5th International/11th Construction Specialty Conference
5e International/11e Conférence spécialisée sur la construction

Vancouver, British Columbia
June 8 to June 10, 2015 / *8 juin au 10 juin 2015*

INFRASTRUCTURE REHABILITATION PLANNING: COMBINED SYSTEM DYNAMICS AND OPTIMIZATION METHODS

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Abstract: To improve the performance of the increasingly deteriorating infrastructure, effective strategic policies must be combined with optimum tactical rehabilitation plans. In the literature, limited efforts have focused on strategic policy analysis and its integration with tactical/operational planning. This paper; therefore, presents a framework that combines the strategic and tactical dimensions of infrastructure rehabilitation. At the strategic level, the System Dynamics (SD) modeling technique has been used to simulate the long-term effect of different policy scenarios on physical performance and backlog accumulation. The optimum policies are then used as inputs to a detailed tactical planning model. The objective of such model is to provide detailed fund allocation plans for the assets that need rehabilitation on a yearly basis. The proposed tactical model deals with large number of asset components over a 5-year plan to determine the best possible combination of repair types and timings. The paper compares the processing time and solution quality of three models that use different optimization approaches: Genetic Algorithms (GA); mathematical mixed integer programming; and Microeconomic-based heuristics. The paper discusses the conceptual formulation of the proposed integrated framework, the developments made so far, present limitations, and future enhancements.

1 INTRODUCTION

A major challenge for asset managers is to determine the appropriate actions needed to preserve the performance of rapidly deteriorating civil infrastructure, over a long service life. Adequately 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. All these are then used 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 among the assets (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 (De la Garza et al. 2011); water and sewer (Halfawy et al. 2008); bridges (Frangopol et al. 2012); buildings (Rashedi and Hegazy 2014). 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; Hegazy and Saad 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 do not provide a comprehensive view that examines strategic decisions and their impact on the life cycle dynamics over a long span of time. Such a comprehensive view, however, is essential for strategic decision-making. This paper therefore attempts to combine the long-term strategic perspective that relates to the setting of budget policies with the short-term tactical perspective that relates to detailed allocation of a decided budget among asset components. The paper explores the potential of the system dynamics (SD) technique as an effective tool for modeling and analysis of the dynamic processes within infrastructure rehabilitation at the strategic level. Also it compares various optimization techniques that can be used to optimize tactical fund allocation decisions. The combination of the two levels of decisions creates a more comprehensive framework for analyzing infrastructure rehabilitation plans.

2 PROPOSED FRAMEWORK FOR REHABILITATION PLANNING

A proposed policy optimization framework is illustrated in Figure 1. The overall objective of this framework is to understand the dynamic interactions among different aspects of asset management, generate various 'what-if' scenarios, and optimize strategic policies. The framework's initial inputs can be categorized into two groups: asset information and organizational information. Asset information is mainly determined using inspection and condition assessment methods. They include asset inventory data, current conditions, historical condition indices, deterioration rates, maintenance costs, and costs of rehabilitation alternatives. Organizational information, on the other hand, includes key performance indicators (KPIs), strategic objectives, and different policies such as budget allocation strategy. To develop the strategic and tactical models of this comprehensive framework, the asset inventory of the Toronto District School Board (TDSB), which administrates a network of more than 550 school buildings, has been used. Also, in this study the key strategic variables have been identified based on reviewing the literature, previous research on TDSB assets, and other guidelines obtained from the TDSB and the Ontario Ministry of Education (OME). The two main components of the proposed framework are as follows:

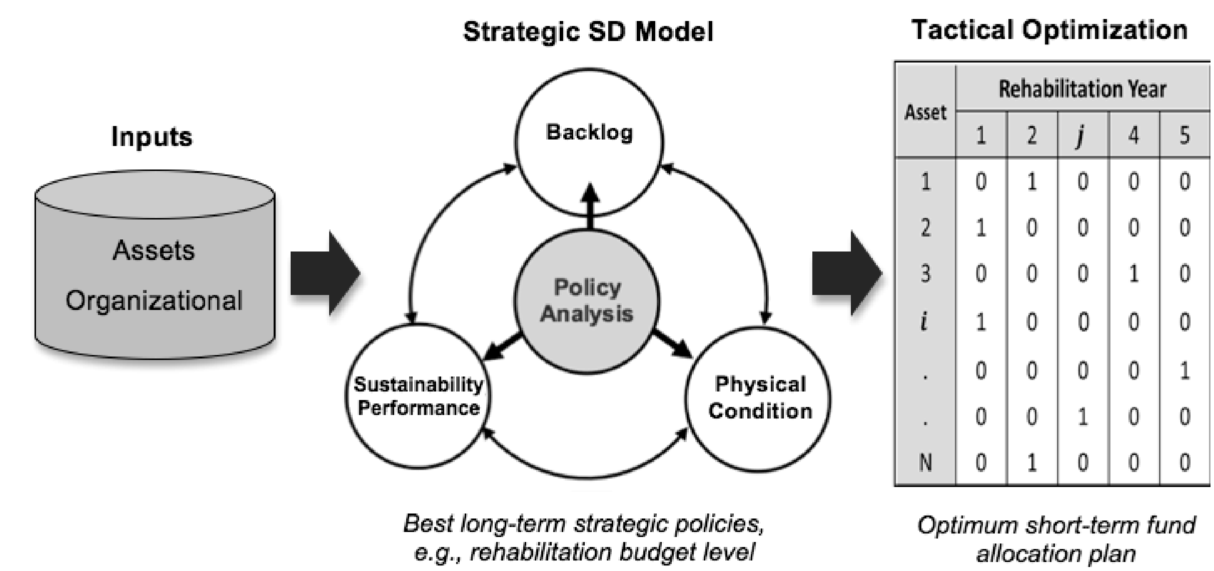


Figure 1: Proposed framework for rehabilitation planning

Strategic System Dynamics (SD) Model: The strategic SD model investigates the long-term organizational objectives and seeks to examine the impact of different strategic policies, such as rehabilitation budgeting, sustainability policy, or public private partnership (PPP), on asset performance and backlog accumulation. As shown in the conceptual framework of Figure 1, the proposed SD model has four integrated modules: 1) the central policy analysis module; 2) physical condition; (3) backlog accumulation; and (4) sustainability performance. Accordingly, the SD model simulates the dynamic interactions within and among these modules, and can be used to provide policymakers with a clearer understanding of the long-term impact of their policies.

Tactical Optimization Model: After performing the strategic SD analysis, the outputs of the model, such as budget policy, is used as an input to the tactical optimization model to perform a detailed fund allocation analysis over a tactical planning horizon. At the tactical level, three approaches: genetic algorithms (GA), mathematical optimization, and microeconomics-based heuristics are used to achieve the most optimum fund allocation plan.

3 STRATEGIC SD MODEL

System dynamics (SD) is perhaps one of the most promising simulation methods in the area of policy optimization and strategic decision-making (Forrester 1961). Sterman (2000) describes it 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." SD has been applied to a variety of domains from construction to politics, HIV control, and even warfare. In all of its applications, SD has proved to be capable of capturing the dynamics and interactions within complex systems from a holistic perspective, thus making it effective for top-level management (Sterman 2000). In the asset management domain, Rehan at al. (2011) developed an SD model for estimating the financial sustainability of water and wastewater systems and the impact of pricing policies on users. In another effort, Xu and Coors (2012) combined SD with GIS and 3D visualization to examine the sustainability of urban residential development. Other applications have also established the significant potential of system dynamics with respect to the development of holistic models for macro-level management.

To examine the dynamics within complex systems, SD models are developed through three main steps: (1) creating causal loop diagrams (CLDs) to capture the dynamic interactions among the key variables/parameters; (2) mapping the developed CLDs into stock-and-flow simulation components; and (3) running the simulation, testing the model, and analysing the long-term impact of various parameters. These steps, along with the proposed rehabilitation analysis model, are discussed in the next section.

3.1 Casual Loop Diagramming

The development of the proposed strategic SD model starts with identifying the interactions among four main groups of key strategic variables (as shown in Figure 1), related to: policy aspects of asset management, physical condition, backlog accumulation, and sustainability performance. Figure 2 depicts the proposed causal loop diagram (CLD) that captures the dynamic interactions among the key strategic variables. 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. 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). As and example, a CLD is highlighted in Figure 2 that involves two variables: "asset condition" and "asset deterioration". 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 highlighted in Figure 2. This positive loop models the dynamic behavior 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.

