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TRILEVEL OPTIMIZATION FRAMEWORK FOR MUNICIPAL CO-LOCATED INFRASTRUCTURE: CITY OF MONTREAL

Abu-Samra, S. [1,3], and Amador, L.[2]

[1,2] Ph.D. Candidate and Research Assistant, Department of Building, Civil, and Environmental Engineering, Concordia University

[3] Associate Professor, Department of Building, Civil, and Environmental Engineering, Concordia University

[4] solimanamr_8@aucegypt.edu

Abstract: Municipalities are experiencing high inefficiency and financial burden imposed by their under-performing infrastructure. One-third of Canada's municipal infrastructure are in fair, poor and failing condition states. The massive number of infrastructure intervention activities occurring in cities leads to detrimental social, environmental, and economic impacts on the community. Thus, coordinating the interventions of the co-located assets (i.e. roads, water, and sewer) to reduce the duplicate activities, service disruptions, and corridor rehabilitation cost, is progressively becoming of paramount importance to cope with those tough challenges. This paper develops a tri-level goal optimization framework to coordinate the intervention planning and efficiently allocate the funds among the co-located assets. The framework revolves through five models: (1) asset inventory, which comprises the asset characteristics of the corridor infrastructure; (2) deterioration and future condition models, which relies on probabilistic Weibull models to obtain the reliability of the co-located assets and account for the uncertainties across the assets' life-cycle; (3) financial model, which computes the direct and indirect costs for interventions and service disruptions; (4) temporal model that computes the disruption time for different intervention scenarios; and (5) Tri-level optimization model that features an integrated non-pre-emptive goal optimization and genetic algorithm engine to maximize the financial, reliability, and temporal improvements, as opposed to the conventional infrastructure management approach. The system was applied to a 9-km stretch on the city of Montreal network and the optimized intervention schedule exposed promising results as opposed to the heuristic-based with an overall improvement of 10% broken-down into 11%, 7%, 6%, for the reliability, life-cycle costs, and time. The developed framework facilitates the decision-making process for planning the corridor infrastructure interventions.

1 INTRODUCTION

Infrastructure is the foundation of our daily lives. The strength of this foundation enables our communities to prosper and local businesses to grow. Infrastructure development is a vital component that encourages the country's economic growth. Finance Canada report has recently shown that $1 billion investment in infrastructure creates 16,700 jobs and boosts the Gross Domestic Product (GDP) by $1.6 billion (MGI 2017;). Developing the infrastructure enhances the country's productivity, consequently making firms more competitive, and boosts the region's economy. Not only does the infrastructure enhance the efficiency of production, transportation, and communication, but it also plays a pivotal role in providing economic incentives to public and private sector participants. The accessibility and quality of infrastructure in a region help in shaping domestic firms' investment decisions and determine the region's attractiveness to foreign investors. Proper management of these vast systems is necessary to ensure that our communities continue to prosper. Infrastructure asset management is defined as "the systematic, coordinated planning and programming of investments or expenditures, design, construction, maintenance, operation, and in-service evaluation of physical facilities" (Haas et al. 1994). It covers all the activities that guarantee a minimal acceptable infrastructure Level of Service (LOS) to be brought up to the public. These activities range from the initial information acquisition that is required for calculating the public need for a specific type of infrastructure, to the maintenance and rehabilitation needed to maintain a proper LOS, from the infrastructure preliminary design and construction to the monitoring and evaluation process. Infrastructure asset management is not just about managing an existing facility to deliver an intended service, but it is also about taking critical decisions for properly investing the limited government resources to both; meet the need for building new infrastructure and keep the existing infrastructure within an acceptable LOS. Deferred investments for the existing infrastructure systems in many countries led to an extreme decline in the systems' LOS, the need for costly replacement, and in some cases sudden catastrophic failures. Even though infrastructure is deemed to be the foundation of the city to develop, Canada's aging municipal infrastructure is placing tremendous pressure on the government through steeply growing deficits to repair/replace the failing assets. The deficit was estimated at $123 billion for existing infrastructure, growing by $2 billion annually, and $115 billion for constructing new infrastructure to satisfy the growing population, which has doubled in 40 years from 17.9 million in 1960 to 35.1 million in 2013 and is expected to be 42.5 million by 2056 (Mirza 2009; Statistics Canada 2017). Recent studies estimated Canada's infrastructure deficit at a range between $110 billion to $270 billion (Berz et al. 2017). Furthermore, urbanization represents another challenge for asset managers. According to the United Nation Population, the world is undergoing the largest wave of urban growth. In 2008, more than 50% of the world's population was living in towns and cities and the figures are expected to exponentially swell throughout the upcoming years (Moir et al. 2014).

