Comparison between Optimization and Heuristic Methods for Large-Scale Infrastructure Rehabilitation Programs

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Civil infrastructure systems are the foundation of economic growth and prosperity in all nations. In recent years, infrastructure rehabilitation has been a focus of attention in North America and around the world. A large percentage of existing infrastructure assets is deteriorating due to harsh environmental conditions, insufficient capacity, and age. Ideally, an assets management system would include functions such as condition assessment, deterioration modeling, repair modeling, life-cycle cost analysis, and asset prioritization for repair along a planning horizon. While many asset management systems have been introduced in the literature, few or no studies have reported on the performance of either optimization or heuristic tools on large-scale networks of assets.

This research presents an extensive comparison between heuristic and genetic-algorithm optimization methods for handling large-scale rehabilitation programs. Heuristic and optimization fund-allocation approaches have been developed for three case studies obtained from the literature related to buildings, pavements, and bridges with different life cycle cost analysis (LCCA) formulations. Large-scale networks were constructed for comparing the efficiency of heuristic and optimization approaches on large-scale rehabilitation programs. Based on extensive experiments with various case studies on different network sizes, the heuristic technique proved its practicality for handling various network sizes while maintaining the same efficiency and performance levels. The performance of the genetic algorithm optimization approach decreased with network size and model complexity. The optimization technique can provide a high performance level, given enough processing time.

Acknowledgements

First and foremost, I thank God for giving me the knowledge, strength, and ability to complete this work.
I would like to dedicate my Master's program to my parents and stepmother, who have committed their lives to me and strongly motivated me throughout my life, particularly during this program. My brave father (Saleh), mother (Aljawharah), and stepmother (Muneerah) have had profound and undeniable roles in my success.

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Dedication

To my mother, Aljawharah, my father, Saleh, and my stepmother, Muneerah

Who

Have dedicated their lives to me

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Acronyms

LCCA	Life-cycle Cost Analysis
ArchSD	the Architecture Services Department
OECD	the Organization for Economic Cooperation and Development
FHWA	the US Federal Highway Administration
TDSB	the Toronto District School Board
PCI	Pavement Condition Index
MCR	Material Condition Rating
PPCI	Probability of PCI
MDP	Markov Decision Process
$P_{i.j}$	Probability of transition from condition state i to condition state j
TPM	Transition Probability Matrix
LCC	Life-cycle Cost
PV	Present Value
FV	Future Value
EAs	Evolutionary Algorithms
GAs	Genetic Algorithms
ABS	Automated Budget System
AHP	Analytical Hierarchy Process
MPB	Maintenance Priority Benchmark
TxDOT	Texas Department of Transportation
GDOT	Georgia Department of Transportation
LRT	Light Rail Transit
BRT	Bus Rapid Transit
PSRC	Puget Sound Regional Council
DI_N	Overall Network Deterioration Index
RIF	Relative Importance Factor
IE	Improvement Effect

EP	Expected Performance
ICMP6	the 6th International Conference on Managing Pavements
AADT	Annual average daily traffic
IRI	International Roughness Index
VBA	Visual Basic for Application
PI	Priority Index
VOC	Vehicle Operating Cost
ME-BMS	Multi-Element Bridge Management System
BCR	Overall Bridge Condition Rating
NCR	Network Condition Rating

Chapter 1
Introduction

1.1 Background

Civil Infrastructure Systems, for example; buildings, water/sewer networks, and roadways, are the foundation for economic growth, and their value is significant in most countries. In Canada, the established total stocks of buildings and constructed infrastructure have a value of more than $2.94 trillion (Statistics Canada, 1994; Statistics Canada, 1996; Statistics Canada, 1999). The yearly average expenditure on infrastructure systems is estimated to be $53 billion, with new assets being built at an increasing rate of $100 billion per year (Elbeltagi & Tantawy, 2011; Vanier, 2001). Table 1.1 shows the federal government infrastructure capital average annual growth by region and type of asset, 1961 to 2005 (Roy, 2008). Figure 1.1 presents the annual federal infrastructure expenditure in Canada from 2006 to 2013 (Dupuis & Ruffilli, 2011)()()()(). In the United States, the total value of infrastructure systems is estimated to be $30 trillion, and the yearly average expenditure on infrastructure systems is estimated to be $303 billion (Elbeltagi & Tantawy, 2011; Vanier, 2001). The operation, maintenance, repair, and renewal of these assets represent a rapidly growing and major cost to Canada and the United States. Similar challenges exist in Australia and other developed countries (Burns, Hope, & Roorda, 1999; Vanier, 2001).

In many regions of the world, a large percentage of existing infrastructure assets are deteriorating due to harsh environmental conditions, insufficient capacity, and age (Elbeltagi & Tantawy, 2011). In Canada, infrastructure has been neglected in the past few decades, so the resulting accelerated deterioration has caused many facilities to become unsafe or no longer serviceable long before the end of their expected service life (Giannini, 2008). The value of current new construction projects ($100 billion) in Canada is less than that of the renewal, repair, and maintenance market ($104 billion) (Vanier, 2001). In the United States, modification and renovation projects represent 35% of the overall turnover in the construction sector (Mitropoulos & Howell, 2002). Therefore, it is crucial to manage and operate these infrastructure assets efficiently and sustainably.

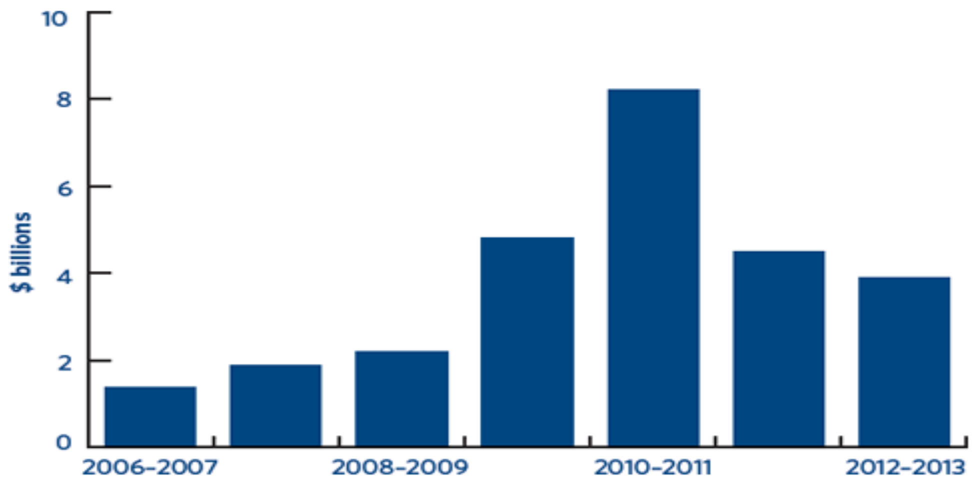


Figure 1.1: Annual Federal Infrastructure Spending (Dupuis & Ruffilli, 2011)

Table 1.1: Average Annual Growth of Federal Government Infrastructure Capital by Region and Type of Asset, 1961 to 2005 (Roy, 2008)

	Atlantic	Quebec	Ontario	Prairies	British Columbia	Canada
				%		
Road	-2.1	-1.8	-0.9	-1.8	-1.5	-1.5
Environment	-2.3	-0.4	-0.8	-1.1	-1.3	-1.1
Water systems	-2.4	-1.4	-0.1	-0.5	-0.8	-0.8
Office building	1.2	1.4	1.0	1.1	1.1	1.1
Culture	-1.0	3.1	0.4	-0.3	-1.1	0.5
Marine construction	-1.4	-0.7	-1.4	-2.4	-1.7	-1.5
Other transportation	-0.3	-0.4	-1.7	-1.1	-1.7	-1.0
Communication	-1.4	-1.4	-1.0	-2.3	-3.4	-1.5
Laboratories	0.3	1.7	-0.2	1.4	-2.3	0.2
Engineering	-2.7	0.4	0.5	1.3	0.6	0.5
Institutional	0.5	-0.4	-0.8	1.9	0.1	0.3
Commercial	0.2	-1.4	-1.6	-0.5	-1.6	-1.1
Security	0.3	1.1	-0.7	1.3	0.3	0.2
Other	-3.4	-2.1	-1.1	-2.0	-2.5	-2.1
All	-0.7	-0.1	-0.3	-0.2	-0.7	-0.3

Civil infrastructure assets are characterized as being complex in nature, vast in size, and of big in asset value. Maintaining such assets is challenging but a very critical task, particularly in light of the lack of available funds for infrastructure rehabilitation and maintenance (Elhakeem, 2005). Consequently, increasing pressure is being brought to bear on municipalities to develop new strategies and tools for allocating limited resources more wisely and to achieve best value for their investment (Elbehairy, 2007; Shen, 1997).

The allocation of available funds across infrastructure classes or programs is one of the main activities in infrastructure asset management. Continuous research efforts have been undertaken in the last few decades to develop tools and methodologies for allocating funds in infrastructure asset management, methodologies that range from being based on subjective prioritization to mathematical programming and optimization.

Prioritization methodologies are the technique most commonly used by authorities in infrastructure asset management (M. Halfawy , Newton, & Vanier, 2006; Shen, 1997). For example, in the UK, the local authorities use prioritization-based programs for fund allocation and ranking projects and works (Shen, 1997). Also, in Hong Kong, the Architecture Services Department (ArchSD) and the Hong Kong Housing Department, the two government departments that are responsible for almost all the infrastructure stocks in Hong Kong, are using prioritization techniques for constructing and managing their assets (Shen, 1997).

Although various researchers have dealt with fund allocation, there is a serious lack of methodologies that can deal with large numbers of infrastructure assets (Elbehairy, 2007). The inadequacy of traditional prioritization and fund allocation methodologies to handle large scale problems, which is the case in infrastructure assets, is considered one of the greatest obstacles in the development of efficient methodology (Elbehairy, 2007). Moreover, most of these methodologies were developed for a single class of asset and lack a comprehensive view of the whole process of infrastructure asset management (M. R. Halfawy, Vanier, & Hubble, 2004). Moreover, few or no studies have reported on the performance of either optimization or heuristic tools on large-scale networks of assets (Elhakeem, 2005).

1.2 Research Objectives

The goal of the current research is to examine the efficiency of both optimization and heuristic techniques in prioritizing fund-allocation for rehabilitation programs which involve a large number of infrastructure assets. The research then presents authorities and decision-makers with recommendations for efficient methods for allocating funds for rehabilitation and maintenance programs with very large numbers of assets. The principal objectives of this research are as follows:

- Investigate current heuristic and optimization methodologies for fund allocation and prioritization of rehabilitation programs
- Develop optimization and heuristic procedures for three case studies obtained from the literature, related to buildings, pavements, and bridges
- Examine and compare the efficiency of heuristic versus optimization methods on large-scale rehabilitation programs created from multiple copies of the original case studies
- Based on the comparison, provide guidelines for handling large-scale problems

In essence, the aim of this research is to conduct an extensive comparison between heuristic and optimization methods for large-scale rehabilitation programs. The research will provide valuable information to assist owner organizations, such as governmental agencies and municipalities, and their consultants to effectively manage and operate their infrastructure assets with the optimum condition and cost.

1.3 Research Methodology

The methodology for achieving the aforementioned research objectives is illustrated in Figure 1.2. Each step is briefly described as follows:

1. **Review of the Existing Methodologies**: A comprehensive survey of the literature is carried out in order to review and examine existing prioritization and fund allocation techniques, models, and methodologies. The most appropriate methodologies and models will be selected to be the base for developing the proposed methodology.

2. **Examination of Available Methodologies**: The limitations and characteristics of the available methodologies will be identified through implementation in a real-life case study.
3. **Heuristic and Optimization Prioritization Methodologies of Fund allocation For Large Number of Infrastructure Assets**: Based on methodologies examination, suggestions for improvement and incorporation will be identified and the evaluation criteria of each infrastructure class will be suggested. A methodology that can effectively prioritize large networks and suit different classes of infrastructure assets will be then developed.
4. **Case Study and Validation**: The proposed methodology will be validated and then tested on three models for different case studies.

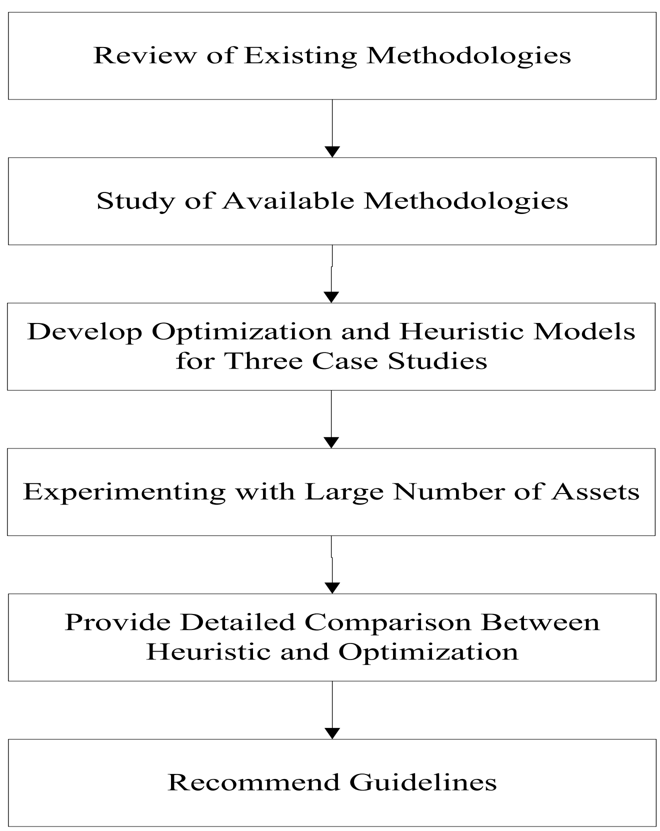


Figure 1.2: Schematic Diagram for Research Methodology

1.4 Thesis Organization

This thesis is organized as follows:

Chapter 2 introduces a detailed review of the most recent efforts related to asset management systems. A review of the basic functions of an asset management system, condition assessment, deterioration model, repair model, and life-cycle cost model is also presented in this chapter.

Chapter 3 presents life-cycle cost models for three different case studies: buildings, pavements, and bridges. An overview of each case study is presented, and the components, inputs, and outputs of each model are discussed.

Chapter 4 introduces two fund-allocation approaches: optimization and heuristic. The validation and testing of these approaches on the three different case studies is presented. The validation results and outputs are discussed.

Chapter 5 presents validation of the optimization and heuristic approaches on large-scale networks. The performance and ability of the two approaches to handle large-scale networks are discussed.

Chapter 6 provides the conclusions and future work

Chapter 2
Literature Review

2.1 Introduction

The allocation of available funds across infrastructure classes (e.g. buildings, pavements, and bridges) or programs (e.g. maintenance, construction) is one of the main activities in infrastructure asset management. Infrastructure is a broad category of assets and is considered to be the basic physical and organizational structures and services needed for an economy, society, or community to function. Asset management is defined by the Organization for Economic Cooperation and Development (OECD) as "a systematic process of maintaining, upgrading and operating assets, combining engineering principles with sound business practice and economic rationale, and providing tools to facilitate a more organized and flexible approach to making the decisions necessary to achieve the public's expectations" (Woodward, 2004). The definition shows that it is important for an asset management system to include a systematic methodology for funding allocations (or trade-off analyses) (Elhakeem, 2005; Gharaibeh, Chiu, & Gurian, 2006).()

In many regions of the world, infrastructure systems are ageing and deteriorating. In Canada, for example, infrastructure has been neglected in the past few decades, and the resulting accelerated deterioration has caused many facilities to become unsafe or no longer serviceable long before the end of their expected service life (Giannini, 2008). An extensive rehabilitation of all deteriorating assets with the current lack of available funds is impossible (Farran & Zayed, 2009). Thus, proper management of available financial resources is needed, and an adequate rehabilitation program that allows decisions on the appropriate intervention at the proper stage and helps minimize total expenditures is crucial. Hence, in North America and around the world, infrastructure renewal has been a focus of attention in recent years (Elbehairy, 2007).

2.2 Infrastructure Asset Management

All economic resources are considered assets. The term "assets" represents all tangible or intangible items that are capable of being owned or held to have a positive economic value. Infrastructure management can be defined as the process which covers the activities involved in providing and maintaining infrastructure at a level of service acceptable to the owners or public (Hudson, Haas, & Uddin, 1997). Also, the US Federal Highway Administration (FHWA) has defined asset management as “a systematic process of maintaining, upgrading and operating physical assets cost effectively” (Elhakeem, 2005). It combines engineering and mathematical analysis with sound business practice and economic theory. Asset management systems are goal-driven and, like the traditional planning process, include components for data collection, strategy evaluation, program selection, and feedback. The asset management model explicitly addresses the integration of decisions made across all program areas.

Infrastructure assets are considered the basic physical and organizational structures and services that are needed for an economy, society, or community to function (Elhakeem, 2005; WIKIPEDIA, 2011). Nowadays, no one would imagine a town or even a village in a developed country without infrastructure such as roads, electricity, water supply services, and communication systems. Whilst maintaining the function of the system as a whole, infrastructure assets are renewed by replacing individual components and not the whole system (Alegre, Covas, Monteiro, & Duarte, 2006). Hence, infrastructure assets have indefinite lives and are characterized by being complex in nature, costly to build, operate, and maintain, huge in size, and highly challenging to manage (Elhakeem, 2005).

Infrastructure is facing a crisis that is affecting economies and social prosperity (Masood, 2008). For instance, in Canada, most infrastructure facilities were built between the 1950s and 1970s, and many of them are due for replacement (Mirza, 2007). According to the Civil Infrastructure Systems Technology Road Map 2003-2013, 41% of Canadian infrastructure is 40 years old or less, 31% is between 40 to 80 years old, and 28% is more than 80 years old, as shown in Figure 2.1 (Masood, 2008). Yet for the past 20 years, reduced revenues and growing responsibilities have caused municipalities to undergo a fiscal squeeze (Mirza, 2007). As a result, needed investments were deferred and infrastructures continued to deteriorate, with the cost of fixing them climbing from $12 billion in 1985 to $60 billion in 2003 to $123 billion in 2007 (Mirza, 2007). This deficit must be addressed in a timely manner or the deteriorating infrastructures will create a domino effect that carries on for years into the future (Masood, 2008). This domino effect and deficit can be eliminated, or at the very least controlled, if the necessary funding is provided and effectively planned and allocated.

