COMPARISON BETWEEN GENETIC OPTIMIZATION AND HEURISTIC METHODS FOR PRIORITIZING INFRASTRUCTURE REHABILITATION PROGRAMS

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Abstract. In recent years, infrastructure rehabilitation has been in the focus of attention in North America and around the world. A large percentage of existing infrastructure assets is deteriorating due to harsh environmental conditions, insufficient capacity, and age. Due to stringent budget limits, however, asset management systems become important to assess the life cycle performance of various assets, and accordingly prioritize the assets for rehabilitation purposes. While many asset management systems have been introduced in the literature, almost no studies have compared the effectiveness of their asset prioritization methods. This paper presents an extensive comparison between heuristic and optimization methods for prioritizing large-scale rehabilitation programs, under budget constraints. The paper first introduces different life cycle cost analysis (LCCA) formulations for three case studies obtained from the literature related to buildings, pavements, and bridges. Based on extensive experiments with the three case studies and on different network sizes, heuristic techniques proved its practicality for handling various network sizes. The performance of genetic optimization, on the other hand, was more efficient on small-scale networks but showed steep degradation in performance with large-scale problems. This research can be beneficial to municipalities and asset managers and can help them design efficient methods to sustain the safety and operability of the civil infrastructure, with least cost.

1. Introduction

In many regions of the world, a large percentage of existing infrastructure assets are deteriorating due to harsh environmental conditions, insufficient capacity, and age (Elbeltagi & Tantawy, 2011). The operation, maintenance, repair, and renewal of these assets represent a rapidly growing and major cost to Canada and the United States. Similar challenges exist in Australia and other developed countries (Burns et al., 1999; Vanier, 2001). Maintaining such assets is even more challenging in light of the lack of available funds for infrastructure rehabilitation and maintenance (Elhakeem, 2005). Consequently, increasing pressure is being brought to bear on municipalities to develop new strategies and tools for allocating limited resources more wisely and to achieve best value for their investment (Elbehairy, 2007; Shen, 1997).

The allocation of available funds across infrastructure classes or programs is one of the main activities in infrastructure asset management. Continuous research efforts have been undertaken in the last few decades to develop tools and methodologies for allocating funds in infrastructure asset management, methodologies that range from being based on subjective prioritization to mathematical programming and optimization. Although various researchers have dealt with fund allocation, there is a serious lack of methodologies that can deal with large numbers of infrastructure assets (Elbehairy, 2007). Moreover, most of these methodologies were developed for a single class of assets and lack a comprehensive view of the whole process of infrastructure asset management (Halfawy et al., 2004). In the literature, few or no studies have reported on the performance of either optimization or heuristic tools on large-scale networks of assets (Elhakeem, 2005).

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

2. Life-Cycle Cost Analysis (LCCA) Case Studies

Typically, LCCA models involve two types of decisions (Hudson et al., 1997): project-level decisions on the appropriate rehabilitation method to use in each asset component (roof, window, foundation, bridge deck, pavement, etc.); and network-level decisions on selecting the components to repair in each year of the plan. Life-Cycle Cost Analysis models for three different real life case studies related to building, pavement, and bridges are presented in this paper. The three case studies offer different formulations of the LCCA model. These models will be used for comparing the efficiency of heuristic or optimization techniques on large-scale asset rehabilitation problems.

2.1. BUILDING CASE STUDY

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

MOST was introduced as an LCCA model that integrates both project-level and network-level decisions. MOST reduces the problem complexity by first optimizing individual project-level sub-problems and then using the results to formulate a network-level optimization (Figure 10). MOST utilized the genetic algorithm (GAs) technique to handle network-level problems.

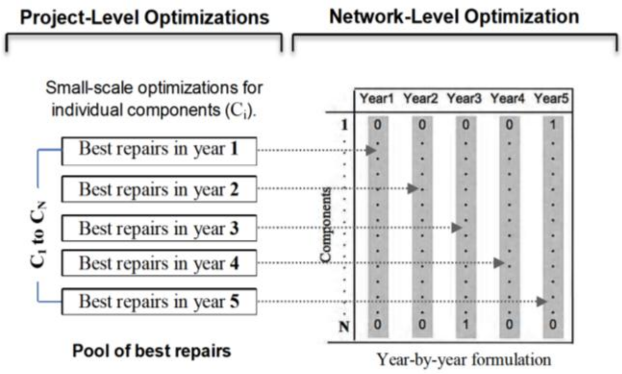

Figure 10. MOST Technique (Hegazy & Elhakeem, 2011)

