LIFE-CYCLE MANAGEMENT FOR SUSTAINABLE INFRASTRUCTURE SYSTEMS USING STOCHASTIC DYNAMIC PROGRAMMING AND EVOLUTIONARY ALGORITHMS

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ABSTRACT

The objective of this paper is to develop a comprehensive framework for Life-Cycle optimization of large infrastructure systems, and identify the procedure of searching optimal multistage maintenance actions and schedules with multi-objective goals. The complex optimization problem is solved by a decomposed two-phase approach. In facility level, an integrated method that combines stochastic duration model with dynamic programming is developed to identify the optimal maintenance actions and schedules for individual infrastructures under various states. In system-level, the problem is formulated by combinatorial optimization with multiple objectives and multiple budget constraints. A heuristic algorithm based on NSGA II and simulation is proposed to identify the systems optimal maintenance decisions and estimate the future budget requirements. To demonstrate the advantage of the model, we present a numerical example of pavement preservation management system. The studies captured the stochastic property of infrastructure deterioration, provided the optimal strategies to allocate the limit budget, analyzed the trade-off between economic costs and emissions, and demonstrated the importance of embracing a life-cycle perspective.

BIOGRAPHICAL SKETCH

Yan Deng began her M.S./Ph.D study at Cornell University in August 2013, majoring in Transportation Systems Engineering, minoring in Operation Research, under the advisement of Professor Oliver Gao. Prior to Cornell, she received her B.S. from Southeast University in Nanjing, China, majoring in Highway and Bridge Engineering. Her research interests focus on the areas of urban infrastructure asset management, life-cycle assessment, life-cycle optimization, and infrastructure resilience.

For my father Weiyin Deng, mother Zhongling Yan,

and my boyfriend Yu Su

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LCA	Life-Cycle Assessment
LCC	Life-Cycle Cost
NSGA II	Non-dominant sort Genetic algorithm II
VOT	Value of Time
AADT	Annual Average Daily Traffic
PSI	Present Serviceability Index
IRI	International Roughness Index
FCF	Fuel Consumption Factor
EF	Emission Factor
GHG	Greenhouse Gas

CHAPTER 1

INTRODUCTION

1.1 Motivation

Infrastructure systems are fundamental elements of the urban systems. It provides substantial socioeconomic benefits to our society and satisfies the ever increasing human demands. The quality of life, economic prosperity and security depend crucially on the conditions of urban infrastructure. However, because of the shortfalls of budget and the increase of the user demand, the deterioration of infrastructure systems has placed huge burdens on the government. It's shown that urban infrastructure maintenance and rehabilitation (M&R) becomes one of the most costly activities [1]. Under the limited budget level, an effective resource allocation strategy is critical for the decision maker to manage the portfolio of infrastructure assets, maximize the economic and social benefits from both agency and user perspectives.

In addition to the economic cost, previous work has proved that infrastructure management decisions have significant impact on environmental emissions [2]. With increasing exhaustion of resources and destruction of the environment globally, the need for more sustainable infrastructure system management becomes even more critical. Therefore, it's important to develop specific tools and strategies for decision making on operating and maintaining urban infrastructure system efficiently and effectively, with attends to optimize and balance the multiple objective goals such as

saving the economic cost and improving the environmental performance for the Life-cycle.

As the magnitude of agency expenditures and user costs, infrastructure management has been an important topic since 1980s. Yeo, and Madanat, etc (2010) developed a bottom-up approach for MR&R activities optimization considers a system with independent infrastructures [3]. Their study demonstrated the feasibility of incorporating the facility level and system level optimization. The study is limited to the single objective formulation and budget planning strategy, which are significant in maintenance decision making. Zhang, and Keoleian, etc (2010) developed a life-cycle optimization (LCO) model for pavement overlay systems [4], and applied it to Michigan Highway systems, to generate the optimal preservation strategies for three overlay systems with the multiple objectives. However, their primary goal is to compare three different construction materials. Ibanez and Gkritza (2010) [5] developed a transportation and energy systems modeling approach by grouping the objective in to three categories as cost, sustainability and resiliency. However, they didn't provide the specific method to quantify multi-objective goal and solve the optimal solutions.

1.2 Research Objectives and Methodology Framework

The work presented therein address the limitation described in the preceding paragraph. The objective of this paper is to develop a comprehensive framework for Life-Cycle optimization of a portfolio of infrastructure assets, and identify the procedure of searching optimal multistage maintenance activities and maintenance

schedules under multiple budget levels with multiple objectives. The methodology framework is shown in Figure 1-1. The specific research tasks includes:

(1) To develop facility-level model for for an infrastructure, captures the infrastructure deterioration uncertainty by stochastic duration model, develops a life-cycle inventory with Life-cycle cost (LCC) and Life-cycle assessment (LCA) models, determines the multistage optimal maintenance activities and schedules.

(2) To develop system-level model for management policy for a portfolio of infrastructure assets, explore the resources allocation strategy for multiple infrastructure assets within the budget constraint, analyze the impact of decision making under various budget levels, explore the policy implication, and predict the future budget plan.

(3) To investigate the maintenance strategies for infrastructure sustainability under different optimization objectives, explore the Pareto-Frontier of non-donimant multi-obejcteive decisions, evaluate the impact on policy implication from the objective as saving economic cost and reducing environmental emissions.

Methodologically, the complex optimization problem is solved by a decomposed two-phase approach. In facility level, an integrated method that combines stochastic duration model with dynamic programming is developed to identify the multistage optimal actions for individual infrastructure. In system-level, the problem is formulated by combinatorial optimization with multiple objectives and multiple budget constraints. A heuristic algorithm based on NSGA II and simulation is proposed to identify the systems optimal maintenance decisions and schedules.

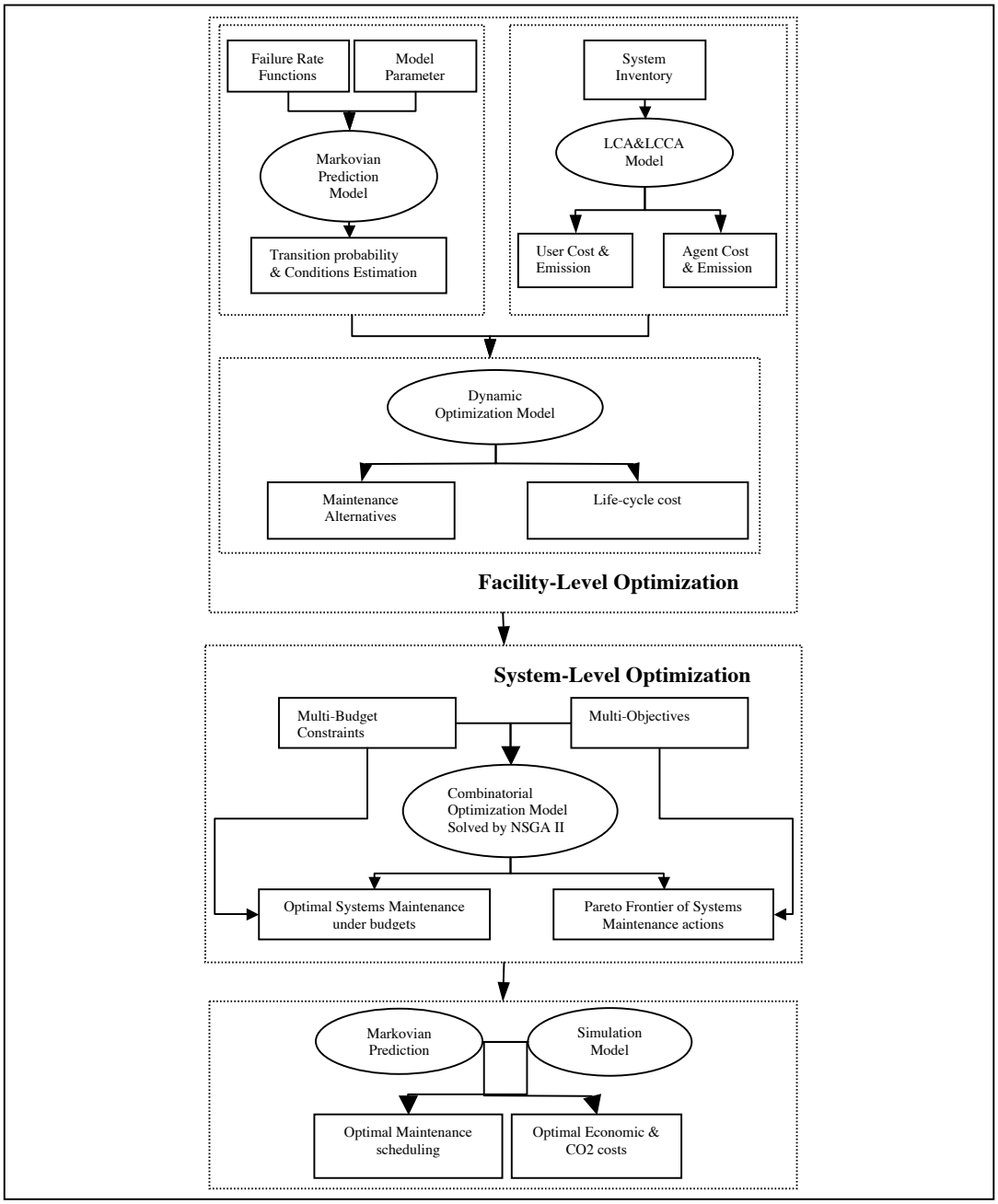

FIGURE 1-1 Methodology Framework

CHAPTER 2

MODELING OF FACILITY-LEVEL INFRATRUCTURE ASSET

2.1 Introduction

There are two levels of infrastructure assets management system: the facility-level and the system-level. For the smaller scale, the facility level asset management focuses on the making the optimal strategy for a specific infrastructure, by assessing the performance condition under the deterioration, comparing different maintenance and rehabilitation options, and make the optimal decision by target objective, such as minimizing the economic cost and environmental emissions. But for another administrative level, the decision makers have to allocate the limited resources, such as the annual budget constraints, to select the maintenance priority scheme for the entire urban infrastructure systems. Here comes to the system-level infrastructure management problem. The system-level infrastructure management strategy discussed in the next chapter will be based on the decision of facility level management. At this chapter, we first discuss the facility-level life-cycle infrastructure asset management.