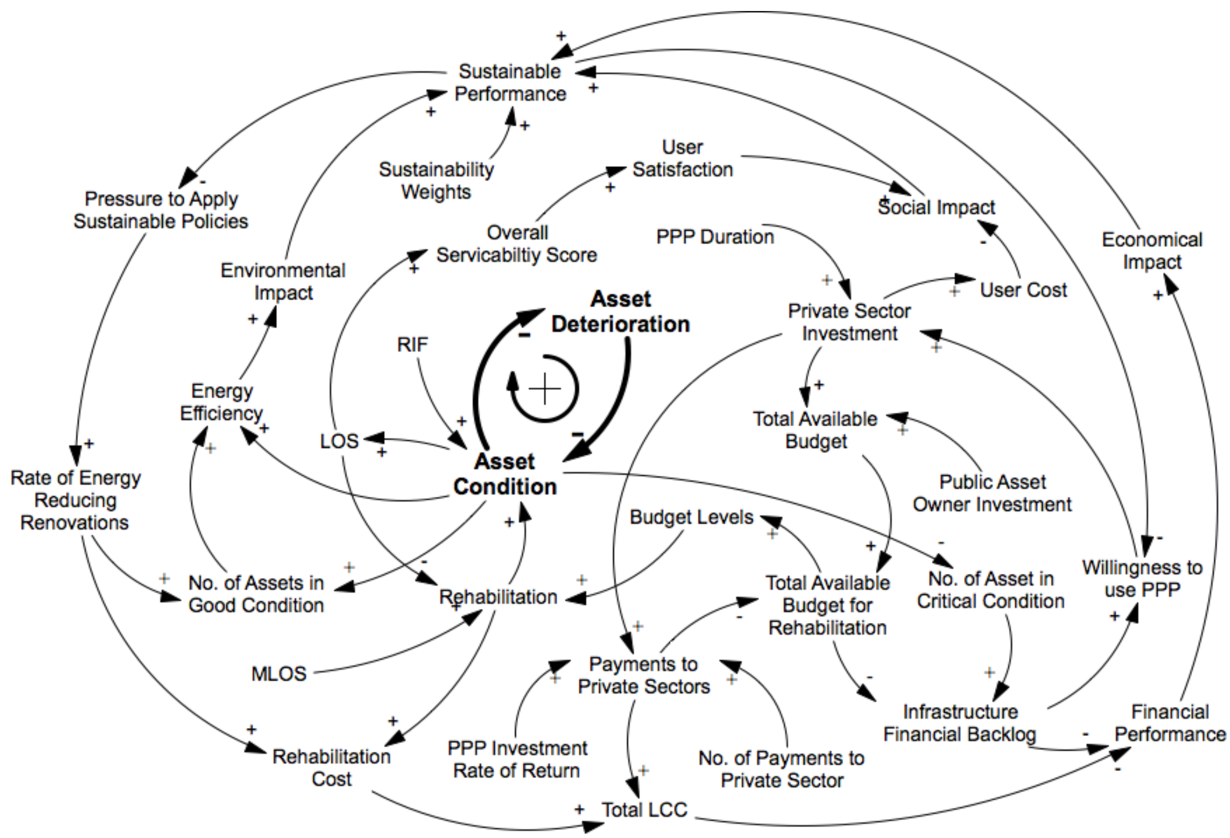


Figure 2: Causal loop diagram for the proposed SD model

3.2 Stock-And-Flow Modeling

After identifying the dynamic interactions among the parameters that are impacted by strategic policy, the developed causal loop diagram (CLD) has been mapped into a stock and flow simulation model. While the CLD shows the underlying feedback structure of the model, the stock and flow diagram captures the physical dynamic structure of the system. 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. Figure 3 shows a partial screen capture of the SD simulation model, which has been developed in the VENSIM software. The model includes around 100 decision variables and equations including key and intermediate parameters. Developing the stock and flow diagram of Figure 3 and its underlying simulation model was a demanding process of translating all the loops in the CLD diagram one by one into stocks and flows and writing the related equations. This iterative process includes numerous rounds of modifications of the stock and flow diagram and performing various tests to verify model relationships and the accuracy of results.

