Combined Strategic-Tactical Planning for Facility Rehabilitation Using System Dynamics and Optimization

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

Rehabilitation programs are essential for efficiently managing large networks of infrastructure assets and sustaining their safety and operability. While numerous studies in the literature have focused on various aspects of infrastructure rehabilitation, such as rehabilitation processes, deterioration modeling, life cycle cost analysis, project financing, etc., limited efforts have investigated the overall dynamics among these functions and the development of holistic models that can analyze the long-term effect of different strategic policies and their impact on tactical rehabilitation decisions. To support strategic level of decision-making and long-term policy analysis, this research utilized System Dynamics (SD) to study the dynamic interactions among the deterioration, rehabilitation, and budgeting feedback loops. Model performance and suggested policies were also checked against reference modes and verified using various model testing methods to ensure adequacy. The proposed System Dynamics model was then expanded to incorporate four main modules including policy, physical condition, life cycle cost, and sustainability, for the purpose of backlog accumulation analysis. School building facilities were used as the focused asset domain of this study. After identification of key variables based on literature analysis, previous researches on school building facilitates, and experts' opinion, the dynamic interactions were studied using causal loop diagraming (CLD) methods. The developed CLD was then mapped into a stock-and-flow simulation model incorporating the four integrated modules with all the underlying mathematical relationships. Numerous experiments with different policy scenarios were conducted to investigate the impact of various policies related to rehabilitation, budget distribution, government investment, and private financing. The simulation results clearly indicated that some of the commonly used policies such as condition-based prioritization methods can lead to significant long-term problems in terms of backlog, and showed that equal distribution of budget can be more effective. Simulation results also indicated that the use of private financing for backlog elimination need to be carefully analyzed to determine a proper payback scheme without a negative effect on long-term backlog projections.

The SD Model was also adopted to provide optimum policy solutions in terms of the level of budget allocated to rehabilitation of exiting school buildings and construction of new facilities to accommodate future enrolment. The proposed model used facility condition index (FCI) as an industry standard to investigate facility performance and also a utilized a facility risk index (FRI) to account for the risk of failure. The model was used to investigate and compare the effect of using enrolment-based budgeting policies versus an optimized policy solution on a network of 438 elementary school buildings. Results

clearly showed that the enrolment-based approach, which has been used by education ministries for a long time, could be significantly improved with the used of policy optimization.

The policy solutions form the strategic-level analysis were used to create detailed tactical rehabilitation plans. To support the tactical level of decision-making this research investigated the performance of mathematical mixed integer programming and genetic algorithm (GA) optimization models to handle the large-scale tactical problems. First, various model formulations including an integer, a one-shot binary, and a year-by-year binary formulation were examined for their performance on large-scale problems. A year-by-year formulation was then selected for the network-level analysis and was used with GA-based optimization. To improve the performance of the GA-based model, a segmentation approach was used that was able to eliminate performance degradation, yet exhibited long processing time. Subsequently, an integer programming model was developed on the GAMS/CPLEX optimization tool that resulted in the best solution quality and fast processing time for very large-scale problems (e.g., 50,000 building components). The promising result of the proposed mathematical model was mainly attributed to the formulation of the optimization model, advancements in the used optimization tools, and the separation between project and network level analysis. Combination of the strategic and tactical models developed in this research provides a comprehensive and systematic framework for a combined analysis of rehabilitation plans at both strategic and tactical levels of facility management.

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To My Beloved Parents

and Brother

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Chapter 1
Introduction

1.1 General

Civil Infrastructure, such as roads, highways, transportation systems, water/sewer networks, schools, etc., are among the most important assets that directly impact a nation's economy and quality of life (Hudson et al. 1997). Despite their importance, the condition of the civil infrastructure in North America is much below acceptable levels. America's infrastructure report cards, for example, show little condition improvement from 2005 to 2013 (ASCE 2005; ASCE 2009; ASCE 2013), while the investment needed to bring the infrastructure to satisfactory level has dramatically increased from $1.6 trillion to $3.6 trillion during this time (Figure 1-1). In Canada also, it is estimated that the infrastructure backlog will be more than $112 billion in 2027, and that 79% of our infrastructure life expectancy has been used (Civil Infrastructure Systems Technology Road Map 2003-2013). The majority of the existing infrastructure was constructed decades ago and has been rapidly deteriorating due to aging, constant use, and exceeded capacity. To sustain infrastructure safety and operability, regular maintenance, rehabilitation, and reconstruction (often refer to as MR&R) are necessary. However, due to the insufficient pubic funding for these actions maintaining the serviceability of civil infrastructure has become a major challenge for asset managers.

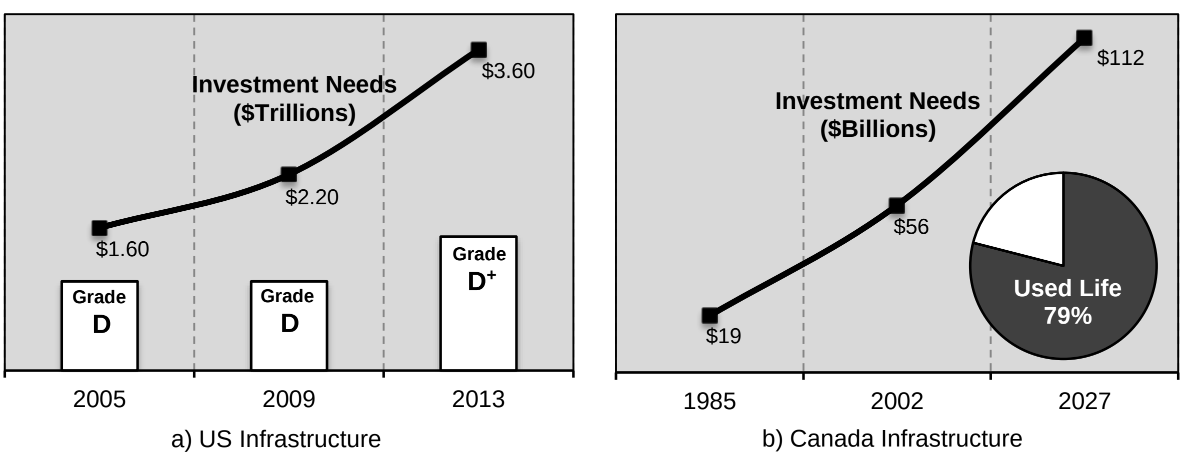

Figure 1-1: Infrastructure backlog and condition in North America (ASCE 2013; Civil Infrastructure Systems Technology Road Map 2003-2013)

Amongst the important public facilities that are facing significant backlog and performance issues are school buildings. The 2013 report cards of America's infrastructure assigned a D (poor) grade to school infrastructure with a projected backlog of at least $270 billion (ASCE 2013). This is while school enrolment is projected to gradually increase through 2019, yet state and local school construction funding continues to decline (ASCE 2013). In Canada, school administrators and facility managers are facing similar problems. Although the 2012 report card of Canadian Infrastructure showed a satisfactory overall grade for Canadian infrastructure, it did not investigate school facilities (The Canadian Infrastructure Report Card 2012). The Toronto District School Board (TDSB), however, reported a $3.2 billion capital renewal backlog with an increasing enrolment trend for the future (TDSB 2014). At the same time, the overall condition of the facilities have been reported to be poor with many facilities in critical condition (TDSB 2007). Another issue with the school facilities is to accommodate the growing enrolment trends that requires substantial funding for new constructions alongside the regular rehabilitation and maintenance funds (ASCE 2013; TDSB 2014). The need for new construction is a widespread fund allocation issue due to population growth and the need to modernize facilities with the advance of new technologies. The financial deficits and the need for new facilities, coupled with the deteriorated state of the existing assets, necessitates novel approaches for determining optimum budgeting strategies that their impact infrastructure performance. As an alternative remedy to face infrastructure deficit, Public Private Partnership (PPP) has been a popular approach for involving the private sector in financing and maintaining complex infrastructure projects. PPP has been predicted to decrease infrastructure backlog, transfer risk from public to private sector, and to bring innovation into infrastructure projects (Sanchez 1998; PPP Canada 2013). In Canada, more than $27.1 billion was invested in different PPP infrastructure projects, such as schools, public transit, local roads, hospitals, or wastewater programs, in the period between 2009 and 2011 (PPP Canada 2013). According to the World Bank, many developing countries have also encouraged the private sector to participate in infrastructure facilities, and between 1990 and 1999, more than 30 developing countries have had at least one project completed by the private sector (Roger 1999; World Bank 1999; World Bank 2003). PPP models can range from private sector to solely finance the project or bring a portion of the required funds, or it can involve private sector in construction, maintenance, or even operation of the facility.

Although a large body of knowledge has been accumulated in the past decade on infrastructure management, capital budgeting, backlog, and public private partnerships (PPP), limited research has been conducted on long-term analysis of their interactions and on developing adequate decision support tools for policy analysis and determining optimum solutions that reduce backlog while enhancing infrastructure performance.

1.2 Research Motivation

This research aims at developing a better understanding of the dynamic interactions amongst asset management functions and analyzing the impact of various strategic policies in terms of budgeting and rehabilitation strategies on long-term infrastructure performance. This research has been motivated by the following:

1.2.1 Strategic and tactical decisions have great impact on infrastructure performance

Infrastructure rehabilitation includes two levels of challenging decisions: Strategic and tactical (Hudson et al. 1997). Strategic decisions relate mainly related to the development of policies (e.g., prioritization, privatization, budgeting, performance measures, etc.), while tactical decisions concern with the actual implementation of the strategic decisions. At the strategic level of decision-making, large amount of information regarding a network of infrastructure asset need to be analyze to find optimum policy solutions that ensure adequate performance over long-term strategic plans. Identifying the optimum policy solutions and avoiding scenarios that can negatively affect future infrastructure performance is of great importance in cost-effective management of infrastructure assets. While there exists a proliferation of management systems for variety of infrastructure assets, their focus is mainly on the tactical decisions, often incorporating few strategic parameters (e.g., budget level, rehabilitation methods, etc.). There is a need for new flexible models that examine the impact of a variety of strategic decisions related to infrastructure performance, privatization, and other policy issues. At the same time, implementation of these policies and developing effective tactical plans is crucial to proper management of infrastructure rehabilitation programs. At the tactical level, the strategic polices must act as effective constraints while maximizing infrastructure performance by identifying optimum rehabilitation timing and treatment types. There is accordingly an apparent need for asset management systems that support both strategic and tactical decision to ensure satisfactory infrastructure performance.

1.2.2 Potential of system dynamics to model strategic policy decisions

In the literature, a new type of simulation models called 'System Dynamics' began in the 1960s and has matured in the past decade (Forrester 1961, Sterman 2000). System dynamics can help top-level mangers to study the behaviors of complex systems and to evaluate long-term policy impacts (Sterman

2000). At the strategic policy-making level, the interactions among the physical performance of infrastructure assets, rehabilitation strategies, life cycle cost, private financing, and backlog over time can be greatly understood using system dynamics. In all of its applications system dynamics proved to be very effective in handling the dynamic complexity of real world system and in analyzing the impact of policy scenarios (e.g., Homer et al. 1993; Lee at al. 2006). Despite the obvious potentials of system dynamics simulations models, they have been rarely used in the area of infrastructure management to analyze strategic policies. Understanding the process of backlog accumulation and identifying proper budget levels to resolve backlog and performance issues is among important strategic policies in the area of infrastructure rehabilitation. Also, the need to modernize existing asset inventories and accommodate population growth, necessitates proper allocation of portions of capital budget to new construction projects versus rehabilitation and maintenance. At the strategic level, policy-makers need to be able to clearly analyze the impact of their budgeting decisions on long-term infrastructure performance and application of system dynamics has the potential to significantly support this policy-making process.

1.2.3 Difficulty in resolving backlog problems

Infrastructure backlog has been a major and consistent problem in the area of infrastructure management. Almost in all infrastructure domains, reports show a huge accumulation of backlog due to inefficient and inadequate budgeting of rehabilitation programs over the life cycle of existing infrastructure (e.g., ASCE 2013). Accumulation of backlog coupled with the need for new infrastructure have created a major challenge for asset managers who strive to preserve the performance of infrastructure above minimum acceptable levels of service. There is a significant need for systems that can analyze the projection of backlog based on current budgeting policies and can devise solution for resolving this issue.

1.2.4 The need to maximize infrastructure performance through efficient tactical plans

Although identifying effective strategic policies is crucial for effective management of civil infrastructure, these policies need to be efficiently implemented at the tactical level to ensure satisfactory performance. At the tactical level, rehabilitation planning usually involves thousands of assets requiring decision about repair type and timing. The number of possible combinations of these decisions over a long-term plan is extremely large and is the main source of the combinatorial complexity associated with the tactical models (Hegazy and Rashedi 2012). Finding optimum solutions for such problems is not an easy task, therefore, new breed of optimization methods and mechanisms should be used in order to solve tactical-level problems. Earlier research on tactical optimization could optimize limited number of assets with exponential increase in processing time as size increased. To devise effective tactical rehabilitation plans, advanced mathematical optimization tools can be used to improve the performance and efficiency of the optimization process on large-scale tactical problems.

1.3 Research Scope & Overall Framework

Figure 1-2 shows the overall framework of this research.

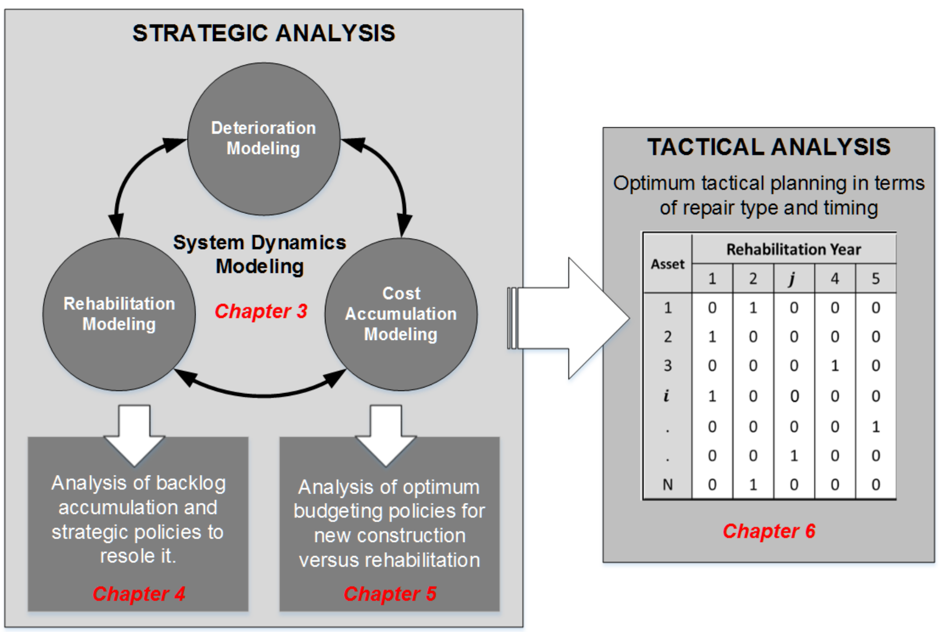

Figure 1-2: Overall framework of the research

This research is mainly focused on developing a decision support tool that can simulate strategic budgeting polices and optimize tactical plans in terms of repair selection and timing. At the strategic level, this research is focused on modeling asset deterioration, rehabilitation, and cost accumulation processes from a holistic point of view. This research also tries to investigate the effect of using private investment as a possible resolution for backlog accumulation. In terms of policy analysis, this research is mainly focused at capital budgeting and budget allocation strategies that includes new construction, rehabilitation, and maintenance, as well as identifying proper allocation of rehabilitation funds to various categories of asset conditions (e.g., poor or critical). At the tactical level, this research compares the performance of GA-based and mathematical optimization approaches based on a previously developed optimization model by the author to determine effective tactical rehabilitation plans.

1.4 Research Objectives

The primary goal of this research is to develop a decision support tool that uses system dynamics to analyze the impact of different strategic budgeting policies on long-term infrastructure performance and to find optimum policy solutions. A secondary goal is to utilize these results at the tactical level for detailed fund allocation planning in terms of repair timing and selections. Main objectives of this research are as follow:

1. Study and identify the dynamics interactions among the key decision variables involved in the strategic decision-making process, with a focus on variables that affect physical deterioration, rehabilitation actions, and life cycle cost.
2. Analyze backlog accumulation processes and the long-term effect of backlog elimination strategies, such as private financing, using the developed system dynamics models.
3. Identify optimum levels of budget that need to be allocated to the rehabilitation of existing deteriorated building facilities and the budget for construction of new school buildings to accommodate the increasing trends of enrolment.
4. Develop and compare the performance of mathematical programming and GA-based optimization models and the effectiveness of various model formulations for rehabilitation planning at the tactical level based on the optimum policies obtained from the strategic-level analysis.

1.5 Research Methodology

Figure 1-3 shows the methodology of this research with its details as follow:

Literature Review: conduct an extensive review on the existing literature about asset management systems (AMS), strategic versus tactical asset management, deterioration and rehabilitation modeling, asset renewal optimization, and system dynamics and its applications.

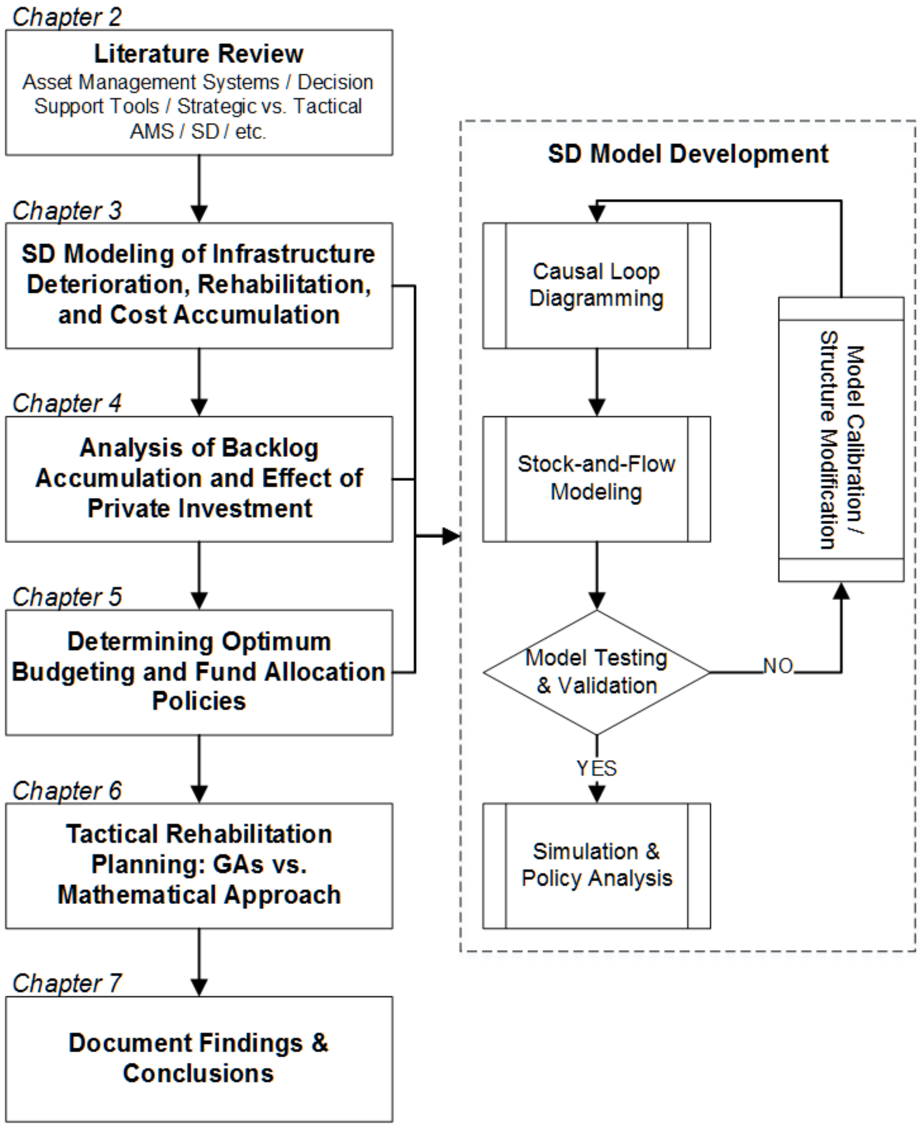

Figure 1-3: Research methodology

SD Modeling of Infrastructure Deterioration, Rehabilitation, and Cost Accumulation: Identify the dynamic interactions between asset deterioration, rehabilitation, and cost accumulation, and develop a system dynamics model to simulate these processes.

Analysis of Backlog Accumulation and Effect of Private Investment: Use the SD model to analyze the backlog accumulation trends and the impact of using private investment and other rehabilitation policies to eliminate backlog.

Determining Optimum Budgeting and Fund Allocation Policies: Develop and SD model considering facility-level performance (i.e., facility performance index) to optimize strategic capital budgeting policies in terms of new construction versus rehabilitation budget, in addition to determining optimum rehabilitation fund allocation strategies.

SD Model Development: All SD models will go through a detailed model development process that includes determining key strategic parameters and development of causal loop diagrams (CLDs). Mapping of the developed CLDs into stock and flow simulation models. Using a rigorous model testing and validation procedure that entailed various tests such as dimensional consistency, structure assessment, comparison with reference modes, conditional tests, extreme condition tests, dynamic input tests, and multi-variate sensitivity analysis, to ensure model robustness and adequacy. And finally, conducting simulation and policy analysis experiments.

Tactical Rehabilitation Planning: Use the results of strategic analysis as effective constraints on the tactical fund allocation model to devise effective rehabilitation plans and comparing the results of using Genetic Algorithm (GA) versus mathematical optimization using integer programing to solve the large-scale tactical rehabilitation planning problem.

Document Findings and Conclusions: Document and report the results of various experiments with the model the provide conclusions of effective strategic policies and their long-term effects.

1.6 Thesis Organization

The organization of the remaining chapters of this thesis is as follow:

Chapter 2 – Literature review: This chapter discusses the literature and background studies related to the asset management dimensions covered in the proposed research, including asset management systems, strategic asset management, tactical asset management, and the limited literature efforts to integrate these dimensions. This chapter also discusses system dynamics concepts and its potentials for handling strategic models.

Chapter 3 – Modeling infrastructure deterioration and rehabilitation using system dynamics: This chapter discusses a holistic view to investigate the dynamics that affect rehabilitation decisions and the long-term performance of an infrastructure network. First, the interactions among the main parameters related to asset deterioration, rehabilitation actions, and cost accumulation have been analyzed using causal loop diagrams (CLDs). Afterward, a system dynamics (SD) model has been developed based on the CLDs and the underlying mathematical relations among the various parameters.

The SD model was then tested on a network of 1,000 assets over a 50-year plan, considering a range of rehabilitation policies regarding budgets, possible rehabilitation actions, and fund allocation options.

Chapter 4 – Strategic analysis to resolve backlog accumulation: This chapter discusses a system dynamics (SD) model to analyze the impact of different strategic policies (e.g. budgeting, private investment) on infrastructure backlog accumulation. The proposed model has been implemented on a network of school buildings from the Toronto District School Board asset inventory. Four sets of experiments with different policy scenarios over a 50-year strategic planning horizon have been conducted to investigate policies related to rehabilitation, budget distribution, government investment and private sector involvement.

Chapter 5 – Optimum budgeting policies for new Construction versus rehabilitation: This chapter discusses an alternative model that can be used at the strategic level to identify the optimum budgeting policies for rehabilitation of existing buildings and construction of new ones. The proposed SD model is tested using a case study from the Toronto District school Board (TDSB) involving 438 elementary school buildings. A rigorous model testing and validation procedure is presented that demonstrates various tests such as structure assessment, dynamic input tests, and multi-variate Monte Carlo sensitivity analysis. The model is then used to perform policy optimization to find an optimum budget allocation strategy that minimizes the overall facility condition index (FCI), facility risk index (FRI), and total life cycle cost (TLCC), by identifying the optimum budget levels for new construction, rehabilitation, and maintenance over a 30-year strategic plan.

Chapter 6 – Tactical fund allocation planning: Earlier efforts using GA could optimize small size problems yet exhibiting steep degradation in solution quality as problem size increases. Even by applying sophisticated mechanisms such as ‘segmentation’ to improve the performance of GA, large processing time hinders the practicality of the algorithm for large-scale problems. This chapter discusses the development of a mathematical optimization model using integer programming and GAMS/CPLEX optimization tool to improve both processing speed and solution quality for very large-scale problems (up to 50,000 assets). The results of GAMS/CPLEX model are then compared with those of GA-based approaches on three different model formulations.

Chapter 7 – Conclusions and future research: This chapter presents the summary and conclusions of the proposed research. The chapter also discusses the main contributions, research limitations, and offers potential avenues for future extensions that can complement and improve this research work.

Chapter 2
Literature Review

2.1 Chapter Summary

This chapter discusses the literature and background studies related to the asset management dimensions covered in the proposed research, including asset management systems, strategic asset management and policy making, modeling of deterioration and rehabilitation processes of infrastructure assets, infrastructure backlog, applications of public-private-partnership, tactical asset management and rehabilitation planning using optimization, in addition to the limited literature efforts to combine these dimensions. This chapter also discusses system dynamics concepts and its potentials for handling strategic models with detailed illustration of causal loop diagramming, stock-and-flow modeling, and example applications of system dynamics in real world.

2.2 Asset Management Systems (AMS)

Due to the importance of civil infrastructure assets and their impact on societies' life quality and economy, effectively managing infrastructure assets is essential to ensure acceptable serviceability. Infrastructure management, however, is not an easy task due to the stringent municipality budgets, large number of existing deteriorated assets, and the multitude and diversity of the constraints involved in the process of asset management decision-making. Asset management systems (AMS) are therefore introduced to help asset managers and strategic decision makers with their asset management decision (Hudson et al. 1997). Transportation Association of Canada (TAC) defines AMS as "a comprehensive business strategy employing people, information and technology to effectively allocate available funds amongst valid and competing asset needs" (TAC 1999). Federal Highway Administration (FHWA) defines AMS as "a systematic process of maintaining, upgrading and operating physical assets cost effectively. 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 integration of decisions made across all program areas" (FHWA 1999). In essence, an AMS has different integrated functions that work together to support managerial decisions and industrial decisions (Vanier 2001). In general, these functions include condition assessment, deterioration modeling, repair modeling, performance modeling, and life cycle cost analysis (LCCA) (Hudson et al. 1997). The calculations associated with these functions are often coupled with the application of soft computing methods such as neural networks, fuzzy logic, or genetic algorithms to come up with optimal strategies and renewal solutions (Flintsch and Chen 2004). In the past decades, different AMS have been developed to support infrastructure projects with variety of needs. Some of the examples include: building assets (Elhakeem and Hegazy 2012); municipal assets (Halfawy et al. 2006); sewer assets (Halfawy 2008); pavement assets (Haas et al. 1994); or bridge assets (Hegazy at al. 2004).

All of the efforts in developing asset management systems must deal with two levels of decisions: strategic and tactical (Hudson et al. 1997). Most of the studies, however, deal with one of these levels without providing an overall understanding of the dynamics between them, i.e., the impact of policy/strategic level of decisions on backlog accumulation and asset performance. The following sections describe both strategic and tactical levels of management, and the little efforts in the literature to integrate these two levels.

2.3 Strategic Asset Management & Policy-Making

Strategic asset management is perhaps the most important aspect of asset management that affects the long-term performance of infrastructure systems. Application of strategic models, however, lacks among the asset management organizations. Australian National Audit Office Report No. 27 (Australian National Audit Office, 1995) in their audit of asset management practices common to 24 organizations stated that one of the main identified weaknesses was related primarily to the lack of a strategic approach to asset management. Transportation Association of Canada (TAC) also suggests that all network level management systems, including pavement management systems, should feed into a strategic level management system for proper capital planning (TAC 2014).

Strategic asset management represents the vision of policymakers. It is about the understanding and managing trade-offs among financial performance and operational performance (Jones 2000; Sklar 2004). The Australian Asset Management Collaborative Group (AAMCoG) defines strategic asset management as a procedure that brings together economics, engineering, information technology, sustainability and human elements to form a holistic approach to the delivery of built assets. Strategic management focuses on long-term results and recognizes the combination of these elements into a greater whole as well as their interrelationships and interdependencies (AAMCoG 2012). AAMCoG suggests that resource scarcity, sustainability issues, and growing population are the main challenges that strategic asset management models face. From strategic asset management point of view, the level of privatization (e.g., government owned corporation, government owned department, full privatization) is also another main factors, which determines the policy of asset owners toward utilizing private sector partnership (Levy 2008; Too 2010). To advise policymakers in developing effective long-term strategic plans, researchers have developed different strategic models and frameworks. Stradford et al. (2010), for example, utilized strategic asset management for long-term planning of large number of bridge assets to forecast the level of expenditure needed to meet a defined LOS, as well as performance implications for a range of policies. Too (2010), introduced a framework for strategic infrastructure asset management for implementing the most effective strategy and plans for renewal actions. None of these methods, however, investigate the interrelationships and interdependencies among different aspects of strategic asset management as a whole. This is while many researchers suggest that to achieve strategic asset management objectives, a holistic view of asset management, effective analytical methods, as well as integration among different levels of strategic and tactical information are essential (Brown 2004; Sklar 2004; Too 2010). As discussed in this section, based on different literature studies and reviews of asset management guidelines, this research investigates three of the main interrelated aspects of strategic asset management including: financial performance and infrastructure backlog accumulation (Jones 2000; Sklar 2004; FCM 2007; Mirza 2008; Evdorides et al. 2012), sustainability related issues (AAMCoG 2013; Mirza 2006; Ugwu et al. 2006), and the level of privatization or application of public private partnership (PPP) (Roger 1999; Gleick et al., 2002; Levy 2008; Too 2010). The following subsections describe these aspects in details. This chapter then explains the fundamentals of system dynamics as an effective method for holistic representation and analysis of strategic asset management models.

2.4 Deterioration and Rehabilitation Modeling

By performing periodic condition assessments, asset managers can create a chronological database about the condition indices and their changes over time for different assets. These changes in the condition indices represent the deterioration behaviors of different assets. Having historical data about asset performance, asset managers can predict the future condition indices by applying deterioration modeling techniques (Hudson et al. 1997; Hegazy 2004). As shown in Figure 2-1, there are different methods such as straight-line extrapolation, regression analysis, curve-fitting models, or Markovian models for deterioration modeling (Morcous at al. 2002). The latter, which is used in this research, is a stochastic deterioration modeling technique based on the probabilities associated with different asset components to transfer from a higher condition state to a lower state (Butt et al. 1987; Jiang et al. 1988). As shown in Figure 2-2, after performing a rehabilitation action on an asset in any year N over the planning horizon the forecasted conditions based on deterioration curves will improve to a higher state. Based on the applied rehabilitation strategy (e.g., routine maintenance, minor repair, major repair, or full replacement) there will be different repair cost and improvement effect associated with various alternatives.

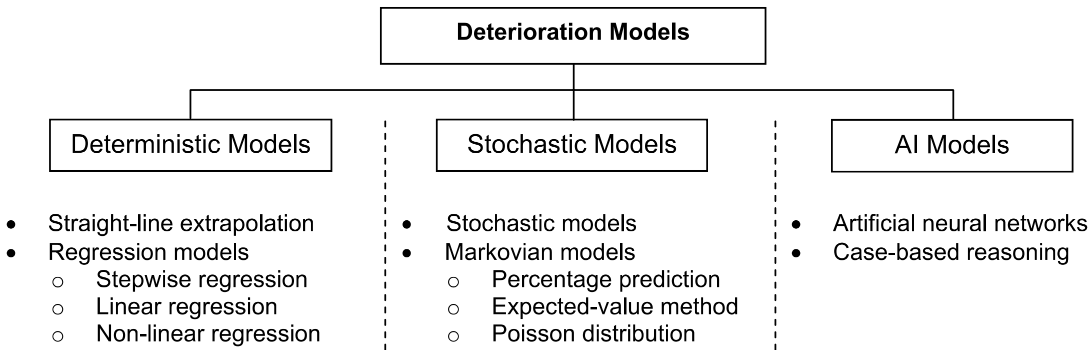

Figure 2-1: Deterioration modeling methods (Morcous et al. 2002)

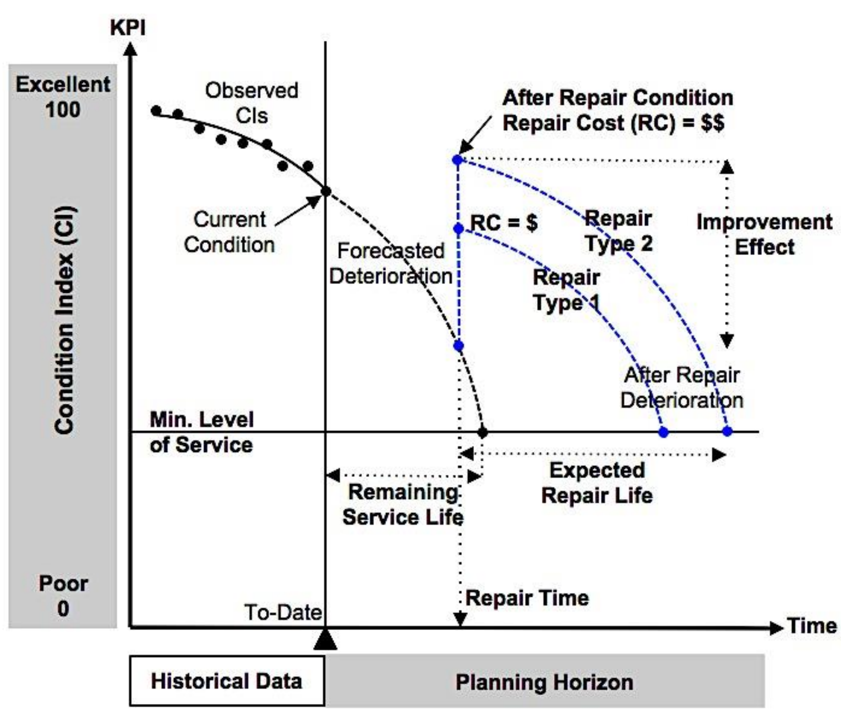

Figure 2-2: Schematic curve showing deterioration and repair modeling

Most of the aforementioned efforts for deterioration and rehabilitation modeling are focused on individual assets from detailed and most likely tactical point of view. From a strategic perspective, however, a detailed modeling of deterioration and rehabilitation actions can be prohibitive due to the enormous amount of information and details required. Furthermore, such detailed analysis may not significantly contribute and impact the long-term analysis at the strategic level, rather over complicates the decision making process. Accordingly, these research presents a different perspective for deterioration and rehabilitation modeling at the strategic level that investigates the deterioration patterns from a holistic point of view by considering groups of assets rather than individual analysis. Details of this approach has been discussed in Chapter 3.

2.5 Infrastructure Backlog

Infrastructure assets require continuous maintenance, rehabilitation, and replacement (i.e., renewal actions) over their lifetime. The renewal needs of existing infrastructure coupled with the demand for new infrastructure due to the growth of population and advances in technology is the main source of infrastructure backlog accumulation (Mirza 2008). Backlog accumulation is therefore a major problem in most infrastructure projects and requires urgent attention of the policymakers. Figure 2-3, for instance, presents an age profile of the educational buildings of the Toronto District School Board (TDSB) with their expected renewal needs, compared to the funding level (RECAPP 2002). As shown in this figure, backlog can accumulate over years and become a major problem for managing infrastructure projects. In U.S., infrastructure report cards - published every four year by American Society for Civil Engineers (ASCE) - show a significant backlog of $3.6 trillion in 2013 (ASCE 2013). In Canada also, infrastructure backlog is expected to reach hundreds of billions of dollars within the coming years (Federation of Canadian Municipalities (FCM) 2007). To this challenging problem, researchers have tried to develop systematic approaches to control or reduce backlog accumulation. County Surveyor Society (CSS), for example, utilizes optimization approach for backlog control taking into account asset conditions and their defectiveness in treatment selection and prioritization (CSS 2004). Edvorides at al. (2012), developed road maintenance strategies to deal with the problem of road maintenance backlog using World Bank’s model for road investment appraisal. Among the studies related to infrastructure backlog, very few efforts in the literature investigate the process of backlog accumulation with regard to different variables involve in asset management decision-making process, also considering other aspects such as privatization strategies in strategic asset management models.

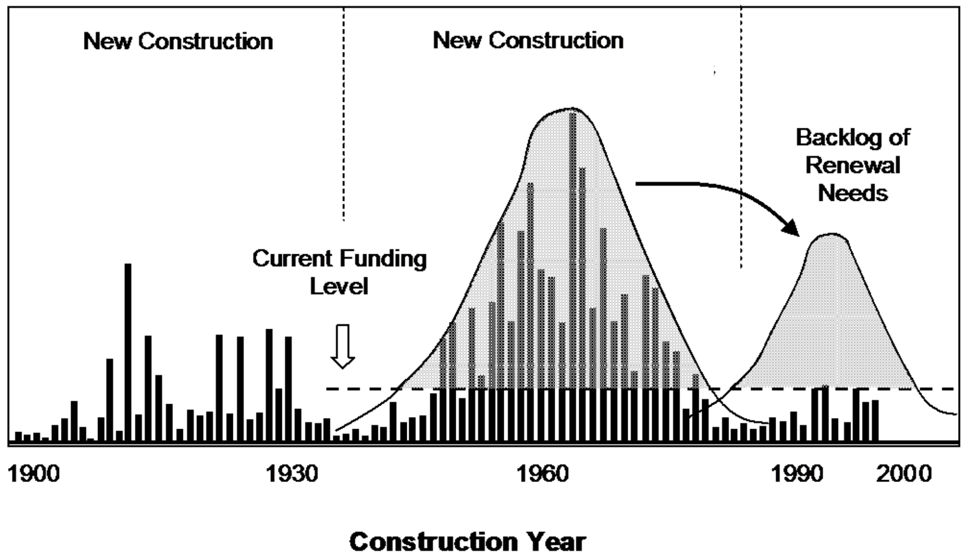

Figure 2-3: Construction-age profile with expected backlog (RECAPP 2002)

2.6 Public Private Partnership (PPP)

Public private partnership (PPP) is an alternative method for procuring large and complex public infrastructure projects by involving the private sector. Using PPP can decrease the infrastructure backlog, optimize risk and resources, and also can bring innovation into the infrastructure projects (PPP Canada 2012). In Canada, more than $27.1 billion was invested in different PPP infrastructure projects, such as schools, public transit, local roads, hospitals, or wastewater programs, in the period between 2009 and 2011 (PPP Canada 2013). According to the World Bank, many developing countries have also encouraged the private sector to participate in infrastructure facilities, and between 1990 and 1999, more than 30 developing countries have had at least one project completed by the private sector, as shown in Table 2-1 (Roger 1999).

Deciding on utilizing PPP at the strategic level can be due to several reasons. Sanchez (1998) suggests five main reasons:

1. Economic: PPP can reduce financial backlogs;
2. Pragmatic: private sector can bring new innovations and technologies;
3. Commercial: PPP brings new opportunity for investors to achieve higher returns;

4. Social: using PPP can improve social services brought by infrastructure facilities; and
5. Ideological: privatization is also based on the idea that smaller government is better.

Given these factors, governments around the world are increasingly turning to private financing to ease the burden on their budgets and to encourage better risk sharing, accountability, monitoring, and management in the provision of infrastructure assets and services (Roger 1999; World Bank 1999; World Bank 2003). There are, however, little efforts in literature to systematically investigate the effects of using PPP investments with regard to other aspects of asset management such as sustainability performance or backlog accumulation.

Table 2-1: Investment in Infrastructure Projects with PPP in Developing Countries ($ billions)

	1990	1991	1992	1993	1994	1995	1996	1997	1998
Telecommunication	6.6	13.1	7.9	10.9	19.5	20.1	33.4	49.6	53.1
Energy	1.6	1.2	11.1	14.3	17.1	23.9	34.9	46.2	26.8
Transport	7.5	3.1	5.7	7.4	7.6	7.5	13.1	16.3	14
Water and sanitation	0	1	1.8	7.3	0.8	1.4	2	8.4	1.5

Source: Roger (1999)

2.7 Optimization Techniques

Optimization, in general, tries to maximize or minimize an objective function (a goal) by determining the optimum values (quantities) for a set of decision variables respecting a set of constraints. Mathematical programming and evolutionary-based optimization techniques are two of the most commonly used optimization methods, particularly, for tactical rehabilitation planning and fund allocation optimization.

Mathematical optimization models has three main components including objective function, decision variables, and problem constraints. A mathematical optimization model can therefore be described in terms of the type of decision variables used in the model (e.g., being discrete or continuous) and the linearity or nonlinearity of objective function and constraint equations involved in the model. The model can also be described in terms of uncertainty associated with the variables and data presented in the model to be a deterministic or stochastic optimization model (Thanedar 1995; Cook et al. 1997). Linearity or nonlinearity of a model is an important factor that can affect the performance of the used optimization engines significantly. Based on the linearity of equations involve in the optimization problem linear programming (LP) or nonlinear programming (NLP) algorithms can be used to solves the problem. If one or more variables are in the form of integer or discrete numbers, then integer programming problem (IP) or mixed integer programming (MIP) methods need to be used to solve the optimization problem. As discussed in the next section, tactical rehabilitation planning usually involves variables with discrete options seeking combinations of possible actions until an optimum solution is obtained that meets all the constrained. These problems are very hard to solve because they exhibit exponential complexity as the problem size and the number of variables increase (Csiszar 2007; Elhakeem and Hegazy 2012), however, the use of evolutionary optimization algorithms can help to handle combinatorial problems.