Although there is a clear need to better manage the existing municipal infrastructure, only a few municipalities have a coordinated asset management plan for their road, water, and sewer systems (InfraGuide 2006). While many municipalities have implemented pavement management systems, most do not have asset management plans for their water and sewer systems (De Leeuw 2015). Typically, these systems have longer service lives as opposed to the roads, but their condition is usually not visible and needs complicated technologies to be assessed. Several cities have developed and documented asset management plans to better utilize their expenditures (i.e Hamilton, Cambridge, Ontario, etc.). However, those plans failed to consider the interdependency among the systems. InfraGuide (2006) outlined an integrated approach for the assessment and evaluation of municipal road, water, and sewer networks. The approach consists of five steps: (a) data inventories, (b) investigations, (c) condition assessment, (d) performance evaluation, and (e) renewal plan. It outlined the need for coordinated renewal planning of municipal road, sewer, and water systems at a network level. Furthermore, it mentioned that the asset management planning framework should include clear policy objectives and established priorities. Elaborating on these perspectives reveals more integration aspects such as; top-down decision-making approach, where goals, objectives, and policies are the main decision-making drivers; and bottom-up management approaches, where the technical conditions of different assets and the daily intervention aspects are the main decision-making drivers. Furthermore, integrating the decision-making across multiple levels (i.e. municipal, city, province, and federal) have not been thoroughly investigated yet.

The application of multi-objectives optimization within the domain of infrastructure asset management has received considerable attention from researchers. Rashedi and Hegazy (2014) compared segmented GAs' and exact numerical optimization methods (GAMS/CPLEX) in the capital renewal planning of large infrastructure systems and came up with a conclusion that numerical methods are more superior. Furthermore, numerous researches have been carried out in the area of multi-objectives techniques including; linear programming, and integer programming. For instance, Abu-Samra et al. (2018) selected the optimal intervention plan for the roads and water networks at a network level. Likewise, other scholars developed bi-level goal optimization for transportation networks, using penalty and compromise methods, to minimize the financial and performance deviations (Saad et al. 2017). Yet, those remaining objectives are mathematically formulated in the form of equalities; such that they should meet certain limits identified by separately running individual optimization for each objective to determine the most efficient value. Similarly, El-Anwar et al. (2016) developed a mixed integer-liner programming and pareto optimization model for scheduling the post-disaster reconstruction plans for transportation networks. Yet, the study only dealt with extreme disastrous events (i.e. hurricanes, earthquakes, and tsunamis) and did not account for the typical aging deterioration.

This paper aims at developing a tri-level multi-objective goal optimization framework for the co-located municipal infrastructure. The system will aid decision-makers in selecting a near-optimum coordinated interventions' schedule/plan for the municipal infrastructure.

2 METHODOLOGY

The methodology stems from the concepts of the asset serviceability approach that relies on physical state, cost, criticality, and risk. It revolves through three phases as shown in Figure 1. The first phase is the data collection and intervention activities breakdown. This phase consists of two processes: (1) asset inventory; where data is collected from GIS maps and municipal reports to acquire the physical, spatial, social, and environmental characteristics of the systems under study, and (2) intervention activities database; where an intervention activities list is identified from multitude of tender documents. Subsequently, the intervention activities are categorized to standalone, parallel, and joint, based on the interdependencies among the systems under study. Thenceforth, the production rates and unit cost are estimated from numerous bills of quantities. The second phase is the intervention quantification modelling. This phase functions through three computational models for the lfie-cycle costs (LCC), disruption duration, and asset condition. In this study, the interventions are classified into three scenarios as follows: (1) combined intervention is carried out on the three networks in the corridor (i.e. roads, water, and sewer); (2) partially-combined intervention is undertaken on two of the networks in the corridor (i.e. roads and water, roads and sewer, water and sewer); and (3) conventional intervention is applied on one asset only in the corridor (i.e. roads, water, sewer). Thenceforth, the multi-dimensional savings models take place to compute the coordination savings as opposed to the conventional scenario. In this study, the time and cost savings along with the condition improvement are computed through the duration savings model, financial saving model and the corridor health model respectively. The duration savings model aims at computing the durations of the combined, partially-combined, and conventional interventions, based on the categorized activities and their production rates. Hence after, the duration savings of the combined intervention is compared with both the partially-combined and conventional interventions. Similarly, based on the activities' unit costs, the LCC model calculates the cost of undertaking combined, partially-combined, and conventional intervention to compute the cost savings of undertaking a combined intervention as opposed to the partially-combined and conventional interventions. The health model aims at computing the deterioration in the health of each asset. The deterioration models featured a modified weibull-based deterioration pattern to account for the extreme events that might take place (i.e. freeze and thaw, pipe break, etc.). The third phase is the optimization. This phase aims at selecting the optimal intervention scenario for each corridor throughout the study planning horizon. Given the fact that there exist various conflicting objectives (i.e. minimize LCC, maximize corridor health, minimize disruption duration), a novel tri-level integrated goal optimization and genetic algorithms was used to reduce the search space and reach a near optimum solution for the conflicting objectives.

