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A Methodology to Determine Non-Fixed Performance Based Thresholds for Infrastructure Rehabilitation Scheduling

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A METHODOLOGY TO DETERMINE NON-FIXED PERFORMANCE BASED THRESHOLDS FOR INFRASTRUCTURE REHABILITATION SCHEDULING

A Dissertation

Submitted to the Faculty

of

Purdue University

by

Jackeline Murillo Hoyos

In Partial Fulfillment of the

Requirements for the Degree

of

Doctor of Philosophy

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To my parents, Nelly and Efrain
To my siblings, Leidy and Efrain
To my lovely nephew, Samuel
Who are the sources of hope and power in my life

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LIST OF ABBREVIATIONS

AAAT	Annual Average Auto Traffic
AADT	Annual Average Daily Traffic
AAFI	Annual Average Freeze Index
AAMEX	Annual Average Maintenance Expenditures
AASHTO	American Association of State Highway and Transportation Officials
AATT	Annual Average Truck Traffic
ABC	Area Bounded by the Performance Curve
AC	Agency Cost
ACDT	Agency Cost at Downtime
ACNO	Agency Cost during Normal Operations
ACS	Agency Cost Savings
ACWZ	Agency Cost at Workzone
AOC	Area Over the Performance Curve
AP	Average Performance
AUC	Area Under the Performance Curve
BCR	Benefit Cost Ratio
BTS	Bureau of Transportation Statistics
CE	Cost Effectiveness
CPI	Construction Price Index, Consumer Price Index
CRF	Capital Recovery Factor
DOT	Department of Transportation
EUACP	Equivalent Uniform Annual Cost to Perpetuity
FHMA	Functional Hot Mix Asphalt
FHWA	Federal Highway Administration

GA	Genetic Algorithm
HMA	Hot Mix Asphalt
INDOT	Indiana Department of Transportation
IRI	International Roughness Index
IS	Interstate
LBC	Lower Boundary Condition
LCCA	Life-cycle Cost Analysis
M&R	Maintenance and Rehabilitation
MOE	Measure of Effectiveness
NHS-NI	National Highway System – Non Interstate
NNHS	Non-National Highway System
PCCP	Portland Cement Concrete Pavement
PI	Performance Indicator
PJ	Performance Jump
PSI	Pavement Serviceability Index
PWC	Present Worth Cost
PWCP	Present Worth Cost to Perpetuity
SHMA	Structural Hot Mix Asphalt
SL	Service Life
SPPW	Single Payment Present Worth
UC	User Cost
UCDT	User Cost at Downtime
UCNO	User Cost during Normal Operations
UCS	User Cost Savings
UCWZ	User Cost at Workzone
UDC	User Delay Cost
UPC	Upper Boundary Condition
VOC	Vehicle Operating Cost

LIST OF SYMBOLS

ABC_{S_i}	Area Bounded by the Performance Curve of the strategy S_i
AOC_{S_i}	Area Over the Performance Curve for the strategy S_i
AP_{S_i}	Average Performance corresponding to Strategy S_i
AUC_{S_i}	Area Under the Performance Curve for the Strategy S_i
C_{AY}	Cost of Intervention in the Analysis Year
C_{BY}	Cost of Intervention in the Reference Year
CPI_{AY}	Construction Price Index or Consumer Price Index for the Analysis Year
CPI_{BY}	Construction price index or Consumer price index for the analysis year
C_{S_i}	Total Cost of Strategy S_i
$CI_{r_{S_i}}$	Cost of an Intervention r_{S_i}
CE_a	Cost-effectiveness Ratio Based on Absolute Change in Effectiveness and Absolute Change in Cost Relative to the Base Case
CE_r	Cost-effectiveness ratio Based on Relative Change in Effectiveness and Relative Change in Cost Relative to the Base Case
CE_{ABC}	Cost-effectiveness ratio Based on Area Bounded by the Performance Curve
CE_{ACS}	Cost-effectiveness Ratio Based on Agency Cost Savings
CE_{AP}	Cost-effectiveness Ratio Based on Average Performance
CE_{PJ}	Cost-effectiveness Ratio Based on Performance Jump
CE_{SL}	Cost-effectiveness Ratio Based on Service Life
CE_{UCS}	Cost-effectiveness Ratio Based on User Cost Savings
$D_{r_{S_i}}$	Project Intervention Duration
E_{S_i}	Effectiveness Associated with Rehabilitation Strategy S_i

PI_{LBC}	Lower Boundary Condition for Performance Indicator
PI_{UBC}	Upper Boundary Condition for Performance Indicator
$PI_{pre,r_{S_i}}$	Initial or Pre-treatment Condition
$PI_{t_{S_i}}$	Annual Performance for Strategy S_i
$PJ_{r_{S_i}}$	Performance Jump Associated with Strategy S_i
PJ_{S_i}	Sum of Magnitudes of Performance Jumps Associated with Strategy S_i
r_{S_i}	Intervention for Strategy S_i (r_{S_i} =1, 2, …, R_{S_i});
R	Optimal Number of Interventions Associated with Strategy S_i
R_{LB}	Lower Boundary Condition for Number of Rehabilitations
R_{UB}	Upper Boundary Condition for Number of Rehabilitations
S_i	Rehabilitation Strategy
$S_{i=0}$	Base Strategy (do-nothing strategy)
SL_{S_i}	Service Life for the Strategy S_i
$t_{r_{S_i}}$	Time to Perform a Rehabilitation at $PI_{pre,r_{S_i}}$
$T_{r_{S_i}}$	Treatment Type to Apply at each Rehabilitation Intervention
u	Interest Rate
Z_a	Objective Function (Cost-effectiveness Ratio Based on Absolute Change)
Z_r	Objective Function (Cost-effectiveness Ratio Based on Relative Change)
w_{AC}	Weighting Factors for Agency Cost
w_{UC}	Weighting Factors for User Cost
Δ	Change
Δ_E	Relative or Absolute Change in Effectiveness from a Base Strategy
Δ_C	Relative or Absolute Change in Cost from a Base Strategy
ΔABC	Change in Area Bounded by the Performance Curve
ΔACS	Change in Agency Cost during Normal Operations
ΔAP	Change in Average Performance
ΔPJ	Change in PJ Magnitudes
ΔSL	Change in Infrastructure Service Life

ΔUCS	Change in User Cost during Normal Operations
φ_{dt}	Weighting Factor for Agency at Downtime
φ_{no}	Weighting Factor for Agency at Normal Operations
δ_{dt}	Weighting Factor for Users at Downtime
δ_{no}	Weighting Factor for Users at Normal Operations
σ_{dy}	Weighting Factor for User Delay
σ_{sr}	Weighting Factor for Capacity Reduction Cost

ABSTRACT

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In an era of increasing demand and loading, aging infrastructure, and funding shortfalls, infrastructure agencies continue to seek cost-effective solutions to persistent and pervasive questions regarding the upkeep of their physical assets. One such question is the appropriateness of the current fixed condition thresholds used at several agencies for rehabilitation timing purposes, whether there is the possibility of having flexible rather than fixed thresholds, and determining what these thresholds should be. A related question is how these flexible thresholds may vary, depending on the objectives of the decision maker, the relative weight of agency and user costs, and the form of expression of the life-cycle cost associated with the candidate rehabilitation schedules. Fortunately, a number of past researchers have developed inputs that are valuable for addressing this issue. Also, there exists data from in-service infrastructure that could be used to test the hypotheses regarding the sensitivity of the optimal schedules.

This dissertation developed a methodology to address this research question. This was done for two constraint scenarios related to the direction of successive threshold levels: unrestricted and restricted. In order to optimize the rehabilitation schedules (strategies), the objective was to maximize the cost-effectiveness ratio, expressed as the change of the cost effectiveness of a candidate strategy schedule compared to that of the do-nothing strategy. Cost was measured in terms of agency cost, user cost, or both, incurred during infrastructure downtime (workzones) or during normal infrastructure operations. Effectiveness (or benefits) was measured in terms of performance jumps, infrastructure service life, infrastructure average performance, the area bounded by the performance

curve, agency cost savings, and user cost savings over the life of the infrastructure. For the life-cycle costs, three interest rates and two alternative life-cycle cost expressions were used; the present worth cost over a given service life or to perpetuity, and the equivalent uniform annual cost over a given service life or to perpetuity.

The results of the analysis suggest that, compared to the restricted scenario, the optimal strategies developed using the unrestricted scenario yield superior objective function levels irrespective of the cost-effectiveness criteria, cost weight ratio, or life-cycle cost expression used in the analysis. The results for restricted and unrestricted scenarios provided valuable insight. For the unrestricted scenario, the developed optimal strategies indicate that the subsequent rehabilitations should be applied at condition levels successively superior to the condition at the time of the previous rehabilitation; whereas the restricted scenario yielded the opposite trend: interventions are triggered when the infrastructure is in a condition worse than the previous intervention. This seems to reflect a tradeoff: while the unrestricted scenario generally yields superior cost-effectiveness values, its practical implementation may face obstacles from a public relations viewpoint. This is because the strategies offered by the restricted scenario (successively lower thresholds) gradually anticipate the infrastructure users to be increasingly tolerant of successively lower levels of service. From the case study, it was also found that the optimal solutions developed using certain cost-effectiveness criteria such as the performance jump, agency cost and user cost savings are less sensitive to life-cycle cost expression and cost component weights compared to other criteria. Finally, this dissertation discussed the consequences of hastened or deferred rehabilitations with respect to an optimal strategy. It was found that deferring rehabilitation has greater adverse consequences than hastening rehabilitation.

CHAPTER 1. INTRODUCTION

1.1 Background

1.1.1 Overall Picture (Infrastructure Challenges)

As a result of increasing populations (and the increased demand for infrastructure services), higher awareness and expectation of users, increasingly scarce resources, and in certain cases, the aging of facilities that are approaching or are past their design lives, infrastructure agencies in the public and private sectors face formidable challenges in keeping their physical infrastructure at acceptable levels of physical condition. This challenge is exacerbated by inadequate or uncertainty of renewal or repair funding (ASCE, 2013; OECD, 2015). This is the case for all the major classes of engineering infrastructure, which has been defined by the National Academy of Engineering as “the combination of fundamental systems that support a community, region, or country, and includes everything from water and sewer systems to road and rail networks to the national power and natural gas grids” (NAE, 2016). The specter and consequences of infrastructure shortfalls has been echoed by reports by OECD (2015), which stated that infrastructure can serve as a “vector of change in addressing some of the most systemic development challenges of today’s world.”

Acknowledging that infrastructure development follows a multi-phase process (Figure 1.1), infrastructure agencies seek to address this challenge during each of the eight phases of infrastructure development. In the infrastructure need assessment phase, agencies seek better ways to identify whether projects are necessary (Steadham, 1980; Zhao and Tseng, 2003); that way, the problem of “white elephants” can be avoided and resources can be channeled instead to projects that are truly needed in order to reduce waste. In the planning phase, infrastructure agencies seek to prioritize and implement projects based on the financial feasibility and technical benefits, among other sustainability-related evaluation criteria (Jeon and Amekudzi, 2005; Bell et al., 2011). This ensures that only projects with maximum yield benefits can be implemented at minimal costs (NAE, 2016). During the design phase, agencies carry out or sponsor research that produces long-lasting and flexible designs, including specification of materials with reasonable costs in order to minimize life-cycle maintenance (Frangopol et al., 2007; Rama Mohan Rao and Shyju, 2009; Flaga, 2000; Cope et al., 2013). In the construction phase, agencies adopt contracting approaches, such as public-private partnerships (PPP) and warranties that exploit the sector-specific strengths, build, operate, and maintain infrastructure cost-effectively over their life-cycle (Queiroz and Motta, 2012; Zhou et al., 2013). During the maintenance phase, they seek to optimize maintenance and rehabilitation (M&R) over the life-cycle of their infrastructure (Lam and Yeh, 1994; Wang et al, 2003; Lamptey et al., 2008; Gu et al., 2012; Yepes et al, 2016; Lee et al., 2016). In the inspections and monitoring phase, agencies seek the most cost-effective combination of manual and/or automated techniques, and their schedules to measure infrastructure usage, physical conditions, and user characteristics (Smilowitz and Madanat, 2002). During the end of life phase, agencies seek to reduce waste by reusing and recycling as much material as possible (Pacheco-Torgal et al., 2013; Smith et al., 1993).

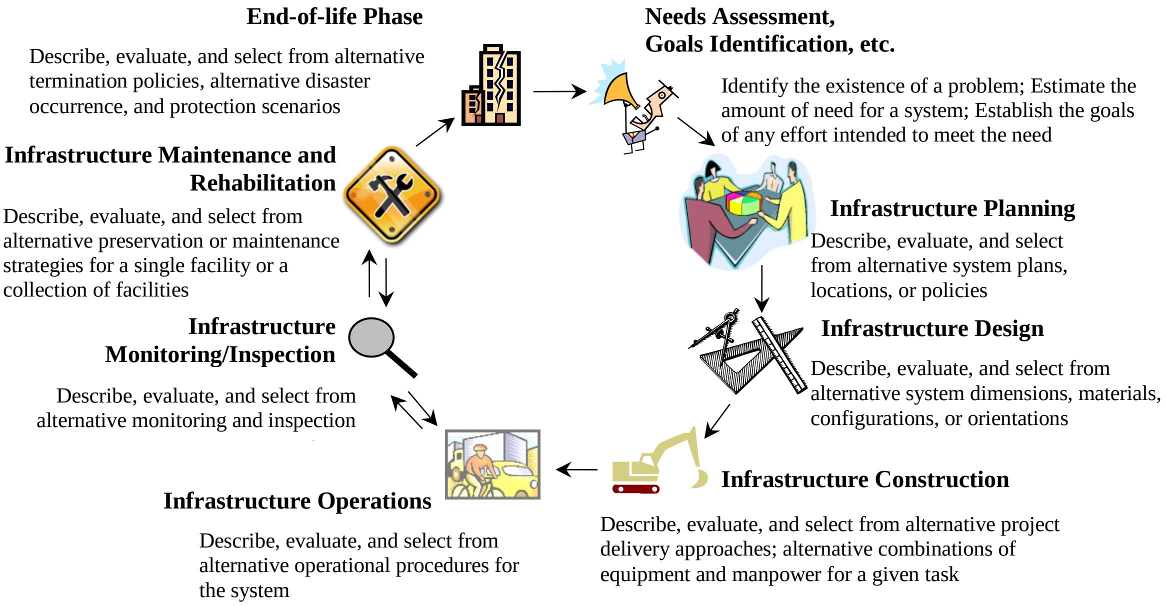


Figure 1.1 Phases of Infrastructure Development and Typical Tasks During each Phase

These efforts towards cost-effective development of engineering infrastructure during all phases are particularly critical in the current era. Anecdotal evidence suggests that, in the past, civil infrastructure have been developed in ways that were not always efficient or cost-effective. For this and other reasons, the current era, which has inherited civil engineering systems built decades ago, poses a unique set of challenges for today's civil engineers. A large portion of this infrastructure, including dams, bridges, roads, and sewers, are functionally obsolete or approaching the end of their design lives and are in need of expansion, rehabilitation, or replacement (ASCE, 2013); inadequate or aging civil infrastructure has deservedly gained international attention due to a series of well-publicized engineering infrastructure failures worldwide. The current problem of aging infrastructure is further compounded by ever-increasing demand and loading, heightened user awareness (and consequently, expectations) of facility performance, increased desires by stakeholders for participation in the decision-making process, pervasive threats of terrorism, increased specter of tort liability, and, above all, inadequate funding for sustained preservation and renewal of these infrastructure systems (NAE, 2016).

1.1.2 The Infrastructure Renewal and Repair Phase

Of the eight phases of infrastructure development, the M&R phase involves a very significant level of resources over the entire life of the asset. In this phase, a large portion of country and state budgets are spent to maintain the infrastructure in a state of good repair. It seems obvious, therefore, that by virtue of the sheer magnitude of spending in this phase, the maintenance phase offers probably the best opportunity to reduce the massive expenditures associated with infrastructure renewal and repair. Given the hundreds of billions (and in certain countries, trillions) of dollars spent annually on maintaining public and/or privately-owned or operated infrastructure, just 1% reduction in spending with the adoption of to be earned by adopting more cost-effective maintenance and rehabilitation (M&R) practices, translates into several billions of dollars.

The issue of prudent M&R choices continues to garner attention as infrastructure owners and operators continue to seek and adopt cost-effective rehabilitation and maintenance practices (Galehouse et al., 2003). Associated with this challenge is the need to adopt optimal timing policies for M&R interventions (Mamlouk and Zaniewski, 2001; Peshkin et al. 2004; Gu et al., 2012; Lee et al., 2016); the term “timing” generally refers to the infrastructure age or condition. From both theoretical as well as empirical perspectives, it has demonstrated amply in the literature that strategically-designed M&R strategies can yield significant reductions in tangible and intangible costs over infrastructure life-cycle. These costs reductions (or, benefits) are typically expressed in terms of an increased physical condition or operational performance of the asset, increase in the asset life, reduction in infrastructure user costs due to workzones or normal operations, reduction in the infrastructure owner’s costs for annual routine maintenance, overall life-cycle cost savings, or improved customer service and public relations (O’Brien, 1989; Carroll et al., 2004; Kuennen, 2005). Premature interventions (i.e., application when the infrastructure is still in good condition) may yield little or no incremental benefit and may even be associated with waste of scarce resources, even if the users enjoy the benefits of superior condition of the infrastructure. On the other hand, deferred or delayed interventions (i.e., when the infrastructure has reached an advanced state of deterioration) generally result in higher user costs due to poor conditions and even reduced asset longevity (Labi et al. 2004; Peshkin et al. 2004; Pasupathy et al. 2007). Between these two extremes of intervention frequency there exists a certain optimal trigger condition level at which the intervention should yield the highest level of cost-effectiveness. If this analysis is done collectively (not individually) for the multiple candidate treatments over the infrastructure life-cycle, the result is an M&R schedule. Then, of the multiple feasible M&R schedules, the optimal schedule (or, optimal strategy) can be identified. This is discussed in the following section.

1.1.3 Optimal Scheduling of Infrastructure Rehabilitation

Infrastructure management can be viewed from two distinct levels that are inter-dependent and synergistic: the network and project levels (Haas et al., 2006). At the network level, the decision-making processes involve the entire network of facilities within a given jurisdiction or having the same characteristics during a given time period (often limited to one year). This process follows a top-down logic and often involves optimization to select deserving infrastructure for some intervention, and aggregate nature of data. At the project level, however, the decision-making process covers an extended period of time (typically the life-cycle) of an individual facility; this level is typically more comprehensive, requires detailed information, involves a bottom-up process that combines procedures, data, software, policies, and decisions to produce solutions for each facility.

At the project level, researchers have sought to optimize M&R decisions (Lam and Yeh, 1994; Wang et al, 2003; Lamptey et al., 2008; Gu et al., 2012; Yepes et al, 2016; Lee et al., 2016). At this level of management, the optimization of rehabilitation activities can be considered a multistage decision-making process. A "stage" can be defined as the time period (number of years) between the initial treatment and the first rehabilitation intervention, two successive rehabilitation interventions, or the most recent rehabilitation intervention and subsequent reconstruction. The analysis period (often, this is the service life of the infrastructure to which the rehabilitation schedule is applied) can be divided into several stages of flexible length; a decision has to be made during each stage regarding whether a rehabilitation intervention is required or not, based on multiple considerations, including agency and user costs and benefits (these involve infrastructure condition, longevity, direct costs, and indirect costs). The application of rehabilitation intervention at any stage causes the infrastructure conditions to change, thus influencing the decision at the next stage, and consequently the entire process of rehabilitation decision making. Analysis period decisions constitute what is referred to in this dissertation as the rehabilitation schedule or strategy.

The optimal scheduling (best solution found by using a suitable optimization technique) of infrastructure rehabilitation can be a complex undertaking, due to the multiplicity of rehabilitation types and timings, the objectives associated with the decision process (Morin, 1979), and the considerable uncertainty associated with infrastructure deterioration, cost, and other decision parameters. In the specific application area of transportation, Markow and Balta (1985) listed four main aspects that describe the complex optimization of maintenance activities. First is the uncertainty of the facility performance under different conditions. Secondly, since the infrastructure performance deteriorates with time and use (loading) without maintenance, there is the need for establishing a minimum level of service or performance threshold because physical civil engineering infrastructure (including transportation infrastructures), unlike mechanical or electrical components, rarely fail catastrophically. The third aspect is the effects of various standard preservation activities on the performance of the infrastructure; these effects, in terms of the benefits and disadvantages to both the system owner and user, need to be quantified. The last is the consideration that the choice of activities in time, space, and magnitude will affect the performance of the infrastructure in different ways.

Determining the appropriate schedule for rehabilitation interventions requires a technique that makes it possible to sort through the explosion of potential combinations of when to perform an intervention and which treatment type to apply that maximizes the overall infrastructure performance and minimizes agency and user cost during workzone and normal operations. This complexity of features equates to an optimization problem with design variables some of which are continuous and others, discrete. Each combination of mixed-discrete design variables, including the number of interventions, time for the intervention, and the intervention type, results in a different design point. Selecting the time for performing an intervention is only one part of the scheduling problem; an optimal schedule features an appropriate intervention treatment regarding the cost-effectiveness between infrastructure performance, and the cost and benefits for the agency and the users. This essentially renders the rehabilitation scheduling challenge a constrained single-objective (that is, the process maximizes the schedule's cost-effectiveness). The mixed discrete non-linear programming (MDNLP) problem, in which the rehabilitation treatment frequency and type represent the discrete decision variables and the times (years) of their respective implementations are integer continuous decision variables. The engineering design literature is replete with similar problems that are single or multi-objective in nature and combine both continuous and discrete decision design variables. The resolution of problems of this nature (i.e., mixed features) continues to pose a challenge in problem settings spanning various engineering disciplines. Also, when solving problems of this general nature, there exist numerous optimization algorithms; however, relatively few algorithms, such as the evolutionary genetic algorithm, are capable of addressing all of the peculiar features of the problem addressed in this dissertation. This problem is discussed in the next section.

1.2 Problem Statement

Consistent with one of the basic tenets of asset management-to strategically and systematically maintain and upgrade the physical infrastructure effectively throughout the life-cycle-infrastructure agencies seek to make most cost-effective rehabilitation treatment decisions at the right time (FHWA, 1999; Nemmers, 2005; AASHTO, 2013). Improper timing of rehabilitation treatments over the infrastructure life can have serious consequences: premature or hastened application (treatments applied too often or too early) could mean wasteful spending, even if the users enjoy the benefits of superior condition; conversely, thrifty application (treatments applied too infrequently or too late) could result in higher user costs due to poor conditions and even reduced longevity of the infrastructure. Such full consequences of transportation investments need to be assessed (Nemmers, 2004). A condition-based “schedule” or “strategy” refers to the set of triggers or pre-treatment levels of infrastructure condition over life-cycle. An optimal schedule is one that maximizes life-cycle utility in terms of benefits (infrastructure longevity and condition), agency costs, and user costs.

Past researchers have shown that spending on infrastructure rehabilitation at the right time can significantly reduce future spending on rehabilitation or reconstruction. For each class of infrastructure, there exists an optimal schedule for different types of repair and timing that is most desirable to the rehabilitation decision maker in terms of the maximum life-cycle benefits or minimum life-cycle costs he/she seeks to earn from that investment.

Furthermore, as will be shown in the literature review of this dissertation (Chapter 2), the traditional performance-based scheduling policy uses fixed threshold values, as evident, for example, in countless pavement or bridge preservation manuals of state highway agencies. Where these thresholds are fixed, the (implicit) assumption seems to be that the specific infrastructure lasts forever because it is rehabilitated when the infrastructure reverts to that trigger level; therefore, reconstruction is never carried out unless the fixed threshold is simply ignored at some point. Clearly, this assumption is neither realistic nor practical. Therefore, a methodology for devising new policies for strategic scheduling needs to be defined. These policies, preferably, should lead to flexible, non-fixed threshold values that are more realistic and practical. It is hypothesized, for the purposes of this dissertation that non-fixed thresholds for infrastructure rehabilitation can be more cost-effective than the fixed thresholds traditionally used by infrastructure agencies. Also, the challenge of solution stability is critical. When determining the best strategy, a key issue is: what does the decision maker seek to maximize or minimize? Is it the infrastructure longevity? Is it the infrastructure condition over the analysis period? Is it the monetary user benefits (reduction in user costs associated with the infrastructure use)? Is it the frequency or intensity of workzones? Or is it some combination of these and/or other criteria? A solution (optimal strategy) that addresses a specific criterion may not do so for another. Recognizing that agency policy can be capricious and decision-makers' objectives can vary from one agency administration to another, it is important to test whether the solution remains consistent across the decision maker's various objectives. Also, due to variations in funding amount or policy (for example, funding may not be readily available at the time it is needed or adequately disbursed before it is really needed), it is useful to quantify the consequences of any departures from the optimal schedules in terms of hastened or deferred intervention. It is hypothesized that these consequences can be significant. Pursuant to the above considerations, it is also hypothesized that the optimal solution can vary due to other decision situations, such as the relative weights of agency and user costs, and the manner by which the life-cycle costs and life-cycle benefits (effectiveness) are formulated or expressed. These hypotheses constitute an essential statement of the infrastructure decision problem addressed in this dissertation.

1.3 Dissertation Objectives

On the basis of the above problem statement, the main objective of this dissertation is to develop an analytical framework for optimal scheduling of interventions over infrastructure life-cycle using flexible, non-fixed thresholds. The objective is to maximize cost effectiveness, where effectiveness and costs can be defined in a variety of ways. In addressing this general objective, the dissertation also incorporates a number of hypotheses identified in the problem statement: does using non-fixed thresholds for infrastructure rehabilitation yield superior results compared to the fixed thresholds traditionally used by infrastructure agencies? Is the solution stable across the different objectives of the decision maker, and is there an explanation for any departures from the optimal schedules when some criteria are used? Does the optimal solution vary in other decision situations, such as the relative weight between the agency and user costs, interest rates, and restricting the number of rehabilitation treatments applied over the analysis period? The dissertation also seeks to demonstrate and validate the developed framework using a case study involving highway pavement rehabilitation.

1.4 Scope of the Dissertation

The overall framework is developed for all classes of infrastructure. Thus, it can be applied to rehabilitation interventions not only in all areas of transportation infrastructure asset management (bridges, pavements, congestion assets, and safety assets), but also for infrastructure in other disciplines, such as electric grid infrastructure, water or waste infrastructure, urban drainage infrastructure, and so on. This study addresses only the project level of management; that is, making scheduling decisions for a specific infrastructure or infrastructure family.

1.5 Organization of the Dissertation

This dissertation has seven chapters. Chapter 1 presents the background including a discussion of the need to develop rehabilitation strategies at the project level, followed by a statement of the research problem at hand, a description of the study objectives, and the approach of this study. Chapter 2 presents a review of the current practices for infrastructure rehabilitation interventions and the optimization approaches that handle the mixed-discrete nature of strategic scheduling for asset rehabilitation interventions. Chapter 3 describes the proposed general framework for selecting an optimal rehabilitation strategy; these strategies duly consider the rate of deterioration of infrastructure assets and the costs of intervention associated with each candidate strategy. Each strategy remains as a flexible (non-fixed) specification of threshold values and the best strategy maximizes the life-cycle utility expressed in terms of both benefits (such as infrastructure longevity and/or condition) and costs (incurred by the agency, user, or both parties). Chapter 4 sets up the demonstrative case study and presents the data input used for such demonstration. Chapter 5 presents the results and sensitivity analysis of the developed framework in order to identify the optimal strategy (best schedule found using a suitable optimization technique) for rehabilitating the case study pavement section. Chapter 6 presents the consequences of deviating from the optimal solution; specifically, the losses in cost effectiveness, benefits, and/or the increased agency and user costs due to hastening or deferring the rehabilitation intervention. Chapter 7 concludes the dissertation by summarizing the study’s approach, findings, and contributions. This final chapter discusses the results in the context of past related studies, identifies the study’s limitations and assumptions, and lays the groundwork for future research in this relatively uncharted terrain of infrastructure management.

CHAPTER 2. LITERATURE REVIEW

This chapter presents a discussion of past and current practices related to rehabilitation scheduling of infrastructure assets. A literature review is performed to recognize the current progress in the area of optimal scheduling of infrastructure rehabilitation activities and to synthesize the state of the art regarding the features and methodological approaches of the existing scheduling techniques. The chapter also identifies past research that uses mathematical optimization approaches to address the mixed discrete nature of strategic scheduling for asset rehabilitation intervention. This is expected to build a knowledge base as a prelude to the analysis, specifically, to provide a platform upon which a methodology will be proposed that addresses some gaps in the methodologies that currently exist.

2.1 Infrastructure Management System

A management system for infrastructure has been defined as "a systematic process incorporating engineering business, and economics, to maintain, upgrade, and operate physical assets cost-effectively, thus facilitating organized and logical decision-making" (FHWA, 1999) and "an effective and efficient directing of the various activities involved in providing and sustaining (infrastructure) in a condition acceptable to the (users) at the least life-cycle cost" (AASHTO, 2003). Since the late 1960s and early 1970s, management system development for all types of infrastructure gained popularity and has since been used to describe decision support tools for various classes of repair interventions, for example, bridge management systems, tunnel management systems, drainage infrastructure management systems, sewer management systems, and so on (Peterson, 1985). In specifying the scope of infrastructure management, some researchers have gone beyond the preservation phase to include other phases, such as planning, design, and construction (Haas and Hudson, 1994).

2.1.1 Levels of Management

Management systems can operate on two levels: network and project levels. Network-level analysis addresses the entire infrastructure network of a given type, and generally is associated with top-level decisions that are linked to network-wide policy, planning, and budgeting. Project level analysis, on the other hand, deals with smaller, more specific network constituents and addresses decisions associated with assignment of reconstruction, rehabilitation, or maintenance based on infrastructure condition. At the project level, alternatives for design, construction, maintenance, and rehabilitation arte considered for specific infrastructures. Infrastructure managers tend to address this bi-level system using either bottom-up (first dealing with project-level analysis and then network-level analysis) or top-down approaches (first dealing with network-level analysis and then project-level analysis). While network-level approaches offer better institutional control, those at the project level provide only basic what-if capabilities; the latter often makes available information of greater detail and accuracy, for supporting decisions for an individual project (Zimmerman et al., 1995). While the selection and prioritization of infrastructure maintenance and rehabilitation activities are network-level decisions, the selection of repair method for a specific individual infrastructure for example, can be considered a project-level decision. A number of analytical frameworks have been developed in the literature to support project-level or network-level decisions.

2.2 Infrastructure Maintenance and Rehabilitation (M&R) Strategy

In a bid to determine the scheduling of rehabilitation and maintenance activities, infrastructure agencies establish the corresponding threshold performance and monitor the asset to identify the appropriate time to perform the intervention. In general, M&R strategies involves a combination of activity types and the corresponding time for application. In some literature, the terms “schedule,” “activity profile,” and “activity timeline” have been used as synonyms for the term “strategy” (Lamptey et al., 2005).

Typical components of a strategy area are as follows: which treatment type and when is the appropriate time for its application? An optimal M&R strategy increases the overall infrastructure service life or benefits. A rehabilitation strategy is the set of rehabilitation treatments applied within the reconstruction cycle (between construction and reconstruction) (Figure 2.1). A preventive maintenance strategy is a "combination of PM activities applied at various times within the rehabilitation life-cycle (between successive rehabilitations)"; these activities, typically, are treatments that are preventive or proactive in nature and are typically applied "before the onset of significant structural deterioration" (O'Brien, 1989).

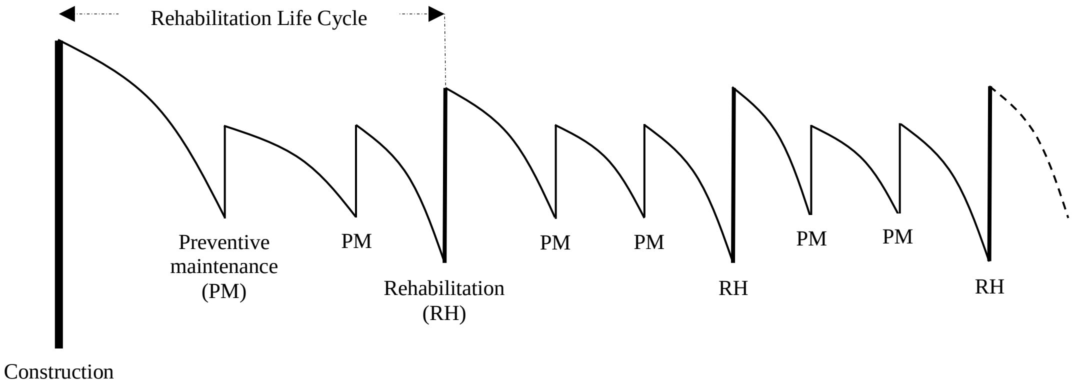


Figure 2.1 Life cycle Rehabilitation Maintenance Strategy Sample

From the agency perspective, infrastructure interventions extend the asset's service life but must be completed at minimal cost when possible. Therefore, such interventions intend to maximize the benefits and minimize the cost as much as possible. In general, an optimal threshold is expected to yield the maximum benefits from an intervention versus the minimum life cycle cost. Thus, if applied after or before such a threshold, the intervention will produce results that are less than optimal. Also, it is expected that the optimal threshold levels will vary between interventions, asset types, system external conditions, and throughout the asset life cycle. Current trigger policies define the infrastructure interventions by using fixed, time-based intervals or performance-based conditions (Labi and Sinha, 2003; Lamptey et al., 2005, Lavrenz et al., 2014). Both approaches are herein discussed (Figure 2.2).

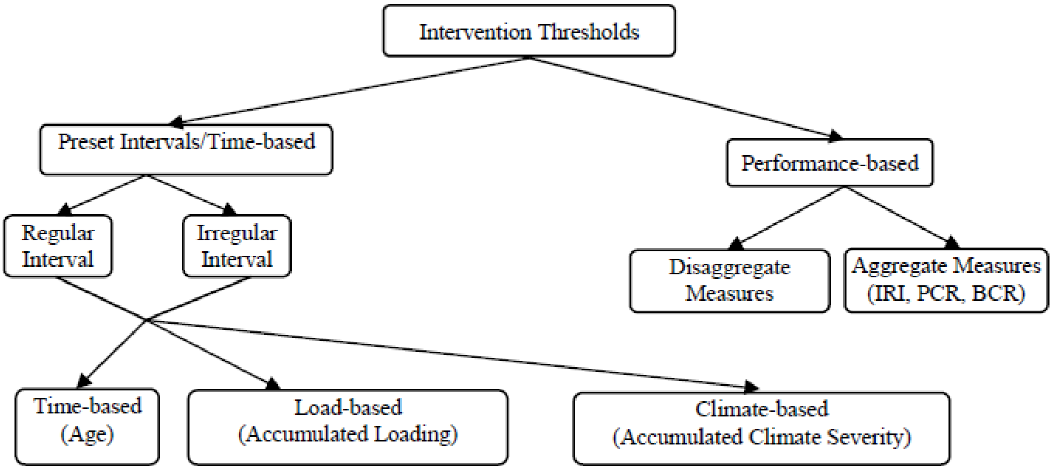


Figure 2.2 Threshold Criteria for Formulating Infrastructure M&R Strategies

Source: Lamptey et al., (2005)

2.2.1 Intervention Application Timings Based on Preset Time Intervals

When infrastructure age is used as a basis for scheduling interventions, the process is time-based and can be described as scheduling based on “preset time intervals”. This process does not consider the infrastructure condition or interventions performed regardless of condition level (Figure 2.2). Irregular intervals or lower frequency interventions are typically associated with newer assets, while smaller intervals (greater frequency) are associated with older assets.

When reviewing current practices, it was found that several infrastructure agencies perform interventions based on preset timing rather than accumulated traffic or climate conditions, because age can be considered a surrogate for factors such as traffic loading, and the accumulated effects of severe climate conditions. Critical aspects of age-based thresholds argue that these strategies may lead to inappropriate decisions because the variations in deterioration factors may result in an infrastructure at an actual performance level that is “superior or inferior to the expected intervention time specified by the age-based approach” (Khurshid, 2010)

2.2.2 Intervention Application Timing Based on Performance Threshold

Performance-based interventions refer to activities that take place any time when the infrastructure reaches a predetermined condition (Figure 2.2). This approach demands an important level of monitoring resources, such as using automated equipment to collect infrastructure condition data and estimate performance models that identify the appropriate time at which the infrastructure will reach the specific threshold and required intervention activities. A combination of condition surveys and nondestructive tests has been used by several agencies to trigger treatments based on the infrastructure condition (Peshkin and Hoerner, 2005). Currently, many types of available condition surveys can be used to provide meaningful information with which to make a treatment decision (FHWA, 1991; Peshkin and Hoerner, 2005). Condition surveys and mechanistic testing of infrastructure material properties, may help determine which network infrastructure requires treatment and the best time for that treatment as discussed by Lamptey (2004) and Peshkin and Hoerner (2005).

2.3 Effectiveness Analysis

Effectiveness is associated with utility benefit, or returns, and represents “the degree to which an alternative is expected to accomplish the objectives in two categories: quantifiable (monetary or non-monetary) or non-quantifiable” (Sinha and Labi, 2007). Based on an agency’s policies and objectives, the selection of measures of effectiveness (MOE) varies. There are MOE for the short and long term. The most commonly-used measures of effectiveness are the performance jump (a short-term measure) or the following long-term measures: infrastructure design life, treatment service life, the area bounded by the infrastructure performance curve, and increased infrastructure performance over treatment life (Peterson, 1985; Peshkin et al., 2004; Lu and Tolliver, 2012). Measures of effectiveness are based on a performance indicator. A performance indicator is an objective stated in measurable terms. At several infrastructure agencies, performance indicators for improvement projects are generally derived from the agencies overall goals or objectives (Sinha and Labi, 2007).

To quantify the benefits of infrastructure interventions (monetized and non–monetized) it can be found two approaches. The analyses are similar, except that for the non-monetized, the benefits are expressed not in terms of dollars but rather as infrastructure condition and/or its life extension. The benefits in terms of dollars can be measured as the reduction in costs (for the agency and users) during the normal operations of the asset (Irfan, 2010).

There is a preponderance of literature related to effectiveness analysis, particularly for highway pavement infrastructure. The mathematical equations used to quantify pavement treatment effectiveness were developed by researchers including Smith et al. (1993), Sebaaly et al. (1995), Labi and Sinha (2003), and Labi et al. (2005). A number of past researchers considered different performance indicators and measures of effectiveness to assess the benefits of interventions applied to flexible or rigid pavements (Hall et al., 2001; 2002; Morian et al., 2003; Ambroz and Darter, 2005; Khurshid et al., 2009; Irfan et al., 2009). Using data from several states, the National Cooperative Highway Research Program (NCHRP) reported the service life ranges of standard treatments interventions for flexible pavements (Hall et al., 2001).

The concept of using monetized benefits, such as agency and user cost savings, has been documented for relatively few studies. A number of past studies have established models that predict the average annual maintenance spending as a function of factors such as infrastructure age, constituent material type, climatic conditions (Al-Mansour and Sinha, 1994; HERS, 2002; Labi and Sinha, 2003; Woldemariam et al, 2015), and user cost models as a function of infrastructure condition (Zaniewski et al., 1982; Al-Mansour and Sinha, 1994; Opus, 1999; Barnes and Langworthy, 2003).

2.3.1 Performance Indicator

Performance indicators are specific qualitative or quantitative measures that reflect, indirectly or directly, the extent to which an infrastructure achieves its objectives including the concerns of the infrastructure user or owner (Poister, 1997; Sinha and Labi, 2007). The chosen performance indicator must reflect infrastructure intervention impacts (Labi and Sinha 2004; Labi et al. 2005; Khurshid et al. 2009). Effectiveness is measured in terms of the performance indicator; for that reason, choosing an appropriate indicator requires critical attention. Some examples of performance indicators for different highway assets are shown in Table 2.1.

Table 2.1 Performance Indicators for Various Highway Assets

Highway Asset/Characteristic	**Performance Indicator**
Pavement	International Roughness Index (IRI) Pavement Condition Rating (PCR) Present Serviceability Index (PSI)
Bridge	Health Index (HI) Bridge Condition Rating (BCR) Deck Condition Ration (DCR) Bridge Sufficiency Rating (BSR)
Safety	Crashes per VMT Fatality Rate Hazard Index
Congestion/Mobility	Volume/Capacity (V/C) Ratio Level of Service (LOS) Travel Time Delay

Source: Camsys, 2000; NCHRP, 2006.

2.3.2 Infrastructure Performance

The main purpose of infrastructure performance modeling is to mimic the patterns of infrastructure deterioration over time. Often, infrastructure performance models estimate the infrastructure condition as a function of independent factors including user frequency, demand or loading, environmental effects, design and construction factors, and maintenance practices. Both pre- and post-intervention infrastructure performance models can be used to measure the intervention effectiveness, to provide information on the deterioration rate before and after the intervention, respectively (Khurshid, 2010).

With regard to highway pavements, researchers have developed performance models for individual treatment types that assess the treatment effectiveness over the long term, and these include Rajagopal and George (1990), Sebaaly et al. (1995), Livneh (1996), Mohamed et al. (1997), Lamptey et al. (2008), Khurshid et al. (2010), Irfan et al. (2010), Ahmed (2012). Those performance models were developed for different functional classes and pavement surface types. Also, a majority use explanatory variables related to the infrastructure loading intensity or frequency, climatic conditions, infrastructure age, and pre-intervention condition of the infrastructure.

2.3.3 Measure of Effectiveness

Effectiveness can be expressed as an increase in asset service life or a reduction of infrastructural operational costs due to infrastructure improvements. MOEs that are commonly-used in infrastructure intervention evaluation are performance jump, intervention service life, area bounded by the performance curve, and infrastructure condition over the service life. MOEs such as these have been used with success in the past by researchers including O'Brien (1989), Joseph (1992), Geoffroy (1996), Lamptey (2004), Peshkin et al. (2004), Singh et al. (2007), Labi et al. (2007), Irfan et al. (2009) and Khurshid et al. (2009).

2.3.3.1 Initial Effectiveness of Interventions

This MOE refers to the vertical or instantaneous increase or reduction in the infrastructure condition due to an intervention. It has also been called *performance jump*, and corresponds to the difference in pre- and post- performance conditions. In the past, this MOE has been used as a performance measure of the effectiveness of pavement preservation treatments (Colluci-Rios and Sinha, 1985; Khurshid et al., 2009; Labi and Sinha, 2003; Labi et al, 2008; Lytton, 1987; Markow, 1991; Rajagopal and George, 1990; Lu and Tolliver, 2012). Figure 2.3 shows a graphical representation of this MOE (vertical reduction for a non-increasing performance indicator).

2.3.3.2 Intervention Service Life (ISL)

The intervention service life can be considered a useful performance measure because all other long-term effectiveness measures are computed partly on the basis of this MOE (Irfan, 2009). The service life of an intervention can be estimated using any of several techniques including measuring the number of years that passes between the time of the intervention and the next intervention of higher or similar level (Figure 2.3).