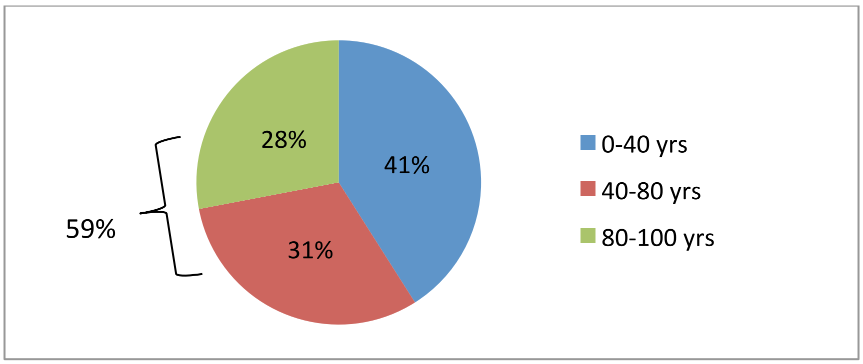


Figure 2.1 Age of Canada's Infrastructure (years) (Masood, 2008)

2.3 Infrastructure Asset Management Systems

The term "Infrastructure Asset Management" is often used to clarify that the topic is the management of physical assets rather than the financial assets. An infrastructure asset management system is the set of tools that can support an owner organization to better manage its assets. According to (Hudson et al., 1997), "infrastructure management system is the operational package (methods, procedures, data, software, policies, decisions, etc.) that links and enables the carrying out of all the activities involved in infrastructure management".

The purpose of asset management is to provide guide in how infrastructure management can be conducted in an optimal manner at minimal cost. An infrastructure asset management system should answer three main questions (Elhakeem, 2005):

i. Which assets/components are to be treated first (have high priorities)

ii. When to treat the selected assets/components

iii. What type of treatment (maintenance, rehabilitation, or reconstruction) should be applied for each selected asset/component

A practical and effective infrastructure asset management system should cover the following aspects (Elhakeem, 2005):

a) Condition assessment

b) Deterioration modeling

c) Repair alternatives and strategies

d) Improvement after repair

e) Asset prioritization and repair fund allocation

2.3.1 Challenges

Developing an infrastructure asset management system is a complex and challenging task due to the large number of asset components. The level of complexity of a system depends on the number of components and type of the considered asset (road, building, power plant, etc.). For example, a typical school building can consist of about 170 components (roof, boiler, interior door, etc.), and each component can have several instances. To illustrate, a roof can have several sections, and school buildings usually have multiple doors, windows, and boilers. The complexity of managing infrastructure assets comes from the fact that each component should be dealt with independently throughout the whole process, from condition assessment to prioritization and fund allocation. Furthermore, an organization is usually responsible for managing tens or even hundreds of assets. One example is the Toronto District School Board (TDSB), which is responsible for 642 schools, where inspections, analysis, and ratings involve more than 300,000 components (Elhakeem, 2005).

In the ideal situation, budgets are sufficient and the repair needs of all assets can be addressed (Hudson et al., 1997). However, in reality, most public infrastructure agencies have limited or constrained budgets (Elhakeem, 2005).

2.4 Asset Management Functions

Asset management systems are systematic procedures intended to achieve the highest benefit from a facility with the lowest cost (best value of money). Generally, asset management systems include different functions (Figure 2.2): (a) condition assessment; (b) deterioration modeling; (c) repair modeling; and (d) life-cycle cost analysis for the allocation of funds to different assets.

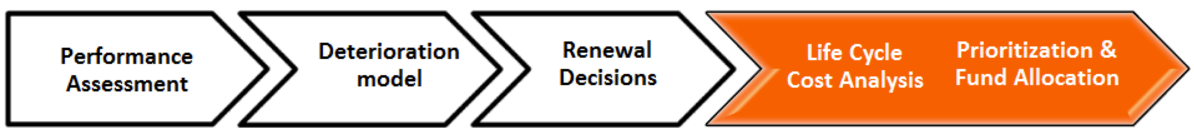


Figure 2.2: Asset Management Functions

2.4.1 Condition Assessment

Condition assessment is one of the most important functions in the asset management process. It is considered the starting point for other functions such as deterioration analysis or repair selection. It describes the existing condition of the asset as compared to its condition at the time of construction (Elbehairy, 2007; Elhakeem, 2005). (Rugless, 1993) defined condition assessment as “a process of systematically evaluating an organization’s capital assets in order to project repair, renewal, or replacement needs that will preserve their ability to support the mission or activities they were assigned to serve”.

A detailed condition assessment can be used directly to determine a repair priority list without having to use deterioration or detailed life-cycle analysis functions (Elhakeem, 2005). The condition of the asset is usually assessed by means of an inspection. Regular inspection of assets is essential for alerting authorities to the deterioration of the asset. Also, inspection results enable engineers to determine future maintenance requirements. Due to the importance of technical expertise and experience in the inspection process, usually an inspection is carried out or at least supervised by a professional engineer (Elbehairy, 2007).

Four main aspects must be addressed for a detailed condition assessment (Elhakeem, 2005):

- Asset Hierarchy
  - Inspection level
  - Inspection techniques
- Evaluation Mechanism
  - Condition scale
  - Required data
  - Required analysis
- Field Inspection
  - Detect deficiencies
  - Measure severities
  - Add notes, pictures, etc.
- Condition Analysis
  - Rate inspected components
  - Calculate condition at any level in the hierarchy

2.4.2 Deterioration Modeling

Asset deterioration is the process of decline of an asset resulting from aging, deferred maintenance decisions, severe environmental conditions, or a combination of these (Abed-Al-Rahim & Johnston, 1995). Each component of the asset has its own unique deterioration rate, and that makes the problem more complicated (Elbehairy, 2007). Maintenance and rehabilitation decisions depend on both the asset's current condition and predicted future condition. At both network and project levels, deterioration models are used for the determination of maintenance and rehabilitation requirements (Shahin, 1994). Therefore, deterioration models are crucial for any management system in predicting future funding needs.

Several techniques are used for developing deterioration models, which can be categorized into three main categories: deterministic, stochastic, and artificial intelligence models (Elhakeem, 2005).

Deterministic Models: Deterministic models are based on mathematically or statistically formulating the relationship between factors affecting asset deterioration and the measurement of asset condition. The output of such models is a deterministic value that represents the average predicted condition. Deterministic models can be classified into three main techniques: straight-line extrapolation, regression, and curve-fitting methods (Morcous, 2000). The different techniques of the deterministic methods are discussed below:

a) *Straight-Line Extrapolation* is considered the simplest technique for predicting future conditions. It is a straight-line exploration of two points with known conditions, given the assumption that the asset's usage, environment, and maintenance history follows a straight line. This method requires performing at least one condition measurement after construction and assuming an initial condition at the time of construction. Then, the future condition at any time is determined by following a line between the two known condition points. The straight-line exploration is used because of its simplicity and the uncertainty of the future deterioration rate. This deterioration prediction method is accurate enough for predicting short-term conditions (a few years), but not for long periods. Also, the straight-line exploration method cannot predict the future condition of a relatively new asset, or of an asset that has recently received a major rehabilitation (Shahin, 1994).

b) *Regression* is a statistical tool which aims to find a function that represents an empirical relationship between two or more variables. These variables are described in terms of their mean and variance. This technique provides more accurate prediction of future condition than straight-line extrapolation. There are several forms of regression, such as linear, non-linear, stepwise, and multiple regression. The technique starts with developing a function that suits the available data. If it fits a line, a regression analysis is performed for optimally determining the coefficients that represent that line. Determining these coefficients is based on minimizing the error between the actual and the predicted values. Multiple linear regression is a linear regression that is performed for more than two variables. In a non-linear case, data is represented by a polynomial or by exponential functions. Then, a correlation factor is calculated to choose the function that best represents the relationship among the variables (Elhakeem, 2005; Shahin, 1994).

Stochastic Models: The theory of stochastic processes is now being increasingly used in engineering and other applied science applications. Stochastic models have significant contributions for the field of infrastructure deterioration modeling because of the uncertainty and random nature of the deterioration process. Stochastic models can be classified into three main categories: (1) Probability Distribution, (2) Markovian Models; and (3) Simulation Techniques. Each category is discussed in detail, as follows.

1) ***Probability Distribution***: Probability distribution is the process of describing the probabilities associated with the values of a random variable (Shahin, 1994). An infrastructure facility condition measure such as Pavement Condition Index (PCI) or Material Condition Rating (MCR) can be treated as a random variable, and the probability distribution will describe the probabilities associated with all its values (Morcous, 2000). For example, if the PCI is the random variable, then its probability distribution can be described by its cumulative distribution function, as shown in Figure 2.3. The vertical axis in this figure is the Probability of PCI (PPCI) being equal or less than a given value.

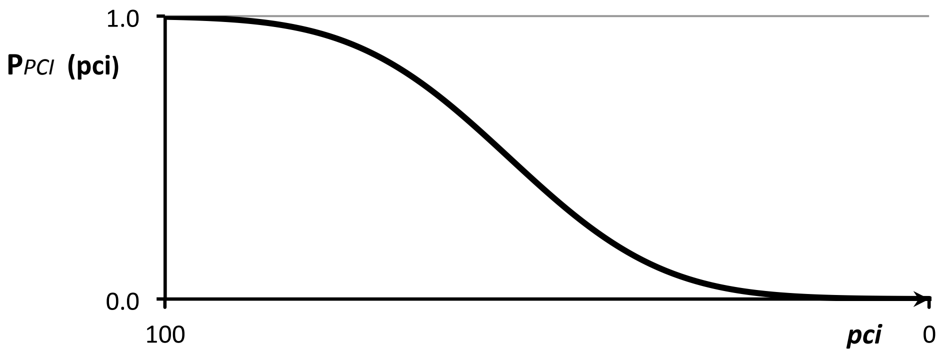


Figure 2.3: Cumulative Distribution Function (Shahin, 1994)

The use of probability distribution in predicting asset condition requires the knowledge of the distribution law for the variable being predicted (Shahin, 1994). Probability distribution has not been applied or tested practically, and this is a main drawback of this technique (Morcous, 2000).

2) ***Markovian Models:*** The Markov Decision Process (MDP) is the most popular technique obtained from operation research. It has been extensively used in developing stochastic deterioration models for different infrastructure facilities (e.g. buildings, pavements, pipes, etc.) (Elbehairy, 2007). Markovian models capture the uncertainty of the deterioration models. They are based on the concept of defining discrete asset condition states and extrapolating the probability of changing from one condition state to another over multiple discrete time intervals. The probabilities of transition ($P_{i.j}$) from one condition state to another are represented by a matrix of order (n x n) called the transition probability matrix (TPM), as follows.

$$\begin{array}{cc} \text{State} & \begin{array}{ccccc} 1 & 2 & \cdots & & n \end{array} \\ \boldsymbol{TPM} = \begin{array}{c} \mathbf{1} \\ \mathbf{2} \\ . \\ . \\ \boldsymbol{n} \end{array} & \begin{bmatrix} \boldsymbol{P_{1.1}} & \boldsymbol{P_{1.2}} & \cdots & \boldsymbol{P_{1.n}} \\ \boldsymbol{P_{2.1}} & \boldsymbol{P_{2.2}} & \cdots & \boldsymbol{P_{2.n}} \\ \vdots & \vdots & \boldsymbol{P_{i.j}} & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \boldsymbol{P_{n.1}} & \boldsymbol{P_{n.2}} & \cdots & \boldsymbol{P_{n.n}} \end{bmatrix} \end{array} \qquad 2.1$$

where (n) is the number of condition states, i is the current condition, and j is the condition of the following state. 1 to *n* represents the condition states, where state 1 is the current or new condition, state 2 is a deteriorated condition, and so on to state *n*, which is the critical condition. Each element ($P_{i.j}$) in the matrix represents the probability of transition from state *i* to state *j* during a given period of time known as the transition period. The sum of probabilities in each row equals 1.0. For example, ($P_{1.2}$) in the matrix represents the probability of transition (deterioration) from condition state 1 to condition state 2, while ($P_{2.1}$) represents the probability of transition (improvement) from condition state 2 to condition state 1 (Elhakeem, 2005).

Although Markovian models are the most widely used approach for deterioration modeling, and great advances have been achieved with their use, they have some limitations:

- The Markovian models assume that the predicted future condition is a function of only the current condition and that past conditions have no effect on predicted ones (S. M. Madanat, Karlaftis, & McCarthy, 1997)
- The Markovian models assume fixed assumptions and transition probabilities throughout the predicted period (Elbehairy, 2007)
- It is difficult for Markovian models to consider the interaction among the deterioration mechanisms of different components (Sianipar & Adams, 1997)
- The Markovian models do not predict the after-repair condition (S. Madanat, Mishalani, & Ibrahim, 1995)
- Transition probabilities are estimated based on subjective engineering judgment, and updating is required when new data are obtained (Tokdemir, Ayvalik, & Mohammadi, 2000)

3) ***Simulation Techniques:*** The simulation technique is another method that can be applied in order to model deterioration behavior. This technique can be achieved by stochastic analysis of the system, since deterioration behavior is a complex process in terms of transition times between various states or conditions. Simulating the deterioration behavior can be achieved if statistics on transition times are available.

This technique will result a probabilistic deterioration model. A main drawback of this technique is that it has not been tested practically (Morcous, 2000).

2.4.3 Repair Modeling

Repair modeling is the process of determining the suitable repair options and estimating the condition improvements and associated costs. In current practice, a fixed cost is assigned as a percentage of replacement cost to subjectively set repair types such as minor, moderate, or major repair (Seo, 1994). However, this classification may be not accurate in the case of buildings because it does not define clear strategies to repair specific deficiencies (Elhakeem, 2005).

Calculating a component's replacement cost is often performed by soliciting quotes to contractors/suppliers or by consulting published data references, and is considered an easy process. In RSMeans (2004), data published for estimating costs for almost all types of building components. Two reference books for elemental estimating were published by RSMeans: *Square Foot Costs*, and *Assemblies Cost Data*. In both references, cost estimates were developed based on an average of over 11,500 actual projects reported to RSMeans from contractors, designers, and owners. RSMeans provides cost per square foot for various projects in a tabular format, in addition to adjustment factors for project size and city indexes.

After defining the replacement cost, calculating the repair cost of a component can be difficult. One common simplification is to assign a fixed cost for repair options as a percentage of the full replacement cost (Elhakeem, 2005). For example, (Seo, 1994) estimated the repair cost for light, medium, and extensive repairs for bridge decks as 28.5%, 65%, and 100% of their respective replacement costs. Another example, the replacement cost in the BUILDER system, is calculated by multiplying the quantity of work by the unit cost and other parameters, such as the area cost factor (ACF), which represents the following differences in costs (BUILDER User Guide, 2002; BUILDER User Guide, 2002)(BUILDER User Guide, 2002; BUILDER User Guide, 2002)(BUILDER User Guide, 2002; BUILDER

User Guide, 2002)(BUILDER User Guide, 2002; BUILDER User Guide, 2002)(BUILDER User Guide, 2002):

- Weather, climate, and seismic requirements
- Local costs of construction labor, equipment, and materials
- Labor productivity
- Labor availability

The repair cost of a component is then calculated based on current conditions, the replacement cost, and a proprietary algorithm. However, not much information is provided on the algorithm itself. The importance of defining the cost of the available repair options has been discussed by many other researchers; however, the cost calculations were discussed without much detail (Elhakeem, 2005).

2.4.4 Life-cycle Cost (LCC) Analysis

Life-cycle cost (LCC) analysis is a systematic process for economically evaluating and comparing competing projects with the aim of optimizing the value of the capital asset()()()()(s). All the expected costs and benefits associated with a project during its life-cycle (initial or installation costs, operation, maintenance, rehabilitation costs, and salvage value) are taken into account. LCC can be defined as "the sum of all expenditures associated with the item during its entire service life" (White, Case, Pratt, & Agee, 1997). The term "item" can be interpreted as a project, system, building, or machine, but in the current research it represents the infrastructure asset. In the context of this research, LCC will be used as a tool to evaluate possible repair scenarios for infrastructure systems in order to select the optimal repair solution. The LCC of each repair scenario should be converted to either the Present Value (PV), the Future Value (FV), or to an equivalent annual value in order to have a common base for comparing those repair scenarios.

Predicting the condition and deterioration behavior of an asset after a rehabilitation or maintenance action is a vital asset management function (Hegazy, Elbeltagi, & El-Behairy, 2004). The deterioration rate of a rehabilitated asset is greater than that of a new constructed asset. Also, after a rehabilitation action, an asset does not revert back to its best condition, as shown in Figure 2.4. However, assuming that the deterioration rate of a newly constructed and a rehabilitated asset are equal is a common practice (Elbehairy, 2007).

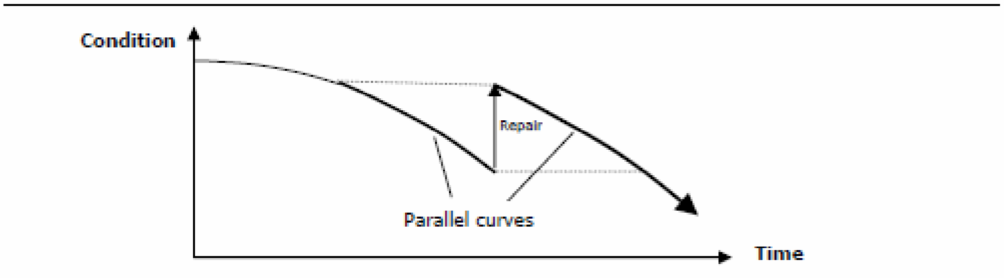


Figure 2.4: After-Repair Deterioration

In the literature, estimating the improvement in condition after a repair action is usually done by performing another round of inspections or through empirical judgments (Elhakeem, 2005). Table 2.1 shows an example of predefined estimates for the after-repair condition for various building rehabilitation options used by (Langevine, Allouch, AbouRizk, & Nicoll, 2005). Another example proposed by (Seo, 1994) for defining the expected condition improvements for bridge decks is presented in Table 2.2.

