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Impact of Budget Uncertainty on Network-Level Pavement

Condition: A Robust Optimization Approach

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**Impact of Budget Uncertainty on Network-Level Pavement
Condition: A Robust Optimization Approach**

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Thesis

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Dedication

This thesis is dedicated to my parents, siblings and wife for their passionate support.

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Abstract

Highway agencies usually face budget uncertainty for pavement maintenance and rehabilitation activities due to limitation in resources and changes in government policies. Highway agencies perform maintenance planning for the pavement network commonly based on the nominal available budget without taking the variability of budget into consideration. The maintenance program based on deterministic budget consideration results in suboptimal maintenance decisions that impact the overall network conditions, if the budget falls short in some future year in the planning horizon. As a result, it is important for highway

agencies to adopt maintenance and rehabilitation policies that are protected against the uncertainty in maintenance and rehabilitation budget.

In this study a multi-period linear integer programming model is proposed with its robust counterpart considering uncertain maintenance and rehabilitation budget. The proposed model is able to provide a maintenance and rehabilitation program for the pavement network that results in minimal impact of budget variability on the network conditions. A case study was carried out for a network of ten pavement sections. The solution of the robust optimization model was compared to those with deterministic model. The results show that the robust optimization model is an attractive method that can minimize the effect of budget uncertainty on pavement conditions at the network level.

TABLE OF CONTENTS

LIST OF TABLES.....	XI
LIST OF FIGURES.....	XII
CHAPTER 1 INTRODUCTION.....	1
1.1 Background.....	1
1.2 Pavement Maintenance and Rehabilitation Planning.....	2
1.3 Motivation of this Research.....	3
1.4 Research Objective and Scope.....	5
1.5 Thesis Organization	5
CHAPTER 2 LITERATURE REVIEW.....	7
2.1 Introduction	7
2.2 Infrastructure Asset Management	8
2.3 Pavement Management System (PMS).....	11
2.4 Pavement Maintenance and Rehabilitation Planning.....	14
2.5 Network Level Pavement Maintenance Optimization Models	15
2.6 Pavement Maintenance and Rehabilitation Planning with Uncertain Budget	17
2.7 Optimization Techniques for Dealing with Uncertainty	19
2.7.1 Stochastic Programming.....	19
2.7.2 Robust Optimization	20
CHAPTER 3 PROBLEM FORMULATION	25

3.1	Introduction	25
3.2	Notations.....	25
3.3	Pavement Deterioration and Prediction of Condition Score	27
3.4	Maintenance and Rehabilitation Planning Model for Deterministic Budget	29
3.5	Maintenance and Rehabilitation Planning Model under Budget Uncertainty.....	32
CHAPTER 4 CASE STUDY		37
4.1	Introduction	37
4.1.1	Maintenance and Rehabilitation Treatment	37
4.1.2	Planning Horizon	38
4.1.3	Performance Measure and Initial Condition.....	39
4.1.4	Condition Score Improvement due to M&R Treatments	40
4.1.5	Maintenance and Rehabilitation Treatment Unit Cost.....	41
4.1.6	Pavement Deterioration Rate	42
4.1.7	Requirements on Condition Scores	43
4.2	Solution of Deterministic Problem	43
4.3	Solution of Robust Counterpart.....	45
CHAPTER 5 DISCUSSION		48
5.1	Discussion of Results.....	48
5.2	Robust Optimization Approach for Maintenance Planning under Budget Uncertainty.....	51

CHAPTER 6 CONCLUSIONS	52
6.1 Summary.....	52
6.2 Conclusions	52
6.3 Recommendations for Future Research	53
REFERENCES	56
VITA	62

LIST OF TABLES

Table 1 Notations.....	25
Table 2 Initial Condition Score for Pavement Sections	40
Table 3 Average Increase in Condition Score.....	41
Table 4 Maintenance and Rehabilitation Unit Cost	42
Table 5 Average Network Condition Scores (Deterministic Budget).....	43
Table 6 Optimal Decision Variables for Deterministic Budget Case	44
Table 7 Average Network Condition Scores (Uncertain Budget)	46
Table 8 Optimal Decision Variables for Uncertain Budget Case.....	46
Table 9 Maintenance and Rehabilitation Decision Comparison between Robust model and Deterministic model.....	51

LIST OF FIGURES

Figure 1 Generic Asset Management Process (FHWA,1999).....	10
Figure 2 Pavement Management System.....	13
Figure 3 Pavement condition and Improvement in condition due to maintenance	28
Figure 4 Network wide Condition Scores	49
Figure 5 M&R Cost to Budget Ratio.....	50

CHAPTER 1 INTRODUCTION

1.1 Background

The roadway networks of a nation provide a critical link between social development and economic growth through moving people and goods. The U.S. has the one of the largest paved roadway networks which provides efficient mobility for both people and freight. Since most of the U.S. highway networks were developed during the construction boom between the 1950's and 1980's, these highways are showing signs of increased deterioration because of age and utilization. American Society of Civil Engineers (ASCE) 2013 report card for America's Infrastructure assigns U.S. roads with a grade "D" due to the present poor conditions. The deteriorating highway infrastructure requires huge amount of investments in highway infrastructure preservation and enhancement. The National Cooperative Highway Research Program (NCHRP) report 102 estimates the total investment need to maintain highways will be about \$250 billion in 2017 and the funding shortfall will be \$66 billion in 2017. This requirement poses a great challenge to the U.S. highway agencies due to the wide gap between available resources and overall needs for maintaining and preserving highway pavement infrastructure. It is evident that there is an urgent need for sound planning and efficient management approaches to address the challenges resulting from the severely constrained resources.

U.S. Highway agencies have gradually transformed their policy from expansion of the network to preservation of the existing infrastructure due to budget fluctuations, changes in government policies and seek of accountability for the use of public funds. This transformation puts more focus on a systematic, asset management approach to maintaining, upgrading, and operating infrastructure facilities such as pavement and bridges with limited resources. Asset management integrates engineering principles, sound business practice, and economic theory to provide efficient solutions to maintain complex networks of infrastructure assets (FHWA, 1999). A Pavement Management System (PMS) is a tool that applies the asset management approach to support pavement maintenance and rehabilitation decision making activities. Pavement Management Systems incorporate analytical tools or methods that help decision makers determine optimal strategies for maintaining pavements in serviceable conditions (Haas et al., 1994). PMS applies mathematical models to develop optimal maintenance and rehabilitation plans within available budget constraints in order to achieve and maintain pavement conditions at the established agency goal level(s).

1.2 Pavement Maintenance and Rehabilitation Planning

A key goal of a Pavement Management System is providing rational information to retard the pavement deterioration or extend the effective life of pavement through pavement maintenance and rehabilitation treatments. Routine

pavement maintenance treatments are reactive and include treatments such as crack sealing, pothole patching, and edge repairs whereas preventive maintenance treatments help extend the life of the pavement and restore surface friction and safety through application of chip seals, micro-surfacing or thin overlays. Pavement rehabilitation includes treatments that enhance the structural capacity of the pavement such as a thick overlay or reconstruction of the underlying pavement layers. (Gao and Zhang, 2010). Pavement Management Systems employ a maintenance and rehabilitation planning process to achieve a desired level of service with the limited available budget. In maintenance and rehabilitation planning of pavements, a PMS can help provide the rational information to decide which pavement section will receive treatment, when the treatment will be carried out, and what type of treatment will be applied (Chan et. al., 1994).

1.3 Motivation of this Research

By 2050, the total U.S. population is projected to reach 420 million; which is a 33% increase in the current population. This growth will result in increased demand for goods and services, and associated increased demands on the transportation system. This will result in vast increase in travel demand on US highway system. But as the current highway infrastructure ages and deteriorates this increased demand will require increased of capital investments for maintenance and capacity improvement. The investment on US highway

infrastructure mainly comes from the highway trust fund based on fuel tax. However, this fund can no longer provide a firm foundation for the highway investment needs due to lack of increases in both state and federal fuel tax, more fuel efficient vehicles, and increasing construction and maintenance costs. This situation has resulted in highway agencies experiencing funding shortfalls for maintaining and upgrading road infrastructure. The present highway funding scenarios are associated with a high level of uncertainty. Texas 2030 Committee estimated that funding shortfalls for Texas's pavements and bridges will be ranges from \$74 billion to \$170 billion from 2011 to 2030. Under this circumstance, the efficient use of the available funding is a challenging problem.