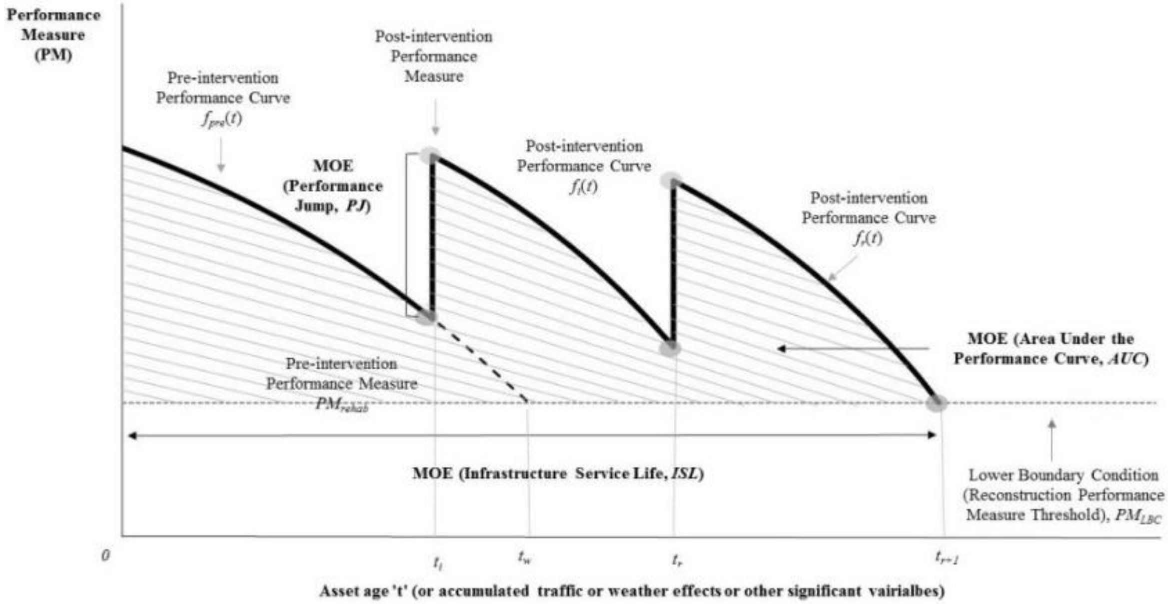


Figure 2.3 Representation of MOE (Non-Increasing Performance Indicator)

Another method is using performance models in terms of the factors experienced by the treated asset before it reverts to a pre-specified threshold. Infrastructure service life (in terms of years, accumulated loading, or accumulated climate effects) can be also determined using pavement condition data to develop a deterioration curve and extrapolate the curve to the point at which the pavement returns to the pre-specified threshold (Figure 2.3). The treatment service life is a well-established concept (Ambroz and Darter, 2005; Geoffroy, 1996; Hall et al., 2001; Irfan et al, 2009a; Irfan et al, 2009b; Khurshid et al., 2011).

2.3.3.3 Area Bounded by the Intervention Performance Curve

Of the various measures of long-term effectiveness, the area bounded by the threshold line and the performance curve is perhaps the most superior (at least, conceptually) because it represents an encapsulation of the concepts of service life and average infrastructure condition (Peterson, 1985; Fwa and Sinha, 1992; Geoffroy, 1996; Wei and Tighe, 2004; Peshkin et al., 2004; Khurshid et al. 2008, 2010). The area bounded is estimated using the performance condition model from the time of the treatment up to the time the infrastructure condition reaches a specified threshold.

The area bounded by the performance curve represents the increase in infrastructure conditions due to an intervention. This MOE is calculated as the percentage change of condition, specifically, the average value of the post-intervention conditions relative to those before the intervention. This can be done using annual field measurements or using performance models developed from data from multiple assets.

This MOE has been used in many past studies, mostly in the area of highway pavement infrastructure.

2.4 Cost Analysis

Infrastructure management decisions require cost analysis as part of the evaluation of alternative courses of actions (Collura et al., 1993). Interventions carried at any infrastructure phase over the infrastructure service life involve costs and benefits (costs reduction) for the agency, users, and community. There exist a number of benefits that can be estimated costs reductions relative to a specified base case (which often is the do-nothing strategy) (Khurshid, 2010). Infrastructure intervention costs are described in the following sections.

Agency Costs:

1. Agency Cost at Downtime Periods (*ACDT*) corresponds to the cost incurred by the agency performing rehabilitation interventions. This is typically estimated in terms of the cost per unit surface area of the constructed infrastructure.
2. Agency Cost during Normal Operations (*ACNO*) corresponds to the maintenance expenditures incurred by the agency during normal operations (time between rehabilitation interventions).

User Costs:

1. User Cost at Downtime Periods (*UCDT*) corresponds to the cost associated with user delays at locations and times of infrastructure downtime (discomfort, inconvenience, detours, delay, and so on, etc.) due to the intervention.

2. User Cost during Normal Operations (*UCNO*) corresponds to the direct or indirect costs to the user during normal use of the infrastructure. Often, this is a function of the infrastructure condition. For example, with regard to highway pavements, a common UCNO is the vehicle operating costs (VOC) associated with fuel, maintenance and repair, tires, and depreciation.

2.4.1 Agency Cost Estimation

The aggregate cost of infrastructure interventions in the planning stage are estimated using at least two approaches. One of these considers the average unit costs ($ per unit output; output may be area, lane-miles, etc., as discussed in Feighan et al. (1986), Hartgen and Talvitie (1995) and Stevens (1995). The second approach refers to cross-sectional statistical models that describe agency cost in terms of explanatory factors that affect the infrastructure costs (Wilmot and Cheng 2003). These factors can be placed in two classes: attributes related to the asset (such as type, location, condition functional class) and those related to the work source (by contract or in-house) as discussed in Carnahan et al. (1987) and Ben-Akiva and Ramaswamy (1990). Only a few studies provide a complete analysis of the historical costs of contract on pavement repair. Due to such a lacuna, the average treatment cost values are used. However, they should be used with circumspection because they fail address the effect of cost factors such as project size and thus can lead to erroneous cost estimates that are routinely made at the planning phase of highway project development (Irfan, 2010).

Each approach for agency cost estimation can be carried out by incorporating the extrapolation of the past cost trends of an intervention using indices including FHWA's highway construction price index (HCPI) (FHWA, 2015). Hartgen et al. (1997) argued that time-series techniques should be used with circumspection because unforeseen surges in potential independent variables including gas price changes and new construction technology may render future costs difficult to predict on the basis of past costs.

Sharaf et al. (1987), Al-Mansour and Sinha (1994), Pasupathy et al. (2007), Irfan et al. (2010) and Khurshid et al. (2010) developed cost models that consider the cost factors.

2.4.1.1 Agency Cost Estimation at Downtime (*ACDT*)

Based on FHWA data from several states, the construction cost of a 4-lane divided highway (depending on terrain type) can be \$3.1 to \$9.1 million per lane-mile. In urban areas, this can increases to \$16.8 to \$74.7 million due to right-of way, utility relocation, and volume traffic control problems (HERS, 2002; GAO, 2004). To account for the effects of pre-intervention conditions, agency cost models that used an exponential form were developed by Khurshid et al. (2010). Irfan et al. (2010) developed an aggregate statistical model for treatment cost per lane-mile that assumed a linear relationship between the total cost and the project size, and ignores the existence of economies or diseconomies due to scale or condition.

2.4.1.2 Agency Cost Estimation during Normal Operations (*ACNO*)

Al-Mansour and Sinha (1994) developed parametric maintenance cost models as a function of traffic volume and pavement condition. Labi and Sinha (2003) developed average cost values for preventive and corrective maintenance treatment types costs and Hegazy and Ayed (1998) found that cost factors can include contract size and duration, season of work, project location, and project type. Neural network models have been used to address the problems associated with parametric cost estimation at the planning phase (Pearce et al., 1999; Adeli and Wu, 1998). Other similar research include those carried out by Gwang-Hee et al. (2004) and Sodikov (2005). Woldemariam et al. (2015) developed an exploratory study at the aggregate level to demonstrate that an artificial neural network approach is feasible and provides reliable predictions of annual expenditures on rural interstate highway pavements. Also, to assist in budgeting and life-cycle cost analysis, Volovski (2011) developed annual maintenance expenditure models using an array of statistical and econometric techniques, including ordinary least square, tobit, panel, and two-stage regression. The develop models identify that variables such geographic region, pavement segment length, and age have significantly influence on maintenance expenditures.

2.4.2 User Cost Estimation

Highway user cost typically includes (a) safety and delay costs incurred by road users during downtime periods and; (2) user costs experienced during the normal facility operations over the asset life. There are rather relatively few past studies that have explicitly considered user cost in M&R decision making. Those who incorporated user cost aspects in M&R strategy development include Friez and Fernandez (1979), Markow and Balta (1985), Mamlouk and Zaniewski (2001), Peshkin et al. (2004), Lamptey et al. (2004), and. Due to the uncertainties and challenging in determining user costs (Papagiannakis and Delwar, 1999; U.S. DOT, 2002), the majority of studies do not include the estimation of user costs as part of the LCCA evaluation. Some of those who exclude user costs argue that user costs are not covered by the agency (Giustozzi, et al. 2012). Under traditional M&R policies (fixed trigger values), it can be assumed that normal operation user costs are essentially the same for various post-treatment interventions (Shober and Friedrichs 1998; Hall et al., 2001; Maurer et al. 2007; Khurshid et al., 2009, 2010). The main focus of this dissertation is to provide rehabilitation schedules based on non-fixed threshold values that consequently cause significant differences (across the different strategies) in user cost during normal operations. Therefore, it would be reasonable to consider user cost during normal operations as part of the analysis.

Users ultimately receive benefit from the infrastructure condition as a result of rehabilitation intervention and user inconvenience and delay costs during the workzones and normal operations should be considered (Walls and Smith, 1998; Najafi and Paredes, 2001; AASHTO, 2003). User cost differences across different M&R strategies can be significant, as demonstrated by past research.

2.4.2.1 User Cost Estimation at Downtime (*UCDT*)

When an infrastructure asset receives an intervention, normal operations are interrupted. In the context of highway pavements, for example, this is referred to as a workzone (Walls and Smith, 1998). Each workzone has its own specific characteristics (traffic volume and duration and frequency of work periods) and must be evaluated as a separate event to quantify the traffic delays and the corresponding user costs (Walls and Smith, 1998; Najafi and Paredes, 2001). The user delay cost per mile can be calculated as follows (Khurshid et al., 2009; Irfan et al., 2009b):

$$User\ Delay\ Cost = \sum_i (V_i \cdot T_i \cdot C_i) \tag{2.1}$$

where: T_i = travel time difference for the speed change for vehicle class i, in hour/mile; V_i = number of vehicles delayed by the speed change for vehicle class i, over the work zone duration; C_i = delay cost rate for vehicle class i, in \$/vehicle-hour; i = vehicle class, i.e., auto and truck.

To estimate the components of user delay cost, project duration intervention is necessary. The relationship between project cost duration has been investigated in past research. Fulkerson (1961) used a linear relationship. Subsequent research used various non-linear forms including concave (Falk and Horowitz, 1972), convex (Foldes and Soumis, 1993), a hybrid of concave and convex (Moder et al., 1995), quadratic (Deckro et al., 1995), or discrete (Skutella, 1998; Zheng and Kumaraswamy, 2004). Hendrickson et al. (1987) estimated hierarchical, rule-based activity duration models. A study in Malaysia estimated the average project duration using a time–cost formula (Chan, 2001). In the recent past, efforts have addressed the possibility of piecewise discontinuous activity time cost functions (Moussourakis and Haksever, 2004). Other research in this area includes the work by (Nassar et al., 2005; Anastasopoulos, 2007; and Chassiakos and Sakellaropoulos, 2005). Yang (2007) developed a time-cost profile using algorithms that consider activity time-cost functions. A study by Irfan, et al. (2010) found that the project duration increases non-linearly with project cost, and the general form of the logistic duration models developed in their study is shown in Equation (2.2):

$$Y = e^{(A+\sum \beta_i X_i)} \tag{2.2}$$

where: y = project duration in days; A = Constant term, β_i = estimated coefficients for project i; and X_i is a vector of explanatory variable such as project cost (in millions of US dollars) and contract type (an indicator variable, 0 indicates that available days were specified for project completion, and 1 indicates that a deadline date was fixed). The specific model for highway rehabilitation (Irfan, et al. 2010) is given by Equation (2.3):

$$y = e^{(4.60 + 0.340 \cdot Cost + 0.253 \cdot Contract_{type})} \tag{2.3}$$

2.4.2.2 User Cost Estimation during Normal Operations (*UCNO*)

VOC includes fuel, tires, maintenance, repairs, and mileage-dependent depreciation (Sinha and Labi, 2007). Infrastructure interventions improve the infrastructure condition, reflected as a reduction in unit *VOC* (Walls and Smith, 1998; Najafi and Paredes, 2001; Forkenbrock and Weisbrod, 2001; Barnes and Langworthy, 2003AASHTO, 2003). Hepburn (1994) developed VOC models (cents/mile) as a function of vehicle class and speed (Equations (2.4) and (2.5)):

$$VOC = C + \frac{D}{S} \qquad \text{(For average speed < 50mph)} \tag{2.4}$$

$$VOC = a_0 + a_1 \cdot S + a_2 \cdot S^2 \qquad \text{(For average speed > 50mph)} \tag{2.5}$$

where: S = speed in mph; C, D, a_0, a_1 and a_2 are functions of the highway functional class. Table 2.2 presents the coefficient values for the developed models.

Table 2.2 Hepburn (1994)VOC Model Parameters

Vehicle Type	**Coefficient Value**				
	C	**D**	**a_0**	**a_1**	**a_2**
Medium Automobile	28.5	95.3	33.5	0.058	0.00029
Truck/Large Automobile	29.8	163.4	38.1	0.093	0.00033

In a Texas study, Zaniewski et al. (1982) suggested that pavement roughness has a significant impact on non-fuel vehicle operating cost. Opus (1999) suggested that additional VOC due to pavement conditions occur when IRI exceeds 100 in/mi (3.33 m/km) (Figure 2.4).

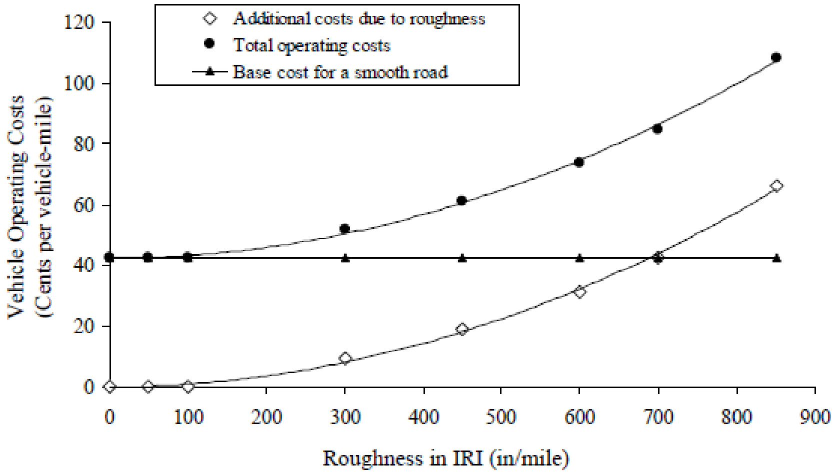


Figure 2.4 Relationship Between VOC and Pavement Roughness
Source: Opus (1999)

According to Papagiannakis and Delwar (1999) a unit increase of IRI (m/km) will lead to a $200 (that is, 1.67 cents/veh-mile, assuming 12,000 annual mileage) increase in vehicle maintenance and repair costs. Also, Barnes and Langworthy (2003) developed adjustment multipliers for all combined VOC components (fuel, maintenance/repair, tires, and depreciation) for highway and city driving conditions, and for poor and smooth pavement quality conditions. The study assumed a PSI baseline of 3.5 and better (smooth pavement with IRI of about 80 inches/mile or 1.2 m/km), at which an increase in pavement condition would have no impact on vehicle operating costs. Those adjustments imply an extra cost of about 1 cent/mile in maintenance and repair cost between the roughest and smoothest pavement. The adjustment multipliers were determined for three specified levels of pavement condition (Figure 2.5). Table 2.3 and Table 2.4 show the baseline VOC for smooth and poor pavement quality condition as a reference for the estimation of intermediate conditions.

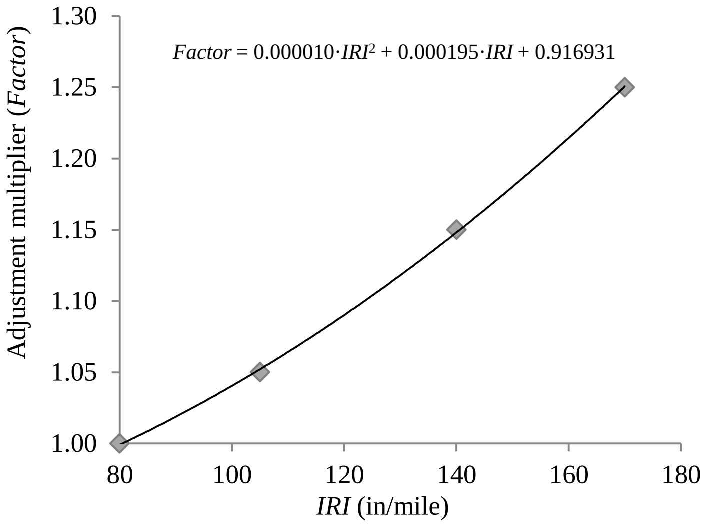


Figure 2.5 Effect of Pavement Roughness on Operating Costs
Source: Barnes and Langworthy (2003)

Table 2.3 Baseline VOC (cents per mile, year 2003) Smooth Highway Pavement

Cost Category	Automobile	Pickup/van/SUV	Commercial Truck
Fuel	5.0	7.8	21.4
Maintenance/Repair	3.2	3.7	10.5
Tires	0.9	1.0	3.5
Depreciation	6.2	7.0	8.0
Total	**15.3**	**19.5**	**43.4**

Source: Barnes and Langworthy (2003)

Table 2.4 Baseline VOC (cents per mile, year 2003) Poor Highway Pavement

Cost Category	Automobile	Pickup/van/SUV	Commercial Truck
Fuel	5.0	7.8	21.4
Maintenance/Repair	4.0	4.7	13.1
Tires	1.1	1.2	4.4
Depreciation	7.8	8.8	10.0
Total	**17.9**	**22.5**	**48.9**

Source: Barnes and Langworthy (2003)

References for VOC baseline cost estimation from different sources are presented in Table 2.5. The results show consistency across the different VOC components and can be considered as the baseline estimations for future studies.

Table 2.5 VOC Baseline Costs Comparison

Cost Category	**Barnes and Langworthy (2003)**	**FHWA “Red book” medium size car (1984)**	**Qin, et al. (1996)**
Fuel	5.0	5.4	4.5
Tires	0.9	1.7	1.0
Repair/Maintenance	3.7	4.0	4.8
Depreciation	7.0	4.2	13.5
Total	**16.5**	**14.8**	**23.8**

Source: Barnes and Langworthy (2003)

2.5 Cost-Effectiveness Evaluation

Cost-effectiveness (CE) evaluation helps to compare money spent by an agency to the benefits accrued by the users (Geoffroy, 1996). CE analysis support agency making decision process. To be a suitable intervention strategy for selection or implementation, an intervention or strategy must be cost-effective. As was described in a previous section (2.3 Effectiveness Analysis), it is not always possible to monetize the benefits and typically non-monetized benefits are the most common measures of effectiveness to do a cost-effectiveness evaluation. (Joseph, 1992; Morian et al., 2003; Peshkin et al., 2004; Khurshid et al, 2008; Khurshid et al., 2009).

For an agency’s perspective, interventions are applied to prolong the infrastructure service life and maintain a fairly reasonable state of good repair while minimizing the related costs (Hicks et al., 1997; Chong, 1990; Geoffroy, 1996; Morian et al., 2003). Li et al. (1997) analyzed the cost effectiveness of interventions using the present worth of agency costs and the area bounded by the performance curve duly adjusted for infrastructure size and usage levels. Hand et al. (1999) in Nevada DOT used present serviceability index, construction costs and annual maintenance costs to identify the most cost-effective rehabilitation treatments. Using a formulation similar to that of Haas et al. (2006), Labi and Sinha (2005) expressed cost effectiveness aas the incremental benefit relative to incremental cost relative to a base case strategy. Irfan et al. (2009a) evaluated

CE under various combinations of traffic loading and climatic conditions for four flexible pavement rehabilitation treatments. The benefits were estimated in terms of performance jump (short-term), service life, and increase in pavement performance (long-term). Khurshid et al. (2011) analyzed CE as the ratio of treatment effectiveness to treatment cost for three standard rehabilitation treatments of rigid pavements. The benefits were estimated in terms of short and long-term measures of effectiveness (performance jump, service life, and increase in average performance). Khurshid et al. (2014) evaluated the CE of asphaltic concrete overlay of rigid pavements across the LTPP regions on the basis of life cycle considerations (long-term service life, increase average pavement conditions over treatment life, and area over the curve). The benefits were estimated for the long-term by using service life and increase in pavement performance, and in the short-term with the performance jump.

The benefits of a well-maintained infrastructure are numerous and may be difficult to quantify in monetary terms, non-monetized benefits may be used as a surrogate for the benefits (Lamptey et al. 2004; Geoffroy 1996; O’Brien 1989). To avoid problems associated with benefit monetization, Morian et al. (2003), Labi et al. (2005), Peshkin et al. (2004), and Labi and Sinha (2005) used non-monetized benefits including the area bounded by the curve, service life, decrease in the structural index, and so on.

In the analysis of alternative schedules for preservation, Labi et al. (2005) utilized the concept of incremental benefits (area bounded by the performance curve) relative to incremental treatment cost relative to a base case strategy. Haas et al. (2006) proposed that the performance effectiveness should be measured both in the initial stage and also over the life-cycle, for purposes of infrastructure evaluation. They stated that the area bounded by the performance curve is a suitable measure of effectiveness and that the ratio of effectiveness to cost is appropriate. This concept was also used by Mahmodi et al. (2007), Irfan et al. (2009a); Irfan et al. (2009b); Khurshid et al. (2009), Labi and Sinha (2003), Palle (2009), Sebaaly et al. (1995), and Smith et al. (1993).

The first of three alternative effectiveness evaluation approaches considers only the benefits obtained from an intervention (the maximum-benefit approach); the second approach focuses on the associate costs of an intervention (least-cost approach); and the third approach combines benefits and cost and the objective is maximizing the cos-effectiveness relationship (an option with the maximum possible benefits at the minimum possible costs). For purposes of highway evaluation, a combination of benefit and cost approaches is recommended (Geoffroy, 1996; Khurshid et al., 2009).

2.5.1 Evaluation Criteria Involving Cost Only

Life-Cycle Cost Analysis (LCCA) is one of the most commonly-used techniques when agencies seek to minimizes cost (Khurshid et al., 2009). LCCA assesses alternatives considering the costs of construction, maintenance and operation (Winfrey and Zellener, 1971; Walls and Smith, 1998, FHWA, 2002). Life-cycle costs can be expressed as Equivalent Uniform Annual Cost or a Net Present Value.

2.5.2 Evaluation Criteria Involving Benefit or Effectiveness Only

The effectiveness of asset intervention can be measured as the increase in “positive” service attributes (or reduction in “negative” attributes). As described in section 2.3.3 (Measure of Effectiveness), this can be observed in the short or long term.

2.5.3 Evaluation Criteria Based on Cost and Effectiveness

This approach considers the benefits and expenditures associated with an intervention. Typical performance measures used for this evaluation criterion are Equivalent Annual Cost (EAC) and Benefit Cost Analysis (Area bounded by the Curve, Service Life, and Equivalent Uniform Annual Cost). The general form of cost-effectiveness (CE) can be express as Equation (2.6):

$$Cost\ Effectiveness\ (CE)\ Index = \frac{Benefit\ (Monetized\ or\ Non-monetized)}{Life\ cycle\ Cost} \qquad (2.6)$$

where, Benefit = Non-Monetized or Monetized Effectiveness (Section 2.3); Life-cycle Cost (Section 2.4).

2.6 Decision Support Tools for Scheduling

From the literature review of infrastructure rehabilitation scheduling practices was found that common practices are based on asset managers and engineer's subjective judgements using questionnaire surveys, historical data of past practice, and optimization procedures. Some of the advantages and disadvantages of those approaches are herein discussed.

The questionnaire survey is a subjective approach based on experts' opinions. Decisions from this approach may not be cost-effective and only reflect past practices. Surveys can be useful for agencies that lack historical records of rehabilitation treatment interventions. An additional limitation of this approach is that infrastructure management parameters available at most infrastructure agencies are not explicitly consider into the strategic scheduling process.

In the past, most infrastructure interventions decisions have been influenced by factors such as funding availability or political interests, rather than engineering concepts or economic feasibility. For example, during periods of favorable funding availability, agencies are more likely to adopt relatively liberal infrastructure practices. On the other hand, when funding availability declines, agencies adopt relatively parsimonious rehabilitation practices by using conservative trigger values or longer intervals of treatment application. Therefore, rehabilitation scheduling decision support mechanisms based merely on historical data and application intervals may lead to inconsistent and indefensible infrastructure preservation decisions.

Infrastructure management systems with an optimization capability can assist infrastructure managers to determine the optimal maintenance and rehabilitation strategies for constituent pavements in a network and subsequently evaluate life-cycle performance and costs with trade-offs measured in economic as well technical terms. Determining the appropriate schedule for rehabilitation interventions requires a method that can both sort through the variety of possible combinations for when to perform an intervention and which treatment to apply regarding agency and user cost during work zone and normal operations. This combination of features makes the scheduling optimization a problem with both discrete and continuous design variables. The methods for discrete-integer-continuous variables nonlinear optimization can be classified into the following categories: branch and bound, simulated annealing, sequential linearization, penalty functions, Lagrangian relaxation, rounding-off, heuristic, cutting-plane, pure discrete, and genetic algorithms. For non-linear problems, none of the methods are guaranteed to produce the global minimizer; however, “good, practical” solutions can be obtained (Huang and Arora, 1997).

In the 60s and 70s, optimization methods for continuous nonlinear programming problems were not well developed, so the focus shifted to the development and evaluation of numerical algorithms for such problems. In recent years, the focus has shifted back to applications of optimization techniques for practical engineering problems that naturally use mixed-discrete and continuous variables in their formulation. Engineering design problems are typically constrained and multi-objective in nature, and required the combination of continuous and discrete types of design variables during the problem formulation. The need of addressing problems with mixed features, has been taking a relevant interest across various disciplines of engineering. Several optimization algorithms are capable of handling some of these features, but only a few can address mixed discrete nature problems Roy, 2012).

Genetic Algorithm (GA) is one of the few algorithms that can handle discrete choices. Enumeration will get the best solution, but if the problem size increases (e.g. the number of possible treatments) the number of combinations required to find an optimal solution using enumeration will be impossible to perform. By using an optimization algorithm, the scope search is reduced (limit the number of search) as it performs a probabilistic search that avoids point-to-point combinations required by enumeration. The Genetic algorithm (GA) developed by Holland (1975) and his students and colleagues at the University of Michigan in the 1960s and 1970s is a computational representation of natural selection and an evolutionary computing technique that mimics the mechanism of the natural selection process.

With regard to infrastructure pavement management, genetic algorithms have been used for solving deterministic, segment-linked optimization models (Fwa et al., 1994, 1996 and 1998; Chan et al., 1994). The research has demonstrated that GAs are robust optimization tools that can be employed to obtain sufficiently good solutions to programming problems within a practical time frame. Fwa et al. (1996) analyzed the trade-offs between pavement maintenance and rehabilitation at the network level. One shortcoming of GA solutions, however, as noted by Fwa et al. (1994 and 1996) and Pilson et al. (1999), is that, in the generation of offspring solutions, each solution is checked against all the constraints to ensure that it is a feasible solution. Non-feasible solutions may be discarded and new solutions generated until the required number of offspring solutions is obtained. It is recognized, therefore, that there can be no guarantee that a GA solution is the global optimum. Pavement management problems guide scheduling problems for which the solution space grows exponentially with the problem size (timing and treatments combination alternatives) so that the solution space size very quickly becomes unmanageable by "true" optimization techniques. Pavement management is thus ideally suited for directed random search heuristics (Pilson et al., 1999).

Fwa et al. (2000) adopted the concepts of rank-based fitness evaluation and Pareto optimality to address multi-objective network level pavement maintenance programming problems. Taha and Hanna (2001) presented a genetic algorithm method and neural network model for selecting optimum pavement maintenance strategies.

There has been much interest in using GA in the transportation engineering field for the advantages of this powerful artificial intelligence optimization technique. Morcous and Lounis (2005) presented an approach to determine the optimal set of maintenance alternatives for a network of infrastructure facilities. This approach uses genetic algorithms to resolve the computational complexity of the optimization problem and Markov chain performance prediction models to account for the uncertainty in infrastructure deterioration. The feasibility and capacity of the proposed approached was demonstrated in programming the maintenance of concrete bridge decks. Hegazy et al. (2004) used a powerful genetic algorithm to consider both project- and network-level variables in bridge deck life-cycle cost optimization. The proposed approach stems from three main aspects: incorporating project-level repair options along with their performance improvements and cost implications; incorporating many flexible and practical features, such as variable yearly budget limits, variable yearly discount rates, and another optional methods for handling project-level repairs.

Herabat and Tangphaisankun (2005) used constraint-based genetic algorithms to combine characteristics of network-level maintenance planning. They developed a multi-objective optimization model to support the multi-year decision making process considering budget limitation and the network-system preservation as two constraints.

Bosurgi and Trifiro (2005) used artificial neural networks and genetic algorithms to find an effective way to use the available economic resources for resurfacing interventions on flexible pavements. The obtained results indicate that the chosen approach provided an optimal solution from a big space of possible solutions in a short period of time. Chootinan et al. (2006) introduced a multi-year pavement maintenance programming methodology that accounts for uncertainly in pavement deterioration. The results indicated that programming the maintenance activities using only the expected pavement conditions is likely to underestimate the required maintenance budget and overestimate the performance of a pavement network. A multi-objective evolutionary optimization algorithm for reducing overall substation cost and improving reliability of electric power distribution was introduced by Yang et al. (2008); decision-varying Markov models relating the deterioration process with maintenance operations were proposed to predict the availability of individual component. Xiao et al. (2008) used genetic algorithms for planning and scheduling pavement MR&R activities for highway elements at both the project- and network-levels. The developed system applies a Markovian process to predict performance deterioration with the inclusion of treatment improvement resulting from MR&R alternatives and comprehensive cost analysis.

The effect of rehabilitation interventions and pavement reliability were modeled using parametric fragility curves based on simulated pavement responses by Deshpande et al. (2010). Three different models with three different interest rates were included: the first minimizes cost and target reliability is set as a constraint; the second maximizes the cumulative life-cycle reliability and budget is set as a constraint; and the third features a cost-effective relationship while minimizes cost and maximizes reliability.

Distress deterioration functions were considered by Chikezie et al. (2011) who developed models using genetic algorithms to determine the warning levels for maintenance interventions. The developed model considers rehabilitation actions for the proposed study, while other models stop at the maintenance level. Gao et al. (2012) suggested a parametric method to solve the bi-objective pavement maintenance scheduling problem (maximizes pavement condition and minimizes the cost).

In another work, Marzouk et al. (2012) introduced the development of a stochastic performance prediction and optimization models as two major parts of an integrated pavement management system. Markov modeling is used to predict pavement condition with the use of a pavement condition index (PCI). The genetic algorithm technique is adopted to build the optimization model. Three objective functions are constructed for minimizing the budgeted cost of maintenance and rehabilitation programs, maximizing the quality of work performed, and maximizing the total percentage of the network area that will be under maintenance and rehabilitation (M&R). The study also presented six types of maintenance and rehabilitation programs for achieving these objective functions. This model ensures that road network maintenance is adjusted to the limits of budgeted cost by maintaining standard quality of performance.

Mathew and Isaac (2014) developed an optimized maintenance strategy for a rural road network using a bi-objective deterministic optimization model which simultaneously satisfies the objectives of both minimization of total maintenance cost and maximization of performance of the road network. Elhadidy et al. (2015) proposed a system that aims to provide a technique for handling maintenance and rehabilitation programs as major components of the network level in a decision support system. Other objectives of the study are: introducing a method for optimizing M&R decisions using multi-objective genetic algorithms in conjunction with Markov chain model, considering available budgeted cost and road network conditions using pavement condition index (PCI), and developing a computerized tool to facilitate the use of the proposed model. The output of the model is a set of planning strategies for the maintenance and repair throughout the planning horizon.

2.7 Gaps in the Literature

All existing scheduling methodologies for infrastructure assets are based on the traditional policy of using fixed-threshold values to perform rehabilitation activities with the implicit assumption that infrastructure systems last forever and that reconstruction is never carried out; this, clearly, is an assumption that is neither realistic nor practical. Therefore, the ultimate goal is to bridge the gap between practicality and reality in this area of infrastructure decision making. The overall framework can be used for varying kinds of infrastructure assets; however, the case study included here is specifically within the context of pavement assets.

2.8 Chapter Summary

This chapter provided a literature review of existing maintenance and rehabilitation strategies and the use of genetic algorithms to develop such strategies. First, the determination of optimal threshold values was studied in detail to support the development of non-fixed threshold values that consider infrastructure performance, agency and user costs, and benefits over the life cycle. Secondly, approaches to scheduling strategy were identified from two main groups: timing based on preset time intervals and timings based on performance condition. Scheduling approaches were reviewed to ascertain their features, and gaps in the current literature were identified for future improvement. The next chapter illustrates the dissertation’s framework for addressing the gaps identified in the literature review.

CHAPTER 3. RESEARCH METHODOLOGY AND FRAMEWORK

The methodological framework for establishing optimal intervention strategies using non-fixed thresholds is illustrated in Figure 3.1. The framework is designed to be applicable to different kinds of infrastructure assets; however, the case study relates to highway pavements specifically. This chapter presents the framework components.

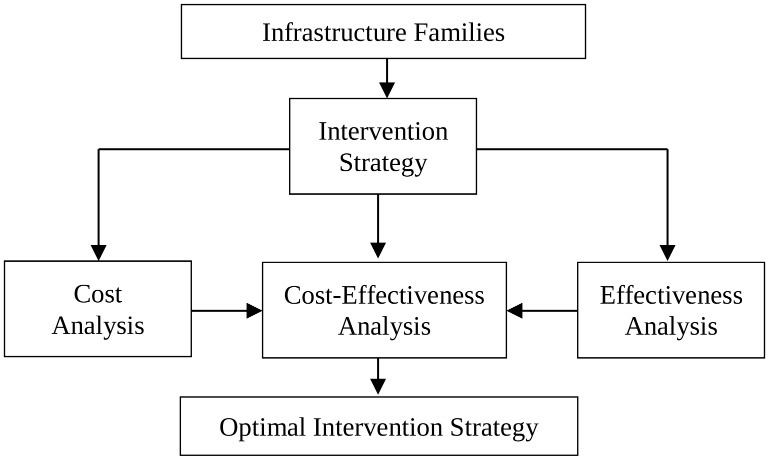
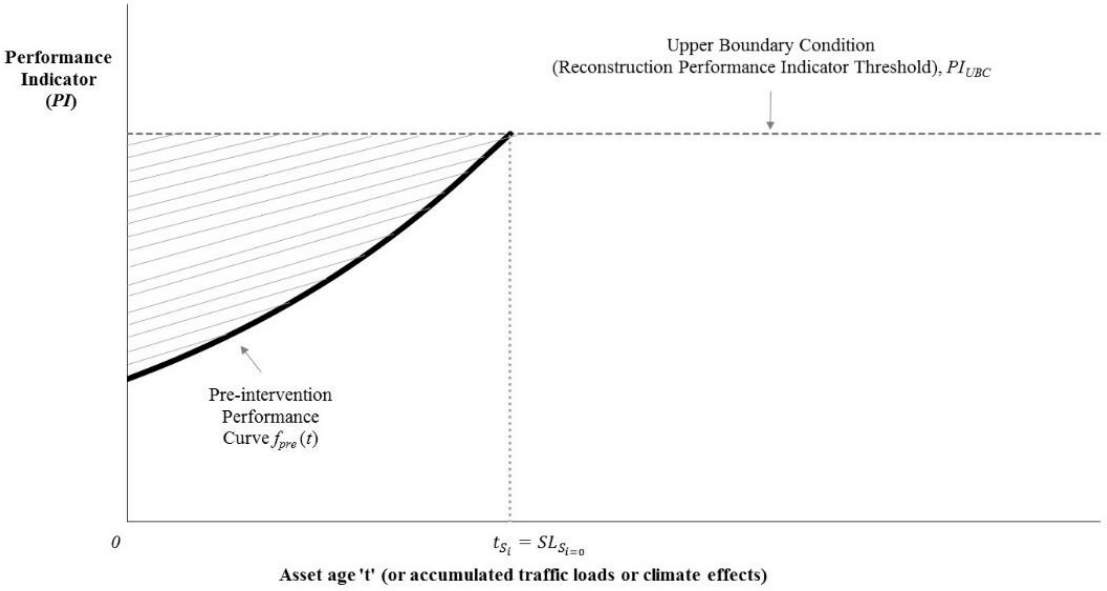


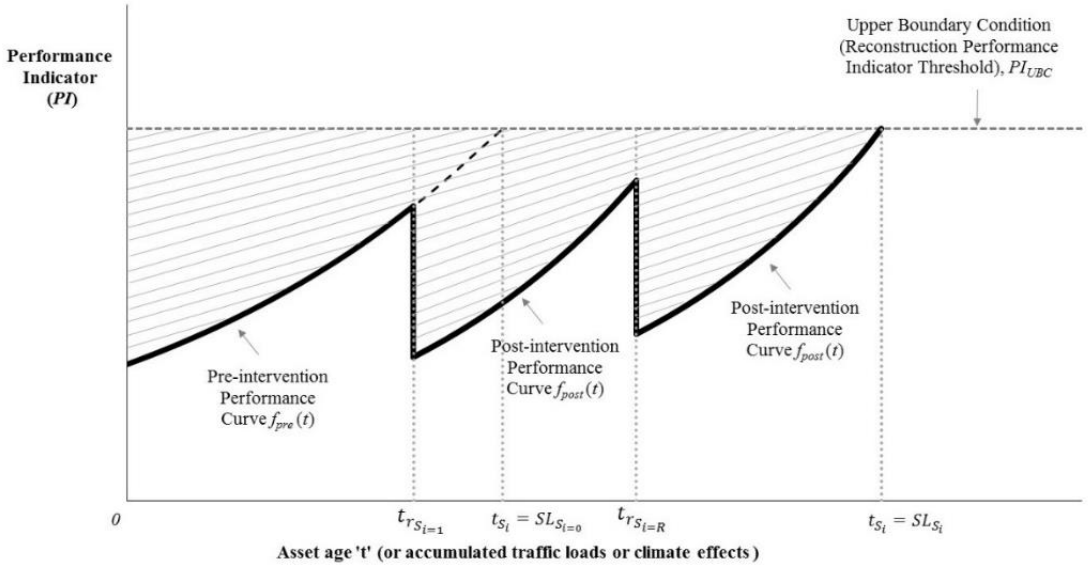
Figure 3.1 Study Framework

3.1 Infrastructure Families and Intervention Strategies

Infrastructure classification refers to grouping that reflects similarities or differences across the families of the infrastructure type under consideration. The intervention strategies are associated with the infrastructure type. An intervention strategy S_i (best solution found by using a suitable optimization technique) represents the set of thresholds and treatments to be performed. An optimal strategy is selected based on the absolute or relative change of some cost-effectiveness criterion for the candidate strategy compared to the base strategy. The base strategy is the strategy for which no interventions are performed during the infrastructure service life (Figure 3.2(a)); this strategy is typically represented by the do-nothing strategy, $S_{i=0}$. Figure 3.2(b) illustrates a non-base strategy which has, for the purposes of illustration, two interventions. In this figure, it can be observed that the infrastructure service life and the area bounded by the performance curve are improved compared to the base strategy.



(a) Base strategy ($S_{i=0}$, Do-nothing)



(b) Rehabilitation strategy S_i

Figure 3.2 Illustration of Base and Non-Base Strategies

3.2 Effectiveness Analysis

In the context of this dissertation, effectiveness refers the benefit obtained by applying an intervention strategy during the analysis period. Effectiveness may be monetized or non-monetized. Non-monetized measures of effectiveness include any of the following attributes corresponding to the strategy: service life, sum of performance jumps, average annual performance jump, average performance over the service life, or area bounded by the performance curve. The monetized measures of effectiveness include savings in the agency's routine maintenance cost, travel time cost, or crash cost, for example. For some of these measures of effectiveness (MOE), the prior development of the infrastructure performance curve is necessary. A performance curve is a function that shows the rate of the infrastructure deterioration with time. The deterioration is expressed in terms of a performance indicator.

3.2.1 Selection of an Appropriate Performance Indicator

The performance indicator (PI) should be one that reflects the effect of the intervention to improve a particular attribute of asset performance (Labi and Sinha 2004). Other properties of an appropriate PI are considered as follows (Poister, 1997; Camsys, 2000; NCHRP, 2006):

Appropriateness: PI should reflect the goal of the intervention.

Measurability and Reliability: The PI should be such that it is rather easy to measure its levels objectively and to generate the levels of performance expected after each intervention, using available analytical tools and data, with acceptable reliability.

Dimensionality: The PI should be such that it can capture the appropriate level of each dimension associated with the evaluation and thus should be comparable across different time periods and geographic regions.

Predictability: It should be possible to predict reliably the performance of the treated infrastructure using existing forecasting tools.

Performance indicators can be classified into two groups depending on their time trends: non-increasing performance indicators and non-decreasing performance indicators.

3.2.2 Performance Models

Infrastructure performance models before and after the intervention are required in the analysis. Pre-intervention models provide information on the rate of deterioration before the intervention, while post-intervention models provide information on the rate of deterioration after the intervention. To develop pre- and post-intervention performance models, historical data on asset performance is required. The models are developed in terms of the performance indicator as the response variable, and traffic load, climate, and other deterioration factors as the explanatory variables, as shown in Equation (3.1):

$$PI_{t_{S_i}} = f(\tilde{x}) \tag{3.1}$$

where $PI_{t_{S_i}}$ = asset performance in terms of the performance indicator at a specific year (age); $f(\tilde{x})$ = relates asset condition to explanatory variables that influence the asset performance, such as asset age, accumulative traffic, environmental factors, design, construction, and maintenance history.

3.2.3 Measure of Effectiveness

Measures of effectiveness (MOE) are used to estimate the benefits of a rehabilitation strategy and can be determined based on non-monetized or monetized benefits. The effectiveness of a rehabilitation strategy, S_i, can be quantified as a relative or absolute change in effectiveness (Δ_E) from a base strategy, as described in Equations (3.2), (3.3), and Figure 3.3 for the non-monetized benefits and Equations (3.4) and (3.5) for the monetized benefits. In this dissertation, the base strategy is the do-nothing strategy($S_{i=0}$), but it could be any other rehabilitation strategy.