Table 2.1: Predicted Condition for Various Repair Options (Langevine et al., 2005)

Condition		Replacement	Major	Minor	Preventive
Best	A	-	-	-	-
	B	-	-	-	-
	C	-	-	B	-
	D	A	B	C	D
Worst	F				

Table 2.2: Predicted Condition After Repair Action (Seo, 1994)

Condition Rating		After Repair Condition	
		5, 6	7, 8
Current Condition	3, 4	Medium	Extensive
	5, 6	Light	Medium
	7, 8	-	Light

Allocating available funds across infrastructure classes or programs is a crucial asset management function. It is the process of finding a balance between costs and benefits while taking all constraints into account. Many research efforts have been undertaken in the last few decades to develop fund allocation and ranking tools and methodologies. These methodologies range from subjective-judgement-based methods to mathematical and computerized methods. The subjective-judgement-based methods are simple, quick, and easy. However, they give inaccurate, unreliable, and far from optimum solutions, while mathematical and computerized methods are accurate, reliable, and give the optimum solution, but take time to develop, are complicated, and are not easy to modify. In between, prioritization methodologies give reliable and near-optimum results. Also, they are flexible and easy to implement and understand. Moreover, prioritization is the technique most commonly used by authorities in infrastructure asset management (M. Halfawy et al., 2006; Shen, 1997). An overview of these techniques is presented in the following subsections.

Optimization Techniques: A maintenance or rehabilitation optimization model is a mathematical model that quantifies costs and benefits and obtains the optimal balance between them while taking into account all constraints (Dekker, 1996). Optimization models can be applied to single or multi-year planning periods. The output of such models is a single or set of alternatives that satisfy a specific objective function where some values are minimized (i.e. costs) or maximized (i.e. benefits, effectiveness) (Haas, Hudson, & Zaniewski, 1994). The majority of researchers' objective function is to minimize the total life-cycle cost in the optimization model (Hegazy et al., 2004). Several variations of dynamic and linear programming are used in formulating these models (Haas et al., 1994). However, the solution's quality depends on the method of formulation of the optimization problem and the optimization tool used (Elhakeem, 2005).

Traditional optimization techniques are not suitable for large-scale problems, particularly when considering both project and network levels together. However, new optimization techniques, known as evolutionary algorithms (EAs), that can suit such problems have evolved (Elhakeem, 2005). Examples of EAs include genetic algorithms (GAs), shuffled frog, particle swarm, ant-colony systems, and mimetic algorithms (Elbeltagi, Elbehairy, Hegazy, & Grierson, 2005).

In principle, optimization models produce the best solutions to certain problems, using the available information. However, the benefits of using such procedures should be balanced against the effort of applying them and getting the required data. In some problem instances, the expected benefits are just too low to justify such sophisticated procedures (Dekker, 1996).

Prioritization Techniques: Prioritization is the process of addressing those issues that are considered most critical and practical to address in terms of time, energy, and resources. Prioritization is a process whereby an individual or group places a number of items in a ranked order based on their perceived or measured importance or significance. Prioritization is an important process to assist decision-makers in identifying the most important issues on which they should focus their limited resources. Usually, all participants have input into the prioritization process. Participants need to be mindful that the perceptions of those around them may be different from their own. An issue that causes difficulty in the prioritization process is that often there is no clear right or wrong order to prioritizing. This is especially true when prioritizing unrelated options or those whose solutions are very different (Centra,).

There are several prioritization techniques and methods. Some methods are focused on baseline data, whereas other methods are more participatory and rely heavily on group participation. Based on the particular needs of a community, case, or group, a prioritization method or technique is chosen and adopted. It is important to know that no one method is best for all cases and needs. In the following section, examples of prioritization techniques/methods are briefly described. The strengths and weaknesses of each process are summarized in Table 2.3.

Simplex Method: This method is a perception-based method. The perceptions of a group of participants are obtained by the use of questionnaires. The participants' perceptions or answers to the questionnaire are scored and ranked, and the highest priority will be given to the issues with the highest scores. This method helps decision-makers to analyze problems more efficiently. Also, in the simplex method, the priority level of a particular problem can be raised by giving it more weight. However, this method depends largely on the way in which the problems and questions are presented in the questionnaire (Centra,).

Nominal Group Planning: The Nominal Group Planning technique was developed for situations where decisions cannot be determined by one person, but where individual judgements are tapped and combined to arrive at a decision. This technique is best suited for priority development, knowledge exploration, program evaluation, program development, and problem exploration. Possible situations where Nominal Group Planning can be used are:

- to determine which community issues are of greatest concern
- to decide on a strategy for dealing with the identified issues
- to design improved community services or programs.

This method involves is mainly based on information exchange and deliberation. Generally, the manner of implementing this method is the same for each application. Decision-making criteria are developed based on the participants' concerns and ideas surrounding the topic being discussed. Ranking and prioritizing these criteria through voting and consensus is the final output of the process. Depending on the type and nature of the topic being discussed, the criteria may be selected by the community (Centra,).

Criteria Weighting Method: The criteria weighting method is a mathematical process whereby group members generate a relevant set of criteria. Then, issues are prioritized and ranked based on assigning a measure for each issue against each criterion. The final output list and values do not necessarily dictate the final decision, but offer a means by which choices can be ordered (Centra,).

A "Quick and Colorful" Approach: This approach is based mainly on the individual votes of the group members, and a secret ballot method or open method may be used. This method is quick and easy, and is perhaps a more entertaining approach to prioritizing. If particular issues or problems are deemed more important than others, the participants can decide to place weights on them (Centra,).

Table 2.3: Summary of Pros and Cons of Prioritization Techniques (Centra,)

	Pros	Cons	Optimal size of group
Simplex	• Efficient and quick to use, once questionnaire is constructed. • Can be used with any size group. • Allows for weighting of problems.	• Requires the development of a questionnaire. • Relies heavily on how questions are asked.	Any size.
Nominal Group Planning	• Motivates and gets all participants involved. • Can be used to identify areas for further discussion and can be used as part of other techniques (e.g. to help develop a Simplex questionnaire). • Allows for many ideas in a short period of time. Stimulates creative thinking and dialogue. • Uses a democratic process.	• Vocal and persuasive group members can affect others. • A biased or strong-minded facilitator can affect the process. • Can be difficult with larger groups (more than 20-25). • May be overlap of ideas due to unclear wording or inadequate discussion.	10-15 (larger groups can be broken down into subgroups.) Not < 6.
Criteria Weighting	• Offers numerical criteria with which to prioritize. • Mathematical process (this is a weakness for some). • Objective; may be best in situations where there is competition among the issues. • Allows group to weight criteria differently.	• Can become complicated. • Requires predetermining criteria.	Any size.
"Quick and Colorful" Approach	• Simple. • Well-suited to customizing. • Blinded responses prevent individuals influencing others. • Less time intensive.	• Less sophisticated (may be a benefit for some groups). • Doesn't offer the ability to eliminate options that may be difficult to address given current laws and resources. • If open voting is used, participants may be influenced by others' votes.	Any size.

2.5 Recent efforts on Prioritization and Fund-Allocation

During the past few decades, research efforts have been undertaken to develop prioritization methodologies and tools for fund allocation in infrastructure asset management. Several methods and tools have been developed to assist decision-makers and engineers in performing efficient asset management that maintains performance and cost-effectiveness.

These methods range from subjective judgement to mathematical and computerized priority-setting.

(Chouinard, Andersen, & Torrey III, 1996) developed a function-based condition indexing methodology for the prioritization of maintenance and repair operations for embankment dams within the purview of the U.S. Army Corps of Engineers. It is a ranking methodology that extracts historical prioritization criteria using the Automated Budget System (ABS) database of the Corps of Engineers in order to assist in efficient fund allocation for maintenance and repair expenditures. The method rates each component in terms of its ability to perform an intended function (meet a particular repair, evaluation, maintenance, or rehabilitation REMR objective). The final output of the method is a representation of the overall condition of the embankment dam. The statistical analysis indicates that under the two REMR objectives of "Prevention of Surface Erosion" and "Collection of Performance Information", physical parameters have a huge influence on the historical prioritizations for individual operations. Important parameters such as downstream hazard, fetch, reservoir size, and economic effect of the dam have not been investigated.

(Shen & Spedding, 1998) proposed a multi-attribute model for priority setting in the maintenance management of large building stocks. The researchers discussed the prioritization criteria selection and the allocation of weights to these criteria. A computer system was developed for testing and implementing the model. The model was validated in the UK and Hong Kong. (Shen, Lo, & Wang, 1998) have modified the multi-attribute model using an analytical hierarchy process (AHP) in deciding the weightings of the criteria set out in the prioritization model. The authors discussed the validation of the modified model and concluded that it was more quantitative and objective than the original model.

(Karydas & Gifun, 2006) proposed a method that employs multi-attribute theory for prioritizing infrastructure renewal projects. The authors defined three categories and performance measures: (1) impact on health, safety, and the environment; (2) economic impact of the project; and (3) coordination with policies, programs, and operations.

Weighting of impact category and performance measure are assigned by a group of members through pairwise comparisons. Then, weights are calculated by the analytic hierarchy process (AHP). For validity and reliability, the authors prioritized several projects and compared the results with priorities previously determined by discussion alone. The results reflected the team's feelings about the relative importance of one project to another and the relative weight of one criterion to another.

(Chang, Huang, & Guo, 2008) designed a maintenance priority benchmark (MPB) for school buildings. The MPB is divided into MPBdaily and MPBannual. The researchers analyzed and selected 14 evaluation criteria through the use of expert interviews, focus groups, questionnaires, and the analytic hierarchy process (AHP). The method projects maintenance needs for each building and is suitable for the evaluation of passive maintenance (that is, the maintenance requested by users), but it cannot be used in the evaluation of legally enforced maintenance, routine scheduled maintenance inspections and repairs, and special or emergency maintenance. Also, the effects of emergent and economical levels are not included.

(Farran & Zayed, 2009) employed the Markov decision process (MDP) with linear programming to determine the optimal rehabilitation profile on a deteriorating slab in a Montreal metro. The researchers used three different methods for calculating life-cycle cost (LCC): (1) the average expected discount cost per time period; (2) continuous rating approach; and (3) dynamic or time-dependent TPM. It was found that using the continuous rating approach obtained lower a LCC than other methods.

(Gurganus & Gharaibeh, 2012) proposed a prioritization methodology for pavement preservation projects. The method uses the analytical hierarchy process (AHP) as a platform for multi-criteria decision-making in a way that mimics how decision-makers operate. Several parameters as well as input from decision-makers were used to create a prioritized preservation project list. Decision parameters include current ADT, current tuck ADT, ride quality, condition score, visual distress, and maintenance costs. The method was implemented on data obtained from the Texas Department of Transportation (TxDOT) and the resulted projects list matched actual decisions by 75 percent.

(Tsai, Wu, Wang, Pitts, & Cressman, 2012) proposed a method for minimizing safety risks caused by deferred resurfacing projects. It is a prioritization method that incorporates safety into Georgia Department of Transportation's (GDOT) fast-paced resurfacing program. The method consists of in-house and field safety evaluations and is integrated into GDOT's resurfacing program. The method was applied to a case study with actual data from Cherokee County, Georgia. The results demonstrated that the method provides a feasible means for incorporating safety into GDOT's fast-paced resurfacing program by reprioritizing and identifying deferred resurfacing projects with safety concerns.

(Outwater, Adler, Dumont, Kitchen, & Bassok, 2012) presented a project prioritization approach to support stakeholder-based weighting for multiple goals and measures. The approach uses the analytical hierarchy process (AHP) for weighting goals, and a conjoint-based method for weighting measures. The approach was applied as part of the Puget Sound Regional Council's Transportation 2040 process and achieves the goals in the long-range land use plan VISION 2040. The approach was applied to eight simple projects to provide a better understanding of the weighting process. These projects were selected to provide for a wide range of types and modes:

- Transit Rail Extension: extend light rail transit (LRT) to a metropolitan city
- Transit Bus Service Expansion: add a bus rapid transit (BRT) route
- Transit Ferry New Route: add a passenger-only ferry route to existing ferry terminals
- Interstate Widening: add general purpose and high-occupancy vehicle lanes in each direction on an interstate route
- State Route Widening: add a general purpose lane in one direction on a state route
- Arterial Widening: add a general purpose lane on a major arterial route in each direction

- Traffic System Management: convert shoulders for use as an additional lane in peak periods in the peak direction of travel
- Travel Demand Management: expansion of the existing vanpool program

The experiments were conducted for two Puget Sound Regional Council (PSRC) committees (the Regional Staff Committee and the Prioritization Working Group). Three scoring methods were used, and accordingly, three sets of case study results were produced, as shown in Table 2.4.

Table 2.4: Project Rank for each Scoring Method

	Total Benefit Score Rank	Total Benefit to Cost Ratio Rank	Monetary Benefit to Cost Ratio Rank
Passenger Ferry New Route	1	2	1
Interstate Widening	2	7	5
Light Rail Extension	3	8	8
Management Peak Shoulder	4	3	4
Bus Rapid Transit	5	4	6
Vanpool Expansion	6	6	7
Arterial Widening	7	1	2
Highway Widening	8	5	3

The results of each scoring process employ different units and so should be interpreted individually, but once cost is accounted for, the results clearly show different prioritization of the projects. A ranking of each scoring process demonstrates that the ranking is affected by the scoring method chosen and that the two methods which incorporate cost are more consistent than the remaining method which includes benefits without cost.

As shown in the literature, solving asset prioritization is still a non-structured problem, and each approach has its own results. No study has compared the quality of solutions produced by different methods. Also, no study has examined the performance of existing heuristic or optimization techniques on large-scale rehabilitation programs.

2.6 Summary

This chapter presented the major issues related to infrastructure asset management. The challenges and complexity of developing an infrastructure management system were discussed. Then, asset management steps were presented as a process for an efficient fund allocation. Different prioritization techniques were explained and their strengths and weaknesses were summarized. Some researchers have proposed improvements to the existing prioritization techniques in order to overcome their drawbacks and suit specific cases and needs, while others have introduced new methods for prioritization. These improved methods and approaches have been also discussed in this chapter.

Chapter 3
Life-cycle Cost Analysis Models

3.1 Introduction

This chapter presents Life-Cycle Cost Analysis models for three different case studies, related to pavement, bridges, and buildings. Typically, LCCA models involve two types of decisions (Hudson et al., 1997): project-level decisions on the appropriate rehabilitation method to use in each asset component (roof, window, foundation, bridge deck, pavement, etc.); and network-level decisions on selecting the components to repair in each year of the plan. Each level of decision is complex, involving trying different combinations of actions until the best decision is reached. While many research efforts have provided useful life-cycle cost models, little information has been reported on their performance on various problem sizes, and none has proved to be able to integrate both project-level and network-level decisions. The three case studies presented in this chapter offer different formulations of the LCCA model. These models will be used for comparing the efficiency of heuristic or optimization techniques on large-scale asset rehabilitation problems. The efficiency of the LLCA formulations will also be tested. The description of the three case studies and their LCCA formulations are provided in the next sections.

3.2 Building Case Study

The data for the case study was obtained from the Toronto District School Board (TDSB related to 800 instances of four major components: roof, boiler, window, and fire alarm system. The data were reported by (Hegazy & Elhakeem, 2011), who introduced a new Multiple Optimization and Segmentation (MOST) approach to formulate the LCCA.

3.2.1 Model Formulation

MOST was introduced as an LCCA model that integrates both project-level and network-level decisions. MOST reduces the problem complexity by first optimizing individual project-level sub-problems and then using the results to formulate a network-level optimization (Figure 3.1). MOST utilized the genetic algorithm (GAs) technique to handle network-level problems.

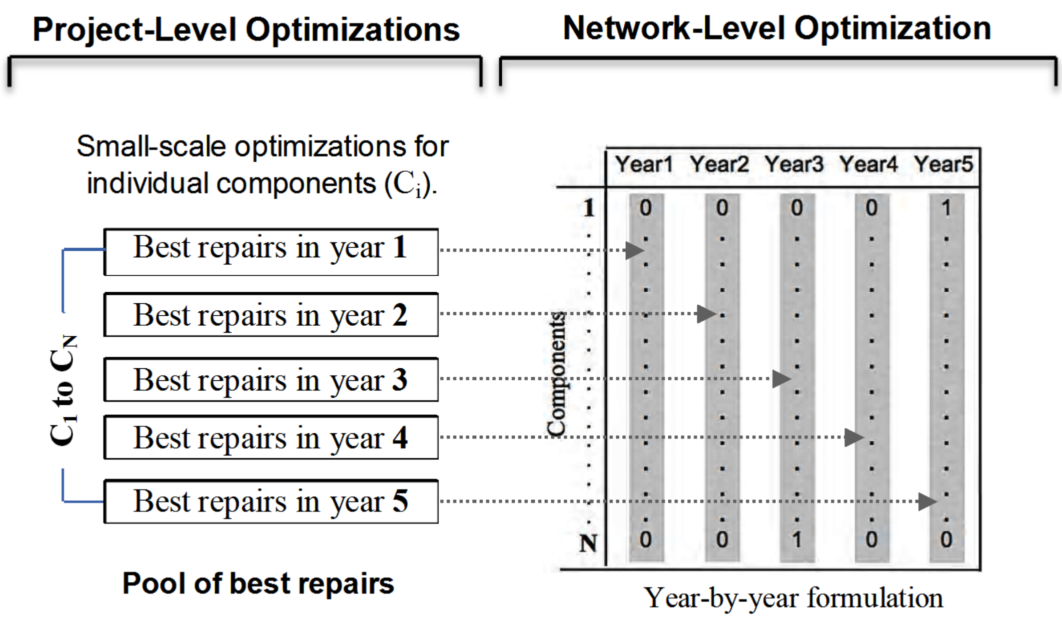


Figure 3.1: MOST Technique (Hegazy & Elhakeem, 2011)

Starting at the project level, each individual optimization considers one building component for one of the possible repair years and determines the best repair method and cost for that component in the selected year. Within each small optimization, the formulation considers the component's condition, deterioration behavior, and expected after-repair condition in order to determine the repair with the highest benefit-to-cost ratio. The result of all individual optimizations (optimal at the project level) is a pool of best repair scenarios and their corresponding costs and benefits. This are used as the input for network-level optimization in order to decide on repair timing. This approach of segmenting project-level from network-level results in a network-level optimization that is reasonable in size, without loss of integration.

