of federal and state mandates
- Greater financing by project beneficiaries
- Reduction of limits on tax-exempt bonds
- An acceleration of innovation through research and development (R&D)
- An acceleration of innovation through more and better training for public works professionals
- Increased incentives for maintenance of existing infrastructure
- Increased incentives for low-capital techniques for obtaining infrastructure
- Capital budgeting for all levels of government

Figure 1-1. Summary List of Recommendations Given by the National Council on Public Works Improvement in 1988 (Gordon, 1997)

The council evaluated the country's infrastructure assets based on the services they provided for society. If an asset was not useful or there was no longer a demand for it, then its condition was not considered important in the evaluation. The various components of the U.S. infrastructure system were rated using a typical academic grading scale of A, B, C, D, and F. The 1988 report rated the nation's overall infrastructure as a "C," indicating an "average" condition. After submitting the report the council was dissolved.

More recently, the American Society of Civil Engineers has issued a series of infrastructure "report cards" based on the same evaluative methods used in the public-works council report. As of 2013, the overall U.S. infrastructure grade reported by the Society of Civil Engineers was a "D+" (American Society of Civil Engineers, 2013).

These reports reveal that the overall condition of the infrastructure falls well short of what is needed for long-term economic stability. (For a more detailed description of the historical grades and grading methodology, see American Society of Civil Engineers, 2013.)

Table 1-1 illustrates the American Society of Civil Engineers' evaluation of the country's yearly infrastructure-investment needs. It reports a shortfall in all areas, with the largest gap in the category of surface transportation. This category was also given one of the lowest ratings in the study, earning a "D" and the description of being in "poor condition." "Surface transportation" refers primarily to the condition of roads, which are used as a case study in this dissertation.

Table 1-1. Cumulative Infrastructure Needs by System, Based on Current Trends Extended to 2020 (Dollars in $2010 Billions) (American Society of Civil Engineers, 2013)

Infrastructures Systems	Total Needs	Estimated Funding	Funding Gap
Surface Transportation	$1,723	$877	$846
Water/Wastewater Infrastructure	$126	$42	$84
Electricity	$736	$629	$107
Airports	$134	$95	$39
Inland Waterways & Marine Ports	$30	$14	$16
Dams	$21	$6	$15
Hazardous & Solid Waste	$56	$10	$46
Levees	$80	$8	$72
Public Parks & Recreation	$238	$134	$104
Rail	$100	$89	$11
Schools	$391	$120	$271
TOTALS	$3,635	$2,024	$1,611
Yearly Investment Needed	$454	$253	$201

The reports from the National Council on Public Works Improvement and the American Society of Civil Engineers both reveal a lack of sufficient funds for preserving and improving the conditions of roads in the U.S. While an overall increase in infrastructure funding remains critical to ensure the country's future, asset managers in the immediate context are confronted with the unenviable task of having to select the most crucial maintenance functions to enact within their limited budgets (i.e., the maintenance issues that will cause the *worst* problems in the future if they are left unattended). Allocating scarce maintenance funds in a way so as to maximize the benefits to taxpayers is thus more crucial than ever.

In an attempt to address the shortcomings of the U.S. transportation system, a bill called Moving Ahead for Progress in the 21st Century (MAP-21) was signed into law by President Obama in 2012. One of the stipulations of MAP-21 is that individual states must implement a rational, risk- and performance-based asset management plan to improve the efficiency of their transportation spending. Several years after the creation of this law, some states are still struggling to fully grasp what such a plan would look like and how their management practices might be improved to increase efficiency. Developing processes and offering suggestions toward a more efficient public-infrastructure asset management decision-making framework is the primary motivation of this research.

1.2 Problem Statement

The condition of public infrastructure in the U.S. is degenerating rapidly. Insufficient funds for the preservation of infrastructure will lead to decreased productivity and social wellbeing over time. To minimize these losses, and to make the most efficient possible use of tax dollars, asset managers need rational, evidence-based models to inform their decisions about how to allocate limited funds.

For some types of infrastructure preservation, such as the maintenance of road pavements, evidence-based decision-support models have been in use for many years. For these assets, hard data about the results of specific maintenance regimens has been painstakingly gathered over time, allowing the development of good empirical performance-prediction models. These models help asset managers to make better decisions regarding the maintenance of the assets and the allocation of funds. In this research, the terms “historical performance” and “past performance” are used interchangeably to describe known asset-performance data gathered over time.

Unfortunately, for many other types of infrastructure there is a gap between large-scale budgeting decisions and reliable information about the results of those decisions (Kher and Cook, 1985). Part of the reason for this gap is the absence of a rational, structured process for decision-making at the highest levels of asset management. Another significant factor, however, is that in many cases hard data about the outcome of asset-management decisions is simply unavailable. For some infrastructure assets, gathering performance data is all but impossible. The asset might be in an inaccessible location, or the processes required to extract useful performance data might be too invasive or too expensive to carry out on a regular basis. In other cases, the historical information needed for modeling purposes is unavailable simply because no one thought to collect it in the past. Thus, one of the central problems addressed in this research was how to model the effects of management decisions when hard data about historical asset performance is limited.

In addition, predictions of future asset performance always entail a degree of uncertainty. When hard data about asset performance is limited, the level of uncertainty increases. In previous asset-performance research, the uncertainty entailed in these predictions was either ignored completely, or else it was minimized using risk-analysis methods that were not appropriate for the relevant levels of uncertainty (this is discussed in detail in chapter 4). As a result most of the previous asset-management support models provided their users with incomplete information about the range of uncertainty entailed in the analysis. Accurate descriptions of uncertainty in modeling can be very complex. However, overlooking the degree of uncertainty that arises in the modeling process can lead to undesirable and unexpected results for the managers who use these models. Therefore, the second central problem in this research was to take into account the degree of uncertainty in asset management and to appropriately incorporate uncertainty and risk into the asset performance model—without entirely bogging down the asset managers in an overabundance of information.

1.3 Research Questions

The overall goal of this research was to develop a risk- and performance-based infrastructure asset management framework that can (a) effectively incorporate uncertainty into the decision-support model, and (b) better account for situations in which there is limited historical data about asset performance. These central concerns provided the research questions for the study:

Research Question 1. How can the range of uncertainty about asset performance be incorporated into a decision-support model and effectively reported to decision makers?

Research Question 2. How can asset performance be predicted effectively when reliable historical data is not available?

1.4 Research Objectives

To answer the research questions, the following list of specific tasks was created:

1. Define the levels of uncertainty that are relevant to asset-management decisions.
2. Evaluate various risk-analysis approaches, and select a practical approach that is suitable to the current needs of asset managers.
3. Develop a method to incorporate the identified risk-analysis approach into the asset performance model, and to assess the impacts of risk and uncertainty on the final asset management decisions.
4. Develop a data-elicitation method for defining the performance of assets when sufficient historical (past performance) data is not available.

5. Using a case study in which historical data is available, assess the applicability of the proposed methods by comparing the modeling results with the results from actual historical data collected in the field over time.
6. Develop recommendations for how asset managers can use the decision support framework during the course of their practical activities.

1.5 Organization of the Dissertation

This dissertation is organized in two sections. The first section explains the methods that were undertaken to answer the research questions, and provides a description of the resulting infrastructure asset management framework. In chapter 2 the existing literature on asset management is reviewed, as well as the relevant literature on scenario analysis, levels of uncertainty, forecasting methods, and data elicitation. Chapter 3 explains the design of the research project in more detail and also discusses some of the more technical elements of the research's significance for the field.

Chapter 4 then describes the methods that were used to model uncertainty and risk (Research Question 1). Chapter 5 describes the data elicitation model that was developed for use in cases where there is inadequate historical asset-performance information (Research Question 2).

The second section of the dissertation focuses on the application of the infrastructure asset management framework in a specific case study. The methods developed in the first part of the research were applied to analyze pavement maintenance in the city of

Bryan, Texas. Chapter 6 describes the sources of historical data and the procedures used to elicit data for this case study. Chapter 7 shows how the data was analyzed using the model's uncertainty framework. In chapter 8 the results of the elicited data and the actual historical data are compared, and the value of the framework in supporting asset-management decisions is demonstrated. Finally, chapter 9 summarizes the research findings, along with their limitations and suggestions for future development.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

The first step in this research was to evaluate the state of the art and practice in the infrastructure asset management profession. The resources that were used in this task were contemporary journal papers, conference papers, Transportation Research Board publications, and national and international asset-management guidebooks. Reviewing and synthesizing this information allowed the researcher to develop a general framework listing the most common components of infrastructure asset management decision-making processes. Learning about the process of asset-management in this fashion also helped in establishing the study's central research questions, based on the most critical data-modeling needs in the profession.

The second aspect of the literature review involved examining specific topics related to the research questions. In the context of Research Question 1 (how to model uncertainty and risk), the topics reviewed included levels of uncertainty, known methods for incorporating uncertainty into decision-making, and effective methods of presenting risk assessments. In relation to Research Question 2 (how to predict asset performance in the absence of adequate historical data), the topics that were reviewed included the most current methods of data-forecasting and data-elicitation. The results of all phases of the literature review are described in detail in this chapter.

2.2 Infrastructure Asset Management

Infrastructure asset management is the process of managing the operation, maintenance, and recycling/disposal of infrastructure assets. In a broad sense, the purpose of this endeavor is to achieve the managing organization's goals during the assets' life cycle (regardless of whether the goal is defined as a for-profit activity, or as service to society). Too (2010) names cost efficiency, capacity matching, meeting customer needs, and market leadership as the primary goals of asset management.

2.2.1 Infrastructure Asset Management as a Process

Infrastructure asset management involves a collection of structured tasks and activities. As can be seen from the definitions presented in Table 2-1, most sources define asset management as a process relating to business, operations, or decision-making. For example, Boshoff et al. (2010) defined asset management as a decision-making process, while Vanier and Rahman (2004) viewed it as a business process and decision-support framework. However, it is not universally defined as a process, as can be seen in Malano et al. (1999), who used the term "strategy," and in Danylo and Lemer (1998), who described it as a "methodology." The current research steered away from broader notions of methodology and strategy, and instead focused on asset management as a specific, well-defined process, one that can be defined by three integral characteristics: target, goal, and time-frame.

Table 2-1. Infrastructure Asset Management Definitions

Area	Definition of Infrastructure Asset Management	Source
Transportation	"A systematic process of maintaining, upgrading, and operating physical assets cost-effectively. It combines engineering principles with sound business practices and economic theory, and it provides tools to facilitate a more organized, logical approach to decision-making. Thus, asset management provides a framework for handling both short- and long-range planning."	FHWA, 1999
Hydraulic	"A strategy for the creation or acquisition, maintenance, operation, rehabilitation, modernization, and disposal of irrigation and drainage assets to provide an agreed level of service in the most cost-effective and sustainable manner."	Malano et al., 1999
Distribution/ Transmission	"Operating a group of assets over the whole technical life-cycle guaranteeing a suitable return and ensuring defined service and security standards."	Schneider et al., 2006
Transportation	"A business process that incorporates the economic assessment of tradeoffs among alternative investment options to help make cost-effective investment decisions."	Cambridge Systematics, 2005
Public Works	"A methodology to efficiently and equitably allocate resources amongst valid and competing goals and objectives."	Danylo and Lemer, 1998

Table 2-1. Continued

Area	Definition of Infrastructure Asset Management	Source
Water Systems	"Maintaining a desired level of service for what you want your assets to provide at the lowest life-cycle cost. Lowest life-cycle cost refers to the best appropriate cost for rehabilitating, repairing, or replacing an asset."	U.S. EPA, 2012
Municipalities	"The process of decision-making, planning, and control over the acquisition, use, safeguarding, and disposal of assets to maximize their service delivery potential and benefits, and to minimize their related risks and costs over their entire life."	Boshoff et al., 2010
General	"Systematic and coordinated activities and practices through which an organization optimally and sustainably manages its assets and asset systems, [and] their associated performance, risk, and expenditures over their life-cycles for the purpose of achieving its organizational strategic plan."	PAS, 2008
Transportation	"Asset management is a business process and decision-support framework that: (1) covers the extended service life of an asset, (2) draws from engineering as well as economics, and (3) considers a diverse range of assets."	Vanier and Rahman, 2004

Asset managers' targets are defined as the type of properties or resources they are expected to oversee. The target assets can be categorized in different ways. One method is to view assets as either current or noncurrent (Bowhill, 2008). In this view, current assets are expected to be traded or used within one year (cash, cash equivalents, inventory, etc.). Noncurrent assets, in contrast, are unlikely to be traded or converted into a current asset during the course of a year. Another method of categorization splits assets into tangible and intangible categories (Daum, 2003). Tangible assets in this view include all physical properties such as highways, airports, communication networks, public facilities, and other civil infrastructures. Intangible assets are non-physical resources such as a trained and assembled workforce, digital resources, and intellectual properties such as copyrights, trademarks, or patents. As can be seen, there are a huge variety of assets that can be involved in the work of asset managers. The specific nature of these resources has a great bearing on the types of activities and accounting requirements that need to be implemented. Most typically, however, the properties that are the targets of asset managers' work tend to be long-standing physical infrastructure assets (as can be seen in the definitions in Table 2-1). The current research likewise focused on the management of long-term physical assets.

Outlooks on the goals of the infrastructure asset management process are diverse. An examination of the definitions in Table 2-1 reveals that most interpretations include some kind of cost-related element as a goal (as indicated by phrases such as "efficiency," "cost-effectiveness," "suitable return," and "lowest cost"). Another frequently-cited goal of asset management is to provide a certain level of service to users—this is described with phrases such as "providing an agreed level of service," "maximizing service delivery potential," or "managing performance." Additional goals mentioned in the asset-management literature include providing a fair resource allocation, minimizing risk, and ensuring asset security.

The final characteristic of the asset-management process is its time-frame. The definitions in Table 2-1 all indicate that the process covers the entire "life-cycle" of the asset. As viewed from the portfolio-management perspective, the life-cycle includes creation, definition, initiation, planning, execution, start-up, operation, and recycling (Woodward, 1997). However, various infrastructure asset management definitions in the literature differ on how they interpret the life-cycle. For example, the U.S. EPA (2012) indicated that the asset-management process is limited to rehabilitating, repairing, or replacing assets, whereas Boshoff et al. (2010) stated that an asset's life-cycle also includes acquisition, use, and disposal. Sources may also invoke different terminologies that can imply slight differences in meaning. For example, PAS (2008) used the standard term "life cycle," while Schneider et al. (2006) used the term "whole technical life cycle" and Vanier and Rahman (2004) referred to the asset's "extended service life." In the current research the understanding of the asset-management process's time-frame does not include the planning and initiation stages of the life-cycle, but it does includes all of the remaining stages of operation, maintenance, and recycling/disposal.

2.2.2 Components of Infrastructure Asset Management

Once the target, goal, and time-frame are established, the asset-management process can be described as a set of specific components. Each component is one step of the process. To gain a sense of how in practice asset managers approach the process, the researcher examined a spectrum of existing asset-management frameworks and reviewed their explanation of the proposed components (Table 2-2). Once these components were identified, they were then ranked based on the frequency with which they appeared in the literature. The most frequently-cited components of the asset-management process are summarized in Table 2-3.

Table 2-2. Components of Infrastructure Asset Management Frameworks

FHWA, 1999	Smith, 2005
• Strategic goals • Inventory of assets • Valuation of assets • Quantitative condition and performance measures • Measures of how well strategic goals are being met • Usage information • Performance-prediction capabilities • Relational databases to integrate individual management systems • Consideration of qualitative issues • Links to the budget process • Engineering and economic analysis tools • Useful outputs, effectively presented • Continuous feedback procedures	• Basic information: Goals, objectives, policies, and inventory data • Performance measures: Condition assessment and desired levels of service • Needs analysis: Performance modeling and Prediction; action and funding analysis • Program analysis: Alternative analysis and program optimization • Program delivery: Program development and program implementation
Krugler et al., 2007	**FHWA, 2007**
• Goals, objectives, and policies • Data inventory • Condition assessment • Desired level of service • Performance modeling • Action and funding analysis • Alternative analysis methodologies • Program optimization • Program development • Program implementation • Performance monitoring • Feedback	• Goals and policies (reflect customer input) • Asset inventory • Condition assessment and performance modeling • Alternatives evaluation and program optimization • Budget allocations • Short- and long-range plans (project selection) • Program implementation • Performance monitoring (feedback)

Table 2-2. Continued

Malano et al., 1999 • Management review • Asset planning strategies • Asset creation/acquisition • Asset operation/maintenance • Asset performance/monitoring • Asset accounting/economics • Asset audit	Amadi-Echendu et al., 2010 • Asset information management • Asset operation and maintenance • Asset creation • Asset planning • Capacity management
Halfawy, 2008 • Condition assessment • Inspection/monitoring • Risk assessment • Deterioration modeling • Performance modeling • Asset prioritization • Rehab methods • Renew planning	OECD, 2001 • Goals and policies of the administration • Data • Resources and budget details • Performance models for alternative strategies and program development • Project selection criteria • Implementation program • Monitoring and feedback loop

Table 2-3. Frequency of Infrastructure Asset Management Components in the Literature

Identified Component	Sources
determining asset conditions/value	FHWA, 1999; Smith, 2005; Krugler et al., 2007; FHWA, 2007; Malano et al., 1999; Halfawy, 2008; U.S. EPA, 2012; Cambridge Systematics, 2002; Cambridge Systematics, 2005; PAS, 2008
reviewing policies, goals, and objectives	FHWA, 1999; Smith, 2005; Krugler et al., 2007; FHWA, 2007; OECD, 2001; Cambridge Systematics, 2002; Cambridge Systematics, 2005; PAS, 2008; Neumann and Markow, 2004
inventory of assets/data	FHWA, 1999; Smith, 2005; Krugler et al., 2007; FHWA, 2007; OECD, 2001; Cambridge Systematics, 2002; PAS, 2008; Neumann and Markow, 2005
option analysis (tradeoffs and alternatives)	Smith, 2005; Krugler et al., 2007; FHWA, 2007; OECD, 2001; Cambridge Systematics, 2002; Neumann and Markow, 2004; Cambridge Systematics, 2005
performance modeling and condition predictions	FHWA, 1999; Smith, 2005; Krugler et al., 2007; Halfawy, 2008; OECD, 2001; Cambridge Systematics, 2002
performance monitoring/feedback	FHWA, 1999; Krugler et al., 2007; FHWA, 2007; OECD, 2001; Cambridge Systematics, 2002
resource allocation (budgeting)	FHWA, 1999; FHWA, 2007; OECD, 2001; Cambridge Systematics, 2002; Cambridge Systematics, 2005
defining performance measures	FHWA, 1999; Smith, 2005; Neumann and Markow, 2004
setting performance targets	FHWA, 1999; Krugler et al., 2007

Based on the analysis of the common infrastructure asset-management components provided in Table 2-3, an overall, general framework of the process was created. These asset-management process components are listed below, and then described in greater detail in the following sections.

1. Policy goals and objectives
    - 1a. Identify goals and objectives
    - 1b. Define performance measures
2. Asset inventory and condition survey
    - 2a. Set up asset inventory
    - 2b. Perform asset inspection
3. Analysis of options and trade-offs
    - 3a. Condition assessment and prediction
    - 3b. Preservation options determination
    - 3c. Performance predication for different options
4. Decision-making and resource allocation

Component 1: Policy Goals and Objectives

Most of the asset-management processes described in the literature begins with the identification of clear goals and objectives. The goals that asset managers are mandated to accomplish are usually established in the managing agency's policy statement, which broadly describes the organization's desired outcomes (Neumann and Markow, 2004). For example, one of the Texas Department of Transportation (TxDOT) Strategic Plan goals for 2015–2019 is “To Maintain a Safe System” (Texas Department of Transportation, 2014). To meet these broad goals, more specific objectives are then developed. Objectives are smaller, concrete tasks that help to determine how the larger policy goal will be accomplished. They also serve another purpose: to help quantify the progress towards achieving the overall policy goal. One example of an objective that supports TxDOT’s broad safety goal is “to improve mobility on highways.”

Performance measures are a way to clearly assess the extent to which goals and objectives have been accomplished. Defining these quantifiable expressions of policy goals is an important part of the infrastructure asset management process. A good performance measure should have two features: quantity, and a unit of measure. So, for example, in order to meet TxDOT’s objective of improved mobility on highways, the asset manager might create a performance measure called the “Travel-Time Index.” By measuring the average time it takes to drive from one point to another, the manager can quantify the current road-mobility conditions and the progress that has been made toward improving those conditions. (Ramani et al., 2009)

In some cases, specific performance targets may also be defined. For example, reducing the average driving time from one side of town to the other to less than fifteen minutes is an example of a performance target related to travel time. Such specific targets may not always be required, especially when the performance measure involves comparing several different improvement options (Hudson et al., 1997).

Component 2: Asset Inventory and Condition Survey

A second component of infrastructure asset management frequently described in the literature involves asset inventories and condition surveys. Asset inventory simply means keeping a database of assets and their physical characteristics. Information in the database may include location, geometrical information, structural information, material type, construction background, and preservation records (Hudson et al., 1997). Condition surveys are the most costly task in infrastructure asset management. They involve the determination of appropriate sampling procedures and measurements in order to assess the current condition and state of repair of the assets that are being managed (Shahin, 2005).

Component 3: Analysis of Options and Trade-offs

Once the asset inventory is developed and the current condition of the asset is measured through a field survey, the next step is to estimate the life-cycle prospects of the asset and define the possible preservation options. To analyze budgetary needs, the manager must begin with an accurate assessment of the asset's performance, relative to the organization's goals. For each performance measure (defined in Component 1 of the process), the current and possible future levels of asset performance are inventoried.

After assessing the condition and performance of an asset, the manager then considers possible options for maintenance and improvement. Ideally, this should begin as an extensive list of possibilities, so that the full array of options can be considered. The option of “doing nothing” in regard to maintenance should also be included.

Asset managers are aware that as assets age, their performance degenerates generally in a non-linear fashion, while the expense of postponed repairs/upgrades increases. Eventually the asset will reach a threshold beyond which it is no longer usable, and/or maintenance is no longer economically feasible. Asset managers need to be able to evaluate the level of performance that can be sustained by various potential maintenance regimes, and to compare the cost of these regimes against the overall life-cycle benefit that the asset can provide. It is in this complex evaluation process that evidence-based performance models are extremely useful to the manager. Prediction models offer forecasts of the future performance of an asset based on its current condition and various potential maintenance regimens (including a “doing nothing” alternative) (Paterson, 1987). Cost of maintenance is an important selection criterion as limited funds challenge asset managers to preserve the assets above a desired level of performance (Faghihi et al., 2014; Kim et al., 2012)

Component 4: Decision-Making and Resource Allocation

The last step of the infrastructure asset-management process is to determine if maintenance is needed, and if so, what type of maintenance regimen should be performed on each section of the asset network over the analysis period. Typically, multiple performance measures and the cost of various forms of maintenance will be taken into account in reaching a decision. To quantify this process, multi-criteria decision-making methods and advanced modeling techniques are needed. In asset management, a cost-effectiveness analysis is commonly implemented to prioritize options. Cost-effectiveness analysis is a more general form of cost-benefit analysis; it is used in situations where assigning specific monetary value to benefits is not necessary or appropriate. Given the complexity of assigning specific financial values to the benefits of good infrastructure, asset managers often find it more practical to generalize the value of assets in non-financial terms, for example, by analyzing how to maintain the highest possible asset “performance value” within a set budget (Udvarhelyi et al., 1992).

Evaluating the cost-effectiveness of a maintenance regimen involves comparing its expense against its long-term benefits. The specific cost of each preservation treatment depends on the amount of deterioration that has occurred and the amount of improvement that is needed to achieve specific performance goals. The effectiveness of maintenance can be quantified by calculating the change in the area underneath the asset’s performance curve. Performance curves are graphs that describe the past and expected future performance of assets. When maintenance is undertaken on an asset, this graph will change, hopefully showing an increase in current performance, and therefore creating a greater area underneath the curve. An example of a performance curve is illustrated in Figure 2-1.

In tandem with these specific evaluations of cost and effectiveness, the asset manager must consider the total available budget (which, as discussed in chapter 1, is often inadequate for all needed maintenance). The cost and effectiveness of any given project must be defined, and projects are prioritized based on the cost-effectiveness ratio.

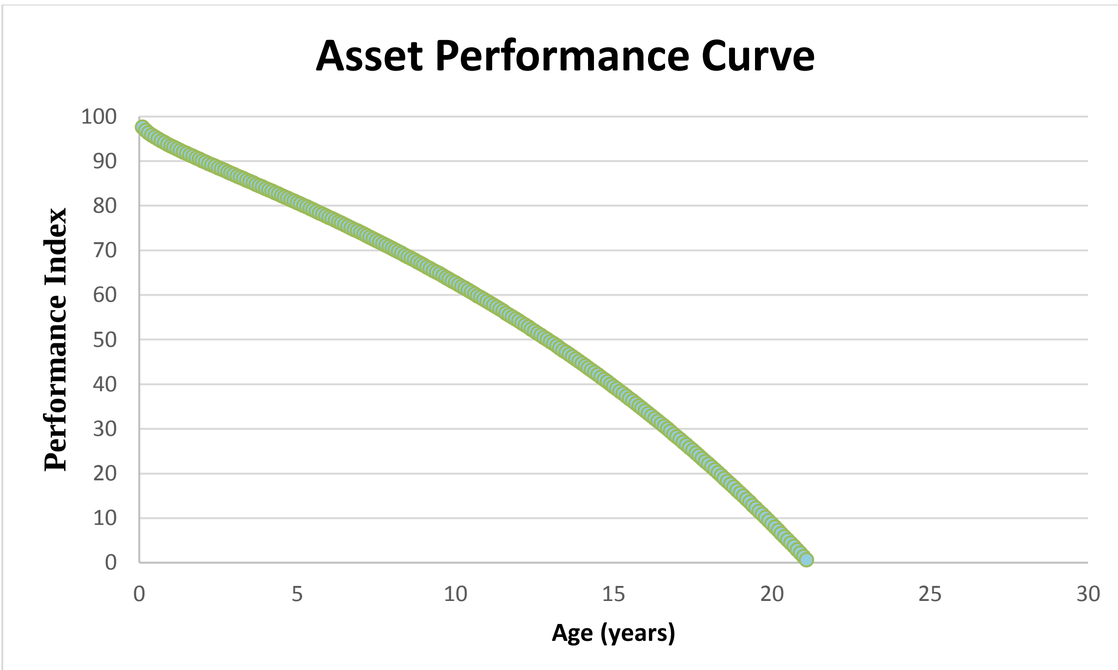

Figure 2-1. Example of an Asset Performance Curve

2.2.3 Decision Levels in Infrastructure Asset Management

Asset management incorporates hierarchical levels of decision-making, which are interrelated in such a way that lower-level conclusions can provide inputs for higher-level decisions. Three decision-making levels are widely recognized in the infrastructure asset-management literature: the strategic level, the network level, and the project level.

The strategic level is the broadest and most inclusive; for decisions at this level all types of infrastructure assets in the community are considered, and the goal is to create a comprehensive plan for long-term infrastructure resource allocation. However, to accomplish this strategic goal, it is necessary for the decision-maker to rely on good information and more specific strategies that are developed at lower decision-making levels. At the network level, decision-makers determine optimal preservation strategies and resource allocation for a specific asset type (for example, the maintenance of a city's road network). At the project level, decision-makers determine the most effective way to allocate resources for a specific preservation/maintenance action (Flintsch and Bryant, 2006; Hudson et al., 1997). The asset-management framework developed in this research is structured to support decision-making at the strategic and network levels.

2.3 Modeling Uncertainty

The first research question in this study was how to model uncertainty in asset performance and effectively present uncertainties/risk-levels to decision-makers. After reviewing various options in the literature, the method that was selected for analyzing uncertainty was outcome-based scenario planning.

2.3.1 Scenario Planning

Scenarios can be defined as brief snapshots of the potential results of future trends (Fontela and Hingel, 1993). They describe hypothetical future conditions, along with the histories and decision-trees that might lead to those conditions (Kanhn and Wiener, 1967; Pillkahn, 2008). Scenarios allow decision-makers to quickly see possible alternative futures in a unified, succinct picture, and to understand how different choices can interact to shape the overall terrain of these future scenarios (Martino, 2003). Thus, scenario planning is very useful for identifying the systemic implications of management choices and devising ways to make the best decisions for a range of possible futures (Strauss and Radnor, 2004).