At the project level, each individual optimization considers one building component for one of the possible repair years and determines the best repair method and cost for that component in the selected year. Within each small optimization, the formulation considers the component's condition, deterioration behavior, and expected after-repair condition. The result of all individual optimizations (optimal at the project level) is a pool of best repair scenarios and their corresponding costs and benefits (left side of Figure 10). These are used as the input for network-level optimization in order to decide on repair timing. This approach of segmenting project-level from network-level results in a network-level optimization that is reasonable in size, without loss of integration. The objective of network-level optimization is to minimize the overall network deterioration index (DI_N) while not exceeding the available rehabilitation budget. Rather than a one-shot optimization over the 5-year planning horizon, MOST uses a year-by-year optimization formulation (step-wise formulation) from the first year until the end of the planning horizon (as indicated in Figure 10). Using this formulation reduces the solution-space size and leads to better solution quality.

2.2. PAVEMENT CASE STUDY

Hegazy et al., (2012) used a case study of the pavement management investment analysis challenge posted in the 6th International Conference on Managing Pavements (ICMP6). This case study is a network of 1293 road sections spanning 3240 km, covering two road classes and varying in traffic use, surface age, and condition. The inter-urban roads experience medium to high traffic, while the rural roads span most traffic and condition categories.

All pavement sections have consistent sub-soil conditions and are located within the same climatic region. Each section has a defined length, width, number of lanes, year of construction, AADT, base material type, base thickness, soil type, surface thickness, and most recent treatment. In addition, the extent of distresses, surface condition assessments (International Roughness Index (IRI), and others), and predicted trigger or needs year are specified for all sections. The rate of annual traffic growth is specified as 2.5% for the inter-urban roads and 1.5% for the rural roads. The discount rate for investment analysis is 6%. The annual rate of increase of IRI, the repair costs, and the IRI improvement after different treatments are defined.

The main difference between the LCCA model of this case study and that of the building case is that it handles both the project and the network-levels at the same time. This is expected to be a much more complex model. A spread-sheet-based LCCA model has been formulated for this case study using Excel's VBA programming language as a macro program. The model is formulated considering a five-year planning horizon. It produces two decisions: Repair Type and Repair Timing. The two decisions are linked by equations to the related functions of performance assessment, deterioration, repair costs, and improvements after repair. The proposed spreadsheet calculates a Priority Index (PI) by combining the IRI with the AADT for each road section. It also predicts the future condition of the roads and estimates the after-repair condition resulting from each repair type. The LCC over the planning horizon is calculated yearly for each pavement section with the Vehicle Operating Cost (VOC) and the cost of the selected repair type taken into consideration.

2.3. BRIDGE CASE STUDY

The third case study relates to a real case of a 47-bridge network reported by (Elbehairy, 2007). The data include general information such as bridge ID, road name, bridge name, annual average daily traffic (AADT), percentage of trucks, bridge length, bridge width, last year of repair, and last repair cost. The data also include details about bridge element condition ratings, element weights, and repair costs. The data has no information about future conditions or the improvement after a repair action.

(Elbehairy, 2007) developed a Multi-Element Bridge Management System (ME-BMS) that optimizes and integrates bridge-element repair decisions (project-level decisions) and the selection of the appropriate timing for implementing the repairs (network-level decisions). The system was implemented on a spreadsheet program using Microsoft Excel, and all the genetic algorithm (GA) procedures were coded with the macro language of Microsoft Excel. The system was formulated considering a five-year planning horizon. Based on the six models incorporated in the system, for condition rating, time-dependent deterioration, repair cost, repair-improvement, and user cost, the system produces the best repair type for each element if the repair is done in year1, year2, etc., in addition to the best year to repair each bridge.

3. Heuristic versus Optimum Fund-Allocation

In this section, heuristic and optimization fund-allocation methods are introduced and used for allocating funds for the three LCCA models presented earlier.

3.1. HEURISTIC APPROACH

The heuristic approach used was developed by Hegazy et al. (2012) and modified for the three case studies addressed in this paper. The approach was developed for near-optimum allocation of pavement rehabilitation funds. It first rank assets (e.g., pavements) based on a calculated priority index (PI), which reflects the need for urgent repair action. Assets with higher PI values are considered first. After prioritizing assets, the proposed heuristic approach is applied for selecting the best treatment types and timing under budget limits. The method allocates budgets year-by-year. Each year is considered separately, starting from year 1 and moving successively to the next, until the end of the planning horizon (Figure 11).