Evolutionary algorithms are naturally inspired stochastic search methods developed for searching near-optimum solutions to large-scale combinatorial optimization problems (Goldberg 1989). Evolutionary optimization approaches usually mimic the process of biological evolution or the social behavior of species (Elbeltagi et al. 2005). Enhancements in artificial intelligence (AI) lead to development of different evolutionary algorithms, such as genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and shuffled frog leaping algorithm (SFLA), which are proved to be promising optimization approaches in handling complex engineering problems (Elbeltagi et al. 2005). Genetic Algorithm (GA) was first introduced by Holland in 1975 and is one of the widely used evolutionary methods in different areas of asset management and civil engineering, such as the site-layout optimization of facilities (Cheung et al. 2002; Li and Love 2000, and Osman et al. 2003), cost optimization and cost trade off problems (Hegazy 1999), and in resource levelling in construction (Leu et al. 2000). The common conclusion among all the previous researches was the efficiency of implementing GA in solving large-scale and complex problems and arriving at near-optimum solutions. Using Genetic algorithm, solution to a given problem is represented in the form of strings called ‘chromosomes’ and each chromosome consists of a set of elements called ‘genes’ represent decision variables. Evolution process starts by generating a random population of solutions, i.e., parent chromosomes, and evaluating them based on a fitness function, which is usually defined with respect to objective function. Subsequently, best parent chromosomes exchange their information through the process of “crossover” or “mutation” and create offspring chromosomes. Each offspring chromosome is evaluated based on its fitness value and the fittest chromosomes are selected to repeat the process of evolution until maximizing the fitness function (Goldberg et al. 1991).

2.8 Tactical Rehabilitation Planning

Optimization of tactical decisions such as repair type or repair timing is an integral part of a comprehensive asset management process that ensures a proper implementation of strategic policies and is essential to achieve long-term objectives. At this stage strategic policy decision regarding budgeting of rehabilitation strategy can act as tactical constraints on the optimization model, while repair type and repair timing are the decision variables with the objective of maximizing performance or minimizing life cycle cost (Hudson et al. 1997; Morcous and Lounis 2005; Rashedi and Hegazy 2014). Although various performance indicators exist for different types of infrastructure assets (e.g., highways, bridges, or buildings), physical performance or the overall condition of the building components (e.g., windows, roofs, boilers, and etc.) is the one the most widely used indicator for school buildings, which is the intended case study of this research (Ben-Akiva1 and Gopinath 1995; Hudson et al. 1997; Hegazy et al. 2004). Physical performance can be then as the average of condition indices for all components in the network taking into account a relative importance factor as indicated by Eq. (2-1).

$$CI_N = \frac{\sum_{j=1}^{N} \sum_{k=1}^{t} CI_{jk} \times RIF_j}{\sum_{j=1}^{N} RIF_j} \quad \forall\, j \in Network \;\&\; \forall\, k \in Planning\ Horizon \qquad (2-1)$$

The objective of asset renewal optimization models is often to maximize the performance of the infrastructure network within the available budget limits and other tactical constraints. As mentioned before, two types of decision variables are defined to address repair selection (type) and timing (Liu et al. 1997; Hegazy and Rashedi 2012). Repair type decision variables are in the form of integer values selected based on the available repair alternatives (Eq. (2-2)) and repair timing variables that can be defined as binary variables along the planning horizon (Eq. (2-3)). Accordingly, a value of 1 for the repair timing decision variable represents a repair in the corresponding year and 0 represent no repair action.

$$Repair\ type\ available\ for\ asset\ j{:}\ X_j = [1, 2, 3, \ldots, M] \quad for\ \ M\ \ repair\ alternatives \qquad (2-2)$$

$$Repair\ timing\ variable\ for\ asset\ j\ in\ year\ t: Y_{ij} = \begin{bmatrix} Y_{11} & 0 & \dots & Y_{1t} \\ 0 & 1 & \dots & 0 \\ . & . & Y_{ij} = [0, 1] & . \\ Y_{n1} & . & \dots & Y_{nt} \end{bmatrix} \qquad (2-3)$$

In the literature, many researchers have introduced asset renewal optimization models in different asset management domains. Examples are: pavement maintenance (de la Garza et al. 2011); renewal of sewer networks (Halfawy et al. 2008); rehabilitation of water networks (Mann and Frey 2011); life cycle cost optimization of steel structures (Sarma and Adeli 2002); bridge maintenance (Elbehairy et al. 2006); building asset management (Hegazy and Elhakeem 2012); mixed municipal assets (Shahata and Zayed 2010); and groundwater remediation (Zou et al. 2009). One of the main challenges that majority of these effort face is the large number of existing asset components that exacerbates the combinatorial complexity of finding optimum solutions in such problems. To solve large-size combinatorial optimization problems, rather than using traditional mathematical techniques, researchers have studied other types of efficient optimization methods. These methods can be categorized in two groups: meta-heuristics (e.g., Genetic Algorithms (GA), and heuristics (e.g., benefit-over-cost ratio). Although these optimization methods, if properly implemented, are capable of reaching high quality solutions (i.e., close to global optima), the quality of solutions, especially in complex problems, degrades by increasing the solution size beyond the limits of applied algorithms (Hegazy and Rashedi 2012). Therefore, practical and efficient mechanisms are required to complement GAs for handling such large-scale problems. Hegazy and Rashedi (2013), for example, proposed a segmentation mechanism to improve the performance of GAs for very large-scale asset management problems. Heuristic approaches, on the other hand, are experienced-based problem solving mechanisms for finding satisfactory solutions (Hudson et al 1997) that are capable of handling problems with large number of variables and constraints, however, cannot results in solutions as high quality as GAs. Although in the literature numerous efforts have been done to develop tactical-level optimization models, they are rarely integrated directly with the strategic level of policy-making.

2.9 Integrated Efforts

The concept of integration in AMS has been discussed in literature from different perspectives. Hudson et al. (1997), describes integrated asset management systems as tools to cover two or more types of similar facilities. Although addressing multiple types of assets is important, integration among the function of AMS itself is also an important issue. Halfawy et al. 2008, proposed an integrated decision support system for optimal renewal planning of sewer networks by integrating condition assessment, risk assessment, prediction of future condition, asset prioritization, selecting appropriate renewal technologies, and evaluating alternative renewal plans. These functions, however, are mostly at the tactical level of decision-making without integration with the strategic policymaking level. To develop an integrated AMS Lemer 1998, proposed an integrated AMS framework with five principal stages including: data collection and analysis, performance modeling, scenario and management policy generation, decision analysis, and management reporting. Recently the Australian Asset Management Collaborative Group (AAMCoG) published their guide to integrated strategic asset management (AAMCoG 2012). The document mainly discusses a general framework of strategic asset management with integration with tactical and operational levels, however, it does not provide any systematic approach for implementation of the integrated AMS. As mentioned in this section, most of the efforts in developing integrated AMS are focused on the tactical level and few just propose a framework for the strategic and tactical integration. There is therefore a huge lack in literature on integrating strategic and policy issues with tactical and operational decisions.

2.10 System Dynamics & Its Potential

2.10.1 Simulation and System Dynamics

In general, simulation is an effective tool to study the behaviour of real systems, such as infrastructure management systems (IMS). Accordingly, various methods are available to model and simulate the behaviour of a real system from different perspectives. The most common simulation methods used by modellers include: system dynamics (SD), discrete-event simulation (DES), and agent-based simulation (ABS). The selection among these methods depends on the characteristics of the problem, the level of decision-making associated with the model (e.g., strategic or tactical), the type of system components being investigated (e.g., individuals, processes, flows, etc.), level of available information, and the time dependency of the phenomena being modelled (i.e., discrete, or continues). Table 1 shows an overall comparison among the characteristics of problems that can be simulated by these methods, and uses a simple ‘amusement park’ example to illustrate the differences among these simulation methods. As indicated by Table 2-2, DES and ABS are more practical at the tactical and operational levels of decision-making.

Table 2-2: A general comparison amongst different simulation methods

	System Dynamics (SD)	**Discreet Event Simulation (DES)**	**Agent Based Simulation (ABS)**
Level of details	Low	Medium/High	High
Decision-Making	Strategic	Tactical/Operational	Mostly Operational
Main Components	Stock variables, flows, feedback loops	Servers, Costumers, Inter-arrival Times	Individual agents, drivers, interactions
Time Dependency	Continuous	Discrete	Continuous
Applications	Policy Investigation, Strategy Evaluation, etc.	Production Analysis, Manufacturing Systems, etc.	Consumer Behaviour, Network Effects, etc.
Analysis Point of View	Policy Maker	Operator	User
Example (Amusement Park)	Strategies of number of rides, discounts, pricing, and future improvements, etc.	Analysis of ride time, waiting time, service time, average number of users in queue, etc.	Analysis of user (agent) satisfaction, pattern of selection (rides, food), etc.
Sample Software	Vensim, Stella	Simul8, Arena	AnyLogic

The level of details in DES and ABS is much higher than system dynamics, which makes them less suitable for strategic modelling (Banks et al. 2006; Swisher et al. 2003, Railsback et al. 2006; Gotts et al. 2003). System dynamics (SD) is perhaps one of the most promising simulation methods in the area of policy optimization (Forrester 1961; Sterman 2000). Sterman (2000), describes system dynamics as "a method to enhance learning in complex systems. Just as an airline uses flight simulators to help pilots learn, system dynamics is, partly, a method for developing management flight simulators, often computer simulation models, to help us learn about dynamic complexity, understand the sources of policy resistance, and design more effective policies". The word 'complex systems' in this definition is mainly used to describe systems that are nonlinear, governed by feedback, history-dependent, and dynamic. To learn about such complex behaviors, SD is grounded in the theory of nonlinear dynamics and feedback control (Sterman 2000). The concept of system dynamics changes the way we model systems involving policy and social aspects that cannot be model efficiently using traditional modeling approaches. Typically, policymakers follow a linear approach to modeling. In this type of thinking, the difference between an existing situation and policymakers' strategic goal represents a problem. The policymaker then makes some decisions according to the problem and obtains results. Although linear modeling is the most common way of modeling among decision-makers, it has been proved to be very inefficient for long-term strategic planning (Sterman 2000). In the real world, decisions and policies may provoke reactions by other parties seeking to restore the upset balance. This phenomenon is called the "counterintuitive behavior of dynamic systems" (Forrester 1971). The counterintuitive behavior and the interrelationships among different aspects of strategic models often lead to issues such as policy resistance, unexpected risks, and unintended consequences that can cause significant problems for policymakers (Meadows et al. 1982). To avoid these problems and to better capture the dynamics of strategic systems, system dynamics suggests a holistic feedback view in which our decisions and others' decision alter our environment and triggers side effects or delayed reactions that lead to new decisions and goals (Forrester 1971; Sterman 2000).

2.10.2 Applications of System Dynamics

System dynamics has been applied to variety of projects form construction to politics to HIV control or even warfare. In all of its application, SD proved to be capable of capturing the dynamics and interaction among different agents from a holistic point of view and therefore is effective for top-level management (Sterman 2000). Homer (1993), for example, has discussed application of SD in large and complex construction projects in details. Using SD, a model was developed for multinational forest company to reduce delivery time in pulp and paper mill construction projects. The model proved to be effective and useful in analyzing different policies and helped identify policies that reduced delivery time by 30% in the next few years (Homer et al. 1993). Lee at al. (2006), used SD to develop and integrated construction management model that contributed to the improvement of construction productivity by sharing reliable information and decisions in a timely manner without the limitations of space and time. Alvanchi et al. (2011), also used SD and discrete event simulation (DES) model to address the conceptual phase of hybrid SD-DES modelling for mega construction projects. Qi and Chang (2011) proposed system dynamics model to reflect the intrinsic relationship between water demand and macroeconomic environment using out-of-sample estimation for long-term municipal water demand forecasts in a fastgrowing urban region. Rehan at al. (2011), used SD for developing financially self-sustaining management policies for water and wastewater systems. The SD model revealed that with no proactive rehabilitation strategy the utility would need to substantially increase its user fees to achieve financial sustainability (Rehan et al. 2011). Xu and Coors (2012), used SD with GIS and 3D visualization in sustainability assessment of urban residential development and concluded that using SD is a feasible and effective strategy to study sustainable developments. All of these applications and many others have shown that system dynamics has a large potential in developing strategic model for policy analysis and can be a viable candidate to use for strategic and tactical asset management.

2.10.3 Development of Simulation Models Using System Dynamics

System dynamics offers tools to capture and analyze a feedback model of strategic systems. In general, the process of applying system dynamics for strategic modeling involves: determining strategic variables; causal loop diagraming; stocks and flows diagraming; simulation; and validation and model testing (Figure 2-4). The following subsections explain the main parts of SD modeling procedure.

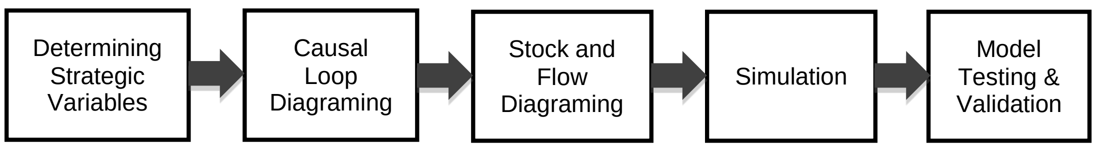

Figure 2-4: System dynamics modeling procedure

2.10.3.1 Key Strategic Variables and Casual Loop Diagraming

In system dynamics, causal loop diagrams (CLDs) are excellent tools for capturing SD hypotheses about the interactions among different variables, causes of dynamics, and determining the important feedbacks in strategic systems. A causal loop diagram consists of variables connected by links denoting the causal influences among them. Casual links show effects of variables on each other by link polarities. A positive link polarity (as shown by a "+" sign in Figure 2-5) implies that "if a cause increases, the effect increases above what it would otherwise have been" and vice versa. Similarly, a negative link polarity (-) means "if the cause increases, the effect decreases below what it would otherwise have been" and vice versa (Sterman 2000).

To illustrate CLD, consider an example of modeling the dynamics that affect the asset condition. In a simplified case, assume asset condition is affected by dynamic time-dependent processes (variables) such as asset deterioration, renewal actions, and the level of service (LOS), as shown in Figure 2-5. In the figure, asset deterioration is linked to asset condition by a negative link polarity. This means, if the deterioration increases, asset condition decays (decreases). Another negative link also connects asset condition to asset deterioration, which indicates that by decreasing the asset condition deterioration rate increases. The combination of these links then creates a reinforcing feedback loop (R) as depicted by Figure 2-5. Reinforcing (or positive) loops cause growth. In the case of asset condition, a cycle is established in which infrastructure deterioration occurs at an accelerated rate (Hudson et al. 1997, Wirahadikusumah and Abraham 2003). On the other hand, improving asset condition increases the level of service, which is presented by a positive link between the two variables. By increasing the LOS the number of renewal actions will decrease (i.e., a negative link). If the number of renewal actions decreases then asset condition decays (i.e., positive link). This behavior, as depicted in Figure 2-5, represents a balancing feedback loop (B). Balancing (or negative) loops cause self-balancing behaviors that lead to equilibriums. The balancing loop in Figure 2-5 suggests that the number of renewal actions is adjusted based on the observed LOS to keep the asset condition within an acceptable serviceability level, which is a very common renewal approach in the area of asset management (Hudson et al. 1997). The CLD technique is a rich and effective method for capturing and analyzing different dynamic behaviors. Also, the polarities and feedback loops have mathematical interpretation that can help modeler in understanding the dynamic behaviors of complex systems.

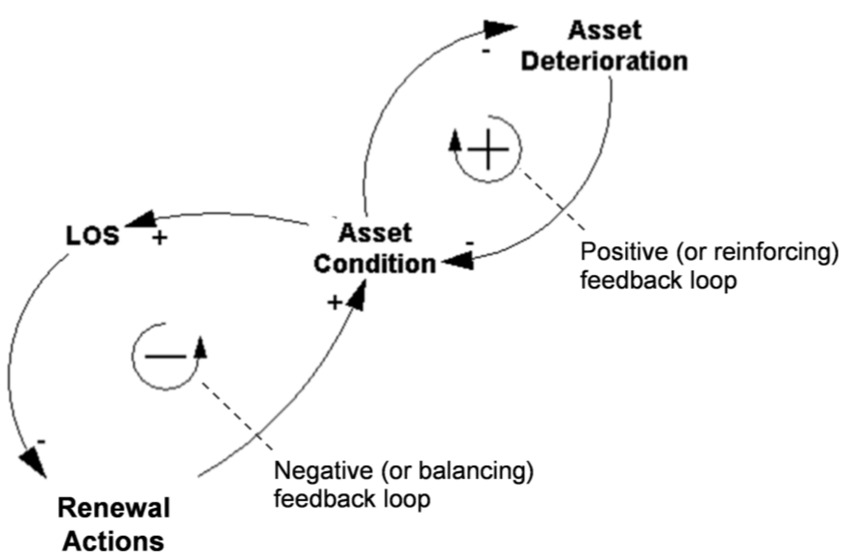

Figure 2-5: A simplified CLD example of deterioration and rehabilitation processes

2.10.3.2 SD Simulation Using Stocks and Flows

Development of an SD model requires mapping of proposed CLD dynamics into a stock and flow model, which is comprised of four main components: stocks, flows, valves, and clouds. The diagramming notations for these components are shown in Figure 2-6. Stocks, represented by rectangles, are accumulations that characterize the state of key system variables over the simulation time. Flows, on the other hand, represent system variables that generate quantities accumulated into (inflows) or out of (outflows) the stocks over time. Valves are flow generators that control the amount of inflow and outflow over the simulation time based on the relationships in the model. Clouds also represent entry or exit boundary points in the model.

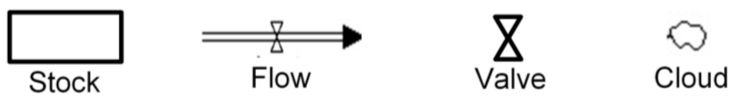

Figure 2-6: Stock and flow diagramming notations

Equations 2-4 and 2-4 represent the basic mathematics behind stock and flow modelling and its calculations. In general, the rate of change in a stock variable is determined based on the difference between the inflows and outflows (Eq. (2-4)). The value of a stock variables at any time t over the simulation time can be also determined using Eq. (2-5).

$$\frac{d(Stock)}{dt} = Inflow(t) - Outflow(t) \qquad (2-4)$$

where Inflow(s) represents the value of the inflow at any time *s* between the initial time to and the current time *t*.

$$Stock(t) = \int_{t_0}^{t} [Inflow(s) - Outflow(s)]ds + Stock(t_0) \qquad (2-5)$$

Considering the asset deterioration example discussed in the previous subsection (Figure 2-5), asset condition can be represented by a stock that accumulates the state of condition over time. On the other hand, asset deterioration can be then represented by an outflow (decreasing the stock), while renewal actions can be represented by an inflow (increasing stock) as shown in Figure 2-7.

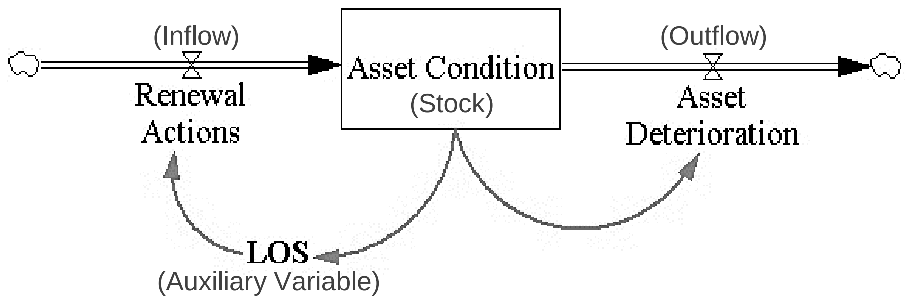

Figure 2-7: Stock and flow diagraming example of asset deterioration and rehabilitation

Based on Figure 2-7 and Eq. (2-5), system starts with an initial condition (Stocl(t_0)). Deterioration is then acts as an outflow, which reduces the condition over time. Renewal actions can increase the stock variable over time based on the number of repair interventions. As discussed in the previous subsection, the renewal action itself depends on the LOS that is represented in Figure 2-7 by an auxiliary variable. Using the mathematical interpretations (Eqs. 2-4 and 2-5) of the stocks and flows diagrams and the link polarities among variables, it is possible to simulate the behavior of strategic models (systems) using system dynamics. Different computer software, such as Vensim, Anylogic, iThink, and Stella, also exists that are capable of simulating system dynamics models. Some of these tools are also capable of combining SD models with other types of simulation to create hybrid models for more realistic analysis (e.g., Anylogic).

2.10.3.3 Model Validation and Testing Methods

Testing and validation of SD models is an important part of the model development. Table 2-3 discusses different types of validation processes including: boundary analysis, structure assessment, sensitivity analysis, extreme condition tests, and dimensional consistency. In general, a valid model should be able to accurately simulate the actual behavior of a real system. To validate, the model needs to be directly compared to historical data and be able to replicate them. In reality, however, historical and quantitative statistical data over a long period of time are not available in many cases. In addition, factors such as the complexity of real systems, the principle of bounded rationality, and lack of information, have made many modelers recognize the difficulty of assertive validation of mathematical models (Sterman 2000). At some level, objective validation of a mathematical model eventually rests on the modeler's judgment or faith that either the procedure or its goals are acceptable without objective proof (Forrester 1961). Despite the difficulties with objective model validation, modelers need to strive to test the robustness of their conclusions and its sensitivity to uncertainty in model assumptions (Sterman 2002).

Table 2-3: Model testing and validation methods (based on Sterman 2000)

Test	Purpose	Procedure
Boundary Adequacy	Are the important concepts for addressing the problem endogenous to the model? Do the policy recommendations change when the model boundary is extended?	Using causal diagrams, stock and flow maps, and direct inspection of model equations. Also conduct interviews to solicit expert opinion, review of literature, and direct inspections will be used.
Structure Assessment	Is the model structure consistent with relevant descriptive knowledge of the system? Is the level of aggregation appropriate?	Using causal diagrams, stock and flow maps, and direct inspection of model equations. Also conduct interviews to solicit expert opinion, review of literature, and direct inspections will be used.
Dimensional Consistency	Is each equation dimensionally consistent without the use of parameters having no real world meaning?	Using dimensional analysis software. Inspect model equations for suspect parameters.
Parameter Assessment	Are the parameter values consistent with relevant descriptive and numerical knowledge of the system? Do all parameters have real world counterparts?	Using statistical methods to estimate parameters. Using judgmental methods based on interviews, expert opinion, direct experience, and etc.
Extreme Conditions	Does each equation make sense even when its inputs take on extreme values?	Inspecting each equation. Test response to extreme values of each input, alone and in combination.
Sensitivity Analysis	Do the policy implications change significantly as variables change?	Performing univariate and multivariate sensitivity analysis.

2.10.4 Benefits of Using System Dynamics

Based on the above discussion application of system dynamics has the following benefits:

- Powerful tool to help understand and leverage the feedback interrelationships of complex management systems;
- Promising for strategic management and studying dynamic behaviors and performing long-run simulations through a holistic representation of complex systems;
- System dynamics models utilize the same graphic language and hierarchical structure, thus creating a universal highly intelligible language for exploring system behavior and communication with clients; and
- Its foundation rests in engineering science and data to control model development.

2.11 Conclusions

This chapter reviewed the literature related to the key concepts that are covered in this research. This chapter started by introducing the concept of asset management systems (AMS) and its importance to help asset managers with their decision-making. Next strategic management and policy-making issues in the area of asset management such as infrastructure backlog were discussed. Based on the reviewed literature, a knowledge gap has been identified in the area of strategic asset management to effectively analyze the long-term impact of strategic policies on key performance indicators such as backlog accumulation or overall infrastructure condition. This chapter also analyzed the literature related to tactical implementation of strategic objectives and policies using optimization and showed that there have been limited efforts to understand the interactions among the parameters involved at the strategic and tactical levels. Finally, this chapter introduced system dynamics (SD) and the main components of SD modeling procedure in details, and identified SD modeling as a potential approach to address the aforementioned strategic and tactical asset management challenges in the area of infrastructure management.

Chapter 3

Deterioration and Rehabilitation Modelling Using System Dynamics

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3.1 Chapter Summary

Modelling deterioration and rehabilitation processes and their interactions with life cycle cost, is at the core of rehabilitation analysis and planning. This chapter takes a holistic view to investigate the dynamics that affect long-term deterioration and rehabilitation of infrastructure networks. First, the interactions among the main parameters related to asset deterioration, rehabilitation actions, and cost accumulation have been analysed using causal loop diagrams (CLDs). Afterwards, a system dynamics (SD) model has been developed based on the CLDs and the underlying mathematical relations among the various parameters. The SD model was then tested on a network of 1000 assets over a 50-year plan, considering a range of possible rehabilitation actions and fund allocation options. The model proved to be a practical and effective tool for quick assessment of the long-term impact of rehabilitation policies on infrastructure performance.

3.2 Introduction

A major challenge for asset managers is to determine the appropriate actions needed to preserve the performance of their rapidly deteriorating infrastructure, over a long service life. Adequate budgeting and planning of infrastructure rehabilitation programs is of extreme importance in achieving this objective (Hudson et al. 1997). Budgeting and planning, however, are complex tasks that require many details about each asset, including present condition, multi-criteria performance, deterioration pattern, possible rehabilitation actions, and rehabilitation impacts. Ideally, as discussed in the literature, these functions are integrated to formulate a detailed life cycle cost analysis (LCCA) model of the whole network of assets to facilitate the appropriate allocation of limited rehabilitation funds (Farran and

Zayed, 2009; Ugarelli and Federico, 2010; Frangopol et al., 2012). In the literature, infrastructure rehabilitation has been extensively studied and a number of life cycle optimization models have been introduced for different asset domains. Examples are: pavements (Ng et al. 2009; de la Garza et al. 2011); water and sewer (Halfawy et al. 2008; Dridi et al. 2008); bridges (Elbehairy et al. 2006; Frangopol et al. 2012); buildings (Tong et al. 2001; Hegazy and Rashedi 2012). Most of the existing models, however, suffer from performance degradation when facing large-scale and complex life cycle optimization problems, yet the results are also difficult to explain or economically interpret (Rashedi and Hegazy 2014).

While existing efforts provide useful life cycle cost models, they do not provide an overall understanding of the rehabilitation dynamics in large networks of assets, over a long period of time. Some efforts focused on individual assets over a long period (more than 50 years) (e.g., Frangopol and Liu, 2007) while others focused on a large number of assets over a short period (5 years) (e.g., Rashedi and Hegazy 2014). These efforts lack examining strategic decisions while considering the life cycle dynamics over a long span of time (Kong and Frangopol 2003). Such a holistic view, however, is essential for strategic decision-making as it can simulate the important dynamics among rehabilitation actions, asset deterioration, and cost accumulation. This chapter therefore attempts to provide such a holistic analysis that is suitable for examining the impact of policy decisions on infrastructure performance and cost in large-scale networks. This chapter explores the potential of the system dynamics (SD) technique as an effective tool for modeling and analysis of the dynamic processes within infrastructure rehabilitation. In the following sections, the SD technique is briefly introduced, followed by a description of how the proposed holistic model is structured and implemented in an SD software. Afterwards, the results of various experiments on a case study are presented and discussed, followed by comments on the model performance and future extensions.

3.3 Holistic SD Model for Rehabilitation Analysis

Detailed rehabilitation planning for a large network of assets can be a cumbersome and tedious task due to the extremely large amount of information and analysis required for each individual asset, as highlighted in the left side of Figure 3-1. Yet, the results of this analysis will mainly suit tactical and operational planning as it shows the type and timing of rehabilitation actions needed for each individual asset. Also, due to the large scale and complexity of the detailed models, the analysis is often limited to short planning horizons that oversees long-term trends. Alternatively, the proposed strategic model takes a holistic analysis point of view and can be carried out with reasonable effort by shifting the focus from individual assets to a group of assets as a whole, as shown in the right side of Figure 3-1. It is important to note that both the detailed and the holistic analyses incorporate project-level (type of rehabilitation) and network-level (timing of rehabilitation) decisions (Rashedi & Hegazy 2014), but with different perspectives. On the one hand, detailed analysis determines these decisions for each individual asset, considering deteriorations, costs, and benefits. Holistic analysis, on the other hand, focuses on the aggregation of these decisions for the entire asset network on the long-term to analyze dynamic system behavior.

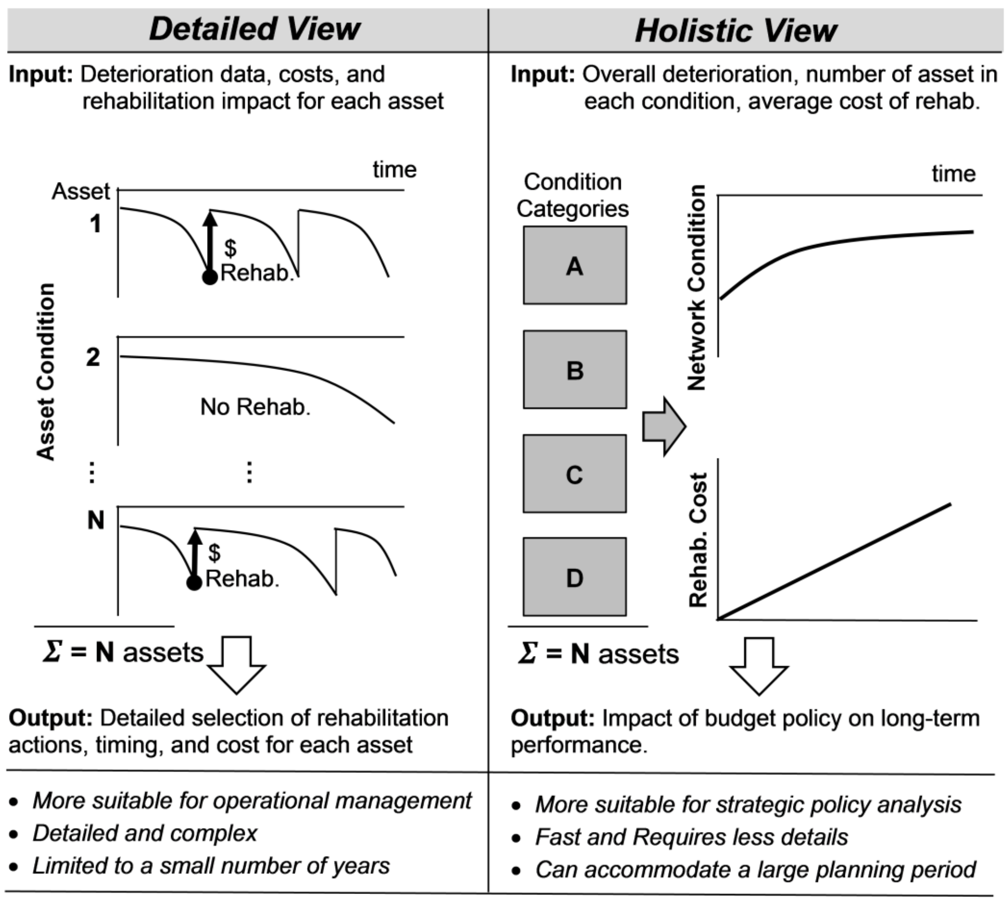

Figure 3-1: Detailed vs. holistic rehabilitation modeling perspectives

In the proposed holistic view, the same N number of assets in the network are categorized into several groups where each group contains a number of assets with similar or close condition. The deterioration can then be modeled by the transition process of some assets moving from a higher category to a lower one, while a rehabilitation improvement can be modeled by a transition of some assets from a lower category to a higher one. Although this perspective might lose some details regarding each individual asset, it is an effective and fast approach to simulate the long-term effects of strategic policies and to assist asset managers in making optimum strategic decisions.

Following the holistic modelling approach, Figure 3-2 illustrates the components of the general framework of the proposed model. As indicated in the figure, the primary input is comprised of asset inventory data, such as age, location, renewal history, etc., as well as current condition assessments and information regarding expected rehabilitation costs. The holistic model has three main functions that work together to provide an analysis of life cycle cost and performance: asset deterioration, rehabilitation actions, and cost accumulation. Accordingly, the dynamic interactions among and within these functions are modelled from a macro-management point of view considering the network of assets as a whole. First, the asset deterioration function uses SD to simulate the overall deterioration patterns, from a network point of view. Then, the rehabilitation actions function introduces various possible rehabilitation alternatives, and their impact, on the overall condition. Finally, the cost accumulation function considers different budgeting policies and their impact on the rehabilitation process. The primary output of the model is also a quantification of the impact of strategic rehabilitation policies on condition performance and life cycle rehabilitation costs over time. The modelling of the three functions is discussed in detail in the following subsections.

Figure 3-2: General framework of the proposed rehabilitation analysis model

3.3.1 Asset Deterioration

A variety of factors can negatively affect the operating condition of infrastructure assets and cause asset deterioration; examples include aging, severe environmental conditions, overcapacity, and deferred maintenance decisions. An initial step towards modelling asset deterioration is to identify the condition of assets through inspections or other assessment methods (Uzasrki 2002, Elhakeem and Hegazy 2005a). The results of these periodic condition assessments are then employed to develop deterioration models as a means of predicting future asset conditions. A number of deterioration modeling approaches have been introduced in the literature (Madanat et al. 1997; Morcous 2002; Elhakeem and Hegazy 2005b). The simplest form of deterioration model is linear (Figure 3a), with a fixed deterioration rate based on the expected life of an asset (e.g., an asset with an expected 10-year life span will deteriorate at a rate of 1/10 or 10 % per year). More realistic deterioration models, however, capture nonlinear behaviours (Figure 3b) as a result of variable deterioration rates that are affected by the current condition of assets.

3.3.1.1 Causal Loop Diagrams

The first step in developing both linear and nonlinear deterioration models is to define causal loop diagrams (CLDs) that consist of variables connected by causal links whose polarities denote the effects of one variables on another. A positive link, i.e., (+) polarity, implies that the cause and effect are moving/changing in the same direction in the model: e.g., if a cause increases, the effect increases, and if a cause decreases, the effect decreases. A negative link, i.e., (-) polarity, means that the cause and effect are moving/changing in opposite directions in the model: e.g., if the cause increases, the effect decreases, and vice versa (Sterman 2000). In the case of linear deterioration (Figure 3-3a), the 'asset deterioration' variable is linked to 'asset condition' by a negative link polarity, which models the fact that deterioration results in a decay in condition over time. In the case of nonlinear deterioration (Figure 3-3b), the CLD shows that 'asset deterioration' negatively affects 'asset condition' and that 'asset deterioration' is itself affected by 'asset condition.' Accordingly, 'asset condition' is connected to 'asset deterioration' by a negative link, indicating that an inferior condition results in faster (greater) deterioration, as suggested by many infrastructure management studies and references, e.g., Hudson et al. (1997). The combination of these links creates a positive (+) feedback loop, as depicted in the middle part of Figure 3-3b. Positive loops, also called 'reinforcing' loops, typically result in exponential growth/decay behaviour. In the case of deterioration modelling, a positive deterioration loop leads to accelerated nonlinear deterioration behaviour over time, as suggested by Figure 3-3b.

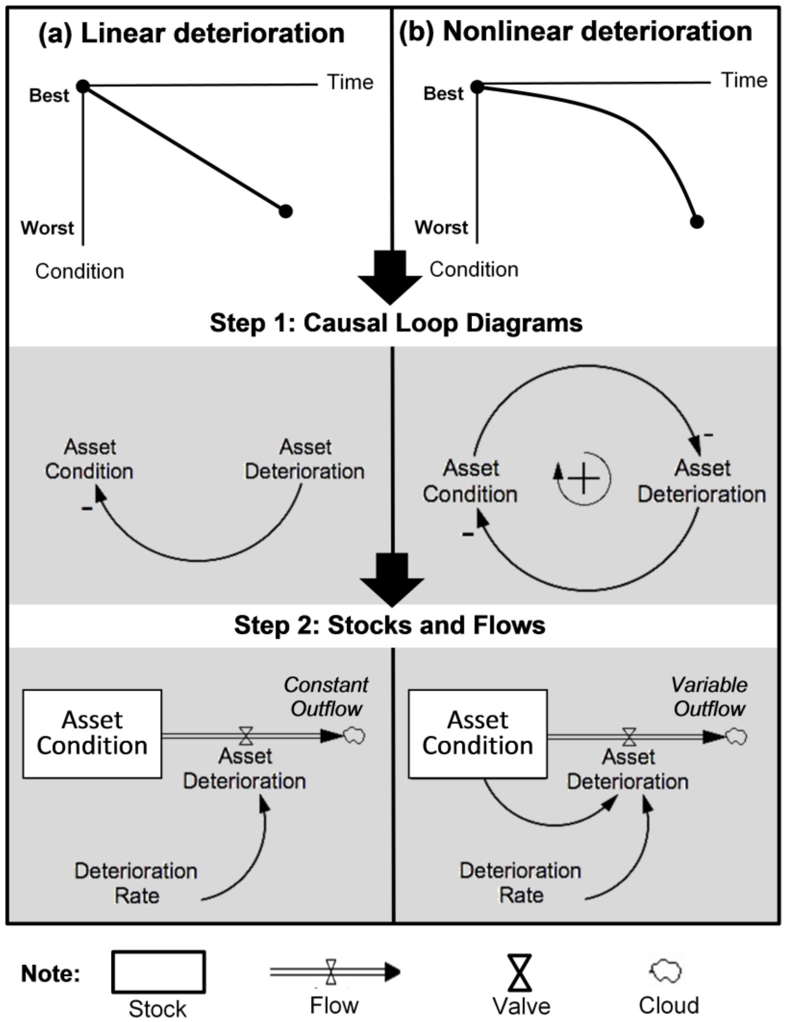

Figure 3-3: System dynamics modeling of single-asset deterioration

3.3.1.2 Stock and Flow Diagrams

The development of an SD model requires the mapping of the CLD dynamics to a stock and flow model, which is comprised of four main components: stocks, flows, valves, and clouds. The diagramming notations for these components are shown at the bottom of Figure 3-3. Stocks, represented by rectangles, are accumulations that characterize the state of key system variables over the simulation time. Flows, on the other hand, represent system variables that generate quantities accumulated into (inflows) or out of (outflows) the stocks over time. Valves are flow generators that control the amount of inflow and outflow over the simulation time based on the relationships in the model. Clouds also represent entry or exit boundary points in the model. In the stock and flow model for linear deterioration, 'asset condition' is thus defined by a stock variable whose value is reduced over time by a fixed deterioration outflow (bottom of Figure 3-3a). In general, the rate of change in a stock variable is determined based on the difference between the inflows and outflows (Eq. (3-1)). In the case of a fixed deterioration outflow the result is therefore a constant rate of change in the stock variable (asset condition) and the creation of a linear behaviour with a constant slope. The value of the stock variables (e.g., asset condition) at any time t over the simulation time can be also determined from the basic mathematics of system dynamics expressed in Eq. (3-2).

$$\frac{d(Stock)}{dt} = Inflow(t) - Outflow(t) \qquad (3-1)$$

$$Stock(t) = \int_{t_0}^{t} [Inflow(s) - Outflow(s)]ds + Stock(t_0) \qquad (3-2)$$

The stock and flow model that results in the case of nonlinear deterioration is illustrated at the bottom of Figure 3-3b, in which the deterioration outflow is affected by both asset condition and deterioration rate. Based on Eq. (3-1), the rate of change in the stock variable is low at the beginning when the condition index is high and increases over time as the condition decays (i.e., variable outflow). Based on this model, the condition index (CI_t) of an asset at time t is calculated as follows:

$$CI(t) = \int_{t_0}^{t} [-Asset\ Deterioration(s)]ds + CI(t_0) \qquad (3-3)$$

Achieving the goal of providing the network-level perspective discussed before (i.e., strategic asset management), however, requires the simultaneous modelling of the deterioration process of an entire network of assets. For the work presented in this chapter, the modelling involved the implementation of a variation of the Markovian process as a common nonlinear modelling approach for asset deterioration (Morcous et al. 2003; Elhakeen and Hegazy 2005b). To accommodate a network of assets with varying conditions, five discrete condition states are defined: 1 = Excellent, 2 = Good, 3 = Fair, 4

= Poor, and 5 = Critical. At any given time, all of the assets are distributed among these condition states ("State1" represents the number of assets in condition state 1, etc.), and their distribution indicates the overall condition of the network (CI_N):

$$CI_N = \frac{State1 \times 1 + State2 \times 2 + State3 \times 3 + State4 \times 4 + State5 \times 5}{Total\ Number\ of\ Assets} \qquad (3-4)$$

As with a Markovian process, the probabilities of transition from one condition state to another over a specific planning time is defined by a 5 x 5 matrix (because 5 condition states are used), called the transition probability matrix (TPM), which is formulated as follows:

$$TPM = \begin{bmatrix} P_{11} & \boldsymbol{P_{12}} & 0 & 0 & 0 \\ 0 & P_{22} & \boldsymbol{P_{23}} & 0 & 0 \\ 0 & 0 & P_{33} & \boldsymbol{P_{34}} & 0 \\ 0 & 0 & 0 & P_{44} & \boldsymbol{P_{45}} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad (3-5)$$

Where, Pii is the probability of an asset in state i remaining in state i, while Pij is the probability of the same asset deteriorating to state j (Pii + Pij = 1). It is important to note that the basic assumption behind this process is that assets move from one condition state only to the next lower sate. TPMs can be determined using historical observations (Ortiz-Garcia et al. 2006). One method of finding transition probabilities, which is used in this study, is to utilize historical condition data and minimize the error between the predicted and the actual condition indices. In this case, TPMs are set as the decision variables (ranging from 0 to 1) with the total error as the objective function to minimize. More details regarding the TPM calculation can be found in Elhakeem and Hegazy (2005b). As such, the transition probabilities are used in the proposed model in order to define the deterioration rates required for modelling the nonlinear behaviour, as explained in relation to Figure 3-2b. The SD model of network deterioration is therefore based on the repetition of the nonlinear model depicted in Figure 3-3b as a means of representing the five condition states. Deterioration outflows then act to move assets from one condition state to the next lower state, while the valve values are determined based on the transition probabilities. In this SD formulation, the values of the stocks represent the number of assets in the corresponding condition state. For example, in a network containing 100 assets, with 30 in fair condition, the initial stock value of the 'State 3' variable will be 30. If the probability of moving from state 3 to state 4 is 10 % (i.e., P34 = 0.1), 3 assets will then deteriorate from 'State 3' to 'State 4' during the corresponding time interval. As shown in Figure 3-4, the SD network deterioration model was implemented using VENSIM software from Ventana Simulation Environment, which is a widely used and powerful SD simulation tool (Khan et al. 2009; Kiani et al. 2009). All system variables and relationships were defined and coded into this software to run simulation scenarios and analyse long-term results.

