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Optimal Infrastructure System Maintenance and Repair Policies with Random Deterioration Model Parameters

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Optimal Infrastructure System Maintenance and Repair Policies

with Random Deterioration Model Parameters

by

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ABSTRACT

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Accurate facility deterioration models are important inputs for the selection of Infrastructure Maintenance, Repair, and Reconstruction (MR & R) policies. Deterioration models are developed based on expert judgment or empirical observations. These resources, however, might not be sufficient to accurately represent the performance of infrastructure facilities. Incorrect deterioration models may lead to wrong predictions of infrastructure performance and selection of inappropriate MR & R policies. This results in higher lifecycle costs. Existing infrastructure MR & R decision-making models assume that deterioration models represent the real deterioration process of infrastructure facilities. This assumption ignores the uncertainty in empirically-derived facility deterioration models.

This dissertation presents a methodology for selecting MR & R policies for systems of infrastructure facilities under uncertainty in the deterioration model parameters. It is

assumed that inspections reveal the true conditions of facilities. Based on the inspection results, the deterioration model parameters can be updated to express the deterioration process more accurately. It is expected that more appropriate maintenance policies will be selected as a result.

In the first part of this dissertation, it is assumed that facility inspections are performed at the beginning of every year. The model parameters are updated and MR & R policies are selected every year using the updated deterioration models. In the second part, the assumption is relaxed and alternate inspection frequencies are considered. In this case, the updates of the model parameters and the selection of optimal MR & R policies are executed only after an inspection.

The results of the parametric analyses demonstrate that updating the deterioration models reduces the expected system costs. The results also show that relaxing the facility inspection frequency can reduce the total costs further.

Professor Samer Madanat Date
Committee Chair

To my parents and my sister for their love and support

Table of Contents

Chapter 1 Introduction **1**

1.1 Background 1

1.2 Research Goal and Scope 2

1.3 Dissertation Outline 3

Chapter 2 Background: Literature Review **6**

2.1 General Description of Infrastructure Management Systems 6

2.2 Optimization Methodologies: Markov Decision Process (MDP) 7

2.3 Model formulations: Dynamic Programming and Linear Programming 8

2.3.1 MDP without Model Uncertainty 8

2.3.2 MDP under Model Uncertainty 10

Chapter 3 Background: Open Loop MR & R Optimization **11**

3.1 The Markov Decision Process (MDP) 11

3.2 Facility-Level Optimization 13

3.3 Network-Level Optimization 14

3.3.1 Long-Term Optimization 15

3.3.2 Short-Term Optimization 17

Chapter 4 Open Loop Feedback Control MR & R Optimization **19**

4.1 Updating the Transition Probability Matrices 19

4.1.1 Updating Algorithm 21

4.2 Open Loop Feedback Control 25

Chapter 5 Parametric Study **30**

5.1 Annual Inspection Strategy 34

5.1.1 Real Process: Fast 34

5.1.2 Real Process: Medium 36

5.1.3 Real Process: Slow 38

5.1.4 Sensitivity to Budget Constraint 40

5.1.5 Sensitivity to User Costs 44
5.1.6 Summary 48
5.2 Alternate Inspection Frequencies 48
Chapter 6 Conclusion 54
6.1 Concluding Remarks 54
6.2 Future Research Directions 55
References 58

List of Tables

Table 1 Costs ($/lane-yard) 31
Table 2 Parametric Study Cases 33
Table 3 Total Costs and Costs Savings (Real: Fast) 35
Table 4 Total Costs and Cost Savings (Real: Medium) 36
Table 5 Total Costs and Cost Savings (Real: Slow) 39

List of Figures

Figure 1 Interrelationship of Long-Term and Short-Term Optimization 15
Figure 2 Performance Model Updating Procedure 22
Figure 3 Convergence 24
Figure 4 Alternate Inspection Frequency 27
Figure 5 Optimization Procedure 29
Figure 6 Total Costs (Real: Fast) 35
Figure 7 Weighted Average Difference (Real: Fast) 36
Figure 8 Total Costs (Real: Medium) 37
Figure 9 Weighted Average Difference (Real: Medium) 38
Figure 10 Total Costs (Real: Slow) 39
Figure 11 Weighted Average Difference (Real: Slow) 40
Figure 12 Sensitivity to Budget Constraints (Real: Fast) 41
Figure 13 Sensitivity to Budget Constraints (Real: Medium) 42
Figure 14 Sensitivity to Budget Constraints (Real: Slow) 43
Figure 15 Sensitivity to User Costs (Real: Fast) 45
Figure 16 Sensitivity to User Costs (Real: Medium) 46
Figure 17 Sensitivity to User Costs (Real: Slow) 47
Figure 18 Total Costs when Inspection Cost is 10% of average MR & R costs 50
Figure 19 Total Costs when Inspection Cost is 20% of average MR & R costs 52

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Chapter 1
Introduction

1.1 Background

Infrastructure Management Systems (IMS) are decision-support tools that aid transportation agencies and public works in planning maintenance activities of their facilities. IMS support the following tasks: inspecting facilities to collect data, predicting the deterioration of facilities through performance models, and selecting optimal Maintenance, Repair, and Reconstruction (MR & R) policies over the planning horizon.

Various IMS have been developed and applied to actual infrastructure networks. For example, the Arizona Pavement Management System was successfully implemented in the early 1980s. It saved $14 million that was almost one third of the Arizona's budget in the first year (fiscal year 1980~1981) when it was applied and $101 million in the first four years (Golabi et al. 1982). Pontis, a system for maintenance optimization and improvement of bridge networks, has been used effectively for Bridge Improvement and Maintenance Planning in more than 40 states in the United States (Golabi and Shepard 1997).

Performance models are used to predict the deterioration process of infrastructure facilities. The deterioration process is probabilistic and represented by a set of condition transition matrices. In previous research, the transition probability matrices were defined on the basis of expert judgment or empirical observations, and assumed to be constant over the planning horizon. Expert judgment or empirical observations, however, might not represent perfectly the real deterioration process. This could cause erroneous predictions and lead to selecting inappropriate MR & R policies, which may result in increasing the total costs for the agency and users. On the other hand, the availability of condition data, collected during the life of the facility, can be used to improve the accuracy of the deterioration models.

1.2 Research Goal and Scope

The objective of this research is to develop optimization methods to select optimal MR & R policies that incorporate updating of deterioration models. It is assumed that an inspection of the facilities in an infrastructure network is performed periodically. Based on the inspection results, the transition probability matrices can be updated to express the deterioration process more accurately. It is expected that more appropriate maintenance policies will be selected as a result. In the first part of this dissertation, it is assumed that the inspection is performed at the beginning of every year. In the second part, the assumption is relaxed and the inspection is performed with alternate inspection frequencies.

It has generally been assumed in the Infrastructure Management literature that the initial transition probability matrices are accurate and thus constant over the planning horizon. In Durango and Madanat (2002), several performance models with different deterioration rates were used to account for model uncertainty. In the present research, the uncertainty in the initial performance model is accounted for by treating the parameters of the performance model as random variables. Such a treatment is consistent with the source of model uncertainty. This is because model uncertainty is primarily due to the randomness in the parameters resulting from the statistical estimation process. This dissertation is focused on a network-level problem and treats a homogeneous network. A homogeneous network is one where all the facilities in the network follow the same deterioration process.

1.3 Dissertation Outline

The remainder of the dissertation is organized as follows.

Chapter 2 reviews relevant research in the field of IMS. A general description of IMS is given in the first section. Thereafter, the Markov Decision Process (MDP) and optimization model formulations in previous research are briefly introduced. In this part, two optimization problems are described: the MDP without model uncertainty and the MDP with model uncertainty.

The MDP and the Open Loop (OL) optimization that does not consider model uncertainty are introduced in Chapter 3. In this chapter, the facility-level optimization and network-level optimization formulations are shown. Since this dissertation is focused on the network-level problem, the network-level optimization formulations are described in detail. Two types of optimization problems: a long-term and a short-term optimization are introduced.

Chapter 4 addresses the Open Loop Feedback Control (OLFC) optimization that considers model uncertainty. The first section of this chapter describes how the transition probabilities can be updated by using the inspection results. The optimization strategy with the updated models is presented in the second section. The OLFC formulation that incorporates the updated transition matrices into the optimization models is described. The OLFC with annual inspection is introduced first. The OLFC with alternate inspection frequencies is explained next. The algorithm used in these OLFC and the optimization procedure are also demonstrated.

We discuss the results of parametric study in Chapter 5. We provide a complete description of the procedure and data used in the parametric study. In the first part, the costs of the OL and the OLFC with annual inspection are compared, and it is shown that the costs savings are achieved by the OLFC relative to the OL. The sensitivity of the results to budget constraints and user costs in the OLFC with annual inspection are demonstrated. In the second part, we show that we can reduce the total costs further by using the OLFC with alternate inspection frequencies.

Chapter 6 addresses the conclusions of the dissertation. Finally, some ideas are presented with respect to the future directions of this line of research.

Chapter 2

Background: Literature Review

There has been significant amount of research focused on methods for selecting optimal MR & R policies and optimal frequencies of inspection for infrastructure systems. In the first section, the general infrastructure management and inspection process are described. The Markov Decision Process (MDP) is briefly introduced as an optimization methodology in the second section. This methodology will be explained in detail in the next chapter. The third section describes optimization model formulations based on MDP.

2.1 General Description of Infrastructure Management Systems

The infrastructure management process is divided into three main areas:

i) Data collection and inspection

ii) Performance modeling and forecasting

iii) Decision making for MR & R activities

These three areas are mutually related. Condition data are collected through inspections of facilities in an infrastructure network. The information from inspections is applied to the performance model to predict the deterioration of facilities, and it is used as an input into determine optimal MR & R policies. The performance model is an input into the MR & R decision-making procedure. The optimal policies selected by using the decision-making procedure are applied to the infrastructure network. These processes are repeated for each time period.

In order to select an optimal maintenance policy, the condition of the infrastructure facilities should be defined. For example, the condition of pavements can be characterized by criteria such as the amount of cracking, rut depth, and surface roughness. Conditions can be measured by inspection technologies such as video imaging, radar and infrared technologies. The condition of pavements is often defined in terms of Pavement Condition Index (PCI), which ranges from 0 to 100 where 100 means the best possible condition (Carnahan et al. 1987). The PCI has sometimes been used in a discretized form. For example, the PCI was classified into 10 categories in Feighan (1988). In these classifications, a higher number indicates a better condition and 0 denotes "Failed".

2.2 Optimization Methodologies: Markov Decision Process (MDP)

The majority of state-of-the-art infrastructure management systems use the Markov Decision Process (MDP) for MR & R policy decision-making. In MDP, the deterioration is represented by transition probabilities. The transition probability matrices can be determined from expert judgment or empirical observations. In the latter case, statistical estimation with time series data was used in Carnahan et al. (1987), Madanat, Mishalani and Wan Ibrahim (1995), Mauch and Madanat (2001), and others.

2.3 Model formulations: Dynamic Programming and Linear Programming

The objective of optimization models is to minimize the total costs associated with agency costs and user costs. Optimal maintenance policies to minimize the total costs are obtained through Dynamic Programming (DP) or Linear Programming (LP). DP has been used for single facility problems (Feighan 1988, Madanat 1993, Madanat and Ben-Akiva 1994, Durango and Madanat 2002) and LP has been utilized for network-level problems (Golabi et al. 1982, Gopal et al. 1991, Smilowitz and Madanat 2000). This section includes descriptions of two problems: MDP without model uncertainty and MDP with model uncertainty.

2.3.1 MDP without Model Uncertainty

In MDP that does not consider model uncertainty the initially selected deterioration models were assumed to be accurate. There were two categories of optimizations in MDP without model uncertainty: MDP without measurement uncertainty and MDP with measurement uncertainty. In MDP, facility condition is represented by a discrete state and the deterioration process is represented by transition probabilities. It is assumed that facilities are inspected at the beginning or at the end of each year with no measurement uncertainty in the inspection (Golabi et al. 1982, Carnahan et al. 1987, Feighan et al. 1988, Gopal et al. 1991) in the first category. The results of inspection are applied to select optimal MR & R policies.

The assumption that inspections reveal the true condition of facilities, however, has been shown to be often incorrect by Humplick (1992), Hudson et al. (1987), and in other empirical studies. Measurement uncertainty may lead to select inappropriate maintenance policies which will increase total costs. The restriction of annual inspections also may increase the total cost when an inspection is not necessarily required.

The Latent Markov Decision Process (LMDP) has been proposed to account for measurement uncertainty and to relax the assumption of annual inspections (Madanat 1993, Madanat and Ben-Akiva 1994). With the LMDP, decision-making includes both selection of optimal maintenance policies and inspection frequencies. In the LMDP, the condition of facilities measured through inspection is probabilistically related to the true condition. The probability of true condition given the measured condition is computed by state augmentation. In the state augmentation, the state is redefined to include all information available to decision makers that is relevant to future decisions such as the history of MR & R activities and the history of inspections.

The LMDP has been applied to single facility-level problems (Madanat and Ben-Akiva, 1994) as well as network-level problems (Smilowitz and Madanat, 2000).

2.3.2 MDP under Model Uncertainty

Previous research in the above two categories assumed that the transition matrices defined initially are accurate, and therefore do not need to be updated. The successive updating of the deterioration models was first considered by Durango and Madanat (2002). Their work represented the uncertainty in performance models by variable deterioration rates. Their computational study showed that expected lifecycle costs can be reduced by accounting for the uncertainty in the deterioration rate.

The following chapter describes the MR & R optimization formulations in more detail.

Chapter 3

Background:

Open Loop MR & R Optimization

3.1 The Markov Decision Process (MDP)

If the change in condition of infrastructure facilities can be expressed as a discrete-time and finite state memoryless process, then deterioration can be represented by a Markov chain. The key assumption of MDP is that the deterioration process follows a Markovian process, which means that the condition state of the facility in a period only depends on the state of the facility and the action taken in the preceding period.