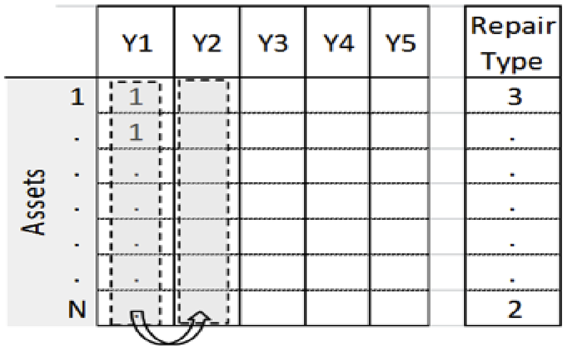

Figure 11. Fund Allocation Heuristic Year-by-Year Process

3.2. OPTIMIZATION APPROACH

An evolutionary optimization tool (Evolver) based on genetic algorithms was used. Evolver is an Excel add-in program that proved suitable for solving large-size problems for which mathematical optimization techniques fail (Elbeltagi et al., 2005).

4. Experimenting on Small-Scale Networks

The heuristic and optimization approaches have been implemented on the building, pavement, and bridge case studies. Each case study has a different limited yearly budget, number of assets, and repair options. The complexity of each model is not equal. The building case study model considers three repair options for each instance; about $10 million yearly budget; and 800 building instances. While, the bridge case study model considers five repair options for each of the seven bridge elements; a $600,000 yearly budget; and 47 bridges. On the other hand, the pavement case study considers five repair options; $25 million yearly budget, and 1,293 pavement sections.

4.1. RESULTS COMPARISON

Implementing the heuristic and optimization tools improved the overall condition and allocated the funds efficiently for the three case study networks (Figure 12). The condition improvement, the money spent, and processing time for all case studies are shown in TABLE 2.

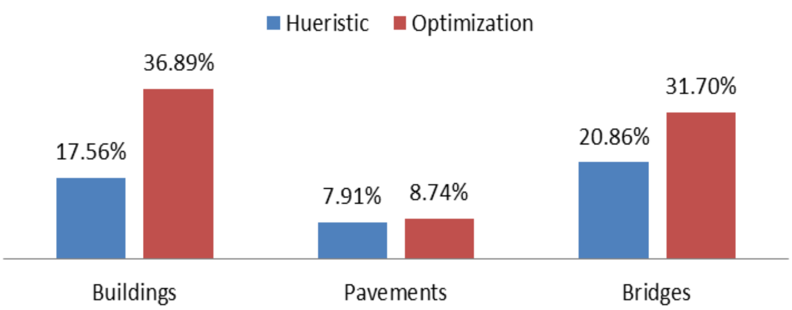

Figure 12. Condition Improvement: Heuristic vs. Optimization

TABLE 2. Results Obtained from the Heuristic and Optimization Techniques

Case Study	**Network Size**	**Technique**	**Before-Repair Condition**	**After-Repair Condition Improvement**	**5-year Budget Limit (million)**	**5-year Spending (million)**	**Processing Time**
Buildings	800 instances	Heuristic	54.33	17.56%	50.062	49.650	7 sec
		Optimization		36.89%		50.004	150 min
Pavements	1,293 pavement sections	Heuristic	1.71	7.91%	125	124.978	34 sec
		Optimization		8.74%		124.900	75 min
Bridges	47 bridges	Heuristic	4.89	20.86%	3	2.992	2 sec
		Optimization		31.70%		2.813	50 min

As shown in TABLE 2, the heuristic approach improved the overall condition for the building case study from 54 (overall condition with no repair action) to 44.8 (i.e., 17.56%) with a processing time of 7 seconds, while with the optimization, the overall condition improved from 54 to 34.3 (36.89%) with a running time of 150 minutes (different processing times were tried and 150 min. provided best results). In the pavement case study, the heuristic approach achieved a 7.9% improvement to the overall condition with a processing time of 34 seconds, while the optimization achieved an 8.7% improvement with a running time of 75 minutes. For the bridge case study, the heuristic approach achieved 20.86% improvement to the overall condition with a processing time of 2 seconds, while with optimization achieved 31.7% improvement with a running time of 50 minutes. The results show that optimization achieves better results for these small-scale problems; however, it requires longer processing time than the heuristic approach.