The advantage of scenario planning is that it is not limited to investigating only one possible expected outcome. It can take into account multiple events and variables, analyzing these factors simultaneously to define the range of what could possibly happen (Schwab et al., 2003). Depending on the complexity of the problem, the degree of uncertainty, and the number of issues examined, an entire set of potential future scenarios can be devised (Schoemaker, 1993). Decision-makers may only need to analyze a few different possible scenarios for simple problems, but in the case of complex situations, they may need to review many different scenarios.

The technique of scenario planning was primarily developed for use by strategic business managers, who need to consider potential ways that the future might unfold and how to best react to these possible futures. However, it also has important implications for infrastructure asset management. In a sense, it is a more explicit way of expressing and developing the mental models that all humans use to anticipate future events (Martelli, 2001). Scenario planning allows for an iterative process in which a manger examines possible futures, uses that information to make a decision that will affect/limit those possible futures, and then reviews a new set of scenarios that include the previous decision as a given. This allows scenario planning to be a powerful tool for implementing changes and gradually working towards a better-defined and more desirable future.

Another benefit of scenario planning is that scenarios can make many complex situations and hypothetical outcomes clearer by separating them into specific, analyzable parts (Schoemaker, 1993). This is beneficial because humans are often incapable of simultaneously processing the entire range of possible events within a complex system. Scenario planning helps to simplify the large number of variables and potential events into a more manageable amount of data to use in decision-making processes (Schwenk, 1984; Schoemaker, 1995).

Scenario planning goes beyond other uncertainty-modeling techniques such as contingency planning and computer simulation, in that it takes into account a wider range of variables. Whereas contingency planning and computer simulation are useful for carefully analyzing a limited set of possibilities, the use of scenarios allows decision-makers to see the "big picture," complete with many different hypothetical situations (albeit with a slight loss of detail). Scenario planning is therefore most useful for analyzing major changes in complex systems where many different and potentially unknown variables are in play.

Scenario planning can be applied to most situations in which decision-makers want to consider potential futures. It has therefore become very widespread as a means of analyzing decisions, especially in cases where there are many unknowns. There is a correlation between the value of scenario planning in the decision-making process and the degree of uncertainty in the decision-making environment. In situations where the future becomes more and more unknown as decision-makers project farther into it, the broad approach of scenario planning provides an increasingly useful means of analyzing these potential futures and their uncertainties (Malaska et al., 1984).

It should be noted that scenario planning is not the same thing as data forecasting (which is discussed later in this chapter). Forecasting focuses on one future path and calculates risks of deviation along the way. Scenario planning, in contrast, takes into account many potential paths and their outcomes (Pillkahn, 2008). Instead of attempting to predict a specific future, scenario planning generates a set of potential futures and describes the paths that might lead to them. This difference can be seen in the process of scenario development, which involves brainstorming various possible scenarios in an attempt to identify the wide range of potential ways that the future might unfold (Pillkahn, 2008; Schoemaker, 1993). Wilkinson (2009) reviews the differences between forecasting and scenario planning in greater detail.

2.3.2 Different Approaches to Scenario Planning

Scenario planning methods can be broken down into event-based or outcome-based approaches. An event-based approach defines the scenario as a set of events that could possibly happen in the future (Pottebaum et al., 2011). For instance, Freedy et al. (2007) used event-based scenarios to assess trust in tactical human-robot collaboration. In Freedy's study, potential plans for the U.S. Department of Defense's "Future Combat System," as well as current uses of robotic systems in combat, are described using event-based scenarios.

This kind of event-based scenario planning has also been used previously in infrastructure asset management support frameworks (Piyatrapoomi et al., 2004). A simple example is an approach that considers the available funding levels that an agency might have in the next budget cycle. Typical event-based scenarios in this example include having full funding in the next cycle for the agency's total maintenance needs, having half-funding for maintenance needs, and having no funding at all for maintenance (FAA, 2014). When planning how to allocate the current budget, it is useful to consider the decision's effects in each of these possible futures. The three scenarios given here do not describe every possible budgeting future (having five-eighths funding is also a possibility); however, the three scenarios allow for a quick and straightforward examination of the range of consequences that can occur as a result of these possible future events.

In outcome-based scenario planning, in contrast, the scenarios are described based purely on possible future conditions, without trying to trace the events that might lead to those conditions. This is useful when the range of possible outcomes is known but the event sequences leading to those outcomes are very complex (for example, instances in which weather variations affect the decline of assets over time). Outcome-based scenario planning is an innovative approach and has only been used in a limited number of research studies. An example is Dorofee et al. (2008), who used outcome-based scenario analysis to assess different potential mission outcomes in a software application development. In the current research, an outcome-based approach to scenario planning is used to describe different conditions based on the possible future performance of assets. Each scenario represents one possible future performance state of the asset. This will be described in more detail in chapter 4.

Another way in which scenario planning approaches are categorized is vision-driven vs. decision-support methods. A vision-driven approach explores trends in the environment to help develop organizational-level outlooks on possible futures (Chermack and Payne, 2006). This allows managers to develop a broad and coherent perspective and to examine how their assumptions support the long-term goals of the organization. Decision-driven scenarios, in contrast, are used to gain understanding about possible future environments as they relate to specific, limited problems. This can help managers to make better decisions when the uncertainty involved in the situation makes it hard to identify the best option. In the current research a decision-driven approach is used. The goal is to help asset managers better understand the possible future states of their assets and thereby make better budgeting and maintenance decisions.

2.3.3 Levels of Uncertainty

Courtney (2001) and Walker et al. (2003) used a hierarchy of levels to describe the extent of uncertainty about future outcomes. While their breakdowns of the various levels were slightly different, the basic approach is the same. The four levels described by Courtney included:

1. A clear, single vision of future.
2. A limited set of possible future outcomes, one of which will occur.
3. A range of possible future outcomes.
4. A limitless range of possible future outcomes. (Courtney, 2001)

Managers can operate more effectively if they have a general understanding of these levels of uncertainty and how they relate to decision-making. Figures 2-2 and 2-3 illustrate the levels of uncertainty as defined by Courtney and Walker respectively.

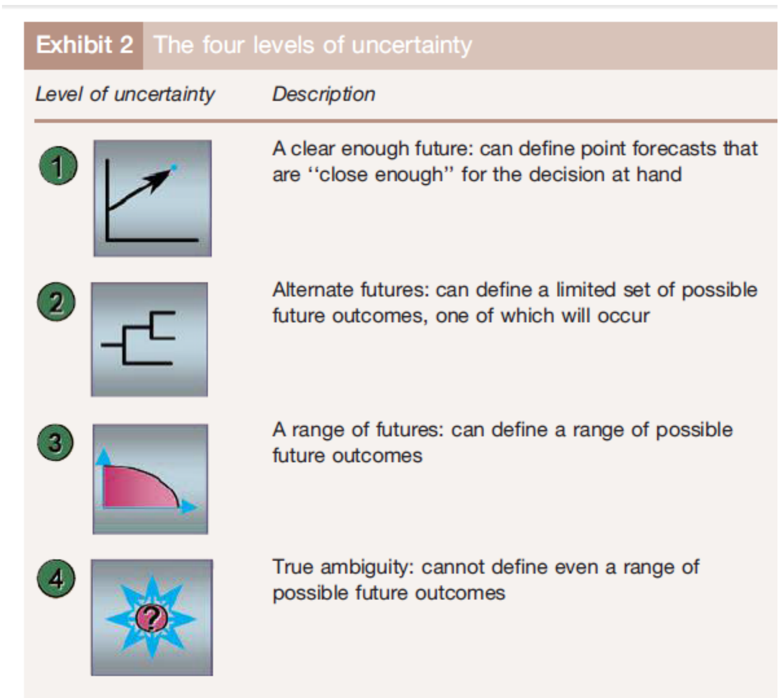

Figure 2-2. The Four Levels of Uncertainty (Courtney, 2003)

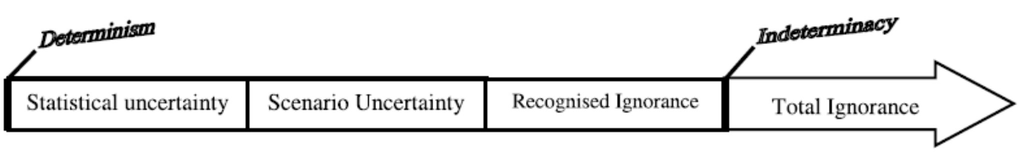

Figure 2-3. The Progressive Transition between Determinism and Total Ignorance (Walker et al., 2003)

When the situation is close to Level 1 uncertainty, the range of relevant potential futures is narrow. In this case, the different possible future conditions will not have much of an impact on the outcomes of the current decision. The decision-maker can assume that the problem is deterministic; in other words, an "ideal situation in which we know everything precisely" (Walker et al., 2003). Though a small amount of uncertainty about future conditions may be present, decision-makers do not need to account for this uncertainty in order to provide analyses that are accurate enough for planning purposes. A straightforward, deterministic analysis can be made on the basis of available data without worrying about different possible future conditions.

At Level 2 uncertainty, a range of discrete possible futures can be identified that are relevant to the outcome of the decision. Furthermore, the probability that each of these futures will happen is also known, to a fairly high degree of accuracy. Managers can therefore consider the outcome of their decision in each possible future, in an exhaustive fashion if necessary. The possible future outcomes can be identified as a mutually exclusive, collectively exhaustive set. An example of this kind of uncertainty is when an investor is making a decision and the outcome will be strongly influenced by the policies of the next U.S. president. If the election is underway in this situation, then there are two primary, well-defined futures to consider based on the candidates of the two major parties (and possibly other futures at a very low level of probability).

Walker et al. (2003) described this level of uncertainty as "statistical," since its outcomes can be entirely modeled with probabilistic analyses. In such an interpretation, however, it is assumed that the identified futures and their likelihood of occurrence are a full, exhaustive, and accurate reflection of real-world conditions. If this assumption cannot be demonstrated to be valid then higher levels of uncertainty should be considered (Walker et al., 2003).

At Level 3 uncertainty there are more potential futures that are relevant to the decision, and due to the complexities of the variables it is not feasible to parse these futures into a discrete and exhaustive set of possibilities. Furthermore, the mechanisms leading to specific future conditions cannot be readily defined, and therefore the specific probability of future outcomes cannot be determined. In this situation, an exhaustive statistical analysis of all potentially relevant results cannot be carried out. Nonetheless, at this level of uncertainty the total range of the possible future outcomes is definable. In such conditions, a scenario-planning approach can be of great benefit. Specific scenarios can be chosen from across the range of possible futures, and these various scenarios can be evaluated. The result is that the decision-maker gains a reliable overview of the range of possible future outcomes.

Walker et al. (2003) described Level 3 uncertainty as “scenario uncertainty,” acknowledging that these Level 3 conditions are most effectively handled through the use of scenarios. However, this terminology may be somewhat misleading, as scenario-based approaches can also be applied at other levels of uncertainty. This is especially true when the statistical analysis of Level 2 conditions is too complex to be effectively carried out. In some situations, managers may prefer a scenario-based overview, even when statistical approaches could theoretically be applied.

Finally, decision-makers face Level 4 uncertainty when the range of relevant futures is unknown and unknowable. Sometimes called “true ambiguity,” this situation occurs when there are too many unknown variables to define the limits of what might happen. While possible futures can be described, the probability of these events happening and the range of other possible outcomes cannot be determined. This level of uncertainty is extremely difficult to deal with, and in many cases it may be better to wait for the situation to resolve itself toward better-defined conditions before any important planning decisions are made on the topic.

2.3.4 Asset Performance Uncertainty

One of the most important goals of infrastructure asset management is to ensure that the performance of assets stays above a certain level. There are many complex variables that can have an effect on the performance of assets over time, including the initial construction conditions, usage patterns, and ongoing weather conditions. In order to make planning decisions and maintain the necessary level of performance, the impact of these variables on asset performance needs to be defined. This definition is no easy task, and due to the complexity of the variables there is almost always some degree of uncertainty in estimating future asset performance levels (Ng et al., 2011).

The methods that asset managers use to model the performance of assets over time are either deterministic or probabilistic. Deterministic methods usually involve regression analysis, which results in a single estimate of average performance over time. (The asset performance curve shown in Figure 2-1 above is an example of this kind of analysis.) However, the average expected asset performance provides only a limited amount of information for asset managers to make decisions based on them. It does not convey the total range of possible future performance conditions. Furthermore, deterministic approaches are prone to making questionable assumptions, because asset behavior often changes based on unknown factors that are not revealed by averaging historical data (e.g. changing environmental conditions, new patterns of traffic loading, etc.). Because of this, the use of deterministic models can lead to poor decisions that fail to maintain assets at the required level of performance (Ferreira et al., 2002; Ng et al., 2011).

There have been many attempts to take uncertainty about future conditions into consideration in an infrastructure asset management context. Most of the methods for doing so involve the use of stochastic prediction models to describe performance over time in a probabilistic fashion. One of the most popular methods is the Markov Decision Process (MDP). The MDP model accounts for uncertainty by describing the likelihood of ending up at different future states after a specific decision or after a given period of time. The Markov model relies only on the current state of an asset as the basis of predicting its likely futures (i.e., the model does not incorporate historical data). For example, if a machine is deteriorating, then its likely condition next week might be described with a set of Markov probability vectors, whose sole input will be the state that the machine is in currently (Ng et al., 2011; White and White, 1989).

The use of MDP in the field of infrastructure asset management was first proposed in the early 1970s, and the sophistication of its application grew over the course of the following decades (Lemer and Moavenzadeh, 1971). Soon, the MDP model was being used to determine the timing of asset maintenance strategies in areas such as road resurfacing (Smith, 1976). Arizona was one of the first states in which these policies were developed in the early 1980s (Golabi et al., 1982). An MDP model was also used by Carnahan and colleagues (1987) to design the decision-making approach of PAVER, a pavement-management system developed by the U.S. Army Corps of Engineers' Construction Engineering Research Laboratory. The approach used in PAVER was more advanced than previous efforts because it drew from a well-defined Pavement Condition Index inventory. It also used dynamic programming to obtain a finite planning horizon, while previous efforts such as those developed in Arizona made use of linear programming to obtain steady-state solutions (Carnahan, 1988).

In more recent years the applications of MDP models in infrastructure asset management have continued to expand. Guignier and Madanat (1999) used an MDP approach for joint optimization in a combined maintenance and improvement task. This had the advantage of improving budget allocation among the different components of the network. The MDP model that was developed for this case is capable of solving for steady-state policies while also relaxing the assumption that a solution will be age-homogenous with condition-state transition probabilities. Another advantage of the model developed by Guignier is that it does not assume the annual budget will be exhausted each year, which means that a portion of the budget can be set aside in cases where the money may be spent more efficiently in the future (Guignier and Madanat, 1999).

Another contemporary application of MDP models is for tracking inspection decisions and accounting for uncertainty in the inspection process. There is a basic assumption in most inspection outlooks that the process will result in a specific and accurate report of facility conditions in a given time-frame. However, there are many ways in which this premise can become untrue—for example, when there is a need for flexible inspection schedules or when measurement errors are made. Thus, the uncertainty in inspection data can be more accurately modeled with a probabilistic approach using latent MDP formulations (Madanat and Ben-Akiva, 1994; Guillaumot et al., 2003).

Deterministic and probabilistic methods of modeling asset performance both have their pros and cons. Deterministic methods cannot account for the range of uncertainty, and in many cases this leaves out information that is crucial to asset managers. On the other hand, deterministic models typically define asset performance in more detailed quantitative terms, and therefore have the capacity to provide more information about specific asset characteristics (such as pavement cracking or rutting) (Ferreira et al., 2002). Furthermore, large-scale MDP probabilistic models can be non-intuitive and challenging to handle. To create a more manageable evaluation process, the complexity of these models often has to be simplified, leading to broader and subjective assumptions about future asset performance.

Part of the purpose of the current research was to develop a new method of handling uncertainty in asset performance modeling. Instead of using complex MDP statistical approaches, a scenario-based approach was used. This allows asset managers to gain a quick and intuitive overview of the range of an asset's potential future performance. The details of this approach to uncertainty in infrastructure asset management are discussed in chapter 4.

2.4 Data Forecasting

The second research question in this study was how to predict asset performance in the absence of adequate historical data. Tackling this issue requires an understanding of the process known as forecasting, which is defined as making specific predictions about future outcomes (Armstrong, 2001). Forecasting processes and techniques based on rigorous methodology have gradually become more reliable and gained greater credibility starting in the 19th century (Hanke et al., 2001).

2.4.1 The Forecasting Process

The process of data forecasting differs depending on the forecast's purpose and the topic of study. In general, though, the major steps of the process can be listed as: data collection, data preparation, model building, and model extrapolation (Hanke et al., 2001). The first step, data collection, most often involves obtaining historical records about what the object of the forecast has done in the past (Wheelwright and Makridakis et al., 2008). In many situations, however, forecasts that are only based on historical data have a limited utility. It is entirely possible that the available data might not be extensive enough to reveal long-term trends (or that no historical data exists at all). It is also possible that a significant change in context has occurred that will affect future trends and that cannot be taken into account merely by looking at past observations (Makridakis et al., 2008). Thus, the best forecasting methods combine the collection of historical data with other information sources, including components of personal experience, judgment, and wide-reaching knowledge (Collopy and Armstrong, 1992; Bunn and Wright, 1991).

After the data is collected, the next step in forecasting is data preparation. This may include steps to “scrub” or “clean” garbled records, duplications, and other errors from the data, and/or steps to reduce complex data into a more manageable format (Ross, 1996; Sumathi and Sivanandam, 2006). Once the data is in a usable state, a forecasting model is built by matching the data to predictive mathematical functions. There are many such models to choose from, and lack of selection is seldom an issue. More frequently, the difficulty in model-building involves deciding which of several possible models best fits the data. The choice of the forecasting model is typically based on the physical nature of the forecasting problem as well as the closeness of fit to the data. Some aspects of model selection ultimately come down to the forecasters’ judgment about which model is most applicable to their problem. During this selection process, forecasters also have to balance the benefits of choosing a more complex/sophisticated model, which may offer increased accuracy, versus a relatively simpler model, which may be easier to implement and explain (Hyndman and Athanasopoulos, 2014).

The fourth and final step in forecasting is using the model to make predictions about future outcomes. This process is known as extrapolation. When new data points are predicted within the existing data (i.e., between two existing historical measurements), the process is called interpolation (Wheelwright and Makridakis, 1985). It is worth emphasizing that extrapolation/interpretation is never an exact science, and that forecasting can become misleading if it has failed to account for important information or changes in conditions. It is thus always advisable to retain a certain skepticism about the accuracy of forecasts and to temper them with the ongoing input of both common sense and expert knowledge (Makridakis et al., 2008; Hanke et al., 2001).

2.4.2 Qualitative Forecasting Methods

Quantitative methods make use of concrete historical data and mathematical models to generate forecasts. These methods are less successful when there is an absence of concrete data or when trends and patterns are expected to change rapidly. In such cases, forecasters must rely more exclusively on expert judgments and wide-reaching knowledge. When this occurs, the forecasting technique becomes less of a quantitative process and more of a qualitative one (Makridakis et al., 2008).

The two major types of qualitative forecasting are called “exploratory” and “normative.” In exploratory methods, forecasters begin with current knowledge about the problem and lead toward future predictions by way of qualitative/judgmental extrapolation from past trends. Normative approaches, in contrast, begin by considering desired future outcomes and then work backward to determine what steps need to be taken in order to move toward those desired outcomes (Twiss, 1992).

2.4.3 Data Elicitation

When there is a lack of historical data, forecasters must by necessity turn toward expert opinions. There are a variety of methods that have been developed to help reduce the subjective element this brings into forecasting. Data elicitation techniques can be usefully applied in this situation. Elicitation is a rigorous process through which forecasters (and other researchers) seek to obtain probabilistic information about specific measurements from experts in the relevant area of knowledge (Shephard and Kirkwood, 1994). The goal of elicitation is to provide a relatively easy way for experts on any given topic to give their opinions in probabilistic terms, even though the experts may not know a great deal of probability theory (Kadane and Wolfson, 1998).

Research fields that take advantage of data-elicitation methods usually apply the experts’ knowledge for analyzing secondary problems that will have a relevant and noticeable effect on the outcome of the primary analysis (O’Hagan et al., 2006). In many cases, the elicitation methods that are chosen must also be tailored to fit the problem at hand.

When creating a specific elicitation process researchers must pay careful attention to the nature of the problem, ensuring that it is not too complex for the experts to accurately analyze and predict outcomes. The researcher must also accurately understand the mathematical principles that underlie elicitation methods in order to achieve the most accurate results (Wolfson, 1999).

Elicitation leads to more reliable results when the questions presented to the experts are worded in the same way that the expert would naturally express ideas about the problem (Kadane and Wolfson, 1998). Thus, it is preferable if the researcher has a solid background in the topic of study and is able to formulate questions in the same kind of language that the experts would typically use to discuss the topic. Researchers have developed many specific methods of eliciting expert opinions in different fields, ranging from more theoretical areas of knowledge to the applied sciences.

Most researchers agree on the primary components of the elicitation process, though there are some minor differences in the details (for example, there is not yet a firm consensus about the order in which the various components should be carried out). Clemen and Reilly (2001) described the primary steps in elicitation as:

1. Background assessment
2. Identification and recruitment of experts
3. Motivating experts
4. Structuring and decomposition

5. Probability and assessment training
6. Probability elicitation and verification
7. Aggregation of experts' probability distributions

Phillips (1999) described the steps as:

1. Collecting experts
2. Introduction and training
3. Motivation
4. Conditioning
5. Encoding

Garthwaite et al. (2005) included:

1. Set-up
2. Eliciting summaries of expert distributions
3. Fitting a probability distribution
4. Assessment of the quality of the elicitation

O'Hagan et al. (2006) proposed a five-stage process that included:

1. Background and preparation
2. Identifying and recruiting experts
3. Motivating and training experts
4. Structuring and decomposition
5. Elicitation

In the current research project, the method of data elicitation that was used is based on the Delphi process. This approach was first developed for forecasting purposes by the RAND Corporation in 1944, for use by the American military. Its earliest applications involved forecasting the effects of technological development on warfare (Sackman, 1974). The Delphi method is a detailed, enhanced, and time-consuming procedure intended to solicit the most accurate possible information from experts.

2.4.4 Overview of the Delphi Method

In the Delphi method, an iterative process is used to narrow in on accurate data (Rowe and Wright, 1999). The moderators of the Delphi process (who include the researcher or decision-maker, statistical consultants, and process facilitators) follow a well-defined set of steps to obtain accurate information from a panel of experts. The experts evaluate a specific aspect of the topic under investigation by responding to questionnaires. These questionnaires may be structured or relatively unstructured; in some cases they may simply ask for the expert's broad insight into the topic. The respondents are often encouraged to provide extensive explanations and justifications for their answers. The moderators then review the results, note the range of responses and the issues that they raise, and design a new questionnaire based on the analysis of the first one. The expert respondents then receive the second questionnaire along with the moderators' analysis of the overall results from the first round of elicitation. When the experts send back their responses to the second questionnaire, the moderators once again review them and, if necessary, create yet another questionnaire. These iterations continue until a consensus is reached (Rowe and Wright, 2001).

The Delphi process is based around providing anonymous peer feedback to the expert participants. Feedback is an important and sensitive issue in the data elicitation process, due to the way in which it may influence an expert. For example, if the researcher or a peer provides feedback by saying, "this value seems to be high when compared with others," this response may strongly encourage the expert to reduce the estimate. At the same time, however, the absence of peer feedback in data elicitation can lead to less accurate results. Thus, the Delphi process is designed to present peer feedback in a measured and neutral fashion. When preparing feedback during the Delphi process, the moderators should be thoughtful and careful about the manner in which it is presented (Campbell et al., 1999; Linstone and Turoff, 1975).

Depending on the nature of the topic, the moderators may present feedback to the expert respondents as a statistical summary and/or as a written overview. Two simple statistical measures that can be used to provide feedback are the mean and median values of the responses. However, using the mean or median may not be a suitable statistical approach when the responses are dispersed in a wide range or when there are outliers. For these occasions the moderators may decide to present the aggregated results in other statistical forms such as quartiles, or to provide a more descriptive summary. If there are outliers in the responses then the moderators may ask those particular respondents to provide further reasoning for their answers (Rowe and Wright, 2001).

The Delphi method is a time-consuming process, but it has a number of advantages over traditional group-thinking methods such as focus groups and individual solicitation methods such as interviews. It was designed to take advantage of the productive characteristics of interpersonal interaction—such as including different sources of knowledge, encouraging the emergence of new ideas, and conceptual screening, while at the same time limiting the negative aspects of group interaction, which can include the uncontrolled proliferations of ideas and biased, destructive criticism (Gupta and Clarke, 1996).

2.4.5 Characteristics and Implementations of the Delphi Method

The Delphi method is characterized by its iterative process, the anonymity of responses, controlled flows of information, and the opportunity to modify responses based on feedback. The iterative nature of the method is valuable because the back-and-forth transfer of information leads to maturity in the results and decreases the range of responses. The participants have the opportunity to consider what others think about the problem and to see how others justify their responses (Hsu and Sandford, 2007). However, since the expert participants do not directly engage with or recognize the other members of the panel, they are less likely to be affected by extraneous social factors (humiliation, intimidation, desire to please, etc.) that might otherwise limit the expression of their insights (Clayton, 1997).

The flow of information in the Delphi method is controlled by the researcher, with the help of the other moderators. The gathered information is reflected back to the participants only in a processed form. This helps to keep the participants focused on the task at hand, and also provides the moderators with opportunities to eliminate stubborn and discredited outliers in the responses (Clayton, 1997). Once the moderators have analyzed and aggregated the results of each round of questions, these results are provided to all of the expert participants, giving them the opportunity to consider alternative views and adjust their previous replies. This process helps the expert respondents to move toward consensus faster, and in a less biased fashion, when compared to other methods of group discussion.

The Delphi method is widely used in program planning to achieve one or more of following objectives:

- Defining or developing possible program alternatives
- Investigating assumptions or information leading to different judgments
- Soliciting information that has the potential of consensus among the respondents
- Correlating informed judgments on cross-cutting topics
- Educating the respondents (Delbecq et al., 1975)

In the context of forecasting, the Delphi method has been used in numerous fields including public administration, medical science, and construction management (Schmidt, 1997; Olumide, 2009; Del Cano and de la Cruz, 2002). Many previous researchers have employed this method to elicit data from experts for the purposes of evaluating risk and uncertainty. De la Cruz et al. (2006) used the Delphi method to identify risk factors and risk responses in civil-service construction projects. Olumide (2009) defined ranges of highway construction cost over different project development phases by conducting a Delphi study. In the area of transportation planning, Robinson (1991) implemented a Delphi approach to forecast infrastructure funding needs and patterns. The method has been used in other areas of construction management to elicit data about delivery processes and to identify highway construction research and development needs (Gunhan and Arditi, 2005; Damron, 2001).

2.4.6 Selection of the Expert Panel

An important aspect of the Delphi process is that it is designed to establish a consensus among a panel of experts. Determining who does and does not fit the description of being an "expert" can be a complex process. The central literature about the Delphi method loosely defines "experts" as those who have ample knowledge or experience to provide insight into the topic under investigation (Clayton, 1997; Cantrill et al., 1996; Rowe and Wright, 2001). One general guiding principle for defining "expertise" might be that the expert has spent a much larger amount of time thinking about or participating in the subject area as compared to the average person. However, the exact definition of an “expert” may vary among different fields (Brown, 1968). The method in which such experts are identified and selected requires a more specific analysis related to the particular field of study.

In some implementations of the Delphi method, the goal of obtaining the most knowledgeable experts as respondents may be intentionally compromised in order to include representative perspectives from the full range of stakeholders in the topic under discussion. This is particularly important when the successful implementation of the outcome requires the willing cooperation of a wide range of participants, in which case the Delphi process can act as an initial exercise in building community consensus. For these representative purposes, the participants in the Delphi panel may be selected using probability sampling techniques (Clayton, 1997).