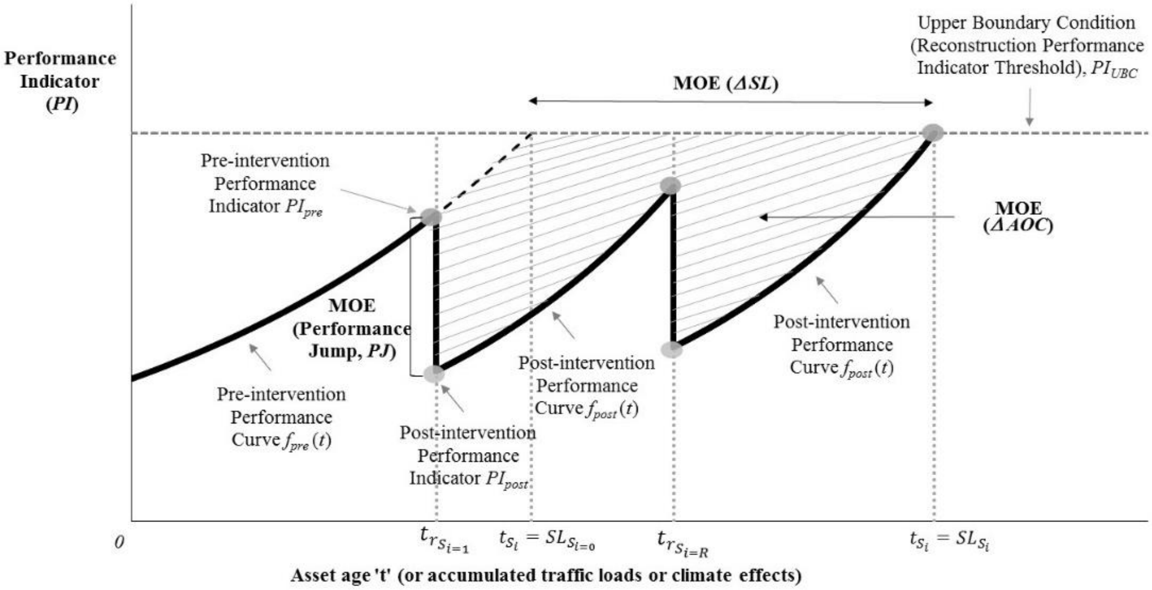


Figure 3.3 Absolute Change in Effectiveness for Non-Monetized Benefits

For non-monetized benefits:

$$Absolute\ \Delta_E = E_{S_i} - E_{S_{i=0}} \tag{3.2}$$

$$Relative\ \Delta_E = \frac{E_{S_i} - E_{S_{i=0}}}{E_{S_{i=0}}} \tag{3.3}$$

For monetized benefits (effectiveness is the reduction in cost):

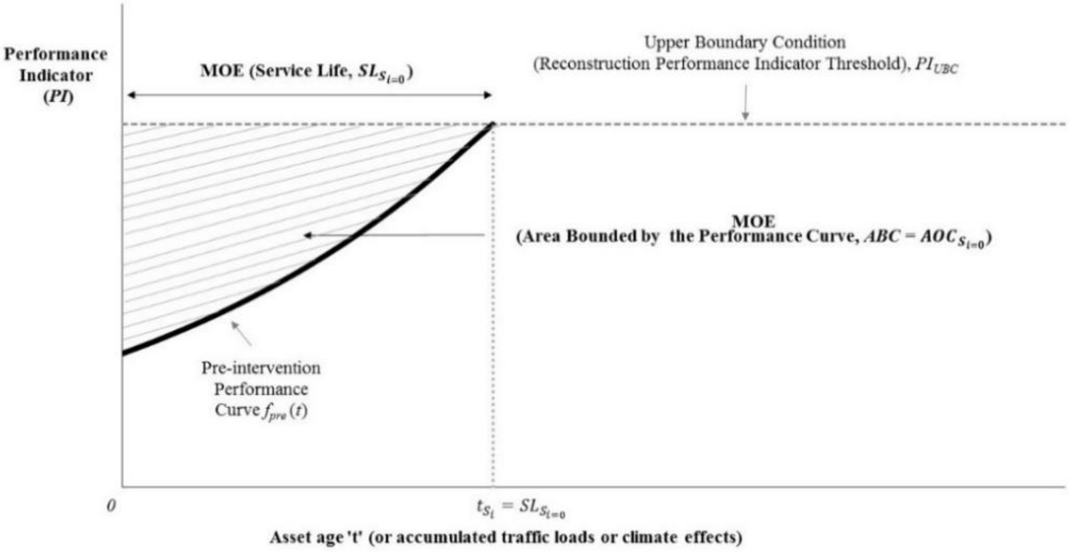
$$Absolute\ \Delta_E = \Delta_C = C_{S_{i=0}} - C_{S_i} \tag{3.4}$$

$$Relative\ \Delta_E = \Delta_C = \frac{C_{S_{i=0}} - C_{S_i}}{C_{S_{i=0}}} \tag{3.5}$$

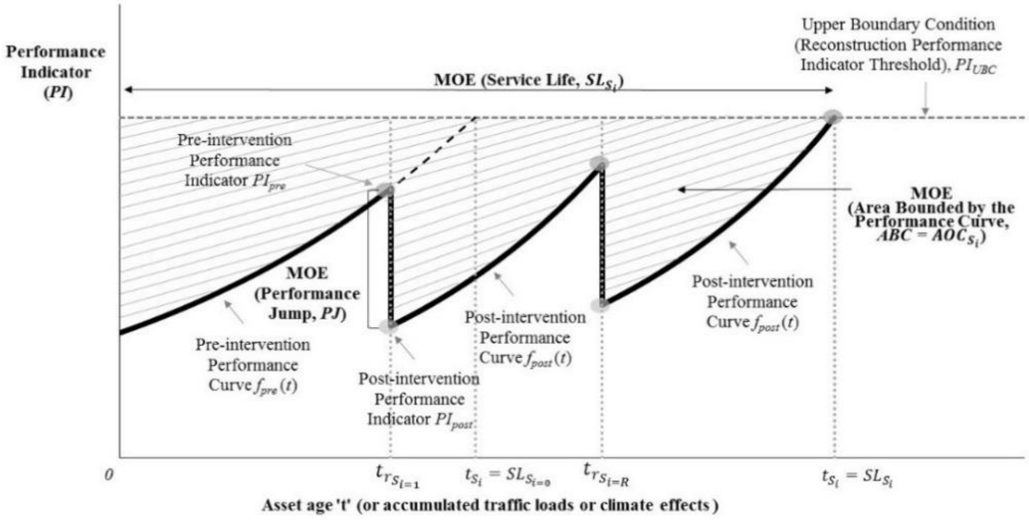
where Δ_E = Relative or absolute change in effectiveness; E_{S_i} = Effectiveness of intervention strategy S_i, and C_{S_i} = Cost of intervention strategy S_i.

3.2.3.1 Non-Monetized Measures of Effectiveness

Using a non-decreasing performance indicator Figure 3.4 illustrates the most commonly-used MOE for two different strategies. Figure 3.4(a) illustrates the do-nothing strategy $S_{i=0}$. The measures of effectiveness are the infrastructure service life, the infrastructure average performance, and the area bounded by the performance curve. From Figure 3.4(b), it is observed that the infrastructure service life and area bounded by the performance curve increases due to performing two interventions. To compare the effectiveness between alternative strategies, the incremental benefits relative to the base case or do-nothing strategy (Figure 3.3) is used.



(a) Base Strategy ($S_{i=0}$, Do-nothing)



(b) Intervention Strategy (S_i)

Figure 3.4 Illustration of MOEs for Non-Decreasing Performance Indicator

(a) Service Life

The infrastructure service life (SL_{S_i}) of an intervention strategy corresponds either to the time elapsed between a new construction and the reconstruction intervention or the time between two reconstruction interventions (Figure 3.4). It can also be estimated as the time (years) that an infrastructure takes to reach the reconstruction threshold value (PI_{LBC} or PI_{UBC}, for non-increasing and non-decreasing PIs, respectively), Equation (3.6):

$$SL_{S_i} = f(\tilde{x}) \tag{3.6}$$

where SL_{S_i} is the time for a strategy S_i to reach a reconstruction threshold; $f(\tilde{x})$ = relates infrastructure performance to the relevant explanatory variables, including the infrastructure age, accumulated loading, environmental severity, design and construction factors, and maintenance history.

When the intervention strategy is applied to an infrastructure, the resulting increase in service life compared to the do-nothing scenario can be expressed in terms of the absolute or relative change of the service life, as shown in Equations (3.7) and (3.8):

$$Absolute\ \Delta SL = SL_{S_i} - SL_{S_{i=0}} \tag{3.7}$$

$$Relative\ \Delta SL = \frac{SL_{S_i} - SL_{S_{i=0}}}{SL_{S_{i=0}}} \tag{3.8}$$

where ΔSL = Change in effectiveness in terms of infrastructure service life.

(b) Performance Jump

This corresponds to the vertical increase or reduction due to a rehabilitation intervention associated with strategy S_i ($PJ_{r_{S_i}}$), (see Figure 3.4). The jump can be expressed as an average value or as a function of infrastructure attributes, as shown in Equation (3.9). The attributes may include the initial or pre-treatment condition ($PI_{pre,r_{S_i}}$) and intervention attributes, such as treatment intensity (Labi et al. 2005).

$$PJ_{r_{S_i}} = f\left(PI_{pre,r_{S_i}}\right) \tag{3.9}$$

Besides the base strategy, each strategy involves a number of performance jumps. The sum of the performance jumps magnitudes that occur through the infrastructure service life (PJ_{S_i}) can be considered as a MOE for comparing the rehabilitation strategies (Equation (3.10)):

$$PJ_{S_i} = \sum_{r_{S_i}}^{R_{S_i}} PJ_{r_{S_i}} \tag{3.10}$$

where r_{S_i} represents an intervention for strategy S_i $(r_{S_i}$ =1, 2, …, $R_{S_i})$ and R is the optimal number of interventions associated with the strategy S_i.

The absolute or relative change in effectiveness of a strategy in terms of the performance jump relative to the base strategy, is given in Equations (3.11) and (3.12):

$$Absolute\ \Delta PJ = PJ_{S_i} - PJ_{S_{i=0}} \tag{3.11}$$

$$Relative\ \Delta PJ = \frac{PJ_{S_i} - PJ_{S_{i=0}}}{PJ_{S_{i=0}}} \tag{3.12}$$

where ΔPJ = Change in effectiveness, in terms of the PJ magnitudes and PJ_{S_i} = Sum of magnitudes of performance jumps associated with the strategy S_i.

(c) Average Performance

This is a long-term measure of effectiveness that represents the average performance (AP_{S_i}) of a strategy throughout the service life of the infrastructure, as shown in Equation (3.13):

$$AP_{S_i} = \frac{1}{SL_{S_i}} \cdot \sum_{t_{S_i}=0}^{t_{S_i}=SL_{S_i}} PI_{t_{S_i}} \tag{3.13}$$

where AP_{S_i} = Average performance of strategy S_i; SL_{S_i} = Service life for the strategy S_i, and $PI_{t_{S_i}}$ = Annual performance for strategy S_i (t_{S_i} = 0, 1, 2, …, SL_{S_i}).

For an asset that received a rehabilitation strategy, the effectiveness in average performance can be determined as the change in average performance relative to the performance from a base strategy, using Equations (3.14) and (3.15):

$$Absolute\ \Delta AP = AP_{S_i} - AP_{S_{i=0}} \tag{3.14}$$

$$Relative\ \Delta AP = \frac{AP_{S_i} - AP_{S_{i=0}}}{AP_{S_{i=0}}} \tag{3.15}$$

where ΔAP is the change in average performance effectiveness; the remaining symbols and subscripts are consistent with their previous definitions.

(d) Area Bounded by the Performance Curve

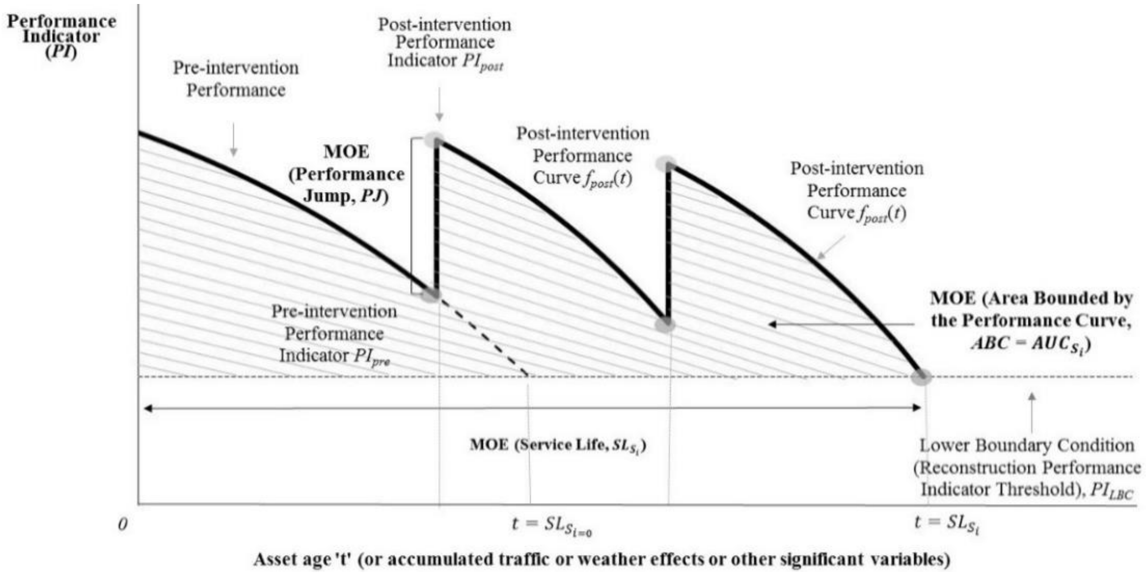
The area bounded between the performance curve of the strategy S_i (ABC_{S_i}) and the threshold line (reconstruction trigger, $PI_{LBC,UBC}$) is sown in Figure 3.5. For the non-increasing performance indicators, the effectiveness is represented as the area bounded by the performance curve and threshold performance line. This is the area under the curve (AUC) (Figure 3.5 (a)). For non-decreasing performance indicators, effectiveness is the area over the curve (AOC), (Figure 3.5 (b)).

An asset that is well maintained is expected to have a performance curve with gentle slope, and therefore, a larger area bounded by the performance curve over its service life; such an asset provides user's benefits greater than those of a poorly-maintained asset (Geoffroy, 1996; Labi and Sinha, 2005; Khurshid et al. 2009, 2010).

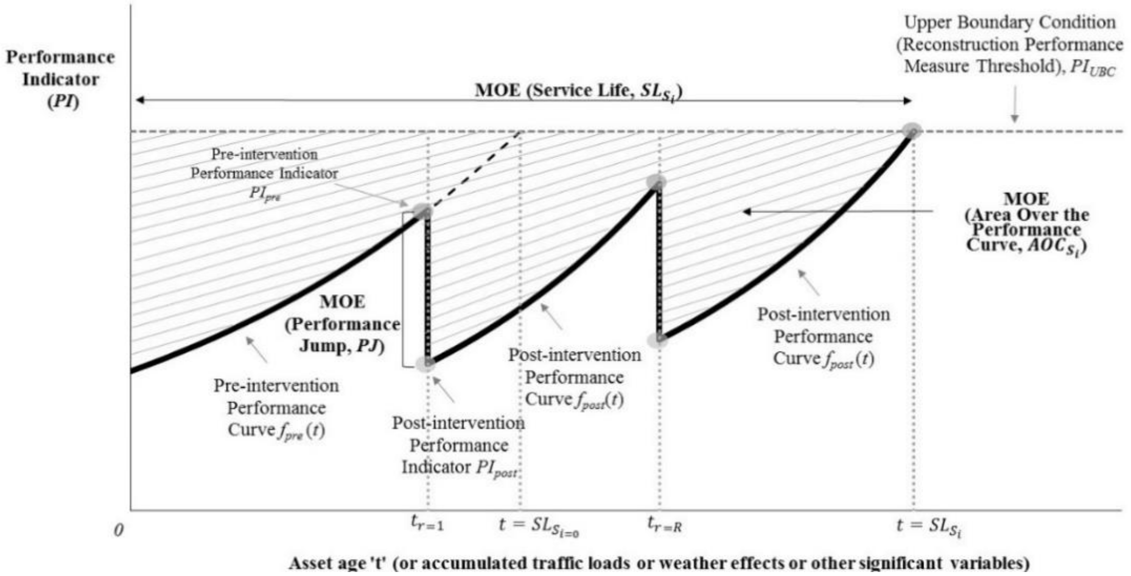
Depending on the nature of the performance indicator (i.e., non-increasing or non-decreasing), pre- and post-intervention performance models, $f_{pre}(t)$ and $f_{post}(t)$, can then be used to estimate the AUC or AOC for each strategy $S_i$using Equations (3.16) and (3.17):

$$AUC_{S_i} = \left[\int_{0}^{t_{r_{S_i}=1}} f_{pre}(t)dt + \sum_{r_{S_i}=1}^{R_{S_i}} \int_{t_{r_{S_i}}}^{t_{r_{S_i}+1}} f_{post}(t)dt + \int_{t_{r_{S_i}=R}}^{SL_{S_i}} f_{post}(t)dt \right] - \left(PI_{LBC} \cdot SL_{S_i}\right) \tag{3.16}$$

$$AOC_{S_i} = \left(PI_{UBC} \cdot SL_{S_i}\right) - \left[\int_{0}^{t_{r_{S_i}=1}} f_{pre}(t)dt + \sum_{r_{S_i}=1}^{R_{S_i}} \int_{t_{r_{S_i}}}^{t_{r_{S_i}+1}} f_{post}(t)dt + \int_{t_{r_{S_i}=R}}^{SL_{S_i}} f_{post}(t)dt \right] \tag{3.17}$$



(a) Non-Increasing Performance Indicator



(b) Non-Decreasing Performance Indicator

Figure 3.5 Illustration of Area Bounded by the Performance Curve

where AUC_{S_i} = Area under the performance curve for the strategy S_i (for non-increasing PIs);

AOC_{S_i} = Area over the performance curve for the strategy S_i (for non-decreasing PIs);

$t_{r_{S_i}} = t$, for rehabilitation intervention at $PI_{pre,r_{S_i}}$;

$PI_{pre,r_{S_i}}$ = Pre-intervention performance level at rehabilitation intervention r_{S_i};

r_{S_i} = Intervention for strategy S_i $\left(r_{S_i} = 1, 2, \ldots, R_{S_i}\right)$

R = optimal number of interventions associated with the strategy S_i;

$f_{pre}(t)$ = Pre-intervention performance model (performance curve for the rest period following a new infrastructure construction);

$f_{post}(t)$ = Post-intervention performance models for rehabilitation strategy S_i;

SL_{S_i} = Service life, time for a strategy S_i to reach a reconstruction threshold ($PI_{LBC,UBC}$);

PI_{LBC} = Lower boundary condition of performance indicator (reconstruction threshold for non-increasing PIs);

PI_{UBC} = Upper boundary condition for performance indicator (reconstruction threshold for non-decreasing PIs).

For the purpose of this dissertation, effectiveness was estimated using the area bounded by the curve in the absolute and relative incremental benefit (area) from the base strategy. Effectiveness can be estimated using Equations (3.18) and (3.19):

$$Absolute\ \Delta ABC = ABC_{S_i} - ABC_{S_{i=0}} \tag{3.18}$$

$$Relative\ \Delta ABC = \frac{ABC_{S_i} - ABC_{S_{i=0}}}{ABC_{S_{i=0}}} \tag{3.19}$$

where ΔABC = Change in area bounded by the performance curve relative to the base strategy; ABC_{S_i} = Area bounded by the performance curve of the strategy S_i (ABC_{S_i} = AUC_{S_i}, for non-increasing PIs and ABC_{S_i} = AOC_{S_i}, for non-decreasing PIs).

3.2.3.2 Monetized Measures of Effectiveness

Monetized benefits correspond to the cost savings during normal operations from the agency and user perspective by comparing normal operation costs for the strategy S_i and a base strategy $S_{i=0}$. This savings can be estimated as a relative or absolute change in effectiveness. To compare strategies using the monetized benefits presented in this section and the cost components described in the following sections, all monetized amounts need to be expressed as Present Worth Cost (PWC), Present Worth Cost to

Perpetuity ($PWCP$), and Equivalent Uniform Annual Cost to Perpetuity ($EUACP$), as commonly practiced in engineering economics. To find the PWC, each monetized component is multiplied by the single payment present worth factor $SPPWF$, as represented by Equation (3.20):

$$PWC = Monetized\ component\ \cdot SPPWF \tag{3.20}$$

where:

$$SPPWF = \frac{1}{(1+u)^N} \tag{3.21}$$

u = Interest Rate and N = Year at which a specific amount is spent or incurred in the infrastructure life cycle.

The $PWCP$ values can be found using Equation (3.22):

$$PWCP = \frac{PWC}{(1+u)^{SL_{S_i}} - 1} \tag{3.22}$$

where SL_{S_i} is the service life for a strategy S_i (time to reach a reconstruction threshold $PI_{LBC,UBC}$); other symbols and subscripts have their aforementioned meanings.

To determine the $EUACP$ amounts, all $PWCP$ values are multiplied by the capital recovery factor CRF,as shown in Equation (3.24):

$$EUACP = PWCP\ \cdot CRF \tag{3.23}$$

$$CRF = \frac{u(1+u)^{SL_{S_i}}}{(1+u)^{SL_{S_i}} - 1} \tag{3.24}$$

where the symbols and subscripts have their usual meanings.

(a) Agency Cost Savings

When the intervention is carried out according to a specific strategy, the average condition throughout the service life is improved compared to the average condition corresponding to the base strategy. That condition improvement reflects the savings in terms of the reduction of annual agency maintenance expenditures. The absolute and relative agency cost savings during normal operations can be estimated using Equations (3.25) and (3.26):

$$Absolute\ \Delta ACS = ACNO_{S_{i=0}} - ACNO_{S_i} \tag{3.25}$$

$$Relative\ \Delta ACS = \frac{ACNO_{S_{i=0}} - ACNO_{S_i}}{ACNO_{S_{i=0}}} \tag{3.26}$$

where ΔACS = Change in agency cost during normal operations (savings in terms of reduction in maintenance expenditures); $ACNO_{S_i}$ = Annual agency maintenance expenditures at $PI_{t_{S_i}}$, for rehabilitation strategy S_i; $PI_{t_{S_i}}$ = Annual performance (t_{S_i} = 0, 1, 2, …, SL_{S_i}); and SL_{S_i} = Service life for strategy S_i.

The estimation of agency cost during normal operations is presented at Section 3.3.1.2 of this Chapter.

(b) User Cost Savings

When the intervention is carried out according to a specific strategy, the average condition throughout the service life is improved compared to the average condition corresponding to the base strategy. Such condition improvement reflects savings from the users' perspective in terms of reduction in the annual user cost. The absolute and relative user cost savings during normal operations can be estimated using Equations (3.27) and (3.28):

$$Absolute\ \Delta UCS = UCNO_{S_{i=0}} - UCNO_{S_i} \tag{3.27}$$

$$Relative\ \Delta UCS = \frac{UCNO_{S_{i=0}} - UCNO_{S_i}}{UCNO_{S_{i=0}}} \tag{3.28}$$

where ΔUCS = Change in user cost during normal operations (savings in terms of reduction in user cost); $UCNO_{S_i}$ = Annual user cost (for example, vehicle operation cost for highways) at $PI_{t_{S_i}}$, for rehabilitation strategy S_i; other symbols and subscripts have their usual meanings.

The estimation of user costs during normal operations is presented in Section 3.3.2.2 of this chapter.

3.3 Cost Analysis

In the study framework, a cost analysis helps to measure the financial impacts of various alternative timings and types of rehabilitation. The methodology presented accounts for both the agency and user during downtime and normal operation periods (Table 3.1). The development of optimal strategies can proceed in any of three ways: (1) using only the agency costs while ignoring the user costs, (2) using only the user costs while ignoring the agency costs, and (3) considering both the agency and user costs, duly weighted. For agencies that are interested in the user perspective, user costs may be included in the analysis to estimate the total cost of an intervention strategy.

Table 3.1 Agency and User Cost Components

	Agency Cost	User Cost
Downtime Periods	$ACDT$: Typically estimated as cost per lane-mile. • Interventions.	$UCDT$: • User delays. For highway infrastructures: detours and speed reduction.
Normal Operations	$ACNO$: Time between interventions. • Maintenance expenditures.	$UCNO$: • Expenditures during normal operations. For highway infrastructures: vehicle operating costs.

Cost analysis is a key component of highway intervention evaluation. In some cases, benefits are estimated as a decrease in the costs accrued by the user, compared to some base case. The costs associated with infrastructure strategies ($Cost_{S_i}$) generally include agency costs and user costs, which are presented in Equation (3.29) and discussed in detail in the following sections. The absolute and relative changes in cost are presented in Equations (3.30) and (3.31):

$$C_{S_i} = w_{AC} \cdot \sum_{\alpha=1}^{p} AC_{S_i,\alpha} + w_{UC} \cdot \sum_{\gamma=1}^{q} UC_{S_i,\gamma} \tag{3.29}$$

$$Absolute\ \Delta C = C_{S_{i=0}} - C_{S_i} \tag{3.30}$$

$$Relative\ \Delta C = \frac{C_{S_{i=0}} - C_{S_i}}{C_{S_{i=0}}} \tag{3.31}$$

where C_{S_i} = Both agency and user cost for the rehabilitation strategy S_i; w_{AC}, w_{UC} = Weighting factors for agency and user costs, $0 \leq w_{AC}, w_{UC} \leq 1$ respectively; AC_{S_i} = Agency cost associated with rehabilitation strategy S_i; α = Component of agency cost at downtime periods $(ACDT)$ and during normal operations ($ACNO$); α = 1, 2, …, p; UC_{S_i} = User cost associated with rehabilitation strategy S_i; γ = Component of user cost at downtime periods $(UCDT)$ and during normal operations ($UCNO$); γ = 1, 2, …, q; and ΔC = Change in costs relative to the base case.

Costs are often estimated using historical records either as average values or regression cost models. In estimating the life cycle cost of an infrastructure, there are instances where a cost component is incurred in different years. Therefore, the costs need to be converted to a constant-year dollar value, Equation (3.32), using the Highway Construction Price Index (Federal Highway Administration, 2015) or the Consumer Price Index (Bureau of Labor Statistics, 2015):

$$C_{AY} = C_{BY} \frac{CPI_{AY}}{CPI_{BY}} \tag{3.32}$$

where C_{AY} = Cost of intervention in the analysis year; C_{BY} = Cost of intervention in the reference year; CPI_{AY} = Construction price index or Consumer price index for the analysis year; CPI_{BY} = Construction price index or Consumer price index for the analysis year.

3.3.1 Agency Cost Estimation

Agency costs (AC), Equation (3.33), includes the following direct costs incurred in the building and operation of an infrastructure facility: (1) initial construction cost and rehabilitation intervention cost ($ACDT$), which includes contract costs, and (2) maintenance and rehabilitation expenditures over a specified analysis period such as the asset life or the time span between two interventions ($ACNO$).

$$AC_{S_i} = \varphi_{dt} \cdot ACDT_{S_i} + \varphi_{no} \cdot ACNO_{S_i} \tag{3.33}$$

where AC_{S_i} = Agency cost associated with strategy S_i; $ACDT_{S_i}$ = Agency cost of initial construction and subsequent rehabilitation interventions associated with strategy S_i; $ACNO_{S_i}$ = Agency cost during normal operations associated with strategy S_i; and φ_{dt}, φ_{no} = Weighting factor for agency at downtime and normal operations, $0 \leq \varphi_{dt}$, $\varphi_{no} \leq 1$ respectively.

3.3.1.1 Agency Cost Estimation at Downtime ($ACDT$) Periods

Downtime occurs when an intervention is performed. One example is the workzone during highway rehabilitation. Downtime periods can be full or partial. The cost of an intervention ($ per lane-mile) is influenced by the pre-intervention infrastructure condition ($PI_{pre,r}$) represented by the chosen performance indicator, Equation (3.34):

$$CI_{r_{S_i}} = f\left(PI_{pre,r_{S_i}}\right) \tag{3.34}$$

The total agency cost during downtime can be estimated from the sum of the cost of each intervention that occurs during the service life of strategy S_i in Equation (3.35):

$$ACDT_{S_i} = \sum_{r_{S_i}}^{R_{S_i}} CI_{r_{S_i}} \tag{3.35}$$

where $ACDT_{S_i}$ = Agency cost of subsequent interventions associated with strategy S_i; $CI_{r_{S_i}}$= Cost of an intervention r_{S_i}; r_{S_i} = Intervention for strategy S_i (r_{S_i} =1, 2, …, R_{S_i}); and R = Optimal number of interventions associated with the strategy S_i.

3.3.1.2 Agency Cost Estimation During Normal Operations ($ACNO$)

The purpose of estimating annual maintenance agency cost during normal operations ($ACNO$) is to account for the overall agency cost of intervention strategies and determinate the optimal (non-fixed thresholds set) based on life cycle cost analysis. The annual maintenance expenditure is a function of annual performance condition (PI_t) in Equation (3.36):

$$ACNO_{S_i} = \sum_{t_{S_i}=0}^{t_{S_i}=SL_{S_i}} f\left(PI_{t_{S_i}}\right) \tag{3.36}$$

where SL_{S_i} = Service life, time for a strategy S_i to reach a reconstruction threshold; and $PI_{t_{S_i}}$ = Annual performance (t_{S_i} = 0, 1, 2, …, SL_{S_i}).

3.3.2 User Cost Estimation

User costs commonly include: (1) delay costs incurred by facility users during downtime periods ($UCDT$) and (2) user costs incurred during the normal use of the asset ($UCNO$) over the service life offered by the strategy over the span of time between successive interventions, Equation (3.37):

$$UC_{S_i} = \delta_{dt} \cdot UCDT_{S_i} + \delta_{no} \cdot UCNO_{S_i} \tag{3.37}$$

where UC_{S_i} = User cost associated with strategy S_i ; $UCDT_{S_i}$ = User cost during interventions associated with strategy S_i; $UCNO_{S_i}$ = User cost during normal operations associated with strategy S_i; and δ_{dt} , δ_{no} = Weighting factor for users at downtime and normal operations, $0 \leq \delta_{dt}$, $\delta_{no} \leq 1$ respectively.

3.3.2.1 User Cost Estimation at Downtime ($UCDT$)

When an infrastructure receives an intervention, the normal use of the intervention is interrupted and this creates user delays and user operational cost due to a reduction in infrastructure capacity. The aggregate sum of these costs is used to estimate the total user cost at downtimes (Equation (3.38)):

$$UCDT_{S_i} = \sigma_{dy} \cdot \sum_{r_{S_i}}^{R_{S_i}} UDC_{r_{S_i}} + \sigma_{sr} \cdot \sum_{r_{S_i}}^{R_{S_i}} UOCcr_{r_{S_i}} \tag{3.38}$$

where $UCDT_{S_i}$ = User cost during interventions associated with strategy S_i; $UDC_{r_{S_i}}$= User delay cost associated with an intervention r_{S_i}; $UOCcr_{r_{S_i}}$= User operation cost due to capacity reduction associated with intervention r_{S_i}; r_{S_i} = Intervention for strategy S_i (r_{S_i} =1, 2, …, R_{S_i}); R = Optimal number of interventions associated with the strategy S_i; and σ_{dy} , σ_{sr} = Weighting factor for user delay and capacity reduction costs, 0 ≤σ_{dy} , $\sigma_{sr} \leq 1$ respectively.

The user delay cost of an intervention can be influenced by the intervention duration ($D_{r_{S_i}}$). This can be estimated as a function of the agency cost intervention ($CI_{r_{S_i}}$) and the construction contract type (e.g., fixed duration or fixed deadline project), Equation (3.39):

$$D_{r_{S_i}} = f\left(CI_{r_{S_i}}, Contract_{type}\right) \tag{3.39}$$

The downtime duration can be estimated as a fraction of the project duration using historical data. Alternatively, a model could be developed for the downtime duration.

3.3.2.2 User Cost Estimation During Normal Operations ($UCNO$)

User costs during normal operations are associated with the cost that users have to cover based on the infrastructure condition that could be reduced with infrastructure improvements (Equation (3.40)):

$$UCNO_{S_i} = \sum_{t_{S_i}=0}^{t_{S_i}=SL_{S_i}} f(x_c) \tag{3.40}$$

where $f(x_c)$ is the components of user cost impacted by infrastructure performance, and SL_{S_i} is the strategy S_i service life or the time for an infrastructure to reach a given reconstruction threshold.

3.4 Cost-Effectiveness Analysis

Cost-effectiveness (CE) analysis can be performed in terms of monetized and non-monetized measures of effectiveness in the short-term by using performance jump as a measure, or in the long-term by using the infrastructure service life, the area bounded by the performance curve, and the average increase in infrastructure performance condition.

In assessing the cost-effectiveness of interventions, considerations include (1) the extent to which the intervention improves the pre-intervention condition; (2) the extent to which the intervention delays the deterioration process thus extending the asset life; and (3) the existence of a specific condition or a specific time at which the intervention is most cost-effective (Chong, 1990; Walls and Smith, 1998).

The present methodology is primarily based on the incremental benefit-cost ratio (BCR) method. The analysis is based on non-monetized and monetized measures of effectiveness and determined by absolute and relative change in effectiveness and cost. The objective is to determine an optimal rehabilitation strategy that yields the minimum possible overall cost at the maximum possible benefit, or the highest CE. The costs and benefits corresponding to various rehabilitation strategies are first estimated and then the corresponding CE is calculated in Equations (3.41) through (3.44):

Cost-effectiveness for non-monetized benefits can be estimated from Equations (3.2), (3.3), (3.30), and (3.31):

$$CE_a = \frac{E_{S_i} - E_{S_{i=0}}}{C_{S_{i=0}} - C_{S_i}} \tag{3.41}$$

$$CE_r = \frac{\frac{E_{S_i} - E_{S_{i=0}}}{E_{S_{i=0}}}}{\frac{C_{S_{i=0}} - C_{S_i}}{C_{S_{i=0}}}} \tag{3.42}$$

Cost-effectiveness for monetized benefits can be estimated from Equations (3.4), (3.5), (3.30), and (3.31):

$$CE_a = \frac{E_{S_{i=0}} - E_{S_i}}{C_{S_{i=0}} - C_{S_i}} \tag{3.43}$$

$$CE_r = \frac{\dfrac{E_{S_{i=0}} - E_{S_i}}{E_{S_{i=0}}}}{\dfrac{C_{S_{i=0}} - C_{S_i}}{C_{S_{i=0}}}} \tag{3.44}$$

where CE_a = Cost-effectiveness ratio based on absolute change in effectiveness and absolute change in cost relative to the base case; CE_r = Cost-effectiveness ratio based on relative change in effectiveness and relative change in cost relative to the base case; E_{S_i} = Effectiveness associated with rehabilitation strategy S_i; and C_{S_i} = Cost associated with rehabilitation strategy S_i.

3.4.1 Cost-Effectiveness Based on Service Life

The cost-effectiveness can be represented by absolute and relative change in service life and cost for the strategy S_i, Equations (3.45) and (3.46).

From Equations (3.7), (3.33), and (3.37):

$$CE_{SL\_a} = \frac{SL_{S_i} - SL_{S_{i=0}}}{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UC_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right)} \tag{3.45}$$

From Equations (3.8), (3.33), and (3.37):

$$CE_{SL\_r} = \frac{\dfrac{SL_{S_i} - SL_{S_{i=0}}}{SL_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UC_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right)}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right)}} \tag{3.46}$$

where CE_{SL_a} = Cost-effectiveness ratio based on absolute change in infrastructure service life and absolute change in cost associated with strategy S_i; CE_{SL_r} = Cost-effectiveness ratio based on relative change in infrastructure service life and relative change in cost associated with strategy S_i; SL_{S_i} = Time for a strategy S_i to reach a specified reconstruction threshold; AC_{S_i} = Agency cost associated with rehabilitation strategy S_i; UC_{S_i} = User cost associated with rehabilitation strategy S_i; and w_{AC}, w_{UC} = Weighting factors for agency and user costs, 0 ≤ w_{AC}, w_{UC} ≤ 1 respectively.

3.4.2 Cost-Effectiveness Based on Performance Jump

This short-term measure of effectiveness is related to user benefits, those who benefit from performance improvement due to an intervention. Therefore, when estimating the absolute and relative changes in cost (Equations (3.47) and (3.48)), the reduced user costs during normal operations over the infrastructure service life must be excluded because they are implicitly considered as benefits, and the inclusion of these costs in the denominator would lead to double counting.

From Equations (3.11), (3.33), and (3.38):

$$CE_{PJ\_a} = \frac{PJ_{S_i} - PJ_{S_{i=0}}}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right) - \left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right)} \tag{3.47}$$

From Equations (3.12), (3.33), and (3.38):

$$CE_{PJ\_r} = \frac{\dfrac{PJ_{S_i} - PJ_{S_{i=0}}}{PJ_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right) - \left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right)}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}} \tag{3.48}$$

where CE_{PJ_a} = Cost-effectiveness ratio based on absolute change in performance jump and absolute change in cost associated with strategy S_i; CE_{PJ_r} = Cost-effectiveness ratio based on relative change in performance jump and relative change in cost associated with strategy S_i; PJ_{S_i} = Sum of performance jumps that occur during the infrastructure service life associated with strategy S_i; AC_{S_i} = Agency cost associated with rehabilitation strategy S_i; $UCDT_{S_i}$ = User cost during downtime periods associated with strategy S_i; and w_{AC}, w_{UC} = Weighting factors for agency and user costs, 0 ≤ w_{AC}, w_{UC} ≤ 1 respectively.

3.4.3 Cost-Effectiveness Based on Average Performance

The average performance is related to user benefits, as those who benefit from performance improvement due to infrastructure rehabilitations. Therefore, when estimating the absolute and relative changes in cost (Equations (3.49) and (3.50)), the reduced user costs during normal operations over the infrastructure service life must be excluded because they are implicitly considered as benefits, and the inclusion of these costs in the denominator would lead to double counting.

From Equations (3.14), (3.33), and (3.38):

$$CE_{AP\_a} = \frac{AP_{S_i} - AP_{S_{i=0}}}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right) - \left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right)} \tag{3.49}$$

From Equations (3.15), (3.33), and (3.38):

$$CE_{AP\_r} = \frac{\dfrac{AP_{S_i} - AP_{S_{i=0}}}{AP_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right) - \left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right)}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}} \tag{3.50}$$

where CE_{AP_a} = Cost-effectiveness ratio based on absolute change in average performance and absolute change in cost associated with strategy S_i; CE_{AP_r} = Cost-effectiveness ratio based on relative change in average performance and relative change in cost associated with strategy S_i; AP_{S_i} = Average performance associated with strategy S_i; remaining symbols and subscripts have their usual meanings.

3.4.4 Cost-Effectiveness Based on Area Bounded by the Performance Curve

The size of the area bounded by the performance curve is a measure that reflects user benefits. Therefore, when estimating the absolute and relative change in cost (Equations (3.51) and (3.52)), the reduced user costs during normal operations of the infrastructure service life must be excluded because those are implicitly considered as benefits. Similar to the situation for average performance, the inclusion of these costs in the denominator would lead to double counting.

From Equations (3.18), (3.33), and (3.38):

$$CE_{ABC\_a} = \frac{ABC_{S_i} - ABC_{S_{i=0}}}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right) - \left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right)} \tag{3.51}$$

From Equations (3.19), (3.33), and (3.38):

$$CE_{ABC\_r} = \frac{\dfrac{ABC_{S_i} - ABC_{S_{i=0}}}{ABC_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right) - \left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right)}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}} \qquad (3.52)$$

where CE_{ABC_a} = Cost-effectiveness ratio based on absolute change in area bounded by the performance curve and absolute change in cost associated with strategy S_i; CE_{ABC_r} = Cost-effectiveness ratio based on relative change in area bounded by the performance curve and relative change in cost associated with strategy S_i; ABC_{S_i} = Area bounded by the performance curve associated with strategy S_i (ABC_{S_i} = AUC_{S_i}, for non-increasing PIs and ABC_{S_i} = AOC_{S_i}, for non-decreasing PI); other symbols and subscripts have their usual meanings.

3.4.5 Cost-Effectiveness Based on Agency Cost Savings

Agency cost savings are related to a reduction in agency cost at normal operations. Therefore, when estimating the absolute and relative changes in cost (Equations (3.53) and (3.54)), reduced agency costs during normal operations over the infrastructure service life must be excluded because those are implicitly considered as benefits. Similar to the case for performance and area bounded by the curve, the inclusion of these costs in the denominator would lead to double counting.

From Equations (3.25), (3.35), (3.36), and (3.37):

$$CE_{ACS\_a} = \frac{ACNO_{S_{i=0}} - ACNO_{S_i}}{\left(w_{AC} \cdot ACDT_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right) - \left(w_{AC} \cdot ACDT_{S_i} + w_{UC} \cdot UC_{S_i}\right)} \qquad (3.53)$$

From Equations (3.26), (3.35), (3.36), and (3.37):

$$CE_{ACS\_r} = \frac{\dfrac{ACNO_{S_{i=0}} - ACNO_{S_i}}{ACNO_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot ACDT_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right) - \left(w_{AC} \cdot ACDT_{S_i} + w_{UC} \cdot UC_{S_i}\right)}{\left(w_{AC} \cdot ACDT_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right)}} \qquad (3.54)$$

where CE_{ACS_a} = Cost-effectiveness ratio based on absolute change in agency cost savings and absolute change in cost expenditures associated with strategy S_i; CE_{ACS_r} =

Cost-effectiveness ratio based on relative change in agency cost savings and relative change in cost expenditures associate with strategy S_i; $ACNO_{S_i}$ = Agency cost during normal operations associated with strategy S_i ; $ACDT_{S_i}$ = Agency cost of initial construction and subsequent rehabilitation interventions associated with strategy S_i; UC_{S_i} = User cost associated with rehabilitation strategy S_i; and w_{AC}, w_{UC} = Weighting factors for agency and user costs, $0 \leq w_{AC}, w_{UC} \leq 1$ respectively.

3.4.6 Cost-Effectiveness Based on User Cost Savings

User cost savings are the reduction in user cost at normal operations. Therefore, when estimating the absolute and relative changes in cost (Equations (3.53) and (3.54)), the reduced user costs during normal operations over the infrastructure service life must be excluded because those are implicitly considered as benefits, and including these costs in the denominator would lead to double counting.

From Equations (3.27), (3.33), (3.38), and (3.40):

$$CE_{UCS\_a} = \frac{UCNO_{S_i} - UCNO_{S_{i=0}}}{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)} \tag{3.55}$$

From Equations (3.28), (3.33), (3.38), and (3.40):

$$CE_{UCS\_r} = \frac{\dfrac{UCNO_{S_i} - UCNO_{S_{i=0}}}{UCNO_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}} \tag{3.56}$$

where CE_{UCS_a} = Cost-effectiveness ratio based on absolute change in user cost savings and absolute change in cost associated with strategy S_i; CE_{UCS_r} = Cost-effectiveness ratio based on relative change in user cost savings and relative change in cost associated with strategy S_i; $UCNO_{S_i}$ = User cost during normal operations associated with strategy S_i; AC_{S_i} = Agency cost associated with rehabilitation strategy S_i; $UCDT_{S_i}$ = User cost during rehabilitation interventions associated with strategy S_i; and w_{AC}, w_{UC} = Weighting factors for agency and user costs, $0 \leq w_{AC}, w_{UC} \leq 1$ respectively.

3.5 Optimization Problem Design

Optimization tools can help infrastructure managers to determine the best rehabilitation strategies for their facilities. In this section, the dissertation presents the objective function, design variables, and constraints. Then the optimization formulation is presented using various benefit types in the objective function; specifically used are the cost-effectiveness based on performance jump, average performance (condition) of the infrastructure over the life cycle, area bounded by the performance curve, agency cost savings, and the user cost savings. This section also discusses details of the optimization technique, namely the genetic operator selection, operator crossover, operator mutation, and the operator elitism.

3.5.1 Objective Function

In the optimal scheduling of infrastructure rehabilitation using non-fixed threshold values, the objective function is the maximization of the relative or absolute change in cost-effectiveness of an intervention strategy S_i from the perspective of non-monetized and monetized benefits in Equations (3.57) and (3.58).

From Equations (3.41):

$$Z_a = \max \frac{E_{S_i} - E_{S_{i=0}}}{C_{S_i} - C_{S_{i=0}}} \tag{3.57}$$

From Equation (3.42):

$$Z_r = \max \frac{\dfrac{E_{S_i} - E_{S_{i=0}}}{E_{S_{i=0}}}}{\dfrac{C_{S_i} - C_{S_{i=0}}}{C_{S_{i=0}}}} \tag{3.58}$$

where Z_a = Objective function that represents the cost-effectiveness ratio based on absolute change in effectiveness and absolute change in cost; Z_r = Objective function that represents the cost-effectiveness ratio based on relative change in effectiveness and relative change in cost; E_{S_i} = Effectiveness associated with rehabilitation strategy S_i; and C_{S_i} = Cost associated with rehabilitation strategy S_i.