In MDP, the deterioration process is represented by transition probability matrices. It is assumed that an inspection is performed periodically and the true state of a facility is revealed through inspections. The following model represents the transition probability.

$$\pi_{ij}(a) = P(s^{t+1} = j \mid s^t = i, c^t = a) \qquad 1 \le i, j \le \mathrm{K},\ t = 0, 1, \ldots, \mathrm{T}\text{-}1,\ a \in A \tag{1}$$

where,

- $\pi_{ij}(a)$: Transition probability of the facility changing state *i* to *j* under maintenance activity *a*
- s^t : Condition state of a facility in year t
- *i* and *j*: Indices of the state of a facility
- K: Number of discrete states of a facility
- c^t : Maintenance activity performed in year t
- a : A maintenance activity in the set of activities
- *A*: Set of maintenance activities
- T: Number of years in the planning horizon

The transition probabilities are arranged in transition matrices. A transition matrix is shown below.

$$\underline{\prod}(a) = \begin{bmatrix} \pi_{11}(a) & \pi_{12}(a) & \ldots & \pi_{1K}(a) \\ \pi_{21}(a) & \pi_{22}(a) & \ldots & \pi_{2K}(a) \\ .. & .. & .. & .. \\ \pi_{K1}(a) & \pi_{K2}(a) & \ldots & \pi_{KK}(a) \end{bmatrix} \qquad \forall a \qquad (2)$$

where, $\underline{\prod}(a)$: The transition matrix given that maintenance activity *a* is performed

The optimization formulations are shown in next subsections. In these sections, the OL optimizations that do not consider the uncertainty in the deterioration models are described. The optimizations considering the model uncertainty are explained in Chapter 4.

3.2 Facility-Level Optimization

The optimal MR & R policy for a single facility can be determined using Dynamic Programming (DP). The objective of the DP is to minimize the total expected costs. The cost-to-go function is a function of time since the optimal MR & R activities change as time. The DP is solved recursively for every state and from year T to year 0. The DP algorithm is as follows:

$$V^T(i) = g(i) \qquad \forall i \tag{3}$$

$$V^t(i) = \underset{c}{Min.}\{g(i,c) + \delta\sum_{j=1}^{K}\pi_{ij}(c)V^{t+1}(j)\} \qquad \forall i,\ t = 0,.....,T-1 \tag{4}$$

where,

- $V^T(i)$: Terminal cost at T given that the facility is in a state *i*
- $V^t(i)$: Minimum expected cost-to-go from year t to year T given that the facility is in a state *i* in year t
- $g(i,c)$: Cost associated with performing MR & R activity when a facility is in a state *i* in year t
- δ : Discount factor

The initial state is assumed to be known. The minimum total expected cost is $V^0(i)$ and the set of optimal policies for each year is obtained for every state. Since this is the facility-level optimization problem, one deterministic policy is assigned for each state. In the following section, the network-level optimization problem is described.

3.3 Network-Level Optimization

The optimal MR & R policy for an infrastructure network can be obtained using Linear Programming (LP). The objective of this network-level optimization is to minimize the expected cost associated with performing MR & R activities, inspection, and the associated user costs subject to budget and level of service constraints. Thus, the optimal policies and inspection frequencies are based on minimizing the expected or total cost, which is composed of maintenance, inspection, and user costs. The decision variables are the fractions of the facilities in the network that are in various states and to which different MR & R actions should be applied. The LP provides randomized MR & R policies rather than a single deterministic policy for each state.

Two types of LP optimizations are usually solved: a long-term and a short-term optimization. The long-term optimization model is based on an infinite planning horizon. It seeks optimal policies that minimize the average cost per period for a steady-state distribution of the facilities and maintenance activities. The short-term optimization minimizes the total discounted cost over a predetermined and finite planning horizon. In the short-term optimization model, the steady-state distribution obtained in the long-term optimization is used as a boundary condition on the distribution of facilities at the end of the planning horizon. This is illustrated in Figure 1. The two models are described in the following sub-sections.

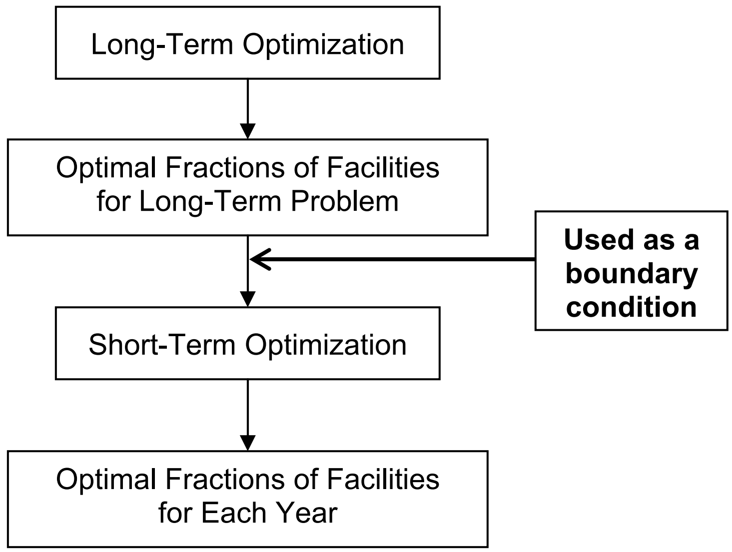


Figure 1 Interrelationship of Long-Term and Short-Term Optimization

3.3.1 Long-Term Optimization

$$Min. \quad \sum_{i=1}^{K}\sum_{a\in A} w(i,a)\cdot(g(i,a)+u(i)+r) \tag{5}$$

$$s.t. \quad w(i,a)\geq 0 \qquad \forall i,a \tag{6}$$

$$\sum_{i=1}^{K}\sum_{a\in A} w(i,a)=1 \tag{7}$$

$$\sum_{a\in A} w(j,a)=\sum_{i=1}^{K}\sum_{a\in A} w(i,a)\cdot \pi_{ij}(a) \qquad \forall j \tag{8}$$

$$B_{\min}\leq \sum_{i=1}^{K}\sum_{a\in A} w(i,a)\cdot g(i,a)\leq B_{\max} \tag{9}$$

$$Q_{\min,i}\leq \sum_{a\in A} w(i,a)\leq Q_{\max,i} \qquad \forall i \tag{10}$$

where,

- $w(i,a)$: Fraction of facilities in the infrastructure network that is in state *i* and receives maintenance activity *a*
- $g(i,a)$: Cost associated with performing MR & R activity *a* when a facility is in state *i*
- $u(i)$: User cost when a facility is in state *i*
- *r*: Inspection cost
- $B_{\min}$: Lower limit of budget
- $B_{\max}$: Upper limit of budget
- $Q_{\min,i}$: Lower limit of the fraction of facilities allowed in state *i*
- $Q_{\max,i}$: Upper limit of the fraction of facilities allowed in state *i*

The objective function given by (5) minimizes the average cost per year. Listed in (6) through (10) are the constraints necessary for this minimization problem. Constraints (6) and (7) specify that each decision variable (i.e. each fraction of facilities) should be nonnegative and that the sum of all the fractions should be equal to one. Constraint (8) shows the Chapman-Kolmogorov equation. This equation in this long-term problem forces the distribution of facilities to remain constant over time. The budget constraints are given by (9) which allow both minimum and maximum values. The level of service constraint (10) forces the condition of the system to fall in an acceptable range. This constraint means that a minimum fraction of facilities, defined in the lower limit, $Q_{\min,i}$, should be in good states and that the fraction in poor states should not exceed the upper limit, $Q_{\max,i}$.

3.3.2 Short-Term Optimization

$$\text{Min.} \quad \sum_{t=1}^{T}\sum_{i=1}^{K}\sum_{a\in A}\delta^{t}\cdot w^{t}(i,a)\cdot(g(i,a)+u(i)+r) \tag{11}$$

$$\text{s.t.} \quad w^{t}(i,a)\geq 0 \qquad \forall i,a,t=1,2,\ldots,\mathrm{T} \tag{12}$$

$$\sum_{i=1}^{K}\sum_{a\in A}w^{t}(i,a)=1 \qquad \forall t=1,2,\ldots,\mathrm{T} \tag{13}$$

$$\sum_{a\in A}w^{1}(i,a)=q^{0}(i) \qquad \forall i \tag{14}$$

$$\sum_{a\in A}w^{t+1}(j,a)=\sum_{i=1}^{K}\sum_{a\in A}w^{t}(i,a)\cdot\pi_{ij}(a) \qquad \forall j,t=1,2,\ldots,\mathrm{T} \tag{15}$$

$$\sum_{i=1}^{K}\sum_{a\in A}w^{T}(i,a)\cdot\pi_{ij}(a)=\sum_{a\in A}w(j,a) \qquad \forall i \tag{16}$$

$$B_{\min}^{t}\leq\sum_{i=1}^{K}\sum_{a\in A}w^{t}(i,a)\cdot g(i,a)\leq B_{\max}^{t} \qquad \forall t=1,2,\ldots,\mathrm{T} \tag{17}$$

$$Q_{\min,i}^{t}\leq\sum_{a\in A}w^{t}(i,a)\leq Q_{\max,i}^{t} \qquad \forall i,t=1,2,\ldots,\mathrm{T} \tag{18}$$

where,

- $w^{t}(i,a)$: Fraction of facilities that is in state *i* and receives maintenance activity *a* in year t
- $q^{0}(i)$: Initial fraction of facilities that is in state *i*

- $w(i,a)$: Steady-state fraction of facilities in the infrastructure network that is in state *i* and receives maintenance activity *a*, obtained from the long-term optimization
- $B^t_{\min}$: Lower limit of budget for year t
- $B^t_{\max}$: Upper limit of budget for year t
- $Q^t_{\min,i}$: Lower limit of the fraction of facilities allowed in state *i* for year t
- $Q^t_{\max,i}$: Upper limit of the fraction of facilities allowed in state *i* for year t

The LP formulation for the short-term optimization model is similar to the long-term optimization model. The difference is that the decision variables and the budget and level of service constraints are time-dependent in the short-term model. This time-dependency is denoted by the superscript *t* in the model. The objective function (11) is to minimize the total discounted cost. The required constraints for this minimization problem are listed in (12) through (18). Constraint (12) is for the nonnegativity of fractions. All fractions should sum to one by constraint (13). Constraint (14) is to identify the initial distribution of facilities. This constraint guarantees that the fraction of facilities in state *i* in year 1 is equal to $q^0(i)$, which is known. Constraint (15) is the Chapman-Kolmogorov equation. This produces the conservation of facilities changing their states from *i* to *j* under maintenance activity *a*. The optimal solution obtained in the long-term optimization, $w(i,a)$, acts as a boundary condition on the distribution of states at the end of the planning horizon in constraint (16). The budget constraint and level of service constraint are stated in (17) and (18).

Chapter 4

Open Loop Feedback Control MR & R Optimization

4.1 Updating the Transition Probability Matrices

This section describes how the transition probabilities can be updated with new data provided by inspections. It is assumed that an inspection of all facilities is performed at the beginning of each year or with a given frequency, revealing the true condition of the facilities.

Notation:

- $x_{ij}^{t}(a)$: Number of facilities that are in state *i* at the beginning of year t to which maintenance activity *a* is applied, and are in state *j* at the beginning of year t+1
- $X_i^t(a) = \sum_{j=1}^{K} x_{ij}^{t}(a) \qquad \forall i, a, t$
- $n_{ij}^{t}(a) = \sum_{h=0}^{t} x_{ij}^{h}(a) \qquad \forall i, j, a, t$

- $N_i^t(a) = \sum_{h=0}^{t} X_i^h(a) \qquad \forall i, a, t$

- $\pi_{ij}^t(a)$: Estimated transition probability of the facility changing state *i* to *j* under maintenance activity *a* in year t

- $\underline{\prod}^t(a)$: Estimated transition probability matrix for maintenance activity *a* in year t

Through the inspection at the beginning of year t+1, we observe the number of facilities whose conditions change from state *i* in year t to state *j* in year t+1 under maintenance activity *a*. This is denoted by $x_{ij}^t(a)$ for all *i*, *j*, t, and *a*. Then, $n_{ij}^t(a)$ and $N_i^t(a)$ are calculated. With this information, the transition probabilities are updated at the beginning of year t+1 by the Maximum Likelihood Estimation (MLE). The Maximum Likelihood Estimate for transition probabilities at the beginning of year t+1 is,

$$\pi_{ij}^t(a) = \frac{\sum_{h=o}^{t} x_{ij}^h(a)}{\sum_{h=0}^{t} X_i^h(a)} = \frac{n_{ij}^t(a)}{N_i^t(a)} \qquad \forall i, j, a, t \tag{19}$$

The Bayesian updating of the transition probabilities provides the same result as in (19) (DeGroot 1970).