The objective of network-level optimization is to minimize the overall network deterioration index (DI_N) while not exceeding the available repair budget. Rather than a one-shot optimization over the 5-year planning horizon, MOST uses a year-by-year optimization formulation (step-wise formulation) from the first year until the end of the planning horizon (as indicated in Figure 3.1). Using this formulation reduces the solution-space size and leads to better solution quality. In general, the overall parameters in the network-level optimization (variables, objective function, and constraints) are as follows:

$$\text{Decision Variables: } \begin{bmatrix} \mathbf{Y_{11}} & \mathbf{Y_{12}} & \mathbf{Y_{13}} & \mathbf{Y_{14}} & \mathbf{Y_{15}} \\ \mathbf{Y_{21}} & \mathbf{Y_{22}} & \mathbf{Y_{23}} & \mathbf{Y_{24}} & \mathbf{Y_{25}} \\ . & . & . & . & . \\ . & . & \mathbf{Y_{jk}} & . & . \\ . & . & . & . & . \\ \mathbf{Y_{j1}} & \mathbf{Y_{j2}} & \mathbf{Y_{j3}} & \mathbf{Y_{j4}} & \mathbf{Y_{j5}} \end{bmatrix} \qquad 3.1$$

where Yjk = 0 (no repair) and Yjk = 1 means component j is to be repaired in year k.

Objective function: minimize the network deterioration index (DI_N)

$$\mathbf{DI_N} = \frac{\sum_j(\mathbf{Average\ DI_{jk}} \times \mathbf{RIF_j}) + \sum_j(\mathbf{IE_{jk}} \times \mathbf{Y_{jk}} \times \mathbf{RIF_j})}{\sum_j \mathbf{RIF_j}} \qquad 3.2$$

$$\forall\, j \in \text{Network} \quad , \quad \forall\, k \in \text{Planning Horizon}$$

where RIFj is the relative importance factor (0 – 100) of component j, DIjk is the deterioration index (0 – 100) of component j in year k, and IEjk is the improvement effect of repairing component j in year k, which is equal to:

$$\mathbf{IE_{jk}} = \mathbf{EP_{jk}} - \mathbf{EP_{j0}} \qquad 3.3$$

where EPjk is the expected value of deterioration indices during the planning horizon when component j is repaired in year k, and is called the 'expected performance (EP)'. EPj0 is the initial performance of the component without any repairs.

Constraint: Total repair cost for the components selected in year k ≤ budget limit in year k.

Using the above formulation, a life-cycle cost analysis (LCCA) model has been implemented in an Excel spreadsheet, as shown in Figure 3.2. Part (a) of Figure 3.2 shows a partial list of asset components, where each row represents a component. The highlighted component (fire alarm system, for example) has a relative importance factor of 90 (defined internally by experts at the TDSB) as shown in the second column. The current performance (deterioration level) before repairs for this component is 72.49. The following columns then represent the cost and performance associated with repairs in years 1 to 5 (results of the project-level optimizations). For example, if the component is repaired in year 2 (as highlighted), its deterioration will be reduced from 72.49 to 24.31, at a cost of $42,350. Part (b) of Figure 3.2 is a continuation of part (a) (horizontals in the spreadsheet) and is used to formulate the LCCA and the optimization parameters. As an example, the decision to repair the fire alarm system in year 2 is selected by assigning a value of 1 to the decision variable of year 2 (as circled in the left side of part b). Accordingly, the LCCA model reads values for RIF (90), expected performance after repair in year 2 (24.31), and repair cost ($42.350). The combination of component decisions determines the overall network deterioration index, using Equations 3.1, 3.2, and 3.3.

3.3 Pavement Case Study

(Hegazy, Rashedi, & Ali, 2012) used a case study of the pavement management investment analysis challenge posted at the 6th International Conference on Managing Pavements (ICMP6). This case study was developed by the committee of the ICMP6 and was initiated to encourage asset management professionals to carry out an analysis and recommend strategies for managing a defined network of inter-urban and rural roads subject to high and light traffic. The network consists of 1293 road sections spanning 3240 km, covering two road classes and varying in traffic use, surface age, and condition. The inter-urban roads experience medium to high traffic, while the rural roads span most traffic and condition categories.

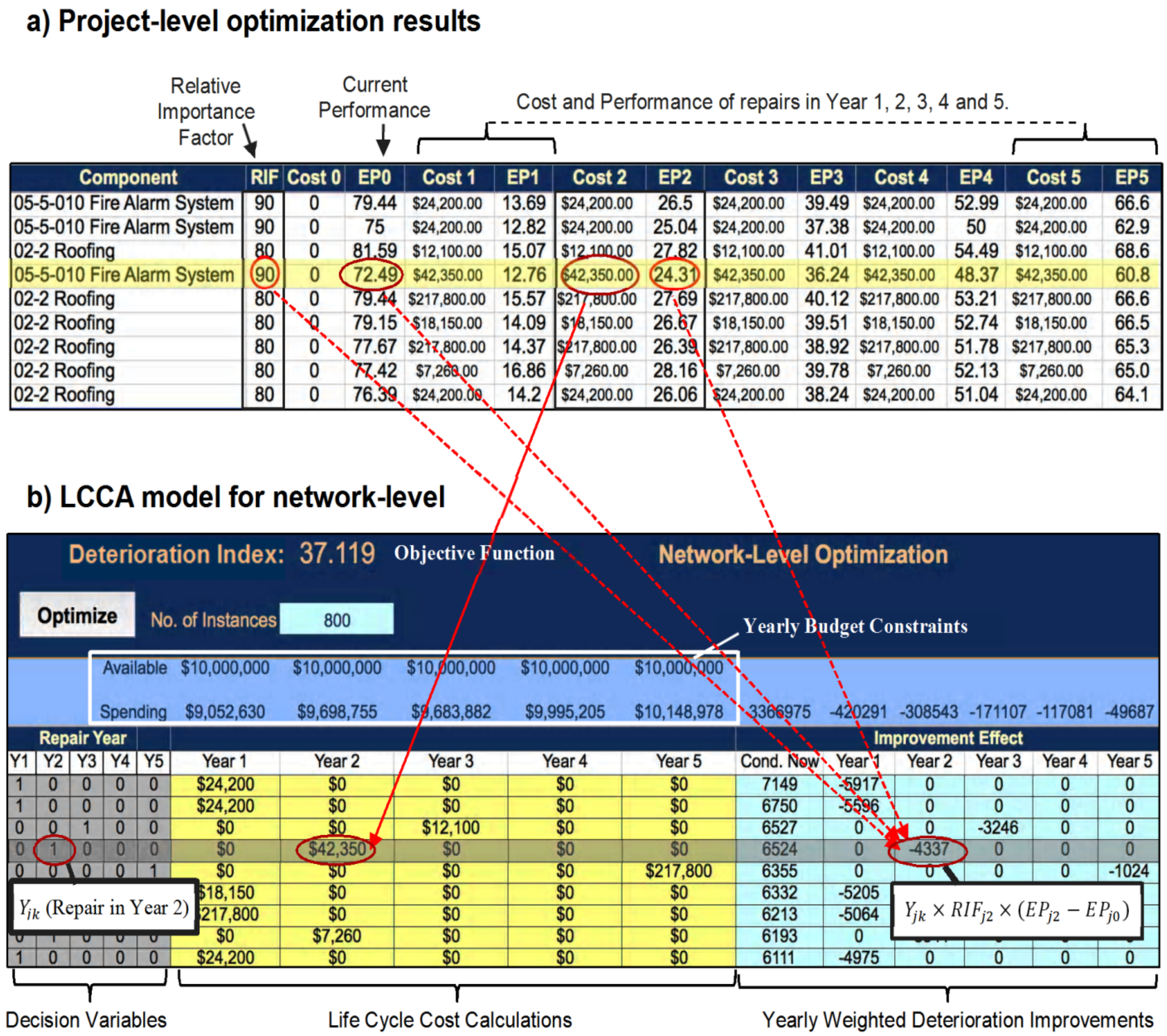


Figure 3.2: Spreadsheet Model for the Building LCCA

All pavement sections have consistent sub-soil conditions and are located within the same climatic region. Each section has a defined length, width, number of lanes, year of construction, AADT, base material type, base thickness, soil type, surface thickness, and most recent treatment. In addition, the extent of distresses, surface condition assessments

(International Roughness Index (IRI), and others), and predicted trigger or needs year are specified for all sections. The rate of annual traffic growth is specified as 2.5% for the inter-urban roads and 1.5% for the rural roads. The discount rate for investment analysis is 6%. The annual rate of increase of IRI, the repair costs, and the IRI trigger levels are shown in Table 3.1, Table 3.2, and Table 3.3, respectively. Figure 3.3 also shows the improvement for roughness after different treatments.

Table 3.1: Annual Increase Rate of IRI

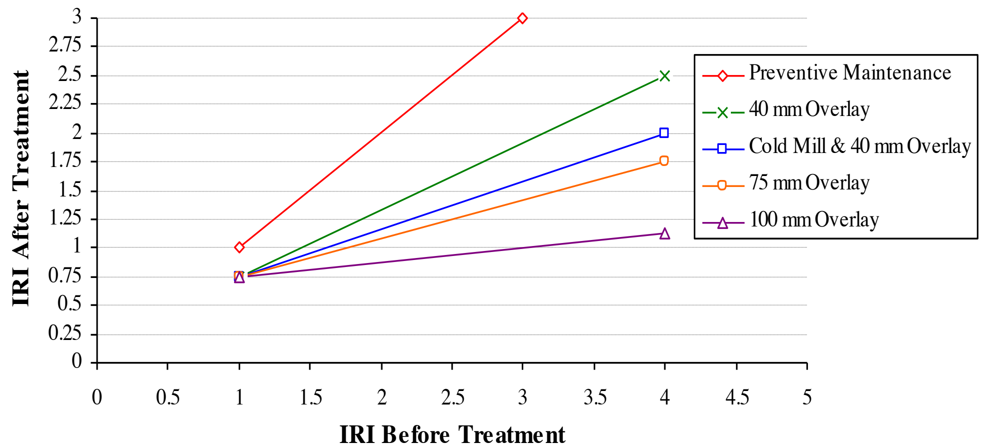
Road Class	AADT	Rate of Increase in IRI (m/Km/Yr.)
Interurban	>8000	0.069
	<8000	0.077
Rural	>1500	0.091
	<1500	0.101

Table 3.2: Repair Unit Cost

Intervention Type	Cost ($)
1. Preventive Maintenance	6.45
2. 40mm Overlay	6.75
3. Cold Mill & 40mm Overlay	10.50
4. 75mm Overlay	15.75
5. 100mm Overlay	16.50

Table 3.3: Trigger Levels of IRI

AADT	IRI Trigger Level (mm/m)
< 400	3.0
400 – 1500	2.6
1500 – 6000	2.3
6000 – 8000	2.1
> 8000	1.9



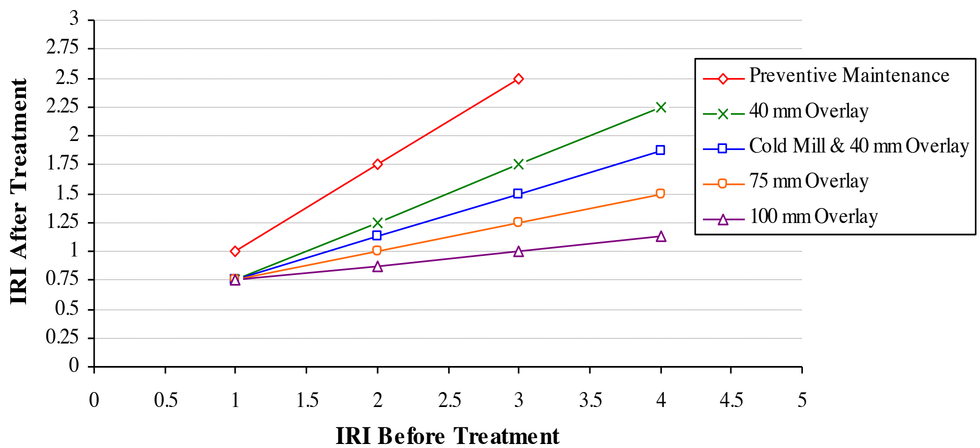


Figure 3.3: The Improvement Effect of Various Treatments

3.3.1 Model Formulation

The main difference between the LCCA model of this case study and that of the building case is that the pavement case study does not use the MOST approach for segmenting the project-level from the network-level analysis. Rather, it develops a model that handles both of them at the same time. This is expected to be a much more complex model. A spread-sheet-based LCCA model has been formulated for this case study, as shown in Figure 3.4, using Excel's VBA programming language as a macro program. Each pavement section is represented as a separate row, and all its related data are represented in columns. The model is formulated considering a five-year planning horizon. It produces two decisions:

- Repair Type: an index to one of the five repair types in column "Repair Type" for each pavement section (integer variables); and
- Repair Timing: an index for each year of the five-year planning horizon (year 1 to year 5) for each pavement section (binary variables).

The two decisions, repair timing and repair type, for each pavement section over the planning period are linked by equations to the related functions of performance assessment, deterioration, repair costs, and improvements after repair.

The proposed spreadsheet calculates a Priority Index (PI) by combining the IRI with the AADT for each road section. This index varies from 0 to 5, where 0 means the road has low priority and high performance and 5 means high priority and low performance. The spreadsheet also predicts the future condition of the roads based on the annual rate of IRI increase shown in Table 3.1 and the AADT. In addition, it estimates the after-repair condition resulting from each repair type, as shown in Figure 3.3. Predicting the future and after-repair conditions enables life-cycle analysis for the five-year planning horizon. Each of the five repair types available for each pavement section is represented in the spreadsheet as an integer value ranging from 1 to 5, while repair timing is referenced using binary variables (1 represents a repair action and 0 means no repair). Since a pavement section can be repaired only once during the planning horizon (i.e. a single visit), all years must have a sum of binary variables of either 1 or 0 (no repair). In the spreadsheet, the LCC over the planning horizon is calculated yearly for each pavement section with the Vehicle Operating Cost (VOC) and the cost of the selected repair type is taken into consideration. Figure 3.4 shows an overview of the spreadsheet model showing all sheet portions that relate to the various functions of asset management. Finally, the equivalent present value of the total LCC is calculated in the spreadsheet according to the following equation:

$$\text{Total LCC} = \text{Sum of } [(\text{Repair Costs} + \text{VOC})_n / (1+i)^n] \qquad 3.4$$

where n is the year number and i is the applicable interest rate per year (user input).

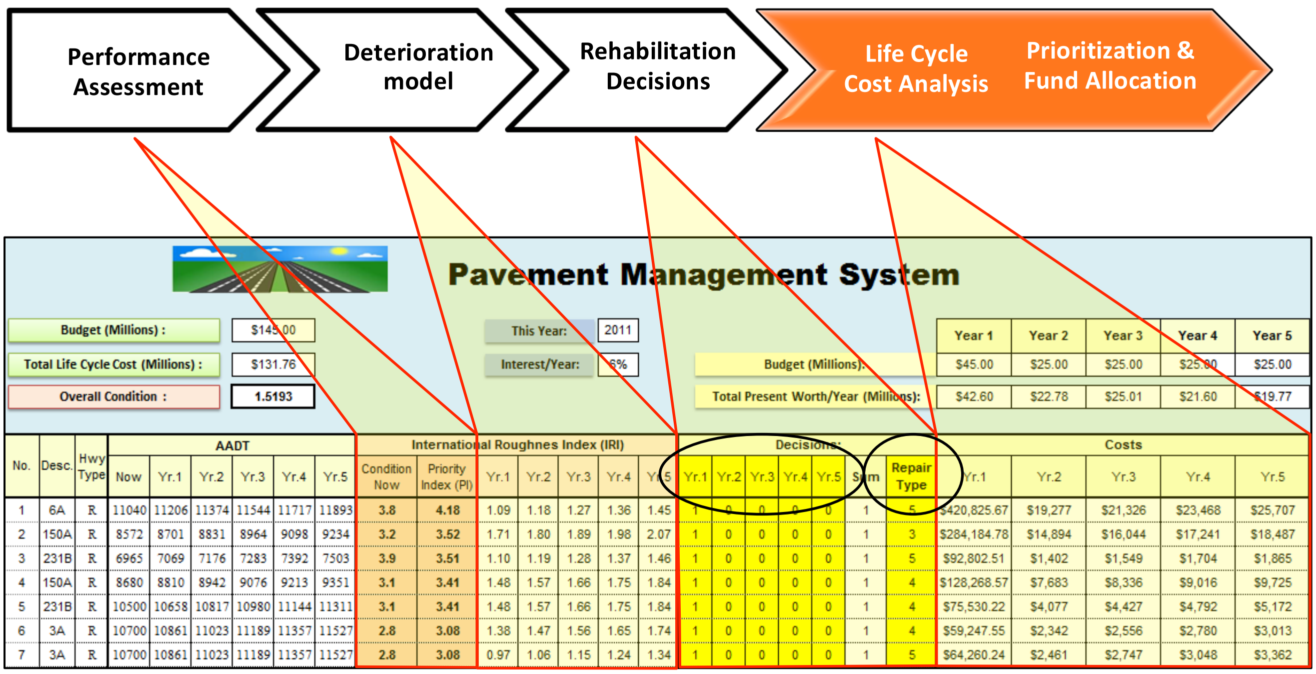


Figure 3.4: Spreadsheet LCCA model for the Pavement Case

3.4 Bridge Case Study

The third case study relates to a real case of a 47-bridge network reported in (Elbehairy, 2007). The data for the case study were collected from a Department of Transportation (DOT). The DOT owns and operates 173 bridges: data for 47 bridges are provided as a case study; however, some of the data were collected through interviews with engineers from the DOT. The data include general information such as bridge ID, road name, bridge name, annual average daily traffic (AADT), percentage of trucks, bridge length (m), bridge width (m), last year of repair, and last value of repair cost (Table 3.4). The data also include details about bridge element condition ratings, element weights, and repair costs.

Table 3.4: Sample of Bridges General Information

Bridge ID	Bridge Name	Construction Year	AADT	% Heavy Veh.	ADT Year	Detour (Km)	Width (m)	Length (m)	Last Repair	Value ($1000s)
102	Hidden for Confidentiality	1960	5111	10	2005	0.168	17.5	8.4	1980	265
103		1998	2095	3	2005	1.06	12.2	53	1998	1165
104		1974	3168	5	2005	0.104	28.5	5.2	1974	266
401		1969	16082	1	2005	0.292	20.1	14.6	1994	527
402		1958	5012	5	2005	0.196	12.6	9.8	1994	221
404		1936	7015	2	2005	0.85	11.4	42.5	2006	873
1603		1960	2348	22	2005	0.136	12.3	6.8	1996	151
1702		1963	6243	10	2005	2.47	11.5	123.5	2001	2556
1703		1967	2265	8	2005	0.754	10.9	37.7	1994	740
1704		1967	2265	8	2005	1.298	10.9	64.9	1994	1273
1705		1963	1329	4	2005	0.414	11.6	20.7	1993	432
1706		1961	1646	10	2005	0.19	11.7	9.5	1961	200

The DOT uses a condition assessment that specifies the percentage of the element that is in excellent (E), good (G), fair (F), or poor (P) condition, as shown in Table 3.6. For example, the condition of bridge 0504's asphalt (surface) is judged to be 21% fair and 79% good. Similarly, the deck and joint conditions for the same bridge are 100% good.