2.1 Duration Savings Model

The duration savings model dynamically computes the durations of the combined, partially-combined, and conventional interventions, based on the categorized activities and their production rates. The benefit of coordinating the intervention actions is generating time savings in the corridor intervention duration compared to conventional approach. Those time savings take place because of the existence of joint activities that are shared among the three systems as well as the possibility of undertaking parallel activities rather than series ones in case proper coordination takes place (i.e. road resurfacing can occur concurrently while working on reinstating sewer laterals). As such, these activities can be undertaken only once, in case of combined approach, rather than ns, in case of partially-combined or conventional approach, where n is the number of standalone interventions and s is the number of systems (i.e. traffic control systems set up, residents notification, and site reinstatement work). Accordingly, those overlaps can be globalized through the basis of Standalone duration (SD), Parallel duration (PD), and Joint duration (JD). The SD represents the duration of the intervention activities required only for one asset and no other work can take place concurrently (i.e. installation of new sewer manholes). However, the PD represents the duration of the intervention activities that can take place concurrently. Furthermore, the JD represents the duration of the intervention actions required for two or more systems. This duration represents the activities that can take place between two or more systems concurrently (i.e. excavation of entrance and exit pits for water and sewer systems is an example of trenchless rehabilitation for both systems, traffic control devices, excavation and backfilling of common areas, site reinstatement works, etc.). A sample of the computations for the standalone could be displayed in Equation 1. The parallel and joint durations were similarly calculated.

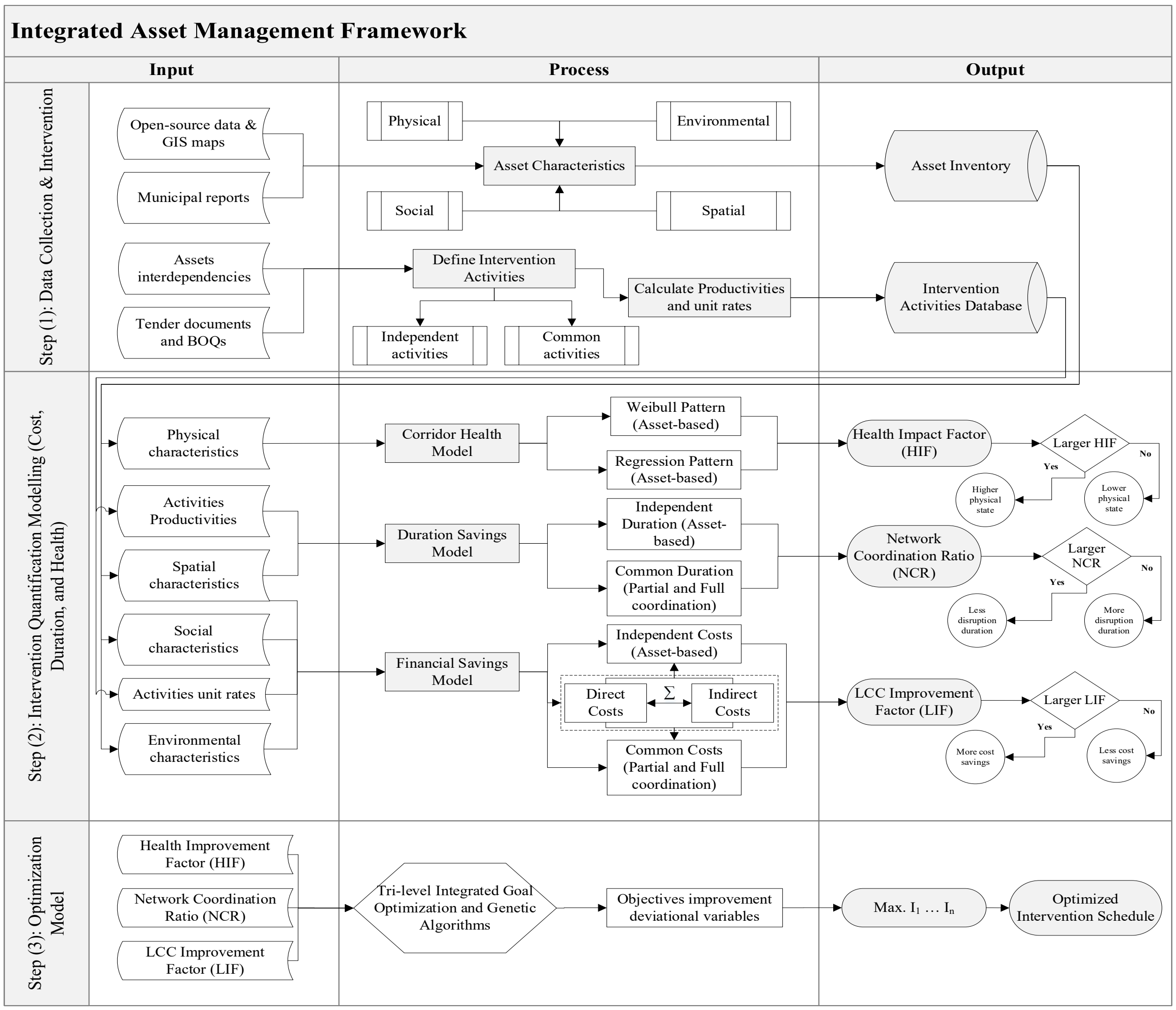

Figure 1: Integrated asset management framework

[1] $SD_{i_o} = \sum_{m=1}^{M} UR_m * Q_{m_o}$

where SD_{i_o} is the standalone of system i in corridor o (hours); m is the counter of the standalone activities respectively for system i, j, and k (number); UR_m is the unit rate for activity m (hours/unit); and Q_{m_o} is the quantity of work needed to complete activity m in corridor o (varies according to the units of measurement of the work).

