Soft Computing-based Life-Cycle Cost Analysis Tools for Transportation Infrastructure Management

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ABSTRACT

Increasing demands, shrinking financial and human resources, and increased infrastructure deterioration have made the task of maintaining the infrastructure systems more challenging than ever before. Life-cycle cost analysis (LCCA) is an important tool for transportation infrastructure management, which is used extensively to support project level decisions, and is increasingly being applied to enhance network level analysis. However, traditional LCCA tools cannot practically and effectively utilize expert knowledge and handle ambiguous uncertainties.

The main objective of this dissertation was to develop enhanced LCCA models using soft computing (mainly fuzzy logic) techniques. The proposed models use available "real-world" information to forecast life-cycle costs of competing maintenance and rehabilitation strategies and support infrastructure management decisions.

A critical review of available soft computing techniques and their applications in infrastructure management suggested that these techniques provide appealing alternatives for supporting many of the infrastructure management functions. In particular, LCCA often utilizes information that is uncertain, ambiguous and incomplete, which is obtained from both existing databases and expert opinion. Consequently, fuzzy logic techniques were selected to enhance life-cycle cost analysis of transportation infrastructure investments because they provide a formal approach for the effective treatment of these types of information.

The dissertation first proposes a fuzzy-logic-based decision-support model, whose inference rules can be customized according to agency's management policies and expert opinion. The feasibility and practicality of the proposed model is illustrated by its

implementation in a life-cycle cost analysis algorithm for comparing and selecting pavement maintenance, rehabilitation and reconstruction (MR&R) policies.

To enhance the traditional probabilistic LCCA model, the fuzzy-logic-based model is then incorporated into the risk analysis process. A fuzzy logic approach for determining the timing of pavement MR&R treatments in a probabilistic LCCA model for selecting pavement MR&R strategies is proposed. The proposed approach uses performance curves and fuzzy-logic triggering models to determine the most effective timing of pavement MR&R activities. The application of the approach in a case study demonstrates that the fuzzy-logic-based risk analysis model for LCCA can effectively produce results that are at least comparable to those of the benchmark methods while effectively considering some of the ambiguous uncertainty inherent to the process.

Finally, the research establishes a systematic method to calibrate the fuzzy-logic based rehabilitation decision model using real cases extracted from the Long Term Pavement Performance (LTPP) database. By reinterpreting the model in the form of a neuro-fuzzy system, the calibration algorithm takes advantage of the learning capabilities of artificial neural networks for tuning the fuzzy membership functions and rules. The practicality of the method is demonstrated by successfully tuning the treatment selection model to distinguish between rehabilitation (light overlay) and do-nothing cases.

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CHAPTER 1: INTRODUCTION

BACKGROUND

Transportation systems provide mobility, access, opportunity and choice for people. Sound transportation infrastructure systems play a vital role in encouraging a productive and competitive national economy (GAO, 2000). With 8,315,121 lane-miles of roadway, 593,813 bridges, 19,820 airports and more than 12,000 miles of inland waterways, the United States is well connected (BTS, 2005). However, many of the nation's infrastructure systems are reaching the end of their service lives. Infrastructure systems have gradually deteriorated with age as a result of environmental action and use that, in many cases, significantly exceeds the design expectations. Shortfalls in funding and changing population patterns have placed an even larger burden on our aging power plants, water systems, airports, bridges, highways, and school facilities. For example, in a recent survey conducted by the American Society of Civil Engineers (ASCE, 2005), America's infrastructure, the nation's critically important foundation for economic prosperity, only received an average grade of D.

Managing the nation's transportation infrastructure assets cost-effectively is important for sustaining economic growth, maintaining our quality of life, and promoting sustainable development. However, increasing demands, shrinking financial and human resources, and increased infrastructure deterioration have made the task more challenging than ever before. Decision-makers are faced with competing investment demands and must distribute limited resources so that the infrastructure systems are maintained in the best possible condition. To support these decisions, transportation infrastructure managers often resort to engineering management systems designed for a specific type of infrastructure (e.g., pavement and bridges) as well as for holistically managing all types of infrastructure assets.

Life-Cycle Cost Analysis

These engineering management systems often include life-cycle cost analysis (LCCA) as part of the decision support modules. Life-cycle costing (LCC) is a concept originally developed by the

U.S. Department of Defense (DoD) in the early 1960s to increase the effectiveness of government procurement. Two related purposes were to encourage a longer planning horizon that would include operating and support costs and increase cost saving by increasing spending on design and development. This represented a dramatic shift away from cost cutting to cost control design (Emblemsvag, 2003). From the very beginning, LCC has been closely related to design and development because it was realized early that it is better to eliminate costs before they are incurred instead of trying to cut costs after they are incurred.

The concept of LCC has spread from defense-related matters to a variety of areas. When the approach is applied by public and private agencies, the common characteristic of the projects are the systems to be studied are dynamic; the properties of the system evolve over time and change with its environment. Assessing and managing the costs incurred during projects' life-span, as well as their associated risks and uncertainties, are therefore vital for both public and private agencies because (Emblemsvag, 2003):

- The MR&R costs after construction will most likely be very significant and should therefore play a major role in project-selection decisions.

- The knowledge about future MR&R costs and their associated risks and uncertainty can be used during negotiations both when it comes to costs/ pricing and risk management.

- The estimation of future costs while designing the projects may allow eliminating some costs even before they are incurred.

LCCA in Transportation

In the field of transportation asset management, LCCA provides decision-support in the design and operation of major transportation systems or components. The Transportation Equity Act for the 21st Century (TEA21) defined LCCA as "… *a process for evaluating the total economic worth of a usable project segment by analyzing initial costs and discounted future costs, such as maintenance, user, reconstruction, rehabilitation, restoring, and resurfacing costs, over the life of*

the project segment." A usable project segment is defined as a portion of a highway that, when completed, could be open to traffic independent of some larger overall project (FHWA, 1998).

For transportation infrastructure projects, LCCA should include costs for construction, operation, maintenance, and disposal. All relevant economic variables should be considered, including both user and nonuser (agency) costs. LCCA plays an important role in many transportation agencies business processes, such as alternative evaluation and project selection. This type of analysis not only provides economic indicators for alternative projects, but also supports agency budget allocation. Since 1996, FHWA has encouraged the use of LCCA when analyzing major investment decisions and it has mandate this type of analysis in particular federally-funded projects (FHWA, 1998).

Currently, there are mainly two categories of LCCA approaches used by local and state agencies: deterministic and probabilistic (risk analysis approach). Deterministic methods are relatively simpler and easier to implement but they cannot evaluate the risk emerging from the consideration of the uncertainty associated with future events. Probabilistic methods can account for the uncertainty in the different input variables, but it is relatively difficult to collect all information needed for applying these models. Furthermore, traditional probabilistic approaches do not include procedures for effectively considering ambiguous input and expert opinion.

Soft computing is an umbrella of artificial intelligence techniques that can be used to develop decision-support tools that effectively handle both subjective and numerical information and "*tolerates imprecision, uncertainty, ambiguity, and partial truth to achieve tractability, robustness, and better rapport with reality*" (Zadeh, 1997). Therefore, soft computing techniques could be a powerful enhancement for transportation infrastructure LCCA. Some soft computing-based LCCA methods have already been studied. For example, Usher and Whifield used fuzzy theory for evaluating and selecting used-systems by means of life cycle cost (Usher and Whifield, 1993). Their method determines the equivalent uniform annual cost of a used system based on a linguistic evaluation of its components.

PROBLEM STATEMENT

LCCA, as a decision-support tool, has the following characteristics:

1. Available data may be uncertain, ambiguous, and incomplete (information availability for different transportation infrastructure projects is highly variable).

2. Both objective (numerical) and subjective (linguistic) information need to be considered in the analysis. While some relevant factors are easily quantifiable in economic (monetary) terms, other factors, such as environmental effects, comfort, aesthetics, versatility, and mobility considerations, may be better evaluated using subjective terms.

3. Estimates of future maintenance and rehabilitation actions and costs often require a lot of expert knowledge and engineering judgments.

Both deterministic and probabilistic LCCA approaches have been used in transportation infrastructure management, but neither of them could comprehensively handle and evaluate all uncertainties involved in LCCA. A method that is capable of processing ambiguous, subjective, and/or empirical information is necessary.

RESEARCH OBJECTIVE

The main objective of this dissertation is to develop an enhanced LCCA model using soft computing (mainly fuzzy logic) techniques. The proposed fuzzy-logic-based decision-support model uses available "real-world" information to forecast life-cycle costs of transportation infrastructures and support asset management decisions. The feasibility and practicality of the proposed model is illustrated by its implementation in a life-cycle cost analysis algorithm for comparing and selecting pavement maintenance, rehabilitation and reconstruction (MR&R) policies.

In order to achieve the overall objective of the investigation, the following tasks were completed:

- *Evaluate the feasibility of application of soft computing techniques in transportation infrastructure management.* A critical review of available soft computing techniques and

their applications in infrastructure management was conducted. This review suggested that these techniques provide appealing alternatives for supporting many of the infrastructure management functions and in particular LCCA.

- *Develop a LCCA model using fuzzy logic techniques*. The algorithm for the project selection was developed as a rule-based fuzzy logic system in which the user can define rules to reflect the agency policies and strategies. The inference rules can be customized according to agency's management policies and expert opinion.

- *Incorporate the fuzzy logic-based LCCA model into transportation infrastructure investment risk analysis*. A fuzzy logic approach for determining the timing of pavement MR&R treatments in a probabilistic LCCA model for selecting pavement MR&R strategies was developed to enhance the traditional probabilistic LCCA model. The novel approach uses performance curves and fuzzy-logic triggering models to determine the most effective timing of pavement MR&R activities.

- *Calibrate the decision-support model using numeric data*. A systematic method to calibrate the fuzzy-logic based rehabilitation decision model using real cases extracted from the Long Term Pavement Performance (LTPP) database was produced. By reinterpreting the model in the form of a neuro-fuzzy system, the calibration algorithm takes advantage of the learning capabilities of artificial neural networks for tuning the fuzzy membership functions and rules.

ORGANIZATION OF THE DISSERTATION

This dissertation follows a manuscript format which includes four manuscripts. Each manuscript is used as an individual chapter of the dissertation. They represent the main research work in which the author was involved at Virginia Tech during the duration of the doctoral studies. The first chapter of the dissertation is this introduction, which provides an outline for the rest of the document. The following four chapters consist of the manuscripts.

Chapter 2: *Soft Computing Applications in Infrastructure Management*. This paper, published in the Journal of Infrastructure Systems (vol. 10, no. 4), contains an extensive literature review on applications of soft computing techniques in infrastructure management. The paper highlights the advantages over traditional approaches and provides an overview of the soft computing techniques that hold the most promise to enhance the various infrastructure management processes. In particular, the review recommends the use of fuzzy stems for project selection.

Chapter 3: *Fuzzy Logic-based Life-Cycle Costs Analysis Model for Pavement and Asset Management*. This paper, published in the proceedings of 6th International Conference on Managing Pavements, presents the conceptual design of a fuzzy-logic-based decision-support model. The model consist of LCCA fuzzy system for project selection whose inference rules can be customized according to agency's management policies and expert opinion. The feasibility and practicality of the proposed model is illustrated by its implementation in a life-cycle cost analysis algorithm for comparing and selecting pavement maintenance, rehabilitation and reconstruction (MR&R) policies.

Chapter 4: *Fuzzy Logic Pavement Maintenance and Rehabilitation Triggering Approach for Probabilistic Life-Cycle Cost Analysis*. This paper, accepted for publication in the Journal of Transportation Research Board in 2007, explores the incorporation of the fuzzy-logic-based models into the risk analysis process to further enhance the traditional probabilistic LCCA method. The paper proposes a novel approach that uses performance curves and fuzzy-logic triggering models to determine the most effective timing of pavement MR&R activities. This paper also compares the proposed approach with the traditional threshold trigger model used in the deterministic and probabilistic LCCA methods. The application of the approach in a case study demonstrates that the fuzzy-logic-based risk analysis model for LCCA can effectively produce results that are at least comparable to those of the benchmark methods while effectively considering some of the ambiguous uncertainty inherent to the process.

Chapter 5: *Calibrating Fuzzy-Logic-based Rehabilitation Decision Models using LTPP Database*. The last paper presents a systematic method to calibrate the fuzzy-logic-based LCCA decision-support model proposed in Chapter 2. By reinterpreting the model in the form of a neuro-fuzzy system, the calibration algorithm takes advantage of the learning capabilities of artificial neural networks for tuning the fuzzy membership functions and rules. The steepest descent method and back-propagation learning are used to tune the model. The practicality of the methods is demonstrated by successfully training the treatment selection model to distinguish between rehabilitation (light overlay) and do-nothing rehabilitation cases extracted from LTPP database.

Finally, Chapter 6 summarizes the key findings and conclusions and provides recommendations for future research to further explore the potential of applying soft computing techniques in life-cycle cost analysis and other decision-support business functions in transportation infrastructure asset management.

RESULTS AND SIGNIFICANCE

The main outcome of this dissertation is a model for transportation infrastructure LCCA with the capability of evaluating risk and uncertainty realistically. The model can help decision-makers assessing alternatives for their relative advantages over each other and can be easily integrated into the asset management practices of transportation agencies.

The conducted research is significant because it produced an innovative application of fuzzy set theory for LCCA. This novel approach allows a better assessment of all uncertainties involved in the cost management of transportation assets. The developed models, algorithms, and tools are expected to support more realistic economic analyses than those achieved using traditional LCCA methods and thus, will support better asset management decisions.

Furthermore, if the proposed tools increase the efficiency of the decisions regarding the management our transportation systems, they could help provide more reliable transportation

systems at a lower cost.   This would eventually translate into enhanced mobility, lower

transportation cost, more economic growth, and better quality of life.

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CHAPTER 2: SOFT COMPUTING APPLICATIONS IN INFRASTRUCTURE MANAGEMENT

Soft Computing Applications in Infrastructure Management

By

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ABSTRACT: Infrastructure management decisions, such as condition assessment, performance prediction, needs analysis, prioritization, and optimization, are often based on data that is uncertain, ambiguous, and incomplete and incorporate engineering judgment and expert opinion. Soft computing techniques are particularly appropriate to support these types of decisions because these techniques are very efficient at handling imprecise, uncertain, ambiguous, incomplete, and subjective data. This paper presents a review of the application of soft computing techniques in infrastructure management. The three most used soft computing constituents, artificial neural networks, fuzzy systems, and genetic algorithms, are reviewed, and the most promising techniques for the different infrastructure management functions are identified. Based on the applications reviewed, it can be concluded that soft computing techniques provide appealing alternatives for supporting many of the infrastructure management functions. Although the soft computing constituents have several advantages when used individually, the development of practical and efficient intelligent tools is expected to require a synergistic integration of complementary techniques into hybrid models.

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INTRODUCTION

Infrastructure management is a very timely issue. On one hand, sound infrastructure systems play a vital role in encouraging a more productive and competitive national economy (GAO, 2000). On the other hand, increasing demands, shrinking financial and human resources, and increased infrastructure deterioration have made the task of maintaining our infrastructure more challenging than ever before.

Many of the nation's infrastructure systems are reaching the end of their service lives. Infrastructure systems have gradually deteriorated with age as a result of environmental action and use that, in many cases, significantly exceeds the design expectations. For example, in a recent survey conducted by the American Society of Civil Engineers (ASCE 2003), America's infrastructure, the nation's critically important foundation for economic prosperity, only received a cumulative grade of D+.

Under these circumstances, decision makers are faced with competing investment demands and must distribute limited resources so that the infrastructure systems are maintained in the best possible condition. Infrastructure management systems have emerged as tools to support these decisions, and as such, they may help bridge the gap between infrastructure condition and user expectations. Engineering management systems have been developed by local, state, and national agencies for a specific type of infrastructure (e.g., pavement and bridges) as well as for holistic management of many types of infrastructure assets, as discussed in the following section.

In many cases, infrastructure management decisions, such as condition assessment, performance prediction, needs analysis, prioritization, and optimization, are based on data that is uncertain, ambiguous and sometimes incomplete; furthermore, they incorporate engineering judgment and expert opinion. The uncertainty and ambiguity in the data has been addressed through optimization methods such as sensitivity analysis, stochastic programming, latent Markov decision process, and adaptive control. However, soft computing applications offer an appealing alternative because this emerging computational paradigm combines several problem-solving technologies that provide complementary reasoning and searching methods to solve real-word problems that involve imprecision, uncertainty, subjectivity, and partial truth. The main technologies included in the soft computing umbrella are artificial neural

networks, fuzzy logic and probabilistic reasoning (including genetic algorithms, evolutionary computing, and belief networks). The objective of this paper is to review applications of soft computing techniques in infrastructure management, highlighting the advantages over traditional approaches. It also provides a quick overview of the soft computing techniques that hold the most promise to enhance the infrastructure management process. Several references for each of the presented applications are provided.

INFRASTRUCTURE MANAGEMENT SYSTEMS

Public and private agencies have always tried to maintain their infrastructure assets in good and serviceable condition at a minimum cost, and thus they practiced infrastructure management. However, as most of the nation's infrastructure systems reached maturity and the demands started to rapidly increase in the mid-1960s, infrastructure agencies started to focus on a systems approach for infrastructure management. The process started with the development of pavement management systems (PMS), continued with bridge management systems (BMS) and infrastructure management systems, and has recently evolved into asset management.

One milestone in the development of engineering management systems is the concept of integrated infrastructure management systems. Hudson et al. (1997) defined an infrastructure management system as "the operational package that enables the systematic, coordinated planning and programming of investments or expenditure, design, construction, maintenance, rehabilitation, and renovation, operation, and in-service evaluation of physical facilities." The system includes methods, procedures, data, software, policies, and decision means necessary for providing and maintaining infrastructure at a level of service that is acceptable to the public or owners.

The evolution towards asset management follows the practice of the private sector. Industry leaders develop tailored asset management systems to monitor and assess the status and condition of their physical and financial assets (real estate, physical plants, inventories, and investments) both individually and collectively. Similarly, public sector officials responsible for the nation's infrastructure need tools that allow them to maintain, replace, and preserve the nation's infrastructure assets in the best possible

condition. This can be achieved effectively using asset management, a systematic process of maintaining, upgrading, and operating physical assets cost-effectively (FHWA 1999).

Asset management combines engineering principles with business practice and economic theory, and it has been proposed as a solution for balancing growing demands, aging infrastructure, and constrained resources in the transportation sector (FHWA 1999). The objectives of asset management include building and preserving facilities more cost effectively and with more satisfying performance, delivering the best value for the available resources to customers, and enhancing the accountability of the agencies (AASHTO 2002). As with all engineering management systems, efficient asset management (Figure 2.1) relies on accurate asset inventory, condition, and system performance information; considers the entire life-cycle cost of the asset; and combines engineering principles with economic methods, thus seeking economic efficiently and cost-effectiveness. The asset inventory, condition, and performance data is used to develop feasible alternatives based on the agency goals and policies, user expectations, and available resources. Alternative investments and funding scenarios are then evaluated to determine their impact on system performance and their compliance with current and future user expectations and agencies' financial constraints. Decision-makers use this information to prepare short and long-term plans that are more systematic, broader in scope, and more supportable by field data than those determined using traditional approaches. Once the plans are implemented, the performance results are monitored to verify the assumptions and predictions made at the planning stages (FHWA 1999).

In its broadest interpretation, asset management covers not only physical assets but also human resources, equipment and materials, and other items of value, such as information, computer systems, right-of-way, etc. A recent national study expanded the framework presented in Figure 2.1 and proposed an approach that focuses on the more strategic aspects of asset management as a philosophy, process, and resource allocation and utilization process (AASHTO 2002). This holistic approach concentrates on the relationships between the different asset management functions and stakeholders.
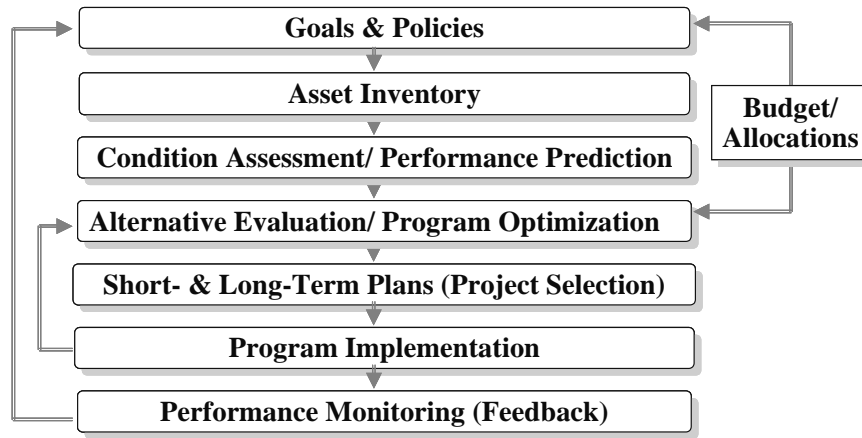
FIGURE 2.1 Generic Asset Management Framework

FUNCTIONAL FRAMEWORK FOR INFRASTRUCTURE ASSET MANAGEMENT

A general functional framework for an infrastructure asset management system is presented in Figure 2.2. This framework builds upon the scheme presented in Figure 2.1 and consists of modules (tools and methods) that can be used for various types of infrastructure assets, individually or holistically.
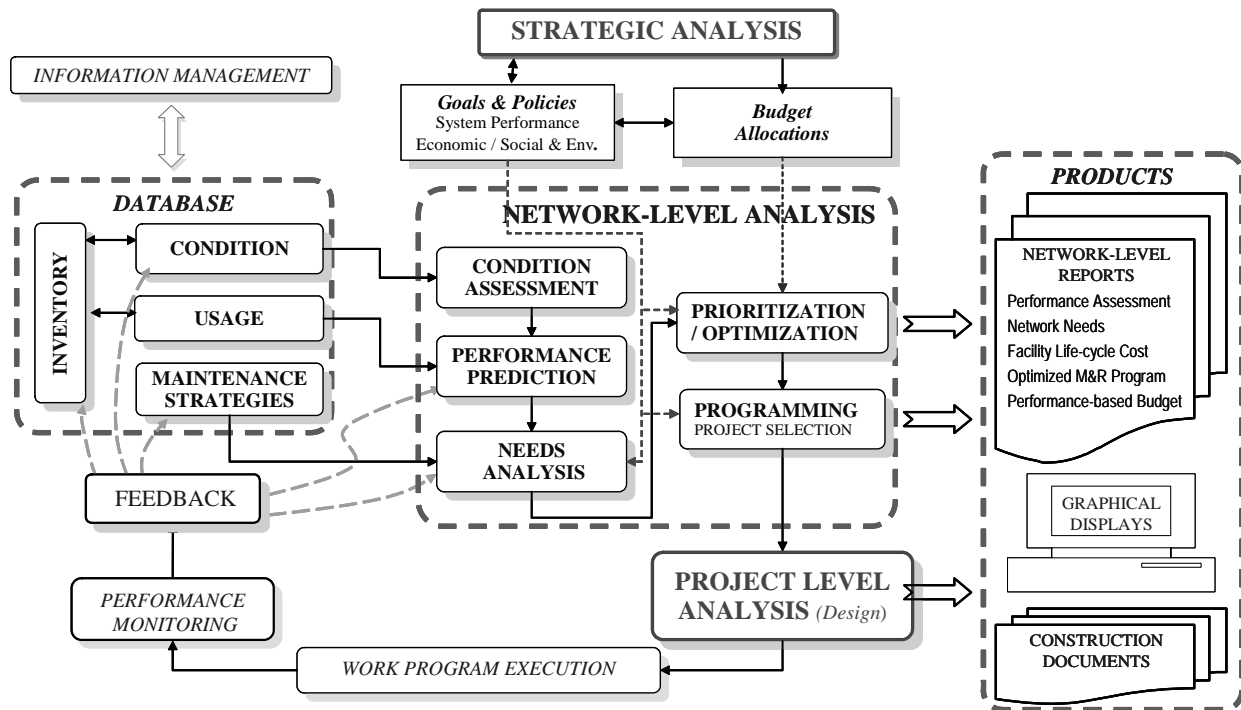
FIGURE 2.2 Intelligent Infrastructure Asset Management System Framework.

The foundation of the system is a database that includes asset inventory, condition, usage, and treatment information. The information is integrated and analyzed though a series of modular applications. Strategic decision-support tools allow the overall goals of system performance and the agency policies to be set by analyzing tradeoffs among competing infrastructure classes and programs.

Network- or program-level tools are used to evaluate and predict asset performance over time; to identify appropriate maintenance, rehabilitation, replacement, or expansion investment strategies for each asset; to evaluate the different alternatives; to prioritize or optimize the allocation of resources; and to generate plans, programs, and budgets. These tools produce reports and graphical displays tailored to different organizational levels of management and executive levels, as well as to the public.

Projects included in the work program are designed using project-level analysis tools. The infrastructure management cycle continues with the execution of the specified work. Changes in the infrastructure assets resulting from the work conducted, as well as from normal deterioration, are periodically monitored, preferably by means of nondestructive techniques, and input into the system.

Asset management require specialized tools for condition assessment, performance prediction, need analysis, project prioritization, and program optimization. This paper reviews how soft computing techniques can be used to develop some of these tools.

SOFT COMPUTING

Soft computing is an umbrella of computational techniques that tolerates imprecision, uncertainty, ambiguity, and partial truth. Soft computing includes three principal constituents: fuzzy mathematical programming, neural networks, and probabilistic reasoning –subsuming belief networks, genetic algorithms, chaotic programming, and parts of machine learning (Zadeh 1997 and 2001). Although the specific techniques included under the soft computing umbrella have evolved since the introduction of the term, the overarching concept has been the same: the integration of complementary reasoning techniques to develop systems that "tolerate imprecision, uncertainty, and partial truth to achieve tractability, robustness, and better rapport with reality" (Zadeh 1997).

There are several infrastructure asset management characteristics that make this approach particularly attractive for the use of soft computing techniques. These characteristics are described below:

1. Available information may be imprecise, uncertain, ambiguous, subjective (expert opinion) and incomplete (the amount of information available for different assets is highly variable). Although many infrastructure agencies are currently in the process of improving their data collection and management practices, existing databases often show many of the aforementioned limitations, and agencies have to make the most efficient use of these available data. Furthermore, while some relevant factors are easily quantifiable, other factors or performance objectives, such as environmental effects, comfort, aesthetics, versatility, and mobility considerations, may be better evaluated using subjective terms.

2. Infrastructure management decisions, such as needs analysis, often involve sophisticated inference rules and require a great deal of expert knowledge. For example, decisions about alternatives for correcting current infrastructure condition problems are more suitable to base on inference rules than on mathematical calculations. Furthermore, resource allocation tradeoffs often involve conflicting asset performance, economical objectives, and constraints.

3. The analysis at the network-level often considers large amount of assets as well as several feasible treatments, which can be applied at many different times along the life of the assets, creating difficult optimization problems. In the case of large networks, some traditional optimization approaches, such as integer programming, may be very time-consuming.

Because of these reasons, the infrastructure management field has been a fertile ground for the application of soft computing techniques as demonstrated by the many applications that have been reported in the literature. Both symbolic, production systems (rule-based) and connectionist or distributed (such as artificial neural networks) models have been used to assist with infrastructure management decisions. The first attempts concentrated on the application of rule-based expert systems, mostly for

project and treatment selection. Knowledge acquisition has been a significant obstacle in the development of these rule-based expert systems.

Many soft computing techniques (mainly artificial neural networks, fuzzy systems, and genetic algorithms) have been used in infrastructure management with various degrees of success. Flintsch (2003) presented a comprehensive review of the application of soft computing techniques in pavement management. Table 2.1 expands this list to include applications relevant to other infrastructure asset types. A brief description of the most often used soft computing techniques follows.

Artificial Neural Networks

Artificial neural networks are models structured upon the organization of a human brain that can learn if provided with a range of examples and that can produce valid answers from noisy data (Taylor 1995). Computational neural networks imitate, to a small extent, some of the operations perceived in biological neurons: they can be trained to assess an observed function when its shape is unknown. Neural networks are able to recognize without defining, which characterizes a highly intelligent behavior (Kosko 1992). This property enables these systems to make generalizations. The architecture of a neural network is characterized by a large number of simple neuron-like processing units interconnected by a large number of connections. The pattern of connectivity among the processing units and the strength of the connections encode the knowledge of a network. Their main weakness of this technology is that neural networks act as a "black box," and it is not possible to easily integrate prior (expert) knowledge or to extract the path followed to explain a solution. The main advantages of neural networks are their learning capabilities and their distributed architecture, which allows for highly parallel implementation. In addition, they have excellent pattern recognition capabilities, can make generalizations, and are particularly appropriate in those cases in which there is a significant amount of examples available.

Fuzzy Logic Systems

Fuzzy logic systems (Zadeh 1965 and 1973) are an extension of the traditional rule-based reasoning (expert systems), which incorporate imprecise, qualitative data in the decision-making process by

combining descriptive linguistic rules through fuzzy logic. The design of the fuzzy system requires the definition of a set of membership functions and a set of fuzzy rules. When various rules are activated, the binary rules that define conventional expert systems usually result in *discontinuities* at the exit of a system. This does not resemble human behavior, where a *smooth* relation usually exists between cause and consequence. Smooth relationships can be achieved by using fuzzy rules that include descriptive expressions, such as poor, fair, or good, to categorize linguistic input and output variables. Fuzzy logic was developed to provide soft algorithms for data processing that can both make inferences about imprecise data and use the data. It enables the variables to partially (up to a certain degree) belong to a particular set and, at the same time, makes use of the generalizations of conventional Boolean logic operators in data processing. Fuzzy systems are convenient to model expert opinions because they handle linguistic rules efficiently and are fault-tolerant regarding small changes in the input or system parameters. One of the limitations of fuzzy systems is that they do not have formal algorithms to learn from existing data. The main advantage of this approach is the possibility of introducing and using rules from experience, intuition, and heuristics, and the fact that a model of the process is not required. Fuzzy systems also provide functional transparency.

Genetic Algorithms

Genetic algorithms are some of the most common evolutionary computing techniques. The evolutionary models of computation also include evolutionary strategies, classifier systems, and evolutionary programming. Genetic algorithms represent search techniques based on the mechanics of natural selection used in solving complex combinatorial optimization problems. These algorithms were developed by analogy with Darwin's theory of evolution and the basic principle of "survival of the fittest." Significant contributions in the field of genetic algorithms were achieved by Holland (1975) and Goldberg (1989). The search is run in parallel from a population of solutions. New generations of solutions are generated through reproduction, crossover, and mutation until a pre-specified stopping condition is satisfied. The main advantage of this approach is that, in many cases, it is very efficient in

producing "good" solutions for difficult combinatorial optimization problems. However, as with any heuristic, genetic algorithms may not find the *true* optimum solution.

Hybrid Systems

Although the soft computing constituents have several advantages when used individually, the development of a practical and efficient system often requires a synergistic integration of the complementary members into hybrid systems (Zadeh 2001). For example, while assessing the feasibility of using fuzzy technologies for life-cycle cost analysis for complex weapon design, Senglaub and Bahill (1995) concluded that the technique had potential only in a hybridized environment--not as a stand alone solution. A combined hybrid system makes it possible to "achieve tractability, robustness, low solution cost, and better rapport with reality" (Zadeh 1997). The full potential of soft computing techniques resides in the development of truly "intelligent" decision-support tools. Hybrid soft computing architectures can cleverly combine several techniques that add to their capabilities and benefits. Fuzzy logic provides a methodology for approximate reasoning and for computing with words; neural networks are efficient for curve fitting learning and system identification; genetic algorithms are efficient random search and optimization heuristics. The combined tools may handle uncertain, subjective, incomplete, and/or ambiguous information; generate knowledge by learning from examples and/or experts; and improve their performance as they are used.

SOFT COMPUTING APPLICATIONS IN INFRASTRUCTURE MANAGEMENT

Soft computing has been used to enhance several asset management functions, as discussed in the many references listed in Table 2.1. Some of the most significant implemented and potential infrastructure management applications are discussed in the following sections.

TABLE 2.1 Summary of AI and Soft Computing Applications in Infrastructure Management.

Technology (1)	Reference (2)	Asset Performance		Needs Analysis		Tradeoff Analysis	
		Condition Asses. (3)	Perform. Prediction (4)	Project Selection (5)	Treatment Selection (6)	Prioriti-zation (7)	Optimi-zation (8)
Artificial Neural Networks	Pant et al. (1993)	✓					
	Kaseko & Ritchie (1993)	✓					
	Hajek & Hurdal (1993)				✓		
	Fwa & Chan (1993)					✓	
	Eldin & Senouci (1995)	✓					
	Flintsch et al. (1996)			✓			
	Razaqpur et al. (1996)						✓
	Cattan & Mohammadi (1997)	✓					
	Huang & Moore (1997)		✓				
	Alsugair & Al-Qudrah (1998)				✓		
	La Torre et al. (1998)		✓				
	Owusu-Ababia (1998)		✓				
	Shekharan (1998)		✓				
	Wang et al. (1998)	✓					
	Van der Gryp et al. (1998)	✓					
	Martinelli & Shoukry (2000)	✓					
	Lou et al. (2001)		✓				
	Farias et al. (2003)		✓				
	Felker et al. (2003)		✓				
	Fontul et al. (2003)	✓					
	Lee & Lee (2004)	✓					
	Lin et al. (2003)	✓					
	Sadek et al. (2003)	✓					
	Yang et al. (2003)		✓				
Fuzzy Logic Systems	Elton & Juang (1988)	✓					
	Zhang et al. (1993)	✓					
	Grivas & Shen (1995)				✓		
	Prechaverakul & Hadipriono (1995)	✓			✓		
	Shoukry et al. (1997)	✓					
	Wang & Liu (1997)						✓
	Fwa & Shanmugam (1998)	✓					
	Cheng et al. (1999)	✓					
	Saitoh & Fukuda (2000)						✓
	Bandara & Gunaratne (2001)	✓	✓			✓	
Genetic Algorithms	Fwa et al. (1996)						✓
	Liu et al. (1997)						✓
	Pilson et al. (1999)						✓
	Shekharan (2000)		✓				
	Miyamoto et al. (2000)						✓
	Chan et al. (2001)					✓	✓
	Hedfi & Stephanos (2001)		✓				
	Ferreira et al. (2002)						✓
Other Hybrid Systems	Ritchie et al. (1991)	✓					
	Chou et al. (1995)	✓					
	Taha & Hanna (1995)				✓		
	Martinelli et al. (1995)	✓					
	Abdelrahim & George (2000)		✓				
	Chiang et al. (2000)	✓					
	Chae & Abraham (2001)	✓					
	Liang et al. (2001)	✓					
	Flintsch (2002)				✓		

Condition Assessment

Condition assessment and performance prediction are two key functions for most Infrastructure Management Systems. These two areas have received significant attention over the last two decades. Most infrastructure management systems include a module that analyzes the condition of the assets and reduces this condition into one or more indices that reflect the overall structural and/or functional condition of the assets.

Generally, condition indices are based on parameters of different natures. Soft computing techniques are particularly appropriate in such cases because they can estimate functions from samples without requiring a mathematical formulation of the dependence of output on input values. Backpropagation neural networks (Pant et al. 1993, Eldin and Senouci 1995, Van der Gryp et al. 1998) and fuzzy systems (Elton and Juang 1988, Zhang et al. 1993, Shoukry et al. 1997, Fwa and Shanmugam 1998, Bandara & Gunaratne 2001) have been used to combine different pavement condition indicators into a condition index or pavement rating assignment.