In most cases, however, the selection should be made based purely on expertise. In these cases the researcher is seeking individuals who have a demonstrated knowledge. Purposive sampling or criterion sampling is the most effective way to select such panel members (Hasson et al., 2000). In purposive sampling, the participants are selected based on the researcher’s judgment of their suitability for the study (Tongco, 2007). In criterion sampling, the participants are selected based on a predetermined benchmark that designates their suitability (Patton, 1990). In either case, one of the ways to identify potential participants is to contact trusted, well-known specialists in the field and ask them to recommend other experts. Since the iterative nature of the Delphi method makes it a lengthy process, the selected experts should be made aware of the time-factor involved. The researcher should seek to verify that the expert participants are motivated enough to complete the entire process.

The researcher may decide to ask the experts to rate their own level of expertise in the area under investigation, and then use these evaluations to weigh responses when analyzing the questionnaire results (Mullen, 2003). However, assigning weights to the expert responses based on self-ratings is a somewhat questionable approach. Clear instructions and solid criteria must be provided when asking people to rate their own expertise, and even when this is done, different experts may have different biases when it comes to rating themselves. Nonetheless, even a flawed comparative assessment of expertise might be helpful in some situations, for example when the researcher is seeking to analyze outlying responses.

2.4.7 Attrition

Due to the length and complexity of the Delphi process researchers may face low response rates and high participant attrition. Scholars have found that the most important factors in motivating participants to remain involved in Delphi studies are the importance of the research to the participants and the persistence of the researchers (Cantrill et al., 1996; McKenna, 1994). The size of the panel of experts also has an effect on the length and complexity of the process and thereby on the attrition rate (with larger panels having higher attrition) (Mullen, 2003). Another issue identified by Hill and

Fowles (1975) is that “many respondents clearly find the exercise more burdensome than anticipated,” and therefore drop out of the process. To help avoid this, researchers should clearly and emphatically describe the process and the time investment that it entails to potential participants. This allows the expert participants to adjust their expectations and consider their commitment more realistically.

2.4.8 Consensus

In the conventional Delphi method the objective of the process is to generate a consensus of opinion among the participants. It should be noted that this is not always the case in some of the method’s more contemporary variations. For example, “Policy Delphi” involves brainstorming research into new scenarios and alternatives, and coming to an agreement about the best one is not considered an important part of the process. Likewise, some implementations of the method in the areas of strategic planning, risk identification, and resource allocation do not require a unitary consensus as an end result (Linstone and Turoff, 1975).

For the purposes of forecasting, however, obtaining a consensus in the traditional fashion remains an important part of the process (Linstone and Turoff, 1975). This consensus should be obtained by the sharing of knowledge and mutual education during the course of the iterative feedbacks (Sackman, 1974). This results in a relatively “authentic” consensus and avoids the pitfall of mere social acquiescence to a dominant perspective.

There are, however, still some situations in which the process must be terminated before full, authentic consensus is achieved. Hasson et al. (2000) pointed out that if the number of participants is decreasing significantly every round due to attrition, then the Delphi process should be halted. In such a situation it is likely that the departing members believe their input is not being heard, and continuing the process will therefore likely lead to a biased result.

There is no overall agreement in the literature about the specific criteria for consensus in the Delphi method. One approach is to consider the variation of the responses in successive rounds. If the results have become stable then the researcher may conclude that a consensus has been obtained (Hasson et al., 2000). Another possible criterion is to measure the percentage of responses which fall into a designated range of variation on a predefined scale (Hsu and Sandford, 2007).

CHAPTER III

RESEARCH DESIGN

The overall goal of this research was to develop a risk- and performance-based infrastructure asset management framework. The literature review described in the previous chapter was the starting point for this work; it involved an assessment of current asset management tools, methods of representing uncertainty in decision-making, and various forecasting and data-elicitations methods. There are currently two major challenges for implementing a risk- and performance-based infrastructure asset management framework: first, there is a lack of a practical method for incorporating uncertainty into the model, and second, in many cases there is a lack of appropriate data for how assets perform over time.

To address these issues, the research study was broken down into six sequential tasks:

1. Define the levels of uncertainty that are relevant to asset-management decisions.
2. Evaluate various risk-analysis approaches, and select a practical approach that is suitable to the current needs of asset managers.
3. Develop a method to incorporate the identified risk-analysis approach into the asset performance model, and to assess the impacts of risk and uncertainty on the final asset management decisions.

4. Develop a data-elicitation method for defining the performance of assets when sufficient historical (past-performance) data is not available.
5. Using a case study in which historical data is available, assess the applicability of the proposed methods by comparing the modeling results with the results from actual historical data collected in the field over time.
6. Develop recommendations for how asset managers can use the decision support framework during the course of their practical activities.

To accomplish Tasks 1, 2, and 3, the method of scenario analysis was used to develop a practical model of uncertainty. Drawing from the analysis of levels of uncertainty in Courtney (2001) and Walker et al. (2003), the researcher first analyzed what kind of uncertainty is present in infrastructure asset management. This analysis helped to indicate the appropriate approach for modeling uncertainty and risk. The method chosen was a three-part, outcome-based scenario analysis—for convenience these scenarios were called the "best case," the "most likely case," and the "worst case" for asset performance. The value of this approach for asset management is that the construction of such scenarios enables decision-makers to draw conclusions about the range of potential impacts of their decisions, while, at the same time, the model's relative simplicity avoids bogging decision-makers down in an excess amount of data. This allows decision-makers who are using the infrastructure asset management tool to quickly see how their allocation of funds is likely affect the overall conditions of their asset network. The explanation of how this approach to risk and uncertainty was selected and developed is described in detail in chapter 4.

To accomplish Tasks 4, it was necessary to determine a method for estimating the performance of assets in the absence of adequate historical (past-performance) data. After examining various forecasting and data-elicitation methods, the researcher developed an approach based on the “Delphi technique,” which involves an iterative and interactive analysis by a panel of experts. This robust technique to elicit estimated performance data can be used to reliably fill in the gaps when actual historical data about asset performance is impossible to obtain. Chapter 5 describes in detail how this technique of data elicitation was selected and developed for use in asset-management contexts.

To accomplish Task 5 the researcher conducted a case study and tested the practical implementation and accuracy of the model. The case study that was selected involved street maintenance in the city of Bryan, Texas. While the proposed asset-management framework is generic and could be used for any type of asset-management situation, in this research the pavement condition index (PCI) of the Bryan road system was used as the relevant measure of performance. The case study was focused on the deterioration of PCI over time, an important consideration for asset managers who need to evaluate the timing and cost of pavement maintenance treatments.

To test the proposed data-elicitation method, pavement samples from varied locations in the city were selected and provided to a panel of road-condition experts. The condition of these samples (their PCI) was measured, and then the experts were asked to evaluate the age of the pavement in the various samples. The data elicited from the experts was aggregated using a Bayesian hierarchical model. Finally, based on the resulting data, the researcher developed a scenario-based model for defining how pavement conditions in the city deteriorated over time. Quantile regression analysis was used to define the performance curve for each of the three possible scenarios (the “best case,” “most likely case,” and “worst case”).

Meanwhile, actual historical (past-performance) data was obtained from the city of Bryan, in the form of road construction records and PCIs measured during city inspections. The existence of actual historical data in this case study allowed for a comparison in which the model based on data-elicitation was measured against a similar model derived from the city’s records. The process of data elicitation/collection and analysis in the case study is described in detail in chapters 6 and 7.

Finally, to accomplish Task 6 the researcher examined the implementation of the case study and developed practical recommendations for when and how the proposed infrastructure asset management framework can best be applied during the course of everyday professional activities. These recommendations are provided in the concluding chapter 8 of the dissertation.

CHAPTER IV

SCENARIO PLANNING IN INFRASTRUCTURE ASSET MANAGEMENT

4.1 Introduction

In recent years scenario planning has become a commonly used technique to support decision-making in uncertain environments. Scenario planning is most useful when the situation involves unknown or hard-to-predict variables and a diverse range of possible future events or outcomes. It allows managers to evaluate several representative possible futures during the course of their decision-making process, and is therefore very beneficial for organizations that are attempting to prepare medium- and long-range plans that can be affected by differing future conditions. Scenario-based approaches to planning involve considering a set of alternative possible futures and evaluating what effects the current decision will have on each of those possible futures.

In general, a scenario can be defined as a cohesive description and clarification of a possible future state of affairs. It also sometimes includes a description of hypothetical events leading up to that future and the potential implications of the events. Part of the process of defining scenarios is the identification of uncertain and uncontrolled factors that decision-makers may have assumed to be static. Thus, scenario planning involves challenging the existing mindset of decision-makers, and breaking the status quo by suggesting possible futures that may not have been adequately considered.

The scope of scenario planning extends to virtually any situation in which the decision-maker confronts a state of uncertainty about relevant future conditions. The strength of scenario-based approaches is to clarify and delimit the broad range of future possibilities, which if considered all together as a whole can overwhelm human capacity for analysis. Unlike other popular methods of uncertainty analysis, such as contingency planning and computer simulation, scenario-based approaches are able to take into account a very wide range of unknown variables. Traditional probabilistic analyses of uncertainty can, in theory, be seen as considering every possible future event as a scenario, but this approach becomes ever more impractical as the range of relevant variables increases. Scenario analysis makes use of a limited number of representative scenarios so that decision-makers can more quickly and effectively comprehend the overall range of possible futures. The scenarios are not assigned a level of probability, thus helping to counter the natural human tendency to ignore outlying possibilities. This encourages managers to more seriously contemplate the full range of possible future conditions (Bishop et al., 2007).

Scenario planning methods can be categorized as event-based or outcome-based. Event-based approaches are oriented around a set of divergent future happenings (for example, receiving full maintenance funding in the upcoming year, receiving half maintenance funding, or receiving no maintenance funding). This kind of event-based scenario-planning approach has been used previously in infrastructure asset management support frameworks (Piyatrapoomi et al., 2004). In contrast, outcome-based scenarios describe possible future conditions, without attempting to specify what events led to those conditions. This approach is more useful when the range of possible future outcomes can be defined, but the event sequences leading to those future outcomes are very complex (for example, instances in which variations in weather conditions affect the decline of an asset over time).

In chapter 2, a more detailed description and review of the previous literature on scenario planning was provided. In this chapter, an outcome-based scenario-planning approach is used to address Research Question 1 of the current study (how to best incorporate uncertainty into a decision-support framework for infrastructure asset management). This chapter includes a discussion of why outcome-based scenario planning is a novel and valuable solution in infrastructure asset management. It also describes how levels of uncertainty are relevant to implementing scenario analysis, and how specific scenarios can be developed for describing possible future asset-performance levels.

4.2 Dimensions of Uncertainty

The first step in structuring a scenario-planning process is to define the purpose of using this method and what it can accomplish for the topic at hand. Asset management is a natural candidate for scenario analysis, due to the frequency with which asset managers have to enact planning decisions in an uncertain environment. However, to more closely define the utility of scenario planning and to select the most appropriate approach, it is important to specify the exact dimensions of uncertainty that need to be handled in asset-management contexts.

Walker et al. (2003) identified three dimensions of uncertainty as its *location*, *nature*, and *level*. The *location* of uncertainty refers to the specific variables that cannot be deterministically modeled. There are many different locations of uncertainty that can be identified in infrastructure asset management, ranging from variations in future funding, to the accuracy of asset inventories, to the rate with which assets degrade. In this research, the location of the uncertainty that will be examined is in the performance of assets over time. This central measure is of great importance to all asset managers, and it combines many elements of uncertainty arising from different sources (data accuracy, future weather/environmental conditions, the variable quality of maintenance work, the amount of traffic, etc.)

The performance of assets over time is frequently expressed using performance curves, a concept that was introduced in chapter 2. By constructing a graph with performance ratings on the vertical axis and time on the horizontal axis, it is possible to quickly see the utility that an asset will provide over the course of its remaining life. Different maintenance decisions will affect the performance curve of an asset in specific ways. However, there is always a degree of uncertainty when defining performance curves for the future of an asset, because this future performance can be subtly affected by many unknowable variables. This uncertainty is further increased when there is limited historical data on which to base the projections, or in cases where environmental conditions and usage patterns are expected to change rapidly.

The *nature* of uncertainty, in Walker's (2003) schema, refers to whether the uncertainty is due to a lack of knowledge about the problem or to natural variability in the environment and other causal effects. In reality this is something of a spectrum, but the importance of the distinction is to clarify how easy it would be to reduce uncertainty by enhancing the state of knowledge about the problem. In the case of future asset performance, the uncertainty is caused by complex phenomena (such as weather patterns and the variable properties of materials) that are extremely difficult, if not impossible, to predict. Thus, it is unlikely that this uncertainty will ever be fully eliminated.

The third dimension in Walker's (2003) schema is the *level* of uncertainty. This dimension has been largely neglected in previous asset-management research. However, the level of uncertainty has an important bearing on selecting the most suitable risk analysis tools and techniques. The levels of uncertainty in infrastructure asset management are discussed in detail in following section.

4.3 Levels of Uncertainty in Infrastructure Asset Management

To implement the best possible risk analysis approach, the level of relevant uncertainty in the situation must first be determined. As was discussed in chapter 2, researchers have frequently divided uncertainty into four categories or levels (Courtney, 2001; Walker et al., 2003). To review, these four levels are:

Level 1: A clear, single vision of the future. The range and impact of relevant possible futures is so narrow that it is acceptable to consider the problem deterministically, without worrying about multiple future scenarios.

Level 2: A limited set of possible future outcomes, one of which will occur. At this level the uncertainty can be expressed as several discrete possible future outcomes. The probability that each of these future outcomes might occur is also known to a fairly high degree of accuracy. All of the relevant possible future outcomes can be expressed as a mutually exclusive, collectively exhaustive set.

Level 3: A range of possible future outcomes. Due to the complexity of the variables it is no longer feasible to identify and analyze every possible future outcome. However, the total range of the possible future outcomes can be described.

Level 4: A limitless range of possible future outcomes. At this level of "true ambiguity," it is impossible to define the limits of what might happen, or to estimate the probability of any given scenario.

These levels of uncertainty were primarily developed for use in strategic planning. However, they also have important implications for decision-making in infrastructure asset management. For example, a typical asset performance curve is presented in a deterministic fashion, mirroring Level 1 uncertainty. A single curve is shown, with no attempt to represent variability in future performance (Figure 4-1). This is the traditional approach to modeling performance in asset management, and several major asset-management decision support frameworks incorporate such models (Santos and Ferreira, 2013). However, assuming a deterministic level of uncertainty in asset performance is questionable, since numerous unknown and complex variables can have important effects on the actual performance of real-world assets (Ng et al., 2011). Deterministic models are fairly easy to interpret, but they include no information about the range of uncertainty and risk.

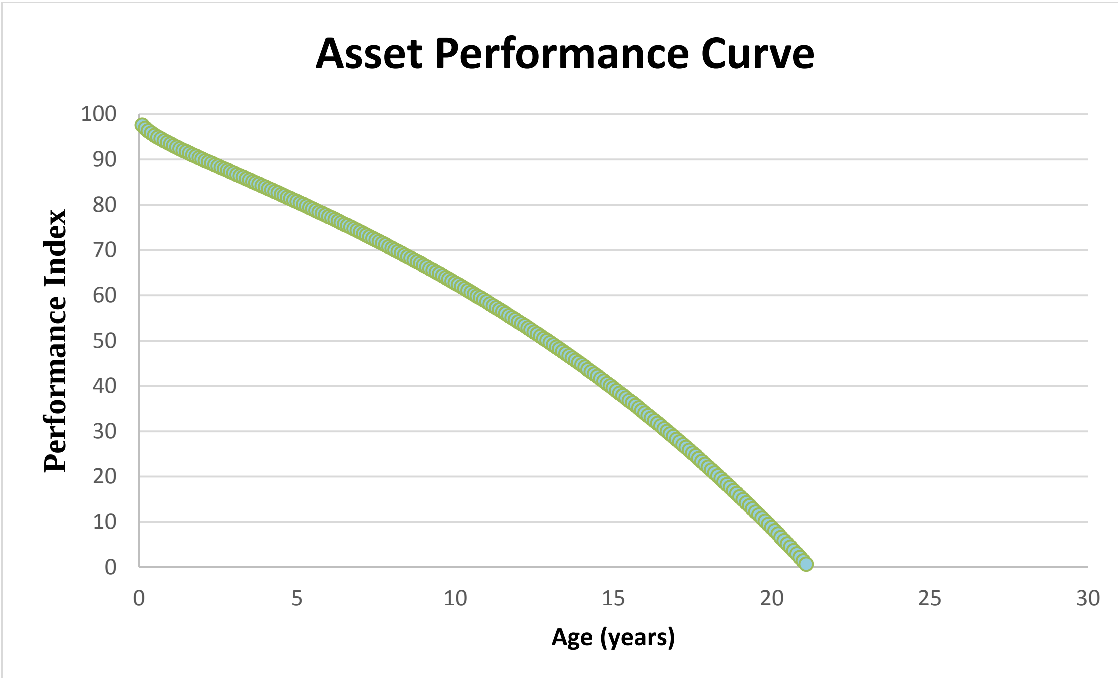

Figure 4-1. Example of a Traditional Asset Performance Curve (Level 1 Uncertainty)

To adopt a Level 2 uncertainty approach in infrastructure asset management, it is necessary to predict performance in a discrete, exhaustive set of possible future outcomes. Since the 1970s, researchers have attempted to develop statistical models to provide such an analysis. One example is the stochastic performance models that are frequently used in pavement management, such as the Markov Decision Process (Figure 4-2). In this method the probability of degrading from one state of performance to another over a given time-frame is defined by a transition matrix. In theory, it is possible to model the life-cycle of an asset by considering all of its identifiable futures, and then assigning a probability to each path. However, in practice, because of the complexity of the variables involved and the difficulty of modeling all identifiable futures, this approach is seldom fully implemented. Furthermore, the amount of information in the matrix makes these models rather awkward and non-intuitive to use.

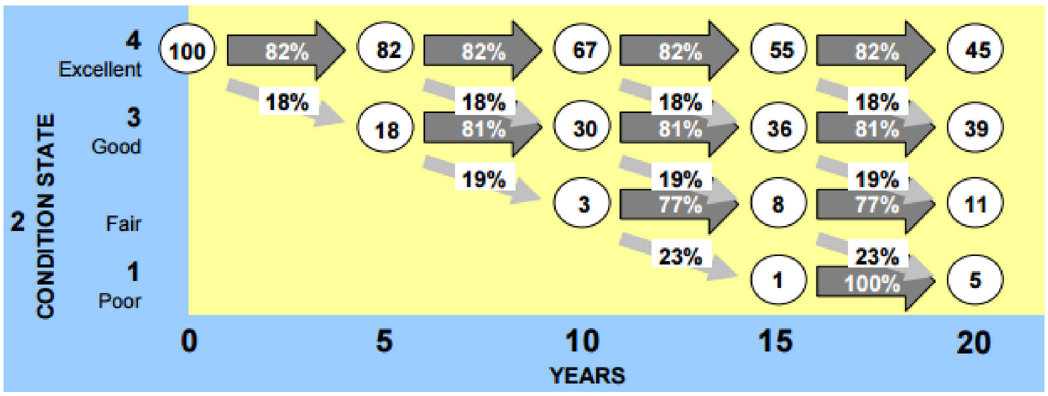

Figure 4-2. Example of a Markov Model (Level 2 Uncertainty) (Carter, 2002)

Level 3 uncertainty is arguably the best interpretation of the decision-making environment for asset managers. Typically, the factors that can affect future asset performance are too complex to allow all relevant future outcomes to be defined in an exhaustive fashion. Attempts to do so (such as the Markov model described above) are inevitably incomplete and imprecise in their attempts to assign probabilities. The modeling assumption that all possible future paths can be exactly and precisely defined in an event-probability matrix is not really true in the practical context of asset performance. Thus, models based on a statistical, Level 2 uncertainty approach end up presenting definitive probabilistic results that obscure the actual uncertainty in the data. At the same time, the complexity that is entailed in this statistical approach, as it tries to become ever more accurate by defining greater and greater numbers of possible futures, makes the model increasingly cumbersome for decision-makers to use.

In the context of infrastructure asset management decisions, it is difficult to describe every single possible performance future. However, the overall *range* of potential asset performance is relatively easy to define. This range of possible future conditions can be described with an upper bound (best-case scenario), a lower bound (worst-case scenario), and a median line (most likely scenario). This is an accurate description of Level 3 uncertainty. Instead of attempting to statistically analyze all possible futures, it can be more effective in this situation for decision-makers to consider a few representative scenarios from within the overall range of uncertainty (Figure 4-3). This form of scenario-based planning has obtained widespread application in other areas of strategic decision-making, but it has not yet been implemented in infrastructure asset management, despite its excellent fit with the level of uncertainty that asset managers commonly encounter.

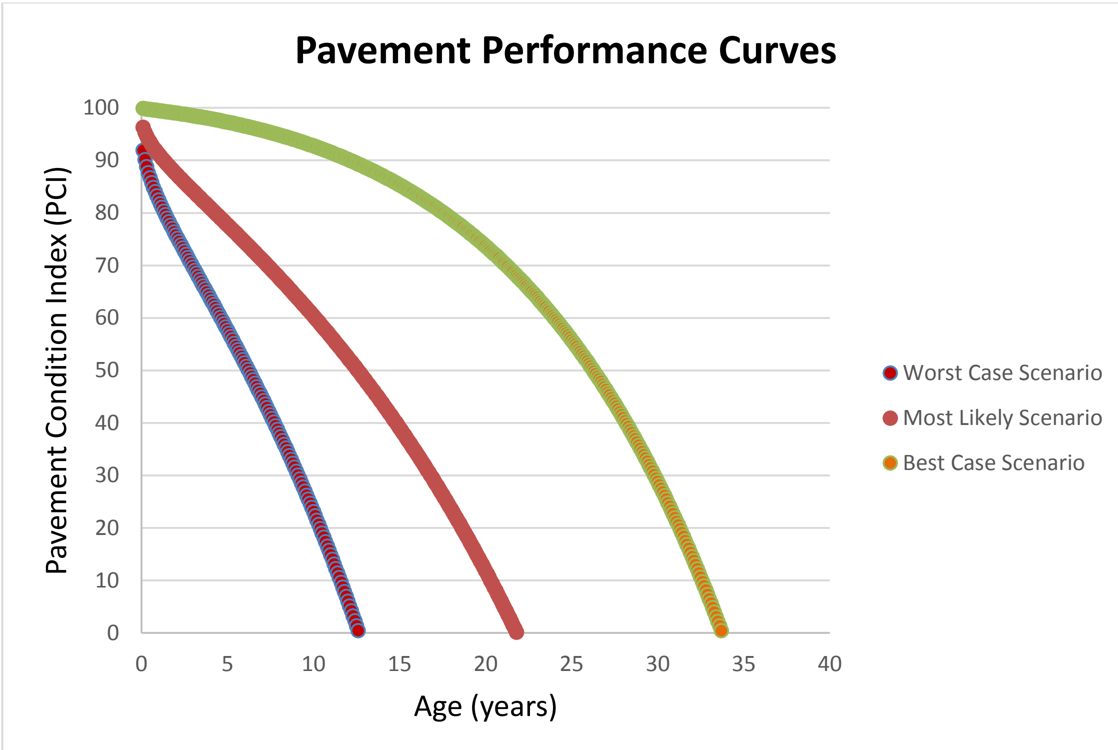

Figure 4-3. Multiple Performance-Curve Scenarios Displaying the Range of Uncertainty (Level 3 Uncertainty)

The drawback of using scenario planning based on Level 3 uncertainty (compared to statistical analysis based on Level 2), is that scenarios do not provide exact probabilities or an exhaustive accounting of future events that would allow for a definitive mathematical/statistical solution. However, as argued above, this goal of statistical precision is difficult if not impossible to accurately accomplish in the context of predicting future asset performance. In this context, it can be more useful and effective for decision-makers to examine a small set of scenarios covering the range of possible futures.

Regardless of the level of uncertainty, only one of the many possible future outcomes will actually occur. Considering this helps us to understand another advantage of scenario analysis. Probabilistic approaches are generally oriented toward determining the decision with the greatest statistical utility, given the likelihood of different future events. Maximizing statistical utility, however, is not the only information that decision-makers need to consider. They also need to consider what the outcome will be if an unlikely future comes to pass, and whether or not that potential outcome is acceptable. Examining "worst case" and "best case" scenarios, as well as the more likely scenarios, encourages managers to take this information into account.

The ability to define a "best case" and "worst case" performance scenario is also what distinguishes the situation of infrastructure asset management from the true ambiguity of Level 4 uncertainty. At Level 4, future events are pretty much impossible to model. The range of what might happen is unknown and unknowable. Fortunately, this is not the case in most situations related to asset performance, because the overall range of performance possibilities can be described with reasonable accuracy. Assets have a maximum performance at the beginning their life cycle, and this performance decreases as the asset deteriorates over time. Many complex factors affect the rate of decrease, but its general "best case" and "worst case" parameters are knowable. Thus, in most cases the true ambiguity of Level 4 uncertainty is not the situation of asset managers.

4.4 Developing and Representing Scenarios for the Performance of Assets

After deciding to adopt a scenario planning approach, based on the Level 3 uncertainty typically faced by asset managers, the next step in this research was to determine how the relevant scenarios should be selected and defined. For the sake of simplicity, it was decided that three scenarios for future asset performance would be considered. This is actually the smallest number of scenarios that can be usefully employed in such an approach, as it allows for a presentation of an upper bound, a lower bound, and a median in regard to possible future performance. The use of three scenarios is a common feature of scenario planning in strategic decision making (Chen, 2003). The three scenarios used in this framework are not assigned specific probabilities of occurrence. Decision makers may generally assume that the upper- and lower-bound scenarios are less likely to occur than the median scenario; however, the lack of assigned probabilities encourages them to weigh each of the scenarios with more equal importance and thereby broaden their view toward the range of potential consequences of their decisions. This helps to counter the natural human tendency to dismiss outlying possibilities (Bishop et al., 2007).

Finally, the specific manner of defining the three scenarios had to be determined. The main basis for representing uncertain outcomes is probability distribution, which is also the most familiar method used in decision analysis (Durbach and Stewart, 2011). However, it is more practical (and a necessary component of scenario analysis) to use summaries of the probability distribution to capture particular features of interest. The most important probability distribution summaries are individual probabilities, quantiles, intervals, location measures (median, mode, and mean), measures of scale or dispersion, and measures of shape (O'Hagan et al., 2006).

In this research the goal was to provide "best case", "worst case", and "median case" scenarios. The most suitable distribution summary to use for this purpose is statistical quantiles. As defined by Gilchrist (2000), "a quantile is "simply the value that corresponds to a specific portion of a sample or population." In other words, it is the data value below which a given portion of the observations fall. The portion of observations that fall below a quantile is called the percentile. For example, at the 20th percentile, 20% of the data observations fall below this number. The actual data number at the 20th percentile is called the quantile.

For the purposes of this study, the "worst case" or lower-limit scenario was defined as the 5th percentile. This means that there is less than 1 in 20 chance that the actual condition of the asset will fall below the lower limit. Likewise, the "best case" or upper-limit scenario was defined as the 95th percentile, meaning that there is less than 1 in 20 chance that the actual condition of the asset will be above the upper limit. (Technically, these percentiles do not represent the absolute "worst" and "best" situations that could happen; these are terms of convenience.) The median scenario was defined as the 50th percentile, the center-point of the data's probability distribution.

CHAPTER V

A MODEL FOR ELICITING EXPERT OPINIONS

5.1 Introduction

To address Research Question 2 of the current study (how to predict asset performance in the absence of adequate historical data), it was necessary to select the most appropriate method of qualitative forecasting. Then, these approaches were used to develop a model specifically tailored for application in infrastructure asset-management contexts. As was discussed in chapter 2, data forecasting processes and techniques are designed to make the most accurate possible predictions about specific future outcomes. These methods have become increasingly rigorous and credible over the past century (Hanke et al., 2001). Forecasting methods incorporate historical data wherever possible to help predict future trends. However, relying solely on historical data in forecasting analyses has a limited utility. Forecasters must also consider potential changes in the environment and draw from a wider range of knowledge in order to assess the likelihood that recorded trends will continue in a set pattern. In cases where there is limited historical data or when trends are expected to change rapidly, these qualitative aspects of forecasting become increasingly important.