Pavement maintenance and rehabilitation requires a large amount of highway funding. Texas Department of Transportation (TxDOT) invested \$2.7 billion in Maintenance and Rehabilitation (M&R) activities for pavements in fiscal year 2007 (TxDOT, 2007). When the funding in highway system is limited, pavement maintenance and rehabilitation activities require proper planning and scheduling. A number of mathematical models are available for pavement maintenance and rehabilitation planning and scheduling. Most of these models were developed with the assumption that available budget for maintenance and rehabilitation is known with certainty to the decision makers. However, present highway funding scenarios make this assumption unrealistic. The funding available for pavement maintenance and rehabilitation programs exhibit random characteristics during the planning horizon because of constrained resources,

policy changes, and competition with other infrastructure needs. Therefore, the actual amount of funds available for pavement maintenance and rehabilitation may fluctuate from the expected amount on a year-to-year basis. Therefore, model based on deterministic budget assumption may lead to suboptimal maintenance plan, if fund falls short for some years in the planning period. A suboptimal maintenance plan may result in unstable pavement conditions. It is therefore important that the pavement maintenance and rehabilitation planning model takes the random nature of budgets into consideration.

1.4 Research Objective and Scope

The objective of this study is to develop an optimization framework that can manage network-level pavement condition fluctuations considering the uncertain characteristics of pavement maintenance and rehabilitation budgets. In order to achieve the research objective, the study proposed an integer programming model using a set-based robust optimization method. The robust optimization model provides feasible solutions for all realizations the parameter belonging to a defined uncertainty set.

1.5 Thesis Organization

The organization of this thesis is as follows: chapter 1 is the introduction to the thesis outlining the research background, motivation of the study, research objective and scope. Chapter 2 focuses on the existing literature on pavement

management systems, pavement maintenance planning, optimization of pavement maintenance planning, and optimization methods capable of handling data uncertainty. Chapter 3 describes the formulation of optimization problems considering the deterministic budget variable, and the robust optimization model with random budget variables. Chapter 4 presents the application of the robust optimization models through a numerical case study. Chapter 5 discusses the results obtained from the numerical study of the models. Chapter 6 provides a summary of the thesis and presents conclusions.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

Roadway infrastructure is composed of pavements, bridges and drainage structure, traffic management systems, safety devices and other related items. However, the pavement infrastructure, which actually carries the traffic, is the most costly component and the heart of highway based surface transportation system. To ensure a desired level of service and the best use of resources, pavement networks require efficient management of maintenance and rehabilitation (M&R) programs. Managing pavement networks is a complex and complicated task. The complexity of pavement management may come from uncertainties associated with the management process such as uncertainty in condition data, pavement performance predictions, and resource availability.

Pavement management system (PMS) is an operational tool developed under the framework of Infrastructure Asset Management (IAM). PMS should consider the uncertainties associated with the management process in order to determine optimal strategies to preserve and upgrade a pavement network at desired condition level(s) utilizing available resources. PMS uses prioritization or optimization techniques to program Maintenance & Rehabilitation activities (Haas et al., 1978). Optimization approaches have received much attention due to limited budgets, changes in transportation policies and increased demands. The optimization framework uses mathematical programming models which

consider specific constraints based on the program requirement to maximize or minimize a predefined objective. These models may consider the uncertainties associated with the management process in order to provide a management program that reduces the risk associated with budget uncertainties.

The following sections provide a review of asset management, pavement management systems, optimization approaches used in pavement M&R planning, optimization techniques dealing with uncertainties, and pavement M&R under budget uncertainties.

2.2 Infrastructure Asset Management

American Association of State Highway and Transportation Officials (AASHTO) and Federal Highway Administration (FHWA) (1996) defined asset management as a systematic approach for management, development, and operation of infrastructure assets in a cost effective way. The asset management derives its framework using engineering principles, economic theory, and sound business practices. Infrastructure asset management facilitates decision making through providing relevant information regarding assets. According to a National Cooperative Highway Research Program report (NCHRP Report 551, 2006) asset management incorporates the following principles:

- Asset management approach reflects the policy goals and objectives. The goal and objective should have a strong tie with a well-defined performance measure;
- Asset management approach should incorporate analysis and tradeoff mechanism for allocation of scarce resources and for evaluations of alternative strategies;
- Asset management process seeks quality information in every stage which facilitates rational decision making consistent with the agency's business process; and
- Asset management process provides monitoring mechanism to ensure accountability and improvement of the program.

Asset management paradigm provides a framework following the above principles to achieve defined policy goals and objectives. FHWA (1999) developed a framework for transportation assets management. Figure 1 illustrates the asset management process and key components involved in the approach.

The asset management framework starts with the identification of agency's policies and goals along with the relevant information regarding available resources. The process relies on high-quality data for present condition assessment and performance modeling to predict the future conditions. Performance modeling is a complicated task under the asset management

framework due to the dynamic and stochastic nature of deterioration process. The performance modeling step has a significant impact on determining the alternatives to preserve and upgrade infrastructure assets.

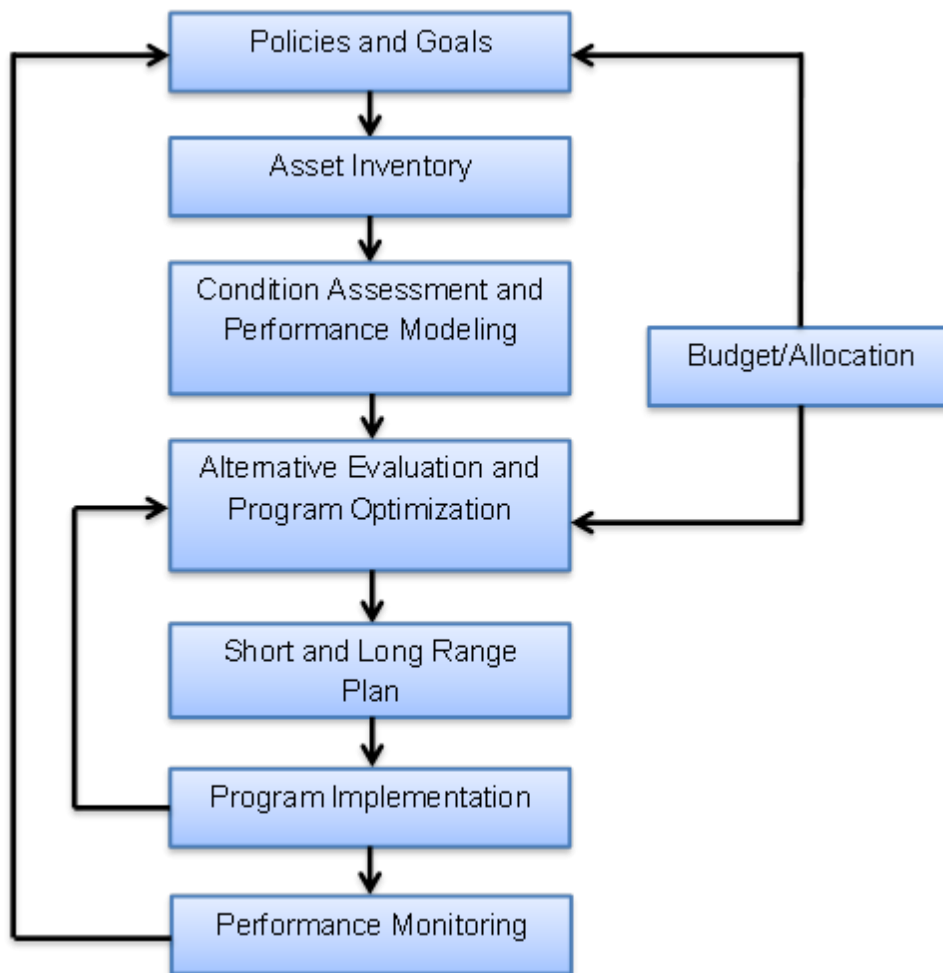


Figure 1 Generic Asset Management Process (FHWA, 1999)

Based on the predicted performance various alternatives are developed to maintain infrastructure assets in order to achieve established goals within a predefined time frame, where optimization techniques are employed to

determine the best resource allocation strategies. The optimization technique might consider the stochastic nature of available funds allocated for the management purposes. Capturing the uncertainties in budget in the program optimization phase would lower the risk associated with the budget fluctuations. In the program optimization phase of the assets management process, robust optimization models can be applied to capture the randomness in available resources and other variables. After evaluation and program optimization, the selected strategies are implemented and the performance of implemented strategies is evaluated through a performance monitoring process. The performance monitoring mechanism provides feedback information for improving the efficiency and reliability of the overall management process.