Furthermore, a combination of neural and fuzzy systems, or neuro-fuzzy models (Nauck et al. 1997), can add the advantages of both techniques. They can be easily trained and have known properties of convergence and stability, as do neural networks, and they can provide a certain amount of functional transparency through the rule dependency, which is important to understand the problem's solution. An example is presented in Figure 2.3. The model depicted has the typical structure of a multilayer neural network, but the weights are modeled as fuzzy sets and the activation, output, and propagation functions implement a conventional fuzzy inference path. Training is conducted using supervised learning, as in multi-layer neural networks. In the example, each input unit, ξ_i, represents a numerical input (e.g., pavement condition parameter). The connections between layer 1 and 2, μ_i, represent a fuzzy number associated with a linguistic term that quantifies the magnitude of a particular input parameter, ξ_i, in a particular rule, R_j, (for example, "very low" or "average"). One difference from neural networks is that some fuzzy connections (μ_i and ν_i) are associated with the same linguistic terms. These connections are

linked connections and, thus, must be represented by the same fuzzy set (they must be changed simultaneously). The connections between layers 2 and 3 represent linguistic terms that describe the level of association between a fuzzy rule, R_j, and a particular output, η_k. For example, the rule highlighted in Figure 2.3 could be the folowing:

> **IF** *cracking* (ξ_1) is *very low* (μ_1) and *rutting* (ξ_2) is *very low* (μ_1)

> **THEN** *most probably* (ν_1) the *pavement condition index* would be *excellent* (η_1).
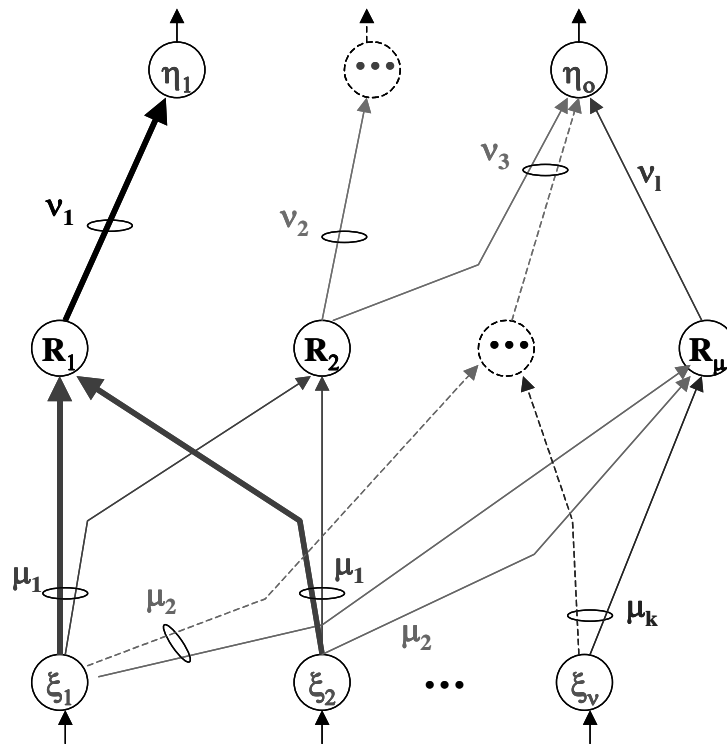
FIGURE 2.3 Example of Neuro-Fuzzy System.

The original structure of the system is based on past experience and knowledge of the process, but the network architecture can be further refined using training with examples (from existing databases) relating the various distresses with the overall condition index in order to learn the criteria applied in the past. During training, the system adjusts the membership functions associated with the fuzzy connection until the compound error between the target and actual output (at the output layer) falls below a tolerance value, or until the number of training epochs exceeds a user-defined maximum threshold.

Another interesting condition assessment aspect that has received significant contribution from the use of soft computing technologies is the automatic distress identification. Neural (Kaseko and Ritchie 1993, Wang et al. 1998), fuzzy (Cheng et al. 1999), and hybrid systems (Ritchie et al. 1991, Chou et al. 1995) have been used for detecting and classifying distresses from visual images. An application of a neural network to classify individual ultrasonic signals obtained from a range of defective and non-defective concrete specimens has been proven to be reasonably accurate (Martinelli and Shoukry 2000).

Performance Prediction

Prediction of the future condition of assets based on the present condition, characteristics of and around the asset, and forecasted use is necessary for all decision making levels. The most common traditional approaches for performance prediction are regression analysis and Markov chains. Other approaches include empirical-mechanistic, mechanistic, survivor curves, semi-Markov, and Bayesian models (AASHTO 2001). Neural networks and other soft computing techniques are increasingly` used instead of the traditional regression methods because this process involves significant subjectivity and uncertainty. Neural models have been used for predicting pavement roughness (Huang and Moore 1997; La Torre et al. 1998), cracking development (Owusu-Ababia 1998, Lou et al. 2001), and the pavement Present Serviceability Rating (Sherkharan 1998). A fuzzy Markov model was formulated that based pavement condition prediction on subjective assessments of the pavement deterioration rates (Bandara and Gunaratne 2001). Genetic algorithms have also been used to develop several pavement deterioration models (Shekharan 2000) and to combine expert knowledge and performance data for the development of transition provability matrices (Hedfi and Stephanos 2001).

Need Analysis

The identification of assets in need of maintenance, rehabilitation, replacement, or improvement, as well as appropriate strategies for these assets, is a critical asset management function that involves a great deal of knowledge about the condition of the assets, the effectiveness of the corrective strategies, and the impact of the action on the system performance. The timing and type of works should be based

on the level of service that the agencies want to provide to their customers, the using public. Decision trees are commonly used for the identification of assets in need of attention and feasible strategies. Trigger values are established for various functional and structural condition parameters (AASHTO 2001). Significant improvements could be obtained if the system could *learn* and adapt these decision trees based on the adopted actions' actual effect on the infrastructure system's performance. Thus, neural networks and fuzzy systems have been considered for enhancing or replacing the traditional decision trees, as depicted by some of the examples discussed below.

Early on, the performance of rule-based expert systems was compared with artificial neural networks for selecting sections for crack routing and sealing (Hajek and Hurda 1993). It was concluded that the two techniques exhibited complementary strengths; thus, it was recommended that these techniques be combined into a hybrid system. A case study was reported in which a fuzzy logic system was developed for selecting pavement maintenance and rehabilitation (M&R) treatments (Grivas and Shen 1995). The system also provided the degree of confidence (certainty) in the proposed treatment. A fuzzy logic, multi-objective, decision-making model has been used for selecting an M&R treatment from a set of feasible treatments prepared using a rule-based expert system (Prechaverakul and Hadipriono 1995). Similarly, neural network have been used for selecting candidate pavement rehabilitation projects (Flintsch et al. 1996), and for recommending appropriate pavement M&R treatments based on pavement distress (Alsugair and Al-Qudrah 1998). Genetic adaptive neural networks have been used for selecting "optimum" M&R strategies (Taha and Hanna 1995, Abdelrahim and George 2000). An adaptive neuro-fuzzy model, which allows for the combination of expert knowledge with knowledge acquired from examples, has recently been proposed for pavement treatment selection (Flintsch 2002).

Prioritization

Since the M&R needs identified usually exceed the available resources, infrastructure decision-makers often must evaluate different investment alternatives and prioritize or optimize the allocation of resources in accordance with user-provided criteria, performance requirements, and budget allocations. Many

agencies use simple ranking systems for the prioritization of the competing investment options, while other agencies have already adopted life-cycle cost analysis approaches.

Typical project prioritization decisions entail evaluating a set of alternatives in terms of a set of decision criteria (goals, attributes). The decision-maker has to select alternatives from a set of known decision alternatives. The alternatives are screened, prioritized, and eventually ranked. Attributes represent the different angles from which every alternative can be viewed and studied, and very often, attributes conflict with each other. For example, a maintenance strategy may maximize the asset performance, but it may also have the highest cost. Therefore, a Multi-Attribute Decision Making method is often necessary to weigh the importance assigned to every attribute.

Reported soft computing-based prioritization schemes include the uses of neural networks for prioritization (Fwa and Chan 1993) and a ranking scheme based on analysis of fuzzy condition indexes (Bandara and Gunaratne 2001). A combined multi-attribute decision-making method, which can handle deterministic, stochastic, and fuzzy attributes provides an appealing alternative to include subjective *linguistic* evaluations of the relative contribution to each alternative to achieve a particular goal, uncertain numerical data, and possibly conflicting objectives.

Optimization

Many infrastructure management agencies conduct mathematical optimization to generate programs and budgets consistent with their performance goals and financial constrains. Linear programming is the most commonly used technique. Nonlinear, integer, and dynamic programming, as well as heuristic techniques, have also been used (Zimmerman 1995).

The most common linear programming formulations allow determining for the length or percentage of the network that should receive each of the various treatments considered to be determined in order to maximize or minimize an utility function (e.g. minimize total costs) while satisfying a set of budgetary and system performance constraints. One problem associated with this approach is that, in general, the optimization does not provide information for selecting specific rehabilitation projects. On the other hand, integer programming formulations allow all infrastructure assets and feasible treatments to

be considered, but for large networks, the solution space becomes so large that it is difficult to search utilizing traditional optimization techniques. Genetic algorithms are heuristics, which are particularly efficient for finding optimum –or near-optimum– solutions in large solution spaces, whose size is beyond the capability of mathematical optimization techniques. This technique has been used for pavement management project-level analysis (Pilson et al. 1999), network-level pavement maintenance and rehabilitation programming (Fwa et al. 1996, Ferreira at al. 2002), bridge deck rehabilitation projects selection (Liu et al. 1997), and bridge maintenance optimization (Miyamoto et al. 2000).

Fuzzy optimization techniques have been proposed as an alternative for dealing with imprecise or incomplete input data in the optimization process. These techniques are able to resolve linear or dynamic programming problems when some of the parameters in the model are fuzzy numbers. Depending on the nature of fuzziness, fuzzy numbers can represent coefficients in an objective function and/or set of constraints. Fuzziness might also appear in the formulation of the constraints (the requirement that quantity x is "approximately less than"). This approach may also help solve the perceived problem with strict mathematical optimization formulations, in which the solution, in some cases, may be too sensitive to small changes in the constraining parameters. Under certain conditions, small changes in the budget allocation can result in significant changes in the optimized work program. A network optimization procedure that utilizes a fuzzy objective function has been proposed by Wang and Liu (1997).

IMPLEMENTATION ISSUES

There are many potential advantages for using soft computing to support infrastructure asset management processes. However, the most appropriate techniques for supporting each function will ultimately depend on the particular conditions of the infrastructure management decision being considered. The soft computing techniques that may be considered as alternatives for the various infrastructure management functions discussed in this paper are summarized in Table 2.2.

TABLE 2.2 Soft Computing Techniques and Their Applicability for Asset Management.

Technique (1)	Condition Assessment (2)	Performance Prediction (3)	Need Analysis (4)	Prioriti-zation (5)	Optimi-zation (6)
Artificial Neural Networks	✓	✓	✓		
Fuzzy Logic Systems (type-I and II)	✓	✓	✓		
Fuzzy Mathematical Programming					✓
Fuzzy Multi-Attribute Decision Making			✓	✓	
Genetic Algorithms					✓
Neuro-Fuzzy Systems	✓	✓	✓		

Although the reviewed applications consists mostly of research efforts rather than implementation projects, these should not lead one to the conclusion that practical benefits from these emerging technologies are still far away. Soft computing has already found its way into mainstream infrastructure management, as it has (almost unnoticed) become part of our daily life. For example, fuzzy logic systems are used to improve image quality in digital camcorders, and artificial neural networks predict stock prices and detect credit card fraud. In addition, in the infrastructure management field, artificial neural networks are an integral part of the new concrete pavement 2002 AASHTO design procedure; fuzzy systems are often used for condition evaluation, and genetic algorithms are used for resource allocation optimization.

However, some agencies and transportation practitioners still have reservations about implementing such techniques. These reservations are usually the result of one or more of the following: resistance to change, difficulty in integrating the principles and techniques with existing practices and legacy systems, lack of understanding of some techniques, lack of quantitative evidence supporting the benefits of using the technologies, and lack of data to develop reliable models. Therefore, a wide implementation of soft computing would require the following: (i) top management commitment; (ii) a comprehensive education effort to promote an understanding of the principles and algorithms used; (iii) a

clear quantification of the benefits of adopting the emerging decision-support technologies; and (iv) tools that are user-friendly and compatible with existing asset management tools and agency practices.

Summary and Conclusions

Infrastructure management decisions, such as condition assessment, performance prediction, need analysis, prioritization, and optimization, are often based on data that is uncertain, ambiguous, and incomplete; furthermore, these decisions incorporate engineering judgment and expert opinion. Soft computing tools are particularly appropriate for supporting these types of decisions. A general modular framework for an Infrastructure Management System, considering its relationship with asset management and the different levels of decision-making, was identified. The most promising techniques for the different infrastructure management functions include the following:

- Neural, fuzzy, and neuro-fuzzy models appear to have potential for enhancing condition assessment and performance prediction. Adaptive hybrid soft computing applications, which are able to acquire knowledge, could be used to develop infrastructure condition assessment and performance models that are updated automatically as part of the feedback process.

- Models that allow for the combination of expert knowledge with knowledge acquired from examples (numerical data) are appropriate for project and treatment selection, and prioritization. Neural networks, fuzzy systems, and a combination thereof have been used with successful outcomes in most of the cases.

- Genetic algorithms, fuzzy mathematical programming, and advanced hybrid systems provide appealing alternatives to the traditional optimization procedures.

Although the soft computing constituents have several advantages when used individually, the development of practical and efficient *intelligent* tools is expected to require a synergistic integration of the complementary members into hybrid systems.

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CHAPTER 3: FUZZY LOGIC-BASED LIFE-CYCLE COSTS ANALYSIS MODEL FOR PAVEMENT AND ASSET MANAGEMENT

Fuzzy Logic-Based Life-Cycle Costs Analysis Model for Pavement and Asset Management

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ABSTRACT: Life cycle cost analysis (LCCA) is a key component in the pavement management process. LCCA is used extensively to support project level decisions, and it has started to be used as a network level analysis tool. Both deterministic and probabilistic LCCA approaches have been used by transportation agencies. Probabilistic methods allow decision makers to evaluate the risk of an investment utilizing uncertain input variables, assumptions, or estimates. However, if the uncertainty in the input is of an ambiguous rather than random nature, soft computing applications can be more appropriate than the probabilistic methods. This paper explores the development of enhanced pavement LCCA tools using soft computing techniques. A fuzzy logic-based algorithm for LCCA (considering only agency costs) is presented. The algorithm for the project selection is a rule-based fuzzy logic system in which the user can define rules to reflect the agency policies and strategies. This algorithm is part of a proposed generic framework, which includes user costs, uses of other soft computing techniques, and handles other types of infrastructure assets.

INTRODUCTION

Coupled with increased pavement deterioration, increasing demands, as well as shrinking financial and human resources, have made the task of maintaining existing pavement networks more challenging than ever before. Highway systems have gradually deteriorated due to environmental wear and general use that, in many cases, significantly exceeded the design expectations. This has resulted in a decrease in the level of service provided to the public. In the United States (U.S.) this decrease has been clearly manifested in a recent survey conducted by the American Society of Civil Engineers (ASCE 2003). According to this survey, one third of U.S. roads are in poor or mediocre condition, and road conditions contribute to as many as 13,800 highway fatalities annually.

Pavement management systems (PMS) have proven successful in closing the gap between pavement condition and user expectations. For this reason, PMS have been widely used by highway agencies. Furthermore, transportation agencies are integrating PMS with other highway management systems and embracing an asset management philosophy. Asset management combines engineering principles with business practice and economic theory, serving as today's best approach for balancing growing demands, aging infrastructure, and constrained resources (FHWA 1999; OECD 2001). This management philosophy requires the use of objective performance-oriented tools, such as engineering economic analysis, to select projects and to evaluate the consequences of different budget and performance scenarios. Pavement Management Systems are a key component of transportation asset management and have provided the framework for their development. A general functional framework for a PMS, considering its relationship with asset management and the different levels of decision-making, is presented in Figure 3.1 (Flintsch 2003a).

Life-cycle cost analysis (LCCA) is an economic analysis tool that is increasingly being used to support pavement and asset management decisions. This technique relies on estimates of future of pavement performance, maintenance and rehabilitation actions, and user cost. Since these estimates are

often based upon uncertain, ambiguous (different solutions for the same set of data), subjective, and sometimes incomplete information, soft computing techniques emerge as a very appealing alternative for developing LCCA tools. Soft computing encompasses computational techniques that tolerate imprecision, uncertainty, and ambiguity. In particular, fuzzy logic systems provide a formal approach for the treatment of these types of information. This paper evaluates the feasibility of developing enhanced soft computing-based life-cycle cost analysis (LCCA) tools. The paper also provides a brief overview of fuzzy logic systems concepts and proposes a generic framework for their use along with other soft computing techniques for supporting the development of robust and efficient tools for economic analysis of pavement maintenance, rehabilitation and rehabilitation (MR&R) projects.
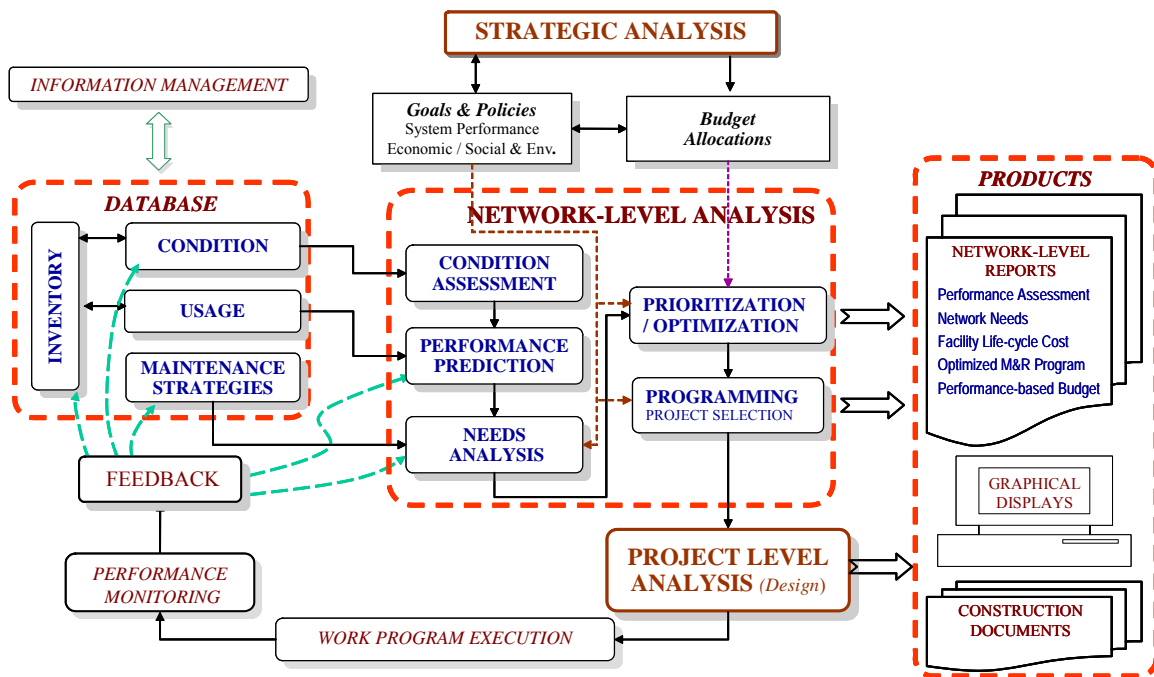
FIGURE 3.1. Pavement management system framework (Flintsch, 2003a).

ENGINEERING ECONOMIC ANALYSIS

Engineering economic analysis encompasses a collection of techniques that can be used to select, evaluate, recommend, and prioritize investment options according to their level of economic efficiency. Tools such as life-cycle cost analysis (LCCA), benefit cost analysis (BCA), risk analysis, and impact

analysis can be used to either identify possible alternatives to achieve performance objectives at the lowest long-term cost or to provide maximum benefits for a given investment level. Economic analysis is a critical component of a comprehensive project evaluation methodology, since it can identify, quantify, and value the economic benefits and costs of the projects for a multiyear period (FHWA 2003).

Life-cycle cost analysis is a decision-support tool commonly used to account for all costs associated with a certain investment. For pavement projects, LCCA includes costs for construction, operation, maintenance, and disposal, and it also includes both user and nonuser (agency) costs. LCCA includes the following activities: (1) developing alternatives to accomplish the objectives of a project, (2) determining the schedule of initial and future activities necessary for each alternative, (3) estimating the costs associated with these activities (or expenditure streams), (4) discounting and adding these costs to compute the total life-cycle costs, and (5) evaluating the results (FHWA 2002). Life-cycle cost analysis can play an important role in pavement management, supporting alternative evaluation, project selection, and budget allocation. The Federal Highway Administration (FHWA) has encouraged and in some cases mandated the use of LCCA in analyzing all major investment decisions (FHWA 1998).

The successful implementation of LCCA is affected by several technical issues (FHWA 1999): selecting an appropriate discount rate, quantifying non-agency costs such as user costs, securing creditable supporting data, including traffic data, projecting costs and travel demand throughout the analysis period, estimating salvage value and useful life, estimating maintenance costs and effectiveness, and modeling asset deterioration.

Before conducting an LCCA, the analyst must define the general parameters, such as analysis period and discount rate. The analysis period should be long enough to reflect the performance difference among alternative projects. The FHWA (1998) recommends an analysis period of at least 35 years, but some Departments of Transportation (DOTs) require a longer analysis period (e.g., 50 years in Virginia). Walls and Smith (1998) and Kirk and Dell'Isola (1995) recommend the use of real discount rates and real dollars. In the United States, the Office of Management and Budget (OMB) annually publishes the discount rate for economic analysis in Appendix C of its Circular A-94.

Once the analysis period is determined, the following five categories of costs should be evaluated and calculated for the project's life-cycle (NCHRP 2001):

- Agency Costs (construction, rehabilitation, maintenance, salvage return, engineering and administration, and investment)

- Vehicle Operating Costs (gas, tires, vehicle maintenance, depreciation, etc.)

- Travel Time Costs (dollar value of time spent on the roadway)

- Accident Costs

- Environmental Costs

Agency costs are those associated with the design, construction, and maintenance of the facilities. For many agencies, existing management systems provide pavement condition and usage information, as well as pavement deterioration models and appropriate maintenance and rehabilitation options and costs. The other four categories of costs are associated with the use of the facility. Many agencies in the U.S. only consider project costs in their LCCA procedures because of the difficulties associated with the quantification of user costs. However, user cost can account for up to 95% of the total highway transportation cost and should not be ignored. Several models for estimating direct user costs as a function of pavement condition and user delay costs as a function of lane closure practices have been proposed (Memmott et al. 1999; Kerali 1999; Pappagiannakis and Delwar 2001; Walls and Smith 1998). However, since the uncertainty in these costs is usually very high and their estimation requires a large amount of information that it is not always available, the use of soft computing tools, which are effective for handling uncertain, subjective, and incomplete data, may help incorporate these user costs into the LCCA process.

Currently, there are two main LCCA approaches used by local and state agencies: deterministic and probabilistic. Deterministic methods are relatively easier to implement, but they cannot evaluate the risk emerging from the uncertainty associated with future events.

In the deterministic methods, all input variables (costs) are assumed to be known and given a single, fixed value. The primary formula used to calculate the total present worth over the life-cycle of the facility under investigation is the following:

$$LCC = InitialCost + \sum_{k=1}^{n} FutureCost_{(k)} \times \left[\frac{1}{(1+i)^k}\right] \qquad (1)$$

where,

LCC = total present worth of life-cycle costs

InitialCost = project costs in the first year

FutureCost$_{(k)}$ = project costs in year k

K = year

N = analysis period

I = discount rate

The uncertainty in the physical and economic aspects considered in the engineering economic analysis has been addressed by adopting probabilistic (risk analysis) approaches. Probabilistic LCCA methods allow for consideration of the variability associated with the different costs incurred over the life-cycle of the pavement or facility studied. However, it is relatively difficult to collect all of the information that is needed for applying this approach.

In a probabilistic model, each variable is given an associated probability distribution function (PDF). Probabilistic LCCA tools conduct a simulation (typically using Monte Carlo simulation) to sample the input and generate a PDF for the different economic indicators considered in the analysis. Walls and Smith (1998) proposed a probabilistic methodology for pavement LCCA, which used Monte Carlo simulation and risk analysis Excel Add-in tools. StratBencost (NCHRP 2001) uses a similar approach and provides default median and ranges for all variables relevant to the user costs.

The main advantage of the probabilistic approach is that it allows decision makers to evaluate the risk of an investment due to uncertain input variables, assumptions, or estimates (FHWA 1998). The probabilistic approach implicitly assumes that the uncertainty is of random nature and that it can be

modeled using a PDF. If the uncertainty in the input is of an *ambiguous* nature, soft computing applications may provide a better alternative than the probabilistic approach.

SOFT COMPUTING APPLICATIONS FOR PAVEMENT MANAGEMENT

Soft computing is an umbrella of computational techniques that handles both subjective and numerical information, and it also tolerates imprecision, uncertainty, and ambiguity. Soft computing includes three principal constituents: neural networks, fuzzy mathematical programming, and evolutionary computing (including genetic algorithms). Minor components include probabilistic programming, chaotic programming, and machine learning, among others (Zadeh 1997).

Table 3.1 presents a summary of the main advantages for these soft computing techniques. However, each soft computing constituent has its own limitations to develop a practical and efficient system. Artificial Neural Networks always require reliable training pattern information which is often difficult to obtain. And it won't perform well when the inputs are out of the range of the training set. Fuzzy Logic Systems need carefully defined membership functions and inference rules. Expert opinions are one of the major sources to design the fuzzy system, but inevitably, subjective bias would be included in the system. Evolutionary computing could produce "good" solutions but can not guarantee the solutions are true optimum. These limitations could be offset to some extent by using hybrid systems (Zadeh 2001). Obviously, more efforts are needed to develop and implement such a system.

Soft computing techniques have proven effective for pavement and infrastructure management applications because they allow for the handling and processing of subjective and ambiguous information, as well as incomplete data sets. Many soft computing techniques, artificial neural networks, fuzzy systems, and genetic algorithms, have been used in infrastructure management with various degrees of success (Flintsch 2003b).

TABLE 3.1. Advantages of the main soft computing techniques (after Flintsch 2003a).

Technique	Main characteristics
Artificial Neural Networks	Excellent pattern recognition capabilities. Can be trained to save, recognize, and search the shapes or elements of databases, solve combinatorial optimization problems, recognize without definitions, and make generalizations.
Fuzzy Logic Systems	Possibility of introducing and using subjective information (including rules from experience, intuition, and heuristics) and providing functional transparency. Type-2 Fuzzy Logic Systems are also capable of handling uncertainty.
Evolutionary Computation	Can produce "good" solutions for difficult combinatorial optimization problems, can tune Fuzzy Logic Systems, and can be used in the Neural Networks training process.
Hybrid Systems	Synergistically integrate complementary members to combine their advantages and allow achieving tractability, robustness, low solution cost, and better rapport with reality.

Utilizing Soft Computing for Engineering Economic Analysis

Soft computing techniques were selected for the development of robust and flexible engineering economic analysis procedures and tools for the following reasons:

1. Available information may be uncertain, ambiguous, and incomplete (information availability for different pavement projects is highly variable).

2. Both objective (numerical) and subjective (linguistic) information may be available and should be considered in the analysis. While some relevant factors are easily quantifiable in economic (monetary) terms, other factors, such as environmental effects, comfort, aesthetics, versatility, and mobility considerations, may be better evaluated using subjective terms.

3. Economic analysis of pavement projects often requires a great deal of expert knowledge, and the resource allocation tradeoffs that LCCA supports often involve conflicting asset performance and economical objectives and constraints.

Soft-computed based LCCA applications have already been developed for other constructed facilities and objects. For example, Furuta *et al.* (1998) used genetic algorithms for highway bridge deck

network-level LCCA *optimization*. Usher and Whifield (1993) used fuzzy theory for evaluating and selecting used-systems by means of life cycle cost. Their study provided a method for determining the equivalent uniform annual cost (EUAC) of a used-system through linguistic evaluation of its components using of fuzzy set theory.

Fuzzy Logic Systems

The LCCA model presented in this paper uses fuzzy logic to estimate future pavement maintenance and rehabilitation costs. Fuzzy logic systems are an extension of the traditional rule-based reasoning (expert systems), which incorporate imprecise, qualitative data in the decision-making process by combining descriptive linguistic rules through fuzzy logic (Zadeh 1973). The design of the fuzzy system requires the definition of a set of membership functions (which enable the system to handle uncertainty), and a set of rules. Smooth relationships can be achieved by using descriptive expressions, such as poor, fair, or good (Figure 3.2), to categorize linguistic input and output variables. Fuzzy logic was developed to provide soft algorithms for data processing that can both make inferences about imprecise data and use the data. It enables the variables to partially belong to a particular set, and at the same time, it makes use of the generalizations of conventional Boolean logic operators in data processing.

Fuzzy logic systems use fuzzy sets. While a traditional crisp set only allows its members' membership function to take values of one or zero (either belongs to the set or not, respectively), members of a fuzzy set can have a membership function in the interval [0, 1]. As a result, a member can belong to a fuzzy set with a certain degree of membership between zero and one.

A rule-based fuzzy logic system is composed by four parts (Zadeh, 2001): a rule base, an input processor (fuzzifier), an inference engine, and an output processor (defuzzifier). The rules of the fuzzy logic system store the *knowledge* of the system. The rules can be provided by experts, extracted from collected cases or examples, or derived from a combination of both. The rules in fuzzy logic systems are often expressed in the form of IF-THEN statements. The input and output processors provide mappings between crisp numbers or verbal statements and fuzzy sets. The inference engine handles the application of pertinent rules.
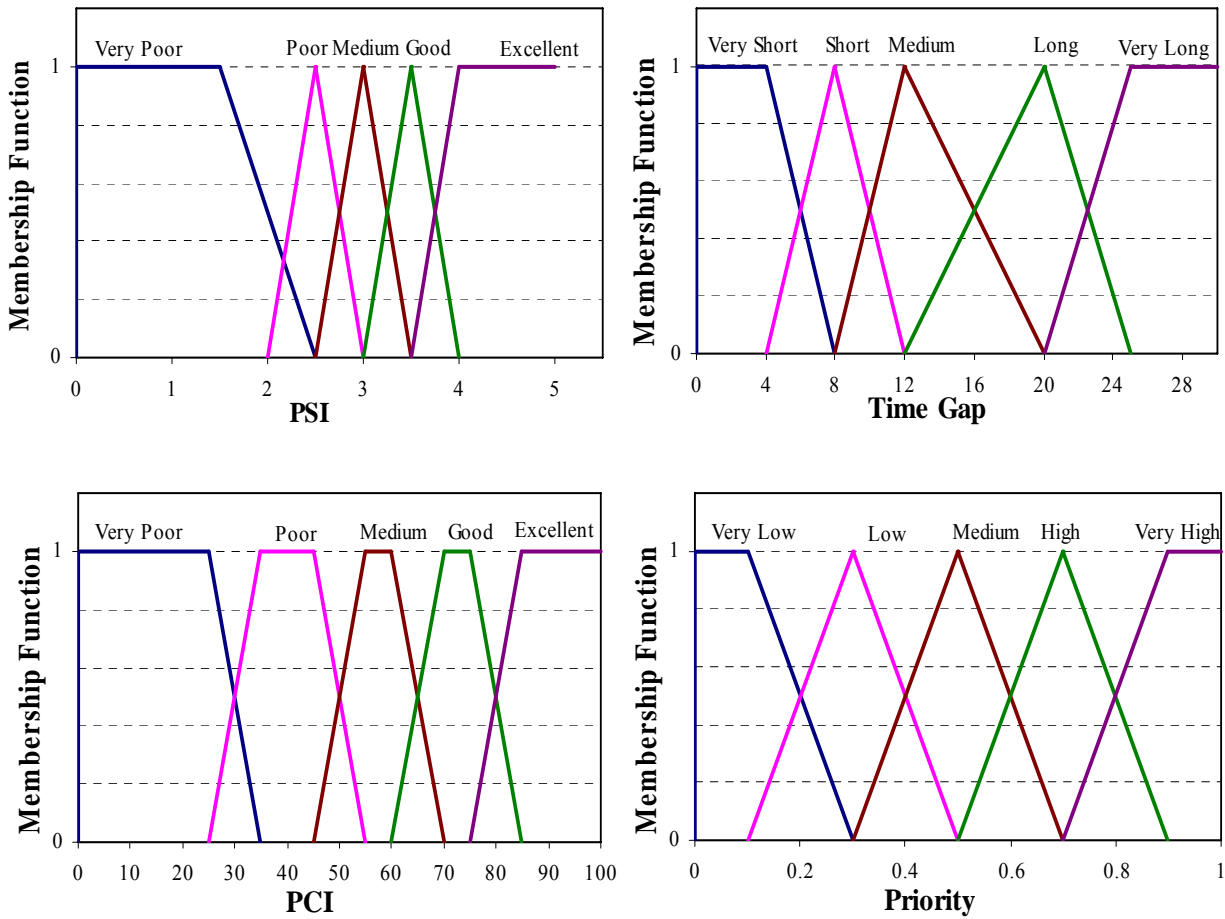
FIGURE 3.2. Membership functions for the various pavement variables considered.

The selection of membership functions, rules, and inference engines depends upon the information available and the condition of each individual case. In general, manually building a fuzzy logic system is difficult and time consuming. Neuro-fuzzy systems have been recommended for extracting rules from existing data. These hybrid soft computing tools take advantage of the learning algorithms used in artificial neural networks (Nauck et al., 1997; Flintsch, 2002).

FUZZY LOGIC-BASED LCCA ALGORITHM

As mentioned, the determination of all the cost incurred through the life-cycle of a facility is by nature uncertain and often requires significant subjective judgment and expert knowledge Thus, a fuzzy logic

approach emerges as an appealing alternative for developing robust LCCA tools. This section presents a simple fuzzy logic-based LCCA model developed to test this hypothesis.

Agency Costs Model

Agency Cost determination is a major part of LCCA; it includes the evaluation of all pavement construction, maintenance, and rehabilitation costs incurred during the analysis period. Although they can be uncertain, initial construction costs can generally be obtained with a certain degree of precision from construction bids, contracts, or pavement management systems. On the other hand, future treatment and expenditures are unknown at the time of conducting the LCCA and can only be estimated based upon agency policies (e.g., PMS) or treatment cost of similar projects. Therefore, the main source of uncertainty in the agency cost comes from unknown pavement performance and future pavement maintenance, rehabilitation, and repaving actions. As a first step and to demonstrate the feasibility of the approach, fuzzy systems were used for project selection; however, they can also be used for modeling pavement deterioration as discussed later in the paper.