4.1.1 Updating Algorithm

Transition Probabilities Updating:

For year t,

i) Inspect all facilities

ii) Observe $x_{ij}^{t-1}(a) \qquad \forall i, j, a, t$

iii) Update transition probabilities:

$$\pi_{ij}^{t-1}(a) = \frac{n_{ij}^{t-1}(a)}{N_i^{t-1}(a)} \qquad \forall i, j, a, t$$

iv) Obtain the updated transition matrices $\underline{\prod}^{t-1}(a) \qquad \forall a$

This process is summarized in Figure 2. Equation (19) shows the updated transition probability at the beginning of year t+1. It can be manipulated as follows:

$$\pi_{ij}^{t}(a) = \frac{n_{ij}^{t}(a)}{N_i^{t}(a)} = \frac{n_{ij}^{t-1}(a) + x_{ij}^{t}(a)}{N_i^{t-1}(a) + X_i^{t}(a)}$$

$$= \frac{N_i^{t-1}(a)}{N_i^{t-1}(a) + X_i^{t}(a)} \times \frac{n_{ij}^{t-1}(a)}{N_i^{t-1}(a)} + \frac{X_i^{t}(a)}{N_i^{t-1}(a) + X_i^{t}(a)} \times \frac{x_{ij}^{t}(a)}{X_i^{t}(a)}$$

$$= \frac{N_i^{t-1}(a)}{N_i^{t-1}(a) + X_i^{t}(a)} \times \pi_{ij}^{t-1}(a) + \frac{X_i^{t}(a)}{N_i^{t-1}(a) + X_i^{t}(a)} \times \frac{x_{ij}^{t}(a)}{X_i^{t}(a)} \qquad \forall i, j, a, t \tag{20}$$

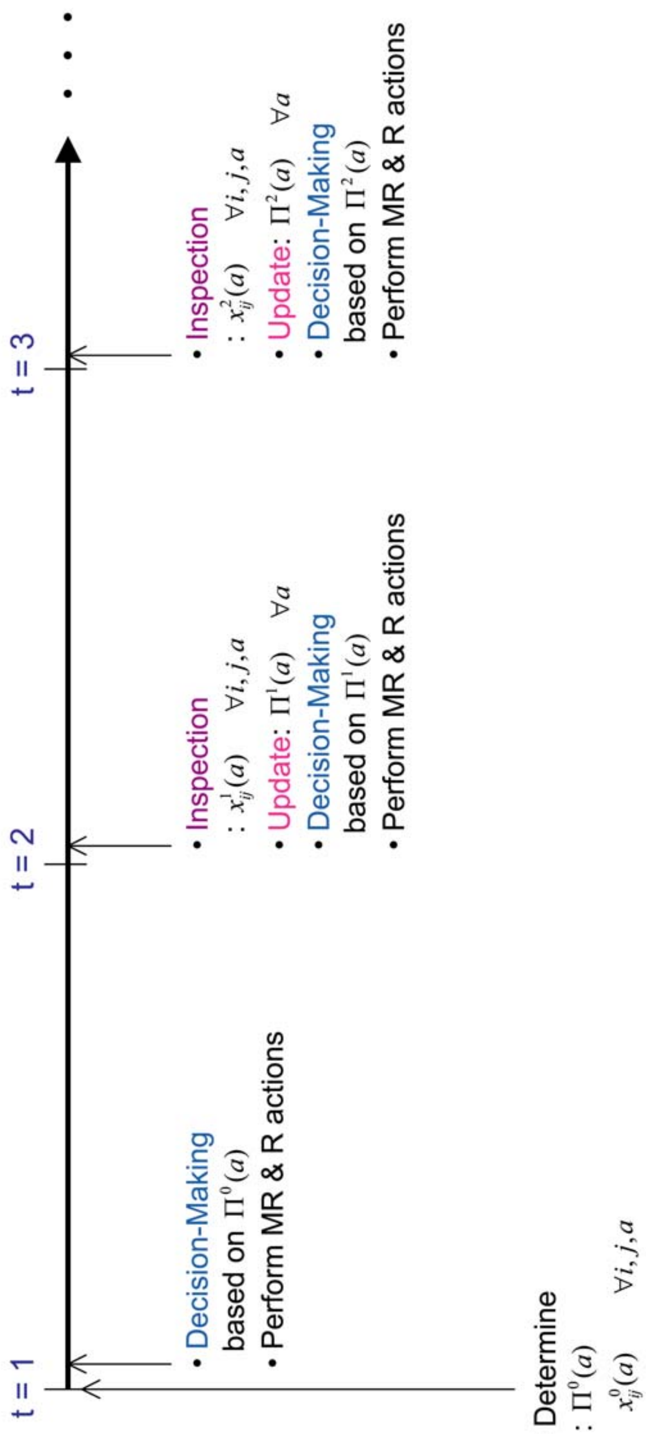


Figure 2 Performance Model Updating Procedure

If the real deterioration process is constant over the planning horizon, in equation (20), as t increases, $N_i^{t-1}(a)$ gets larger compared to $X_i^t(a)$ since $N_i^{t-1}(a)$ is equal to $\mathrm{N}_{\mathrm{i}}^{\mathrm{t}-1}(\mathrm{a}) = \sum_{\mathrm{h}=0}^{\mathrm{t}-1} \mathrm{X}_{\mathrm{i}}^{\mathrm{h}}(\mathrm{a})$ for all *i* and *a*. As t goes to infinity, $\frac{N_i^{t-1}(a)}{N_i^{t-1}(a) + X_i^t(a)}$ goes to one, and $\frac{X_i^t(a)}{N_i^{t-1}(a) + X_i^t(a)}$ goes to zero. Then, $\pi_{ij}^t(a)$ becomes equal to $\pi_{ij}^{t-1}(a)$, after which the transition probabilities converge to some value. After obtaining the limiting probabilities, they can be applied constantly up to the end of the planning horizon. This is illustrated in Figure 3.

An issue that can be raised is if the transition probabilities would converge to the true values when t goes to infinity. In Kumar and Varaiya (1986) and Bertsekas (2000), there are examples where the parameters do not converge at all or converge to wrong values. However, we can guarantee that the transition probabilities corresponding to the selected policy will converge to the true values when t goes to infinity if, under that policy, all acceptable states are visited a large number of times. This is because, if a state is visited sufficiently often, there will be a large number of observations of transitions from that state. By "acceptable," we mean a state that is allowed as defined by policy constraints. As will be shown in the parametric study, the transition matrices corresponding to the selected policy each consist of a single class of recurrent states consisting of all acceptable states so every state is visited and every selected action is applied sufficient number of times as t goes to infinity. Thus, the transition probabilities corresponding to the selected policy will converge to the true values by update using MLE with data from inspection.

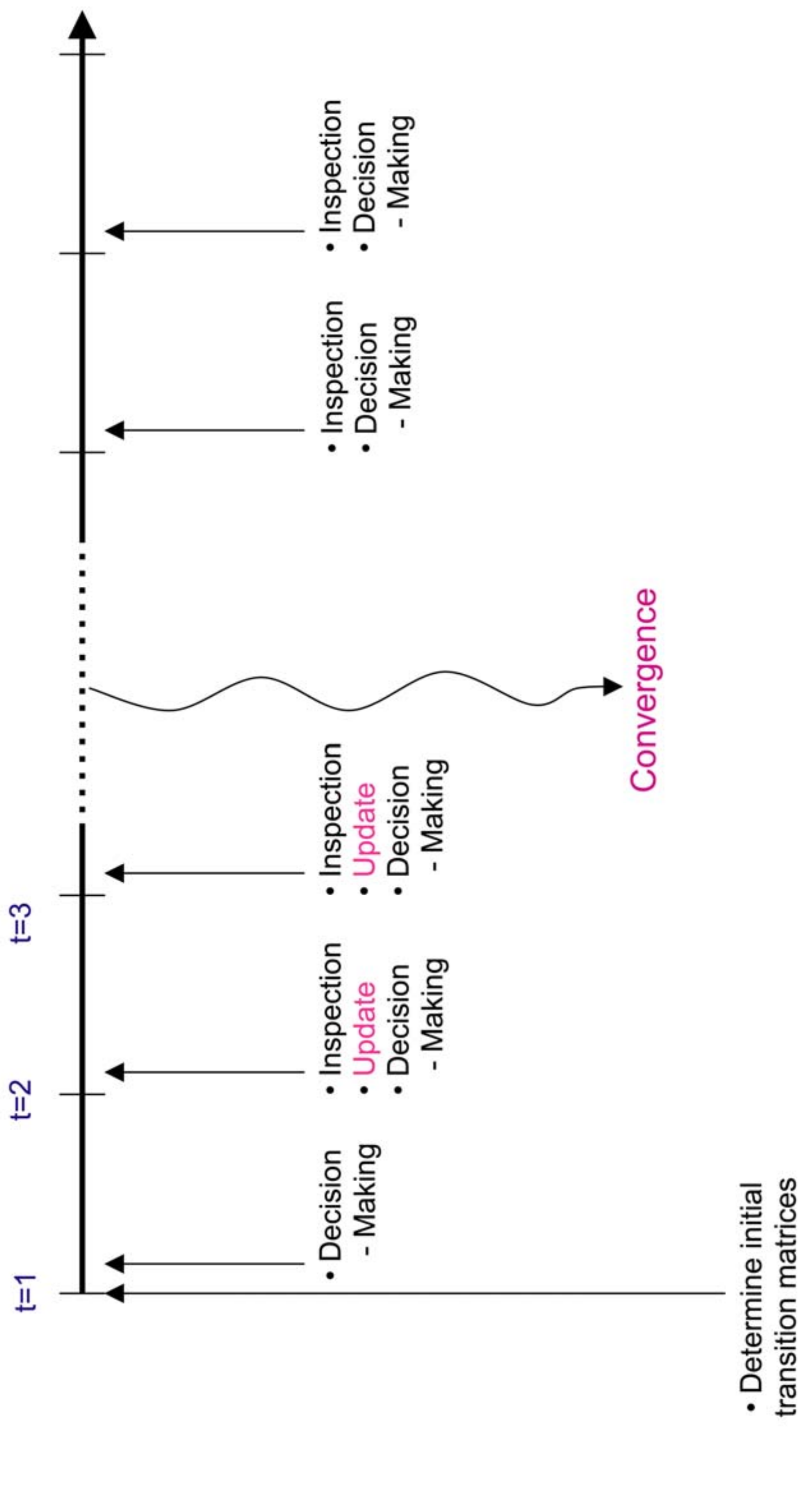


Figure 3 Convergence

When the real deterioration process is varying over time, the transition probabilities do not converge even if t goes to infinity. The time-varying characteristics, however, can be captured slowly by updating.

4.2 Open Loop Feedback Control

In Chapter 3, two optimization models and their relationship were described. The optimization that does not consider the model uncertainty is referred as the Open Loop (OL) optimization. In the OL, the transition probabilities are assumed to be accurate thus can be applied constantly over the planning horizon. In this dissertation, we consider the uncertainty in initially selected transition matrices, and we updated those matrices with the information from inspections. An Open Loop Feedback Control (OLFC) was used to incorporate the updated transition probability matrices into the optimization models. In the OLFC, the updated deterioration models are used, but the policies are selected as if no further updating will occur in the future. In other words, when the optimization problems are solved every year or with a given frequency, the updated transition probability matrices are assumed to be true and constant, but they will be updated in future years. This process is illustrated in detail in this section.

Before presenting these details, the relation between the "selected policy" and "optimal policy" must be discussed. It is shown in the following example. When we have 4 states and 4 actions, we need to update 64 transition probabilities. However, only a subset of the 64 transition probabilities corresponding to the selected activities and visited states is updated and converges to the true values when t goes to infinity. Since all 64 transition probabilities are used in the optimization model, the policy that is selected by the optimization problem is not necessarily optimal for the real problem. In other words, a_i^s and a_i^* could be different where a_i^s is the action selected for facilities in state *i* by the optimization and a_i^* is the optimal action for the real problem for all *i* and *a*.

For simplicity, we will refer the selected policy as the optimal policy in the remainder of this document.

As mentioned earlier, we solved two OLFC problems: the OLFC with annual inspection and the OLFC with alternate inspection frequencies. In the OLFC with annual inspection, the short-term and long-term optimizations are performed with the updated transition matrices every year. In each year, the set of optimal MR & R policies over the planning horizon is obtained based on the updated transition matrix, and only the optimal policy for the current year is performed.

In the OLFC with alternate inspection frequencies, the assumption of annual inspection is relaxed to select both optimal MR & R policies and inspection frequency. The basic strategy with this relaxation is that an inspection is performed according to a given frequency and the decision-making and transition probabilities updating are carried out only after an inspection is implemented. This process is illustrated in Figure 4 where inspections are carried out every τ years. If public agencies do not inspect facilities and

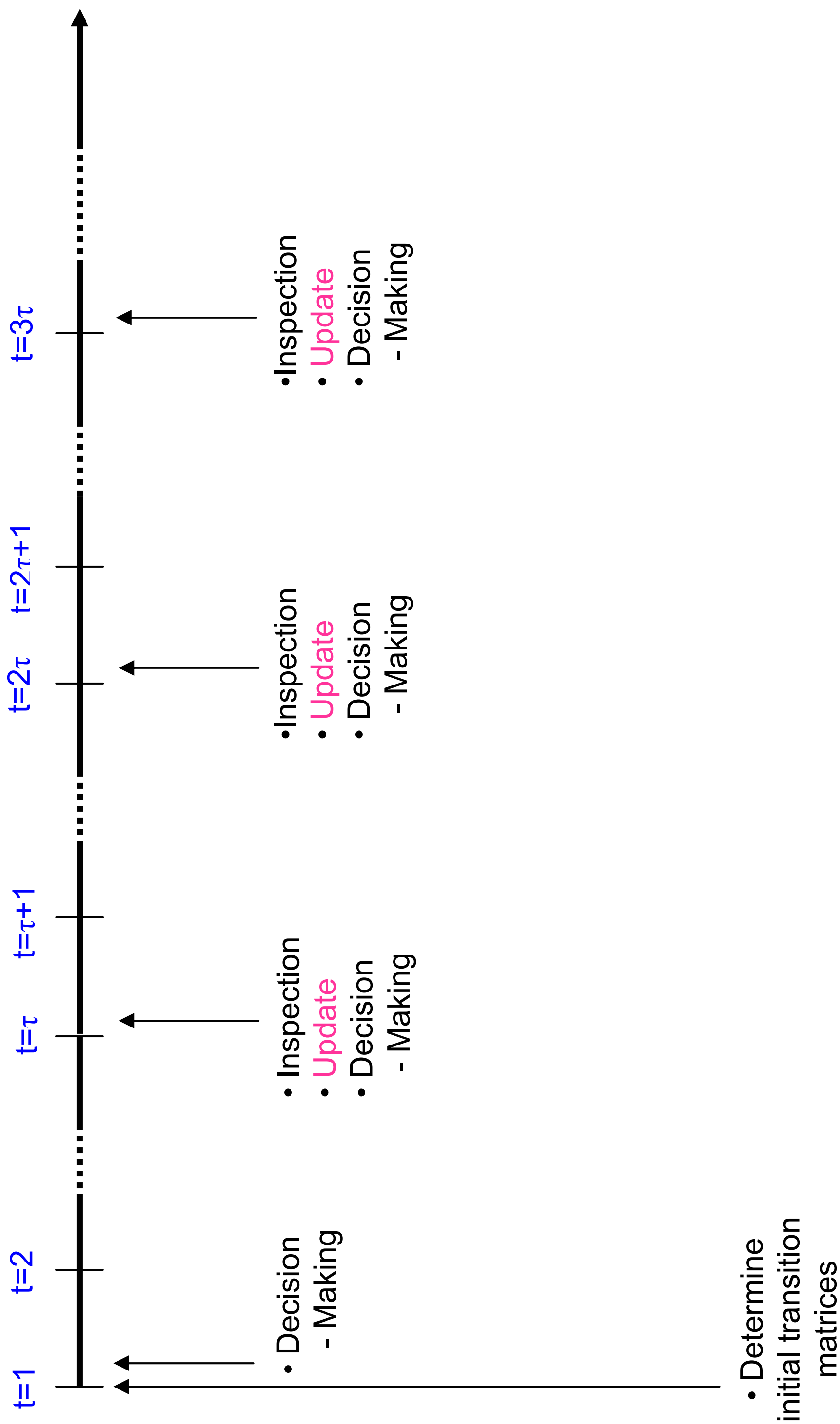


Figure 4 Alternate Inspection Frequency

do not perform MR & R activities annually, they may have to apply more severe MR & R actions later that are more expensive. User costs may also increase. Inspection costs, however, are reduced. Therefore, the sum of all agency and user costs is minimized with an optimal inspection frequency.