2.3 Pavement Management System (PMS)

Pavement is the basic and primary component of a modern highway system which requires the largest capital investment to build and maintain. Maintenance and operation of pavement networks in a highway system involves complex decision-making processes regarding pavement M&R under available resources. A pavement management system is defined as a coordinated set of activities to achieve the best utilization of available public funds for operating safe, smooth and economical pavements (Hudson et al., 1979). According to the American Association of State Highway and Transportation Officials (AASHTO) (2001), a Pavement Management System (PMS) is a system

comprised of a set of tools or methods that help decision makers in determining optimal strategies for providing, evaluating, and maintaining pavements in a serviceable condition over a time horizon. Therefore, a PMS can be interpreted as a decision support tool for decision makers to make more informed decisions on pavement operations and maintenance. Typically a pavement management system is composed of three components: a system that collects pavement condition data on a regular basis, a comprehensive data management system, and an analysis package that evaluates alternative strategies and suggests the best possible strategies for pavement maintenance. Figure 2 demonstrates a typical pavement management system.

The pavement management system process starts with the collection of necessary data such as pavement condition, traffic, and climate region data.. The data is stored in a database and a data management system is used to ensure systematic use of the data. In the next step, the focus is on predicting the future performance of the pavement sections and assessing the M&R needs based on performance requirements. A prioritization or optimization tool using the results of the need assessment along with system wide information such as policy, resource constraints provides the decision makers with the best possible M&R strategies for pavement management.

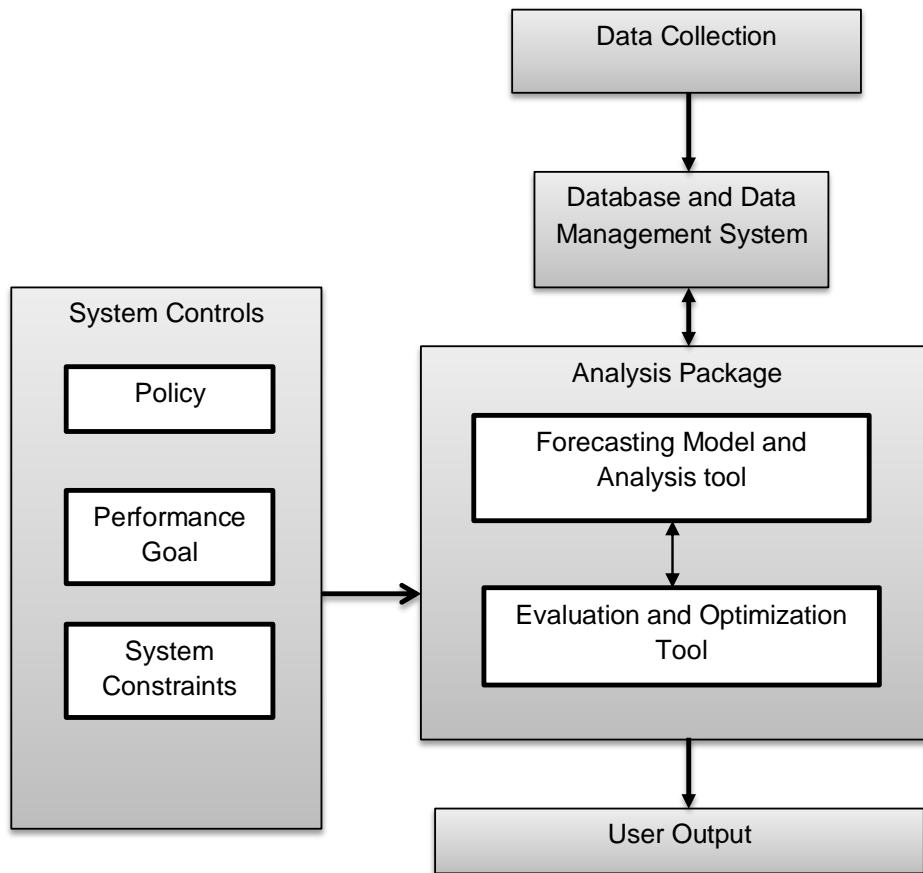


Figure 2 Pavement Management System

Pavement management systems are typically implemented in two working levels (Jaypuria, 2010):

- Network-level PMS
- Project-level PMS

Network-level PMS is used to assess and predict pavement performance over time; determine appropriate investment strategies for maintenance, rehabilitation, and replacement; prioritize or optimize allocation of resources;

and generate different kinds of work plans and programs. Decisions made at this level affect the entire network and involve tradeoffs between projects and activities. Project-level PMS is employed for trade-offs of alternatives for a specific section or project; for design, construction, material evaluation, and improvement, among others.

2.4 Pavement Maintenance and Rehabilitation Planning

Pavement maintenance and rehabilitation is the most important aspect of modern pavement management. Pavement maintenance and rehabilitation planning involves in developing alternative M&R plans to achieve the desired performance goal. An M&R plan is the selection of sequence of M&R treatments over a planning horizon (Gao, 2011). The objective of pavement M&R planning is to retard the deterioration process and extend the service life of pavements with the best use of available resources. Because there are limitations of resources, PMSs usually implement prioritization or optimization techniques in M&R planning of pavements.

There are two types of M&R planning process (Gao, 2011). The first one is the network-level problem, where decision-makers face great challenges of determining which pavement section to receive what type of treatment at what time in the planning horizon. The other is the project-level maintenance problem, in which the maintenance of only one facility is considered.

2.5 Network Level Pavement Maintenance Optimization Models

Optimization is a mathematical programming technique to maximize or minimize certain objective functions of some decision variables by satisfying the established constraints affecting the objective functions.

A number of approaches for network-level M&R planning have been proposed by various researchers in recent years. Common characteristics of these approaches are as follows (Garza et al., 2011):

- Identification of network characteristics;
- Evaluation of current needs;
- Definition of treatment strategies;
- Prediction of future conditions;
- Development of optimization algorithm; and
- Selection of appropriate treatments.

Most of the proposed optimization approaches have two essential components in common: optimization algorithm and pavement performance prediction model. Since the development of pavement management systems, many optimization algorithms have been adopted by various researchers, such as integer programming, linear programming, dynamic programming, and heuristic method.

Many researchers used integer programming with binary decision variables to formulate pavement M&R program. The solution to integer programming

assigns maintenance treatment directly to individual facilities. Mahoney et al. (1978), Fwa et al. (1988), Li et al. (1998), Ferreira et al. (2002) and Wang et al. (2003) used integer programming model for M&R planning problem. Li et al. (1998) developed a cost effectiveness based M&R programming on year by year basis. The objective of the optimization is to select the most effective M&R projects for the programming year and the model was able to calculate the minimum budget requirement to maintain a prescribed level of pavement performance. Ferreira et al. (2002) proposed a mixed integer programming model with the objective of minimizing the expected total discounted M&R costs subject to pavement quality standards, maximum number of heavy M&R treatments, and annual budget constraints. Wang et al. (2003) proposed integer programming model with multi objective for budget planning and allocation. The problem associated with the integer programming model is that, it can be applied in a small scale problem with few number of pavement sections and five to ten year planning horizon.

Linear programming with Markov prediction models have been used for network-level pavement M&R programming. Linear programming models usually cannot provide schedules for individual pavement sections; rather these models provide- schedules for a group of pavement sections with similar characteristics. Mbwana et al. (1996) developed a large scale linear optimization model from dynamic programming model. Wu et al. (2009) proposed a linear programming model for formulating M&R problem with bi-

objective functions. Gao et al. (2010) used linear programming model for network-level optimal performance improvement and budget utilization.

Dynamic programming methods are used when a number of decisions need to be made in a sequential manner. Feighan et al. (1988) employed dynamic programming formulation with Markov chain prediction models. The objective of the proposed formulation was to achieve the minimum expected cost over an analysis period. Gao et al. (2008) used an approximate dynamic programming model for network-level pavement maintenance planning problems.

Heuristic based methods are approximate algorithms that can be used to obtain the solution for discrete optimization problems and nonlinear programming problems. Genetic algorithms are one of most popular methods applied in network-level maintenance programming. Chan et al. (1994), Fwa et al. (1996, 2000), and Pilson et al. (1999) used genetic algorithm for maintenance planning problem.