Thenceforth, the activities are categorized and the potential parallel activities for each coordination scenario are defined. Afterwards, the durations for three intervention scenarios. Let Asset Standalone Duration (ASDi) represent the duration of all the intervention activities required for system i without interruptions, assuming no coordination takes place; and Corridor Coordinated Duration (CCD) represents the total duration of the entire project, assuming either partial or full coordination scenarios. Finally, the Network

Coordination Ratio (NCR) is computed to reflects the potential time savings that could be attained from coordinating the intervention activities, either partially or fully, during the execution phase. The greater NCR is, the less the extent of time savings resulting from coordination. A ratio of 100% represents no possible time savings due to the absence of either joint activities or activities that can be undertaken in parallel. They could be mathematically formulated as follows:

[2] $ASD_{i_o} = SD_{i_o} + JD_{ijk_o} + \sum_{i=1}^{n_s} JD_{ij_o} \ (i \neq j)$

[3] $CCD_o = \sum_{i=1}^{n_s} SD_{i_o} + \sum_{i=1}^{n_s} PD_{ijk_o} + \left\{JD_{ijk_o} * n_a\right\} + \sum_{i=1}^{n_s} \sum_{j=1}^{n_s} JD_{ij_o} \ (i \neq j)$

[4] $NCR\ (I_1{}^{+}) = \sum_{o=1}^{O} (\frac{\sum_{i=1}^{n_s} ASD_{i_o}}{CCD_o})$

where ASD_{i_o} is the standalone duration for all the systems n_s in corridor o (hours); i is the counter for the systems (number); n_s is the total number of systems (number); CCD_o is the corridor coordinated duration for all the systems n_s in corridor o (hours); n_a is the number of intervention actions that occurred at the same corridor (number); j is the counter for the systems (number); NCR is the network coordination ratio (%); o is the corridors' counter (number); and *O* is the total number of corridors (number).

2.2 Financial Savings Model

The financial savings model calculates the direct and indirect ownership and operational costs of the infrastructure systems. The direct costs represent the costs of the intervention activities needed to be undertaken throughout the planning horizon to deliver the services in an "acceptable" manner without interruption. On the other hand, the indirect costs, sometimes referred to as "Social" or "User" costs, reflect all the costs that are not directly related to the intervention (i.e. traffic disruption, vehicles or properties repair, business loss, noise disturbance, dirt and dust, environmental or health and safety issues, etc.). Those costs are subjective and rely on probabilistic approaches for predicting their amounts over the systems' service lives (Qin and Cutler 2014). The calculations of the indirect costs were based on the output of the duration savings model to consider the time extent of disruption. In order to compute the LCC for each intervention scenario, the cost centers were divided into three categories: (1) Standalone direct and indirect costs (SDC_i and 〖SIC〗_i), (2) Joint direct and indirect cost centers between systems i and j (JDC_ij and JIC_ij), and (3) Joint direct and indirect cost centers among systems i, j, and k (JDC_ijk and JIC_ijk). A sample of the standalone direct and indirect costs could be displayed in Equations 5 and 6 respectively. The joint direct and indirect costs among two or three systems was similarly computed.

[5] $\mathrm{SDC}_{\mathrm{i}_o} = \sum_{m=1}^{M} Q_{m_o} * \mathrm{UC}_m$

[6] $SIC_{i_o} = ASD_i * \frac{A_{i_o}}{\sum_{i=1}^{n_s} A_{i_o}} * \left[\left((1 - \mathrm{T_p}) * \mathrm{AADT} * \mathrm{UUC_p}\right) + \left(\mathrm{T_p} * \mathrm{AADT} * \mathrm{UUC_T}\right)\right]$

where $\mathrm{SDC}_{\mathrm{i}_o}$ is the total direct costs for the standalone activities of system i in corridor o (\$); UC_m is the unit cost for each standalone activity in system i (\$); SIC_{i_o} is the total indirect costs for the standalone activities of system i in corridor o (\$); $\mathrm{T_p}$ is the percentage of trucks (%); AADT is the average annual daily traffic representing the average number of daily vehicles (vehicles); $\mathrm{UUC_p}$ is the unit user cost for the passenger cars (\$); $\mathrm{UUC_T}$ is the unit user cost for the trucks (\$);