The algorithm applied to incorporate the updated matrices into the optimization model is described below.

The Algorithm

For year t,

i) Inspect all facilities at the beginning of year t

ii) Update transition matrices

iii) Use the updated transition matrices in the LP to determine the fractions of the facilities in the network in different states at the beginning of year t on which maintenance activity *a* is performed in year t

$$\Rightarrow \{w^t(i,a),.....,w^T(a)\}$$

iv) Apply $w^t(i,a)\ \ \forall i,a$ for the network in year t only

OLFC Linear Programming (LP) for the Network-Level Problem

The LP that is applied in the OLFC is the same as the LP shown earlier. The only difference is that the transition matrix is updated every year or with a given frequency.

Figure 5 illustrates the relationship between the long-term problem and the short-term problem, and the optimization procedure.

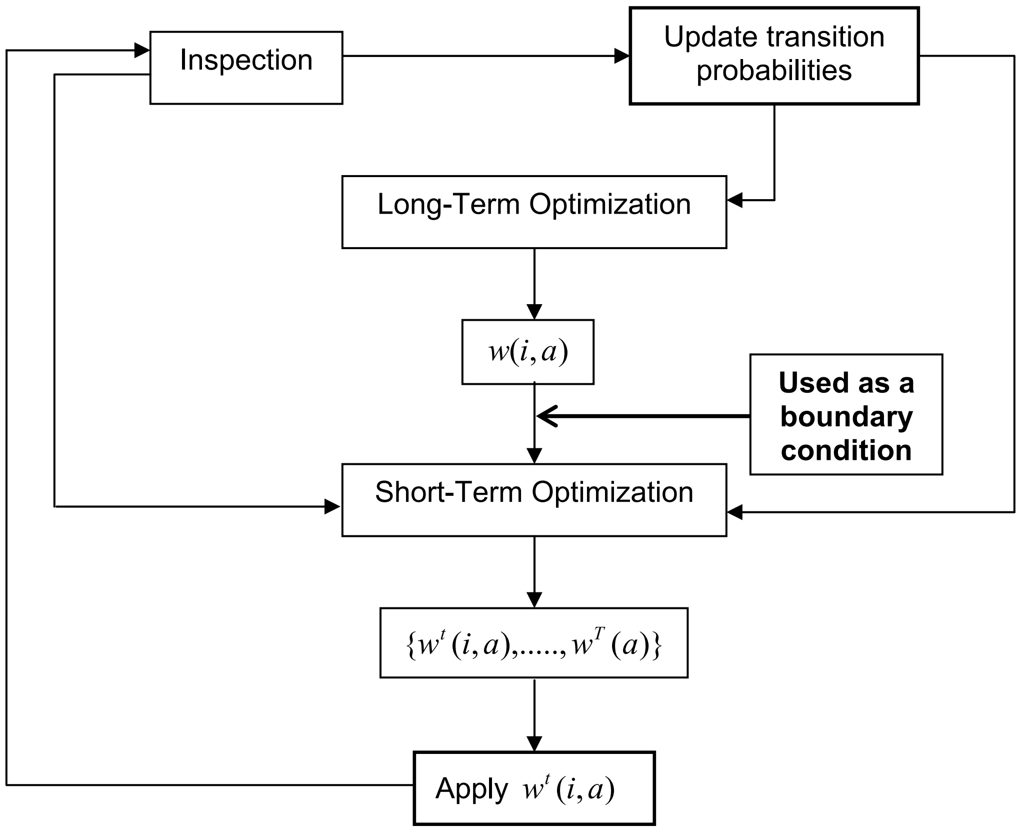


Figure 5 Optimization Procedure

Chapter 5

Parametric Study

A parametric study was conducted to compare the optimization with constant transition matrices, referred as the Open Loop (OL), the Open Loop Feedback Control (OLFC) with annual inspection, and the OLFC with alternate inspection frequencies. This parametric study demonstrates the usefulness of updating the transition probabilities and relaxing the inspection frequency. The savings achieved by the OLFC over the OL case are quantified in the parametric study. It will also be shown that the total costs can be reduced further by using alternate inspection frequencies.

We used a case study in the field of pavement management. The data such as transition probability matrices, costs of performing MR & R activities, and user costs were taken from Durango and Madanat (2002). The condition of pavement was expressed by PCI rating from one to eight as in Carnahan et al. (1987). A higher number means a better condition. Seven MR & R activities exist: do nothing (1), routine maintenance (2), 1-in overlay (3), 2-in overlay (4), 4-in overlay (5), 6-in overlay (6), and reconstruction (7). The costs associated with performing MR & R activities and the user costs are shown in Table 1, which were taken from Carnahan et al (1987). The user costs represent vehicle operation costs that depend on the condition of pavement. The inspection cost was assumed to be 10% of the average MR & R costs, which is \$1.22/lane-yard. For the short-term optimization, the planning horizon (T) was assumed to be 25 years. We used a discount rate of 5%.

Table 1 Costs (\$/lane-yard)

Condition of Pavement	MR & R Activities							User Costs
	1	2	3	4	5	6	7	
1	0.00	6.90	19.90	21.81	25.61	29.42	25.97	100.00
2	0.00	2.00	10.40	12.31	16.11	19.92	25.97	25.00
3	0.00	1.40	8.78	10.69	14.49	18.30	25.97	22.00
4	0.00	0.83	7.15	9.06	12.86	16.67	25.97	14.00
5	0.00	0.65	4.73	6.64	10.43	14.25	25.97	8.00
6	0.00	0.31	2.20	4.11	7.91	11.72	25.97	4.00
7	0.00	0.15	2.00	3.91	7.71	11.52	25.97	2.00
8	0.00	0.04	1.90	3.81	7.61	11.42	25.97	0.00

The following initial distribution of facilities was assumed: 60% of facilities are in state 8, 20% in state 7, 10% in state 6, 5% in state 5, 3 % in state 4, 2 % in state 3, 0% in state 2, and state 1. The maximum level of service constraint restricts that no facilities should be in state 1. The budget was limited to \$100/lane-yard-year in the base case.

For computational reasons, we included some tolerance limits in constraint (16) so that the steady-state distribution of facilities and maintenance activities is attained with the specified tolerance. We used a tolerance ϕ of 0.01. Constraint (16) was modified to:

$$\sum_{a \in A} w^T(i,a) \cdot \pi_{ij}(a) \geq \sum_{a \in A} w(i,a) \cdot (1-\phi) \qquad \forall i \qquad (21)$$

$$\sum_{a \in A} w^T(i,a) \cdot \pi_{ij}(a) \leq \sum_{a \in A} w(i,a) \cdot (1+\phi) \qquad \forall i \qquad (22)$$

where, ϕ: tolerance

The basic logic of the computational study is that the initial transition matrices do not represent the true deterioration process, and the infrastructure facilities perform according to their true deterioration characteristics. The initial matrices and the true matrices were selected among three categories of deterioration of Durango and Madanat (2002): slow, medium, and fast. For example, the slow deterioration process was selected as the initial process while the real one was the medium deterioration rate. In this case, we predicted the performance of infrastructure facilities, and selected MR & R activities with the matrices corresponding to the slow deterioration in the first year. The optimal policy for the first year was applied, but the deterioration of infrastructure facilities after implementing the optimal policy was predicted based on the medium transition matrices. The inspection results at the beginning of the second year were generated using the medium transition matrices. We updated the initial transition matrices with the information from the inspections. Then, the optimal MR & R policies for the second year or the next time period according to the given inspection frequency were selected with the updated transition matrices. The selected policies were performed and the results of inspection at the beginning of next year were generated based on the medium transition matrices. This procedure was repeated similarly over the planning horizon, and the updated transition matrices are expected to eventually converge to the real transition matrices. Sensitivity analyses were performed on budget constraints, user costs, and inspection costs. Table 2 shows the nine cases performed in the parametric study. The optimization problems were programmed in AMPL, and EXCEL was used to update the transition probability matrices and generate inspection results.

Table 2 Parametric Study Cases

Assumed True Process	OL		OLFC	
	Initial Process	Continue	Initial Process	Continue
Fast	Fast Medium Slow	Fast Medium Slow	Fast Medium Slow	Fast Update Update
Medium	Fast Medium Slow	Fast Medium Slow	Fast Medium Slow	Update Medium Update
Slow	Fast Medium Slow	Fast Medium Slow	Fast Medium Slow	Update Update Slow

The cost savings were calculated as the difference between the total costs obtained with the OL and the OLFC strategies. The total costs with the annual inspection and with the alternate inspection frequencies were also compared. In each year or every τ years, where τ is the inter-inspection headway, the long-term and short-term optimizations were performed and the optimal MR & R policies over the planning horizon were obtained. Only the optimal policy for the current year was applied. The actual cost in each year or every τ years was the cost to implement the optimal policy for that year. The total cost was the sum of costs actually incurred over the planning horizon.

The convergence of the transition probability matrices was represented by the weighted average difference between the real transition probabilities and the estimated probabilities in each year or with a given frequency. The weighted average difference for year *t* was calculated as follows.

$$\sum_{a \in A} \sum_{i=1}^{K} w^t(i,a) \cdot \{ \sum_{j=1}^{K} | \pi_{ij}^t(a) - \pi_{ij}^*(a) | \} \qquad \forall t \qquad (23)$$

where, $\pi_{ij}^*(a)$: the real transition probability from state *i* to state j under action *a*

5.1 Annual Inspection Strategy

The results of the parametric study with the annual inspection for nine cases in Table 2 are shown below. The nine cases were categorized into three classes according to the real deterioration process. The total costs obtained by using the OL and the OLFC optimizations are shown and discussed. The cost savings obtained by using the OLFC over the OL are also presented. It is shown how the transition probabilities converge to the real transition probabilities by updating with the weighted average difference.

5.1.1 Real Process: Fast

The costs obtained by using the OL and the OLFC optimizations, for three cases that have the fast deterioration process as the real process, are shown in Table 3 and Figure 6. It is intuitive that the larger the difference between the real and initial matrices, the higher the total cost, as shown in the case when the initial matrices are slow. It can be seen that the total costs obtained by using the OLFC were lower than that obtained with the OL. The OLFC approach produced cost savings with the percentage savings of 2.05% when the initial deterioration process was medium, and 24.72% when the initial deterioration process was slow.

Table 3 Total Costs and Costs Savings (Real: Fast)

Deterioration Process		Total costs ($/lane-yard)		Cost savings	Cost savings
Real	Initial	OL	OLFC	($/lane-yard)	(%)
Fast	Fast	38.54	38.54	0.00	0.00
	Medium	46.45	45.5	0.95	2.05
	Slow	52.15	39.26	12.89	24.72

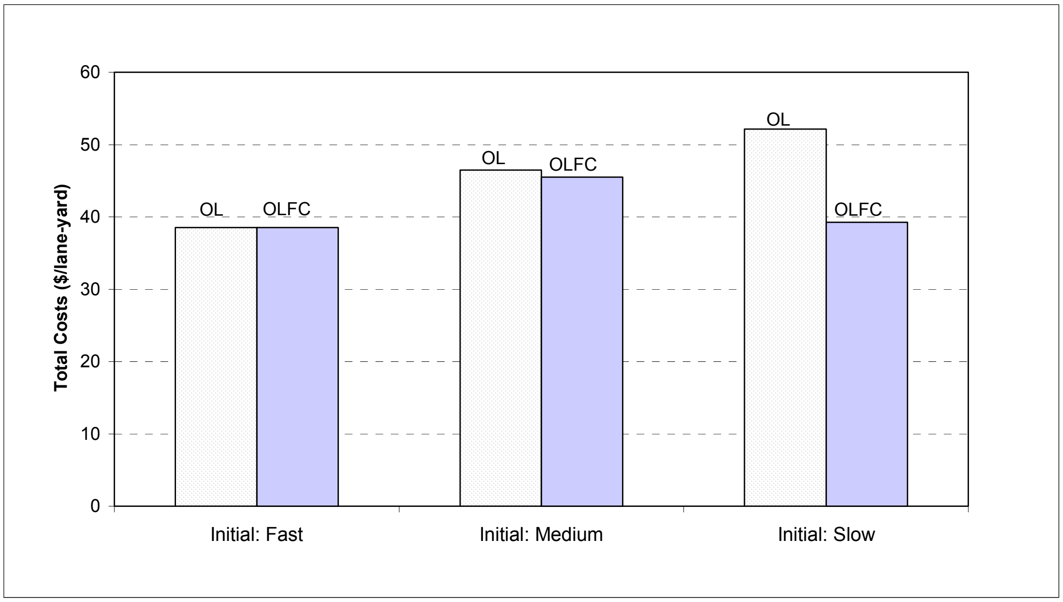


Figure 6 Total Costs (Real: Fast)

The weighted average difference between the real transition probabilities and the estimated probabilities in each year is shown in Figure 7. It can be seen that most of the improvement in the convergence occurred in the first five years in both cases: when the initial process was medium and when the initial one was slow. Clearly, the cost savings shown in the above result from the improvement of transition probability matrices. This means that the transition probabilities converge to the real probabilities through the updating procedure in each year and thus represent the real deterioration process better than the initial matrices.