2.6 Pavement Maintenance and Rehabilitation Planning with Uncertain Budget

Most research in pavement maintenance and rehabilitation programming assumes the budget as a precisely known parameter (i.e., the fund available for M&R works as fixed in amount) and cannot deviate from its nominal value. However, over the years, highway agencies have – experienced fluctuations of budget in terms of resource available for highways M&R. The resources

allocated to an M&R program can become unstable due to various economic and political reasons. The actual amount of resources distributed to the maintenance activities may deviate from the original projected estimates. If the budget falls short for one or more years within the planning horizon, part of the scheduled maintenance activities might be unfunded, delayed or rescheduled leading to potential pavement condition fluctuations compared with expectations. As a result, the M&R plan based on the assumption of a fixed nominal budget may lead to a sub-optimal plan.

In recent years, several researchers have explored the problem of managing budget uncertainty in M&R planning. Li and Puyan (2006) proposed a project selection problem under budget uncertainty as a multi-choice multidimensional Knapsack problem with multi-stage budget recourses. Their proposed methodology selects a subset of candidate projects satisfying the objective of maximum system benefits under budget and other constraints. Gao and Zhang (2008) developed a complex linear robust optimization model to determine the optimal M&R decisions. They investigated the uncertainties in the pavement deterioration process and the pavement condition improvements due to M&R actions. A prominent feature of their formulations is that the decision maker able to control the probability of attain at certain levels of condition requirement Wu and Flintsch (2009) developed a chance-constrained programming model that can control the probability of going over budget for network-level facility maintenance planning problems. The solution is obtained by first choosing a

conservative value for the budget from an assumed range and then optimization model is solved for that conservative budget. However, the obtained scheduling solution of this model is only optimal at a given probability. Gao (2011) proposed a multistage linear stochastic model for network-level infrastructure maintenance scheduling problem subject to uncertain budget constraint. Gao showed that the proposed stochastic programming approach differs from its deterministic counterpart in that it attempts to achieve the best expected objective value over all possible realizations of the random budgets.

2.7 Optimization Techniques for Dealing with Uncertainty

2.7.1 Stochastic Programming

Stochastic programming directly incorporates uncertainty in the formulation. In stochastic optimization, the data values are assumed to be random, rather than, systematic bias. In the simplest case, these random data obey a known probability distribution, while in more advanced settings, this distribution is partially known. A simple stochastic linear programming model can have the formulation as follows (Ben – Tal et al., 2008):

$$\min_{x,t} \{t: \text{Prob}_{(C,A,b) \sim P} \{C^T x \leq t \ \& \ Ax \leq b\} \geq 1 - \varepsilon\} \quad (2.1)$$

In the above equation, x , t be the variables, C is a vector of coefficients for objective functions, A is the coefficient matrix for the constraints, and b is the vector for boundary conditions. Where $\varepsilon \ll 1$ is a given tolerance and P is the distribution of the data (c, A, b) . When this distribution is only partially known, that is P belongs to a given family of probability distribution (\mathcal{P}) on the space of the data, the equation (2.1) is replaced with:

$$\min_{x,t} \{t: \text{Prob}_{(c,A,b) \sim P} \{C^T x \leq t \ \& \ Ax \leq b\} \geq 1 - \varepsilon \ \forall P \in \mathcal{P}\} \quad (2.2)$$

2.7.2 Robust Optimization

In many optimization applications, the data is assumed to be known precisely. However, in most cases this assumption is unrealistic. Naturally Data is subject to uncertainty due to inherent randomness (random variability), measurement or estimation errors (error term), and other reasons (systematic variability or bias). Since the solution of an optimization problem often exhibits high sensitivity to the data perturbations as demonstrated by Ben-Tal and Nemirovski (2000), ignoring the data uncertainty can lead to solutions which are suboptimal or even infeasible for practical applications.

Robust optimization is a novel methodology that deals with optimization problems with data uncertainty. In this methodology, a deterministic data set is defined within the uncertain space, and the best solution which is feasible for

any realization of the data variability in the given set is computed through the solution of the robust counterpart optimization problem. One major motivation for studying robust optimization is that in many applications the data is an appropriate notion of uncertainty, e.g., for applications in which infeasibility cannot be accepted at all (e.g., design of engineering structures like trusses, bridges (Ben-Tal & Nemirovski, 1997)), and for those cases where the parameter uncertainty is not stochastic i.e., uncertainty due to measurement error, systematic bias, or if no distributional information is available.

In robust optimization, the uncertain parameters are assumed to be varying in a given uncertainty set and the goal is to find out the best solution among those immunized against data uncertainty. The robust solution is feasible for all data realizations from the given uncertainty set.

The first step in the direction of robust optimization was taken by Soyster (1973) who proposed the worst case model for linear optimization. This approach was very conservative as it ensures feasibility against all realizations of uncertain data. Ben-Tal and Nemirovski (1999, 2000) proposed ellipsoidal uncertainty set based robust model formulations to address the over-conservatism. They showed that with ellipsoidal uncertainty set the linear programming model becomes a conic quadratic problem. Bertsimas and Sim (2004) proposed a new approach for robust linear programming that can handle the conservatism without formulating it as conic problem. This approach reduces the computation complexities associated with conic problems. Lin et al. (2004) extended the

robust optimization formulation for linear programming to mixed integer linear programming problem.

The general robust optimization formulation is:

$$\begin{aligned} & \text{Minimize } f_0(x) \\ & \text{Subjected to } f_i(x, \mathbf{u}_i) \leq 0, \quad \forall \mathbf{u}_i \in \mathcal{U}_i, i = 1, 2, \dots, m \end{aligned} \quad (2.3)$$

Here $x \in \mathbb{R}^n$ is a vector of decision variables, f_0, f_i are the objective function and constraint functions respectively; $\mathbf{u}_i \in \mathbb{R}^k$ are the disturbance vectors or parameter uncertainties and $\mathcal{U}_i \subseteq \mathbb{R}^k$ are uncertainty sets which will always be convex.

We can extend the idea of the robust optimization problem to a general linear optimization problem. Considering the following linear optimization problem with uncertainty in the left hand side constraint coefficient, right hand side parameter, and the objective function coefficients:

$$\begin{aligned} & \text{Max } \sum_j \tilde{c}_j x_j \\ & \text{Subject to } \sum_j \tilde{a}_{ij} x_j \leq \tilde{b}_i, \quad \forall i \end{aligned} \quad (2.4)$$

Where x_j can either a continuous or an integer variable. The above formulation can be transformed into left hand-side uncertainty as follows:

$$\begin{aligned} & \text{Max } z \\ \text{Subject to } & z - \sum_j \tilde{c}_j x_j \leq 0 \end{aligned} \quad (2.5)$$

$$b_i x_0 + \sum_j \tilde{a}_{ij} x_j \leq 0, \forall i$$

$$x_0 = -1$$

If we consider the uncertainty only in the coefficients of the i -th constraint, that is only \tilde{a}_{ij} are subject to uncertainty:

$$\sum_j \tilde{a}_{ij} x_j \leq b_i \quad (2.6)$$

If we define the uncertainty as follows:

$$\tilde{a}_{ij} = a_{ij} + \xi_{ij} \widehat{a}_{ij}, \quad \forall j \in J_i$$

Where, a_{ij} represents the nominal value of the parameter, \widehat{a}_{ij} represents constant perturbations, ξ_{ij} represents independent random variables which are subject to uncertainty, and J_i represents the index subset that contains the variables whose coefficients are uncertain. In the set induced robust optimization method, the goal is to choose the best solution that remains feasible for any ξ in the given uncertainty set U , that is

$\sum_j a_{ij} x_j + \max_{\xi \in U} \{ \sum_j \xi_{ij} \widehat{a}_{ij} x_j \} \leq b_i$ In the present study, the network level pavement maintenance programming problem under budget uncertainty is

formulated as a multi-period integer programming model. The robust optimization method is applied to capture the budget uncertainty. The proposed model is discussed in the following chapter in details.

CHAPTER 3 PROBLEM FORMULATION

3.1 Introduction

The mathematical programming model developed in this thesis is presented in this chapter. First, an integer linear programming model has been developed with the assumption of fixed available budget for the M&R of a pavement network. This model is termed as the deterministic model. Next, the uncertain version of the deterministic model has been developed considering the budget available for the pavement M&R program is uncertain but varies in a given set of uncertainty.

3.2 Notations

The sets, parameters, and variables used in the formulation of mathematical models are described in table 1.