3.5.2 Design Variables

Design variables, which can be continuous, discrete, or mixed-discrete continuous, are quantities that define the objective function. In the case of the optimal scheduling of infrastructure interventions using non-fixed threshold values, the design variables ($\widehat{X_{S_i}}$) correspond to the components of strategy S_i : time to perform a rehabilitation ($t_{r_{S_i}}, t_{r_{S_i}+1}, .., t_{R_{S_i}}$), and the treatment type to apply ($T_{r_{S_i}}, T_{r_{S_i}+1}, .., T_{R_{S_i}}$). Each strategy S_i is defined as a vector with size $2R_{S_i}$, where R_{S_i} represents the optimal number of interventions associate with rehabilitation strategy S_i, Equation (3.59):

$$\widehat{X_{S_i}} = \begin{bmatrix} t_{r_{S_i}} \\ t_{r_{S_i}+1} \\ \vdots \\ t_{R_{S_i}} \\ T_{r_{S_i}} \\ T_{r_{S_i}+1} \\ \vdots \\ T_{R_{S_i}} \end{bmatrix} \tag{3.59}$$

3.5.3 Constraints

Constraints are the restrictions that must be satisfied before a feasible solution can be produced; for example, an intervention that can take place between a specific range of threshold values. The developed framework has bound and inequality constraints (Equation (3.60)). The bound constraints are set for the minimum and maximum number of rehabilitation interventions usually considered by agencies during an analysis period. Two inequality constraints were analyzed to define the unrestricted and restricted conditions in terms of performance condition. The unrestricted condition only establishes the agency policy boundaries for which a rehabilitation intervention can take place. The restricted condition establishes the agency policy boundaries and the intervention ($r_{S_i} + 1$) must be performed in a condition worse than that of the intervention r_{S_i}. From the conditions defined by the inequality constraints, it is noticed that the unrestricted condition provides the autonomy to choose the intervention threshold set between the agency policy rehabilitation ranges to the optimization algorithm. While the restricted condition forces the algorithm to search for optimal combinations by reducing the searching scope, this scenario also prepares the users for infrastructure deterioration in a progressive way by forcing future interventions to be triggered when the infrastructure is in a condition worse than the last intervention until reaching the reconstruction threshold (defined by agency policy).

Subject to:
(*Bound Constraint*)

$$R_{LB} \leq r_{S_i} \leq R_{UB}$$

Subject to:
(*Inequality Constraint: unrestricted condition*$^{(1)}$)

$$PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC} \qquad (3.60)$$

Subject to:
(*Inequality Constraint: restricted condition*$^{(2)}$)

$$PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1}$$

where R_{LB}, R_{UB} = Lower and upper boundary condition for number of rehabilitations; r_{S_i} = Intervention for strategy S_i (r_{S_i} =1, 2, …, R_{S_i}); R = Optimal number of interventions associated with the strategy S_i ; $PI_{pre,r_{S_i}}$ = Pre-intervention performance level for rehabilitation r_{S_i}; and PI_{LBC}, PI_{UBC} = Lower and upper boundary conditions, respectively, in terms of the performance indicator (reconstruction thresholds).

Then, using the appropriate optimization techniques based on the mathematical formulation of the problem, the strategy that yields the highest CE value, or the optimal non-fixed rehabilitation thresholds set, is identified.

3.5.4 Optimization Formulation

Each cost-effectiveness criterion described in Section 3.4 was formulated to determine the optimal rehabilitation threshold set (time, treatment) based on different measures of effectiveness. The formulation considered the absolute and relative changes in effectiveness and the cost relative to the base scenario strategy, as shown in Equations (3.61) and (3.62) respectively.

From Equations (3.41) and (3.60):

Maximize: $$CE_a = \frac{E_{S_i} - E_{S_{i=0}}}{C_{S_i} - C_{S_{i=0}}}$$

Subject to: $^{(1,\,2)}\; R_{LB} \leq r_{S_i} \leq R_{UB}$ (3.61)

$^{(1)}\; PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC}$

$^{(2)}\; PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1}$

From Equations (3.42) and (3.60):

Maximize: $$CE_r = \frac{\dfrac{E_{S_i} - E_{S_{i=0}}}{E_{S_{i=0}}}}{\dfrac{C_{S_i} - C_{S_{i=0}}}{C_{S_{i=0}}}}$$

Subject to: $^{(1,\,2)}\; R_{LB} \leq r_{S_i} \leq R_{UB}$ (3.62)

$^{(1)}\; PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC}$

$^{(2)}\; PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1}$

where CE_a = Cost-effectiveness ratio based on absolute change in effectiveness and absolute change in cost; CE_r = Cost-effectiveness ratio based on relative change in effectiveness and relative change in cost; E_{S_i} = Effectiveness associated with rehabilitation strategy S_i; C_{S_i} = Cost associated with rehabilitation strategy S_i; R_{LB}, R_{UB} = Lower and upper boundary condition for number of rehabilitations acceptable for agency policy; r_{S_i} = Intervention for strategy S_i (r_{S_i} =1, 2, …, R_{S_i}); R = Optimal number of interventions associated with the strategy S_i; $PI_{pre,r_{S_i}}$ = Pre-intervention performance level at the time of rehabilitation r_{S_i}; PI_{LBC} , PI_{UBC} = Lower and upper boundary conditions for performance indicator (reconstruction threshold for PIs).

3.5.4.1 Optimization of Cost-Effectiveness Based on Service Life

The formulation to determine the optimal rehabilitation threshold set based on the ratio of the absolute and relative changes in the infrastructure service life and the associated cost is presented in Equations (3.63) and (3.64).

From Equations (3.45) and (3.60):

Maximize: CE_{SL_a}

$$= \frac{SL_{S_i} - SL_{S_{i=0}}}{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UC_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right)}$$

Subject to: $^{(1,2)}\ R_{LB} \le r_{S_i} \le R_{UB}$ (3.63)

$^{(1)}\ PI_{LBC} \le PI_{pre,r_{S_i}} \le PI_{UBC}$

$^{(2)}\ PI_{pre,r_{S_i}} \le PI_{pre,r_{S_i}+1}$

From Equations (3.46) and (3.60):

Maximize: CE_{SL_r}

$$= \frac{\dfrac{SL_{S_i} - SL_{S_{i=0}}}{SL_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UC_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right)}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right)}} \qquad (3.64)$$

Subject to: $^{(1,2)}\ R_{LB} \le r_{S_i} \le R_{UB}$

$^{(1)}\ PI_{LBC} \le PI_{pre,r_{S_i}} \le PI_{UBC}$

$^{(2)}\ PI_{pre,r} \le PI_{pre,r_{S_i}+1}$

where CE_{SL_a} = Cost-effectiveness ratio based on absolute change in infrastructure service life and absolute change in cost associated with strategy S_i; CE_{SL_r} = Cost-effectiveness ratio based on relative change in infrastructure service life and relative change in cost associated with strategy S_i; SL_{S_i} = Time for a strategy S_i to reach a reconstruction threshold (PI_{LBC} or PI_{UBC}); AC_{S_i} = Agency cost associated with rehabilitation strategy S_i; UC_{S_i} = User cost associated with rehabilitation strategy S_i; w_{AC}, w_{UC} = Weighting factors for agency and user costs, $0 \le w_{AC}, w_{UC} \le 1$ respectively, other symbols and subscripts are consistent with their previous meanings.

3.5.4.2 Optimization of Cost-Effectiveness Based on Performance Jump

The formulation to determine the optimal rehabilitation threshold set based on the ratio of the absolute and relative changes in performance jump and cost is presented in Equations (3.65) and (3.66).

From Equations (3.47) and (3.60):

Maximize: $$CE_{PJ\_a} = \frac{PJ_{S_i} - PJ_{S_{i=0}}}{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}$$

Subject to: $$^{(1,2)}\, R_{LB} \leq r_{S_i} \leq R_{UB} \tag{3.65}$$

$$^{(1)}\, PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC}$$

$$^{(2)}\, PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1}$$

From Equations (3.48) and (3.60):

Maximize: $$CE_{PJ\_r} = \frac{\dfrac{PJ_{S_i} - PJ_{S_{i=0}}}{PJ_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}}$$

Subject to: $$^{(1,2)}\, R_{LB} \leq r_{S_i} \leq R_{UB} \tag{3.66}$$

$$^{(1)}\, PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC}$$

$$^{(2)}\, PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1}$$

where CE_{PJ_a} = Cost-effectiveness ratio based on absolute change in performance jump and absolute change in cost associated with strategy S_i; CE_{SL_r} = Cost-effectiveness ratio based on relative change in performance jump and relative change in cost associated with strategy S_i; PJ_{S_i} = Sum of jump magnitudes associated with rehabilitation strategy S_i; w_{AC}, w_{UC} = Weighting factors for agency and user costs, $0 \leq w_{AC}, w_{UC} \leq 1$ respectively; AC_{S_i} = Agency cost associated with rehabilitation strategy S_i; $UCDT_{S_i}$ = User cost during rehabilitation interventions associated with strategy S_i; other symbols and subscripts have their usual meanings.

3.5.4.3 Optimization of Cost-Effectiveness Based on Average Performance

The formulation to determine the optimal rehabilitation threshold set based on the ratio of the absolute and relative changes in average performance and cost is presented in Equations (3.67) and (3.68).

From Equations (3.49) and (3.60):

$$\text{Maximize:} \quad CE_{AP\_a} = \frac{AP_{S_i} - AP_{S_{i=0}}}{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}$$

$$\text{Subject to:} \quad {}^{(1,\,2)}\, R_{LB} \leq r_{S_i} \leq R_{UB} \tag{3.67}$$

$${}^{(1)}\, PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC}$$

$${}^{(2)}\, PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1}$$

From Equations (3.50) and (3.60):

$$\text{Maximize:} \quad CE_{AP\_r} = \frac{\dfrac{AP_{S_i} - AP_{S_{i=0}}}{AP_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}}$$

$$\text{Subject to:} \quad {}^{(1,\,2)}\, R_{LB} \leq r_{S_i} \leq R_{UB} \tag{3.68}$$

$${}^{(1)}\, PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC}$$

$${}^{(2)}\, PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1}$$

where CE_{AP_a} = Cost-effectiveness ratio based on absolute change in average performance and absolute change in cost associated with strategy S_i; CE_{AP_r} = Cost-effectiveness ratio based on relative change in average performance and relative change in cost associated with strategy S_i; AP_{S_i} = Average performance corresponding to strategy S_i; other symbols and subscripts have their usual meanings.

3.5.4.4 Optimization of Cost-Effectiveness Based on Area Bounded by the Performance Curve

The formulation to determine the optimal rehabilitation threshold set based on the ratio of the absolute and relative change of the area bounded by the performance curve and cost is presented in Equations (3.69) and (3.70).

From Equations (3.51) and (3.60):

$$\text{Maximize:} \quad CE_{ABC\_a} = \frac{ABC_{S_i} - ABC_{S_{i=0}}}{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}$$

$$\begin{aligned} \text{Subject to:} \quad & ^{(1,\,2)}\, R_{LB} \le r_{S_i} \le R_{UB} \\ & ^{(1)}\, PI_{LBC} \le PI_{pre,r_{S_i}} \le PI_{UBC} \\ & ^{(2)}\, PI_{pre,r_{S_i}} \le PI_{pre,r_{S_i}+1} \end{aligned} \tag{3.69}$$

From Equations (3.52) and (3.60):

$$\text{Maximize:} \quad CE_{ABC\_r} = \frac{\dfrac{ABC_{S_i} - ABC_{S_{i=0}}}{ABC_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}}$$

$$\begin{aligned} \text{Subject to:} \quad & ^{(1,\,2)}\, R_{LB} \le r_{S_i} \le R_{UB} \\ & ^{(1)}\, PI_{LBC} \le PI_{pre,r_{S_i}} \le PI_{UBC} \\ & ^{(2)}\, PI_{pre,r_{S_i}} \le PI_{pre,r_{S_i}+1} \end{aligned} \tag{3.70}$$

where CE_{ABC_a} = Cost-effectiveness ratio based on absolute change in area bounded by the performance curve and absolute change in cost associated with strategy S_i; CE_{ABC_r} = Cost-effectiveness ratio based on relative change in area bounded by the performance curve and relative change in cost associated with strategy S_i; ABC_{S_i} = Area bounded by the performance curve of the strategy S_i (ABC_{S_i} = AUC_{S_i}, for non-increasing PIs and ABC_{S_i} = AOC_{S_i}, for non-decreasing PI); other symbols and subscripts maintain their usual meanings.

3.5.4.5 Optimization of Cost-Effectiveness Based on Agency Cost Savings

The formulation to determine the optimal rehabilitation threshold set based on the ratio of the absolute and relative changes in the agency cost savings and cost is presented in Equations (3.71) and (3.72).

From Equations (3.53) and (3.60):

$$\begin{aligned}
&\text{Maximize:} && CE_{ACS\_a} = \frac{ACNO_{S_i} - ACNO_{S_{i=0}}}{\left(w_{AC} \cdot ACDT_{S_i} + w_{UC} \cdot UC_{S_i}\right) - \left(w_{AC} \cdot ACDT_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right)} \\
&\text{Subject to:} && ^{(1,\,2)}\; R_{LB} \leq r_{S_i} \leq R_{UB} \\
& && ^{(1)}\; PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC} \\
& && ^{(2)}\; PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1}
\end{aligned} \tag{3.71}$$

From Equations (3.54) and (3.60):

$$\begin{aligned}
&\text{Maximize:} && CE_{ACS\_r} = \frac{\dfrac{ACNO_{S_i} - ACNO_{S_{i=0}}}{ACNO_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot ACDT_{S_i} + w_{UC} \cdot UC_{S_i}\right) - \left(w_{AC} \cdot ACDT_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right)}{\left(w_{AC} \cdot ACDT_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}}\right)}} \\
&\text{Subject to:} && ^{(1,\,2)}\; R_{LB} \leq r_{S_i} \leq R_{UB} \\
& && ^{(1)}\; PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC} \\
& && ^{(2)}\; PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1}
\end{aligned} \tag{3.72}$$

where CE_{ACS_a} = Cost-effectiveness ratio based on absolute change in agency cost savings and absolute change in cost associated with strategy S_i ; CE_{ACS_r} = Cost-effectiveness ratio based on relative change in agency cost savings and relative change in cost associated with strategy S_i ; $ACNO_{S_i}$ = Agency cost during normal operations associated with strategy S_i; $ACDT_{S_i}$ = Agency cost of initial construction and subsequent rehabilitation interventions associated with strategy S_i; UC_{S_i} = User cost associated with rehabilitation strategy S_i; other symbols and subscripts have their usual meanings.

3.5.4.6 Optimization of Cost-Effectiveness Based on User Cost Savings

The formulation to determine the optimal rehabilitation threshold set based on the ratio of the absolute and relative changes in the user cost savings and cost is presented in Equations (3.73) and (3.74).

From Equations (3.55) and (3.60):

Maximize:
$$CE_{UCS\_a} = \frac{UCNO_{S_i} - UCNO_{S_{i=0}}}{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}$$

Subject to:
$$\begin{aligned} &^{(1,2)}\, R_{LB} \leq r_{S_i} \leq R_{UB} \\ &^{(1)}\, PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC} \\ &^{(2)}\, PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1} \end{aligned} \tag{3.73}$$

From Equations (3.56) and (3.60):

Maximize:
$$CE_{UCS\_r} = \frac{\dfrac{UCNO_{S_i} - UCNO_{S_{i=0}}}{UCNO_{S_{i=0}}}}{\dfrac{\left(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}\right) - \left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}{\left(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}}\right)}}$$

Subject to:
$$\begin{aligned} &^{(1,2)}\, R_{LB} \leq r_{S_i} \leq R_{UB} \\ &^{(1)}\, PI_{LBC} \leq PI_{pre,r_{S_i}} \leq PI_{UBC} \\ &^{(2)}\, PI_{pre,r_{S_i}} \leq PI_{pre,r_{S_i}+1} \end{aligned} \tag{3.74}$$

where CE_{UCS_a} = Cost-effectiveness ratio based on absolute change in user cost savings and absolute change in cost associated with strategy S_i; CE_{UCS_r} = Cost-effectiveness ratio based on relative change in user cost savings and relative change in cost associated with strategy S_i; $UCNO_{S_i}$ = User cost during normal operations associated with strategy S_i; AC_{S_i} = Agency cost associated with rehabilitation strategy S_i; $UCDT_{S_i}$ = User cost during rehabilitation interventions associated with strategy S_i; other symbols and subscripts have their usual meanings.

3.5.5 Optimization Technique

Genetic Algorithm (GA) is considered as one of the few algorithms that can adequately handle problems involving discrete choices. While it is true that enumeration will guarantee the best solution, such a solution technique becomes a handicap if the problem size is very large, as the number of combinations becomes excessive. Using an optimization algorithm, the scope’s search can be reduced (in other words, the number of searches can be drastically reduced) because it performs a probabilistic search that avoids the point-to-point combinations required by enumeration. The differences between GA and classical, calculus-based optimization techniques are (Goldberg, 1989; Chootinan et al., 2006): (i) GA does not use the traditional point-to-point search method but rather explore the solution space by searching simultaneously from a population of points; (ii) GA uses probabilistic transition rules for its operators as a guide to search the solution space; (iii) GA is capable of using differentiable and non-differentiable functions, continuous and discrete parameters, uni-modal and multi-modal functions, and convex and non-convex feasible regions.

Genetic Algorithm (GA) is a global optimizer and a population-based algorithm (class of evolutionary algorithm). GA can handle both continuous and discrete design variables. Also, GA is popular for its performance when exploring huge design spaces and locating global, optimal solutions using probabilistic techniques, rather than the point-to-point search gradient-based methods. This approach keeps the algorithms from stopping at local minima but precludes any guarantee of convergence (Morin, 1982). The main disadvantages of GA, like other evolutionary algorithms, is that cannot directly enforce constraints and does a poor job of locating the exact minima. To address these constraint handling limitations, GA search adopts a penalty concept; that way, the fitness function reflects the objective function value and accounts for violated constraints (Roy, 2012).

Traditional algorithms generate a single point with each iteration and the sequence of points approaches an optimal solution. On the other hand, GA generates a population of points with each iteration; the best point in the population approaches an optimal solution. A population is a set of points in the design space. The GA uses a set of operators applied to the population. The initial population is randomly generated by default. The next generation of the population is defined using the fitness of the individuals in the current generation, while classical algorithms select the next point in the sequence using deterministic computations. Figure 3.6 presents the flow chart of the optimization routine used in the developed framework to determine the non-fixed thresholds for scheduling rehabilitation interventions.

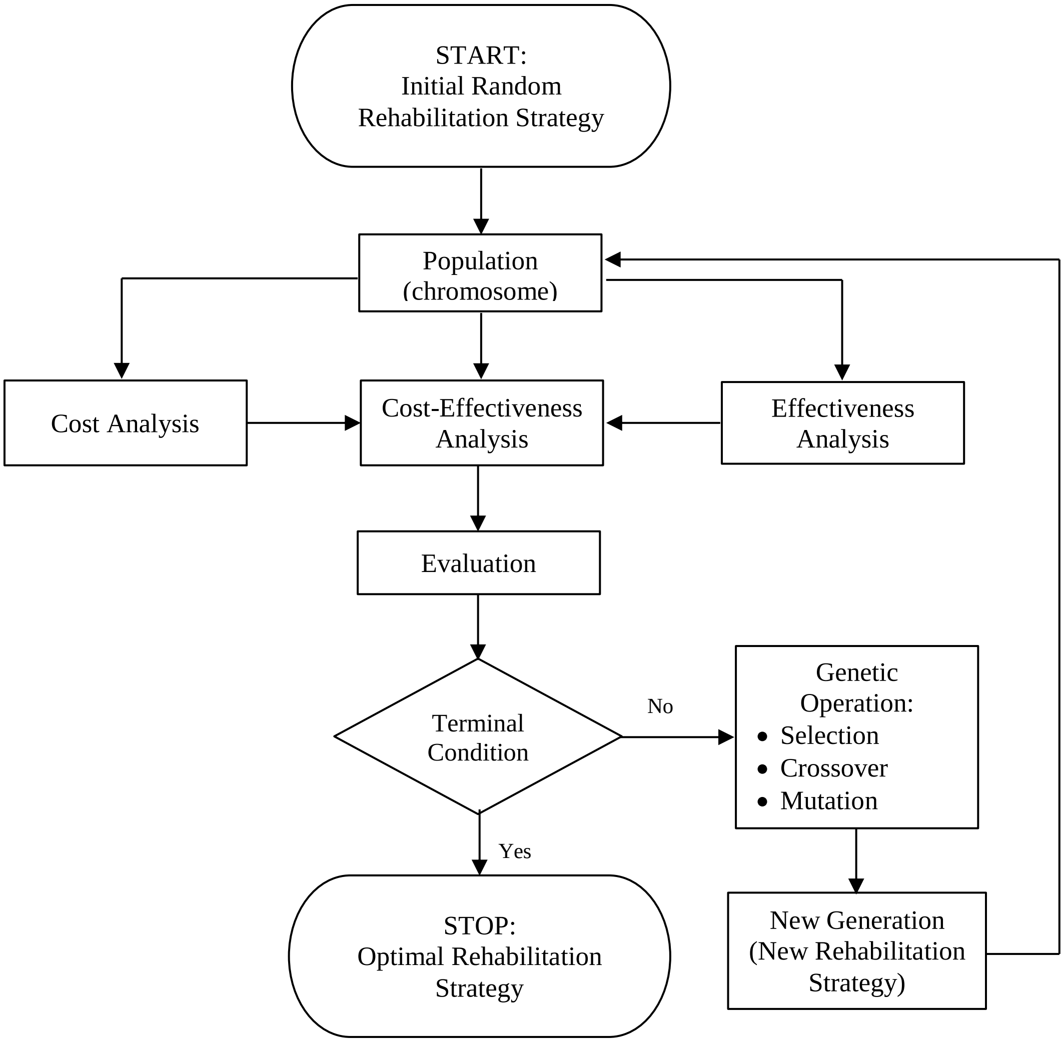


Figure 3.6 Genetic Algorithm Optimization Routine

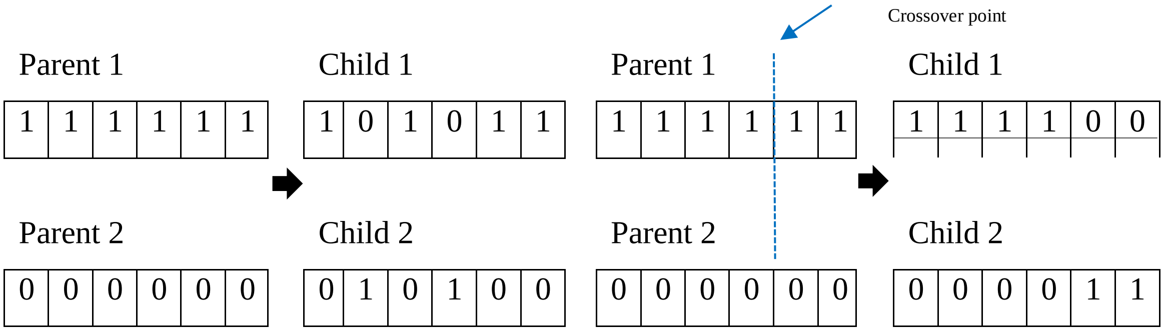
Genetic algorithms convert continuous variables into discrete segments. The decision variables are encoded using a gene chromosome (a real or binary number string) to represent an individual in the population. The Grady coding is used to encode or decode the design variables. The assumption is that the upper and lower values of the design variables follow a uniform distribution and a specific combination of 1s and 0s yields a value within the pre-specified range. The most common operators used by GA during the optimization routine are: selection, crossover, and mutation.

3.5.5.1 Genetic Operator Selection

Selection is the first operator of the algorithm. This process mimics natural selection. From the whole population, the selection operator randomly determines the individuals who are to become parents and give birth to offspring for the subsequent generation. Several techniques are described in the literature for the selection of parents, and the classical binary tournament selection technique is widely accepted with applications in numerous GA implementations. The method begins with the current generation individuals in an empty pot (P1). Two individuals are removed from the pot at random and without replacement and compared on the basis of their fitness values. With regard to problems that seek to maximize the objective function, the individual with the higher fitness value moves to the parent pool (P2) and this tournament selection process continues until the original pot is left with no individual. After this step, the parent pool is half full. Then P1 is refilled with individuals of the current generation, and the entire process is repeated. The population size must be even and the best individual always receives two copies of the parent pool. This makes it evident that its offspring are desired to a greater extent. The process eliminates from consideration the worst individual (Roy, 2012).

3.5.5.2 Genetic Operator Crossover

The crossover among the selected parents to create offspring is the next operation, mimicking the biological process of reproduction. Traditionally, two parents procreate two children in the GA. Figure 3.7 shows the two possible crossover techniques. Williams and Crossley (1998) suggested the binary crossover that has “proven effective with the binary-coded GA and tournament selection approaches”. In a binary crossover, the bit transfer from a parent to a child depends on a probability function. A bit from the first parent goes to the first child if it meets a certain criterion; otherwise, the bit goes to the second child. Besides the uniform crossover, there are additional strategies including the single- and multi-point crossovers. In the former, after a certain point in the chromosome, all bits are swapped. This preserves the schema (pattern) of the parent to a great extent. Similarly, multi-point crossover bits are swapped at multiple points (Roy, 2012).



a) Uniform binary crossover b) Single point crossover

Figure 3.7 Illustration of the Various GA Crossover Operators

3.5.5.3 Genetic Operator Mutation

To guide the exploration of the design space, random changes in an individual occurs by mutation. The most common way to bring mutation to an individual is the probability-based mutation rate. If the probability criterion is met, the bit flips to its complimentary value. An illustration of GA mutation is shown in Figure 3.8:

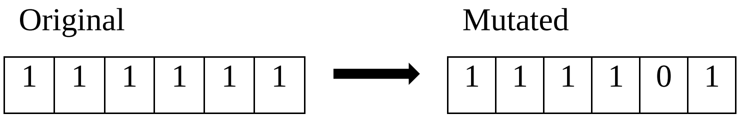


Figure 3.8 Illustration of GA Mutation Operator

3.6 Chapter Summary

The framework was built based on a decision making process methodology using a project-level life-cycle cost and an optimization routine to schedule rehabilitation strategies for various kinds of infrastructure. The methodology presented in this dissertation is flexible enough to accommodate the cost perspectives of both the agency and the user during the downtime and normal operation periods. Effectiveness, cost, and cost-effectiveness analysis are described as part of the preliminary estimations needed to define the inputs for the optimization routine. The routine determines the optimal strategy as a combination of rehabilitation treatments types and timings. This chapter presented the framework requirements. Table 3.2 presents a summary of the MOEs and their corresponding expressions to estimate rehabilitation effectiveness in terms of non-monetized and monetized benefits.

Table 3.2 MOEs and Expressions of Intervention Effectiveness

Expression MOE	Raw	Absolute Δ change (relative to base scenario)	Relative Δ change (relative to base scenario)
Service Life (SL)	$SL_{S_i} = f(\tilde{x})$	$SL_{S_i} - SL_{S_{i=0}}$	$\frac{SL_{S_i} - SL_{S_{i=0}}}{SL_{S_{i=0}}}$
Performance Jump (PJ)	$PJ_{S_i} = \sum_{r_{S_i}}^{R_{S_i}} PJ_{r_{S_i}}$ $PJ_{r_{S_i}} = f\left(PI_{pre,r_{S_i}}\right)$	$PJ_{S_i} - PJ_{S_{i=0}}$	$\frac{PJ_{S_i} - PJ_{S_{i=0}}}{PJ_{S_{i=0}}}$
Average Performance (AP)	$AP_{S_i} = \frac{1}{SL_{S_i}} \cdot \sum_{t_{S_i}=0}^{t_{S_i}=SL_{S_i}} PI_{t_{S_i}}$	$AP_{S_i} - AP_{S_{i=0}}$	$\frac{AP_{S_i} - AP_{S_{i=0}}}{AP_{S_{i=0}}}$
Area Bounded by the Performance Curve (ABC)	ABC_{S_i} = AUC_{S_i}, for non-increasing PIs $AUC_{S_i} = \left[\int_{0}^{t_{r_{S_i}=1}} f_{pre}(t)dt + \sum_{r_{S_i}=1}^{R_{S_i}} \int_{t_{r_{S_i}}}^{t_{r_{S_i}+1}} f_{post}(t)dt + \int_{t_{r_{S_i}=R}}^{SL_{S_i}} f_{post}(t)dt \right] - \left(PI_{LBC} \cdot SL_{S_i}\right)$ ABC_{S_i} = AOC_{S_i}, for non-decreasing PIs $AOC_{S_i} = \left(PI_{UBC} \cdot SL_{S_i}\right) - \left[\int_{0}^{t_{r_{S_i}=1}} f_{pre}(t)dt + \sum_{r_{S_i}=1}^{R_{S_i}} \int_{t_{r_{S_i}}}^{t_{r_{S_i}+1}} f_{post}(t)dt + \int_{t_{r_{S_i}=R}}^{SL_{S_i}} f_{post}(t)dt \right]$	$ABC_{S_i} - ABC_{S_{i=0}}$	$\frac{ABC_{S_i} - ABC_{S_{i=0}}}{ABC_{S_{i=0}}}$
Agency Cost Savings (ACS)		$ACNO_{S_i} - ACNO_{S_{i=0}}$	$\frac{ACNO_{S_i} - ACNO_{S_{i=0}}}{ACNO_{S_{i=0}}}$
User Cost Savings (UCS)		$UCNO_{S_i} - UCNO_{S_{i=0}}$	$\frac{UCNO_{S_i} - UCNO_{S_{i=0}}}{UCNO_{S_{i=0}}}$

Note: Rehabilitation Strategy, S_i. Base strategy, $S_{i=0}$ (Do-nothing).

The agency and user cost components during downtime periods and normal operations are summarized in Table 3.3.

Table 3.3 Agency and User Cost Components

Perspective		Cost
Agency + User	Total	$C_{S_i} = w_{AC} \cdot \sum_{\alpha=1}^{p} AC_{S_i,\alpha} + w_{UC} \cdot \sum_{\gamma=1}^{q} UC_{S_i,\gamma}$
Agency	Total	$AC_{S_i} = \varphi_{dt} \cdot ACDT_{S_i} + \varphi_{no} \cdot ACNO_{S_i}$
	Downtime	$ACDT_{S_i} = \sum_{r_{S_i}}^{R_{S_i}} CI_{r_{S_i}}$
	Normal Operations	$ACNO_{S_i} = \sum_{t_{S_i}=0}^{t_{S_i}=SL_{S_i}} f\left(PI_{t_{S_i}}\right)$
User	Total	$UC_{S_i} = \delta_{dt} \cdot UCDT_{S_i} + \delta_{no} \cdot UCNO_{S_i}$
	Downtime	$UCDT_{S_i} = \sigma_{dy} \cdot \sum_{r_{S_i}}^{R_{S_i}} UDC_{r_{S_i}} + \sigma_{sr} \cdot \sum_{r_{S_i}}^{R_{S_i}} UOCcr_{r_{S_i}}$
	Normal Operations	$UCNO_{S_i} = \sum_{t_{S_i}=0}^{t_{S_i}=SL_{S_i}} f(x_c)$

A summary of the objective functions considered in this dissertation to determine the optimal set of thresholds for the strategy are described in Table 3.4.

Table 3.4 Cost-Effectiveness Criteria Based on Absolute and Relative Δ Change

Criteria	MAX CE_{MOE_a}, MAX CE_{MOE_r} (relative to base scenario)
Service Life (SL)	$CE_{SL\_a} = \frac{SL_{S_i} - SL_{S_{i=0}}}{(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UC_{S_i}) - (w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}})}$
	$CE_{SL\_r} = \frac{\frac{SL_{S_i} - SL_{S_{i=0}}}{SL_{S_{i=0}}}}{\frac{(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UC_{S_i}) - (w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}})}{(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}})}}$
Performance Jump (PJ)	$CE_{PJ\_a} = \frac{PJ_{S_i} - PJ_{S_{i=0}}}{(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}) - (w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}$
	$CE_{PJ\_r} = \frac{\frac{PJ_{S_i} - PJ_{S_{i=0}}}{PJ_{S_{i=0}}}}{\frac{(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}) - (w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}{(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}}$
Average Performance (AP)	$CE_{AP\_a} = \frac{AP_{S_i} - AP_{S_{i=0}}}{(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}) - (w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}$
	$CE_{AP\_r} = \frac{\frac{AP_{S_i} - AP_{S_{i=0}}}{AP_{S_{i=0}}}}{\frac{(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}) - (w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}{(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}}$
Area Bounded by the Performance Curve (ABC)	$CE_{ABC\_a} = \frac{ABC_{S_i} - ABC_{S_{i=0}}}{(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}) - (w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}$
	$CE_{ABC\_r} = \frac{\frac{ABC_{S_i} - ABC_{S_{i=0}}}{ABC_{S_{i=0}}}}{\frac{(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}) - (w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}{(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}}$
Agency Cost Savings (ACS)	$CE_{ACS\_a} = \frac{ACNO_{S_i} - ACNO_{S_{i=0}}}{(w_{AC} \cdot ACDT_{S_i} + w_{UC} \cdot UC_{S_i}) - (w_{AC} \cdot ACDT_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}})}$
	$CE_{ACS\_r} = \frac{\frac{ACNO_{S_i} - ACNO_{S_{i=0}}}{ACNO_{S_{i=0}}}}{\frac{(w_{AC} \cdot ACDT_{S_i} + w_{UC} \cdot UC_{S_i}) - (w_{AC} \cdot ACDT_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}})}{(w_{AC} \cdot ACDT_{S_{i=0}} + w_{UC} \cdot UC_{S_{i=0}})}}$
User Cost Savings (UCS)	$CE_{UCS\_a} = \frac{UCNO_{S_i} - UCNO_{S_{i=0}}}{(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}) - (w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}$
	$CE_{UCS\_r} = \frac{\frac{UCNO_{S_i} - UCNO_{S_{i=0}}}{UCNO_{S_{i=0}}}}{\frac{(w_{AC} \cdot AC_{S_i} + w_{UC} \cdot UCDT_{S_i}) - (w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}{(w_{AC} \cdot AC_{S_{i=0}} + w_{UC} \cdot UCDT_{S_{i=0}})}}$

Note: Rehabilitation Strategy, S_i. Base strategy, $S_{i=0}$ (Do-nothing)
MAX $CE_{Measure\ of\ effectiveness\_absolute\_relative}$ (relative to base scenario)

CHAPTER 4. DATA COLLECTION

To illustrate the developed framework, this dissertation used highway pavements as a case study. In this, chapter the collection and collation of the case study data, is described. This chapter presents the data collected for the pre- and post-deterioration models, cost models, and project duration models for the rehabilitation interventions considered in this dissertation. Additionally, the data used for calculating the agency and user costs that served as analysis inputs, are described in this chapter.

4.1 Pavement Families for Present Study

Infrastructure classification refers to grouping that reflects similar features across the clustering of the infrastructure assets so that intervention strategies can be developed for each cluster. The highway pavements were placed into classes based on their functional class and surface material type (Figure 4.1).

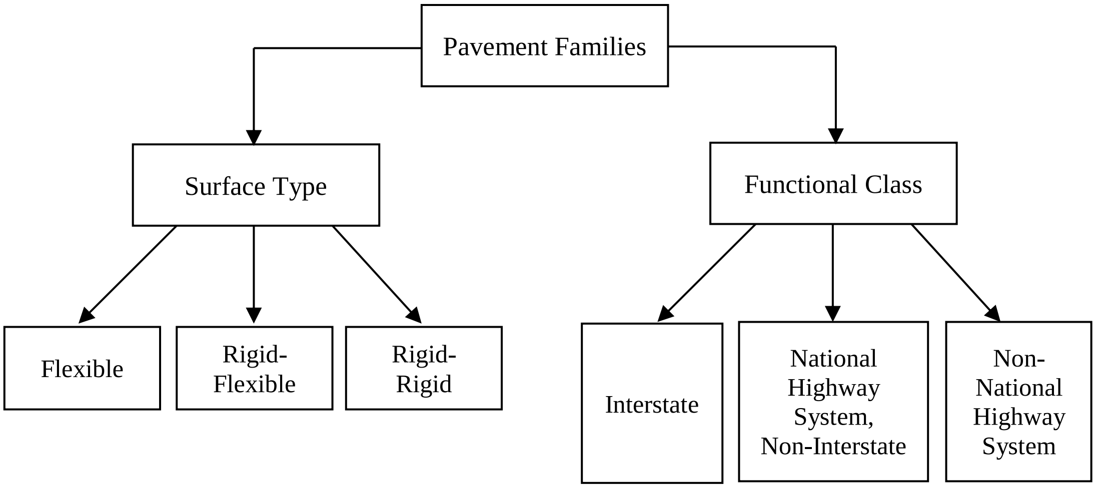


Figure 4.1 Pavement Families Considered in the Analysis

4.1.1 Classification by Surface Type

Flexible (asphaltic concrete) pavements derive their strength from the tight interlocking of crushed rocks and asphalt material binding them together. Full-depth hot mix asphalt (HMA) consists of a surface or wearing course (the top layer that directly bears the traffic and may be composed of one or several different HMA sub layers), a base course (layer underneath the surface layer), and typically consists of HMA or aggregates followed by a sub-base course, which may not always be required (WSDOT, 2009). This pavement structure deflects traffic loading and exerts pressure on the sub-grade. Rigid pavement is laid in slabs with or without steel reinforcement. Rigid pavement construction comprises a series of actions carried out in rapid succession: the placement, consolidation, jointing, finishing, and curing of the PCC. PCC pavement is long lasting and offers the significant benefit of low cost of rehabilitation and maintenance activities (ACPA, 1995). In the case study, two types of rigid pavements are considered based on the rehabilitation interventions: (i) rigid-flexible pavement type, when rehabilitation is performed using an HMA overlay and (ii) rigid-rigid pavement type, when rehabilitation is performed using a PCCP overlay.

4.1.2 Classification by Functional Class

In terms of functional class classification, Interstates (*IS*), National Highway System - Non-Interstates (*NHS-NI*) Roads, and Non-National Highway System (*NNHS*) Roads are considered in this dissertation.

Interstates (IS): These highways are, by far, associated with the highest levels of pavement loading because operators of larger vehicle classes (FHWA classes 4 and above) prefer such highways due to their being prohibited from using certain sections of lower class roads due to weight restrictions (Labi and Sinha, 2003). Interstates also attract long distance light-load and heavy-load traffic due to their low levels of accessibility, high levels of mobility, and superior geometric design, construction, maintenance, and safety standards.

National Highway System, Non-Interstate (NHS-NI): Some U.S. federal and state roads are included in this road classification. The geometric design, construction, maintenance, and safety standards for NHS-NI roads are inferior to those of Interstates.

Non-National Highway System (NNHS): These roads mainly consist of state roads and a few U.S. roads. The NNHS generally has the lowest levels of traffic loading. Also, the geometric design, construction, maintenance, and safety standards are the lowest for NNHS roads but are generally close to those of NHS-NI highways.

4.2 Rehabilitation Treatments Options

Rehabilitation, defined as a "functional or structural enhancement of a pavement structure", improves pavement condition, ride quality, and therefore substantially extends the service life (Hall et al., 2001). The selection of rehabilitation treatment is influenced by the pavement surface type, distress type, and local conditions. The next section describes the rigid and flexible pavement rehabilitation treatments that were considered in this study.

4.2.1 Rehabilitation Treatment Options for Flexible Pavements

4.2.1.1 Functional HMA Overlay

Functional HMA overlays augment or replace the existing pavement wearing course. They are placed on existing surfaces with or without prior milling (NAPA, 1995) to restore pavement smoothness. This non-structural treatment type adds little to structural support (WSDOT, 2009; Roberts et al., 1996).

4.2.1.2 Structural HMA Overlay

Structural HMA overlays, whose application thickness is often twice that of functional (non-structural) overlays, add strength to the existing pavement, and restore the surface smoothness of the pavement. The decision support for using structural overlays is based on subjective engineering judgment or analytical methods, such as component analysis. These take into consideration the pavement condition and thicknesses, layer types, and test results (Roberts et al., 1996).

4.2.2 Rehabilitation Treatment Options for Rigid – Flexible Pavements

4.2.2.1 Crack-and-Seat PCCP and HMA Overlay

An effective way to rehabilitate a PCCP (Portland Cement Concrete Pavement) that has lost its structural capacity is to crack and seat the existing PCCP and overlay with HMA (with two or three layers). Prior to placing the HMA overlay, the cracked-and-seated pavement is compacted using a vibratory steel wheel and pneumatic-tired rollers (INDOT, 2013).

4.2.2.2 Repair PCCP and HMA Overlay

In this treatment, partial- or full-depth patching is carried out, and the PCCP or HMA overlay is placed. HMA overlays over PCCP are used for adding structural support and wearing course to the existing rigid pavement (Irfan, 2010).

4.2.3 Rehabilitation Treatment Options for Rigid – Rigid Pavements

4.2.3.1 PCCP Patching

For this treatment, additional patching is carried out to remove and replace defective patches. For localized areas of slab damage, depth patches are used. A full depth parch is required when the damage extends beyond the upper one-third of the slab depth or originates from the slab bottom. A partial-depth patch is carried out if the distress is restrained to the upper one-third of the slab depth.

4.2.3.2 PCCP Overlay of Existing PCC Pavement

This overlay treatment is appropriate for all types of rigid pavement designs. It involves the removal and replacement of existing defective patches and other general preparatory work followed by the placement of a PCC overlay that offers a highly durable wearing course with a significant structural capacity. This could be bonded or unbonded (Mack et al., 1988)

4.3 Traffic Data Estimation

The estimation of traffic loading is vital for a full description and estimation of the pavement performance and the corresponding needs of infrastructure rehabilitation interventions. In this dissertation, the primary source of traffic data was INDOT's Pavement Management System (PMS) database and INDIPAVE 2000 which include traffic volume and percentages of single-unit and multiple-unit trucks. INDOT (2010) recommends the use of 2.8% to 3.3% as the compound annual growth rate for pavement design purposes. The traffic volume (AADT) for all pavement families considered in this dissertation were updated to the analysis year (2015) by using a growth factor of 1.5% suggested by Ahmed (2012) based on the traffic growth pattern noted for the past ten years in Indiana. Average values of traffic volumes for flexible and rigid pavements in Indiana are shown in Table 4.1 and Table 4.2, respectively.

Table 4.1 AADT and Truck Percentages for Flexible Pavements (year 2015)

Functional Class	Low		Medium		High	
	AADT	Truck %	AADT	Truck %	AADT	Truck %
Interstate	20,529	23	27,321	31	34,214	39
National Highway System, Non-Interstate	6,469	16	8,625	21	10,782	26
Non-National Highway System	3,919	9	5,226	12	6,532	15

Table 4.2 AADT and Truck Percentages for Rigid Pavements (year 2015)

Functional Class	Low		Medium		High	
	AADT	Truck %	AADT	Truck %	AADT	Truck %
Interstate	21,815	21	29,087	28	36,538	35
National Highway System, Non-Interstate	9,835	10	13,113	13	16,391	17
Non-National Highway System	8,897	8	11,863	11	14,829	13

4.4 Performance Models for Pre- and Post- Rehabilitations

Asset managers have the responsibility to enhance the asset's physical condition or operational characteristics by predicting the asset performance condition based on past trends and determine the impact of the intervention on subsequent asset performance and the corresponding remaining asset service life. In order to demonstrate the developed framework for highway pavements, the International Roughness Index (IRI) was chosen as the performance indicator (PI). Performance models developed by Irfan (2010) for flexible and rigid pavement type by functional class were used to illustrate the framework of this dissertation. The developed models (Equation (4.1)) have an exponential form and estimate IRI as a function of accumulated traffic loading and climatic effects.

$$IRI = e^{(\beta_0 + \beta_1 \cdot AATT \cdot t + \beta_2 \cdot AAFI \cdot t)} \tag{4.1}$$

where β_0 is the constant term; β_1 and β_2 are the estimated coefficients for the explanatory variables; $AATT \cdot t$ and $AAFI \cdot t,$ are the accumulated truck traffic loading (millions) and accumulated climate effect (thousands of degree-days), respectively. Table 4.3 through Table 4.5 present the performance model coefficients for pre- and post- rehabilitation treatments by pavement type and highway functional class considered in this dissertation.