5. Experimenting on Large-Scale Networks

Larger networks (up to about 10,000 assets) were constructed by repeating the assets in the building, pavement, and bridge networks several times. Repeating the networks' assets provides a quantitative approach for measuring the performance of large-scale networks.

Experiments were conducted using the heuristic and optimization approaches on different network sizes. The summary of experiment results for all network sizes is presented in Table 3. The results show that the heuristic approach allocated funds efficiently and improved the overall condition for the three case study networks. The results show that the optimization approach achieved higher overall network condition and allocated funds efficiently for different network sizes.

5.1. HEURISTIC VS. OPTIMIZATION: RESULTS COMPARISON

As shown in Table 3, the heuristic approach has sufficiently improved the overall network condition for all network sizes. In terms of processing time, the final decisions were produced efficiently and in a very short for the building and the pavement case studies, but not for the bridge case study.

Table 3. Experiment Results for Large-Scale Networks

Case Study	Network Size	Overall Condition	Budget Limit	Approach	Condition Improvement	Processing Time (h:m:s)
Buildings	1,600	54.332	100,062,500	Heuristic	17.83%	0:00:26
				Optimization	34.27%	2:30:00
	3,200		200,062,500	Heuristic	17.83%	0:00:51
				Optimization	31.66%	2:30:00
	6,400		400,062,500	Heuristic	17.84%	0:04:27
				Optimization	24.94%	2:30:00
	10,400		650,062,500	Heuristic	17.93%	0:14:08
				Optimization	21.02%	2:30:00
Pavements	2,586	1.7097	250,000,000	Heuristic	7.88%	0:02:02
				Optimization	5.32%	1:15:00
	5,172		500,000,000	Heuristic	7.78%	0:08:33
				Optimization	4.22%	1:15:00
				Optimization	5.98%	10:00:00
	10,344		1,000,000,000	Heuristic	7.80%	0:38:25
				Optimization	2.68%	1:15:00
Bridges	94	4.89	6,000,000	Heuristic	20.45%	0:00:03
				Optimization	31.70%	0:50:00
	752		48,000,000	Heuristic	18.81%	0:05:38
				Optimization	29.86%	0:50:00
	1,504		96,000,000	Heuristic	19.84%	0:28:50
				Optimization	27.40%	0:50:00
	3,008		192,000,000	Heuristic	19.84%	3:00:05
				Optimization	23.52%	0:50:00
	6,016		384,000,000	Heuristic	19.84%	17:01:35
				Optimization	22.29%	0:50:00

In the 6,016-bridge network, a processing time of more than 17 hours was needed to produce the final results, which is considered a long processing time as compared to the 14- and 38-minute processing times for the 10,400-building instance network and the 10,344-pavement network, respectively. The reason for this is that the model for the bridge case study is more complex than the models of the building and pavement case studies. The bridge model considers seven elements for each asset and five repair options for each element. This complexity increased the processing time. On the other hand, the optimization approach shows better improvement to the overall network condition than the heuristic approach, but shows steep performance degradation with problem size (under fixed processing time), as shown in Figure 13.

6. Conclusion

LCC analysis models for three types of assets (pavements, bridges, and buildings) have been implemented to facilitate the comparison of heuristic versus optimization techniques on large-scale problems.

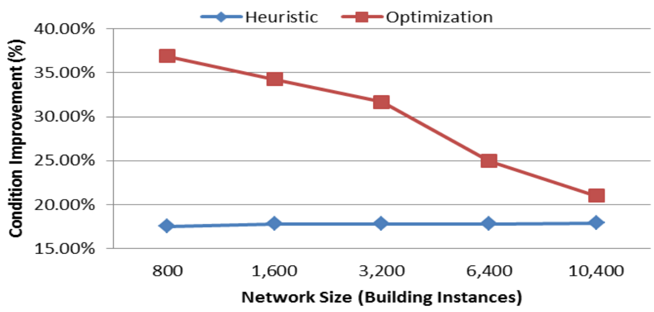

Figure 13. Degradation of Condition Improvement Results with network size (Buildings)

The large-scale networks were constructed by repeating the assets of the three case studies several times. Based on the results of the experiments, the heuristic approach proved to be a simple tool to provide a quick solution, while optimization is still needed to further improve the results, given enough processing time. More work is still needed to devise new heuristic and optimization techniques that can further improve the results.

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