Afterwards, the LCC has been calculated for the three intervention scenarios. The conventional intervention scenario will result in the highest amount as all the joint direct and indirect cost centers, either between two systems or among the three systems, will be applied n_s times, dramatically increasing the direct and indirect costs. However, the partially-combined intervention scenario will experience na repetitions for the joint activities as there has been some potential activities that were not coordinated. Thenceforth, the combined intervention scenario will not experience any repetitions as the systems were fully coordinated and all the potentially coordinated activities were applied only once, decreasing the overall costs over the planning horizon as well as the amount/extent of disruption. Finally, the LCC Impact Factor (LIF) was calculated to compare the partially-combined or combined intervention scenarios with the conventional intervention scenario to visualize their potential cost savings. For instance, an LIF of "2" indicates that the combined intervention scenario utilizes two times less cost compared to the conventional intervention scenario. The LCC of the conventional scenario as well as the LIF of the combined scenario could be displayed in Equations 7 and 8 respectively. The other scenarios are similarly computed.

[7] $LCC_{CN_o} = \sum_{i=1}^{n_s}(\mathrm{SDC}_{\mathrm{i}_o} + SIC_{i_o}) + \sum_{i=1}^{n_s}\sum_{j=1}^{n_s}\left(\mathrm{JDC}_{\mathrm{ij}_o} + \mathrm{JIC}_{\mathrm{ij}_o}\right) * n_s + \sum_{i=1}^{n_s}\sum_{j=1}^{n_s}\sum_{k=1}^{n_s}\left(\mathrm{JDC}_{\mathrm{ijk}_o} + \mathrm{JIC}_{\mathrm{ijk}_o}\right) * n_s$

[8] $LIF_C\ (I_2{}^+) = \sum_{\mathrm{o}=1}^{\mathrm{O}}(\frac{LCC_{CN_O}}{LCC_{C_O}})$

where LCC_{CN_o} is the life-cycle costs of corridor o for the conventional intervention scenario ($); and LIF_C is the life-cycle costs impact factor of the combined network intervention scenario over the conventional intervention one (%).

2.3 Corridor Health Model

The corridor health model computes the health of the corridor. It features n_s deterioration models for all the n_s systems and compiles their outcomes to a corridor health state based on the weights of importance of each system. Due to their different service lives, deterioration patterns, surrounding conditions, etc., various Weibull-based deterioration models were built for the n_s systems. Based on the outcome of each integrated deterioration model, the health state (H_i) of each system (i) at each point of time (t) is available for all the intervention scenarios, considering the intervention actions' as well as the extreme events' effects on the health state. Accordingly, the systems' health states are compiled based on the systems' weights of importance and the corridor health state is computed. The deterioration models have pre-set LOS thresholds that alerts the decision makers in case the health state of any system reaches a value below the threshold to undertake rapid intervention decisions and avoid experiencing an increased probability of failure. Then, the corridor health is computed for the conventional, partially-combined, and combined scenarios represented by H_{CN}, H_{PC}, and H_C respectively as highlighted in Equation 9. Finally, the Health Impact Factor (HIF) is computed to compare the partially-combined or combined intervention scenarios with the conventional intervention scenario and visualize their potential corridor health improvement as displayed in Equation 10. An HIF<1 indicates that the considered intervention scenario resulted in an improved corridor health, compared to the conventional intervention scenario, and vice versa. For instance, a HIF of "1.2" indicates that the considered intervention scenario has 20% less health state compared to the conventional intervention scenario.

[9] $\mathrm{H_C} = \sum_{i=1}^{n_s}\left(W_i * \sum_{\mathrm{o}=1}^{\mathrm{X}}(\frac{L_o}{L_h} * H_{i_{C_o}})\right)$

[10] $HIF_C\ (\mathrm{I}_3^-) = \frac{H_{CN}}{H_C}$

where; W_i is the weight of importance assigned to system i (%); L_o represents the corridor length (m); L_h is the overall network length (m); H_C is the network health state in the conventional intervention scenario (%); $H_{i_{C_o}}$ is the health state of system i in corridor o for the combined intervention scenario (%); and HIF_C is the network health impact factor of the combined intervention scenario over the conventional intervention scenario (%).