Table 4.3 Post-Rehabilitation Flexible Pavement Performance (IRI) Models

Functional Class	Parameter	New Pavement		Functional HMA Overlay		Structural HMA Overlay	
		Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Interstate	Constant	4.009	198.39	4.007	134.77	3.858	100.80
	$AATT$	0.024	9.16	0.020	2.45	0.019	4.97
	$AAFI$	0.020	4.25	0.089	4.17	0.151	4.51
National Highway System, Non-Interstate	Constant	4.037	106.46	4.255	177.94	4.083	42.04
	$AATT$	0.137	9.18	0.015	2.69	0.024	1.79
	$AAFI$	0.035	3.10	0.061	6.89	0.133	3.57
Non-National Highway System	Constant	4.082	266.74	4.097	102.80	4.148	189.88
	$AATT$	0.017	3.73	0.093	8.58	0.020	1.48
	$AAFI$	0.054	14.30	0.113	7.41	0.095	9.42

Source: Irfan (2010)
$AATT$: Annual Average Truck Traffic (millions).
$AAFI$: Annual Average Freeze Index (thousands of degree-days)

Table 4.4 Post-Rehabilitation Rigid-Flexible Pavement Performance (IRI) Models

Functional Class	Parameter	New Pavement		Crack-and-Seat PCCP & HMA Overlay		PCCP & HMA Overlay(1)	
		Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Interstate	Constant	4.343	222.34	4.030	183.39	3.774	150.62
	$AATT$	0.020	17.25	0.011	8.81	0.026	3.46
	$AAFI$	0.005	2.27	0.051	10.99	0.052	5.64
National Highway System, Non-Interstate	Constant	4.125	256.34	3.140	204.18		
	$AATT$	0.008	2.00	0.070	7.70		
	$AAFI$	0.091	9.80	0.011	2.12		
Non-National Highway System	Constant	4.373	53.01	3.100	74.77		
	$AATT$	0.081	4.54	0.136	2.71		
	$AAFI$	0.065	7.01	0.103	5.37		

Source: Irfan (2010)

(1) Same coefficients for all functional classes

$AATT$: Annual Average Truck Traffic (millions)

$AAFI$: Annual Average Freeze Index (thousands of degree-days)

Table 4.5 Post-Rehabilitation Rigid-Rigid Pavement Performance (IRI) Models

Functional Class	Parameter	New Pavement		PCCP Patching(1)		PCCP & PCCP Overlay(1)	
		Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Interstate	Constant	4.343	222.34	4.335	224.21	3.645	134.77
	$AATT$	0.020	17.25	0.020	7.46	0.018	2.45
	$AAFI$	0.005	2.27	0.011	5.25	0.041	4.17
National Highway System, Non-Interstate	Constant	4.125	256.34				
	$AATT$	0.008	2.00				
	$AAFI$	0.091	9.80				
Non-National Highway System	Constant	4.373	53.01				
	$AATT$	0.081	4.54				
	$AAFI$	0.065	7.01				

Source: Irfan (2010)

(1) Same coefficients for all functional classes

$AATT$: Annual Average Truck Traffic (millions)

$AAFI$: Annual Average Freeze Index (thousands of degree-days)

4.5 Performance Jump Models for Rehabilitation Treatments

Performance jump models, developed by Irfan (2010) for rigid and flexible pavement type and by functional class, were used to illustrate the framework of this dissertation. The developed models, which have a non-linear form, estimate the performance jump as a function of the pre-intervention condition (Equation (4.2)):

$$PJ_{rs_i} = \beta_0 + \beta_1 \cdot \ln\left(IRI_{pre,rs_i}\right) \tag{4.2}$$

where PJ_{rs_i} represents the performance jump due to an intervention; β_0 is the constant term; β_1 is the estimated coefficient for the explanatory variable; and IRI_{pre,rs_i} is the pre-intervention performance level. Table 4.6 to Table 4.8 present the performance jump models for the rehabilitation treatments considered in this dissertation.

Table 4.6 Performance Jump Models for Flexible Pavement Treatments

Functional Class	Parameter	Functional HMA Overlay		Structural HMA Overlay	
		Coefficient	t-value	Coefficient	t-value
Interstate	Constant	-244.080	-5.92	-266.360	-8.01
	IRI_{pre}	66.109	7.79	70.713	10.43
National Highway System, Non-Interstate	Constant	-231.579	-13.16	-451.358	-7.01
	IRI_{pre}	63.988	18.34	109.659	8.33
Non-National Highway System	Constant	-327.366	-9.37	-386.027	-18.53
	IRI_{pre}	81.237	10.96	97.064	23.30

Source: Irfan (2010). IRI_{pre}: pre-intervention level (in/mile)

Table 4.7 Performance Jump Models for Rigid-Flexible Pavement Treatments

Functional Class	Parameter	Crack-and-Seat PCCP & HMA Overlay		PCCP & HMA Overlay[1]	
		Coefficient	t-value	Coefficient	t-value
Interstate	Constant	-443.410	-10.67	-188.351	-5.30
	IRI_{pre}	107.420	12.77	51.531	6.48
National Highway System, Non-Interstate	Constant	-345.530	-7.39		
	IRI_{pre}	87.870	9.30		
Non-National Highway System	Constant	-264.290	-4.92		
	IRI_{pre}	71.470	6.74		

Source: Irfan (2010)

(1) All Interstate sections. IRI_{pre}: pre-intervention level (in/mile)

Table 4.8 Performance Jump Models for Rigid-Rigid Pavement Treatments

Functional Class	Parameter	PCCP Patching[(1)]		PCCP & PCCP Overlay[(2)]	
		Coefficient	t-value	Coefficient	t-value
Interstate	Constant			-159.039	-4.21
	IRI_{pre}			42.903	5.28
National Highway System, Non-Interstate	Constant	-339.452	-5.60		
	IRI_{pre}	83.448	6.42		
Non-National Highway System	Constant	-339.452	-5.60		
	IRI_{pre}	83.448	6.42		

Source: Irfan (2010)

(1) All NHS-NI or NNHS sections. (2) All Interstate sections. IRI_{pre}: pre-intervention level (in/mile)

The initial performance condition after a rehabilitation takes place was estimated subtracting the jump (PJ_{rs_i}) from the pre-intervention performance $\left(PI_{pre,rs_i}\right)$. In all cases, the initial performance condition for a post-intervention segment was restricted to not deteriorate beyond the post-construction performance. This restriction was defined under the assumption that any rehabilitation intervention brings the infrastructure to a performance level that is not superior to that of new construction.

4.6 Agency Cost Estimation

The agency costs associated with highway infrastructure interventions can be classified in two ways: workzones ($ACWZ$), such as the cost incurred by the agency for performing new construction or reconstruction and rehabilitation interventions; and normal operations ($ACNO$), such as the annual maintenance expenditures during the regular use of the infrastructure. Since the existing average values and models that estimate agency cost are from various years, they were converted to the analysis-year dollars using the construction price index (FHWA, 2015) and Equation (3.32).

4.6.1 Agency Cost Estimation at Workzones ($ACWZ$)

To demonstrate the framework, this dissertation uses the rehabilitation intervention cost models developed by Khurshid (2010). The models are of exponential form Equation (4.3). This due to the expectation that assets in more advanced states of deterioration will require more material, repair and preparatory work when they are being treated, and therefore incur higher repair expenditures (in a manner that increases non-linearly with the level of deterioration).

$$CI_{rs_i} = \alpha \cdot e^{\left(\beta \cdot IRI_{pre,rs_i}\right)} \tag{4.3}$$

where CI_{rs_i} = rehabilitation intervention cost in 41000s/lane-mile (CPLM) in year 2006-dollar value; α= constant term, β= estimated coefficient for model explanatory variable, and IRI_{pre,rs_i} = pre-intervention performance level at rehabilitation intervention rs_i. To address rehabilitation interventions carried out in different years, the CI_{rs_i} values were converted to the equivalent cost at the analysis year used in this dissertation (2015), using the construction price index (FHWA, 2015) and Equation (3.32). The estimated parameters for functional HMA overlay treatment developed by Khurshid (2010) are presented in Table 4.9.

Table 4.9 Functional HMA Overlay Treatment Cost (IRI) Model

Highway Class	Coefficient Symbol	Functional HMA Overlay	t-value
Interstate	α	41.311	35.42
	β	0.0039	4.27
National Highway System, Non-Interstate	α	50.836	48.31
	β	0.0044	8.13
Non-National Highway System	α	92.403	85.62
	β	0.0025	8.54

Source: Khurshid (2010), (2006 constant thousand $/lane-mile)

Due to the lack of published literature on cost models for the other rehabilitation treatments considered in this dissertation, the average unit cost (Table 4.10) for the treatments considered in this dissertation was used to estimate the change in average unit cost relative to the functional HMA overlay treatment (Table 4.11). Since the models to estimate the cost of functional HMA overlay treatment are in year 2006 dollars value, they were converted to the analysis-year equivalents using the construction price index (FHWA, 2015) and Equation (3.32).

Table 4.10 Unit Agency Cost (average cost, $/lane-mile, 2007 constant $)

Treatment	Functional Class	Mean	Minimum	Maximum	Standard Deviation
Functional HMA Overlay	Interstate	89,824	41,658	186,812	61,337
	National Highway System, Non-Interstate	110,663	49,362	182,745	40,241
	Non-National Highway System	108,546	40,620	200,417	38,852
Structural HMA Overlay	Interstate	154,746	56,107	227,227	78,133
	National Highway System, Non-Interstate	140,466	86,937	180,104	31,988
	Non-National Highway System	144,991	52,455	372,540	109,394
Crack-and-Seat PCCP & HMA Overlay	Interstate	283,039	192,748	432,129	80,929
	National Highway System, Non-Interstate	286,251	124,927	452,068	51,182
PCCP & HMA Overlay	Interstate	113,654	54,822	382,759	104,483
	National Highway System, Non-Interstate	135,535	30,264	297,036	47,715
PCCP Patching	Interstate	117,974	76,291	172,040	20,717
	National Highway System, Non-Interstate	168,561	118,481	284,355	18,469
PCCP & PCCP Overlay	Interstate, National Highway System, Non-Interstate, Non-National Highway System	328,665	264,915	387,684	26,338

Source: Irfan (2010)

Table 4.11 Agency Cost for Rehabilitation Intervention Relative to Functional HMA

Treatment	Functional Class	CI_{rs_i}
Structural HMA Overlay	Interstate	$1.43 \cdot \left[41.311 \cdot e^{\left(0.0039 \cdot IRI_{pre,rs_i}\right)}\right]$
	National Highway System, Non-Interstate	$1.34 \cdot \left[50.836 \cdot e^{\left(0.0044 \cdot IRI_{pre,rs_i}\right)}\right]$
	Non-National Highway System	$1.50 \cdot \left[92.403 \cdot e^{\left(0.0025 \cdot IRI_{pre,rs_i}\right)}\right]$
Crack-and-Seat PCCP & HMA Overlay	Interstate	$3.36 \cdot \left[41.311 \cdot e^{\left(0.0039 \cdot IRI_{pre,rs_i}\right)}\right]$
	National Highway System, Non-Interstate	$2.53 \cdot \left[50.836 \cdot e^{\left(0.0044 \cdot IRI_{pre,rs_i}\right)}\right]$
	Non-National Highway System	$2.66 \cdot \left[92.403 \cdot e^{\left(0.0025 \cdot IRI_{pre,rs_i}\right)}\right]$
PCCP & HMA Overlay	Interstate	$1.54 \cdot \left[41.311 \cdot e^{\left(0.0039 \cdot IRI_{pre,rs_i}\right)}\right]$
	National Highway System, Non-Interstate	$1.15 \cdot \left[50.836 \cdot e^{\left(0.0044 \cdot IRI_{pre,rs_i}\right)}\right]$
	Non-National Highway System	$1.16 \cdot \left[92.403 \cdot e^{\left(0.0025 \cdot IRI_{pre,rs_i}\right)}\right]$
PCCP Patching	Interstate	$1.36 \cdot \left[41.311 \cdot e^{\left(0.0039 \cdot IRI_{pre,rs_i}\right)}\right]$
	National Highway System, Non-Interstate	$1.83 \cdot \left[50.836 \cdot e^{\left(0.0044 \cdot IRI_{pre,rs_i}\right)}\right]$
	Non-National Highway System	$1.96 \cdot \left[92.403 \cdot e^{\left(0.0025 \cdot IRI_{pre,rs_i}\right)}\right]$
PCCP & PCCP Overlay	Interstate	$4.03 \cdot \left[41.311 \cdot e^{\left(0.0039 \cdot IRI_{pre,rs_i}\right)}\right]$
	National Highway System, Non-Interstate	$3.49 \cdot \left[50.836 \cdot e^{\left(0.0044 \cdot IRI_{pre,rs_i}\right)}\right]$
	Non-National Highway System	$3.86 \cdot \left[92.403 \cdot e^{\left(0.0025 \cdot IRI_{pre,rs_i}\right)}\right]$

4.6.2 Agency Cost Estimation During Normal Operations ($ACNO$)

Due to the lack of available models for estimating the annual maintenance expenditures based on the current condition, this dissertation used the models developed by Al-Mansour and Sinha (1994) (Equations (4.4) and (4.5)) to demonstrate the framework. These models account for differences in traffic volume, but not differences in highway functional class or pavement type.

$$Log\ \left(ACNO_{t_{S_i}}\right) = 4.028 - 0.462\ \cdot PSI_{t_{S_i}}, \qquad AADT > 2000 \tag{4.4}$$

$$Log\ \left(ACNO_{t_{S_i}}\right) = 3.780 - 0.452\ \cdot PSI_{t_{S_i}}, \qquad AADT < 2000 \tag{4.5}$$

where $ACNO_{t_{S_i}}$ = Annual agency cost during normal operations for roadway or shoulder maintenance expenditure in \$/lane-mile; $PSI_{t_{S_i}}$ = Annual pavement serviceability index (t_{S_i} = 0, 1, 2, …, SL_{S_i}); and SL_{S_i} = Service life, time for a strategy S_i to reach a reconstruction threshold. Since the models to estimate $ACNO_{t_{S_i}}$ are in1993 dollar values, they were converted to the dissertation analysis year dollar value using the construction price index (FHWA, 2015) and Equation (3.32).

The performance measure $PSI_{t_{S_i}}$ was converted to $IRI_{t_{S_i}}$, as the framework was tested using IRI as a performance indicator. To convert PSI to IRI, the following relationship, Equation (4.6), developed by Gulen et al. (1994), was used:

$$PSI = 9.0\ e^{(-0.008747\ \cdot IRI)} \tag{4.6}$$

4.7 User Cost Estimation

For highway pavements, user costs commonly include: (i) delay and safety costs incurred by facility users during workzone ($UCWZ$), and (ii) user costs (VOC, crash costs, and so on) incurred during the normal use ($UCNO$) of the asset over the service life or the span of time between successive interventions.

4.7.1 User Cost Estimation at Workzones ($UCWZ$)

In the maintenance and construction of highways, there is often a reduced number of lanes available to traveling public (Walls and Smith, 1998). In this case study, the user delay cost and VOC due to speed reduction were included as the components to determine the user cost at workzones, Equation (4.7):

For the case study, Equation (3.38) can be rewritten as:

$$UCDT_{S_i} = \sigma_{dy} \cdot \sum_{r_{S_i}}^{R_{S_i}} UDC_{r_{S_i}} + \sigma_{sr} \cdot \sum_{r_{S_i}}^{R_{S_i}} VOCsr_{r_{S_i}} \tag{4.7}$$

where: $UCDT_{S_i}$ = User cost during rehabilitation interventions for the strategy S_i; $UDC_{r_{S_i}}$= User delay cost for a rehabilitation intervention r_{S_i}, Equation (4.8); $VOCsr_{r_{S_i}}$= Vehicle operation cost due to speed reduction for a rehabilitation intervention r_{S_i}, Equation (4.9); r_{S_i} = Intervention for strategy S_i (r_{S_i} =1, 2, …, R_{S_i}); R = Optimal number of interventions associated with the strategy S_i; and σ_{dy} , σ_{sr} = Weighting factor for user delay and speed reduction cost, respectively, $0 \leq \sigma_{dy}$, $\sigma_{sr} \leq 1$.

$$UDC_{r_{S_i}} = \sum_{v} (V_v \cdot T_v \cdot C_v) \tag{4.8}$$

$$VOCsr_{r_{S_i}} = \sum_{v} (V_v \cdot T_v \cdot Fc_v \cdot Fp) \tag{4.9}$$

where: V_v = Nr. of vehicles in class v that suffer delay due to the speed change, over the work zone duration; T_v = Travel time difference (hour/mile) for vehicle class v due to the speed change; C_v = Delay cost rate for vehicle class v, in \$/vehicle-hour; v = Vehicle class, i.e., auto and truck; Fc_v = Average fuel consumption rate for vehicle class v, gallon/hour of delay; and Fp = Average fuel price, \$/ gallon.

The number of vehicles affected by the workzone delay corresponds to the traffic flow impact during the time spent to perform the rehabilitation. Therefore, the project duration must be estimated to compute the overall user delay costs associated with a rehabilitation strategy. In this case study, the workzone duration models for the case study are taken from a previous study that estimated the duration (in days) of highway pavement maintenance and rehabilitation projects as a function of the contract type project cost (Irfan et al., 2010), as shown in Equation (4.10):

$$D_{rs_i} = e^{\left(4.700 + 0.307 \cdot CI_{rs_i} + 0.237 \cdot Contract_{type,rs_i}\right)} \tag{4.10}$$

where project duration is estimated in days; the rehabilitation cost is in millions of US dollars; and contract type is an indicator variable: 0 indicates that available days were specified for project completion, and 1 indicates that a deadline date was fixed.

Equation (4.10) was used to estimate the project duration for functional HMA treatment, and this was used as the base-line to estimate the average increase in project duration of the other rehabilitation treatments considered in this case study (Table 4.12).

Table 4.12 Project Duration Increase Relative to Functional HMA

Treatment	Project Duration (days)
Structural HMA Overlay	$1.10 \cdot e^{\left(4.700 + 0.307 \cdot CI_{rs_i} + 0.237 \cdot Contract_{type,rs_i}\right)}$
Crack and Seat PCCP & HMA	$1.15 \cdot e^{\left(4.700 + 0.307 \cdot CI_{rs_i} + 0.237 \cdot Contract_{type,rs_i}\right)}$
Repair PCCP &HMA Overlay	$1.20 \cdot e^{\left(4.700 + 0.307 \cdot CI_{rs_i} + 0.237 \cdot Contract_{type,rs_i}\right)}$
PCCP Patching on PCCP	$1.20 \cdot e^{\left(4.700 + 0.307 \cdot CI_{rs_i} + 0.237 \cdot Contract_{type,rs_i}\right)}$
PCCP Overlay of PCCP	$1.25 \cdot e^{\left(4.700 + 0.307 \cdot CI_{rs_i} + 0.237 \cdot Contract_{type,rs_i}\right)}$

Prior to using Equations (4.8) and (4.9), some preliminary computtaions were carried out. For autos and trucks separately, the Annual Average Daily Traffic (*AADT)* was multiplied by the workzone duration (in days) to yield the total number of trucks and autos that were affected by the workzone conditions. The travel time cost (in $/vehicle-hour) was developed using data from Walls and Smith (1998). For automobiles the value was $11.58 and trucks $22.31 in 1996 dollars; the figures were adjusted using the consumer price index (BLS, 2015) and Equation (3.32). Typical traffic conditions were assumed as follows: two lanes per direction and closure of one lane in each direction during the workzone operations; the following average speed limits: 65 mph, 55 mph, and 45 mph, for the non-work zone sections; and 45 mph, 40 mph, and 20 mph for the workzone sections on Interstate, NHS-NI, and Non-NHS highways, respectively. An average fuel consumption rate (gallon/min of delay) for autos and trucks was assumed as 0.034 and 0.345, respectively (AASHTO, 2003, Sinha and Labi, 2007). Having determined all elements of Equations (4.8) and (4.9), the user costs ($/lane-mile) was then calculated for each rehabilitation r_{S_i}, and the sum will determine the user cost at workzones for the rehabilitation strategy S_i.

4.7.2 User Cost Estimation During Normal Operations ($UCNO$)

The user cost during normal operations, in the case of highways, are a function of the vehicle operating costs (VOC) in terms of the fuel, maintenance and repair, tires, and depreciation (Equation (4.11)). VOC varies with the level of vehicle use and is often expressed as a rate (cents/VMT). Rehabilitation improves the pavement surface and thus causes a reduction in VOC rate.

$$VOC_{S_i} = \sum_{t_{S_{i=0}}}^{t_{S_i}=SL_{S_i}} \left(V_v \cdot \sum_{v} [Adj_{voc} \cdot (Fuel_v + Maint_v + Tires_v + Dep_v)] \right) \qquad (4.11)$$

where: VOC_{S_i} = Vehicle operating cost for the strategy S_i; V_v = Annual number of vehicles for vehicle class v;Adj_{voc} = Vehicle operating cost adjustment factor based on $PI_{t_{S_i}}$; $PI_{t_{S_i}}$ = Annual performance (t_{S_i} = 0, 1, 2, …, SL_{S_i}); and SL_{S_i} = Service life or the time for a strategy S_i to reach a reconstruction threshold. To illustrate the framework of this dissertation, the VOC were estimated using the adjustment factors and base-line cost (cent per mile) for smooth highway pavement conditions (Table 2.3) and the adjustment factors (Figure 2.5) for different pavement conditions with IRI values above 80 in/mi determined by Barnes and Langworthy (2003). The VOC were estimated by vehicle type (autos and trucks) and their corresponding values were converted to the dollar value of the analysis year using the consumer price index (BLS, 2015) and Equation (3.32). The total VOC were determined by multiplying the VOC (in dollars per vehicle-mile) by the respective *AADTs* and by 365 to yield the yearly VOC.

4.8 Chapter Summary

This chapter presents the required inputs for testing the developed framework using highway pavements as a case study. During the data collection and collation processes, it was found that some input data or models were unavailable for certain pavement families. The chapter describes the assumptions that were made to address this lacking information where encountered. Table 4.13 presents a summary of the data items and their corresponding sources.

Table 4.13 Summary of Data Input Used in the Case Study

Data component	Description / Equation	Source
Traffic	AADT, truck percentage	INDIPAVE (2000)
Performance deterioration	$IRI = e^{(\beta_0 + \beta_1 \cdot AATT \cdot t + \beta_2 \cdot AAFI \cdot t)}$	Irfan (2010)
Performance jump	$PJ_{rs_i} = \beta_0 + \beta_1 \cdot \ln\left(IRI_{pre,rs_i}\right)$	Irfan (2010)
Intervention cost	$CI_{rs_i} = \alpha \cdot e^{\left(\beta \cdot IRI_{pre,rs_i}\right)}$	Khurshid (2010)
Annual maintenance expenditures	$Log\left(ACNO_{ts_i}\right) = 4.028 - 0.462 \cdot PSI_{ts_i}, AADT > 2000$ $Log\left(ACNO_{ts_i}\right) = 3.780 - 0.452 \cdot PSI_{ts_i}, AADT < 2000$	Al-Mansour and Sinha (1994)
Project duration	$D_{rs_i} = e^{\left(4.700 + 0.307 \cdot CI_{rs_i} + 0.237 \cdot Contract_{type,rs_i}\right)}$	Irfan et al., (2010)
Travel time cost	Auto \$11.58 Trucks \$22.31	Walls and Smith (1998)
Traffic operations	Two lanes per direction and closure of one lane in each direction during the workzone operations. Average speed limits of 65 mph, 55 mph, and 45 mph for the non-work zone sections and 45 mph, 40 mph, and 20 mph for the workzone sections on Interstate, NHS-NI and Non-NHS highways, respectively.	Typical traffic conditions
Average fuel consumption rate	Autos = 0.034 (gallon/min delay) Trucks = 0.345 (gallon/min delay)	AASHTO (2003) Sinha and Labi (2007)
Vehicle operation cost	$Adj_{factor} = 0.000010 \cdot IRI^2 + 0.000195 \cdot IRI + 0.916931$	Barnes and Langworthy (2003)

Table 4.13 continued

Cost adjustment	$C_{AY} = C_{BY} \frac{CPI_{AY}}{CPI_{BY}}$	Highway Construction Price Index (Federal Highway Administration, 2015) Consumer Price Index (Bureau of Labor Statistics, 2015)

CHAPTER 5. CASE STUDY RESULTS AND SENSITIVITY ANALYSIS

The case study for the developed framework is an in-service two-lane per direction, 10-mile Interstate road segment with a flexible pavement surface and moderate traffic in a region of moderate climate. As described in Section 3.5.3, two scenarios involving performance condition restrictions were investigated: one where the successive rehabilitation thresholds were restricted to be successively lower than the threshold of the previous rehabilitation, and one where they were unrestricted. For each of these two scenarios, three cases involving the agency-user cost relative weight were investigated: (a) equal weights, (b) using only the agency costs while ignoring the user costs, (c) using only the user costs while ignoring the agency costs. Then, for each scenario and case, the optimal strategy was determined for each of several objective functions of the asset manager. The objective functions (also referred loosely herein as the cost-effectiveness criteria) consisted of a monetary or non-monetary combination of the infrastructure performance (also referred to as effectiveness, or benefits) and cost (agency, user, or both). Also, for each cost-effectiveness criterion, it was determined whether the solutions differ across the relative and absolute expressions of the cost-effectiveness value. For the fully-monetary objective functions (described in Chapter 3), the analysis was carried out from two different life-cycle cost expressions: present worth cost to perpetuity (PWCP) and equivalent uniform annual cost to perpetuity (EUACP) with three different interest rate values (1%, 4%, and 10%). The optimal strategy (best solution found by using a suitable optimization technique) represents the rehabilitation schedule (treatment types and timings). In these two respects, the sensitivity of the optimal solution with respect to the performance condition restrictions, the agency-user cost relative weight, the interest rate, and the effectiveness criteria, were investigated using the case study. This chapter presents detailed results and a description of the findings, including a sensitivity analysis.

5.1 Unrestricted Scenario

The unrestricted scenario establishes the agency policy boundaries only, for which a rehabilitation intervention can take place (see Equation 3.56 in Chapter 3). This condition provides full flexibility for the asset managers to choose the intervention threshold set within these two boundaries for the purposes of the optimization. The results suggest that for the unrestricted scenario, the optimal thresholds are insensitive to the form of expression of the cost-effectiveness criterion-whether in relative or absolute form.

The analysis for the different agency and user costs weights yielded interesting insights. It was observed that for most cost-effectiveness criteria and for both life-cycle cost expressions, two of the relative weight cases: case 1 (equal weights of agency and user cost components) and case 3 (user cost only) yielded the same optimal strategy due to the small fraction of agency cost on the overall total cost. This result can be attributed to the far smaller size of agency cost compared to user cost. For relative weight case 2 (that is, agency cost only), it was found that two of the cost-effectiveness criteria (service life and performance jump) yielded the same optimal strategy irrespective of life-cycle cost expression; on the other hand, the other three criteria (average performance, area bounded by the performance curve, and agency cost savings) were found to be sensitive to the life-cycle cost expression.

5.1.1 Unrestricted Scenario, Case 1

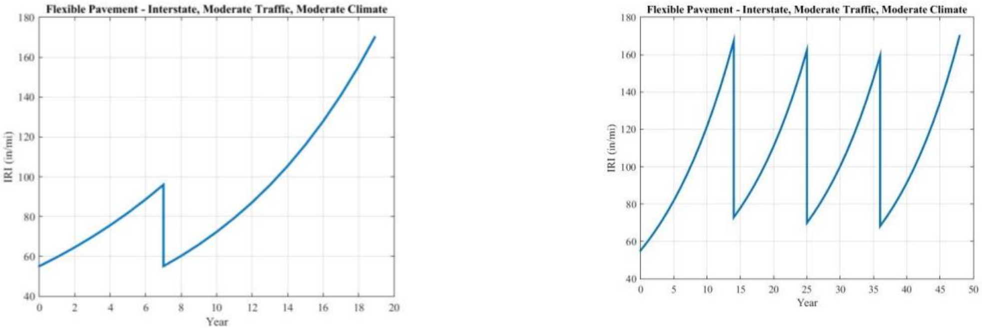
As stated in the Introduction above, case 1 was defined as the case where the agency and user costs are both considered and equally weighted ($w_{AC} = 1, w_{UC} = 1$) into the cost analysis. In a normalized scale, this weight scheme is equivalent to $w_{AC} = 0.5, w_{UC} = 0.5$, and means that \$1 for agency is equal to \$1 for users, and that both cost perspectives are considered The optimal strategies for this case are presented in Table 5.1. The results suggest that rehabilitation interventions are most cost-effective when the first intervention is performed when the infrastructure is in a condition greater or equal to that of the subsequent interventions (Figure 5.1). Additionally, it can be noticed that of the candidate treatment types across the optimal strategies, structural HMA is the most common when only one intervention is required; functional HMA is the most common when more than one intervention is required.

Table 5.1 Optimal Strategies for the Unrestricted Scenario, Case 1

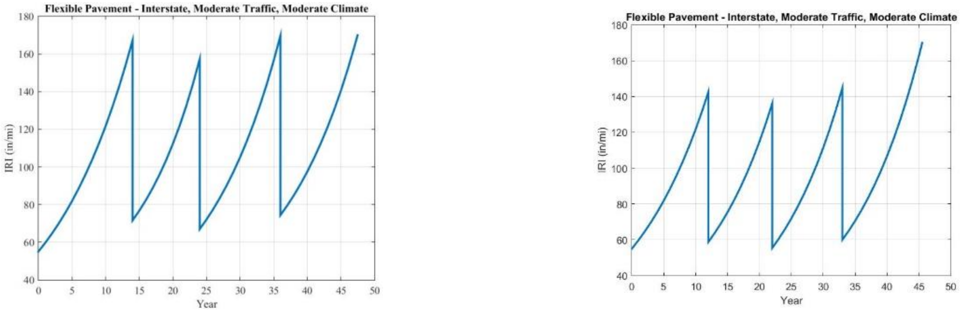
CE criteria		Rehabilitation (Year)			Treatment(1)			IRI (in/mile) performance condition at rehabilitation			Service Life (Years)
PWCP	CE_{SL}	7			2			96			18.915
	CE_{PJ}	14	25	36	1	1	1	167	162	159	47.934
	CE_{AP}	14	25	36	1	2	1	167	162	169	47.506
	CE_{ABC}	12	22	33	1	1	1	143	136	145	45.162
	CE_{ACS}	7			2			96			18.915
	CE_{UCS}	7			2			96			18.915
EUACP	CE_{SL}	7			2			96			18.915
	CE_{PJ}	14	25	36	1	1	1	167	162	159	47.934
	CE_{AP}	14	25	36	1	2	1	167	162	169	47.506
	CE_{ABC}	13	24	35	1	1	1	154	155	155	47.117
	CE_{ACS}	7			2			96			18.915
	CE_{UCS}	7			2			96			18.915

(1) Treatment 1-Functional HMA, Treatment 2-Structural HMA

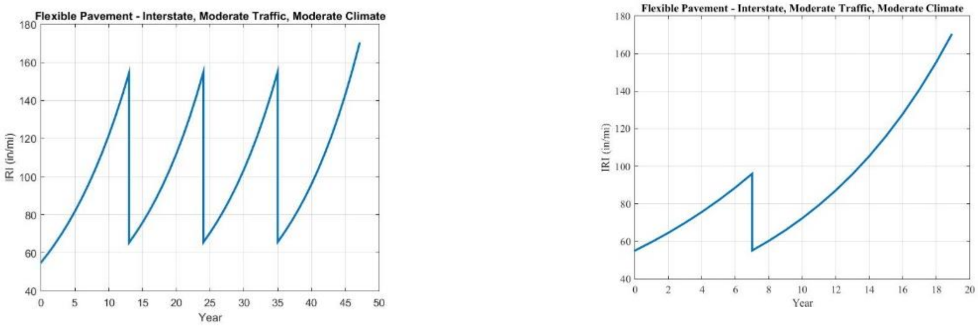
For different cost-effectiveness criteria and life-cycle cost expressions, the optimal strategies as well as their corresponding agency, user, and total costs are shown in Figure 5.2. It can be noticed that from agency and user perspectives, the highest expenditure corresponds to strategies with early workzones. It can be understood as the effect of discounting from the agency perspective and inferior performance condition (higher costs of vehicle operations during periods of normal operations) from the users' perspective. It was found that the user cost during normal operations is by far the largest share of the total cost while agency cost constitutes a far smaller fraction. Where the cost-effectiveness is measured in terms of service life, agency cost and user cost savings, and where the agency and user cost are both included and equally weighted (case 1), the optimal strategy was observed to be associated with the highest agency and user costs due to the effect of discounting: early expenditures have greater present worth compared to later expenditures, *ceteris paribus*. Where the cost-effectiveness is measured in terms of performance jump, average performance, and area bounded by the performance curve, it was observed that the optimal strategies have relatively low agency and user costs compared to those of the other measures of cost-effectiveness. Again, this is consistent with expectations.



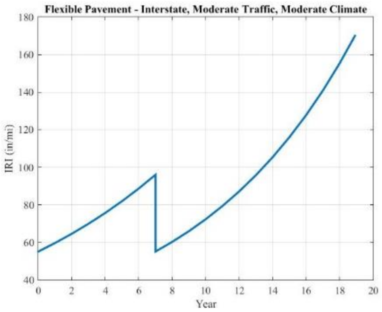
(a) CE$_{\text{service life}}$ (PWCP, EUACP) (b) CE$_{\text{performance jump}}$ (PWCP, EUACP)



(c) CE$_{\text{average perfromance}}$ (PWCP, EUACP) (d) CE$_{\text{area bounded by the performance curve}}$ (PWCP)

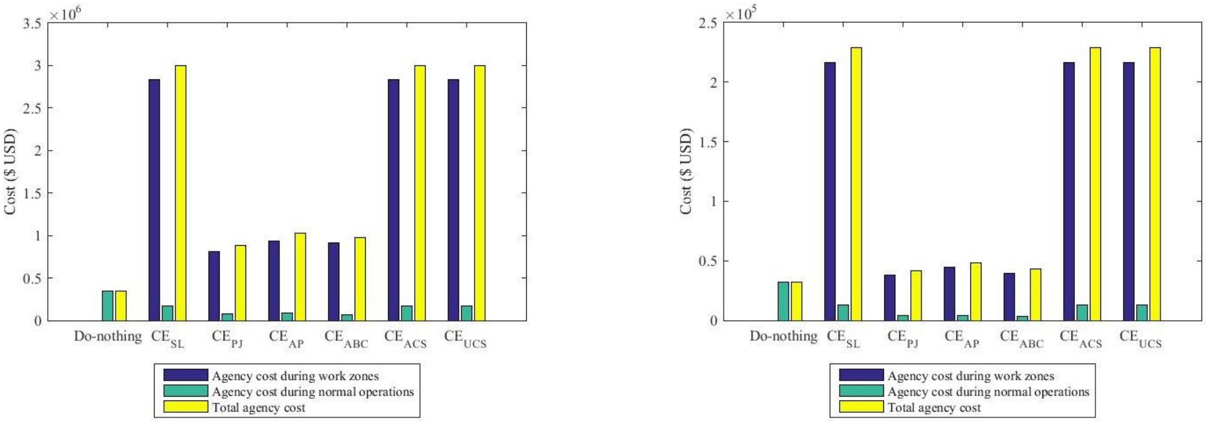


(e) CE$_{\text{area bounded by the performance curve}}$ (EUACP) (f) CE$_{\text{agency cost savings}}$ (PWCP, EUACP)

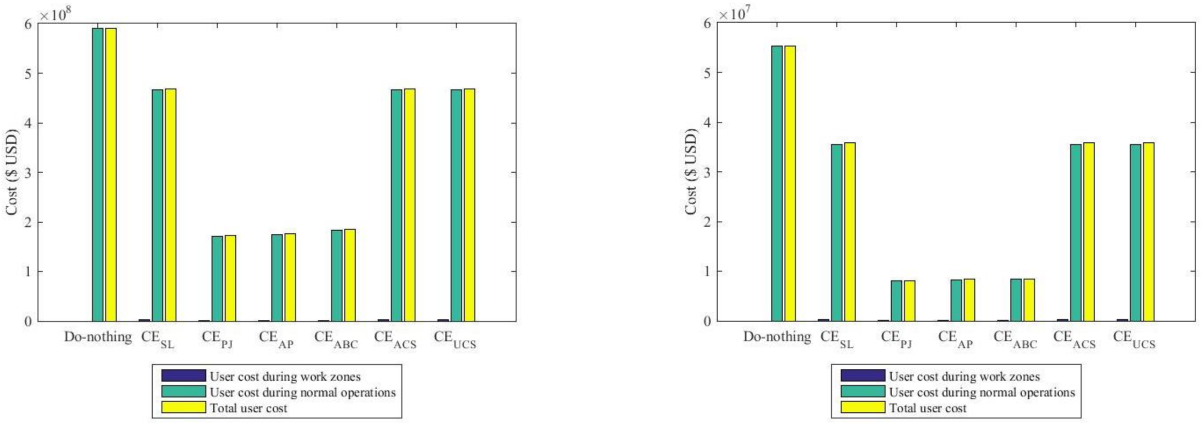


(g) CE$_{\text{user cost savings}}$ (PWCP, EUACP)

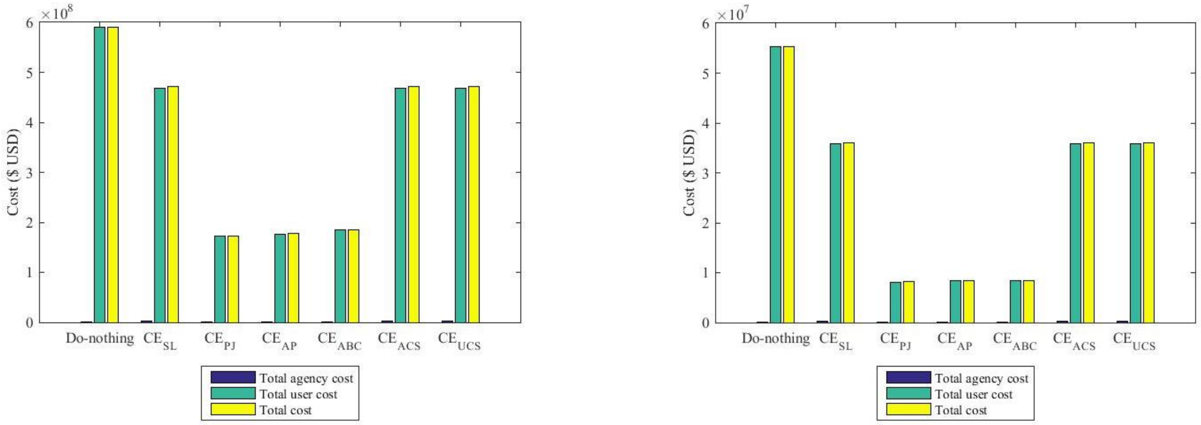
Figure 5.1 Optimal Strategies for the Unrestricted Scenario, Case 1



(a) Agency cost (PWCP) (b) Agency cost (EUACP)



(c) User cost (PWCP) (d) User cost (EUACP)



(e) Total cost (PWCP) (f) Total cost (EUACP)

Figure 5.2 Costs Associated with Optimal Strategies for the Unrestricted Scenario, Case 1

5.1.2 Unrestricted Scenario, Case 2

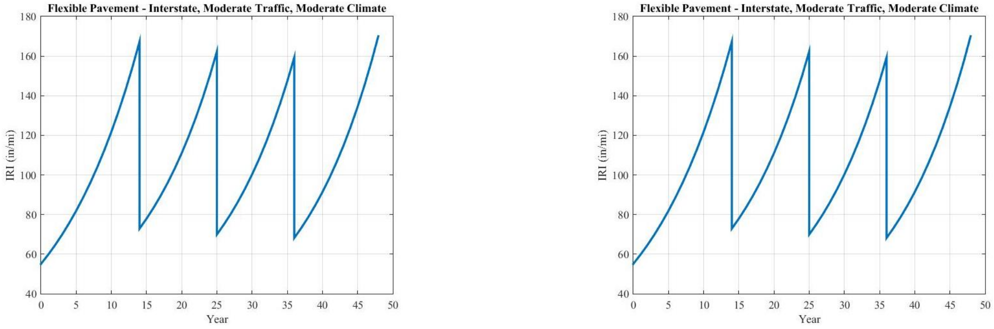
The unrestricted scenario, case 2, uses the agency costs only and ignores the user costs (thus, $w_{AC} = 1, w_{UC} = 0$)˙. At certain agencies, this is the case because they consider agency costs to be hard cash spent out of agency coffers, while user costs are not borne directly. The optimal strategies for this case (Table 5.2) suggest that the rehabilitation interventions are most cost-effective when the first intervention is applied at a condition greater than or equal to those of subsequent interventions. This was found to be the case for all cost-effectiveness criteria (Figure 5.3). It can also be noticed that across all the cost-effectiveness criteria that functional HMA is the treatment that appears most often in the optimal strategies.