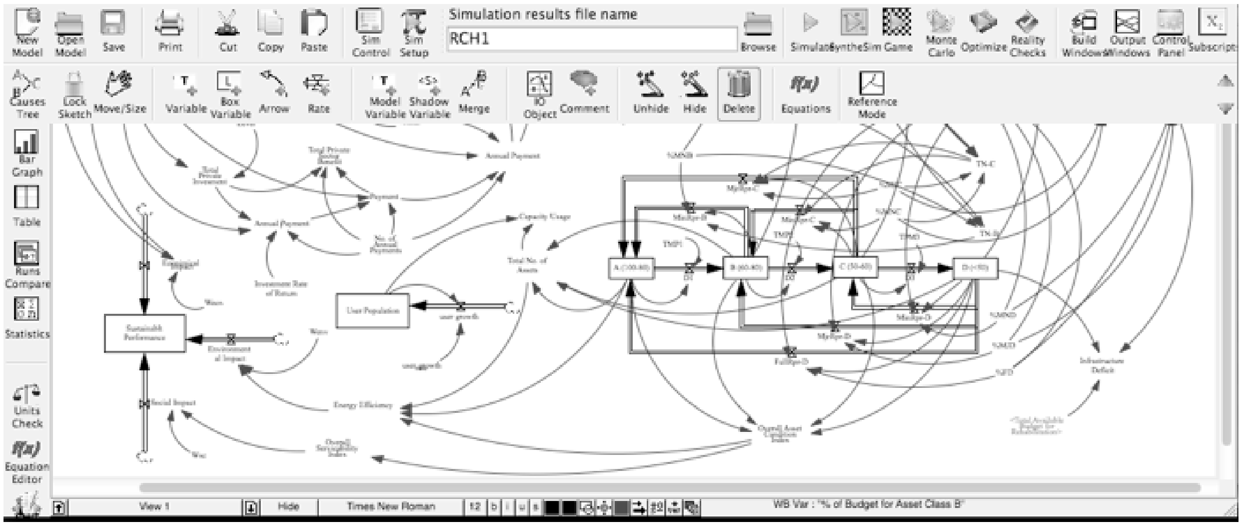


Figure 3: Strategic SD Model in the VENSIM software

3.3 Analyzing Budget Policy

As an example to show the application of the proposed model in determining different strategic policies, a set of experiments was performed to investigate the effect of government investment on asset condition and backlog accumulation, to determine a proper annual budget level. Four scenarios have been generated based on different investment values. Scenario 1 allows assets to deteriorate over time without any rehabilitation (i.e., \$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 shows the backlog and condition 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). Increasing government investment, as shown in Figure 4, can significantly reduce backlog accumulation and improve asset condition. Sustainable performance results also indicated 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 presented analysis 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).

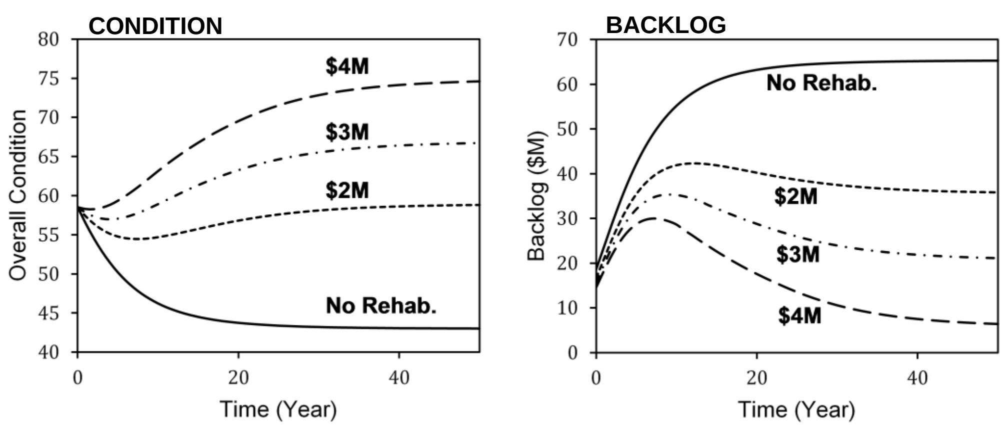
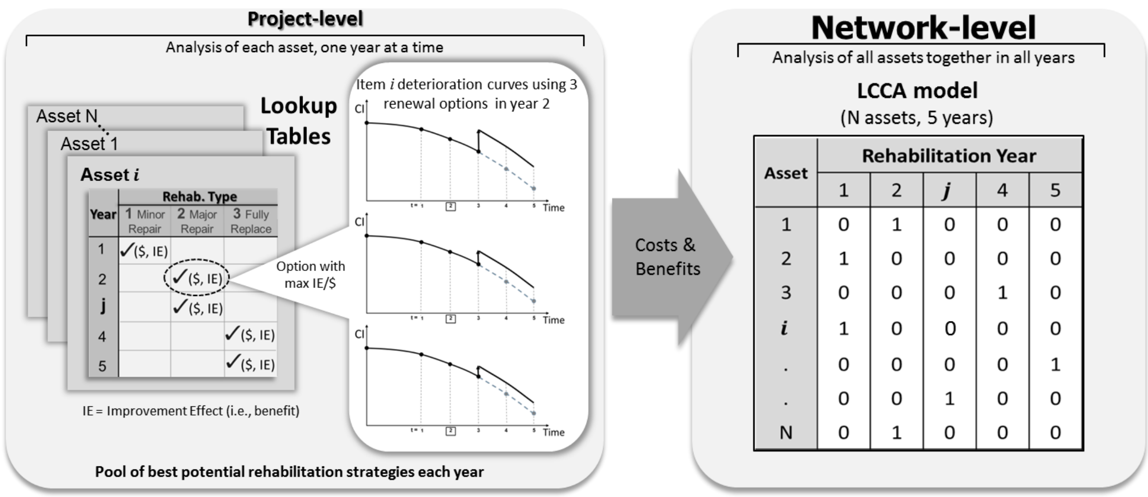