2.4 Optimization Model

The complexity of the problem on hand arises due to the spatial interdependency among the assets under study as well as the varying intervention scenarios. Thus, it would be computationally impossible to manually reach an optimal scenario due to the outsized search space. The scenario of "n_s" systems, "x" corridors, "t" planning horizon, and "c" coordination scenarios will yield a total of c ns*x*t possible solutions. Even though, previous scholars utilized dynamic programming and phased optimization for fund allocation problems (Atef et al. 2012), they result in near optimal solutions, based on a micro-level, which are not necessarily optimal for the macro-level problem on hand. Thus, this paper proposes a trilevel integrated non-pre-emptive goal optimization and genetic algorithms approach that opts at reaching an optimum or near optimum solution for n_s systems in x corridors to reach a global optimal solution for the overall network. It functions through three integrated models that compute the repair duration, cost, and health of each corridor, accounting for all the possible combinations. Thenceforth, the decision making is undertaken through three layers where two of them are inner layers that act as an output for the outer optimization problem. Those layers represent the hierarchal management levels where the outer layer represents the strategic level decisions, the inner layers represent the tactical and operational levels' decisions respectively. The optimization runs the three layers runs in parallel where decisions in the outer optimization layer guide the outcomes of the two inner layers and the outcomes of the two inner layers provides the outer optimization layers with feedback on the implication of the selected alternative on the assessment indicators. The outer optimization layer, decision-making layer, aims at taking coordination decisions on a network level. In this level, the model answers two questions. The 1st one is "should we undertake an intervention for this corridor?", and if the answer is yes, the 2nd question is "how many systems should undertake interventions at this point of time?". The answers of those questions are then processed within the two inner layers. The 1st inner layer, systems layer, deals with each system within each corridor separately. Based on the health of each system within the corridor, the model aims at answering one question which is "which system(s) need intervention(s)?". For instance, if the answers of the outer layer were "yes for corridor 2" and "two in the 2nd year", the model will select the two-least health out of the n_s systems for interventions. Finally, the 2nd inner layer, operational layer, deals with the intervention actions along with their associated costs, time, and health improvement. Based on the answer of the question of the predecessor layer, the model will answer one question, which is "what type of intervention is required to enhance the system health within the least cost and time. For instance, let's continue the previous case of corridor 2 where the model selected system i and i+1 for interventions. In this case, the 2nd inner layer selects whether minor or major intervention is suitable for this section, based on the weights of importance associated with the conflicting objectives. If the municipality has limited budget, then the model will select the alternative with minimum cost to meet their tight budget. Similarly, if the municipality is looking for a better LOS, then the model will select the alternative that best enhances the system health state and LOS accordingly. The outcome of the 2nd inner layer directly provides the outer layer with feedback on the financial, temporal, and health improvement implications of the selected intervention scenario on all the network corridors.

This newly developed tri-level optimization approach dramatically reduces the search space through removing the illogical solutions (i.e. undertake a pipe replacement for a newly installed pipe, do resurfacing for a newly constructed road, etc..). To better imagine the enormous savings in the computational time, let's assume a case of 20 corridors, with 3 systems in each corridor, 2 intervention types for each system (minor and major), and 25-year planning horizon. In a typical one-level decision making, the number of decision variables will range from 0 (Do nothing) to 10 to account for all the coordination scenarios, systems and their corresponding types of interventions. Thus, the number of possible solutions will be 11^{20*25}. In tri-level decision making, the decision variables will range from 0 (Do nothing) to 3 (number of systems per intervention). The number of possible solutions in that case will be 4^{20*25}. The reduction of the search space, represented through savings in the number possible solution, for the tri-level approach would be the difference between both approaches, which is 7^{20*25}, almost three times less number of possible solutions, when compared to the typical one-level decision making. Moreover, given the complexity of the optimization problem, integrated non-pre-emptive goal optimization, integer programming, and genetic algorithms were utilized to enable decision makers trade-off their interventions based on conflicting goals as displayed in the equations below. The $s_{x_{tcir}}$_tcir integer-programming-based decision variable is used to represents the three-level dimensional space of "x" corridors, "t" planning horizon, "c" coordination scenario (i.e. conventional, partially combined, or combined), "i" system(s) selected for intervention, and "r" intervention type. For instance, if $s_{3_{52138}}$ is equal to 2, then the corridor 3 at year 5 will experience a partial integration for systems 1 and 3 using intervention 8. The model's objective, decision variables, and constraints could be mathematically represented in the equations below.

$$[11]\ \textbf{Decision variables} = \begin{bmatrix} s_{1_{1cir}} & \cdots & s_{X_{1cir}} \\ \vdots & \ddots & \vdots \\ s_{1_{Tcir}} & \cdots & s_{X_{Tcir}} \end{bmatrix}$$

For $x = 1, 2, \ldots X$
$t = 1, 2, \ldots N$
$c = 1, 2, \ldots n_s+1$
$i = 1, 2, \ldots n_s$
$r = 1, 2, \ldots R$

$$[12]\ \mathbf{Max}(\mathbf{Z}) = \sum_{j=1}^{m} w_j * (I_j^- + I_j^+)$$

$$[13]\ \mathbf{I_1^+} = \sum_{P=1}^{T} \left[\frac{\sum_{i=1}^{n_s}\left(\sum_{o=1}^{X}(ASD_{i_{o_p}})\right) - \sum_{i=1}^{n_s}\left(\sum_{o=1}^{X}(D_{i_{o_p}})\right)}{\sum_{i=1}^{n_s}\left(\sum_{o=1}^{X}(ASD_{i_{o_p}})\right)} \right]$$

$$[14]\ \mathbf{I_2^+} = \sum_{P=1}^{T} \left[\frac{\sum_{o=1}^{X}(LCC_{CN_{o_p}} * (1+in)^p) - \sum_{o=1}^{X}(LCC_{SC_{o_p}} * (1+in)^p)}{\sum_{o=1}^{X}(LCC_{CN_{o_p}} * (1+in)^p)} \right]$$