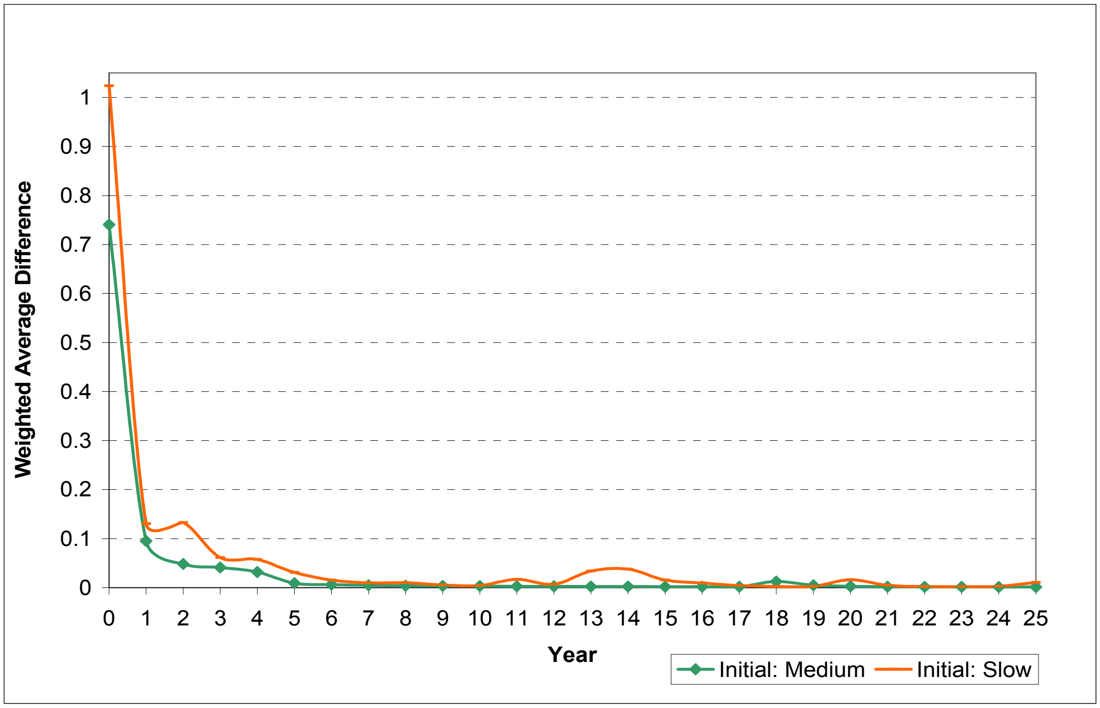


Figure 7 Weighted Average Difference (Real: Fast)

5.1.2 Real Process: Medium

In this section, the total costs and cost savings, for three cases having the medium deterioration rate as the real deterioration rate, are given. The total costs in the OL and OLFC and the cost savings achieved by the OLFC are shown in Table 4 and Figure 8.

Table 4 Total Costs and Cost Savings (Real: Medium)

Deterioration Process		Total costs ($/lane-yard)		Cost savings	Cost savings
Real	Initial	OL	OLFC	($/lane-yard)	(%)
Medium	Fast	37.01	25.69	11.32	30.59
	Medium	24.51	24.51	0.00	0.00
	Slow	28.77	25.3	3.47	12.06

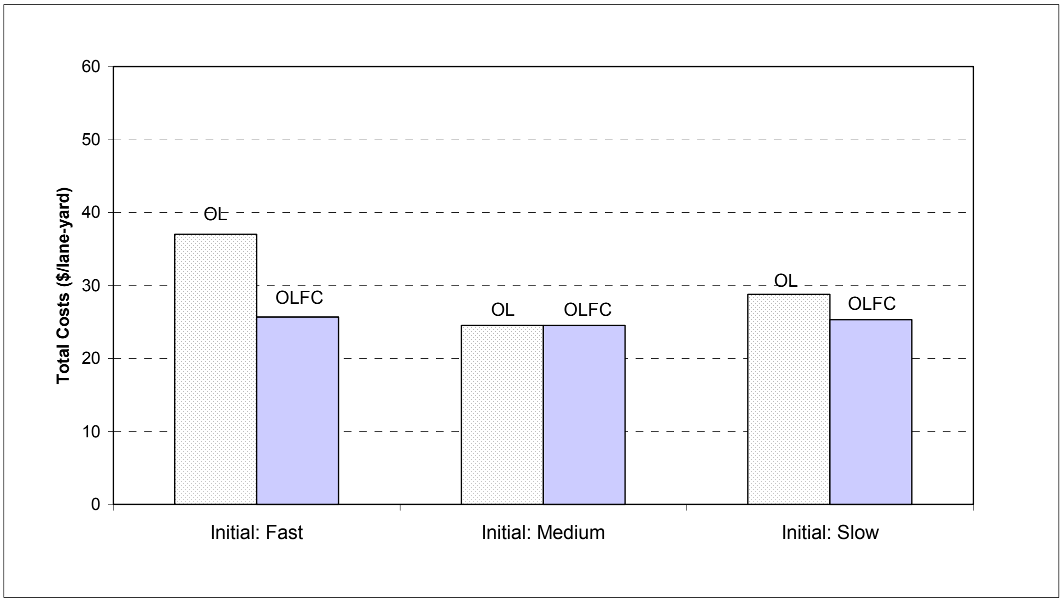


Figure 8 Total Costs (Real: Medium)

As can be seen, the total costs when the initially selected transition matrices do not represent the real deterioration process are higher than the total costs when the correct matrices are selected. In other words, the total costs were reduced by using the OLFC approach. The percentage savings are 30.59% and 12.06% when the initial deterioration rate was fast and when the initial rate was slow, respectively.

Figure 9 shows the weighted average difference between the real transition probabilities and the estimated probabilities being updated in each year. By updating the initial transition matrices with the available information from inspections, the transition probabilities converge to the real probabilities in both cases. The major improvement in the convergence in both cases happened in the first three years. Clearly, the cost savings shown in Table 4 and Figure 8 result from the improvement of the transition probability matrices.

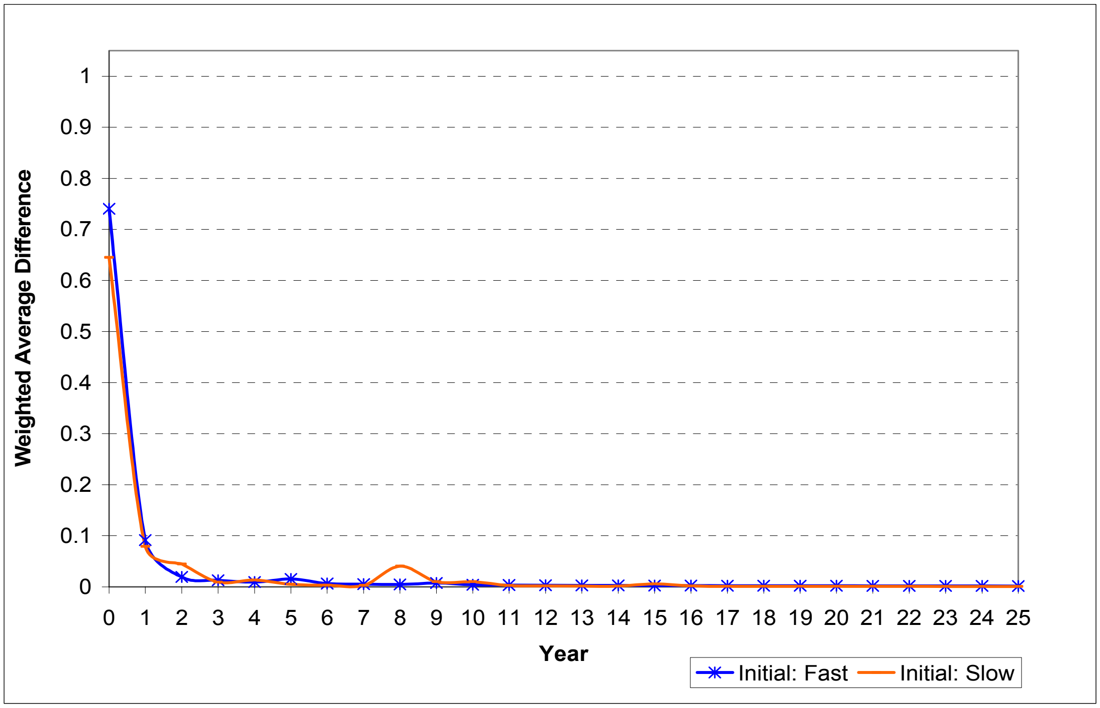


Figure 9 Weighted Average Difference (Real: Medium)

5.1.3 Real Process: Slow

The total costs obtained by using the OL and the OLFC optimizations in the three cases having the slow deterioration rate as the real deterioration rate are discussed in this section. The total costs and cost savings are demonstrated in Table 5 and Figure 10. As expected, the bigger the gap between the real and initial deterioration rates, the higher the costs incurred. It can be seen that costs savings of 0.12 % and 29.92% in the cases where the initial deterioration rates were fast and medium, respectively, were achieved by using the OLFC approach. As in the previous cases, these cost savings result from the improvement of transition probability matrices. This is shown in Figure 11. It can be observed that most of the improvement in the convergence occurred in the first two years.

Table 5 Total Costs and Cost Savings (Real: Slow)

Deterioration Process		Total costs ($/lane-yard)		Cost savings	Cost savings
Real	Initial	OL	OLFC	($/lane-yard)	(%)
Slow	Fast	36.86	25.83	11.03	29.92
	Medium	17.07	17.05	0.02	0.12
	Slow	16.92	16.92	0.00	0.00

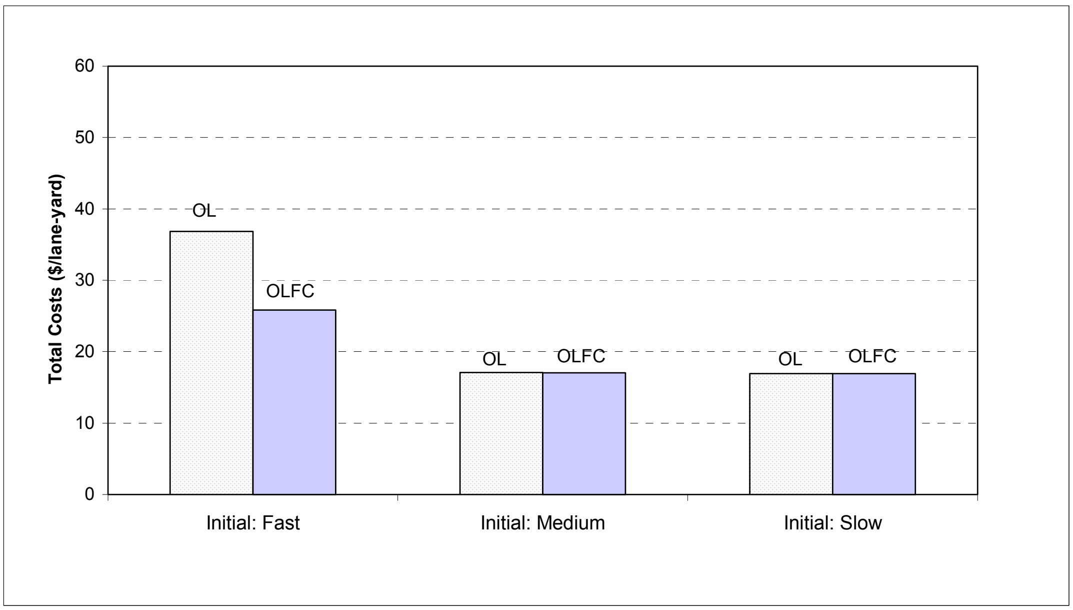


Figure 10 Total Costs (Real: Slow)

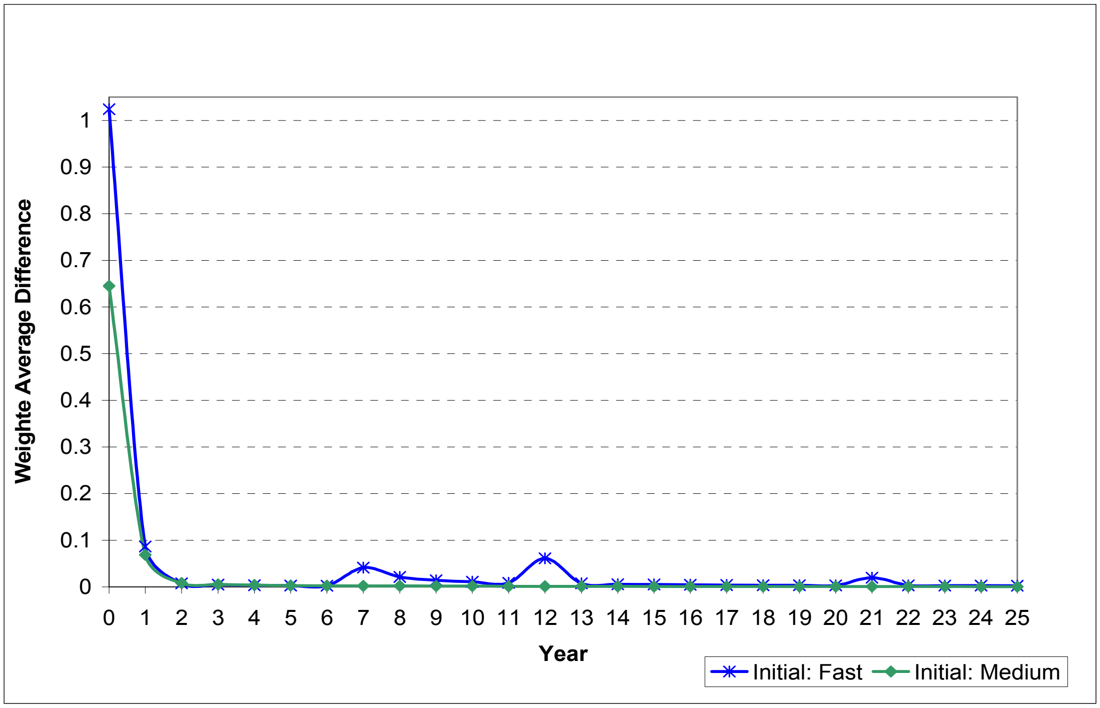
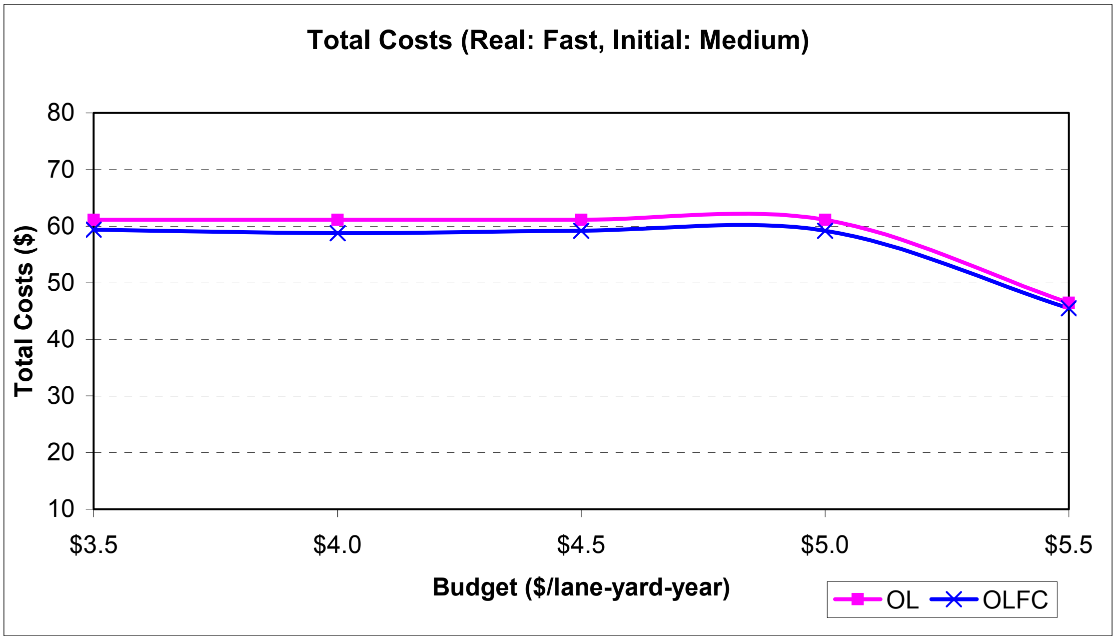