In the absence of robust historical data, drawing from the opinions of experts is one of the best ways to improve the accuracy of forecasting. Through a process known as data elicitation, researchers can fill in unknown data points by consulting individuals who have expert knowledge of the topic that is being studied. Several rigorous methods have been developed that can increase the accuracy of forecasting and data elicitation and limit their subjective elements. One of the most sophisticated approaches is known as the Delphi method, and it was this approach that was selected for use in the current research. The details of forecasting, data elicitation, and the Delphi method were described more fully in chapter 2. In this chapter, an application of the Delphi method was developed to create a model for eliciting data about asset performance.

5.2 Using the Delphi Method to Elicit Data on Asset Performance

The Delphi method is an iterative process that allows the researcher to narrow in on accurate information from a panel of experts. Through multiple rounds of questionnaires, the experts have an opportunity to review summarized analyses from their peers, thereby obtaining feedback and refining their outlooks until a consensus is reached. The flow of information is controlled by the researcher/moderator, and the peer analyses are distributed in an anonymous fashion. This helps to reduce the impact of undesirable social factors such as destructive criticism, intimidation, face-saving, the desire to please, and so forth. Although the Delphi method is a time-consuming process, it can lead to better results than other methods of data elicitation, such as focus groups or interviews.

The Delphi method was chosen for use in this research for three reasons. First, it does not require the experts to meet the researcher in person. The questionnaires can be completed at the experts' convenience, which greatly improves the logistics of conducting the elicitation and allows for more flexibility in the selection of expert participants. Secondly, the anonymity that the method provides to the expert participants is very useful in a professional field where many of the experts may interact with one another outside of the study. This is particularly critical because of the possibility that some respondents might be employed at different ranks of the same organization. Finally, using the Delphi method in this research allowed for feedback and discussion among the participants, which is not possible in other anonymity-preserving approaches. The use of feedback and discussion is a very powerful tool for increasing the accuracy of data elicitation (Jenkinson, 2005).

Twelve steps were identified in the data-elicitation model. These steps are listed below, and then discussed in detail in the following sections. In some of the discussion, examples from the implementation of the model in the city of Bryan, Texas are provided in order to better illustrate the processes involved in using the method. These illustrations are only for the sake of clarity. In practice, this model for data-elicitation can be adapted for use in a wide range of infrastructure asset-management contexts.

1. Select the moderators
2. Define the parameters of the data elicitation
3. Select samples from the current asset

4. Gather information on the samples
5. Select the panel of experts
6. Develop the questionnaire package for the first round
7. Run a pilot test
8. Conduct the first round of the elicitation
9. Analyze the responses from the first round and provide controlled feedback
10. Develop the questionnaire package for the subsequent round
11. Conduct the subsequent round of the elicitation
12. Review and analyze the responses from the subsequent round

1. Select the Moderators

When applying the Delphi method to the data-elicitation process, there are several different roles that need to be considered. These roles fall into two major categories. The first is a panel of moderators, which will be discussed in this section. The second is a panel of experts, which will be described in Step 5 below. The first step is to select the panel of moderators. The members of this panel should include the primary researcher (or decision-maker), statisticians, and facilitators (O'Hagan et al., 2006). The researcher or decision-maker is the ultimate client of the elicitation process. This person oversees the design and implementation of the method in order to obtain needed information. Statisticians provide technical consultation for the statistical aspects of the process. This often includes helping to develop questionnaires and analyze data. Facilitators assist in the implementation of the data-elicitation process. Their responsibilities often include contacting the panel of experts, gathering information from the experts, and conducting analyses under the supervision of the primary researcher and statisticians. Depending on the size of the research project, it is possible that one person might serve multiple roles on the panel of moderators.

When selecting the panel of moderators, a degree of expertise in the knowledge-area of the elicitation is important. At a minimum, the primary researcher should have a high level of expertise in the relevant subject area.

2. Define the Parameters of the Data Elicitation

This is one of the most important steps in data elicitation process. The selection of the parameters to elicit information about is based on the objectives of the elicitation process and the extent to which the available experts are familiar with the parameters. For example, for eliciting data about the performance of road pavements over time, two parameters could be identified as: (1) the age of the pavement; and (2) an indicator of performance. In the first option, experts would be asked to provide their assessment of performance given information about the age of pavement samples. In the second option, experts would be given information about the road performance and asked to assess the age of the samples. Both processes would lead to the same information—data about performance at a particular time. When deciding what parameters to use, the researcher should focus on what forms of evaluation would be easiest for the expert participants to make. It should also be mentioned that different parameters may affect the complexity of the statistical analysis that will need to be applied to the data.

In the context of asset performance, it is generally desirable for the experts to provide their data estimates as a range. The performance of assets over time is not deterministic, but depends on many unknown variables (weather conditions, etc.). Moreover, when an expert reviews an asset sample, it is merely representative of the asset's overall condition, which may vary from place to place within the asset. A pavement sample, for instance, does not exhaustively demonstrate the conditions along the entire road. For this reasons, experts who provide data in asset-performance contexts are usually more comfortable estimating a range of possible conditions rather than a specific outcome. For the model developed in this research, the experts were asked to provide their evaluations in the form of quantiles.

3. Select Samples from the Current Asset

In the absence of any other motivating factors, the samples taken from the current asset should be selected randomly. If possible, they should cover a complete range of the performance. It is preferable if the samples are spaced evenly across the range of performance (however, in practice this is often impossible). The other consideration in selecting the asset samples is that they should represent the average performance of the network.

4. Gather Information on the Samples

When the asset samples are selected, related information about the performance of the samples may also be obtained. This information will be provided to the experts as part of the questionnaire package. The purpose of this step is to provide as much data as possible to help inform the experts' evaluation. The information may include visual descriptions of the sample location (pictures and video recordings), field condition surveys, physical specifications, and any available historical information.

5. Select the Panel of Experts

The panel of experts consists of individuals who have a great familiarity with the topic under investigation. These experts should have adequate knowledge to provide a reliable assessment of the asset and its performance. A more detailed discussion of who qualifies as an expert was given in in chapter 2. There are several ways to identify candidates for the panel of experts. One practical method is to select them from the local pool of experienced professionals in the field of study. During this step of the elicitation process, a clearly defined criterion for evaluating the knowledge of prospective experts should be defined. This criterion may vary in different infrastructure asset management contexts; one broadly applicable criterion might be the number of years of experience that the expert has in the field of study.

6. Develop the Questionnaire Package for the First Round

The main instrument that is used in the elicitation process is the questionnaire package. The purpose of the package is to provide the expert participants with a user-friendly environment through which they can provide their inputs. Elements of the package may include an invitation letter, an information sheet, a description of the Delphi process, the questionnaire itself, and a demographic form. The package should be developed using a format that the experts are familiar with and are comfortable working within. For example, a simple platform such as Microsoft Office may work better than sophisticated statistical packages or researcher-designed input applications.

7. Run a Pilot Test

To improve the questionnaire package, the researcher should conduct a pilot test. A volunteer participant from the panel of experts should be instructed to fill out the pilot questionnaire. In addition to the normal questionnaire answers, this participant is asked to comment on the clarity of the questionnaire instructions, the utility of the included information, the method of response, and the overall format. After feedback is received from the pilot test, the questionnaire package may need to be adjusted.

8. Conduct the First Round of the Elicitation

After conducting the pilot test and making any necessary changes, the questionnaire package is sent to each member of the panel of experts. Typically, the package may be sent via e-mail. The expert participants should be instructed to inform the researchers if they need any further information, or if they wish to meet with a facilitator in person for further discussion of the process or the questionnaire.

9. Analyze the Responses from the First Round and Provide Controlled Feedback

The first step in analyzing the experts' responses is to review all returned questionnaires for reliability and consistency. The moderators should confirm that each expert appears to fully understand the concepts and the elicitation process. A useful approach to this review is to plot the responses and compare the range of answers, which allows the moderators to identify outlying responses. The moderators may decide to discard the outliers or to contact those respondents for further clarification. After this review, the moderators should summarize and aggregate the responses from the experts. Ouchi (2004) provided a detailed review of different aggregation methods that can be used. The aggregated results of the first round of elicitation will be provided to the experts as part of the second-round questionnaire package.

10. Develop the Questionnaire Package for the Subsequent Round

The questionnaire for the subsequent rounds of the Delphi process is developed based on the results of the first round. The moderators may repeat questions from the first round and allow the experts a chance to adjust their responses. Additional questions may be added based on issues that the moderators identified as critical in the first-round responses, thereby encouraging the experts to elaborate, reconsider, or confirm their view of those topics. The new questionnaire package also includes feedback from the previous round of elicitation. This use of anonymous feedback is a very important aspect of the data-elicitation model (Wolfson, 1999). Two recommended forms of feedback are: (1) the aggregated results of the previous rounds using one of the statistical methods described above; and (2) selected samples of the responses from the previous round. The panel of moderators should work together to define which new questions to add and what combination of feedback best suits the needs of the project. It is important to select the feedback carefully to avoid overwhelming or frustrating the experts, and to avoid introducing bias into the process.

11. Conduct the Subsequent Round of the Elicitation

The elicitation process for subsequent rounds is similar to the first round. Each member of the expert panel should receive the new questionnaire package, and should be instructed to contact the researcher if there are any questions or concerns. It is important when sending the new questionnaire package to clearly indicate to the experts that this is a new round of elicitation, and to describe its importance and its differences from the previous round.

12. Review and Analyze the Responses from the Subsequent Round

The results of subsequent elicitation rounds are reviewed and analyzed in a fashion similar to the first round. At the end of the analysis the moderators determine whether or not there is a need to conduct a further round of elicitation (if so, they return to Step 10 of the process). If the moderators determine that a consensus has been reached in the experts' replies, or that further rounds of elicitation would be unproductive, then they end the process. Chapter 2 includes a more detailed discussion of how consensus may be defined and other criteria that moderators may consider when determining the need for another round of elicitation.

CHAPTER VI

DATA COLLECTION FOR A CASE STUDY IN THE CITY OF BRYAN, TEXAS

6.1 Introduction

The previous chapters of this dissertation described the infrastructure asset-management framework and model that was developed during the current research. This framework was created to help meet two of the most critical information-modeling needs in the asset-management context—how to report uncertainty and risk, and how to predict asset performance in the absence of adequate historical and past performance data. The second portion of the research, which is described starting in this chapter, was conducted to test the applicability and implementation of the proposed asset-management framework.

For the purpose of testing the new model, a case study was conducted. The asset performance measure that was chosen for evaluation was pavement conditions on the city streets of Bryan, Texas. Pavement performance is a paradigmatic maintenance concern for asset managers, and one that is fairly conspicuous to the public. It is commonly quantified using a measure called the Pavement Condition Index (PCI), which ranges from 0 to 100. Pavement with a PCI of 0 is regarded as "failed" and incapable of providing satisfactory service to users, while pavement with a PCI of 100 is in immaculate condition. PCI evaluations take into account both the structural integrity of the pavement and its surface operational conditions (though some structural characteristics, such as skid resistance and weight-bearing capacity, are not considered in PCI evaluations) (Shahin, 2005). For maintenance purposes, mapping the changes in a road's PCI over time provides a good description of the rate of pavement deterioration.

For testing purposes, data about the PCI over time in Bryan, Texas, was obtained from two different sources. The first source of information was data elicitation from experts, following the model described in chapter 5 of this dissertation. This is the proposed method for obtaining predictions of asset performance in the absence of robust historical information. In this case study, however, an infrastructure asset-management context was chosen in which a good amount of past performance data was in fact readily available. The second source of data, obtained for comparative purposes, was past performance records from pavement surveys conducted by the City of Bryan.

This chapter describes the two sources of the data that were used in the case study, and the processes used to collect and prepare the data for analysis. The details of the data analysis are then provided in chapter 7.

6.2 Institutional Review Board (IRB) Approval

The data-elicitation process involves human subjects (the expert participants) who could potentially be affected by the research. Therefore, as mandated by Texas A&M University and the U.S. Department of Health and Human Services, the design for this case study was submitted for IRB review and approval. This research was filed for review under the Study Number IRB2014-0241, and the waiver was approved by the Institutional Review Board. A copy of the approval letter is provided in Appendix A.

6.3 Data Elicitation from Experts

To elicit data about pavement performance over time in the city streets of Bryan, Texas, the model described in chapter 5 was implemented. The theoretical background and design of this model were described in previous chapters. However, reviewing how this model was applied in a case study can be a very useful exercise for asset managers who are working to adapt the framework to their own unique contexts and asset responsibilities.

As described in chapter 5, the elicitation model is based on the Delphi method and includes twelve steps:

1. Select the moderators
2. Define the parameters of the data elicitation
3. Select samples from the current asset
4. Gather information on the samples
5. Select the panel of experts
6. Develop the questionnaire package for the first round
7. Run a pilot test
8. Conduct the first round of the elicitation

9. Analyze the responses from the first round and provide controlled feedback
10. Develop the questionnaire package for the subsequent round
11. Conduct the subsequent round of the elicitation
12. Review and analyze the responses from the subsequent round

In the following sections, the implementation of each of these steps in the case study is explained.

1. Select the Moderators

The first step of the data-elicitation process was to select the panel of moderators. The relevant roles to be filled included that of primary researcher, statisticians, and facilitators. In this small case study, the dissertation author served to fulfill all the required roles (thus, in the rest of this chapter the terms “moderator” and “researcher” are used interchangeably).

2. Define the Parameters of the Data Elicitation

The purpose of the data elicitation was to model levels of pavement performance (in PCI) over time. Thus, the researcher had two choices for how to proceed. The experts could be presented with pavement samples of a known age, and then asked to estimate the samples’ PCI. Alternatively, the researcher could present the experts with pavement samples of a known PCI, and then ask them to estimate the age of the samples. Either approach would allow the researcher to elicit the PCI-vs.-age relationship.

In this study, either approach would also have been pragmatically feasible (this might not always be the case, for example in situations where current performance indicators cannot readily be surveyed). Thus, the primary consideration in this case study was what form of evaluation would be easiest and most convenient for the experts to make. The researcher determined that estimates of pavement age based on known PCI were more straightforward and accurate. It was decided that the experts would be provided with information about the pavement samples' condition, including their calculated PCI and photographs of the sample locations. However, the experts would not be told the age of the pavement in the samples; the age variable would be treated as an unknown and elicited from the experts.

Another important constraint in this study was the type of streets that were examined. The researcher decided to limit the scope of the study to asphalt concrete pavements and to residential streets. This decision helped to focus the accuracy of the elicitation and to simplify the data-collection process.

3. Select Samples from the Current Asset

Since PCI was defined as the independent variable in this study, the strategy of pavement sampling was designed to cover the full range of current pavement conditions.

The researcher began by examining an aerial map of the city of Bryan and selecting potential sampling sites. Field visits were also conducted to gain an overview of the street conditions and the major types of pavement distresses that were present (longitudinal cracking, raveling, etc.) (Shahin, 2005). For convenience, the range of pavement performance was divided into five intervals:

PCI 0–40	“Failed”
PCI 41–55	“Poor”
PCI 56–70	“Fair”
PCI 71–85	“Good”
PCI 86–100	“Excellent”

Pavement samples were selected from each of these performance intervals. Furthermore, the researcher identified the major types of pavement distress that were present within each PCI interval, and samples were selected to include each of these different distress types.

A total of nine pavement samples were selected for the elicitation. This was the minimum number of samples that satisfied the criteria given above. While additional samples could potentially increase the accuracy of the data elicitation, the researcher was also concerned that a large number of samples might overwhelm the experts and decrease their enthusiasm for the elicitation process. It was therefore necessary to find a careful balance between these two concerns.

While narrowing in on potential sampling sites, the researcher reviewed photos obtained from the Google Streetview platform. These pictures provided more details about the pavement conditions and the kinds of distress that were present at each site, as well as possible obstacles that might inhibit field inspections. The last step of the selection process was to visit each sample site, confirm that it met the intentions of the survey, and obtain detailed and precise information. A list of the selected pavement sample locations is provided in Table 6-1.

Table 6-1. Name and Location of Selected Pavement Samples in Bryan, Texas

Sample Number	Location
201	Esther Blvd. (at Wayside Dr.)
202	Windowmere St. (Enfield St. to North Ave.)
203	Tanglewood Dr. (Southview Cr. to Barak Ln.)
204	Forestwood Dr. (Wedgewood Cir. to Verde Dr.)
205	Forestwood Dr. (Mistywood Cir. to Crestwood Dr.)
206	5th St. (E North Ave. to College View Dr.)
207	Ethel Blvd. (Morningside Dr. to Burton Dr.)
208	Cambridge Dr. (Manchester Dr. to Windsor Dr.)
209	Bristol St. (Ruskin Dr. to 2303 Bristol St.)

4. Gather Information on the Samples

Once the pavement samples were selected, the researcher compiled as much relevant information as possible to present to the experts. In this case study the relevant information included the PCI calculations, multiple pictures of each pavement sample, the sample locations and dimensions, and a description of observed distresses from the field survey. (As noted above, any available information about the age of the pavement in the samples was intentionally omitted.)

The relevant information about pavement performance was gathered by implementing a visual pavement condition survey for each sample location. This standardized method for recording pavement conditions data and calculating PCIs is provided in the *Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys* (ASTM D6433 – 11). After reviewing the available maps, pictures, and city information about the site, the researcher conducted an in-person inspection with the help of a student worker. The first task was to review the site and ensure that it was reasonably representative of the street as a whole—for example, to verify that the location was not at a street intersection or other position where higher-than normal volumes of traffic might lead to unrepresentative results. When the suitability of a sampling site was confirmed, the location was marked using spray paint. This facilitated the inspection process and ensured that the site could be readily located again in the future. Clearly identified sample locations can be very useful, both for reviewing/confirming the study results and for any future studies that may want to investigate changes over time in the same area.

Prior to conducting the inspections, the researcher undertook a day-long training session with a professional pavement surveyor. The appropriate measurement tools were employed following the recommendations of ASTM D6433 – 11; these included standardized data sheets, a hand odometer wheel, a string line, and a scale (Figure 6-1).

The type and severity of distresses throughout the pavement sample were measured and recorded, and then this data was verified through a second examination.

The StreetSaver® software package was used to store the collected data and to calculate the PCI for each pavement sample. Pictures of the sample site were also taken to better communicate the condition of the samples to the experts. This included one overall picture of pavement condition, several pictures of individual distresses, and several pictures of the surrounding environment (Figure 6-2). These pictures were provided to the panel of experts as part of the elicitation process.

Figure 6-1. Apparatus Used in the Field Inspection

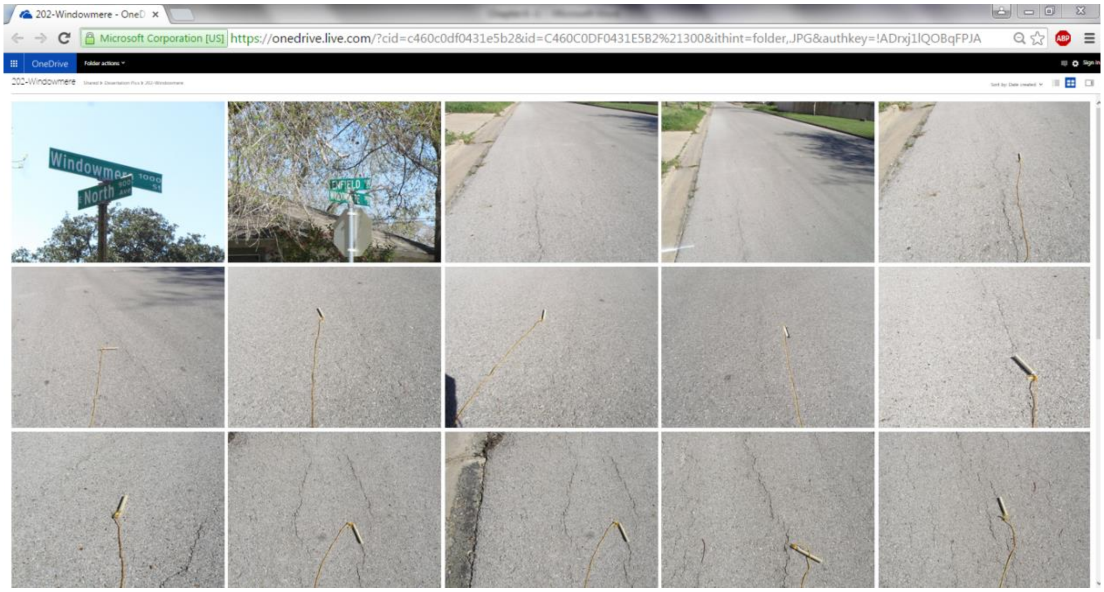

Figure 6-2. Pictures of Pavement Sample 202

5. Select the Panel of Experts

The expert participants in the data-elicitation process were selected from the pool of local pavement and maintenance professionals. The researcher consulted with trusted contacts in the profession to help compile and expand the list of potential candidates. The minimum qualifications for expertise were established as having at least two years of experience in pavement engineering or road maintenance, as well as having a familiarity with the network of streets under investigation. After the list of potential candidates was compiled, invitation letters were sent via e-mail. These letters provided a brief background of the study and described the process that would be used to elicit data. They explained the extent of the time involvement required, potential risks and benefits, the participants' rights, and the fact that there was no financial reimbursement for participation. The package also included a response form to indicate willingness to participate, and a profession-oriented survey intended to confirm that the participants possessed the relevant experience to make accurate judgments.

Five professionals agreed to participate in the study as experts. Their levels of experience in pavement maintenance ranged from five to thirty years. These experts received a follow-up letter thanking them for their participation in the study and affirming the importance of their expert opinion to the outcome of the research. They were also provided with the date on which they would receive the first questionnaire package. All five of the experts responded to the first-round questionnaire. One expert dropped out of the study during the second round of elicitation; therefore, the second round was conducted with only four experts. This level of attrition is not unusual or particularly troubling for the success of the Delphi process. While the total number of experts in the second round was less than the recommended minimum in the literature, the purpose of the case study was merely to demonstrate the applicability and implementation of the proposed models. No conclusive recommendations were made to the city on the basis of this research, and so maintaining the minimum number of experts was not a crucial concern.

6. Develop the Questionnaire Package for the First Round

The purpose of the questionnaire package was to supply the participants with a convenient and user-friendly environment through which they could provide their inputs.

The package included an information sheet, the questionnaire itself, and the forms used to provide responses.

Most of the relevant information about the pavement samples was included directly in the questionnaire package. The pictures of the samples were located on cloud storage, and could be accessed by clicking on provided hyperlinks. Instructions were included about how to fill out the data forms. The package also provided detailed information about the process and purpose of the Delphi method.

For simplicity and ease of access, the participants were asked to submit their estimates of pavement age using the provided forms in Microsoft Excel. An example of these response forms is shown in Figure 6-3. (The entirety of the first round questionnaire package is included in Appendix B).

A separate response form was provided for each pavement sample. In each form, the following information was listed:

- Sample number
- Pavement type
- Location of the sample
- Length and width of the pavement sample
- Hyperlink to pictures of the sample
- PCI calculated during the field survey
- Types and severity of distresses in the sample

The participants were asked to fill in their estimates for the possible range of the pavement's age. These estimates were provided by indicating the 5th percentile (the "lower limit" of the possible age range), the 50th percentile (the "best estimate" of the pavement's age), and the 95th percentile (the "upper limit" of the possible age range). The definition of percentiles and an example were provided in the questionnaire package. An optional section on the data forms allowed the experts to provide comments about their age estimates.

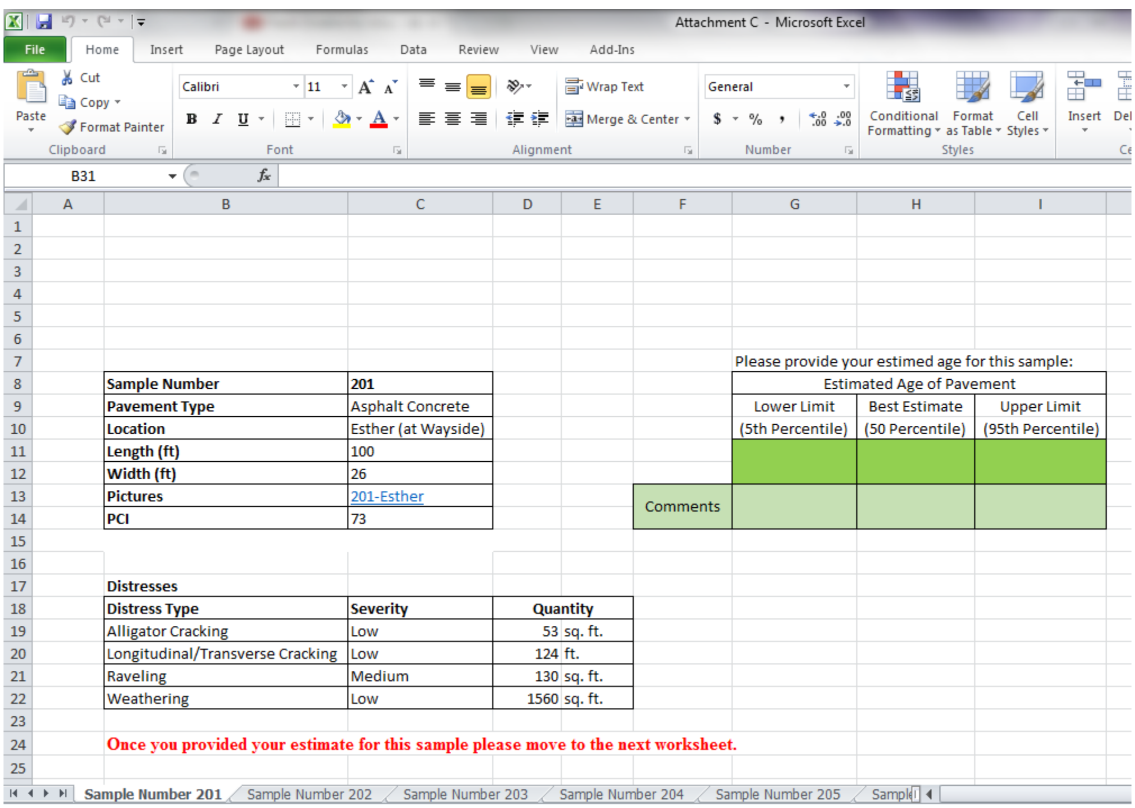

Figure 6-3. First-round Questionnaire Response Form

7. Run a Pilot Test

To improve the questionnaire, the researcher conducted a pilot test. One of the five experts volunteered to fill out the initial questionnaire and to comment on the clarity of the instructions, the sufficiency of the provided information, and the coherence of the response forms. The comments received during this pilot test helped the researcher to create a more user-friendly questionnaire package. In addition, the pilot test responses were reviewed to determine if there were any unexpected answers or difficulty in assessing the data.

8. Conduct the First Round of the Elicitation

The round-one questionnaire was sent to the panel of experts via e-mail. The participants were asked to inform the moderator if they needed any additional in-person instructions to help them understand and fill out the questionnaire. One of the five expert participants did request additional in-person assistance. The experts were asked to carefully review the questionnaire instructions and the description of the Delphi method. They were also encouraged to review the *Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys* (ASTM D6433 – 11) if needed to refresh their knowledge about the distress survey method and the different kinds of pavement distresses. Finally, the experts were instructed to open the Excel forms, review the information and pictures provided for each pavement segment, and contribute their age estimates and comments. Having filled out their assessments for each of the nine pavement samples, they saved the Excel file and e-mailed it back to the moderator.

9. Analyze the Responses from the First Round and Provide Controlled Feedback

The first step in analyzing the responses was to verify that all sections of the questionnaires were filled out correctly. The moderator discovered that one respondent had provided only the 50th percentile assessment for the pavement ages, leaving the fields for the 5th and 95th percentiles blank. Therefore, the moderator contacted the respondent and explained the missing information. This expert expressed a desire to meet with the moderator in person and get better instructions. After the meeting the expert was able to return the questionnaire with all of the necessary information completed.