Agency decisions concerning the timing and type of maintenance, rehabilitation, and repaving (MR&R) actions are mainly based upon pavement condition and/or time since last treatment. Fuzzy logic techniques could be used to predict future pavement conditions and to determine the necessary MR&R actions. The prototype model presented in this paper (Figure 3.3) uses deterministic models to predict pavement condition based upon pavement structure, age, and traffic, as well as a fuzzy logic model to select treatments based upon pavement condition and time since last treatment.
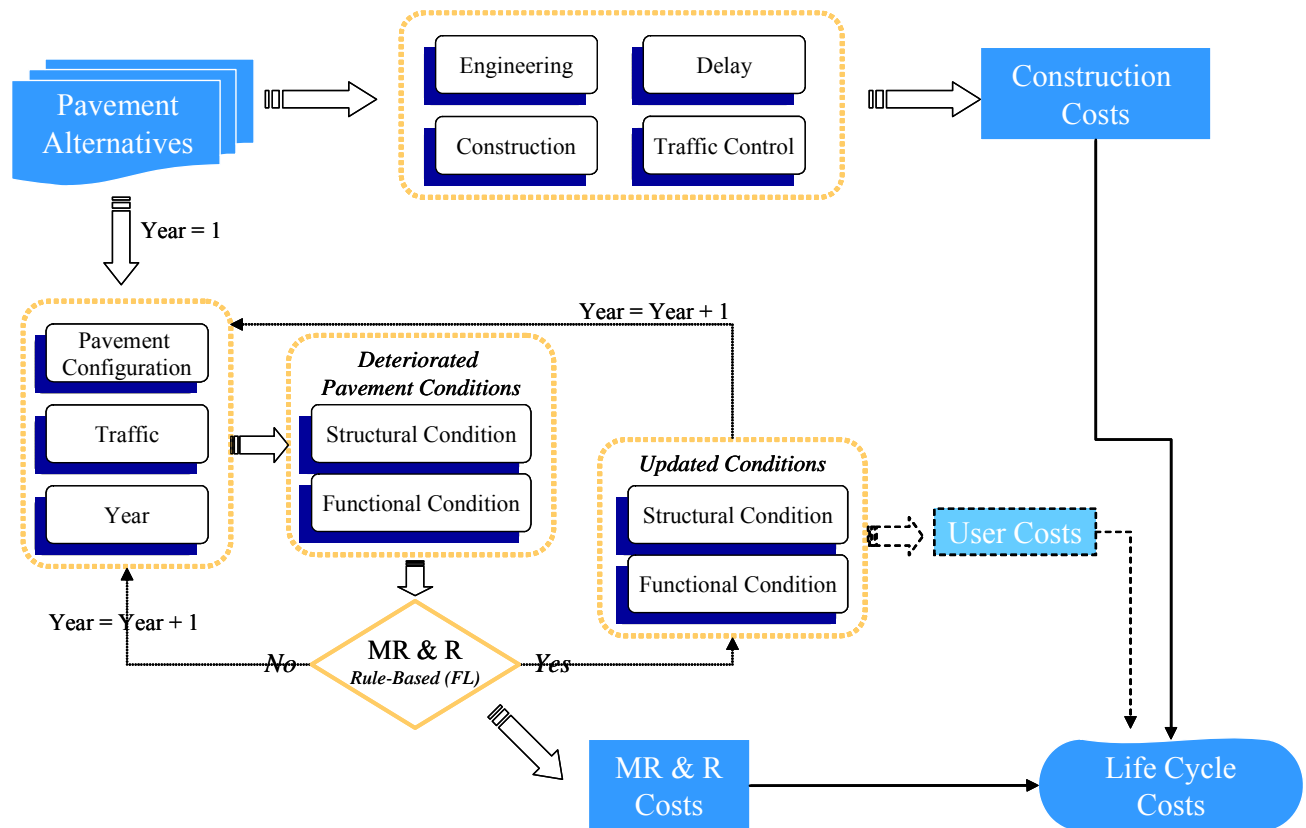
FIGURE 3.3. Fuzzy logic-based LCCA framework.

User Costs Considerations

User cost may include vehicle operating costs, travel time, and accident and environmental costs. Accident cost analysis involves an estimation of accident rate; that is, which kind of accident and how often it will happen. The estimation should be based upon the roadway geometric characteristics, pavement condition, and traffic distribution, among other factors. Both vehicle operating and travel time cost estimation need information about traffic and pavement condition, as well as cost of time, gasoline, repairs, etc. Environmental costs include emissions and noise, among other factors. These costs cannot easily be computed. Rather, they are *estimated* based upon often uncertain, incomplete, and sometimes ambiguous information. Although the user costs are of great importance, they were not considered in this, the feasibility study, because it was preferred to have a simpler application for evaluating the

technology. This is also consistent with current agency practices in the U.S., which in general do not consider user costs. However, the overall framework of the application being considered includes user cost as shown by dotted lines in Figure 3.2.

CASE STUDY

This section presents an example that illustrates the use of the developed fuzzy logic model for project-level LCCA. The example evaluates different MR&R policies for a flexible pavement structure, which consisted of 40mm (1.5in) of hot mix asphalt (HMA) wearing course, a 180mm (7in) HMA base layer, a 75mm (3in) asphalt-treated open-graded drainage layer, and 220mm (8.5in) of cement-treated aggregate subbase. Cost data from the Virginia Department of Transportation (VDOT, 2002) were used to calculate the project cost. The initial construction cost (without considering non-pavement items) was $204,475.92 per lane-mile. Routine maintenance costs were assumed similar for all alternatives. Initial traffic was 306,301 annual equivalent single axle loads (ESALs), and a traffic growth rate of 4% was assumed.

Future MR&R costs were estimated using fuzzy logic models that select treatments based upon user-defined rules. The variables considered are pavement structural and functional condition, which were measured using the Present Serviceability Index (PSI) and Pavement Condition Index (PCI) respectively, and time since last treatment (time gap). The AASHTO pavement design equation (AASHTO 1993) was used to predict PSI progression. An S-shaped regression equation that was developed for new flexible pavements at the Washington State DOT (Jackson and Mahoney 1990) was used for predicting PCI.

Decision Making Model

Figure 3.4 presents the project selection algorithm used in this example. The algorithm consists of two rule-based fuzzy logic models, a trigger model, and a policy model. Users can define rules for both models. The trigger model computes the priority of a do-nothing policy, while the policy model is used to evaluate the priority of specific MR&R treatments.
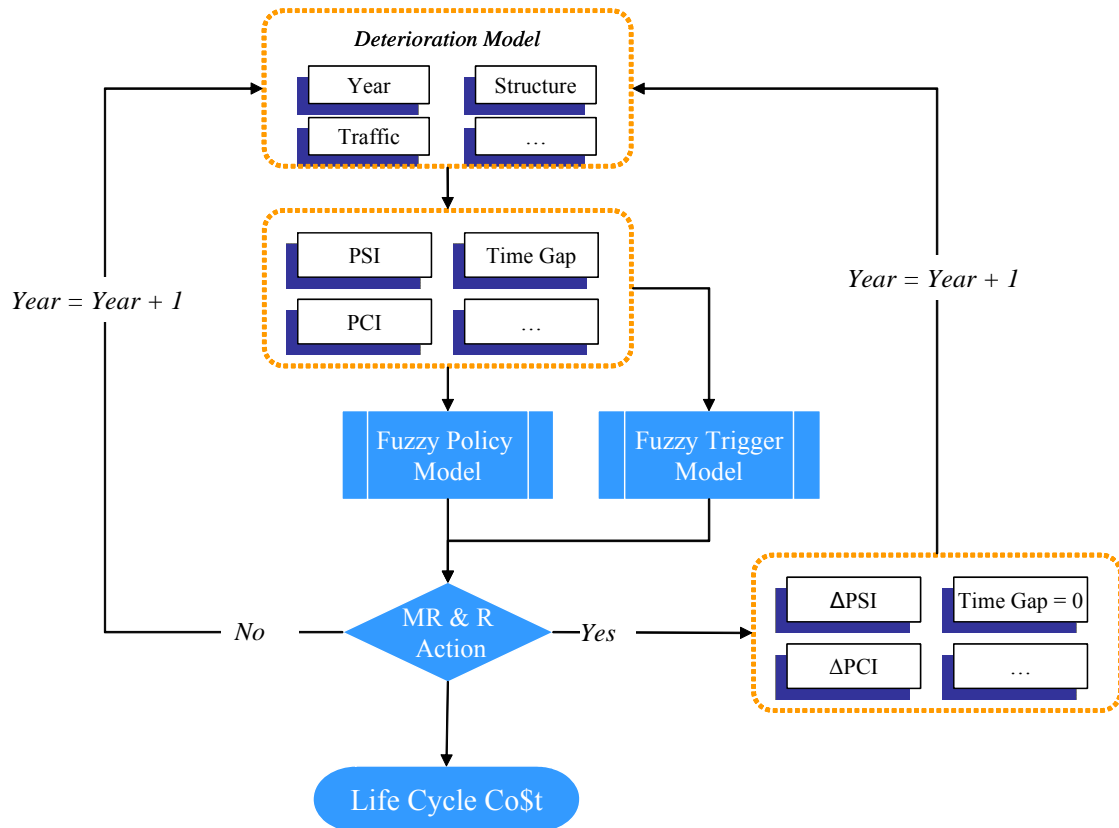
FIGURE 3.4. Fuzzy logic-based project selection algorithm.

For each year, the algorithm evaluates the *priorities* of a do-nothing policy and the various treatments defined by the policies/criteria provided in the form of user-defined fuzzy rules. If the priority of a treatment exceeds that of the do-nothing alternative, the treatment is applied and the pavement variables adjusted accordingly. Otherwise, only routine maintenance is applied and the pavement is deteriorated according to the default prediction curves. The process is repeated for each year in the analysis period. The life-cycle costs are then computed annually using user-defined typical cost for the different treatments. The algorithm was implemented in a MatLab-based computer program that provides default values for all the input variables and criteria.

MR&R Policies

The membership functions for the various pavement variables and levels (linguistic descriptions) considered in this case study were presented in Figure 3.2. Table 3.2 summarizes the fuzzy logic-based model.

TABLE 3.2. Example of fuzzy logic-based project selection model

INPUT PARAMETERS		
Variable	*Meaning*	*Fuzzy Sets*
PSI	Present serviceability index	{very poor, poor, medium, good, excellent}
PCI	Pavement condition index	{very poor, poor, medium, good, excellent}
Time Gap	Time between two treatments	{very short, short, medium, long, very long}

OUTPUT PARAMETERS		
Variable	*Meaning*	*Fuzzy Sets*
Priority	Priority of a certain action	{very low, low, medium, high, very high}

MODELS

1. Do nothing (trigger model)
2. Preventive maintenance (policy model)
3. Thin overlay (policy model)
4. Medium overlay (policy model)
5. Thick overlay (policy model)
6. Reconstruction (policy model)

EXAMPLE FUZZY RULES (Do-Nothing treatment)

1. IF **PSI** is *excellent*, THEN the **Priority** of Do-Nothing is ***very high***
2. IF **PSI** is *good*, THEN the **Priority** of Do-Nothing is ***medium***
3. IF **PSI** is *medium*, THEN the **Priority** of Do-Nothing is ***low***
4. IF **PSI** is *poor*, THEN the **Priority** of Do-Nothing is ***very low***
5. IF **PSI** is *very poor*, THEN the **Priority** of Do-Nothing is ***very low***
6. IF **PCI** is *excellent*, THEN the **Priority** of Do-Nothing is ***very high***
7. IF **PCI** is *good*, THEN the **Priority** of Do-Nothing is ***medium***
8. IF **PCI** is *medium*, THEN the **Priority** of Do-Nothing is ***very low***
9. IF **PCI** is *poor*, THEN the **Priority** of Do-Nothing is ***very low***
10. IF **PCI** is *very poor*, THEN the **Priority** of Do-Nothing is ***very low***
11. IF **Time Gap** is *very short*, THEN the **Priority** of Do-Nothing is ***very high***
12. IF **Time Gap** is *short*, THEN the **Priority** of Do-Nothing is ***medium***
13. IF **Time Gap** is *medium*, THEN the **Priority** of Do-Nothing is ***low***
14. IF **Time Gap** is *long*, THEN the **Priority** of Do-Nothing is ***very low***
15. IF **Time Gap** is *very long*, THEN the **Priority** of Do-Nothing is ***very low***

Five MR&R policies were evaluated in this case study:

- Preventive maintenance

- Thin overlay (50mm [2in])

- Medium overlay (100m [4in])

- Thick overlay (150mm [6in]) and

- Reconstruction

Six groups of fuzzy logic rules were developed – one for the do-nothing policy (trigger model) and one for each of the five policies investigated. The case study only considered one treatment in each policy. This is a simplification used only to illustrate the effectiveness of the approach and verify the reasonableness of the algorithms.

The case study was run using a fifty-year analysis period and a discount rate of 4%. The MR&R activities and their timing were determined by the fuzzy logic models. The agency costs were then computed for each policy using the various treatment costs presented in Table 3.3. This table also presents the effect of treatments on pavement condition variables PSI, PCI, and time gap. The salvage values were considered proportional to the remaining service life (based on PSI) at the end of the analysis period and the reconstruction cost. Pavement condition parameters were reset after a treatment in accordance with the treatment effect indicated in Table 3.3.

TABLE 3.3. Cost and effect of the MR&R treatments considered

Treatment	Cost (per lane-mile)	Treatment Effect		
		PSI	PCI	Time Gap
Preventive Maintenance	$ 10,560.00	min(PSI+0.5, 4.5)	min(PCI+20, 100)	Reset to 0
Thin Overlay	$ 37,875,20	4.5	100	Reset to 0
Medium Overlay	$ 68,710.40	4.5	100	Reset to 0
Thick Overlay	$ 99,575.60	4.5	100	Reset to 0
Reconstruction	$ 218,552.92	4.5	100	Reset to 0

The present worth of the total life-cycle costs over the 50 years for the five policies evaluated is presented in Table 3.4. Figures 3.5 and 3.6 present the priority progression with time for medium overlay and reconstruction policies, respectively. The expenditure stream diagrams for the two policies are as shown in Figures 3.7 an 3.8.

TABLE 3.4. Results obtained with the fuzzy logic-based LCCA model

Policy	Fuzzy Logic Based LCCA Result		
	Total Cost (Present worth)	Average PSI	Average PCI
Preventive Maintenance	$ 233,720.44	3.77	98.9
Thin Overlay	$ 240,163.68	4.05	93.3
Medium Overlay	$ 263,609.52	4.14	89.2
Thick Overlay	$ 279,239.19	4.13	85.6
Reconstruction	$ 258,110,28	3.38	80.2
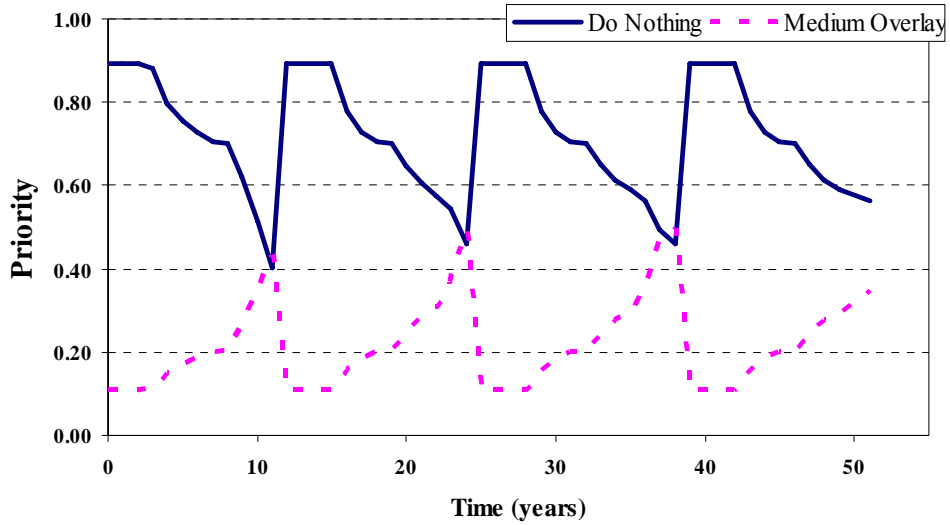
FIGURE 3.5. Priority progression for the medium overlay policy.
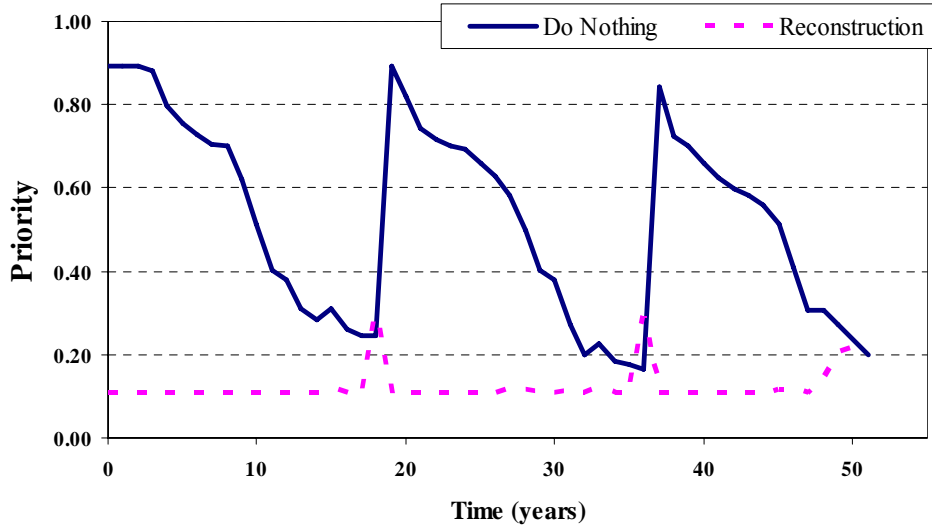
FIGURE 3.6. Priority progression for the reconstruction policy.

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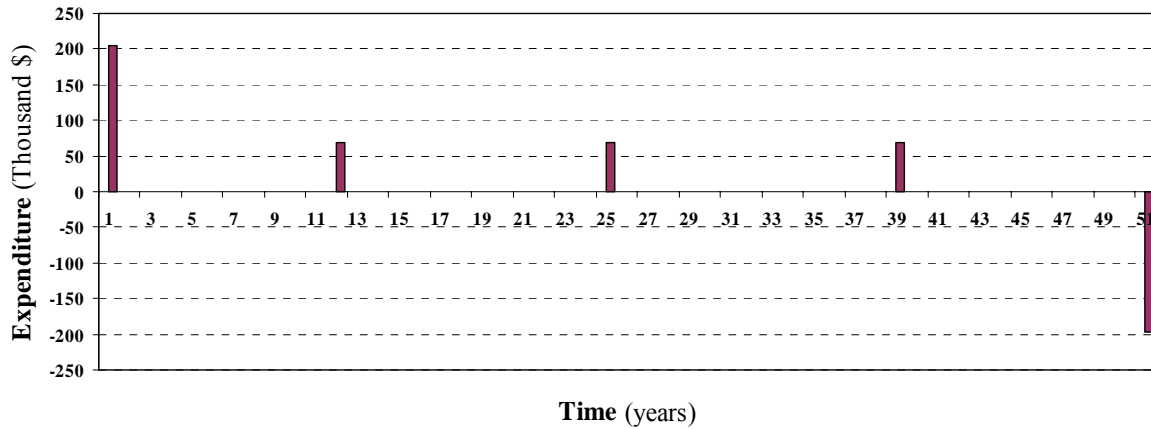
FIGURE 3.7. Expenditure stream for the medium overlay policy.
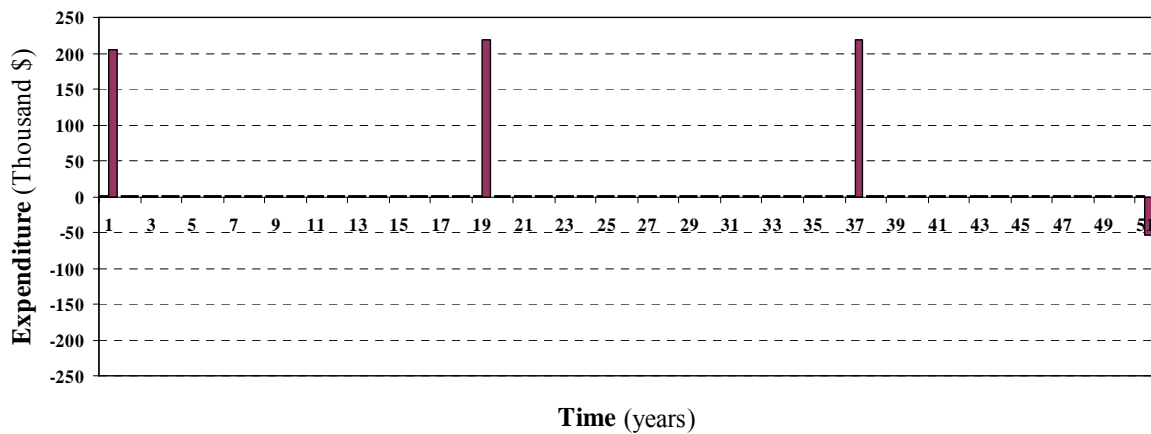
FIGURE 3.8. Expenditure stream for the reconstruction policy.

The results show a reasonable tendency among different policies. The preventive maintenance policy has the lowest LCC and results in the highest average PCI. However, the average PSI is the lowest because of the low effect of this treatment on PSI, as shown in Table 3.3; preventive maintenance mainly retards the deterioration progress. The three overlay policies result in similar and acceptable average PSI and PCI throughout the analysis period. The total present worth of agency costs increases with the thickness of overlay. This tendency indicates that a treatment applied earlier could save more money than a thick overlay applied later, while providing a similar average serviceability level. The reconstruction policy has the lowest average PSI and PCI values. While the policies studied represent only a

hypothetical and simplified version of those generally considered by most highway agencies, the results are very promising and suggests the feasibility of the approach.

DISCUSSION

Although the example presented in this paper helped establish the feasibility of the proposed approach, there are still many possible enhancements to the model. For example, soft computing-based multi-attribute decision support algorithms may facilitate the incorporation of non-monetary factors (e.g., environmental impacts and sustainability) into the engineering economic analysis process. This could be a step towards the development of reliable procedures for long-term LCCA and BCA (i.e., 100 years and more). Soft-computing based models for predicting pavement performance may also further enhance the capabilities of the model. Furthermore, although the algorithms in this paper were developed for the LCCA of pavements, they have been designed considering future expansion for their use with other infrastructure assets. The use of consistent LCCA procedures for different kinds of transportation assets (e.g., pavements, bridges, signs, and tunnels) is expected to facilitate the holistic integration of the decision-making process for asset management.

CONCLUSION

Life cycle cost analysis (LCCA) is a key component in the pavement management process. LCCA is used extensively to support project level decisions, and it has started to be used as a network level analysis tool. Since LCCA is often based upon uncertain, ambiguous, subjective, and sometimes incomplete information, soft computing techniques are particularly appropriate. Fuzzy logic systems provide a formal approach for the treatment of these types of information. The feasibility and practicality of using soft computing for developing LCCA tools was illustrated with the formulation and testing of a fuzzy logic-based algorithm. Planned enhancements for the LCCA model include the incorporation of user costs and the potential use of other soft computing techniques for performance modeling and for incorporating non-monetary variable into the analysis process. The algorithm has the capability to be expanded to handle other types of infrastructure assets.

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CHAPTER 4: FUZZY LOGIC PAVEMENT MAINTENANCE AND REHABILITATION TRIGGERING APPROACH FOR PROBABILISTIC LIFE-CYCLE COST ANALYSIS

Fuzzy Logic Pavement Maintenance and Rehabilitation Triggering Approach for Probabilistic Life-Cycle Cost Analysis

By

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ABSTRACT: Life-cycle cost analysis (LCCA) is an important tool in the transportation Asset Management process. Transportation agencies have used both deterministic and probabilistic LCCA approaches. Probabilistic approaches allow decision makers to evaluate the risk of an investment utilizing uncertain input variables, assumptions, or estimates. This paper explores the incorporation of fuzzy-logic-based models into the risk analysis process to further enhance the traditional probabilistic LCCA method. It proposes a fuzzy logic approach for determining the timing of pavement maintenance, rehabilitation and reconstruction (MR&R) treatments in a probabilistic LCCA model for selecting pavement MR&R strategies. Instead of using predefined service life for initial construction and future rehabilitations, the proposed approach uses performance curves and fuzzy-logic triggering models to determine the most effective timing of MR&R activities. The paper also compares this new approach to the deterministic and traditional probabilistic approaches in a simple case study. The case study demonstrates that the fuzzy-logic-based risk analysis model for LCCA can effectively produce results that are at least comparable to those of the benchmark methods while effectively considering some of the uncertainty inherent to the process.

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INTRODUCTION

Economic analysis is a critical component of today's transportation Asset Management [1, 2].

Transportation Asset Management combines engineering principles and economic theory to facilitate a

more organized, logical approach to decision making [3]. Valuing the costs and impacts of highway

projects is an effective way to assess project-level alternatives, network-level plans, and strategic-level

policies. At the state-of-the-art level, the concept of economic analysis has been applied to every aspect

of the transportation Asset Management framework.

Life-cycle cost analysis (LCCA) is an important economic analysis tool in highway project

decision making. The concept of LCCA was originally developed by the U.S. Department of Defense in

the early 1960s to increase the effectiveness of government procurement. Since then, the concept of

LCCA has spread from defense-related issues to a variety of areas. From the very beginning, LCCA has

been closely related to design and development because it allows costs to be eliminated before they are

incurred as opposed to cutting costs afterward [4]. A common characteristic shared by most projects to

which LCCA is applied is that the studied systems are dynamic, which means their properties evolve over

time and change with their environments. This characteristic introduces a variety of uncertainties and risk

assessment requirements into the LCCA process.

The main purpose of LCCA in transportation is to support decisions in the planning, design, and

operation of major transportation projects. FHWA policy recommends LCCA as a decision support tool,

emphasizing that the results are not decisions in and of themselves. Often, the logical-analytical

framework implied in such analyses is as important as the LCCA results themselves [5].

The progress toward transportation Asset Management requires efficient economic analysis tools

to help state highway agencies with investment decisions. However, transportation agencies tend to avoid

LCCA and other economic analysis tools or hesitate to use their results as a reliable source to support

their decisions because:

1. The parameters and variables used in economic analysis are always uncertain and often produce results that are also uncertain and possibly hard to interpret.

2. Agencies have the impression that economic analysis requires a lot of effort to determine input values, run scenario iterations, and generate final results.

3. The scenarios recommended by the economic analysis tools may conflict with some of the practices of the transportation agencies.

Some of these problems are due to misunderstanding of today's economic analysis. For example, economic analysis does not require significantly more information once the appropriate engineering details are obtained. The level of effort required should reflect project costs, complexity, and possible controversy over the evaluated project.

The traditional economic analysis approaches have some limitations. For LCCA, deterministic methods cannot access the inherent uncertainty surrounding the input variables of economic analysis. Thus this approach often ignores information that could improve the decision. A limited sensitivity analysis may be conducted with various combinations of inputs, but it still often conceals uncertainty that may be crucial to the decision-making process and may lead to debate over the validity of the results.
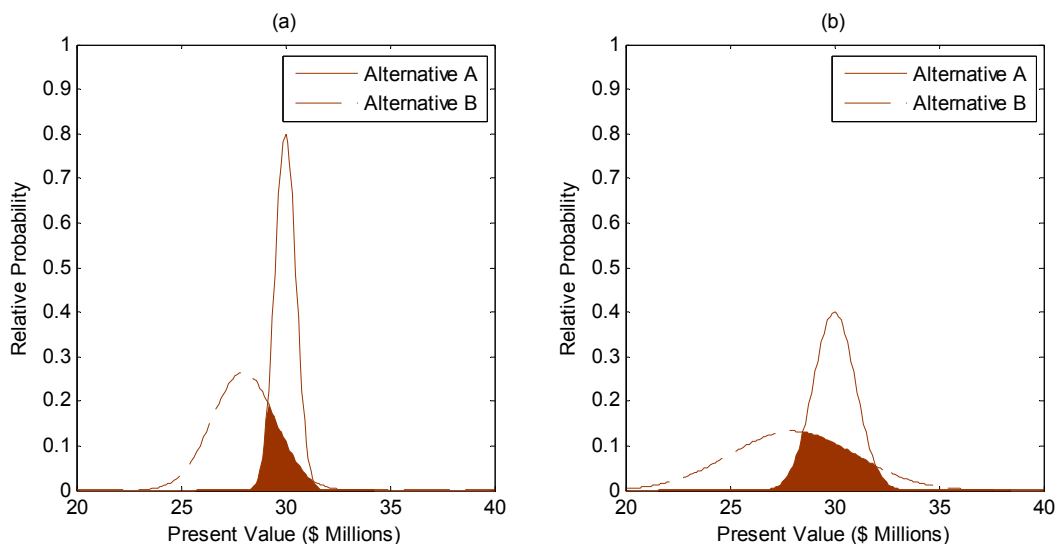
FIGURE 4.1. Probabilistic LCCA result example

The probabilistic LCCA approach considers the random uncertainty in the LCCA process. However, in many cases, the decisions based on understanding of the risks associated with different alternatives are not straightforward. Figure 4.1 shows examples of the risk analysis results of an LCCA. In Figure 4.1(a) alternative A has higher total life-cycle costs but a smaller variance than alternative B. Since lower costs are preferred under normal situations, alternative B would be selected with an acceptable risk (the shade area). However, LCCA may predict a larger variability (uncertainty) in the results, as in Figure 4.1(b). If the decision maker prefers smaller risk, alternative A would be selected, even if the mean life-cycle costs of the alternatives are same with the example in Figure 4.1(a).

While the probabilistic approach is more powerful than the deterministic one in terms of uncertainty evaluation, it cannot handle all the sources of variability inherent in LCCA. Because the information about initial construction is more complete and reliable, the majority of uncertainty in economic analysis comes from future activities. Properly scheduling future activities in economic analysis is a prerequisite for accurately estimating risks; this paper proposes a fuzzy logic solution to this problem.

OBJECTIVE

This paper explores the incorporation of fuzzy-logic-based models into the risk analysis process for selecting pavement maintenance, rehabilitation and reconstruction (MR&R) strategies using LCCA. Instead of using predefined service life for initial construction and future rehabilitations, this research used performance models coupled with a fuzzy-logic-based decision model to determine the timing of MR&R activities. The prototype fuzzy-logic-based LCCA model was proposed by Chen *et al*. [6]. This paper compares this approach with the traditional threshold trigger model used in the deterministic and probabilistic LCCA methods. The practicality of the approach is illustrated with a simple case study.

LIFE-CYCLE COST ANALYSIS

The framework of LCCA approach includes five sequential steps [7]:

1. Establish design alternatives.

2. Determine activity timing.

3. Estimate costs (agency and user).

4. Compute life-cycle costs.

5. Analyze the results.

In terms of uncertainty consideration, there are two traditional LCCA approaches: deterministic and probabilistic (risk analysis). Deterministic methods are simpler and easier to implement, but they do not assess any risk that might be incurred. Probabilistic methods can account for the uncertainty in variables, parameters, and results. Both methods require rehabilitation timings and costs as input variables to their models.

Common Assumptions

Before any analysis can take place, several basic assumptions are needed, such as the same-benefit assumption, analysis period length, and inclusion or exclusion of user costs. These issues directly affect the reliability of final results. For example, if the same-benefit assumption does not hold, LCCA method should not be used in the selection process. Other methods, like benefit-cost analysis, are more appropriate in such conditions. Furthermore, if the selected period length is shorter than the design service life of an alternative's initial design, the results of LCCA would not be sufficient to reflect the performance difference among different alternatives. Inclusion or exclusion of user costs is another critical question faced by analysts in LCCA. While including user costs can make the final decision making more justified, the credibility of available user-cost models is still disputed. The difficulty of quantifying user-cost data discourages transportation agencies from considering this portion of costs.

Deterministic LCCA

In the deterministic LCCA method, all input variables and parameters are assumed to be known and are assigned single, fixed values. The basic formula, as shown in Equation (1), calculates the present value (PV) of costs over a facility's life cycle.

$$PV = \text{Initial\_Cost} + \sum_{k=1}^{N} \text{Rehab\_Cost}_k \left[\frac{1}{(1+i)^{n_k}} \right] \qquad (1)$$

where:

PV = present value of life-cycle costs,

Initial_Cost = initial construction costs,

Rehab_Cost = rehabilitation costs,

i = discount rate,

n = year of expenditure, and

k = rehabilitation number.

Interpretation of deterministic LCCA results is simple and straightforward. The alternative with lowest expected life-cycle costs is favored. However, deterministic LCCA does not evaluate any uncertainties. This limitation may lead to debates over the final results.

Probabilistic LCCA

The uncertainty in engineering economic analysis has been partially addressed by adopting probabilistic methods and simulation techniques. Probabilistic LCCA methods allow the model to consider the variability associated with input parameters over the life cycle of a project. Each input variable is associated with a probability density function (PDF). Then, a simulation model is run for a certain number of iterations or until some criteria are met. The statistical characteristics of output results, such as mean and variance, represent the risk associated with future outcomes. A variety of computer-based tools can realize such functions. Probabilistic LCCA assesses three basic questions about risk [5]:

1. What can happen?

2. What is the likelihood of it happening?

3. What are the consequences of it happening?

The computational capability of today's computers has made possible the use of simulation for risk analysis. Monte Carlo simulation is widely used in risk analysis. The statistical characteristics of output variables can be captured with sufficient accuracy by running the simulation thousands or even tens of thousands of times. For probabilistic LCCA, the final outputs would be the full range of possible life-cycle costs and the relative probability of any particular total cost actually occurring.

The interpretation of probabilistic LCCA results goes beyond a simple comparison of the alternatives' mean life-cycle costs. The risks associated with each alternative are also important in decision making. Alternatives with lower mean cost but higher risk would be difficult to compare to those with higher mean cost but lower risk if the difference of mean values is not significant, as is the case in Figure 4.1(b). Selection of an alternative would thus depend on the decision makers' tolerance to risk. Such judgments require reliable estimations of risk associated with alternatives. Otherwise, the analysis will lead decision makers to an erroneous understanding of the risks associated with the alternatives and thus compromise the efficiency of the decisions.

Therefore, the decision can be better supported when final outputs approach the realities. As previously mentioned, both overestimated and underestimated risks may lead to sub-efficient decisions. Since the variances of final outputs are determined by both input variables and internal inference mechanics and since the quality of input information is generally given, increasing the accuracy of results by improving the model's internal inference mechanics is more realistic than improving data qualities.

UNCERTAINTIES IN LCCA INPUTS

Equation (1) describes the fundamental concept behind LCCA calculation: discounting all the costs associated with the facility over its life cycle and summing them up. The variables in the equation include initial construction costs, future rehabilitation costs, rehabilitation timing, and discount rate. Figure 4.2 shows that these variables, except for discount rate, depend on more elementary items and are

often interrelated. For simplicity, the policies considered in this paper use only one type of maintenance and rehabilitation treatment per alternative, but the treatment can be applied more than once. This assumption simplifies the decision-making task to a to-do or not-to-do choice in the asset's life cycle, which eliminates the needs to first select proper type of rehabilitation and then determine the optimal timing. The simplification is acceptable because the objective of LCCA is to investigate the relative advantage between alternatives. As long as the model treats different alternatives in the same manner, the results will not be affected. Many examples of such simplification can be found in the literature [5, 7].
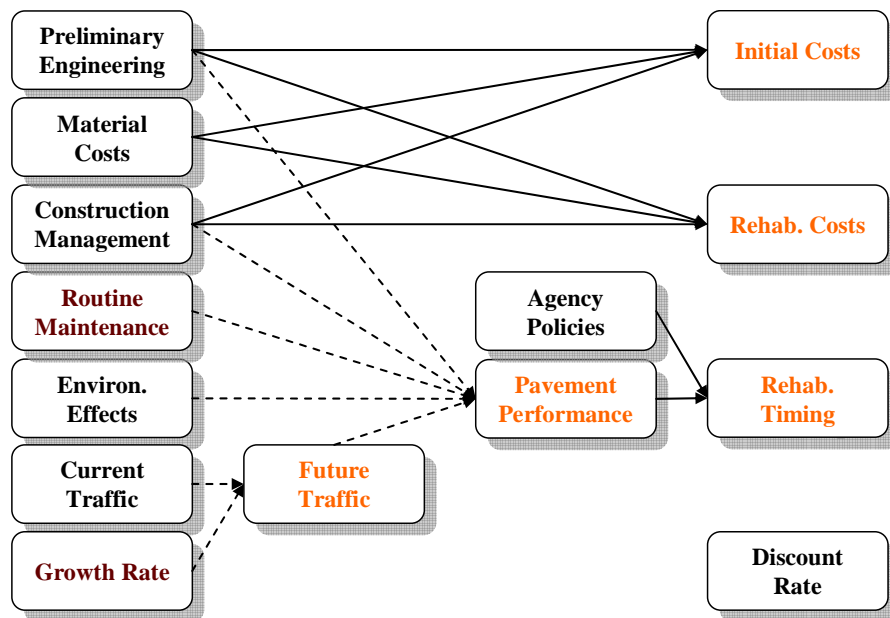
FIGURE 4.2. Relationship map of LCCA input variables and parameters

This section discusses the uncertainties in the four variables of the general LCCA model: discount rate, initial construction costs, rehabilitation costs, and rehabilitation timing. Although the uncertainties and their relationships can be analytically studied, the mathematical formulations will be significantly cumbersome. This is one major reason why it is more practical to conduct a computer simulation as previously discussed.