Figure 11 Weighted Average Difference (Real: Slow)

5.1.4 Sensitivity to Budget Constraint

The sensitivity of the results to the budget constraints is analyzed in this subsection. It was found that the total costs do not change if the budget is higher than or equal to \$5.5/lane-yard-year. When the budget was lower than \$3.5/lane-yard-year, the optimization problem was infeasible. Total costs with five budget constraints: \$3.5/lane-yard-year, \$4.0/lane-yard-year, \$4.5/lane-yard-year, \$5.0/lane-yard-year, and \$5.5/lane-yard-year are shown in Figure 12, 13, and 14. These Figures show that cost savings were achieved by the OLFC over the OL in all cases.



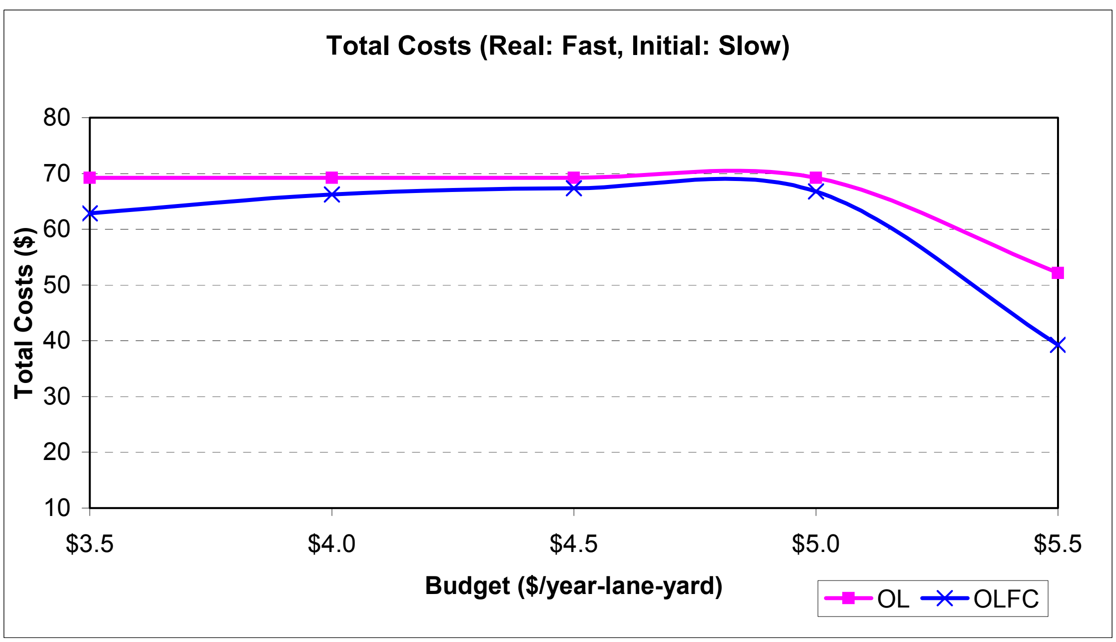
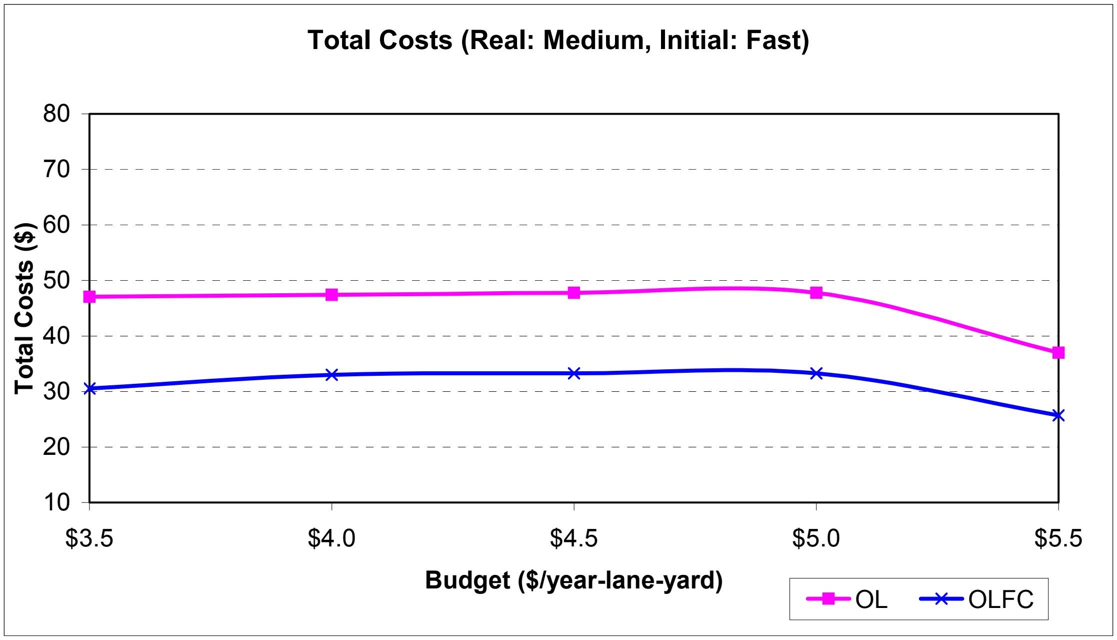


Figure 12 Sensitivity to Budget Constraints (Real: Fast)



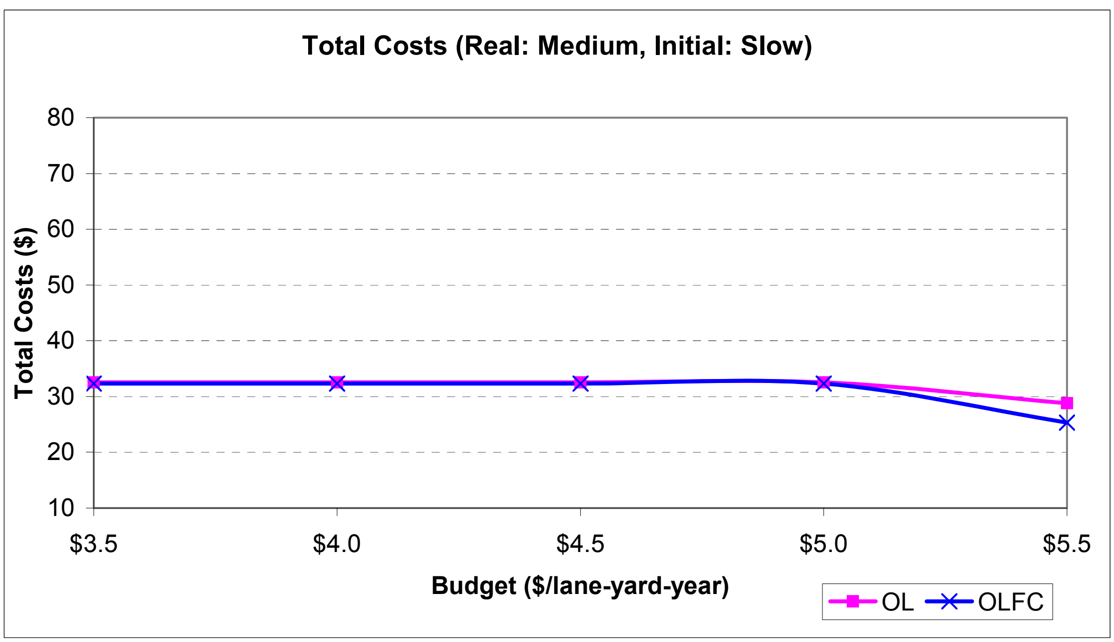
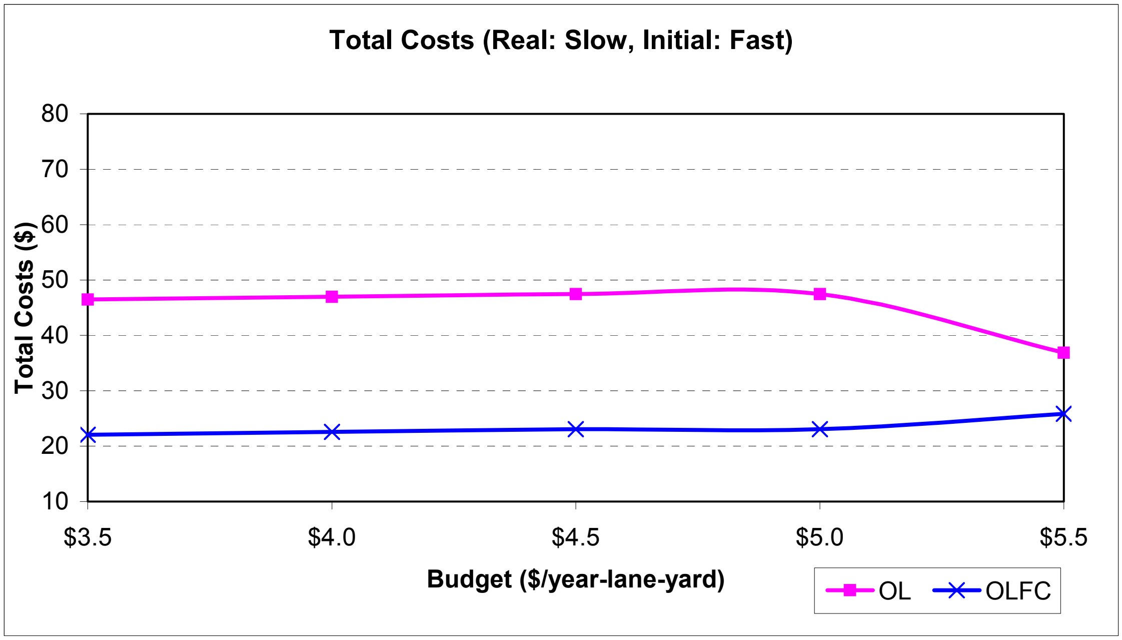


Figure 13 Sensitivity to Budget Constraints (Real: Medium)



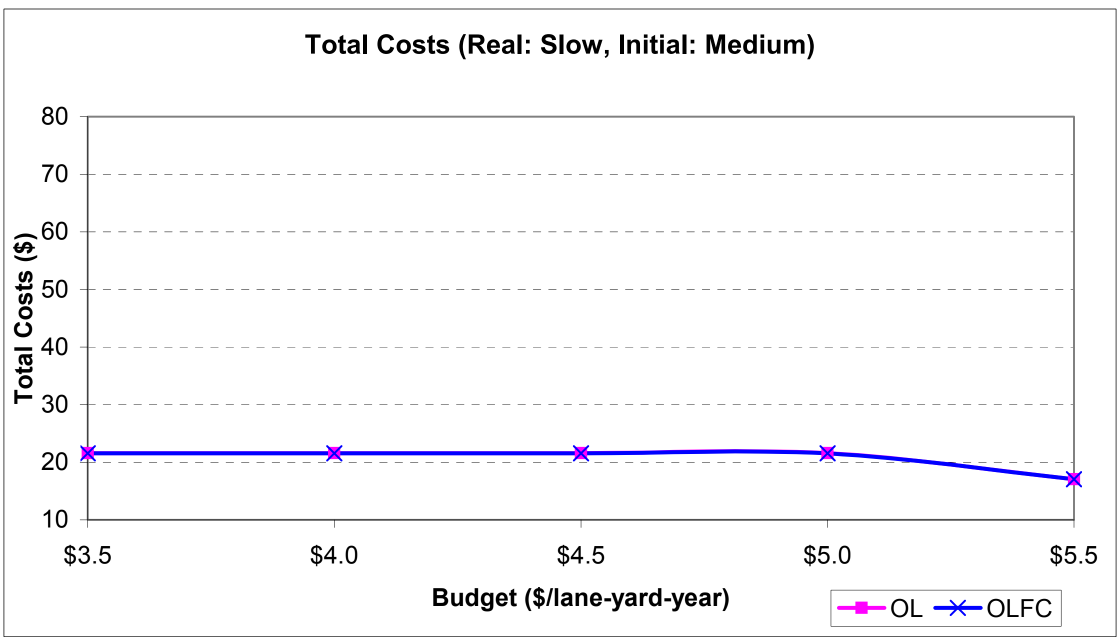


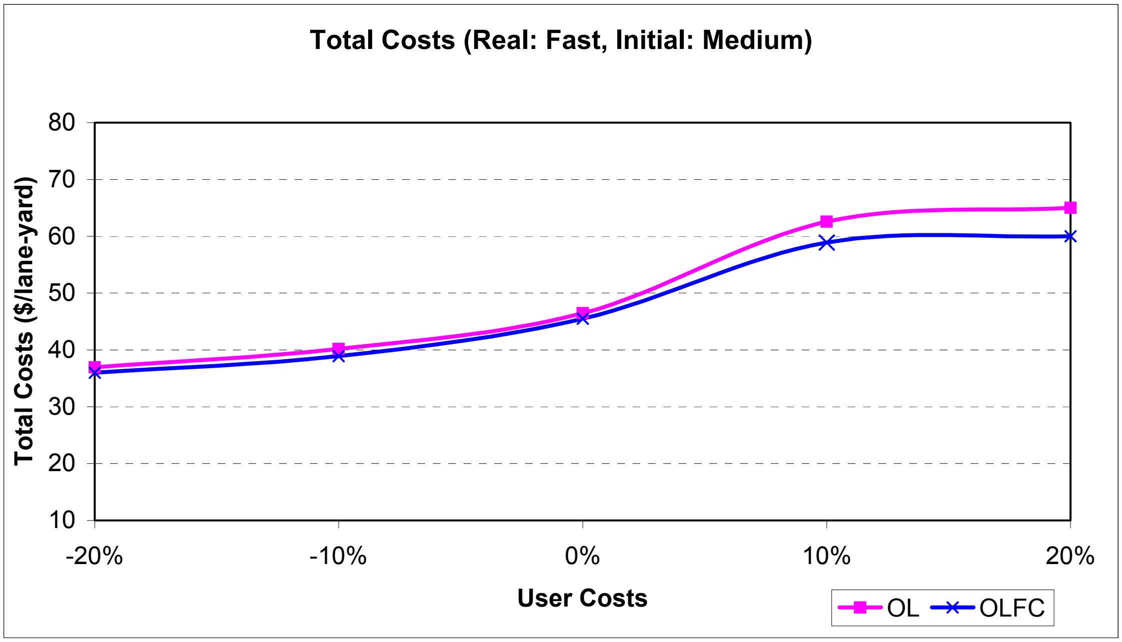
Figure 14 Sensitivity to Budget Constraints (Real: Slow)