Once the completeness of the information was verified, the second step in the analysis was to identify outlying responses. In this step, only strong outliers were automatically removed from the data set (Eriksson et al., 2013). To define these outliers the data related to each percentile (5th, 50th, and 95th) was treated separately. For each percentile, the data was examined using a modified version of Lockhart's (1998) outliers' identification by interquartile range (IQR) analysis, which measures the relative distance of a data point from others in the set. IQR is defined as the range between the first quartile and third quartile of the data. Therefore, if Q1 is the first quartile, and Q3 is the third quartile, then:

IQR = Q3 - Q1

Strong outliers were defined as data points that diverged from the first and third quartile by more than three times the IRQ:

Lower limit of acceptable data = Q1 - (3.0 x IQR)

Upper limit of acceptable data = Q3 + (3.0 x IQR)

Weak outliers were also identified, but were not automatically removed from the data. These were defined as data points that diverged from the first and third quartile by more than 1.5 times the IRQ:

Lower limit of the data for defining weak outliers = Q1 - (1.5 x IQR)

Upper limit of the data for defining weak outliers = Q3 + (1.5 x IQR)

In the case of weak outliers, the experts who provided the data were contacted and asked to reconfirm their estimates and explain the reasons why these data points should be included in the set.

After addressing the outliers in the data, the overall results were aggregated into a format that could be returned to the expert participants as feedback. Several viable aggregation methods were described by Ouchi (2004); in the current research Bayesian hierarchical modeling was the chosen technique. The details of this data-aggregation process are described in chapter 7.

10. Develop the Questionnaire Package for the Subsequent Round

Once the data was aggregated the second-round questionnaire was prepared. The moderator took the opportunity to make several improvements. First, the layout of the questionnaire was changed so that feedback from the first round could be provided in an intuitive and user-friendly fashion. This feedback included the aggregated data from the Bayesian analysis, as well a simple statistical average of the first-round results.

Second, the ordering of the pavement samples was revised to follow the descending order of their PCI number. This was done so that the experts could better gauge their responses in comparison to what they had said about the other samples.

During the analysis process of the first-round questionnaire the moderator determined that the model would perform better if the experts were to define the general shape of the distribution curve in their responses. Thus, a third change was made to the questionnaire to allow the experts to describe whether they believed the distribution was normal, or skewed toward the lower or upper bounds (see Figure 6-5).

Finally, during the analysis of the first-round questionnaire the moderator determined that it would be useful to elicit information about the marginal probability distribution of the current performance of the street network in Bryan. To achieve this purpose, a fourth change was made to the questionnaire to allow the experts to estimate what percentage of the city’s street network was in better condition than the current pavement sample.

New, detailed instructions were written to inform the experts how to fill out the second-round questionnaire. Figures 6-4 and 6-5 show sample response forms from this second round of data elicitation. (The entirety of the second round questionnaire package is included in Appendix C).

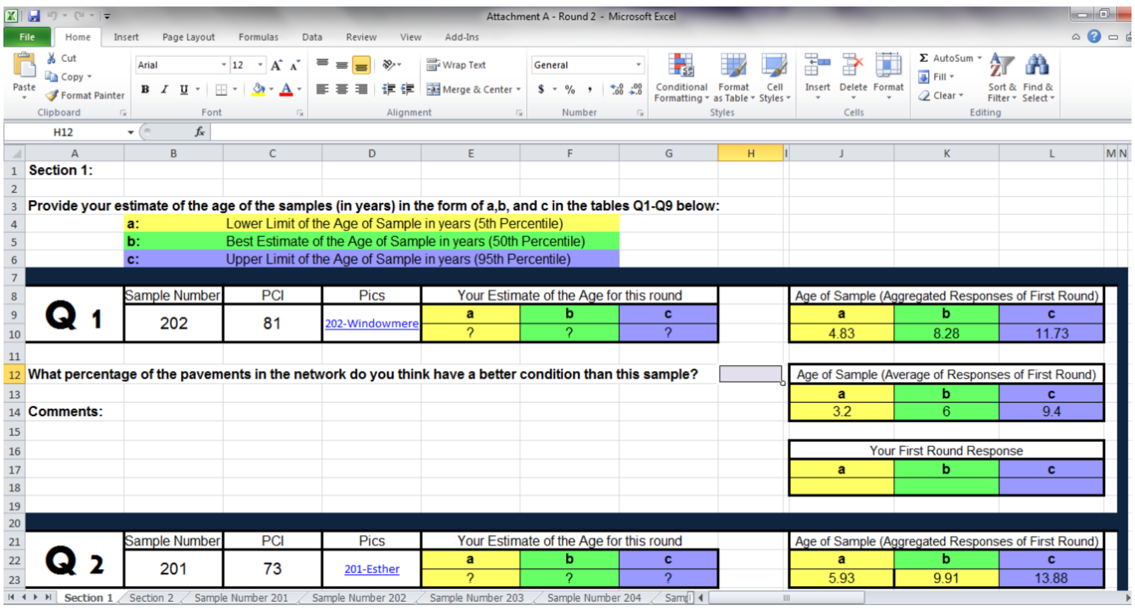

Figure 6-4. Second-round Questionnaire Response Form, Sheet 1

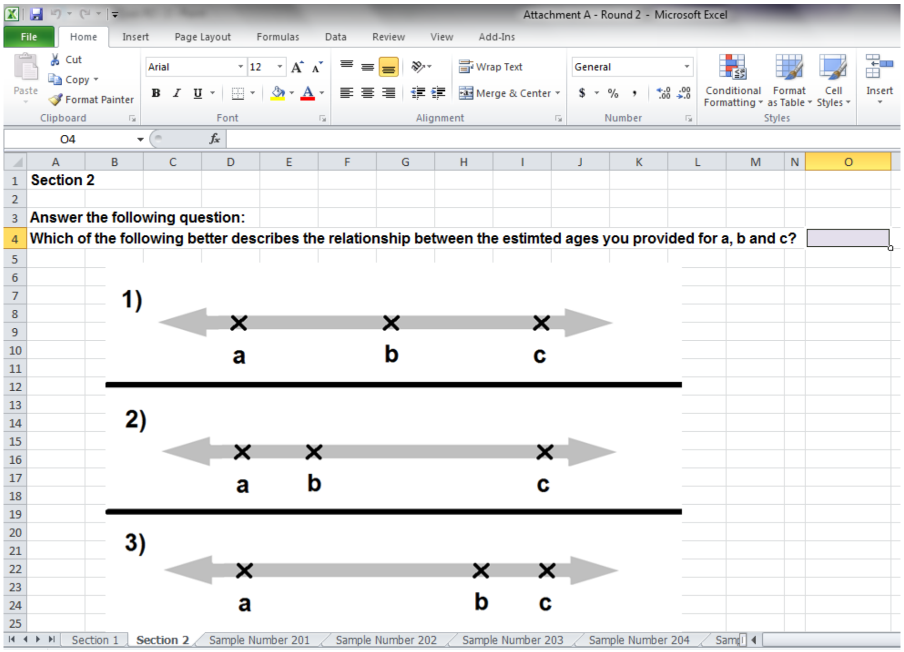

Figure 6-5. Second-round Questionnaire Response Form, Sheet 2

11. Conduct the Subsequent Round of the Elicitation

The implementation of the second-round questionnaire was similar to the first round. However, as noted above, one of the five experts dropped out of the process and failed to return the second-round questionnaire. The researcher several times attempted to contact the participant to inquire about the reason for dropping out of the process, but these attempts were not successful. Another of the respondents did not fully understand the instructions and returned the questionnaire incomplete. The researcher contacted this expert and provided more detailed explanations, which ultimately allowed the respondent to fill out the forms correctly. At the end of the process, four of the five experts were able to return completed questionnaires.

12. Review and Analyze the Responses from the Subsequent Round

Data obtained during the second round was analyzed in a similar fashion to the first round (the details of this process are explained in chapter 7). After completing this analysis the researcher determined that the variation among the responses had narrowed to such an extent that a consensus could be reasonably declared. The measure that was used for this purpose was reaching a standard deviation of 1 in the estimated ages provided by the experts for each sample. The researcher therefore ended the elicitation process and sent the appropriate notes of completion and gratitude to the participants.

6.4 Past Performance Data

To determine the effectiveness of the elicitation model, the data obtained from the experts was compared against actual past performance information from the city of Bryan. The city conducts pavement-performance surveys on a biannual basis, and also tracks maintenance actions and new construction activities in a database. These records were provided to the researcher by the city. A portion of the spreadsheet that contains this data is shown in Figure 6-6. The records include the name of the pavement sections surveyed, a section ID number, the last construction date on that street (LCD), the pavement type (SurTyp), the city zone where the segment is located (Rank), the sample size (Area), the last inspection date (Insp Date), the number of samples from the section (# Samps) and the PCI that was calculated during the most recent inspection.

	Name	Section	LCD	SurTyp	Rank	Area	Insp Date	# Samps	PCI
2	14th St W (West 14th Street)	Sims-Parke	05/21/1981	AAC	N	7,272	07/30/2008	27	55.00
3	14th St W (West 14th Street)	Ster-Hwy21	06/17/1978	AC	E	9,552	07/31/2008	30	52.00
4	14th St W (West 14th Street)	Sterl-Sims	01/04/1974	AC	N	6,468	07/31/2008	34	47.00
5	15th St E (East 15th Street)	Hous-Just	05/26/1950	AC	N	3,345	07/28/2008	58	31.00
6	15th St E (East 15th Street)	Plum-Tex	09/01/2010	AC	E	10,678	09/01/2010	0	100.00
7	15th St E (East 15th Street)	Tabor-Tex	01/01/2005	AC	E	20,430	07/30/2008	3	94.00
8	15th St W (West 15th Street)	Sims-Hall	12/01/1976	ST	E	24,300	07/31/2008	32	87.00
9	15th St W (West 15th Street)	Tabor-Sims	05/01/2008	AC	E	34,368	07/30/2008	0	100.00
10	16th St E (East 16th Street)	Tabor-Wash	12/01/2008	AC		9,131	12/01/2008	0	100.00
11	16th St W (West 16th Street)	Bryan-Tab	02/06/1952	AC		4,960	07/30/2008	56	35.00
12	16th St W (West 16th Street)	Parke-Brya	10/01/1988	AAC		5,008	07/30/2008	20	57.00
13	16th St W (West 16th Street)	Sims-Hwy21	08/01/1967	PCC		45,120	07/31/2008	41	12.00
14	16th St W (West 16th Street)	Sims-Parke	10/01/1988	AC	E	6,220	07/30/2008	20	57.00
15	16th St W (West 16th Street)	Star-Hwy21	11/01/2005	AC	E	26,514	08/05/2008	3	76.00
16	17th St E (East 17th Street)	Tex-18th	08/01/1975	AC	E	14,300	07/28/2008	33	52.00
17	17th St E (East 17th Street)	Wash-Tex	01/01/2005	AAC	E	6,710	07/30/2008	3	63.00
18	17th St W (West 17th Street)	Bryan-Park	11/01/2005	AC	E	5,598	07/30/2008	3	56.00
19	17th St W (West 17th Street)	Cali-Flori	01/01/2004	PCC		8,556	08/04/2008	4	45.00
20	17th St W (West 17th Street)	Flor-Hwy21	01/01/2004	AAC		67,983	08/04/2008	4	59.00
21	17th St W (West 17th Street)	Hwy21-Rand	09/01/1965	PCC	E	30,225	07/31/2008	43	30.00
22	17th St W (West 17th Street)	NY-Cali	01/01/2004	APC		8,277	08/04/2008	4	50.00
23	17th St W (West 17th Street)	Rand-Sims	09/01/1965	PCC	E	30,039	07/31/2008	43	36.00
24	17th St W (West 17th Street)	Sims-Parke	05/01/1966	PCC	E	9,672	07/31/2008	42	23.00
25	18th St E (East 18th Street)	17th-Texas	12/01/2008	AC	E	12,072	12/01/2008	0	100.00
26	18th St E (East 18th Street)	MLK-17th	08/01/2001	AAC	N	9,625	11/10/2008	7	98.00
27	18th St E (East 18th Street)	Polk-End	05/10/1948	AC	N	3,456	07/28/2008	60	23.00
28	18th St E (East 18th Street)	Tex-Wash	12/01/2008	AC	E	8,008	12/01/2008	0	100.00
29	18th St E (East 18th Street)	Wash-Tabor	12/01/2008	AC	E	5,795	12/01/2008	0	100.00
30	18th St W (West 18th Street)	Bowe-Colu	08/01/1967	PCC	E	24,210	08/05/2008	41	14.00
31	18th St W (West 18th Street)	Colu-Hwy21	05/01/2005	PCC	E	8,401	08/05/2008	3	68.00
32	18th St W (West 18th Street)	Harl-Chic	01/01/1999	AAC	N	2,831	08/05/2008	9	14.00
33	18th St W (West 18th Street)	NY-Mucklry	05/01/2005	AAC	N	20,574	11/10/2008	3	76.00
34	18th St W (West 18th Street)	Parke-Bry	11/01/2005	AC	E	6,426	07/30/2008	3	77.00
35	18th St W (West 18th Street)	Parke-Sims	11/01/2005	AC	E	6,160	07/30/2008	3	36.00
36	18th St W (West 18th Street)	Reno-NY	01/01/1988	AAC	N	4,530	11/10/2008	20	59.00
37	18th St W (West 18th Street)	Sims-Hwy21	09/01/1968	PCC	E	68,944	07/31/2008	40	31.00
38	21st St E (East 21st Street)	Dans-Mili	01/01/1997	AAC	E	21,060	07/07/2008	11	13.00
39	21st St E (East 21st Street)	Hous-Prest	11/01/2005	AC	E	6,220	10/01/2008	3	89.00
40	21st St E (East 21st Street)	Main-Texas	01/01/2001	AAC	E	21,230	10/30/2008	7	69.00
41	21st St E (East 21st Street)	Mili-Weav	10/01/1988	AC	E	25,200	07/07/2008	20	96.00
42	21st St E (East 21st Street)	Pierc-Robe	11/01/2005	AC	E	6,000	10/01/2008	3	62.00
43	21st St E (East 21st Street)	Polk-Pierc	11/01/2005	AC	E	5,920	10/01/2008	3	78.00
44	21st St E (East 21st Street)	Prest-Polk	11/01/2005	AC	E	6,000	10/01/2008	3	79.00
45	21st St E (East 21st Street)	Tex-Houst	11/01/2005	AC	E	8,260	10/01/2008	3	80.00
46	21st St W (West 21st Street)	Bryan-Main	11/01/2005	AC	E	9,240	10/30/2008	3	99.00
47	21st St W (West 21st Street)	Hall-Bayl	08/01/1979	ST	N	18,216	07/17/2008	29	71.00
48	21st St W (West 21st Street)	Logan-Ster	11/01/2005	AAC	E	6,264	07/17/2008	3	100.00

Figure 6-6. Sample of the Data Obtained from City of Bryan

After reviewing this data, the researcher extracted the sections that were relevant to the current research. Part of the parameters of this case study were that it was limited to asphalt concrete pavements and to residential streets. By visual inspection it is usually impossible to tell if the asphalt concrete pavement is asphalt overlay or new construction. Therefore, all records pertaining to asphalt overlays (SurType = ACC) and asphalt concrete pavements (SurType = AC) were selected. These records were further narrowed down by selecting only those in residential zones.

Once the relevant records were identified, the age of the pavement at the time of inspection was calculated based on the difference between “Last Construction Date” and “Inspection Date.” This measure of pavement age, combined with the PCI at the time of the inspection, provided the relevant data points to measure performance versus time.

The resulting raw past performance data was processed using a heuristic data-cleaning algorithm for pavement performance. This algorithm is based on the natural characteristics of pavements (such as the maximum and minimum rates of deterioration over time), and it is frequently used in the profession. Figure 6-7 demonstrates the results from the cleaned past performance data.

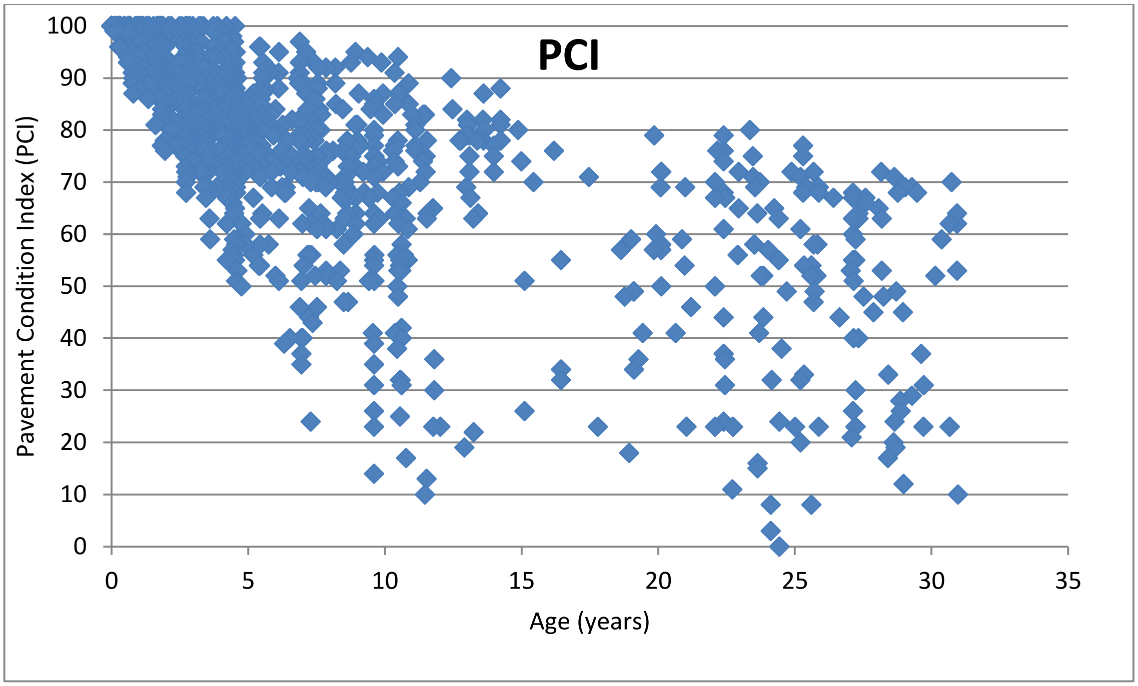

Figure 6-7. Pavement Deterioration over Time in the City of Bryan, Texas (From Historical Records)

CHAPTER VII

MODEL DEVELOPMENT

7.1 Introduction

In the first phase of this research, a new infrastructure asset-management framework was proposed in response to two primary research questions:

Research Question 1. How can the range of uncertainty about asset performance be incorporated into a decision-support model and effectively reported to decision makers?

Research Question 2. How can asset performance be predicted effectively when reliable historical data is not available?

Chapter 4 explained how the proposed infrastructure asset-management model was developed to address the first research question by using an outcome-based scenario-planning approach. Information about the range of uncertainty is incorporated into the model by defining asset performance in terms of the “worst case,” “most likely case,” and “best case” scenarios.

Chapter 5 explained how the proposed infrastructure asset-management model was developed to address the second research question by eliciting data about the performance of assets over time from experts in the relevant field. Drawing from the previous literature on forecasting and data-elicitation techniques, a rigorous process for obtaining performance data from experts was developed and tailored specifically for use in infrastructure asset management contexts.

The second phase of the research focused on testing the proposed model and its implementation through a case study. The performance of pavement surfaces on the city streets of Bryan, Texas, was selected as a paradigmatic example of an infrastructure asset-management context in which the proposed model could be implemented. Chapter 6 of the dissertation explained how two separate sources of data were gathered in the case study. First, information about pavement performance over time in the city was obtained from pavement experts following the proposed method of data-elicitation in the new asset-management model. Second, actual historical records about the pavement performance were obtained from the city archives. The existence of historical records in this case study allows for a comparative examination of how successful the data-elicitation model was in providing accurate information.

This chapter explains the statistical techniques that were used to analyze each source of data in the case study. The goal of the data analysis was to define the performance of the asset (in this case, pavement performance) over time. In the case study there were two separate data sets to be examined—one from the expert elicitation and another from the historical records.

7.2 Statistical Model Development

To analyze the data, two models were developed using the R programming language. R language is a specialized software package designed for statistical computing, modeling, and visualization (R Core Team, 2000).

The first model that was developed in R (Model #1) was used to define the asset performance curve in each of the three scenarios (the "worst case," "most likely case," and "best case"). This model was applied to both data sets. For the historical data, quantile regression analysis was used. This was a relatively straightforward process of establishing the three performance scenarios based on the 5^{th} percentile, 50^{th} percentile, and 95^{th} percentile of the existing historical data. Using this analysis method, it is possible to define the performance curve for any desired quantile. For the performance data obtained through elicitation from the experts, however, further processing had to be applied to convert the information into a form suitable for input into a quantile regression analysis.

The second model that was developed in R (Model #2) was created for the purpose of processing the data from the experts (in other words, converting it into a form that could be used in Model #1). The most important part of this process was to aggregate the data obtained from different experts. Once this was done, the model could simulate data points comparable to the historical records for use in the quantile regression analysis.

In the next four sections, the statistical concepts that were used in the modeling process are described. These concepts include quantile regression, Bayesian hierarchical modeling, and the Markov-chain Monte Carlo algorithm. Once these concepts have been introduced, the remainder of the chapter describes their specific application in creating the models for asset-performance data analysis.

7.3 Quantile Regression

Quantile regression is a semi-parametric method for estimating relationships between variables. The goal of using this method is to estimate the quantiles of a distribution rather than the mean (which is most commonly used in linear regression). By using quantiles, two benefits are immediately realized:

- The effects of outliers, especially extreme outliers, are mitigated
- Normality is not required

Because of the manner in which the quantiles are evaluated, for a regression line ($y = mx + b$), the resultant y is actually based on multiple reference points of the predictor x. This is fundamentally different from classic regression in which y is based on a single point on x. This outcome is due to the mathematics behind quantile regression being matrix-based, while classical linear regression is vector-based. Since multiple x-points are used in each calculation of y, the focus is not restricted to the conditional mean. Instead, it can approximate the whole conditional distribution of the response variable.

Quantile regression was first introduced by Koenker and Bassett (1978) as an extension of classical linear regression (based on the method of least squares estimation) for conditional models. Koenker (2001) stated that quantile regression can also be approached by estimating conditional quantile functions as an optimization problem, which allows for the use of the same mathematical tools that are used to solve conditional mean functions.

The quantile regression model, as introduced by Koenker and Basset (1978), is:

$$y_{it} = x_{it}^{'}\beta_\tau + u_{\tau it} \text{ with } Quant_\tau\left(y_{it} \mid x_{it}\right) = x_{it}^{'}\beta_\tau$$

where:

y_{it} is the dependent variable

x is the vector of regressors

β is the parameter vector to be estimated

u is the vector of residuals

$Quant_\theta\left(y_{it} \mid x_{it}\right)$ is the τ^{th} conditional quantile of y_{it} given x_{it}

Solving this equation directly is difficult. However, by treating it as an optimization problem the necessary mathematical tools can be simplified. Given that quantiles are positive and can be expressed as a decimal between zero and one:

$$\tau \in [0,1]$$

With n observations of the independent predictor x_i (and the resultant y_i) the τ^{th} parametric quantile *b* for the regression can be expressed as:

$$\min_{b \in \mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau \left(y_i - x_i^T b \right)$$

where:

$$\rho_\tau \left(u \right) = u \left(\tau - I \left(u < 0 \right) \right)$$

Koenker and Ng (2004) reduced the minimized solution of this linear equation to:

$$\min_{u^T, v^T, b^T} \left\{ \tau e^T u + \left(1 - \tau \right) e^T v \mid Xb + u - v = y \right\}, \left(u^T, v^T, b^T \right) \in \mathbb{R}^{2n} \times \mathbb{R}^p$$

where:

e is an n-sized identity vector

u and v are regression residuals, both positive and negative.

This transformation was required in order to be able to implement a practical algorithmic/computational solution to the quantile regression equation. This minimized solution is the basis for the implementation of quantile regression in statistical computing software, including the R programming language and the SAS statistical package, among others (Chen, 2005; Koenker, 2015).

7.4 Methods of Aggregating Experts' Opinions

Ouchi (2004) argued that there are three primary mathematical modeling approaches that have been well-developed for aggregating data derived from expert opinions. These three approaches are known as (a) the non-Bayesian axiomatic models, (b) the Bayesian models, and (c) the psychological scaling models.

The non-Bayesian axiomatic models for aggregating expert opinions were prevalent in the early days data aggregation. In this approach, specific variables and regularity conditions ("axioms") for the aggregation of probability distributions are established. Thus, this approach requires that the relationships established in each expert's opinion, as well as the combined data, satisfy the pre-existing set of axioms. Typically these axiom-based models establish some type of "weights" to use as data parameters (Morris, 1983; Ouchi, 2004). Axiom-based approaches are somewhat controversial today, largely due to the fact that axioms are not universal. In addition to the ongoing disagreement about the applicability of different axioms, there are also issues with proper axiomatic notation (Winkler, 1986).

The Bayesian models are widely considered to be the most robust method for aggregating expert opinions. In these models the experts' probability assessments are used in order to obtain a better understanding about the probability distribution of an unknown quantity. The Bayesian models operate in accordance to Bayes' Theorem, which describes the best means of updating prior probabilities in the light of new information (Ouchi, 2004). The Bayesian approach is ideal for most situations in which existing understandings of the topic are normative and well-developed. However, there are also some disadvantages to Bayesian models. The main disadvantage is that they can be mathematically complex and thus impractical to use in certain real-world tasks. In addition, coming up with an appropriate likelihood function for an expert opinion typically involves guesswork, which means that accuracy can be a concern. These limitations have been partially overcome in recent years as researchers have developed a means of using the Markov Chain Monte Carlo method to evaluate more complex distributions (described in section 7.6 below) (Jacobs, 1995).

Psychological scaling models for aggregating expert opinions begin with the assumption that experts have personal values attached to the variable of interest. In this outlook, experts are only capable of providing qualitative input (not quantitative). Psychological scaling approaches involve the researcher or decision-maker asking experts about their personal preferences regarding pairwise comparisons. This approach originated in a study where researchers attempted to estimate intensities of physical stimuli, but found that they were actually estimating the relative intensities of psychological stimuli in the experts that they consulted (Hogarth, 1977; Ouchi, 2004). In the current research, it is assumed that the experts do not have strong personal values attached to their evaluations of asset performance; therefore, a Bayesian approach to data aggregation can be used.

7.5 Bayesian Hierarchical Modeling

The Bayesian approach allows for a hierarchical model in which ample parameters can be employed to fit the data, while also avoiding the problem of overfitting. In nonhierarchical approaches all parameters have the same weight; thus attempting to incorporate more detailed structures into the model can lead to overfitting for some parameters. Hierarchical models, in contrast, are capable of nesting dependencies among several model parameters. This structure provides a means to update the prior model with new levels of observed data, therefore arriving at a more refined posterior distribution (Schmid and Brown, 2000).

By using Bayes' Theorem it is possible to update a prior distribution, $\pi(\theta)$, once new information is obtained, $\pi(x|\theta)$, in order to define the posterior distribution, $\pi(\theta|x)$. The mathematical expression of the Theorem is as follows:

$$\pi(\theta|x) = \frac{\pi(x|\theta)\,\pi(\theta)}{\int \pi(x|\theta)\,\pi(\theta)d\theta}$$

In the Bayesian hierarchical model for data aggregation, this formula is used to progressively update the model's distribution parameters. An initial (prior) distribution is formed, and then after obtaining additional information for this distribution, the prior model is reassessed and re-defined to incorporate new parameters and form a posterior distribution. The update of the prior distribution can be initiated from any of the previous levels of the model. Consequently, this update could result in changing one or more of the higher levels.

One practical use for applying a Bayesian hierarchical model is in a case where several sets of observed data are known to follow a distribution with unknown parameters. These unknown parameters also follow a general distribution for a universal class of data. In this setting an inference about one set of parameters will affect the inferences about the other sets of parameters. Therefore, each of these distributions could be structured as one level of a hierarchical Bayesian model. Bayes' Theorem describes the relationship between these different levels, as well as the uncertainty involved in the outcome. A more detailed discussion about the Bayesian hierarchical model and its applications is provided by Schmid and Brown (2000) and Banerjee et al. (2014).