2.2 Multistage Maintenance Decisions Modeling

As an infrastructure manager, the goal is to choose a sequence of maintenance actions based on the conditions to allow the infrastructure performs optimally. Infrastructure condition is fluctuated because of the deterioration processes.

Infrastructure deterioration process is continuous, but the performance indicator, such as infrastructure rating, is discrete. It's appropriate to divide the infrastructures into a set of states based on the discrete rating indicators. Discrete numbers, ranging from 1 to m, can be used to represent the states of infrastructures from the worse condition to the best condition. Therefore, infrastructure deterioration can be transferred into a discrete-state processes. Decisions are made at points of time, which we called it decision epochs [8]. The objective of the decision is to minimize the total costs from all epochs, in another word, to achieve the optimal life cycle costs. The mathematical formulation of the life-cycle cost optimization model would be represented in equation 2.1.

$$Min \sum_{t=0}^{T-1} \rho^t \, \mathrm{C}(x_{i,t}, \mathrm{i}) + \rho^T s_T \qquad 2.1$$

Where,

t is the epoch stage, t=0, 1… T-1 year;

i is the infrastructure condition state variable, the state set is named as S;

$x_{i,t}$ is the control variables, it's the decision made for state i at epoch t, the decision action set is named as A;

$C(x_{i,t}, \mathrm{i})$ is the net costs associated with state i, and action x_t, the cost will include both agency cost and user cost;

s_T is the salvage value function at the last stage. The value is dependent on infrastructure state.

This is a T stage optimization problem. The decisions will be made for T years, at each year we have m possible choices. In total, there are m^T possible outcomes. Basically, the optimal strategy could be ranked by comparing the costs for all possible plans by enumeration methods. However, the enumeration methods is time consuming and not feasible to find the final optimal solution for a complex problem. One of the most efficient methods which could break down this complicate problem into the some simpler sub-problems is dynamic programming [6]. Dynamic programming reduces a single n-dimensional problem into n one-dimensional problems [7]. Each of the sub-problems is defined as a stage. Then an optimal sequence of decisions can be made in the multistage from epoch 1 to T-1. The possible outcome could be reduced from dimension m^T to mT . Dynamic programming usually starts searching the optimal solution from the last state T-1, and work towards to the first stage of the optimal decision optimization problem. We called it "backward algorithm". With dynamic programming, the sub-problems with of equation (1) can be formulated by as follow:

At epoch T-1, for all states $i \in S$:

$$\begin{aligned} &V(i,T-1) = \min_{x_{i,\mathrm{T}-1} \in A} \mathrm{C}(x_{i,\mathrm{T}-1}, i) + \rho \times \sum_{j \in S} S_T(j) \times P(\mathrm{j} \mid \mathrm{i}, x_{T-1}) \\ &x^*_{i,T-1} = \arg\min_{x_{i,\mathrm{T}-1} \in A} \mathrm{C}(x_{i,\mathrm{T}-1}, i) + \rho \times \sum_{j \in S} S_T(j) \times P(\mathrm{j} \mid \mathrm{i}, x_{T-1}) \\ &\sum_{j \in S} P(\mathrm{j} \mid \mathrm{i}, x_{i,T-1}) = 1 \end{aligned} \qquad 2.2$$

…

At epoch t, for all states $i \in S$:

$$V(i,t) = \min_{x_{i,t} \in A} \mathrm{C}(x_{i,t}, \mathrm{i}) + \rho \times \sum_{j \in S} V(j, t+1) \times P(\mathrm{j} \mid \mathrm{i}, \mathrm{x}_{i,t})$$
$$x^*_{i,t} = \arg\min_{x_{i,t} \in A} \mathrm{C}(x_{i,t}, \mathrm{i}) + \rho \times \sum_{j \in S} V(j, t+1) \times P(\mathrm{j} \mid \mathrm{i}, \mathrm{x}_{i,t}) \qquad 2.3$$
$$\sum_{j \in S} P(\mathrm{j} \mid \mathrm{i}, \mathrm{x}_{i,t}) = 1$$

…

At epoch 1, for all states $i \in S$:

$$V(i,1) = \min_{x_{i,1} \in A} \mathrm{C}(x_{i,1}, i) + \rho \times \sum_{j \in S} V(j, 2) \times P(\mathrm{j} \mid \mathrm{i}, \mathrm{x}_{i,1})$$
$$x^*_{1,1} = \arg\min_{x_{i,1} \in A} \mathrm{C}(x_{i,1}, i) + \rho \times \sum_{j \in S} V(j, 2) \times P(\mathrm{j} \mid \mathrm{i}, \mathrm{x}_{i,1}) \qquad 2.4$$
$$\sum_{j \in S} P(\mathrm{j} \mid \mathrm{i}, \mathrm{x}_{i,1}) = 1$$

Where,

$V(i,t)$ denotes the optimal expected cost-to-go at epoch t for state i. It is the expected costs for infrastructure from epoch t to the end of the finite period T.

$P(\mathrm{j} \mid \mathrm{i}, \mathrm{x}_t)$ is the transition probability function, it denotes the probability that the infrastructure transfers to state j at time t+1, given that it was in state i and action x_t was chosen at time t. We usually assume that the summation of $P(\mathrm{j} \mid \mathrm{i}, \mathrm{x}_t)$ by all state j is equal to 1;

ρ denotes the discount factor.

Based on equation 2.2, 2.3, 2.4, the optimal decision $x^*_{i,t}$ for all epochs at state i can be selected from the candidates set *A*. According to the principle of optimality, the

optimal solution of the original optimization problem is made up of the optimal sequence of solutions at epochs from t=1 to T-1 [7]. By the same method, the alternative decisions can be identified, while the superior decisions are excluded in the decision set A. The alternative activities $\{x_{i,t}^{1}, \ldots x_{i,t}^{m}\}$ can be found by equation 2.5.

$$
\begin{aligned}
x_{i,t}^{1} &= \arg\min_{x_{i,t} \in A - x_{i,t}^{*}} \mathrm{C}(x_{i,t}, \mathrm{i}) + \rho \times \sum_{j \in S} V(j, t+1) \times P(\mathrm{j} \mid \mathrm{i}, \mathrm{x}_{i,t}) \\
&\ldots \\
x_{i,t}^{m} &= \arg\min_{x_{i,t} \in A - x_{i,t}^{*} - \ldots - x_{i,t}^{m-1}} \mathrm{C}(x_{i,t}, \mathrm{i}) + \rho \times \sum_{j \in S} V(j, t+1) \times P(\mathrm{j} \mid \mathrm{i}, \mathrm{x}_{i,t})
\end{aligned}
\qquad 2.5
$$

Here,

$x_{i,t}^{1}$: denotes the first alternative maintenance decision; it means the first optimal choice if we cannot select the optimal maintenance decision

$x_{i,t}^{m}$: denotes the mth alternative maintenance decision.

2.3 Infrastructure Deterioration and State Transition

In this section, we are going to predict the infrastructures condition in the future years by quantifying the transition probability $P(\mathrm{j} \mid \mathrm{i}, x_{i,t})$ formulated in section 2.2. Because of the external factors, the infrastructure deterioration occurs after the construction. The management strategy is made based on the current and future condition states of infrastructures. In order to accurately predicting the infrastructures condition in the future years, a reliable infrastructure deterioration prediction model is essential. The degradation of infrastructures is a stochastic process that varies widely with several factors. Assume that within an appropriate small time interval, the

infrastructure state can only transfer from the neighborhood state, that is the infrastructure can only transferred to one state worse or remaining in the same state in the natural scenario without any maintenance activities.

There are two types of discrete-state probability model for infrastructure deterioration: the state-based model and time-based model [19]. State-based model characterize the probability that the infrastructure undergoes a change from state i to another state j at a given time, while the time-based model characterize the probability density function of the duration time of staying at state i before jumping to another state j. This paper derives a time based model from the state-based model, then the transition probability can be determined by estimating the infrastructure life distribution function $F(t)$, as shown in equation 2.6. The hazard rate function or failure rate function is derived in equation 2.7 to characterize the life distributions property.

$$\begin{aligned} P_t\left(s_{t+\Delta t} = j \mid s_t = i \right) &= P(t < T < t + \Delta t \mid T > t) \\ &= \frac{F\left(t+\Delta t\right) - F\left(t\right)}{1 - F\left(t\right)} = \frac{F(t+\Delta t) - F\left(t\right)}{R\left(t\right)} \end{aligned} \tag{2.6}$$

$$\begin{aligned} \lambda\left(t\right) &= \lim_{\mathrm{V}t \to 0} \frac{P(t < T < t + \Delta t \mid T > t)}{\Delta t} \\ &= \lim_{\mathrm{V}t \to 0} \frac{F\left(t+\Delta t\right) - F\left(t\right)}{\Delta t \times \left(1 - F\left(t\right)\right)} = \frac{f\left(t\right)}{R\left(t\right)} \end{aligned} \tag{2.7}$$

$R(t)$: denoted as the reliability function, which shows the probability that a system is still functioning after time t;

$\lambda(t)$: The hazard rate function. Assume the existent of failure distribution $F(t)$, in a continuous time sense, the hazard rate function reflect the instantaneous failure rate as Δt approaching zero.