[15] $\mathbf{I}_3^- = \sum_{\mathbf{P=1}}^{\mathbf{T}} \left[\frac{\sum_{i=1}^{n_S}\left(W_i * \sum_{o=1}^{X}\left(\frac{L_o}{L_h} * H_{i_{SC_{o_p}}}\right)\right) - H_{\mathrm{CN}_p}}{H_{\mathrm{CN}_p}} \right]$

Subject to the following constraints:

[16] $H_{i_{SC_{o_p}}} \geq H_{i_{TH}}$

where $s_{x_{tcir}}$ is an integer-programming-based decision variable that represents the three dimensional space of “x” corridors, “t” planning horizon, “c” coordination scenario, “i” system(s) selected for intervention, and “r” intervention type (number); R is the total number of intervention types available for each system i (number); *Z* represents the maximized value for all the negative (I_i^-) and positive improvements (I_i^+) for m goals (%); *j* is the improvement deviational variables counter (number); *m* is the total number of improvement deviational variables (number); W_j represents the deferential weights among the conflicting goals (%); I_i is the improvement deviational variables (%); p is the age counter (years); T is the planning horizon (years); $H_{\mathrm{CN}_\mathrm{p}}$ is the overall network health for the conventional scenario at year p (%); $\mathrm{H}_{\mathrm{i}_{\mathrm{SC}_{\mathrm{o}_\mathrm{p}}}}$ is the optimized health of corridor o at year p for system i (%); $\mathrm{LCC}_{\mathrm{SC}_{\mathrm{op}}}$ is the optimized life-cycle cost of corridor o at year p ($); *in* is the annual inflation rate (%); $\mathrm{LCC}_{\mathrm{CN}_{\mathrm{op}}}$ is the conventional scenario life cycle cost of corridor o at year p ($); $\mathrm{D}_{\mathrm{i}_{\mathrm{op}}}$ is the optimized repair duration of corridor o at year p (hours); $ASD_{i_{o_p}}$ is the asset standalone duration for corridor o at year p (hours); and $\mathrm{H}_{\mathrm{i}_{\mathrm{TH}}}$ is the corridor health threshold for system i (%).

3 RESULTS AND ANALYSIS

To demonstrate the functionality of the proposed framework, the system was applied to a 9 km stretch from the city of Montreal roads, water, and sewer networks (Ville de Montreal 2017). The network comprises 20 corridors and was equally divided into four areas, five corridors each. The dataset scale/size, in terms of the number of corridors, is scaled down several times to enable the use of optimization techniques. It is worth noting that the condition states of the 20 corridors were assumed to represent the overall network condition states of each system. Time value of money has been considered with an interest rate of 2%. Furthermore, the study planning horizon was 25 years. The weights of the systems were assumed according to the overall LCC of each system across 100 years, using the longest life method. The results displayed 45%, 25%, and 30% for the roads, water, and sewer systems respectively. However, those weights are subject to change according to the stakeholders’ preferences (i.e. condition, replacement cost, crews’ availability, etc.).

The presented multi-objective tri-level optimization was applied to the case study and displayed encouraging results in terms of financial, temporal, and reliability indicators. The optimization engine used was Evolver$_{\mathrm{TM}}$ Version 7.5, which features a GAs’ optimization engine. The cross over and mutation rates were 80% and 20% respectively. The population size was 200 and the stopping criteria was the progress where the optimization will stop in case there was no change in the objective function after 50,000 trials. The weights of importance for the financial, temporal, and physical were 60%, 10%, and 30% respectively. The optimization showed promising results for the combined intervention system as opposed to the conventional one in terms of: (1) number of interventions; (2) delay time for service disruptions; (3) indirect costs resulting from the service disruption; (4) combined interventions for the road, water, and sewer networks; and (5) LCC across the planning horizon. The conventional system was modelled using meta-heuristic rules to ensure that the reliability threshold is met. As shown in Figure 2 (a), the reliability of the combined intervention program was better and much effective with an HIF of 11% as opposed to the conventional intervention program. The financial savings represented through LCC are shown in Figure 2 (b). The combined intervention program displayed 50% savings in terms of indirect costs compared to the conventional intervention program, implying less both number of interventions and delay time for service disruptions due to combining the interventions of the co-located systems sharing the same spatial location. Moreover, it showed 7% savings in terms of LCC compared to the conventional intervention program, which represents the financial savings resulting from combining the intervention actions of the three systems due to the existence of common and joint activities. Similarly, as displayed in Figure 2 (c), the combined intervention program displayed 6% savings in the repair time as opposed to the conventional intervention program. Those savings reflect the coordination of the intervention activities where the common activities have been carried out once instead of n_a or n_s times for the partially-combined and conventional intervention scenarios. Furthermore, undertaking the combined intervention increased the number of parallel activities, which increased the temporal savings as opposed to the conventional approach in which n_s interventions are separately undertaken for each system. Finally, the overall network results were integrated in an overall improvement factor (Z) of 10%, based on the objective weights of importance (w_j).