The conversion values shown in Table 3.5 are used to convert the DOT's condition percentages to the Federal Highway Administration (FHWA) condition rating scale (0-9). For example, the asphalt of bridge 0504 has a condition rating of 5.58 (0.79 x 6 + 0.21 x 4) (Table 3.6).

Table 3.5: FHWA Condition Rating Conversion Values

Condition state	Condition Rating Range
Excellent	8
Good	6
Fair	4
Poor	1.5

For elements weights, the DOT engineers were asked to evaluate the importance of each bridge element (1-10) to the overall bridge condition rating. Based on these evaluations, the importance factors were determined and used to calculate the contribution weight for each element to the overall bridge, as shown in Table 3.7. The cost data were collected from previous DOT contracts and through interviews with the DOT engineers. The collected cost data does not provide unit prices; however, it was possible to obtain unit price estimates from contract documents for sample bridges and with the use of CAD drawings (Table 3.8). The data provided by the DOT has no information about future conditions or condition improvement after a repair action.

3.4.1 Model Formulation

(Elbehairy, 2007) developed a Multi-Element Bridge Management System (ME-BMS) that optimizes and integrates bridge-element repair decisions (project-level decisions) and the selection of the appropriate timing for implementing the repairs (network-level decisions). The model uses a non-traditional evolutionary algorithm (EA) optimization technique. It also incorporates two models for estimating user costs resulting from the deteriorated conditions of a bridge and users crossing a work zone during repair activities.

The system was implemented on a spreadsheet program using Microsoft Excel, and all the genetic algorithm (GA) procedures were coded with the macro language of Microsoft Excel. The system was formulated considering a five-year planning horizon. Based on the six models incorporated in the system, for condition rating, time-dependent deterioration, repair cost, repair-improvement, and user cost, the system produces two decisions:

- Project-level decision: the best repair type for each element if the repair is done in year1, year2, etc.
- Network-level decision: for each bridge, determining the best year to implement the project-level decisions.

Table 3.6: Sample Condition Data for Bridge Elements

Bridge ID	joints	E	G	F	P	Surface	E	G	F	P	Deck		E	G	F	P
0102	---					Asphalt		100			Thick Slab	Cast-in-place concrete		99	1	
0103	Seals/sealants		100			Asphalt		100			Thin Slab	Cast-in-place concrete		100		
0104	---					Asphalt		100			Thin Slab	Cast-in-place concrete		100		
0401	---					Asphalt		100			Thick Slab	Cast-in-place concrete		100		
0402	---					Asphalt		100			Thick Slab	Cast-in-place concrete		90	10	
0404	Seals/sealants			100		Asphalt			65	35	Thin Slab	Corrugated Steel			60	40
0501	Seals/sealants		50	50		Asphalt		95		5	Thick Slab	Cast-in-place concrete		95	5	
0502	Seals/sealants		100			Asphalt			95	5	Thick Slab	Cast-in-place concrete		100		
0504	Seals/sealants		100			Asphalt		79	21		Thin Slab	Cast-in-place concrete		100		
0505	---					Asphalt	100					Cast-in-place concrete			100	
0506	---					Asphalt	100					Cast-in-place concrete			100	

Table 3.7: Weights of Elements

Element	Importance Factor	Weight
Deck	9	0.191
Overlay	6	0.128
Joints	4	0.085
Bearings	8	0.170
Superstructure	10	0.213
Substructure	8	0.170
Finishing (coating)	2	0.043
	$\Sigma = 47$	$\Sigma = 1.0$

Table 3.8: Cost Data

Element	Repair Option	Unit	Unit Price ($)
Deck	Concrete patches	m^3	4,530.00
	Concrete removal (partial depth)	m^3	1,667.00
	Concrete deck repairs	m^2	340.00
	Deck waterproofing	m^2	16.83.00
Overlay	Removal of asphalt pavement	m^2	8.00
	Concrete overlay and curing	m^2	88.50
	Concrete overlay	m^3	730.00
Joints	Hot rubberized asphalt joint	m	1,671.00
Bearings	Repair/replacement	each	600.00
Substructure	Excavation for structure footing	m^3	52.71
	Concrete in footings	m^3	430.00

The condition rating model calculates the overall bridge condition rating (BCR) based on the conditions and weights of its elements according to the following equation:

$$BCR = \frac{\Sigma(element\ condition\ rating \times element\ weight)}{\Sigma weights} \qquad 3.5$$

The deterioration model estimates the deterioration behavior for each element using two different methods: Markov deterioration (e.g. the deck, the superstructure, and the substructure), and linear deterioration (the remaining bridge elements) (Figure 3.5).

As shown in Figure 3.5, a bearing of Type 2 has an expected life of 10 years under a severe working environment and 12 years under a moderate working environment.

Six repair options are proposed for each element, ranging from 0 (do nothing) to 5 (extensive repair). The extent of each repair option is determined in a percentage, as shown in the second column of each section of **Error! Reference source not found.**.

Main Menu

Element types

Element	Deterioration model	Linear Expected life (years)				Markov				
		Type1		Type2		Type1		Type2		Creat Matrix
		Severe	Moderate	Severe	Moderate	Severe	Moderate	Severe	Moderate	
Deck	☐ Linear ☑ Markov					Matrix	Matrix	Matrix	Matrix	
Overlay	☑ Linear ☐ Markov	12	15	10	13					
Joints	☑ Linear ☐ Markov	12	14	12	15					
Bearings	☑ Linear ☐ Markov	8	10	10	12					
SupperStructure	☐ Linear ☑ Markov					Matrix	Matrix	Matrix	Matrix	
SubStructure	☐ Linear ☑ Markov					Matrix	Matrix	Matrix	Matrix	
Finishing	☑ Linear ☐ Markov	10	12	12	16					

Linear/Markov Deterioration

Expected Lifespan

Hyperlink to TPM values

Hyperlink to matrix customization

Figure 3.5: ME-BMS Deterioration Model

For example, a joint element of Type 1 (steel) with a repair Type 1 (repair) would cost \$800/m. Using the data in **Error! Reference source not found.**, the total cost of repairing bridge *i* is calculated as follows:

$$RC_i = \sum_{j=1}^{7} C_{jmp} \times Size_j \tag{3.6}$$

where RC_i = the repair cost for bridge *i*, *j*= the bridge element, *m* = the repair option (0 - 5), *p* = the element type (Type 1 or Type 2), C_{jmp} = the unit cost of repairing element *j* using repair option *m* for type *p*, and $Size_j$ = the dimension or quantity of element *j*. For example, the size of the bearing component is the total number of bearings in the bridge, while the size of a deck is its width multiplied by its length.

The improvement model calculates the after-repair condition by the amount of condition improvement that corresponds to the repair type according to the values shown in **Error!**

Reference source not found.. For example, if the current condition of an element is 5, and repair option 3 is used, then the condition rating after improvement will be 6 (5+1).

The user cost model considers the annual traffic growth, the annual accident rates, the vehicle operating costs, and the user delay costs. However, the vehicle operating costs and the user delay costs are considered only when a bridge load capacity and/or a vertical clearance limit are posted. The user costs are calculated in the model according to the following equation:

$$UC_i = AC_i \times A_{cost} + VOC_i + UD_i \qquad 3.7$$

where AC_i= the accident count for bridge i, A_{cost} = the accident cost, VOC_i = the vehicle operating costs for bridge i, and UD_i = the user delay costs for bridge i. As shown in **Error! Reference source not found.**, bridge 404, for example, has an accident cost of \$28,068, VOC of \$54/km, and delay cost of \$87/hour.

After performing all the calculations related to the condition rating, deterioration, repair cost, repair-improvement, and user cost, the system now produces the project-level and network-level decisions. Part (A) of Figure 3.6 shows the repair options decided for each element (project-level decisions), part (B) shows the year chosen for repair (network-level decision), part (C) shows the overall Bridge Condition Rating (BCR), and part (D) shows the cost of repairs.

Table 3.9: Improvement after Repair Action

Repair Type	Condition before improvement		Condition after improvement				
			8.0 – 9.0	7.0 – 8.0	6.0 – 7.0	5.0 – 6.0	4.0 – 5.0
0	8.0	9.0	0				
1	7.0	8.0	1				
2	6.0	7.0	2	1			
3	5.0	6.0	3	2	1		
4	4.0	5.0	4	3	2	1	
5	3.0	4.0	5	4	3	2	1

Table 3.10: Repair Cost for Elements Repair Types

Repair Type	Condition Rating		Extent of Repair	Deck						Overlay					
				Concrete			Steel			Concrete			Asphalt		
	Min	Max		Repair Option	Cost	Unit	Repair Option	Cost	Unit	Repair Option	Cost	Unit	Repair Option	Cost	Unit
0	8.0	9.0	0%	Do nothing	$0		Do nothing	$0		Do nothing	$0		Do nothing	$0	
1	7.0	8.0	25%	Crack sealin	$100	m2	Paint (10% a	$200	m2	Sealing	$40	m2	Sealing	$20	m2
2	6.0	7.0	35%	Partial replac	$200	m2	Paint and rep	$350	m2	Patch	$50	m2	Patch	$20	m2
3	5.0	6.0	50%	Partial replac	$200	m2	Paint + Repla	$350	m2	Patch	$70	m2	Patch	$30	m2
4	4.0	5.0	70%	Replace top	$300	m2	Paint + Repla	$500	m2	Replace	$70	m2	Replace	$30	m2
5	3.0	4.0	80%	Replacetop +	$300	m2	Paint + Repla	$500	m2	Replace	$70	m2	Replace	$40	m2

Repair Type	Condition Rating		Extent of Repair	Joints						Bearings					
				Steel			Rubber			Steel			Neubrane		
	Min	Max		Repair Option	Cost	Unit	Repair Option	Cost	Unit	Repair Option	Cost	Unit	Repair Option	Cost	Unit
0	8.0	9.0	0%	Do nothing	$0		Do nothing	$0		Do nothing	$0		Do nothing	$0	
1	7.0	8.0	25%	Repair	$800	m	Patch	$800	m	Repair	$600	unit	Repair	$600	unit
2	6.0	7.0	35%	Replace	$1,600	m	Replace	$1,600	m	Replace	$600	unit	Replace	$600	unit
3	5.0	6.0	50%	Replace	$1,600	m	Replace	$1,600	m	Replace	$600	unit	Replace	$600	unit
4	4.0	5.0	70%	Replace	$1,600	m	Replace	$1,600	m	Replace	$600	unit	Replace	$600	unit
5	3.0	4.0	80%	Replace	$1,600	m	Replace	$1,600	m	Replace	$600	unit	Replace	$600	unit

Repair Type	Condition Rating		Extent of Repair	SupperStructure						SubStructure					
				Concrete			Steel			Concrete			Steel		
	Min	Max		Repair Option	Cost	Unit	Repair Option	Cost	Unit	Repair Option	Cost	Unit	Repair Option	Cost	Unit
0	8.0	9.0	0%	Do nothing	$0		Do nothing	$0		Do nothing	$0		Do nothing	$0	
1	7.0	8.0	25%	Repair	$500	m2	Paint	$350	m2	Repair	$1,000	m2	Paint	$500	m2
2	6.0	7.0	35%	Replace	$600	m2	Repair	$1,500	m2	Replace	$1,500	m2	Repair	$500	m2
3	5.0	6.0	50%	Replace	$700	m2	Replace	$1,500	m2	Replace	$2,000	m2	Replace	$500	m2
4	4.0	5.0	70%	Replace	$700	m2	Replace	$2,500	m2	Replace	$2,000	m2	Replace	$500	m2
5	3.0	4.0	80%	Replace	$700	m2	Replace	$2,500	m2	Replace	$2,000	m2	Replace	$500	m2

Repair Type	Condition Rating		Extent of Repair	Finishing					
				Class A			Class B		
	Min	Max		Repair Option	Cost	Unit	Repair Option	Cost	Unit
0	8.0	9.0	0%	Do nothing	$0		Do nothing	$0	
1	7.0	8.0	25%	Repair	$50	m2	Paint	$50	m2
2	6.0	7.0	35%	Replace	$100	m2	Repair	$100	m2
3	5.0	6.0	50%	Replace	$100	m2	Replace	$100	m2
4	4.0	5.0	70%	Replace	$100	m2	Replace	$100	m2
5	3.0	4.0	80%	Replace	$100	m2	Replace	$100	m2

Table 3.11: User Cost Input Data and Calculation Sample

		Network Level Decisions	2007	After Repair User Costs								Total User Cost
Bridge ID	BR. Name		ADT	Accident Rate	Accident Cost	Load posting (tons)	%detoured veh. (weight limit)	%detoured veh. (Height limit)	Detoured Veh.	VOC cost	Delay Cost	$4,324,249
102		0	5,315	0.85	$32,073	26.55	1.66%	6.23%	419	$6,108	$9,844	$48,024
103		0	2,179	0.06	$2,134	32.85	1.15%	0.00%	25	$2,302	$3,711	$8,147
104		0	3,295	0.38	$14,424	24.45	1.86%	0.90%	91	$820	$1,321	$16,565
401		0	16,725	3.63	$136,505	31.45	1.24%	0.90%	358	$9,060	$14,602	$160,167
402		0	5,212	0.96	$36,037	31.45	1.24%	0.00%	65	$1,098	$1,770	$38,905
404		1	7,296	0.75	$28,068	36	0.00%	0.01%	1	$54	$87	$28,208
702		1	2,460	0.22	$8,257	36	0.00%	0.90%	22	$3,205	$5,165	$16,626
802		0	21,011	5.48	$206,147	34.95	0.96%	0.90%	391	$8,470	$13,650	$228,267
803		0	23,430	5.91	$222,049	33.55	1.06%	0.90%	459	$106,610	$171,820	$500,479
804		0	28,605	6.62	$248,735	29	1.41%	0.90%	661	$64,613	$104,135	$417,484

Bridge ID	Element Repair Decision							Network-Level Decision		BCR		Repair Cost	
	2007												
	Slab	Overlay	joint	Bearing	Supper	Sub	Finish	2007	2008	2007	2008	2007	2008
102	0	0	0	0	0	0	0	0	1	5.72	7.55	$0	$13,607
103	0	0	0	0	0	0	0	0	1	6.57	7.07	$0	$23,424
104	0	0	0	0	0	0	0	0	1	5.76	7.17	$0	$7,298
401	0	0	0	0	0	0	0	0	0	5.59	5.31	$0	$0
402	0	0	0	0	0	0	0	0	0	5.60	5.32	$0	$0
404	5	5	1	0	3	3	2	1	0	7.18	6.93	$257,094	$0
501	0	0	0	0	0	0	0	0	0	5.50	5.20	$0	$0
502	1	5	0	0	1	2	0	1	0	7.27	7.00	$83,312	$0
504	0	0	0	0	0	0	0	0	0	5.58	5.30	$0	$0
505	0	0	0	0	0	0	0	0	1	4.86	7.52	$0	$24,314

(A) (B) (C) (D)

Figure 3.6: Project-Level and Network-Level Decisions

Table 3.12: Summary of Three Case Studies

	Asset Type	No. of Assets	Planning Horizon	Approach Classification	Used Tool	LCCA Variables	Constraints
Case 1	Buildings	N1 = 801	5 years	Optimization: Non-traditional EA optimization technique (GA Optimization technique)	Microsoft Excel-add-in program Evolver	Network-Level Decision: year by year Formulation No. of variables: [Tear of repair (binary) = N1 × 5 years planning horizon]	• Budget Limit: $10M/year • One visit/planning period
Case 2	Pavement	N2 = 1293	5 years	Heuristic	Microsoft Excel	Project + Network Level Decisions: one formulation No. of variables: [Year of repair (binary) = N2 × 5 years planning horizon] + [Type of repair = N2 × 5 repair types (integer)]	• Budget Limit: $10M/year • One visit/planning period • Minimum acceptable IRI values
Case 3	Bridges	N3 = 47	5 years	Optimization: Non-traditional EA optimization technique	Microsoft Excel-add-in program Evolver	Project + Network Level Decisions: one formulation No. of variables: [Year of repair (binary) = N3 × 5 years planning horizon] + [type of repair = N3 ×	• Budget Limit: $40M/year • One visit/planning period

3.5 Summary

In this chapter, LCCA models for three types of assets (pavement, bridges, and buildings) have been introduced. An overview of each model has been presented. The implementation of the three models in the form of spreadsheets was presented using a publically available database.

Chapter 4
Optimization and Heuristic Fund-Allocation Results

4.1 Introduction

In this chapter, optimization and heuristic approaches are introduced and used for allocating funds for the three LCCA models presented in Chapter 3. The proposed approaches were programed and executed on a personal computer with 2.8 Ghz of speed processor and 8GB of RAM. Experiments and results of both approaches are presented and discussed. Later, in Chapter 5, large-scale networks will be discussed.