According to the structure of stochastic dynamic programming, it's often treated as a Markov decision process [8]. The qualifier "Markov" is used because the transition probability depends on the past only through the current state of the system and the action selected by the decision maker in that state. This reflects the process is memoryless. One of the most popular life distributions with the property of lack memory is exponential distribution. We assume that the duration time T follows the exponential distribution. In that case, the probability of the transition out of the state is independent of the time spent in that state. The assumption is reasonable based on the inspect data in the previous research [9]. The cumulative life distribution function and the hazard rate function of exponential distribution shown in equation 2.8.

$$F(t) = 1 - e^{-\lambda t} \tag{2.8}$$

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{\lambda e^{-\lambda t}}{e^{-\lambda t}} = \lambda \tag{2.9}$$

$$P_t\left(s_{t+\Delta t} = j \mid s_t = i\right) = \frac{F(t+\Delta t) - F(t)}{R(t)} = e^{-\lambda \times \Delta t} \tag{2.10}$$

From the equation 2.8, 2.9, 2.10, λ is the single unknown parameter that defines the transition probability. A set of explanatory variables can be used to determine the infrastructure deterioration rate, for example, the infrastructure state and age,

surrounding environment and condition. Hence the λ is not static from all the epochs. It's necessary to replace the constant parameter λ with a function dependent on the explanatory variables. In order to ensure that λ is non-negative, we assume the deterioration rate with a non-negative function g.

$$\lambda = g(X, \beta) \tag{2.11}$$

In equation 2.11, X is a vector of explanatory variables; β is the corresponding parameter to show the weight of the explanatory variables.

The transition probability we derived before is for measuring the deterioration uncertainty in natural scenario. In our maintenance model, the infrastructure transition probability depends on the random behavior of natural deterioration, as well as the maintenance intensity which could make the infrastructure undergoes a state upgrade. Assuming that after maintenance activities, the infrastructure state upgrade can be represented as a function $h\left(x_{i,t}\right)$, while the state after upgraded cannot excesses the best state. Therefore, the facility-level infrastructure multistage maintenance decision modeling based on stochastic dynamic programming can be summarize in equation 2.12. This optimization has not constraint.

$$x_{i,t}^{*} = \arg\min_{x_{i,t}\in A} \mathrm{C}(x_{i,t},\mathrm{i}) + \rho \times \sum_{j\in S} V(j,t+1) \times P(\mathrm{j}\,|\,\mathrm{i},x_{i,t})$$

$$x_{i,t}^{m} = \arg\min_{x_{i,t}\in A - x_{i,t}^{*} - \ldots - x_{i,t}^{m-1}} \mathrm{C}(x_{i,t},\mathrm{i}) + \rho \times \sum_{j\in S} V(j,t+1) \times P(\mathrm{j}\,|\,\mathrm{i},x_{i,t})$$

$$P(\mathrm{j}\,|\,\mathrm{i},x_{i,t}) = P\left(s_{t+1} = j \,|\, s_t = \min(h\left(x_{i,t}\right) + i, m)\right) = \begin{cases} e^{-g(X,\beta)}, \; if \;\; j = \min(h\left(x_{i,t}\right) + i, m) - 1; \\ 1 - e^{-g(X,\beta)}, \; if \;\; j = \min(h\left(x_{i,t}\right) + i, m); \\ 0, \qquad Otherwise. \end{cases} \tag{2.12}$$

2.4 Infrastructure Maintenance Model Implementing Procedures

The computation for optimal multistage maintenance decisions starts at the final year of the target period, then loop back along to the first year with "backward algorithm". At the final year T, the value of the infrastructure is pre-determined based on its condition states. At each decision epoch, an inventory model is used to quantify the return of costs for each maintenance decision. The costs in this study may include agency, user economic cost, and environmental cost. For the single objective problem, for instant, if the cost refers to the economic cost, $\mathrm{C}(i, x_{i,\mathrm{t}})$ would be the summation of all the economic costs. For a given year and a given state, the programming predicts and quantifies the infrastructure expected cost-to-go for all alternatives $x_{i,\mathrm{t}}$, then the optimal decision will be the one with the minimum expected cost-to-go. The same procedure will be repeated for all the states S, and all years in analysis period T. Figure 2-1 shows the procedure of implementing infrastructure multistage

maintenance decision by stochastic dynamic programming. By completing this programming, a sequence of maintenance decisions will be generated to show the suggested optimum actions for each state in each year.

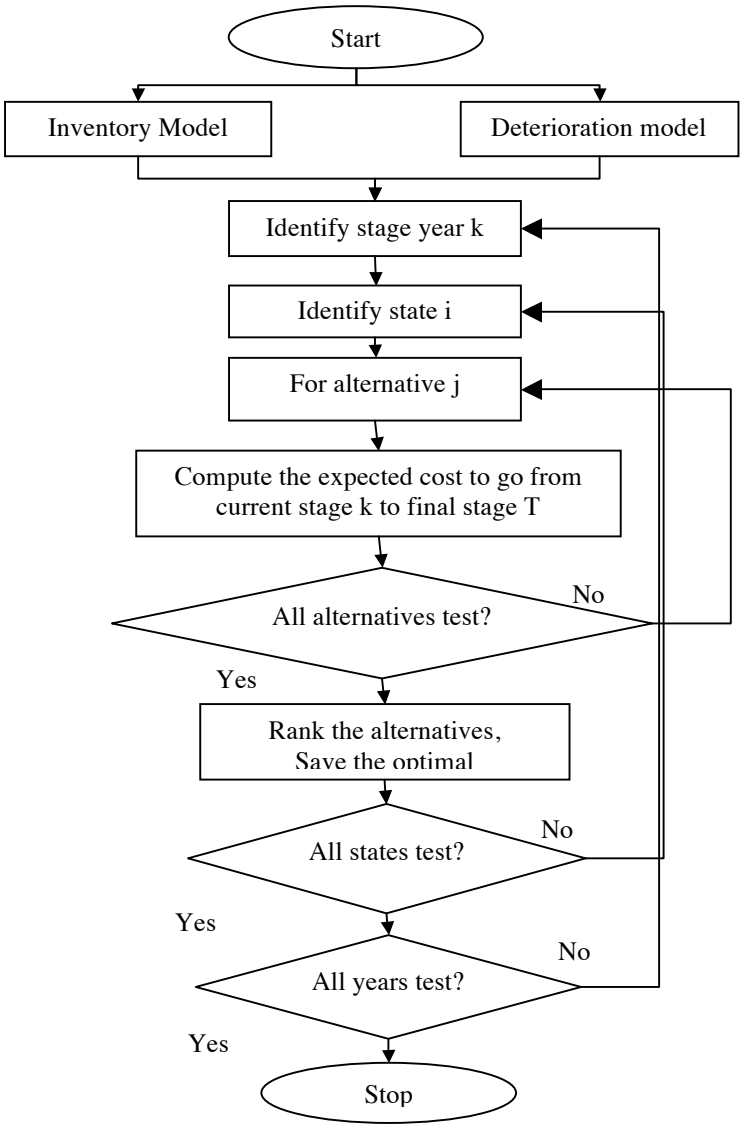

FIGURE 2-1. Facility-level optimization implementing procedure

2.5 Summary

This chapter discussed the facility-level infrastructure modeling and multistage decision making processes, which would also provide as the underlined information for the system-level infrastructure management problem in the next chapter. For the facility-level infrastructure maintenance model, a stochastic dynamic programming is proposed to solve the complicate multistage maintenance decision making. By breaking down the multistage problem into the some simpler sub-problems with dynamic programming solved by backward algorithm, the optimal maintenance decision at each epoch is identified based on the minimization of expected cost to go. Infrastructure deterioration uncertainty is capture by a stochastic duration model where the infrastructure transition probability can be quantified the based on the current state and maintenance activities. The procedure of implementing infrastructure multistage maintenance decision by stochastic dynamic programming is provided. By implementing this model, a sequence of maintenance decisions could be chosen to allow the infrastructure performs optimally with the minimum life-cycle cost.

CHAPTER 3

MODELING OF SYSTEM-LEVEL INFRASTRUCTURE ASSETS

3.1 Introduction

In the previous chapter, the facility-level infrastructure asset management model could predict the infrastructure deterioration condition, identify the optimal maintenance activities, and generate the optimum preservation schedule. Under a realistic constrained budget environment and multi-objective decision goals, prioritization scheme is essential for operating and sustainment of assets. From the perspective of urban administrative agency, a system-level optimization is important for decision maker to manage a variety of assets by allocating the limited resources, and select the maintenance priority scheme within the limited budget. There are two main functions of our system-level infrastructure management model: to provide the optimal maintenance decision for a set of infrastructures based on their conditions and the budget constraint; to estimate the system wide maintenance scheduling and plan the future budget for an analysis period.

3.2 System-Level Infrastructures Asset Management Model

By implementing the facility-level optimization model presented in chapter 2, at each decision epoch t, a set of ranked maintenance alternatives $\{x_{i,t}^{*}, x_{i,t}^{1}, x_{i,t}^{2} \ldots\}$ and their corresponding expected cost-to-go $\{V_n^{*}(i,t),\ V_n^{1}(i,t),\ V_n^{2}(i,t) \ldots\}$ are identified for

each facility n for a given condition. Based on the decisions alternatives and their expected cost to go, for any given epoch, the objective of the system-level model is to identify the optimal maintenance decisions for all facilities, to minimize the total expected cost to go for in the system, but keep the system maintenance costs under the annually budget constraint. This model is formulated as a combinatorial optimization problem, shown in equation 3.1

$$\begin{aligned} &obj: \\ &\qquad \text{Min} \sum_{n=1}^{N} f_n\left(i, x_{n,t}\right) \\ &s.t. \\ &\qquad \sum_{n=1}^{N} M_n\left(x_{n,t}\right) \le B_t \end{aligned} \tag{3.1}$$

Where,

$f_n\left(i, x_{n,t}\right)$: The value of expected cost-to-go for the infrastructure n. It depends on the infrastructure states and maintenance activities $x_{n,t}$.