Table 5.2 Optimal Strategies for the Unrestricted Scenario, Case 2

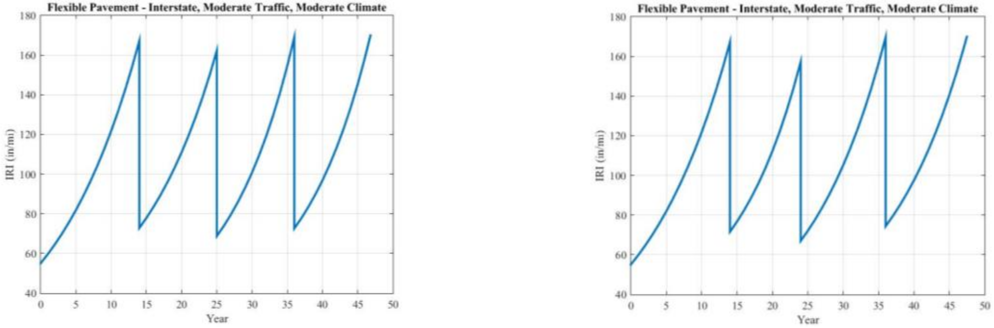
CE criteria		Rehabilitation (Year)			Treatment(1)			IRI (in/mile) performance condition at rehabilitation			Service Life (Years)
PWCP	CE_{SL}	14	25	36	1	1	1	167	162	159	47.934
	CE_{PJ}	14	25	36	1	1	1	167	162	159	47.934
	CE_{AP}	14	25	36	1	2	1	167	162	169	47.506
	CE_{ABC}	13	23	34	1	1	1	154	143	148	46.385
	CE_{ACS}	7			2			96			18.915
EUACP	CE_{SL}	14	25	36	1	1	1	167	162	159	47.934
	CE_{PJ}	14	25	36	1	1	1	167	162	159	47.934
	CE_{AP}	14	25	36	1	1	1	167	162	159	47.934
	CE_{ABC}	14	25	36	1	1	1	167	162	159	47.934
	CE_{ACS}	7			2			96			18.915

(1) Treatment 1-Functional HMA, 2-Structural HMA

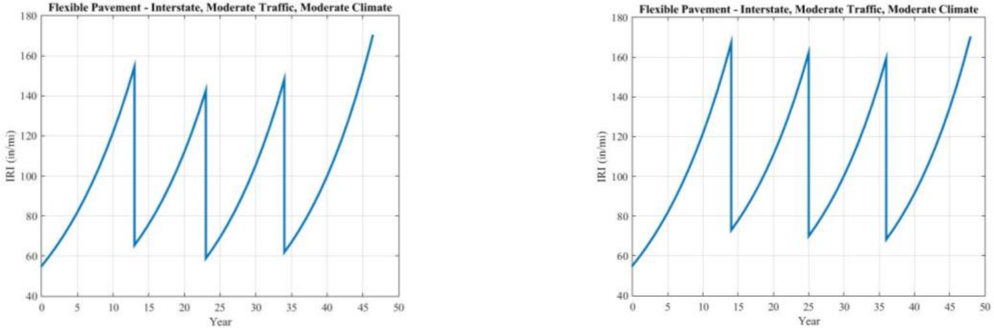
Figure 5.4 presents the agency costs associated with the optimal strategies in terms of the different criteria of cost-effectiveness and the different life-cycle cost expressions. Across all cost-effectiveness criteria from the agency perspective, it can be noticed that the do-nothing strategy has the lowest overall cost; the highest agency expenditure, corresponds to the workzone periods, as expected. It is observed that where the cost-effectiveness is measured in terms of the agency cost savings, the optimal strategy has the highest agency cost values. This is intuitive because this cost-effectiveness measure is associated with the infrastructure condition during normal operations, the effect of discounting early expenditures have greater present worth compared to later expenditures,



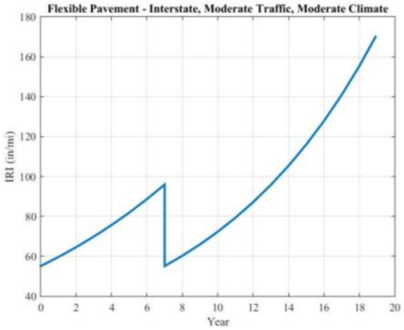
(a) CE$_{\text{service life}}$ (PWCP, EUACP) (b) CE$_{\text{performance jump}}$ (PWCP, EUACP)



(c) CE$_{\text{average perfromance}}$ (PWCP) (d) CE$_{\text{average perfromance}}$ (EUACP)



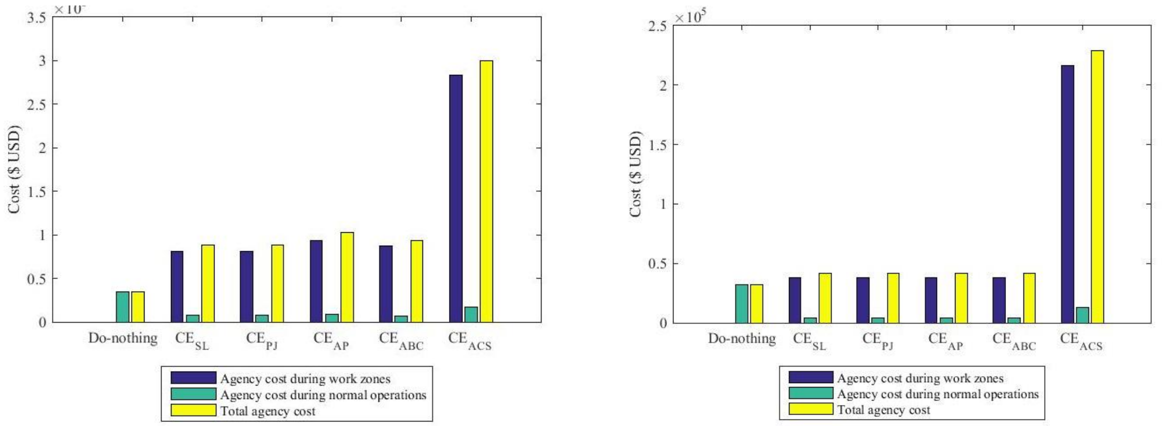
(e) CE$_{\text{area bounded by the performance curve}}$ (PWCP) (f) CE$_{\text{area bounded by the performance curve}}$ (EUACP)



(g) CE$_{\text{agency cost savings}}$ (PWCP, EUACP)

Figure 5.3 Optimal Strategies for the Unrestricted Scenario, Case 2

and additionally because this strategy has structural HMA as a treatment, which is more expensive compared to the other treatments. The optimal strategies found using service life, performance jump, and area bounded by the performance curve as the cost-effectiveness measures were associated with the lowest agency cost, compared to the optimal strategies obtained using other criteria.



(a) Agency cost (PWCP)

(b) Agency cost (EUACP)

Figure 5.4 Costs Associated with Optimal Strategies for the Unrestricted Scenario, Case 2

5.1.3 Unrestricted Scenario, Case 3

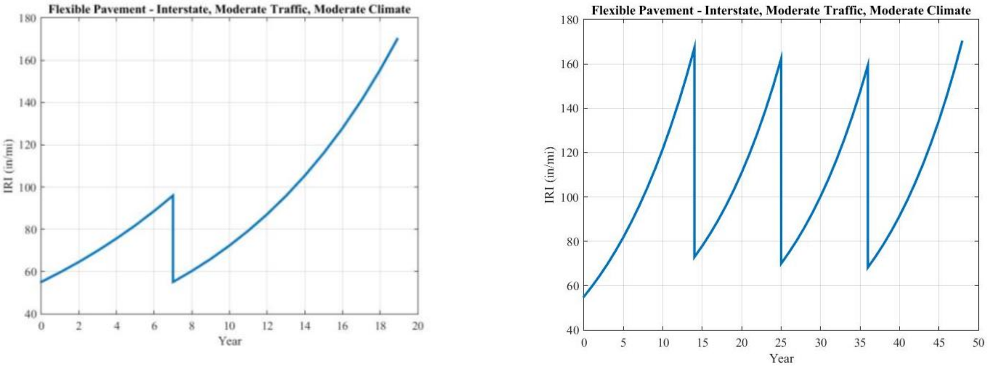
The unrestricted scenario, case 3, uses the user costs only (the agency costs are ignored), hence, $w_{AC} = 0, w_{UC} = 1$˙. The optimal strategies for this case are presented in Table 5.3.

Table 5.3 Optimal Strategies for the Unrestricted Scenario, Case 3

CE criteria		Rehabilitation (Year)			Treatment(1)			IRI (in/mile) performance condition at rehabilitation			Service Life (Years)
PWCP	CE_{SL}	7			2			96			18.915
	CE_{PJ}	14	25	36	1	1	1	167	162	159	47.934
	CE_{AP}	14	25	36	1	2	1	167	162	169	47.506
	CE_{ABC}	13	23	34	1	1	1	154	143	148	46.385
	CE_{UCS}	7			2			96			18.915
EUACP	CE_{SL}	7			2			96			18.915
	CE_{PJ}	14	25	36	1	1	1	167	162	159	47.934
	CE_{AP}	14	25	36	1	2	1	167	162	169	47.506
	CE_{ABC}	12	22	33	1	1	1	143	136	145	45.516
	CE_{UCS}	7			2			96			18.915

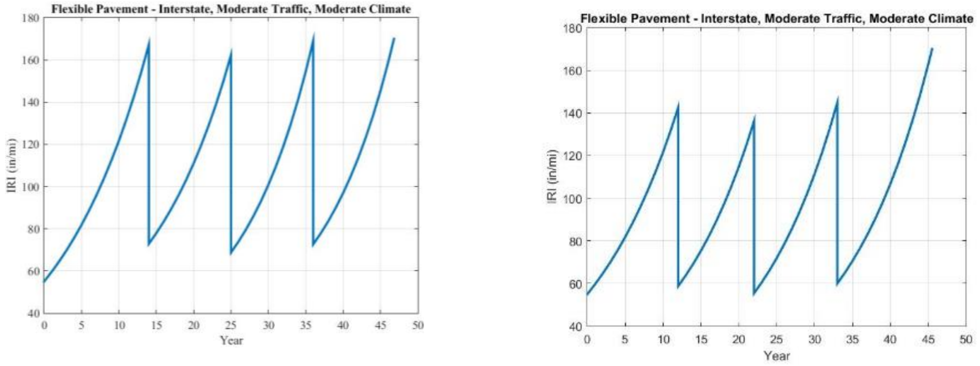
(1) Treatment 1-Functional HMA, 2-Structural HMA

The results suggest that rehabilitation interventions are most cost-effective when the first intervention is performed at a condition that is greater or equal to those of the subsequent interventions (Figure 5.5). Again, it was noticed that across the different cost-effectiveness criteria, functional HMA is the most common treatment appearing in the optimal strategies.



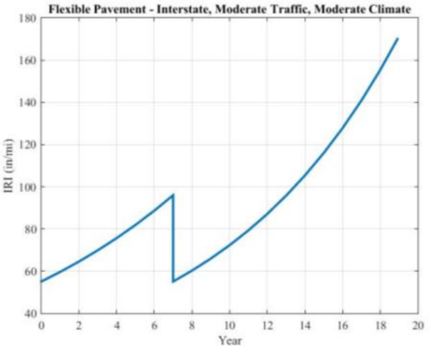
(a) CE$_{\text{service life}}$ (PWCP, EUACP)

(b) CE$_{\text{performance jump}}$ (PWCP, EUACP)



(c) CE$_{\text{average performance}}$ (PWCP, EUACP)

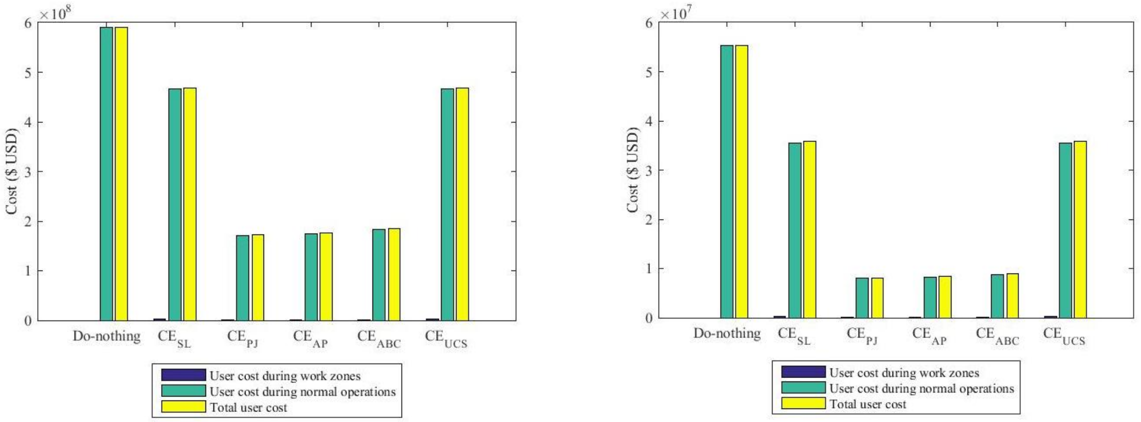
(d) CE$_{\text{area bounded by the performance curve}}$ (PWCP, EUACP)



(e) CE$_{\text{user cost savings}}$ (PWCP, EUACP)

Figure 5.5 Optimal Strategies for the Unrestricted Scenario, Case 3

For different cost-effectiveness criteria and life-cycle cost expressions, Figure 5.6 presents the detailed user costs associated with the optimal strategies. It was noticed that of the cost-effectiveness criteria, service life and user cost savings were associated with the highest user costs because these strategies are rather sparse (with one intervention only) and thus, the performance condition, on average, will not be at a level that promotes low user costs of vehicle operation. It can be also observed that optimal strategies found using the infrastructure average performance, performance jump, and area bounded by the performance curve as the measures of effectiveness, that have the lowest user cost.



(a) User cost (PWCP)

(b) User cost (EUACP)

Figure 5.6 Costs Associated with Optimal Strategies for the Unrestricted Scenario, Case 3

5.1.4 Discussion for Unrestricted Scenario

In order to demonstrate the flexibility of the framework and to carry out a sensitivity analysis, the estimation of the optimal strategies using the different cost-effectiveness criteria was carried out for three cases of agency-user cost relative weights. Additionally, for the cost-effectiveness criteria based on the area bounded by the performance curve, the sensitivity was explored in terms of the interest rate across the three cases of agency-user cost relative weights.

5.1.4.1 Sensitivity to Agency and User Cost Relative Weights

The optimal strategies for the unrestricted scenario were analyzed for three cases regarding the agency and user cost relative weights: (1) using agency costs only (2) using user costs only, and (3) considering both the agency and user costs duly weighted.

(a) Service Life

Using this criterion, the optimal strategies developed were found to be insensitive to the life-cycle cost expressions, but sensitive to the cost component weights (Figure 5.7). This criterion yielded the same optimal strategy for two of the relative weight cases; namely, equal weights for agency and user cost where only user cost was considered.

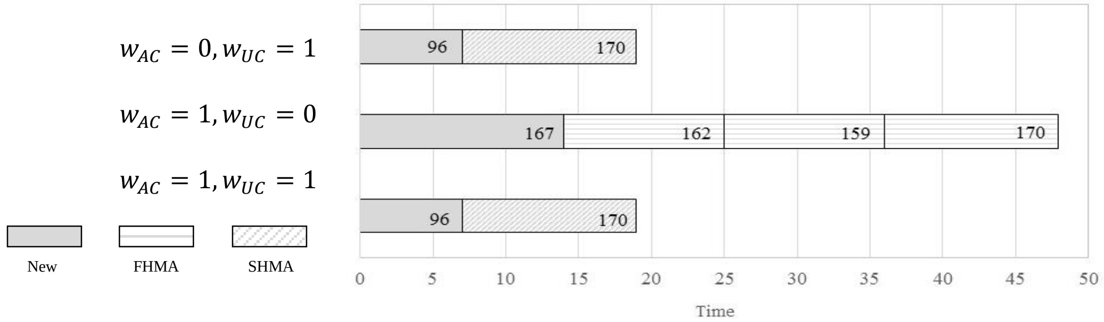


Figure 5.7 Optimal Strategies Based on Service Life as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

(b) Performance Jump

Where the cost-effectiveness criterion was the infrastructure performance jump in the analysis, the same optimal strategy was obtained for all cost component weights. This criterion was not sensitive to cost component relative weights or life-cycle cost expressions. Across the different cost component relative weight cases and life-cycle cost expressions, the optimal strategies were found to be the same (Figure 5.8).

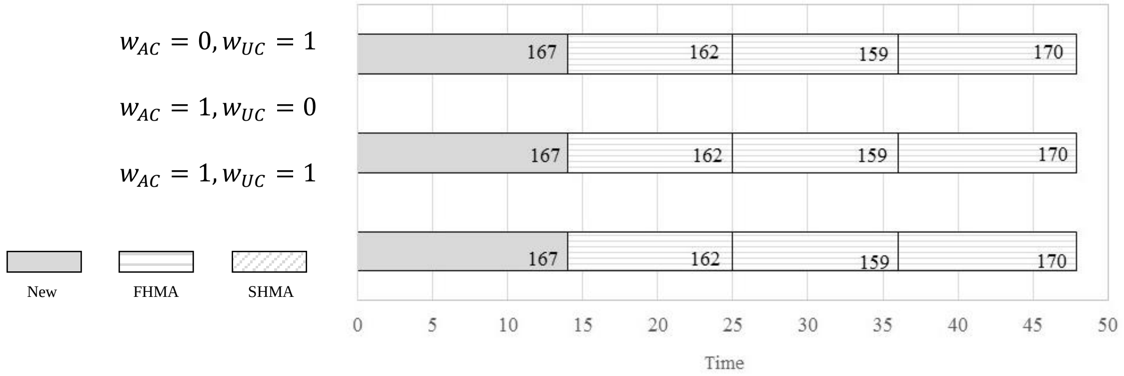


Figure 5.8 Optimal Strategies Based on Performance Jump as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

(c) Average Performance

Where the cost-effectiveness was expressed in terms of the average performance of the infrastructure over its life cycle; the optimal strategy was found to be insensitive to cost component weights and life-cycle cost expressions. Across the different cost component relative weight cases and life-cycle cost expression, the optimal strategies were the same (Figure 5.9).

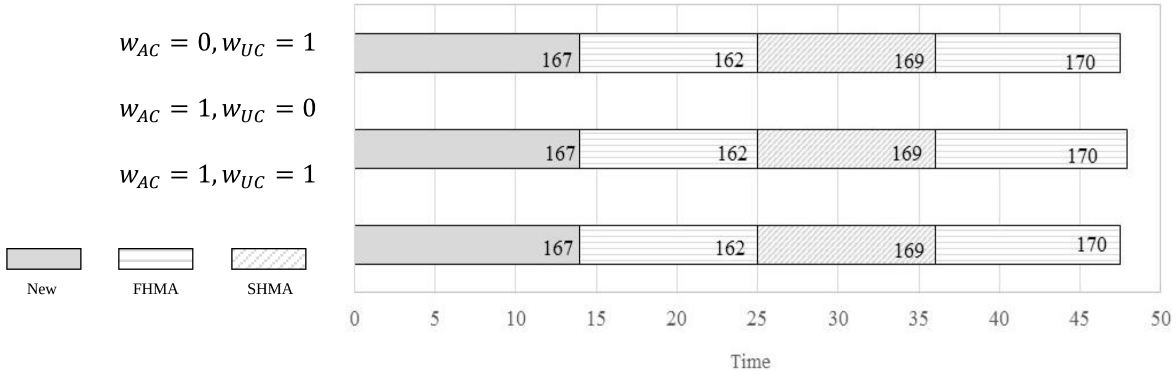
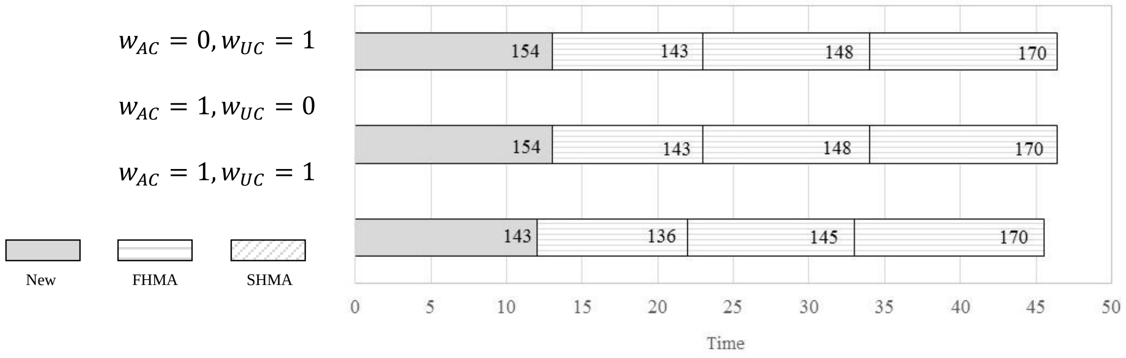


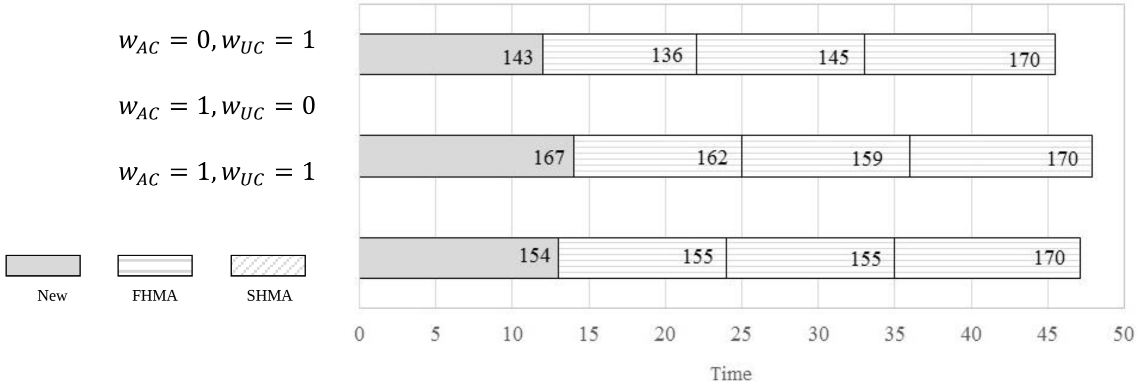
Figure 5.9 Optimal Strategies Based on Average Performance as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

(d) Area Bounded by the Performance Curve

The optimal strategy, where the cost-effectiveness criterion is the area bounded by the performance curve, was found to be sensitive to cost component weights and life-cycle cost expressions. Where the life-cycle cost expression was PWCP, this criterion yielded the same optimal strategy for two of the cases: case 2 (agency cost only) and case 3 (user cost only). Where the life-cycle cost expression was the EUACP, each component weight case yielded a different optimal strategy. Figure 5.10 presents the optimal strategy for this criterion across the different cost component weight cases and life-cycle cost expressions.



(a) PWCP as the Life-cycle Cost Expression



(b) EUACP as the Life-cycle Cost Expression

Figure 5.10 Optimal Strategies Based on Area Bounded by the Performance Curve as the Cost-Effectiveness Criterion

(e) Agency Cost Savings

Where the cost-effectiveness was expressed in terms of the agency cost savings, the optimal strategy was found to be insensitive to cost component weights and life-cycle cost expressions. Across the different cost component relative weight cases and life-cycle cost expressions, the optimal strategies were the same (Figure 5.11).

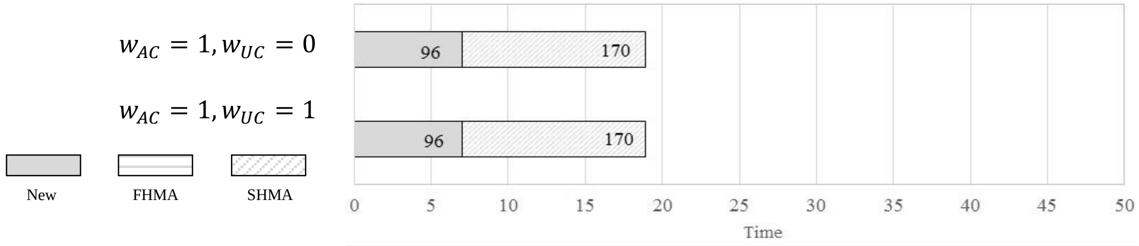


Figure 5.11 Optimal Strategies Based on Agency Cost Savings as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

(f) User Cost Savings

In situations where cost-effectiveness was measured in terms of the user cost savings criterion, the optimal strategy was the same irrespective of cost component weights. When this criterion was used, the optimal strategy was found to be insensitive to cost component relative weight or life-cycle cost expressions. Figure 5.12 presents the optimal strategy across the different cost component relative weights and life-cycle cost expressions.

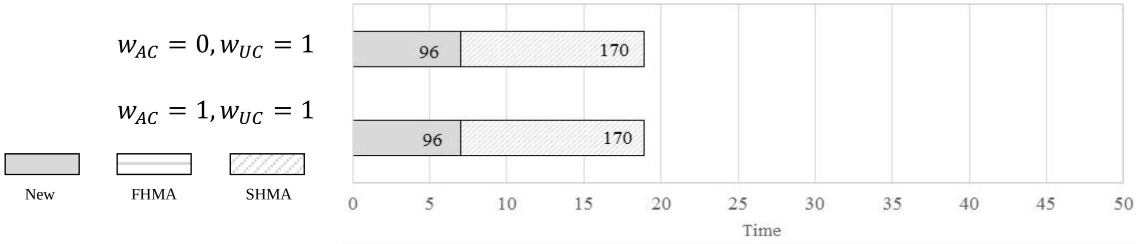


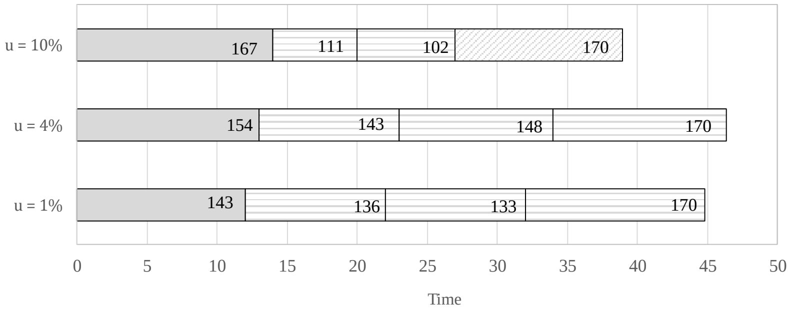
Figure 5.12 Optimal Strategies Based on User Cost Savings as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

5.1.4.2 Sensitivity to the Interest Rate

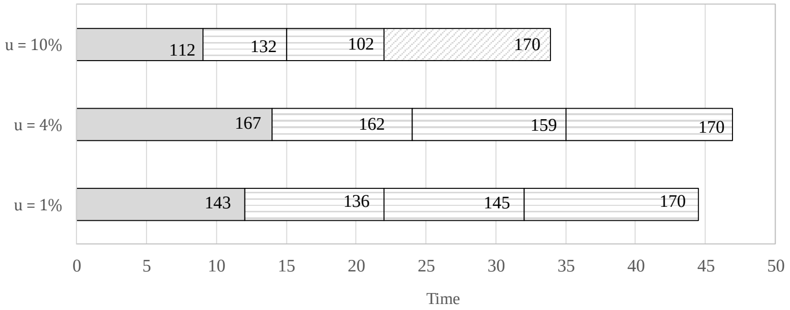
For the cost-effectiveness criterion based on the area bounded by the performance curve three different interest rates (u): 1%, 4%, and 10% were used to test the sensitivity to this input variable across agency and user cost relative weights.

(a) Using only the Agency Costs

The optimal strategy, where the cost-effectiveness criterion is the area bounded by the performance curve and only the agency costs are included, was sensitive to the interest rate and life-cycle cost expressions. For both life-cycle cost expressions, each interest rate yielded a different optimal strategy. Figure 5.13 presents the optimal strategy found for this criterion across the different interest rates and life-cycle cost expressions.



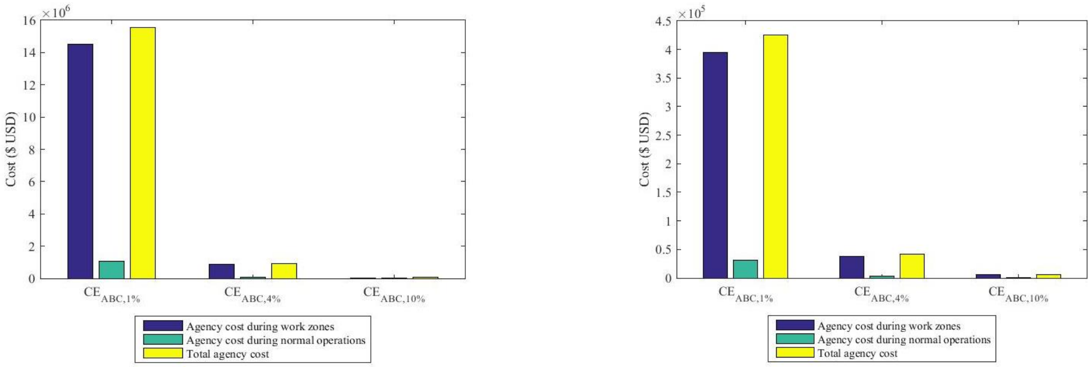
(a) PWCP as the Life-cycle Cost Expression



(b) EUACP as the Life-cycle Cost Expression

Figure 5.13 Optimal Strategies Based on Area Bounded by the Performance Curve as the Cost-Effectiveness Criterion; only Agency Costs Included

Figure 5.14 presents the agency costs associated with the optimal strategies in terms of the different interest rates and the different life-cycle cost expressions. Across the interest rates from the agency perspective, it can be noticed that a lower interest rate has the highest overall cost, and that the highest agency expenditure corresponds to the workzone periods, as expected. Where the life-cycle cost expression was PWCP, it is observed that the overall cost for the optimal strategy, estimated using interest rate of 4% (case study), is approximately 6% of the overall agency costs of the optimal strategy estimated using a 1% interest rate. Where the life-cycle cost expression was the EUACP, the overall agency costs for the optimal strategy estimated using an interest rate of 4% is about 10% of the overall agency costs of the optimal strategy estimated using a 1% interest rate.

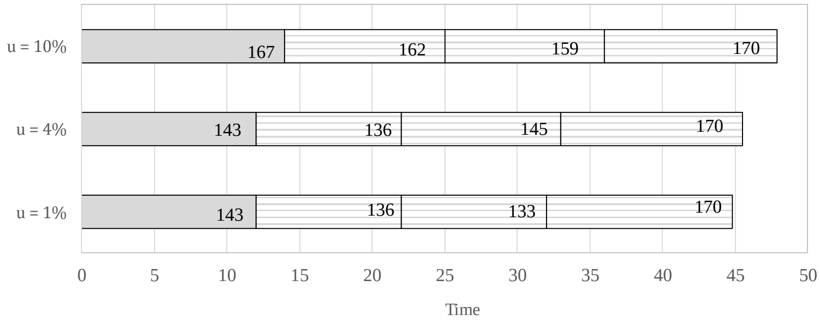


(a) Agency cost (PWCP) (b) Agency cost (EUACP)

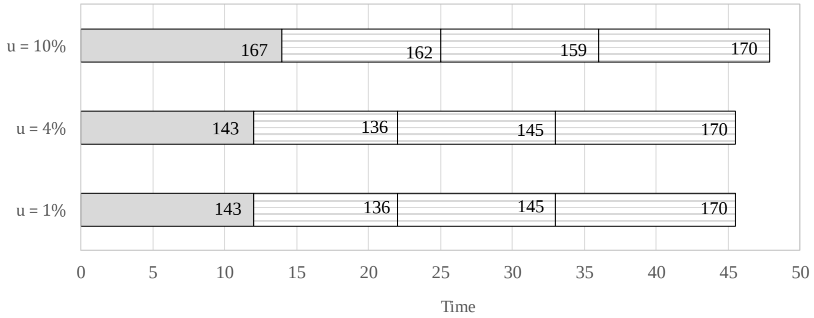
Figure 5.14 Agency Costs Associated with Optimal Strategies for the Unrestricted Scenario; for PWCP and EUACP life-cycle expressions; only Agency Costs included

(c) Using only the User Costs

Across the different interest rates and life-cycle cost expressions, the optimal strategies were found to be different where the cost-effectiveness was expressed in terms of the area bounded by the performance curve and only user costs are included (Figure 5.15).



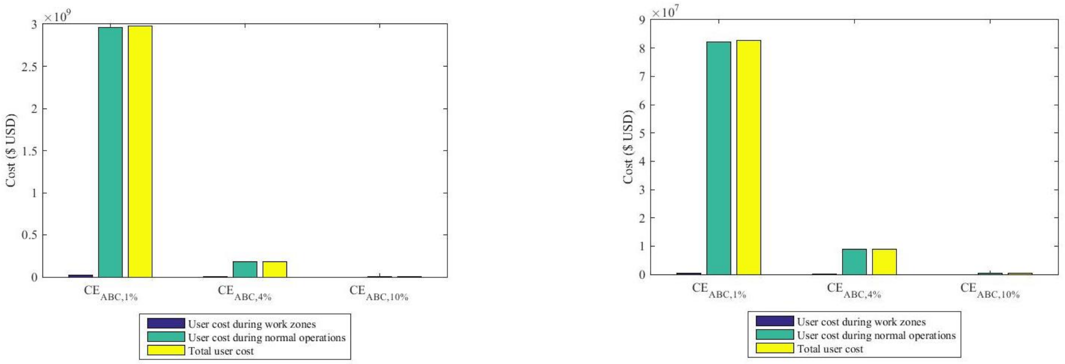
(a) PWCP as the Life-cycle Cost Expression



(b) EUACP as the Life-cycle Cost Expression

Figure 5.15 Optimal Strategies Based on Area Bounded by the Performance Curve as the Cost-Effectiveness Criterion; only User Costs Included

For different interest rates and life-cycle cost expressions, Figure 5.16 presents the detailed user costs associated with the optimal strategies. It can be observed that the optimal strategies found using higher interest rates have the lowest user cost, as expected. Where the life-cycle cost expression was PWCP, it is observed that the overall cost for the optimal strategy estimated using interest rate of 4% (case study) is approximately 6% of the overall user costs of the optimal strategy estimated using a 1% interest rate. Where the life-cycle cost expression was the EUACP, the overall user costs for the optimal strategy estimated using an interest rate of 4% is about 11% of the overall user costs of the optimal strategy estimated using a 1% interest rate.



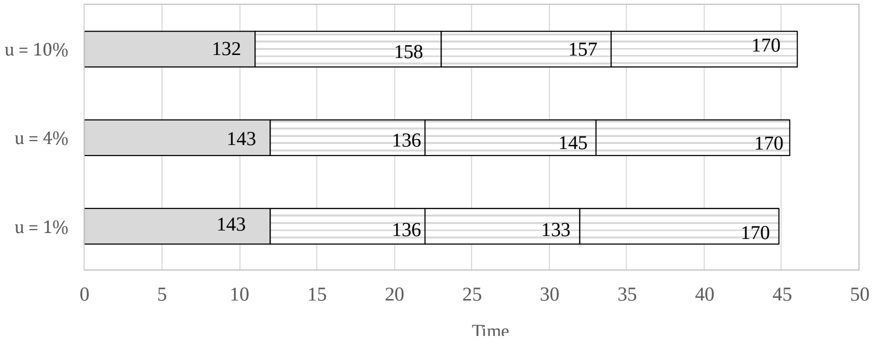
(a) User cost (PWCP) (b) User cost (EUACP)

Figure 5.16 User Costs Associated with Optimal Strategies for the Unrestricted Scenario; for PWCP and EUACP Life-cycle Cost Expressions; only User Costs included

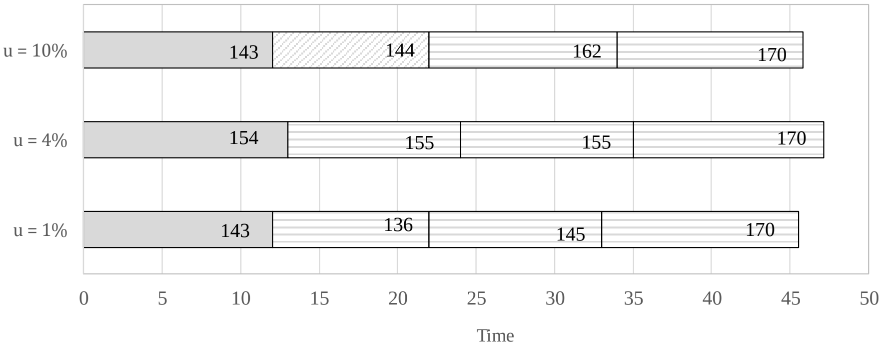
(c) Considering Agency and User Costs

In the analysis where the cost-effectiveness criterion was the area bounded by the performance curve and both agency and user costs are included and duly weighted, the optimal strategy was found to be sensitive to the interest rate and life-cycle cost expressions (Figure 5.17). For different interest rates and life-cycle cost expressions, the optimal strategies as well as their corresponding agency, user, and total costs are shown in Figure 5.18. It can be noticed that from both agency and user perspectives, the highest expenditure corresponds to strategies estimated using a lower interest rate. From the agency perspective, the highest expenditures correspond to workzones, and from the user perspective correspond to normal operations, as expected.

Where the life-cycle cost expression was PWCP, it is observed that the overall total cost for the interest rate of 4% (case study) is approximately 6% of the overall total costs of the optimal strategy estimated using a 1% interest rate. Where the life-cycle cost expression was the EUACP, the overall total costs for the optimal strategy estimated using an interest rate of 4% is about 10% of the overall total costs of the optimal strategy estimated using a 1% interest rate. For the optimal strategies estimated using the interest rate of 10%, it can be observed that the overall total cost is less than 1% of the overall total cost of the optimal strategies estimated using a 4% interest rate for both life-cycle cost expressions.

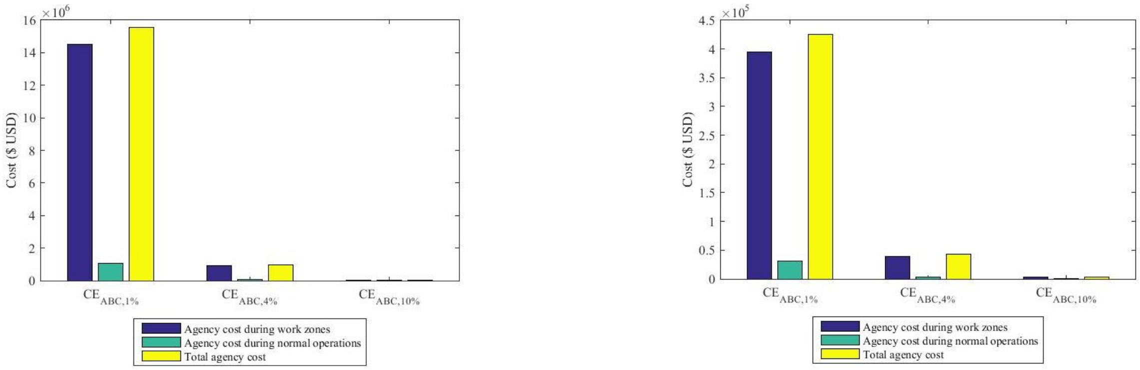


(a) PWCP as the Life-cycle Cost Expression

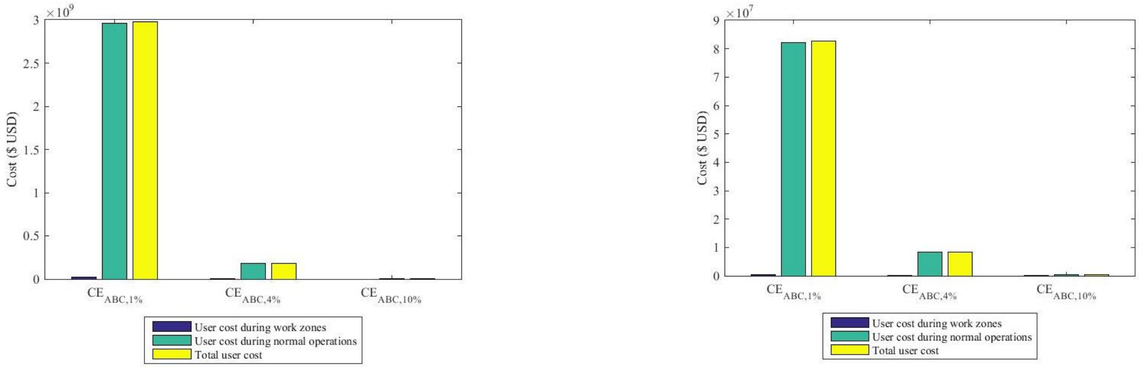


(b) EUACP as the Life-cycle Cost Expression

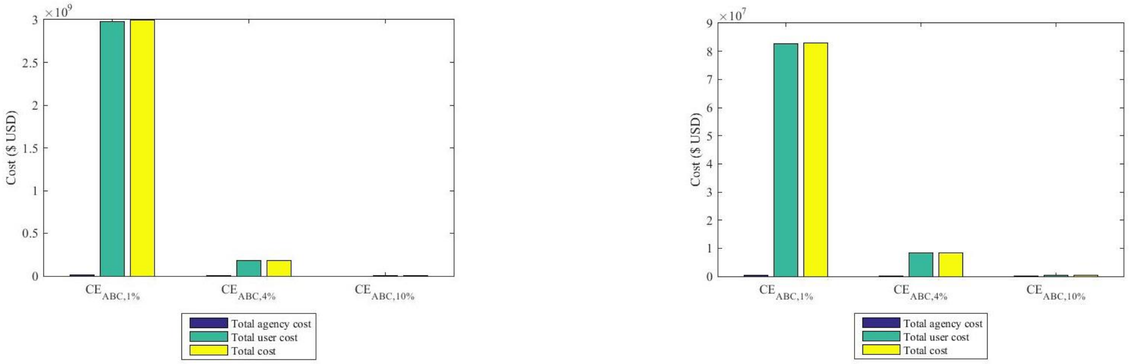
Figure 5.17 Optimal Strategies Based on Area Bounded by the Performance Curve as the Cost-Effectiveness Criterion; Agency and User Costs Included



(a) Agency cost (PWCP) (b) Agency cost (EUACP)



(c) User cost (PWCP) (d) User cost (EUACP)



(e) Total cost (PWCP) (f) Total cost (EUACP)

Figure 5.18 Costs Associated with Optimal Strategies for the Unrestricted Scenario; for PWCP and EUACP Life-cycle Cost Expressions; Agency and User Costs included

5.2 Restricted Scenario

Similar to the unrestricted scenario, the restricted scenario establishes the agency policy boundaries; however, unlike the former, the restricted scenario also imposes the condition that the infrastructure condition at which the intervention $(r_{s_i} + 1)$ is applied must be inferior to that at which the previous intervention r_{S_i} was applied (see Equation 3.56 in Chapter 3). From an analytical perspective, this constraint is useful because it reduces the search scope for the optimization algorithm. From a practical perspective, this constraint duly recognizes the notion that as the infrastructure deteriorates, its users progressively become more inured to (or at least, tolerant of) lower levels of service (poorer condition), and therefore thresholds for the intervention can be set at successively lower condition levels until the point of reconstruction is met.

The results suggest that, using the restricted scenario, the optimal thresholds are not affected by the cost-effectiveness criterion being expressed in a relative or absolute form. With regard to the relative weight between agency and user costs, the analyses indicated that due to the overwhelming dominance of user cost over agency cost, case 1 (equal weights) and case 3 (user cost component only) yielded the same optimal strategy for most of the cost-effectiveness criteria and both life-cycle cost expressions. With regards to case 2 (the agency cost component only), the optimal solutions provided by the three cost-effectiveness criteria (performance jump, agency cost savings, and user cost savings) yielded the same optimal strategy irrespective of life-cycle cost expression; on the other hand, the optimal solutions provided by service life, average performance, and area bounded by the performance curve as the cost-effectiveness criteria, were sensitive to the life-cycle cost expressions.

5.2.1 Restricted Scenario, Case 1

In the restricted scenario, case 1, agency and user costs were equally weighted; thus, $w_{AC} = 1, w_{UC} = 1$. The optimal strategies for this case are presented in Table 5.4 and illustrated as Figure 5.19. Similar to the unrestricted situation, functional HMA was found to be the most common treatment intervention in all the long-term life-cycle strategies and all the cost-effectiveness criteria.

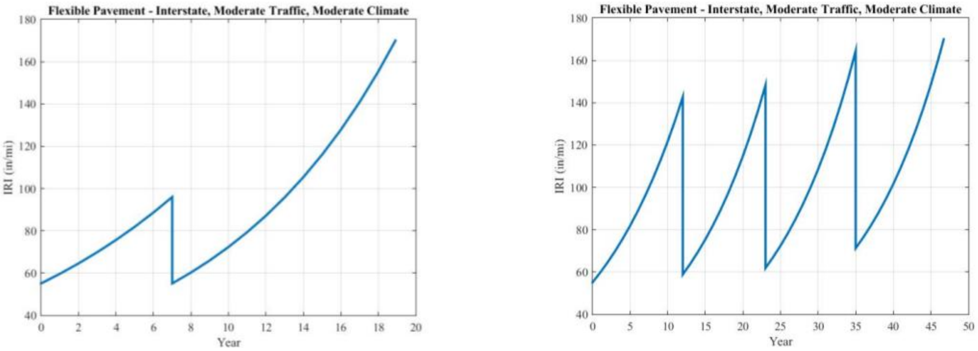
The costs to the agency, user, and total cost associated with the optimal strategies are presented in Figure 5.20. This is represented for the different cost-effectiveness criteria and life-cycle cost expressions. Across all cost-effectiveness criteria, it can be noticed that from the agency perspective, the highest expenditure corresponds to strategies that have frequent workzones; from the user perspective, the highest expenditure occurs during normal operations, as expected.