Discount Rate

As shown in Figure 4.2, discount rate is a stand-alone variable within the framework of LCCA. LCCA has two options for discount rates: real or nominal. Real discount rates reflect the true monetary opportunity value of time with no inflation components while nominal discount rates consider inflation components as part of discounting concerns. In public transportation agencies, real discount rates should be used because public sector project benefits should be dependent only on real gains (costing savings or expanded output) rather than purely price effects [7].

A technical FHWA bulletin recommends a range of 3 to 5% as typical values for real discount rates [5]. A symmetrical triangular distribution with a minimum, most likely, and maximum of 3, 4, and 5%, respectively, was used in this study.

Initial Construction Costs

An alternative's initial construction costs pertain to putting the asset into initial service. Data on construction are usually obtained from historical records, current bids, and engineering judgment. Since nearly every alternative is more or less different from other alternatives, appropriate calculation and deduction is necessary to obtain good estimations. According to Figure 4.2, the factors affecting the estimation of initial construction costs include preliminary engineering (or engineering design), material costs, and construction management. A simplified formula to estimate initial construction costs could be:

$$\text{Initial\_Cost} = \sum_{i=1}^{n} UC_i \cdot X_i \qquad (2)$$

where:

Initial_Cost = initial construction costs,

i = material type,

UCi = unit cost of material i, and

Xi = quantity of material i.

The quantity of each type of material is determined by engineering design and construction management. In this research, the quantities and unit costs of materials for each pavement layer are simulated using independent random variables. Using equation(2), the initial costs of alternatives are calculated in each iteration of simulation. The quantity of materials (pavement layer thicknesses) required by engineering design is also used in the performance prediction models.

Rehabilitation Costs

As a rule of thumb, rehabilitation activity needs to be applied to the asset at least once over its life cycle to be able to capture long-term cost differences associated with reasonable design strategies. The purpose of such activity is to maintain the asset above some predetermined condition, performance, and safety level. With the assumption of single rehabilitation type, the costs of rehabilitation are related to the same factors as initial construction costs: preliminary engineering, materials costs, and construction management. The formula to estimate rehabilitation costs is shown in Equation 3:

$$\text{Rehab\_Cost} = \sum_{i=1}^{n} UC_i \cdot X_i \tag{3}$$

Similar to the estimation of initial construction costs, the quantity and unit cost of materials are simulated using independent random variables. The quantity of materials (layer thickness) of each rehabilitation activity is incorporated with those of previous construction and rehabilitation activities to predict the project's performance.

The material quantity and unit cost variability of the rehabilitation treatments are considered to be independent of each other. This is reasonable because it is unlikely that an agency would hire the same contractor, use the same techniques, and manage the project with same level of quality on all activities. It is more realistic to use independent random variables to simulate the activities rather than one random variable for all rehabilitation events in the simulation.

Rehabilitation Timings

Traditionally, maintenance and rehabilitation in a project's analysis period are determined using predefined service life (SL). Some probabilistic LCCA methods consider a random variable for the SL of initial construction and another independent random variable for all the rehabilitations [5]. A major drawback of such a method is that rehabilitation activities are not likely to have same service lives. A modified method uses a new independent random variable to predict the SL of each new rehabilitation activity. However, this technique implies that the SLs of initial construction and rehabilitation are independent of each other, which is apparently not true; the correlation between construction and rehabilitation activities will be explained analytically in this section.

Rehabilitation costs are discounted using the present worth factor given by Equation (4):

$$PWF = \frac{1}{(1+i)^n} \qquad (4)$$

Thus, Equation (1) could be reformulated as Equation (5) by expanding the summation notation and substituting the present worth factors of each activity into the equation:

$$PV = \text{Initial\_Cost} + \text{Rehab\_Cost}_1 \times PWF_1 + \ldots + \text{Rehab\_Cost}_N \times PWF_N \qquad (5)$$

Let PW_Rehab_k denote $\text{Rehab\_Cost}_k \times PWF_k$. Then Equation (5) becomes:

$$PV = \text{Initial\_Cost} + \text{PW\_Rehab}_1 + \ldots + \text{PW\_Rehab}_N \qquad (6)$$

Then the expected value of the final results of LCCA is:

$$E(PV) = E(\text{Initial\_Cost}) + E(\text{PW\_Rehab}_1) + \ldots + E(\text{PW\_Rehab}_N) \qquad (7)$$

And the variance of the final results of LCCA is:

$$\begin{aligned}
\text{var}(PV) = {} & \text{var}(\text{Initial\_Cost}) + \text{var}(\text{PW\_Rehab}_1) + \ldots + \text{var}(\text{PW\_Rehab}_N) \\
& + 2\text{corr}(\text{Initial\_Cost},\text{PW\_Rehab}_1)\sqrt{\text{var}(\text{Initial\_Cost})\,\text{var}(\text{PW\_Rehab}_1)} \\
& + 2\text{corr}(\text{Initial\_Cost},\text{PW\_Rehab}_2)\sqrt{\text{var}(\text{Initial\_Cost})\,\text{var}(\text{PW\_Rehab}_2)} \\
& + \ldots \\
& + 2\text{corr}(\text{Initial\_Cost},\text{PW\_Rehab}_N)\sqrt{\text{var}(\text{Initial\_Cost})\,\text{var}(\text{PW\_Rehab}_N)} \\
& + 2\text{corr}(\text{PW\_Rehab}_1,\text{PW\_Rehab}_2)\sqrt{\text{var}(\text{PW\_Rehab}_1)\,\text{var}(\text{PW\_Rehab}_2)} \\
& + \ldots \\
& + 2\text{corr}(\text{PW\_Rehab}_1,\text{PW\_Rehab}_N)\sqrt{\text{var}(\text{PW\_Rehab}_1)\,\text{var}(\text{PW\_Rehab}_N)} \\
& + \ldots \\
& + 2\text{corr}(\text{PW\_Rehab}_{N\text{-}1},\text{PW\_Rehab}_N)\sqrt{\text{var}(\text{PW\_Rehab}_{N\text{-}1})\,\text{var}(\text{PW\_Rehab}_N)}
\end{aligned} \tag{8}$$

The impacts of correlation between construction and rehabilitation events are represented by the correlation coefficient items in Equation (8). For example, if an agency invests more today, it is likely that the rehabilitation costs will happen later in the future. This relationship implies negative correlation between adjacent events in LCCA. Therefore, if the correlation is properly considered, the variance of final results should be reduced and could provide decision makers better supporting information.

As depicted in Figure 4.2, rehabilitation timing is the variable with the most explanatory factors among the four inputs of LCCA models. It is determined by the studied project's performance and the rehabilitation policy, which determines the conditions under which the rehabilitation activity is applied. The project's performance can be predicted based on the engineering design, traffic load, and routine maintenance level. Rehabilitation policies or strategies should be extracted from the agency's previous practices and knowledge. These practices can be simulated in LCCA by using either fuzzy logic models—as proposed in this research—or threshold trigger models.

Potential Error Sources in Probabilistic LCCA

The primary source of error in simulation modeling is failure to recognize the dependent relationship between input variables and parameters [5]. For accurate risk estimation, every iteration of a risk analysis simulation must be of a scenario that can actually occur. For example, as shown in Figure 4.2, traffic and pavement performance are correlated. The number of Equivalent Single-Axle Loads (ESALs) can be used for traffic measurement and SL for pavement performance. For the same pavement structure,

greater ESALs will result in shorter SLs. Therefore, if the sampling mechanics for the two variables are independent, unrealistic scenarios with high SL and high ESAL could occur in the simulation.

One way to consider the relationship among the variables is by using a correlation matrix in the random sampling process. However, it would be very time and energy consuming to obtain the matrix analytically. Most available pavement LCCA tools leave such tasks to the user. But if reliable performance models are available, it is possible to incorporate them with decision models to predict rehabilitation timing. The performance-based method implicitly considers the correlation between rehabilitation events, as shown in Equation (8), and thus could estimate the variance of LCCA results more accurately.

FUZZY-LOGIC-BASED LCCA ALGORITHM

Fuzzy logic systems were developed to provide soft algorithms for data processing that can make inferences based on imprecise data. There are several characteristics of transportation asset LCCA that make it particularly appropriate for using fuzzy logic techniques [8]. For example, the decisions about rehabilitation level and timing are usually based on linguistic information like "good condition" or "poor condition," which is perfectly compatible with the inference pattern of fuzzy logic systems. This section will briefly introduce the mechanics of fuzzy logic systems and review the fuzzy-logic-based rehabilitation scheduling algorithm proposed by Chen *et al*. [6].

Fuzzy Logic Systems

The fuzzy logic system is an extension of the traditional rule-based reasoning (expert systems) that incorporates imprecise, qualitative data in the decision-making process by combining descriptive linguistic rules through fuzzy logic [9]. A typical framework of fuzzy logic systems includes four parts: input processors (fuzzifier), rule base, inference engine, and output processors (defuzzifier). The fuzzifier and defuzzifier provide mapping between crisp values and fuzzy sets. The concept of fuzzy set is the fundamental basis of fuzzy logic systems. A fuzzy set is a set whose members have an associated membership function value between 0 and 1, while the traditional crisp sets allow its members to take

values of only 0 or 1. The rule base is where the knowledge of models is stored. The knowledge can be provided by experts, extracted from collected data, or both. The inference engine determine how the rules are triggered and processed to map input values into outputs [10].

Determination of Rehabilitation Timing

Fuzzy logic systems can process uncertain information efficiently and can often generate good solutions even with incomplete or imprecise data. This feature has been used in this research to determine asset rehabilitation timing based on agency policies and performance models. Figure 4.3(a) presents the fuzzy-logic-based MR&R triggering algorithm [6]. The algorithm consists of two rule-based fuzzy logic models, a trigger model, and a policy model. Rules for both models can be customized according to the agency's policies or expert opinions. The trigger model computes the priority of a do-nothing policy, while the policy model is used to evaluate the priority of specific rehabilitation treatments. Figure 4.3(b) presents an example of the priority surfaces of three strategies five years after the initial construction for a particular pavement structure and traffic level.

In this research, the fuzzy-logic-based trigger and policy model use same definition of membership functions of input and output variables. A group of distinct inference rules are defined for each model in the form of IF-THEN statements such as:

IF *PSI* is *excellent*, THEN the *Priority* of Do-Nothing is *very high*.

A complete description of membership functions and rules could be found elsewhere in [6]. The algorithm evaluates the priorities of do-nothing activity and rehabilitation treatment year by year. If the priority of rehabilitation exceeds that of the do-nothing activity, the treatment schedule is set to the year, and all pavement conditions are adjusted accordingly. Otherwise, only routine maintenance is applied, and the pavement is deteriorated following predefined performance models. The process is repeated for every year in the analysis period. Finally, a schedule of rehabilitation events is generated for every iteration and then used to calculate present worth factors.

(a)

	Alternative A	Alternative B
Policy Model	Thin Overlay	Thick Overlay
Trigger Model	Do-nothing	Do-nothing

(b)
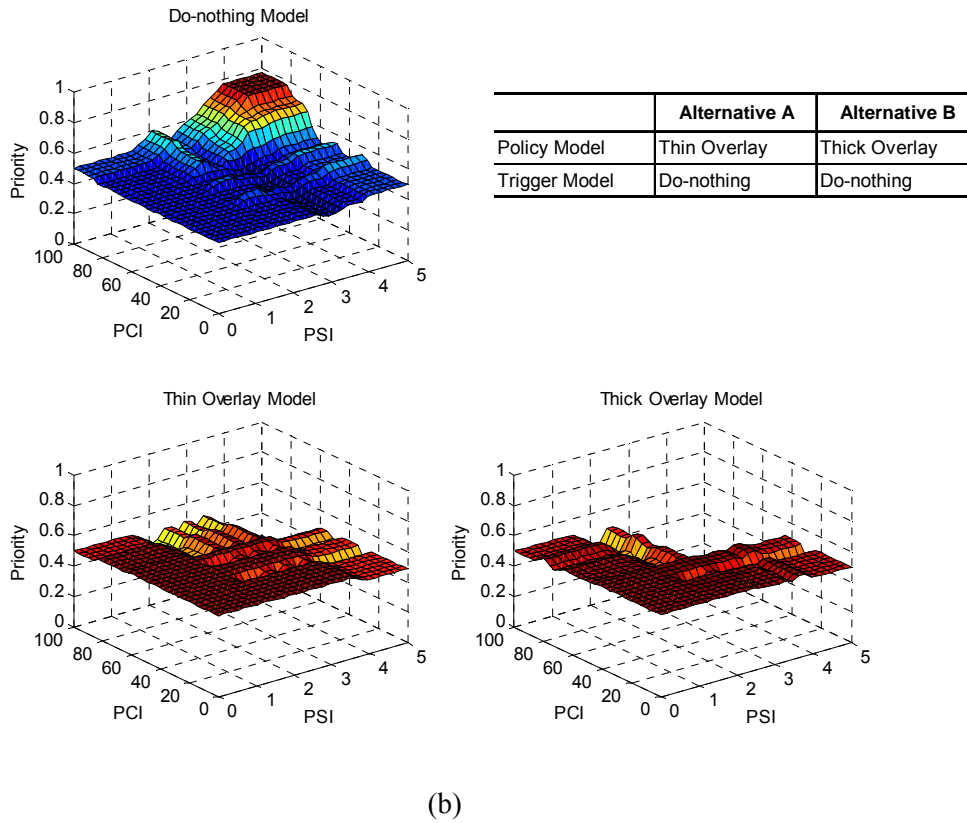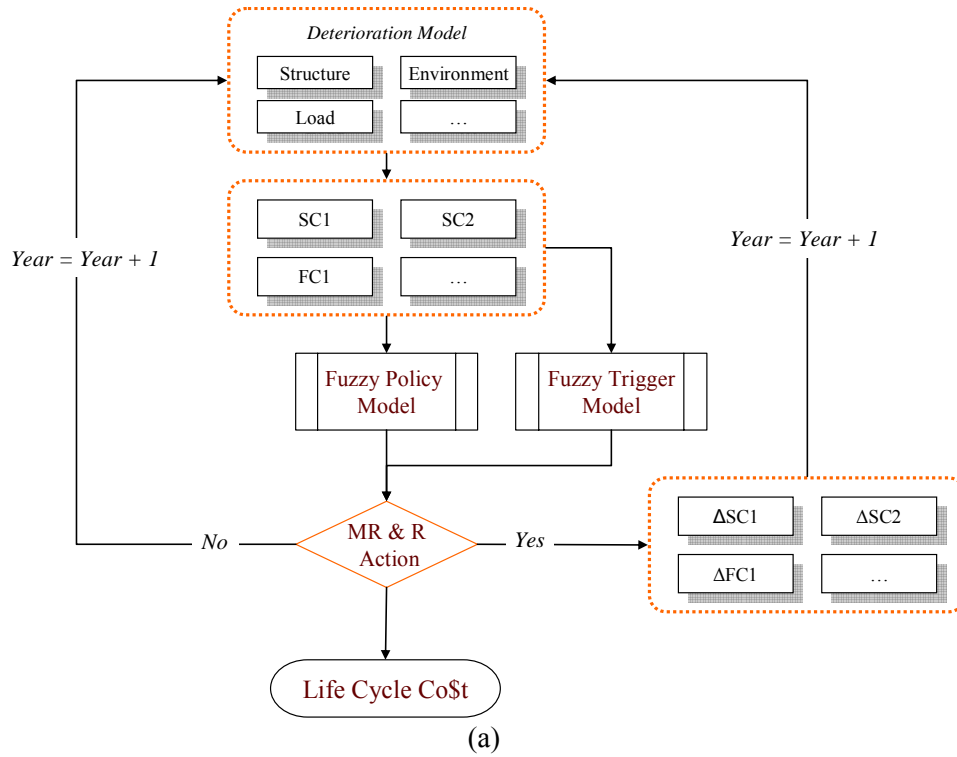
**FIGURE 4.3. (a) Fuzzy-logic MR&R triggering algorithm;
(b) Solution surfaces produced by the fuzzy logic models**

COMPARATIVE CASE STUDY

This section presents a case study to compare the three LCCA approaches: (1) deterministic approach with threshold trigger decision models; (2) probabilistic approach with threshold trigger decision models; and (3) probabilistic approach with fuzzy logic triggering models. The objective of this case study is to compare two MR&R strategies on one flexible pavement segment: thin overlay and thick overlay.

The segment is a single-lane, one-direction, one-mile-long, twelve-foot-wide section. As shown in Table 4.1, its pavement structure consists of a 50-mm (2-inch) hot-mix asphalt (HMA) wearing course; a 125-mm (5-inch) HMA intermediate layer; a 225-mm (9-inch) base layer; and a 150-mm (6-inch) cement-treated aggregate subbase layer. The subgrade modulus is 5,000 psi. The two rehabilitation strategies, thin overlay (Alternative A) and thick overlay (Alternative B), are also summarized in the table. The initial average daily traffic was 12,000 vehicles. The traffic loads have a growth rate of 6% according to the traffic monitoring data on Interstate Highway I–81 from 1997 to 2002.

TABLE 4.1. Engineering Design Parameters for Alternatives A and B

Variable	Alternative A (thin-overlay)	Alternative B (thick-overlay)
Initial Construction		
Surface Layer Thickness (in.)	2 inch	
Intermediate Layer Thickness (in.)	5 inch	
Base Layer Thick	9 inch	
Traffic growth rate (yearly)	6 inch	
Rehabilitation		
Mill Depth (in.)	1 inch	2 inch
Surface Layer Thickness (in.)	2 inch	2 inch
Intermediate Layer Thickness (in.)	0 inch	4 inch

Cost data from the Virginia Department of Transportation (VDOT) were used to estimate mean construction and rehabilitation costs [11] shown in Table 4.2. While the uncertainty of user costs could be reflected in a higher variance in the results using the presented models, to simplify the example, user costs were not considered in the case study. The analysis period in this study is selected as 50 years, which is sufficient to reflect the performance difference of alternatives.

TABLE 4.2. Input Variables for Different LCCA Models and Assumed Statistics for Each Variable

Variable	Symbol	Unit	C.V. (%)	Mean	Standard Deviation
Discount rate	i	%	-	4	tri(3, 4, 5)
Initial average daily traffic	ADT_0	-	15	12,000	1800
Truck factor	T_f	-	36.5	0.52	0.19
Percentage of trucks	T	%	10	30	3
Traffic growth rate (yearly)	r	%	10	6	0.6
Initial serviceability index	PSI_0	-	4.3	4.6	0.2
Initial condition index	PCI_0	-	2.6	95	2.5
Surface strength factor	a_1	-	10	0.44	0.044
Surface thickness	D_1	inch	10	2	0.2
Intermediate strength factor	a_{inter}	-	10	0.44	0.044
Intermediate thickness	D_{inter}	inch	10	5	0.5
Base strength factor	a_2	-	14.3	0.14	0.02
Base drainage factor	m_2	-	10	1	0.1
Base thickness	D_2	inch	10	9	0.9
Subbase strength factor	a_3	-	18.2	0.11	0.02
Subbase drainage factor	m_3	-	10	1	0.1
Subbase thickness	D_3	inch	10	6	0.6
Subgrade resilient modulus	M_R	psi	15	5000	750
Overlay surface thickness	D_{OL1}	inch	10	2	0.2
Overlay surface strength factor	a_{OL1}	-	10	0.44	0.044
Overlay intermediate thickness	$D_{OLinter}$	inch	10	4	0.4
Overlay intermediate strength factor	$a_{OLinter}$	-	10	0.44	0.044
Overlay mill depth	D_{mill}	inch	10	1 or 2	0.1 or 0.2
Surface material unit cost	UC_1	$/SY-in	10	2.19	0.219
Intermediate material unit cost	UC_{inter}	$/SY-in	10	1.86	0.186
Base material unit cost	UC_2	$/SY-in	10	1.78	0.178
Subbase material unit cost	UC_3	$/SY-in	10	1.18	0.118
Mill unit cost	UC_{mill}	$/SY-in	10	0.50	0.05

The pavement functional condition, in terms of present serviceability index (PSI), is assumed to deteriorate according to the 1993 AASHTO equation [12] and the pavement surface condition, in terms of a pavement condition index (PCI), according to the prediction models developed by the state of Washington [13].

Table 4.2 lists input variables and their associated distribution used in the case study. Only the mean values of input variables were used in the deterministic approach. The two probabilistic approaches in this case study used distributions for each variable with the statistics presented in Table 4.2. Independent random variables were used for each construction and rehabilitation event.

In the second approach, rehabilitation treatments were triggered at threshold performance indexes. This was different from most of the state-of-the-practice methods used by many LCCA tools on the market whose rehabilitation timing is determined by predefined service lives of initial construction or rehabilitations. The fuzzy-logic-based model uses the fuzzy-logic MR&R triggering model and the same pavement performance models to determine rehabilitation timings. Both simulation models were run for 1,000 iterations.

Distributions of Input Variables

According to the distribution determination method, input variables can be divided into two groups: elementary variables and derived variables. Distribution of elementary variables can be obtained from existing data or expert opinion. When existing data are available, such as bid price list and tested structural capacity, both the distribution type and related controlling parameters need to be investigated. The goodness-of-fit test is required to justify specific distributions. If no data exist, eliciting information from expert opinion would be an effective way to set up distributions and evaluate the possible interrelationships and codependencies among the input variables.

In this case study, truncated normal distributions were assumed for all variables to eliminate unrealistic negative values. The only exception is with the discount rate, which was modeled using a triangular distribution. The ranges of truncated normal distributions are the length of four standard deviations. Therefore, for a symmetric distribution, its range is from two standard deviations less than the mean value to two standard deviations greater than the mean value.

The coefficient of variations for the pavement performance parameters and other elementary variables were obtained from Huang [14] when available. One exception is the initial serviceability index. The 1993 AASHTO pavement design guide recommended using a value of 4.6 instead of the 4.2 used in the original 1986 guide based on a survey of the practices of the country [12]. Therefore, a standard deviation of 0.2 is the maximum variance that could possibly have been considered in this study

to avoid an unrealistic PSI value larger than 5.0. Since there is no information available for the variances of unit costs of materials, they were all assigned a coefficient of variation of 10% based on engineering judgment.

Derived variables include initial construction costs, rehabilitation costs, rehabilitation timing, and final total present worth. Their variances are all determined during the simulation. The initial construction and rehabilitation costs are calculated using Equations (2) and (3), respectively. The total present worth, which is actually the final output of LCCA, is calculated using Equation (1).

Performance Models and Decision Models

As previously mentioned, the AASHTO pavement design equation and pavement condition index developed by the state of Washington were used to predict the pavement PSI and PCI, respectively. The original AASHTO pavement design equation was rewritten to estimate PSI based on traffic loads, structure number, and subgrade modulus as shown in Equations (9) and (10):

$$PSI_t = PSI_0 - \Delta PSI \tag{9}$$

$$\Delta PSI = (4.2 - 1.5) \times 10^{\left(0.4 + \frac{1094}{(SN+1)^{5.19}}\right) \times [\log W_t - 9.36 \log(SN+1) + 0.2 - 2.32 \log M_R + 8.07]} \tag{10}$$

where:

PSIt = predicted PSI at year t,

ΔPSI = difference between the initial PSI and current PSI,

SN = structural number (adjusted after every rehabilitation according to overlay thicknesses),

Wt = cumulative ESALs applied to pavement from the last construction/rehabilitation, and

MR = subgrade modulus.

The reliability item was removed from the equation because the variability of the variables was considered by directly assigning a distribution to them as shown in Table 4.2. The structure number of pavement was adjusted according to the mill depth and overlay thicknesses every time a rehabilitation activity was applied.

The following PCI models developed for Washington were used for the different types of pavement [13]:

1. New flexible pavement:

$$PCI = PCI_0 - 0.22(AGE)^{2.0} \qquad (11)$$

2. AC overlay (1.2 inches to 2.4 inches):

$$PCI = PCI_0 - 0.76(AGE)^{1.75} \qquad (12)$$

3. AC overlay (over 2.4 inches):

$$PCI = PCI_0 - 0.54(AGE)^{1.75} \qquad (13)$$

After every rehabilitation activity, both PSI and PCI were reset to their new condition values, which were randomly sampled from an independent distribution according to Table 4.2. Then, the performance of pavement progressed according to the corresponding models.

The decision models proposed in this research are the fuzzy-logic-based models described in the previous section. They are compared with traditional threshold trigger models used in deterministic and probabilistic methods. For thin overlay policy (Alternative A), the thresholds values considered were 3.5 for PSI and 65 for PCI, whichever comes first; for thick overlay policy (Alternative B), they were 2.5 for PSI and 45 for PCI, whichever comes first. These were adopted based on engineering judgment.

LCCA Results

The results of the deterministic LCCA method are summarized in Figure 4.4. Figure 4.5 presents the risk analysis results using (a) the threshold trigger model and (b) the fuzzy-logic triggering model. As expected, the mean values of the probabilistic model's outputs are close to the results of the deterministic model; the differences are due mostly to the random sampling of the simulation model.
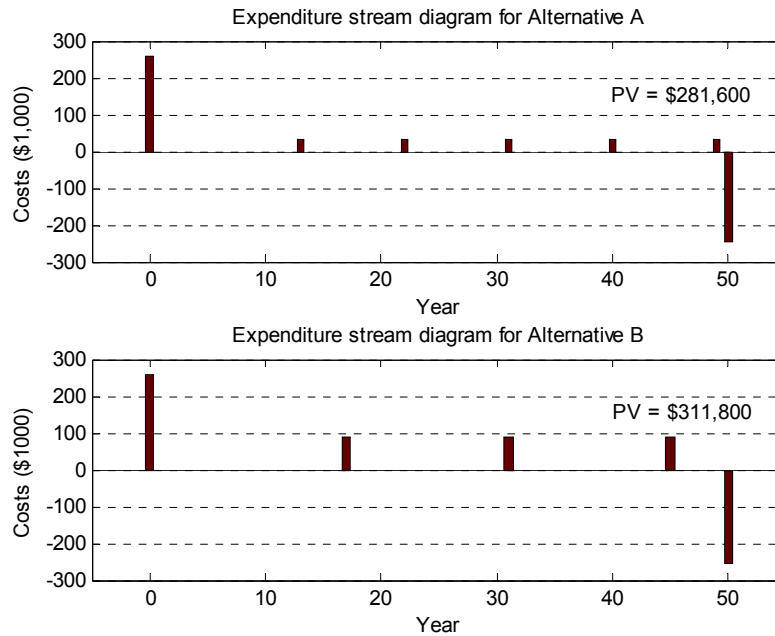
FIGURE 4.4. Expenditure stream diagram for alternative A and B using deterministic method

Although the decision-making mechanics are different, the risk analysis results of the method using fuzzy-logic-based models are also comparable with the results using threshold trigger models. However, in fuzzy-logic-based models, a group of rules is defined according to the policy of transportation agencies and activated by the inference engine to determine the rehabilitation timing. Such mechanism allows the fuzzy-logic-based models to make decisions that mimic common human behavior better than simple threshold trigger methods. The use of more elementary variables in the inference process, such as layer thicknesses, also improves the credibility of final results.
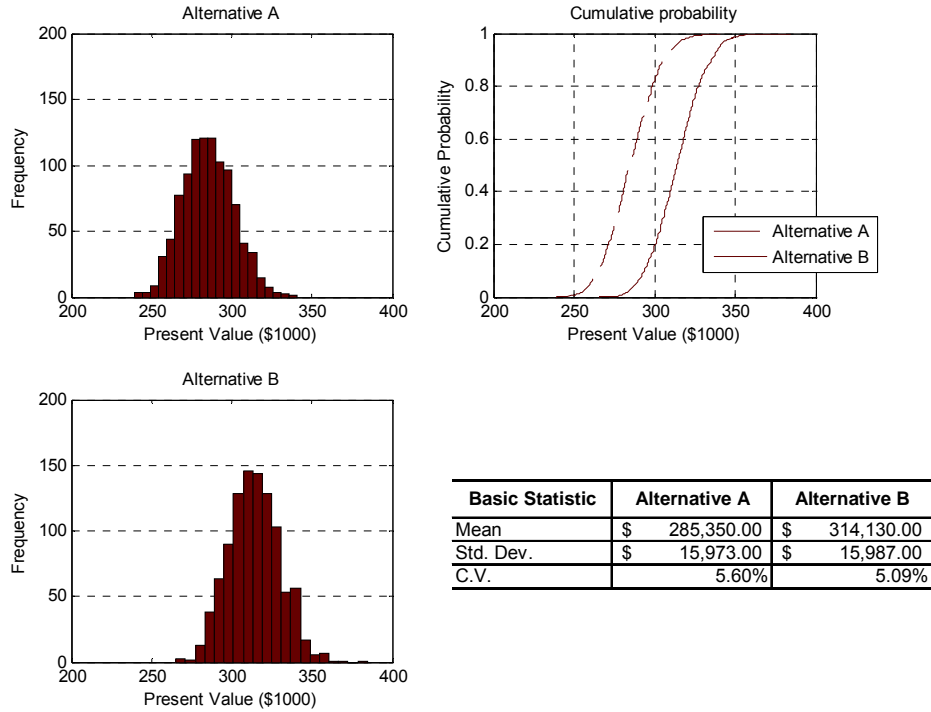
(a)
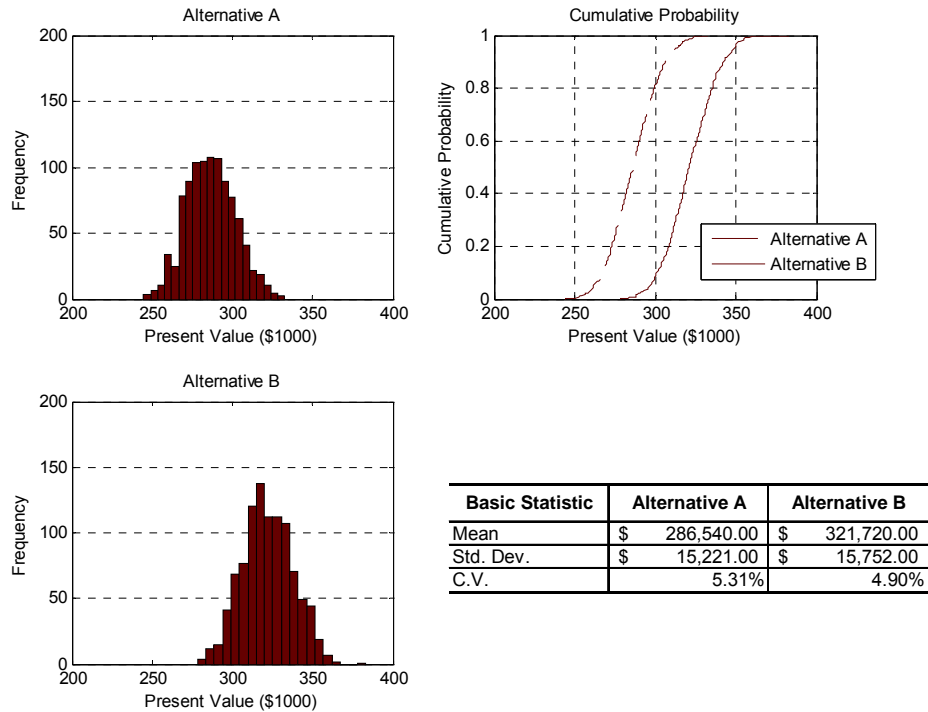
(b)

FIGURE 4.5. Risk profile of PV for alternatives A and B using (a) threshold trigger model and (b) fuzzy-logic triggering model

It can be seen that the results of all three models favor Alternative A in the case study. This is reasonable because thin-overlay treatments applied earlier are in general more economic than thicker-overlays applied later. In the deterministic method, Alternative A is preferred because its PV of $297,530 is lower than that of Alternative B, $311,800. In the threshold-trigger-model-based probabilistic method, Alternative A is preferred again because it has lower PV costs and similar variance. However, because the cost distributions of the two alternatives have a large overlap, the risk of selecting B over A solely based on lower PV costs is high. In the fuzzy-logic-based probabilistic method, the decision also favors Alternative A in terms of lower PV costs and similar variance. One interesting finding is the fuzzy-logic-based risk analysis gives a slightly lower variance than trigger-model-based risk analysis. This feature is desirable in decision making because it increases the significance of alternative preference. However, more extensive research is needed to draw a solid conclusion about it.

The results of the case study indicate that the statistical characteristics of output results could be effectively captured in the risk analysis of fuzzy-logic-based LCCA algorithms. When rehabilitations are triggered by performance and decision models, the correlations are implicit in the simulation; thus, they accurately estimate the variance of final PV results.

Sensitivity Analysis

Figure 4.6 illustrates the probability of performing rehabilitation, via thin or thick overlay, at a particular year for both models. The probabilities of rehabilitation timing using the threshold-trigger-model-based probabilistic LCCA method concentrate more on several discrete years while the probability distribution using fuzzy-logic-based decision models spread over a 4- or 5-year period flatly. This could be a sign that if the results of the probabilistic LCCA approach are sensitive to the decision models, a small change of threshold value in the traditional trigger decision model could cause a big difference in the final decision. Considering threshold values as the only parameters in trigger decision models, a sensitivity analysis was performed to evaluate the effects of PSI and PCI threshold values on final results. Its results

were compared with the findings by Chen and Flintsch [15] on the sensitivity analysis for fuzzy-logic-based LCCA approaches.
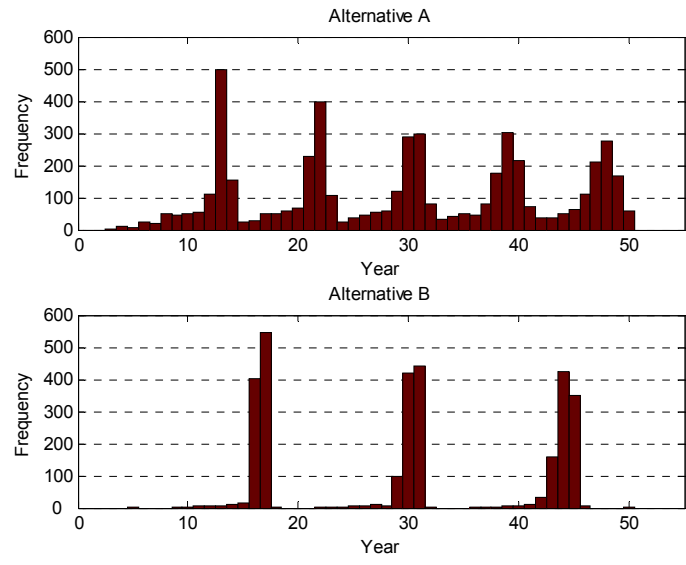
(a)
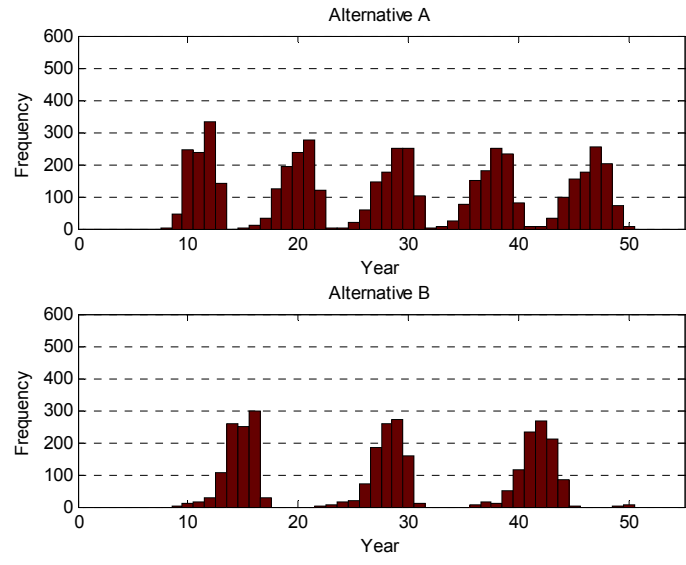
(b)

FIGURE 4.6. Probability of rehabilitation timing using (a) threshold trigger model and (b) fuzzy-logic triggering model

The sensitivity analyses were implemented separately for Alternative A and Alternative B. The variation ranges for PSI and PCI threshold were [3.0, 4.0] and [55, 75], respectively, for Alternative A

and [2.0, 3.0] and [35, 55], respectively, for Alternative B. The resulting correlation coefficients are as shown in Table 4.3. It is significant that final PV results were highly correlated with the threshold values. This relationship indicates that the quality of the decisions based on LCCA results of the probabilistic approach using trigger models is greatly affected by the threshold values. If the threshold values are not properly selected or cannot accurately represent the agency's practices, decision makers may be misled by the LCCA results.