$M_n\left(x_{n,t}\right)$: The maintenance costs for facility m. It depends on the maintenance activities $x_{n,t}$.

B_t : The budget constraint for epoch t.

For a given state and a given epoch, the corresponding expected cost-to-go of maintenance activity $x_{n,t}$ is quantified by facility-level optimization model. The optimal decisions would be varied depends on the objectives. In order to balance the goals from multiple stakeholders, a multi-objective optimization is necessary to

generate the Pareto-frontier for the compromised optimal decisions with multiple criteria. By simply adding multiple objectives, the system-level optimization could be formulated as a multi-objective optimization problem.

3.3 Solution algorithm

To search the optimum solution for infrastructure systems optimization, we first choose the optimal actions $x_{i,t}^{*}$ for each the infrastructures, depends on the infrastructure state and decision epoch. Then we compute the system wide maintenance cost to check if it's within the budget limit. If yes, that combination is the optimum solution. If not, the optimal action will be changed to the first alternative, if the budget constraint criteria is met, the procedure will stop and the optimum solution is found, otherwise the procedure will be repeated and the next alternative will be checked until the criteria is satisfied. Assume that there are K alternatives for N infrastructure. In the worse case, K^N combinations have to be searched. As the infrastructure increase, the problem will be computation complexity. Therefore, a heuristic optimization method will be proposed to reduce the exponential order of complexity.

Evolutionary algorithm is proposed for solve this combinatorial optimization. Genetic algorithm is one of the most popular evolutionary algorithms that mimic the mechanism of natural selection process. Genetic algorithm has the distinguish property that it can work with continuous and discrete variables, differentiable and non-differentiable functions, convex and non-convex feasible regions [10]. This property is suitable for our maintenance optimization model. For the multi-objective optimization,

Non-dominant sort genetic algorithm II (NSGA II) is used for search a set of compromised optimum solution in the Pareto-frontier [11]. The algorithm of NSGA II is developed on the foundation of GA, by adding a Non-dominant sort. There are several steps to implement the NSGA II algorithm.

(1) Decision Variable Representation and population initialization

Integer variables are used to represent the maintenance alternatives. In the Genetic algorithm, the binary number and the integer are transferable. For system wide optimization for a set of N facilities, we use a N dimension integer to represent the decision variable. Instead of randomly generating the initial population, we first choose the optimal actions for each facility.

(2) Fitness evaluation and Constraint handling

The objective value of each decision is evaluated by the summation of expected cost-to-go from each facility generated from facility-level optimization. To ensure the decision variables are feasible, the procedure utilizes a penalty method to converts a constrained problem to an unconstrained problem. An extremely large value is assigned as the penalty cost for this minimization problem, so that it could avoid the procedure to select the infeasible decision.

(3) Genetic operator

Genetic operator is used to generate the offspring from the current population. It includes parents' selection, offspring generation by crossover and mutation. Based on the fitness value, parents with a size N are selected by tournament method. The integer decision variables are transferred to a binary variables, from which we implement the single-point crossover by randomly selected a crossover point, then switch the

portions of the binary strings that occurs before the crossover point between the parents. Mutation is implemented by flipped the value (e.g. 0 to 1) with a predetermined probability. Then the offspring with a size N is generated from the parents.

(4) Non-dominant sort

The parents and offspring are combined to form a new population $R_t = P_t + Q_t$ with a size of 2N. Then we perform non-dominating sort to R_t and identify different fronts F_1, F_2… The individuals with the best multi-objective value will be in the first front. The new generation population P_{t+1} is added from F_1, F_2 and so on until the size exceeds N. The last front that makes the selection exceeds N will be sorted by crowding distant. The individuals with smaller crowding distant in the last front will be eliminated to make the size of new generation equals to N.

By implementing the NSGA II algorithm, the processes will be iterated until it exceeds the maximum generation. We compared NSGA II algorithm with other accurate optimization method in a small case to test the performance of the heuristic algorithm. After reliability verification, NSGA II is extended it to a larger case to fulfill the task of selecting approximate optimal maintenance decision for a large system network. By checking the stable converge rate after a predefined number of iteration, the efficiency of heuristic algorithm could be explored.

3.4 Summary

This chapter demonstrates the feasibility of applying two-phase optimization method for infrastructure asset management system. The phase II system-level maintenance model is used to propose the resource allocation strategy for a system of infrastructures under the limited budget constraint. It's formulated as a combinatorial optimization problem and solved with NSGA II heuristic algorithm. The steps of implementing NSGA II algorithm is described, Decision Variable Representation and population initialization, Fitness evaluation and Constraint handling, Genetic operator, and Non-dominant sort, which are the key elements of NSGA II algorithm, are described in this chapter. A system-level optimization is essential for decision maker to manage a variety of assets by allocating the limited resources, and select the maintenance priority scheme within the limited budget.

CHAPTER 4

CASE STUDY: PAVEMENT ASSET MANAGEMENT SYSTEM

4.1 Introduction

The proposed model for infrastructure system asset management can work with any kinds of infrastructures. Here a pavement system based on realistic data is created as a case to illustrate the feasibility of the proposed method.

The facility-level pavement management model is used to generate the optimal decision for one facility, and estimate the optimal maintenance scheduling in analysis period. The system-level pavement management model is used to provide the maintenance decisions for a set of infrastructures with budget constraints, and search the Pareto-frontier for the compromised optimal decisions with multiple criteria. The assumptions used, results, and policy implication are list in this chapter. A basic scenario is used to illustrate the function and present the results of this model, while sensitivity analysis is implemented to compare the fluctuation of the results when we modify the parameter of the input variables.

The parameters for the basic scenario of pavement system asset management model can be summarized as follow:

Objectives: Minimize life-cycle economic cost and the environmental emissions

Analysis period: 50 years

Functional unit: one lane mile pavement

State: Pavement serviceability level, represented by the surface roughness

Stage: Index of year in the analysis period

Decision variables: No maintenance, minor maintenance, major maintenance and reconstruction

Constraint: Keep the maintenance costs within the budget constraint

Return: Optimal maintenance decisions and the values of expected-cost to go of pavement system at each state and stage

4.2 Life-Cycle Inventory

(1) Agency and User Economic Cost

The Economic cost for maintenance includes agent cost and user cost. The agent cost is the direct cost results from the investment of maintenance activities. From the DOT construction contrast, for the Minor maintenance: Replace 10% seal, crack seal any cracked slab, the corresponding cost is $8,000/lane mile. For major maintenance: replace 30% seals, replace 15% joints, crack seal any cracked slab, its corresponding cost is $46,000/lane mile; for the reconstruction, the cost is $154,000 /lane mile. [19]

The user cost is the indirect cost that the users have to pay, it includes two parts: the detour cost and the fuel consumption results from the roughness, etc. Detour cost is the summation of detour time delay cost and detour fuel cost. The delay cost can be calculated by multiplying the time value with the additional time that the drivers have to spend in work zone compared with normal traffic condition. With the dynamic traffic growth and fuel economy improvement rate, the total user detour cost for the pavement maintenance per lane mile is described by equation 4.1:

$$Cost_{Detour} = \frac{s}{v} * VOT * AADT * (1 + r_A)^{(t-1)} * T_c + \frac{s * P}{mpg * (1 + r_f)} * AADT * (1 + r_A)^{(t-1)} * T_c \quad 4.1$$

Where,

s is the detour distance; v is the detour speed; VOT is the value of time; AADT is the Annual Average Daily Traffic volume; r_A is the traffic growth rate; r_f is the fuel economy improvement rate; T_c is the maintenance construction period; P is fuel price; mpg is mile per gallon for fuel economy evaluation.

For the baseline scenario of highway pavement system, we assumed that the detour distant is 2 mile, and the detour speed is 55 mile per hour; the value of time for vehicle is $24.5/vehicle hour; The Annual Average Daily Traffic (*AADT)* is 70000; The vehicle is assumed to have a fuel economy of 23 mpg (bureau of Transportation Statistics 2006) [20]. The fuel price is US $3 per gallon. Construction period for maintenance depends on the intensity of maintenance activities. Assuming that the construction period for minor maintenance is 35 days per lane mile, major maintenance is 65 days per lane mile, and reconstruction is 125days per lane mile.

Another important part of user cost is the user's fuel consumption cost results from the roughness of pavement surface. Discrete rating indicators K ranging from 1 to 10 is used to represent the pavement's condition, which holds the linear relation from the present serviceability index (PSI). On the other hand, we used a continuous variable, International Roughness Index (IRI) to investigate the effect of the roughness on the

fuel consumption. Since the international roughness index (IRI) has the direct impact on user cost, we use the transfer equation by Later Hall and Correa to converted PSI values to IRI [17]. IRI depends on different pavement factors including age, environment, traffic loading, pavement structure and drainage, pavement layer strength, and the amount and severity of cracking, potholes, raveling, rutting and so on. From Hall and Correa, PSI and IRI is convertible by using a transfer equation. From Zhang, H, a linear equation is used to represent the relationship between fuel consumption factor (FCF) and road surface roughness (IRI) [21]. The relations between PSI, IRI, FCF and vehicle fuel cost are represented in equation 4-2.

$$\begin{gathered} PSI = 0.5(K-1) \\ IRI = \frac{4.9879 - PSI}{0.0078 \times 63.36} \\ FCF = 0.0397 * IRI + 0.9524 \\ Cost_{IRI} = FCF * \frac{P}{mpg * \left(1 + r_f\right)^{t-1}} * AADT * \left(1 + r_A\right)^{t-1} * T_s \end{gathered} \qquad 4.2$$

Where, K is the discrete rating indicators; PSI is present serviceability index; IRI is International Roughness Index. is the each analysis period. The decision is made in each year, T_s, the length of analysis period, equals to 1 year.