Figure 4: Simulation results for different levels of annual rehabilitation budget

4 TACTICAL OPTIMIZATION

With a budget level imposed on a public agency as a constraint on rehabilitation work (as a result of strategic analysis), tactical decisions are concerned with determining the optimum rehabilitation type (project-level decisions) and rehabilitation timing within a planning horizon (network-level decisions). At the tactical level, this paper utilizes a fund allocation method that integrates both project and network levels of decision. The method is built upon the Multiple Optimization and Segmentation Technique (MOST) of Hegazy and Elhakeem (2011) that reduce problem size to handle large-scale problems. In the MOST technique, the project-level analysis is done first, one year at a time, to determine the most cost-effective rehabilitation scenario (e.g., minor, major, or full replacement) for each asset that maximizes overall condition. This analysis provides a pool of best potential repair strategies, and their associated costs. This information is then used as a lookup input table to simplify the network-level analysis. At the network-level, the problem is segmented into yearly smaller-size optimizations to determine optimum renewal timings (facilitated only by the pre-analysis at the project level) using genetic algorithm (GA), as shown below in Figure 5.



Asset	Rehabilitation Year				
	1	2	*j*	4	5
1	0	1	0	0	0
2	1	0	0	0	0
3	0	0	0	1	0
i	1	0	0	0	0
.	0	0	0	0	1
.	0	0	1	0	0
N	0	1	0	0	0

Figure 5: Schematic of MOST and its adaptation to the network-level fund allocation model

The performance of GAs, however, is highly sensitive to problem size, problem formulation and other operational parameters that govern the GA evolutionary process. As such, a steep degradation of solution quality has been noticed from experimenting with GA on larger problems (Rashedi and Hegazy 2014). Thus, at the network-level, this paper presents three different models to improve solution quality: 1) GA + Segmentation optimization, 2) Mathematical optimization, and 3) Microeconomic Enhanced benefit-cost analysis (EBCA) heuristic. To compare solution quality, the three models are applied to a base case involving 800 school building asset components. The models have a planning horizon of 5 years, an assumed $10M annual budget yielding from the strategic-level SD model, and the objective function of maximizing the overall network condition.