3.3.1.3 SD Simulation

Figure 3-4 shows the D model of asset deterioration using the VENSIM software. The testing of the SD deterioration model was based on consideration of a network of 100 assets, with 15, 22, 30, 26, and 7 assets in condition states 1 to 5, respectively. This network and the condition assessment values is a subset of Toronto District School Board's asset inventory that contains assets with variety of condition states and rehabilitation needs.

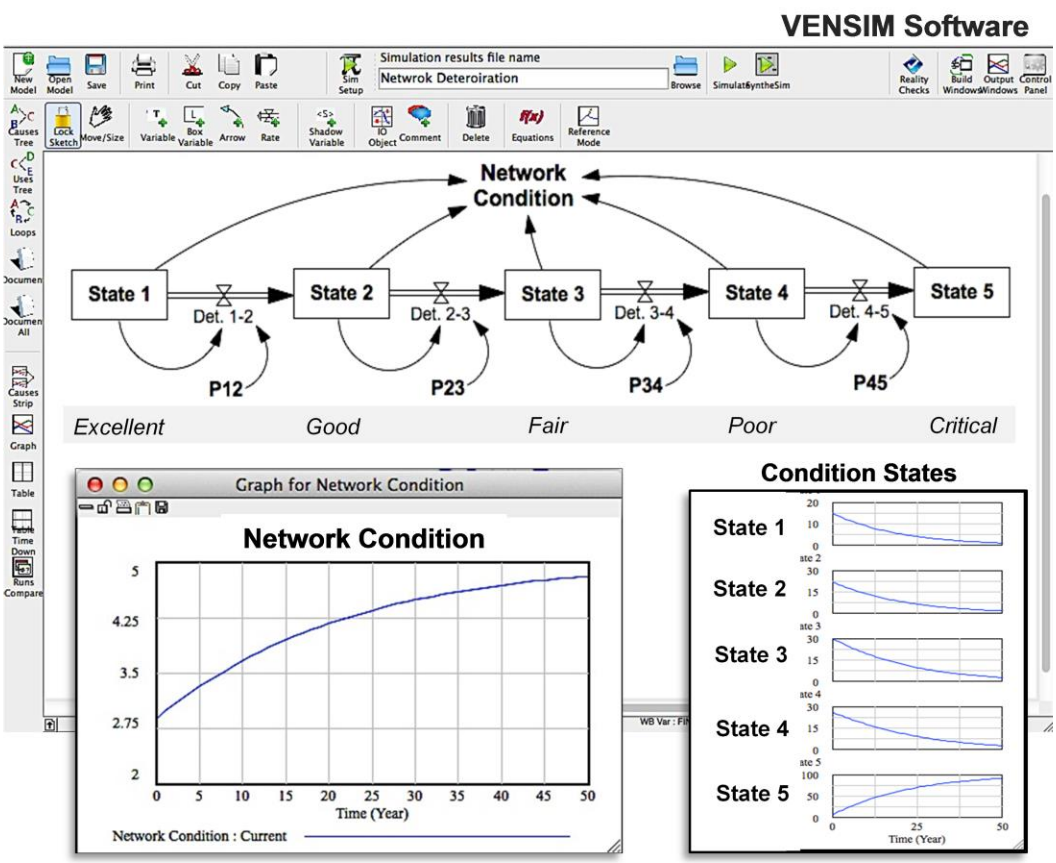

Figure 3-4: SD model of network deterioration using VENSIM® software

To test the model, the transition probabilities P_{12}, P_{23}, P_{34}, and P_{45}, were set to 0.5, 0.08, 0.1, and 0.15, respectively. As shown in Figure 3-4, the primary output of the model at this stage is the network condition curve, which starts at an initial condition of 2.88 (fair) at time zero and gradually decays over time to a condition index of 4.81 (critical) at year 50. This decay is considered to be due to deterioration from one condition state to a worse one, assuming that no rehabilitation action takes place over the duration of the plan. The model also provides the ability to track the number of assets in each condition state up to the planning horizon, by which point the majority of assets will have deteriorated to state 5 (critical condition).

3.3.2 Rehabilitation Actions

The SD deterioration model discussed in the previous subsection was extended to enable the incorporation of rehabilitation actions. The additional loop representing the rehabilitation process can be seen in the revised causal loop diagram of Figure 3-5. The combination of positive and negative links in the rehabilitation process creates a balancing loop resulting in a goal-seeking behaviours (Sterman 2000) that moves towards a desired minimum condition. Transferring the CLD shown in Figure 3-5 into a stock and flow model required the modelling of a number of possible rehabilitation alternatives, such as minor, major, and full replacement options.

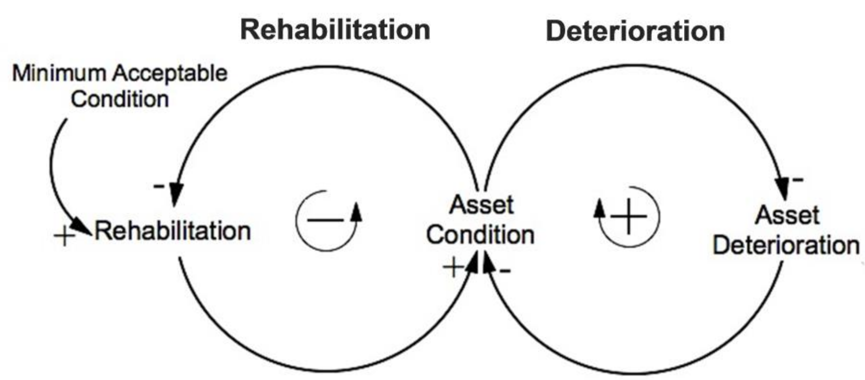

Figure 3-5: CLD of combined rehabilitation and deterioration processes

The model assumptions specify that full replacement is employed only when the asset condition reaches a critical state. Other alternatives (minor or major rehabilitation) are used for assets in fair and poor as well as critical conditions (i.e., states 3, 4, and 5). Minor rehabilitation is assumed to have the capacity to improve a condition by one state (e.g., from state 4 to 3, or from 3 to 2) while major rehabilitation improves a condition by two states (e.g., from state 4 to 2, or from 3 to 1). Based on these assumptions, the SD deterioration model depicted in Figure 3 was extended to incorporate the rehabilitation process depicted in Figure 3-5. As indicated in Figure 3-6, a rehabilitation action is represented by an outflow from one state to higher (better) condition states. For example, three outflows emanate from state 5 to states 4, 3, and 1 as representations of minor, major, and full replacement strategies, respectively. Other auxiliary variables used in the SD model determine values for different rehabilitation alternatives. These variables (e.g., '%S5-FR') specify the percentage of the assets in any state for which a particular rehabilitation alternative is applied. For example, '% S5-FR' designates the percentage of state 5 assets that will undergo full replacement, as shown in Table 3-1.

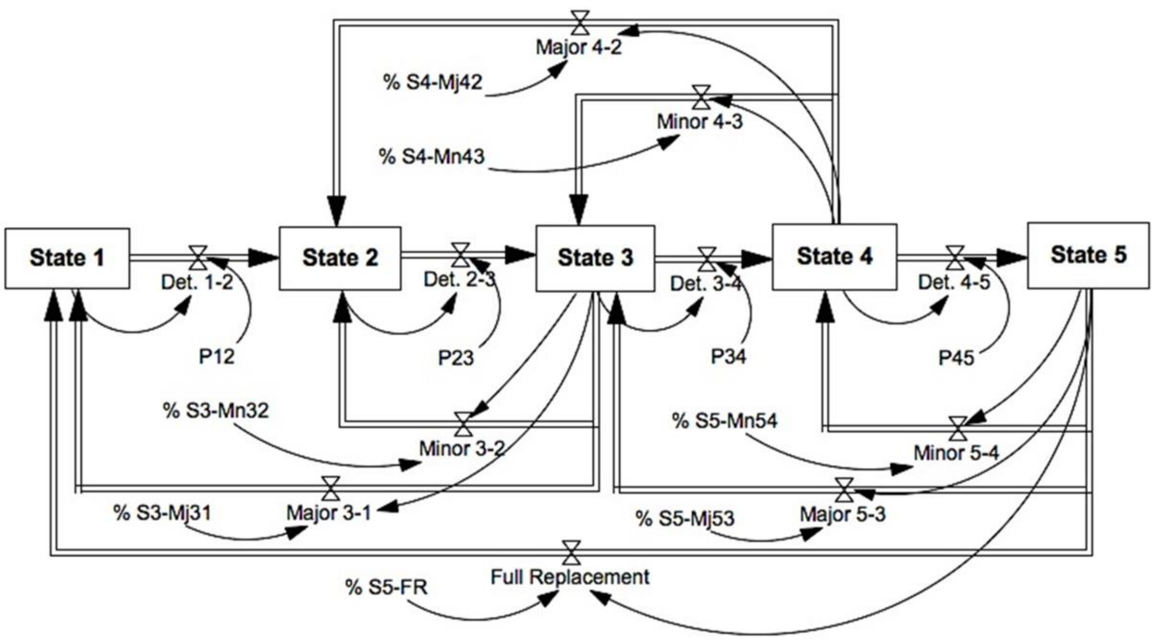

Figure 3-6: SD model incorporating both deterioration and rehabilitation processes

The SD model shown in Figure 6 enables the behaviour of assets exhibiting different condition states over time to be formulated so that the number of assets in each condition state X at time t (CS_{Xt}) can be determined using Eq. (3-6).

Table 3-1: Auxiliary rehabilitation strategy variables

State	Variable	Meaning
3	%S3-Mn32	% of assets in State 3 using minor rehabilitation
3	%S3-Mj31	% of assets in State 3 using major rehabilitation
4	%S4-Mn43	% of assets in State 4 using minor rehabilitation
4	%S4-Mj42	% of assets in State 4 using major rehabilitation
5	%S5-Mn54	% of assets in State 5 using minor rehabilitation
5	%S5-Mj53	% of assets in State 5 using major rehabilitation
5	%S5-FR	% of assets in State 5 using full replacement

$$CS_{Xt} = \int_{t_0}^{t} [Minor_X(s) + Major_X(s) + FullRplc_X(s) - Det._{X-X+1}(s)]ds + CS_X(t_0) \qquad (3-6)$$

where $Minor_X(s)$ denotes the inflow values of minor rehabilitations added to state X at any time s between the initial time t_0 and the current time t, $Major_X(s)$ represents the inflow values of major rehabilitations added to state X at any time s, $FullRplc_X(s)$ indicates the inflow values of full replacements added to state X at any time s, $Det._{X\text{-}X+1}(s)$ designates the outflow values of the deterioration of state X to state X+1 at any time s, and CS_{Xt0} signifies the initial stock value at time zero.

The rate of change in each state (dCS_X/dt) is determined based on the difference between the rehabilitation inflows and the deterioration outflows, as expressed in Eq. (3-8). The predominance of rehabilitation or deterioration loops thus indicates the behaviour of the network as a whole with respect to an improvement or decline in the overall condition.

$$\frac{dCS_X}{dt} = Minor_X(t) + Major_X(t) + FullRplc_X(t) - Det._{X-X+1}(t) \qquad (3-8)$$

To test the effect of the addition of the rehabilitation processes on the model, the same asset network used in the previous deterioration tests was examined, with the repair percentage parameters set to 10 % for all repair types. Figure 3-7 shows the simulation results for a 50-year plan.

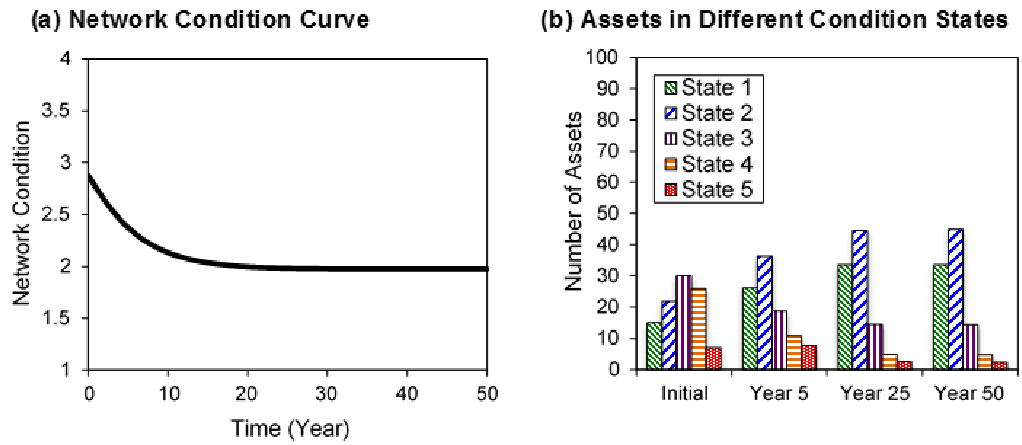

Figure 3-7: Simulation results produced by the SD rehabilitation model

A 50 ear plan has been used as a long-term horizon for the strategic analysis (typically 30 to 50 years). As can be seen in Figure 3-7a, the addition of the rehabilitation processes has resulted in a dramatic change in the overall network condition curve. The overall network condition has improved from 2.88 (Fair) to 1.97 (Good). This improvement is due primarily to the predominance of the balancing rehabilitation loop throughout the simulation, but particularly during the first 15 years. In the following period, neither the rehabilitation nor the deterioration loop is dominant, and the model reaches equilibrium. Figure 3-7b also includes statistics that indicate the number of assets in each condition state for the duration of the planning period. Initially a high percentage of assets are in low condition sate and as the rehabilitation actions improve the condition of specific assets to better states the number of asset in these states increases. By around year 25 in the plan the majority of the assets have been preserved in an excellent or good state and this distribution is maintained until the end of the 50 year plan as the model reaches an equilibrium between the rehabilitation and deterioration processes.

3.3.3 Cost Accumulation

The links between the asset deterioration, rehabilitation actions, and cost accumulation play an important role in accurate life cycle rehabilitation cost analysis and predictions of future infrastructure performance. The rehabilitation budget available plus the rehabilitation costs for different alternatives directly influence the number of repairs possible and, consequently, the network condition. The CLD presented in Figure 3-5 was hence extended to include all three functions of the proposed model with rehabilitation costs and the budgeting process being incorporated, as illustrated in Figure 3-8.

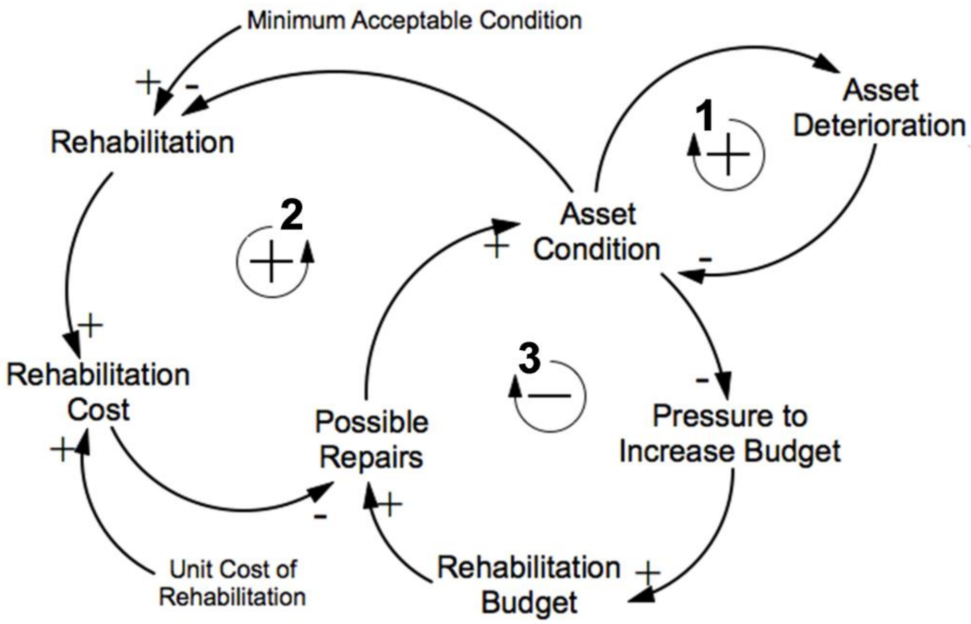

Figure 3-8: CLD for the proposed rehabilitation model

The new CLD is comprised of three interactive loops:

- Loop 1: a positive/reinforcing Deterioration Loop
- Loop 2: a positive/reinforcing Rehabilitation Loop
- Loop 3: a negative/balancing Budgeting Loop

The interactions among these loops enable the modelling of the main dynamic behaviours. The Deterioration Loop (Loop 1) remains as discussed in previous sections. The Rehabilitation Loop (Loop 2) has been altered from the version shown in the Figure 3-5 diagram with the addition of two new variables: 'rehabilitation cost' and 'possible repairs.' In Loop 2, each rehabilitation action is associated with a rehabilitation cost that can be determined from the unit costs for individual rehabilitation alternatives. The number of possible repairs, i.e., the total number of assets that can be repaired based on the rehabilitation strategies selected and the total rehabilitation budget available, is determined from the 'rehabilitation cost' from Loop 2 and the 'rehabilitation budget' from Loop 3. The third Loop, which represents budgeting process, includes consideration of the effect of different rehabilitation budget levels set by the policymakers. The ‘rehabilitation budget’ variable can be also affected by the overall condition of the network, which creates pressure on the asset owners to authorize additional funds for rehabilitation. Figure 3-9 illustrates the enhanced model based on the proposed CLD, with some of the intermediate variables hidden for presentation purpose. Also for further clarity, shadow variables (e.g., <Budget S4>) are used to limit the number of links visible. Figure 3-9 also indicates the new model parameters in bold font, including the rehabilitation budget; the budget allocated to assets at condition states 3, 4, and 5 (Budget S3, Budget S4, Budget S5); the rehabilitation costs associated with minor, major, and full replacement ($Minor, $Major, $FullRplc); the total life cycle cost (TLCC); and the number of repairs possible for condition states 3, 4, and 5 (PR-S3, PR-S4, PR-S5).

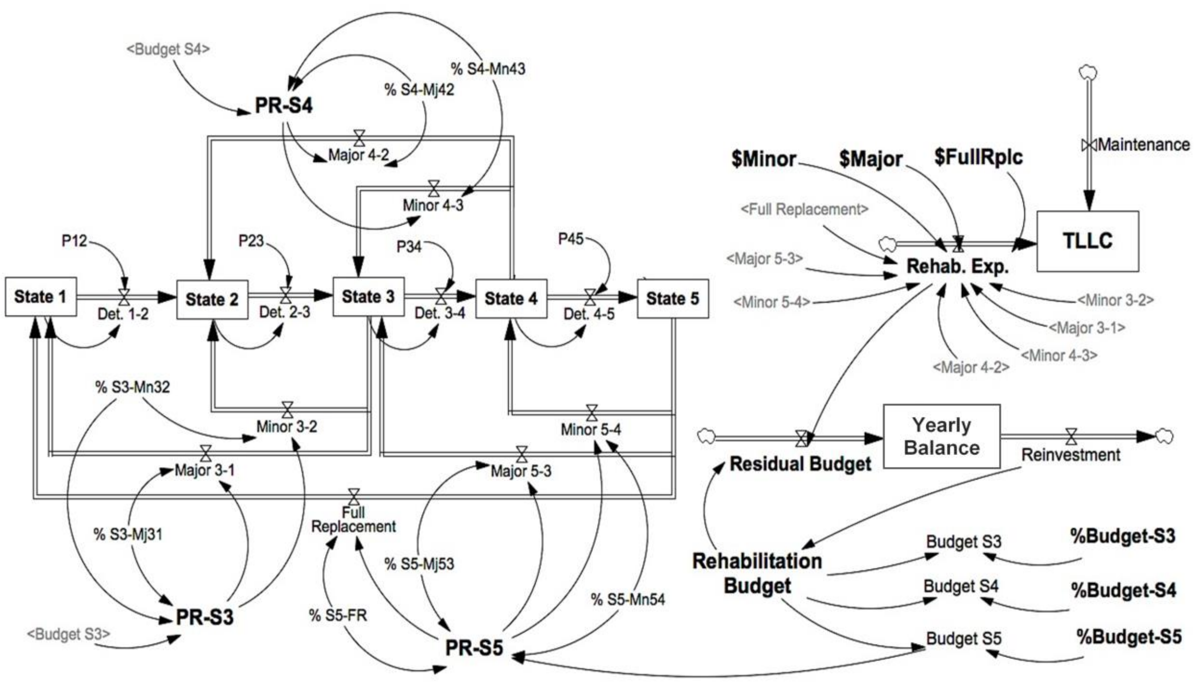

Figure 3-9: Holistic SD model for life cycle rehabilitation cost and budgeting analysis

The rehabilitation budget is a primary strategic variable in the model, along with its distribution among the condition states. In the model, the portion of the total rehabilitation budget that is allocated to assets in condition states 3, 4, and 5 are denoted by parameters ‘%Budget-S3,’ ‘%Budget-S4,’ and ‘%Budget-S5.’ From a decision-making perspective, these variables represent the budget allocation strategy as one form of model input. Accordingly, experimentation with a variety of values enables the determination of the best budgeting strategy that will result in the highest performance level. In the proposed model, the rehabilitation budget is also influenced by the residual budget. At each year of the plan, depending on the number of repairs completed and their associated cost, surplus funds may remain. The model includes a feature that collects the residual budget on a yearly basis in a stock variable called ‘yearly balance’ and reinvests these funds into the budget available for subsequent years. Unit rehabilitation costs of minor, major, and full replacements for a typical asset are designated in the model by \$Minor, \$Major, and \$FullRplc, respectively, and are used in the calculation of the total life cycle cost ($TLCC_t$) at time t as shown in Eq. (3-9).

$$TLCC_t = \int_{t_0}^{t} [FullReplcement(s) \times \$FullRplc + Major_{5-3}(s) \times \$Major + Minor_{5-4}(s) \times \$Minor + Major_{4-2}(s) \times \$Major + Minor_{4-3}(s) \times \$Minor + Major_{3-1}(s) \times \$Major + Minor_{3-2}(s) \times \$Minor)]ds \qquad (3-9)$$

In this process, the number of rehabilitated assets is bounded by the number of possible repairs for each condition state X at year t (PR_{Xt}), which is calculated using Eq. (3-10). This number is basically the ratio of the total yearly budget allocated to a specific condition state and the weighted average cost of repairing any assets in that state. In Figure 3-9, PR-S3, PR-S4, and PR-S5 indicate the ‘possible repair’ values that affect the values of the rehabilitation outflows from condition states 3, 4, and 5, respectively.

$$PR_{Xt} = \frac{B_t \times \%B_X}{\%Minor_{Xt} \times \$Minor + \%Major_{Xt} \times \$Major + \%FullRplc_{Xt} \times \$FullRplc} \qquad (3-10)$$

where B_t indicates the total budget available for rehabilitation at year t, $\%B_X$ is the percentage of the budget allocated to state X, $\%Minor_{Xt}$ is the percentage of minor repairs for condition state X at time t, \$Minor is the cost of the minor repair, $\%Major_{Xt}$ is the percentage of major repairs for condition state X at time t, \$Major is the cost of the major repair, $\%FullRplc_{Xt}$ is the percentage of full replacements for condition state X at time t, and \$FullRplc is cost of full- replacement.

3.4 Life Cycle Cost Analysis Using the SD Model

This section presents the application of the proposed SD model on a network of 1000 assets over a 50-year strategic plan. The case study data related to school building assets administered by the Toronto District School Board (TDSB) is used to set the number of assets in each condition state. TDSB's asset inventory involves a network of more than 550 school buildings. The assets have been categorize in a hierarchical manner based on building system (e.g., Architectural, mechanical, electrical, etc.), sub-systems (e.g., exterior closures, HVAC, etc.) and asset components (e.g., windows, fire alarm, etc.). Periodic condition assessments data and deterioration information were also available for these assets from previous studies by the authors on this network with a relative importance factor for different components based on expert interviews (more information regarding TDSB asset network can be find on Elhakeem and Hegazy (2005a,b) and Rashedi and Hegazy (2014)). To test the SD model a group of 1000 asset components has been selected from the exterior closure sub-system in the network with close deterioration patterns and relative importance factors. Assets of a certain system (electrical or mechanical) are assumed to have a similar deterioration pattern. Also, for practicality, the SD model considers a user-defined relative importance factor (from 0 to 100) for each building system that signify the importance of each system to the operation of the building. The SD model was then used to test the effectiveness of different rehabilitation budgets on the performance of this network, as well as to determine the budget level that would be adequate for keeping the overall network condition above minimum acceptable levels (Figure 3-100.

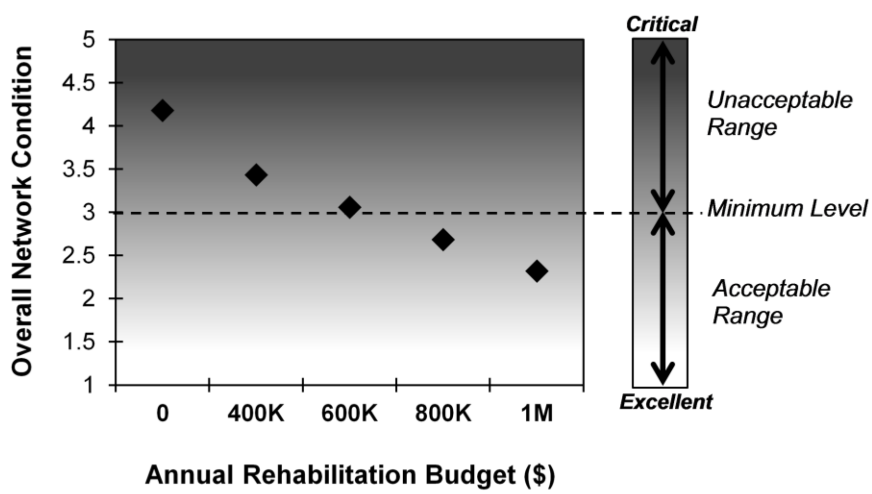

Figure 3-10: Effects of rehabilitation budgeting on the overall network condition

Four scenarios with annual rehabilitation budgets ranging from $400K to $1M were tested. After setting a minimum acceptable condition level of 3 and running the simulation, the decision-maker can view the sensitivity analysis chart shown in Figure 3-10. As expected, increasing the annual budget has a direct impact on the overall condition of the network. The analysis shows that the annual budget of $400K results in a decaying network with an unacceptable overall condition. The $600K annual budget leads to a better network condition than the $400K scenario, yet it still does not ensure an overall condition that falls within the acceptable range. Setting an annual budget of $800K and above improves the overall condition and brings it within the acceptable range. Another set of experiments were also conducted to investigate the effect of various budget distribution strategies. In these experiments, various policy scenarios are generated in which an annual rehabilitation budget of $1M is allocated to different categories of assets based on their condition states, as shown in Table 3-2. As shown in the table, the first budget distribution policy (Scenario 1) allocates the entire rehabilitation budget to only critical assets that are in condition state 5 (i.e., %B5 = 1). Municipalities often utilize such a so-called worst-first policy when condition-based prioritization or a ranking approach is used for fund allocation. Scenario 2 distributes the total available budget equally among the two condition states immediately below the acceptable level (i.e., states 4 and 5) by setting the values of %B_4 and %B_5 to 0.5. Scenario 3 shares the total available budget equally among all three states; %B_3 = 0.33, %B_4 = 0.33, and %B_4 = 0.34. Scenario 4 assigns 50 % of the rehabilitation budget to condition state 3 and 50 % to condition state 4. Scenario 5, allocates the entire rehabilitation budget to assets in fair condition, i.e., condition state 3. Scenario 6 allocates half of the budget to assets in critical condition and divides the rest between poor and fair conditions. Scenario 7 allocates half of the budget to assets in poor condition and divides the other half between fair and critical assets. Scenario 8 allocates half of the budget to assets in fair condition and divides the other half between poor and critical assets.

Table 3-2: Rehabilitation budget allocation scenarios

Policy Scenario	%B3 (Fair)	%B4 (Poor)	%B5 (Critical)
Scenario 1	0	0	1
Scenario 2	0	0.5	0.5
Scenario 3	0.33	0.33	0.34
Scenario 4	0.5	0.5	0
Scenario 5	1	0	0
Scenario 6	0.25	0.25	0.5
Scenario 7	0.25	0.5	0.25
Scenario 8	0.5	0.25	0.25

The results of these experiments are displayed in Figure 3-11; where the impact of these scenarios are investigated on the overall network condition, total life cycle cost (TLCC), and performance improvement, as compared to the no rehabilitation base case. Figure 3-11a shows the simulated results of network condition index based on the different policy setting of Table 3-2. Figure 3-11b also shows the total life cycle cost (TLCC) as these policies are applied. The expected total life cycle cost is $50M based on the used $1M annual budget, however, in certain cases, such as scenarios 4 and 5, TLCC can be lowered. Figure 3-11c shows the performance improvement resulted from applying different budget allocation scenarios of Table 3-2.

As shown in the results, Scenario 1 causes small improvements in the condition of the network over the 50-year simulation time with a TLCC of $50M (Figure 11a and 11b). As shown by Figure 3-11c, it represents the second worst policy in terms of performance improvement despite its frequent use by municipalities. Scenario 2 shows better a network condition curve with an overall performance improvement of 37%. The third scenario (Scenario 3), equal distribution of the rehabilitation budget, provides the second best network condition curve over the plan and improve condition to an index of 1.8, with a total life cycle cost of $50M (Figure 11b). As shown in Figure 3-11a and 3-11c, Scenario 4 is not among the best policies and is ranked number 5 in term of performance improvement. This scenario, however, results in a lowered TLCC suggesting an over-allocation of the budget to assets in fair and poor condition states and accumulation of residual funds over the plan.

As expected, Scenario 5, allocation of the entire budget to assets in fair condition is also another case of over-allocation with the lowest performance improvement. Scenarios 6, 7, and 8 try to distribute the budget among all categories such that a TLCC of $50M is achieved and budget is fully used for rehabilitation. As shown in Figure 3-11b, all of these scenarios almost reach a TLCC of $50M over the plan. A Comparison between condition curves and improvement effects also shows that policy scenario 8, allocating half of the budget to asset in fair condition and divides the rest between poor and critical condition states, results in the best network condition with a 48% improvement on performance. These experiments show that while defining an adequate level of rehabilitation budget is an essential policy to achieve a desirable network condition, the allocation of this budget among assets also plays an important role in improving the overall performance of the network.

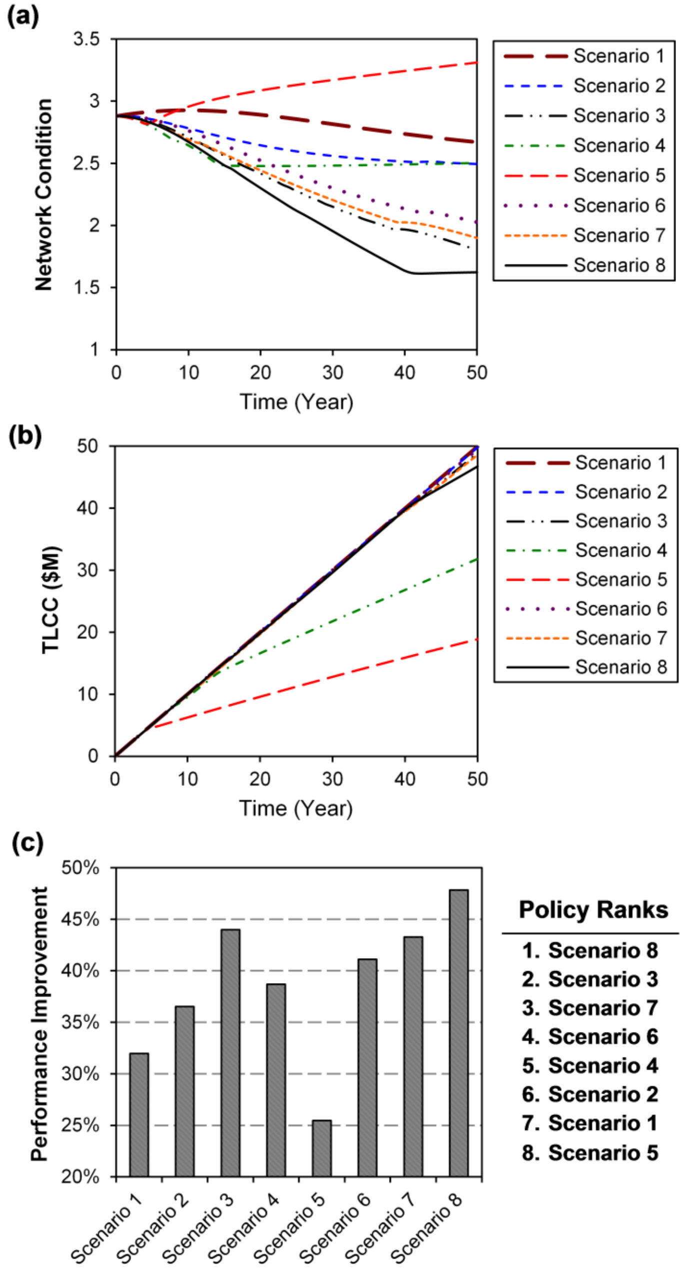

Figure 3-11: Rehabilitation analysis results for a variety of budget allocation policies

3.5 Comments on the SD Model

The SD model presented in this chapter demonstrates the potential of system dynamics to incorporate a strategic decision-making perspective into the modelling and analysis of life cycle interactions in the infrastructure rehabilitation domain. VENSIM® software proved a promising platform for SD model development and for detailed analysis of the results. The developed model is considered to be medium sized, with 97 causal links, 7 stock variables, 64 equations, and 52 variables. The 50-year simulation time for testing the 1,000 assets required about 4 seconds on a laptop computer, which is considered fast performance. During the modelling and simulation processes, regular checks were performed in order to verify the model and its relationships. For example, the total number of assets was constantly monitored to ensure that the stock variables and flow functions were operating correctly. The dimensional consistency of the model and the values of the variables were also scrutinized to confirm the adequacy of the causal relationships. Along with effective formulation, these checkpoint tests constitute the main reasons for the consistent and promising performance of the model.

At the current stage, the proposed model has some limitations. The transition probabilities are designed to cause asset deterioration from one state to only the next lower stage. The proposed model was also limited to similar assets from a particular sub-system. This can be resolve, in future extensions of model, by introducing several deterioration models for different asset components with different relative importance. The formulation of the model presented in this chapter also considers only a 5-state network. However, it can be easily extended to include more states (10-state deterioration models are sometimes used in the domain of infrastructure management). In addition, cost calculations can be extended to take into account the costs of routine maintenance and its effects on performance, by adjusting the TPM values based on the applied maintenance plans. There is also a significant potential for the expansion of this model to include additional aspects of strategic asset management, such as backlog analysis, public private partnership (PPP) options, and/or sustainability analysis. Optimization tools can also be employed as a means of identifying the optimal strategic solutions among a variety of scenarios. While software such as VENSIM includes its own optimization module, it generally uses a brute force approach that might not be efficient in the case of larger asset renewal problems. As a future extension to this study, the VENSIM model could be linked to external optimization tools with engines more suited to large-scale problems. Multi-criteria analysis can also be used to improve the analysis considering performance to be a function of multiple criteria (e.g., level of service, sustainability, and risk of failure) rather than only condition.

3.6 Conclusions

This chapter has presented the development of a holistic rehabilitation analysis model based on system dynamics (SD) simulation techniques. The discussion included an explanation of the modelling of nonlinear deterioration and rehabilitation processes for the creation of a comprehensive SD model. The testing of the proposed model using a variety of policy scenarios was also described. The results proved the effectiveness of the model for analysing the impact of different rehabilitation budget levels on the long-term performance of the asset network. The research presented in this chapter demonstrated the potential of SD as a modelling tool in the areas of infrastructure management and strategic decision-making. The authors are currently extending the model to include more diverse asset categories, the modelling of other strategic aspects of infrastructure management such as sustainably analysis, and public private partnerships options. The model can also be employed as a means of defining best practices for backlog elimination using a variety of budgeting and financing schemes. The ultimate use of the proposed SD model could include improving the insight of asset managers with respect to strategic policy decisions as well as assisting municipalities with effective allocation of the scarce financial resources for infrastructure renewal.

Chapter 4
Strategic Analysis of Infrastructure Backlog

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4.1 Chapter Summary

Accumulation of backlog and the need to analyse possible policies to resolve backlog-related issues is of extreme importance in strategic asset management. To support strategic analysis of backlog, this chapter presents a system dynamics (SD) model to analyse the impact of different strategic policies (e.g. capital budgeting, or PPP involvement) on infrastructure condition, backlog accumulation, and sustainability performance. The proposed model has been implemented on a network of school buildings from the Toronto District School Board asset inventory. Four sets of experiments have been conducted over a 50-year strategic planning horizon to investigate backlog accumulation with regard to policies related to rehabilitation, budget distribution, government investment, and PPP involvement. The proposed model has been implemented on a commercial SD software incorporating all the dynamic interactions among the strategic parameters. The experiment results showed that the model works as a practical decision support tool that enables asset managers to analyse the effectiveness of various strategic policy scenarios on backlog and long-term infrastructure performance.

4.2 Introduction

In the past few decades, public asset owners, such as municipalities, are facing increasing challenges in managing their rapidly deteriorating inventories of assets. In Canada, it is estimated that the infrastructure backlog will be more than \$112 billion in 2027, and our infrastructure has been reached 79% of its useful service life (Civil Infrastructure Systems Technology Road Map 2003-2013). Other parts of the world, particularly U.S., are facing similar financial and serviceability challenges (as reported by the U.S. infrastructure report cards in 2013, the infrastructure backlog is estimated to be \$3.6 trillion, ASCE 2013). Since, the majority of the existing infrastructure assets were constructed decades ago, they have been rapidly deteriorating due to aging, constant use, and exceeded capacity. The poor condition of existing infrastructure is compounded by insufficient pubic funds that results in huge rehabilitation backlogs and causes a major challenge for asset managers who strive to keep infrastructure safe and operable.

Reducing backlog, however, is not the only challenge asset managers are facing today. New regulations for sustainable development also increase the intricacy of infrastructure management. In 1987, the World Commission on Environment and Development (WCED 1987) defined sustainable development as “a process of change in which the exploitation of resources, the direction of investments, the orientation of technical development, and institutional change are all in harmony and enhance both current and future potential to meet human needs and aspirations”. As such, the decisions at each life cycle stage of an infrastructure, including rehabilitation, have to contribute to achieving the strategic goals in terms of environmental, social, and economic impacts (Ugwu at al. 2006a,b; ISI 2011).

In addition to sustainability, Public Private Partnership (PPP) has been a popular alternative for involving the private sector in financing and maintaining complex infrastructure projects. As such, modelling PPP introduces additional complexities to the infrastructure decision-making process. Although a detailed analysis of PPP impact is lacking, PPP has been predicted to decrease infrastructure backlog, transfer risk from public to private sector, and to bring innovation into infrastructure projects (Sanchez 1998; PPP Canada 2013). In Canada, more than $27.1 billion was invested in different PPP infrastructure projects, such as schools, public transit, local roads, hospitals, or wastewater programs, in the period between 2009 and 2011 (PPP Canada 2013). According to the World Bank, many developing countries have also encouraged the private sector to participate in infrastructure facilities, and between 1990 and 1999, more than 30 developing countries have had at least one project completed by the private sector (Roger 1999; World Bank 1999; World Bank 2003).

Generally, there is an obvious lack in the literature on strategic asset management. Australian National Audit Office Report No. 27 (Australian National Audit Office, 1995) in their audit of asset management practices common to 24 organizations stated that one of the main identified weaknesses was related primarily to the lack of a strategic approach to asset management. Strategic planning represents the vision of policymakers and is about the understanding and managing trade-offs among financial performance and operational performance (Jones 2000; Sklar 2004). The Australian Asset Management Collaborative Group (AAMCoG) defines strategic asset management as a procedure that brings together economics, engineering, information technology, sustainability and human elements to form a holistic approach to the delivery of built assets (AAMCoG 2012). Other researchers, such as Levy (2008) and Too (2010), have also emphasized on the importance of PPP policies in strategic planning.

In the literature, a large body of knowledge has been accumulated in the past decade on individual aspects of strategic asset management, including: financial performance and infrastructure backlog accumulation (Jones 2000; Sklar 2004; FCM 2007; Mirza 2008; Evdorides et al. 2012), sustainability related issues (AAMCoG 2013; Mirza 2006; Ugwu et al. 2006a,b), and the application of public private partnership (PPP) (Roger 1999; Gleick et al., 2002; Levy 2008; Too 2010). However, limited research has been conducted on long-term analysis of their interactions and on developing adequate decision support tools for policy analysis and policy solutions that reduce backlog while enhancing infrastructure condition and sustainability performance. This chapter therefore focuses on developing a strategic policy analysis model in the infrastructure domain that uses system dynamics to simulate and analyse the impact of budget levels, PPP contributions, etc., on the infrastructure serviceability, backlog accumulation, and sustainability.

4.3 Strategic Policy Analysis Framework

Based on a review of asset management literature, a SD model has been designed to investigate the dynamic interactions among four main aspects of strategic asset management as shown in Figure 4-1.