(2) User and Agency Environmental Emissions

Another objective is used to represent sustainability. We view the sustainability in terms of environmental impact and air quality control. The most relevant emissions that result from maintenance management are the emissions of criteria and toxic pollutants (CO, NO_x, SO_2 particulate and VOC) and green house gas emissions (CO_2).

The objective function formula is similar with the economic cost, where the coefficients is the emission factor (EF) representing the impact per unit of energy flow in the maintenance management activities. The major source for emission production is the vehicle emissions due to the construction activities, such as detour and congestion, and the roughness related vehicle emissions. We assumed the CO_2 emission depends on the thickness of maintenance activities. The CO_2 emissions results from construction, detour, and pavement roughness are described as equation 4.3:

$$\begin{aligned} CO_{2\ construct} &= \gamma * H \\ CO_{2\ detour} &= d * \frac{EF}{mpg * \left(1 + r_f\right)^{t-1}} * AADT * \left(1 + r_A\right)^{t-1} * T_c \\ CO_{2\ IRI} &= \frac{FCF * EF}{mpg * \left(1 + r_f\right)^{t-1}} * AADT * \left(1 + r_A\right)^{t-1} * T_s \end{aligned} \qquad 4.3$$

Where, γ is the volume of CO_2 emissions per lane mile from construction; H is the maintenance pavement overlay thickness; EF is the emission factors of fuel consumption; FCF is the fuel consumption rate. The EPA estimates that for light vehicles with gasoline, there are 2.32 kg CO_2 emissions per liter of fuel [22]. Agency emissions are approximately 45,000 kg CO_2e per two-lane kilometer per cm thickness of asphalt overlay applied (Sathaye et al. 2010) [13].

4.3 Results of facility-level maintenance decisions

By implementing the facility-level pavement asset management system, we identify the global optimal solutions of the pavement maintenance strategy for the current year,

with the goal of saving the life-cycle costs of infrastructure in analysis period. The optimal maintenance decisions and the maintenance alternatives with the objective of minimizing cost are shown in Table 4-1, while the maintenance decisions with the objective of minimizing CO_2 emissions are shown in Table 4-2. With different objectives, the maintenance decisions would be varied.

Table 4-1 Maintenance alternatives for a facility with cost objective

Maintenance Alternatives	Pavement Condition									
	I	II	III	IV	V	VI	VII	VIII	IX	X
Optimal	3	3	2	2	2	0	0	0	0	0
1st	2	2	3	0	0	2	2	1	1	1
2nd	0	0	0	1	1	1	1	2	2	2
3rd	1	1	1	3	3	3	3	3	3	3

a. 3: Reconstruction, 2: Major maintenance, 1: Minor Maintenance, 0: Do nothing

b. Optimal: Optimal maintenance action, 1st, 2nd, 3rd is the first, second, and third maintenance alternatives if the optimal maintenance action cannot be implemented

c. I , II …, X represent the levels of pavement condition. I is the worst state, X is the best state

Table 4-2 Maintenance alternatives for a facility with environmental objective

Maintenance Alternatives	Pavement Condition									
	I	II	III	IV	V	VI	VII	VIII	IX	X
Optimal	3	3	3	2	2	2	2	1	0	0
1st	2	2	2	3	3	1	0	0	1	1
2nd	0	0	1	1	0	0	1	2	2	2
3rd	1	1	0	0	1	3	3	3	3	3

a. 3: Reconstruction, 2: Major maintenance, 1: Minor Maintenance, 0: Do nothing

b. Optimal: Optimal maintenance action, 1st, 2nd, 3rd is the first, second, and third maintenance alternatives if the optimal maintenance action cannot be implemented

c. I , II …, X represent the levels of pavement condition. I is the worst state, X is the best state

In addition to provide the optimal maintenance decision, another important module of this model is providing the optimal long-term maintenance scheduling. We assumed that at the beginning of the analysis period, the infrastructure is right after construction

with a perfect state, i.e. at state X. After the construction of a pavement, deterioration occurs because of the traffic load, weather condition and environmental impacts, which results in the increase of pavement roughness and decrease of serviceability level. Therefore, the pavement user's cost increase and maintenance decisions are required to satisfy the public need. Our proposed model is used to generate optimal sequence of maintenance actions for an individual pavement facility. The maintenance sequence could help the decision maker to plan their budget over the future years, maximize the resource utilization and minimize the overall life cycle cost, from both agent and user perspective.

The optimal maintenance schedules for a pavement facility in the analysis period of 50 years are shown in Figure 4-1. Because of the deterioration uncertainty, the maintenance intervals are not evenly distributed. The optimal maintenance decisions and intervals are different between the objectives of minimizing total CO_2 emissions and total cost. Compared with the two scenarios, the strategy for CO_2 objective is implementing minor maintenance with the average interval around 5 years while the strategy for cost objective is implementing major maintenance with the average interval around 12 years. This phenomenon can be explained as follows. Because of the dominance of user time delay results from maintenance activities, for the objective of minimizing economic cost, the strategy of minimizing preservation frequency or substituting several minor maintenances to a major maintenance is preferred. However, the phenomenon that higher frequency is preferred for CO_2 objective can be attributed to the absolute predominance of vehicle CO_2 emissions related with pavement surface

condition. With higher maintenance frequency, smoother pavement condition is provided to the users, which results in the saving of roughness related CO_2 emissions.

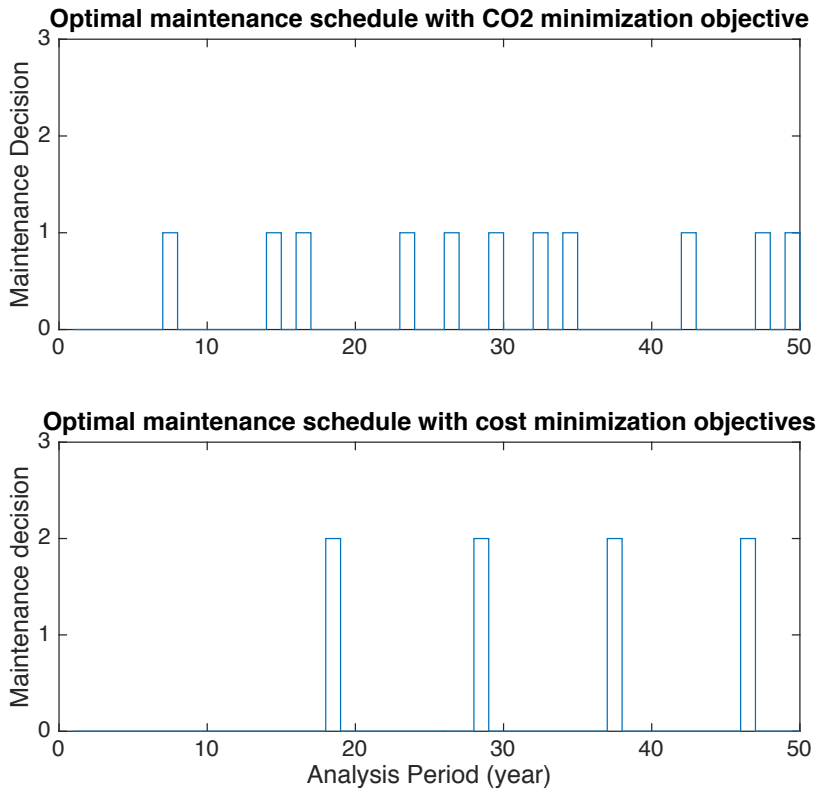

FIGURE 4-1 Maintenance schedule for a pavement facility

4.4 Results of multi-objective system-level maintenance decisions

For the system level infrastructure management, highway agencies face annual budget constraint. The budget constraint refers to the minimum available resources for highway agency to allocation among various maintenance and rehabilitation activities for a set of pavement assets in any given year. The system-level infrastructure asset management model is going to provide the optimal maintenance decisions and policy for a set of infrastructures based on their condition states and the annual budget

constraints. For illustration, we randomly generate seven facilities in the pavement system with the state {I, II, IV, V, VI, VII, VIII} at the current decision year. By implementing this models, the recommended maintenance decisions for the current year under the different budget levels with the objectives of cost and CO_2 minimization over 50 decision horizon are shown in Table 4-3, Table 4-4, respectively. Table 4-3, 4-4 also provide the agency cost, user detour cost, roughness related user fuel cost at the current year, and the saving for expected cost to go of economic cost and CO_2 emission in life-cycle.

Table 4-3 Optimal maintenance decisions with cost minimization objective

Budget (10^3\$)	Decisions	Agency cost (10^3\$)	Expected saving in economic cost-to-go (10^3 \$)	Expected saving in CO2 cost-to-go (10^3 t)	User delay time cost (10^6 \$)	User detour fuel cost (10^6 \$)	IRI related fuel cost (10^6 \$)
0	[0,0,0,0,0,0,0]	0	0	0	0.00	0.00	28.08
100	[0,0,2,2,0,0,0]	92	1170	4231	4.07	1.19	26.75
200	[2,2,2,2,0,0,0]	184	1767	7619	8.13	2.37	25.41
300	[3,2,2,2,0,0,0]	292	2100	8957	9.85	2.88	24.87
400	[3,3,2,2,0,0,0]	400	2143	9902	11.57	3.38	24.47
Infinite	[3,3,2,2,0,0,0]	400	2143	9902	11.57	3.38	24.47

Table 4-4 Optimal maintenance decisions with CO2 minimization objective

Budget (10^3\$)	Decisions	Agency cost (10^3\$)	Expected Saving in Economic Cost (10^3 \$)	Expected Saving in CO2 Emission (10^3 t)	CO2 cost (10^6 t)	Detour CO2 cost (10^6 t)	IRI related CO2 cost (10^6 t)
0	[0,0,0,0,0,0,0]	0	0	0	0.00	0.00	82.32
100	[0,0,2,2,0,0,1]	100	1166	4852	1.13	4.68	77.61
200	[2,2,2,2,0,1,1]	200	1285	8496	2.25	9.37	72.51
300	[2,2,2,2,2,2,1]	284	1455	9988	2.93	11.64	70.94
400	[3,2,2,2,2,2,1]	392	1788	11326	3.38	13.11	69.37
500	[3,3,2,2,2,2,1]	500	1831	12271	3.83	14.58	68.19
Infinite	[3,3,2,2,2,2,1]	500	1831	12271	3.83	14.58	68.19

(1) Strategy for resource allocation at multiple budget levels

Table 4-3 and Table 4-4 show how maintenance decisions change as the budget increases for the two objectives: saving life-cycle expected cost to go and CO_2 emissions. At low budget level, highway agent has limited resources to implement appropriate maintenance activities. Appropriate maintenance activity can be implemented as the relaxation of the constraint, so that the optimal set of decisions change because the available budget allows more maintenance activities. As a consequence, the costs and CO_2 emissions increase for the current year, but the saving life-cycle expected cost to go and GHG emissions for the next 50 years is decreased, as shown in Figure 4-2, 4-3.