Table 1 Notations

Sets	
<i>I</i>	Set of pavement section in the network, $I = \{1, 2, 3, \dots, I\}$
<i>M</i>	Set of Maintenance and Rehabilitation Treatment levels $M = \{1, 2, 3, \dots, M\}$ with M^{th} treatment being the most effective and expensive
<i>T</i>	Set of Planning Periods $T = \{1, 2, 3, \dots, T\}$

Table 1 (continued)

K	Set of Budget Scenario, $K = \{1, 2, 3, \dots, K\}$
Parameters	
B_t	Budgets available for Pavement Maintenance and Rehabilitation at period t .
\widetilde{B}_t	Random variable represent the budget available for Pavement Maintenance and Rehabilitation at period t
b_t^k	random deviations of available budget for pavement maintenance and rehabilitation in scenario k at period t
C_{imt}	Unit cost of applying m^{th} treatment to pavement section i at period t
CS_{it}	Condition score for pavement section i at period t
CS_{it}	Initial condition score of pavement section i
\overline{CS}_t	Average condition score for the pavement network at period t
CS_t^*	Network wide condition score requirement at period t
e_{im}	Improvement in condition score for pavement section i due to maintenance and rehabilitation treatment m
L_i	Length of pavement section i
N_{im}	Maximum number of times treatment m can be applied to pavement section i over the planning period

Table 1 (continued)

S_{min}	Minimum possible condition score for each of the pavement section in the network
γ_i	Pavement deterioration rate for pavement section i
S_{max}	Maximum possible condition score for each of the pavement section in the network
$S_{network}$	Minimum condition score required for the pavement network
Variables	
X_{itm}	Decision variable

3.3 Pavement Deterioration and Prediction of Condition Score

A pavement deterioration model should be used to evaluate a pavement network in order to understand when the condition of a pavement sections will reach a critical level that requires an M&R treatment. In this study, a pavement deterioration model which triggers M&R intervention was adopted from the study of Wang et al. (2003).

The study considers the pavement condition score as a performance measure for both a pavement section and the pavement network. The condition score is an index that combines ride quality and pavement distress measure to evaluate a pavement with a score ranging from 1 (worst condition) to 100 (best

condition). This index is used by the Texas Department of Transportation (TxDOT, 2005).

The pavement condition deterioration and improvement due to maintenance intervention is demonstrated in figure 3

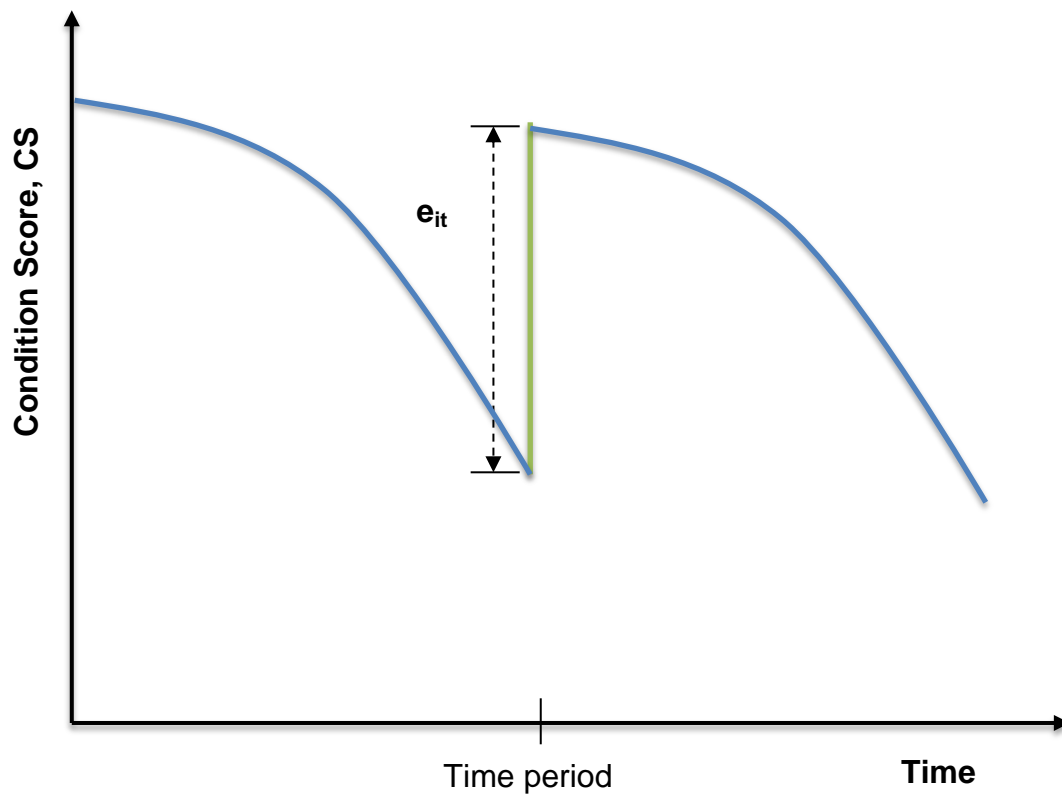


Figure 3 Pavement condition and Improvement in condition due to maintenance

In this study, to estimate the pavement condition for a future time, an additive condition transition model with constant deterioration rates (Wang et. al., 2003) is used. As illustrated in figure 3, when pavement section i is given an M&R

treatment at year t , the condition score is increased by an amount e_{it} . A constant rate of deterioration γ_i for pavement section i could be determined from historical data for that pavement section. Although a constant rate for the pavement deterioration process is assumed in this study, the pavement deterioration rate may vary across individual section. If the initial condition score for pavement section i is CS_{i0} , then in a future time t^* ($t^* > t$), the condition score for pavement section i can be calculated with equation 3.1:

$$CS_{it^*} = CS_{i0}(1 - \gamma_i)^{t^*} + \sum_{t=1}^{t^*} e_{it}(1 - \gamma_i)^{t^*-t} \quad (3.1)$$

Equation (3.1) can be established for pavement deterioration process and calibrated for each pavement section. This equation is used in the proposed optimization model.

3.4 Maintenance and Rehabilitation Planning Model for Deterministic Budget

Consider a pavement network as a set of $I = \{1, 2, 3, \dots, I\}$ pavement sections. A set of pavement M&R treatments is defined as $M = \{1, 2, 3, \dots, M\}$ where the M^{th} treatment level is the most effective and expensive maintenance intervention. The planning horizon is represented by the discrete set of time periods $T = \{1, 2, 3, \dots, T\}$. During each time period, the conditions of pavement

sections deteriorate due to traffic, aging, and climate. The maintenance treatment applied during a given time period t will affect the condition for time period $t+1$.

The integer linear programming model with deterministic budget for maintenance and rehabilitation of pavement network is formulated by equations (3.2) – (3.11)

$$\text{Minimize } \sum_{t=1}^T |\overline{CS}_t - CS_t^*| \quad (3.2)$$

$$\sum_{i=1}^I \sum_{m=1}^M L_i C_{imt} X_{imt} \leq B_t, \quad \forall t \in T \quad (3.3)$$

$$CS_{it} = CS_{i0}(1 - \gamma_i)^t + \sum_{j=1}^t \sum_{m=1}^M X_{ijm} e_{im}(1 - \gamma_i)^{t-j}, \quad \forall i \in I \quad (3.4)$$

$$CS_{it} \geq s_{min}, \quad \forall t \in T \quad (3.5)$$

$$CS_{it} \leq s_{max}, \quad \forall t \in T \quad (3.6)$$

$$\overline{CS}_t = \frac{\sum_{i=1}^I CS_{it}L_i}{\sum_{i=1}^I L_i}, \quad \forall t \in T \quad (3.7)$$

$$\overline{CS}_t \geq s_{network}, \quad \forall t \in T \quad (3.8)$$

$$\sum_{t=1}^T \sum_{m=1}^M X_{itm} \leq N_{im}, \quad \forall i \in I \quad (3.9)$$

$$\sum_{m=1}^M X_{itm} = 1, \quad \forall i \in I, t \in T \quad (3.10)$$

$$X_{itm} \in \{0, 1\} \quad (3.11)$$

Equation (3.2) represents the objective function of the pavement maintenance planning problem which seeks to minimize fluctuations of average network condition scores from a defined network condition score for every period of the planning horizon. Constraint (3.3) represent the budget constraint that the total cost of M&R treatments performed in a period in the planning horizon must be less than or equal to the budget available. Constraint (3.4) represents the predicted pavement condition score at a time period t subject to constant

deterioration and M&R intervention. Constraint (3.5) ensures that the condition score of any pavement section at any point of time in the planning horizon should be above the minimum condition score requirement for each of the pavement sections in the network. This minimum requirement is established by the decision maker. Constraint (3.6) defines the maximum possible condition score for a pavement section in the network at a specific period in the planning horizon. Constraint (3.7) defines the length weighted average condition score for the pavement network at any time period in the planning horizon. Equation (3.8) ensures the minimum condition score for the whole network at any time period in the planning horizon. Constraint (3.9) defines the maximum number of treatments allowed on a pavement section over the planning horizon. Constraint (3.10) ensures that only one maintenance treatment will be applied on a pavement section within a specific planning period. Constraint (3.11) represents the definition of the decision variable for a pavement section at any particular period with a specific M&R treatment. The decision variable takes a value of 1 if any treatment is selected for a pavement section at specific point of time, otherwise it returns a zero.