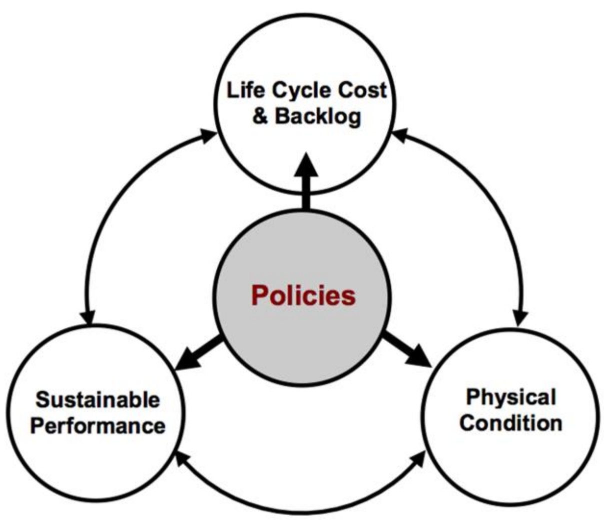

Figure 4-1: Schematics of the strategic planning framework

These four integrated modules analyse: (1) policies related to potential budget levels and PPP strategies; (2) the impact of strategic policies on physical infrastructure condition; (3) backlog accumulation and life cycle cost projections over the strategic plan; and (4) consequent sustainable performance. As such, the SD model simulates the dynamic interactions within and among these modules to provide policymakers with a clearer understanding of the long-term impact of their policies.

4.3.1 Key Strategic Parameters

As a first step toward developing the strategic SD model, the key strategic parameters that influence the infrastructure behaviour within the four modules of Figure 4-1 were identified. Key strategic parameters (Table 4-1) are basically parameters that must be considered in the SD model, and are continuously monitored during the simulation. These parameters include independent inputs and calculated values (intermediate and final). These parameters are defined based on full understanding of the system, past experience, and experts' knowledge. To facilitate practical development, a case study of educational facilities from the inventory of the Toronto District School Board (TDSB) has been used, which administrates a network of more than 550 school buildings. The key strategic parameters have been identified based on literature review about each module, previous research on TDSB assets (Elhakeem and Hegazy 2012; Hegazy and Rashedi 2012), and general guidelines on capital renewal from the TDSB and the Ministry of Education. Accordingly, a total of 27 key strategic parameters (it is noted that the overall SD model contains around 90 model parameters of different types) have been identified as shown in Table 4-1. These variables have been identified to have the highest impact on system performance based on literature studies and expert opinions. Table 4-1 highlights the assumptions made with respect to the interrelationships among these parameters based on available information. The details of these interactions are discussed in the following subsections.

Table 4-1: Key strategic parameters

Modules	Key Parameter	*Type**	*Name*	*Assumptions / Comments*
Policies	Budget Level	I	$\%B_B$ $\%B_C$ $\%B_D$	*Percentage of budget allocated to a certain asset category.*
	Pubic Investment	I	$Govinv_t$	*Rehabilitation budget set by government.*
	Private Investment	I	$Prvinv_t$	*Investment from private sector.*
	PPP Duration	I	*D*	*The duration of private sector investment (e.g., year 1 to 10).*

	Interest Rate	I	*i*	*Annual rate of return or interest for the private investment.*
	No. of Payments	I	*L*	*Number of annual payments to private sector.*
	Sustainability Weights	I	W_{ecn} W_{env} W_s	*Weights for environmental, social, and economical effects.*
Physical Condition	Asset Condition	I	AC_X	*Based on field condition assessment [0 – 100].*
	Overall Condition	C	OC_t	*Overall condition of the asset network.*
	Asset Deterioration	C	D_{ij}	*Uses a Markovian process. TPMs are assumed to be available.*
	Rehab. Actions	C	*Min, Maj, Rplc*	*1) Full Replacement; 2) Major Rehab.; & 3) Minor Rehab.*
	No. of Assets	C	N_{Xt}	*Number of assets in a certain condition states (A, B, C, and D).*
	Total No. of Assets	I	N_{total}	*Total number of existing assets.*
	Relative Importance	I	RIF	Relative Importance Factor *obtained from surveys among experts.*
	Level of Service	C	*LOS*	*Calculated based on asset condition.*
Life Cycle Cost & Backlog	Total Available Budget	C	B_t	*Sum of public and private investments.*
	PPP Payments	C	AP_t	*Based on an agreed interest rate, invested amount, and duration.*
	Rehabilitation Cost	C	$\$C_{min}$ $\$C_{maj}$ $\$C_{Rplc}$	*Cost of each rehabilitation actions.*
	User Cost	C	*$UC*	*Public fees and tolls (assumed to be increased by using PPP).*
	Total Life Cycle Cost	C	*TLCC*	*Sum of rehabilitation cost and payments over strategic period.*
	Infrastructure Backlog	C	BL_t	*Difference between available budget for rehabilitation and the amount required to bring all critical assets to acceptable condition.*
	Financial Performance	C	FP_t	*Function of expected backlog and TLCC [0 – 100].*
Sustainable Performance	Environmental Impact	C	I_{ENV}	*Determined based on energy efficiency.*
	Social Impact	C	I_{SC}	*Determined based on user satisfaction, serviceability, overcapacity, etc.*
	Economical Impact	C	I_{ECN}	*Determined based on financial performance.*
	Energy Efficiency	C	EF_t	*Based on asset condition and the percentage of assets in good condition.*
	Sustainability Performance	C	SP_t	*Determined based on environmental, social, and economical impacts.*

4.3.2 Dynamics Interactions among Strategic Parameters

In system dynamics, Causal Loop Diagrams (CLDs) are tools for capturing SD hypotheses about the interactions among different variables/parameters, causes of dynamics, and determining the important feedbacks in the strategic model. A causal loop diagram consists of variables connected by links denoting the causal influences among them (e.g., Figure 4-2). Casual links show effects of variables on each other by link polarities. A positive link, i.e., (+) polarity, implies that the cause and effect are moving in the same direction meaning if a cause increases, the effect increases and if a cause decreases, the effect decreases. A negative link, i.e., (-) polarity, means if the cause increases, the effect decreases and vice versa (Sterman 2000). To demonstrate CLDs, a simplified case is presented involving four variables from the physical condition module including: asset condition, asset deterioration, renewal actions, and level of service (LOS). In this CLD, "asset deterioration" is linked to "asset condition" by a negative link polarity, which models the fact that higher deterioration typically results in lower condition. Similarly, another negative link in the same loop represents the causal relationship in which higher condition leads to lower deterioration. The combination of these two links then creates a positive (or reinforcing) feedback loop as depicted in the top right part of Figure 4-2. This positive loop models the dynamic behaviour of infrastructure deterioration in which growing deterioration rates results in decaying physical condition in a continuous cycle. With time, such a reinforcing loop exhibits an accelerated rate of deterioration and lower condition indices, until other parameters take part to influence these dynamics (e.g., the left side loop in Figure 4-2).

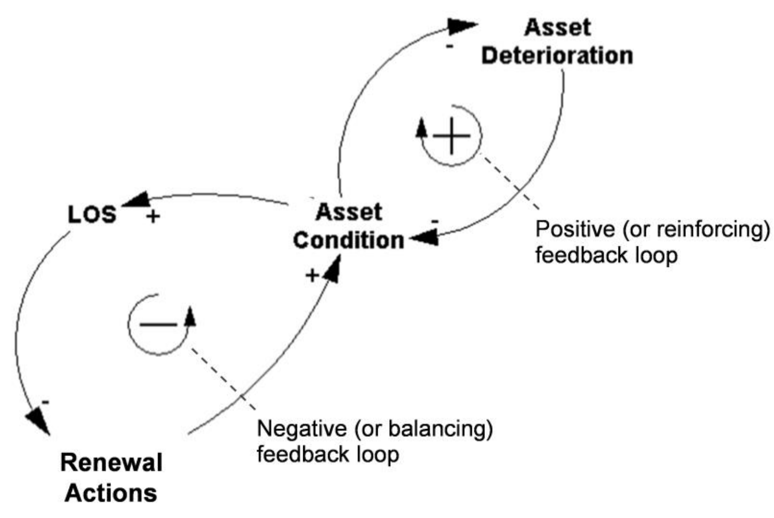

Figure 4-2: A sample causal loop diagram for the physical condition module

In the left side loop, more "renewal actions" leads to a higher "level of service (LOS)" (a positive link between the two variables). Also, a higher "LOS" reduces the number of required "renewal actions" (i.e., a negative link) and subsequently, less "renewal actions" reduces "asset condition" (i.e., positive link). The combination of these links, thus, represents a negative (or balancing) feedback loop with a goal seeking behaviour, in which renewal actions are adjusted to achieve a desired condition. The above demonstration of using CLDs shows that this technique can be used as an effective method for capturing and analyzing different dynamics within infrastructure systems. Also, the polarities and feedback loops have mathematical interpretation that can help in accurately modelling the dynamic behaviours. As such, using CLDs, the interactions among the parameters in Table 4-1 have been modelled as shown in Figure 4-3 that links all four modules of policy analysis together. Developing this CLD took some effort to identify possible causalities and tie all concepts together in an iterative process of studying all variables based on their possible impacts on each other. To establish the CLD of Figure 4-3, rounds of CLD development and adjustments were used, in addition to consulting with asset management experts from the TDSB. To avoid complexity and maintain the clarity of the dynamic hypothesis presented by the causal loop diagram of Figure 4-3, it was drawn to show the essential links only. The feedback loops in the model are presented in Appendix A.

As an example, a long feedback loop in the model is explained. As asset condition deteriorates the number of assets in critical state increases (negative link between 'Asset Condition' and 'No. of Asset in Critical Condition'). This increase in the number of critical assets will increase the backlog (positive link) and consequently the high level of backlog puts more pressure on the authorities to use private financing (positive link between 'Infrastructure Backlog' and 'Willingness to us PPP'). Accordingly, private sector investments are increased and in return the total available budget and the rehabilitation budget will increase (positive links connecting 'Total Available Budget' to 'Total Available Budget for Rehabilitation' and 'Total Available Budget for Rehabilitation' to 'Budget Levels'). This increase in budget levels will increase the number of rehabilitation actions and in return improves the overall asset condition (positive link between 'Rehabilitation' and 'Asset Condition'). The combination of these links create a balancing loop that adjusts the level of private investment based on the observed backlog in the system. All the other connections and loops in the model have been investigated and translated with the same approach to ensure adequacy in explaining the real dynamics behind the system

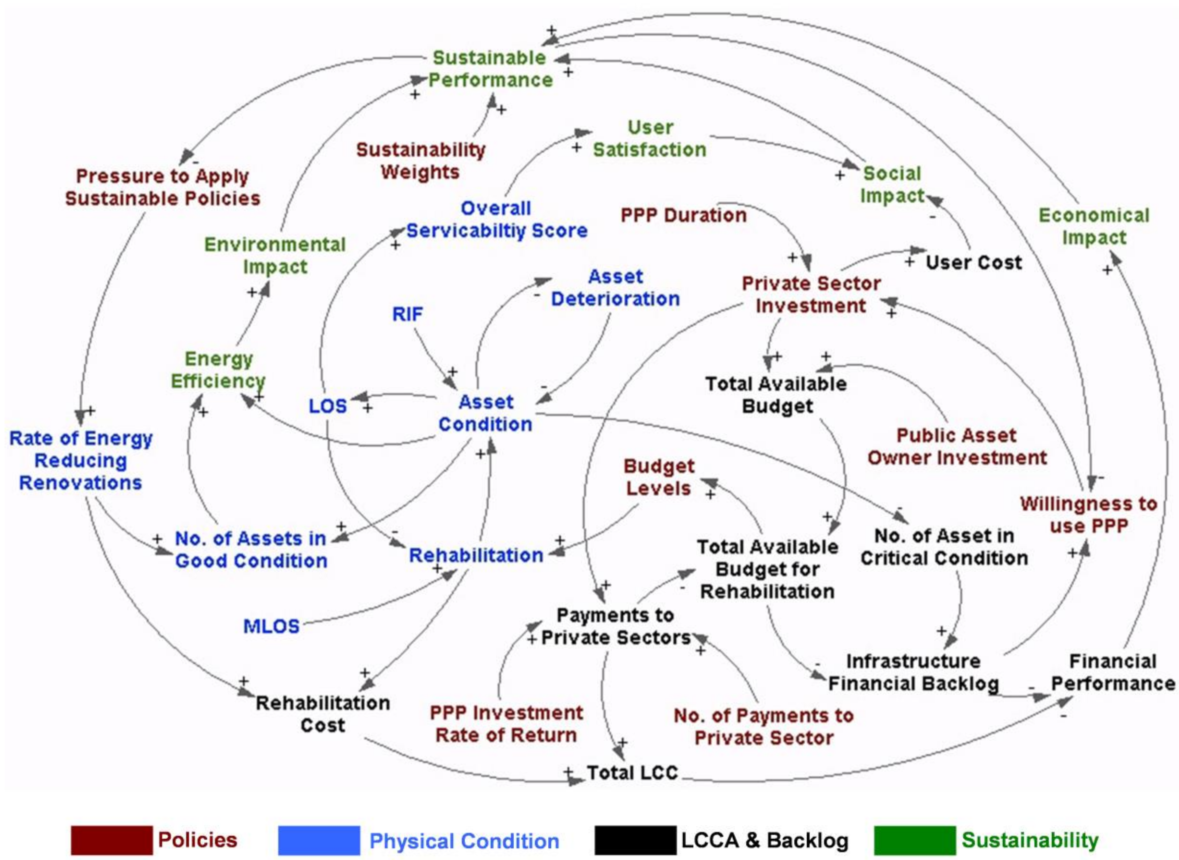

Figure 4-3: Causal loop diagram for the proposed SD model

4.3.3 SD Simulation Modelling

To carry out system dynamics simulation, the developed CLD was first translated into a stock and flow diagram (simulation components) that incorporates all mathematical equations to create the SD model. In the stock and flow diagrams, stocks are accumulations that characterize the state of key system variables (Sterman 2000). Flows, on the other hand, represent the system variables that generate quantities that are accumulated in the stocks over time. Considering the variables discussed in the sample diagram of Figure 4-2, “asset condition” is represented in the stock and flow diagram of Figure 4-4 by a stock that accumulates the state of condition indices over time. “Asset deterioration”, on the other hand, is represented as an outflow that decreases the stock value (i.e., causes condition to decay), while renewal actions is an inflow that increases the stock value (i.e., improves the condition). Since, the net flow of the stock variable is its rate of change, system dynamics models the behaviour of stocks and flows using the differential equation in Eq. (4-1).

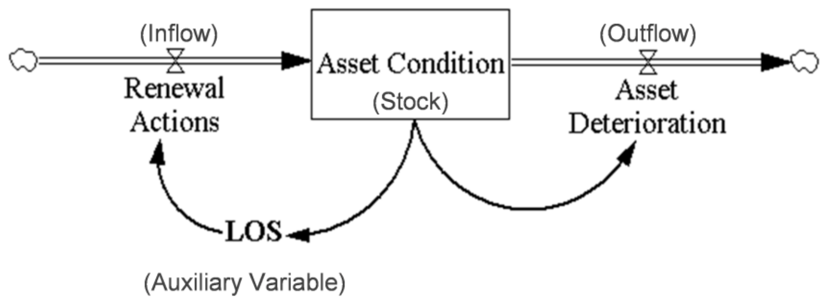

Figure 4-4: The stock and flow diagram of the CLD presented in Figure 4-2

$$Stock(t) = \int_{t_0}^{t} [Inflow(s) - Outflow(s)]ds + Stock(t_0) \qquad (4-1)$$

where Inflow(s) represent the value of the inflow (e.g., condition change) at any time *s* between the initial time t_0 and the current time *t*. Equivalently, the net rate of change of any stock (i.e., the derivative), is the inflow minus the outflow, defined in the differential equation (Eq. (4-2)), as follows:

$$\frac{d(Stock)}{dt} = Inflow(t) - Outflow(t) \qquad (4-2)$$

In the stock and flow diagram of Figure 4-4, the simulation process starts with an initial condition CI_0 (i.e., Stock(t_0)). As time goes, deterioration acts as an outflow, which reduces the condition over time. Renewal actions then increase/improves overall condition based on the number of repair interventions. Also, renewal actions and the number of interventions itself depends on the LOS as represented in Figure 4-4 by an auxiliary variable. Using stock and flows and their related differential equations, causal loop diagram (CLD) of Figure 4-3 has been mapped into a stock and flow simulation model with more than 90 variables and equations. Figure 4-5 shows the overall structure of the strategic SD model with its four distinct modules. It is noted that for the purpose of presentation, the model has a moderate level of aggregation and not all the model details are shown. Developing the stock and flow diagram and its underlying simulation model is a demanding process of translating all the loops in the CLD diagram one-by-one into stocks, flows, and auxiliary components with all the related equations. This step-by-step process was suitable for testing and verifying the accuracy of the relationships in the model and to test the logic behind its calculations. Important details regarding the interactions among the four strategic modules are discussed in the following subsection.

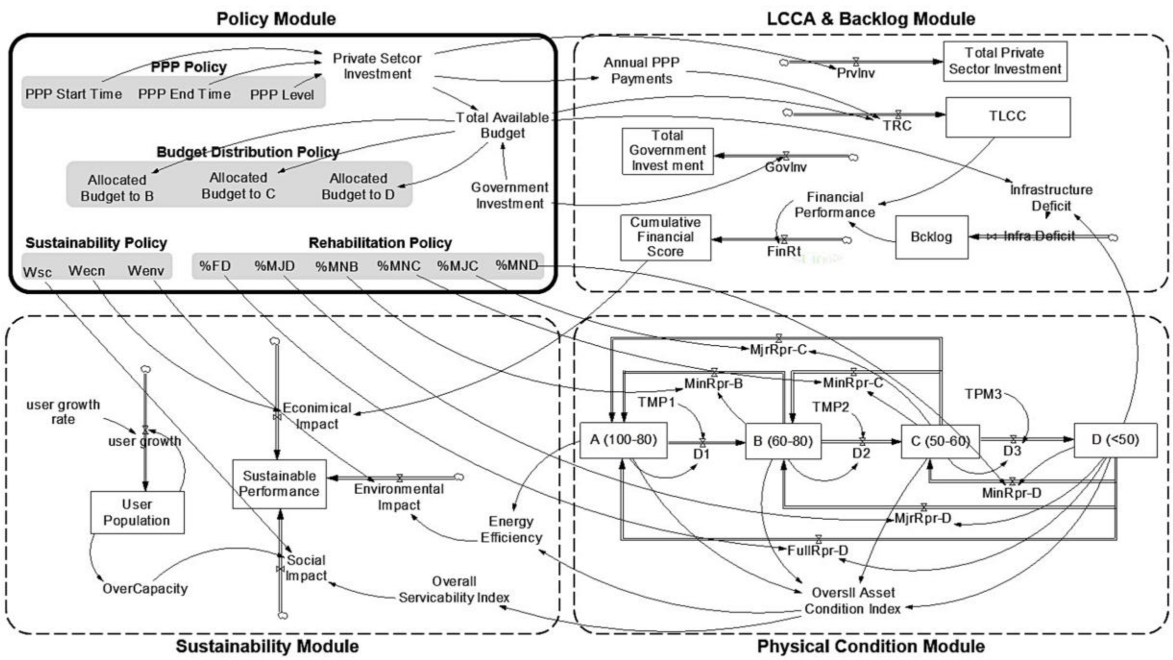

Figure 4-5: Strategic SD model

4.3.4 Model formulation

4.3.4.1 Physical Condition

At the core of physical condition module is an asset deterioration and repair model to dynamically evaluate the overall asset condition during the simulation process. The model is intended to consider the whole inventory of existing assets at the strategic level, and as such, it models deterioration from a system-level view (electrical, mechanical, architectural, etc.). Presently, the model considers only architectural assets. For system deterioration, four condition states (based on condition indices, CIs) are used in the model:

- Category A: represents assets in good condition, i.e., a CI between 80 and 100;
- Category B: represents assets in fair condition, i.e., a CI between 60 and 80;
- Category C: represents assets in poor condition, i.e., a CI between 50 and 60; and
- Category D: represents assets in critical condition, i.e., a CI lower than 50.

The advantage of categorizing assets as A, B, C, and D in the model is to later investigate the effectiveness of different budget distribution polices. Based on the asset inventory obtained from TDSB, Table 4-2 shows the number of sample assets considered in the SD model and the average condition for each category.

Table 4-2: Information about architectural assets

Asset Category	Linguistic Condition	CI Range	No. of Assets	Average Condition
A	Good	80 to 100	31	87
B	Fair	60 to 80	213	68
C	Poor	50 to 60	143	55
D	Critical	< 50	154	43
Total			541	59

To model the deterioration process of architectural systems, the proposed model utilizes Markovian deterioration process, which is one of the commonly used stochastic techniques for deterioration modelling (Butt et al. 1987; Jiang et al. 1988). The model predicts the deterioration of a component by defining discrete condition states and accumulating the probability of transition from one condition state to another, represented by a Transition Probability Matrix (TPM), over the simulation time. TPMs are assumed to be known based on prior research on TDSB data (Elhakeem and Hegazy 2005) and represent the portability of changing asset condition from one asset category to another (e.g., A to B). In terms of repair modelling, the proposed model considers three alternatives including: minor repair, major repair, and full replacement. Each of these three alternatives has an associated improvement effect and repair cost as shown in Table 4-3. Based on this table, for example, a major repair on an asset with critical condition (category D) is assumed to improve the condition from critical to fair (category B). In the stock and flow representation of the deterioration and repair model, these improvements are represented by outflows from the current condition state and inflow into the after-repair condition state. The percentages of the assets in each condition category that use the repair alternative are policy parameters defined by the decision-maker. In the model, to calculate the overall condition at time *t* (OC_t), the following equation (Eq. (4-3)) is used, based on the percentages of assets in each condition state.

Table 4-3: Improvement effect and cost of different repair alternatives

	Minor Repair	Major Repair	Full Replacement
Cost	25% of Full Replacement	60% of Full Replacement	$$$
Condition Before Repair	Condition After Repair		
A	N/A	N/A	N/A
B	A	N/A	N/A
C	B	A	N/A
D	C	B	A

$$OC_t = \frac{N_{At} \times AC_A + N_{Bt} \times AC_B + N_{Ct} \times AC_C + N_{Dt} \times AC_D}{N_{Total}} \qquad (4-3)$$

where, N_{Xt} is number of assets in category X at year t, AC_X is the average condition index of assets in category X (last column of Table 3), and N_{Total} is the total number of assets in the system.

4.3.4.2 Life cycle cost analysis

The Life cycle cost analysis (LCCA) module of the SD model is directly influenced by policy parameters such as public budget policy, private sector investment, total life cycle cost, backlog, and financial performance. In this module, total available budget is defined as the sum of government (public owner) and private sector investments. The government rehabilitation investment is a fixed yearly value defined by the decision-maker (e.g., $4 million/year). The private sector investment, on the other hand, is the additional contribution to rehabilitation budget by a private partner. By incorporating these parameters, the decision maker can test various budgeting policies and private investments based on different investment start and end time, duration, amount, rate of return, and payback schemes. The associated value of these important policy parameters could impact backlog accumulation, overall asset condition, sustainable performance, and the level of incentive offered to the private sector. Budget distribution policies are also modelled by allowing flexible portions of the rehabilitation budget to be allocated to different asset categories (i.e., B, C, and D). The effect of budget distribution policies on parameters such as backlog or overall asset condition is determined based on the interactions between LCCA and physical condition modules. Financial backlog is defined as the difference between the available budget for rehabilitation and the amount required to bring all critical assets (category D) to higher condition states (considering that categories A, B, and C are above the acceptable level). Based on this definition the financial backlog at year t (BL_t) can be calculated using the following equation.

$$BL_t = N_{Dt} \times \left(\%Min_D \times \$C_{min} + \%Maj_D \times \$C_{maj} + \%Rpl \times \$C_{Rplc}\right) - B_t \qquad (4-4)$$

where N_{Dt} is the number of critical assets at time t, $\%Min_D$, $\%Maj_D$, and $\%Rplc_D$ are the percentages of critical assets that receive minor repairs, major repairs, and full replacement, respectively, and $\$C_{min}$, $\$C_{maj}$, $\$C_{Rplc}$, are the unit cost of minor repair, major repair, and full replacement, respectively, and B_t is the total available budget. The various financial interactions also determine the total life cycle cost (TLCC), which is defined as a stock variable in the proposed model, as follows:

$$TLCC = \int_0^{t_s} GovInv_t + PrvInv_t - AP_t - B_{Residual_t}\, dt \qquad (4-5)$$

where t_s is the strategic planning horizon (e.g., 50 years), AP_t is the annual payment to private sector at year t, and $B_{residual\ t}$ is the residual budget at year t (i.e., the remaining budget not enough to be allocated to any repair alternative). AP_t is calculated using the monthly payment equation with fixed interest rate as follows:

$$AP_t = \frac{PrvInv \times D \times i}{1 - \left(\frac{1}{(1-i)^{D+L}}\right)} \qquad (4-6)$$

where D is private investment duration, *i* is the interest rate, and L is the payback duration or the number of payments to private sector.

4.3.4.3 Sustainability

The Sustainability module of the model considers the sustainability performance of the infrastructure based on environmental, social, and economical impacts. The sustainable performance is defined as a stock variable that accumulates the economical, environmental, and social inflows over time. Based on its stock and flow representation, sustainable performance at year t (SP_t) is calculated (Eq. (4-7)) using different weights for economical (I_{ecn}), environmental (I_{env}), and social (I_{sc}) impacts that are indicated in the model by W_{ecn} , W_{env} , and W_{sc} , respectively. Values for these weights (between 0 and 1) represent decision-makers' attitude toward the importance and of each impact (Yao et al. 2011).

$$SP_t = \int_0^t [W_{ecn} \times I_{ecn} + W_{env} \times I_{env} + W_{sc} \times I_{sc}]\, dt \qquad (4-7)$$

Also, the sustainable performance calculation is defined such that its value varies between 0 and 100 based on different key performance indicators. The sustainability impacts (i.e., the economical, environmental, and social inflows) are calculated based on the interactions between the sustainability module and the LCCA and physical condition modules. For instance, energy efficiency of assets is used in the present model as a parameters that affects the environmental impact (other parameters can be considered in future extensions). In the model assumptions, energy efficiency is assumed to be a function of overall asset condition and the percentage of assets in good condition that are less susceptible to energy loss as compared to other asset categories.

4.4 Model Testing and Validation

Testing and validation of SD models is an important part of the model development. In general, a valid model should be able to accurately simulate the actual behaviour of a real system. This claim is only true when the model is directly compared to actual data from the real system and proven to be valid. In reality, however, in many cases such as the asset management case study presented in this chapter, actual data over a long period of time are not available. In addition, factors such as the complexity of real systems, the principle of bounded rationality, and lack of information, have made many modellers recognize the difficulty of assertive validation of mathematical models. As famously said by Forrester (1961): "Any objective model-validation procedure rests eventually at some lower level on a judgment or faith that either the procedure or its goals are acceptable without objective proof." To validate each component of the model and verify its performance a step-by-step progression in model development from deterioration to repair modelling to policy analysis has been used. Accordingly, the dynamic behaviour of each component is studied and confirmed to be logical and in accordance with reference behaviours and expectations. In addition, to test and verify the proposed model, structure assessment tests, condition and dynamic input tests, and sensitivity analysis have been used as follow:

4.4.1 Structure Assessment

One of the first steps toward verifying the proposed SD model is to assess the structure of the model and to confirm its consistency with the descriptive knowledge of the asset management systems. This is achieved by closely studying the CLDs and stock and flow diagrams and consulting with experts in the infrastructure management domain. Model structures and relationships are also assessed using dimensional consistency tests for each individual equation in the model. In addition, tools such as "cause trees" or "effect trees" are utilized to further analyse the causal structures and to study relationships at different hierarchical levels.

4.4.2 Model Conditions and Dynamic Input Tests

SD model results are analysed to make sure that they are logical and follow expected behaviours based on reference modes. For instance, reference modes indicate that when rehabilitation budget decreases backlog should increase. These kind of simple yet important checks are essential to make sure that model relationships are adequate. The model is also subjected to several condition tests. For example, under any policy settings the total number of asset in the model must be constant and equal to 541, or the overall assert condition must have a value between 0 and 100 over the simulations time. Extreme condition tests are also used to assure the robustness of the model when parameters reach extreme values. Dynamic test inputs that cause sudden changes to model parameters are also used to test model response under surprise behaviours. For example, a dynamic input was designed in which the rehabilitation budget faces a sudden drop from $4 million to zero at year 20 for 5 year and then goes back to its original value. The effect of such dynamic test input is then checked on other parameters to make sure there are no condition violations or anomalous behaviours.

4.4.3 Sensitivity Analysis

Due to the uncertainty involved in the model assumptions and numerical parameters, sensitivity analysis tests has been performed to check the robustness of the model conclusions. Various tests have been conducted considering different parameters such as TMPs, rates of return, and PPP parameters. Details of the sensitivity analysis tests have been discussed in the following section.

4.5 Experimentation and Results

At the strategic level, four sets of experiments have been conducted by varying different policy-related parameters, as shown in Table 4-4, and examining the results of a 50-year simulation.

Table 4-4: List of policy related variables and experiments

Parameter	Value Range	*Description*	Exp1	Exp2	Exp3	Exp4
$\%B_B$	0 – 100%	*Percentage of budget to asset category B.*	**Var***	33%	33%	33%
$\%B_C$	0 – 100%	*Percentage of budget to asset category C.*	**Var**	33%	33%	33%
$\%B_D$	0 – 100%	*Percentage of budget to asset category D.*	**Var**	33%	33%	33%
$\%Min_D$	0 – 100%	*Percentage of category D to have minor repairs.*	25%	**Var**	50%	50%
$\%Maj_D$	0 – 100%	*Percentage of category D to have major repairs.*	50%	**Var**	25%	25%
$\%Rplc_D$	0 – 100%	*Percentage of category D to be fully replaced.*	25%	**Var**	25%	25%
GovInv	> = $0	*Annual available budget funded by public.*	$5M	$5M	**Var**	$4M
PrvInv	> = $0	*Annual investment by private sector.*	$0M	$0M	$0M	**$2M**
InvStart	0 – 50	*Private sector investment starting time.*	0	0	0	**0**
InvEnd	0 – 50	*Private sector investment ending time.*	0	0	0	**10**
L	0 – 30	*Number of future payments to private sector.*	0	0	0	**30**
I	0 – 0.1	*Investment rate of return.*	0	0	0	**0.05**
$\%Min_B$	0 – 100%	*Percentage of category B to have minor repairs.*	100%	100%	100%	100%
$\%Min_C$	0 – 100%	*Percentage of category C to have minor repairs.*	50%	50%	50%	50%
$\%Maj_C$	0 – 100%	*Percentage of category C to have major repairs.*	50%	50%	50%	50%
W_{env}	0 – 1	*Associated weight of environmental impacts.*	0.3	0.3	0.3	0.3
W_{ecn}	0 – 1	*Associated weight of economical impacts.*	0.4	0.4	0.4	0.4
W_{sc}	0 – 1	*Associated weight of social impacts.*	0.3	0.3	0.3	0.3

* Var: Represents the focus policy parameter that the effect of its variation is investigated.

The preliminary results focused on three main strategic parameters that can be monitored by TDSB asset managers at the strategic level: (1) overall asset condition; (2) backlog accumulation; and (3) sustainability performance. Table 4-4 shows main policy-related parameters in the model (1st column) and highlights the parameters that change in each of the four experiments (last four columns). It is important to note that the results of these experiments are dependent on the asset inventory of TDSB and care must be taken in generalization and interpretation of the results.

4.5.1 Experiment 1 – Budget Distribution Policy

As shown in the fourth column of Table 4-4, this experiment fixes all parameters except for the first three, which relate to the percentages of the budget allocated to asset categories B, C, and D. As such, four policy scenarios (simulations) have been tested with different values for the $\%B_B$, $\%B_C$, and $\%B_D$ percentages, as shown in the top-left corner of Figure 4-6.

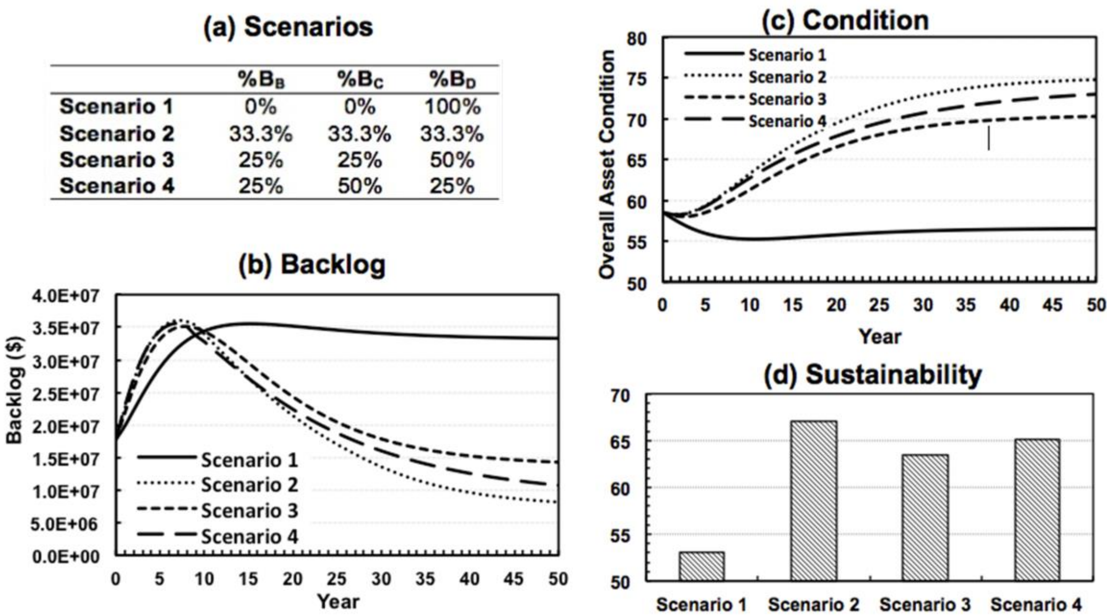

Figure 4-6: Simulation results for different budge distribution policies

In this set of simulations, an annual rehabilitation budget of $5 million/year (with no private investment) has been used. The first scenario allocates the available rehabilitation budget only to critical assets (i.e., category D gets 100% of the budget, or $\%B_D = 100\%$). The second scenario distributes the available budget equally among the three categories. The third scenario allocates more budget to critical assets, while the fourth scenario allocates more budget to assets in poor condition (Category C). The SD model was then modified for each of the scenarios separately and the simulation was performed to document the backlog, condition, and sustainability performance. The results are shown in Figure 6. Although allocating most of the budget to rehabilitate critical assets (Scenario 1) is a common practice, simulation results show that this policy creates the highest backlog, the lowest condition, and the lowest sustainable performance (as indicated by the solid line of Figure 4-6b-c-d). Scenario 1 shows that, despite its common use by asset owners, allocating the entire budget to assets in the worst condition (worst-first strategy) is not the best policy, which agrees with several practitioners reports (e.g., City of Brent 2014; PBOT 2014). The second scenario (distributing the budget equally), on the other hand, is proved to be the best strategy among the four policies, as it creates the lowest backlog accumulation, highest overall asset condition, and the highest sustainable performance amongst the four scenarios.

4.5.2 Experiment 2 – Rehabilitation Policy

In this experiment (fifth column in Table 4-4), the effect of applying different rehabilitation alternatives for critical assets (category D only) have been tested by varying the percentage of critical assets that receive minor repairs, major repairs, and full replacement (i.e., $\%Min_D$, $\%Maj_D$, and $\%Rplc_D$). Four scenarios have been tested as shown in Figure 4-7a.

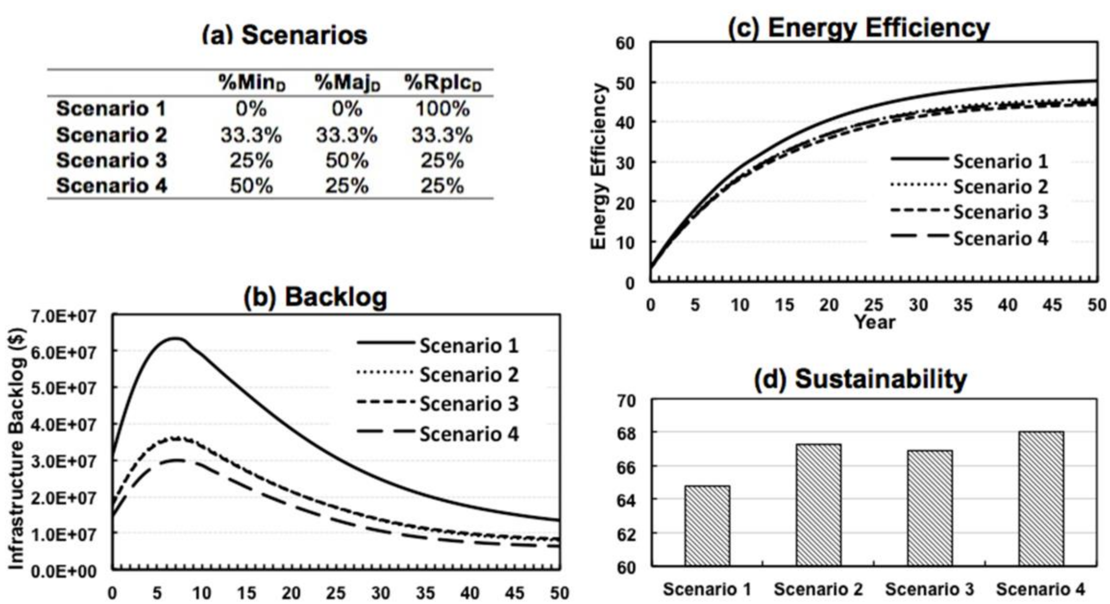

Figure 4-7: Simulation results for different rehabilitation policies

The first scenario considers a policy of full replacement actions only. The second scenario uses a policy of a balanced use of different repair methods, while the third and fourth scenarios favour more use of major and minor repairs, respectively. The simulation results are presented in Figure 4-7b-c-d. As expected, Scenario 1 (full replacement only) exhibits the highest energy efficiency (see Figure 4-7c) as more assets are fully renewed. This policy, however, produces the highest expected backlog (Figure 4-

7b), which is mainly due to the high cost of full replacements. Considering energy efficiency, condition, and backlog results, Scenario 4 (using more Minor repairs) turned out to be the best policy.

4.5.3 Experiment 3 – Government Investment Policy

In this experiment (column six of Table 4-4), the effect of government investment on backlog, asset condition, and sustainability performance has been investigated. Four scenarios have been generated based on different investment values (i.e., GovInv) as shown in Figure 4-8.

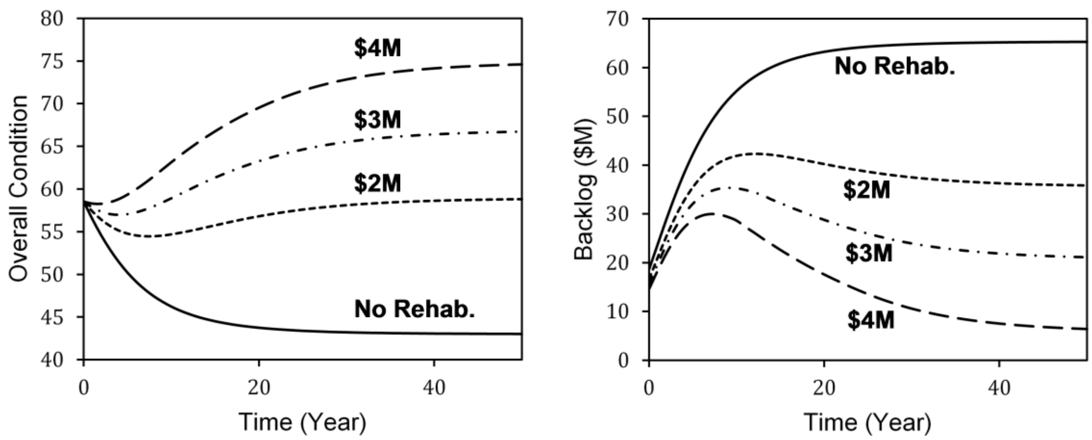

Figure 4-8: Simulation results for different government investment policies

Scenario 1 allows assets to deteriorate over time without any rehabilitation (i.e., GovInv = \$0/year), and the next three scenarios (Scenario 2, 3, and 4) investigate the effect of increasing the annual government investment from 0 to \$2, \$3, and \$4 million, respectively. Figure 4-8 shows the backlog and condition trend results. As expected, the no rehabilitation scenario causes significant backlog accumulation (almost 7 times more than the \$4 million/year scenario at year 50) and results in a decaying overall asset condition (Figure 4-8). Increasing government investment, as shown in Figure 4-8, can significantly reduce backlog accumulation and improve asset condition. Sustainable performance results also indicate that increasing the annual budget by only \$1 million (e.g., form \$3 to \$4 million/year) can improve the sustainable performance by 39%. The positive effect of increasing investment on condition and backlog might be obvious, however, the type of analysis presented by Experiment 3 can be very useful for the TDSB administrators (or other asset owners) to justify the required budget and its impact on their inventory while negotiating with the ministry of education (or other authorities).

4.5.4 Experiment 4 – PPP Policy

In this experiment a private sector annual investment of $2 million/year over a 10-year period (i.e., D = 10) from year 1 to 10, with a return rate of 0.05 (5%) has been used, in addition to a GovInv of $4 million/year. Also, the government will repay to the private sector 30 annual payments after the PPP investment period ends (i.e., L = 30). In order to examine the effect of PPP investment, first the backlog and condition results with a $4 million annual government investment is obtained as shown in Figure 4-9a-c. These results are then compared with those obtained by incorporating the PPP investment into the model (Figure 4-9b-d). As shown in Figure 4-9 applying the PPP policy can affect the behaviour of both backlog and condition curves. By applying the PPP policy, the backlog has been reduced significantly in the first 10 to 20 years of the plan (comparing Figure 4-9a and Figure 4-9b). At year 10, for example, the backlog was estimated to be $28.6 million in the case of $4 million/year government investment (Figure 4-9a), which is double the backlog amount at year 10 after using PPP (i.e., $14.2 million). Condition also improves with higher rate in the first 10 years of the plan by applying the PPP policy. At year 10, for example, condition is improved from 63.1 to 73.1 by using the $2 million/year PPP investment.