When the budget increase to a certain level that it is no longer a constraint for pavement system, the maintenance decision for each facility in the system should be identical to the facility-level optimal decision shown in Table 4-1 and 4-2. For example, when the budget increases to $400,000 per mile for scenario I, and $500,000 per mile for scenario II, the facility-level optimal decisions are applied to all the facilities.

However, when the budget cannot satisfy the optimal maintenance decisions for all the facilities, alternative activities are adopted to meet the constraint. Interestingly, at a very low budget level, the optimal maintenance strategy is to spread the budget to improve the performance of all the pavements in the bad conditions, rather than spending the entire available budget to maintain the pavements in the worst condition. For instant, when the budget is equals to 200,000 dollar, the optimal maintenance strategies for both scenarios are implementing the appropriate maintenances activities

for more facilities, instead of spending all the budgets for reconstruction of facilities at very bad states, such as I and II.

(2) Maintenance strategies comparison with cost and GHG objectives

By comparing the maintenance decisions for the two scenarios at Table 4.3, and Table 4.4, when the budget increases and no longer a constraint for the system, the optimal maintenance strategy for the two scenarios are different. The explanation is similar with what we have discussed in facility-level management section. With the cost minimization objective, the optimal decision for pavement above state 5 is "doing nothing", while the maintenance decision for GHG objectives is either doing major maintenance or minor maintenance for pavement at state VI, VII, VIII. This phenomenon can be explained by the dominance of user time delay cost change as a part of user cost change in scenario 1, as shown in Figure 4-2. User time delay costs are related to traffic congestion and the vehicle extra detour time cost caused by maintenance activities. Therefore, when the pavement state is not too bad, "doing nothing" is preferred because minimizing preservation frequency or substituting several minor maintenances with a major maintenance can effectively decrease the traffic distraction from the maintenance activities. For scenario 2, however, the absolute predominance of CO2 emissions results from vehicles operating when driving through a deteriorated pavement with the increase of surface roughness (IRI), as shown in Figure 4-3. The maintenance strategy with GHG minimization objective is in favor of increasing the pavement performance, because a smoother pavement

condition is provided to the users which results in the saving in roughness related CO2 emissions.

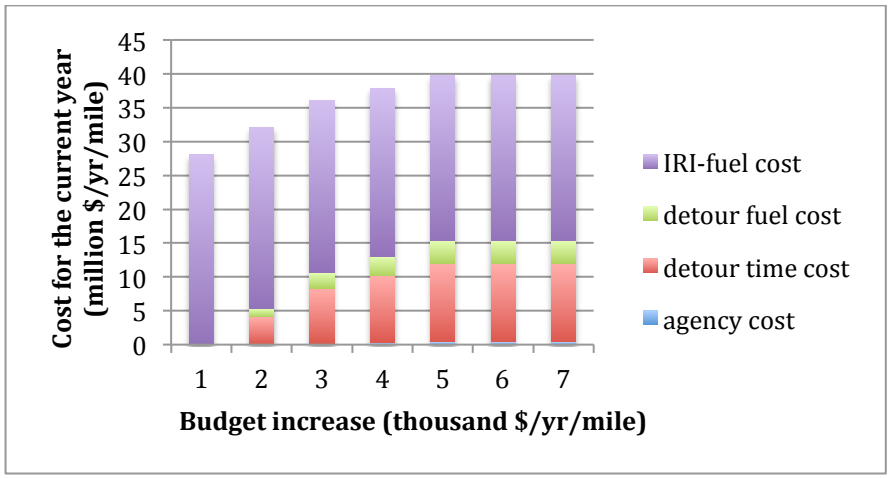

FIGURE 4-2 Economic cost for the current year as budget increase

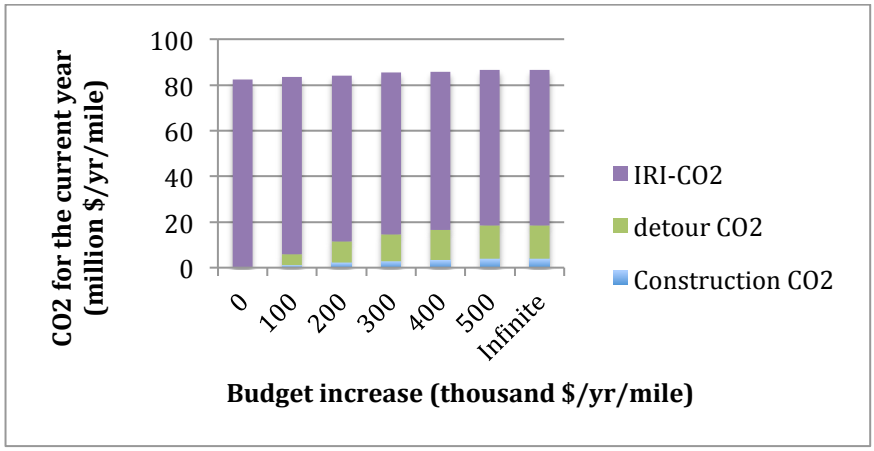

FIGURE 4-3 CO2 emissions for the current year as budget increase

(3) Pareto-frontier of maintenance decisions with cost and GHG objectives

The multi-objective pavement optimization problem is solved by NSGA II with the objectives of both economic cost and environmental cost simultaneously. The progress

of searching Pareto Frontier with generation shows in Figure 4-4. Because of the non-dominated sort and elitism selection, the algorithm converges to the optimal Pareto-frontier very quick, before generation 50. We used the solution at 500 generation as the approximate optimal solution. The same condition states {I, II, IV, V, VI, VII, VIII} are used again for the pavement system as illustration. Based on multiple budget constraints, the multi-objective non-dominant optimal solutions for each budget level are shown at table 3-3. In addition, Table 3-3 presents the life cycle expected cost-to-go with economic cost and CO2 emissions for 50-year analysis period for each maintenance decision. All the costs are scaled to represent the extra costs or emissions compared with the minimum scenario.

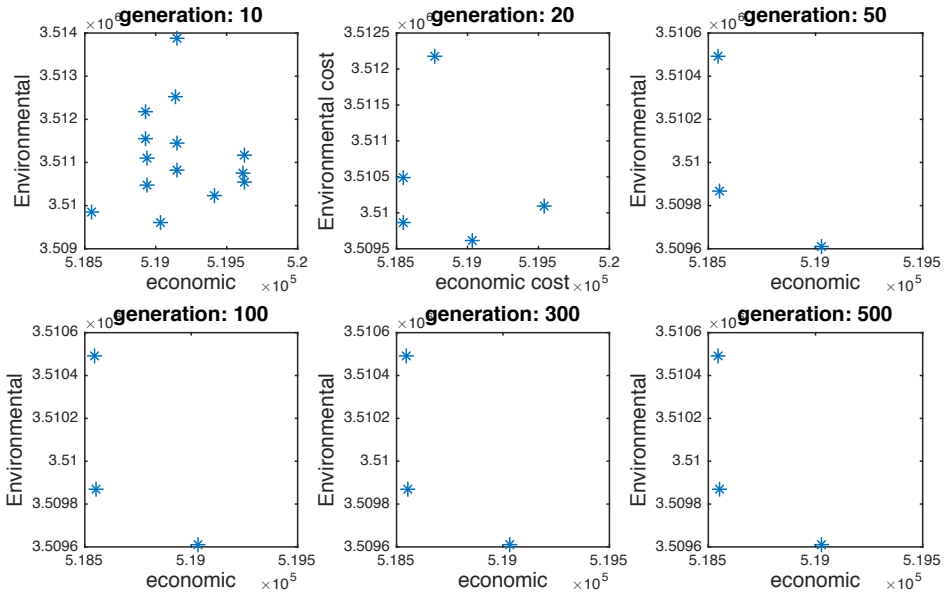

FIGURE 4-4 Multi-objective Pareto Frontier of maintenance decisions

Table 4-5 Pareto Frontiers of maintenance decisions for multi-objective goals

Budget levels (Thousand $)	Pareto frontier of Maintenance decisions							Scaled economic cost (Thousand $)	Scaled CO2 emissions (Ton)
100	0	0	2	2	0	0	0	0.0	621
	0	0	2	2	0	0	1	3.6	0
200	2	2	2	2	0	0	0	0.0	877
	2	2	2	2	0	0	1	3.6	256
	2	2	2	2	0	1	1	482.1	0
300	3	2	2	2	0	0	0	0.0	1031
	3	2	2	2	0	0	1	3.6	410
	2	2	2	2	2	2	1	644.3	0
400	3	3	2	2	0	0	0	0.0	1424
	3	2	2	2	2	0	0	53.1	1299
	3	2	2	2	2	0	1	56.7	678
	3	2	2	2	2	2	0	351.7	621
	3	2	2	2	2	2	1	355.3	0
500	3	3	2	2	0	0	0	0.0	2369
	3	3	2	2	0	0	1	3.6	1748
	3	3	2	2	2	0	0	9.5	1299
	3	3	2	2	2	0	1	13.1	678
	3	3	2	2	2	2	0	308.1	621
	3	3	2	2	2	2	1	311.7	0

This multi-objective optimization analysis makes the infrastructure management more flexible and easy to control. From table V, if the agent faces a huge economic burden, the decision maker could adjust the preservation strategy by reducing the maintenance frequency and allocate their resources to maximize the benefits; on the contrary, if the budget is allowable, the decision maker can increase the maintenance frequency to reduce the pavement roughness, improve their environmental performance and enhance the comfort level for users. The decision selection among all the non-dominating optimal solutions will depends on the weight of each objective. At this special case with the multi-objectives of saving economic cost and reducing CO_2

emissions, if a carbon price is defined, the multiple non-dominant solutions will be converted to a single solution, which could be suggested as the optimal maintenance strategy with multi-objective goals under a certain carbon price.