3.5 Maintenance and Rehabilitation Planning Model under Budget Uncertainty

In this study, the budget uncertainty in the network-level M&R planning is taken into consideration using the set-based robust optimization technique. A robust

optimization technique is a mathematical programming method that deals with uncertain parameters defined by a closed convex uncertainty set. The objective of the robust optimization method is to identify a solution that is feasible for all realizations of the data within the given uncertainty set.

In this section, we consider the available budget B_t to be uncertain and belong to a bounded set \mathcal{U}_B , and all parameters in the model except budget are known with certainty. To extend the model with known budget parameter B_t in equations (3.2) – (3.11) in robust optimization setting, B_t in equation (3.3) is replaced with random budget parameter \widetilde{B}_t . We consider the uncertainty set which is constructed as deviation around the nominal budget value B_t . The possible direction of deviations from these nominal values are fixed and captured by scenario vectors $b^k \in \mathbb{R}^n$, where n represents the number of nodes. The scenario vectors are allowed to take negative deviation values. For a given number of scenario vectors K , the uncertainty set \mathcal{U}_B is defined as a linear combination of scenario vectors with weights $w \in \mathbb{R}^K$ which belongs to a bounded set $w \in W$. The bounded set W is defined as a convex hull (Ben Tal and Nemirovoski, 1999):

$$\mathcal{U}_B = \left\{ \widetilde{B}_t \mid B_t + \sum_{k=1}^K w_k b_t^k, w \in W \right\} \quad (3.12)$$

$$W = \left\{ w \in \mathbb{R}^K \mid w \geq 0, \sum_{k=1}^K w_k \leq 1 \right\} \quad (3.13)$$

We now propose the robust counter part of the network-level pavement M&R planning model with deterministic budget, where the budget available for the M&R work is not known precisely to the decision maker and the budget parameter belongs to the uncertainty set \mathcal{U}_B . In other words, the uncertainty is associated only with the constraint (3.3). The robust M&R planning problem for pavement networks determines the optimal schedule of M&R activities over the planning horizon that satisfies all possible budget outcomes within set \mathcal{U}_B . This means that the problem has to determine an M&R plan such that equation (3.14) is satisfied.

$$\sum_{i=1}^I \sum_{m=1}^M L_i C_{imt} X_{imt} \leq \widetilde{B}_t, \quad \forall t \in T, \widetilde{B}_t \in \mathcal{U}_B \quad (3.14)$$

Now it can be stated that the robust optimization model minimizes objective function (3.2) satisfying constraints (3.4) – (3.11) and (3.14). If we plug in the definition of uncertainty set, the robust budget constraint (3.14) can be written as the following inequality:

$$\sum_{i=1}^I \sum_{m=1}^M L_i C_{imt} X_{imt} - \sum_{k=1}^K w_k b_t^k \leq B_t, \quad \forall t \in T, w \in W \quad (3.15)$$

For a given decision variables X , we denote the left hand side of the above equation as $g(X)$. Then to ensure that the above inequality holds for all $w \in W$, it is sufficient to ensure $\inf_{w \in W} \sum_{k=1}^K w_k b_t^k = \inf_{w \in W} w' B_t$, where $B = [b^1, b^2, \dots, b^K]$ is the matrix of scenario vectors and $B_t = (b^1_t, b^2_t, \dots, b^K_t)'$ is a column vector of budgets for different time periods in the planning horizon. We also denote d as a column vector of 1 of appropriate dimensions.

Now we can propose that under the given uncertainty set, the robust counterpart is obtained by replacing constraint (3.3) in the deterministic model formulation with equation (3.16)

$$\sum_{i=1}^I \sum_{m=1}^M L_i C_{imt} X_{imt} - \min_k b_t^k \leq B_t, \quad \forall t \in T, k \in K \quad (3.16)$$

This formulation can be proved using duality. We can write the $\inf_{w \in W} w' B_t$ and its dual problem as:

(Primal)	$\min w' B_t$	(dual)	$\max \lambda$
Subject to	$d' w \geq 1$	Subject to	$\lambda d \leq B_t$
	$w \geq 0$		$\lambda \geq 0$

From weak duality, $g(X) \leq \inf_{w \in W} w^T B_t$, is equivalent to, $g(X) \leq \lambda$ for some feasible λ . This means that, $g(X) \leq 0$ and $g(X) \leq b^k_t$. Combining these conditions we can write equation (3.16).

The above models are demonstrated using a numerical case study. The following chapter discusses the case study in details.

CHAPTER 4 CASE STUDY

4.1 Introduction

In this chapter a simple numerical study of the proposed optimization scheme for an example pavement network is presented. The numerical study demonstrates the applicability of the proposed models in M&R planning. The numerical analysis was conducted with General Algebraic Modeling System (GAMS) on a standard laptop computer with 6.0 GB ram and 2.2 GHz Processor. The objective of the case study is to demonstrate the application of the proposed model in pavement M&R scheduling.

Taking the work of Wang et al. (2003) as the base case, the case study was conducted with a small network of ten flexible pavement sections. To be consistent with the base case, the input data and basic assumptions for the case study were taken from the study of Wang et al. (2003), as discussed in the following sections.

4.1.1 Maintenance and Rehabilitation Treatment

M&R treatments that are applied to the pavement sections in the case study are grouped into five treatment level categories. These are Need Nothing (NN), Preventive Maintenance (PM), Light Rehabilitations (LR), Medium rehabilitation (MR), and Heavy Rehabilitation (HR). Among the treatment categories “Need Nothing” represents that no M&R treatment is applied to the pavement section.

The specific M&R treatment types associated with the rest of the four categories for asphalt pavement are as follows (Gharaibeh et al., 2011):

- PM: chip seals, micro-surfacing;
- LR: HMA overlay (2-inch to 3-inch), application of full width seal coat, base repair and seal; milling, sealing and thin overlay;
- MR: Mill and inlay; mill, stabilize base and seal; level up and overlay; widen pavement, level up and overlay or seal coat; 3- to 5-inch HMA overlay; thick overlay (without any other activity such as milling); mill, patch, under seal and inlay; base repair, spot seal, edge repair and overlay; mill, cement stabilize base and overlay or seal; and
- HR: Includes reconstruction of the base and surface, milling, and thick overlay or similar activities that restore the pavement functional and structural condition to nearly original conditions.

4.1.2 Planning Horizon

A five-year planning horizon is assumed for the purpose of the case study, where M&R treatments will be applied at the beginning of each period in the planning horizon. Also each pavement section will receive only one M&R treatment in each year and the maximum number of treatments allowed on each pavement section was restricted to five (Wang et al., 2003). Wang et al. (2003) did not impose any constraint to limit number of rehabilitation treatments

allowed on each pavement section over planning horizon. To be consistent, the same formulation was used for the case study. As a result, the optimal maintenance schedule may yield results where multiple treatments are applied to the same pavement section over the planning horizon.

4.1.3 Performance Measure and Initial Condition

In this study, the Texas Department of Transportation (TxDOT) Pavement Management Information System (PMIS) Condition Score (CS) is used as the performance measure for a pavement section. The condition score of a pavement section represents the overall condition combining both ride quality and pavement distress of that pavement section. The condition score index ranges from 1 to 100, where 1 represents the worst pavement condition and 100 represents the best pavement condition. The initial condition scores, number of lane, and length of lane for the pavement sections used in this study are shown in table 2.