4.1 GA + Segmentation Model

To suit real-life problems that are much larger in size, a segmentation method by Hegazy and Rashedi (2013) has been applied to enhance the performance of GAs. The GA+Segmentation process divides the original network-level problem into smaller sub-problems (segments), handles them separately, and combines their results to produce the final solution. To implement the segmentation process within the tactical model, the available budget, decision variables and optimization constraints have been segmented, without compromising the integrity of the model. Also, the model has been modified to accommodate the redistribution of 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. In the GA+Segmentation method, the budget is divided among segments (e.g., size of 200 assets) based on the relative criticality (RC) of each segment, which is calculated as a function of the relative importance and the deterioration behaviour of the components within each segment. Subsequently, the budget constraint in year j for the components within a segment is proportional to the segment's RC value divided by the sum of RCs for all segments. Application of the GA+Segmentation model on the building case study showed significant improvement to solution quality in comparison to the traditional GAs (comparison is shown in Table 1), and effectiveness in handling large-scale problems. The major drawback of this approach, however, was its processing time that showed exponential increase on larger size problems.

Table 1: Comparison among tactical optimization approaches

Tactical Optimization Approach	**Network * Condition**	**Comment**
No Rahabilitiaton	54.15	
Simple Ranking	44.89	*Poor Solution Quality*
GA (Hegazy & ElHakeem 2011)	33.18	*Limited to 800 assets*
GA+Segmentation (Hegazy & Rashedi 2013)	32.09	*Applicable to large-scale; long processing tim; suitable for nonlinear problems*
GAMS/CPLEX (Rashedi & Hegazy 2014)	31.71	*Applicable to large-scale; very fast; provides close to global optimum results*
EBCA Heuristic (Saad 2014)	31.79	*Applicable to large-scale; high quality solutions; provides economic justifications*

** Smaller is better*

4.2 Mathematical Optimization Model

To reduce processing time and to find globally optimum solutions, Rashedi and Hegazy (2014) developed a mathematical optimization model that utilizes an advanced mathematical optimization tool, General Algebraic Modeling System (GAMS), which consists of an array of integrated high-performance built-in solvers. The model uses CPLEX solver engine, a powerful mathematical optimization solver that uses advanced algorithms for variety of optimization problems, including mixed-integer programming. The optimization model is designed to be generic enough to accommodate any type of data. The model's objective function is to maximize the assets' overall network condition index, which is an aggregation of one or more performance parameters of all individual assets. Each asset can be selected in a year over the planning horizon using a binary decision variable (e.g., X_{ij}). If X_{ij} for a certain asset i and year j is equal to 1, then the asset is selected for rehabilitation at this year, and the associated rehabilitation cost and benefit would be retrieved from the appropriate lookup tables (value of zero represents no action). The Objective function is set to maximize the network overall condition index, which is the weighted sum of all assets' condition, considering the relative importance factor of each asset. The total rehabilitation cost, which is the sum of all assets' costs in any year j, is another constraint that is limited by the available budget for that year. Also, each asset can only be selected once for rehabilitation within the planning horizon to satisfy a single-visit criterion (Rashedi and Hegazy 2014). The GAMS/CPLEX model proves to be promising in terms of both solution quality and processing time and can be effectively used by asset mangers for tactical optimization solutions. Using this model a network of more than 50,000 asset components, that is close to the real size of the problem, has been optimized in a matter of minutes resulting in a close to global optimum network condition of 31.71 as shown in Table 1.

4.3 Microeconomic EBCA Heuristic Model

While the previous two models are effective in handling large-scale tactical optimization problems, their development was not simple, thus it is difficult to provide an economical interpretation for the optimization results. The results are typically a set of decisions (usually binary, i.e., a combination of [0, 0, 1, 0, 0] represents a decision to repair an asset in year 3 of a 5-year plan). In case of thousands of assets, which is typical, the combination of zeroes and ones is not easy to interpret or justify economically. Several combinations of zeroes and ones might lead to close-to-optimum solutions, and thus it is not easy to determine the logic behind those solutions.

To handle this issue, an Enhanced Benefit-Cost Analysis (EBCA) heuristic approach has been introduced that uses the microeconomic consumer theory of equal marginal utility per dollar, to arrive at near optimum balanced fund-allocation decisions in a structured way, while providing an economic justification behind decisions (Saad 2014). This theory of equal marginal utility per dollar has been proven, in the microeconomics literature (Chugh 2014), to arrive at optimum allocation of a limited fund by targeting equilibrium (equality) among the marginal utility per dollar spent on the different consumption categories, rather than the typical approach of maximizing benefits or minimizing costs. The basic premise of this approach is an analogy between a consumer who has a limited income to spend on various expenditure categories, and a public agency with a limited budget, from taxpayers' money, to allocate to various rehabilitation expenditures. As such, optimum fund-allocation is represented by an equilibrium state at which the marginal utilities (benefits) per dollar (MU/$) associated with the rehabilitation of the last selected asset from each category (e.g., Architectural, Mechanical, etc.) are equal. This approach involves a five-step process that is applied one year (j) at a time to facilitate mapping the consumer case in each year in the planning horizon. To arrive at the optimum decision that maintains equilibrium state among the different asset categories the heuristic process is applied to the building case study as follows:

1. For each year in the planning horizon group unfunded assets into their categories (Architectural, Mechanical, and Electrical);
2. List the performance improvement and the renewal cost for each asset based on the LCCA calculations, assuming all assets will be funded this year;
3. Compute the Marginal utility per dollar (MU/$) for each asset by dividing the performance improvement by the renewal cost;
4. Sort the assets in a descending order, according to the MU/$; and
5. Select assets for funding starting from the top of the sorted list in each category till the MU/$ value of the last selected asset in each category is almost equal, and the budget for this year is fully exhausted. Move unfunded assets beyond this equilibrium point to the next year in the planning horizon.

Architectural Assets		
No.	MU/$	Cum. Cost
1	2.6726	$1,815
2	2.6207	$3,630
3	2.2804	$5,445
:	:	:
:	:	:
:	:	:
:	:	:
:	:	:
124	**0.0452**	**$4,509,670**
125	0.0450	$4,558,070
126	0.0447	$4,606,470

Mechanical Assets		
No.	MU/$	Cum. Cost
1	0.2516	$6,050
2	0.2309	$18,150
3	0.2040	$36,300
:	:	:
:	:	:
:	:	:
:	:	:
46	0.0439	$2,968,170
47	0.0438	$3,064,970
48	0.0436	$3,161,770
49	0.0435	$3,234,370
50	0.0435	$3,325,120
51	**0.0434**	**$3,415,870**

Electrical Assets		
No.	MU/$	Cum. Cost
1	0.2445	$24,200
2	0.2312	$48,400
3	0.1996	$66,550
:	:	:
:	:	:
42	0.0482	$1,960,200
43	**0.0431**	**$2,069,100**
44	0.0409	$2,165,900
45	0.0398	$2,238,500

Figure 6: Sample of selected assets in first year using EBCA approach

Figure 6 shows the application of the heuristic process steps to the school building case study in first year. The assets are grouped according to their system-level categories (Architectural, Mechanical, and Electrical), and sorted in a descending order according to their marginal utility per dollar values. The “Cum. Cost” column represents the total cumulative rehabilitation costs that correspond to a total number of allocated assets in each category. The shaded part shows the optimum (equilibrium) combination of assets for year 1, which is 124 architectural, 51 mechanical, and 43 electrical assets. The total cost associated with this combination is $9,994,640 ($4,509,670 + $3,415,870 + $2,069,100), which almost fully exhausts the available budget while maintaining an equilibrium state among the asset categories. The microeconomic EBCA approach can handle large-scale problems due to its formulation, and it is comparable to the mathematical model in terms of solution quality, yet with a structured strategy supported with economic justification.

5 CONCLUDING REMARKS

This paper discussed a comprehensive infrastructure rehabilitation framework that combines a strategic SD-based policy analysis model with tactical optimization to create detailed fund allocation plans. At the strategic level, the development of a holistic the SD model, including casual loop diagrams and stock-and-flow simulation model, have been discussed. The model was experimented on a policy analysis example with regard to rehabilitation budgeting. Using an appropriate budget level, three tactical optimization models have been discussed, each with a particular advantage, to effectively allocate the selected rehabilitation budget. The GA+Segmentation model can handle large-scale and nonlinear problems, but its processing time increased exponentially as problem size increased. The mathematical GAMS/CPLEX model had the highest solution quality and could optimize large-size problems within a very short processing time. The microeconomic-based enhanced benefit-cost analysis (EBCA) also results in high quality solution that can be economically interpreted, and can handle large-scale problems due to its formulation. The proposed framework of this paper can be applied to variety of asset types and can address the asset management needs at both strategic and tactical levels. This comprehensive model can be used to ultimately improve the economics of infrastructure rehabilitation by allowing asset owners to align all levels of decisions to maximize the impact on asset condition and backlog accumulation.

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