4.2 Experimenting with the Heuristic Approach

The heuristic approach used in this research was developed by (Hegazy et al., 2012) and modified for the three case studies addressed in this research. The approach was developed for near-optimum allocation of pavement rehabilitation funds. It first rank assets (pavements) based on a calculated priority index which reflects the need for urgent repair action. A Relative Importance Factor (RIF) for the priority index is calculated as follows:

$$\mathrm{RIF_j} = \mathrm{IRI_{MAX}} - \text{IRI Trigger Levels} \qquad 4.1$$

where $\mathrm{RIF_j}$ is the relative important factor for pavement j, $\mathrm{IRI_{MAX}}$ is the maximum IRI value of 4, and IRI Trigger levels are the acceptable level of IRI for a certain road (based on its traffic). Using Equation 1, therefore, Table 4.1 shows the IRI trigger levels for various pavements and their calculated relative importance factors. Then, the Priority Index (PIj) for repairing pavement j is calculated as follows:

$$PI_j = RIF_j \times IRI_{0j} \qquad 4.2$$

where $\mathrm{IRI_{0j}}$ is the current IRI value for pavement j. Finally, an Overall Pavement Network Condition is calculated as follows:

$$\text{Overall Pavement Newotk Condition} = \frac{\sum_{j=1}^{N}\sum_{k=1}^{5} \mathrm{IRI}_{jk}}{N} \qquad 4.3$$

$$\forall\, j \in \text{network}, \forall\, k \in \text{planning horizon}$$

Table 4.1: Relative Importance Factor

AADT	IRI Trigger Level (mm/m)	Relative Importance Factor (RIF)
<400	3.0	1
400-1500	2.6	1.4
1500-6000	2.3	1.7
6000-8000	2.1	1.9
>8000	1.9	2.1

Pavements with higher priority (higher PI value) are considered first. After prioritizing pavements, the proposed heuristic approach is applied for selecting the best treatment types and timing under budget limits. The method allocates budgets year-by-year. Each year is considered separately, starting from year 1 and moving successively to the next, until the end of the planning horizon (Figure 4.1). One by one, assets with IRIs that violate the trigger level in the year under consideration are repaired with the least-cost treatment that keeps the assets above an acceptable level throughout the planning horizon until the budget limit of that year is reached. The same heuristic approach will be used in the three case studies.

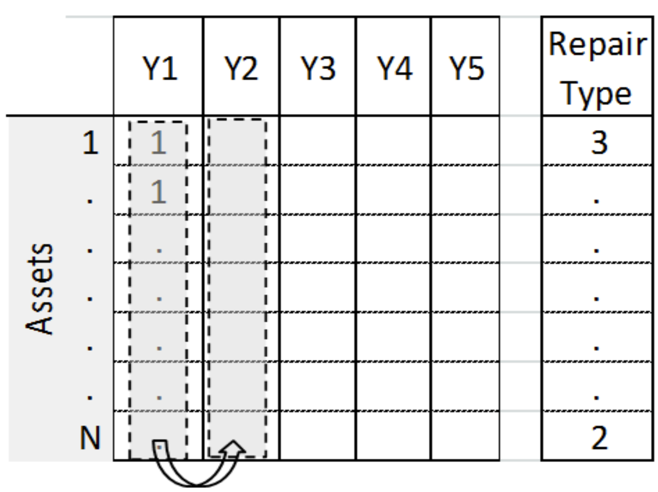


Figure 4.1: Fund Allocation Heuristic Year-by-Year Process

The aforementioned fund allocation heuristic approach is implemented on three LCC models for three different types of real-life case studies (buildings, pavements, and bridges). Implementation details and results are presented in the following subsections.

4.2.1 Building Case Study

This case study consists of data related to a network of 800 school building instances with a limited yearly budget of about 10 million dollars. The overall network condition represents a deterioration index (DI) ranging from 0 to 100, where 0 is the best. The network has a current overall condition of 54. Following the steps and procedures of the heuristic approach mentioned in section 4.2, building instances were first prioritized based on a Priority Index (PI) that is calculated by combining RIF with the DI for each building instance, according to the following equation:

$$PI_j = RIF_j \times DI_{0j} \qquad 4.4$$

wherew $DI_{0\mathrm{j}}$ is the current DI value for instance j, and RIF_j is the relative importance factor for instance j.

The relative importance factor for an instance is determined as a value ranging from 0 to 100, where the value of 100 implies high importance. To determine a RIF's value, the impacts of the instance's bad condition (failure) on three main parameters (decided after discussions with the administrators at the TDSB) are evaluated. These three parameters are safety, building performance, and effect on other components. The PI ranges from 3 to 72, where 72 mean high priority and low performance. After calculating the PI values for each instance, the heuristic approach's remaining procedures are followed, as explained in section 4.2.

After applying the heuristic approach considering the five-year planning horizon, the overall network condition has improved to 44. 99.18% of the budget was spent using the heuristic approach. The processing time for producing the final decisions was 7 seconds, which is considered very rapid and efficient.

4.2.2 Pavement Case Study

This case study consists of data related to a network of 1293 pavement sections with a limited yearly budget of 25 million dollars. The IRI values for each pavement section are used to represent the condition of the network, where lower IRI value means better condition. Following the steps and procedures of the heuristic approach mentioned in section 4.2, pavement sections were first prioritized based on a Priority Index (PI) that is calculated by combining IRI with the AADT for each section. The PI values range from 0 to 5, where 5 means high priority and low performance and a PI of 0 means the pavement has low priority and high performance. Without any repair action, the network has an overall condition of 1.7097. After applying the heuristic approach considering the five-year planning horizon, the overall network condition has improved to 1.5745. 99.98% of the budget was spent using the heuristic approach. The processing time for producing the final decisions was 34 seconds, which is considered rapid and efficient.

4.2.3 Bridge Case Study

The bridge case study consists of data related to a network of 47 bridges with a limited yearly budget of about 600,000 dollars. The condition rating scale ranges from 0 to 9, where 0 means poor condition and 9 means excellent condition. Without any repair action, the network has an overall condition of 4.89. The first step of applying the heuristic approach is prioritizing bridges based on a Priority Index (PI) that is calculated by combining current condition (BCR) with the AADT for each bridge, according to the following equation:

$$PI_j = AADT_j \times BCR_{0j} \quad 4.5$$

where BCR_{0j} is the current condition rating for bridge j, and $AADT_j$ is the annual average daily traffic for bridge j.

The PI ranges from 7 to 165, where 165 means high priority and 7 means low priority. After calculating the PI values for each bridge, the heuristic approach's remaining procedures are followed as explained in section 4.2.

After applying the heuristic approach considering the five-year planning horizon, the overall network condition has improved to 5.91. 99% of the budget was spent using the heuristic approach. The processing time for producing the final decisions was 2 seconds, which is considered very quick and efficient.

4.2.4 Discussion of Results

The heuristic approach has been implemented on building, pavement, and bridge case studies, using three LCC models. Each case study has a different limited yearly budget, number of assets, and repair options. Based on the data provided in each case study, each model was formulated to deal with a different number of details. Accordingly, the complexity of each model is not equal. For example, the building case study model considers three repair options for each instance, about 10 million dollar yearly budget, and 800 building instances, while the bridge case study model considers five repair options for each of the seven elements considered for each bridge, a 600,000 dollar yearly budget, and 47 bridges. Nevertheless, implementing the heuristic approach has improved the overall condition and allocated funds efficiently for the three case study networks (Figure 4.2). The condition improvement, percentage of the money spent, and processing time for all case studies are shown in Table 4.2.

Table 4.2: Summary of Results Obtained Using the Heuristic Approach

Case Study	Network Size	Overall Condition	After Repair Overall Condition	Condition Improvement	Total Budget	Total Spending	Percentage of Spending	Processing Time
Buildings	800 instances	54.33	44.79	17.56%	50,062,500	49,650,279	99.18%	7 sec
Pavements	1,293 pavements	1.7097	1.5745	7.91%	125,000,000	124,978,800	99.98%	34 sec
Bridges	47 bridges	4.89	5.91	20.86%	3,000,000	2,992,277	99.74%	2 sec

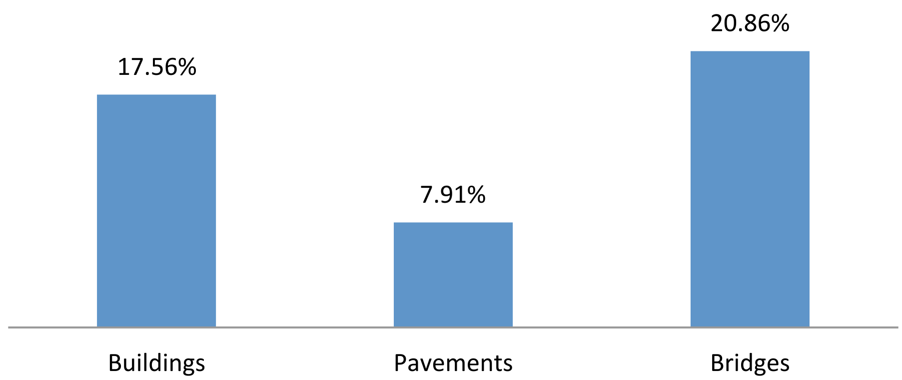


Figure 4.2: Heuristic Approach: Condition Improvement

4.3 Experimenting with the Optimization Approach

This section presents the implementation of the aforementioned optimization fund allocation approach. The results and outputs of implementing the approach are presented in the following subsections. For the optimization approach, a non-traditional optimization tool based on genetic algorithms (Evolver) was used as a random search method. Evolver is an Excel add-in program that proved suitable for solving large-size problems for which mathematical optimization techniques fail (Elbeltagi et al., 2005).

4.3.1 Building Case Study

As mentioned earlier, the building case study consists of a network of 800 school building instances with a limited yearly budget of about 10 million dollars. The network condition is represented by a deterioration index (DI). The DI values ranges from 0 to 100, where 0 means the best condition. The network has a current overall condition of 54. The genetic algorithm-based optimization tool Evolver is used and formulated to allocate the available funds and to maximize the condition improvement. The objective function is formulated to minimize the overall network DI_N, whereas lower a DI value means better condition, as follows:

$$Objective = \quad min\, DI_N \qquad 4.6$$

where DI_N is the Deterioration Index value for the whole network.

The objective function is subject to the following constraints:

- The repair cost at a specific year t for the network should be within the allowed budget:

$$repair\ cost_T \leq\ allowed\ budget_T \qquad 4.7$$

- Each instance receives one repair action (i.e. a single visit) during the planning horizon.

The optimization has been performed considering 5 minutes per year (25 minutes total running time) and 30 minutes per year (150 minutes total running time). It also considers the five-year planning horizon, a 10 million dollar yearly budget, and 800 instances. Considering 5 minutes per year running time has improved the overall network condition to 35.748, 99.67% of the budget was spent, with a total running time of 25 minutes. On the other hand, the 30 minutes per year running time improved the overall network condition to 34.288, 99.88% of the budget was spent, with a total running time of 150 minutes. Processing times of both 25 and 150 minutes for producing the final decisions are considered short and efficient. It can be noted that increasing the processing time will increase the condition improvement. However, a long processing time will have a very limited effect on the output condition improvement.

4.3.2 Pavement Case Study

In this model, the optimization process considers a network of 1293 pavement sections with a limited yearly budget of 25 million dollars. The IRI values are used to represent the condition of the network; where, lower IRI value means better condition. Evolver, an Excel add-in optimization program, has been used for maximizing the overall network condition (minimizing IRI_{OV}). The overall network condition (IRI_{OV}) is the average of IRI values for all pavement sections. The optimization model has been formulated as follows:

$$Objective = \quad min\, IRI_{OV} \tag{4.8}$$

where IRI_{OV} is the overall network condition.

This objective function is subject to the following constraints:

- The repair cost at a specific year t for the network should be within the allowed budget:

$$repair\ cost_T \leq \ allowed\ budget_T \tag{4.9}$$

- Each section receives one repair action (i.e. a single visit) during the planning horizon.

The optimization has been performed considering 15 minutes per year (75 minutes total running time), a five-year planning horizon, a 25 million dollar yearly budget, and 1293 pavement sections. Without any repair action, the network has an overall condition of 1.7097. The overall network condition has improved from 1.7097 to 1.5602. 99.92% of the budget was spent. The processing time for producing the final decisions was 75 minutes, which is efficient.

4.3.3 Bridge Case Study

In this case study, the optimization model has been formulated to maximize the overall network condition (NCR) as follows:

$$Objective = \max(NCR) \tag{4.10}$$

where *NCR* is the overall network condition.

This objective function is subject to the following constraints:

- The repair cost at a specific year t for the network should be within the allowed budget:

$$repair\ cost_T \leq\ allowed\ budget_T \qquad 4.11$$

- Each bridge receives one repair action (i.e. a single visit) during the planning horizon.

With this formulation, the model has succeeded with allocating the available funds and improving the overall network condition. 93.79% of the budget was allocated. The overall network condition has improved from 4.89 to 6.44.

4.3.4 Discussion of Results

The optimization technique used is genetic algorithm-based, and randomly searches for a feasible solution among the possible combinations and solutions. Then, it selects the solution that best satisfies the objective function and constraints. The genetic algorithm technique has proved to be capable of arriving at near-optimal solutions.

This technique has been implemented on the three case studies. The optimization technique allocated funds and improved the overall condition successfully for all three case studies (Figure 4.3). Based on the results, the condition improvement, the percentage of the money spent, and the processing time for all case studies are shown in Table 4.3.

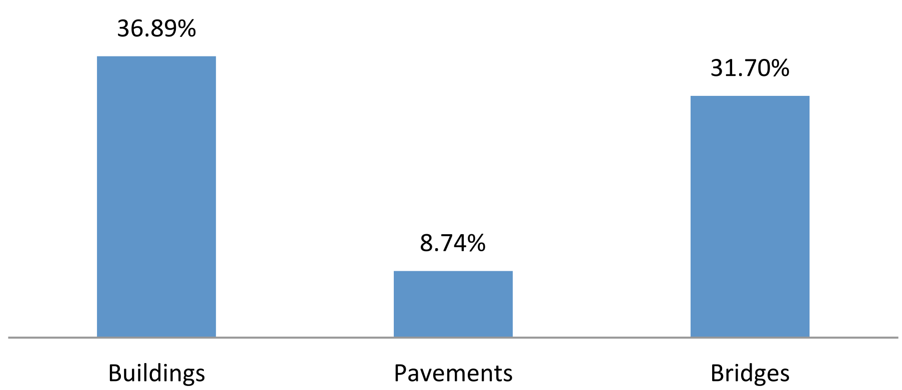


Figure 4.3: Optimization Approach: Condition Improvement

Table 4.3: Summary of Results Obtained Using the Genetic Algorithm Optimization

Case Study	Network Size	Condition	After Repair Overall Condition	Condition Improvement	Total Budget	Total Spending	Percentage of Spending	Processing Time
Buildings	800 instances	54	34	36.89%	50,062,500	50,004,590	99.88%	150 minutes
Pavements	1,293 pavements	1.7097	1.5602	8.74%	125,000,000	124,900,886	99.92%	75 minutes
Bridges	47 bridges	4.89	6.44	31.70%	3,000,000	2,813,555	93.79%	50 minutes

4.4 Heuristic vs. Optimization: Results Comparison

Heuristic and genetic algorithm optimization techniques have been used and implemented on real-life case studies for buildings, pavements, and bridges. Each case study is formulated in a separate spreadsheet-based model. In terms of budget and planning horizon, the three models consider a 5-year planning horizon and a limited yearly budget; however, in terms of number of repair options and asset components they are not equal.

For example, the building case study has three repair options for each instance (building component), where in the pavement case study the model considers five repair options for each pavement section. On the other hand, the bridge case study consists of seven bridge elements with five repair options for each element. Thus, the problem size and complexity of the three models are different. However, both the heuristic and optimization techniques have successfully allocated budget and improved the overall condition (Figure 4.4).

As shown in Table 4.4, the heuristic approach has improved the overall condition for the building case study from 54 (overall condition with no repair action) to 44.8 with a processing time of 7 seconds, while with the optimization, the overall condition has improved from 54 to 34.3 with a running time of 150 minutes. In the pavement case study, the heuristic approach has improved the overall condition from 1.7097 (overall condition without any repairs) to 1.5747 with a processing time of 34 seconds, while with the optimization, the overall condition has improved from 1.7097 to 1.5602 with a running time of 75 minutes. For the bridge case study, experimenting with the heuristic approach has improved the overall condition from 4.89 to 5.91 with a processing time of 2 seconds, while with the optimization, it improved to 6.44 with a running time of 50 minutes. Table 4.4 summarizes the output results of both the heuristic and optimization approaches for the building, pavement, and bridge case studies.

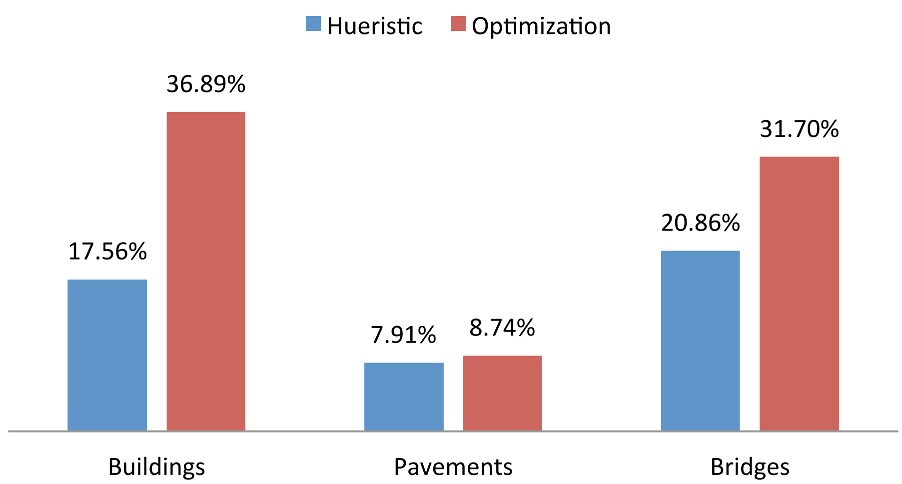


Figure 4.4: Condition Improvement: Heuristic vs. Optimization

Table 4.4: Summary of Results Obtained from the Heuristic and Optimization Techniques

Case Study	Network Size	Technique	Overall Condition	After-repair overall Condition	Condition Improvement	Total Budget	Spending	Budget Spent	Processing Time
Buildings	800 instances	Heuristic	54.33	44.79	17.56%	50,062,500	49,650,279	99.18%	7 sec
		Optimization		34.3	36.89%		50,004,590	99.88%	150 min
Pavements	1,293 pavement sections	Heuristic	1.7097	1.5745	7.91%	125,000,000	124,978,800	99.98%	34 sec
		Optimization		1.5602	8.74%		124,900,886	99.92%	75 min
Bridges	47 bridges	Heuristic	4.89	5.91	20.86%	3,000,000	2,992,277	99.74%	2 sec
		Optimization		6.44	31.70%		2,813,555	93.79%	50 min

Observations and comments:

- The outputs show that the optimization technique has improved the overall network condition 10% more than the heuristic approach did.
- In terms of processing time, the heuristic approach has produced the final decisions in a much shorter processing time than the optimization did. The processing time for the heuristic approach experiments ranges from 2 to 34 seconds, where the processing time for the optimization experiments ranges from 50 to 150 minutes.
- Both the heuristic and optimization approaches have improved the overall condition in the building and bridge case studies much more than in the pavement case study. The reason for this is that the budget provided in the pavement case study was estimated to be the minimum required budget to bring the pavement network above an acceptable level. Accordingly, it was less efficient than in the other two case studies.