Table 2 Initial Condition Score for Pavement Sections

Pavement Section	No of Lanes	Length (mile)	Condition Score
A	2	0.5	65
B	2	0.5	75
C	2	0.5	85
D	2	0.5	65
E	2	0.5	55
F	2	0.5	75
G	2	0.5	70
H	2	0.5	90
I	2	0.5	65
J	2	0.5	95

4.1.4 Condition Score Improvement due to M&R Treatments

Condition score improvements because of M&R treatments can be measured by the increase in condition scores. The exact amount of such increases can be estimated from pavement-related history data that is usually available in a pavement management system (Wang et. al. 2003). The average increase in condition scores used in this study were taken from the work conducted by Wang et al. (2003), as shown in table 3. It is understood that these values may not fully reflect the actual increases in condition score resulted from the M&R treatments because an identical M&R treatment may yield different

improvements when it is applied to pavement sections that have different existing conditions.

Table 3 Average Increase in Condition Score

Maintenance and Rehabilitation Treatment	Average increase in Condition Score
Need Nothing (NN)	0
Preventive Maintenance (PM)	3
Light Rehabilitation (LR)	15
Medium Rehabilitation (MR)	25
Heavy Rehabilitation (HR)	40

4.1.5 Maintenance and Rehabilitation Treatment Unit Cost

Application of each maintenance and rehabilitation treatment incurs a specific cost to the implementing agency. This cost is calculated based on the unit cost of the treatment in the unit of per lane mile and amount of lane miles treated. In this study, the unit costs for M&R treatments were taken from the 4-year pavement management plan analysis report (TxDOT, 2013). The unit costs are shown in table 4.

Table 4 Maintenance and Rehabilitation Unit Cost

Maintenance and Rehabilitation Treatment	Unit Cost (per lane per mile)
Need Nothing (NN)	\$0
Preventive Maintenance (PM)	\$29,000
Light Rehabilitation (LR)	\$173,000
Medium Rehabilitation (MR)	\$237,000
Heavy Rehabilitation (HR)	\$442,000

4.1.6 Pavement Deterioration Rate

In this study a constant pavement deterioration rate is assumed. The deterioration rate for each pavement section can be determined from pavement related history data (Wang et. al. 2003). In this study a deterioration rate of 5 percent of condition score per year is assumed for all pavement sections in the network. The constant rate of deterioration may not be able to describe the complex transition process of the pavement conditions. Also a pavement section may show different transition process when an M&R treatment level applied to the section. However, the constant rate of deterioration simplifies the complexity with the computations.

4.1.7 Requirements on Condition Scores

In this study, the minimum and maximum condition score for each pavement section in the network is set at 50 and 100 respectively (Wang et al., 2003).

4.2 Solution of Deterministic Problem

In this study, a stringent mean budget of \$400,000 per year is established to solve the deterministic problem using GAMS. This budget level is established to generate budget scenarios where an agency is experiencing a budget shortfall. The study considers a network as shown in table 2. The solution yields the average network-level conditions for each year in the planning horizon shown in table 5.

Table 5 Average Network Condition Scores (Deterministic Budget)

Year	Condition Scores (1-100)
1	74.30
2	74.59
3	74.86
4	75.11
5	75.11

The detailed maintenance plans for the problem with deterministic budget are shown in table 6, where 1 indicates a specific M&R treatment is selected for a particular pavement section at a given year.

Table 6 Optimal Decision Variables for Deterministic Budget Case

Section. Year	NN	PM	LR	MR	HR
A.year1				1	
A.year2	1				
A.year3	1				
A.year4				1	
A.year5	1				
B.year1	1				
B.year2		1			
B.year3		1			
B.year4		1			
B.year5		1			
C.year1	1				
C.year2		1			
C.year3		1			
C.year4		1			
C.year5		1			
D.year1	1				
D.year2	1				
D.year3		1			
D.year4		1			
D.year5			1		
E.year1		1			
E.year2	1				
E.year3				1	
E.year4	1				
E.year5		1			
F.year1		1			
F.year2		1			
F.year3		1			
F.year4	1				

Table 6 (Continued)

F.year5		1			
G.year1		1			
G.year2		1			
G.year3	1				
G.year4	1				
G.year5		1			
H.year1	1				
H.year2		1			
H.year3		1			
H.year4		1			
H.year5		1			
I.year1		1			
I.year2				1	
I.year3	1				
I.year4	1				
I.year5	1				
J.year1		1			
J.year2	1				
J.year3	1				
J.year4		1			
J.year5		1			

4.3 Solution of Robust Counterpart

For the robust counterpart, the budget value is modified to solve the robust optimization problem. Ten scenarios within the allowed percentage deviation for the budget uncertainty set for each year in the planning horizon are randomly selected. Specifically, a deviation of 20 percent of mean budget is used to find the robust feasible solution. The average network level conditions for each year in the planning horizon are shown in table 7.

Table 7 Average Network Condition Scores (Uncertain Budget)

Year	Condition Scores (1-100)
1	74.30
2	74.29
3	74.57
4	74.24
5	74.53

The detailed maintenance plans for the problem with uncertain budget are shown in table 8, where 1 indicates a specific M&R treatment is selected for a particular pavement section at a given year.

Table 8 Optimal Decision Variables for Uncertain Budget Case

Section .Year	NN	PM	LR	MR	HR
A.year1				1	
A.year2	1				
A.year3	1				
A.year4				1	
A.year5		1			
B.year1	1				
B.year2				1	
B.year3	1				
B.year4	1				
B.year5	1				
C.year1		1			
C.year2	1				

Table 8 (Continued)

C.year3		1			
C.year4	1				
C.year5		1			
D.year1		1			
D.year2		1			
D.year3		1			
D.year4		1			
D.year5		1			
E.year1		1			
E.year2	1				
E.year3		1			
E.year4	1				
E.year5		1			
F.year1	1				
F.year2		1			
F.year3				1	
F.year4	1				
F.year5	1				
G.year1	1				
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G.year5				1	
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H.year5	1				
I.year1	1				
I.year2	1				
I.year3	1				
I.year4		1			
I.year5		1			
J.year1		1			
J.year2	1				
J.year3		1			
J.year4		1			
J.year5	1				

CHAPTER 5 DISCUSSION

5.1 Discussion of Results

In the case study described in chapter 4, only negative random deviations of deterministic budget bounded by the convex hull of the robust counterpart of the problem are considered. In other words, the robust optimization model considered only funding shortage over the planning horizon. The objective function value for deterministic model is 1.42 that means that the summation of deviations of condition scores over the planning horizon is 1.42 which is better than the objective function value of robust optimization model. The difference in objective functions mean that in robust optimization model yields lower average condition score for each year in the planning horizon. This is no surprise since the deterministic model ignores the random characteristics of budget and yields solution based on the upper bounds on the space of budget random variable. Figure 4 shows the variation of condition scores over the planning horizon. The condition scores for robust optimization model falls below of those from deterministic model since the robust optimization model allows random funding shortage within the defined range of the uncertainty set. However, ignoring the random characteristics of budget variable may lead to suboptimal solution. If deterministic budget is allowed to fall short to worst boundary of the uncertainty set the deterministic model becomes infeasible due to minimum requirements on condition scores of each pavement section. But the robust optimization

model is feasible for all realization of budget within the uncertainty set.

