Resilience-Driven Sustainability-Based Rehabilitation Planning for Water Distribution Networks

Ahmed Assad, S.M. ASCE[1*]; Osama Moselhi, F. ASCE[2]; and Tarek Zayed, F. ASCE [3]

Abstract

Water distribution networks (WDNs) confront momentous challenges including the need to meet continuously increased demand, combat unforeseen disruptions, and reduce carbon emissions. Developing efficient plans for resilience enhancement of WDNs is thus essential recognizing the ubiquitous nature of WDNs and increased frequency and destructive severity of hazardous events. This paper presents a resilience-driven multi-objective optimization model to maximize the resilience of WDNs while minimizing the life cycle cost and carbon emissions. Enhancement actions are firstly determined and clustered into work packages before an optimized schedule is generated considering various operational and managerial factors. A real WDN in the City of London, Ontario, was utilized to demonstrate the proposed model's practicality. The resilience increased by 24% with 1.6 Million CAD investment. Additionally, a cost-saving around 33% is achievable if the proposed model is employed instead of a current utilized practice. The developed model is expected to help City managers establish optimal resilience enhancement plans, considering tight available budgets and limited workforce.

Keywords: Resilience, Sustainability, Water distribution networks, rehabilitation planning, Multi-objective optimization.

[1] Ph.D. Candidate, Department of Building, Civil and Environmental Engineering, Concordia University, Montréal, QC, Canada H3G 1M8; ahmed.assad@mail.concordia.ca
[2] Professor and Director of the Centre for Innovation in Construction and Infrastructure Engineering and Management (CICIEM), Department of Building, Civil and Environmental Engineering, Concordia University, Montréal, QC, Canada; moslhi@encs.concordia.ca
[3] Professor, Department of Building and Real Estate (BRE), The Hong Kong Polytechnic University, Kowloon, Hong Kong; tarek.zayed@polyu.edu.hk

Introduction

Water distribution networks (WDNs) are complex critical infrastructure systems that are vital to the health and safety of any society. Over decades, water utility managers have been trying to sustain functionality of WDNs to endure stresses imposed by service requirements, natural and human-made disruptions, and limited renewal expenditures. Classical approaches to manage WDNs have focused on minimizing the cost of these systems (Wu et al. 2010). However, increasing attention has been recently directed to consider the concepts of resilience and sustainability. While both resilience and sustainability encompass technical, social, and economic aspects, they emphasize distinct concepts. Sustainability is the ability to meet the present's needs without compromising future ones (WCED 1987). Resilience is the ability to mitigate risks and restore services after hazardous events (Ayyub 2014). Sustainability of WDNs can be achieved by maximizing service life, minimizing rehabilitation and lifecycle cost, minimizing emissions and energy requirements, and addressing the social criticality of different zones and segments. On the other hand, resilient WDNs shall be prepared to withstand disruptions with minimum degradation and to rapidly recover in case of service interruption (Assad et al. 2019). Municipalities are required to develop optimal rehabilitation plans to uphold the resilience and sustainability of WDNs. Such programs are essential acknowledging the ubiquitous nature of WDNs, continuous deterioration of their components, increased frequency and destructive consequences of disruptive events, and more compelling need to cut down carbon emissions. The development of such optimal plans shall consider various repair options, distinct targeted performance levels for different zones across the network, and clustering required actions into work packages based on shared commonalities. In Addition, scheduling tools are necessary considering the scarcity in resources and budgets. As such, this paper presents a comprehensive resilience enhancement framework for sustainable WDNs. The developed model suggests an optimal rehabilitation action for each water pipe segment along with the implementation time.

Literature Review

In recent years, many researchers have developed resilience-based asset management tools for WDNs. Most of those researchers focused their attention on developing metrics for assessing resilience of WDNs and on incorporating these metrics in the restoration phase of WDNs. (Assad et al. 2020; Bałut et al. 2019). These approaches are generally classified as either qualitative or quantitative approaches (Klise et al. 2015). Qualitative approaches can be either conceptual frameworks or semi-quantitative indices (Faust and Kaminsky 2017; Hosseini et al. 2016; Fiksel et al. 2014). Most of these approaches are subjective such that obtained results cannot be generalized on a large scale. On the other hand, quantitative approaches aim at identifying some quantifiable performance functions that can be observed before and after disruptive events. These approaches can be either probabilistic or deterministic based on whether the system's stochastic nature is considered. In addition, some of these approaches are dynamic as they consider time-dependent system performance functions (Cutter et al. 2008; Pant et al. 2014; Dessavre et al. 2016). Some researchers employed various hydraulic indicators as the system performance function to assess resilience of WDNs, flow-based metrics (Todini 2000; Suribabu 2017). Resilience of WDNs was also assessed utilizing graph-based methods, structural-based metrics (Yazdani et al. 2011; Meng et al. 2018; Shuang et al. 2019).