4.5 Summary

In this chapter, two fund allocation techniques, heuristic and optimization, have been introduced. LCCA models for real-life case studies for networks of building instances, pavements, and bridges were presented and used for validating the fund allocation techniques. Experiments have been conducted for allocating limited budgets for the purpose of maximizing the overall network condition. The results show that both the heuristic and optimization techniques have allocated the available funds and efficiently improved the overall condition.

Chapter 5
Experimenting on Large-Scale Networks

5.1 Introduction

One of the greatest obstacles to the development of efficient LCCA models is the inadequacy of existing models and tools to handle large-scale problems, which is the case in infrastructure asset management problems (Elbehairy, 2007). Therefore, it is crucial to validate the proposed approaches on large-scale networks.

In this chapter, the assets of the case studies and models presented in Chapter 3 and Chapter 4 have been repeated several times to construct large-scale networks. Both the heuristic and optimization approaches are experimented on these large-scale networks to investigate their performance and ability to handling large-scale networks. The implementation and results of the experiments are presented, compared, and discussed.

5.2 Using the Heuristic Approach on Large-Scale Networks

Larger networks (up to about 10,000 assets) were constructed by repeating the assets in the building, pavement, and bridge networks several times. Repeating the networks' assets provides a quantitative approach for measuring the performance of large-scale networks. Experiment results are presented in the following sections. The heuristic approach presented in Chapter 4 is now validated and tested on large-scale networks.

5.2.1 Building Case Study

Larger networks (1,600, 3,200, 6,400, and 10,400) were constructed by repeating the 800-building instance network several times. As mentioned in Chapter 4, the main objective is to maximize the overall network condition (minimum deterioration index) during the five-year planning horizon, given a limited yearly budget. Networks of 1,600, 3,200, 6,400, and 10,400 instances were allocated yearly budgets of \$100,062,500, \$200,062,500, \$400,062,500, and

$650,062,500, respectively. The results of implementing the heuristic approach on these networks are summarized in Table 5.1.

Table 5.1: Summary of Large-Scale Building Case Study and Model Implementation

Case Study	Approach	Network Size	Overall Condition	After Repair Overall Condition	Condition Improvement	Budget	Spending	% Spent	Processing Time
Buildings	Heuristic	800	54.332	44.793	17.56%	50,062,500	49,650,279	99.18%	0:00:07
		1,600		44.646	17.83%	100,062,500	99,894,864	99.83%	0:00:26
		3,200		44.642	17.83%	200,062,500	199,789,728	99.86%	0:00:51
		6,400		44.638	17.84%	400,062,500	399,579,456	99.88%	0:04:27
		10,400		44.589	17.93%	650,062,500	649,523,916	99.92%	0:14:08

Implementing the heuristic approach has successfully allocated funds and improved the overall condition for all network sizes. As shown in Figure 5.1, the overall network condition for all network sizes has improved by around 18%. In terms of budget spending, more than 99% of budgets in all network sizes were allocated. The processing time ranged from 7 seconds with the 800-instance network to 14 minutes with the 10,400-instance network, which is considered a short and efficient processing time (Figure 5.2).

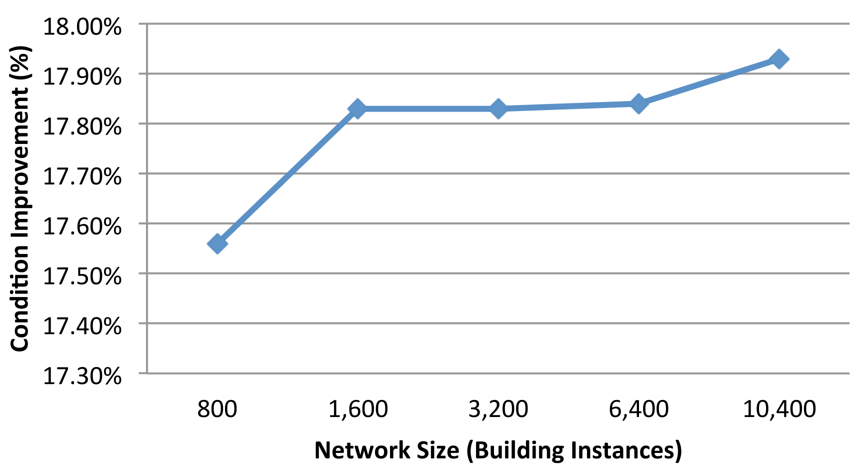


Figure 5.1: Heuristic Approach: Condition Improvement for Large-Scale Building Instance Networks

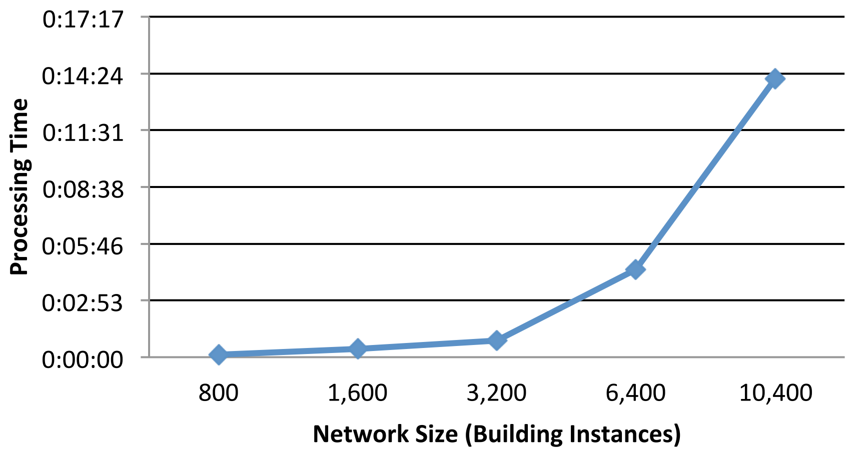


Figure 5.2: Heuristic Approach: Processing Time for Large-Scale Building Networks

5.2.2 Pavement Case Study

Larger networks of 2,586, 5,172, and 10,344 pavement sections were constructed by repeating the 1,293-pavement network several times. As mentioned in the previous chapter, the main objective is to maximize the overall network condition (minimum IRI) during the five-year planning horizon, given a limited yearly budget. Networks of 2,586, 5,172, and 10,344 pavements were allocated yearly budgets of $250,000,000, $500,000,000, and $1,000,000,000, respectively. The results of implementing the heuristic approach on these networks are summarized in Table 5.2.

Table 5.2: Summary of Large-Scale Model and Case Study Implementation for Large-Scale Pavement Networks

Case Study	Approach	Network Size	Overall Condition	After Repair Overall Condition	Condition Improvement	Budget	Spending	% Spent	Processing Time
Pavement	Heuristic	1,293	1.7097	1.5745	7.91%	125,000,000	124,978,800	99.98%	0:00:34
		2,586		1.575	7.88%	250,000,000	249,990,000	100%	0:02:02
		5,172		1.5767	7.78%	500,000,000	499,980,000	100%	0:08:33
		10,344		1.5764	7.80%	1,000,000,000	999,990,000	100%	0:38:25

As shown in Table 5.2, the heuristic approach has performed well on the large-scale pavement networks. Implementing the heuristic approach has successfully allocated funds and improved the overall condition for all network sizes. As shown in Figure 5.3, the overall network condition for all network sizes has improved by around 8%. In terms of budget spending, 100% of budgets in 3 cases were allocated, with the remaining budget having 99.98 allocated. The processing time ranged from 34 seconds with the 1,293-pavement network to 38 minutes with the 10,344-pavement network (Figure 5.4), which are efficient processing times.

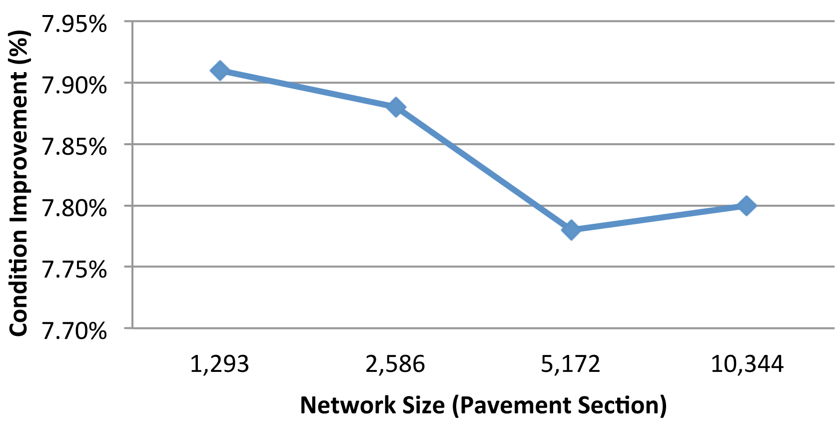


Figure 5.3: Heuristic Approach: Condition Improvement for Large-Scale Pavement Networks

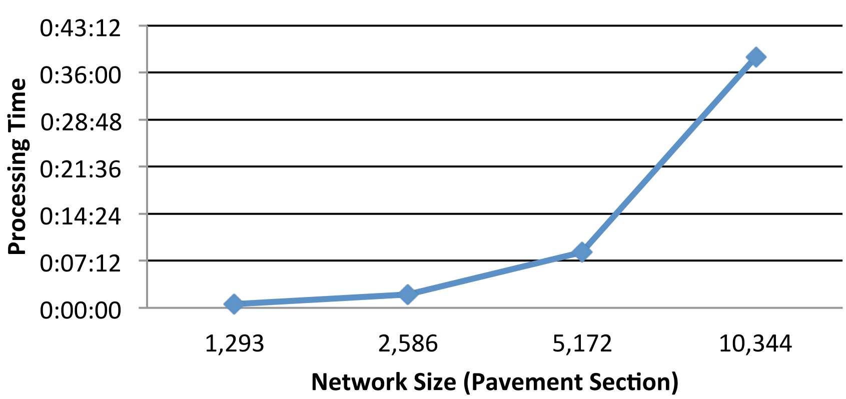


Figure 5.4: Heuristic Approach: Processing Time for Large-Scale Pavement Networks

5.2.3 Bridge Case Study

In this case study, larger networks of 94, 752, 1,504, 3,008, and 6,016 bridges were constructed by repeating the 47-bridge network several times. The main objective is to maximize the overall network condition (maximum NCR) during the five-year planning horizon, given a limited yearly budget. Networks of 94, 752, 1,504, 3,008 and 6,016 bridges were allocated yearly budgets of $6,000,000, $48,000,000, 96,000,000, 192,000,000, and $384,000,000, respectively. The results of applying the heuristic approach on these networks are summarized in Table 5.3.

Table 5.3: Summary of Large-Scale Model and Case Study Implementation for Large-Scale Bridge Networks

Case Study	Approach	Network Size	Overall Condition	After Repair Overall Condition	Condition Improvement	Budget	Spending	% Spent	Processing Time
Bridges	Heuristic	47	4.89	5.91	20.86%	3,000,000	2,992,277	99.74%	0:00:02
		94		5.89	20.45%	6,000,000	5,990,457	99.84%	0:00:03
		752		5.81	18.81%	48,000,000	47,999,281	100%	0:05:38
		1,504		5.86	19.84%	96,000,000	95,999,018	100%	0:28:50
		3,008		5.86	19.84%	192,000,000	191,999,420	100%	3:00:05
		6,016		5.86	19.84%	384,000,000	383,999,423	100%	17:01:35

Implementing the heuristic approach has successfully allocated funds and improved the overall condition for all network sizes. The overall network condition for all network sizes has improved by around 20% (Figure 5.5). In terms of budget spending, almost 100% of budgets in all network sizes were allocated. The processing time ranged from 2 seconds with the 47-bridge network to 17 hours with the 6,016-bridge network (Figure 5.6). Compared to a processing time of 14 minutes for the 10,400-instance network and 38 minutes for the 10,344-pavement network, a processing time of 17 hours for producing the final decisions in the 6,016-bridge network is considered to be a long processing time. The reason for this is that the bridge model is more complicated than the building and pavement models.

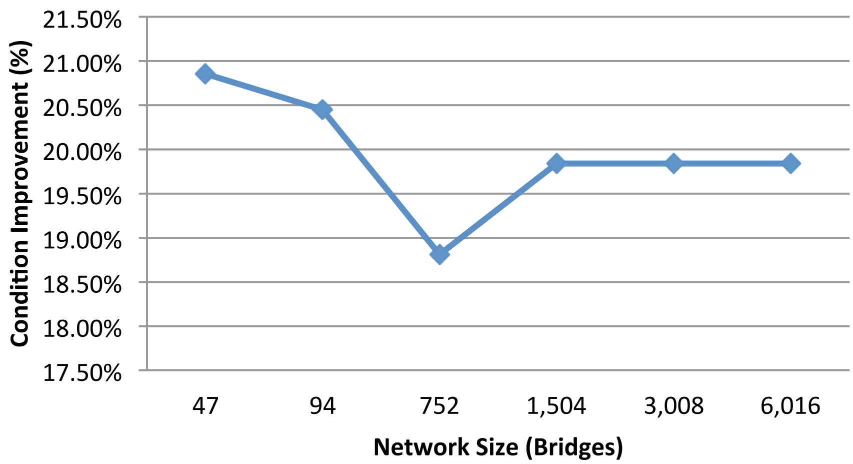


Figure 5.5: Heuristic Approach: Performance in Large-Scale Bridge Networks

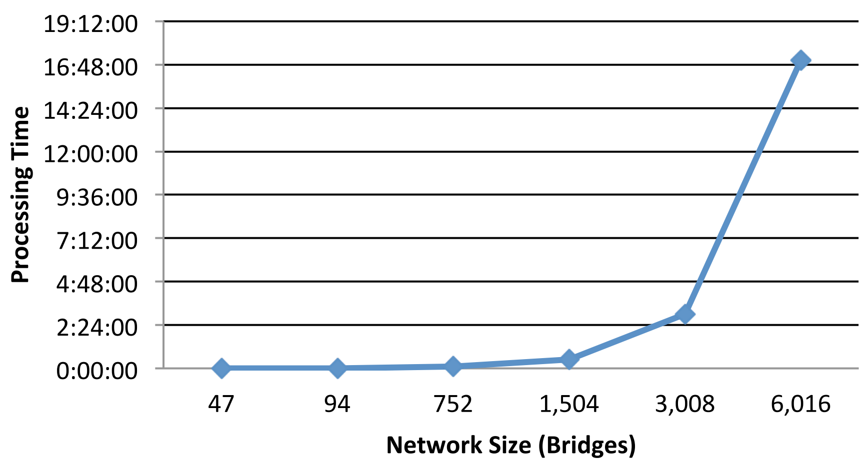


Figure 5.6: Heuristic Approach: Processing Time for Large-Scale Bridge Networks

5.2.4 Discussion of Results

The heuristic approach has been experimented with on models for different network sizes of the building, pavement, and bridge case studies. Each case study has been repeated several times to construct large-scale networks. Experimenting with the heuristic approach on different network sizes shows that the approach has allocated funds efficiently and improved the overall condition for the three case study networks. In terms of processing time, the heuristic approach has also performed very well with large-scale networks except for the bridge case study. The reason for this is that the model for the bridge case study is more complex than the models of the building and pavement case studies. The bridge model considers seven elements for each asset and five repair options for each element. This complexity increased the processing time. The summary of experiment results for all network sizes and case studies is presented in Table 5.4.

Table 5.4: Summary of the Heuristic Approach Results on Large Networks

Case Study	Approach	Network Size	Overall Condition	After Repair Overall Condition	Condition Improvement	Budget	Spending	% Spent	Processing Time
Buildings	Heuristic	800	54.332	44.793	17.56%	50,062,500	49,650,279	99.18%	0:00:07
		1,600		44.646	17.83%	100,062,500	99,894,864	99.83%	0:00:26
		3,200		44.642	17.83%	200,062,500	199,789,728	99.86%	0:00:51
		6,400		44.638	17.84%	400,062,500	399,579,456	99.88%	0:04:27
		10,400		44.589	17.93%	650,062,500	649,523,916	99.92%	0:14:08
Pavement		1,293	1.7097	1.5745	7.91%	125,000,000	124,978,800	99.98%	0:00:34
		2,586		1.575	7.88%	250,000,000	249,990,000	100.00%	0:02:02
		5,172		1.5767	7.78%	500,000,000	499,980,000	100.00%	0:08:33
		10,344		1.5764	7.80%	1,000,000,000	999,990,000	100.00%	0:38:25
Bridges		47	4.89	5.91	20.86%	3,000,000	2,992,277	99.74%	0:00:02
		94		5.89	20.45%	6,000,000	5,990,457	99.84%	0:00:03
		752		5.81	18.81%	48,000,000	47,999,281	100.00%	0:05:38
		1,504		5.86	19.84%	96,000,000	95,999,018	100.00%	0:28:50
		3,008		5.86	19.84%	192,000,000	191,999,420	100.00%	3:00:05
		6,016		5.86	19.84%	384,000,000	383,999,423	100.00%	17:01:35

5.3 Using the Optimization Approach on Large-Scale Networks

For the heuristic approach, the optimization approach has been experimented with on these large-scale networks. Its performance and ability to handling large-scale networks have been investigated and are presented in the following subsections.

5.3.1 Building Case Study

For the heuristic approach experiments, larger networks (1,600, 3,200, 6,400, and 10,400) were constructed by repeating the 800-building instance network several times. The objective is to maximize the overall network condition (minimum deterioration index) during the five-year planning horizon, given a limited yearly budget and a processing time of 150 minutes. Networks of 1,600, 3,200, 6,400, and 10,400 instances were allocated yearly budgets of \$100,062,500, \$200,062,500, \$400,062,500, and \$650,062,500, respectively. The results of implementing the optimization approach on these networks are summarized in Table 5.5.