As shown in Figure 4-9b, the PPP investment period is followed by a payback phase in which the government pays its debt to the private sector. Over this period, therefore, the available budget for rehabilitation decreases by the annual payment amount (AP). The negative effect of this payback period on the backlog accumulation is substantial (see Figure 4-9b). Due to the budget reduction caused by paybacks, the decreasing backlog accumulation trend during the investment phase (between years 0 to 10, particularly after year 5) is changed into an increasing trend over the payback period. This trend continues until the end of payback period and is followed by another decreasing trend in the end of the strategic plan when the budget level returns to $4 million/year (from year 40 to 50 in Figure 4-9b). Based on the results of Experiments 4, it is possible to conclude, although using PPP can significantly reduce backlog and improve condition in the first 10 to 20 years, the negative effect of the future payments dominates the initial benefits.

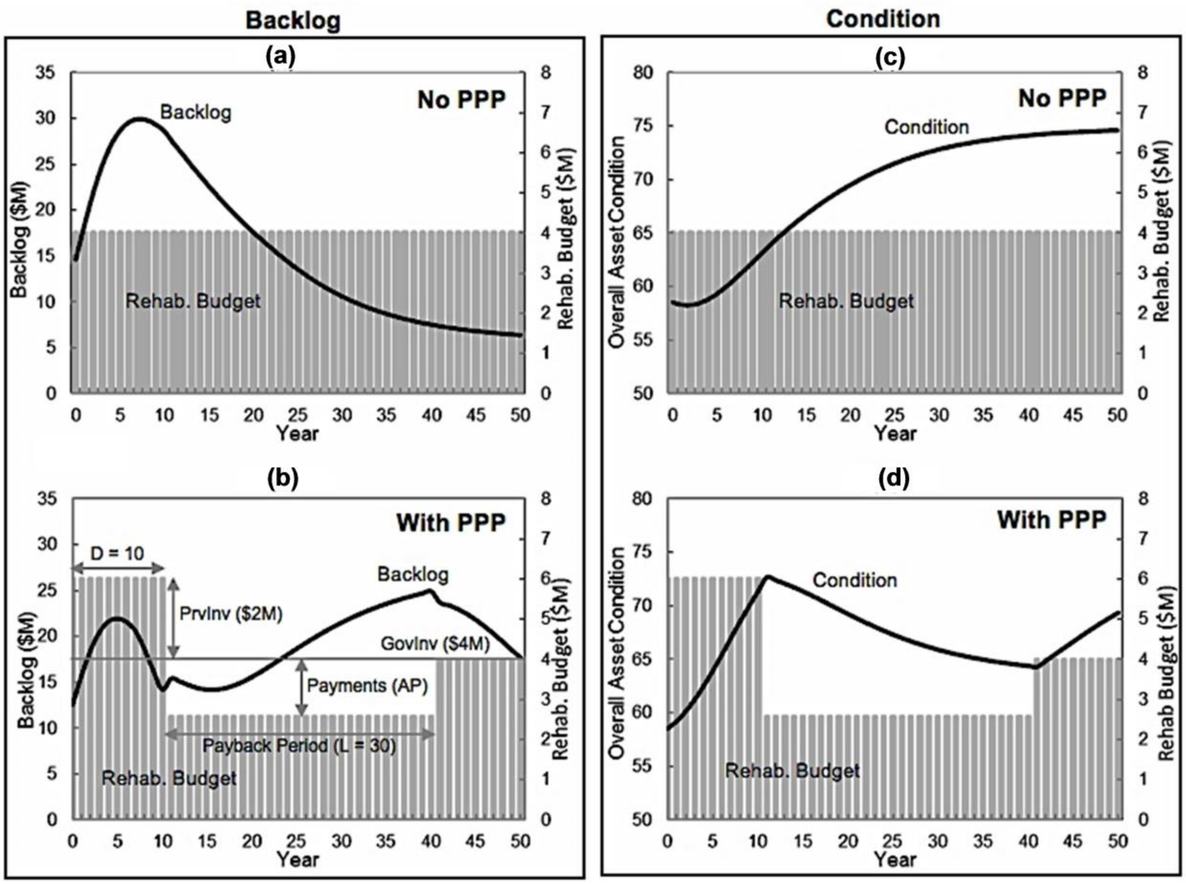

Figure 4-9: Simulation results for a PPP example

Experiment 4 is an example of the potential of system dynamics to analyse the impact of using private investments on long-term performance of infrastructure assets. Analysing different PPP scenarios helps asset managers to identify the best PPP schemes that can address the short-term financial problems while minimizing the negative long-term effects on performance due to paybacks. Making decisions regarding PPP parameters, such as the duration of the investment, payback length, or interest rates, is also dependent on the pressures on the asset owners for urgent rehabilitations due to critical asset conditions. In such cases, authorities might decide to uses private investments for short-term need despite the negative effect of paybacks on performance in later year over the planning horizon. Experiment 4 is intended to show the effectiveness and capability of the model in analysing the impact of private investment from a strategic point of view. Sensitivity analysis results suggest that other combination of PPP parameters can improve backlog significantly. In addition, other PPP approaches can lead to large cost savings to all stakeholders. For instance, one of the interesting approaches that TDSB used in a recent project was to involve the private sector in demolishing an old school and building a new state-of-the-art one at no cost to TDSB, in return for the right to use the remaining surplus land to build two adjacent residential towers. It is possible to also model other PPP options, such as finance-operate, as a future extension to the proposed SD model.

4.5.5 Sensitivity Analysis Experiments

Figure 4-10 shows the result of three sensitivity analysis tests with 50%, 75%, 95%, and 100% confidence bounds. Figure 4-10a shows the results of a multivariate Monte Carlo sensitivity analysis of the transition probabilities with a 30% variation in their values and its effect on the overall asset condition. As shown in Figure 4-10a the 95% confident bound has arrange of between overall conditions of 70 to 80. Accordingly, the overall and average behaviour of resulting network condition is not likely to affect the model conclusion and recommended policies. In another test (Figure 4-10b), the sensitivity of experiment 4 results has been tested against 'investment rate of return' with a range from 0 to 10% using a uniform distribution. As shown in the figure, the overall behaviour of the backlog trend is consistent, however, the rate of return significantly affects the outcome and thus a properly decided value must be used in the analysis. The third experiment in Figure 4-10c also shows the sensitivity towards PPP policies. In this multivariate analysis, all parameters are set as discussed in experiment 4 but with the values of 'private investment duration' ranging from 1 to 20 years, 'investment start time' ranging from year 0 to 10, and the 'number of payments' ranging from 1 to 20. As shown in Figure 4-10c, the sensitivity analysis results and the mean value plot (i.e., the solid line in Figure 4-10c) suggest that effectively adjusting and selecting these values can improve backlog. These results indicate the need of further investigation to find optimum PPP parameters.

4.6 Conclusions

This chapter presented a strategic policy investigation model for infrastructure rehabilitation and management. The proposed model utilizes system dynamics simulation as an effective method for policy analysis. The model has four integrated modules for analysing the main interactions among physical condition, life cycle cost, backlog, sustainability, and strategic policies of asset managers. The framework proved to be promising in analysing long-term performance of an infrastructure network considering different what-if scenarios. The strategic policy investigation framework presented in this study is also capable of demonstrating the dynamics amongst different aspects of asset management.

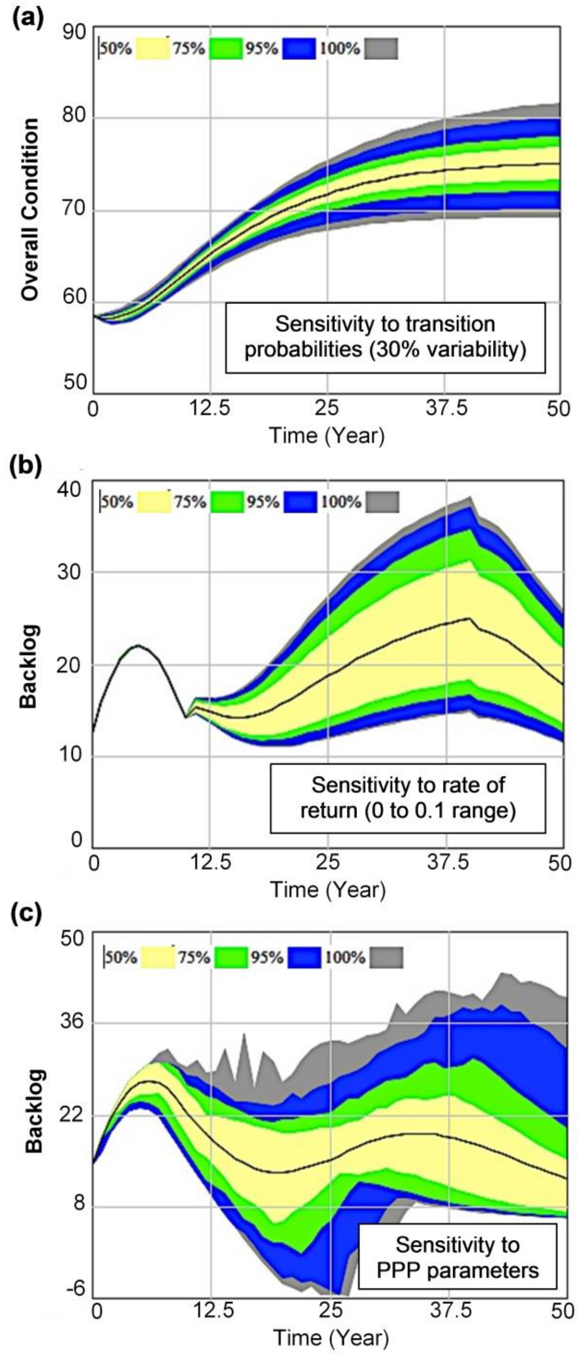

Figure 4-10: Sensitivity analyses results

It enables asset managers to investigate the effectiveness of their strategic decisions and acquire better understanding of the impacts of strategic decision-making. Although the current research only discusses one approach for involving PPP participation in infrastructure management, the framework is capable of considering other options. For example, the effect of using surplus lands can be investigated as an alternative payback scheme based on the value of the land and the resulting backlog projections. Future extensions of this study include: introducing more strategic parameters and performance indicator for different modules, addressing the existing limitations of the model such as modelling other types of PPP options (e.g., finance-operate), incorporating a more detailed sustainability analysis module and include various key sustainability performance indicators, and integrating the existing strategic model with long-term tactical planning models.

Chapter 5
Optimum Budgeting Policies for New Construction versus Rehabilitation

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Rashedi, R. & Hegazy, T. (2016). Optimum Budgeting Policies for New Construction, Rehabilitation, and Maintenance of Deteriorated Facilities: A System Dynamics Modelling Approach, Canadian Journal of Civil Engineering, (in press).

5.1 Chapter Summary

Sustaining acceptable service in large facility networks (e.g., schools, hospitals, etc.) is a complex task, particularly under limited budgets, rapid deterioration, and increasing service demands. Policy-makers for government and large organizations are challenged to make efficient balance between the construction of new facilities and the renewal of existing ones to suit both the short and the long-term needs. To support policy-makers, this chapter proposes an efficient decision support system that uses the System Dynamics (SD) simulation technique to analyze the impact of various policy scenarios and optimize policy decisions. First, a causal loop diagram was developed to capture the interactions among 30 parameters related to budgeting polices and facilities' performance. Afterwards, a simulation model was developed to examine the long-term impact of different budget allocation policies to new and existing facilities. The proposed system was tested using a case study from the Toronto District school Board involving more than 400 schools. It can find the optimum budgeting strategy that minimizes the overall facility condition index, facility risk index, and total life cycle cost, over a long-term strategic plan. The system proved its ability to find a budget allocation policy with much better results than the typical enrolment-based approach.

5.2 Introduction

One of the key challenges for managing a large network of facilities is to preserve the performance of existing facilities and introduce new ones to modernize the inventory and accommodate additional service demands. From a strategic perspective, therefore, it is important to determine the optimum level of funds that should be allocated to the rehabilitation of existing facilities, as well as to the construction of new ones, particularly for the facilities that affect the health and welfare of citizens. At the strategic level of facility management, therefore, decisions must be made regarding rehabilitation budget limits, the level of allocated budget to rehabilitation, new construction, and maintenance, in addition to, examining various policy scenarios and their long-term impacts. Such a difficult strategic decision must be carefully analyzed considering short-term and long-term needs and constraints. Among the important public facilities that are facing significant backlog and performance issues are school buildings. In the Unites States, the 2013 report card of America's infrastructure assigned a D (poor) grade to the school infrastructure, with a projected backlog of at least $270 billion (ASCE 2013). Meanwhile, school enrolment is projected to gradually increase through 2019, while state and local funding continues to decline (ASCE 2013). In Canada, school administrators and facility managers are facing similar problems. The Toronto District School Board (TDSB), which is the largest school board in Canada, alone reported a $3.2 billion capital renewal backlog with an increasing enrolment trend for the future (TDSB 2014) that requires substantial funding for new constructions. The large deficit and the need for new facilities, coupled with the deteriorated state of existing assets, necessitates novel approaches for determining optimum budgeting strategies.

In the literature, some efforts have attempted to address the above fund allocation problem. Johnstone (1995), for example, used an actuarial model to decide between rehabilitation and new construction, for each facility. The study, however, did not take a strategic long-term view of the analysis. In another example, Wilkins et al. (2015), compared the costs of producing multifamily housing through new construction or acquisition-rehabilitation over a 50-year life cycle and concluded that new constructions were associated with 25% to 45% higher lifecycle costs.

While new construction has its challenges, it applies to few facilities in some years. Rehabilitation, on the other hand, has to consider the whole existing inventory of facilities every year, which is very challenging, particularly under budget limits. Prioritizing all the components of all facilities for rehabilitation over a multi-year plan is not a simple task, particularly when the inventory has many old facilities. In the literature, researchers proposed decision support tools to help with rehabilitation fund allocation for various asset domains (e.g., bridges, pavements, buildings, etc.). Frangopol and Liu (2007), for example, proposed a model for prioritizing the rehabilitation of bridges by considering multiple criteria including condition and safety. Halfawy et al. (2008), proposed a GIS-based system to support the renewal planning of sewer networks considering costs, condition improvement, and risk reduction. For pavements, de la Garza et al. (2011) developed a pavement maintenance optimization subject to budget constraints and performance goals. In the facility domain, Rashedi and Hegazy (2014) compared mathematical and evolutionary optimization techniques to maximize the overall condition of more than 50,000 building components over a five-year plan. All these systems, however, work at the operational level, under a given budget limit.

For strategic analysis, a powerful simulation concept, called System Dynamics (SD) was introduced in 1961by Forrester (1961). System dynamics modelling generally rests upon the idea of system thinking in which all strategic decisions take place in the context of dynamic feedback loops (Sterman 2001). Because of the promising results of SD-based simulation tools and models, they have been utilized in a variety of domains from construction to politics, and even warfare (Sterman 2000). In the area of construction management, Lee at al. (2006) used SD to improve the overall construction productivity and to analyse schedule changes. Alvanchi et al. (2011), also used SD and discrete event simulation to address the conceptual phase of hybrid SD-DES modelling for mega construction projects. In the facility management domain, Rashedi and Hegazy (2015) developed an SD model to analyse the dynamics of deterioration and rehabilitation mechanisms for a network of assets over 50 years.

Typically, decisions regarding budget limits are made at the strategic level, where many factors related to the strategic and operational dynamics of the whole asset network need to be considered. This paper thus proposes a decision support framework that utilizes the system dynamics (SD) simulation technique to examine the variety of factors that affect budget policy (for new and rehabilitation projects) and the consequent impact on the long-term performance of facilities and the consequent backlog accumulation.

5.3 Proposed Decision-Support Framework

Figure 5-1 shows the three-step research methodology behind the proposed decision support framework. At its heart lies a system dynamics (SD) model that simulates the long-term behaviour of the key system parameters. In step 1, facility inventory data, such as facility condition index (FCI), age, facility gross floor area (GFA), etc., are inputs to the SD model, along with the long-term goals and performance indicators. The SD model is then developed and validated in step 2. Upon validation the SD model is then used to simulate the long-term effects of various strategic policies in step 3. In this step, the simulation dashboard allows the user to change several policy parameters and see the real-time impact on various performance indicators. The SD model can also be used to determine the optimum budgets for new construction and rehabilitation actions that maximize various performance parameters for the network of facilities over a long-term strategic plan (e.g., 30 years). Details of the developments made in these three steps using data from the Toronto District School Board (TDSB) in Canada which administers more than 550 schools in Toronto are discussed in the following sections.

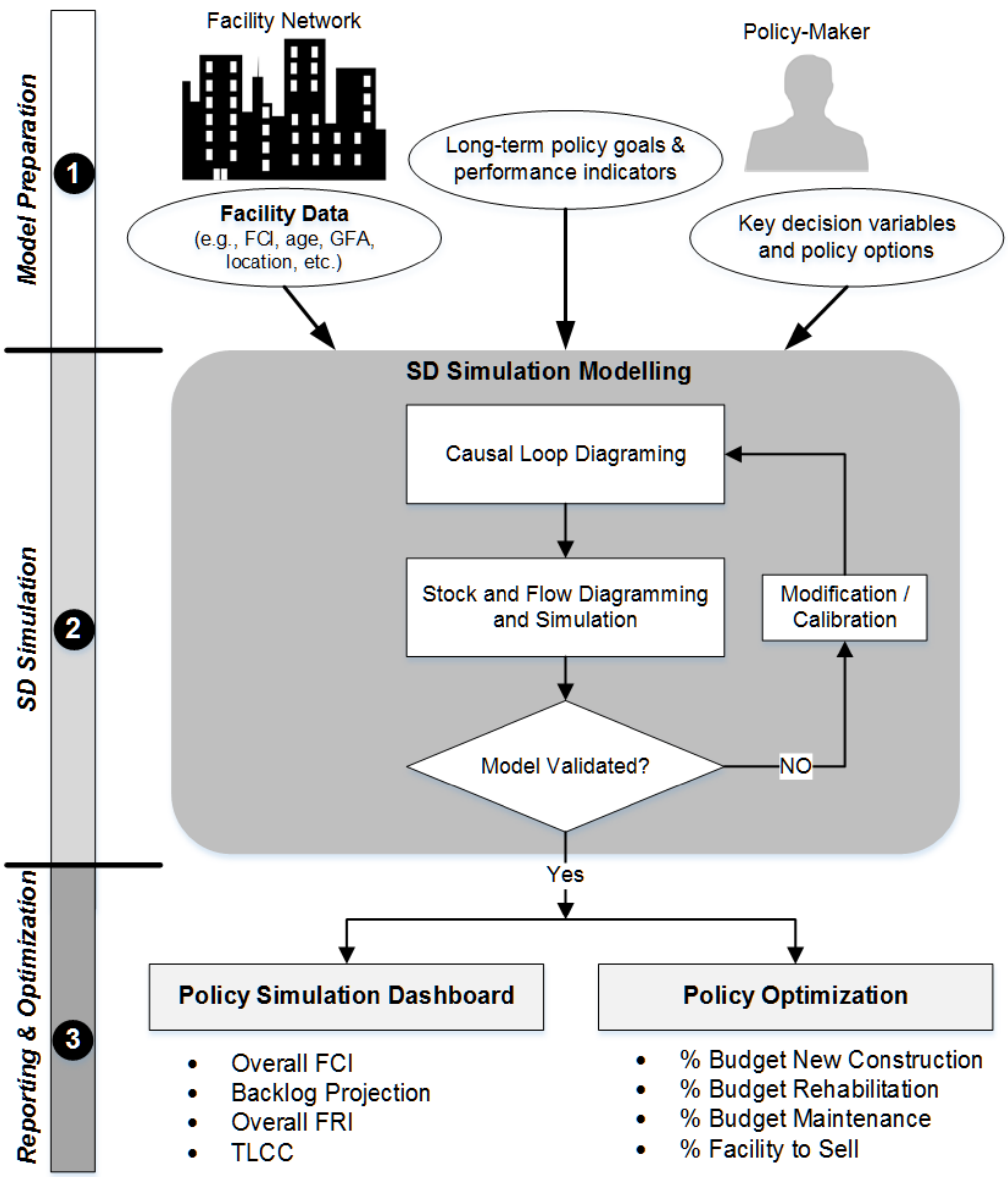


Figure 5-1: Research methodology for the proposed SD-based decision support framework

5.4 Step 1 – Data Preparation

To build the simulation model, datasets regarding the overall operating condition of around 438 elementary schools, administrated by TDSB, have been used. The facilities have been categorize in a hierarchical manner based on building system (e.g., Architectural, mechanical, electrical, etc.), subsystems (e.g., exterior closures, HVAC, etc.) and components (e.g., windows, fire alarm, etc.). Periodic condition assessments data and deterioration information were also available for these assets from previous studies by the authors on this network with a relative importance factor for different components based on expert interviews (more information regarding TDSB asset network can be find on Rashedi and Hegazy (2014)). Annual TDSB reports regarding their facilities' condition and financial plans have been also used for model preparation. A measure of the performance of a facility *j* at time *t* is first determined using an industry standard measure called the Facility Condition Index (FCI), which is represented as follows:

$$FCI_{jt} = \frac{Renewal\ Backlog\ of\ Facility\ j\ at\ time\ t}{Facility\ j\ Replacement\ Cost} \qquad (5-1)$$

Thus, FCI represents a facility need for renewal. A lower FCI value then represent a better facility performance and vice versa. Using linguistic terms for different ranges of FCI, the following (Rush 1991) can be defined:

- 0 < FCI < 5 represents a facility in '**good**' condition
- 5 < FCI < 10 represents a facility in '**fair**' condition
- 10 < FCI < 30 represents a facility in '**poor**' condition
- FCI > 30 represents a facility in '**critical**' condition
- FCI > 65 represents a facility that is 'Prohibited to Repair (**PTR**)'

The last category (PTR) was added by the Ministry of Education (TDSB 2014) for the facilities that are deemed financially infeasible to be renewed as the renewal cost is too high. The possibility of selling these properties and the overall impact on the asset network is an important debate in the education sector (TDSB 2014; TDSB 2007). Overall, the distribution of the FCI for TDSB facilities (assessed in 2007) is shown in Figure 5-2. 84% of the facilities are in 'poor' or 'critical' conditions (TDSB 2007) and the overall average FCI of the whole inventory is 20%, representing an overall 'poor' condition.

Using this information, the key challenge at the strategic level is to determine the level of budget to be allocated to new construction versus renewal work so that the overall FCI is brought to an acceptable level.

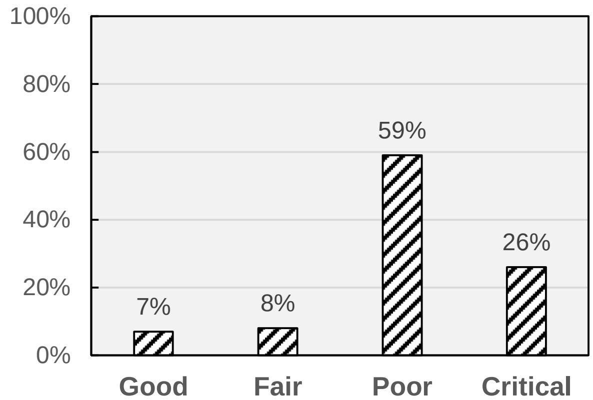


Figure 5-2: FCI distribution for TDSB facilities

In addition to detailed facility data, key strategic decision variables need to be determined prior to development of the strategic SD model. In the case of TDSB facilities, a total of 30 key decision parameters and policy options have been identified as shown in Table 5-1, based on information in their annual reports and published data. The table also provides a brief description for each parameter in addition to their relationships, which are discussed in terms of causal loops diagrams in the following section.

Table 5-1: Model parameters and their relationship

No.	Parameter Name	Description/Assumption	Governing Parameters
1	% Sell PTR	Percentage of PTR schools to sell each year	No. of PTR schools
2	%New Construction Budget	Percentage of total budget allocated to new construction each year	%Rehab. Budget, Pressure to Build New Schools
3	%Rehab. Budget	Percentage of total budget allocated to rehabilitation (renewal) each year	%New Construction Budget, Pressure to Increase Rehab. Budget
4	Capital Budget (CAPBUD)	Total capital budget, determined based on enrolment	Income from Sold Property, Total Enrolment
5	Deterioration Rate	Higher maintenance means lower deterioration rate	Routine Maintenance
6	Facility Age	Average age of the whole facility network	New Construction
7	FCI	Overall average Facility Condition Index of all facilities	New Construction, Rehab. Backlog

8	Income from Sold Property	Depends on the number of sold properties and their expected value	% Sell PTR
9	Maintenance Budget	$ amount of budget for maintenance	Maintenance Factor, Maintenance Needs
10	Maintenance Factor	A factor between 0.5 to 1 representing the level of maintenance work relative to needs	N/A (Exogenous)
11	Maintenance Needs	Depends on the total school Gross Floor Area (GFA) and level of maintenance	Routine Maintenance, Total School GFA
12	New Construction	Number of new facilities to built	New Construction Budget
13	New Construction Budget	$ amount of budget that goes to new construction	%New Construction Budget, Renewal Budget
14	Over-Capacity	A measure of the number of students versus the capacity of schools	Total Enrolment, School Capacity
15	Population Growth	Can affect enrolment trends	N/A (Exogenous)
16	Pressure to Build New Schools	A soft parameter representing the pressure on authorities to build new facilities	Over-Capacity
17	Pressure to Increase Rehab. Budget	A soft parameter representing the pressure on authorities to increase rehab. budget	Risk
18	PTR	Number of prohibitive to repair facilities	FCI
19	Rehab. Actions	Rehabilitation intervention over the plan	Rehab. Budget
20	Rehab. Backlog	Required investment to bring network into a satisfactory level of performance	Rehab. Actions, Rehab. Needs
21	Rehab. Budget	$ amount of budget that goes to rehab.	%Rehab. Budget, Renewal Budget
22	Rehab. Needs	As facilities age and deteriorate, more are in critical state with rehab. needs	Deterioration Rate, Total School GFA
23	Renewal Budget	An intermediate variable determining the portion of CAPBUD going to both rehab and new construction	Capital Budget, Maintenance Budget
24	Residential Intensification	Can significantly affect enrolment trends	N/A (Exogenous)
25	Risk	Facilities in critical condition, older, and over-populated contribute more to the overall risk of failure.	FCI, Facility Age, Over-capacity
26	Routine Maintenance	Maintenance operations over the plan	Maintenance Budget
27	School Capacity	Determined based on the average capacity of schools	Total No. of Schools
28	Total Enrolment	Depends on demographic changes or projected trends by school administrators	Population Growth, Residential Intensification
29	Total No. of Schools	New constructions adds schools while selling old ones decreases the total number	New Construction, % Sell PTR
30	Total School GFA	Determined based on average school size	New Construction

5.5 Step 2 – SD Simulation

5.5.1 Causal Loop Diagram

As a first modelling step toward SD simulation, a causal loop diagram (CLD) has been developed to identify the main dynamic interactions and feedback loops in the system. A CLD consists of variables connected by causal links whose polarities denote the effects of one variables on another. A positive link, i.e., (+) polarity, implies that the cause and effect are moving/changing in the same direction: e.g., if a cause increases, the effect increases, and if a cause decreases, the effect decreases. A negative link, i.e., (-) polarity, means that the cause and effect are moving/changing in opposite directions in the model (Sterman 2000). The developed CLD for the case study (Figure 3) considers all the dynamic relations among of the key parameters (listed in the last column of Table 1). Key policy decision variables are highlighted in bold red text in Figure 5-3.

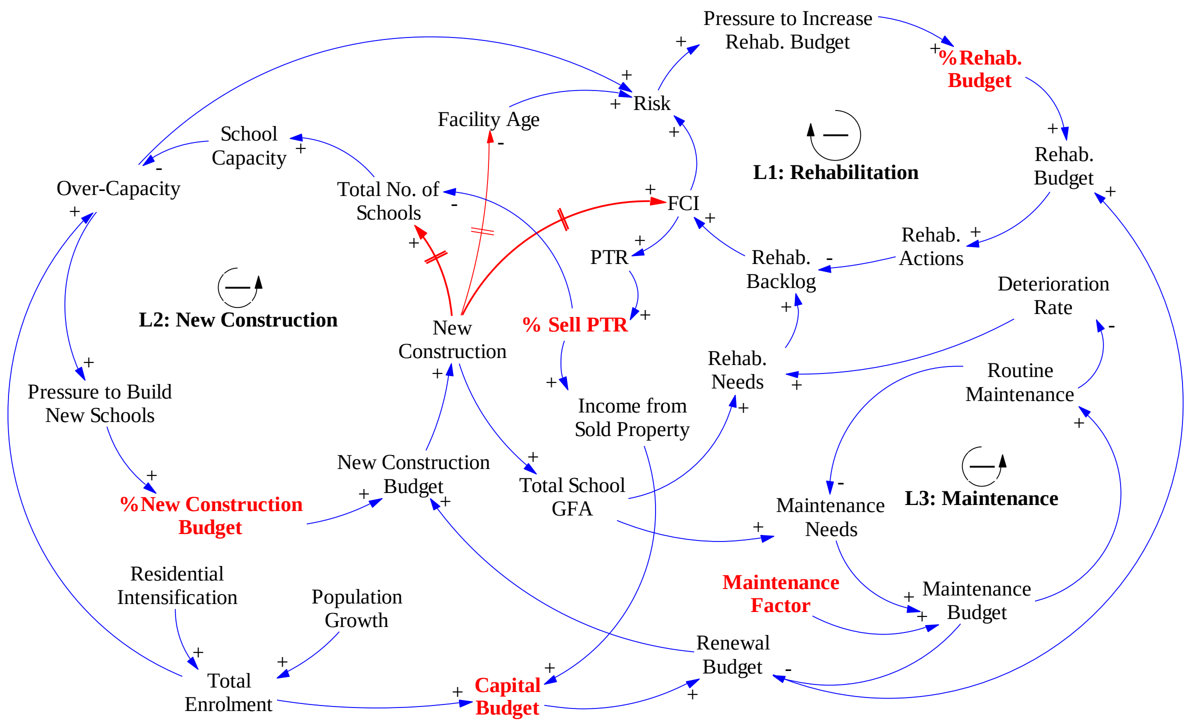


Figure 5-3: Proposed causal loop diagram (CLD)

In the CLD of Figure 5-3, combination of causal links create feedback loops that generally are positive (+) or negative (-). Positive loops (also called reinforcing loops) generate growth behaviour while negative loops (also called balancing) generate goal seeking or equilibrium behaviour. The interaction amongst the feedback loops is the key to generating complex dynamic behaviours (Sterman 2001). A total of 71 feedback loops can be identified in Figure 5-3 (Appendix B). As examples, three highlighted loops reasonably model the rehabilitation (L1), new construction (L2), and maintenance (L3) processes. In loop L1, for instance, more rehabilitation actions reduce backlog and consequently FCI (as indicated in Eq. 1). In turn, lower FCI will result in a lower risk index that reduces the pressure on authorities to increase rehabilitation budget. Accordingly, the level of rehabilitation budget (i.e., '% Rehab. Budget' in Figure 5-3 and Table 5-1) will be reduced and will result in a lower rehabilitation budget, thus less rehabilitation actions. This negative (balancing) feedback loop seeks the goal of adjusting rehabilitation actions (and budget) based on a desired FCI level determined by facility managers or other authorities. Loops L2 and L3, on the other hand) can be studied in the same manner as loop L1 using the polarity of causal links depicted in Figure 5-3. The objective of the negative loop L2 is to adjust the amount of new construction based on the capacity of existing schools and the total enrolment (see 'over-capacity' parameter in Table 5-1), while L3 is to adjust routine maintenance based on the maintenance needs of existing school buildings. It is important to note that in loop L2, 'New Construction' is linked to 'Total No. of Schools' by a positive link with a delay mark '||' (see red links in Figure 5-3). Since construction of a new school can take considerable amount of time (e.g., 5 years for design development, approvals, and construction), the effect of this delay has been taken into account in the model by using a delay link and a delay function.

5.5.2 Stock and Flow Simulation Model

Figure 5-4 shows the proposed stock and flow simulation model developed based on the CLD of Figure 5-3. Table 5-2 also provides a summary of key parameters presented in the proposed SD model and their equations in the model. It is important to note that for presentation purpose, some of the intermediate variables used in model calculations are not shown in Figure 5 and only the key parameters are presented. Figure 5-4a shows the central stock and flow model that simulates the process of FCI changes in the system, where the five FCI states are represented as five stocks that accumulate the number of schools in good, fair, poor, critical, and PTR states, respectively. The figure also shows two flows that represent two rehabilitation actions that improve FCI from poor to fair (Rehab. Level 1) and from critical to fair condition (Rehab. Level 2). To simulate new construction, an inflow is linked directly to the stock for FCI_{Good} (left side of Figure 5-4a). Also, an outflow from the FCI_{PTR} stock is used to simulate the selling of old facilities. Furthermore, the deterioration from each FCI sate (stock) to a lower state is simulated by flows such as D12 (deterioration from FCI_{Good} to FCI_{Fair}). Details of the FCI calculations are presented in Table 5-2. In the proposed model, maintenance affects deterioration rates by using a variable called 'maintenance factor' (MF). In the model, maintenance reduces the deterioration rates, thus, reduces the rate by which FCI worsens with time (see Table 5-2 'DR12').

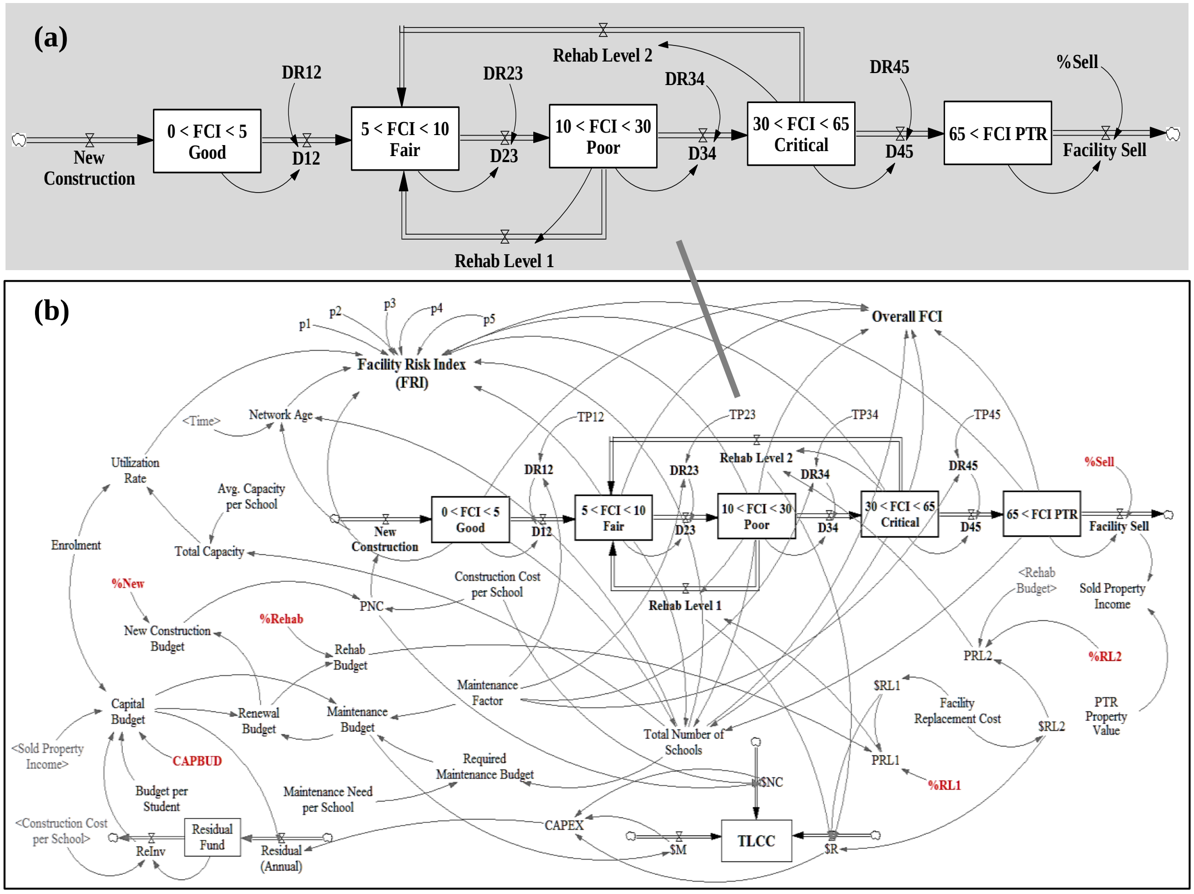


Figure 5-4: Proposed stock and flow simulation model

Table 5-2: Key parameters and equations of the stock-and-flow simulation model

Parameter	**Unit**	**Model Equation / Description**
$FRC	$	Facility replacement cost
$\$M_t$	$	Maintenance expenditure at time t
$\$NC_t$	$	New construction expenditure at time t
$\$R_t$	$	Rehabilitation expenditure at time t
%RL1	%	% of rehab. budget allocated to rehab. level 1
%RL2	%	% of rehab. budget allocated to rehab. level 2
$CAPEX_t$	$	Capital Expenditure = $\$M_t + \$R_t + \$NC_t$
D12	No. of Facilities	Deterioration from good to fair = $DR12 \times FCI_{Good}$
D23	No. of Facilities	Deterioration from fair to poor = $DR23 \times FCI_{Fair}$
D34	No. of Facilities	Deterioration from poor to critical = $DR34 \times FCI_{Poor}$
D45	No. of Facilities	Deterioration from critical to PTR = $DR45 \times FCI_{Critical}$

DR12	[0, 1]	Deterioration rate from good to fair = $TP12 \times \left(\frac{1}{MF}\right)$
DR23	[0, 1]	Deterioration rate from fair to poor = $TP23 \times \left(\frac{1}{MF}\right)$
DR34	[0, 1]	Deterioration rate from poor to critical = $TP34 \times \left(\frac{1}{MF}\right)$
DR45	[0, 1]	Deterioration rate from critical to PTR = $TP45 \times \left(\frac{1}{MF}\right)$
FCI%critical-fair	%	Different between FCI of state fair and critical = 32.5%
FCI%poor-fair	%	Different between FCI of state fair and poor = 12.5%
$FCI_{Critical}$	No. of Facilities	$\int_0^t (D34 - D45 - RL2)ds + FCI_{Critical}(t_0)\,,\ \ FCI_{Critical}(t_0) = 105$
FCI_{Fair}	No. of Facilities	$\int_0^t (D12 + RL1 + RL2 - D23)ds + FCI_{Fair}(t_0),\ \ FCI_{Fair}(t_0) = 35$
FCI_{Good}	No. of Facilities	$\int_0^t (NC - D12)ds + FCI_{Good}(t_0)\,,\ \ FCI_{Good}(t_0) = 31$
FCI_{Poor}	No. of Facilities	$\int_0^t (D23 - D34 - RL1)ds + FCI_{Poor}(t_0),\ \ FCI_{Poor}(t_0) = 258$
FCI_{PTR}	No. of Facilities	$\int_0^t (D45 - FS)ds + FCI_{PTR}(t_0),\ \ FCI_{PTR}(t_0) = 9$
FS_t (Facility Sell)	No. of Facilities	Number of sold facilities at time t
MF (Maintenance Factor)	Factor [0.1, 1]	[0.1, 1]
NC_t (New Construction)	No. of Facilities	Number of constructed new facilities at time t
N_{Total}	No. of Facilities	Total number of schools
Overall FCI	[0, 100]	Average of the network FCI values
Overall FRI	[0, 100]	$\left(\Sigma\left(\frac{FCI_{jt}}{N_{Total}}\right) \times p_j\right) \times UR_t \times \frac{Network\ Age}{100}$
Over-Capacity	N/A	$Max(UR_t - 1, 0)$
p_j	%	Probability of failure for facilities in FCI state j
RL1 (Rehab. Level 1)	No. of Facilities	$\frac{\%RL1 \times Rehab.\ Budget}{FCI\%_{Poor-Fair} \times \$FRC}$
RL2 (Rehab. Level 2)	No. of Facilities	$\frac{\%RL2 \times Rehab.\ Budget}{FCI\%_{Critical-Fair} \times \$FRC}$
TLCC	$	$\int_0^t (\$M + \$R + \$NC)ds\,,\ \ initial\ value = 0$
TPmn	%	Transition probability from FCI state m to n
UR_t (Utilization Rate)	N/A	total enrolment / total school capacity

In the SD model of Figure 5-4b, three key variables represent the main performance indicators that need to be monitored throughout the simulation: overall facility condition index (FCI); overall facility risk index (FRI), and the total life cycle cost (TLCC) with their corresponding equations in Table 5-2. The overall FCI is a weighted average determined based on the distribution of facilities in different FCI states. Overall FRI is also determined based on the probability of failure of the facilities in different FCI states, network over-capacity, and the age of the facility network. As suggested by FRI equation in Table 5-2, FRI is higher when the network age is older (i.e., no new schools are added) and when the schools are overpopulated. The TLCC is accumulated in a stock at the bottom of Figure 5-4b. Additionally, since the whole budget might not be fully consumed in a simulation year, a stock variable 'Residual Fund' has been added to reinvest the unused funds in the following year (see bottom left part of Figure 5-4b). Another key variables in the model that directly affect the deterioration process are the deterioration flows (e.g., D12 in Table 2). The flow values are governed by the transition probability between FCI states in addition to the level of maintenance. To determine a reasonable value for the transition probabilities, previous research on the deterioration modelling of building facilities (Elhakeem and Hegazy 2012) has been used to reasonably estimate and to provide adequate constraints on the deterioration process for the pool of facilities based on the previously observed reference modes. The rates are then calibrated and tested based on these constraints and observed FCI trends to ensure adequacy as discussed in the following section.