TABLE 4.3. Correlation Sensitivity for Alternatives A and B

Variable	Alternative A (thin-overlay)			Alternative B (thick-overlay)		
	Interval	Mean	Std. Dev.	Interval	Mean	Std. Dev.
PSI Threshold	[3.0, 4.0]	0.9130	0.8917	[2.0, 3.0]	0.9401	0.7824
PCI Threshold	[55, 75]	0.9869	-0.3094	[35, 55]	0.9952	0.6722

With a similar case study, the research by Chen and Flintsch [15] found that as long as the system structure could correctly capture the decision process practiced by an agency, the LCCA results and final preference based on them were relatively stable when small changes were made on membership functions of fuzzy logic systems. Compared to the finding in sensitivity analysis of trigger-model-based LCCA, the stability of fuzzy-logic-based model is more desirable for transportation agencies in decision making because a stable LCCA model means the decisions based on it will be consistent.

SUMMARY AND CONCLUSIONS

LCCA is a powerful economic analysis tool for supporting transportation Asset Management decision making. It is used to support project-level decisions and to evaluate agency-level Asset Management strategies. Fuzzy logic systems provide a formal approach for making inferences based on the uncertain, ambiguous, and subjective information commonly available for LCCA. This paper proposes a fuzzy-logic-based approach for determining the timing for pavement MR&R treatments in a probabilistic LCCA model for selecting pavement MR&R strategies. This approach enhances the traditional probabilistic

LCCA method by adding the capability of processing some of the ambiguous uncertainty involved in the decision process. The paper illustrates the feasibility of the proposed approach through a comparative case study. The case study compared threshold trigger-based deterministic, threshold-trigger-based probabilistic, and fuzzy-logic-based probabilistic approaches. The example demonstrated that the fuzzy-logic-based risk analysis model for LCCA can effectively produce results that are at least comparable to those of the benchmark methods, while allowing consideration of some of the ambiguous uncertainty inherent to the process.

FUTURE ENHANCEMENT

While the research shows the feasibility and some potential advantages of fuzzy-logic-based probabilistic method, further efforts are necessary to improve the methodology and promote its application in pavement management practice. The following list discusses some of the possible improvements:

1. One advantage of fuzzy logic system is it can include linguistic information as well as numerical information. Considering today's pavement management practices rely on engineering experience heavily while more and more numeric data are accumulated, fuzzy logic techniques provide a unique solution to combine the two categories of information. Mendel [10] indicated that using fuzzy basis functions (FBF) could produce strong coupling between rules from knowledge mining and numeric data. The next phase of this research is to tune the fuzzy logic models with real world data, such as the pavement conditions before appropriate MR&R treatment.

2. Accurately capturing the probability distribution of input variables is a prerequisite of efficient decision-support from probabilistic LCCA. Although normal distribution and symmetric triangular distribution are popular choices in most cases, more accurate distribution functions could be built based on real information. Defining more reliable distribution functions would help produce results and risk evaluations closer to the actual conditions.

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CHAPTER 5: CALIBRATING FUZZY-LOGIC-BASED PAVEMENT REHABILITATION DECISION MODELS USING THE LTPP DATABASE

Calibrating Fuzzy-Logic-based Pavement Rehabilitation Decision Models Using the LTPP Database

By

Chen Chen[1] and Gerardo W. Flintsch[2]

ABSTRACT: This paper establishes a systematic method to calibrate a fuzzy-logic-based pavement rehabilitation decision model using real cases extracted from the Long Term Pavement Performance (LTPP) database. The fuzzy system was developed to conduct life cycle costs analysis (LCCA) of transportation infrastructure assets. The following tasks had to be completed to develop the proposed method: (1) extract representative rehabilitation events and related pavement information from the database; (2) identify proper input areas for engineering knowledge and numeric data; and (3) simultaneously tune two fuzzy logic systems with shared membership functions for input variables. A total of eight tables in the LTPP database were used to extract pavement performance and rehabilitation information. The investigation started with 62 rehabilitation cases but only six overlay rehabilitations with thicknesses between 1.5 and 2.5 inches had all the required information and were thus selected to calibrate the decision model. To make the dataset unbiased, six do-nothing cases were created based on the rehabilitation cases. By reinterpreting the model in the form of neural fuzzy system, the calibration algorithm was able to successfully tune the decision model to distinguish between the rehabilitation and do-nothing cases.

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INTRODUCTION

Business decisions regarding pavement, bridges, and other infrastructure assets are made daily in the operation of transportation agencies. Engineering management systems have been developed by local, state, and national agencies to support these decisions. The process started with the development of pavement management systems (Hudson et al., 1968), continued with bridge management systems (Hudson et al., 1987) and infrastructure management systems (Hudson and Hudson, 1994), and has recently evolved into asset management. The implementation of these systems allows transportation agencies integrating massive data management, intensive computing capability, and sound engineering experience from engineering and management staff to support their transportation infrastructure investment decisions.

Transportation asset management decisions generally consist of two steps: (1) collecting quality supporting information and (2) using the information, together with previous experience and knowledge on the issue, to reach a decision. Modern engineering techniques such as automated data collection and information technologies have made it possible for a transportation agency to obtain quality information in an acceptable timeframe and at reasonable cost; however, the development of a sound knowledge base still requires considerable time and tremendous efforts to achieve. The discovery of procedures and approaches for effectively summarizing and extracting engineering knowledge from previous experience is important for advancing transportation asset management.

Engineering economic analysis is a widely accepted technique to evaluate and measure the effectiveness of decision options in transportation asset management (FHWA, 1999; OECD, 2001). Valuing the costs and impacts of transportation projects in a monetary form is an objective way to assess project-level alternatives, network-level plans, and strategic-level policies. Most economic analysis methods used in transportation asset management, such as benefit cost analysis (BCA) and life cycle cost analysis

(LCCA), require the prediction of future project performance and future expenditures to control or correct the deterioration of transportation infrastructures. Therefore, performance prediction models are critical to support maintenance, rehabilitation and reconstruction (MR&R) decisions, which are based on the progression of those dynamic properties (e.g., pavement roughness and cracking).

Infrastructure management MR&R decisions often consider many factors such as infrastructure design and rehabilitation models, policies, availability of funding, and agency experience (FHWA, 1999). From an engineer's point of view, the most relevant factors are the infrastructure condition and treatment effectiveness. The condition of a facility is usually determined by its structural and functional properties. Studies to predict the condition of pavement, bridges, and other transportation assets are abundant in the literature (Cattan and Mohammadi, 1997; Huang and Moore, 1997; Owusu-Ababia, 1998).

While asset performance models are abudant, efforts that summarize and consolidate real life decision-making cases and experiences are rare in the transportation field. However, in practice project-level decisions are often based on engineering judgment and experience. With first-hand management experience and the best knowledge of their assets, engineers and asset managers are making decisions everyday regarding pavements, bridges and other assets. Therefore, it would be appropriate to use an agency's specific experience to predict future MR&R activities in engineering economic analysis. Utilizing the opinion and experience of the asset management staff should lead to realistic predictions.

OBJECTIVE

This paper establishes a systematic method for calibrating the fuzzy-logic-based rehabilitation decision model proposed by Chen et al. (2004) using real cases extracted from the Long Term Pavement Performance (LTPP) database. The steepest descent method and back-propagation learning algorithm were used to tune the model. To achieve the objective, the following tasks had to be accomplished:

1. Extract reliable cases of overlay treatment from the LTPP database;

2. Identify proper input areas for engineering knowledge and numeric data;

3. Simultaneously tune two fuzzy logic systems with shared membership functions for input variables.

FUZZY-LOGIC-BASED DECISION MODEL

The decision model to be calibrated in this research was first proposed by Chen et al. (2004) as a module to schedule rehabilitation activities for LCCA. As shown in Figure 5.1, the decision model consists of two fuzzy logic systems, namely, Fuzzy Trigger Model and Fuzzy Policy Model. Rules for both models can be customized according to the agency's policies or expert opinions. The trigger model computes the priority of a do-nothing policy, and the policy model evaluates the priority of specific rehabilitation treatments. The LCCA algorithm simulates the two mutually exclusive activities, do nothing and rehabilitation, selects the most appropriate treatment for each year, and produces a rehabilitation schedule for the analysis period. The algorithm compares the priorities computed by the two fuzzy logic models each year, and the treatment with the highest priority is selected for that year.

Figure 5.1 shows that the algorithm's prediction relies heavily on the deterioration model and the fuzzy-logic-based decision model. With the help of modern mathematic techniques, including statistical methods and adaptive modeling, the deterioration model could be established and calibrated to be used in a specific geographic region with confidence. However, the studies of project-level decision models are not abundant in today's transportation asset management literature. An optimal, or adequate, decision requires proper understanding of the properties of assets and the impacts of MR&R treatments. When reliable history records are not available, the major, if not the only, source of information for constructing the decision models is expert opinions and engineering experience. In this case, the decision-support model can be initially developed based on the subjective experience. As objective data becomes available, the decision models can be improved by calibrating these models with the accumulation of real cases, which accurately reflect an agency's MR&R practice. Therefore, a systematic approach is required to incorporate existing expert knowledge and accumulated actual cases.
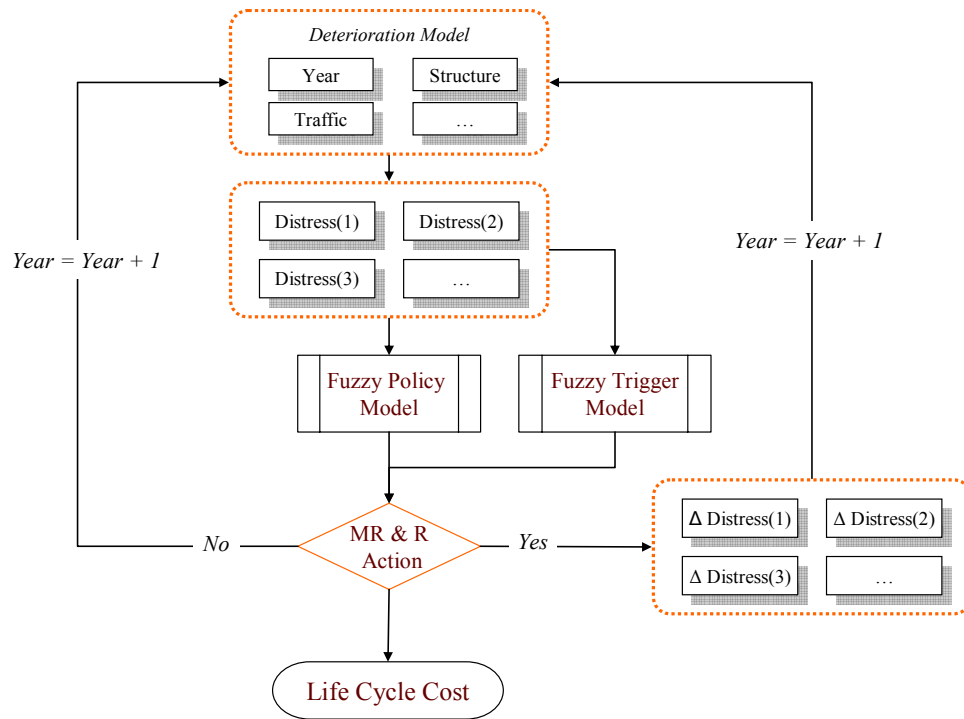
FIGURE 5.1. Fuzzy-Logic-based Decision Model (Chen et al., 2004)

DATA PREPARATION

Ideally, if not enough historical information is available at the time of developing of the models, the fuzzy-logic-based decision model can be initially designed mainly using expert knowledge and then periodically reviewed and tuned as quality data accumulates. This approach was followed in this research. The data used to tune the decision model were extracted from the LTPP database. The LTPP program, initiated under the Strategic Highway Research Program (SHRP), has accumulated substantial pavement condition information from in-service pavements throughout the United States and Canada. The LTPP database is probably the largest pavement condition data source in the world available for public access. This fact makes it an ideal data source for this research. Figure 5.2 summarizes the procedure used for extracting the required data from the database. The main steps of this process are elaborated following.

```
┌─────────────────────────────────────────┐
│ IDENTIFY GEOGRAPHICAL REGION              │
│ • Virginia                                │
│ • and Vicinity Regions (DC, DE, MD, WV, NC)│
└─────────────────────────────────────────┘
                    │
                    ▼
┌─────────────────────────────────────────┐
│ EXTRACT PAVEMENT DATA                     │
│ • Performance Condition                   │
│ • Rehabilitation Type                     │
│ • Rehabilitation Reason                   │
└─────────────────────────────────────────┘
                    │
                    ▼
┌─────────────────────────────────────────┐
│ SELECT REHABILITATION TYPE                │
│ • 2" Asphalt Overlay                      │
│ • and Overlay Thickness within 2 ± 0.5"   │
└─────────────────────────────────────────┘
                    │
                    ▼
┌─────────────────────────────────────────┐
│ REMOVE DEFICIENT CASES                    │
│ • with Incomplete Pavement Condition      │
│ • with rehabilitation for Non-Pavement Reason│
│ • with conflicted condition data (2 types)│
└─────────────────────────────────────────┘
```

FIGURE 5.2. Procedure for Extracting Training Data from LTPP Database

Geographical Area of Interest

Since climate and environment have significant impacts on pavement performance and rehabilitation effectiveness, it is inevitable that rehabilitation decisions are also affected by the factors. Therefore, identifying a specific region from which to extract cases would be helpful to reduce the complexity of the model. The state of Virginia is the area of interest in this research. However, to have enough data for the calibration study, five neighboring Mid-Atlantic States (the District of Columbia, Delaware, Maryland, West Virginia, and North Carolina) were also included in the queries.

Pavement Condition Indicators

Pavement condition is usually measured by the severity of the distresses preset in the surface. Three types of distresses were considered in the research: alligator cracking, rutting, and roughness. Alligator cracking generally occurs when the pavement has been reached its fatigue life because of repetitive axle load application. Rutting is depressions occurring in the pavement's wheel path as a result of traffic loads. Wire-line rut indices were used in this research for rutting measurement because the method usually obtains rutting values with a wider range compared with traditional straight-edge methods. The

two distresses have been widely accepted as important indicators of soundness of pavement structures. Pavement roughness is a measure of the surface deviations that produce a response in the suspension system of the vehicles traveling over the road. It is important because it is directly noticeable to the traveling public. The decision model was calibrated based on the pavement conditions immediately before a certain type of rehabilitation.

Rehabilitation Treatments

The prevailing type of rehabilitation in Virginia is 1.5-inch overlay after pretreatment of the existing pavement. However, other states might have different practices. After reviewing the rehabilitation records of sections in the LTPP database, overlays between 1.5 and 2.5 inches were categorized as one rehabilitation type. This rehabilitation type was referred as thin overlay for this research. Usually, an overlay with thickness in this range is selected to repair pavements that have not suffered severe losses in structural capacity, at which point major rehabilitation or reconstruction has yet become necessary.

Deficient Records

Not all rehabilitation records were ready to be used to calibrate a decision model capable of reflecting the intended practices. Three types of deficient records were removed from the dataset to be used in calibration. The first group is those with some desired information missing, such as no roughness data collected before rehabilitation. Then, rehabilitations incurred by reasons other than poor pavement conditions are deleted because this research only focuses on decisions due to engineering considerations. The records removed in a last step are those conflicting with their sections' major trend. Typical abnormalities are unexpected performance improvement without any documented rehabilitations.

Building Dataset for Calibration

Once the rehabilitation events have been identified, section information, rehabilitation type and data, and pavement conditions were extracted from the database to build the dataset as shown in Figure 5.3. Sixty-

two cases were originally extracted. However, after the cleansing, a total of six cases, as listed in Table

5.1, were finally used to calibrate the fuzzy-logic-based decision model in this study.
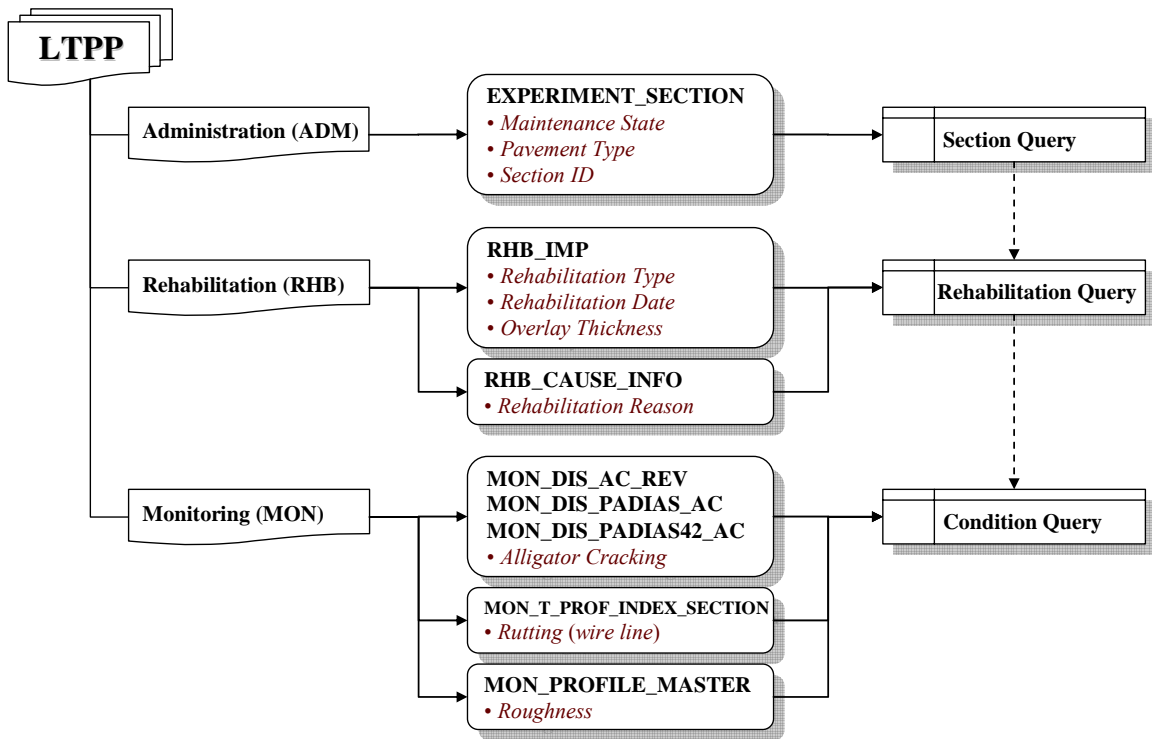
FIGURE 5.3. Data Extracted from the LTPP Database

TABLE 5.1. Rehabilitation Cases

Case #	State	ID	Alligator Cracking (%)	Rutting (*inches*)	Roughness (*inches/mile*)	Overlay Thickness (*inches*)
1	MD	0505	18.42%	0.24	116.11	2.0
2	MD	0561	23.90%	0.39	70.96	2.5
3	VA	1002	6.15%	0.20	172.74	1.5
4	VA	1023	4.59%	0.63	121.14	1.5
5	VA	1417	3.71%	0.24	175.63	1.5
6	VA	1423	5.09%	0.28	137.36	1.5

One potential drawback of the dataset is that all of the cases lead to the decision of thin-overlay treatment

which might introduce bias to the calibrated model. The solution is to add cases that lead to do-nothing

decisions. However, it is not easy to directly find suitable cases from the LTPP database because what

the dataset needs are cases such that current pavement conditions lead to do-nothing, but any further development of distress would lead to rehabilitation. Conceptually, the rehabilitation cases were used to create do-nothing cases by reducing the current distresses by 15%. The percentage was selected based on engineering judgment. Adding these do-nothing cases made the dataset balanced. As a result, only a very small dataset was used; however, it was large enough to illustrate the practicality of the approach.

DESIGN OF FUZZY LOGIC SYSTEMS

Fuzzy logic systems are an extension of the traditional rule-based reasoning (expert systems) that incorporate imprecise, qualitative data in the decision-making process by combining descriptive linguistic rules through fuzzy logic (Zadeh, 1973). A typical fuzzy logic system consists of four components: fuzzifier (input processor), rule base, inference engine, and defuzzifier (output processor). The fuzzifier and defuzzifier provide mapping between crisp values and fuzzy sets. The concept of fuzzy sets provides the basis of fuzzy logic systems. There have been many references that explain the concept (Lin and Lee, 1996; Mendel, 2001). A fuzzy set is a set whose members have an associated membership function value between 0 and 1, while the traditional crisp sets only allow its members to take value of 0 or 1. The rule base is where the knowledge of models is stored. The knowledge needed to build the rules can be provided by experts, extracted from collected data, or both. A form of IF-THEN clauses is often used to store the knowledge. The inference engine determines how the rules are triggered and processed to map input values into outputs.

Each of the four components has multiple options in designing the architecture of a fuzzy logic system, which create almost infinite possibilities. The fuzzifier could be either singleton or non-singleton. The membership functions could be triangular, trapezoidal, or Gaussian, among others. Typical composition methods (operations) include max-min, max-product, etc. Examples of defuzzifier schemes include centroid, height, and modified height. For simplicity, the fuzzy logic systems studied in this research were designed using singleton fuzzification, Gaussian membership functions, product implication and t-

norm operations, and height defuzzification. The following discussion will focus on this specific architecture unless indicated otherwise.

Selecting the architecture for a fuzzy logic system is more or less arbitrary and relies heavily on the previous knowledge of a specific configuration. When numerical training data are also available, the design methods could be categorized into the following 3 groups:

1. Let the data determine the key parameters for the fuzzy sets of input and output variables and then establish inference rules;

2. Pre-define fuzzy sets for input and output variables and use data to determine inference rules; and

3. Manually design the architecture and then use the data to optimize its parameters according to performance measures.

The first two approaches are called "one-pass methods" (Mendel, 2001) because the training data are only used once in the design of the fuzzy logic system. The third approach usually needs to visit the training data many times to obtain the best possible performance and therefore is called a "multiple-pass methods". When available data are accurate and sufficient for designing fuzzy logic systems, the two one-pass methods may suffice. However, if it is time-consuming to collect quality information, the third design method provides a more practical solution because it allows fully relying on expert knowledge at the beginning and fine-tuning the model as quality information becomes available. This paper uses the multiple-pass method to optimize the parameters of fuzzy-logic-based decision models.

Membership Functions

Gaussian functions are used in this paper to define the membership of each element in a fuzzy set. So for a single input value of x, its fuzzy membership is given in equation (1).

$$\mu_{F_k^i}(x) = \exp\left(-\frac{(x - m_{F_k^i})^2}{2\sigma_{F_k^i}^2}\right) \quad i = 1, \ldots, N \tag{1}$$

Where $m_{F_k^l}$ = the mean value of Gaussian function of the kth input in the lth rule;

$\sigma_{F_k^l}$ = the standard deviation of Gaussian function of the kth input in the lth rule.

The number of membership function terms for a specific input or output variable depends on the previous experience about how many categories are enough. The simplest configuration (used in this research) is categorizing each pavement distress condition into two groups: good or poor. For example, the rutting condition was defined by two membership functions, one for good rutting condition and one for poor. A specific rutting value could partially belong to good and poor at the same time in fuzzy logic systems.

Inference Rules

The Rule-bases store the knowledge of fuzzy logic systems. To fully utilize available expert knowledge, the proposed tuning method starts by defining inference rules. If a fuzzy logic system has p inputs x_1, x_2, …, x_p, one output y, and M inference rules, then the lth rule has the form:

$$R^l: \text{IF } x_1 \text{ is } F_1^l \text{ and } \cdots \text{ and } x_p \text{ is } F_p^l, \text{THEN is } y \text{ is } G^l; \quad l = 1, \ldots, M$$

Where F_k^l is the membership function term of the kth input ($k = 1, \ldots, p$) in the lth rule and G^l is the membership function term of the output.

Since the decision model has three distress conditions as inputs, at least eight inference rules are required to fully cover all possible premise conditions. Table 5.2 gives the inference rules and initial mean values of output membership functions of the two fuzzy logic systems utilized in this research. If all three conditions are good, the do-nothing option is of the highest priority, 1, and the rehabilitation option is of the lowest priority, 0. As the pavement conditions deteriorate, the priorities of do-nothing decrease while those of rehabilitation increase. Finally, when all three conditions are poor, rehabilitation gains an overwhelming priority, 1, over do-nothing, 0.

TABLE 5.2. Inference Rule Bases of the Decision Model

Rule	Alligator Cracking	Rutting	Roughness	Do-Nothing Priority	Rehabilitation Priority
		Premise		*Consequences*	
1	Good	Good	Good	1	0
2	Poor	Good	Good	0.75	0.25
3	Good	Poor	Good	0.75	0.25
4	Good	Good	Poor	0.75	0.25
5	Poor	Poor	Good	0.25	0.75
6	Poor	Good	Poor	0.25	0.75
7	Good	Poor	Poor	0.25	0.75
8	Poor	Poor	Poor	0	1

The logic behind this rule base is valid from the engineering perspective; do nothing to pavements in good condition and rehabilitate pavements in poor condition. However, the challenge is to find the correct value for priorities in each rule and the parameters, mean values and standard deviations, of the various membership functions to make the decision model consistent with previous practices. To achieve this ultimate goal, it is necessary to have a systematic procedure to calibrate the model using real cases. The multi-pass method to tune a single fuzzy logic system based on system feedback was selected. This method uses fuzzy basis function as a bridge connecting rule-based fuzzy logic system and mathematic programming techniques.

Fuzzy Basis Functions

The concept of fuzzy basis functions was first introduced by Wang and Mendel (1992). Their objective was to develop a mathematical formula representing how a crisp input $\mathbf{x}$ is mapped into a crisp output $y = f(\mathbf{x})$ through fuzzy logic systems. Let $\bar{y}^l$ denote the mean value of output membership function in the lth rule. The mapping formula was constructed as follows:

$$y = f(\mathbf{x}) = \sum_{l=1}^{M} \bar{y}^l \phi_l(\mathbf{x}) \quad l = 1, \ldots, M \tag{2}$$

Where $\phi_l(\mathbf{x})$ is the fuzzy basis function which is given based on specific choices for fuzzifier, membership functions, composition, implication, t-norm and defuzzifier. For the architecture used in this study, the fuzzy basis function is:

$$\phi_l(\mathbf{x}) = \frac{\prod_{k=1}^{p} \mu_{F_k^l}(x_k)}{\sum_{l=1}^{M} \prod_{k=1}^{p} \mu_{F_k^l}(x_k)} \qquad (3)$$

Where $\mu_{F_k^l}(x_k)$ is the value of membership of the kth input ($k = 1, \ldots, p$) in the lth rule ($l = 1, \ldots, M$).

Equation (2) indicates that, for output membership functions, only their mean values have impacts on final results; the standard deviations do not affect the outputs when using the height defuzzification method. The concept of fuzzy basis functions is very useful because it provides a general form of function approximation for fuzzy logic systems. More explanation about fuzzy basis functions can be found elsewhere (Wang and Mendel, 1992).

Steepest Descent Method

Steepest descent methods are also known as gradient descent methods. These methods have been widely applied for solving nonlinear programming problems, such as learning algorithms of neural network. To find the optimal solution, i.e., the maximum or minimum of a cost function $f(\mathbf{x})$, it starts from a pre-selected initial position, P_0, and as many times as needed, moves from P_i to P_{i+1} along the direction of steepest gradient, $-\nabla f(P_i)$. Selecting the initial position is critical to the convergence of the solution. Poorly selected initial positions may cause extremely long converging time and even result in stopping at a local optimal position. However, expert knowledge usually gives a start point close to the optimal. If this is the case, the tuning process would be dramatically simplified and expedited.

Tuning Fuzzy Logic Systems

Based on the idea of steepest descent method, Mendel (2001) developed a method to tune the antecedent and consequent parameters in fuzzy logic systems. This method was used as the basis of the calibration algorithm used in the paper and is briefly explained in this section.

If N groups of paired input-output data are available to tune a fuzzy logic system and $\mathbf{x}$ denotes the inputs and y for output, the cost function for the ith group can be defined as follows:

$$e^{(i)} = \frac{\left[f_s(\mathbf{x}^{(i)}) - y^{(i)} \right]^2}{2} \quad i = 1, \dots, N \tag{4}$$

Following the principle of steepest descent methods, three equations were developed to minimize $e^{(i)}$ ($i = 1, \dots, N$, $l = 1, \dots, M$ and $k = 1, \dots, p$):

$$m_{F_k^l}(i+1) = m_{F_k^l}(i) - \alpha_m \left[f_s(\mathbf{x}^{(i)}) - y^{(i)} \right] \left[\overline{y}^l(i) - f_s(\mathbf{x}^{(i)}) \right]$$
$$\times \frac{\left[x_k^{(i)} - m_{F_k^l}(i) \right]}{\sigma_{F_k^l}^2(i)} \phi_l(\mathbf{x}^{(i)}) \tag{5}$$

$$\overline{y}^l(i+1) = \overline{y}^l(i) - \alpha_{\overline{y}} \left[f_s(\mathbf{x}^{(i)}) - y^{(i)} \right] \phi_l(\mathbf{x}^{(i)}) \tag{6}$$

$$\sigma_{F_k^l}(i+1) = \sigma_{F_k^l}(i) - \alpha_\sigma \left[f_s(\mathbf{x}^{(i)}) - y^{(i)} \right] \left[\overline{y}^l(i) - f_s(\mathbf{x}^{(i)}) \right]$$
$$\times \frac{\left[x_k^{(i)} - m_{F_k^l}(i) \right]^2}{\sigma_{F_k^l}^3(i)} \phi_l(\mathbf{x}^{(i)}) \tag{7}$$

Because $\overline{y}^l$, $m_{F_k^l}$ and $\sigma_{F_k^l}$ are parameters associated with membership functions for physically meaningful quantities, it is usually possible to obtain very good initial values for them. Choosing them smartly will help this algorithm to converge much faster (Chu and Mendel, 1994). The learning parameters, α_m, $\alpha_{\overline{y}}$ and α_σ must also be chosen with some care. Frequently, the same value of α is chosen for all three equations.

MODEL CALIBRATION

A challenge associated with the tuning of the decision model in Figure 5.1 is how to simultaneously optimize the design of two fuzzy logic systems. Since they share the same input variables, it will be ideal if they would share the definition of membership functions of each input variable. Using the same language in the two fuzzy logic systems facilitates expert knowledge acquisition and makes the model easier to understand and accept by decision makers. However, this also means one more objective and

several more constraints in the calibration phase, which usually makes the nonlinear programming problem more difficult to solve.

Fortunately, shared membership functions also provide direct connections between the two systems. With these connections, the competition among two fuzzy logic systems can be reinterpreted as an integrated neural fuzzy system. As shown in Figure 5.4, a feed-forward multilayer network was constructed to describe the decision model in terms of a neural fuzzy system. The membership functions and inference rules connected by solid lines are components of the trigger model and those connected by broken lines belong to the policy model.
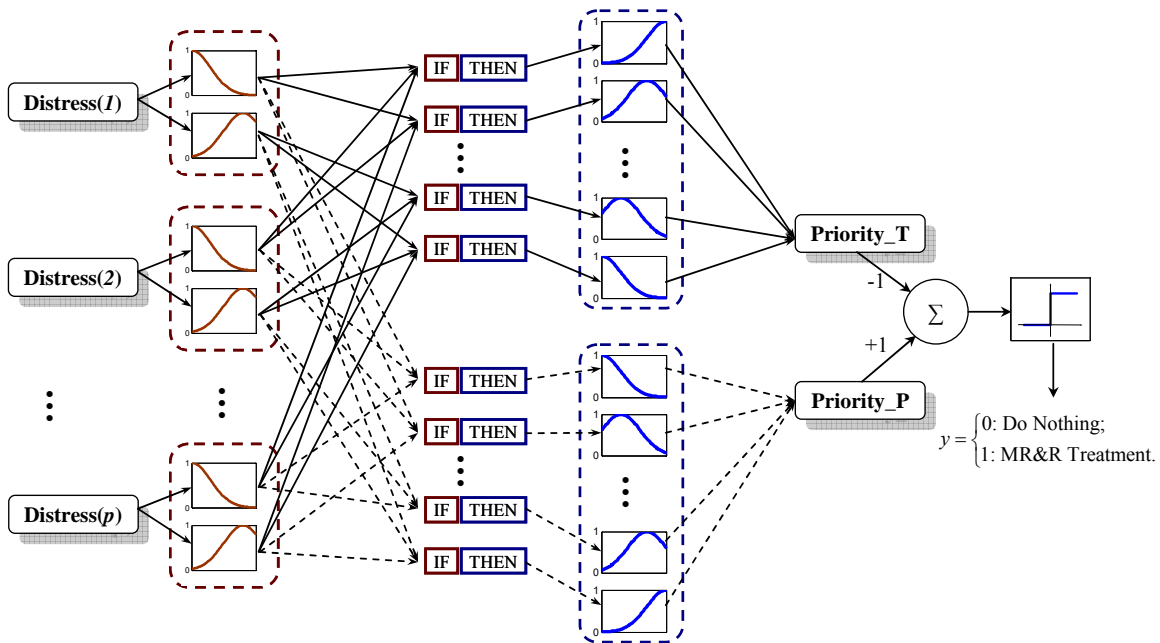
FIGURE 5.4. Reinterpreting the Decision Model in the form of a Neural Fuzzy System

Under this network structure, the input nodes represent transportation infrastructure conditions; the hidden layers consist of nodes functioning as membership functions, fuzzy logic rules, and comparison of priorities; and the output layer represents final decisions. The detailed explanation of the layers is as follows:

- *Input*: Input nodes represent current condition of transportation assets. They are measured by the extent or magnitude of the distresses considered.

- *Hidden Layer 1*: Each single node in this layer performs one membership function for a certain input variable, i.e., a distress type in this study. Therefore, links between layer 1 and input nodes only occur when the nodes are designated to a specific distress type.

- *Hidden Layer 2*: This layer represents the inference rules designed for the two fuzzy logic models. It is possible to have multiple inputs for nodes of this layer when the represented rule has multiple antecedents.

- *Hidden Layer 3*: Nodes in this layer are essentially the membership functions for the output variables, the priorities of do-nothing or rehabilitation. Together with layer 2, this layer functions as the inference engine of the two fuzzy logic models.

- *Hidden Layer 4*: The layer combines the outputs from the fuzzy logic rules in each of the two models. A defuzzification method has to be pre-specified in the initial design phase.

- *Output*: The output layer gives the final recommended treatment. It compares the two output priorities and selects a winner, i.e., the treatment with the higher priority. Therefore, the weight of link is 1 between output node and the priority of the policy model and -1 for the priority of the trigger model.