It was expected that the total costs would decrease when we relaxed the budget constraints, but the results did not show this pattern. This is because the total costs are the sum of costs actually incurred over the planning horizon. When we run the optimization model in each year, we obtain the MR & R policies and total costs over the planning horizon. The costs of each year are distributed over 25 years. Among them, we select MR & R policies for current year only. Thus, even though the total costs at each time that the optimization was solved are reduced, the actual total costs that are the sum of costs actually incurred can fluctuate.

5.1.5 Sensitivity to User Costs

In this subsection, the sensitivity of the total costs to user costs is analyzed. The sensitivity analysis was performed for five different cases. The user costs in Table 1 were decreased and increased by 10% up to -20% and +20%.

When the MR & R costs are higher than the user costs, less expensive MR & R activities are selected due to the presence of budget constraints. On the other hand, when the user costs are higher, more expensive MR & R activities are chosen. Thus, the total costs increase when the user costs are higher than the MR & R costs. As shown in Figure 15, 16, and 17 the total costs increased with the user costs in all cases. Moreover, cost savings were achieved by the OLFC in all cases.



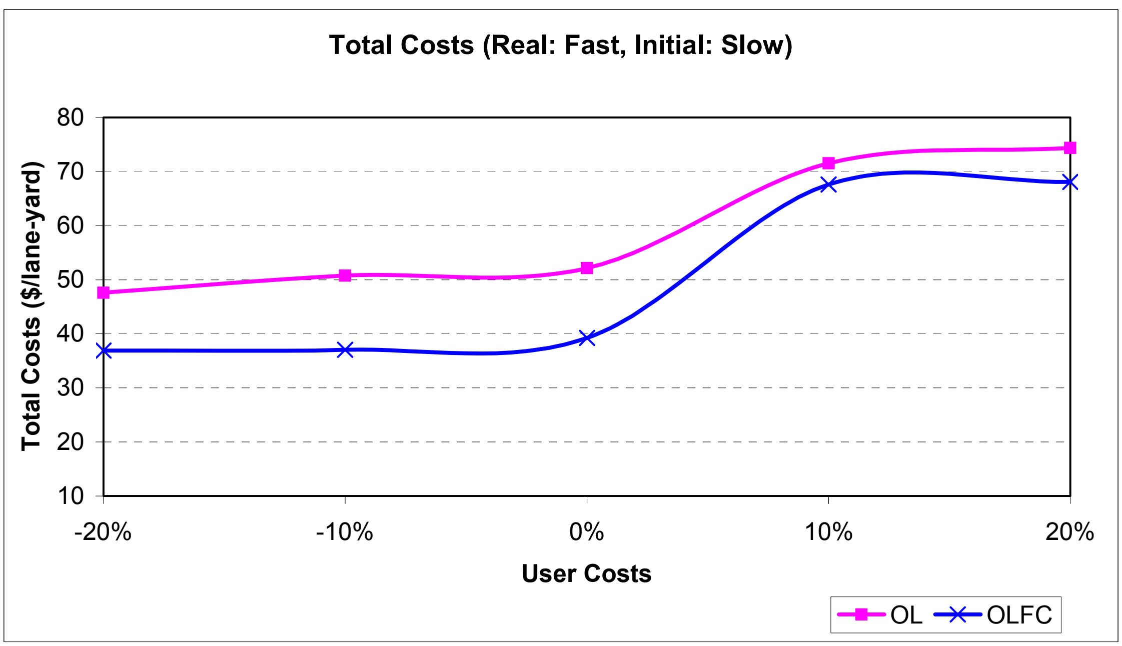
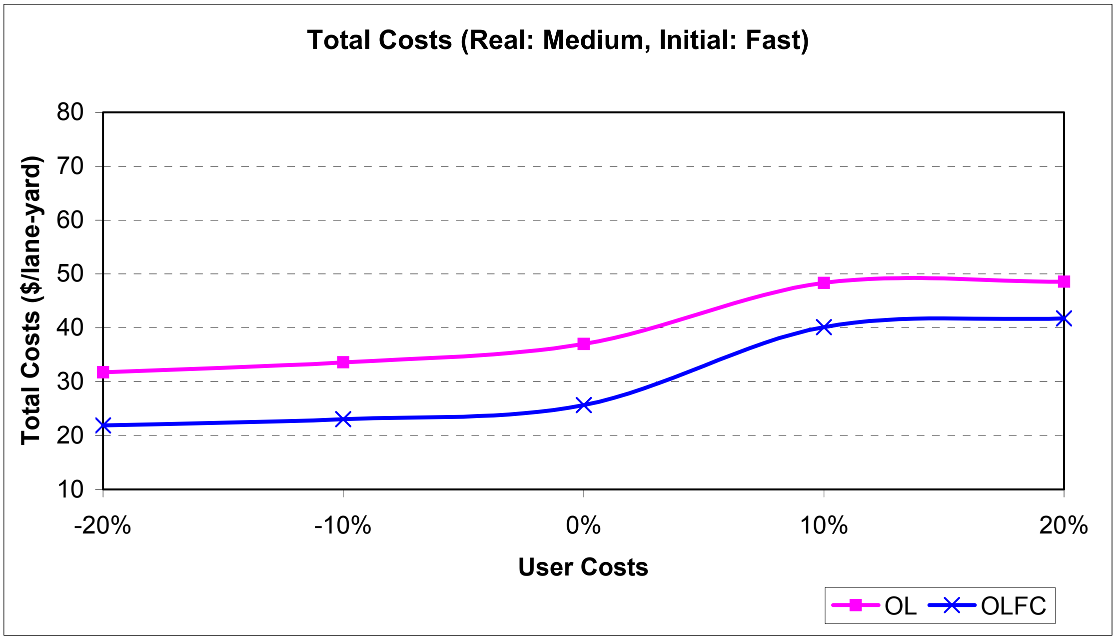


Figure 15 Sensitivity to User Costs (Real: Fast)



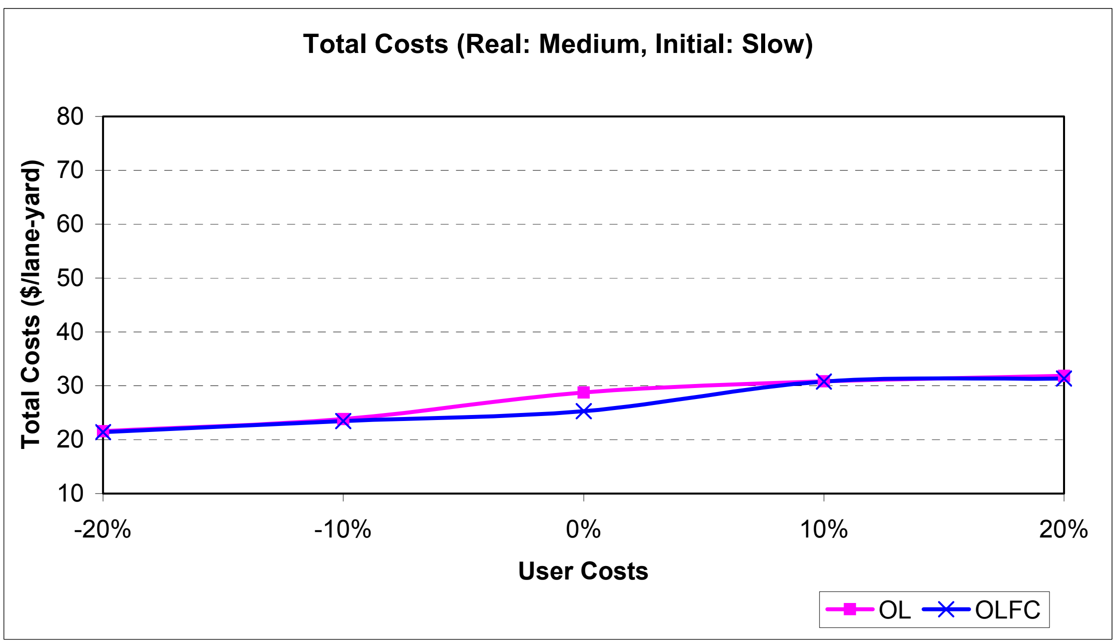
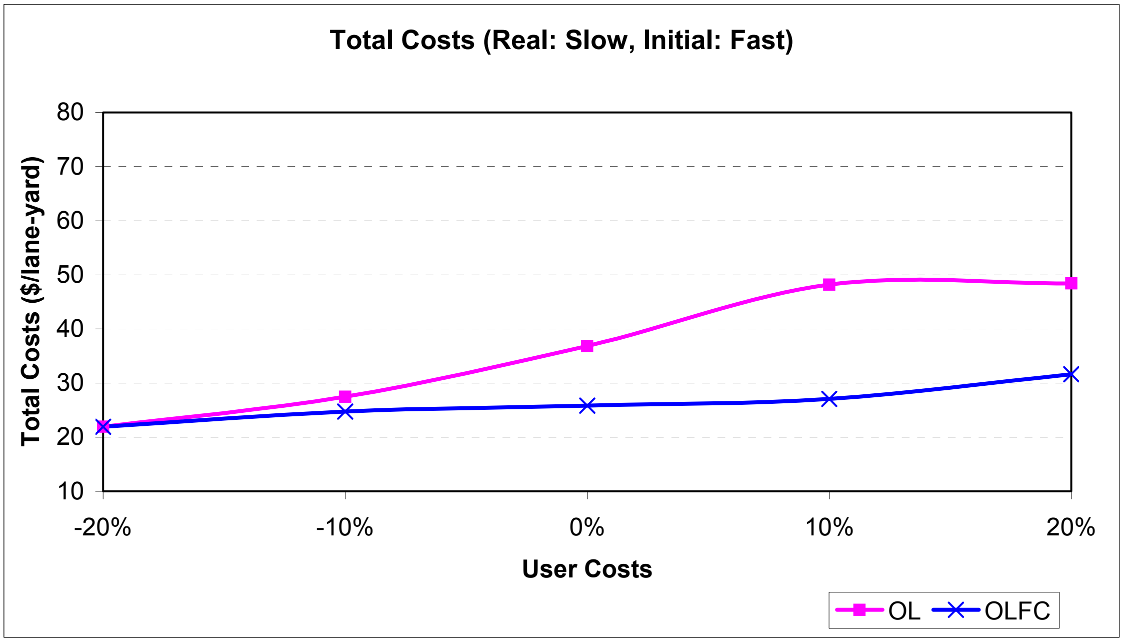


Figure 16 Sensitivity to User Costs (Real: Medium)



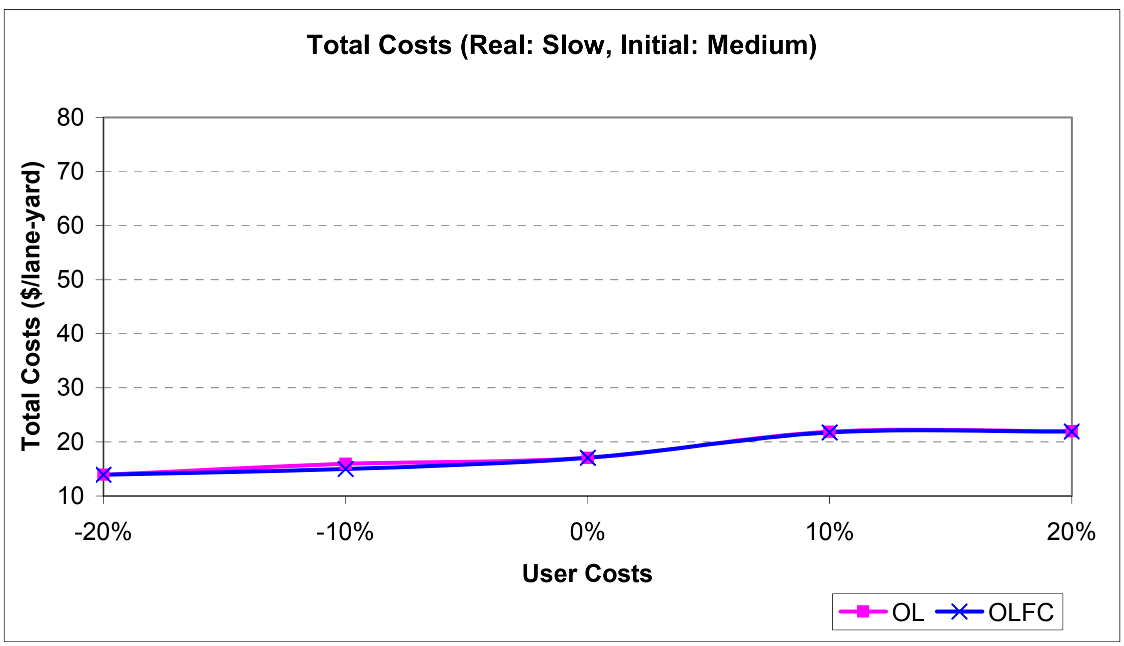


Figure 17 Sensitivity to User Costs (Real: Slow)

5.1.6 Summary

The total costs obtained by using the OL and the OLFC optimizations in all cases were shown in the above Figures. It can be seen that the total costs from the OLFC were lower than the total costs from the OL in all cases. The OLFC approach produced cost savings with the percentage savings ranging from 0.12% to 30.59%. The weighted average differences between the real transition probabilities and the estimated probabilities in each year in all cases were shown in Figure 7, 9, and 11. When the real deterioration rate is slower, most of the convergence in transition probability matrices occurred in a short period.