5.6 Model Implementation and Validation

Testing and validation of SD models is an important part of model development (Sterman 2002). In this paper, therefore, upon the development of the SD model for the TDSB case study involving 438 school buildings, various validation tests have been conducted. Facility replacement costs, new construction costs, network age, and other assumptions have been made based on TDSB and Ministry of Education reports on school buildings. The SD model was then implemented using a commercial SD simulation tool, VENSIM®, and all of the parameters and equations in Tables 5-1 and 5-2 were input to the software to perform simulation tests and later policy optimization.

5.6.1 Calibration of Deterioration Rates

A set of FCI values representing actual data over a 10-year period was used for model calibration (Figure 6). Calibration has been done using optimization with an objective of minimizing the error between the projected FCI values and those of actual data by adjusting deterioration rates. During the calibration process, specific constraints were applied to ensure that the rates are in accordance with the previous study on the building facilities deterioration models and also the three-phase deterioration process defined in asset management books (e.g., Hudson et al. 1997). The result of DR calibration suggest values of 0.1, 0.158, 0.135, and 0.187 for DR12, DR23, DR34, and DR45, respectively. Detailed analysis of possible variations in the transition probabilities has also been conducted using multivariate Monte Carlo analysis to investigate the impact of possible variations on the recommend policies (use of multivariate Monte Carlo analysis is discussed in the later part of this section). Results of this analysis clearly indicated that the possible variation can affect the confidence bound of the long-term behaviours, however, the overall trend are very consistent and there is no sign of significant impact on the policy recommendations. The used rates are therefore the best possible and reasonable results that could be obtained for the deterioration modelling at the strategic level.

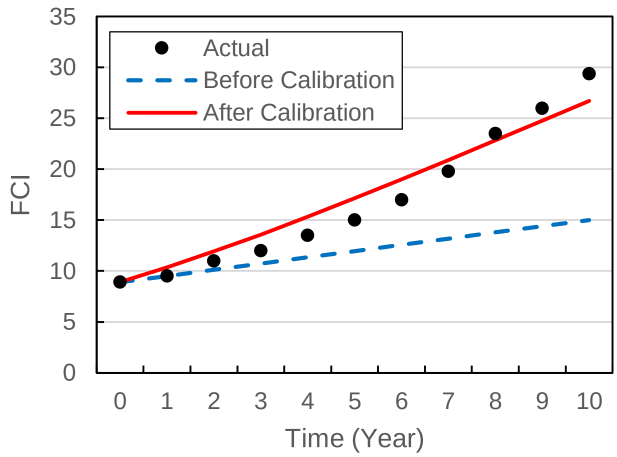


Figure 5-5: Calibration of deterioration rates (DRs)

5.6.2 Dimensional Consistency & Structure Assessment

One of the useful features of VENSIM® is that it can perform dimensional consistency test as long as all variable units are defined, which was satisfied in the present case study. The software also includes several tools such as 'cause/effect trees' that can be utilized to analyse the model relationships at different hierarchical levels. Figure 5-6 shows an example of a causal tree used to make sure that all the calculations related to the 'Overall FCI' were correctly represented. Such a process was followed to verify all the relations in the SD model. In this example, 'Overall FCI' can be selected as a target variables and then by generating a tree structure it is possible to check the variables affecting 'Overall FCI' at different levels with the direction of their impact (i.e., positive or negative). Using such diagrams, a process was followed to verify all the relations in the proposed SD model.

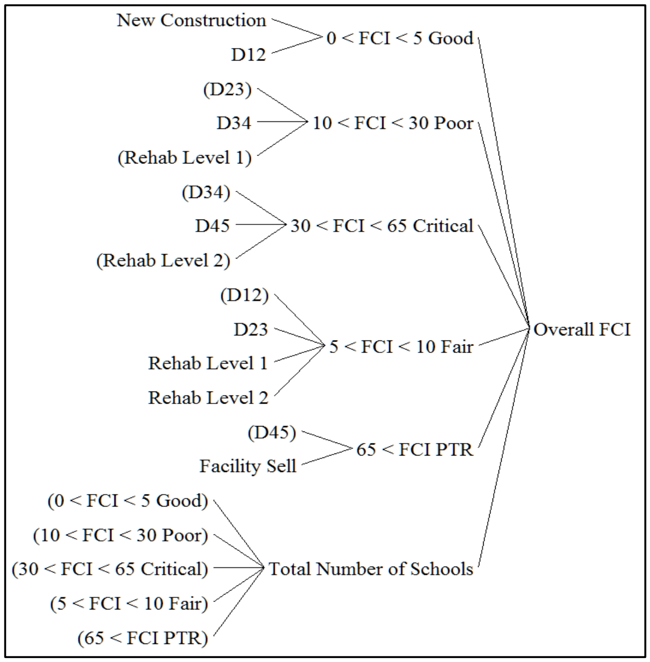


Figure 5-6: Causal tree example

5.6.3 Model Conditions and Dynamic Input Tests

As part of model testing, it was subjected to several condition tests that must hold true over the simulation process. For example, FCI values should always be between 0 and 100, or the total life cycle cost (TLCC) must be less than or equal to the accumulated capital budget (CAPBUD). These logical conditions ensure that all relationships are adequate. To perform these tests, the Reality Check® feature of the VENSIM software was used. In another set of experiments, the model was subjected to various dynamic input tests (DITs) to examine its robustness and response to sudden dynamic changes and extreme conditions. Figure 5-7 shows the results of a series of tests in which a base CAPBUD of $80 million was subjected to various dynamic inputs, including STEP, RAMP, and PULSE inputs, and model response was recorded in terms of FCI.

Figure 5-7a shows a ramp input (red dashed line) that sets CAPBUD to zero for the first 10 years and then slopes upward to its full value over a 10 year period (form year 10 to 20). In this experiment, the steady increase of CAPBUD reduces the slope of FCI curve gradually, as expected. Figure 5-7b also shows a sudden step changes in the value of CAPBUD which results in a sudden reduce of FCI slope. Figure 5-7c shows model response to a pulse input effective form year 10 to 20. As shown in the figure, over the pulse period FCI is maintained without deterioration, while after the sudden drop at year 20 it starts to increases. In all of the DITs, model behaviour was consistent with logical expectations without any anomalous behaviour. Also all model conditions are checked simultaneously with DITs for possible violations to ensure model's robustness and adequacy under extreme conditions

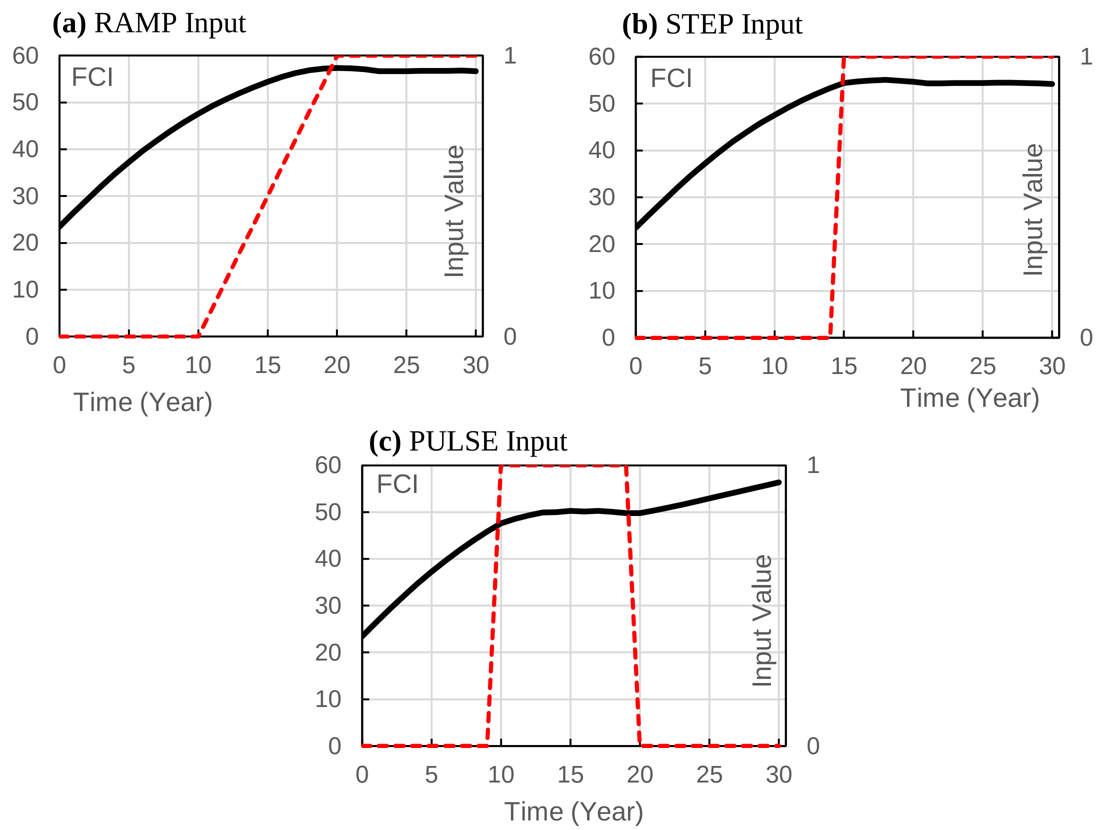


Figure 5-7: Model response to dynamic input tests

5.6.4 Sensitivity Analysis

Due to the uncertainty involved in some of the model assumptions and numerical parameters, multi-variate Monte Carlo sensitivity-analysis were performed to check the impact of possible variations in these parameters on key performance indicators to ensure the robustness of the model conclusions. In one set of experiments, effects of variations in two cost-related and uncertain parameters have been investigated: average facility replacement cost ($FRC) and facility maintenance need ($MN). The initial model values for $FRC and $MN were set to $10M and $100K, respectively, which are close to the real numbers used at the TDSB. A 30% variation is then used for both parameters to test FCI and FRI projections as shown in Figure 5-8a,b which shows the results of sensitivity analysis tests within 50%, 75%, 95%, and 100% confidence bounds. This variation produced a range of values for FCI and FRI, however, the pattern of behaviour of FCI and FRI did not seem to be affected by the 30% uncertainty level, thus the impact of uncertainty is not likely to affect the policy recommendation significantly. Based on these experiments, the current values can be presumed to be reasonable for the purpose of policy simulation.

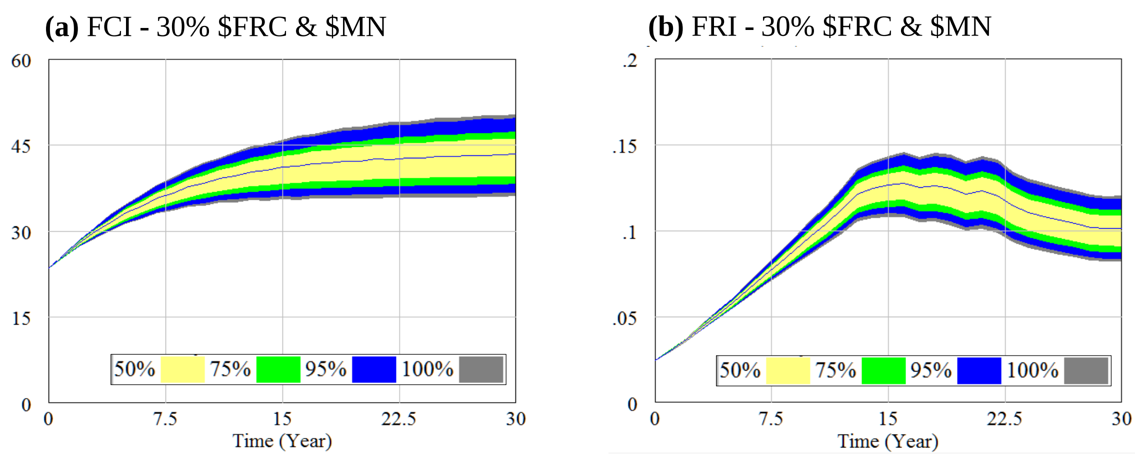


Figure 5-8: Multi-variate sensitivity analyses results for FRI

5.7 Step 3 – Experiments, Reporting, and Optimization

5.7.1 Policy Simulation Dashboard

Using the customization features of VENSIM, a policy simulation dashboard has been developed with a user-friendly interface that enables a policymaker to setup various policy scenarios and investigate their impact on key performance indicators (Figure 5-9). A series of sliders representing the value of various policy-related parameters are shown on the left side of the dashboard. By changing the value of these parameters, a policy-maker can create various policy scenarios and see their real-time impact on performance indicators shown by the output graphs of the dashboard. This can significantly help a policy-maker to get a deeper understating of system's behaviours and the effectiveness of various policy scenarios. In addition to its use for strategic decision-making and policy optimization, such decision support tool (DST) can be very useful in high-level analysis, and allows individuals with little or no training in modelling to get meaningful access to the model.

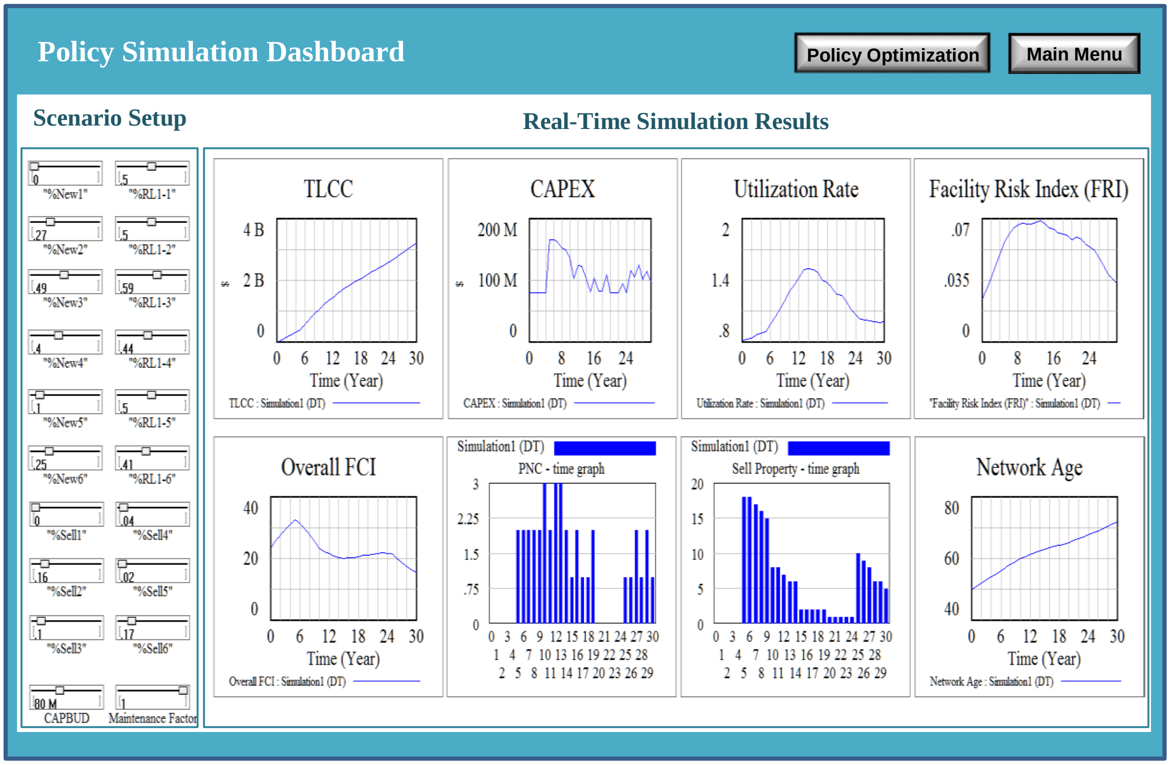


Figure 5-9: Policy simulation dashboard

5.7.2 Analysis of Enrolment-Based Budgeting Policy

One of the common practices for education ministries is to authorize capital budget for school boards based on the expected enrolment (TDSB 2014). This means more budget is authorized when enrolment is increasing and less as enrolment drops. Using the proposed SD model, this enrolment-based budgeting policy is investigate by simulating the effect of five different enrolment trends (Figure 5-10a): a constant trend (T1-Cnt); an increasing trend (T2-Inc); a declining trend (T3-Dec); a variable trend starting with an increasing rate followed by a decline (T4-Var); and a variable declining trend followed by a sharp increase (T5-Var). Capital budget is set based on an initial enrolment of 154,600 students and a \$516 annual budget per students (this assumed number is close to reality based on available data from TDSB). Figure 5-10b shows the resulting capital budget (CAPBUD) based on an enrolment-based budgeting policy.

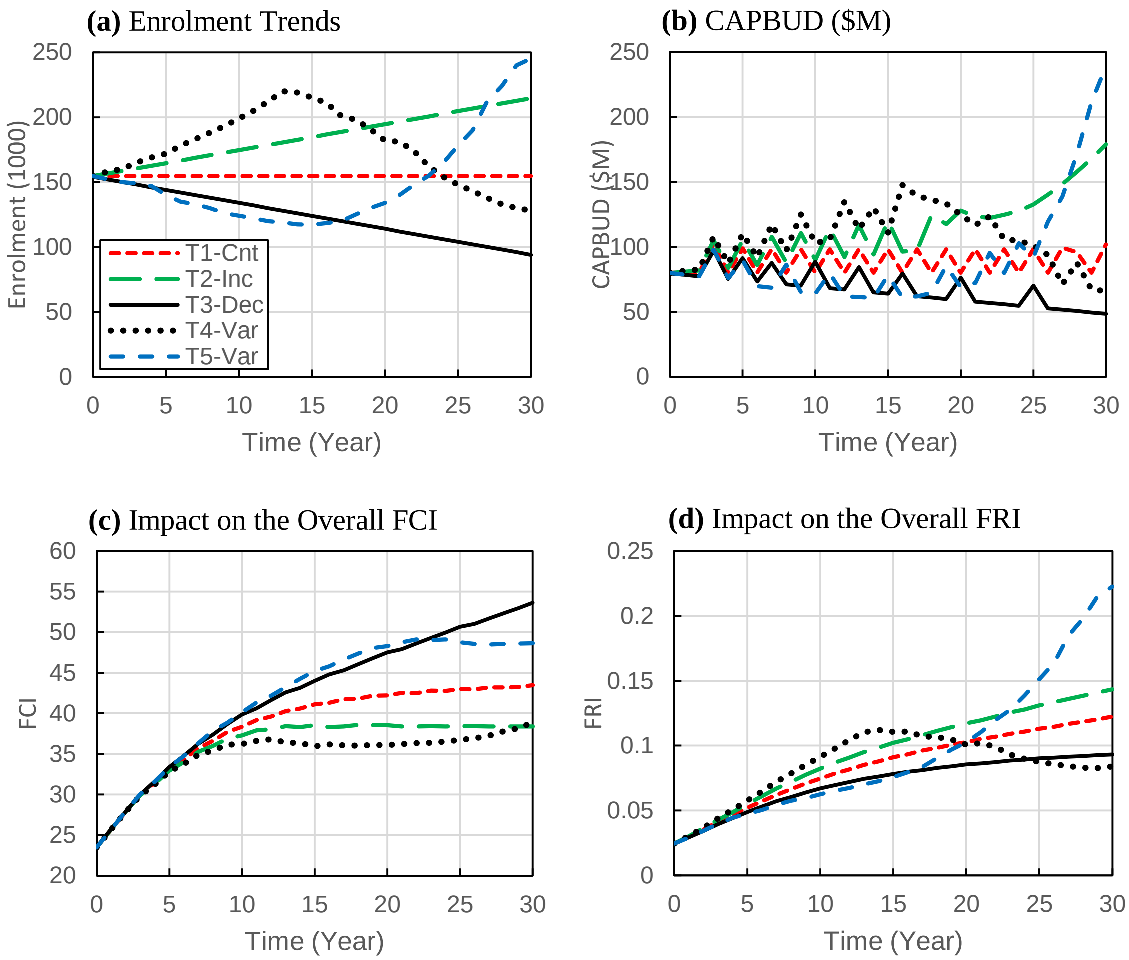


Figure 5-10: Effect of enrolment-based budgeting policies

An overall look at the FCI results in Figure 5-10c indicates that in all scenarios the FCI tends to increase over time, suggesting that the current level of budget is not adequate. One of the key problems with enrolment-based budgeting is in the case of declining enrolment. As enrolment declines, allocated capital budget is reduced, although the number of deteriorated facilities and their rehabilitation needs does not change. Thus, the reduced budget becomes inadequate and can result in an accelerated deterioration process over time (see T3-Dec in Figure 5-10c). In the case of increasing trend, it can be seen that overall FCI reaches an equilibrium at around 38%, however, overall FRI is now increasing over time mainly due to over-capacity. From a general perspective and with regard to the main feedback loops in the model, the equilibrium state of FCI can be related to the dominance of the balancing (negative) ‘Rehabilitation’ loop (L1) over the simulation horizon due to the increase in rehabilitation budget and consequently higher number of rehabilitation actions. On the other hand, risk has been increased over time since the balancing ‘New Construction’ loop (L2) cannot subside the effect of increasing enrolment trend on over-capacity, because of the inadequate budgeting for new constructions. The worst situation in these experiments is a combination of a declining enrolment and a sharp increase in enrolment (this can happen due to residential intensification for example). As shown in Figure 5-10c,d, this results in the worst performance in terms of FCI and FRI. In this case, due to the diminished budget in the first 15 years, the network condition is getting critical (Figure 5-10c). When the enrolment trend is shifted in around year 15, now a seriously deteriorated network does not have the capacity to accommodate the increasing enrolment and results in a high level of risk and poor performance. The experiments presented in this section, showed the usefulness of the proposed framework in analysing strategic policies. Furthermore, the results of enrolment-based budgeting polices clearly indicate that this policy can result in poor facility performance over time as it ignores a variety of dynamics within the system.

5.7.3 Optimum Budgeting Policy

This section presents a set of policy optimization experiments seeking best policy solutions to achieve strategic objectives and a satisfactory performance level. The enrolment trend ‘T5-Var’ was used in optimization experiments to determine the optimum budget levels and budget allocation strategies to improve performance in terms of FCI and FRI. As indicated in Eq. (5-2), the optimization model is set up to minimize an objective function that combines three weighted performance indicators: FCI, FRI, and TLCC. Since high percentage of over-capacity is not acceptable in the case of school buildings, the objective function in the optimization has to a penalty function representing over-capacity, formulated in Eq. (5-3). The decision variables of the optimization experiments are presented in Eq. (5-4), where, %NC is the percentage of capital budget (CAPBUD) allocated to new construction; %Rehab is the percentage of CAPBUD allocated to rehabilitation; %RL1 is the percentage of rehabilitation budget allocated to rehabilitation level 1; %RL2 is the percentage of rehabilitation budget allocated to rehabilitation level 2; MF is the maintenance factor ranging from 0.1 to 1; and CAPBUD is capital budget ranging from 0 to $200 million.

$$Objective:\ Minimize\ Z = w_1.FCI + w_2.FRI + w_3.TLCC + Penalty \qquad (5-2)$$

$$Penalty\ for\ \ overcapacity = w_4.\,[Max(UR_t - 1, 0)] \qquad (5-3)$$

$$Decision\ Variables:\ \ [\%NC_t, \%Rehab_t, \%RL1_t, \%RL2_t, MF, CAPBUD_t] \qquad (5-4)$$

All decision variables that represent budget levels were analysed over 5-year intervals until the end of the 30-year strategic plan to dynamically identify the optimum values during each interval. The value of weights w_1, w_2, w_3, and w_4 are set to 0.6, 0.2, 0.2, and 1, respectively. These weights were identified through an iterative process such that they adequately reflect the contribution of each parameter in the objective and penalty functions. Also, the values for FCI, FRI, and TLCC are normalized into a similar scale to avoid bias toward a specific parameter. The model then utilizes an efficient Powell hill climbing algorithm used by VENSIM® to search through a large simulation space to minimize the objective function, while identifying the optimum budget levels for new construction, rehabilitation, and maintenance over a 30-year strategic plan. Figure 5-11 shows the policy optimization results. As shown in Figure 5-11,a,b, both FCI and FRI are significantly improved as compared to the enrolment-based budgeting policy. Renewal backlog and the overall FCI have been reduced and remained at around 19% over the strategic plan, showing a 60% improvement as compared to the enrolment-based policy. Likewise, FRI showed a 74% improvement as compared to the enrolment-based policy with a small increase in value over the strategic plan.

Figure 5-11c shows the optimized CAPBUD level, which is determined to be higher than the enrolment-based policy. As shown in Fig. 5-11c,d, prior to the shift in the enrolment trend from decreasing to increasing, the budget is accumulated to spend on new constructions to accommodate future enrolment and to avoid over-capacity. The actual capital expenditure (CAPEX) is shown in Figure 5-11d. CAPEX is composed of three costs including new construction, rehabilitation, and maintenance. In the first five years, the majority of CAPEX is spent on rehabilitation and maintenance. Policy optimization also resulted in a value of 1 for maintenance factor recommending full maintenance over the entire plan. Maintenance cost, which is determined based on the number of schools and maintenance needs, stays at around $43 million until year 25 and gradually increases as new schools are added to the network. At around year 20, there is a peak in CAPEX due to large new construction expenditures (Figure 5-11d). The model observes the enrolment trend and the current capacity of the schools, which is around 190,000 students, and allocates substantial amount of budget to new construction considering a 5-years delay for construction to be done. Accordingly, new schools will be in service at around year 26 when enrolment is above the current capacity (see T5-Var in Figure 5-10a).

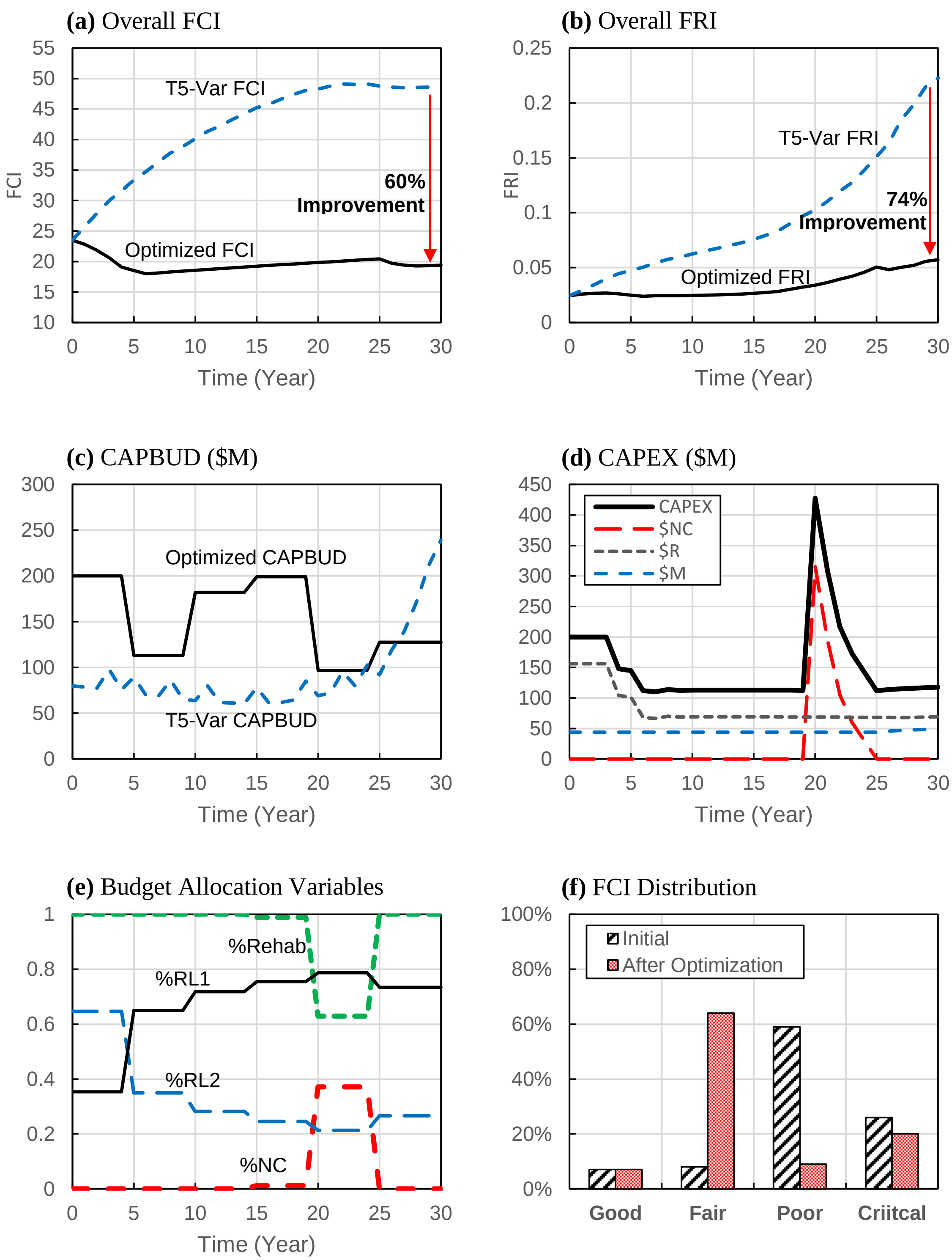


Figure 5-11: Policy optimization results

It is also possible to distribute new construction spending over a larger period to relax this peak of expenditure. The important insight from Figure 5-11d, however, is that the model clearly indicates the need for new construction, suggests a level of spending, and shows when is the latest time over the plan to start new constructions. Figure 5-11e shows the value of the main budget allocation variables over the strategic plan. As discussed before, majority of CAPBUD is allocated to rehabilitation and maintenance until around year 20 when new construction is started. Also in the first 5 years of the plan, the optimum budgeting policy recommends using rehabilitation level 2 (major rehabilitation from critical to fair condition) more than rehabilitation level 1, suggesting an immediate major rehabilitation action. After year 5, policy optimization results suggest more spending on rehabilitation level 1 than level 2. Figure 5-11f also shows a comparison between FCI distribution in the beginning and at the end of the strategic plan. As shown in this figure, the number of facilities in good condition remains almost the same by constructing new facilities over the plan. Also, the number of facilities in fair condition is much higher and the number of facilities in poor condition is significantly reduced. The number of facilities in critical condition is also slightly reduced. This is due to the fact that some facilities are deemed PTR, so they will not be repaired over the plan. Selling these facilities can have a substantial positive impact on the overall performance, however, it has a negative impact on total school capacity. Selling PTR facilities that are under-enrolled and its impact on the school boards is a point of debate in education sector. Analysing the local impact of selling these facilities from a social or real-state point of view is beyond the scope of this paper, however, the proposed model can analyse and show the impact of selling PTR facilities on several performance indicators. By adding '%Sell' to decision variables, policy optimization results showed that by selling PTR facilities, overall FCI improved from 19.4 to 11.3 and FRI from 0.057 to 0.021. Also the number of facility in critical condition significantly reduced from 20% to only 6%.

5.8 Conclusions

This chapter presented a novel System Dynamics (SD) model to analyse the impact of various budgeting policies for the rehabilitation of deteriorated facilities versus the construction of new facilities. Detailed discussion on how to develop, test, and validate a system dynamics model were presented in this chapter. The proposed dynamic hypothesis were illustrated in a causal loop diagram (CLD), and was then mapped into a stock and flow simulation model with all the underlying relationships and mathematical formulations. A rigorous model testing and validation procedure was then presented that entailed various tests and sensitivity analyses to verify the developed SD model.

The model was then used to perform policy optimization in order to determine optimum budget levels for new construction, rehabilitation, and maintenance, using a case study involving more than 400 schools from the TDSB asset inventory. Simulation results clearly indicated that the enrolment-based budgeting policy, which has been used by education ministries, is not an effective strategy, specifically in the case of declining enrolment trends. This policy can result in significant deterioration and backlog in addition to a high level of risk when a shift in enrolment trends happens. Consequently, using the proposed model, budget allocation variables were optimized, considering both rehabilitation of existing facilities and construction of new ones, and resulted in significant improvement of the overall facility condition index (around 60%). The SD model presented in this chapter provides effective tactical constraints in terms of budget limits for rehabilitation and construction of new facilities. These policies need to be combined with effective tactical planning model to ensure an optimized rehabilitation plan, which is capable of implementing the strategic goals.

Chapter 6
Tactical Rehabilitation Planning

This chapter is the author's accepted manuscript of an article published as the version of record in Structure and Infrastructure Engineering http://www.tandfonline.com/. This chapter has been reproduced with permission from the publisher with editorial modifications in accordance with the University of Waterloo thesis format.

Rashedi, R. & Hegazy, T. (2014). Capital renewal optimization for large-scale infrastructure networks: genetic algorithms versus advanced mathematical tools. Structure and Infrastructure Engineering, 11(3), 253–262.

6.1 Chapter Summary

Effective implementation of strategic policies and optimization of tactical rehabilitation plans is crucial for successful infrastructure management. Allocating the limited rehabilitation budget among numerous asset components, however, represents a complex optimisation problem. Earlier efforts using genetic algorithm (GA) could optimise small size problems yet exhibiting steep degradation in solution quality as problem size increases. Even by applying sophisticated mechanisms such as 'segmentation' to improve the performance of GA, large processing time hinders the practicality of the algorithm for large-scale problems. This chapter aims at improving both processing speed and solution quality for very large-scale problems (up to 50,000 assets). This chapter discusses the development of optimization models for tactical rehabilitation planning, using both GA and mathematical optimization using integer programming and GAMS/CPLEX optimization tool. This chapter also compares their results of GA-based and mathematical approaches on three different model formulations. Both approaches proved to be beneficial, yet the mathematical optimization model showed superior performance.

6.2 Introduction

Capital renewal plans (including repair, rehabilitation, and replacement) are essential to cost-effectively preserve the value and performance of infrastructure assets. At the tactical level of decision-making one of the main objective is effectively implement the strategic decisions. As discussed in the previous chapters, from the strategic analysis is was possible to determine optimum budgeting polices that maximize the long-term performance in terms of overall condition or backlog. Those budgeting polices and the corresponding budget levels (or annual budget limits) need to be used at the tactical level as key constraints on the optimization models. Optimizing renewal plans at the tactical level, however, is not a simple task due to the large number of building components that need to be considered in the analysis. In general, tactical planning starts by detailed inspection of all asset components, modeling their deterioration process, analysis of renewal options, and detailed analysis of life cycle cost (Ugarelli 2010). The latter analysis is used as basis for allocating the limited renewal funds obtained from the strategic-level analysis among the competing asset components. In the absence of a comprehensive and practical tool for optimum fund allocation at the commercial level, a ranking process of assigning money to top priority assets is typically used by municipalities. Ranking, however, does not consider alternative funding levels, where it can sometimes be optimal to try to cut costs on one component to enable another component with steeper deterioration behavior to be funded (Hegazy and Elhakeem 2011). The SD-based analysis provided in Figure 4-6 also indicates that the condition-based prioritization is not the best long-term policy. In addition, because fund allocation decisions involve millions of dollars each year, even a small percentage of saving (achieved by arriving at a near-optimum solution) will mean millions of dollars saved annually.

From an optimization perspective, fund allocation represents a complex problem (Abaza 2007) that is very difficult to solve due to the exponential increase in the large number of decision possibilities (i.e., solution space), particularly when the problem is large. To handle complex combinatorial problems, the trend in recent literature has been to use evolutionary optimization techniques, such as Genetic Algorithm (GA) (Liu et al. 2006; Elbeltagi et al. 2005). GA-based techniques are inspired by the improved fitness of natural selection and the "survival of the fittest" approach in living species. Using GA, solutions (sets of values for the decision variables) are constantly generated and assessed based on a fitness function, which is derived from the objective function and the constraints, until the best solution is found (Goldberg 1989). Many GA optimization models have been introduced for life cycle analysis and renewal planning in different asset domains, including: pavements (de la Garza et al. 2011; Ng et al. 2009); water/sewer networks (Halfawy et al. 2008; Dridi et al. 2008); bridges (Elbehairy et al. 2006; Morcous and Lounis 2005; Liu and Frangopol 2004; Itoh et al. 1997); buildings (Tong et al. 2001; Hegazy and Elhakeem 2011); groundwater remediation (Zou et al. 2009); and mixed assets (Shahata and Zayed 2010).

While literature efforts provided useful life cycle cost analysis models, their solution quality and speed greatly depend on problem size and model efficiency (Al-Bazi and Dawood 2010). Increasing problem size significantly affects the optimization results and degrades the performance and takes huge processing time (Csiszár 2007; Hegazy and Elhakeem 2011; Thanedar and Vanderplaats 1995; Cook et al. 1997). In the literature, little information has been reported on optimization performance on various problem sizes; and none proved to be able to handle very large-scale problems. Therefore, performance degradation and the very large processing time are two serious drawbacks that need to be resolved before models can be put to practical use.

This chapter attempts to optimize tactical decisions for very large-scale problems that involve thousands of building components (e.g., 50,000). With each building involving about 150 components, the 50,000 size represents about 300 building, thus allowing organizations such as real-estate companies, school boards, and other government agencies to make decisions considering their full inventory. A recently introduced mathematical optimization modeling tools (GAMS/CPLEX) has been used and examined in comparison with a previous GA-based model, called 'GA+Segmentation' that could handle 20,000 assets but took more than a day of processing time to reach suboptimal results. This chapter examines three different formulations and investigates their effectiveness on both the GA and the mathematical optimization approach, using a real-life case study of school building. In the following sections, the life cycle cost analysis formulations are first discussed. Afterwards, both the GA+Segmentation and the GAMS/CPLEX optimization models are explained, followed by a detailed comparison and discussion of their results.

6.3 Tactical Rehabilitation Decisions

Tactical rehabilitation planning models involve two types of decisions (Hudson et al. 1997): (1) network-level decisions of selecting (from the network of all competing asset components, e.g., roofs, windows, foundations, bridge decks, pavements, etc.) the optimum combination of components to renew in each year of a tactical plan (usually five years) that maximizes the return from the yearly budget limit; and (2) project-level decisions (i.e., one component at a time) of the appropriate renewal method (minor rehabilitation versus full replacement, etc.) to use for each selected component, considering its current condition and predicted deterioration pattern. These two decisions are inter-related and the renewal year decision affects the renewal type decision. For example, it can be cost effective to apply some rehabilitation in year 1 to a component, but if left to deteriorate until year 4, it is more cost effective to fully replace the component with a new one. To formulate effective tactical model for rehabilitation considering both levels of decisions for the whole network of components, the next subsection discusses network level first, followed by an efficient model that integrates both levels of decisions.

6.3.1 Network-Level Formulations

Because network level decisions involve a competition among a large number of components in all years, the ability to produce good solutions becomes very sensitive to problem size and how the optimization model is setup. At the network level, therefore, three possible formulations are examined in this chapter, as shown in Figure 6-1. The figure schematically shows how each model is setup, along with the associated number of decision variables and expected search-space size (number of all possible decision combinations). These formulations are as follows:

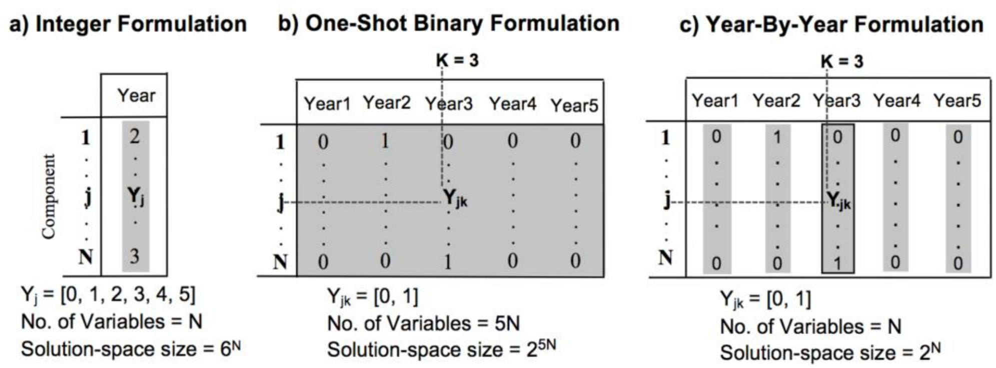


Figure 6-1: Formulations of decision variables in the network-level optimization

6.3.1.1 Integer formulation (Figure 6-1a)

For each asset component (j), a decision variable (Y_j) represents the integer index to the year of renewal, varying from 0 (i.e., no renewal) to 5 (the number of years in the planning horizon). Given N asset components being considered for renewal, the optimization problem has N variables (Eq. (6-1)), and the number of possible decision combinations (solution-space) in this formulation being 6^N.

$$Decision\,Variables: \begin{bmatrix} Y_1 \\ \vdots \\ Y_j \\ \vdots \\ Y_N \end{bmatrix} \quad , \qquad [Y_j \ = 0, 1, 2, 3, 4, \text{or } 5] \qquad (6-1)$$

6.3.1.2 One-shot binary formulation (Figure 6-1b)

In this formulation, each asset component (j) has five binary decision variables (Y_{jk}s) for the five years ($k = 1, 2, 3, 4, or\ 5$) in the renewal plan. If $Y_{jk} = 0$, then component j is not selected for renewal in year k, otherwise, if $Y_{jk} = 1$ represents a decision to renew it. Given N asset components being considered for renewal, the optimization problem has 5N variables, as shown in the matrix of Eq. (6-2). To avoid having each component selected for renewal more than once during the plan, a constraint is used to limit the sum of its five decision variables in all years to 1 (Eq. (6-3)). In this formulation, while the solution-space size (2^{5N}) is larger than the first model, the use of binary variables can make this model easier to solve.

$$\textit{Decision Variables:}\quad \begin{array}{c} \\ \mathbf{1} \\ \vdots \\ \boldsymbol{j} \\ \vdots \\ \boldsymbol{N} \end{array} \begin{array}{c} \begin{array}{ccccc} \mathbf{1} & \ldots & \boldsymbol{k} & \ldots & \mathbf{5} \end{array} \\ \begin{bmatrix} Y_{11} & \cdots & Y_{1k} & \ldots & Y_{15} \\ \vdots & \ddots & \vdots & & \vdots \\ Y_{j1} & & Y_{jk} & & Y_{j5} \\ \vdots & & \vdots & \ddots & \vdots \\ Y_{N1} & \cdots & Y_{Nk} & \ldots & Y_{N5} \end{bmatrix} \end{array} \qquad (6-2)$$

$$\textit{Constraints:}\quad For\ j = 1\ to\ N \qquad \textstyle\sum_k Y_{jk} \le 1 \qquad (6-3)$$

6.3.1.3 Year-by-year binary formulation (Figure 6-1c)

This formulation is a special case of the one-shot formulation, which uses one year at a time. It has the benefits of the two earlier models by being a binary model (simpler than integer) and has only N variables in each yearly optimization (one column of the matrix in Eq. (6-2) at a time). As such, this formulation uses five yearly sequential optimizations; each has a solution-space size of 2^N, which is the smallest of the three formulations. Also, once the components to renew in the first year are selected from year 1 optimization, these components are omitted from consideration in subsequent years. As such, the optimizations of later years get much smaller in size (i.e., uses N variables minus the sum of all selected components in prior years), and do not require the constraints of Eq. (6-3).