The five-layer neural fuzzy system makes it possible to use neural network learning techniques for this research. The following section will further explain the benefits from integrating fuzzy logic and neural network for calibrating the decision-support model.

Neural Fuzzy System

It has been widely accepted that fuzzy logic and neural networks are complementary technologies. When expert knowledge is the major source for constructing a fuzzy logic system, the design process is more or

less arbitrary. Once the system is constructed, it will be difficult to identify the part to tune according to numeric training data. On the other side, neural networks are good at learning from historic data, but the links and nodes in hidden layers are usually hard to assign meaningful roles in a model. Combining them into one integrated system allows for combining their advantages and minimizing the drawbacks.

Several previous studies suggested that the complementary features and characteristics of fuzzy systems and neural networks warrant their integration (Werbos, 1992; Bersini et al., 1993; Pedrycz, 1993). On the neural network side, by combining it with a fuzzy system, the structure provides more transparency and allows a possible interpretation of the links and nodes following the learning stage. On the fuzzy set side, neural networks' learning algorithms allow automatic tuning of the parameters that characterize the fuzzy system. Therefore, neural networks can improve their transparency, while fuzzy systems can self-adapt.

One major advantage of using the concept of neural fuzzy systems in this research is that the learning abilities from neural networks make fuzzy systems adaptive to the process of accumulating reliable MR&R cases. The membership functions were fine-tuned using the training data. At the same time, the model also provides human-understandable meaning to the feed-forward multilayer neural network in which the nodes are often opaque to users (Lin and Lee, 1996). This feature makes it possible to use expert knowledge in both initial design and final validation phases.

Calibrating the Decision-support Models

With the network-structured decision model in Figure 5.4, it is a natural choice to use a back-propagation (BP) learning algorithm to do the calibration work. The concept of BP learning was one of the most important developments in neural networks (Werbos, 1974; Rumelhart and Zipser, 1986). In the algorithm, the error(s) at the output layer is propagated backward to adjust the connection weights of preceding layers to minimize output errors. After a number of iterations, multilayer feed-forward networks can be systematically optimized by this algorithm. The back-propagation algorithm is employed in most neural network applications.

As shown in Figure 5.4, the proposed decision-support model of this research consists of two fuzzy logic systems. The definitions of the membership functions for the individual input variables are shared by the two models, but each rule of the two systems has its own output membership function. The reasons for such design are the following: (1) using the same language for input variables provides extra convenience to incorporate expert knowledge; but (2) more flexibility is desired for the output membership functions to improve the tuning of the model.

To implement the back-propagation learning algorithm, an error function is required to measure the deviation from target output values. Mathematically, the outputs are 0 for do-nothing or 1 for thin-overlay in this research. Because the raw data from the LTPP database are assumed to be pavement conditions at which thin overlay rehabilitations are properly and timely triggered, the priority from policy model is desired to be slightly larger than the priority from trigger model. Similarly, for the do-nothing cases, the pavement conditions are assumed to be just before thin-overlay rehabilitation is properly triggered. Therefore, when pavement conditions are deteriorated to a level just severe enough for triggering thin overlay rehabilitation, the priority from the policy model is desired to be slightly lower than the priority from trigger model. In other words, for the pavement conditions used in calibration, the outputs from two fuzzy logic systems expected to be very close but still capable differentiate do-nothing cases from rehabilitation cases. Based on this consideration, the error function was formulated as:

$$e^{(i)} = (d^{(i)} - f^{(i)}) \left| \text{Priority}_{policy}^{(i)} - \text{Priority}_{trigger}^{(i)} \right| \tag{8}$$

Where $d^{(i)}$ = the desired decision based on the ith pair of pavement conditions;

$f^{(i)}$ = the decision by decision model based on the ith pair of pavement conditions;

$\text{Priority}_{policy}^{(i)}$ = the priority of rehabilitation produced by policy model;

$\text{Priority}_{trigger}^{(i)}$ = the priority of do-nothing produced by trigger model;

The errors calculated by equation (8) are for the entire neural fuzzy system. Following the principle of back-propagation method, the error propagated to trigger model is $-e^{(i)}$; the error propagated to policy model is $e^{(i)}$. The calibration essentially becomes tuning the two fuzzy logic systems. The parameters to be tuned in the decision model include 6 mean values and 6 standard deviations for input membership functions shared by the two fuzzy logic systems, and 16 mean values for output membership functions (their standard deviations do not influence final results). An epoch is defined as the collection of N training cases. It is important to notice that each of the 28 parameters only need to be updated once using equations (5), (6) and (7) based on the error from one case. The six mean values and six standard deviations for the input variables have to be updated simultaneously for both fuzzy logic systems. Otherwise, their updating is not synchronous with the mean values of output membership functions which may make it hard, or impossible, for the model to converge.

A number of variations of the algorithm exist by preprocessing the training dataset differently and/or using different convergence criteria. The training dataset was preprocessed in the way shown in Figure 5.5. A calibration dataset was constructed by increasing the pavement distresses of do-nothing cases by 5% and decreasing those of rehabilitation cases by 5%. The preprocessing means that the decision model is subject to a stricter calibration dataset but still the target is to differentiate the original do-nothing cases from rehabilitation cases. Since only six cases were used, the convergence criteria used in this research was to run the calibration until the decisions regarding all cases could be accurately predicted. As shown in Figure 5.6, a total of 72 epochs were sufficient to get the decision model to converge.

Table 5.3 gives the values of the parameters of the decision model before and after calibration. All values are rounded to numbers that are easily understandable from an engineer's perspective. The principles to determine the initial values are simple. First, the mean values of membership functions for good and poor conditions should cover the range of training set. Secondly, the standard deviations are roughly one third to half of the ranges.
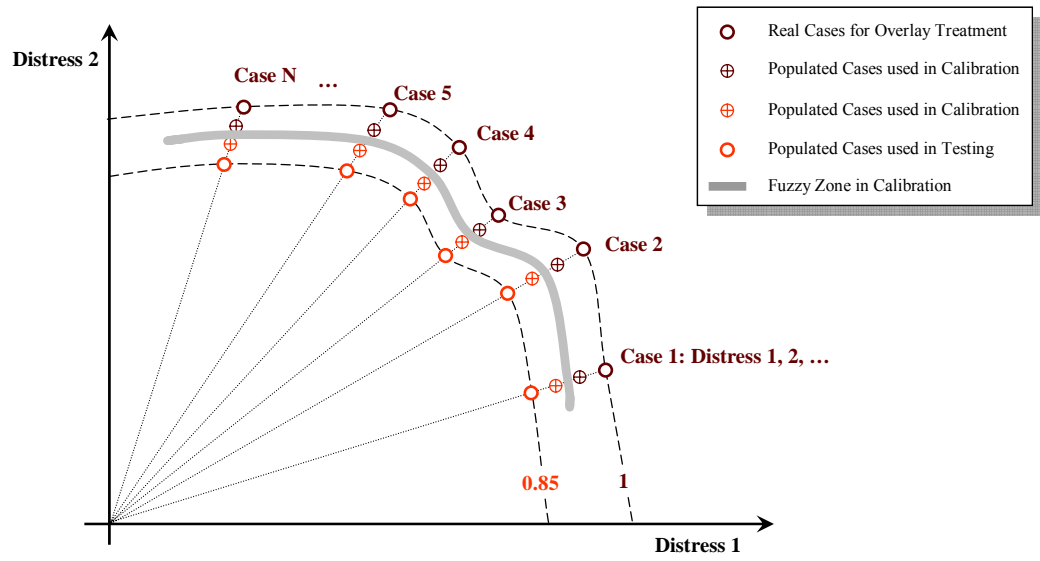
FIGURE 5.5. Cases of Overlay Treatment
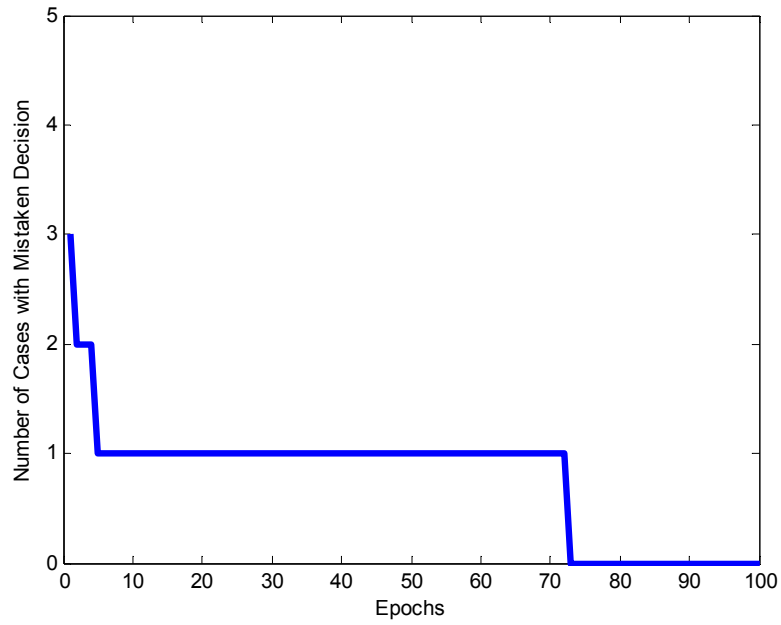
FIGURE 5.6. Number of cases with mistaken decisions decreasing through multi-pass calibration

TABLE 5.3. Fuzzy-Logic-based Decision Model

Variable	Membership Function	Initial Values		Values after Tuning	
		m	*σ*	*m*	*σ*
Alligator Cracking	*Good*	5%	10%	0%	11%
	Poor	25%	10%	17%	18%
Rutting	*Good*	0.1	0.3	0.07	0.32
	Poor	1	0.3	0.92	0.45
Roughness	*Good*	50	50	50	50
	Poor	200	50	200	50
Do-Nothing Priority	*Rule 1*	1	-	0.88	-
	Rule 2	0.75	-	0.60	-
	Rule 3	0.75	-	0.77	-
	Rule 4	0.75	-	0.75	-
	Rule 5	0.25	-	0.30	-
	Rule 6	0.25	-	0.25	-
	Rule 7	0.25	-	0.25	-
	Rule 8	0	-	0.00	-
Rehabilitation Priority	*Rule 1*	0	-	0.12	-
	Rule 2	0.25	-	0.40	-
	Rule 3	0.25	-	0.23	-
	Rule 4	0.25	-	0.25	-
	Rule 5	0.75	-	0.70	-
	Rule 6	0.75	-	0.75	-
	Rule 7	0.75	-	0.75	-
	Rule 8	1	-	1.00	-

DISCUSSION

The procedures for data extraction, initial design, and model calibration proposed in this research can be

readily adopted by transportation agencies to develop their own regional decision-support models. The

region could be state, district(s), or county(s) where the rehabilitation activities are conducted under

consistent policies. Building such models would benefit a specific area's asset management from at least

two aspects. First, the engineering economic analysis can more accurately evaluate the impacts of

alternatives to the area because the decision models are based on their actual practices. Second, besides

the application in engineering economic analysis, the results of model calibration could also be used to

compare the impacts on rehabilitation decisions of a single distress and/or a combination of several

distresses.

Data Preparation

Although data from six states were initially selected for consideration, finally only six cases from two states (Virginia and Maryland) were identified as adequate to be used in this research. There were 62 rehabilitation events recorded in the database. Most of them were deleted due to incomplete information. The LTPP program requires pavement conditions data to be collected before and after any rehabilitation events (Elkins et al., 2005). Participating agencies are requested to notify the LTPP regional office for anticipated rehabilitation events. However, the LTPP database does not contain complete data for all rehabilitation events. Although not in the database, it is reasonable to expect that most of the missing information could be located somewhere in the responsible transportation agency because, usually, rehabilitation is applied to address the issues that have been discovered. When similar research is conducted to investigate the decision behaviors of an agency, it is recommended to exhaust all possible sources before excluding a rehabilitation case. Useful complementary information might be found in pavement condition reports, project proposals, and/or district records. The pool of rehabilitation events would be significantly enlarged if the information about them is completed.

The phase of data extraction also suggested that the table, RHB_CAUSE_INFO, would have provided useful information to the study of decision behaviors if its data were more complete. However, it looks like the table has not received the same degree of attention as have other tables containing numeric data. If the rehabilitation reasons are coded and recorded as other data, the table could be used to categorize rehabilitation events and help to locate those events of interests.

Architecture Design of Fuzzy Logic Systems

The initial design of decision model is essentially a process of consolidating engineering experience and expert knowledge. For simplicity, only two fuzzy terms, good or poor, were defined for each input variable in the research. The architecture could be further elaborated to implement an agency's existing

policy or reflect the understanding of engineering professionals by adding more fuzzy terms to the input variables to compare several rehabilitation options (Chen et al., 2004).

Another variation of the architecture design could be to incorporate some fixed rules into the system. For considerations such as safety, traffic, environmental, etc., some crisp rules are required for rehabilitation decisions. The research had all parameters tunable but, with the help of fuzzy basis functions, it would be convenient to incorporate such rules. Also considering that today's pavement management relies on both engineering experience and accumulated numeric data, fuzzy logic techniques provide a quite unique solution to combine the two categories of information. Mendel (2001) indicated that using fuzzy basis functions (FBF) could produce strong coupling between rules from knowledge mining and numeric data.

Impacts of Distress(es) on Rehabilitation Decision

It is no surprise that different types of distress have different impacts on rehabilitation decisions. The results of model calibration give a quantified comparison. In this research, the premises of rules 2, 3 and 4 have only one type of distress in poor condition. For example, by comparing the mean values of their output membership functions, the finding is that alligator cracking has a higher impact than rutting and roughness. When two types of distress are present, the combination of alligator cracking and rutting has the highest impact, as can be seen in Table 5.3.

SUMMARY AND CONCLUSIONS

This paper proposes a systematic method to calibrate a fuzzy-logic-based rehabilitation decision model using real cases extracted from the Long Term Pavement Performance (LTPP) database. A total of six complete overlay rehabilitation events with thickness between 1.5 and 2.5 inches were obtained to calibrate the decision model. To make the dataset unbiased, six do-nothing cases were created from the rehabilitation cases. The initial architecture of fuzzy-logic-based decision model was designed based on engineering knowledge; inference rules were developed to cover all possible combinations of the three pavement distresses considered. The decision-support model was tuned to distinguish between

rehabilitation cases and do-nothing cases by reinterpreting the model as a neuron-fuzzy system. The application of the proposed method in a simple example to select thin overlay treatments demonstrated that the approach is feasible and practical.

The results of the investigation suggest that accumulated numeric data can help study the decision behavior of a transportation agency. If properly designed and maintained, a DOT asset management database stores the corporate knowledge of the agency. Fuzzy systems were found suitable to study the decision behavior. Rule-based fuzzy logic systems provided a user-friendly platform to elicit experts' opinions and agency practices. Rules with the form of "IF-THEN" are easily understood by engineering and managing professionals. By reinterpreting the model in the form of a neuro-fuzzy system, the calibration algorithm takes advantage of the learning capabilities of artificial neural networks for tuning the fuzzy membership functions and rules. With limited time and effort, the initial model was tuned to reflect the rehabilitation decisions made on the LTPP sections.

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CHAPTER 6: SUMMARY, CONCLUSIONS AND FUTURE WORKS

Transportation infrastructure asset management decisions, such as need analysis, project selection, prioritization, and optimization, are often based on data that is uncertain, ambiguous, and incomplete, and often incorporate engineering judgment and expert opinion. Life cycle cost analysis is a powerful economic analysis tool that is used for supporting both project and network level decisions. However, traditional LCCA tools can not effectively evaluate and process all uncertainties involved in predicting future project expenditures. The dissertation produced enhanced LCCA models using soft computing (mainly fuzzy logic) techniques. The proposed models use available "real-world" information to forecast life-cycle costs of competing maintenance and rehabilitation strategies and support infrastructure management decisions. Furthermore, these models can be easily adopted by transportation agencies and calibrated with limited time and efforts.

FINDINGS

Each chapter of this dissertation represented a different stage of the research undertaken and includes its specific finding and conclusions. The major findings from the research can be summarized as follows.

- Soft computing tools provide appealing alternatives for supporting many of the infrastructure management functions. The development of practical and efficient "intelligent" soft-computing-based tools can enhance the existing decision-support tools because these decisions are commonly based on a combination of numerical data and expert opinion, which are often uncertain, ambiguous, and/or incomplete.

- Fuzzy logic systems provide a formal approach for processing the often uncertain, ambiguous, and subjective information considered in LCCA. The development of fuzzy-logic-based LCCA models is feasible and results in decision-support tools that can be customized according to agency's management policies and practices. Furthermore, the approach is practical, as illustrated by its implementation in the case study presented in

Chapter 3 for comparing and selecting pavement maintenance, rehabilitation and reconstruction (MR&R) policies.

- The fuzzy logic-based LCCA model is compatible, and can be integrated, with the traditional risk analysis framework for LCCA. A comparison of threshold-trigger-based deterministic and probabilistic approaches, with the fuzzy-logic-based approach, demonstrated that the fuzzy-logic-based risk analysis model for LCCA can effectively produce results that are at least comparable to those of the benchmark methods, while allowing consideration of the ambiguous uncertainty inherent to the process.

- The fuzzy-logic LCCA model can be initially designed based on expert opinion and then calibrated using real cases extracted from existing infrastructure management databases. The membership function and inference rules in a simple case study were calibrated to distinguish between rehabilitation (light overlay) and do-nothing cases extracted the Long Term Pavement Performance (LTPP) database. By reinterpreting the model in the form of a neuro-fuzzy system, the calibration algorithm takes advantage of the learning capabilities of artificial neural networks. This hybrid soft computing application could be extrapolated to other applications that need to acquire knowledge from a combination of expert knowledge and numerical data.

CONCLUSIONS

The dissertation proposed an innovative application of fuzzy set theory for infrastructure LCCA. A fuzzy logic-based LCCA model was developed for selecting pavement MR&R treatments and supporting transportation infrastructure asset management decisions. The model's rule-based inference module provides a user-friendly platform to elicit experts' opinions. The model is capable of predicting future project expenditures that mimic the practices of a specific transportation agency. The incorporation of the fuzzy system into the traditional risk analysis framework resulted in an algorithm capable of processing both the ambiguous and random

uncertainties involved in LCCA. Finally, the re-interpretation of the fuzzy system in the form of neuro-fuzzy system provided a practical methodology to calibrate the fuzzy system using numeric data.

The proposed LCCA model and calibration methodology have the potential to support more realistic economic analyses than those achieved using traditional LCCA methods. These enhanced methods could results in more efficient transportation infrastructure investments which would eventually help provide more reliable transportation systems at a lower cost.

IMPLEMENTATION ISSUES

The proposed models can be easily applied in the infrastructure management of transportation agencies. As shown in chapter 5, the fuzzy logic based model could be calibrated to reflect the management practices of engineering professionals. With more rehabilitation cases accumulated, the decision model needs to be re-calibrated. The target is to obtain a final product that can successfully predict proper decisions to infrastructures under different combinations of condition measurements. Since the model is adaptive, more reliable cases will lead the resulted model to a higher accuracy. Therefore building a pool of rehabilitation examples is a critical step of implementation.

Many aspects of transportation asset management will benefit from the well calibrated models. As a major tool of engineering economic analysis, LCCA is fully compatible with the fuzzy logic based decision models. Replacing predefined scenarios of maintenance and rehabilitation with fuzzy decision models lets analysis procedure better imitate the real practices of infrastructure management. Besides project level LCCA, the models could be further used in project selection and prioritization level by developing models for different levels of maintenance and rehabilitation (as shown in chapter 3). At the network level, the proposed models could help to quickly assess individual infrastructures and generate aggregated system results.

The biggest challenge of implementation is on the user's side. Most transportation asset management practitioners still have reservations about implementing soft computing techniques. Additional potential obstacles include resistance to change and the difficulty in integrating the new techniques with existing systems. To fully achieve the benefits of the developed models, an agency needs firstly to obtain the commitment from top management. A comprehensive education effort to promote an understanding of the principles and algorithms used is also needed. Finally, it is extremely helpful to the successes of implementation to deploy tools that are user-friendly and compatible with existing asset management tools and agency practices.

RECOMMENDATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

While the presented research demonstrates the feasibility and potential advantages of a fuzzy-logic approach for LCCA, further efforts are necessary to improve the methodology and promote its application in transportation infrastructure management practice. The following list presents some of the possible improvements:

- *Incorporating user costs:* User costs, including vehicle operating costs, travel time costs, accident costs and environmental costs, cannot easily be computed. However, they can provide valuable information for project level decisions and incorporating them into the overall LCCA model should improve the quality of the decisions supported. Since theses costs are estimated based upon often uncertain, incomplete, and sometimes ambiguous information, soft computing techniques could facilitate their calculation.

- *Determining more realistic probability distribution function for the LCCA inputs:* Accurately capturing the probability distribution of the input variables is necessary for an accurate probabilistic LCCA. Although normal distribution and symmetric triangular distribution are popular choices in most cases, more accurate distribution functions could be built based on real information. Defining more reliable distribution functions would help produce results and risk evaluations closer to the actual conditions.

- *Further calibration of the model using more extensive data sources:* it is recommended to explore the availability of other reliable data source for calibrating the fuzzy-logic-based LCCA model. Both expert knowledge and knowledge from numeric data will help improve the model. It is desired to develop different family models for different maintenance strategies, such as preventive maintenance, corrective maintenance, restorative maintenance, and combinations thereafter. A complete set of decision-support models will help decision-makers select optimal strategy for infrastructure management.

- *Application of the neuro-fuzzy calibration method to other asset management problems:* Accumulated numeric data could be of critical help to study the decision behavior of a transportation agency in other business functions not considered in this research. While rules with the form of "IF-THEN" could be easily understood and reviewed by engineering and managing professionals, an effective decision-support system need to have the ability of acquiring knowledge from objective historical records. The learning capability of neural networks plays a key role in the hybrid neuron-fuzzy system. With limited time and efforts, the initial model can easily be tuned to reflect past agency practices.

APPENDIX A: MATLAB SCRIPTS

TRADITIONAL DETERMINISTIC LCCA MODEL

```matlab
%*************************************************
% Common Parameters
%*************************************************

% General Configuration
Ana_Period = 50;
Iteration_Num = 1;
Disc_Rate = 0.04;

% Generate Traffic Information
ADT = 12000;
T = 0.30;
Tf = 0.52;
DDF= 0.50; LF = 0.90;

ESAL0 = ADT.*T.*Tf*DDF*LF*365;
Growth_Rate = 0.06;
ESAL = zeros(Ana_Period,1);
for year=1:Ana_Period
    ESAL(year) = ESAL0.*(1+Growth_Rate).^(year-1);
end


% Unit costs of initial construction ($/SY-inch)
Initial_Surface_UC = 2.19;
Initial_Inter_UC = 1.86;
Initial_Base_UC = 1.78;
Initial_Subbase_UC = 1.18;

% Unit costs of rehabilitation: thin overlay and thick overlay
Mill_UC = 0.50; % ($/SY-in)
OL_Surface_UC = 2.19; % ($/SY-in)
OL_Inter_UC = 1.86; % ($/SY-in)

% Initial Pavement Design (Layer thickness)
Area = 7040; % Unit: Sq-yard; based on one mile long 12 feet width
%% AC Surface Layer
Surface_Thickness = 2; % (in)
Surface_Coeff = 0.44;
%% AC Intermediate Layer
Inter_Thickness = 5; % (in)
Inter_Coeff = 0.44;
%% Base Layer
Base_Thickness = 9; % (in)
Base_Coeff = 0.14;
Base_Drain = 1;
%% Subbase Layer
Subbase_Thickness = 6; % (in)
Subbase_Coeff = 0.11;
Subbase_Drain = 1;
%% Subgrade
Subgrade_Mr = 5000; % (psi)
```

```matlab
%*****************************************************
%% Alternative A: Thin Overlay Rehabilitation (2-in)
%*****************************************************

% Rehabilitation Design (Overlay thickness)
OL_Mill_A = 1;
OL_Surface_A = 2;
OL_Inter_A = 0;

% Calculate Initial Construction Costs
Initial_Cost_A = Area*Surface_Thickness*Initial_Surface_UC + ...
    Area*Inter_Thickness*Initial_Inter_UC + ...
    Area*Base_Thickness*Initial_Base_UC + ...
    Area*Subbase_Thickness*Initial_Subbase_UC;

% Calculate Initial SN
iSN_A = ones(Iteration_Num, 1)*(Surface_Thickness*Surface_Coeff +...
    Inter_Thickness*Inter_Coeff + ...
    Base_Thickness*Base_Coeff*Base_Drain + ...
    Subbase_Thickness*Subbase_Coeff*Subbase_Drain);

% PSI and PCI
PSI_A = zeros(Iteration_Num, Ana_Period+1);
PSI_A(:,1) = 4.5;
iPSI_A = PSI_A(:,1);
PCI_A = zeros(Iteration_Num, Ana_Period+1);
PCI_A(:,1) = 95;
iPCI_A = PCI_A(:,1);
TGap_A = zeros(Iteration_Num, Ana_Period+1);

% Reliability
R_A = 0.50; S0_A = 0;

% Variables to save iteration information
Rehab_Cost_A = zeros(Iteration_Num,1);
Rehab_Timing_A = zeros(Iteration_Num,1);
Salvage_A = zeros(Iteration_Num,1);


% Predict pavement performance: PSI, and PCI and schedule
Rehabilitation
% activities.
for iteration = 1: Iteration_Num
    % Iteration Parameters (Initial Conditions)

    cESAL_A = 0;
    HMA_Thickness = Surface_Thickness + Inter_Thickness;
    Rehab_Num = 0;
    pavement_type_A = 2; % new pavement

    for year = 1: Ana_Period
        %Year means the end of a year
```

```matlab
        % Calculate the cumulative traffic volume (ESAL)
        cESAL_A = cESAL_A + ESAL(year);

        % If pavement conditions hit the threshhold values, schedule a
        % rehabilitation activity at current year
        if PSI_A(iteration, year)<=3.5 || PCI_A(iteration, year)<=65
            Rehab_Num = Rehab_Num + 1;
            if size(Rehab_Cost_A,2)<Rehab_Num
                Rehab_Cost_A = [Rehab_Cost_A, zeros(Iteration_Num,1)];
            end

            Rehab_Cost_A(iteration, Rehab_Num) =
Area*OL_Mill_A*Mill_UC+...
                Area*OL_Surface_A*OL_Surface_UC + ...
                Area*OL_Inter_A*OL_Inter_UC;
            Rehab_Timing_A(iteration, Rehab_Num) = year;

            SN_eff_A(iteration,Rehab_Num) = ...
                sneff(cESAL_A, iPSI_A(iteration, Rehab_Num),...
                iSN_A(iteration, Rehab_Num), Subgrade_Mr(iteration),...
                R_A, S0_A);
            iSN_A(iteration, Rehab_Num+1) = ...
                SN_eff_A(iteration,Rehab_Num)-...
                - OL_Mill_A*...
                (Surface_Coeff - ...
                (iSN_A(iteration, Rehab_Num)-...
                SN_eff_A(iteration,Rehab_Num))/HMA_Thickness)+...
                OL_Surface_A*Surface_Coeff +...
                OL_Inter_A*Inter_Coeff;
            iPSI_A(iteration, Rehab_Num+1) = iPSI_A(iteration,
Rehab_Num);
            iPCI_A(iteration, Rehab_Num+1) = iPCI_A(iteration,
Rehab_Num);
            pavement_type_A = 7; % pavement with overlay < 2.4in
            HMA_Thickness = HMA_Thickness - OL_Mill_A +...
                OL_Surface_A + OL_Inter_A;
            TGap_A(iteration, year) = 0;
            PSI_A(iteration, year) = iPSI_A(iteration, Rehab_Num+1);
            PCI_A(iteration, year) = iPCI_A(iteration, Rehab_Num+1);
            TGap_A(iteration, year+1) = TGap_A(iteration,year)+1;
            PSI_A(iteration, year+1) = iPSI_A(iteration, Rehab_Num+1) -
...
                psiloss(ESAL(year), iSN_A(iteration, Rehab_Num+1),...
                Subgrade_Mr, R_A, S0_A);
            PCI_A(iteration, year+1) = ...
pci_predict(TGap_A(iteration,year+1),pavement_type_A,...
                iPCI_A(iteration, Rehab_Num+1));
            cESAL_A = ESAL(year);
        else
            TGap_A(iteration, year+1) = TGap_A(iteration,year)+1;
            PSI_A(iteration, year+1) = iPSI_A(iteration, Rehab_Num+1) -
...
                psiloss(cESAL_A, iSN_A(iteration, Rehab_Num+1),...
                Subgrade_Mr, R_A, S0_A);
            PCI_A(iteration, year+1) = ...
```

```matlab
            pci_predict(TGap_A(iteration,year+1),pavement_type_A,...
                        iPCI_A(iteration, Rehab_Num+1));
        end
    end
end

% Salvage value
Salvage_A = Initial_Cost_A.*(PSI_A(:,Ana_Period+1)-1.5)./(PSI_A(:,1)-
1.5);

% Present Worth Factor
PWF_A = (kron((1+Disc_Rate)',ones(size(Rehab_Cost_A,2),1))').^(-
Rehab_Timing_A);
NPV_A = [Initial_Cost_A, Rehab_Cost_A.*PWF_A, -
Salvage_A.*(1+Disc_Rate).^(-Ana_Period)];
LCC_A = sum(NPV_A')';

hold off; cdfplot(LCC_A);
LCC_Mean_A = mean(LCC_A)
LCC_Std_A = std(LCC_A)

disp('Alternative A has been done...');

%*************************************************
%% Alternative B: Thick Overlay Rehabilitation (6-in)
%*************************************************

% Rehabilitation Design (Overlay thickness)
OL_Mill_B = 2;
OL_Surface_B = 2;
OL_Inter_B = 4;

% Calculate Initial Construction Costs
Initial_Cost_B = Area*Surface_Thickness*Initial_Surface_UC + ...
    Area*Inter_Thickness*Initial_Inter_UC + ...
    Area*Base_Thickness*Initial_Base_UC + ...
    Area*Subbase_Thickness*Initial_Subbase_UC;

% Calculate Initial SN
iSN_B = ones(Iteration_Num, 1)*(Surface_Thickness*Surface_Coeff +...
    Inter_Thickness*Inter_Coeff + ...
    Base_Thickness*Base_Coeff*Base_Drain + ...
    Subbase_Thickness*Subbase_Coeff*Subbase_Drain);

% PSI and PCI
PSI_B = zeros(Iteration_Num, Ana_Period+1);
PSI_B(:,1) = 4.5;
iPSI_B = PSI_A(:,1);
PCI_B = zeros(Iteration_Num, Ana_Period+1);
PCI_B(:,1) = 95;
iPCI_B = PCI_A(:,1);
TGap_B = zeros(Iteration_Num, Ana_Period+1);
```

```matlab
% Reliability
R_B = 0.50; S0_B = 0;

% Variables to save iteration information
Rehab_Cost_B = zeros(Iteration_Num,1);
Rehab_Timing_B = zeros(Iteration_Num,1);
Salvage_B = zeros(Iteration_Num,1);

% Predict pavement performance: PSI, and PCI and schedule
Rehabilitation
% activities.
for iteration = 1: Iteration_Num
    % Iteration Parameters (Initial Conditions)

    cESAL_B = 0;
    HMA_Thickness = Surface_Thickness + Inter_Thickness;
    Rehab_Num = 0;
    pavement_type_B = 2; % new pavement

    for year = 1: Ana_Period
        %Year means the end of a year

        % Calculate the cumulative traffic volume (ESAL)
        cESAL_B = cESAL_B + ESAL(year);

        % If pavement conditions hit the threshhold values, schedule a
        % rehabilitation activity at current year
        if PSI_B(iteration, year)<=2.5 || PCI_B(iteration, year)<=45
            Rehab_Num = Rehab_Num + 1;
            if size(Rehab_Cost_B,2)<Rehab_Num
                Rehab_Cost_B = [Rehab_Cost_B, zeros(Iteration_Num,1)];
            end

            Rehab_Cost_B(iteration, Rehab_Num) =
Area*OL_Mill_B*Mill_UC+...
                Area*OL_Surface_B*OL_Surface_UC + ...
                Area*OL_Inter_B*OL_Inter_UC;
            Rehab_Timing_B(iteration, Rehab_Num) = year;


            SN_eff_B(iteration,Rehab_Num) = ...
                sneff(cESAL_B, iPSI_B(iteration, Rehab_Num),...
                iSN_B(iteration, Rehab_Num), Subgrade_Mr(iteration),...
                R_B, S0_B);
            iSN_B(iteration, Rehab_Num+1) =
SN_eff_B(iteration,Rehab_Num)-...
                - OL_Mill_B*...
                (Surface_Coeff - ...
                (iSN_B(iteration, Rehab_Num)-...
                SN_eff_B(iteration,Rehab_Num))/HMA_Thickness)+...
                OL_Surface_B*Surface_Coeff +...
                OL_Inter_B*Inter_Coeff;

            iPSI_B(iteration, Rehab_Num+1) = iPSI_B(iteration,
Rehab_Num);
```

```matlab
            iPCI_B(iteration, Rehab_Num+1) = iPCI_B(iteration,
Rehab_Num);
            pavement_type_B = 8; % pavement with overlay > 2.4in
            HMA_Thickness = HMA_Thickness - OL_Mill_B +...
                OL_Surface_B + OL_Inter_B;
            TGap_B(iteration, year) = 0;
            PSI_B(iteration, year) = iPSI_B(iteration, Rehab_Num+1);
            PCI_B(iteration, year) = iPCI_B(iteration, Rehab_Num+1);
            TGap_B(iteration, year+1) = TGap_B(iteration,year)+1;
            PSI_B(iteration, year+1) = iPSI_B(iteration, Rehab_Num+1) -
...
                psiloss(ESAL(year), iSN_B(iteration, Rehab_Num+1),...
                Subgrade_Mr, R_B, S0_B);
            PCI_B(iteration, year+1) = ...
pci_predict(TGap_B(iteration,year+1),pavement_type_B,...
                iPCI_B(iteration, Rehab_Num+1));
            cESAL_B = ESAL(year);
        else
            TGap_B(iteration, year+1) = TGap_B(iteration,year)+1;
            PSI_B(iteration, year+1) = iPSI_B(iteration, Rehab_Num+1) -
...
                psiloss(cESAL_B, iSN_B(iteration, Rehab_Num+1),...
                Subgrade_Mr, R_B, S0_B);
            PCI_B(iteration, year+1) = ...
pci_predict(TGap_B(iteration,year+1),pavement_type_B,...
                iPCI_B(iteration, Rehab_Num+1));
        end
    end
end

% Salvage value
Salvage_B = Initial_Cost_B.*(PSI_B(:,Ana_Period+1)-1.5)./(PSI_B(:,1)-
1.5);

% Present Worth Factor
PWF_B = (kron((1+Disc_Rate)',ones(size(Rehab_Cost_B,2),1))')...
    .^(-Rehab_Timing_B);
NPV_B = [Initial_Cost_B, Rehab_Cost_B.*PWF_B,...
    -Salvage_B.*(1+Disc_Rate).^(-Ana_Period)];
LCC_B = sum(NPV_B')';

hold on; cdfplot(LCC_B);
LCC_Mean_B = mean(LCC_B)
LCC_Std_B = std(LCC_B)

disp('Alternative B has been done...');
```