Table 5.4 Optimal Strategies for the Restricted Scenario, Case 1

CE criteria		Rehabilitation (Year)			Treatment(1)			IRI (in/mile) performance condition at rehabilitation			Service Life (Years)
PWCP	CE_{SL}	7			2			96			18.915
	CE_{PJ}	12	23	35	1	1	1	143	148	165	46.708
	CE_{AP}	14			1			167			25.589
	CE_{ABC}	12	23	34	1	1	1	143	148	151	46.265
	CE_{ACS}	7			2			96			18.915
	CE_{UCS}	7			2			96			18.915
EUACP	CE_{SL}	7			2			96			18.915
	CE_{PJ}	12	23	35	1	1	1	143	148	165	46.708
	CE_{AP}	14			1			167			25.589
	CE_{ABC}	12	23	34	1	1	1	143	148	151	46.265
	CE_{ACS}	7			2			96			18.915
	CE_{UCS}	7			2			96			18.915

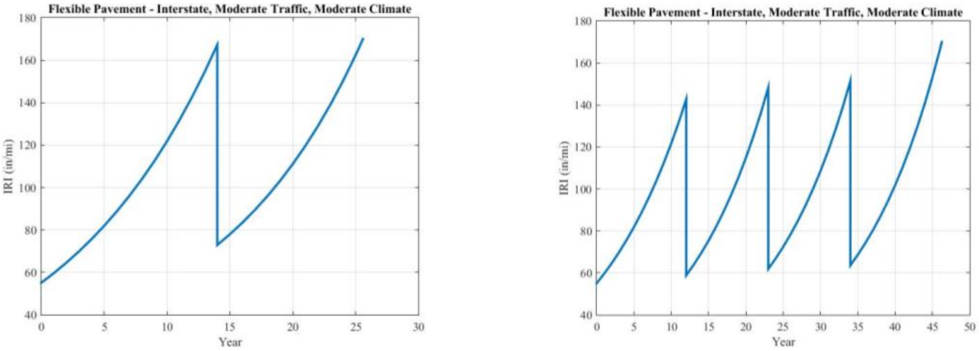
(1) Treatment 1-Functional HMA, 2-Structural HMA

With regard to the overall cost, it was found that user cost (during normal operations) accounts for the greatest share of total cost by far, while the agency cost is relatively small. When the agency and user costs are equally weighted (case 1) and the service life, agency and user cost savings, are the cost-effectiveness criteria, it is seen that the optimal strategy has the highest cost from both agency and user perspectives, followed by the optimal strategies that use average performance as the cost-effectiveness criterion. It can be also observed that the optimal strategies that use performance jump and area bound by the performance curve as the measure of cost-effectiveness have lower agency and user costs.



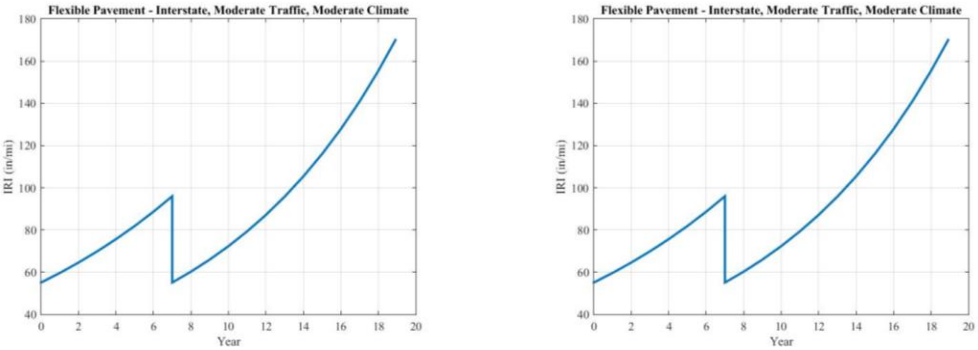
(a) $\text{CE}_{\text{service life}}$ (PWCP, EUACP)

(b) $\text{CE}_{\text{performance jump}}$ (PWCP, EUACP)



(c) $\text{CE}_{\text{average performance}}$ (PWCP, EUACP)

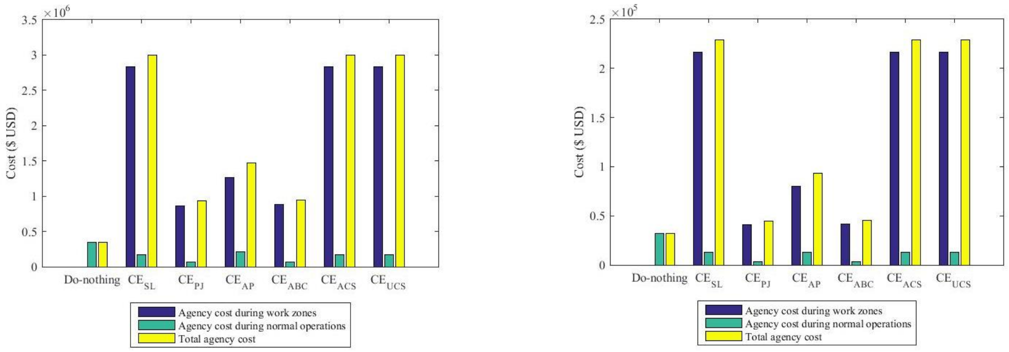
(d) $\text{CE}_{\text{area bounded by the performance curve}}$ (PWCP, EUACP)



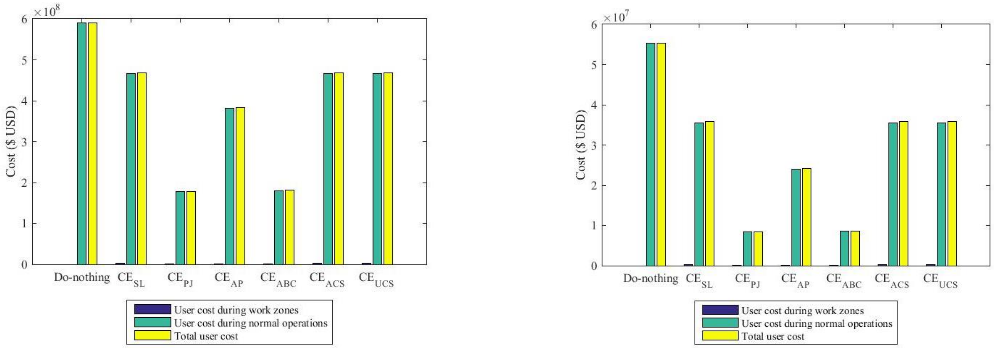
(e) $\text{CE}_{\text{agency cost savings}}$ (PWCP, EUACP)

(f) $\text{CE}_{\text{user cost savings}}$ (PWCP, EUACP)

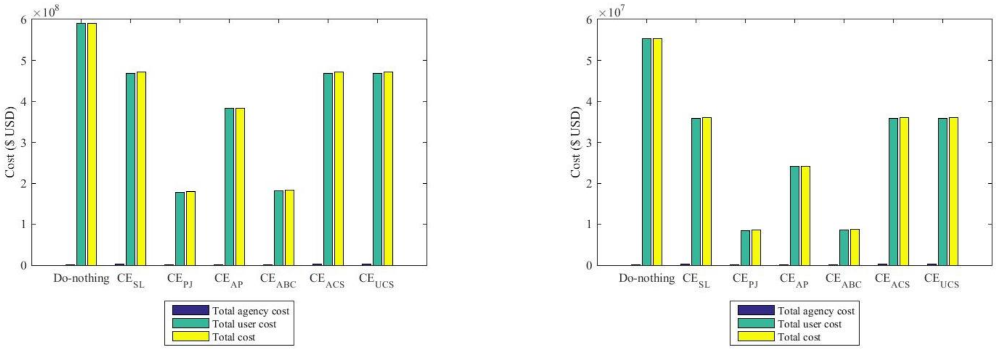
Figure 5.19 Optimal Strategies for the Restricted Scenario, Case 1



(a) Agency cost (PWCP) (b) Agency cost (EUACP)



(c) User cost (PWCP) (d) User cost (EUACP)



(e) Total cost (PWCP) (f) Total cost (EUACP)

Figure 5.20 Costs Associated with Optimal Strategies for the Restricted Scenario, Case 1

5.2.2 Restricted Scenario, Case 2

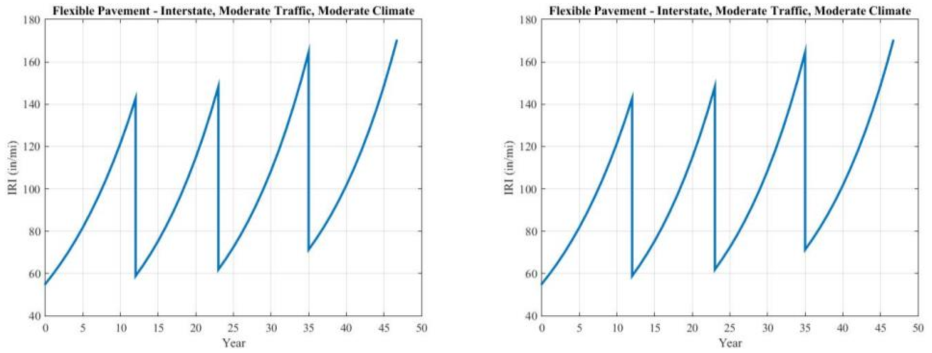
The restricted scenario, case 2, uses only the agency costs while ignoring the user costs ($w_{AC} = 1, w_{UC} = 0$). The optimal strategies for this scenario and case are presented in Table 5.5 and Figure 5.21. Similar to the unrestricted scenario for agency costs only, functional HMA appears most frequently across the identified optimal strategies.

Table 5.5 Optimal Strategies for the Restricted Scenario, Case 2

CE criteria		Rehabilitation (Year)			Treatment(1)			IRI (in/mile) performance condition at rehabilitation			Service Life (Years)
PWCP	CE_{SL}	12	23	35	1	1	1	143	148	165	46.708
	CE_{PJ}	12	23	35	1	1	1	143	148	165	46.708
	CE_{AP}	14			1			167			25.589
	CE_{ABC}	12	23	34	1	1	1	143	148	151	46.265
	CE_{ACS}	7			2			96			18.915
EUACP	CE_{SL}	12	23	35	1	1	1	143	148	165	46.708
	CE_{PJ}	12	23	35	1	1	1	143	148	165	46.708
	CE_{AP}	14			1			167			25.589
	CE_{ABC}	12	23	35	1	1	1	143	148	165	46.708
	CE_{ACS}	7			2			96			18.915

(1)Treatment 1-Functional HMA, 2-Structural HMA

Values of agency costs associated with the optimal strategies are presented in Figure 5.22 in terms of the different measures of cost-effectiveness and the different life-cycle cost expressions. Across all of the cost-effectiveness criteria, it can be noticed that from the agency perspective, the do-nothing strategy has the lowest overall cost, and that the optimal strategies with the highest agency expenditure are those that have early and less frequent workzones (instances of rehabilitation treatments). Where the cost-effectiveness measure of interest is the agency cost savings, it can be observed that the optimal strategy is that with the highest agency costs followed by the average performance criterion. This is because, at advanced levels of the deterioration (which is consistent with late interventions), it costs more to carry out rehabilitation, as evident in the rehabilitation cost models for the effect of early discounting. The agency cost for other cost-effectiveness criteria were found to be in the same cost range.

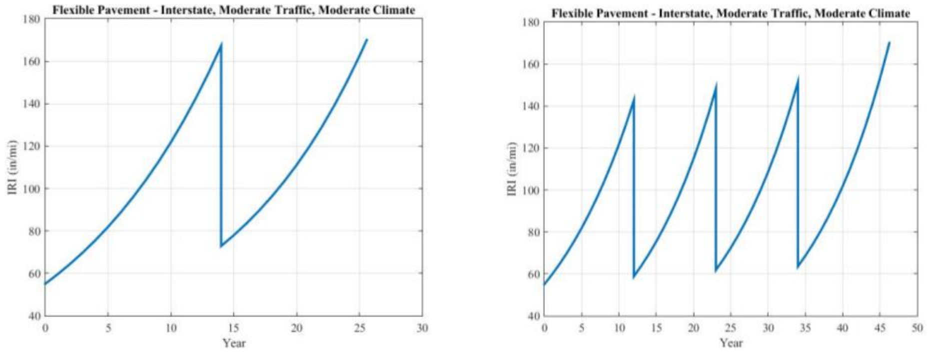


(a) $CE_{\text{service life}}$

(PWCP, EUACP)

(b) $CE_{\text{performance jump}}$

(PWCP, EUACP)

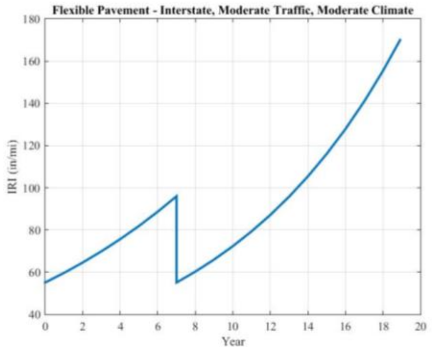


(c) $CE_{\text{average performance}}$

(PWCP, EUACP)

(d) $CE_{\text{area bounded by the performance curve}}$

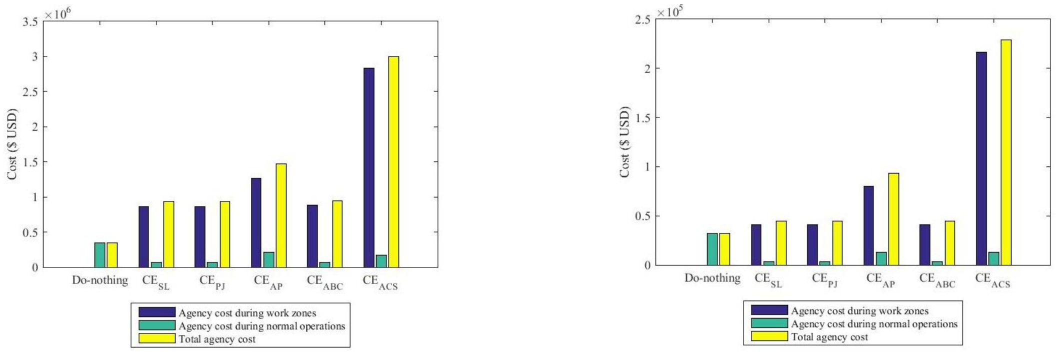
(PWCP, EUACP)



(e) $CE_{\text{agency cost savings}}$

(PWCP, EUACP)

Figure 5.21 Optimal Strategies for the Restricted Scenario, Case 2



(a) Agency cost (PWCP)

(b) Agency cost (EUACP)

Figure 5.22 Costs Associated with Optimal Strategies for the Restricted Scenario, Case 2

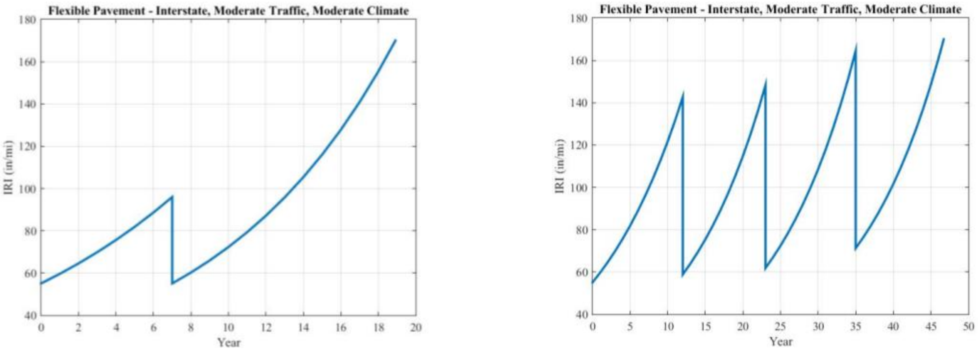
5.2.3 Restricted Scenario, Case 3

For case 3 of the restricted scenario, the user costs are considered fully but agency costs are ignored, that is, $w_{AC} = 0, w_{UC} = 1$˙. For this case, the optimal strategies are presented in Figure 5.23 and Table 5.6.

Table 5.6 Optimal Strategies for the Restricted Scenario, Case 3

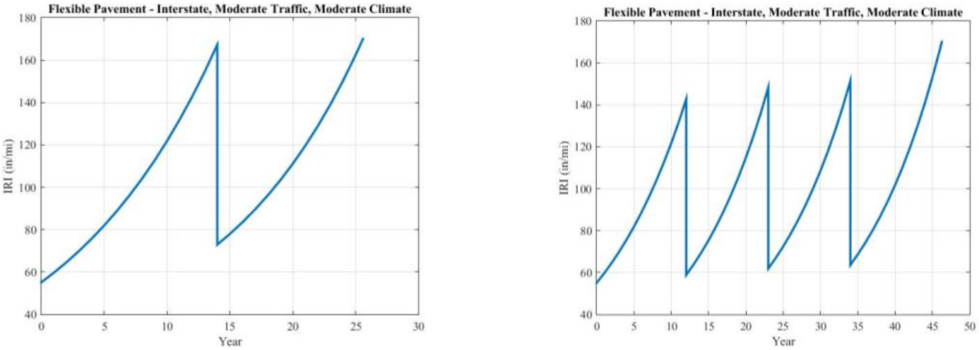
CE criteria		Rehabilitation (Year)			Treatment(1)			IRI (in/mile) performance condition at rehabilitation			Service Life (Years)
PWCP	CE_{SL}	7			2			96			18.915
	CE_{PJ}	12	23	35	1	1	1	143	148	165	46.708
	CE_{AP}	14			1			167			25.589
	CE_{ABC}	12	23	34	1	1	1	143	148	151	46.265
	CE_{UCS}	7			2			96			18.915
EUACP	CE_{SL}	7			2			96			18.915
	CE_{PJ}	12	23	35	1	1	1	143	148	165	46.708
	CE_{AP}	14			1			167			25.589
	CE_{ABC}	12	23	34	1	1	1	143	148	151	46.265
	CE_{UCS}	7			2			96			18.915

(1) Treatment 1-Functional HMA, 2-Structural HMA



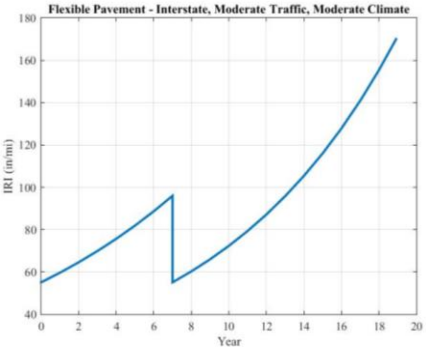
(a) $\text{CE}_{\text{service life}}$ (b) $\text{CE}_{\text{performance jump}}$

(PWCP, EUACP) (PWCP, EUACP)



(c) $\text{CE}_{\text{average performance}}$ (d) $\text{CE}_{\text{area bounded by the performance curve}}$

(PWCP, EUACP) (PWCP, EUACP)

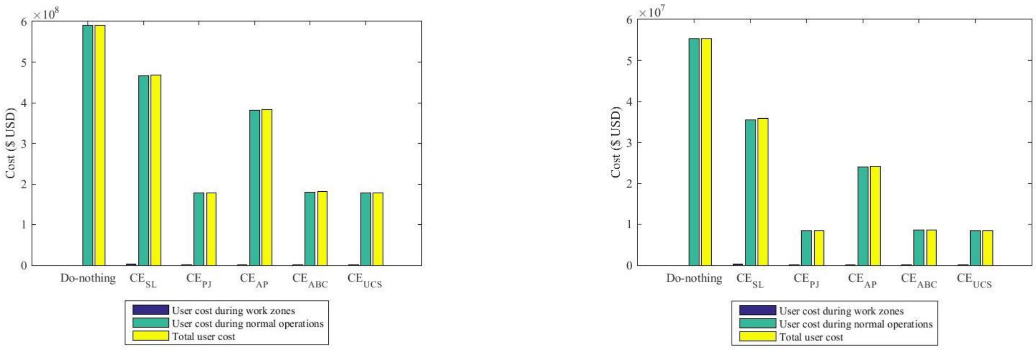


(e) $\text{CE}_{\text{user cost savings}}$

(PWCP, EUACP)

Figure 5.23 Optimal Strategies for the Restricted Scenario, Case 3

Figure 5.24 presents the user costs associated with the optimal strategies where the asset manager is interested in any of the several criteria of cost-effectiveness and life-cycle cost expressions. The results suggest that across all cost-effectiveness criteria, the service life and average performance are associated with the highest agency costs; this is not surprising because user cost is strongly linked to the infrastructure performance condition, and the low level of the infrastructure condition in the parsimonious optimal strategies (Figure 5.18(a) and (c)) is due to the fact that those strategies consists of only one rehabilitation intervention and therefore the users incur high costs of infrastructure usage. It is observed that the optimal strategies established, using the other cost-effective criteria, have similar levels of user cost.



(a) User cost (PWCP) (b) User cost (EUACP)

Figure 5.24 Costs Associated with Optimal Strategies for the Restricted Scenario, Case 3

5.2.4 Discussion for Restricted Scenario

Similar to the unrestricted scenario, the optimal strategies from all cost-effectiveness criteria for the restricted scenario were analyzed for three cases regarding the agency and user cost relative weights. Also, the cost-effectiveness criteria based on the area bounded by the performance curve was analyzed for three interest rates across the three cases for agency-user cost relative weights.

5.2.4.1 Sensitivity to Agency and Users Relative Weights

The optimal strategies for the unrestricted scenario were analyzed for three cases regarding the agency and user cost relative weights: (1) using only the agency costs (2) using only the user costs, and (3) considering both the agency and user costs duly weighted.

(a) Service Life

In the analysis situations where the cost-effectiveness was defined in terms of the infrastructure service life, the optimal strategy was found to be sensitive to the agency-user cost component weights, but not to the life-cycle cost expression. This criterion yielded the same optimal strategy for only two of the cases (equal weights for agency and user costs; and where only user cost was considered). Figure 5.25 presents the optimal strategies for this criterion across the different cost component weight cases and life-cycle cost expressions (PWCP and EUACP).

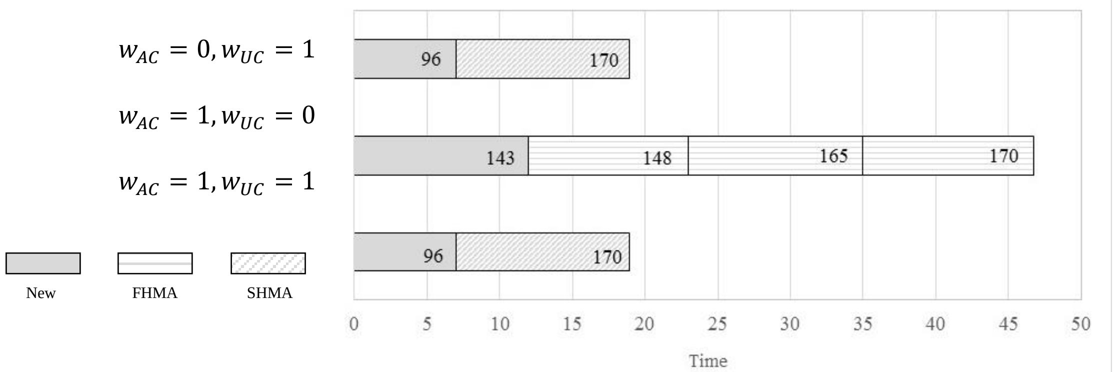


Figure 5.25 Optimal Strategies Based on Service Life as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

(b) Performance Jump

The results of the analysis suggests that the cost-effectiveness in terms of the performance jump criterion yielded consistent optimal strategies across all three cases of agency-user cost component weights and life-cycle cost expressions (Figure 5.26).

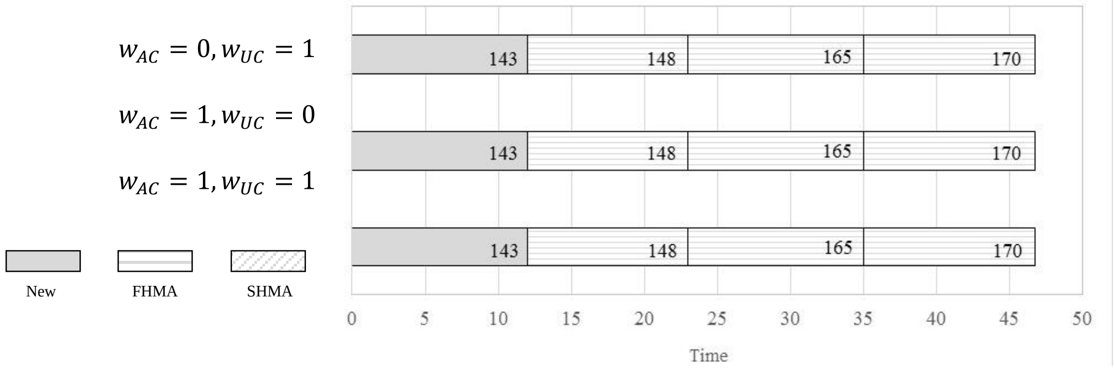


Figure 5.26 Optimal Strategies Based on Performance Jump as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

(c) Average Performance

In the analysis where the cost-effectiveness was defined in terms of the average performance, the optimal strategy was found to be insensitive to agency-user cost weight ratio and life-cycle cost expression. The optimal strategies determined using this criterion were the same across the different cases of cost component relative weights and the different life-cycle cost expressions (Figure 5.27).

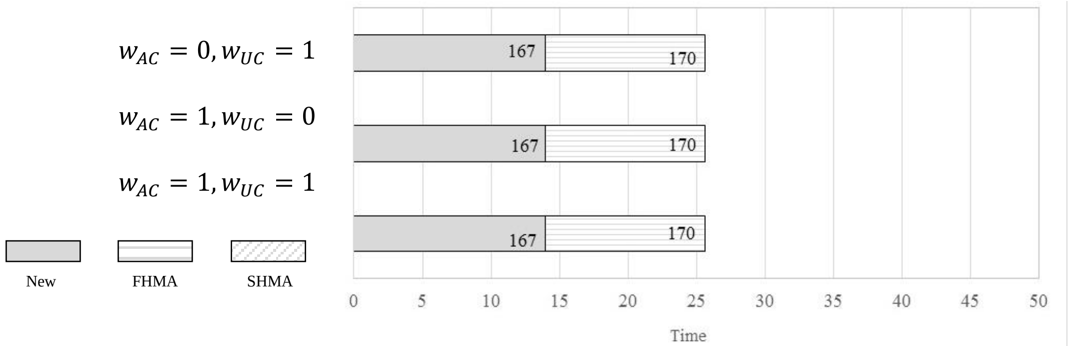
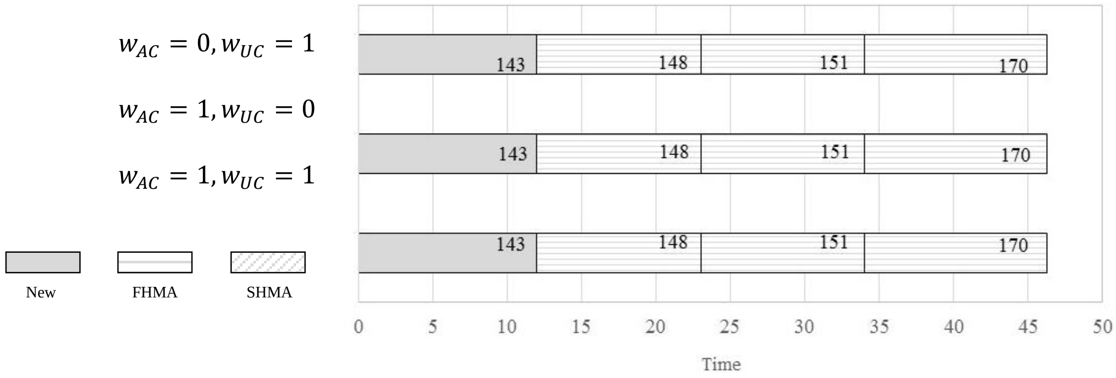


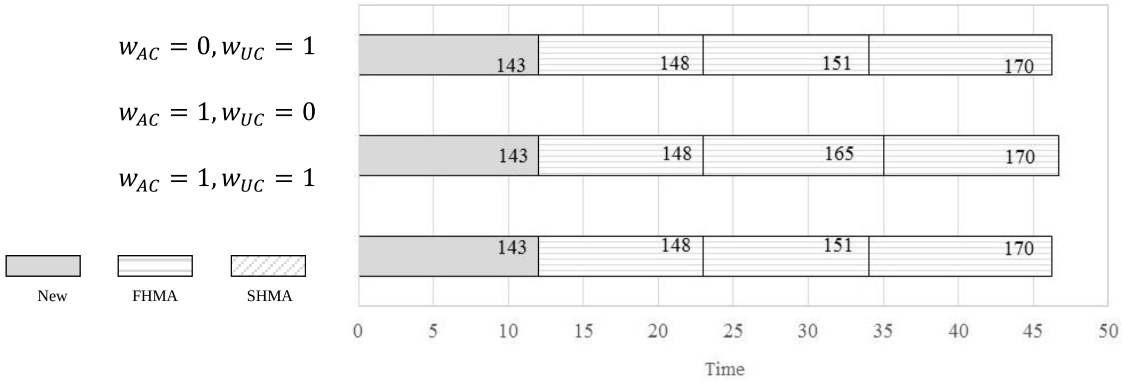
Figure 5.27 Optimal Strategies Based on Average Performance as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

(d) Area Bounded by the Performance Curve

The optimal strategy, where the cost-effectiveness criterion is the area bounded by the performance curve, was found to be sensitive to cost component weights and life-cycle cost expressions for case 2 (agency cost only). Where the life-cycle cost expression was PWCP, this criterion yielded the same optimal strategy for all component weights. Where the life-cycle cost expression was EUACP, this criterion yielded the same optimal strategy for only two of the cases: case 1 (agency and user costs and agency cost only) and case 3 (user cost only). Figure 5.28 presents the optimal strategy found for this criterion across the different cost component weight cases and life-cycle cost expressions.



(a) PWCP as the Life-cycle Cost Expression



(b) EUACP as the Life-cycle Cost Expression

Figure 5.28 Optimal Strategies Based on Area Bounded by the Performance Curve as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

(e) Agency Cost Savings

Where the cost-effectiveness was defined in terms of the agency cost savings, the optimal strategy was found to be not sensitive to the agency-user cost component weights and to the life-cycle cost expression (Figure 5.29). This criterion yielded the same optimal strategies for the two cases considered (equal weights for agency and user cost, and agency cost only).

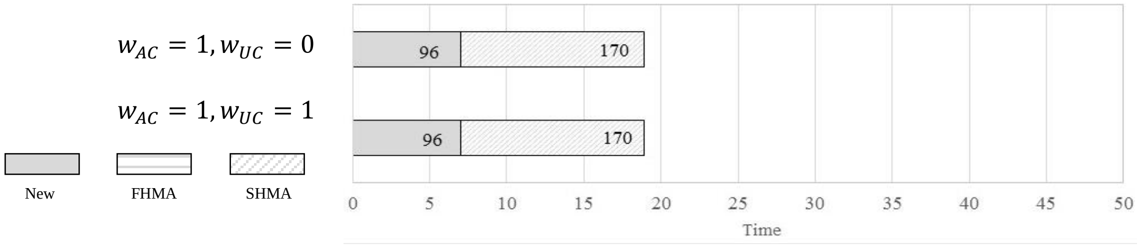


Figure 5.29 Optimal Strategies Based on Agency Cost Savings as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

(f) User Cost Savings

The analysis was carried out for situations where the asset manager is interested in cost-effectiveness in terms of the infrastructure user cost savings. It was found that the optimal strategy is consistent across the two cases of cost component relative weights and across the different expressions of life-cycle cost as well (Figure 5.30).

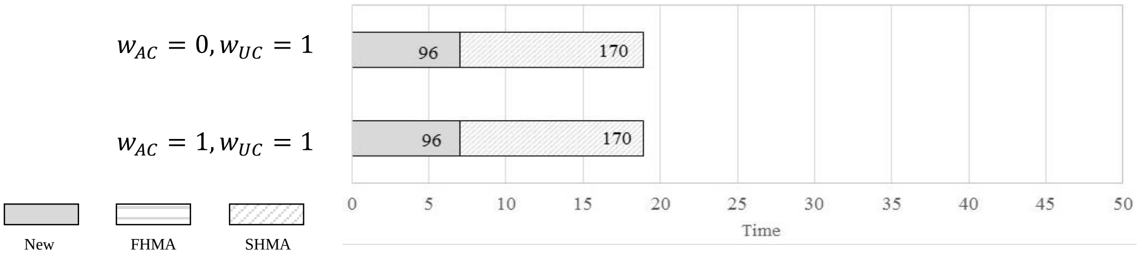


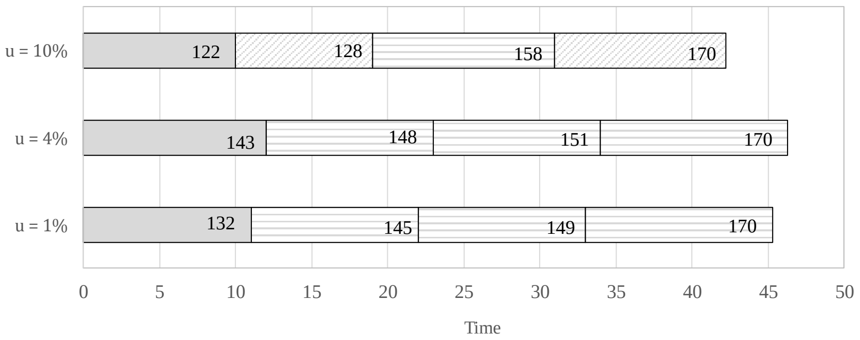
Figure 5.30 Optimal Strategies Based on User Cost Savings as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression

5.2.4.2 Sensitivity to the Interest Rate

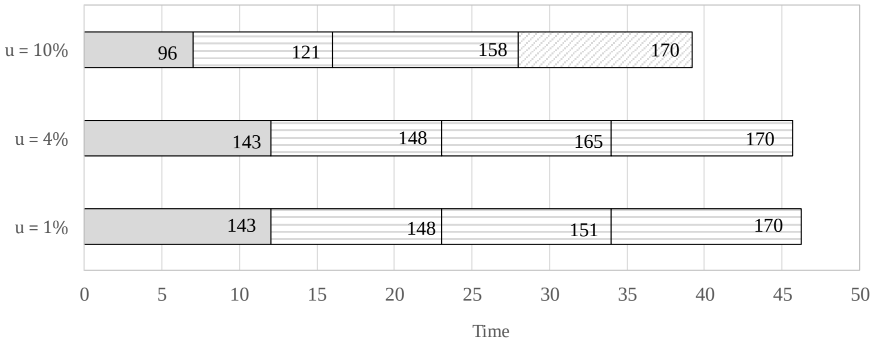
The cost-effectiveness criteria based on area bounded by the performance curve was analyzed for three interest rates: 1%, 4%, and 10% to test the sensitivity to this input variable across the different agency-user cost relative weights.

(a) Using only the Agency Costs

Across the different interest rates and life-cycle cost expressions, the optimal strategies were found to be different where the cost-effectiveness was expressed in terms of the area bounded by the performance curve and only agency costs are included (Figure 5.31).



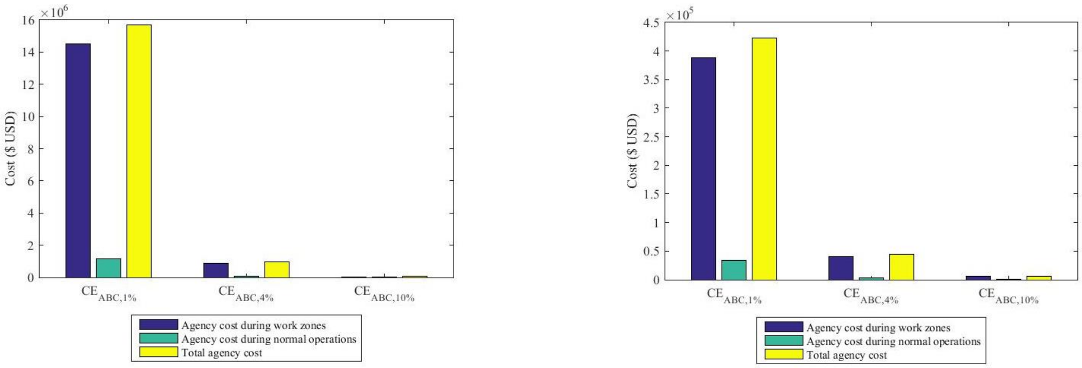
(a) PWCP as the Life-cycle Cost Expression



(b) EUACP as the Life-cycle Cost Expression

Figure 5.31 Optimal Strategies Based on Area Bounded by the Performance Curve as the Cost-Effectiveness Criterion; only Agency Costs Included

Figure 5.32 presents the agency costs associated with the optimal strategies in terms of the different interest rates and the different life-cycle cost expressions. From the agency perspective and across the different interest rates, it can be noticed that a lower interest rate has the highest overall cost; the highest agency expenditure, corresponds to the workzone periods, as expected. Where the life-cycle cost expression was PWCP, it is observed that the overall cost for the optimal strategy estimated using interest rate of 4% (case study) is approximately 6% of the overall agency costs of the optimal strategy estimated using a 1% interest rate. Where the life-cycle cost expression was the EUACP, the overall agency costs for the optimal strategy estimated using interest rate of 4% is about 11% of the overall agency costs of the optimal strategy estimated using a 1% interest rate.



(a) Agency cost (PWCP) (b) Agency cost (EUACP)

Figure 5.32 Agency Costs Associated with Optimal Strategies for the Restricted Scenario; for PWCP and EUACP Life-cycle Cost Expressions; only Agency Costs included

(b) Using only the User Costs

The optimal strategy, where the cost-effectiveness criterion is the area bounded by the performance curve and only the user costs are included, was found to be insensitive to the life-cycle cost expressions. For both life-cycle cost expressions each interest rate yielded the same optimal strategy. Figure 5.33 presents the optimal strategy found for this criterion across the different interest rates.

Figure 5.34 presents the detailed user costs associated with the optimal strategies. It can be observed that optimal strategies found using higher interest rates have the lowest user cost, as expected. Where the life-cycle cost expression was PWCP, it is observed that the overall cost for the optimal strategy estimated using interest rate of 4% (case study) is approximately 6% of the overall user costs of the optimal strategy estimated using a 1% interest rate. Where the life-cycle cost expression was the EUACP, the overall user costs for the optimal strategy estimated using interest rate of 4% is about 10% of the overall user costs of the optimal strategy estimated using a 1% interest rate.

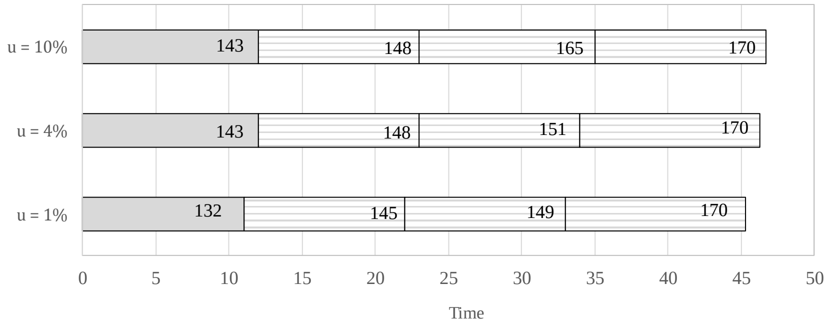
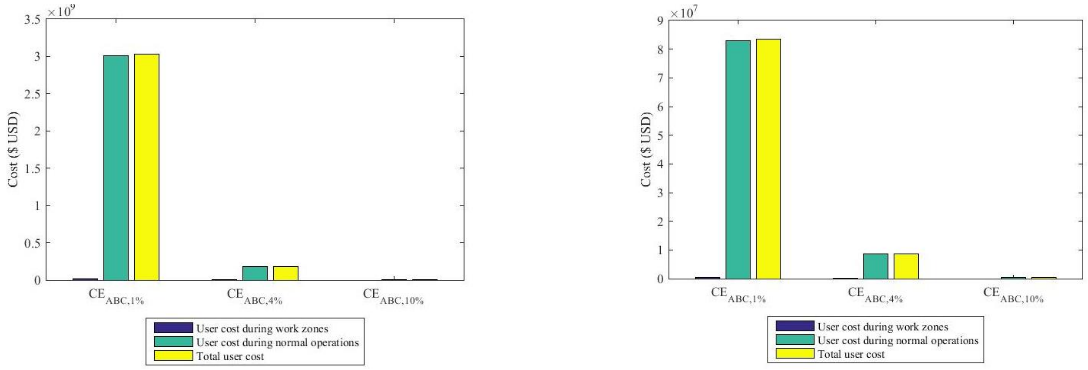


Figure 5.33 Optimal Strategies Based on Area Bounded by the Performance Curve as the Cost-Effectiveness Criterion; PWCP or EUACP as the Life-cycle Cost Expression; only User Costs Included



(a) User cost (PWCP)

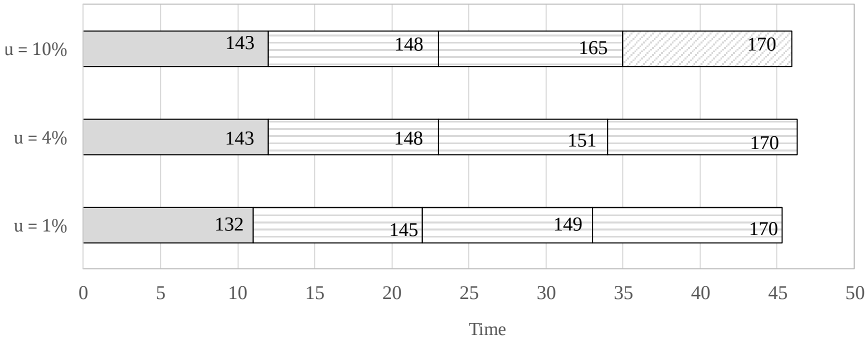
(b) User cost (EUACP)

Figure 5.34 User Costs Associated with Optimal Strategies for the Restricted Scenario; for PWCP and EUACP Life-cycle Cost Expressions; only User Costs included

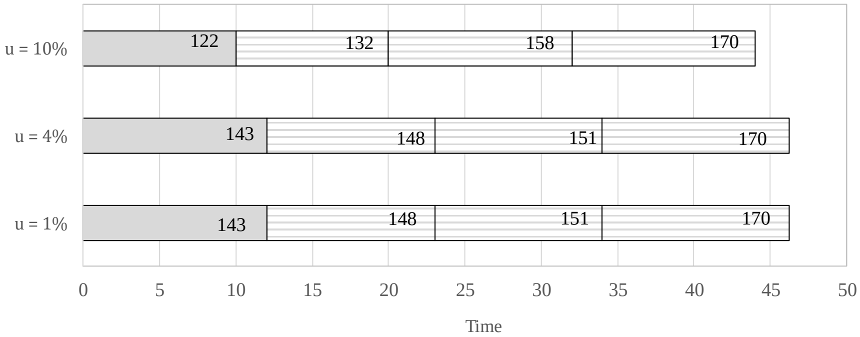
(c) Considering Agency and User Costs

In the analysis where the cost-effectiveness criterion was area bounded by the performance curve and both agency and user costs duly weighted are included, the optimal strategy was found to be sensitive to the interest rate and life-cycle cost expressions (Figure 5.35). For different interest rates and life-cycle cost expressions, the optimal strategies as well as their corresponding agency, user, and total costs are shown in Figure 5.36. From the agency perspective, the highest expenditures correspond to work zones, and from the user perspective correspond to normal operations; from both agency and users’ perspective, the highest expenditure corresponds to strategies estimated using a lower interest rate, as expected.

Where the life-cycle cost expression was PWCP, it is observed that the overall total cost for the optimal strategy estimated using an interest rate of 4% (case study) is approximately 6% of the overall total costs of the optimal strategy estimated using a 1% interest rate. Where the life-cycle cost expression was the EUACP, the overall total costs for the optimal strategy estimated using an interest rate of 4% is about 11% of the overall total costs of the optimal strategy estimated using a 1% interest rate. For the optimal strategies estimated using the interest rate of 10%, it can be observed that the overall total cost is less than 1% of the overall total cost of the optimal strategies estimated using a 4% interest rate for both life-cycle cost expressions.