6.3.2 Integration of Network-Level and Component-Level Decisions

Among the recent efforts to integrate network-level and component-level decisions within a unified model is the Multiple Optimization and Segmentation Technique (MOST) of Hegazy and Elhakeem (2011), which is utilized in this research. The technique is highlighted in Figure 6-2.

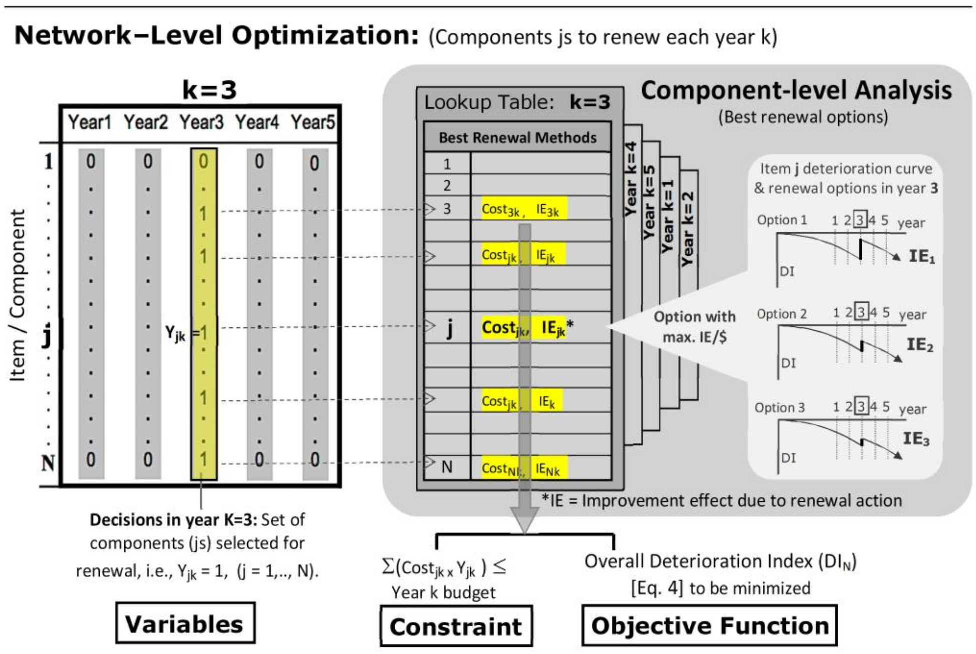


Figure 6-2: Network-level optimization using MOST with year-by-year formulation

It handles problems by first optimizing small-scale component-level analysis (right side of Figure 6-2) to create lookup tables of the renewal costs and the condition improvement effects associated with any renewal-year decision. Subsequently, these lookup tables can be readily used in the network-level optimization. The lookup table for year 3 (K=3) for example, is created by performing small optimizations to analyse the performance of each component *j* assuming that it will be renewed in year 3. The small optimizations consider the deterioration behaviour of the component and all the renewal options for that year, then determines the best renewal option and records its cost and benefit in the lookup table. The model utilizes a Markovian deterioration model that uses optimization to determine the optimum values in the transition probability matrix (TPM) to generate a deterioration curve that best fits previously inspected conditions. The model also assigns a relative importance factor (RIF) to each sub-system and component obtained from surveys among experts, and calculates improvement effects with regard to changes associated with the expected performance by using different repair alternatives. More details about the deterioration models and the RIFs can be found in (Hegazy and Elhakeem 2011). Once all the lookup tables are created, they are readily used in the network-level optimization of the MOST technique. Hegazy and Elhakeem (2011) used the year-by-year binary formulation (left side of Figure 6-2) due to its smaller search space size. However, it is possible to use the other formulations as well. In general, however, pre-performing the component-level analysis in lookup tables greatly simplifies network-level optimization and puts the objective function in a simple additive and multiplicative form, without complex interrelationships. The objective function in Eq. (6-4) minimizes the overall network deterioration index (DI_N), which is a number between 0 and 100, where 0 represents the best (zero deterioration) and 100 is the worst.

$$Min\ DI_N = \frac{\sum_{j=1}^{N}\left(EP_j^0 \times RIF_j\right) + \sum_{j=1}^{N}\sum_{k=1}^{t} RIF_j \times (\mathrm{EP_j^k} - \mathrm{EP_j^0})\ \times Y_{jk}}{\sum_i RIF_j} \qquad (6-4)$$

where, RIF_j is the relative importance factor (0 – 100) of component j; N is the number of components; and EP_j^k is the expected performance of asset j when repaired in year k; and EP_j^0 is the expected performance of component j without any repairs. Both EP_j^k and EP_j^0 are calculated as the average of the deterioration indices (DI_s) over the planning years. Deterioration indices are calculated with regard to the severity of inspected defects and the weight of defects for each component (Hegazy and Elhakeem 2011). As such, the term $(EP_j^k - EP_j^0)$ represents a measure of the condition improvement effect (IE_{jk}), due to a selected renewal action, as shown in Figure 2.

As an important constraint on the optimization, in each year k, is that the sum of renewal costs (RC_{jk}) associated the components js selected for renewal in that year should be equal or less than the budget limit (B_k) at year k (Eq. (6-5)). While this formulation for network-level optimization applies to year-by-year formulation in Figure 1, it has been modified to suit the other formulations in this study.

$$\sum_j (RC_{jk}\ x\ Y_{jk}) \ \leq \ B_k \quad , Y_{jk} = [0,1] \qquad (6-5)$$

6.4 Optimization Using Genetic Algorithm (GA)

6.4.1 Case Study

Hegazy and Elhakeem (2011) implemented the aforementioned model on a real case study of 800 components of school buildings obtained from the Toronto District School Board (TDSB), which administers more than 550 school buildings in the Toronto area. The components of the case study include roof sections, windows, boilers, and fire alarm systems. The data of each component include: current conditions (from visual inspection), relative importance (obtained through a survey among TDSB experts), deterioration behaviours (Markovian models), costs associated with different repair alternatives, annual budget limit ($10 million), and planning horizon (5 years). The overall objective is to minimize the network deterioration within the budget limits. The base case of 800 components has been used throughout this study (for both GA-based and mathematical approaches) and various larger size models have been created using randomized multiple copies of the base-case.

6.4.2 Experiments Using Traditional GA

To optimize renewal decisions in large-scale problems and to test the performance of GA with regard to solution quality and processing time, this study uses a commercial GA-based optimization tool, called EVOVLER. It finds a near-optimum solution fast by generating an initial population of feasible solutions and then generating numerous offspring solutions based on crossover and mutation. Fitness of the generated solutions is then examined based on the objective function and constraints to find an optimum result. The performance of GA, however, is highly sensitive to problem size, problem formulation, and other operational parameters (e.g., initial population) that govern the GA evolutionary process (Csiszár 2007).

An initial population of 100 parent chromosomes; 50% crossover rate and a dynamic mutation rate have been used for the TDSB case study. Testing the GA model on the three proposed formulations in Figure 6-1 for the TDSB case showed steep performance degradation as problem size increased. The GA model was able to optimize up to 8,000 components (only in the case of year-by-year), beyond which it offers no improvement over a simple ranking approach of selecting the components with worst condition first. Detailed results are presented later in section 6.5.

6.4.3 Experiments Using GA+Segmentation

To suit real-life problems that are much larger in size, a segmentation method (Hegazy and Rashedi 2012) has been applied to enhance the performance of GA. The GA+Segmentation process resembles divide-and-conquer concepts (Dasgupta et al. 2006) that are used to handle complex computational problems. This method decomposes the original network-level problem into smaller sub-problems (segments), handles them separately, and combines their results to find the final solution (Figure 6-3). Implementing the segmentation process within the tactical model required segmenting the available budget, decision variables, and optimization constraints, without compromising the integrity of the model. It also mandated adjustments to redistribute any unallocated (leftover) money from one segment to the next. Considering these aspects, the GA+Segmentation approach has been fully automated, which makes it practical for real-life applications.

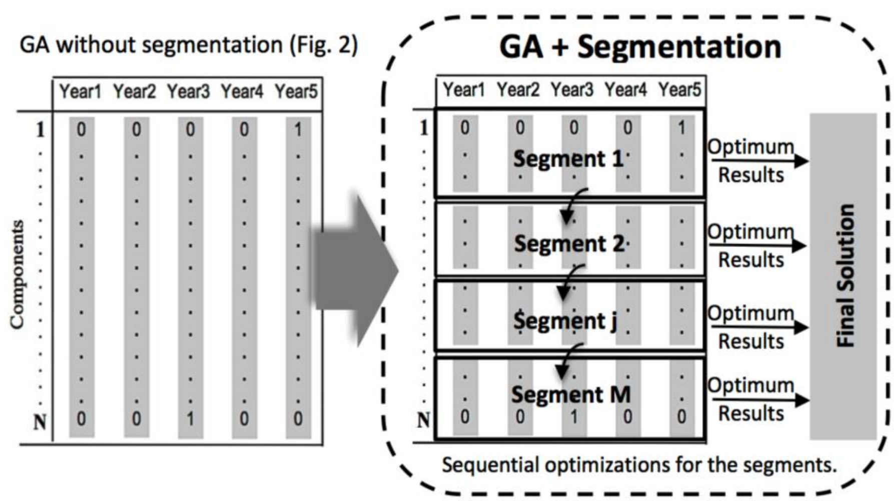


Figure 6-3: Network-level optimization using GA+Segmentation approach

Since GA (even with segmentation) is sensitive to problem size, experiments were made to determine the best segment size that offers best trade-off between solution quality and processing time. Accordingly, a segment size of 200 (selected at random) has been used in this study (Hegzay and Rashedi 2012). In the GA+Segmentation method, the budget is divided amongst segments based the relative criticality (RC) of each segment, which is calculated as a function of relative importance and deterioration behaviour of the components within each segment. Subsequently, the budget constraint in year k on the components within a segment is proportional to the segment's RC value divided by the sum of RCs for all segments. Testing the GA model on the three proposed formulations in Figure 1 for the TDSB case showed that GA+Segmentation is effective in handling large-scale problems, with significant improvement to solution quality. However, its processing time showed exponential increase on larger size problems. The case of 20,000 components, for example, took about 25 hours to finish. The full results of GA+Segmentation are compared with other approaches in section 6.5.

6.5 Optimization Using Mathematical Programming

In an effort to devise a better way to reach closer to global-optimum solutions and speed the processing time, this research implements the network-level formulation as an integer programming model using a powerful mathematical optimization tool called GAMS (General Algebraic Modelling System) and its CPLEX optimizer. GAMS requires an optimization problem to be modelled in its high-level programming/modelling language, and afterwards, different built-in solvers can be used on the model to execute the optimization (GAMS user guide 2010). For the large-scale asset renewal problem in hand, one of its powerful solvers, CPLEX, has been used as the optimization engine. The CPLEX optimizer is mostly applicable to difficult linear, quadratically constrained, and mixed integer programming problems, which fits the IP (integer programming) nature of the tactical rehabilitation planning problems. CPLEX uses enhanced branch-and-bound methods (Winston and Venkataramanan 2003) that solve an IP problem by generating LP (linear programming) sub-problems in which the integer constraints are relaxed into continuous constraints (i.e., LP relaxation). Using a branch-and-bound algorithm, the LP relaxations of an IP are branched on different decision variables and bounded by the LP results until the global optimum is found by comparing the results of these sub-problems based on the optimality criteria (Winston and Venkataramanan 2003). While applying branch-and-bound technique, CPLEX also uses a dynamic heuristic search to generate integer solutions faster.

Although GAMS, as an IP mathematical technique, is capable of reaching globally optimum solutions in simple cases, the huge amount of calculations in large-scale problems sometime make processing time prohibitively long with no convergence to a global optimum. To increase the efficiency of IP solvers, therefore, GAMS uses a 'relative termination tolerance'. By using a relative termination tolerance the solver is allowed to report an optimum solution within a specific range from the estimated best solution, thus finding a near-optimum solution much faster (Winston and Venkataramanan 2003). In this study, a tolerance factor of 0.1% is used.

By applying the MOST technique, which simplifies the network-level calculations, the LCCA models introduced in this study are mostly in accordance with characteristics of 'easy-to-solve' formulations (Wolsey 1989). Before developing the LCCA model in GAMS, however, the three aforementioned formulations were evaluated and the integer model in Figure 6-1a was found not suited to work with GAMS/CPLEX, as the range of variations in decision variables in this case is high as compared to binary formulations. Between the two binary formulations, on the other hand, the year-by-year binary formulation involves a loop relation from one year to another. Implementing the year-by-year loop thus overcomplicates the relationships, involves iterative calculations in each year, and requires adjustments of the tolerance factor in each year. The tolerance factor was reduced in later years in the planning horizon. As such, the process starts the optimization with a wider solution space, and as the solution gets closer to optimum value in later years, the smaller tolerance factor allows a deeper search for a global optimum. Amongst the three proposed formulations in Figure 1, the one-shot binary formulation (case b) is expected to be easier to optimize by GAMS/CPLEX. This formulation includes linear equations, avoids over-complexities, and formulates decision variables with minimum variations.

To test the performance of advanced mathematical tools, the tactical model has been coded in GAMS language and CPLEX was selected as the solver engine. The model also included creating different links to the input data stored in an Excel file to reduce the amount of unnecessary calculations by the IP solver and to increase efficiency. Using the VBA programming language of Excel, the GAMS input file has been generated from the original spreadsheet-based LCCA model used in the GA experiments. The input data are arranged and pre-set in this file and then linked to GAMS through the GAMS data exchange (GDX) files. After performing the optimization, the GAMS/CPLEX results are retrieved and sent back to the original model to show the final solution. Figure 6-4 shows the GAMS modelling environment and the full optimization code for the TDSB asset renewal problem using the one-shot binary formulation for 800 assets over a 5-year planning horizon.

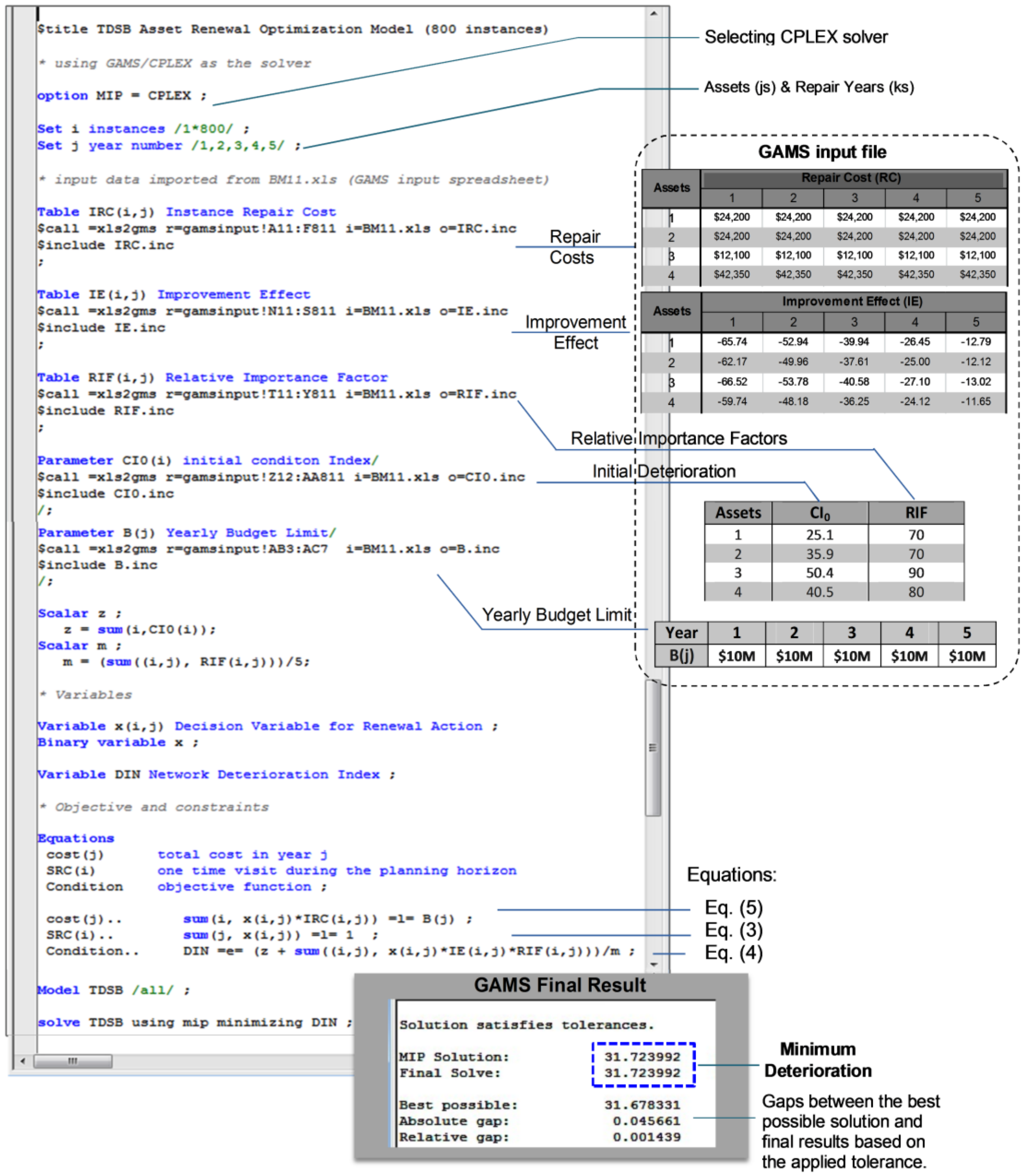


Figure 6-4: IP Programming Using GAMS/CPLEX

6.6 Results and Comparison

In order to clearly assess the improvements on the overall network deterioration index caused by applying GA-based and mathematical optimization, results are compared with those of simple ranking (SR). Using a simple ranking based on the initial conditions and relative importance of components, the overall deterioration index for the TDSB's school building network improved from 54.33 to 44.89.

This deterioration index (i.e., 48.89) is then used as a benchmark to evaluate the effectiveness of optimization approaches, as shown in Figure 6-5. Accordingly optimization results that offer no improvement over this result are not feasible and dominated by the simple ranking. Figure 6-6 shows optimization results using both GA-based and mathematical approaches for the three proposed formulations. Using GA without segmentation, the one-shot binary formulation was found to be the worst in terms of solution quality with no improvements over the SR results. This can be attributed to the large solution space associated with this formulation (see Figure 6-1). The integer formulation was able to improve the SR results by 4% on the base case and reached to a network deterioration index of 43.09. The year-by-year binary formulation, which has been used originally by the MOST, resulted in the best solution by around 25% improvement over the SR results for the 800 case. Its performance, however, declined dramatically as problem size increased. At 8,000 components, its solution was no longer feasible (see Figure 6-5).

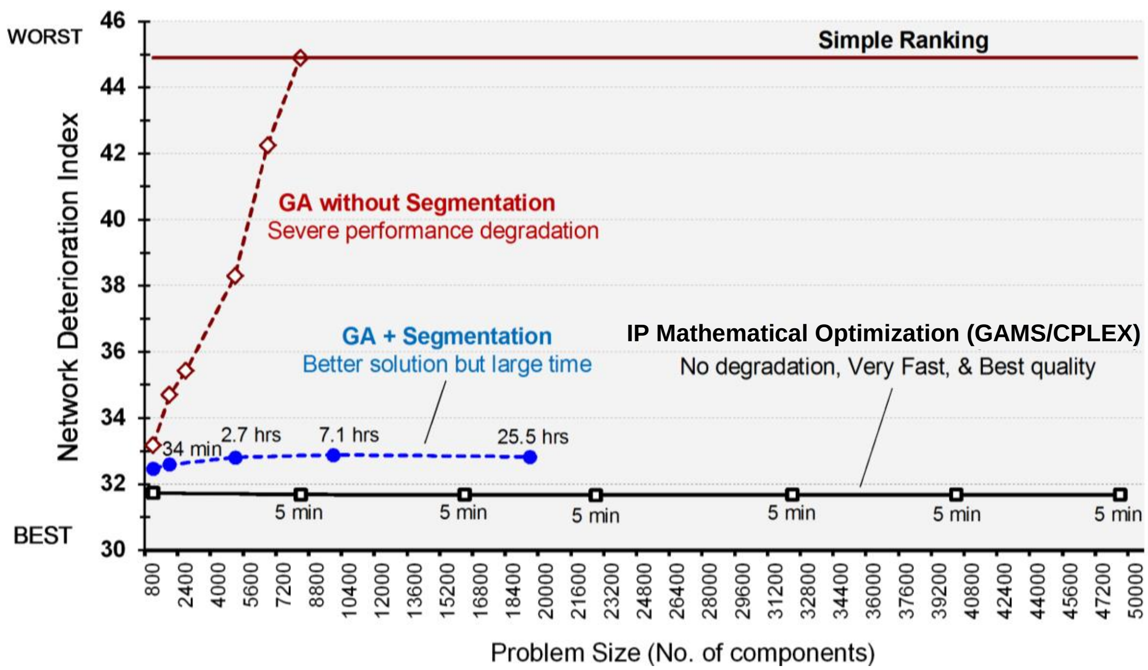


Figure 6-5: Optimization performance of different approaches

Using the GA+Segmentation approach, performance of GA without segmentation improved in all three formulations. As expected from previous experiments, the best result was obtained from the year-by-year formulation by 27% improvement over the SR result (DI_N = 32.09). Although GA+Segmentation improved the best result of GA without segmentation by only 2%, it is important to note that in such large-scale fund allocation problems, even 2% of improvement can cause substantial cost savings. In addition to improving the solution quality, GA+Segmentation resulted in consistent solution quality without performance degradation for any problem size, which is a major advantage (Figure 6-5). Using this approach, around 50,000 components were optimized with almost no decline in solution quality as compared to smaller cases. The processing time, however, showed exponential increase on larger size problems and increased from 9 minutes for the 800-component case to 1,517 minutes for the 18,400-component case, and more than 3 days for the 50,000-component case. It is noted that all experiments are performed using a laptop machine with 4 GB of memory and a 2.4 GHz processor.

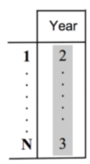
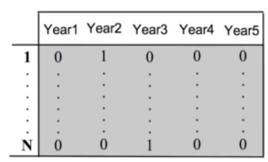
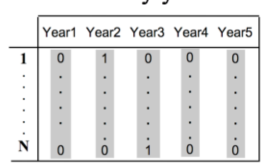
	Model Formulations					
	Integer		One-shot binary		Year-by-year	
						
800-component base case results.						
Optimization Approach	**DI_N**	**Processing Time**	**DI_N**	**Processing Time**	**DI_N**	**Processing Time**
Simple Ranking	44.89	10 min	44.89	10 min	44.89	10 min
GA	43.09	50 min	44.89	50 min	33.18	50 min
GA+Segmentation	38.60	40 min	42.19	40 min	**32.09**	**9 min**
GAMS/CPLEX	N/A		**31.72**	**5 min**	31.72	50 min
Large-scale performance (1,600 to 50,000 components)						
GA	Unsuitable for problems larger than 1,600 components.		Unsuitable for problems larger than 1,600 components.		Could optimize up to 8,000 components.	
GA+Segmentation	Exponential increase in processing time. Suitable for problems up to 5,000 components.		Exponential increase in processing time. Suitable for problems up to 5,000 components.		Exponential increase in processing time. Suitable for problems up to **20,000** components.	
GAMS/CPLEX	Difficult to formulate.		Suitable for very large-scale problems (e.g., **50,000** or more).		Longer processing time. Not the best approach for very large-scale problems	

Figure 6-6: Optimization results and comparison

Using the IP programming with GAMS/CPLEX, the one-shot binary formulation resulted in the most promising solution with 30% improvement over the SR results (DI_N = 31.72). The model could easily optimize a network of 50,000 components with a very fast processing time (few seconds for the 800 case and slightly less than 5 minutes in the 50,000 case). Processing speed, therefore, represents a major advantage of the GAMS/CPLEX model. The year-by-year formulation was also tested by the GAMS/CPLEX and resulted in the same result, however, was much slower than the one-shot binary formulation. As mentioned before, the integer formulation was not modelled by GAMS/CPLEX due to the format of its objective function. Comparing all methods as depicted in Figure 6-5, GAMS/CPLEX outperformed the other approaches in both solution quality and processing time, and proved to be very promising for handling very large-scale asset renewal problems. Among the three formulations, year-by-year proved to be the best formulation for GA applications, and coupled with the proposed segmentation mechanism proved to be very promising for large-scale problems. It is important to note that although the results of the mathematical approach are better than those of the GA+Segmentation, the latter is still useful, particularly for nonlinear and more complex problems that are difficult to handle by IP solvers.

6.7 Conclusions

This chapter investigated and compared the performance of GA-based and mathematical optimization approaches for handling the tactical-level rehabilitation planning. Three different optimization formulations for both GA-based and mathematical optimization were investigated. This study showed that the application of a segmentation method could supplement GAs and significantly improved the performance in large-size problems. However, while the solution quality was high and performance degradation was avoided, processing time shows exponential increase with the problem size. In an effort to optimize much larger models fast and to achieve better quality solutions, an integer programming model was develop that used the advanced GAMS/CPLEX optimization tool. The mathematical model was to be able to handle very large-size problems (50,000 assets) very fast and improved the quality of final solution by 30%. Although the mathematical model was very promising in this case study, the GA+Segmentation technique is still a valid mechanism for handling complex large-scale problems. Combination of the tactical models presented in this chapter and the policy analysis models presented in previous chapters, provide a comprehensive and systematic framework for a combined strategic-tactical analysis of rehabilitation plans for building facilities.

Chapter 7

Summary, Conclusions, Contributions, and Future Extensions

7.1 Thesis Summary and Conclusions

This research investigated rehabilitation planning for building facilities at both strategic and tactical levels of decision-making. The research addressed the strategic-level analysis by the application of system dynamics (SD) and identifying the dynamics among the key strategic decision variables. Accordingly, SD-based models were developed to simulate the deterioration, rehabilitation, and life cycle budgeting of school building facilities from a holistic view. The developed SD models were then utilized to simulate the long-term performance and backlog behaviors to analyze the impact of various budgeting policies. In addition to long-term policy effect analysis, the strategic models were used to identify the optimum budgeting and rehabilitation strategies that can minimize the overall backlog projections and also maximize the building performance in terms of overall facility condition index (FCI). The investigated budgeting policies included the allocation of capital budget to various asset categories based on their condition states (e.g., fair, poor, or critical conditions) and also the trade-off between the rehabilitation budge for existing facilities and the new construction budget. The strategic-level analysis investigated some of the commonly used rehabilitation policies, such as allocation of budget based on condition ratings from worst to best or the enrolment-based budgeting of school facilities. Results clearly indicated that some of these policies can lead to significant problems over the strategic horizon and provided optimum policy alternatives that can lead to significant cost-savings and performance improvement. At the tactical level, several model formulations were investigated for detailed rehabilitation planning in terms of repair timing and repair types for a large network of building asset components. The tactical model significantly improved the performance of the previous models that used Genetic Algorithm (GA) through the application of a divide-and-conquer process called ‘segmentation’, however, the processing time for large-size problems was still prohibitively long. A mathematical integer programing model was then developed with the application of GAMS/CPLEX optimization tool that could significantly improve the efficiency of the model and was able to optimize models with more than 50,000 asset components. In summary, this research showed the application of SD modeling and the important dynamic interactions among key variables at the strategic level in addition to effective optimization approaches at the tactical level of decision-making in order to develop detailed fund allocation plans. The SD-based technology and tools such as the presented policy simulation dashboard can be effectively used at the higher levels of asset management where long-term policies are made. Tactical-level models can be used by middle level asset managers and engineer to ensure effective implementation of strategic policies through optimized rehabilitation plans. Combination of the strategic and tactical models provide a comprehensive and systematic framework for a combined analysis of rehabilitation plans at both strategic and tactical levels of facility management. The methods and models proposed by this work can be used in the industry to ensure effective allocation of limited financial resources, to provide effective rehabilitation plans with significant cost savings, and ultimately to improve the operating condition of school buildings that directly impact students' quality of life.

This thesis was presented in seven chapters. Chapter 1 discussed the key objectives and motivations behind this research. Chapter 2 of this thesis discussed the literature and background studies related to the asset management dimensions covered in the proposed research, including asset management systems, strategic asset management and policy making, modeling of deterioration and rehabilitation processes of infrastructure assets, infrastructure backlog, applications of public-private-partnership, tactical asset management and rehabilitation planning, in addition to the limited literature efforts to combine these dimensions. This chapter also discussed system dynamics concepts and its potentials for handling strategic models with detailed illustration of causal loop diagramming, stock-and-flow modeling, and example applications of system dynamics in real world. Chapter 3 of this thesis investigated the dynamics that affect long-term deterioration and rehabilitation of infrastructure networks. First, the interactions among the main parameters related to asset deterioration, rehabilitation actions, and cost accumulation were analysed using causal loop diagrams (CLDs). Afterwards, a system dynamics (SD) model was developed based on the CLDs and the underlying mathematical relations among the various parameters. The SD model was then tested on a network of 1000 assets over a 50-year plan, considering a range of possible rehabilitation actions and fund allocation options. The model proved to be a practical and effective tool for quick assessment of the long-term impact of rehabilitation policies on infrastructure performance and costs. Chapter 4 of this thesis presented a system dynamics (SD) model to analyse the impact of different strategic policies (e.g. capital budgeting, or PPP involvement) on infrastructure condition, backlog accumulation, and sustainability performance. The proposed model was implemented on a network of school buildings from the Toronto District School Board asset inventory. Four sets of experiments were conducted over a 50-year strategic planning horizon to investigate backlog and condition performance with regard to policies related to rehabilitation, budget distribution, government investment, and PPP involvement. The proposed model was implemented on a commercial SD software incorporating all the dynamic interactions among the strategic parameters. The experiment results showed that the model works as a practical decision support tool that enables asset managers to analyse the effectiveness of various strategic policy scenarios on backlog and long-term infrastructure performance. Chapter 5 of this thesis introduced a novel decision support tool that can be used at the strategic level to identify the optimum budgeting policies for new construction versus rehabilitation. The proposed model used System Dynamics (SD) to analyse the long-term effects of various budgeting policies and is tested using a case study from the Toronto District school Board (TDSB) involving 438 elementary school buildings. A rigorous model testing and validation procedure was presented that demonstrated various tests such as structure assessment, dynamic input tests, and multi-variate Monte Carlo sensitivity analysis. The model was then used to perform policy optimization to find an optimum budget allocation strategy that minimizes the overall facility condition index (FCI), facility risk index (FRI), and total life cycle cost (TLCC), by identifying the optimum budget levels for new construction, rehabilitation, and maintenance over a 30-year strategic plan. The proposed model proved to be an effective tool that provides a deeper understanding of the impacts of various strategic policies and was capable of finding optimum policy solutions. Chapter 6 of this thesis aimed at improving both processing speed and solution quality in optimizing large-scale tactical rehabilitation plans developed with regard to the strategic analysis. This chapter discussed the development of optimization models for tactical rehabilitation planning, using both GA-based and mathematical optimization, and compared their results on three different model formulations. Both approaches proved to be beneficial, yet the mathematical model showed superior performance.

7.2 Research Contributions

This research has made a number of contributions in asset management domain. The details of the main contributions and research conclusions are discussed in the following subsections.

7.2.1 Holistic Analysis of Infrastructure Deterioration and Rehabilitation

An apparent gap was identified in the literature for asset management models that are capable of handling strategic level of analysis for large-scale asset networks and with limited information regarding individual assets. This research tackled the problem of strategic modeling and demonstrated the development of a holistic rehabilitation analysis model based on system dynamics (SD) simulation techniques. This research introduced a step-by-step model development procedure for identifying CLDs and the corresponding stock-and-flow models for deterioration, rehabilitation, and cost accumulation processes. The proposed model enables asset managers and civil engineers to analyse the nonlinear deterioration and rehabilitation processes with the creation of a comprehensive SD model.

7.2.2 Strategic Analysis of Backlog Accumulation and Elimination Policies

Infrastructure backlog has been a major and consistent problem in the area of infrastructure management. Almost in all infrastructure domains, reports show a huge accumulation of backlog due to inefficient and inadequate budgeting of rehabilitation programs over the life cycle of existing infrastructure (e.g., ASCE 2013). With the use of holistic SD modeling, this research developed a policy investigation model with four integrated modules for analysing the main interactions among physical condition, infrastructure backlog, sustainability, and policy-related parameters. The model proved to be a promising tool in analysing long-term backlog projections and the impact of various policies, such as involvement of private sector, to resolve backlog issues. The model is also a versatile tool that can be adopted to other domain of infrastructure management and be used by policy-makers to better understand the impact of various strategic policy scenarios.

7.2.3 Determining Optimum Budgeting Policies

The need for new construction is a widespread fund allocation issue due to population growth and the need to modernize facilities with the advance of new technologies. The financial deficits and the need for new facilities, coupled with the deteriorated state of the existing assets, necessitates novel approaches for determining optimum budgeting strategies that their impact infrastructure performance. This research presented and developed an SD-based model to analyze the impact of various budgeting policies for new construction versus rehabilitation and maintenance of deteriorated facilities. The SD model and its associated policy simulation dashboard proved to be an effective decision support tool that could determine optimum budgeting policies and fund allocations solutions for both new construction and rehabilitation of deteriorated facilities.

7.2.4 Optimum Tactical Rehabilitation Planning

At the tactical level, rehabilitation planning usually involves thousands of assets requiring decision about repair type and timing. The number of possible combinations of these decisions over a long-term plan is extremely large and is the main source of the combinatorial complexity associated with the tactical models. Finding optimum solutions for such problems is not an easy task, therefore, new breed of optimization methods and mechanisms should be used in order to solve tactical-level problems. This research showed that the application of a segmentation method could supplement GAs and significantly improved the performance in large-size problems. However, while the solution quality was high and performance degradation was avoided, processing time shows exponential increase with the problem size. In an effort to optimize much larger models fast and to achieve better quality solutions, mathematical optimization using integer programming and the GAMS/CPLEX optimization tool were used for large-scale modeling. The efficient modeling of a complex problem were discussed through an easy-to-solve mathematical model at the network-level and the mathematical model proved to be able to handle very large-size problems (50,000 assets) very fast while improving the quality of final solution.

7.3 Future Extensions

The SD models presented in this research are mainly focused on school building facilities and therefore the key variables in the model are associated with this type of assets. It is, however, possible to expand and use the modelling approach presented in this research for other types of assets such as roads or bridges. The process of deterioration and rehabilitation for these assets required modification of the model structure but can be done within the framework introduced in this research. In terms of deterioration and rehabilitation modeling, the proposed models use a sequential Markovian process that models deterioration from one state to the next lower sate only. In reality, sudden deteriorations can occur that pass through several states as the same time. The models, has the potential to capture these kind of deteriorating patters buy adding corresponding flows into the stock-and-flow simulation models. Also, the formulation of the model in chapter 3 involves only a 5-state deterioration pattern, which can be extended to include more states (10-state deterioration models are sometimes used in the domain of infrastructure management).

The SD model of chapter 4 is limited to similar assets from a particular sub-system. This can be resolved by introducing several deterioration models for different asset components with different relative importance. The sustainability module also considers a limited number of KPIs only to show the potential of the model to incorporate sustainability performance in the calculations. For a more accurate representation of sustainability, the number of environmental, economical, and social KPIs need to be expanded. In terms of PPP, the model only investigates PPP as a finance or private investment option. Other PPP options, such as finance-operate, are interesting approaches that can be added for further investigation of the impact of PPP.

Although the SD model presented in chapter 5 recommends the balance between new construction and rehabilitation actions, it does not identify the exact location of new constructions in terms of community or neighborhoods. The model also considers only an average cost of construction and do not take into account the level of technology and sustainability performance of the new buildings (e.g., LEED certified projects) that can increase the total cost but improves the overall performance. In terms of risk calculations, it can be improved by incorporating a comprehensive risk register and possible mitigation solutions.

This research tried to use variety of validation techniques, however, it was limited to the data available for this research and ultimately requires a direct comparison with actual data over a long period of time. Based on the above discussion, some of the potential future extensions of this research are as follows:

7.3.1 Full Integration between Strategic and Tactical Models

This research presented a model development framework for strategic analysis of rehabilitation policies, such as capital budgeting, in addition to optimization of tactical rehabilitation plans. As a future direction of research, it is possible to fully integrate the two levels of decision making within one comprehensive decision support tool. This integration can be done using dynamic link libraries (DLL) and other data exchange files. The full version of VENSIM® software is capable of being linked with other platforms for this reason. Using such integrated model, a detailed fun allocation plan can be produced in one-shot based on various strategic policies. Such an integrated model, can be more convenient for use by decision-makers and results in easier evaluation of alternatives. Also, policy optimization can be done using external optimization engines (e.g., EVOLVER, or CPLEX) within a more comprehensive frame work that considers the tactical implantation during the analysis. In general, investigating the performance of other optimization methods on the strategic model to find higher quality solutions can be an important contribution.

7.3.2 Expansion of the Deterioration and Rehabilitation Model

The deterioration and rehabilitation models presented in this research have some limitations as discussed in the previous section. As a future research, these models can be expanded to solve the current limitations. The formulation of the model can be expanded to 10-state condition formulations that are sometimes used in the domain of infrastructure management. Also, to include variety of asset component multiple deterioration sub-models for different asset components with different relative importance can be added to the proposed SD models. Flow processes that passes through several condition states can be also added to the model to incorporate sudden deterioration pattern with modification to the proposed Markovian process. The models can be also adapted for strategic analysis of other types of assets such as roads or bridges with required modification for deterioration analysis and treatment selections. Considering roads, for example, deterioration can be presented based on indices such as IRI (international roughness index) or PQI (pavement quality index). Segments of roads can be use to perform the analysis and to simulate the impact of various treatments.

7.3.3 Incorporating Social Parameters

Effect of social parameters such as user satisfaction or social costs of infrastructure projects is an important consideration in the decision making process. These types of soft data have been used in SD models for policy analysis (Sterman 2000). Factors such as user satisfaction can greatly influence the end results in policy-making process. Accordingly, the social implications of infrastructure rehabilitation and constructing new facilities can be an interesting addition to the models presented in this thesis. This expansion may help in identifying a proper location for building new schools, understating the effect of residential intensification, and understanding the social impacts of budgeting policies.

7.3.4 User-Friendly Policy Simulation Dashboard

Figure 5-10 showed an example of a policy simulation dashboard as a user interface that enables a policymaker to setup various policy scenarios and investigate their impact on key performance indicators. A fully integrated model with a user-friendly interface can be effectively used in the industry. This can significantly help a policy-maker to get a deeper understating of system's behaviours and the effectiveness of various policy scenarios and can be very useful in high-level meetings or negotiations by allowing individuals with little or no training in modelling to get meaningful access to the model.

7.3.5 Investigating Other Optimization Approaches

Other alternative optimization methods can be used to improve the performance of both strategic and tactical models, specifically, for larger-scale and longer-term solutions. Alternative evolutionary algorithms such as ant colony optimization, particle swarm optimization, or shuffled frog leaping can be tested on the tactical model.

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Appendix A

Feedback Loops (Chapter 4, Figure 4-3)

This Appendix shows a list of feedback loops affecting main key parameters of the CLD presented in Figure 4-3 for the SD model in Chapter 4.