7.6 The Markov Chain Monte Carlo Algorithm

The Markov Chain Monte Carlo (MCMC) algorithm is a practical method developed in recent years to define the posterior distribution parameters in a Bayesian hierarchical model. In this method a Markov chain is developed for sampling from a probability distribution, meaning that samples for the new distribution are drawn from the previous one. After multiple iterations the chain provides the target distribution.

There are several types of MCMC algorithms available, depending on the method of sampling. Two sampling methods used in this research were Gibbs sampling and

Metropolish-Hastings sampling. One of the most widely applied approaches in MCMC is the Gibbs sampling method (Gelfand and Smith, 1990). The most important feature of Gibbs sampling is that it only considers the univariate conditional distribution. This means that only one variable is considered random, while all others are assigned fixed values (Walsh, 2004). Another, more general, sampling method for MCMC is the Metropolish-Hastings method. This approach is used for more complex probability distributions where no known method of drawing a random number from the distribution is available. (Walsh, 2004).

7.7 Defining Scenario-based Performance Curves Using Quantiles (Model #1)

As described at the start of this chapter, the first task in the data analysis was to create a model to define the asset performance curves in each of three scenarios (the "worst case," "most likely case," and "best case"). The quantile regression analysis method was used to create this model. The input for Model #1 is data points describing the age and condition of asset samples. In the Bryan, Texas, case study this input took the form of a pavement sample's age and its Pavement Condition Index (PCI) number.

The main reason that quantile regression is a suitable approach for this research is that it can describe the entire conditional distribution of the dependent variable. Therefore, it enables the model to define any desired quantile of the performance of the asset at any given time. This is in contrast to conventional regression analysis, where only the mean of the asset performance is definable. The use of quantile regression thus allows for a representation of the range of uncertainty in the model by describing the “best case” (95th percentile), “most likely case” (50th percentile) and “worst case” (5th percentile) from the distribution.

As described in section 7.3 above, the general objective of quantile regression is to minimize this equation:

$$\min_{b \in \mathbb{R}^p} \sum_{i=1}^{n} \rho_\tau \left(y_i - F(x_i) \right)$$

The values relevant to the infrastructure asset-management problem at hand were incorporated into the general quantile regression model. In this research it was assumed that performance of pavement over time generally follows the sigmoidal equation below. This equation is often used in pavement analysis and is considered an accurate reflection of how pavement performance declines over time (Deshmukh, 2009):

$$y_i = PCI_i = 100 - \frac{\rho}{\left[ln\left(\frac{\alpha}{Age_i} \right) \right]^{\frac{1}{\beta}}}$$

where:

Age is the age of the current pavement surface

ln is the natural logarithm

α, β, and ρ are regression constants.

Based on this equation, the loss function $L(\alpha, \beta, \rho)$ can be written as follows:

$$e_i(\alpha, \beta, \rho) = y_i(\alpha, \beta, \rho) - \hat{y}_i(\alpha, \beta, \rho)$$

$$L(\alpha, \beta, \rho) = (\tau - 1) \sum_{i=1}^{n} e_i(\alpha, \beta, \rho)\, 1(e_i < 0) + \tau \sum_{i=1}^{n} e_i(\alpha, \beta, \rho)\, 1(e_i \geq 0)$$

where:

$1(e_i < 0)$ is the indicator function and is defined as:

$$1(e_i < 0) = \begin{cases} 1 \; if \; e_i < 0 \\ 0 \; if \; e_i \geq 0 \end{cases}$$

α, β, and ρ are the regression constants in the sigmoidal equation

τ is the quantile under investigation.

The three quantiles that were considered in this research are:

$\tau = 0.05$ 5th percentile performance curve

$\tau = 0.5$ 50th percentile (median) performance curve

$\tau = 0.95$ 95th percentile performance curve

The objective in the quantile regression analysis was to find values for α, β, and ρ that minimize the loss function L(α, β, ρ) for each relevant quantile, and therefore indicate the best fitted performance curve for that quantile. This is a nonlinear programming problem, which was solved using a grid-search method.

7.8 A Model for Aggregating Experts' Opinions (Model #2)

The second model that was developed in this analysis was used to aggregate the data gathered from the expert participants as described in chapter 6, and then based on that information to simulate data points suitable for incorporation into Model #1.

The approach to data aggregation that was adopted in this research is based on the Bayesian hierarchical modeling method (Schmid and Brown, 2000). The model assumed a non-informative prior distribution for the age of the pavement samples. This distribution was updated with the new information obtained from the experts using the Bayesian Theorem to define the posterior distribution. Choosing a non-informative prior distribution gives the model the flexibility to take any possible quantity as a candidate value.

The notations used in the aggregation model are defined as follows:

i = a number assigned to each pavement sample (1–9)

j = a number assigned to each expert (1–5)

k = a number assigned to each of the three quantiles (5^{th}, 50^{th}, and 95^{th} percentile) (1–3)

PCI_i is the condition of sample i, as calculated during the field condition surveys

X_{ijk} is the k^{th} quantile age of i^{th} sample provided by j^{th} expert

It is assumed in the model that the experts' assignment of X (the possible age of the pavement sample) was intended to follow a normal distribution pattern. This assumption was confirmed by the experts in the second-round questionnaire. Thus, for each quantile:

$$X_{ij} \sim N\ (\mu_i, S_i^2)$$

where μ_i is the mean of the true age of the sample and S_i^2 is the variance of the true age.

Also, it is assumed in the model that the experts' assignment of X includes a range of error (e), which also follows a normal distribution pattern:

$$e_{ijk} \sim N\ (0, \sigma_j^2)$$

Based on these variables, the relevant Bayesian hierarchical model levels are described as follows:

Level 1

Based on the normal distribution assumption for each sample the estimated age would be:

$X_{ij1} \sim N\ (\mu_i - 1.65\ S_i\ ,\ \sigma_j^2)$

$X_{ij2} \sim N\ (\mu_i,\ \sigma_j^2)$

$X_{ij3} \sim N\ (\mu_i + 1.65\ S_i\ ,\ \sigma_j^2)$

Level 2

In the second layer of the hierarchical model it was assumed that the true age of the samples (μ_i) follows a normal distribution pattern. It was also assumed that the variance of the true age (S_i^2) and the variance of the estimate error (σ_j^2) for each expert follow the inverse gamma distribution:

$\mu_i \sim N\ (\mu_0,\ \sigma_\mu^2)$

$S_i^2 \sim IG\ (\alpha_1,\ \beta_1)$

$\sigma_j^2 \sim IG\ (\alpha_2,\ \beta_2)$

Level 3

If the value of μ_0 is specified in the second level then it provides strong prior information about μ_i's, which is not desired. Therefore, instead it is assumed that μ_0 follows a uniform distribution. This allows the model to incorporate the μ_0 value that maximizes the whole likelihood function:

$\mu_0 \sim U\ (0, \infty)$

$\sigma_\mu^2 \sim IG\ (0.001, 0.001)$

$\alpha_1 \sim \exp(1)$

$\beta_1 \sim \exp(1)$

$\alpha_2 \sim \exp(1)$

$\beta_2 \sim \exp(1)$

where,

$\exp(1) = f(X=x) = e^{-x}$

Now, to apply the Markov-chain Monte Carlo algorithm, 50,000 values were generated from the marginal distribution of μ_i:

$\pi(\mu_i \mid \text{data, other parameters})$

Similarly, random values were generated from $\pi(S_i^2 \mid \text{data, other parameters})$ and $\pi(\sigma_j^2 \mid \text{data, other parameters})$. The estimate of μ_i is the center of the posterior distribution:

$$\hat{\mu}_i = \text{mean of } \pi\ (\mu_i \mid \text{data, other parameters})$$

$$\hat{\sigma}_i = \text{mean of } \pi\ (\sigma_i'^2 \mid \text{data, other parameters})$$

For each given performance rating (PCI_i, where i = 1, 2, … 9), the distribution of the age estimated by the experts ($\hat{\mu}_i$ and $\hat{S}_i$) were defined using this process. Then, the next step was to define the distribution of the age for the whole range of performance (PCI = 0 to 100). For this purpose two assumptions were made. First, it was assumed that the relationship between the pavement age and performance followed the sigmoidal equation shown in section 7.7. The second assumption was that the variance of age had a linear relationship with the condition of the pavement (the possible age range of a pavement sample with higher PCI has less variance, while the possible age range of a more deteriorated pavement sample has a higher variance). Based on these two assumptions and the marginal distribution of pavement performance (PCI), data suitable for use in Model #1 was simulated for the performance of the pavement over time.

CHAPTER VIII

MODEL ANALYSIS AND RESULTS

8.1 Introduction

In this chapter the process of model analysis and the results of the analyses are presented. The models described in chapter 7 were run to create scenario-based performance curves using both the historical (past performance) data and the data elicited from experts. First, the experts' estimates were aggregated using Model #2. Then, the aggregated experts' estimates and the historical data were each processed using Model #1. Finally, the results from the aggregated experts' estimates and the historical data were compared against each other. The final section of this chapter shows how the framework can be used by asset managers during the decision-making process.

8.2 Aggregated Experts' Opinions

Model #2 was employed to aggregate the experts' estimates of the age of the pavement samples using Bayesian hierarchical modeling (BHM). For comparison, the simple arithmetic average of the experts' estimates was calculated as well. This data aggregation took place after each round of the data-elicitation process (a total of two rounds). The results of this aggregation are shown in Tables 8-1 through 8-4.

Table 8-1. Aggregated Estimated Age of Samples (BHM Method, First Round)

Sample Number	PCI	Estimated Age		
		5th Percentile	50th Percentile	95th Percentile
202	81	4.83	8.28	11.73
201	73	5.93	9.91	13.88
207	73	7.82	11.81	15.80
203	72	5.93	9.89	13.84
209	57	9.77	13.75	17.74
208	56	8.78	14.21	19.65
206	45	5.97	9.98	13.98
204	26	9.86	13.85	17.85
205	11	8.79	13.31	17.83

Table 8-2. Aggregated Estimated Age of Samples (Arithmetic Average Method, First Round)

Sample Number	PCI	Estimated Age		
		5th Percentile	50th Percentile	95th Percentile
202	81	3.20	6.00	9.40
201	73	3.80	7.00	11.60
207	73	4.20	7.20	12.00
203	72	3.80	7.40	11.60
209	57	6.80	11.20	15.80
208	56	9.60	13.60	18.60
206	45	4.40	8.00	13.80
204	26	8.00	12.60	17.40
205	11	8.60	15.00	20.40

Table 8-3. Aggregated Estimated Age of Samples (BHM Method, Second Round)

Sample Number	PCI	Estimated Age		
		5th Percentile	50th Percentile	95th Percentile
202	81	4.90	7.96	11.02
201	73	6.63	10.14	13.66
207	73	6.71	10.20	13.69
203	72	6.62	10.20	13.79
209	57	9.79	13.83	17.87
208	56	9.99	14.94	19.90
206	45	6.04	9.99	13.93
204	26	11.75	14.90	18.05
205	11	9.93	15.02	20.11

Table 8-4. Aggregated Estimated Age of Samples (Arithmetic Average Method, Second Round)

Sample Number	PCI	Estimated Age		
		5th Percentile	50th Percentile	95th Percentile
202	81	4.00	7.25	11.50
201	73	5.25	8.25	13.50
207	73	6.00	8.75	13.50
203	72	5.00	8.75	13.75
209	57	7.75	11.50	16.75
208	56	9.75	13.75	20.00
206	45	6.50	9.50	13.75
204	26	10.25	13.25	19.00
205	11	10.00	14.00	21.00

The performance of the BHM method for aggregating the elicited data was compared against the simple arithmetic average. For each of the elicited percentiles, and for each round of data elicitation, the difference between the results of the two aggregation methods was calculated. In the first round of data elicitation the BHM approach resulted in a higher estimate of the sample ages in 89% of the aggregated responses. In the second round of data elicitation the BHM approach resulted in higher estimates in 78% of the aggregated responses.

The extent to which the two methods diverged was much smaller in the second round of data elicitation (max. difference = 2.33 years; average difference = 0.72 years) than in the first round of the process (max. difference = 4.61 years; average difference = 1.63 years). In the elicitation process the feedback was structured to help the experts consider the possibility of symmetry in the responses. The smaller difference in the second round is likely due to the fact that the experts provided more consistent and symmetric estimates after receiving feedback (Tables 8-5 and 8-6).

Table 8-5. Differences between the BHM Method and the Arithmetic Average Method for Aggregating Experts' Estimates (First Round)

Sample Number	PCI	Difference of Estimated Age		
		5th Percentile	50th Percentile	95th Percentile
202	81	1.63	2.28	2.33
201	73	2.13	2.91	2.28
207	73	3.62	4.61	3.80
203	72	2.13	2.49	2.24
209	57	2.97	2.55	1.94
208	56	-0.82	0.61	1.05
206	45	1.57	1.98	0.18
204	26	1.86	1.25	0.45
205	11	0.19	-1.69	-2.57

Max = 4.61
Average = 1.63

Table 8-6. Differences between the BHM Method and the Arithmetic Average Method for Aggregating Experts' Estimates (Second Round)

Sample Number	PCI	Difference of Estimated Age		
		5th Percentile	50th Percentile	95th Percentile
202	81	0.90	0.71	-0.48
201	73	1.38	1.89	0.16
207	73	0.71	1.45	0.19
203	72	1.62	1.45	0.04
209	57	2.04	2.33	1.12
208	56	0.24	1.19	-0.10
206	45	-0.46	0.49	0.18
204	26	1.50	1.65	-0.95
205	11	-0.07	1.02	-0.89

Max = 2.33
Average = 0.72

To measure the convergence of the experts' estimates between the first round of data elicitation and the second round, the standard deviation of the responses was evaluated. In each round, the standard deviation was calculated for each of the elicited percentiles of each sample, and then the overall results for each percentile were averaged. When using iterative rounds of elicitation based on the Delphi method, it is expected that the feedback provided to the respondents will result in less diverse responses in latter rounds. This was confirmed in the current study, as the results showed that the average standard deviations were considerably lower in the second round. This demonstrates the effectiveness of feedback in the data-elicitation process (Table 8-7).

One interesting feature of the standard deviations is that the 95th percentile estimates had a larger average standard deviation than the 5th percentile estimates, in both rounds of the data elicitation. This indicates that the experts had a less diverse opinion about the minimum possible age of the samples as compared to the maximum possible age.

For the purposes of data elicitation, the researcher defined reaching an average standard deviation of 1.00 as the measure of adequate consensus among the experts. Based on the second-round standard deviations it was determined that this measure had been acceptably reached, and thus a third round of feedback and elicitation was deemed unnecessary.

Table 8-7. Standard Deviation of Responses Averaged over All Samples for the First and Second Rounds

Standard Deviation of Estimates	5th Percentile	50th Percentile	95th Percentile
First Round	1.90	2.56	2.80
Second Round	0.99	1.24	1.18

Another way of comparing the first and second round of data elicitation is to examine the change in the median (50th percentile) estimate, and the change in the interval between the lower and upper limit estimates (95th percentile - 5th percentile). The experts provided a slightly higher estimate for the median age in the second round of the data elicitation (+0.24 years).

Meanwhile, the interval of the assessed ages decreased in the second round (-0.55 years). The details of these evaluations are provided in Table 8-8.

Table 8-8. Comparison of the Median and the Interval of the Estimated Age of Samples from the First and Second Rounds of Data Elicitation

Sample Number	PCI	First Round Age Estimates		Second Round Age Estimates		Difference of Median	Difference of Interval
		Median	Interval	Median	Interval		
202	81	8.28	6.90	7.96	6.12	-0.32	-0.78
201	73	9.91	7.95	10.14	7.03	0.23	-0.92
207	73	11.81	7.98	10.20	6.98	-1.61	-1.00
203	72	9.89	7.91	10.20	7.17	0.31	-0.74
209	57	13.75	7.97	13.83	8.08	0.08	0.11
208	56	14.21	10.87	14.94	9.91	0.73	-0.96
206	45	9.98	8.01	9.99	7.89	0.01	-0.12
204	26	13.85	7.99	14.90	6.30	1.05	-1.69
205	11	13.31	9.04	15.02	10.18	1.71	1.14
Average:						0.24	-0.55

Median = 50th percentile
Interval = 95th percentile - 5th percentile

The final assessment of the aggregated expert data was a comparison of changes in the lower and upper limits (the “worst case” and “best case” scenarios). Comparing the 5th percentile responses for the first and second round of elicitation revealed that the average lower-limit estimate of the age of the samples was higher in the second round (+.052 years). This increase is similar to the increase of the median in the second round as described above, but it is more than twice as large. Meanwhile, there was very little difference in the average upper-limit age estimate in the first and second rounds of data elicitation (-0.03 years). The decrease of the interval between round one and round two is thus mainly a result of the higher estimates for the lower limit. Table 8-9 shows the analysis of the lower and upper limits for each round of data elicitation.

Table 8-9. Comparison of the Lower and Upper Limits of the Estimated Age of Samples from the First and Second Rounds of Data Elicitation

Sample Number	PCI	First Round Estimates		Second Round Estimates		Difference of Lower Limit of Estimated Age	Difference of Upper Limit of Estimated Age
		5th Percentile	95th Percentile	5th Percentile	95th Percentile		
202	81	4.83	11.73	4.90	11.02	0.07	-0.71
201	73	5.93	13.88	6.63	13.66	0.70	-0.22
207	73	7.82	15.80	6.71	13.69	-1.11	-2.11
203	72	5.93	13.84	6.62	13.79	0.69	-0.05
209	57	9.77	17.74	9.79	17.87	0.02	0.13
208	56	8.78	19.65	9.99	19.90	1.21	0.25
206	45	5.97	13.98	6.04	13.93	0.07	-0.05
204	26	9.86	17.85	11.75	18.05	1.89	0.20
205	11	8.79	17.83	9.93	20.11	1.14	2.28
Average:						0.52	-0.03

8.3 Simulated Experts Data

After the information obtained from the experts was aggregated, the next step was to simulate data points suitable for use in Model #1. As described in chapter 7, this was implemented using Bayesian hierarchical modeling and the Markov Chain Monte Carlo algorithm. The resulting data set is shown in Figure 8-1. This experts' data was used as one of the two sets of input for Model #1.

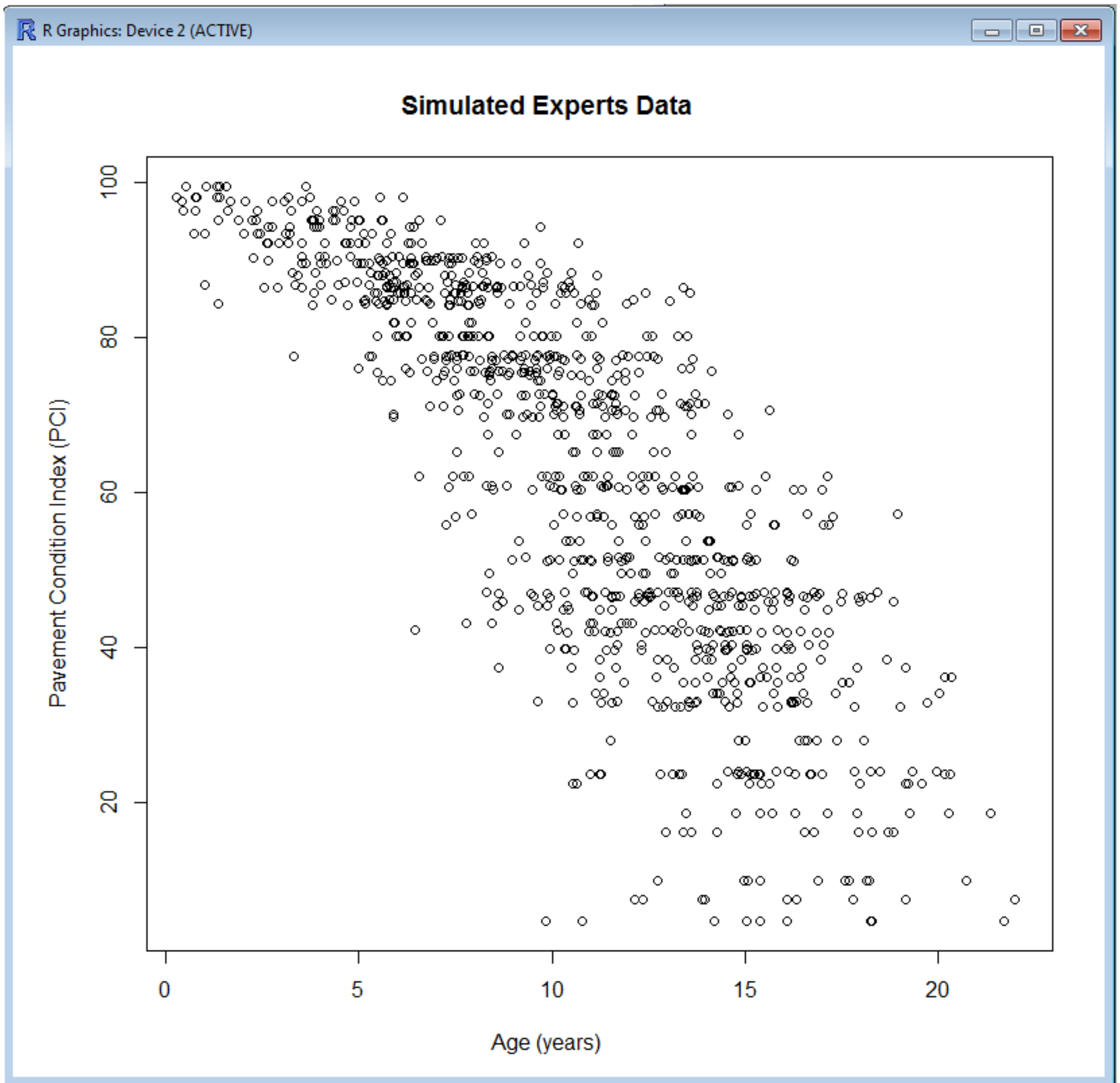

Figure 8-1. Simulated Experts' Data, Ready for Use in Model #1

8.4 Historical Performance Data

The second data set used as an input for Model #1 was the historical pavement-performance information obtained from the city of Bryan, Texas. The manner of obtaining, vetting, and cleaning this data was described in chapter 6. The historical data set, cleaned and ready to use in Model #1, is illustrated in Figure 8-2.

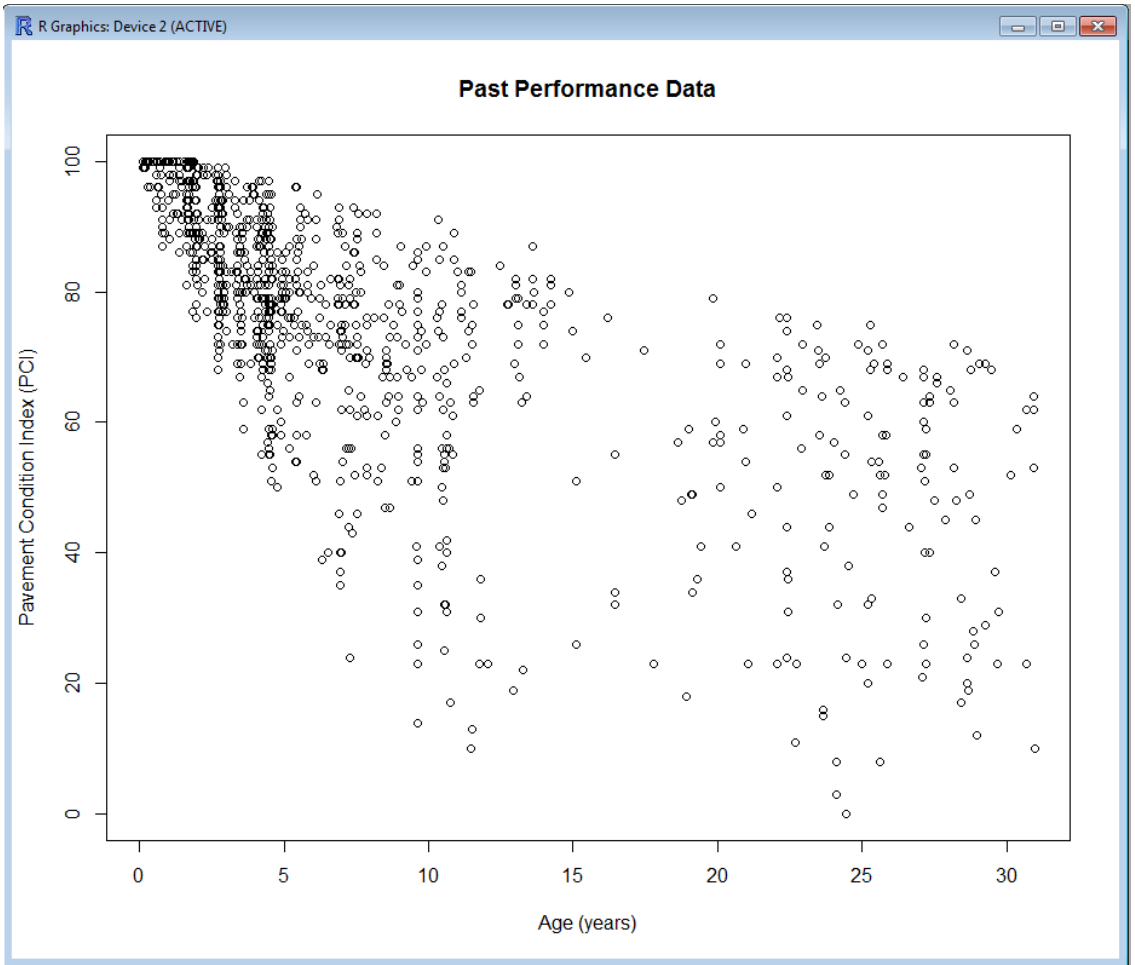

Figure 8-2. Historical Performance Data, Cleaned and Ready for Use in Model #1

When analyzing this historical data it was determined that further processing would be necessary. The use of this data in Model #1 led to significant aberrations, with the age of the pavement in the performance curves being much higher than the expected performance life of asphalt pavements. The general range of this performance life is well-established, and barring the development of new materials, or the application of unrecorded maintenance treatments, it is unlikely to change in such a drastic fashion.

The researcher therefore concluded that some of the historical data obtained in this study was unreliable.

In practice, there is a high chance that historical data about very old, unmaintained pavement or simply the result of maintenance treatments on that pavement is not being accurately recorded. It is uncommon for roads to go for 25 or 30 years without pavement maintenance; therefore, the historical data points at that end of the age spectrum are more likely to be either biased as the result of aberrant usage conditions or simply an outcome of data-reporting mistakes. Therefore, it is safe to assume that the data points at the lower end of the age range are more accurate/realistic representations of the rate of pavement decline.

Working under this assumption, the researcher decided to perform a staged analysis of the data set. The available data was split into sections based on the age of the samples. First, all observations of pavement less than five years old were considered. When this data was used in Model #1 the results were well within the expected parameters of deterioration based on the known characteristics of asphalt pavements. Next, the researcher examined whether or not it would be possible to expand the data set by considering observations of pavement up to ten years old. This results from this expanded data set also fit within the expected parameters.

Following this iterative process, it was eventually determined that data indicating a maximum pavement age of 15 years would be used in the analysis. Incorporating observations of pavement ages older than this range led to unacceptably aberrant results in the model. (By examining the data in Figure 8-2, it is possible to visually confirm how the data at ages of greater than 15 years diverges from the trend established in the lower age range. The pattern of data points above 15 years reveals an inconsistent shift toward higher PCIs, which again was most likely caused by bias and/or error in the data reporting.)

In summary, it was determined that for the greatest accuracy only observations of pavement ages less than 15 years would be included in the historical data set. This information was labeled as the “First Split” of the historical data, and it is illustrated in Figure 8-3. This data was used as the second set of input for Model #1, for the purposes of comparison against the data set elicited from the experts.