TRADITIONAL PROBABILISTIC LCCA MODEL

```matlab
%****************************************************
% Common Parameters
%****************************************************

% General Configuration
Ana_Period = 50;
Iteration_Num = 1000;
Disc_Rate = lhsdraw('tri', [0.03,0.04,0.05], Iteration_Num);
Std_Width = 2;

% Generate Traffic Information
ADT_Mean = 12000; ADT_COV = 0.15;
ADT = trnormdraw(ADT_Mean,ADT_COV,Std_Width,Iteration_Num);
T_Mean = 0.30; T_COV = 0.1;
T = trnormdraw(T_Mean,T_COV,Std_Width,Iteration_Num);
Tf_Mean = 0.52; Tf_COV = 0.365;
Tf = trnormdraw(Tf_Mean,Tf_COV,Std_Width,Iteration_Num);
DDF= 0.50; LF = 0.90;

ESAL0 = ADT.*T.*Tf*DDF*LF*365;
Growth_Rate_Mean = 0.06; Growth_Rate_COV = 0.1;
Growth_Rate = trnormdraw(Growth_Rate_Mean,Growth_Rate_COV,...
    Std_Width,Iteration_Num);
ESAL = zeros(Iteration_Num,Ana_Period);
for year=1:Ana_Period
    ESAL(:,year) = ESAL0.*(1+Growth_Rate).^(year-1);
end

% Unit costs of initial construction ($/SY-inch)
Initial_Surface_UC_Mean = 2.19; Initial_Surface_UC_COV = 0.1;
Initial_Surface_UC = trnormdraw(Initial_Surface_UC_Mean,...
    Initial_Surface_UC_COV,Std_Width,Iteration_Num);
Initial_Inter_UC_Mean = 1.86; Initial_Inter_UC_COV = 0.1;
Initial_Inter_UC = trnormdraw(Initial_Inter_UC_Mean,...
    Initial_Inter_UC_COV,Std_Width,Iteration_Num);
Initial_Base_UC_Mean = 1.78; Initial_Base_UC_COV = 0.1;
Initial_Base_UC = trnormdraw(Initial_Base_UC_Mean,...
    Initial_Base_UC_COV,Std_Width,Iteration_Num);
Initial_Subbase_UC_Mean = 1.18; Initial_Subbase_UC_COV = 0.1;
Initial_Subbase_UC = trnormdraw(Initial_Subbase_UC_Mean,...
    Initial_Subbase_UC_COV,Std_Width,Iteration_Num);

% Unit costs of rehabilitation: thin overlay and thick overlay ($/SY-in)
Mill_UC_Mean = 0.50; Mill_UC_COV = 0.1;
Mill_UC = trnormdraw(Mill_UC_Mean,...
    Mill_UC_COV,Std_Width,Iteration_Num);
OL_Surface_UC_Mean = 2.19; OL_Surface_UC_COV = 0.1;
OL_Surface_UC = trnormdraw(OL_Surface_UC_Mean,...
    OL_Surface_UC_COV,Std_Width,Iteration_Num);
OL_Inter_UC_Mean = 1.86; OL_Inter_UC_COV= 0.1;
```

```matlab
OL_Inter_UC = trnormdraw(OL_Inter_UC_Mean,...
    OL_Inter_UC_COV,Std_Width,Iteration_Num);


% Initial Pavement Design (Layer thickness)
Area = 7040; % Unit: Sq-yard; based on one mile long 12 feet width
%% AC Surface Layer
Surface_Thickness_Mean = 2; % (in)
Surface_Thickness_COV = 0.1;
Surface_Thickness = trnormdraw(Surface_Thickness_Mean,...
    Surface_Thickness_COV,Std_Width,Iteration_Num);
Surface_Coeff_Mean = 0.44;
Surface_Coeff_COV = 0.1;
Surface_Coeff = trnormdraw(Surface_Coeff_Mean,...
    Surface_Coeff_COV,Std_Width,Iteration_Num);
%% AC Intermediate Layer
Inter_Thickness_Mean = 5; % (in)
Inter_Thickness_COV = 0.1;
Inter_Thickness = trnormdraw(Inter_Thickness_Mean,...
    Inter_Thickness_COV,Std_Width,Iteration_Num);
Inter_Coeff_Mean = 0.44;
Inter_Coeff_COV = 0.1;
Inter_Coeff = trnormdraw(Inter_Coeff_Mean,...
    Inter_Coeff_COV,Std_Width,Iteration_Num);
%% Base Layer
Base_Thickness_Mean = 9; % (in)
Base_Thickness_COV = 0.1;
Base_Thickness = trnormdraw(Base_Thickness_Mean,...
    Base_Thickness_COV,Std_Width,Iteration_Num);
Base_Coeff_Mean = 0.14;
Base_Coeff_COV = 0.143;
Base_Coeff = trnormdraw(Base_Coeff_Mean,...
    Base_Coeff_COV,Std_Width,Iteration_Num);
Base_Drain_Mean = 1;
Base_Drain_COV = 0.1;
Base_Drain = trnormdraw(Base_Drain_Mean,...
    Base_Drain_COV,Std_Width,Iteration_Num);
%% Subbase Layer
Subbase_Thickness_Mean = 6; % (in)
Subbase_Thickness_COV = 0.1;
Subbase_Thickness = trnormdraw(Subbase_Thickness_Mean,...
    Subbase_Thickness_COV,Std_Width,Iteration_Num);
Subbase_Coeff_Mean = 0.11;
Subbase_Coeff_COV = 0.182;
Subbase_Coeff = trnormdraw(Subbase_Coeff_Mean,...
    Subbase_Coeff_COV,Std_Width,Iteration_Num);
Subbase_Drain_Mean = 1;
Subbase_Drain_COV = 0.1;
Subbase_Drain = trnormdraw(Subbase_Drain_Mean,...
    Subbase_Drain_COV,Std_Width,Iteration_Num);
%% Subgrade
Subgrade_Mr_Mean = 5000; % (psi)
Subgrade_Mr_COV = 0.15;
Subgrade_Mr = trnormdraw(Subgrade_Mr_Mean,...
    Subgrade_Mr_COV,Std_Width,Iteration_Num);


% Variables to extract random values from
```

```matlab
Rnd_Mill_UC = Mill_UC;
Rnd_OL_Surface_UC = OL_Surface_UC;
Rnd_OL_Inter_UC = OL_Inter_UC;
Rnd_Surface_Coeff = Surface_Coeff;
Rnd_Inter_Coeff = Inter_Coeff;


%%***************************************************
%% Alternative A: Thin Overlay Rehabilitation (2-in)
%%***************************************************

% Rehabilitation Design (Overlay thickness)
OL_Mill_A_Mean = 1; OL_Mill_A_COV = 0.1;
OL_Mill_A = trnormdraw(OL_Mill_A_Mean,...
    OL_Mill_A_COV,Std_Width,Iteration_Num);
OL_Surface_A_Mean = 2; OL_Surface_A_COV = 0.1;
OL_Surface_A = trnormdraw(OL_Surface_A_Mean,...
    OL_Surface_A_COV,Std_Width,Iteration_Num);
OL_Inter_A_Mean = 0; OL_Inter_A_COV = 0.1;
OL_Inter_A = trnormdraw(OL_Inter_A_Mean,...
    OL_Inter_A_COV,Std_Width,Iteration_Num);

% Calculate Initial Construction Costs
Initial_Cost_A = Area*Surface_Thickness.*Initial_Surface_UC + ...
    Area*Inter_Thickness.*Initial_Inter_UC + ...
    Area*Base_Thickness.*Initial_Base_UC + ...
    Area*Subbase_Thickness.*Initial_Subbase_UC;

% Calculate Initial SN
iSN_A = Surface_Thickness.*Surface_Coeff(:,1) +...
    Inter_Thickness.*Inter_Coeff(:,1) + ...
    Base_Thickness.*Base_Coeff.*Base_Drain + ...
    Subbase_Thickness.*Subbase_Coeff.*Subbase_Drain;

% PSI and PCI
PSI_A = zeros(Iteration_Num, Ana_Period+1);
PSI_A(:,1) = lhsdraw('normaltrunc',[4.2,5.0,4.6,0.2],Iteration_Num);
iPSI_A = PSI_A(:,1);
PCI_A = zeros(Iteration_Num, Ana_Period+1);
PCI_A(:,1) = lhsdraw('normaltrunc',[90,100,95,2.5],Iteration_Num);
iPCI_A = PCI_A(:,1);
TGap_A = zeros(Iteration_Num, Ana_Period+1);

% Reliability
R_A = 0.50; S0_A = 0;

% 07/20/2006 Stop here
% Variables to extract random values from
Rnd_OL_Mill_A = OL_Mill_A;
Rnd_OL_Surface_A = OL_Surface_A;
Rnd_OL_Inter_A = OL_Inter_A;
Rnd_iPSI_A = iPSI_A;
Rnd_iPCI_A = iPCI_A;

% Variables to save iteration information
Rehab_Cost_A = zeros(Iteration_Num,1);
```

```matlab
Rehab_Timing_A = zeros(Iteration_Num,1);
Salvage_A = zeros(Iteration_Num,1);
SN_eff_A = zeros(Iteration_Num,1);


% Predict pavement performance: PSI, and PCI and schedule
Rehabilitation
% activities.
for iteration = 1: Iteration_Num
    % Iteration Parameters (Initial Conditions)

    pavement_type_A = 2; % new pavement
    cESAL_A = 0;
    HMA_Thickness = Surface_Thickness(iteration)+...
        Inter_Thickness(iteration);
    Rehab_Num = 0;

    for year = 1: Ana_Period
        %Year means the end of a year

        % Calculate the cumulative traffic volume (ESAL)
        cESAL_A = cESAL_A + ESAL(iteration,year);

        % If pavement conditions hit the threshhold values, schedule a
        % rehabilitation activity at current year
        if PSI_A(iteration, year)<=3.5 || PCI_A(iteration, year)<=65
            Rehab_Num = Rehab_Num + 1;
            %Check Random source size. Generate random data if not
enough
            if size(Rnd_Mill_UC,2)<Rehab_Num
                Rnd_Mill_UC = [Rnd_Mill_UC, trnormdraw(Mill_UC_Mean,...
                    Mill_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Surface_UC,2)<Rehab_Num
                Rnd_OL_Surface_UC = [Rnd_OL_Surface_UC,...
                    trnormdraw(OL_Surface_UC_Mean,...
                    OL_Surface_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Inter_UC,2)<Rehab_Num
                Rnd_OL_Inter_UC = [Rnd_OL_Inter_UC,...
                    trnormdraw(OL_Inter_UC_Mean,...
                    OL_Inter_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_Surface_Coeff,2)<Rehab_Num+1
                Rnd_Surface_Coeff = [Rnd_Surface_Coeff,...
                    trnormdraw(Surface_Coeff_Mean,...
                    Surface_Coeff_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_Inter_Coeff,2)<Rehab_Num+1
                Rnd_Inter_Coeff = [Rnd_Inter_Coeff,...
                    trnormdraw(Inter_Coeff_Mean,...
                    Inter_Coeff_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Mill_A,2)<Rehab_Num
                Rnd_OL_Mill_A = [Rnd_OL_Mill_A,...
                    trnormdraw(OL_Mill_A_Mean,...
```

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                OL_Mill_A_COV,Std_Width,Iteration_Num)];
        end
        if size(Rnd_OL_Surface_A,2)<Rehab_Num
            Rnd_OL_Surface_A = [Rnd_OL_Surface_A,...
                trnormdraw(OL_Surface_A_Mean,...
                OL_Surface_A_COV,Std_Width,Iteration_Num)];
        end
        if size(Rnd_OL_Inter_A,2)<Rehab_Num
            Rnd_OL_Inter_A = [Rnd_OL_Inter_A,...
                trnormdraw(OL_Inter_A_Mean,...
                OL_Inter_A_COV,Std_Width,Iteration_Num)];
        end
        if size(Rnd_iPSI_A,2)<Rehab_Num+1
            Rnd_iPSI_A = [Rnd_iPSI_A,...
                lhsdraw('normaltrunc',[4.2,5.0,4.6,0.2],...
                Iteration_Num)];
        end
        if size(Rnd_iPCI_A,2)<Rehab_Num+1
            Rnd_iPCI_A = [Rnd_iPCI_A,...
                lhsdraw('normaltrunc',[90,100,95,2.5],...
                Iteration_Num)];
        end
        %Check data record dimension
        if size(Mill_UC,2)<Rehab_Num
            Mill_UC = [Mill_UC, zeros(Iteration_Num,1)];
        end
        if size(OL_Surface_UC,2)<Rehab_Num
            OL_Surface_UC = [OL_Surface_UC,
zeros(Iteration_Num,1)];
        end
        if size(OL_Inter_UC,2)<Rehab_Num
            OL_Inter_UC = [OL_Inter_UC, zeros(Iteration_Num,1)];
        end
        if size(Surface_Coeff,2)<Rehab_Num+1
            Surface_Coeff = [Surface_Coeff,
zeros(Iteration_Num,1)];
        end
        if size(Inter_Coeff,2)<Rehab_Num+1
            Inter_Coeff = [Inter_Coeff, zeros(Iteration_Num,1)];
        end
        if size(OL_Mill_A,2)<Rehab_Num
            OL_Mill_A = [OL_Mill_A, zeros(Iteration_Num,1)];
        end
        if size(OL_Surface_A,2)<Rehab_Num
            OL_Surface_A = [OL_Surface_A, zeros(Iteration_Num,1)];
        end
        if size(OL_Inter_A,2)<Rehab_Num
            OL_Inter_A = [OL_Inter_A, zeros(Iteration_Num,1)];
        end
        if size(iPSI_A,2)<Rehab_Num+1
            iPSI_A = [iPSI_A, zeros(Iteration_Num,1)];
        end
        if size(iPCI_A,2)<Rehab_Num+1
            iPCI_A = [iPCI_A, zeros(Iteration_Num,1)];
        end
        % Assign random values to data records
        Mill_UC(iteration, Rehab_Num) = ...
```

```matlab
        Rnd_Mill_UC(iteration, Rehab_Num);
    OL_Surface_UC(iteration, Rehab_Num) = ...
        Rnd_OL_Surface_UC(iteration, Rehab_Num);
    OL_Inter_UC(iteration, Rehab_Num) = ...
        Rnd_OL_Inter_UC(iteration, Rehab_Num);
    Surface_Coeff(iteration, Rehab_Num+1) = ...
        Rnd_Surface_Coeff(iteration, Rehab_Num+1);
    Inter_Coeff(iteration, Rehab_Num+1) = ...
        Rnd_Inter_Coeff(iteration, Rehab_Num+1);
    OL_Mill_A(iteration, Rehab_Num) = ...
        Rnd_OL_Mill_A(iteration, Rehab_Num);
    OL_Surface_A(iteration, Rehab_Num) = ...
        Rnd_OL_Surface_A(iteration, Rehab_Num);
    OL_Inter_A(iteration, Rehab_Num) = ...
        Rnd_OL_Inter_A(iteration, Rehab_Num);
    iPSI_A(iteration, Rehab_Num+1) = ...
        Rnd_iPSI_A(iteration, Rehab_Num+1);
    iPCI_A(iteration, Rehab_Num+1) = ...
        Rnd_iPCI_A(iteration, Rehab_Num+1);

    % Rehabilitation cost and timing record
    Rehab_Cost_A(iteration, Rehab_Num) = Area*(...
        Mill_UC(iteration, Rehab_Num)*...
        OL_Mill_A(iteration, Rehab_Num)+...
        OL_Surface_UC(iteration, Rehab_Num)*...
        OL_Surface_A(iteration, Rehab_Num)+...
        OL_Inter_UC(iteration, Rehab_Num)*...
        OL_Inter_A(iteration, Rehab_Num));
    Rehab_Timing_A(iteration, Rehab_Num) = year;

    SN_eff_A(iteration,Rehab_Num) = ...
        sneff(cESAL_A, iPSI_A(iteration, Rehab_Num),...
        iSN_A(iteration, Rehab_Num), Subgrade_Mr(iteration),...
        R_A, S0_A);
    iSN_A(iteration, Rehab_Num+1) = ...
        SN_eff_A(iteration,Rehab_Num)-...
        - OL_Mill_A(iteration, Rehab_Num)*...
        (Surface_Coeff(iteration, Rehab_Num) - ...
        (iSN_A(iteration, Rehab_Num)-...
        SN_eff_A(iteration,Rehab_Num))/HMA_Thickness)+...
        OL_Surface_A(iteration, Rehab_Num)*...
        Surface_Coeff(iteration, Rehab_Num+1) +...
        OL_Inter_A(iteration, Rehab_Num)*...
        Inter_Coeff(iteration, Rehab_Num+1);

    pavement_type_A = 7; % pavement with overlay < 2.4in
    HMA_Thickness = HMA_Thickness -...
        OL_Mill_A(iteration, Rehab_Num) +...
        OL_Surface_A(iteration, Rehab_Num) + ...
        OL_Inter_A(iteration, Rehab_Num);
    TGap_A(iteration, year) = 0;
    PSI_A(iteration, year) = iPSI_A(iteration, Rehab_Num+1);
    PCI_A(iteration, year) = iPCI_A(iteration, Rehab_Num+1);
    TGap_A(iteration, year+1) = TGap_A(iteration,year)+1;
    PSI_A(iteration, year+1) = iPSI_A(iteration, Rehab_Num+1) -
...
```

```matlab
            psiloss(ESAL(year), iSN_A(iteration, Rehab_Num+1),...
            Subgrade_Mr(iteration), R_A, S0_A);
        PCI_A(iteration, year+1) = ...

pci_predict(TGap_A(iteration,year+1),pavement_type_A,...
            iPCI_A(iteration, Rehab_Num+1));
        cESAL_A = ESAL(year);
    else
        TGap_A(iteration, year+1) = TGap_A(iteration,year)+1;
        PSI_A(iteration, year+1) = iPSI_A(iteration, Rehab_Num+1) -
...
            psiloss(cESAL_A, iSN_A(iteration, Rehab_Num+1),...
            Subgrade_Mr(iteration), R_A, S0_A);
        PCI_A(iteration, year+1) = ...

pci_predict(TGap_A(iteration,year+1),pavement_type_A,...
            iPCI_A(iteration, Rehab_Num+1));
    end
    end
end

% Salvage value
Salvage_A = Initial_Cost_A.*(PSI_A(:,Ana_Period+1)-1.5)./(PSI_A(:,1)-
1.5);

% Present Worth Factor
PWF_A = (kron((1+Disc_Rate)',ones(size(Rehab_Cost_A,2),1))').^(-
Rehab_Timing_A);
NPV_A = [Initial_Cost_A, Rehab_Cost_A.*PWF_A, -
Salvage_A.*(1+Disc_Rate).^(-Ana_Period)];
LCC_A = sum(NPV_A')';

hold off; cdfplot(LCC_A);
LCC_Mean_A = mean(LCC_A)
LCC_Std_A = std(LCC_A)

disp('Alternative A has been done...');

%***************************************************
%% Alternative B: Thick Overlay Rehabilitation (6-in)
%***************************************************

% Rehabilitation Design (Overlay thickness)
OL_Mill_B_Mean = 2; OL_Mill_B_COV = 0.1;
OL_Mill_B = trnormdraw(OL_Mill_B_Mean,...
    OL_Mill_B_COV,Std_Width,Iteration_Num);
OL_Surface_B_Mean = 2; OL_Surface_B_COV = 0.1;
OL_Surface_B = trnormdraw(OL_Surface_B_Mean,...
    OL_Surface_B_COV,Std_Width,Iteration_Num);
OL_Inter_B_Mean = 4; OL_Inter_B_COV = 0.1;
OL_Inter_B = trnormdraw(OL_Inter_B_Mean,...
    OL_Inter_B_COV,Std_Width,Iteration_Num);

% Calculate Initial Construction Costs
Initial_Cost_B = Area*Surface_Thickness.*Initial_Surface_UC + ...
```

```matlab
        Area*Inter_Thickness.*Initial_Inter_UC + ...
        Area*Base_Thickness.*Initial_Base_UC + ...
        Area*Subbase_Thickness.*Initial_Subbase_UC;

    % Calculate Initial SN
    iSN_B = Surface_Thickness.*Surface_Coeff(:,1) +...
        Inter_Thickness.*Inter_Coeff(:,1) + ...
        Base_Thickness.*Base_Coeff.*Base_Drain + ...
        Subbase_Thickness.*Subbase_Coeff.*Subbase_Drain;

    % PSI and PCI
    PSI_B = zeros(Iteration_Num, Ana_Period+1);
    PSI_B(:,1) = lhsdraw('normaltrunc',[4.2,5.0,4.6,0.2],Iteration_Num);
    iPSI_B = PSI_B(:,1);
    PCI_B = zeros(Iteration_Num, Ana_Period+1);
    PCI_B(:,1) = lhsdraw('normaltrunc',[90,100,95,2.5],Iteration_Num);
    iPCI_B = PCI_B(:,1);
    TGap_B = zeros(Iteration_Num, Ana_Period+1);

    % Reliability
    R_B = 0.50; S0_B = 0;

    % 07/20/2006 Stop here
    % Variables to extract random values from
    Rnd_OL_Mill_B = OL_Mill_B;
    Rnd_OL_Surface_B = OL_Surface_B;
    Rnd_OL_Inter_B = OL_Inter_B;
    Rnd_iPSI_B = iPSI_B;
    Rnd_iPCI_B = iPCI_B;

    % Variables to save iteration information
    Rehab_Cost_B = zeros(Iteration_Num,1);
    Rehab_Timing_B = zeros(Iteration_Num,1);
    Salvage_B = zeros(Iteration_Num,1);
    SN_eff_B = zeros(Iteration_Num,1);


    % Predict pavement performance: PSI, and PCI and schedule
    Rehabilitation
    % activities.
    for iteration = 1: Iteration_Num
        % Iteration Parameters (Initial Conditions)

        pavement_type_B = 2; % new pavement
        cESAL_B = 0;
        HMA_Thickness = Surface_Thickness(iteration)+...
            Inter_Thickness(iteration);
        Rehab_Num = 0;

        for year = 1: Ana_Period
            %Year means the end of a year

            % Calculate the cumulative traffic volume (ESAL)
            cESAL_B = cESAL_B + ESAL(iteration,year);
```

```matlab
        % If pavement conditions hit the threshhold values, schedule a
        % rehabilitation activity at current year
        if PSI_B(iteration, year)<=2.5 || PCI_B(iteration, year)<=45
            Rehab_Num = Rehab_Num + 1;
            %Check Random source size. Generate random data if not
enough
            if size(Rnd_Mill_UC,2)<Rehab_Num
                Rnd_Mill_UC = [Rnd_Mill_UC, trnormdraw(Mill_UC_Mean,...
                    Mill_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Surface_UC,2)<Rehab_Num
                Rnd_OL_Surface_UC = [Rnd_OL_Surface_UC,...
                    trnormdraw(OL_Surface_UC_Mean,...
                    OL_Surface_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Inter_UC,2)<Rehab_Num
                Rnd_OL_Inter_UC = [Rnd_OL_Inter_UC,...
                    trnormdraw(OL_Inter_UC_Mean,...
                    OL_Inter_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_Surface_Coeff,2)<Rehab_Num+1
                Rnd_Surface_Coeff = [Rnd_Surface_Coeff,...
                    trnormdraw(Surface_Coeff_Mean,...
                    Surface_Coeff_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_Inter_Coeff,2)<Rehab_Num+1
                Rnd_Inter_Coeff = [Rnd_Inter_Coeff,...
                    trnormdraw(Inter_Coeff_Mean,...
                    Inter_Coeff_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Mill_B,2)<Rehab_Num
                Rnd_OL_Mill_B = [Rnd_OL_Mill_B,...
                    trnormdraw(OL_Mill_B_Mean,...
                    OL_Mill_B_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Surface_B,2)<Rehab_Num
                Rnd_OL_Surface_B = [Rnd_OL_Surface_B,...
                    trnormdraw(OL_Surface_B_Mean,...
                    OL_Surface_B_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Inter_B,2)<Rehab_Num
                Rnd_OL_Inter_B = [Rnd_OL_Inter_B,...
                    trnormdraw(OL_Inter_B_Mean,...
                    OL_Inter_B_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_iPSI_B,2)<Rehab_Num+1
                Rnd_iPSI_B = [Rnd_iPSI_B,...
                    lhsdraw('normaltrunc',[4.2,5.0,4.6,0.2],...
                    Iteration_Num)];
            end
            if size(Rnd_iPCI_B,2)<Rehab_Num+1
                Rnd_iPCI_B = [Rnd_iPCI_B,...
                    lhsdraw('normaltrunc',[90,100,95,2.5],...
                    Iteration_Num)];
            end
            %Check data record dimension
            if size(Mill_UC,2)<Rehab_Num
```

```matlab
                Mill_UC = [Mill_UC, zeros(Iteration_Num,1)];
            end
            if size(OL_Surface_UC,2)<Rehab_Num
                OL_Surface_UC = [OL_Surface_UC,
zeros(Iteration_Num,1)];
            end
            if size(OL_Inter_UC,2)<Rehab_Num
                OL_Inter_UC = [OL_Inter_UC, zeros(Iteration_Num,1)];
            end
            if size(Surface_Coeff,2)<Rehab_Num+1
                Surface_Coeff = [Surface_Coeff,
zeros(Iteration_Num,1)];
            end
            if size(Inter_Coeff,2)<Rehab_Num+1
                Inter_Coeff = [Inter_Coeff, zeros(Iteration_Num,1)];
            end
            if size(OL_Mill_B,2)<Rehab_Num
                OL_Mill_B = [OL_Mill_B, zeros(Iteration_Num,1)];
            end
            if size(OL_Surface_B,2)<Rehab_Num
                OL_Surface_B = [OL_Surface_B, zeros(Iteration_Num,1)];
            end
            if size(OL_Inter_B,2)<Rehab_Num
                OL_Inter_B = [OL_Inter_B, zeros(Iteration_Num,1)];
            end
            if size(iPSI_B,2)<Rehab_Num+1
                iPSI_B = [iPSI_B, zeros(Iteration_Num,1)];
            end
            if size(iPCI_B,2)<Rehab_Num+1
                iPCI_B = [iPCI_B, zeros(Iteration_Num,1)];
            end
            % Assign random values to data records
            Mill_UC(iteration, Rehab_Num) = ...
                Rnd_Mill_UC(iteration, Rehab_Num);
            OL_Surface_UC(iteration, Rehab_Num) = ...
                Rnd_OL_Surface_UC(iteration, Rehab_Num);
            OL_Inter_UC(iteration, Rehab_Num) = ...
                Rnd_OL_Inter_UC(iteration, Rehab_Num);
            Surface_Coeff(iteration, Rehab_Num+1) = ...
                Rnd_Surface_Coeff(iteration, Rehab_Num+1);
            Inter_Coeff(iteration, Rehab_Num+1) = ...
                Rnd_Inter_Coeff(iteration, Rehab_Num+1);
            OL_Mill_B(iteration, Rehab_Num) = ...
                Rnd_OL_Mill_B(iteration, Rehab_Num);
            OL_Surface_B(iteration, Rehab_Num) = ...
                Rnd_OL_Surface_B(iteration, Rehab_Num);
            OL_Inter_B(iteration, Rehab_Num) = ...
                Rnd_OL_Inter_B(iteration, Rehab_Num);
            iPSI_B(iteration, Rehab_Num+1) = ...
                Rnd_iPSI_B(iteration, Rehab_Num+1);
            iPCI_B(iteration, Rehab_Num+1) = ...
                Rnd_iPCI_B(iteration, Rehab_Num+1);

            % Rehabilitation cost and timing record
            Rehab_Cost_B(iteration, Rehab_Num) = Area*(...
                Mill_UC(iteration, Rehab_Num)*...
                OL_Mill_B(iteration, Rehab_Num)+...
```

```matlab
                OL_Surface_UC(iteration, Rehab_Num)*...
                OL_Surface_B(iteration, Rehab_Num)+...
                OL_Inter_UC(iteration, Rehab_Num)*...
                OL_Inter_B(iteration, Rehab_Num));
            Rehab_Timing_B(iteration, Rehab_Num) = year;

            SN_eff_B(iteration,Rehab_Num) = ...
                sneff(cESAL_B, iPSI_B(iteration, Rehab_Num),...
                iSN_B(iteration, Rehab_Num), Subgrade_Mr(iteration),...
                R_B, S0_B);
            iSN_B(iteration, Rehab_Num+1) =
SN_eff_B(iteration,Rehab_Num)-...
                - OL_Mill_B(iteration, Rehab_Num)*...
                (Surface_Coeff(iteration, Rehab_Num) - ...
                (iSN_B(iteration, Rehab_Num)-...
                SN_eff_B(iteration,Rehab_Num))/HMA_Thickness)+...
                OL_Surface_B(iteration, Rehab_Num)*...
                Surface_Coeff(iteration, Rehab_Num+1) +...
                OL_Inter_B(iteration, Rehab_Num)*...
                Inter_Coeff(iteration, Rehab_Num+1);

            pavement_type_B = 8; % pavement with overlay > 2.4in
            HMA_Thickness = HMA_Thickness -...
                OL_Mill_B(iteration, Rehab_Num) +...
                OL_Surface_B(iteration, Rehab_Num) + ...
                OL_Inter_B(iteration, Rehab_Num);
            TGap_B(iteration, year) = 0;
            PSI_B(iteration, year) = iPSI_B(iteration, Rehab_Num+1);
            PCI_B(iteration, year) = iPCI_B(iteration, Rehab_Num+1);
            TGap_B(iteration, year+1) = TGap_B(iteration,year)+1;
            PSI_B(iteration, year+1) = iPSI_B(iteration, Rehab_Num+1) -
...
                psiloss(ESAL(year), iSN_B(iteration, Rehab_Num+1),...
                Subgrade_Mr(iteration), R_B, S0_B);
            PCI_B(iteration, year+1) = ...

pci_predict(TGap_B(iteration,year+1),pavement_type_B,...
                iPCI_B(iteration, Rehab_Num+1));
            cESAL_B = ESAL(year);
        else
            TGap_B(iteration, year+1) = TGap_B(iteration,year)+1;
            PSI_B(iteration, year+1) = iPSI_B(iteration, Rehab_Num+1) -
...
                psiloss(cESAL_B, iSN_B(iteration, Rehab_Num+1),...
                Subgrade_Mr(iteration), R_B, S0_B);
            PCI_B(iteration, year+1) = ...

pci_predict(TGap_B(iteration,year+1),pavement_type_B,...
                iPCI_B(iteration, Rehab_Num+1));
        end
    end
end

% Salvage value
Salvage_B = Initial_Cost_B.*(PSI_B(:,Ana_Period+1)-1.5)./(PSI_B(:,1)-
1.5);
```

```matlab
% Present Worth Factor
PWF_B = (kron((1+Disc_Rate)',ones(size(Rehab_Cost_B,2),1))').^(-
Rehab_Timing_B);
NPV_B = [Initial_Cost_B, Rehab_Cost_B.*PWF_B, -
Salvage_B.*(1+Disc_Rate).^(-Ana_Period)];
LCC_B = sum(NPV_B')';

hold on; cdfplot(LCC_B);
LCC_Mean_B = mean(LCC_B)
LCC_Std_B = std(LCC_B)

disp('Alternative B has been done...');
```

FUZZY-LOGIC-BASED LCCA MODEL

```matlab
%*****************************************************
% Common Parameters
%*****************************************************

% General Configuration
Ana_Period = 50;
Iteration_Num = 1000;
Disc_Rate = lhsdraw('tri', [0.03,0.04,0.05], Iteration_Num);
Std_Width = 2;

% Construct Fuzzy Models
donth=readfis('DoNth.fis');
policy_A=readfis('ThnOL.fis');
policy_B=readfis('ThkOL.fis');

% Generate Traffic Information
ADT_Mean = 12000; ADT_COV = 0.15;
ADT = trnormdraw(ADT_Mean,ADT_COV,Std_Width,Iteration_Num);
T_Mean = 0.30; T_COV = 0.1;
T = trnormdraw(T_Mean,T_COV,Std_Width,Iteration_Num);
Tf_Mean = 0.52; Tf_COV = 0.365;
Tf = trnormdraw(Tf_Mean,Tf_COV,Std_Width,Iteration_Num);
DDF= 0.50; LF = 0.90;

ESAL0 = ADT.*T.*Tf*DDF*LF*365;
Growth_Rate_Mean = 0.06; Growth_Rate_COV = 0.1;
Growth_Rate = trnormdraw(Growth_Rate_Mean,Growth_Rate_COV,...
    Std_Width,Iteration_Num);
ESAL = zeros(Iteration_Num,Ana_Period);
for year=1:Ana_Period
    ESAL(:,year) = ESAL0.*(1+Growth_Rate).^(year-1);
end

% Unit costs of initial construction ($/SY-inch)
Initial_Surface_UC_Mean = 2.19; Initial_Surface_UC_COV = 0.1;
Initial_Surface_UC = trnormdraw(Initial_Surface_UC_Mean,...
    Initial_Surface_UC_COV,Std_Width,Iteration_Num);
Initial_Inter_UC_Mean = 1.86; Initial_Inter_UC_COV = 0.1;
Initial_Inter_UC = trnormdraw(Initial_Inter_UC_Mean,...
    Initial_Inter_UC_COV,Std_Width,Iteration_Num);
Initial_Base_UC_Mean = 1.78; Initial_Base_UC_COV = 0.1;
Initial_Base_UC = trnormdraw(Initial_Base_UC_Mean,...
    Initial_Base_UC_COV,Std_Width,Iteration_Num);
Initial_Subbase_UC_Mean = 1.18; Initial_Subbase_UC_COV = 0.1;
Initial_Subbase_UC = trnormdraw(Initial_Subbase_UC_Mean,...
    Initial_Subbase_UC_COV,Std_Width,Iteration_Num);

% Unit costs of rehabilitation: thin overlay and thick overlay ($/SY-in)
Mill_UC_Mean = 0.50; Mill_UC_COV = 0.1;
Mill_UC = trnormdraw(Mill_UC_Mean,...
```

```matlab
    Mill_UC_COV,Std_Width,Iteration_Num);
OL_Surface_UC_Mean = 2.19; OL_Surface_UC_COV = 0.1;
OL_Surface_UC = trnormdraw(OL_Surface_UC_Mean,...
    OL_Surface_UC_COV,Std_Width,Iteration_Num);
OL_Inter_UC_Mean = 1.86; OL_Inter_UC_COV= 0.1;
OL_Inter_UC = trnormdraw(OL_Inter_UC_Mean,...
    OL_Inter_UC_COV,Std_Width,Iteration_Num);


% Initial Pavement Design (Layer thickness)
Area = 7040; % Unit: Sq-yard; based on one mile long 12 feet width
%% AC Surface Layer
Surface_Thickness_Mean = 2; % (in)
Surface_Thickness_COV = 0.1;
Surface_Thickness = trnormdraw(Surface_Thickness_Mean,...
    Surface_Thickness_COV,Std_Width,Iteration_Num);
Surface_Coeff_Mean = 0.44;
Surface_Coeff_COV = 0.1;
Surface_Coeff = trnormdraw(Surface_Coeff_Mean,...
    Surface_Coeff_COV,Std_Width,Iteration_Num);
%% AC Intermediate Layer
Inter_Thickness_Mean = 5; % (in)
Inter_Thickness_COV = 0.1;
Inter_Thickness = trnormdraw(Inter_Thickness_Mean,...
    Inter_Thickness_COV,Std_Width,Iteration_Num);
Inter_Coeff_Mean = 0.44;
Inter_Coeff_COV = 0.1;
Inter_Coeff = trnormdraw(Inter_Coeff_Mean,...
    Inter_Coeff_COV,Std_Width,Iteration_Num);
%% Base Layer
Base_Thickness_Mean = 9; % (in)
Base_Thickness_COV = 0.1;
Base_Thickness = trnormdraw(Base_Thickness_Mean,...
    Base_Thickness_COV,Std_Width,Iteration_Num);
Base_Coeff_Mean = 0.14;
Base_Coeff_COV = 0.143;
Base_Coeff = trnormdraw(Base_Coeff_Mean,...
    Base_Coeff_COV,Std_Width,Iteration_Num);
Base_Drain_Mean = 1;
Base_Drain_COV = 0.1;
Base_Drain = trnormdraw(Base_Drain_Mean,...
    Base_Drain_COV,Std_Width,Iteration_Num);
%% Subbase Layer
Subbase_Thickness_Mean = 6; % (in)
Subbase_Thickness_COV = 0.1;
Subbase_Thickness = trnormdraw(Subbase_Thickness_Mean,...
    Subbase_Thickness_COV,Std_Width,Iteration_Num);
Subbase_Coeff_Mean = 0.11;
Subbase_Coeff_COV = 0.182;
Subbase_Coeff = trnormdraw(Subbase_Coeff_Mean,...
    Subbase_Coeff_COV,Std_Width,Iteration_Num);
Subbase_Drain_Mean = 1;
Subbase_Drain_COV = 0.1;
Subbase_Drain = trnormdraw(Subbase_Drain_Mean,...
    Subbase_Drain_COV,Std_Width,Iteration_Num);
%% Subgrade
Subgrade_Mr_Mean = 5000; % (psi)
Subgrade_Mr_COV = 0.15;
```