Asset Condition Feedback Loops

```
  Loop Number 1 of length 1
    Asset Condition
          Asset Deterioration
  Loop Number 2 of length 2
    Asset Condition
          LOS
          Rehabilitation
  Loop Number 3 of length 8
    Asset Condition
          No. of Asset in Critical Condition
          Infrastructure Financial Backlog
          Willingness to use PPP
          Private Sector Investment
          Payments to Private Sectors
          Total Available Budget for Rehabilitation
          Budget Levels
          Rehabilitation
  Loop Number 4 of length 8
    Asset Condition
          No. of Asset in Critical Condition
          Infrastructure Financial Backlog
          Willingness to use PPP
          Private Sector Investment
          Total Available Budget
          Total Available Budget for Rehabilitation
          Budget Levels
          Rehabilitation
```

```
Loop Number 5 of length 9
  Asset Condition
       Energy Efficiency
       Environmental Impact
       Sustainable Performance
       Willingness to use PPP
       Private Sector Investment
       Payments to Private Sectors
       Total Available Budget for Rehabilitation
       Budget Levels
       Rehabilitation
Loop Number 6 of length 9
  Asset Condition
       Energy Efficiency
       Environmental Impact
       Sustainable Performance
       Willingness to use PPP
       Private Sector Investment
       Total Available Budget
       Total Available Budget for Rehabilitation
       Budget Levels
       Rehabilitation
Loop Number 7 of length 10
  Asset Condition
       No. of Assets in Good Condition
       Energy Efficiency
       Environmental Impact
       Sustainable Performance
       Willingness to use PPP
       Private Sector Investment
       Payments to Private Sectors
       Total Available Budget for Rehabilitation
       Budget Levels
       Rehabilitation
Loop Number 8 of length 10
```

Asset Condition
No. of Assets in Good Condition
Energy Efficiency
Environmental Impact
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Total Available Budget
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation

Loop Number 9 of length 11
Asset Condition
LOS
Overall Serviceability Score
User Satisfaction
Social Impact
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Total Available Budget
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation

Loop Number 10 of length 11
Asset Condition
LOS
Overall Serviceability Score
User Satisfaction
Social Impact
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Payments to Private Sectors
Total Available Budget for Rehabilitation

Budget Levels
Rehabilitation
Loop Number 11 of length 11
Asset Condition
No. of Asset in Critical Condition
Infrastructure Financial Backlog
Financial Performance
Economical Impact
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Total Available Budget
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation
Loop Number 12 of length 11
Asset Condition
No. of Asset in Critical Condition
Infrastructure Financial Backlog
Financial Performance
Economical Impact
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Payments to Private Sectors
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation

Sustainable Performance Feedback Loops

Loop Number 1 of length 4
Sustainable Performance
Willingness to use PPP
Private Sector Investment
User Cost

```
       Social Impact
Loop Number 2 of length 5
  Sustainable Performance
       Pressure to Apply Sustainable Policies
       Rate of Energy Reducing Renovations
       No. of Assets in Good Condition
       Energy Efficiency
       Environmental Impact
Loop Number 3 of length 6
  Sustainable Performance
       Pressure to Apply Sustainable Policies
       Rate of Energy Reducing Renovations
       Rehabilitation Cost
       Total LCC
       Financial Performance
       Economical Impact
Loop Number 4 of length 6
  Sustainable Performance
       Willingness to use PPP
       Private Sector Investment
       Payments to Private Sectors
       Total LCC
       Financial Performance
       Economical Impact
Loop Number 5 of length 7
  Sustainable Performance
       Willingness to use PPP
       Private Sector Investment
       Payments to Private Sectors
       Total Available Budget for Rehabilitation
       Infrastructure Financial Backlog
       Financial Performance
       Economical Impact
Loop Number 6 of length 7
  Sustainable Performance
```

```
      Willingness to use PPP
      Private Sector Investment
      Total Available Budget
      Total Available Budget for Rehabilitation
      Infrastructure Financial Backlog
      Financial Performance
      Economical Impact
Loop Number 7 of length 9
  Sustainable Performance
      Willingness to use PPP
      Private Sector Investment
      Total Available Budget
      Total Available Budget for Rehabilitation
      Budget Levels
      Rehabilitation
      Asset Condition
      Energy Efficiency
      Environmental Impact
Loop Number 8 of length 9
  Sustainable Performance
      Willingness to use PPP
      Private Sector Investment
      Payments to Private Sectors
      Total Available Budget for Rehabilitation
      Budget Levels
      Rehabilitation
      Asset Condition
      Energy Efficiency
      Environmental Impact
Loop Number 9 of length 10
  Sustainable Performance
      Willingness to use PPP
      Private Sector Investment
      Total Available Budget
      Total Available Budget for Rehabilitation
```

Budget Levels
Rehabilitation
Rehabilitation Cost
Total LCC
Financial Performance
Economical Impact
Loop Number 10 of length 10
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Payments to Private Sectors
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation
Rehabilitation Cost
Total LCC
Financial Performance
Economical Impact
Loop Number 11 of length 10
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Payments to Private Sectors
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation
Asset Condition
No. of Assets in Good Condition
Energy Efficiency
Environmental Impact
Loop Number 12 of length 10
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Total Available Budget

Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation
Asset Condition
No. of Assets in Good Condition
Energy Efficiency
Environmental Impact

Loop Number 13 of length 11
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Total Available Budget
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation
Asset Condition
No. of Asset in Critical Condition
Infrastructure Financial Backlog
Financial Performance
Economical Impact

Loop Number 14 of length 11
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Total Available Budget
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation
Asset Condition
LOS
Overall Serviceability Score
User Satisfaction
Social Impact

Loop Number 15 of length 11
Sustainable Performance

Willingness to use PPP
Private Sector Investment
Payments to Private Sectors
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation
Asset Condition
LOS
Overall Serviceability Score
User Satisfaction
Social Impact

Loop Number 16 of length 11

Sustainable Performance
Willingness to use PPP
Private Sector Investment
Payments to Private Sectors
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation
Asset Condition
No. of Asset in Critical Condition
Infrastructure Financial Backlog
Financial Performance
Economical Impact

Life Cycle Cost Feedback Loops

Loop Number 1 of length 6

Total LCC
Financial Performance
Economical Impact
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Payments to Private Sectors

Loop Number 2 of length 6

Total LCC
Financial Performance
Economical Impact
Sustainable Performance
Pressure to Apply Sustainable Policies
Rate of Energy Reducing Renovations
Rehabilitation Cost
Loop Number 3 of length 10
Total LCC
Financial Performance
Economical Impact
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Total Available Budget
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation
Rehabilitation Cost
Loop Number 4 of length 10
Total LCC
Financial Performance
Economical Impact
Sustainable Performance
Willingness to use PPP
Private Sector Investment
Payments to Private Sectors
Total Available Budget for Rehabilitation
Budget Levels
Rehabilitation
Rehabilitation Cost

Appendix B

Feedback Loops (Chapter 5, Figure 5-3)

This Appendix shows a list of feedback loops affecting main key parameters of the CLD presented in Figure 5-3 for the SD model in Chapter 5.

New Construction Feedback Loops

```
  Loop Number 1 of length 5
    New Construction
         Total School GFA
         Maintenance Needs
         Maintenance Budget
         Renewal Budget
         New Construction Budget
  Loop Number 2 of length 6
    New Construction
         FCI
         Risk
         Pressure to Increase Rehab. Budget
         %Rehab. Budget
         %New Construction Budget
         New Construction Budget
  Loop Number 3 of length 6
    New Construction
         Total No. of Schools
         School Capacity
         Over-Capacity
         Pressure to Build New Schools
         %New Construction Budget
         New Construction Budget
  Loop Number 4 of length 6
    New Construction
         Facility Age
         Risk
```

```
       Pressure to Increase Rehab. Budget
       %Rehab. Budget
       %New Construction Budget
       New Construction Budget
Loop Number 5 of length 7
  New Construction
       FCI
       PTR
       % Sell PTR
       Income from Sold Property
       Capital Budget
       Renewal Budget
       New Construction Budget
Loop Number 6 of length 8
  New Construction
       Total No. of Schools
       School Capacity
       Over-Capacity
       Risk
       Pressure to Increase Rehab. Budget
       %Rehab. Budget
       %New Construction Budget
       New Construction Budget
Loop Number 7 of length 9
  New Construction
       Facility Age
       Rehab. Needs
       Rehab. Backlog
       FCI
       Risk
       Pressure to Increase Rehab. Budget
       %Rehab. Budget
       %New Construction Budget
       New Construction Budget
Loop Number 8 of length 9
```

```
  New Construction
       FCI
       PTR
       % Sell PTR
       Total No. of Schools
       School Capacity
       Over-Capacity
       Pressure to Build New Schools
       %New Construction Budget
       New Construction Budget
Loop Number 9 of length 9
  New Construction
       Total School GFA
       Rehab. Needs
       Rehab. Backlog
       FCI
       Risk
       Pressure to Increase Rehab. Budget
       %Rehab. Budget
       %New Construction Budget
       New Construction Budget
Loop Number 10 of length 10
  New Construction
       Facility Age
       Rehab. Needs
       Rehab. Backlog
       FCI
       PTR
       % Sell PTR
       Income from Sold Property
       Capital Budget
       Renewal Budget
       New Construction Budget
Loop Number 11 of length 10
  New Construction
```

Total School GFA
Rehab. Needs
Rehab. Backlog
FCI
PTR
% Sell PTR
Income from Sold Property
Capital Budget
Renewal Budget
New Construction Budget

Loop Number 12 of length 11

New Construction

FCI
PTR
% Sell PTR
Total No. of Schools
School Capacity
Over-Capacity
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
%New Construction Budget
New Construction Budget

Loop Number 13 of length 12

New Construction

Total School GFA
Rehab. Needs
Rehab. Backlog
FCI
PTR
% Sell PTR
Total No. of Schools
School Capacity
Over-Capacity
Pressure to Build New Schools

%New Construction Budget

New Construction Budget

Loop Number 14 of length 12

New Construction

Facility Age

Rehab. Needs

Rehab. Backlog

FCI

PTR

% Sell PTR

Total No. of Schools

School Capacity

Over-Capacity

Pressure to Build New Schools

%New Construction Budget

New Construction Budget

Loop Number 15 of length 13

New Construction

Total School GFA

Maintenance Needs

Maintenance Budget

Renewal Budget

Rehab. Budget

Rehab. Actions

Rehab. Backlog

FCI

Risk

Pressure to Increase Rehab. Budget

%Rehab. Budget

%New Construction Budget

New Construction Budget

Loop Number 16 of length 13

New Construction

Total School GFA

Maintenance Needs

Maintenance Budget
Routine Maintenance
Deterioration Rate
Rehab. Needs
Rehab. Backlog
FCI
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
%New Construction Budget
New Construction Budget

Loop Number 17 of length 14
New Construction
Facility Age
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
Rehab. Budget
Rehab. Actions
Rehab. Backlog
FCI
PTR
% Sell PTR
Income from Sold Property
Capital Budget
Renewal Budget
New Construction Budget

Loop Number 18 of length 14
New Construction
Total School GFA
Maintenance Needs
Maintenance Budget
Routine Maintenance
Deterioration Rate
Rehab. Needs

```
        Rehab. Backlog
        FCI
        PTR
        % Sell PTR
        Income from Sold Property
        Capital Budget
        Renewal Budget
        New Construction Budget
Loop Number 19 of length 14
  New Construction
        Facility Age
        Rehab. Needs
        Rehab. Backlog
        FCI
        PTR
        % Sell PTR
        Total No. of Schools
        School Capacity
        Over-Capacity
        Risk
        Pressure to Increase Rehab. Budget
        %Rehab. Budget
        %New Construction Budget
        New Construction Budget
Loop Number 20 of length 14
  New Construction
        Total School GFA
        Rehab. Needs
        Rehab. Backlog
        FCI
        PTR
        % Sell PTR
        Total No. of Schools
        School Capacity
        Over-Capacity
```

Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
%New Construction Budget
New Construction Budget

Loop Number 21 of length 16

New Construction
Total School GFA
Maintenance Needs
Maintenance Budget
Routine Maintenance
Deterioration Rate
Rehab. Needs
Rehab. Backlog
FCI
PTR
% Sell PTR
Total No. of Schools
School Capacity
Over-Capacity
Pressure to Build New Schools
%New Construction Budget
New Construction Budget

Loop Number 22 of length 16

New Construction
Total No. of Schools
School Capacity
Over-Capacity
Pressure to Build New Schools
%New Construction Budget
%Rehab. Budget
Rehab. Budget
Rehab. Actions
Rehab. Backlog
FCI

PTR
% Sell PTR
Income from Sold Property
Capital Budget
Renewal Budget
New Construction Budget
Loop Number 23 of length 16
New Construction
Total No. of Schools
School Capacity
Over-Capacity
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
Rehab. Budget
Rehab. Actions
Rehab. Backlog
FCI
PTR
% Sell PTR
Income from Sold Property
Capital Budget
Renewal Budget
New Construction Budget
Loop Number 24 of length 16
New Construction
Total School GFA
Maintenance Needs
Maintenance Budget
Renewal Budget
Rehab. Budget
Rehab. Actions
Rehab. Backlog
FCI
PTR

% Sell PTR
Total No. of Schools
School Capacity
Over-Capacity
Pressure to Build New Schools
%New Construction Budget
New Construction Budget

Loop Number 25 of length 16

New Construction
Facility Age
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
Rehab. Budget
Rehab. Actions
Rehab. Backlog
FCI
PTR
% Sell PTR
Total No. of Schools
School Capacity
Over-Capacity
Pressure to Build New Schools
%New Construction Budget
New Construction Budget

Loop Number 26 of length 18

New Construction
Total School GFA
Maintenance Needs
Maintenance Budget
Routine Maintenance
Deterioration Rate
Rehab. Needs
Rehab. Backlog
FCI

PTR

% Sell PTR

Total No. of Schools

School Capacity

Over-Capacity

Risk

Pressure to Increase Rehab. Budget

%Rehab. Budget

%New Construction Budget

New Construction Budget

Loop Number 27 of length 18

New Construction

Total School GFA

Maintenance Needs

Maintenance Budget

Renewal Budget

Rehab. Budget

Rehab. Actions

Rehab. Backlog

FCI

PTR

% Sell PTR

Total No. of Schools

School Capacity

Over-Capacity

Risk

Pressure to Increase Rehab. Budget

%Rehab. Budget

%New Construction Budget

New Construction Budget

Rehab. Actions Feedback Loops

Loop Number 1 of length 6

Rehab. Actions

Rehab. Backlog
FCI
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
Rehab. Budget
Loop Number 2 of length 8
Rehab. Actions
Rehab. Backlog
FCI
PTR
% Sell PTR
Income from Sold Property
Capital Budget
Renewal Budget
Rehab. Budget
Loop Number 3 of length 11
Rehab. Actions
Rehab. Backlog
FCI
PTR
% Sell PTR
Total No. of Schools
School Capacity
Over-Capacity
Pressure to Build New Schools
%New Construction Budget
%Rehab. Budget
Rehab. Budget
Loop Number 4 of length 11
Rehab. Actions
Rehab. Backlog
FCI
PTR
% Sell PTR

Total No. of Schools
School Capacity
Over-Capacity
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
Rehab. Budget

Loop Number 5 of length 13

Rehab. Actions
Rehab. Backlog
FCI
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
%New Construction Budget
New Construction Budget
New Construction
Total School GFA
Maintenance Needs
Maintenance Budget
Renewal Budget
Rehab. Budget

Loop Number 6 of length 14

Rehab. Actions
Rehab. Backlog
FCI
PTR
% Sell PTR
Income from Sold Property
Capital Budget
Renewal Budget
New Construction Budget
New Construction
Facility Age
Risk

Pressure to Increase Rehab. Budget
%Rehab. Budget
Rehab. Budget
Loop Number 7 of length 16
Rehab. Actions
Rehab. Backlog
FCI
PTR
% Sell PTR
Total No. of Schools
School Capacity
Over-Capacity
Pressure to Build New Schools
%New Construction Budget
New Construction Budget
New Construction
Total School GFA
Maintenance Needs
Maintenance Budget
Renewal Budget
Rehab. Budget
Loop Number 8 of length 16
Rehab. Actions
Rehab. Backlog
FCI
PTR
% Sell PTR
Income from Sold Property
Capital Budget
Renewal Budget
New Construction Budget
New Construction
Total No. of Schools
School Capacity
Over-Capacity

```
        Risk
        Pressure to Increase Rehab. Budget
        %Rehab. Budget
        Rehab. Budget
Loop Number 9 of length 16
  Rehab. Actions
        Rehab. Backlog
        FCI
        PTR
        % Sell PTR
        Total No. of Schools
        School Capacity
        Over-Capacity
        Pressure to Build New Schools
        %New Construction Budget
        New Construction Budget
        New Construction
        Facility Age
        Risk
        Pressure to Increase Rehab. Budget
        %Rehab. Budget
        Rehab. Budget
Loop Number 10 of length 16
  Rehab. Actions
        Rehab. Backlog
        FCI
        PTR
        % Sell PTR
        Income from Sold Property
        Capital Budget
        Renewal Budget
        New Construction Budget
        New Construction
        Total No. of Schools
        School Capacity
```

Over-Capacity
Pressure to Build New Schools
%New Construction Budget
%Rehab. Budget
Rehab. Budget
Loop Number 11 of length 18
Rehab. Actions
Rehab. Backlog
FCI
PTR
% Sell PTR
Total No. of Schools
School Capacity
Over-Capacity
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
%New Construction Budget
New Construction Budget
New Construction
Total School GFA
Maintenance Needs
Maintenance Budget
Renewal Budget
Rehab. Budget

Routine Maintenance Feedback Loops

Loop Number 1 of length 2
Routine Maintenance
Maintenance Needs
Maintenance Budget
Loop Number 2 of length 13
Routine Maintenance
Deterioration Rate
Rehab. Needs

Rehab. Backlog
FCI
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
%New Construction Budget
New Construction Budget
New Construction
Total School GFA
Maintenance Needs
Maintenance Budget

Loop Number 3 of length 14
Routine Maintenance
Deterioration Rate
Rehab. Needs
Rehab. Backlog
FCI
PTR
% Sell PTR
Income from Sold Property
Capital Budget
Renewal Budget
New Construction Budget
New Construction
Total School GFA
Maintenance Needs
Maintenance Budget

Loop Number 4 of length 16
Routine Maintenance
Deterioration Rate
Rehab. Needs
Rehab. Backlog
FCI
PTR
% Sell PTR

Total No. of Schools
School Capacity
Over-Capacity
Pressure to Build New Schools
%New Construction Budget
New Construction Budget
New Construction
Total School GFA
Maintenance Needs
Maintenance Budget

Loop Number 5 of length 18

Routine Maintenance
Deterioration Rate
Rehab. Needs
Rehab. Backlog
FCI
PTR
% Sell PTR
Total No. of Schools
School Capacity
Over-Capacity
Risk
Pressure to Increase Rehab. Budget
%Rehab. Budget
%New Construction Budget
New Construction Budget
New Construction
Total School GFA
Maintenance Needs
Maintenance Budget

Appendix C

SD Model (Chapter 4, Figure 4-5)

This Appendix shows the SD model developed for backlog analysis in chapter 4 of this thesis. The stock and flow model is presented in Figure 4-5.

```
"% of Budget for Asset Class B" = 0.333

"% of Budget for Asset Class C" = 0.333

"% of Budget for Asset Class D" = 0.333

"%FD" = 0.25

"%MJC" = 0.5

"%MJD" = 0.25

"%MNB" = 1

"%MNC" = 0.5

"%MND" = 0.5

"A (100-80)" = INTEG( "FullRpr-D" + "MinRpr-B" + "MjrRpr-C" - D1 , 31)

Allocated Budget to B = "% of Budget for Asset Class B" * Total Available
Budget for Rehabilitation


Allocated Budget to C = "% of Budget for Asset Class C" * Total Available
Budget for Rehabilitation


Allocated Budget to D = ( "% of Budget for Asset Class D" * Total
Available Budget for Rehabilitation
           ) + Residual Budget from B + Residual Budeget from C

Annual Payment = IF THEN ELSE ( Time > Investment End Time , IF THEN ELSE
(
                Time <= ( Investment End Time + "No. of Annual Payments" )
                , Payment , 0) , 0)

Annual Payment 1 = ( Total Private Invesment * Investment Rate of Return )
           / ( 1 - ( 1 / ( ( 1 + Investment Rate of Return ) ^ ( "No. of
Annual Payments"
```

```
                    + ( Investent Duration / 2) ) ) ) )

Asset Condition RC :THE CONDITION: 1 :IMPLIES: Oversll Asset Condition
Index
           >= 0 :AND: Oversll Asset Condition Index <= 100

"Average RC-C" = "RC-Minor" * "%MNC" + "RC-Major" * "%MJC"

"Average RC-D" = "%FD" * "RC-Full" + "%MJD" * "RC-Major" + "%MND" * "RC-
Minor"


"B (60-80)" = INTEG( D1 + "MinRpr-C" + "MjrRpr-D" - D2 - "MinRpr-B" , 213)

Backlog = Infrastructure Deficit

Backlog Integral = INTEG( Backlog , 0)

"C (50-60)" = INTEG( D2 + "MinRpr-D" - D3 - "MinRpr-C" - "MjrRpr-C" , 143)

Capacity Usage = ( User Population / 100) / "Total No. of Assets"

"D (<50)" = INTEG( D3 - "FullRpr-D" - "MinRpr-D" - "MjrRpr-D" , 154)

D1 = "A (100-80)" * TMP1

D2 = "B (60-80)" * TMP2

D3 = "C (50-60)" * TPM3

Econimical Impact = ( ( 0.7 * Financial Performance Backlog + 0.3 *
Financial Performance LCC
                ) / 50) * Wecn

Energy Efficiency = Oversll Asset Condition Index * ( "A (100-80)" /
"Total No. of Assets"
                )

Environmental Impact = ( Energy Efficiency / 50) * Wenv

Financial Performance Backlog = 100 - ( ( Backlog Integral / 3.43e+009) *
100
           )

Financial Performance LCC = 100 - ( ( TLCC / 5e+008) * 100)

"FullRpr-D" = IF THEN ELSE ( "D (<50)" > "TN-D" , "TN-D" * "%FD" , "D
(<50)"
           * "%FD" )

Government Investment = 4e+006

GovInv = Government Investment
```

```
Infrastructure Deficit = ( "D (<50)" - ( ( Total Available Budget for
Rehabilitation
           ) / "Average RC-D" ) ) * "Average RC-D"

Investent Duration = Investment End Time - Investment Start Time

Investment End Time = Investment Start Time + Priv Inv Duration

Investment Rate of Return = 0.05

Investment Start Time = 0

leftover = Residual Budget from D

"MinRpr-B" = IF THEN ELSE ( "B (60-80)" > "TN-B" , "TN-B" * "%MNB" , "B
(60-80)"
           * "%MNB" )

"MinRpr-C" = IF THEN ELSE ( "C (50-60)" > "TN-C" , "TN-C" * "%MNC" , "C
(50-60)"
           * "%MNC" )

"MinRpr-D" = IF THEN ELSE ( "D (<50)" > "TN-D" , "TN-D" * "%MND" , "D
(<50)"
           * "%MND" )

"MjrRpr-C" = IF THEN ELSE ( "C (50-60)" > "TN-C" , "TN-C" * "%MJC" , "C
(50-60)"
           * "%MJC" )

"MjrRpr-D" = IF THEN ELSE ( "D (<50)" > "TN-D" , "TN-D" * "%MJD" , "D
(<50)"
           * "%MJD" )

"No. of Annual Payments" = 30

Overall Servicability Index = MIN ( ( Oversll Asset Condition Index /
0.861
           ) - 0.52, 100)

Oversll Asset Condition Index = ( ( "A (100-80)" * 87) + ( "B (60-80)" *
68
           ) + ( "C (50-60)" * 55) + ( "D (<50)" * 43) ) / 541

Payment = Annual Payment 1 * ( ( "No. of Annual Payments" + ( Investent
Duration
                / 2) ) / "No. of Annual Payments" )

Payments = Annual Payment

Priv Inv Duration = 10
```

```
Private Sector Annual Investment Level = 0

Private Sector Invstment = IF THEN ELSE ( Time >= Investment Start Time ,
IF THEN ELSE (
                Time <= Investment End Time , Private Sector Annual
Investment Level
                , 0) , 0)

"RC-Full" = 230000

"RC-Major" = "RC-Full" * 0.6

"RC-Minor" = "RC-Full" * 0.25

Residual Budeget from C = MAX ( 0, Allocated Budget to C - ( "Average RC-
C"
                * "C (50-60)" ) )

Residual Budget from B = MAX ( 0, Allocated Budget to B - ( "B (60-80)" *
"RC-Minor"
                     * "%MNB" ) )

Residual Budget from D = MAX ( 0, Allocated Budget to D - ( "D (<50)" *
"Average RC-D"
                     ) )

Social Impact = ( Overall Servicability Index / 50) * Wsc

Sustainablt Performance = INTEG( Econimical Impact + Environmental Impact
+
                Social Impact , 0)

TestInput Govinv Ramp :TEST INPUT: Government Investment = RC RAMP (
Government Investment
                , 0, 5, 20)

TLCC = INTEG( Payments + TRC , 0)

TMP1 = 0.1

TMP2 = 0.2

"TN-B" = IF THEN ELSE ( "%MNB" = 0, 0, ( Allocated Budget to B ) / (
"%MNB"
                * "RC-Minor" ) )

"TN-C" = IF THEN ELSE ( "%MJC" + "%MNC" = 0, 0, ( Allocated Budget to C )
/
                ( "%MNC" * "RC-Minor" + "%MJC" * "RC-Major" ) )

"TN-D" = ( Allocated Budget to D ) / ( "%MND" * "RC-Minor" + "%MJD" * "RC-
Major"
                     + "%FD" * "RC-Full" )
```

```
Total Asset RC :THE CONDITION: 1 :IMPLIES: "Total No. of Assets" = 541

Total Available Budget = Government Investment + Private Sector Invstment

Total Available Budget for Rehabilitation = Total Available Budget -
Annual Payment

Total Government Invest ment = INTEG( GovInv , 0)

Total leftover = INTEG( leftover , 0)

"Total No. of Assets" = "A (100-80)" + "B (60-80)" + "C (50-60)" + "D
(<50)"

Total Private Invesment = Private Sector Annual Investment Level *
Investent Duration

Total Private Sector Benefit = ( Payment * "No. of Annual Payments" ) -
Total Private Invesment

TPM3 = 0.3

TRC = Total Available Budget for Rehabilitation - leftover

user growth = user growth rate * User Population

user growth rate = 0.08

User Population = INTEG( user growth , 35000)

Wecn = 0.4

Wenv = 0.3

Wsc = 0.3
```

Appendix D
SD Model (Chapter 5, Figure 5-4)

This Appendix shows the SD model developed for analysis of rehabilitation and new construction budget as discussed in chapter 5 of this thesis. The stock and flow model is presented in Figure 5-4.

```
"$M" = Maintenance Budget

"$NC" = PNC * Construction Cost per School

"$R" = Rehab Level 1 * "$RL1" + Rehab Level 2 * "$RL2"

"$RL1" = ( 0.2 - 0.075) * Facility Replacement Cost

"$RL2" = ( 0.4 - 0.075) * Facility Replacement Cost

"%New" = IF THEN ELSE ( Time >= 0 :AND: Time < 5, "%New1" , IF THEN ELSE (
                Time >= 5 :AND: Time < 10, "%New2" , IF THEN ELSE ( Time
>=
                          10 :AND: Time < 15, "%New3" , IF THEN ELSE (
Time
                          >= 15 :AND: Time < 20, "%New4" , IF THEN ELSE (
Time
                               >= 20 :AND: Time < 25, "%New5" , "%New6" )
)
                     ) ) )

"%New1" = 0.2 [0,1]

"%New2" = 0.2 [0,1]

"%New3" = 0.2 [0,1]

"%New4" = 0.2 [0,1]

"%New5" = 0.2 [0,1]

"%New6" = 0.2 [0,1]

"%Rehab" = 1 - "%New"

"%RL1" = IF THEN ELSE ( No Rehab = 1, 0, IF THEN ELSE ( Time >= 0 :AND:
Time
                     < 5, "%RL1-1" , IF THEN ELSE ( Time >= 5 :AND: Time <
                               10, "%RL1-2" , IF THEN ELSE ( Time >= 10
:AND:
```

```
                               Time < 15, "%RL1-3" , IF THEN ELSE ( Time
>=
                                    15 :AND: Time < 20, "%RL1-4" , IF THEN
ELSE (
                                    Time >= 20 :AND: Time < 25, "%RL1-5" ,
                                    "%RL1-6" ) ) ) ) ) )

"%RL1-1" = 0.5 [0,1]

"%RL1-2" = 0.5 [0,1]

"%RL1-3" = 0.5 [0,1]

"%RL1-4" = 0.5 [0,1]

"%RL1-5" = 0.5 [0,1]

"%RL1-6" = 0.5 [0,1]

"%RL2" = IF THEN ELSE ( No Rehab = 0, 1 - "%RL1" , 0)

"%Sell" = IF THEN ELSE ( Time >= 0 :AND: Time < 5, "%Sell1" , IF THEN ELSE
(
                Time >= 5 :AND: Time < 10, "%Sell2" , IF THEN ELSE ( Time
>=
                          10 :AND: Time < 15, "%Sell3" , IF THEN ELSE (
Time
                          >= 15 :AND: Time < 20, "%Sell4" , IF THEN ELSE (
                               Time >= 20 :AND: Time < 25, "%Sell5" ,
"%Sell6"
                               ) ) ) ) )

"%Sell1" = 0 [0,1]

"%Sell2" = 0 [0,1]

"%Sell3" = 0 [0,1]

"%Sell4" = 0 [0,1]

"%Sell5" = 0 [0,1]

"%Sell6" = 0 [0,1]

"0 < FCI < 5 Good" = INTEG( New Construction - D12 , 31)

"10 < FCI < 30 Poor" = INTEG( D23 - D34 - Rehab Level 1 , 258)

"30 < FCI < 65 Critical" = INTEG( D34 - D45 - Rehab Level 2 , 105)

"5 < FCI < 10 Fair" = INTEG( D12 + Rehab Level 1 + Rehab Level 2 - D23 ,
35
           )
```

```
"65 < FCI PTR" = INTEG( D45 - Sell Property , 9)

A1 = INTEG( I1 , 0)

A2 = INTEG( I2 , 0)

"Avg. Capacity per School" = 435

Backlog = Overall FCI * Facility Replacement Cost

Budget per Student = 516

"Capacity Check (0-delay)" = IF THEN ELSE ( "Avg. Capacity per School" *
"No. of Schls (0-delay)"
                > Enrolment , 0, 1)

CAPBUD = IF THEN ELSE ( Time >= 0 :AND: Time < 5, CB1 , IF THEN ELSE (
Time
                >= 5 :AND: Time < 10, CB2 , IF THEN ELSE ( Time >= 10
:AND:
                          Time < 15, CB3 , IF THEN ELSE ( Time >= 15 :AND:
                               Time < 20, CB4 , IF THEN ELSE ( Time >= 20
:AND:
                                    Time < 25, CB5 , CB6 ) ) ) ) )
[0,?,1e+006
      ]

"CAPBUD ALOC (Enrl, Var)" = 1 [0,1,1]

CAPEX = "$M" + "$R" + "$NC"

Capital Budget = IF THEN ELSE ( "CAPBUD ALOC (Enrl, Var)" = 0, Budget per
Student
           * Enrolment , CAPBUD ) + ReInv + Sold Property Income

CB1 = 8e+007

CB2 = 8e+007

CB3 = 8e+007

CB4 = 8e+007

CB5 = 8e+007

CB6 = 8e+007

Construction Cost per School = 1.5e+007

D12 = "0 < FCI < 5 Good" * DR12

D23 = "5 < FCI < 10 Fair" * DR23
```

```
D34 = "10 < FCI < 30 Poor" * DR34

D45 = "30 < FCI < 65 Critical" * DR45

DIT = 0

DR12 = TP12 * ( 1 / Maintenance Factor )

DR23 = TP23 * ( 1 / Maintenance Factor )

DR34 = TP34 * ( 1 / Maintenance Factor )

DR45 = TP45 * ( 1 / Maintenance Factor )

Enrolment := GET XLS DATA('Enrolmenttest.xls', 'Sheet1', '1', 'B2')

Facility Replacement Cost = 1e+007

"Facility Risk Index (FRI)" = ( ( "0 < FCI < 5 Good" * p1 + "5 < FCI < 10
Fair"
           * p2 + "10 < FCI < 30 Poor" * p3 + "30 < FCI < 65 Critical" *
p4
                + "65 < FCI PTR" * p5 ) / Total Number of Schools ) *
Vulnerability


I1 = New Construction

I2 = A1

Maintenance Budget = IF THEN ELSE ( Maintenance Factor * Required
Maintenance Budget
                < Capital Budget , Maintenance Factor * Required
Maintenance Budget
                , Capital Budget )

Maintenance Factor = 1 [0.1,1]

Maintenance Need per School = 100000

NC = PNC

Network Age = ( tnew + ( ( 50 + Time ) * ( 438 - Total Sold Properties ) )
      ) / Total Number of Schools

New Construction = DELAY FIXED ( PNC ,5, PNC )

New Construction Budget = "%New" * Renewal Budget

No Rehab = 0 [0,1,1]

"No. of Schls (0-delay)" = INTEG( NC , 438)
```

```
Norm FCI = Overall FCI / 100

Norm Residual Fund = Residual Fund / ( 1e+009)

Norm TLCC = TLCC / ( 3e+009)

"Over-Capacity" = IF THEN ELSE ( ( Utilization Rate - 1) > 0, Utilization
Rate
           - 1, 0)

Overall FCI = ( "0 < FCI < 5 Good" * 2.5 + "5 < FCI < 10 Fair" * 7.5 + "10
< FCI < 30 Poor"
           * 20 + "30 < FCI < 65 Critical" * 40 + "65 < FCI PTR" * 65) /
Total Number of Schools


p1 = 0

p2 = 0.01

p3 = 0.05

p4 = 0.1

p5 = 0.3

PNC = ACTIVE INITIAL( INTEGER ( New Construction Budget / Construction
Cost per School
                     ) , 0)

PRL1 = ( "%RL1" * Rehab Budget ) / "$RL1"

PRL2 = ( "%RL2" * Rehab Budget ) / "$RL2"

PTR Property Value = 5e+006

Pulse1 = PULSE ( 10, 10)

PulseTrain1 = PULSE TRAIN ( 0, 5, 10, FINAL TIME )

Ramp1 = RAMP ( 0.1, 10, 20)

Rehab Budget = "%Rehab" * Renewal Budget

Rehab Level 1 = IF THEN ELSE ( PRL1 < "10 < FCI < 30 Poor" , PRL1 , "10 <
FCI < 30 Poor"
           )

Rehab Level 2 = IF THEN ELSE ( PRL2 < "30 < FCI < 65 Critical" , PRL2 ,
"30 < FCI < 65 Critical"
           )
```

```
ReInv = IF THEN ELSE ( Residual Fund > Construction Cost per School ,
Residual Fund
           , 0)

Renewal Budget = Capital Budget - Maintenance Budget

Required Maintenance Budget = Maintenance Need per School * Total Number
of Schools


"Residual (Annual)" = ACTIVE INITIAL( Capital Budget - CAPEX , 0)

Residual Fund = INTEG( "Residual (Annual)" - ReInv , 0)

Sell Property = INTEGER ( "%Sell" * "65 < FCI PTR" )

Sold Property Income = Sell Property * PTR Property Value

Step1 = STEP ( 1, 15)

Test PNC = New Construction Budget / Construction Cost per School

TLCC = INTEG( "$M" + "$NC" + "$R" , 0)

tnew = IF THEN ELSE ( A1 = 0, 0, A2 / A1 )

Total Capacity = "Avg. Capacity per School" * Total Number of Schools

Total Number of Schools = "0 < FCI < 5 Good" + "10 < FCI < 30 Poor" + "30
< FCI < 65 Critical"
           + "5 < FCI < 10 Fair" + "65 < FCI PTR"

Total Sold Properties = INTEG( Sell Property , 0)

TP12 = 0.1

TP23 = 0.158

TP34 = 0.135

TP45 = 0.187

Utilization Rate = Enrolment / Total Capacity

Vulnerability = ( Network Age / 100) * Utilization Rate
```

Appendix E

Mathematical Optimization Model (Chapter 6)

This Appendix shows the mathematical optimization model developed in chapter 6 for tactical rehabilitation planning.

```
$title Tactical Level Rehabilitation Model
* using GAMS/CPLEX as the solver
option MIP = CPLEX ;

Set i instances /1*800/ ;
Set j year number /1,2,3,4,5/ ;

* input data imported from BM10.xls (GAMS input spreadsheet)
Parameter IRC(i,j) Instance Repair Cost ;
$call "gdxxrw i=BM10.xls o=IRC.gdx par=IRC rng=gamsinput!A11:F811"
$gdxin IRC.gdx
$load IRC
display IRC;

Parameter IE(i,j) Improvement Effect ;
$call "gdxxrw i=BM10.xls o=IE.gdx par=IE rng=gamsinput!M11:R811"
$gdxin IE.gdx
$load IE
display IE;

Parameter RIF(i,j) Repair Cost ;
$call "gdxxrw i=BM10.xls o=RIF.gdx par=RIF rng=gamsinput!S11:X811"
$gdxin RIF.gdx
$load RIF
display RIF;

Parameter CI0(i) initial conditon Index ;
$call "gdxxrw i=BM10.xls o=CI0.gdx par=CI0 rng=gamsinput!Y12:Z811 rdim=1"
$gdxin CI0.gdx
$load CI0
display CI0;

Parameter B(j) Yearly Budget Limit ;
$call "gdxxrw i=BM10.xls o=B.gdx par=B rng=gamsinput!AA3:AB7 rdim=1"
$gdxin B.gdx
$load B
display B;

Scalar z ;
   z = sum(i,CI0(i));
Scalar m ;
   m = (sum((i,j), RIF(i,j)))/5;
```

```
* binary decision variables (BIP formulation)
Variable x(i,j) Decision Variable for Renewal Action ;
Binary variable x ;

Variable DIN Network Deterioration Index ;

* objective and constraints
Equations
        cost(j)      total cost in year j
        SRC(i)       one time visit during the planning horizon
        Condition    objective function ;

  cost(j)..       sum(i, x(i,j)*IRC(i,j)) =l= B(j) ;
  SRC(i)..        sum(j, x(i,j)) =l= 1  ;
  Condition.. DIN =e= (z + sum((i,j), x(i,j)*IE(i,j)*RIF(i,j)))/m ;

* solving asset renewal model using GAMS/CPLEX
Model TDSB /all/ ;

solve TDSB using mip minimizing DIN ;

Display x.l, DIN.l ;

solve TDSB using mip minimizing DIN ;
execute_unload "result.gdx" x.l
execute 'gdxxrw.exe result.gdx o=BM10.xls var=x.l rng=gamsresult!'

file results /results.txt/ ;
put results;
loop((i,j), put x.l(i,j)/);
```

Glossary

$\$C_{min}$ $\$C_{maj}$ $\$C_{Rplc}$	Cost of each rehabilitation actions
$FRC	Facility replacement cost
$FullRplc	Rehabilitation costs associated with full replacement
$Major	Rehabilitation costs associated with major
$Minor	Rehabilitation costs associated with minor
$\$M_t$	Maintenance expenditure at time t
$\$NC_t$	New construction expenditure at time t
$\$R_t$	Rehabilitation expenditure at time t
$UC	Public fees and tolls
% S5-FR	Percentage of state 5 assets that will undergo full replacement
$\%B_B$ $\%B_C$ $\%B_D$	Percentage of budget allocated to asset category B, C, and D
%Budget-Sj	Percebtage of rehabilitation budget allocated to assets in condition states j
%RL1	Percentage of rehab. budget allocated to rehab. level 1
%RL2	Percentage of rehab. budget allocated to rehab. level 2
%S3-Mj31	Percentage of assets in State 3 using major rehabilitation
%S3-Mn32	Percentage of assets in State 3 using minor rehabilitation
%S4-Mj42	Percentage of assets in State 4 using major rehabilitation
%S4-Mn43	Percentage of assets in State 4 using minor rehabilitation
%S5-FR	Percentage of assets in State 5 using full replacement
%S5-Mj53	Percentage of assets in State 5 using major rehabilitation
%S5-Mn54	Percentage of assets in State 5 using minor rehabilitation
AAMCoG	Australian Asset Management Collaborative Group
ABS	Agent Based Simulation
AMS	Asset Management Systems
AP_t	Annual Payments
ASCE	American Society of Civil Engineering
BL_t	Backlog at year t
B_t	Total budget available for rehabilitation at year t
Budget Sj	Budget allocated to assets at condition state j

CAPBUD	Capital Budget
CAPEX	Capital Expenditure
CI	Condition Index
CI_N	Network Condition Index
CLD	Causal Loop Diagram
CSS	County Surveyor Society
CS_{Xt}	Number of assets in each condition state X at time t
CS_{Xt0}	Initial CS stock value at time zero
D	Duration of private sector investment
DES	Discrete Event Simulation
$Det._{X\text{-}X+1}(s)$	Outflow values of the deterioration of state X to state X+1 at any time s
DI_N	Network Deterioration Index
DIT	Dynamic Input Test
DLL	Dynamic Link Library
DR_{ij}	Deterioration rate from state i to j
DST	Decision Support Tool
EF_t	Efficiency factor
EP_j^k	Expected performance of asset j when repaired in year k
FCI	Facility Condition Index
FCI%critical-fair	Different between FCI of state fair and critical
FCI%poor-fair	Different between FCI of state fair and poor
FCM	Federation of Canadian Municipalities
FHWA	Federal Highway Administration
FP_t	Financial Performance at year t
FRI	Facility Risk Index
FS_t	Number of sold facilities at time t
$FullRplc_X(s)$	Inflow values of full replacements added to state X at any time s
GA	Genetic Algorithm
GAMS	General Algebraic Modelling System
GFA	Gross Floor Area
$Govinv_t$	Rehabilitation budget set by government
i	Annual rate of return or interest for the private investment

I_{ECN}	Economical impact
IE_{jk}	Improvement effect of repairing asset j in year k
I_{ENV}	Environmental impact
IP	Integer Programming
I_{SC}	Social impact
KPI	Key Performance Indicator
L	Number of annual payments to private sector
LCCA	Life Cycle Cost Analysis
LOS	Level of Service
LP	Linear Programming
$Major_X(s)$	Inflow values of major rehabilitations added to state X at any time s
MF	Maintenance factor
MIP	Mixed Integer Programming
MOST	Multiple Optimization and Segmentation Technique
MR&R	Maintenance, Rehabilitation, and Reconstruction
NC_t	Number of constructed new facilities at time t
N_{total}	Total number of existing assets
N_{Total}	Total number of schools
N_{Xt}	Number of assets in a certain condition states (A, B, C, and D)
OC_t	Overall condition of the asset network
P_{ij}	Probability of the asset in state i deteriorating to state j
PPP	Public Private Partnership
PR-Sj	Number of repairs possible for condition states j
$Prvinv_t$	Investment from private sector
RC_{jk}	Repair cost for asset j at year k
RIF	Relative Importance Factor
SD	System Dynamics
SP_t	Sustainability performance
TAC	Transportation Association of Canada
TDSB	Toronto District School Board
TLCC	Total Life Cycle Cost
TPM	Transition Probability Matrix

UR_t	Utilization Rate
WCED	World Commission on Environment and Development
W_{ecn} W_{env} W_s	Weights for environmental, social, and economical effects
X_j	Repair type available for asset j
Y_{ij}	Repair timing variable for asset j in year t