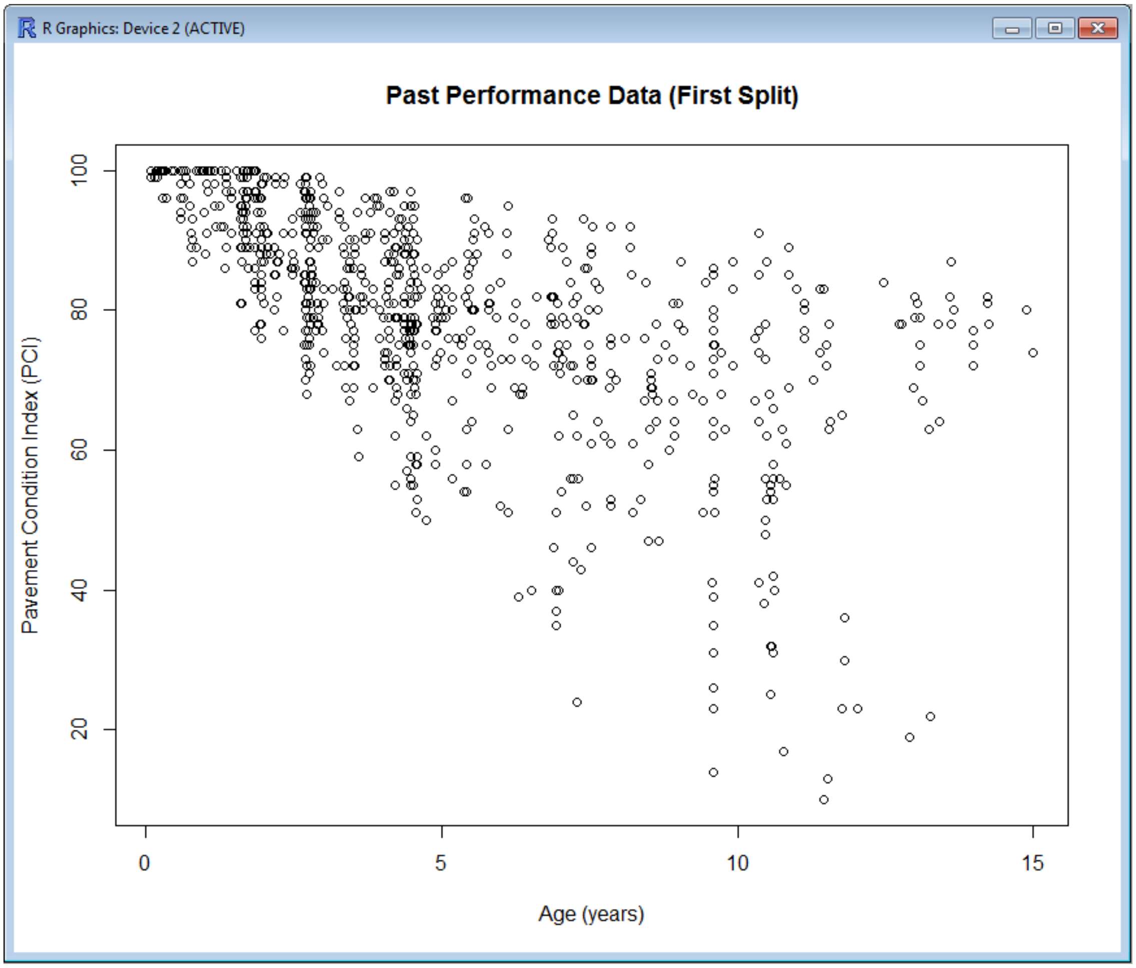

Figure 8-3. First Split of the Historical Performance Data (Final Input for Model #1)

8.5 Creating Scenario-based Performance Curves

The purpose of Model #1 was to define the asset performance curve in each of three scenarios (the "worst case," "most likely case," and "best case"). This model was implemented for each of the two data sets (the experts' data and the historical data). As described in chapter 7, it can be assumed that performance of pavement over time generally follows the sigmoidal equation below:

$$y_i = PCI_i = 100 - \frac{\rho}{\left[ln\left(\frac{\alpha}{Age_i}\right)\right]^{\frac{1}{\beta}}}$$

where:

Age is the age of the current pavement surface

ln is the natural logarithm

α, β, and ρ are regression constants.

The results of Model #1 were in the form of equation parameters for use in this sigmoidal formula. These results are shown in Table 8-10.

Table 8-10. Performance Curve Parameters for Historical Data and Experts' Data

Parameters	**"Worst Case" Performance Scenario**		**"Most Likely Case" Performance Scenario**		**"Best Case" Performance Scenario**	
	Historical Data	**Experts' Data**	**Historical Data**	**Experts' Data**	**Historical Data**	**Experts' Data**
A	50	70	88	70	135	70
B	0.6	0.56	0.48	0.38	0.24	0.28
P	170	190	200	170	390	140

Once these parameters were determined the curves were drawn using the conventional pavement-performance sigmoid equation. After examining the curves from the historical data set it was discovered that the lack of data points above age 15 was causing the far end of two scenario curves ("most likely" and "best case," for ages > 25) to behave in an aberrant fashion. Therefore, the parameters for these curves were slightly modified so that they behaved similarly to the "worst case" curve for the historical data.

Figures 8-4 and Figure 8-5 show the resulting scenario-based performance curves for the experts' data and the historical data. As a reminder, the "worst case" is defined as the 5th percentile of the performance of the asset at a given age. The "most likely case" is the 50th percentile (median) of the performance of the asset at a given age. The "best case" is the 95th percentile of the performance of the asset at a given age.

The quantiles used to define the performance curves should not be confused with the quantiles elicited from the experts. In the elicitation process the quantiles given by the experts described the range of age of samples with specific PCI. In the performance curves, however, quantiles are used to describe the range of PCI for a specific age. These quantiles are not the same since the distribution of the ages is not the same as the distribution of the PCI at any given point. This difference is the reason why it was necessary to simulate data points from the experts' evaluation for use in the quantile regression analysis of Model #1.

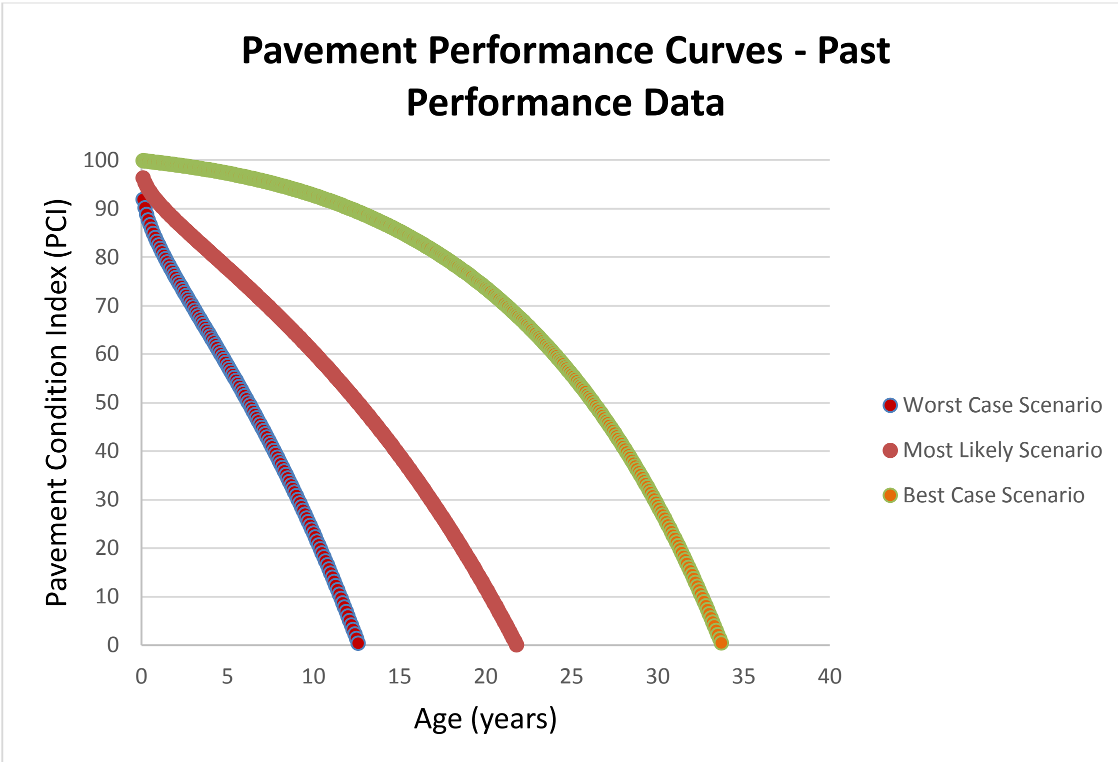

Figure 8-4. Scenario-based Pavement Performance Curves, from Historical Data

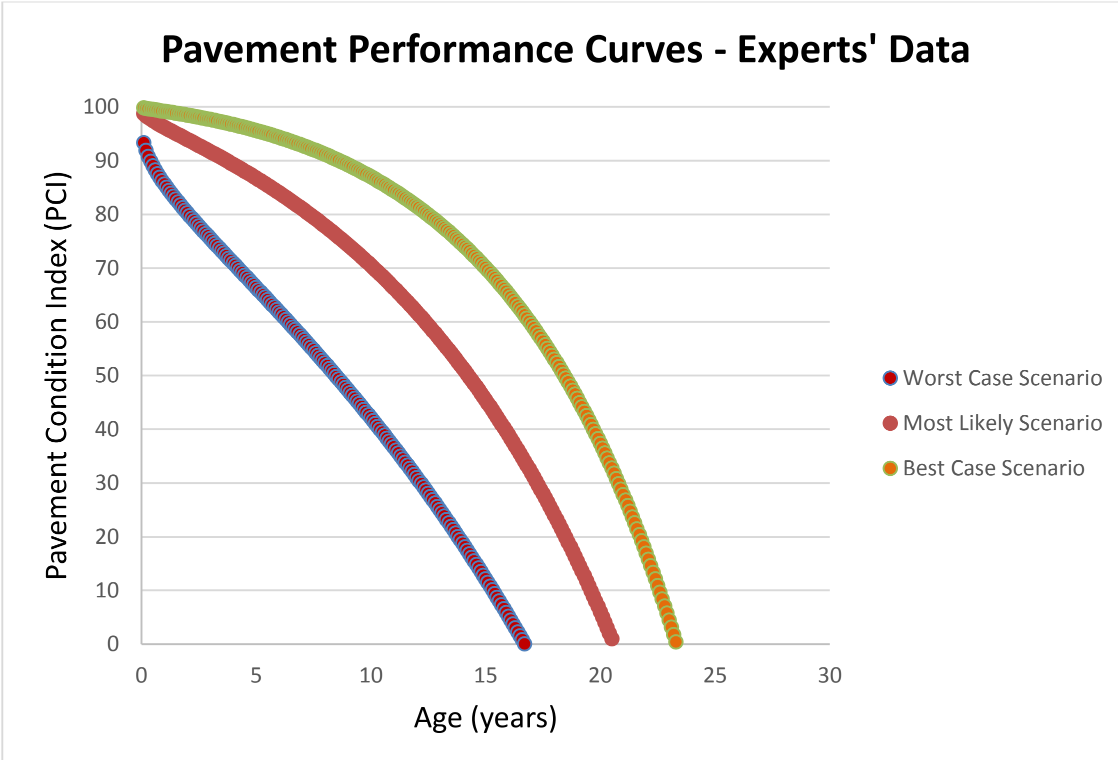

Figure 8-5. Scenario-based Pavement Performance Curves, Data Elicited from Experts

To compare the performance curves from the elicited data against those from the historical data, the area underneath each performance curve was measured. This area measurement is a common quantifier used as a performance measure in infrastructure asset management to evaluate the cost-effectiveness of an asset. As discussed in chapter 2, cost-effectiveness analysis is similar to cost-benefit analysis, but it is simpler in that it does not require assigning a specific dollar value to the benefits of an asset (Garber and Phelps, 1997). It is only necessary to note that an asset with a higher area under the performance curve provides more value to the network, compared to a similar asset with less area under the performance curve. Since roads are seldom left to degenerate to a PCI of zero, the base-line for these area-under-the-curve measurements was set at a PCI of 25.

Figure 8-6 shows the cumulative area under the performance curves for each scenario, in each data set. This graph demonstrates several interesting results. First, by comparing the upper and lower limits it can be seen that the curves obtained from the past performance data had a wider range compared to the curves from the experts' data. The best-case scenario from the historical data had higher value for the performance measure than what was predicted by the experts, and the worst-case scenario from the historical data had lower value for the performance measure than what was predicted by the experts.

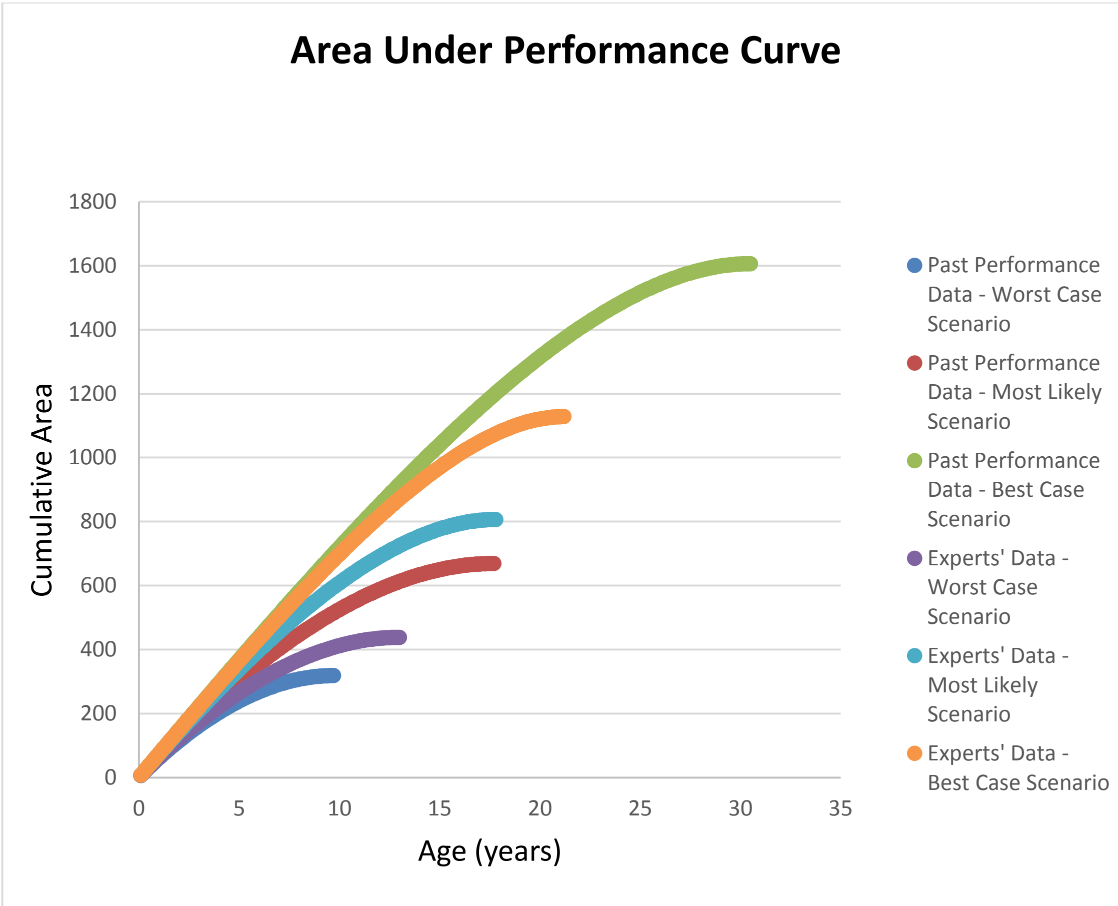

Figure 8-6. Cumulative Area under the Performance Curves for Each Scenario

For the median ("most likely") performance curves, the behavior is similar to the worst-case scenario; the experts predicted a better median result than the historical information revealed. Thus, it was only in the upper limit ("best-case" scenario) that the experts' predictions were more conservative than the historical performance records.

As discussed in previous chapters, an important purpose in developing this approach to infrastructure asset management was to incorporate a representation of risk and uncertainty into the model. This was implemented through the use of the three outcome-based performance scenarios ("best case," "most likely case," and "worst case"). Comparing the results of this approach to conventional deterministic modeling is therefore an important part of the analysis.

Conventionally, when using a deterministic (single-curve) representation of asset performance either the mean or median of the data is presented. The median performance curve would be equivalent to the "most likely case" in the current analysis. Using the performance measures (area under the curves) from Figure 8-6, a calculation was performed to determine how far off the median curve was from the "best case" and "worst case" scenarios. This provides a measure of the expanded range of information that is included in the scenario-based analysis.

Table 8-11 shows the results of this measurement for both the historical data set and the elicited data set. The ratio H50/H5 indicates how far the area under the 5^{th} percentile curve diverged from the area under the median curve in the historical data set. Likewise, the ratio H50/H95 indicates how far the area under the 95^{th} percentile curve diverged from the area under the median curve in the historical data set. The ratios E50/E5 and E50/E95 convey the same information for the elicited data.

The results from this analysis indicate that if asset managers assume deterministic behavior for the performance of pavement, using the median performance curve, then there is a possibility of up to 66% overestimation of cost-effectiveness compared to the worst-case scenarios (based on the maximum E50/E5). There is also a possibility of up to 42% underestimation of cost-effectiveness compared to the best-case scenarios (based on the minimum H50/H95).

Table 8-11. Ratio of Area Under Performance Curves, Deterministic Median vs. Scenario-based Analysis

Year	H50/H5	H50/H95	E50/E5	E50/E95
1	1.11	0.92	1.13	0.97
2	1.15	0.89	1.17	0.96
3	1.19	0.87	1.21	0.95
4	1.23	0.85	1.24	0.94
5	1.27	0.83	1.27	0.93
6	1.32	0.81	1.31	0.92
7	1.38	0.79	1.35	0.91
8	1.45	0.77	1.39	0.9
9	1.54	0.75	1.43	0.88
10		0.73	1.48	0.87
11		0.71	1.53	0.86
12		0.69	1.59	0.85
13		0.67	1.66	0.83
14		0.65		0.82
15		0.62		0.8
16		0.6		0.78
17		0.58		0.77

Finally, to analyze the success of the elicitation process, the experts' predictions were compared against the historical data. It was assumed that the historical performance curves represent what actually happened in the field in reality. Using the area under these historically-based curves (from past performance data) as a benchmark, ratios were calculated to determine the divergence of the elicited predictions.

Table 8-12 shows the results of these calculations. The ratio E50/H50 is the comparison of the elicited and historical median performance. By comparing E50/H50 it was revealed that relying on elicited data could result in up to 20% overestimation of cost-effectiveness in the most-likely (median) performance scenario.

Table 8-12. Ratio of Area Under Performance Curves, Elicited Data vs. Historical Data

Year	E50/H50	E5/H5	E95/H95	E5/H95	E95/H5
1	1.06	1.04	1	0.86	1.21
2	1.07	1.05	1	0.82	1.29
3	1.09	1.07	0.99	0.78	1.36
4	1.10	1.09	0.99	0.75	1.44
5	1.11	1.11	0.99	0.72	1.52
6	1.12	1.13	0.99	0.69	1.62
7	1.13	1.16	0.98	0.66	1.73
8	1.14	1.2	0.98	0.63	1.85
9	1.15	1.24	0.98	0.6	2.01
10	1.16		0.97	0.57	
11	1.17		0.97	0.54	
12	1.18		0.96	0.51	
13	1.19		0.95	0.48	
14	1.20		0.94		
15	1.20		0.93		
16	1.20		0.92		
17			0.91		
18			0.89		
19			0.87		
20			0.85		
21			0.83		

The values in the E5/H5 column of Table 8-12 indicate that relying on experts' data could result in up to 24% overestimation in cost-effectiveness analysis in the worst-case performance scenario. Similarly, by comparing E95/H95 it was revealed that relying on elicited data could result in up to 17% underestimation of cost-effectiveness in the best-case performance scenario.

The final two columns of the Table 8-12 represent the extreme situations in which the worst-case scenario happened in reality and the best-case expert prediction was used for planning purposes (or vice-versa). In these cases it is possible that the predictive scenario could underestimate the cost-effectiveness by up to 52%, or underestimate it by up to 100%. Asset managers should be advised to keep these numbers in mind as they consider the range of uncertainty presented in the scenario-based model.

8.6 The Asset-Management Framework in Practical Decision-Making

To demonstrate the usefulness of the scenario-based asset-management framework in practical decisions, the model was tested using a popular commercial asset-management software package, known as StreetSaver®. StreetSaver® was developed by Metropolitan Transportation Commission (MTC) in the San Francisco Bay Area, California. This package is used to develop pavement maintenance and rehabilitation strategies and to estimate expenses. Performance curves for various segments of a city's streets are used as input by the StreetSaver® software. These curves follow the pavement-oriented sigmoidal equation that was introduced in chapter 7, which means that the regression constants (α, β, and ρ) are the primary input values (Wang el al., 2014; Cheng, 2010). In the sample test conducted here, the various scenarios developed to predict pavement performance in Bryan, Texas, were used to estimate how much it would cost the city to improve the overall PCI of its road network from 55 to 75, over the course of 20 years and in a linear fashion. However, the network model used was the test model provided by StreetSaver® for testing and research purposes. In this test model the length of pavement sections are unrealistically short to better control the process and compare the results.

In this analysis each source of data (the scenarios derived from historical performance and elicited experts' data) was considered as a separate case. The performance curves for each scenario were inserted into the software by defining the α, β, and ρ values of the sigmoidal equation. Then, a target-driven analysis was performed using the software, which resulted in a report of the cumulative costs required to reach the desired network PCI. The graphs of these cumulative costs over time, based on the different estimated performance curves, are illustrated in Figures 8-7 and 8-8.

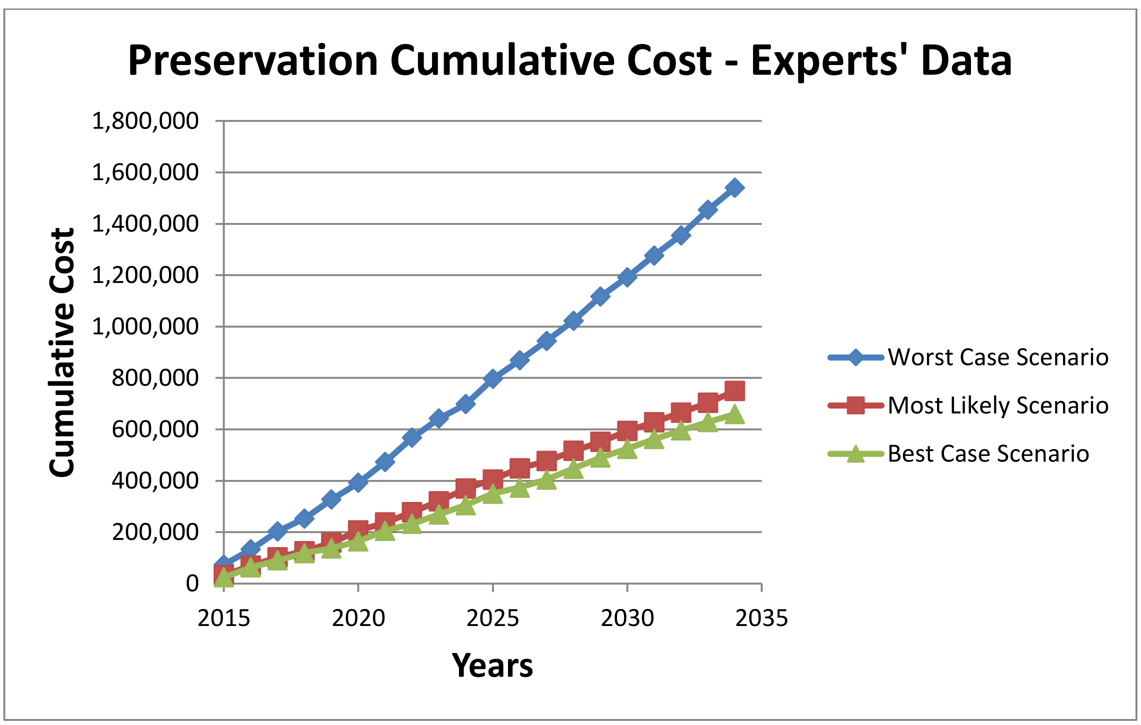

Figure 8-7. Cumulative Preservation Cost for Each Scenario to Reach PCI=75 (Experts' Data)

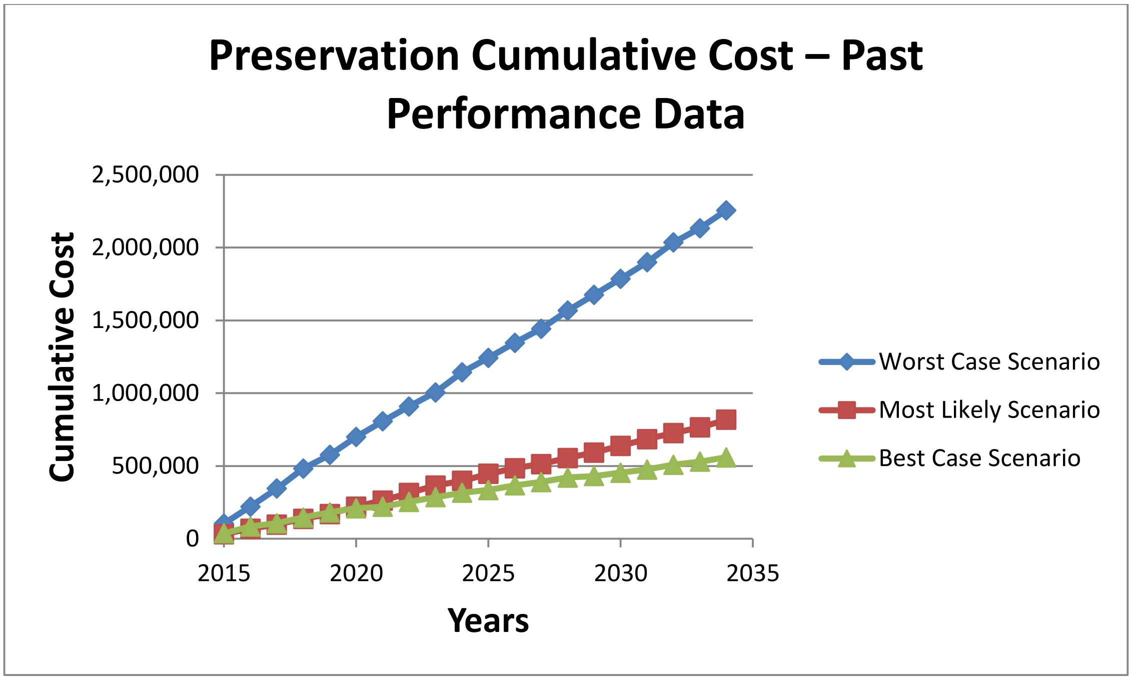

Figure 8-8. Cumulative Preservation Cost for Each Scenario to Reach PCI=75 (Historical Data)

The total budget that would be required to increase the overall network PCI from 55 to 75 over 20 years, based on different possible performance scenarios, is reported in Table 8-13.

Table 8-13. Required Budget to Reach PCI=75 in Different Performance Scenarios

	Worst Case Scenario	Most Likely Case Scenario	Best Case Scenario
Experts' Data	$1,540,071	$748,874	$659,395
Historical Data	$2,256,262	$817,922	$559,592

Analyzing this table reveals the significant amount of new information that a scenario-based asset management framework can provide for the decision-making process. Relying on a simple deterministic model to estimate the most likely asset performance would result in a straightforward predicted budget of roughly $750,000 (using the experts' data) or $820,000 (using the historical data). However, by including the "worst case" and "best case" scenarios, decision-makers can see that the potential range of the costs required to reach the desired performance level is actually quite large—especially in the direction of potentially increased expenses. In the worst-case scenario for both the expert and historical data, the budget required to meet the target performance is more than double the mainline estimate. Many factors beyond the manager's control, including weather conditions, material properties, and variations in usage patterns, can result in divergent outcomes. Understanding the range of this uncertainty can be vitally important in providing a broader perspective for asset managers who are making decisions about budget allocations and performance targets.