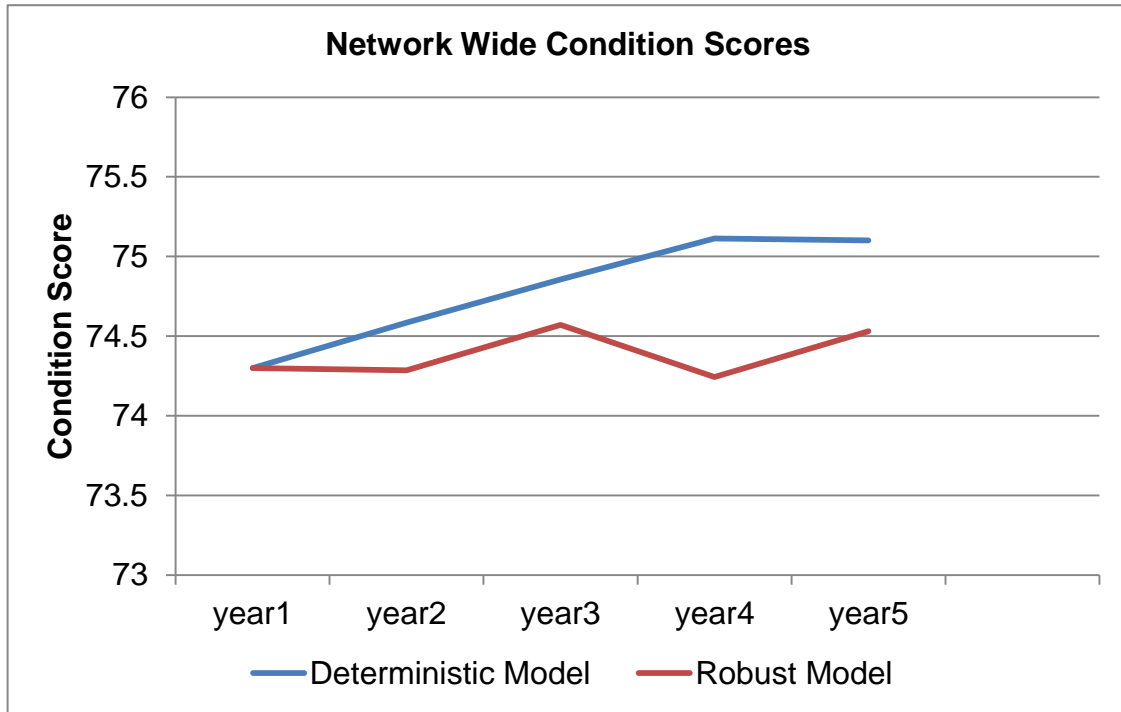


Figure 4 Network wide Condition Scores

Figure 5 shows the ratio of total cost of maintenance and rehabilitation to budget for both deterministic and robust optimization models. It is reveals that both robust optimization model and deterministic model utilizes more than 92 percent of the available budget. Therefore, robust optimization is able to utilize the variable budget more efficiently than the model with deterministic budget.

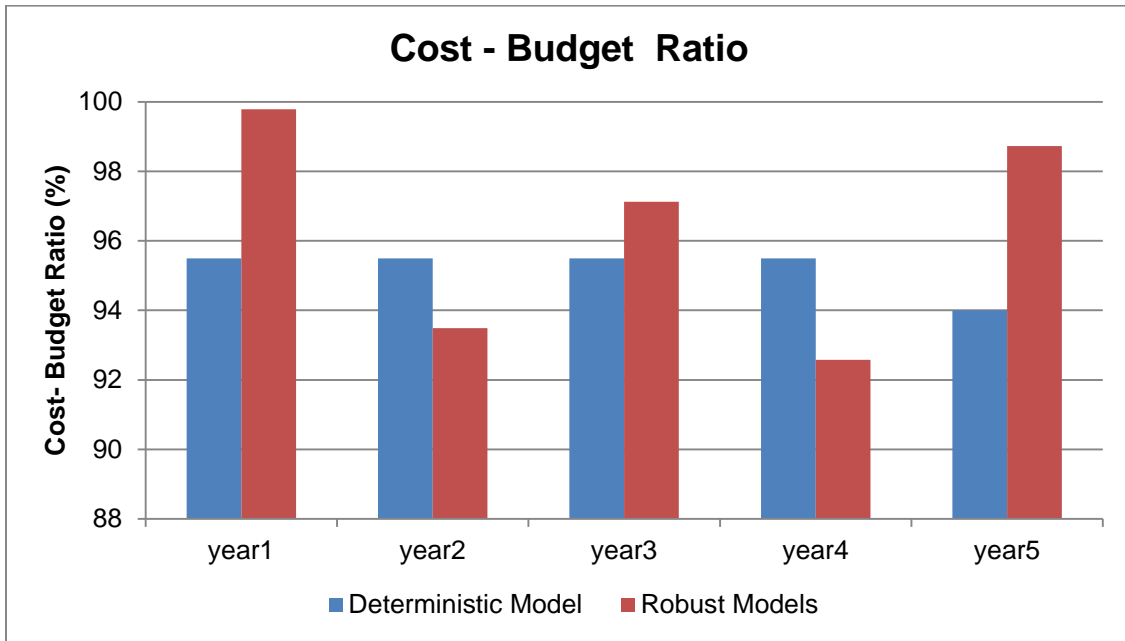


Figure 5 : M&R Cost to Budget Ratio

In order to identify the effect of taking uncertainty into consideration through robust optimization approach, table 9 compares the total numbers of projects selected for M&R treatments in each category over the planning horizon for both deterministic model and robust optimization models. As can be seen from Table 9, the robust model selected less number of treatment level compared to deterministic model, as the robust model has more stringent budget. Robust model tries to minimize the network wide condition score fluctuations with less number of treatment levels, as budget is more stringent.

Table 9 Maintenance and Rehabilitation Decision Comparison between Robust model and Deterministic model

M&R Treatment	Deterministic Model	Robust Model
NN	18	23
PM	27	22
LR	1	0
MR	4	5
HR	0	0

5.2 Robust Optimization Approach for Maintenance Planning under Budget Uncertainty

Robust optimization approach is a novel methodology for handling data uncertainty in mathematical programming. In this study a robust optimization base integer programming model is used to obtain pavement M&R schedule considering the random characteristic of maintenance and rehabilitation budget. It is revealed that the robust optimization is an attractive alternative for formulating pavement M&R planning problem under budget variability, as it does not require probability distribution assumption on the uncertain parameter and cumbersome representation of scenarios. The proposed robust optimization model is defined in a way that the right hand-side uncertain parameters can be efficiently handled without compromising the tractability of the model. The proposed model can also be used with positive direction of deviation; in other words, it also can capture the increase in funding level.

CHAPTER 6 CONCLUSIONS

6.1 Summary

The objective of this study is to formulate a methodological framework that can manage the pavement maintenance and rehabilitation planning problem under budget uncertainty so that the impact of budget fluctuations on pavement conditions can be minimized. In order to achieve the objective, a multi-period linear integer programming model with its robust counterpart is proposed. A numerical case study is carried out to demonstrate the efficiency of the proposed model in capturing the uncertainty in pavement maintenance and rehabilitation budget.

6.2 Conclusions

The following conclusion can be drawn based on the findings of the present research:

- Robust optimization approach can be applied to pavement maintenance and rehabilitation planning in order to take uncertainty in the available maintenance budget into consideration. The deterministic model can be extended to a robust counterpart through defining sets of space for the uncertain parameters. The robust optimization method does not require probability distribution of uncertain parameters. The model is only

applicable for small-scale network problem due to computational intractability of the model for large-scale problems.

- A case study is carried out as a part of this research. The results shows that the robust optimization model efficiently capture the random characteristics of the budget. The robust model is capable of producing feasible solutions considering the possible funding shortfall while keeping the pavement condition above the minimum acceptable condition.
- Because of the complex nature of the problem being formulated in this study, a number of assumptions had to be made to simplify the problem and solution process, leading to results that are theoretically possible but practically infeasible. Additional research has to be conducted to address these issues as detailed in the following section.

6.3 Recommendations for Future Research

This present study can be extended for further development of the model from the aspects summarized as follows:

- The proposed model has computational limitation due to combinatorial effect of integer programming framework. Therefore, as part of the future research, a solution algorithm should be developed to alleviate this limitation so that the outcome will be more consistent with real problems in practice.

- The proposed model is based on the additive pavement performance prediction model with constant deterioration rate. Improved pavement performance models should be considered to more accurately represent the pavement deterioration process and the effect of maintenance and rehabilitation treatments.
- The proposed formulation of the problem does not have constraints that limit the number of M&R treatments being applied to a pavement section over the planning horizon, producing results that are not consistent with practice. Appropriate constraints should be considered in the future work so that such impractical solutions can be eliminated.
- The proposed study only considers a single budget category. In practice, the budget for pavement maintenance and rehabilitation may come from multiple categories with varying investment regulations. Such budget scenario of multiple categories should be considered in the formulation. In addition, the model should also consider budget fluctuations in both positive and negative directions.
- Currently, the model can only capture uncertainty in budget. However, other parameters such as pavement performance, maintenance and rehabilitation effectiveness, and treatment costs should also be treated as variables with uncertainty.
- In the current formulation, only a single objective function is considered. The formulation can also be further improved by considering multiple

competing objective functions such as maximizing the pavement condition, while at the same time minimizing the fluctuations of pavement conditions and minimizing the total M&R costs.

- To make more efficient use of funds, alternatives options should be explored that meet the minimum objective requirements without expending all funds. In this way, the remaining funds could potentially be invested in other portions of the roadway network (assuming that not all portions of the network are incorporated in the analysis) or in other infrastructure asset components such as bridges and traffic operation facilities among others.

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