(4) Strategy to design the budget at current year

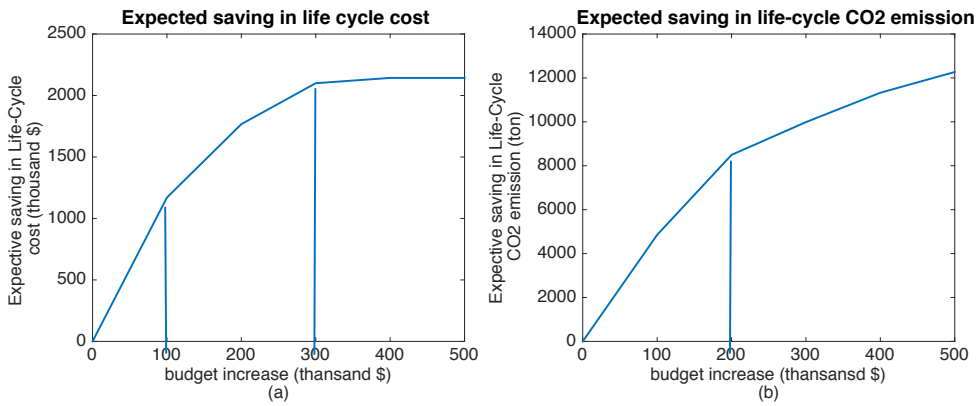

FIGURE 4-5 Expected saving in life-cycle cost and CO2 emission as budget increase

From Figure 4-5 (a), as the budget increases from 100, 000 dollar per mile to unlimited, the expected life-cycle economic cost saving increases while the marginal saving decreases. The first 100,000 to 200,000 dollar is strongly recommended by the marginal improvement of pavement systems. From Figure 4.5 (b), the first 200,000 dollar is strongly recommended by the marginal improvement of CO_2 emissions the pavement system.

(5) Pavement system state transition under optimal maintenance schedule

The pavement deterioration is a stochastic processes that each individual facility has a different randomly deterioration manner. Our proposed method is capable to capture the stochastic deterioration path, estimate the expected state and generate the optimum strategies. Figure 4-6 shows one simulation sample of the state transition for

a pavement facility and pavement systems under the optimal maintenance activity. It indicates that when the pavement condition falls to the state of 5, a major maintenance activity is recommended to implement. The maintenance activities result in a large improvement of pavement condition. The result is identical with the facility-level optimal maintenance strategy shown in Table 4-1 and Table 4-2, no maintenance is recommended before state 5 then a major maintenance is implemented for cost minimization objective, a minor maintenance is recommended at state 8 for CO_2 minimization objective. Figure 4-6 also represents the fact that heterogeneous behavior of seven facilities in the pavement system results from the stochastic deterioration property, but their maintenance criteria are identical.

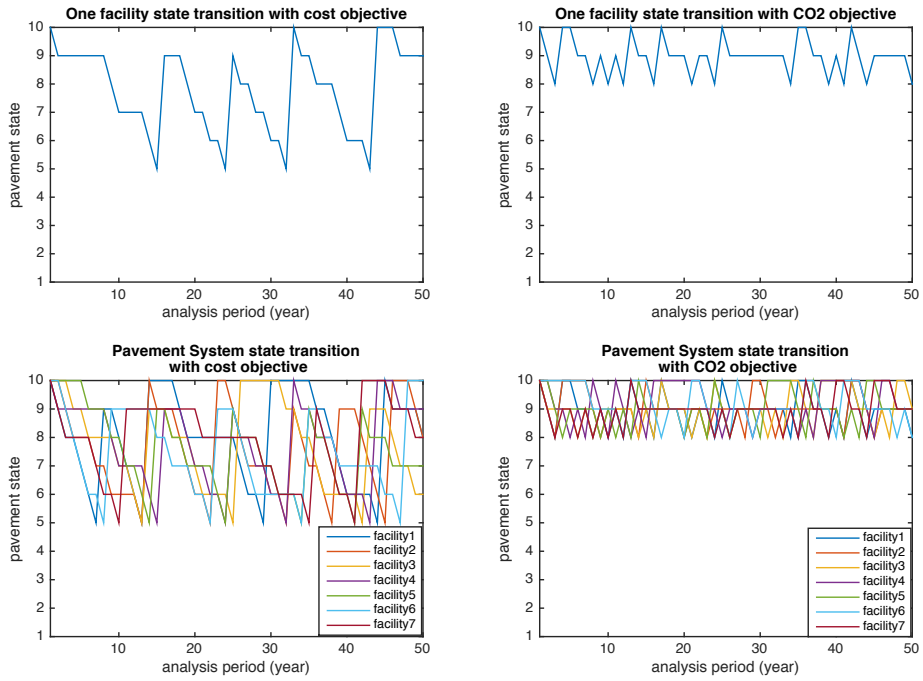

FIGURE 4-6 Infrastructure state transition under optimal maintenance

(6) Strategy to predict long-term budget plan

Figure 4-7, 4-8 represent the expected annual agency cost for maintaining the pavement systems with both management objectives, which is generated from twenty iterations of simulations. The agency cost is the agency maintenance costs from optimal maintenance schedule without the budget constraint. The maintenance sequence could help the decision maker to plan their budget over the future years, maximize the resource utilization and minimize the overall life cycle cost, from both agent and user perspective. Figure 4-7 shows the annual agency cost for optimal maintenance schedule with cost minimization objective. The average expected annual agency cost is 26.4 thousand dollar. Figure 4-8 shows the annual agency cost for optimal maintenance schedule with CO_2 minimization objective. The average expected annual agency cost is 11.6 thousand dollar. Compared with the maintenance strategy with cost objective, the agency annual expenditure for maintenance with CO_2 objective is much less and more stable. The results indicate that the minor maintenance strategy with higher frequency can help agency to save annual expenditure, because of the maintenance cost of minor maintenance as $8000 per lane mile is much less than the major maintenance, with $ 46,000 per lane mile. However, with the objective of minimizing life-cycle cost of both agency and user, the higher frequency of maintenance is not preferred because of the disruption of traffic flow would results in a huge user costs.

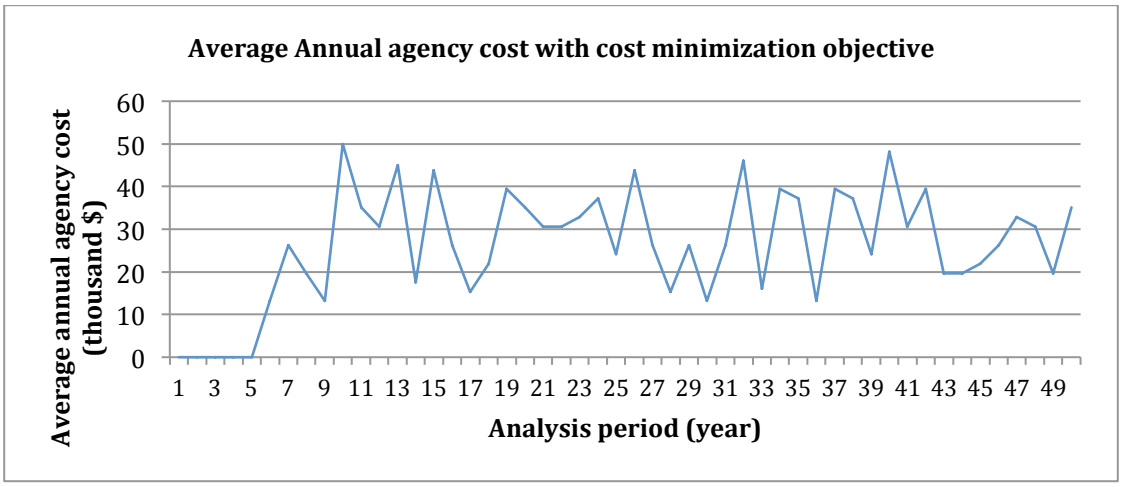

FIGURE 4-7 Average annual agency maintenance cost estimation with cost objective

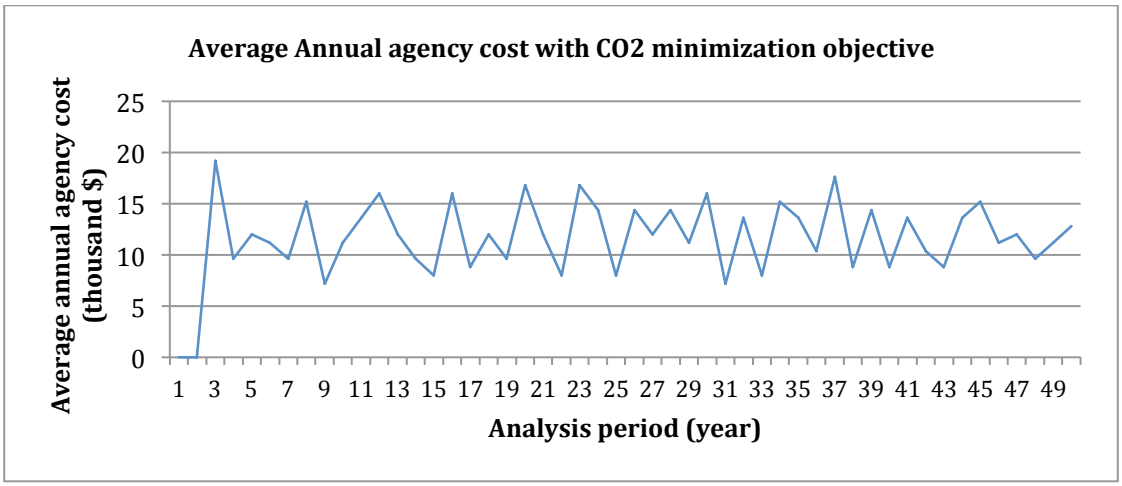

FIGURE 4-8 Average annual agency maintenance cost estimation with CO2 objective

4.5 Sensitivity Analysis

The results presented before are based on a baseline scenario that represents standard industry practices. It's worthwhile to examine the influences of different parameters on the result of optimal maintenance strategy. In this section, several key input parameters are systematically varied and then compared to the base scenario.