Nonetheless, fewer researchers presented holistic rehabilitation frameworks as means to enhance the resilience of existing WDNs. For example, Cimorelli et al. (2018) developed a rehabilitation methodology to improve resilience of WDNs subject to a limited budget. The authors utilized genetic algorithm, GA, and pressure-driven hydraulic simulation to investigate a flow-based resilience index's practicality in rehabilitation planning. They considered only one rehabilitation method, replacement, and analyzed one single failure. Other researchers focused on improving resilience of WDNs against seismic hazards such as (Zhao et al. 2015; Farahmandfar and Piratla 2017). Farahmandfar and Piratla (2017) considered two main rehabilitation actions, relining and replacement, to enhance resilience of WDNs to seismic hazards. GA was employed to determine the pipe segments that require rehabilitation considering their current condition and an expected earthquake scenario. However, the analysis was limited to one year, a snapshot in time, without considering the effect of deterioration and life cycle cost on the rehabilitation planning decisions. Zhao et al. (2015) compared the effects of two strategies for enhancing resilience of WDNs. They analyzed the impact of ductile retrofitting and meshed expansion on the seismic resilience of an actual WDN in China. The authors found that ductile retrofitting was a preferred resilience improvement strategy in cases of fund scarcity. In a different effort, Suribabu et al. (2016) proposed a model to enhance resilience of WDNs considering pipe diameter’s increase and parallel piping. The authors modeled two benchmark networks and iteratively increased the segments' diameters that have maximum flow velocity to the next available commercial size. Similarly, pipes were added parallel to those through which water flows with maximum velocity. This simplified approach is however not feasible for large networks. In addition, some scholars attempted to determine the rehabilitation priority of water segments to enhance their robustness against future hazards. Based Yoo et al. (2014) introduced a multi-criteria methodology for determining the rehabilitation priority of pipe segments to withstand seismic hazards. The authors ranked the needs of rehabilitations based on the importance of each segment. However, they did not investigate different types of rehabilitation actions or their impact on the overall network robustness. Earlier, Jayaram and Srinivasan (2008) developed a resilience-based rehabilitation model for WDNs using life cycle cost. The authors modeled the deterioration of pipe segments by simulating a sample network with an increasing roughness coefficient over an extended period. Their main finding was a significant cost saving when considering design and rehabilitation in a single analysis rather than solely focusing on overdesigning. However, the roughness increase rate was arbitrary assumed without considering an accurate deterioration estimation.

On the other hand, environmental aspects were not considered despite extensive research on rehabilitation of WDNs until recently (Roshani and Filion 2015). Some researchers compared the emissions associated with regular open-cut and trenchless rehabilitation techniques (Alsadi and Matthews 2020; Tavakoli et al. 2017; Lueke et al. 2015). For example, Alsadi and Matthews (2020) evaluated the carbon emissions during the entire life cycle of water pipelines. The authors analyzed different material types and installation methods to determine those that release the lowest amount of carbon emissions. They found that polyvinyl chloride, PVC, pipe segments installed using pipe bursting generate the least amount of carbon dioxide, CO_2. However, the authors did not consider the maintenance and repair needs in their analysis. Similarly, Lueke et al. (2015) compared the carbon footprint of two common water trenchless renewal techniques: pipe bursting and cured-in-place pipe. The study observed two actual projects in the United States to gather required data about the types of equipment utilized, cycle times, crews' productivities, and performed activities. In a different effort, Beale et al. (2013) investigated the impact of various rehabilitation strategies on the cost and carbon emissions of three networks in Australia. The authors reported an insignificant monetized value of carbon emissions released by rehabilitation works. However, they recommended expanding the application to include trenchless technologies, given the direct and indirect potential cost reduction that can be achieved. Roshani and Filion (2015) studied the influence of carbon-abatement polices during water pipe segments' rehabilitation process. The authors did not report considerable impacts of adopting a low discount rate and imposing a low carbon tax in reducing greenhouse gas, GHG, emissions. However, applying carbon tax enhanced rehabilitation during the early stages to avoid the accumulated costs of repairs, energy, and GHG emissions. In a previous effort, Roshani et al. (2012) investigated the impact of the same policies on the expansion design of a real network in Canada. They had also found no significant effect of such policies on the expansion design outputs. Earlier, Wu et al. (2010) proposed a multi-objective model that explicitly minimizes the life cycle GHG emissions in determining the optimal design of WDNs. Their work represented an enhanced version of the first multi-objective optimization model that considered GHG emissions and life cycle costs in designing WDNs proposed by (Dandy and Engelhardt 2006; Dandy et al. 2008). In a different effort, Meng et al. (2018) studied the relationship between national culture and infrastructure sustainability. Through qualitative comparative analysis, the authors identified the most critical cultural factors that influence the infrastructure sustainability projects (Meng et al. 2018). In addition to these studies, rehabilitation optimization of WDNs was investigated by many authors such as (Elshaboury 2020; Așchilean and Giurca 2018; D'Ercole et al. 2018; Muhammed et al. 2017).