```matlab
Subgrade_Mr = trnormdraw(Subgrade_Mr_Mean,...
    Subgrade_Mr_COV,Std_Width,Iteration_Num);

% Variables to extract random values from
Rnd_Mill_UC = Mill_UC;
Rnd_OL_Surface_UC = OL_Surface_UC;
Rnd_OL_Inter_UC = OL_Inter_UC;
Rnd_Surface_Coeff = Surface_Coeff;
Rnd_Inter_Coeff = Inter_Coeff;

%****************************************************
%% Alternative A: Thin Overlay Rehabilitation (2-in)
%****************************************************

% Rehabilitation Design (Overlay thickness)
OL_Mill_A_Mean = 1; OL_Mill_A_COV = 0.1;
OL_Mill_A = trnormdraw(OL_Mill_A_Mean,...
    OL_Mill_A_COV,Std_Width,Iteration_Num);
OL_Surface_A_Mean = 2; OL_Surface_A_COV = 0.1;
OL_Surface_A = trnormdraw(OL_Surface_A_Mean,...
    OL_Surface_A_COV,Std_Width,Iteration_Num);
OL_Inter_A_Mean = 0; OL_Inter_A_COV = 0.1;
OL_Inter_A = trnormdraw(OL_Inter_A_Mean,...
    OL_Inter_A_COV,Std_Width,Iteration_Num);

% Calculate Initial Construction Costs
Initial_Cost_A = Area*Surface_Thickness.*Initial_Surface_UC + ...
    Area*Inter_Thickness.*Initial_Inter_UC + ...
    Area*Base_Thickness.*Initial_Base_UC + ...
    Area*Subbase_Thickness.*Initial_Subbase_UC;

% Calculate Initial SN
iSN_A = Surface_Thickness.*Surface_Coeff(:,1) +...
    Inter_Thickness.*Inter_Coeff(:,1) + ...
    Base_Thickness.*Base_Coeff.*Base_Drain + ...
    Subbase_Thickness.*Subbase_Coeff.*Subbase_Drain;

% PSI and PCI
PSI_A = zeros(Iteration_Num, Ana_Period+1);
PSI_A(:,1) = lhsdraw('normaltrunc',[4.2,5.0,4.6,0.2],Iteration_Num);
iPSI_A = PSI_A(:,1);
PCI_A = zeros(Iteration_Num, Ana_Period+1);
PCI_A(:,1) = lhsdraw('normaltrunc',[90,100,95,2.5],Iteration_Num);
iPCI_A = PCI_A(:,1);
TGap_A = zeros(Iteration_Num, Ana_Period+1);

% Reliability
R_A = 0.50; S0_A = 0;

% 07/20/2006 Stop here
% Variables to extract random values from
Rnd_OL_Mill_A = OL_Mill_A;
Rnd_OL_Surface_A = OL_Surface_A;
Rnd_OL_Inter_A = OL_Inter_A;
Rnd_iPSI_A = iPSI_A;
```

```matlab
    Rnd_iPCI_A = iPCI_A;

% Variables to save iteration information
Rehab_Cost_A = zeros(Iteration_Num,1);
Rehab_Timing_A = zeros(Iteration_Num,1);
Salvage_A = zeros(Iteration_Num,1);
SN_eff_A = zeros(Iteration_Num,1);


% Predict pavement performance: PSI, and PCI and schedule
Rehabilitation
% activities.
for iteration = 1: Iteration_Num
    % Iteration Parameters (Initial Conditions)

    pavement_type_A = 2; % new pavement
    cESAL_A = 0;
    HMA_Thickness = Surface_Thickness(iteration)+...
        Inter_Thickness(iteration);
    Rehab_Num = 0;

    for year = 1: Ana_Period
        %Year means the end of a year

        % Calculate the cumulative traffic volume (ESAL)
        cESAL_A = cESAL_A + ESAL(iteration,year);

        % Evaluate fuzzy models at the beginning of analysis period
        Priority_Donth_A(iteration,year) = evalfis(...
            [PSI_A(iteration,year), TGap_A(iteration,year),...
            PCI_A(iteration,year)], donth);
        Priority_Policy_A(iteration,year) = evalfis(...
            [PSI_A(iteration,year), TGap_A(iteration,year),...
            PCI_A(iteration,year)], policy_A);

        % If priority of rehabilitation is higher than donoth, schedule
a
        % rehabilitation activity at current year
        if Priority_Policy_A(iteration,year)>=...
            Priority_Donth_A(iteration,year)
            Rehab_Num = Rehab_Num + 1;
            %Check Random source size. Generate random data if not
enough
            if size(Rnd_Mill_UC,2)<Rehab_Num
                Rnd_Mill_UC = [Rnd_Mill_UC, trnormdraw(Mill_UC_Mean,...
                    Mill_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Surface_UC,2)<Rehab_Num
                Rnd_OL_Surface_UC = [Rnd_OL_Surface_UC,...
                    trnormdraw(OL_Surface_UC_Mean,...
                    OL_Surface_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Inter_UC,2)<Rehab_Num
                Rnd_OL_Inter_UC = [Rnd_OL_Inter_UC,...
                    trnormdraw(OL_Inter_UC_Mean,...
```

```matlab
                OL_Inter_UC_COV,Std_Width,Iteration_Num)];
        end
        if size(Rnd_Surface_Coeff,2)<Rehab_Num+1
            Rnd_Surface_Coeff = [Rnd_Surface_Coeff,...
                trnormdraw(Surface_Coeff_Mean,...
                Surface_Coeff_COV,Std_Width,Iteration_Num)];
        end
        if size(Rnd_Inter_Coeff,2)<Rehab_Num+1
            Rnd_Inter_Coeff = [Rnd_Inter_Coeff,...
                trnormdraw(Inter_Coeff_Mean,...
                Inter_Coeff_COV,Std_Width,Iteration_Num)];
        end
        if size(Rnd_OL_Mill_A,2)<Rehab_Num
            Rnd_OL_Mill_A = [Rnd_OL_Mill_A,...
                trnormdraw(OL_Mill_A_Mean,...
                OL_Mill_A_COV,Std_Width,Iteration_Num)];
        end
        if size(Rnd_OL_Surface_A,2)<Rehab_Num
            Rnd_OL_Surface_A = [Rnd_OL_Surface_A,...
                trnormdraw(OL_Surface_A_Mean,...
                OL_Surface_A_COV,Std_Width,Iteration_Num)];
        end
        if size(Rnd_OL_Inter_A,2)<Rehab_Num
            Rnd_OL_Inter_A = [Rnd_OL_Inter_A,...
                trnormdraw(OL_Inter_A_Mean,...
                OL_Inter_A_COV,Std_Width,Iteration_Num)];
        end
        if size(Rnd_iPSI_A,2)<Rehab_Num+1
            Rnd_iPSI_A = [Rnd_iPSI_A,...
                lhsdraw('normaltrunc',[4.2,5.0,4.6,0.2],...
                Iteration_Num)];
        end
        if size(Rnd_iPCI_A,2)<Rehab_Num+1
            Rnd_iPCI_A = [Rnd_iPCI_A,...
                lhsdraw('normaltrunc',[90,100,95,2.5],...
                Iteration_Num)];
        end
        %Check data record dimension
        if size(Mill_UC,2)<Rehab_Num
            Mill_UC = [Mill_UC, zeros(Iteration_Num,1)];
        end
        if size(OL_Surface_UC,2)<Rehab_Num
            OL_Surface_UC = [OL_Surface_UC,
zeros(Iteration_Num,1)];
        end
        if size(OL_Inter_UC,2)<Rehab_Num
            OL_Inter_UC = [OL_Inter_UC, zeros(Iteration_Num,1)];
        end
        if size(Surface_Coeff,2)<Rehab_Num+1
            Surface_Coeff = [Surface_Coeff,
zeros(Iteration_Num,1)];
        end
        if size(Inter_Coeff,2)<Rehab_Num+1
            Inter_Coeff = [Inter_Coeff, zeros(Iteration_Num,1)];
        end
        if size(OL_Mill_A,2)<Rehab_Num
            OL_Mill_A = [OL_Mill_A, zeros(Iteration_Num,1)];
```

```matlab
    end
    if size(OL_Surface_A,2)<Rehab_Num
        OL_Surface_A = [OL_Surface_A, zeros(Iteration_Num,1)];
    end
    if size(OL_Inter_A,2)<Rehab_Num
        OL_Inter_A = [OL_Inter_A, zeros(Iteration_Num,1)];
    end
    if size(iPSI_A,2)<Rehab_Num+1
        iPSI_A = [iPSI_A, zeros(Iteration_Num,1)];
    end
    if size(iPCI_A,2)<Rehab_Num+1
        iPCI_A = [iPCI_A, zeros(Iteration_Num,1)];
    end
    % Assign random values to data records
    Mill_UC(iteration, Rehab_Num) = ...
        Rnd_Mill_UC(iteration, Rehab_Num);
    OL_Surface_UC(iteration, Rehab_Num) = ...
        Rnd_OL_Surface_UC(iteration, Rehab_Num);
    OL_Inter_UC(iteration, Rehab_Num) = ...
        Rnd_OL_Inter_UC(iteration, Rehab_Num);
    Surface_Coeff(iteration, Rehab_Num+1) = ...
        Rnd_Surface_Coeff(iteration, Rehab_Num+1);
    Inter_Coeff(iteration, Rehab_Num+1) = ...
        Rnd_Inter_Coeff(iteration, Rehab_Num+1);
    OL_Mill_A(iteration, Rehab_Num) = ...
        Rnd_OL_Mill_A(iteration, Rehab_Num);
    OL_Surface_A(iteration, Rehab_Num) = ...
        Rnd_OL_Surface_A(iteration, Rehab_Num);
    OL_Inter_A(iteration, Rehab_Num) = ...
        Rnd_OL_Inter_A(iteration, Rehab_Num);
    iPSI_A(iteration, Rehab_Num+1) = ...
        Rnd_iPSI_A(iteration, Rehab_Num+1);
    iPCI_A(iteration, Rehab_Num+1) = ...
        Rnd_iPCI_A(iteration, Rehab_Num+1);

    % Rehabilitation cost and timing record
    Rehab_Cost_A(iteration, Rehab_Num) = Area*(...
        Mill_UC(iteration, Rehab_Num)*...
        OL_Mill_A(iteration, Rehab_Num)+...
        OL_Surface_UC(iteration, Rehab_Num)*...
        OL_Surface_A(iteration, Rehab_Num)+...
        OL_Inter_UC(iteration, Rehab_Num)*...
        OL_Inter_A(iteration, Rehab_Num));
    Rehab_Timing_A(iteration, Rehab_Num) = year;

    SN_eff_A(iteration,Rehab_Num) = ...
        sneff(cESAL_A, iPSI_A(iteration, Rehab_Num),...
        iSN_A(iteration, Rehab_Num), Subgrade_Mr(iteration),...
        R_A, S0_A);
    iSN_A(iteration, Rehab_Num+1) = ...
        SN_eff_A(iteration,Rehab_Num)-...
        - OL_Mill_A(iteration, Rehab_Num)*...
        (Surface_Coeff(iteration, Rehab_Num) - ...
        (iSN_A(iteration, Rehab_Num)-...
        SN_eff_A(iteration,Rehab_Num))/HMA_Thickness)+...
        OL_Surface_A(iteration, Rehab_Num)*...
```

```matlab
                Surface_Coeff(iteration, Rehab_Num+1) +...
                OL_Inter_A(iteration, Rehab_Num)*...
                Inter_Coeff(iteration, Rehab_Num+1);

            pavement_type_A = 7; % pavement with overlay < 2.4in
            HMA_Thickness = HMA_Thickness -...
                OL_Mill_A(iteration, Rehab_Num) +...
                OL_Surface_A(iteration, Rehab_Num) + ...
                OL_Inter_A(iteration, Rehab_Num);
            TGap_A(iteration, year) = 0;
            PSI_A(iteration, year) = iPSI_A(iteration, Rehab_Num+1);
            PCI_A(iteration, year) = iPCI_A(iteration, Rehab_Num+1);
            TGap_A(iteration, year+1) = TGap_A(iteration,year)+1;
            PSI_A(iteration, year+1) = iPSI_A(iteration, Rehab_Num+1) -
...
                psiloss(ESAL(year), iSN_A(iteration, Rehab_Num+1),...
                Subgrade_Mr(iteration), R_A, S0_A);
            PCI_A(iteration, year+1) = ...

pci_predict(TGap_A(iteration,year+1),pavement_type_A,...
                iPCI_A(iteration, Rehab_Num+1));
            cESAL_A = ESAL(year);
        else
            TGap_A(iteration, year+1) = TGap_A(iteration,year)+1;
            PSI_A(iteration, year+1) = iPSI_A(iteration, Rehab_Num+1) -
...
                psiloss(cESAL_A, iSN_A(iteration, Rehab_Num+1),...
                Subgrade_Mr(iteration), R_A, S0_A);
            PCI_A(iteration, year+1) = ...

pci_predict(TGap_A(iteration,year+1),pavement_type_A,...
                iPCI_A(iteration, Rehab_Num+1));
        end
    end
end

% Salvage value
Salvage_A = Initial_Cost_A.*(PSI_A(:,Ana_Period+1)-1.5)./(PSI_A(:,1)-
1.5);

% Present Worth Factor
PWF_A = (kron((1+Disc_Rate)',ones(size(Rehab_Cost_A,2),1))').^(-
Rehab_Timing_A);
NPV_A = [Initial_Cost_A, Rehab_Cost_A.*PWF_A, -
Salvage_A.*(1+Disc_Rate).^(-Ana_Period)];
LCC_A = sum(NPV_A')';

hold off; cdfplot(LCC_A);
LCC_Mean_A = mean(LCC_A)
LCC_Std_A = std(LCC_A)

disp('Alternative A has been done...');

%**************************************************
%% Alternative B: Thick Overlay Rehabilitation (6-in)
%**************************************************
```

```matlab
% Rehabilitation Design (Overlay thickness)
OL_Mill_B_Mean = 2; OL_Mill_B_COV = 0.1;
OL_Mill_B = trnormdraw(OL_Mill_B_Mean,...
    OL_Mill_B_COV,Std_Width,Iteration_Num);
OL_Surface_B_Mean = 2; OL_Surface_B_COV = 0.1;
OL_Surface_B = trnormdraw(OL_Surface_B_Mean,...
    OL_Surface_B_COV,Std_Width,Iteration_Num);
OL_Inter_B_Mean = 4; OL_Inter_B_COV = 0.1;
OL_Inter_B = trnormdraw(OL_Inter_B_Mean,...
    OL_Inter_B_COV,Std_Width,Iteration_Num);

% Calculate Initial Construction Costs
Initial_Cost_B = Area*Surface_Thickness.*Initial_Surface_UC + ...
    Area*Inter_Thickness.*Initial_Inter_UC + ...
    Area*Base_Thickness.*Initial_Base_UC + ...
    Area*Subbase_Thickness.*Initial_Subbase_UC;

% Calculate Initial SN
iSN_B = Surface_Thickness.*Surface_Coeff(:,1) +...
    Inter_Thickness.*Inter_Coeff(:,1) + ...
    Base_Thickness.*Base_Coeff.*Base_Drain + ...
    Subbase_Thickness.*Subbase_Coeff.*Subbase_Drain;

% PSI and PCI
PSI_B = zeros(Iteration_Num, Ana_Period+1);
PSI_B(:,1) = lhsdraw('normaltrunc',[4.2,5.0,4.6,0.2],Iteration_Num);
iPSI_B = PSI_B(:,1);
PCI_B = zeros(Iteration_Num, Ana_Period+1);
PCI_B(:,1) = lhsdraw('normaltrunc',[90,100,95,2.5],Iteration_Num);
iPCI_B = PCI_B(:,1);
TGap_B = zeros(Iteration_Num, Ana_Period+1);

% Reliability
R_B = 0.50; S0_B = 0;

% 07/20/2006 Stop here
% Variables to extract random values from
Rnd_OL_Mill_B = OL_Mill_B;
Rnd_OL_Surface_B = OL_Surface_B;
Rnd_OL_Inter_B = OL_Inter_B;
Rnd_iPSI_B = iPSI_B;
Rnd_iPCI_B = iPCI_B;

% Variables to save iteration information
Rehab_Cost_B = zeros(Iteration_Num,1);
Rehab_Timing_B = zeros(Iteration_Num,1);
Salvage_B = zeros(Iteration_Num,1);
SN_eff_B = zeros(Iteration_Num,1);



% Predict pavement performance: PSI, and PCI and schedule
Rehabilitation
% activities.
for iteration = 1: Iteration_Num
```

```matlab
    % Iteration Parameters (Initial Conditions)

    pavement_type_B = 2; % new pavement
    cESAL_B = 0;
    HMA_Thickness = Surface_Thickness(iteration)+...
        Inter_Thickness(iteration);
    Rehab_Num = 0;

    for year = 1: Ana_Period
        %Year means the end of a year

        % Calculate the cumulative traffic volume (ESAL)
        cESAL_B = cESAL_B + ESAL(iteration,year);

        % Evaluate fuzzy models at the beginning of analysis period
        Priority_Donth_B(iteration,year) = evalfis(...
            [PSI_B(iteration,year), TGap_B(iteration,year),...
            PCI_B(iteration,year)], donth);
        Priority_Policy_B(iteration,year) = evalfis(...
            [PSI_B(iteration,year), TGap_B(iteration,year),...
            PCI_B(iteration,year)], policy_B);

        % If priority of rehabilitation is higher than donoth, schedule
a
        % rehabilitation activity at current year
        if Priority_Policy_B(iteration,year)>=...
            Priority_Donth_B(iteration,year)
            Rehab_Num = Rehab_Num + 1;
        %Check Random source size. Generate random data if not enough
            if size(Rnd_Mill_UC,2)<Rehab_Num
                Rnd_Mill_UC = [Rnd_Mill_UC, trnormdraw(Mill_UC_Mean,...
                    Mill_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Surface_UC,2)<Rehab_Num
                Rnd_OL_Surface_UC = [Rnd_OL_Surface_UC,...
                    trnormdraw(OL_Surface_UC_Mean,...
                    OL_Surface_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Inter_UC,2)<Rehab_Num
                Rnd_OL_Inter_UC = [Rnd_OL_Inter_UC,...
                    trnormdraw(OL_Inter_UC_Mean,...
                    OL_Inter_UC_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_Surface_Coeff,2)<Rehab_Num+1
                Rnd_Surface_Coeff = [Rnd_Surface_Coeff,...
                    trnormdraw(Surface_Coeff_Mean,...
                    Surface_Coeff_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_Inter_Coeff,2)<Rehab_Num+1
                Rnd_Inter_Coeff = [Rnd_Inter_Coeff,...
                    trnormdraw(Inter_Coeff_Mean,...
                    Inter_Coeff_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Mill_B,2)<Rehab_Num
                Rnd_OL_Mill_B = [Rnd_OL_Mill_B,...
                    trnormdraw(OL_Mill_B_Mean,...
```

```matlab
                    OL_Mill_B_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Surface_B,2)<Rehab_Num
                Rnd_OL_Surface_B = [Rnd_OL_Surface_B,...
                    trnormdraw(OL_Surface_B_Mean,...
                    OL_Surface_B_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_OL_Inter_B,2)<Rehab_Num
                Rnd_OL_Inter_B = [Rnd_OL_Inter_B,...
                    trnormdraw(OL_Inter_B_Mean,...
                    OL_Inter_B_COV,Std_Width,Iteration_Num)];
            end
            if size(Rnd_iPSI_B,2)<Rehab_Num+1
                Rnd_iPSI_B = [Rnd_iPSI_B,...
                    lhsdraw('normaltrunc',[4.2,5.0,4.6,0.2],...
                    Iteration_Num)];
            end
            if size(Rnd_iPCI_B,2)<Rehab_Num+1
                Rnd_iPCI_B = [Rnd_iPCI_B,...
                    lhsdraw('normaltrunc',[90,100,95,2.5],...
                    Iteration_Num)];
            end
            %Check data record dimension
            if size(Mill_UC,2)<Rehab_Num
                Mill_UC = [Mill_UC, zeros(Iteration_Num,1)];
            end
            if size(OL_Surface_UC,2)<Rehab_Num
                OL_Surface_UC = [OL_Surface_UC,
zeros(Iteration_Num,1)];
            end
            if size(OL_Inter_UC,2)<Rehab_Num
                OL_Inter_UC = [OL_Inter_UC, zeros(Iteration_Num,1)];
            end
            if size(Surface_Coeff,2)<Rehab_Num+1
                Surface_Coeff = [Surface_Coeff,
zeros(Iteration_Num,1)];
            end
            if size(Inter_Coeff,2)<Rehab_Num+1
                Inter_Coeff = [Inter_Coeff, zeros(Iteration_Num,1)];
            end
            if size(OL_Mill_B,2)<Rehab_Num
                OL_Mill_B = [OL_Mill_B, zeros(Iteration_Num,1)];
            end
            if size(OL_Surface_B,2)<Rehab_Num
                OL_Surface_B = [OL_Surface_B, zeros(Iteration_Num,1)];
            end
            if size(OL_Inter_B,2)<Rehab_Num
                OL_Inter_B = [OL_Inter_B, zeros(Iteration_Num,1)];
            end
            if size(iPSI_B,2)<Rehab_Num+1
                iPSI_B = [iPSI_B, zeros(Iteration_Num,1)];
            end
            if size(iPCI_B,2)<Rehab_Num+1
                iPCI_B = [iPCI_B, zeros(Iteration_Num,1)];
            end
            % Assign random values to data records
            Mill_UC(iteration, Rehab_Num) = ...
```

```matlab
                Rnd_Mill_UC(iteration, Rehab_Num);
            OL_Surface_UC(iteration, Rehab_Num) = ...
                Rnd_OL_Surface_UC(iteration, Rehab_Num);
            OL_Inter_UC(iteration, Rehab_Num) = ...
                Rnd_OL_Inter_UC(iteration, Rehab_Num);
            Surface_Coeff(iteration, Rehab_Num+1) = ...
                Rnd_Surface_Coeff(iteration, Rehab_Num+1);
            Inter_Coeff(iteration, Rehab_Num+1) = ...
                Rnd_Inter_Coeff(iteration, Rehab_Num+1);
            OL_Mill_B(iteration, Rehab_Num) = ...
                Rnd_OL_Mill_B(iteration, Rehab_Num);
            OL_Surface_B(iteration, Rehab_Num) = ...
                Rnd_OL_Surface_B(iteration, Rehab_Num);
            OL_Inter_B(iteration, Rehab_Num) = ...
                Rnd_OL_Inter_B(iteration, Rehab_Num);
            iPSI_B(iteration, Rehab_Num+1) = ...
                Rnd_iPSI_B(iteration, Rehab_Num+1);
            iPCI_B(iteration, Rehab_Num+1) = ...
                Rnd_iPCI_B(iteration, Rehab_Num+1);

            % Rehabilitation cost and timing record
            Rehab_Cost_B(iteration, Rehab_Num) = Area*(...
                Mill_UC(iteration, Rehab_Num)*...
                OL_Mill_B(iteration, Rehab_Num)+...
                OL_Surface_UC(iteration, Rehab_Num)*...
                OL_Surface_B(iteration, Rehab_Num)+...
                OL_Inter_UC(iteration, Rehab_Num)*...
                OL_Inter_B(iteration, Rehab_Num));
            Rehab_Timing_B(iteration, Rehab_Num) = year;

            SN_eff_B(iteration,Rehab_Num) = sneff(cESAL_B,
iPSI_B(iteration, Rehab_Num),...
                iSN_B(iteration, Rehab_Num), Subgrade_Mr(iteration),...
                R_B, S0_B);
            iSN_B(iteration, Rehab_Num+1) =
SN_eff_B(iteration,Rehab_Num)-...
                - OL_Mill_B(iteration, Rehab_Num)*...
                (Surface_Coeff(iteration, Rehab_Num) - ...
                (iSN_B(iteration, Rehab_Num)-...
                SN_eff_B(iteration,Rehab_Num))/HMA_Thickness)+...
                OL_Surface_B(iteration, Rehab_Num)*...
                Surface_Coeff(iteration, Rehab_Num+1) +...
                OL_Inter_B(iteration, Rehab_Num)*...
                Inter_Coeff(iteration, Rehab_Num+1);

            pavement_type_B = 8; % pavement with overlay > 2.4in
            HMA_Thickness = HMA_Thickness -...
                OL_Mill_B(iteration, Rehab_Num) +...
                OL_Surface_B(iteration, Rehab_Num) + ...
                OL_Inter_B(iteration, Rehab_Num);
            TGap_B(iteration, year) = 0;
            PSI_B(iteration, year) = iPSI_B(iteration, Rehab_Num+1);
            PCI_B(iteration, year) = iPCI_B(iteration, Rehab_Num+1);
            TGap_B(iteration, year+1) = TGap_B(iteration,year)+1;
            PSI_B(iteration, year+1) = iPSI_B(iteration, Rehab_Num+1) -
...
```

```matlab
                psiloss(ESAL(year), iSN_B(iteration, Rehab_Num+1),...
                Subgrade_Mr(iteration), R_B, S0_B);
            PCI_B(iteration, year+1) = ...

pci_predict(TGap_B(iteration,year+1),pavement_type_B,...
                iPCI_B(iteration, Rehab_Num+1));
            cESAL_B = ESAL(year);
        else
            TGap_B(iteration, year+1) = TGap_B(iteration,year)+1;
            PSI_B(iteration, year+1) = iPSI_B(iteration, Rehab_Num+1) -
...
                psiloss(cESAL_B, iSN_B(iteration, Rehab_Num+1),...
                Subgrade_Mr(iteration), R_B, S0_B);
            PCI_B(iteration, year+1) = ...

pci_predict(TGap_B(iteration,year+1),pavement_type_B,...
                iPCI_B(iteration, Rehab_Num+1));
        end
    end
end

% Salvage value
Salvage_B = Initial_Cost_B.*(PSI_B(:,Ana_Period+1)-1.5)./(PSI_B(:,1)-
1.5);

% Present Worth Factor
PWF_B = (kron((1+Disc_Rate)',ones(size(Rehab_Cost_B,2),1))').^(-
Rehab_Timing_B);
NPV_B = [Initial_Cost_B, Rehab_Cost_B.*PWF_B, -
Salvage_B.*(1+Disc_Rate).^(-Ana_Period)];
LCC_B = sum(NPV_B')';

hold on; cdfplot(LCC_B);
LCC_Mean_B = mean(LCC_B)
LCC_Std_B = std(LCC_B)

disp('Alternative B has been done...');
```

CALIBRATION ALGORITHM FOR FUZZY-LOGIC-BASED DECISION SUPPORT MODELS

```
%% Written by Chen Chen @ 10/20/2006
% The function tunes a fuzzy-logic-based decision model for one epoch
using
% the training dataset.

% A training dataset and the model's structure are inputed into the
% function.  Final output is the tuned decision model.

% Two fuzzy-logic systems are defined in the decision model.  They
share
% the membership functions of input and output variables.  However,
% the rules are different.

% The function was written temparily for FLS with three input variables
% and one output variables.  The sequence of output MF should be
specified
% in an input parameter in the future, but is directly given now.

%% Calib_FDM.m
function
[M,sigma,T_C,P_C,MSE,F,Priority_Before,Priority_After]=Calib_FDM(X,T_Ru
le,P_Rule,M,sigma,T_C,P_C,alpha)
% X: Training data set;
% T_Rule: Rule Array for Trigger Model;
% P_Rule: Rule Array for Policy Model;
% M: the mean of antecedent MFs.  The array should be defined by
variables.
%   Each variable takes one row.  The number of MFs should be same for
each
%   variable.
% sigma: the std of antecedent MFs.  The array is defined by variables.
%   Each variable takes one row.  The number of MFs should be same for
each
%   variable.
% T_C: the height of consequences in Trigger Model.
% P_C: the height of consequences in Policy Model.
% alpha: the learning parameter (rate). The array has three elements:
the
%   learing rate for M, sigma, and c0, respectively.

%% Step 1: Validate Inputs and Get Dimensional Information.
% 1. T_Rule should be of the same dimension of P_Rule;
% 2. The column number of Training dataset, X, shoudl equal to the
column
%   number of T _Rule number;
% 3. The row number of M and sigma should be less by one than the
coulmn
%   number of T_Rule number;
% 4. T_C should be of the same dimension of P_C;
```

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% 5. The vector length of T_c0 should be same as the row number of
T_rule;
% 6. alpha is a 3 by 1 verctor.

% Read total case number, variable number, MF number and rule number.
% The variable number only includes input variables.
% rule_number = MF_number^var_number
case_number=size(X,1);
var_number=size(M,1);
% MF_number=size(M,2);
rule_number=size(T_Rule,1);
alpha_M = alpha(1);
alpha_sigma = alpha(2);
alpha_C = alpha(3);

%% Step 2: Calibrate Models
F = [];

for i=1:case_number
    E_Trigger=[]; E_Policy=[];
    C_Trigger=[]; C_Policy=[];
    U_Trigger=0; U_Policy=0;
    V_Trigger=0; V_Policy=0;

    % Calculate output of each rule in Trigger Model
    for j=1:rule_number
        u=1;
        for t=1:var_number

u=u*(gaussmf(X(i,t),[sigma(t,T_Rule(j,t)),M(t,T_Rule(j,t))]));
        end
        C_Trigger = [C_Trigger; T_C(T_Rule(j,var_number+1))];
        E_Trigger=[E_Trigger,u];
    end

    V_Trigger=sum(E_Trigger);
    fa_Trigger=E_Trigger/V_Trigger; % Fuzzy Basis Function
    U_Trigger=E_Trigger*C_Trigger;
    f_Trigger=U_Trigger/V_Trigger; % Height Defuzzification

    % Calculate output of each rule in Policy Model
    for j=1:rule_number
        u=1;
        for t=1:var_number

u=u*(gaussmf(X(i,t),[sigma(t,P_Rule(j,t)),M(t,P_Rule(j,t))]));
        end
        C_Policy = [C_Policy; P_C(P_Rule(j,var_number+1))];
        E_Policy=[E_Policy,u];
    end

    V_Policy=sum(E_Policy);
    fa_Policy=E_Policy/V_Policy;  % Fuzzy Basis Function
    U_Policy=E_Policy*C_Policy;
    f_Policy=U_Policy/V_Policy; % Height Defuzzification
```

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        % Priority Records
        Priority_Before(i,:)=[f_Policy,f_Trigger];

        % Error Item
        % could e be (f_Policy-f_Trigger)?
        f = hardlim(f_Policy-f_Trigger);
        e=(X(i,var_number+1)-f)*abs(f_Policy-f_Trigger);
        F= [F, f];

%     dU_M = zeros(var_number, MF_number);
%     dV_M = zeros(var_number, MF_number);
%     dU_sigma = zeros(var_number, MF_number);
%     dV_sigma = zeros(var_number, MF_number);

        % Save original system parameters
        M0=M; %var_number by MF_number
        sigma0=sigma; %var_number by MF_number
        T_C0=T_C; % rule_number by 1
        P_C0=P_C; % rule_number by 1

        % Trigger Model
        for j=1:rule_number
%           for t=1:var_number-1
%               M(t, T_Rule(j,t)) = M(t, T_Rule(j,t))+...
%                   alpha_M*e*((X(i,t)-M0(t,T_Rule(j,t)))/...
%                   (sigma0(t,T_Rule(j,t))^2))*...
%                   (c00(T_Rule(j,var_number))-f)*...
%                   E_Trigger(j)/sum(E_Trigger);
%               sigma(t, T_Rule(j,t)) = sigma(t,T_Rule(j,t))+...
%                   alpha_sigma*e*(((X(i,t)-M0(t,T_Rule(j,t)))^2)/...
%                   (sigma0(t,T_Rule(j,t))^3))*...
%                   (c00(T_Rule(j,var_number))-f)*...
%                   E_Trigger(j)/sum(E_Trigger);
%           end
            T_C(T_Rule(j,var_number+1)) =...
                T_C0(T_Rule(j,var_number+1))-alpha_C*e*...
                E_Trigger(j)/sum(E_Trigger);
        end

        % Policy Model
        for j=1:rule_number
            for t=1:var_number
                M(t, P_Rule(j,t)) = M(t, P_Rule(j,t))+...
                    alpha_M*e*((X(i,t)-M0(t,P_Rule(j,t)))/...
                    (sigma0(t,P_Rule(j,t))^2))*...
                    (P_C0(P_Rule(j,var_number+1))-f_Policy)*...
                    E_Policy(j)/sum(E_Policy);
                sigma(t, P_Rule(j,t)) = sigma(t,P_Rule(j,t))+...
                    alpha_sigma*e*(((X(i,t)-M0(t,P_Rule(j,t)))^2)/...
                    (sigma0(t,P_Rule(j,t))^3))*...
                    (P_C0(P_Rule(j,var_number+1))-f_Policy)*...
                    E_Policy(j)/sum(E_Policy);
            end
            P_C(P_Rule(j,var_number+1)) =...
                P_C0(P_Rule(j,var_number+1))+alpha_C*e*...
```

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                    E_Policy(j)/sum(E_Policy);
        end
end

%% Step 3: Calculate Mean Squared Error (MSE)
MSE = 0;
for i=1:case_number
    E_Trigger=[]; E_Policy=[];
    C_Trigger=[]; C_Policy=[];
    U_Trigger=0; U_Policy=0;
    V_Trigger=0; V_Policy=0;

    % Calculate output of each rule in Trigger Model
    for j=1:rule_number
        u=1;
        for t=1:var_number

u=u*(gaussmf(X(i,t),[sigma(t,T_Rule(j,t)),M(t,T_Rule(j,t))]));
        end
        C_Trigger = [C_Trigger; T_C(T_Rule(j,var_number+1))];
        E_Trigger=[E_Trigger,u];
    end

    V_Trigger=sum(E_Trigger);
    fa_Trigger=E_Trigger/V_Trigger; % Fuzzy Basis Function
    U_Trigger=E_Trigger*C_Trigger;
    f_Trigger=U_Trigger/V_Trigger; % Height Defuzzification

    % Calculate output of each rule in Trigger Model
    for j=1:rule_number
        u=1;
        for t=1:var_number

u=u*(gaussmf(X(i,t),[sigma(t,P_Rule(j,t)),M(t,P_Rule(j,t))]));
        end
        C_Policy = [C_Policy; P_C(P_Rule(j,var_number+1))];
        E_Policy=[E_Policy,u];
    end

    V_Policy=sum(E_Policy);
    fa_Policy=E_Policy/V_Policy;  % Fuzzy Basis Function
    U_Policy=E_Policy*C_Policy;
    f_Policy=U_Policy/V_Policy; % Height Defuzzification

    % Priority after calibration
    Priority_After(i,:)=[f_Policy,f_Trigger];

    % Error Item
    f = hardlim(f_Policy-f_Trigger);
    e=X(i,var_number+1)-f;

    MSE = MSE + e^2;
end
```