Table 5.5: Optimization Results for Large-Scale Building Networks

Case Study	Approach	Network Size	Overall Condition	After Repair Overall Condition	Condition Improvement	Budget	Spending	% Spent	Processing Time
Buildings	Optimization	800	54.33	34.288	36.89%	50,062,500	50,004,590	99.88%	2:30:00
		1,600		35.714	34.27%	100,062,500	100,028,336	99.97%	2:30:00
		3,200		37.133	31.66%	200,062,500	199,822,003	99.88%	2:30:00
		6,400		40.781	24.94%	400,062,500	399,920,796	99.96%	2:30:00
		10,400		42.913	21.02%	650,062,500	649,934,604	99.98%	2:30:00

As shown in Table 5.5, the processing time was set to be 150 minutes for all network sizes. The optimization approach has performed well on the large-scale building networks. Implementing the optimization approach has successfully allocated funds and improved the overall condition for all network sizes. However, the approaches' performance decreased with large-scale networks (Figure 5.7). To illustrate, the overall condition improvement for the 800-instance network was 36.89%, while the overall network condition improvement for the 10,400 was only 21%. In terms of budget spending, more than 99% of budgets in all network sizes were allocated.

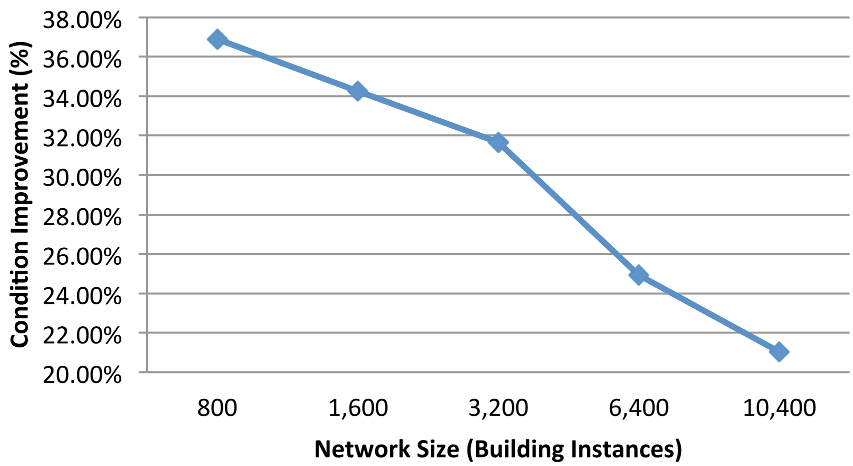


Figure 5.7: Optimization Approach: Condition Improvement for Large-Scale Building Instance Networks

5.3.2 Pavement Case Study

The optimization model has been formulated, as explained in section 4.3. Experiments with this approach on large-scale networks show that it produced a limited improvement to the overall network condition as compared to the heuristic approach's results (Table 5.6). The reason for this is that the pavement case study model considers both the project and network levels at the same time, which significantly increased the number of possible solutions and combinations. Accordingly, the optimization technique needs a very long time (days) to find a good result. For example, when a processing time of 675 minutes (about 11 hours) was applied to the 2,586 pavement network, the condition improved to 1.563 (8.58% improvement), which is slightly better than the heuristic result. Another example, the 5,172 pavement network, was given 1,480 minutes' (about a day) processing time, which produced a condition improvement of 6.4% (1.6), which is less than the heuristic result. Accordingly, with very large-scale networks that involve a more complex LCCA model, the optimization technique may fail to reach a better solution, even with a longer processing time.

Table 5.6: Optimization Results for Large-Scale Pavement Networks

Case Study	Approach	Network Size	Overall Condition	After Repair Overall Condition	Condition Improvement	Budget (million)	Spending	% of Spent	Processing Time
Pavement	Optimization	1,293	1.7097	1.5602	8.74%	125	124,900,886	99.92%	1:15:00
		2,586		1.6188	5.32%	250	249,928,364	99.97%	1:15:00
		5,172		1.6375	4.22%	500	499,921,382	99.98%	1:15:00
		10,344		1.6638	2.68%	1,000	999,834,320	99.98%	1:15:00

5.3.3 Bridge Case Study

The optimization model was formulated as mentioned in section 4.3.3 and implemented on large-scale bridge networks. The outputs of the experiments are shown in Table 5.7.

Table 5.7: Optimization Results for Large-Scale Bridge Networks

Case Study	Approach	Network Size	Overall Condition	After Repair Overall Condition	Condition Improvement	Budget	Spending	% of Spent	Processing Time
Bridges	Optimization	47	4.89	6.44	31.70%	3,000,000	2,813,555	93.79%	0:50:00
		94		6.44	31.70%	6,000,000	5,809,083	96.82%	0:50:00
		752		6.35	29.86%	48,000,000	47,370,407	98.69%	0:50:00
		1,504		6.23	27.40%	96,000,000	95,694,751	99.68%	0:50:00
		3,008		6.04	23.52%	192,000,000	185,486,341	96.61%	0:50:00
		6,016		5.98	22.29%	384,000,000	357,928,674	93.21%	0:50:00

As shown in Table 5.7 and Figure 5.8, the performance of the optimization approach decreases with the increase of the network size. The overall network condition has improved 31% for the 47-bridge network, while for the 6,016-bridge network the overall network condition improvement was 22%. In terms of fund allocation, a range of 93 to almost 100% of the budget was allocated.

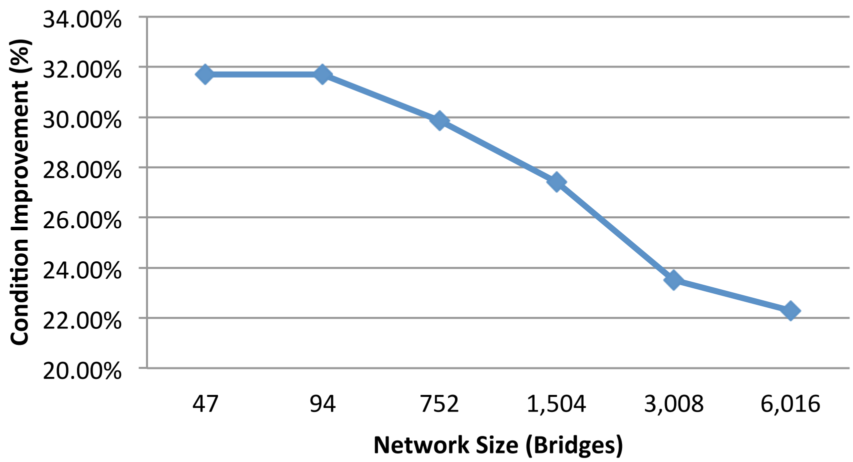


Figure 5.8: Optimization Approach: Performance of Large-Scale Networks

5.3.4 Discussion of Results

For the heuristic approach experiments, large-scale networks have been constructed to be experimented on with the optimization approach. The optimization approach has been formulated to optimize the fund allocation process in order to maximize the overall network condition improvement. Experiments with the optimization approach on different network sizes have been performed. For the building and bridge case studies, processing times of 150 and 50 minutes have been set for the building and bridge models, respectively. The outputs show that the optimization approach has improved the overall network condition (20 to 30% improvement) and allocated funds efficiently for different network sizes. On the other hand, a processing time of 75 minutes was given to the pavements model. The overall network condition in the pavement model had a limited improvement. The reason for this is that the model of the pavements case study considers both the network- and project-level decisions at the same time, which increases the number of possible solutions and combinations. Accordingly, a very long processing time is needed to improve the overall network condition.

5.4 Heuristic vs. Optimization: Results Comparison

Table 5.8 shows the experiment results for both the heuristic and optimization approaches for different network sizes of the building, pavement, and bridge case studies.

Table 5.8: Summary of Experiment Results for Large-Scale Networks

Case Study	Network Size	Overall Condition	Budget	Approach	After Repair Overall Condition	Condition Improvement	Spending	% of Spent	Processing Time
Buildings	800	54.332	50,062,500	Heuristic	44.793	17.56%	49,650,279	99.18%	0:00:07
				Optimization	34.288	36.89%	50,004,590	99.88%	2:30:00
	1,600		100,062,500	Heuristic	44.646	17.83%	99,894,864	99.83%	0:00:26
				Optimization	35.714	34.27%	100,028,336	99.97%	2:30:00
	3,200		200,062,500	Heuristic	44.642	17.83%	199,789,728	99.86%	0:00:51
				Optimization	37.133	31.66%	199,822,003	99.88%	2:30:00
	6,400		400,062,500	Heuristic	44.638	17.84%	399,579,456	99.88%	0:04:27
				Optimization	40.781	24.94%	399,920,796	99.96%	2:30:00
	10,400		650,062,500	Heuristic	44.589	17.93%	649,523,916	99.92%	0:14:08
				Optimization	42.913	21.02%	649,934,604	99.98%	2:30:00
Pavements	1,293	1.7097	125,000,000	Heuristic	1.5745	7.91%	124,978,800	99.98%	0:00:34
				Optimization	1.5602	8.74%	124,900,886	99.92%	1:15:00
	2,586		250,000,000	Heuristic	1.575	7.88%	249,990,000	100%	0:02:02
				Optimization	1.6188	5.32%	249,928,364	99.97%	1:15:00
	5,172		500,000,000	Heuristic	1.5767	7.78%	499,980,000	100%	0:08:33
				Optimization	1.6375	4.22%	499,921,382	99.98%	1:15:00
	10,344		1,000,000,000	Heuristic	1.5764	7.80%	999,990,000	100%	0:38:25
				Optimization	1.6638	2.68%	999,834,320	99.98%	1:15:00
Bridges	47	4.89	3,000,000	Heuristic	5.91	20.86%	2,992,277	99.74%	0:00:02
				Optimization	6.44	31.70%	2,813,555	93.79%	0:50:00
	94		6,000,000	Heuristic	5.89	20.45%	5,990,457	99.84%	0:00:03
				Optimization	6.44	31.70%	5,809,083	96.82%	0:50:00
	752		48,000,000	Heuristic	5.81	18.81%	47,999,281	100%	0:05:38
				Optimization	6.35	29.86%	47,370,407	98.69%	0:50:00
	1,504		96,000,000	Heuristic	5.86	19.84%	95,999,018	100%	0:28:50
				Optimization	6.23	27.40%	95,694,751	99.68%	0:50:00
	3,008		192,000,000	Heuristic	5.86	19.84%	191,999,420	100%	3:00:05
				Optimization	6.04	23.52%	185,486,341	96.61%	0:50:00
	6,016		384,000,000	Heuristic	5.86	19.84%	383,999,423	100%	17:01:35
				Optimization	5.98	22.29%	357,928,674	93.21%	0:50:00

As shown in Table 5.8, the heuristic approach has sufficiently improved the overall network condition for all network sizes. In terms of processing time, the final decisions were produced efficiently and in a very short for the building and the pavement case studies, but not for the bridge case study. In the 6,016-bridge network, a processing time of more than 17 hours was needed to produce the final results (Figure 5.9), which is considered a long processing time as compared to the 14- and 38-minute processing times for the 10,400-building instance network and the 10,344-pavement network, respectively. On the other hand, the optimization approach experiments show a good improvement to the overall network condition of the buildings and bridges case studies (Figure 5.10 and Figure 5.11), while a limited improvement to the pavement networks' overall conditions has been achieved.

5.5 Observations and Recommendations

Based on the results of the experiments conducted on the different LCCA models, and on different-size problems, some observations and recommendations for optimizing fund allocation are as follows:

- The optimization results on the building and bridge network models produced better improvement to the overall network condition than to the pavement networks' overall conditions. The reason for this is that the pavement model considers both the project- and the network-level decisions. The MOST technique of (Hegazy & Elhakeem, 2011), therefore, proved to be a good model for large-scale LCCA.
- For the heuristic approach, the processing time for all network sizes was short and efficient, except for the large-scale bridge networks. The reason for this is that the bridge model is more complex than the building and pavement models. Therefore, prioritizing bridges and allocating funds takes a long time to be performed.
- Based on the results, the heuristic approach proved to be a simple tool to provide a quick solution, while optimization is still needed to further improve the results, given enough processing time.
- More work is still needed to devise new heuristic and optimization techniques that can further improve the results.

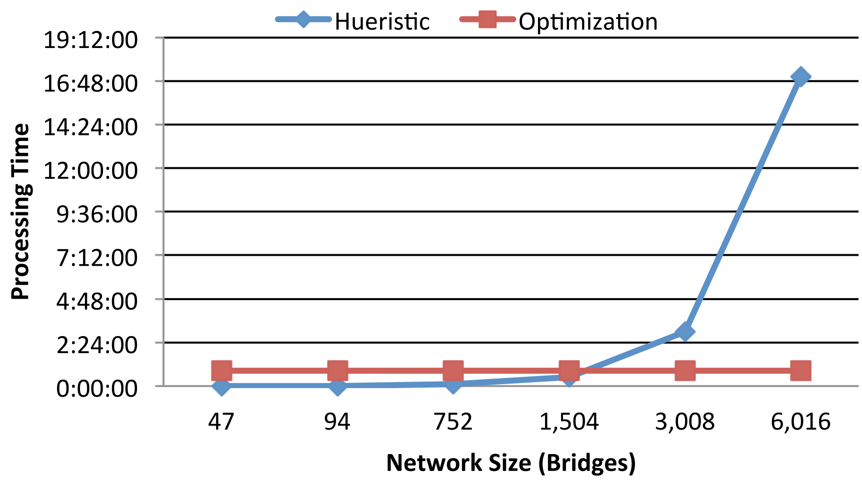


Figure 5.9: Heuristic vs. Optimization: Processing Time for Large-Scale Bridge Networks

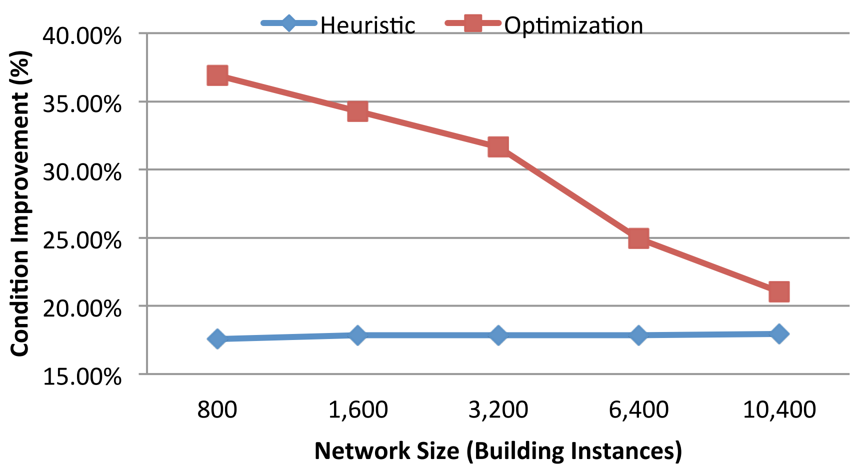


Figure 5.10: Heuristic vs. Optimization: Condition Improvement for Large-Scale Building Instance Networks

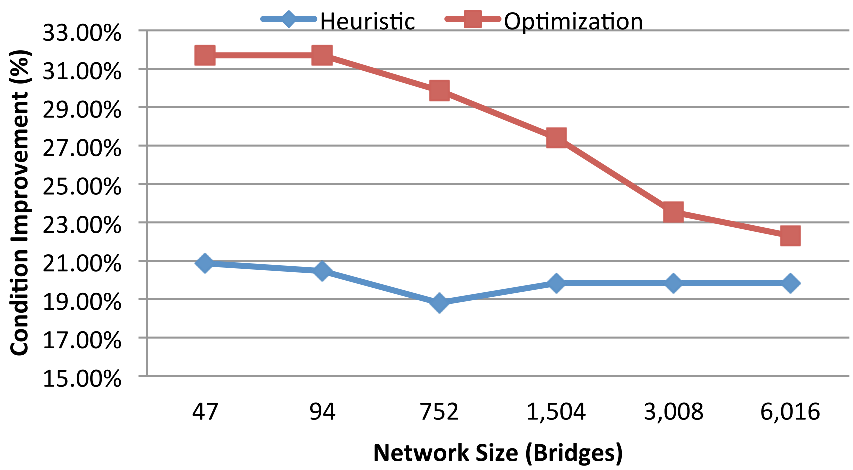


Figure 5.11: Heuristic vs. Optimization: Condition Improvement for Large-Scale Bridge Networks

5.6 Summary

In this chapter, the heuristic and optimization approaches presented in Chapter 4 were applied to large-scale networks. The large-scale networks were constructed by repeating the assets of the three case studies presented in Chapter 4 several times. Both approaches have been experimented with for allocating limited funds on large-scale networks. The results show that the heuristic approach has efficiently allocated available funds and improved the overall condition for all case studies and network sizes. However, the processing time for allocating funds for large-scale bridge networks was inefficiently long. On the other hand, the optimization approach performed very well for the large-scale building and bridge networks. However, combining both project level and network level analysis together for the pavement network makes the problem much more complex and this produces less than optimum results.

Chapter 6
Conclusions

6.1 Summary and Conclusion

With infrastructure assets aging and requiring increasing attention, governments and large owner organizations are faced with increasing pressure to keep their infrastructure safe and operable with limited repair funds. Asset prioritization and fund allocation, therefore, are crucial processes in the management of large networks of infrastructure assets. The main objective of this research was to examine techniques on several LCCA models for different types of real-life infrastructure case studies.

In this research, the major problems facing infrastructure asset management were presented, and the challenges and complexity of developing an infrastructure management system were discussed. Then, prioritization was presented as a powerful process for efficient fund allocation, as well as the fact that it is flexible and easy to implement and understand. Different prioritization techniques were explained, and their strengths and weaknesses were summarized.

LCC analysis models for three types of assets (pavements, bridges, and buildings) have been introduced and implemented on spreadsheets in order to facilitate further analysis of heuristic versus optimization techniques for large-scale problems. The large-scale networks were constructed by repeating the assets of the three case studies several times. Both the heuristic and optimization approaches have been experimented with for allocating limited funds on large-scale networks. The results show that the heuristic approach efficiently allocated the available funds and improved the overall condition for all case studies and network sizes. However, the processing time of allocating funds for large-scale bridge networks was inefficiently long. On the other hand, the optimization approach performed very well for the large-scale building and bridge networks. However, combining both project level and network level analysis together for the pavement network makes the problem much more complex, and this produces less than optimum results. Based on the results, the heuristic approach proved to be a simple tool to provide a quick solution, while optimization is still needed to further improve the results, given enough processing time.

6.2 Future Work

- Experiment with advanced mathematical optimization techniques using recent powerful tools such as GAMS and CPLEX in order to try different optimization mechanisms.

- Experiment with other evolutionary systems such as Ant Colony, Shuffled Frog Leaping, etc.

- Introduce other heuristic approaches for fund allocation.

- Examine changes to the LCCA model itself by building upon the MOST technique as segment parts of the network level analysis.

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