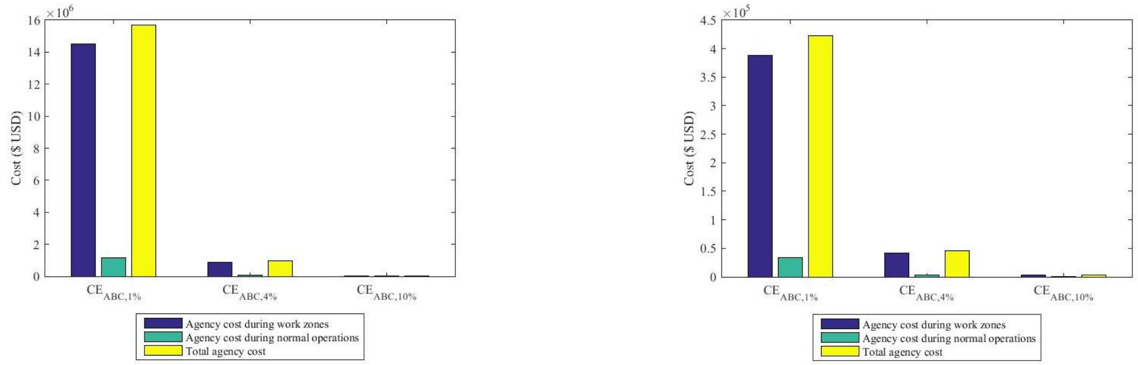


(a) PWCP as the Life-cycle Cost Expression

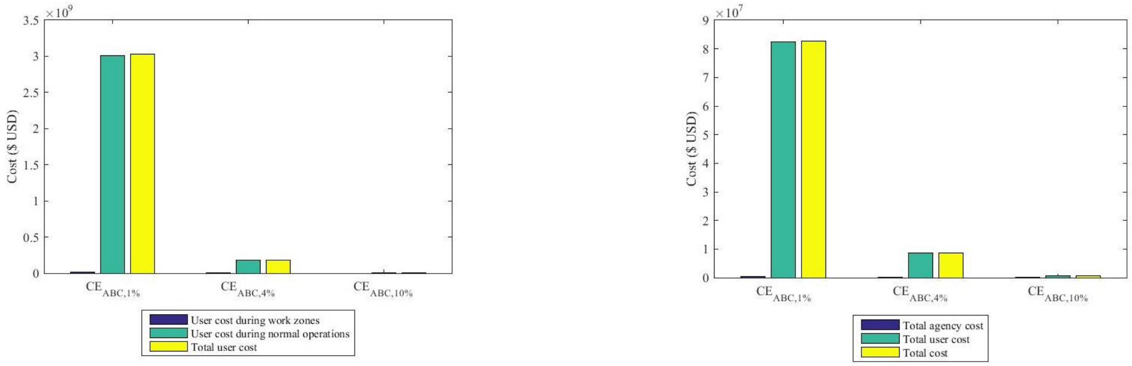


(b) EUACP as the Life-cycle Cost Expression

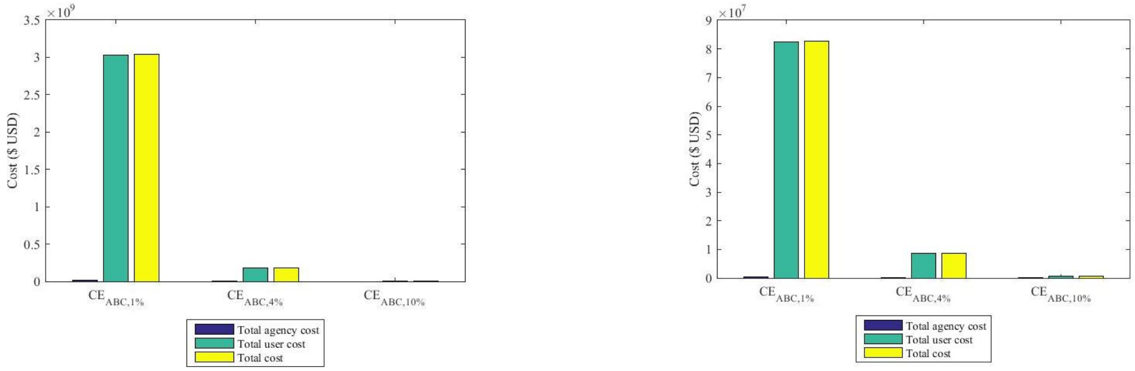
Figure 5.35 Optimal Strategies Based on Area Bounded by the Performance Curve as the Cost-Effectiveness Criterion; Agency and User Costs Included



(a) Agency cost (PWCP) (b) Agency cost (EUACP)



(c) User cost (PWCP) (d) User cost (EUACP)



(e) Total cost (PWCP) (f) Total cost (EUACP)

Figure 5.36 Costs Associated with Optimal Strategies for the Restricted Scenario; for PWCP and EUACP Life-cycle Cost Expressions; Agency and User Costs included

5.3 Chapter Summary

From the two main scenarios that were considered for demonstrating the framework for determining non-fixed optimal intervention strategies, it was found that having a restriction for subsequent interventions yields a pattern of threshold trends opposite to that obtained without the restriction. This restricted scenario was considered to reflect the optimal strategies that prepare infrastructure users to be increasingly tolerant of successively lower levels of service because interventions are triggered when the infrastructure is in a condition worse than the previous intervention. However, when this restriction was not considered (the unrestricted scenario), all optimal strategies indicate that the most cost-effective strategies suggest an opposite trend: the subsequent rehabilitations are applied at condition levels successively superior to the condition at the time of the previous rehabilitation.

Consistently across both restriction scenarios, the optimal strategy determined the cost-effectiveness criteria in terms of the service life of the infrastructure, and agency and user cost saving were found to have the largest agency and user costs, compared to the optimal strategy developed using other cost-effectiveness criteria. This is due to the rather peculiar nature of the strategy developed using the service life criterion: it consists of only one rehabilitation intervention that occurs in year seven 7. The rather sparse nature of this strategy translates into poor infrastructure condition and high user cost associated with normal operations. For this criterion, the optimal value of the objective function (the cost-effectiveness) associated with the optimal solution was found to be insensitive to the different expressions of life-cycle cost.

Where the cost-effectiveness criteria were expressed in terms of the performance jump, average performance, and agency and user savings, the cost-effectiveness associated with the objective function was found to be insensitive to cost component weights and life-cycle cost expression. Where the cost-effectiveness criteria were expressed in terms of service life and area bounded by the performance curve, the cost-effectiveness associated with the objective function was found to be sensitive to the cost component weight ratio.

From the case study, it was also found that the optimal solutions developed using certain cost-effectiveness criteria, such as the performance jump, average infrastructure performance, and agency and user cost savings are less sensitive to life-cycle cost expression and cost component weights, compared to other criteria. A close look at the optimal strategies for the former shows that they are identical for a given life-cycle cost expression and cost component weight ratio.

For the unrestricted scenario it was found that cost-effectiveness criteria in terms of performance jump, infrastructure average performance, and agency and user cost savings criteria were insensitive to weight cost component ratio and life-cycle cost expressions. The optimal strategies developed using cost-effectiveness criteria in terms of service life, was found to be insensitive to the life-cycle cost expression, but sensitive to the cost component weights ratio. For the restricted scenario, it was found that all the optimal strategies developed using any cost-effectiveness criterion (except the area bounded by the performance curve) are insensitive to cost component relative weights and life-cycle cost expressions.

When the area bounded by the performance curve was used as the cost-effectiveness criteria in both scenarios, the cost-effectiveness associated with the objective function was found to be sensitive to the interest rate across the different cost component relative weights and life-cycle cost expressions.

CHAPTER 6. CONSEQUENCES OF HASTENED OR DEFERRED REHABILITATIONS

6.1 Introduction

In several countries, increasing population growth has generally outstripped the provision or expansion of most public facilities including water, energy, and transport infrastructure. Capacity is not the only problem; for existing facilities, continual deferment of maintenance has left most of such infrastructure in a state of poor repair (Dowall and Whittington, 2003; ASCE 2013). Butler (1985), in his pioneering study that addressed this persistent and pervasive problem, argued that the difference between various service levels is the consequence of deferring maintenance; maintenance levels can be evaluated in terms of agency, user, occupancy interference impacts, and costs relative to a baseline standard strategy.

In the specific context of highway infrastructure rehabilitation and maintenance (M&R), agencies apply M&R treatments to retard the rate of deterioration and to restore the infrastructure condition. Agencies seek to apply each treatment at an optimal time; in other words, not too early when the infrastructure is still in good state of repair and not too late when the infrastructure has deteriorated to a poor state. However, in actual practice, constraints associated with funding, legal, political, or institutional may preclude the application of rehabilitation at the right time. For example, a highway agency encountering financial difficulties may have no option but to defer a treatment. Such budgetary limitations, coupled with increasing demands on the transportation network, continue to pose pressing challenges for transportation infrastructure managers (Peshkin et al. 2004). Therefore, it is important for agencies to assess all the necessary timing tradeoffs to ensure that infrastructure preservation programs and projects are timed to yield maximum cost-effectiveness (Peshkin et al. 2004; Khurshid et al. 2010).

These tradeoffs include the levels of service (condition, safety, mobility, etc.) that can be "bought" at different budgetary levels, the expenditures needed to attain specific levels of service, the levels of a performance measure that can be traded for a given total budget, the performance or life-cycle cost impacts of deferring rehabilitation or maintenance, and the impact of maintenance on capital investment (Peshkin et al. 2004; Sharaf et al. 1988; NCHRP, 1979; Khurshid et al. 2010). Quantifying these tradeoffs is at the heart of infrastructure management methodology (Peshkin et al. 2004; Khurshid et al. 2010). For example, as part of a highway asset valuation study, Poovadol et al. (2003) explored the use of valuation methods to capture the trade-offs in the type and timing of maintenance, thus assessing the impact of deferred overall maintenance efforts on the overall asset value.

Unfortunately, such deferment practice has not been accompanied by ex-poste studies that document the consequences in terms of long-term facility performance and/or future preservation costs (NCHRP, 1979; Sharaf et al. 1988). As such, decision makers are not always aware of what they have traded or lost for more time. Often, what they have traded (the consequences of such deferments) includes poorer infrastructure performance and subsequent reduction in service, early onset of advanced defects, high user cost, accelerated infrastructure deterioration, and the application of high level treatments (such as replacement) earlier than the time when they are typically applied. Similarly, an infrastructure intervention may be applied earlier than when it is typically or actually needed, yielding incremental benefits that are negligible and causing waste of taxpayer funds (NCHRP, 1979; Sharaf et al. 1988; Khurshid et al. 2010).

The consequences of deferred maintenance can be analyzed using network-level data or project-level data. Network-level data is inherently aggregate in nature and may be characterized by spending levels and resultant performance for each county in a state, or for each state in a country. Using existing frameworks or software packages, such as FHWA's HERS model, the analyst may specify different amounts of M&R spending for each year to determine the outcome in terms of the system performance. This, way, the impact of large investments made at an early time in the analysis period can be compared with investments made at later stages of the analysis period. Project-level data, on the other hand, is disaggregate in nature and helps ascertain the consequences of different timing options for preservation actions in general, or for a specific category or type of preservation applied to a given infrastructure system.

The only quantitative results from past research at the project level, is one study that indicated that preservation action carried out early in the life of the infrastructure can lead to a multiple-fold reduction in subsequent preservation at a later time in the infrastructure life (Sharaf and Sinha, 1988). The increase in data at agency databases permits infrastructure systems analysts to assess this relationship in greater detail. The exact nature of the timing trade-off relationships could vary for different infrastructure system classes, intervention categories, performance indicators, and evaluation criteria. In the context of highway system preservation, the severity of consequences of deferring or hastening highway pavement rehabilitation or maintenance treatments may differ across different highway classes (Interstates, US Roads, State Roads, for example), intervention categories (rehabilitation, preventive maintenance, and routine maintenance, for example), and tradeoff evaluation criteria (cost, cost-effectiveness, and effectiveness, for example). Furthermore, because past work has only focused on deferment (conceptually or quantitatively), there also exists a need to examine the issue of mistiming from a hastening perspective.

This chapter focuses on the project-level consequences. The chapter examines the trade-offs involving the performance or life cycle that impacts agency and user cost associated with the hastening or deferring of specific rehabilitation treatments. The issue of deferred actions and their consequences is gaining increased visibility, not only in highway infrastructure systems, but also in other infrastructure systems, such as public transportation rolling stock and fixed facilities (Karlaftis, 2003).

Rehabilitation treatment can be deferred from an earlier to a later year, for reasons such as the lack of funding. The consequences of deferring a treatment from a given point to a later point, or the impacts of hastening or “accelerating” a treatment from a given point to an earlier point, needs to be quantified so that the highway pavement manager can quantify the pavement performance and costs that are being traded off for time. For decision support, it can be an important exercise to measure the impacts of hastening or deferment for each treatment category (maintenance, rehabilitation, construction), treatment types within each category, functional classes, performance indicators, and evaluation bases (cost, effectiveness, and cost-effectiveness).

In this dissertation, “deferred intervention” represents the rehabilitation treatment applied after the time of optimal application; thus, the infrastructure is treated in a relatively advanced state of deterioration. This is a common state for agencies with lack of satisfactory funding (Pasupathy et al. 2007; Earl 2006). A “hastened intervention” refers to a rehabilitation treatment applied well before it is needed; thus, the infrastructure receives the intervention when it is in relatively appropriate condition. This is a common state for agencies whose policies are guide by the lack of infrastructure management or to political influences (Khurshid et al. 2010). Interventions can be hastened or deferred not only because of funding, political or institutional constraints, but also due to an agency’s inflexible implementation of optimal intervention schedules.

6.2 A Review of Literature on the Consequences of Deferred Intervention

There exists a plethora of past research studies that yielded analytical tools to provide input for estimating the performance level and corresponding cost of applying an intervention at a given time during the infrastructure life (Sharaf et al. 1987; Walls and Smith 1998; Pasupathy et al. 2007; Irfan et al. 2009; Khurshid et al. 2009, Mizusawa and McNeil 2009). However, as noted by the NCHRP (1979) and Khurshid (2010a), the consequences of deferred or hastened M&R interventions have quantitatively analyzed in a few studies. According to Kuennen (2005), infrastructure preservation expenditures for about $1 before the point of rapid deterioration has been shown to eliminate or delay spending $6-$10 in future rehabilitation or reconstruction costs. In another study, Galehouse et al. (2003) graphically showed the effects of delaying pavement preservation with hypothetical examples based on past experiences. Using data available from in-service pavements, the impacts that delayed M&R leads to higher M&R costs in the long term were quantified by Sharaf et al. (1987); they found four-fold savings for M&R activities when timely preservation interventions were performed. The NCHRP, 1979 report highlighted that agencies had critical issues delaying pavement maintenance because the lack of a clear reference point to measure the extent to which maintenance interventions influence the levels of infrastructure condition. Chasey et al. (2002) defined maintenance deferment as a decrease in ordinary maintenance expenditures and consequently simulated the outcomes of different M&R investment levels using hypothetical data to describe the effect of reduced maintenance spending on highway system user benefits. The study provided interesting expenditure-benefit tradeoffs at a system-wide level, but did not address the consequences of delaying specific treatments.

Overall, the review of the rather limited literature on the subject indicated that there exists a gap in the literature regarding a quantification of the effects of adjusted rehabilitation schedules (in the form of delayed and/or hastened treatments) and, more importantly, a need for a flexible framework to carry out such an analysis. First, there exists a need to move beyond the conceptual discussions of the consequences of deferred maintenance that has characterized the literature on this subject. Secondly, there is a need to utilize actual data from in-service pavements, rather than hypothetical data, to demonstrate any tradeoff analysis methodology. Thirdly, not only should the consequences of deferred intervention be examined; the consequences of hastened intervention should also be assessed. Fourth, there is a need for a methodology that assesses the consequences of specific policy (such as thresholds) for a specific type of intervention and not merely the system-wide investment levels of performance vs. expenditures. The need for examining intervention timing vs. performance tradeoffs at this level has been referenced at the conclusion of numerous past research efforts. Fifth, in presenting a methodology that is applicable to all infrastructure types and their associated performance measures, the chapter helps the knowledge base to extend beyond the domain of pavement infrastructure to other program areas such as bridge, safety, or congestion. For example, the methodology could be used to ascertain the user cost penalties of delaying bridge deck rehabilitation, the safety consequences of delayed guardrail reconstruction, or the congestion impacts of delayed mobility-related ITS investments.

This chapter therefore seeks to address such gaps in the literature by providing a methodology to assess the penalties of deviating from the optimal rehabilitation schedules. To demonstrate the practical application of the proposed methodology, this chapter presents a case study with real life data that quantifies the consequences of hastened or deferred pavement rehabilitation treatments within an M&R schedule. The methodology presented in the chapter can help highway agencies better assess the tradeoffs associated with deferring specific interventions aimed at infrastructure maintenance and rehabilitation. The ultimate benefit is to help agencies make better-informed decisions regarding investment scheduling by understanding the implicit performance and cost tradeoffs associated with alternative scheduling options.

As discussed in Chapter 3 of this dissertation, rehabilitation application thresholds should be flexible enough to take on any value that may be higher, same, or lower than the application threshold of the preceding rehabilitation treatment; another option is to restricted the thresholds to be at an interior condition compared to the preceding treatment. These are referred to as the hastened and restricted scenarios, respectively. This chapter presents the consequences of hastened or deferred the optimal strategies found for both unrestricted and restricted scenarios for case 1 (agency and user costs are equally weighted), based on the area bounded by the performance curve as the cost-effectiveness criterion. Those consequences were estimated as a change in cost-effectiveness, benefits (area bounded by the performance curve), and agency and user costs. Regression models were also developed to estimate the consequences for any given different year.

6.3 The Unrestricted Scenario

Table 6.1 presents the consequences of rehabilitation schedules that represent when treatments are hastened and/or deferred compared to the optimal rehabilitation schedule or strategy. The results confirm that hastening or deferring rehabilitation intervention leads to significant loss in cost-effectiveness. This is an interesting finding, but is not unexpected. With regard to the change in benefits, it was found that the highest benefit is not necessarily obtained through the optimal strategy alone; in other words, there exists at least one schedule besides the optimal (and the non-optimal contains some treatment deferments and/or hastening) that yields the maximum benefit in terms of facility condition or service life, for example. With regard to costs, both the agency and user costs were considered, and expressed as an annual total cost. The results of the analysis suggest that, from an agency cost perspective, any hastening or deferment of rehabilitation intervention will lead to increased overall agency costs. From the user perspective, on the other hand, hastening the interventions will reduce the user costs; deferring them will increase the user costs. In the sections below, the detailed results and interpretation is provided.

Table 6.1 Consequences of Hastened or Deferred Intervention from Optimal Rehabilitation Strategy, Unrestricted Scenario

Strategy* (Applied years)	**Hastened (-) Deferred (+) (years)**	**Δ Cost-Effectiveness (%)**	**Δ Benefit (ABC) (%)**	**Δ Agency Cost (%)**	**Δ User Cost (%)**
7, 17, 28	-5	-19.53	-6.46	14.37	-2.47
8, 18, 29	-4	-14.39	-4.39	10.57	-2.12
9, 19, 30	-3	-9.52	-2.55	7.16	-1.72
10, 20, 31	-2	-5.03	-0.99	4.15	-1.26
11, 21, 32	-1	-1.03	0.29	1.55	-0.74
*12, 22, 33	0	0.00	0.00	0.00	0.00
13, 23, 34	+1	-4.12	-3.12	-0.21	1.16
14, 24, 35	+2	-10.26	-7.26	0.27	2.52
15, 25, 36	+3	-18.50	-12.53	1.53	4.16
16, 26, 37	+4	-28.76	-19.04	3.42	4.82
17, 27, 38	+5	-41.12	-26.91	6.56	7.07

* Optimal strategy based on $CE_{\text{area bounded by the performance curve(ABC)}}$ criterion

(a) Change in Cost-Effectiveness

The percentage loss in cost-effectiveness for deferred interventions is generally about twice that of hastened interventions. For example, hastening the intervention by a 5-year period will cause a cost-effectiveness loss of approximately 19.53%, while deferring the intervention by a period of 5 years will cause a cost-effectiveness loss of 41.12%. Therefore, from an overall (cost-effectiveness) viewpoint, deferring rehabilitation has greater adverse consequences compared to hastening.

(b) Change in Benefits

The change in benefits was estimated on the basis of the area bounded by the performance curve, which is a convenient measure of the overall effectiveness of M&R because it encapsulates both the infrastructure condition as well as the service life, as discussed in Chapter 3 of this dissertation. The results of the analysis suggest that deferring the rehabilitation interventions causes a greater loss in benefits compared to hastening of the interventions. Specifically, for the case study, deferring the rehabilitation causes a loss of benefits of a magnitude that is approximately four times the loss in such benefits when the intervention is hastened. It is important to note that the optimal strategy is not necessarily the schedule with the highest benefit. From the set of strategies analyzed, it can be noticed that the highest benefit (area bounded by the performance curve) corresponds to the strategy in which rehabilitations are hastened by 1 year. This is not unexpected. In general, a rehabilitation intervention is carried out with the intent to improve the infrastructure condition and extend the service life. Early interventions correlate with to superior condition and a corresponding extension in service life. The results quantify the extent to which the benefits change due to hastening or deferment. For example, hastening the rehabilitation intervention by a 3-year period will lead to a 2.55% loss in benefit, while deferring the intervention by 3 years will cause a benefit loss of 12.53%.

(c) Change in Agency Cost

From the agency perspective, any rehabilitation schedule that reflects a departure from the optimal strategy (schedule) is associated with an increase in agency cost. Specifically, hastening the rehabilitation intervention causes increased agency costs. This finding is intuitive because, for a non-zero discount rate, early interventions will have a higher present value (and equivalent annual value) compared to late interventions. For example, an intervention hastened by 4 years will cause a 10.57% increase in agency cost, while deferring the intervention by 4 years will cause a 3.42% increase in agency cost.

(d) Change in User Cost

The results indicate that from the user perspective, hastening the rehabilitation interventions will lead to a reduction in user costs. This is because the normal-operations user cost is a function of the infrastructure condition (Opus, 1999; Barnes and Langworthy, 2005; Delwar and Papagianakis, 2006). Hastening the intervention helps ensure that users enjoy superior levels of service compared to the optimal (even though this comes at a cost agency expenditure and higher workzone-related user costs); the reduced user cost associated with normal operations far exceeds the increased user costs associated with workzones. Accordingly, the net effect of hastening is a reduction in user costs. On the other hand, deferring the rehabilitation intervention will cause an increase in user cost. By deferring the intervention, users are left with an infrastructure of relatively inferior levels of service compared to the optimal (lower agency expenditures and lower workzone-related user costs); the increased user cost associated with normal operations far exceeds the reduced user costs associated with workzones. Accordingly, net effect of deferring is an increase in user costs. The results also suggest that solely from a user cost perspective, the overall reward of hastening (in terms of reduced user cost) varies one-half of the overall penalty of deferment (in terms of increased user cost). For example, hastening the rehabilitations by 3 years will reduce the user cost by approximately 1.72%, while deferring the rehabilitation by 3 years will increase the user cost by 4.16%.

From Figure 6.1, it can be observed that deferred interventions have worse consequences (greater losses in cost-effectiveness and benefits, and greater increases in user costs). Regression models were developed to help serve as guidance, in lieu of the charts, for predicting the consequences of hastened and deferred interventions (Table 6.2).

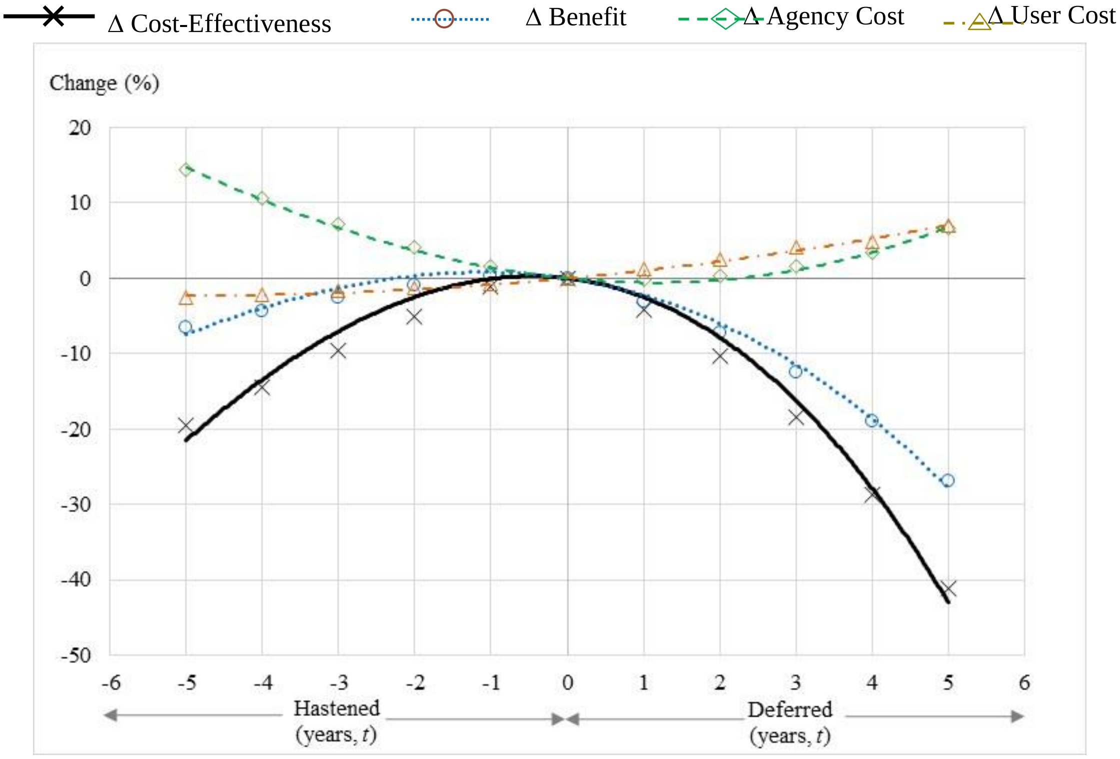


Figure 6.1 Extended Consequences of Hastened or Deferred Optimal Rehabilitation Strategy, Unrestricted Scenario

Table 6.2 Regression Models to Estimate Changes from Optimal Rehabilitation Strategy, Unrestricted Scenario

Equation Model Change			$\mathbf{R^2}$
Δ in Cost-Effectiveness (%)	=	$-0.0389\,t^3 - 1.2896\,t^2 - 1.1791\,t$	0.98
Δ in Benefit (ABC) (%)	=	$-0.0221\,t^3 - 0.7052\,t^2 - 1.4866\,t$	0.99
Δ in Agency Cost (%)	=	$0.0090\,t^3 + 0.4312\,t^2 - 1.0166\,t$	0.99
Δ in User Cost (%)	=	$0.0003\,t^3 + 0.0948\,t^2 + 0.9268\,t$	0.99

6.4 The Restricted Scenario

Table 6.3 presents, for the restricted scenario, the consequences of hastening or deferring the rehabilitation interventions from the optimal strategy. Overall, the results confirm, similar to the unrestricted scenario, the results were consistent with expectations: hastening or deferring rehabilitation interventions will lead to a loss in cost-effectiveness. With regard to the change in benefits, the results suggest that the highest benefit does not necessary correspond to the optimal strategy. From the agency cost perspective, it was found that any hastening or deferment of rehabilitation intervention causes an increase in agency cost. From the user perspective, hastened interventions reduce the user cost, while deferred interventions increase such cost to the user.

Table 6.3 Consequences of Hastened or Deferred from Optimal Rehabilitation Strategy, Restricted Scenario

Strategy* (Applied years)	**Hastened (-) Deferred (+) (years)**	**Δ Cost-Effectiveness (%)**	**Δ Benefit (ABC) (%)**	**Δ Agency Cost (%)**	**Δ User Cost (%)**
7, 18, 29	-5	-18.13	-5.56	13.86	-2.48
8, 19, 30	-4	-12.86	-3.43	10.11	-2.16
9, 20, 31	-3	-7.88	-1.55	6.75	-1.48
10, 21, 32	-2	-3.28	0.06	3.78	-1.36
11, 22, 33	-1	0.80	1.38	1.21	-0.86
*12, 23, 34	0	0.00	0.00	0.00	0.00
13, 24, 35	1	-4.63	-3.55	-0.09	1.19
14, 25, 36	2	-11.77	-8.18	0.27	1.35
15, 26, 37	3	-20.95	-14.01	1.68	3.06
16, 27, 38	4	-32.27	-21.14	3.98	5.08
17, 28, 39	5	-45.60	-29.70	7.31	7.40

* Optimal strategy based on $CE_{\text{area bounded by the performance curve(ABC)}}$ criterion

(a) Change in Cost-Effectiveness

The results indicate that for deferred interventions, the percentage of loss in cost-effectiveness is approximately three times that of hastened interventions. For example, hastening the rehabilitation intervention by 3 years will lead to a cost-effectiveness loss of approximately 7.88%; on the other hand, deferring the intervention by 3 years will cause a 20.95% loss in cost-effectiveness.

(b) Change in Benefits

For the purposes of comparison with the unrestricted scenario, the change in benefits for the restricted was also assessed in terms of the same measure of effectiveness: the area bounded by the performance curve. The results suggest that deferring the rehabilitation intervention causes a benefit loss that is greater than the benefit loss due to hastening the intervention; specifically, deferred interventions have approximately four times greater loss in benefit compared to hastened interventions. Again, the strategy deemed optimal (in terms of cost-effectiveness) is not necessarily that which yields the highest benefit. It is observed that the strategy that hastens rehabilitation by 1 year is that which yields the maximum benefit (in the area bounded by the performance curve). For deferred interventions, the loss in benefit is several times more than that of hastened interventions. For example, a rehabilitation hastened by 4 years will yield a loss in benefit of approximately of 3.43%, while a rehabilitation deferred by 4 years will cause a loss in benefit of 21.14%.

(c) Change in Agency Cost

The results of the analysis indicate that from the agency perspective, any deviation from the optimal strategy will lead to an increase in agency cost; however, such an increase is larger for hastened interventions compared to deferred interventions. This finding can be considered intuitive because the present worth of early interventions is higher than that of late interventions, ceteris paribus. For example, the results show that an intervention hastened by 4 years will cause a 10.11% increase in agency cost, while a deferment by 4 years will lead to a 3.98% increase in agency cost.

(d) Change in User Cost

The results of the analysis, for user cost, were similar to that of the unrestricted scenario. The results suggest that from the users' perspective, hastening the rehabilitation will reduce user costs, while deferred interventions increase the user cost. On average, deferring the rehabilitation will cause an increased user cost of a magnitude twice that of hastened intervention. For example, hastening the intervention by 3 years will reduce the user cost by 1.48%, while deferring the intervention by 3 years will increase the user cost by 3.06%.

From Figure 6.2, it can be observed that deferred rehabilitation interventions generally have worse consequences (that is, a greater loss in cost-effectiveness and an increase in user costs) compared to hastening the intervention. Regression models were developed to estimate the consequences of hastened and deferred interventions (Table 6.4)

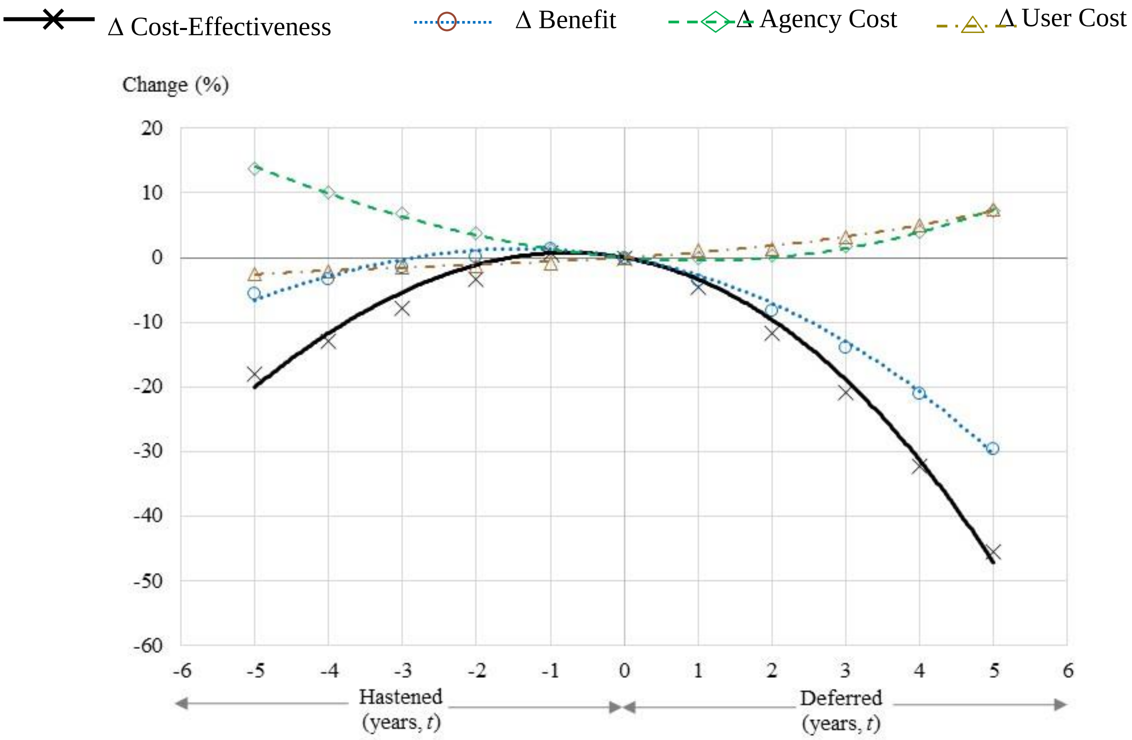


Figure 6.2 Extended Consequences of Hastened or Deferred Optimal Rehabilitation Strategy, Restricted Scenario

Table 6.4 Regression Models to Estimate Changes from Optimal Rehabilitation Strategy, Restricted Scenario

Equation Model Change			**R^2**
Δ in Cost-Effectiveness (%)	=	$-0.0289\,t^3 - 1.3478\,t^2 - 2.0002\,t$	0.99
Δ in Benefit (ABC) (%)	=	$-0.0165\,t^3 - 0.7401\,t^2 - 1.9815\,t$	0.99
Δ in Agency Cost (%)	=	$0.0098\,t^3 + 0.4329\,t^2 - 0.9089\,t$	0.99
Δ in User Cost (%)	=	$0.0120\,t^3 + 0.0941\,t^2 + 0.6904\,t$	0.99

6.5 Chapter Summary

This chapter analyzed the consequences of hastened or deferred strategies for both unrestricted and restricted scenarios. The consequences were assessed in terms of the change in cost-effectiveness, benefits, and the cost to the agency and users. It was observed that compared with the unrestricted scenario, the restricted scenarios of hastened and deferred strategies generally (i) yielded lower percentage decrease in cost-effectiveness and a lower percentage decrease in benefits, (ii) caused a smaller percentage increase in agency cost, and (iii) caused a similar percentage change in user cost.

CHAPTER 7. CONCLUSIONS AND FINAL REMARKS

7.1 Synopsis of the Research

This dissertation addressed the vital issue of optimal scheduling of infrastructure rehabilitation using non-fixed (flexible), performance-based thresholds to help agencies make more informed decisions regarding investment scheduling by understanding the implicit performance and cost tradeoffs associated with alternative scheduling options. The study began with an extensive review of literature on the subject of infrastructure rehabilitation, thus facilitating the identification of the gaps in the existing practice and research. Another objective of the literature review is to understand the mixed-discrete nature of strategic scheduling of asset rehabilitation interventions and to determine the most appropriate optimization technique for the analysis.

Two main constraint scenarios were considered: (i) unrestricted conditions, which provide complete flexibility to the optimization routine to specify any threshold level within the specified upper and lower boundaries of infrastructure conditions, and (ii) restricted conditions, which force the algorithm to search for optimal combinations by reducing the searching scope. This latter scenario also prepares users for deterioration of the infrastructure conditions in a progressive way by forcing future interventions when the infrastructure worsens to a condition more severe than the last intervention, until the reconstruction threshold (defined by agency policy) is reached. The optimal rehabilitation strategies (best solutions found by using a suitable optimization technique) were defined based on the maximum cost-effectiveness ratio, and expressed as a relative or absolute change from a base strategy (that is, the do-nothing strategy). The cost-effectiveness criteria were investigated based on non-monetized benefits (infrastructure service life, performance jump, infrastructure average performance, and the area bounded by the performance curve) and monetized benefits as well (agency and user cost saving). This was carried out for each of two different expressions of life-cycle cost: present worth cost to perpetuity and equivalent uniform annual cost to perpetuity and for three different interest rates. Also, the analysis was carried out for each of three different weight ratios of the cost components by (i) using the agency costs only and ignoring the user costs, (ii) using the user costs only and ignoring the agency costs, and (iii) using both the agency and user costs, duly weighted.

The framework was designed to be applicable to different kinds of infrastructure assets; however, a case study for highway pavements was used due to the availability of data for this purpose. The case study involved an in-service two-lane per direction, 10-mile interstate road segment with flexible pavement surface and moderate traffic in a region of moderate climate. For the case study, the framework considered pavement families based on surface type and functional class. Using the developed framework, a set of optimal strategies were determined for each of the constraint scenarios, cost-effectiveness criteria, weigh cost components, interest rate, and life-cycle cost expressions, as part of a sensitivity analysis (Chapter 5).

From the two main scenarios considered for demonstrating the framework, this dissertation found that the optimal strategies developed for the unrestricted scenario have superior (higher) values for the objective function than for the restricted scenario. This was found to be the case across all cost-effectiveness criteria, cost component weight ratios, interest rates, and life-cycle cost expressions. It was found that having a restriction for subsequent interventions (restricted scenarios) yields a pattern of threshold trends opposite to that obtained without imposing a restriction (unrestricted scenarios). The restricted scenario yielded optimal strategies for interventions triggered when the infrastructure is in a condition worse than the previous intervention; this recognizes the prudence of adopting strategies that prepare infrastructure users to be increasingly tolerant of successively lower levels of service. However, when this restriction was not imposed (an unrestricted scenario), all optimal strategies indicated that the most cost-effective strategies suggest an opposite trend: the subsequent rehabilitations are applied to condition levels successively superior to the condition at the time of the previous rehabilitation. For the both scenarios, the optimal thresholds were found to be insensitive to the form of expression for the cost-effectiveness criterion (yields the same values), whether in relative or absolute form. From the case study, it was also found that the optimal solutions developed using certain cost-effective criteria—such as the performance jump, infrastructure average performance, and agency and user cost savings—are less sensitive than other criteria to life-cycle cost expression, interest rate, and cost component weights. A close look at the optimal strategies for the former shows that they are identical for a given life-cycle cost expression and a cost component weight ratio. Finally, this dissertation measured the consequences of hastening or deferring the rehabilitations (compared to the optimal strategy). It was also determined that deferring rehabilitation has greater adverse consequences than hastening rehabilitation in terms of both agency and user costs and benefits.

7.2 Contribution of this Research

The overarching goal of this dissertation was to develop and demonstrate a framework for strategic "non-fixed threshold" scheduling of infrastructure interventions. The demonstration used various forms of the cost-effectiveness ratio as the objective function. This methodology can serve as a useful tool for decision makers grappling with how best to justify their rehabilitation investment schedules; this approach will facilitate agencies that seek optimal investment decision-making that is more objective, data-driven, systematic, and performance–based. The developed framework will guide the decision makers to know not only the best time (in terms of performance condition or years) for scheduling an intervention, but also the corresponding costs and benefits from both the agency and user perspectives associated with this optimal strategy (the best solution estimated from a suitable optimization technique). The methodology will also help to understand the implicit cost and performance tradeoffs associated with alternative scheduling options and quantify the consequences of hastening or deferring an intervention relative to an optimal timing.

When infrastructure agencies are able to identify their optimal schedules for intervention, they are placed in a better position to (a) enhance their budgeting and programming-related business practices, (b) communicate their needs to the infrastructure funding sources and financial institutions, (c) build a stronger case to justify their funding requests to such institutions, not only for infrastructure rehabilitation but also for infrastructure provision (from construction to end-of-life). Also, because the budgeting and programming of infrastructure is best carried out at the project level (rather than the network level), optimal strategies developed using the framework proposed in this dissertation, will yield a set of rehabilitation timing and types over the life of each family of infrastructure. Then, with cost models for each rehabilitation type, the funding needs at each future year of rehabilitation can be established.

The framework provides a decision support tool for addressing the mixed-discrete nature of *scheduling* (an infrastructure decision problem) that is applicable to all surface types, functional classes, traffic loading, climate zones, interest rates, and weighting schemes that overcome the limitations of problem size.

7.3 Limitations and Future Research Directions

The developed framework involves an optimization problem based on the cost-effectiveness ratio. The input data needed for this framework includes models for infrastructure performance, benefits (effectiveness models such as performance jumps), and cost models. The accuracy of the input represents a critical impact during the search for optimal strategies. Accordingly, the following future research directions are identified and proposed as extensions and improvements of the current work.

- *Rehabilitation Types*. Future research could investigate a wider range of rehabilitation options, including emerging or innovative materials for pavement rehabilitation (Chen et al., 2011; Hossain et al., 2012).
- *Performance jump models.* Available performance jump models are based on pre-intervention conditions, but do not account for the number (1st, 2nd, … nth) of the rehabilitation across the infrastructure service life. In the literature review, current models assume that an infrastructure has the same recovery capacity, regardless of age and loss of performance conditions (deterioration) due to the normal use of the infrastructure (traffic loading and climate exposition). Performance jump models that

reflect the sequential rehabilitation number need to be developed in order to improve the estimation of post-intervention condition levels.

- *Project duration models.* The case study featured in this dissertation used some adjustment factors based on a specific treatment available from the literature for estimating the number of days required for a rehabilitation. Specific treatment project duration models based on pre-treatment performance conditions need to be developed to refine the agency cost component.
- *Cost models.* The case study used some adjustment factors based on average values ($ per lane-mile) and a specific treatment available from the literature for estimating the cost of a treatment for a specific pre-intervention condition. Specific treatment cost models based on pre-treatment performance conditions need to be developed to refine the agency cost component.
- *Measure of effectiveness.* It is necessary to explore the use of additional criteria to address other effectiveness measures, such as energy consumption.
- *Weight ratios.* It is necessary to investigate different weight ratios across cost components to account for the difference between the value of agency and user expenditures.
- *Cost Components.* Including additional cost components, such as community cost, as part of the cost component analysis is necessary in order to perform an integrated cost analysis.
- *Stochastic analysis.* Estimate optimal intervention strategies through a stochastic analysis by treating input and output variables with the corresponding probability distributions.
- *Optimization techniques.* Exploring the use of alternative global optimization algorithms is necessary in order to address the mixed-discrete nature of scheduling as an infrastructure decision problem.

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VITA

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Jackeline Murillo-Hoyos was born in Santiago de Cali, Colombia on June 25, 1980. She received her Bachelor of Science degrees in Topographic Engineering and Civil Engineering from Universidad del Valle, Colombia in June 2002 and April 2007, respectively. Jackeline has been a faculty member in the School of Civil Engineering and Geomatics at Universidad del Valle since August 2007. In January 2011, she was granted a study leave from the Colombian Government's Department of Science and Technology and her home institution, Universidad del Valle, to continue her academic career in Purdue University's School of Civil Engineering. At Purdue University she joined the Transportation Engineering and Infrastructure Systems group and received a Master's of Science in Civil Engineering in August 2013. She completed her Ph.D. in Civil Engineering in August 2016. She has made significant methodological contributions to transportation engineering by invoking knowledge from diverse disciplines including econometrics, finance, management, economics, and operations research. Her contributions include the innovative use of tools that are both descriptive (simulation, statistical and econometric, fuzzy logic, neural networks, and artificial intelligence modeling) and prescriptive (multi-criteria, stochastic, simulation-based, and dynamic optimization). She has creatively used these tools to form building blocks for her methodological contributions. Thus, her contributions provide a solid science-driven and data-based platform to make infrastructure development decisions that are consistent with greater cost effectiveness, condition-related resilience to natural and man-made stressors, and the long-term sustainability of infrastructure longevity. Jackeline's current interests are asset management, transportation funding, investment decision making, systems evaluation, and econometric modeling.

PUBLICATIONS

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Refereed Journal Papers:

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