CHAPTER IX

SUMMARY AND CONCLUSIONS

9.1 Overview

The goal of this research was to develop a risk- and performance-based infrastructure asset management framework that can be used to support rational and effective decision-making by the professionals charged with the critical task of maintaining the infrastructure. Two major concerns were identified in the previously existing asset-performance models. First, there is a need for a practical method of incorporating uncertainty and risk into the model. This is because without information about the uncertainty entailed in asset performance predictions, managers who rely on these predictions may experience unanticipated and unfortunate results. Second, in many cases there is a lack of appropriate data about how assets perform over time. To build a useful predictive model, a robust technique is needed for estimating this performance data in cases where the historical asset-performance records are unreliable or non-existent.

The framework developed in this research employs an outcome-based scenario analysis to report uncertainty and risk. Rather than providing a single deterministic prediction of asset performance, the model provides a “best-case scenario,” “most-likely scenario,” and “worst-case scenario.” The levels of asset performance over time in these scenarios were defined by conducting a quantile regression analysis on the asset-performance data.

For situations in which there is a lack of historical performance data, an elicitation model was developed based on the Delphi technique. This approach provides a rigorous process for obtaining data from a panel of experts. The elicitation proceeds in a series of iterative rounds. First, each expert provides an independent and anonymous estimate of the data that being elicited. Then, in subsequent rounds, the experts receive feedback based on the overall aggregated results, and they are given an opportunity to revise or defend their previous estimates. The goal is to encourage the experts to narrow in on a reasonable consensus around the most accurate data estimations. Using this technique, an elicitation process was developed tailored to the specific needs of infrastructure asset management. In the proposed elicitation model, the experts provide information about the performance of the asset over time in the form of quantiles. This allows the researcher or decision-maker to obtain information about the overall range of possible performance outcomes.

To test the implementation and applicability of the proposed framework, a case study was conducted in the City of Bryan, Texas. While the proposed infrastructure asset-management framework is generic and could be used for any type of asset-management situation, in this research the pavement condition index (PCI) of the Bryan road system was used as the relevant measure of performance. The case study was focused on the deterioration of PCI over time, an important consideration for asset managers who need to evaluate the timing and cost of pavement maintenance treatments. In this case study, actual historical data about pavement performance was available from the city of Bryan, in the form of road construction records and PCIs measured during city inspections. The existence of these records allowed the researcher to test the success of the data-elicitation model, by comparing its results against the actual historical (past-performance) information.

9.2 Conclusions

This research expanded the body of knowledge in the area of infrastructure asset-management in the following respects:

- Defining four levels of uncertainty in asset management shows how a consideration of these levels of uncertainty, ranging from deterministic situations to truly ambiguous situations, can help asset managers to choose the most suitable decision-support framework for their needs. Previous models have tended to adopt a deterministic or discrete-probability outlook on uncertainty; however, most infrastructure asset-management contexts involve higher levels of uncertainty that are more adequately handled using a scenario-based approach. The use of deterministic performance models, in particular, was shown in this research to lead to potential overestimation or underestimation of the value of different treatment alternatives (as much as 66% overestimation or 42% underestimation, in the Bryan, Texas, case study). Furthermore, both deterministic and discrete-probability models have the liability of presenting definitive conclusions and thereby obscuring the true level of uncertainty that exists in the data-modeling process. This research suggests that scenario-based approaches can be very useful for helping asset managers to understand the full range of uncertainty and risk that is present in the model. At the same time, the scenario-based approach provides intuitive and easy-to-use results, which is not the case in complex probabilistic models (such as the Markov Decision Process).

- The models and the case study developed in this research demonstrate that an outcome-based scenario analysis for infrastructure asset-management can be successfully implemented in practice. Describing the boundaries of asset performance (in the form of the "worst-case scenario" and the "best-case scenario") can be a very useful tool for encouraging asset managers to incorporate evaluations of uncertainty and risk into their planning—without becoming entirely bogged down in an overabundance of information. This gives asset managers a better understanding of the fact that factors beyond their control or knowledge—including weather conditions, material properties, and unforeseen load and usage patterns—will often cause real-world results to deviate from the "most-likely scenario." This approach, therefore, helps them to more accurately interpret the model as expressing of a range of asset-performance possibilities. Outcome-based asset-performance scenarios allow the managers to define possible futures and consider the consequences on their planning and programming decisions in each of those futures, without needing to bother themselves with attempts to trace the complex chains of events that might lead to a particular performance outcome. Using quantile regression analysis to define the range of possible performance scenarios is a novel approach that was introduced to the infrastructure asset-management context for the first time in this work.

- The data-elicitation model provides a new tool, tailored specifically for the needs of asset managers, to obtain estimated asset-performance information. This rigorous approach to estimating data will be invaluable in situations where there are no reliable or adequate records of the past performance of assets. While the existence of robust historical data is the ideal situation for creating models of asset performance, the case study in this research provides evidence that data obtained through a rigorous elicitation process can provide an accurate-enough input for modeling purposes. In some cases, when the existing empirical data has not been rigorously collected, data elicited from experts may be even more accurate than historical records, as was shown by the anomalous results and need for repeated data-cleaning attempts in processing the city's historical maintenance records in this study. Furthermore, in cases where reliable historical data is available for only a limited duration of the asset's life-cycle, the data-elicitation model can be used to estimate the asset's performance over a broader range of time.

- The statistical model developed in this research offers a specific method of data aggregation for infrastructure asset management based on Bayesian hierarchical modeling and the Markov Chain Monte Carlo algorithm. This approach to aggregating the data elicited from experts captures their estimated probability distributions for the performance of the asset. Moreover, the Bayesian structure of this model enables asset managers to easily update the resulting asset-performance curves when new information is obtained.

- Overall, the asset-management framework developed in this research provides a powerful and yet flexible approach toward risk analysis that asset manager can implement in conjunction with current software packages to better support their decision-making processes in uncertain environments.

9.3 Limitations

The infrastructure asset-management framework that was developed in this research has a generic form, and the intent was to create a model that can be used for any type of asset to support decisions at the strategic and network levels. However, only one case study was conducted to test this approach to asset-performance modeling, and the development of the framework within this case study included a great deal of contextual information related specifically to pavement maintenance. Furthermore, the sample size in the case study's data-elicitation process was limited in relation to both the number of experts consulted and the number of pavement samples selected. Therefore, caution should be employed in generalizing the results of the case study to other assets-management contexts. More research is needed to further test and develop the applicability of the model.

Another limitation of the study was the use of raw historical data from the city of Bryan, which was collected under unknown conditions. Although the data was cleaned using conventional data-scrubbing algorithms, it still resulted in anomalous results, requiring the researcher to conduct a second round of processing and to ultimately discard all historical observations of pavement conditions older than 15 years. The questionability of this data set means that its utility for calibrating/confirming the elicitation model is limited. Further comparative studies should be undertaken in situations where robust historical data is available.

Finally, it is worth noting that the framework in its current implementation does not include the kind of detailed information that is necessary to evaluate maintenance and rehabilitation treatments at the project level. Instead, it merely incorporates data about the average results of those project-level efforts in order to assist with broader strategic and network planning. Additional efforts can and should be made to help improve financial efficiency at the project level.

9.4 Recommendations for Future Research

In addition to the research directions described in the previous section, there are several other areas in which this work could be expanded. One possibility is to use the framework and elicitation model to generate broad recommendations for effective practices in infrastructure asset management decision making at the strategic and network levels. These best-practice recommendations could be tailored to specific types of assets and specific geographical regions. Another potential direction of research is to conduct empirical studies comparing the results of using outcome-based scenario planning against the results achieved by using conventional probabilistic asset-management frameworks such as the Markov Decision Process.

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APPENDIX A

INSTITUTIONAL REVIEW BOARD (IRB) FORM APPROVAL

DIVISION OF RESEARCH

Research Compliance and Biosafety

TEXAS A&M UNIVERSITY

DATE: June 03, 2014

MEMORANDUM

TO: Stuart D Anderson
TEES - College Of Engineering - Civil Engineering

FROM: Dr. James Fluckey
Chair
Institutional Review Board

SUBJECT: Expedited Approval

Study Number:	IRB2014-0241
Title:	A Risk-based Performance-based Model for Infrastructure Management Planning
Approval Date:	06/03/2014
Continuing Review Due:	05/01/2015
Expiration Date:	06/01/2015

Documents Reviewed and Approved:

Title
Survey Instrument - Attachment C
Survey Insrument
recruitment_email-1
dissertatiom proposal - amirhessami - 20130722-1
information sheet

Document of Consent: Waiver approved under 45 CFR 46.117 (c) 1 or 2/ 21 CFR 56.109 (c)1
Waiver of Consent:

Provisions:

Comments:

This research project has been approved. As principal investigator, you assume the following responsibilities:

1. **Continuing Review:** The protocol must be renewed by the expiration date in order to continue with the research project. A Continuing Review application along with required documents must be submitted by the continuing review deadline. Failure to do so may result in processing delays, study termination, and/or loss of funding.
2. **Completion Report:** Upon completion of the research project (including data analysis and final written

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papers), a Completion Report must be submitted to the IRB.

3. **Unanticipated Problems and Adverse Events:** Unanticipated problems and adverse events must be reported to the IRB immediately.
4. **Reports of Potential Non-compliance:** Potential non-compliance, including deviations from protocol and violations, must be reported to the IRB office immediately.
5. **Amendments:** Changes to the protocol must be requested by submitting an Amendment to the IRB for review. The Amendment must be approved by the IRB before being implemented.
6. **Consent Forms:** When using a consent form or information sheet, you must use the IRB stamped approved version. Please log into iRIS to download your stamped approved version of the consenting instruments. If you are unable to locate the stamped version in iRIS, please contact the office.
7. **Audit:** Your protocol may be subject to audit by the Human Subjects Post Approval Monitor. During the life of the study please review and document study progress using the PI self-assessment found on the RCB website as a method of preparation for the potential audit. Investigators are responsible for maintaining complete and accurate study records and making them available for inspection. Investigators are encouraged to request a pre-initiation site visit with the Post Approval Monitor. These visits are designed to help ensure that all necessary documents are approved and in order prior to initiating the study and to help investigators maintain compliance.
8. **Recruitment**: All approved recruitment materials will be stamped electronically by the HSPP staff and available for download from iRIS. These IRB-stamped approved documents from iRIS must be used for recruitment. For materials that are distributed to potential participants electronically and for which you can only feasibly use the approved text rather than the stamped document, the study's IRB Protocol number, approval date, and expiration dates must be included in the following format: TAMU IRB#20XX-XXXX Approved: XX/XX/XXXX Expiration Date: XX/XX/XXXX.
9. **FERPA and PPRA:** Investigators conducting research with students must have appropriate approvals from the FERPA administrator at the institution where the research will be conducted in accordance with the Family Education Rights and Privacy Act (FERPA). The Protection of Pupil Rights Amendment (PPRA) protects the rights of parents in students ensuring that written parental consent is required for participation in surveys, analysis, or evaluation that ask questions falling into categories of protected information.
10. **Food:** Any use of food in the conduct of human subjects research must follow Texas A&M University Standard Administrative Procedure 24.01.01.M4.02.
11. **Payments:** Any use of payments to human subjects must follow Texas A&M University Standard Administrative Procedure 21.01.99.M0.03.

This electronic document provides notification of the review results by the Institutional Review Board.

APPENDIX B

FIRST ROUND QUESTIONNAIRE PACKAGE

Invitation Follow-up Letter

<Date>

<Title> <First Name> <Last Name>

<Company name>

<Company Address>

Invitation to participate in a Delphi Study

Dear <Title> <Name>,

Thank you for volunteering to participate in this research study regarding a method to predict pavement condition over time using expert opinion. As mentioned in the email invitation you received on <date> you will be required, using your expert judgment, to provide an appropriate estimate for age of the pavement samples. You are asked to give your estimates as ranges. The first round query would be emailed to you with instructions on <date>. Typically, one to two more rounds are required to achieve consensus among the expert panel. The input for each round should be completed in approximately 20 minutes.

Once again, thank you for your time, interest and cooperation. For more information contact Dr. Stuart Anderson by email to s-anderson5@tamu.edu or Amir Hessami by email to hessami_amir@tamu.edu.

Sincerely,

Amir Hessami

Graduate Research Assistant, CEM Program

Texas A&M University

Questionnaire – Round 1
Background and Instructions

You are receiving this questionnaire because you volunteered to participate in this research project. The questionnaire package is comprised of Questionnaire – Round 1 (current document), Attachment A (Participant Information Form), Attachment B (Method Description), Attachment C (Forms) and soft copy of ASTM D 6433 – 11 "Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys." The pictures for the pavement samples are located on a shared drive. You can access the pictures by clicking on the hyperlinks provided in the forms (Attachment C).

The next sections provide the background and instructions to complete the forms.

Background

This questionnaire is prepared as part of a research study titled "A Risk-based Performance-based Model for Infrastructure Management Planning". The goal of this research is to develop a performance-based infrastructure management framework at the network planning level that incorporates the network condition uncertainty in maintenance decision making. One of the research objectives of this project is developing a method for defining pavement performance curves using expert opinion as input data. The developed method incorporates the uncertainty in predicting the future performance in order to define the upper and lower limits of performance over the life cycle of the infrastructure segment.

A total of five participants from the pavement industry make up the panel of experts for this study using the Delphi technique. Your input will be vital in determining the ranges of pavement performance over time.

Instructions

The researchers gathered condition data for several pavement segments in the City of Bryan network. This information was used to define the Pavement Condition Index (PCI) for these segments. PCI is a number between 0 and 100 which is used to indicate the general condition of a pavement. A PCI of 100 represents the best possible condition and a PCI of 0 represents the worst possible condition.

You have been provided with the information of each pavement segment including its location, segment size, the pavement distresses, calculated PCI for the segment, along with several pictures for each segment showing the condition of that segment. You are asked to answer questions about the range of the age of pavement segments over a range of pavement conditions in a structured survey using the Delphi method. The Delphi method is an iterative method to solicit the appropriate data from expert participants involved in this research project. You will provide your opinion by responding to questionnaires. The current document is the first questionnaire. Once you provide your responses to this questionnaire and return it to the research team, the research team will review the answers and design a new questionnaire. You will have a chance to modify your first round answers based on the analysis of the results of the first round by the research team. These iterations will continue until consensus reached. The questions would help to define the condition curves. In the Delphi method, at least two rounds of data collection through the survey would be implemented.

The method of condition survey and calculating the PCI is based on ASTM D 6433 – 11 "Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys." A soft copy of this standard is provided for your information in case you would like to refresh or enhance your knowledge about this method and the definition of the distresses.

You are asked to give your estimate of the pavement age of the segments as 5^{th}, 50^{th} and 95^{th} percentiles. The definition of percentiles and a simple example are provided in the Attachment B of this document.

Once you reviewed the attached documents, begin responding to the questionnaire as instructed below:

Open the excel file with the file name "Attachment C". Open Sheet 1 which is titled "Sample Number 201". In this worksheet you are provided with the following information:

- Sample Number
- Pavement Type
- Location (location of the sample in City of Bryan)
- Length and Width of the sample
- Pictures (link to the folder containing pictures for the sample)
- PCI (calculated PCI based on the field survey)
- Distresses

Review these information along with the pictures of the sample and in the same worksheet answer the following questions in the same worksheet:

Estimated Age of Pavement - Lower Limit (5th Percentile)

Estimated Age of Pavement - Best Estimate (50 Percentile)

Estimated Age of Pavement - Upper Limit (95th Percentile)

Once you have provided your estimated answer for the first worksheet, open the second worksheet which is titled “Sample Number 202”. For this sample, follow the process described above. Please do the same for the rest of the worksheets. After completing all the worksheets, save the excel file on your personal computer and email it to the following email address: hessami_amir@tamu.edu

Please direct any questions you may have to:

Amir Hessami
Graduate Research Assistant,
CEM Program, Department of Civil Engineering
3136 TAMU
Texas A & M University
College Station 77843-3136
Phone: (979) 229-4334
Email: hessami_amir@tamu.edu

Attachment A

Participant Information Form

Name:
Organization:
Number of years in the Transportation Industry:
Position:
Years in current position:
Email:

In what area(s) of the Transportation Industry have you worked within the last 10-15 years, and how many years in each. Please specify below:

Area of primary responsibility	Number of years
Pavement Maintenance and Management	
Pavement Maintenance	
Pavement Engineering\Construction	
Pavement Management	

Would you qualify your exposure to Pavement Engineering, Maintenance and Management Practices (during those years as indicated above)	Level of Exposure to Practices (LOW, MIEDIUM or HIGH)
Pavement Maintenance	
Pavement Engineering\Construction	
Pavement Management	

Please provide any additional comments about your experience in the space provided below:

The information requested here is intended to ascertain the level of professional experience of the participants in areas of expertise relevant to this study. All information provided by participants during this study is considered confidential and will be used solely for the purpose of this study.

Attachment B - Method Description

Delphi Method

The Conventional Delphi technique is a method used to gather opinions from a group of individuals. This information is analyzed and used to solve problems for which there is little or no empirical evidence. Therefore, this technique relies more on the judgment of experts to achieve results.

The iterative process of information gathering is achieved by administering a series of questionnaires called rounds to a panel of experts and giving controlled feedback to the respondents after each round. The aim of the Delphi technique is to achieve a consensus among the group of experts. The number of rounds could vary but is typically a minimum of two rounds. The first round is typically more exploratory and identifies issues which would be further addressed in subsequent rounds. Responses from the first round are compiled and form the basis for the second round; they are presented to the participants who would then have an opportunity to revise their earlier judgment/opinion if necessary in the light of new information from the aggregated results of the previous round. Subsequent rounds if required are conducted in a similar manner until consensus is achieved.

One key feature of the Delphi process is anonymity among the expert panel; panelists would not necessarily know one another nor would they know the source of each of the other responses. This eliminates intimidation, persuasion, individual dominance, conflict and the effects of status, and other drawbacks of face-to-face interaction. The use of controlled feedback to the participants ensures that panelists can revise their earlier opinions easily in the light of new evidence.

Ranges of Pavement Age

The condition of the pavement at specific point in time is not deterministic. There are several factors such as weather condition, the quality of construction and traffic load that may cause the pavement to deteriorate more than or less than what is typically expected. Because of this indeterministic feature of pavement condition it is more suitable to present the condition as a range instead of a single number. Here a method of presenting the condition as a range is presented.

One way of defining the ranges of condition is to use the concept of percentile in statistics. A percentile is a measure used in statistics indicating the value below which a given percentage of observations in a group of observations fall. For example, the 20th percentile is the value (or score) below which 20 percent of the observations may be found. In this research the lower limit of condition is defined as the 5th percentile. This means that there is less than 1 in 20 chance that the actual condition of the pavement will be below the lower limit which is estimated by the experts. Similarly the upper limit of condition is defined as the 95th percentile. This means that there is less than 1 in 20 chance that the actual condition of the pavement will be above the estimated upper limit. The experts are also asked to provide the best estimate. The best estimate is the 50th percentile, which is the median of the data.

The following simple practical example helps to better understand this concept.

For a project the estimator's estimation of the cost of the project is $380M. However, the estimator cannot definitely tell what the final cost of construction will be. There are ranges of uncertainty in the estimate of cost. Therefore, it is appropriate that the estimator presents the cost estimate as a range, with the limits and the "best estimate". In this example, the best estimate of the cost is $380M. Now consider the lower limit scenario. To define the lower plausible limit of the cost estimate the estimator should ask what cost of the project is for which there is only 1 in 20 chance that the final cost will fall below. This is the 5th percentile. In the case of this example, this lower limit is $250M. Similarly, the upper limit of possibility of the cost of the project is defined. The plausible upper limit is the cost that in the estimator's opinion there is only 1 in 20 chance that the final cost will exceed it. This is the 95th percentile. For the example provided in Figure B-1, the upper limit is $450M.

The interpretation of the lower limit and the upper limit is that there is very unlikely the final cost of the project will be out of this range.

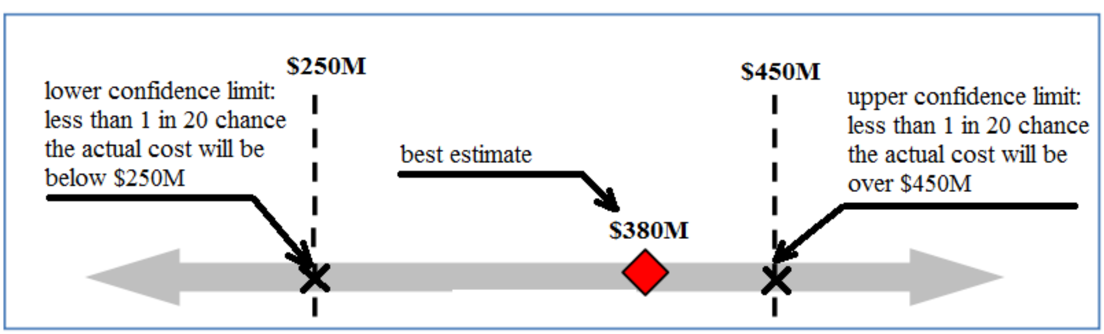

Figure B-1. Ranges of Cost Estimate for a Hypothetical Construction Project

Questionnaire Attachment C – Forms

Sample Number	
Pavement Type	
Location	
Length (ft)	
Width (ft)	
Pictures	
PCI	

Please provide your estimated age for this sample:

	Estimated Age of Pavement		
	Lower Limit (5th Percentile)	Best Estimate (50 Percentile)	Upper Limit (95th Percentile)
Comments			

Distresses

Distress Type	Severity	Quantity

Once you provided your estimate for this sample please move to the next worksheet.

APPENDIX C

SECOND ROUND QUESTIONNAIRE PACKAGE

Questionnaire – Round 2

Background and Instructions

You are receiving this questionnaire because you volunteered to participate in this research project. You have responded to the first round questionnaire. This is the second round questionnaire. The questionnaire package for the second round is comprised of Questionnaire – Round 2 (current document) and Attachment A (Forms). The pictures for the pavement samples are located on a shared drive. You can access to the pictures by clicking on the hyperlinks provided in the forms (Attachment A).

Next sections provide the background and instructions to complete the forms.

Background

This questionnaire is prepared as part of a research study titled "A Risk-based Performance-based Model for Infrastructure Management Planning". The goal of this research is to develop a performance based infrastructure management framework at the network planning level that incorporates the network condition uncertainty in maintenance decision making. One of the research objectives of this project is developing a method for defining pavement performance curves using expert opinion as input data. The developed method incorporates the uncertainty in predicting the future performance in order to define the upper and lower limits of performance over the life cycle of the infrastructure segment.

The researchers gathered condition data for several pavement segments in the City of Bryan network. This information was used to define the Pavement Condition Index (PCI) for these segments. PCI is a number between 0 and 100 that is used to indicate the general condition of a pavement. A PCI of 100 represents the best possible condition and a PCI of 0 represents the worst possible condition.

In the first round, you were provided with the information of each pavement segment including its location, segment size, the pavement distresses, calculated PCI for the segment along with several pictures for each segment showing the condition of that segment. In that round, you were asked to answer questions about the range of the age of pavement segments over a range of pavement conditions. The current document is the second round questionnaire. The research team reviewed the answers of the first round and designed this questionnaire. In this round, you have a chance to modify your first round answers based on the analysis of the results of the first round by the research team.

The method of condition survey and calculating the PCI is based on ASTM D 6433 – 11 "Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys." A soft copy of this standard is provided for your information in case you would like to refresh or enhance your knowledge about this method and the definition of the distresses.

A total of five participants from the pavement industry make up the panel of experts for this study using the Delphi technique. Your input will be vital in determining the ranges of pavement performance over time.

Instructions

Open the excel file with the file name "Attachment A - Round 2". The questionnaire has two sections. Open Sheet 1 which is titled "Section 1". Section 1 has nine subsections: Q1-Q9. Each of the subsections is about one of the pavement samples.

In these subsections you are provided with the following information:

- Sample Number
- PCI (calculated PCI based on the field survey)
- Pictures (link to the folder containing pictures for the sample)

In worksheets 3-12, the detailed characteristics of the samples along with the pavement distresses are provided.

For each sample you are also provided with the results of the estimated age of the samples from the first round. Three different types of results are provided. The first type is titled "Age of Sample (Aggregated Responses of First Round)". These are the results after the responses from all participants are statistically aggregated. In the aggregation process it is assumed that the estimated age of a sample has a normal distribution. This means that the estimated age for the 5th percentile and the 95th percentile are symmetric about the estimated age for the 50th percentile. You may not agree with this assumption. The second type of results is titled "Age of Sample (Average of Responses of First

Round)”. This is the simple average of the estimated age of the sample from all respondents. The third type of results is titled “Your First Round Response”. This is your responses for the first round.

Review these results, the PCI and the pictures of the sample and decide if you would like to modify your answers for the first round. Fill in the boxes in the table titled “Your Estimate of the Age for this round”. Similar to the first round, you are asked to give your estimate of the pavement age of the segments as 5^{th}, 50^{th} and 95^{th} percentiles in each of these subsections.

You are also asked to answer the following question for each sample:

“What percentage of the pavements in the network do you think have a better condition than this sample?"

In the last part of Section 1 of the questionnaire provide your comments.

Complete subsections Q1-Q9.

Now open Sheet 2 which is titled “Section 2”. There is one question in this section. The goal of this question is to define if you believe the answers should be symmetric or not. Review the provided figure in Section 2 and define which answer is the best description of your responses in Section 1. After completing all the questionnaire save the excel file on your personal computer and email it to the following email address: hessami_amir@tamu.edu

Please direct any questions you may have to:

Amir Hessami
Graduate Research Assistant,
CEM Program, Department of Civil Engineering
3136 TAMU
Texas A & M University
College Station 77843-3136
Phone: (979) 229-4334
Email: hessami_amir@tamu.edu

Questionnaire – Round 2

Summary of Instructions:

Open the excel file with the file name "Attachment A - Round 2". The questionnaire has two sections. Open Sheet 1 which is titled "Section 1". Section 1 has nine subsections: Q1-Q9. Each of the subsections is about one of the pavement samples.

In these subsections you are provided with the following information:

- Sample Number
- PCI (calculated PCI based on the field survey)
- Pictures (link to the folder containing pictures for the sample)

In worksheets 3-12, the detailed characteristics of the samples along with the pavement distresses are provided.

For each sample you are also provided with the results of the estimated age of the samples from the first round. Three different types of results are provided. The first type is titled "Age of Sample (Aggregated Responses of First Round)". These are the results after the responses from all participants are statistically aggregated. In the aggregation process it is assumed that the estimated age of a sample has a normal distribution. This means that the estimated age for the 5th percentile and the 95th percentile are symmetric about the estimated age for the 50th percentile. You may not agree with this assumption. The second type of results is titled "Age of Sample (Average of Responses of First Round)". This is the simple average of the estimated age of the sample from all respondents. The third type of results is titled "Your First Round Response". This is your responses for the first round.

Review these results, the PCI and the pictures of the sample and decide if you would like to modify your answers for the first round. Fill in the boxes in the table titled "Your Estimate of the Age for this round". Similar to the first round, you are asked to give your estimate of the pavement age of the segments as 5th, 50th and 95th percentiles in each of these subsections.

You are also asked to answer the following question for each sample:

"What percentage of the pavements in the network do you think have a better condition than this sample?"

In the last part of Section 1 of the questionnaire provide your comments.

Complete subsections Q1-Q9. Now open Sheet 2 which is titled “Section 2”. There is one question in this section. The goal of this question is to define if you believe the answers should be symmetric or not. Review the provided figure in Section 2 and define which answer is the best description of your responses in Section 1.

Attachment A – Forms

Section 1:

Provide your estimate of the age of the samples (in years) in the form of a,b, and c in the tables Q1-Q9 below:

a:	Lower Limit of the Age of Sample in years (5th Percentile)
b:	Best Estimate of the Age of Sample in years (50th Percentile)
c:	Upper Limit of the Age of Sample in years (95th Percentile)

Q 1	Sample Number	PCI	Pics	Your Estimate of the Age for this round		
				a	b	c
				?	?	?

Age of Sample (Aggregated Responses of First Round)		
a	b	c

What percentage of the pavements in the network do you think have a better condition than this sample?

Age of Sample (Average of Responses of First Round)		
a	b	c

Comments:

Your First Round Response		
a	b	c

Section 2

Answer the following question:

Which of the following better describes the relationship between the estimted ages you provided for a, b and c?