5.2 Alternate Inspection Frequencies

A parametric study was performed with the relaxation of the annual inspection assumption. As explained before, in the optimization with alternate inspection frequencies, it was assumed that inspections are implemented with a given frequency, and the updating and selection of MR & R policies are performed only when inspections are carried out.

In this section, the total costs with the annual inspection strategy and with the alternate inspection frequencies are compared. In the OLFC with alternate inspection frequencies, the total costs were calculated with five different inspection frequencies: 1 year, 2 years, 3 years, 4 years, and 5 years. Inspection frequencies longer than 5 years were not considered because they are not realistic. For the alternate inspection frequencies, only the OLFC was considered. The optimal inspection frequency was selected by choosing the frequency that produced the minimum total cost. First, it was assumed that the inspection cost was 10% of the average MR & R costs, which is \$1.22/lane-yard. Then, the total costs were computed assuming that the inspection cost was 20% of the average MR & R costs: \$2.44/lane-yard. Finally, the optimal inspection frequencies in these two cases were compared. Figure 18 shows the total costs for each inspection frequency when the inspection costs are 10% of the average MR & R costs.

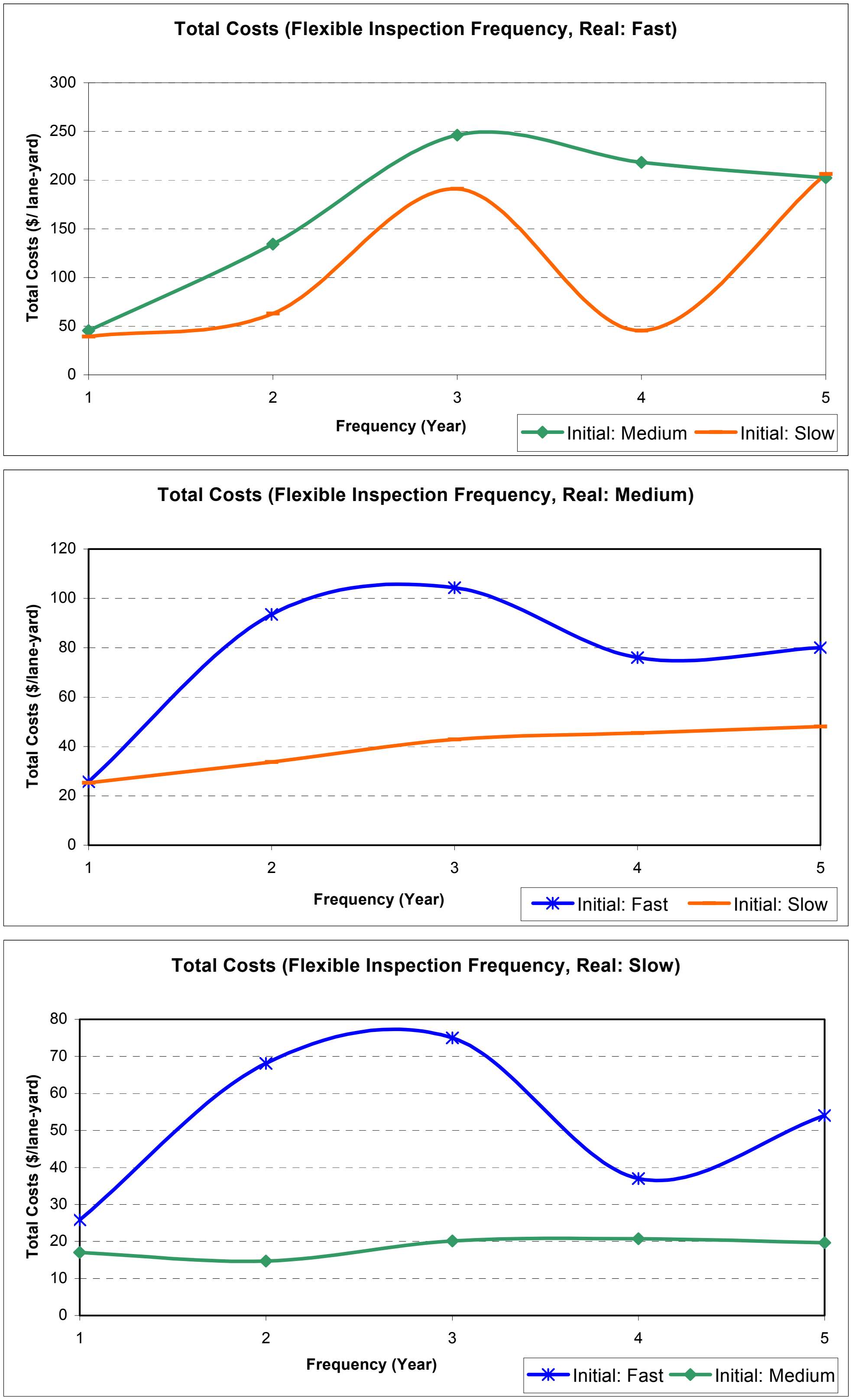


Figure 18 Total Costs when Inspection Cost is 10% of average MR & R costs

As can be seen in the above Figures, the annual inspection is the optimal policy except in one case: the real process is slow and the initial process is medium. In some cases, the total costs decreased significantly with 4-year inspection frequency. Here, the savings in inspection cost were very large but the savings were not large enough to offset the increased costs associated with performing MR & R activities.

The total costs for each inspection frequency when the inspection costs are 20% of the average MR & R costs are shown in Figure 19.

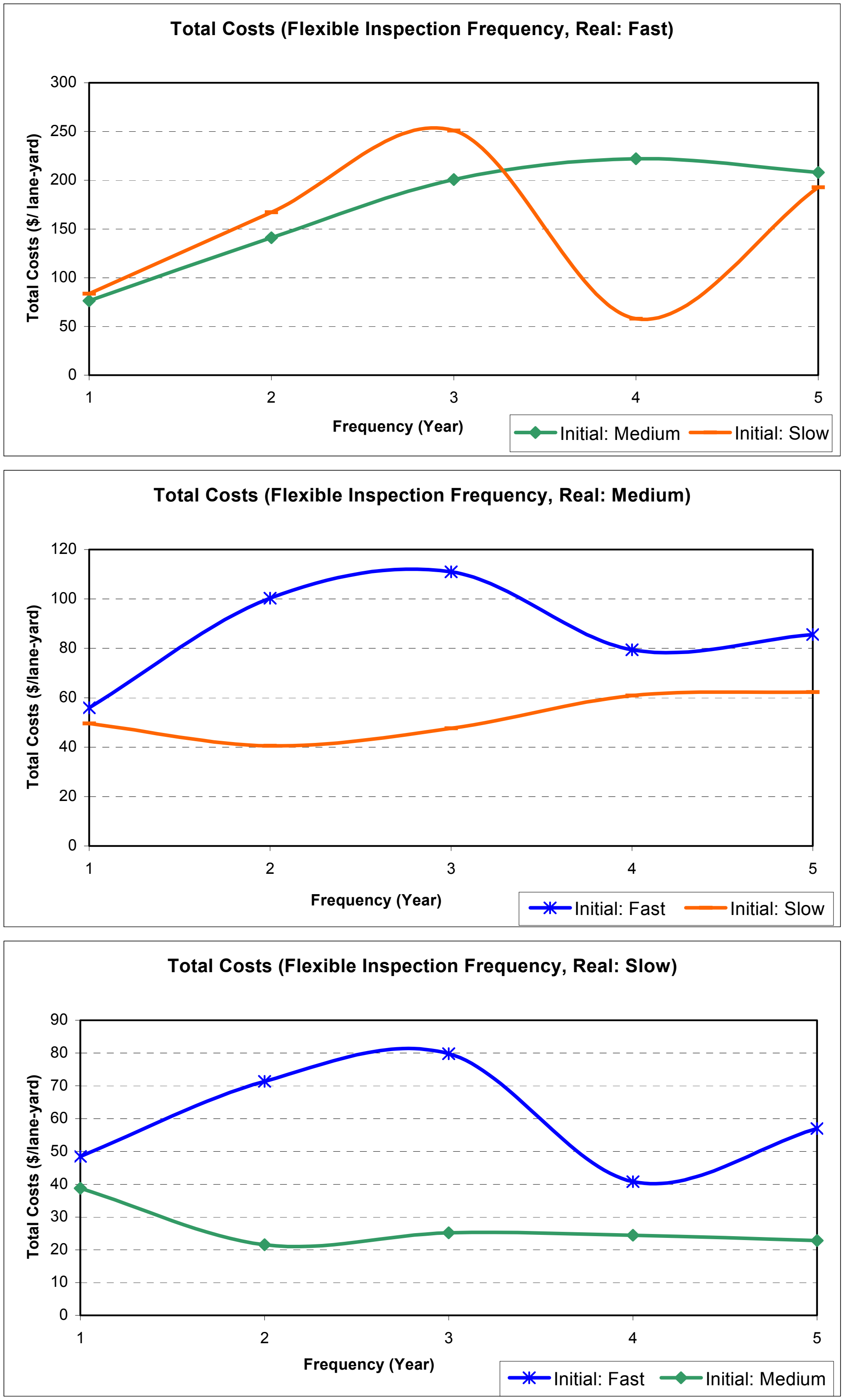


Figure 19 Total Costs when Inspection Cost is 20% of average MR & R costs

When the inspection cost increases to the 20% of average MR & R costs, in two cases that the optimal frequency was once every four years. A two-year inspection headway was optimal in two other cases: the real rate was medium and the initial rate was slow and vice versa. Thus, in these four cases, optimal inspection frequencies were longer than when the inspection cost was 10% of average MR & R costs. This is because the cost savings in inspection cost were large enough to offset the increased costs associated with performing MR & R actions.

Chapter 6
Conclusion

6.1 Concluding Remarks

In Infrastructure Management, it has been traditionally assumed that the initially selected performance model represents the real facility deterioration process, so it can be applied constantly over the planning horizon. This assumption ignores the limitations of expert judgment and empirical observations. The initially selected performance model may not represent the real deterioration process so inappropriate MR & R policies may be selected with the incorrect performance models. As a result, total costs may increase. On the other hand, if we can update the initially selected deterioration models with data from inspections, the updated deterioration models are expected to represent the real performance of infrastructure facilities more accurately. It is expected that more appropriate MR & R policies are selected, thus reducing the total costs.

In this dissertation, an adaptive infrastructure network MR & R optimization methodology that incorporates updating of transition matrices was presented. The methodology is based on an Open Loop Feedback Control (OLFC) approach. This methodology was also extended to select both optimal MR & R policies and inspection frequency. The results from the parametric studies underscore the importance of the improvement of performance models. Parametric studies showed that the OLFC can lead to substantial cost savings over the Open Loop (OL) approach where the transition matrices are assumed fixed over time. The parametric study also demonstrated that the total costs were further reduced by using alternate inspection frequencies. This is consistent with the results obtained by Madanat and Ben-Akiva (1994), which proved that savings in total costs were achieved by jointly optimizing MR & R and inspection policies when the initial performance models were assumed to be accurate.

This dissertation showed that the transition probabilities corresponding to the selected policies converge to the true values by updating using MLE when t goes to infinity. However, the selected policy and the optimal policy are not necessarily the same since only a subset of transition probabilities of the selected actions and visited states converges to the true values.

6.2 Future Research Directions

There are three issues to be resolved as extensions of this research. First, it was assumed that the infrastructure network is homogeneous in this dissertation. In reality, however, infrastructure facilities in a network might have different deterioration processes. When the deterioration processes of each facility can be determined, the facilities can be grouped according to their deterioration processes. The optimization method proposed in this dissertation can be applied to each subgroup. When the deterioration process of each facility cannot be determined, the research presented in this paper can be extended to consider heterogeneous networks. A possible approach to use in that case: the optimization method for heterogeneous network with the OL was developed by Durango (2002).

Second, it was assumed that transition probabilities representing the deterioration process of infrastructure facilities were constant over time. In Mishalani and Madanat (2002), however, it was shown that facility deterioration is more accurately represented by time-varying transition probabilities. As mentioned earlier, the time-variance can be captured slowly by the updating. However, the optimization methodology presented in this dissertation, will not be used to consider time-variant transition probabilities since the condition states of facilities cannot reach a steady-state distribution in that case. Therefore, a different optimization methodology needs to be developed.

The third issue is the question of whether the selected policies are the same as the optimal policies for the real deterioration process. It was stated that the selected policies could be different from the optimal policies because only a subset of transition probabilities that corresponds to the selected policies and is updated and converges to the true values. One way to solve this discrepancy is to use systematic probing.

An early period of the planning horizon is defined as a probing period in the systematic probing. During the probing period, every MR & R action is applied to every state to have sufficiently large number of observations to update all transition probabilities. In year t, $(1-\varepsilon^t)\cdot 100\,\%$ of facilities receive the optimal actions which are selected by the optimization while $\varepsilon^t \cdot 100\,\%$ of facilities receive random actions. Here, ε^t is the fraction of facilities to which random actions are applied. We will reduce this fraction with t since the number of observations corresponding to every MR & R action and every state gets larger with t. As a result of probing, all transition probabilities will be updated because all MR & R actions have been applied to all states. At the conclusion of the probing period, the selected policy and the optimal policy will coincide after all transition probabilities converge to the true values.

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