(a) Reliability

(b) Repair costs

(c) Repair time

Figure 2: City of Montreal – Optimization results

4 CONCLUSIONS

Even though plentiful modelling computations approaches have been utilized in the last decade, most of them focused on the development of decision-making frameworks for silo asset management systems. Few researchers built computational/optimization models for planning and scheduling the intervention activities for interdependent assets. This paper presented a novel coordination framework that can be used for intervention scheduling and fund allocation of municipal integrated infrastructure. It developed a tri-level goal optimization technique that combines meta-heuristics, binary coding, integer programming, and non-pre-emptive goal optimization procedure to trade-off the scheduling of different intervention alternatives. Furthermore, it quantified the temporal, financial, and health savings of the coordination decisions as opposed to the silo ones. The novelty of the optimization technique significantly reduced the search space and allowed the framework to be scaled up either to include more than three infrastructure systems or extend the planning horizon. The results of the implementation case study showed great savings in favor of the coordination over the silo one in terms of cost, time, and health. Despite the capabilities and flexibility of the system, the future work is underway to address some of the limitations including but not limited to: (1) incorporating more than three infrastructure systems in the multiple-system level to maximize the coordination benefits; (2) including other assessment indicators such as; space, risk, and intervention efficiency and effectiveness, (3) extending the study's planning horizon to the water and sewers' pipes service life, and (4) increase the data set size to incorporate larger number of corridors.

5 REFERENCES

Abu-Samra, S., Ahmed, M., Hammad, A., and Zayed, T. 2018. "Multiobjective framework for managing municipal integrated infrastructure." *Journal of Construction Engineering and Management*, ASCE, **144**(1).

Atef, A., Osman, H., and Moselhi, O. 2012. "Multi-objective Genetic Algorithm to allocate budgetary resources for condition assessment of water and sewer networks." *Canadian Journal of Civil Engineering*, **39**(9), 978–992.

Berz, K., Leech, J., and Shandal, V. 2017. *You Can Guide the Future of Canadian Infrastructure*. The Globe and Mail. ⟨https://beta.theglobeandmail.com/report-on-business/rob-commentary/you-can-guide-the-future-of-canadian-infrastructure/article36439075/⟩ (Nov. 7, 2017).

De leeuw, V. 2015. "*Integrated Asset Information Management Practices for Water and Wastewater Utilities*." ARC Advisory Group, 1-19, Dedham, Massachusetts, United States of America.

El-Anwar, O., Ye, J., and Orabi, W. 2016. "Efficient optimization of post-disaster reconstruction of transportation networks." *Journal of Computing in Civil Engineering*, ASCE, **30**(3).

Haas, R., Hudson, W., and Zaniewski, J. 1994. *Modern Pavement Management*. Krieger Publishing Company, Malabor, Florida, United States of America.

InfraGuide. 2006. *Managing risks*. FCM (Federation of Canadian Municipalities) and (National Research Council), Ottawa, Ontario, Canada.

MGI (Mckinsey Global Institute). 2017. "*Bridging Global Infrastructure Gaps: Has the World Made Progress?*" ⟨https://www.mckinsey.com/industries/capital-projects-and-infrastructure/our-insights/bridging-infrastructure-gaps-has-the-world-made-progress⟩ (Nov. 22, 2017).

Mirza, S. 2009. "*Canadian Infrastructure Crisis Still Critical.*", The Canadian Council for Public-Private Partnerships, <http://www.pppcouncil.ca/pdf/mirza_032009.pdf> (Jan. 18, 2017).

Moir, E., Moonen, T., and Clark, G. 2014. *The future of cities: what is the global agenda?* The Business of Cities, UK.

Qin, X., and Cutler, C. 2013. "*Review of road user costs and methods*" South Dakota University, Vermillion, South Dakota, United States of America.

Rashedi, R., and Hegazy, T. 2014. "Capital renewal optimisation for large-scale infrastructure networks: Genetic algorithms versus advanced mathematical tools." *Structure and Infrastructure Engineering*, Taylor and Francis, 11(3), 253-262.

Saad, D., Mansour, H., and Osman, H. 2017. "Concurrent bilevel multi-objective optimisation of renewal funding decisions for large-scale infrastructure networks". *Structure and Infrastructure Engineering*, Taylor and Francis, 1-10.

Statistics Canada. 2017. "*Canadian Demographics at a Glance: Population growth in Canada*", < http://www.statcan.gc.ca/daily-quotidien/140917/dq140917a-eng.htm > (Nov. 7, 2017).

Ville de Montreal. 2017. "View Performance Indicators." ⟨http://ville.montreal.qc.ca/vuesurlesindicateurs/⟩ (Nov. 16, 2017).