This analysis focuses on the following parameters: analysis horizon, discount rate, traffic volume, vehicle fuel economy, and time value.

(1) Decision horizon

In the base scenario, the time horizon for analysis period is 50 years. Additional scenarios are created in sensitivity analysis to represent a range of time horizon from 1 year to 100 years. The goal is to compare the pavement systems cumulative cost in 100 years for various analysis periods. When the analysis period is shortening to 1 year, the optimal maintenance decision is determined by the minimization of the total cost in the current year. The results shown in Figure 4-9 indicate that the cumulative economic cost for one mile pavement is decreased exponentially as the analysis horizon increases. In additions, the cumulative cost decrease as the extension of decision period, while the decreasing rate is diminished. The difference of cumulative costs results from 50 year decision period and 100 year decision period is not significant. The importance of long-term decision making could also be demonstrated from Figure 4-3 and Figure 4-4 that the optimal maintenance actions turn out to increase the cost of the current year but save the expected total cost in the analysis period. This indication particularly emphasizes the importance of taking the life-cycle perspective into decision-making, instead of the current decision year.

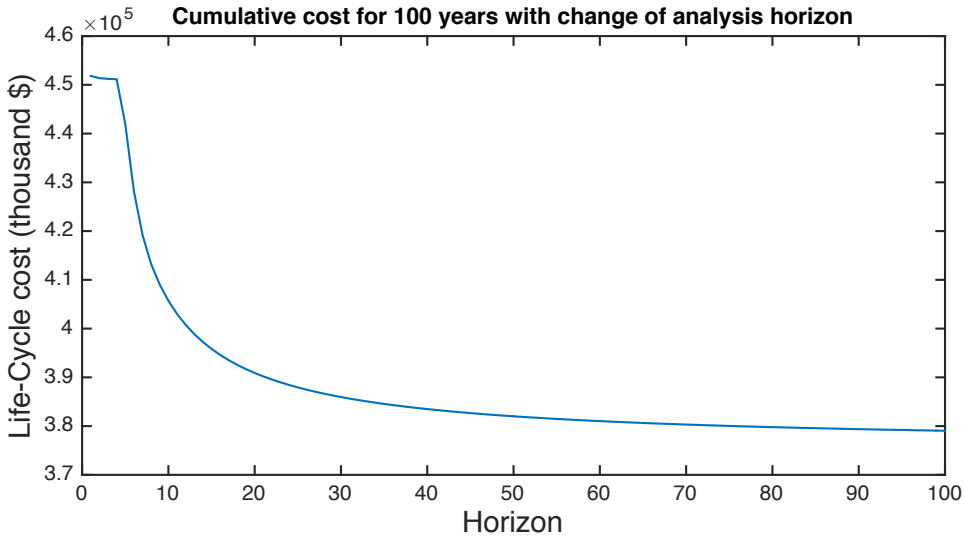

FIGURE 4-9 Cumulative cost for 100 years with the change of analysis horizon

(2) Discount rate

The discount rate used in the baseline scenario is 5%. A higher discount rate of 10% and was used for the analysis. From the sensitivity results, the maintenance decisions are exactly the same as the baseline scenario, though the expected life-cycle cost and life-cycle CO_2 emissions are much smaller as expected. Similarly, a lower discount rate as 3% doesn't change the maintenance decision. The maintenance decision is not sensitivity to the change of discount rate.

(3) Traffic volume

The traffic growth rate in the baseline scenario is 70000 vehicles per day. However, the traffic volume will affect user cost, traffic related fuel consumption, and CO_2 emissions by increasing the total vehicle miles traveled. By increasing the traffic volume from 70000 to 700000 AADT, we found that the maintenance strategy

changed a lot for cost objective case but change very little for emission objective case. The preservation activities occur earlier and expected life-cycle cost is much larger compared with baseline scenario. In the baseline scenario, no maintenance activities is recommended before the pavement deteriorates to state 5, while with higher traffic volume, a major maintenance is recommended when the pavement deteriorates to state 6. The maintenance decisions remain the same for CO_2 minimization case, while the expected life-cycle CO_2 emissions are much larger as expected.

(4) Vehicle fuel economy

The vehicle fuel economy as 23 mile mpg in baseline scenario were reduced by half and then doubled. In both scenarios, the change in expected life-cycle CO_2 emissions is larger than the change in cost. But the maintenance decision doesn't change in both scenarios. It shows that the optimal maintenance decision is not sensitive to vehicle fuel economy.

(5) Time value

The time value of $24.5 per vehicle hour was reduced by half and then doubled. The maintenance policy and life cycle CO_2 emission didn't change in both cases as expected. However, when half reduces the time value, the maintenance strategy for cost objective has significant change. A minor maintenance with higher frequency is recommended when the time value decreases. The result can also be explained as when the user delay cost is decreased, minor maintenance with higher frequency is preferred to improve the pavement roughness condition.

4.6 Summary

A case study with pavement management is provided to illustrate the feasibility of the proposed model. Life-cycle inventory illustrated the data modeling as the input of the optimization model. The inventory includes the quantification of pavement agency cost, user cost and CO_2 emissions. The facility-level pavement asset management model identifies the optimal maintenance strategy and estimates the maintenance scheduling for an asset in the analysis period. A pavement system with seven facilities is used to illustrate the main functions of the system-level infrastructure management model. It provides the optimal maintenance strategy for resource allocation for the system under the budget constraint, simulate the infrastructure state transition under the maintenance activities, and estimate the agency annual required maintenance expenditures with the goals of minimizing the total cost over the 50 years analysis periods.

There are some interesting policy implications. First, at a very low budget level, the optimal maintenance strategy is to spread the budget to improve the performance of all the pavements in the relatively bad conditions, rather than spending the entire available budget to maintain the pavements in the worst condition. By comparing the optimal strategies with minimizing life-cycle cost and CO_2 emissions, we found that minimizing preservation frequency or substituting several minor maintenances with one major maintenance is preferred with the objective of minimizing economic cost, while higher maintenance frequency is preferred for CO2 minimization objective because of the predominance of vehicle emissions results from pavement surface roughness condition.

CHAPTER 5

CONCLUSION

This paper developed a comprehensive framework and methodology for life-cycle management of infrastructure assets. The infrastructure asset management model identifies the procedure of searching optimal multistage maintenance decisions and long-term preservation schedules with multi-objective goals: minimizing the life-cycle cost, and minimizing the life-cycle CO_2 emissions. This model uses a two-phase decomposition formulation to identify the optimal maintenance decisions for the infrastructure systems.

Phase I is a facility-level infrastructure maintenance model. A stochastic dynamic programming is proposed to solve for the complicate multistage maintenance decision. By breaking down the multistage problem into the some simpler sub-problems with dynamic programming solved by backward algorithm, the optimal maintenance decision at each epoch is identified based on the minimization of expected cost to go. Infrastructure deterioration uncertainty is capture by a stochastic duration model. A Monte Carlo simulation is used to predict the infrastructure states under the stochastic transition. By implementing this model, a sequence of maintenance decisions for one infrastructure facility could be determined to allow the infrastructure performs optimally with the minimum life-cycle cost.

Phase II is a system-level infrastructure maintenance model. This model is formulated as a combinatorial optimization problem and solved with NSGA II heuristic algorithm. A system-level optimization is essential for decision maker to

manage a variety of assets by allocating the limited resources, select the maintenance priority scheme and make a long-term budget plan.

A case study with pavement asset management system is provided to illustrate the feasibility of the proposed model. The model explores the optimal maintenance strategies for both facility-level and system-level. It provides the optimal resource allocation for the infrastructure system under the budget constraint, simulate the infrastructure state transition under the maintenance activities, and estimate the agency annual required maintenance expenditures with the goals of minimizing the total cost over the 50 years analysis periods. The maintenance policy with minimizing life-cycle cost and CO_2 emissions are compared and discussed.

The methodologies and models proposed in the research could be further improved and extended in the following directions:

First, the infrastructure asset management system could be extended to a system composed of infrastructure with heterogeneous property. For example, the extended model could provide the resource allocation strategy for a pavement system composed diverse traffic volume for each facility, and for a system composed diverse types of infrastructures of pavements, bridges, and other types of facilities. Such extension could help the strategy making in multi-asset management. Second, the future system will be incorporated the infrastructure interdependency in modeling, evaluate the risk and enhance the infrastructure reliability and resilience in the extreme events under infrastructure interdependency.

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