Most of the previous studies employed hydraulic simulation in evaluating resilience enhancement of WDNs. However, this may not be an ideal choice in strategic planning of WDNs rehabilitation due to the extended computational time compared to other topology-based metrics. The reduction in computational time gained from utilizing such metrics is expected to grow as the network's size and complexity increase (Farahmandfar and Piratla 2018; Shuang et al. 2019). Previous studies on sustainability also attempted to include environmental aspects during the design or expansion of water networks with little efforts directed towards the operation phase. Some crucial issues were also disregarded in models that investigated resilience enhancement, rehabilitation, and sustainability of WDNs such as 1) integrating both sustainability and resilience objectives into one single analysis; 2) considering various repair methods along with their extended impact on the network resilience, lacking explicit models that estimate the updated deterioration behavior after rehabilitation actions are taken; 3) addressing the uncertainty in estimating repair time and cost; 4) accounting for distinct levels of importance of different zones when considering resilience planning of large networks; 5) clustering scattered required enhancement actions into deliverable work packages to facilitate efficient resource allocation and scheduling. To this end, this paper aims to develop an optimization model for determining and scheduling resilience enhancement interventions of WDNs. Sustainability objectives are also considered by minimizing both the cost and carbon emissions of the resilience enhancement actions. The output is an optimal intervention action for each segment. A schedule is also established to visualize rehabilitation work packages of the enhancement process.

Methodology

This paper introduces a newly developed model for resilience enhancement planning of WDNs. This work presents the third component of a holistic resilience-driven management framework of WDNs. The first work presented in Assad et al. (2019) introduced a newly developed multi-attribute metric for assessing and evaluating resilience of WDNs. Next, Assad et al. (2020) utilized this metric in a stochastic study to analyze the resilience restorative capacity of WDNs. Several hazardous scenarios were studied, performance impact was analyzed, and various restoration strategies were examined to select the most optimal one that minimizes the time and cost of recovery process under uncertainty. This paper extends the analysis to investigate the resilience enhancement process before disruption occurrence, absorptive capacity. It captures the resilience degradation due to aging and resilience improvement due to rehabilitation interventions actions. The resilience enhancement model developed in this paper encompasses two main phases: 1) determining enhancement actions, and 2) scheduling these actions. In the first phase, segments selected for enhancement along with the enhancement actions and their timings are determined. The second phase aims at clustering the resulted actions into work packages based on specific similarities before scheduling them. Resilience absorptive capacity is the resilience objective that is aimed to be improved in this work. Absorptive capacity is the ability of WDNs to withstand disruptions without significant degradation. It can be boosted through proactive mitigation measures that strengthen the current condition of WDNs and shorten the time of recovery following a disruptive event. In addition, life cycle cost and carbon emissions associated with various enhancement actions are considered to account for the sustainability of WDNs. Life cycle cost includes the costs of any minor or major rehabilitation actions taken at any time along the planning horizon. Additionally, the costs of replacing severely deteriorated segments by installing new ones are included. Costs of breaks and leaks in various pipe segments are not included in this formulation.

The developed method encompasses three main modules plus a previously developed one by Assad et al. (2019), as shown in Figure 1. The details of each module are presented subsequently. Figure 1 depicts the components of the proposed framework and the interactions between them.

Insert Figure 1

Resilience Assessment Module

Resilience of WDNs in this work is assessed based on a resilience metric proposed by (Assad et al. 2019). This metric integrates robustness and redundancy of WDNs in assessing resilience, as shown in Equation 1. Robustness is the ability of water networks to withstand disruptive events without significant degradation. It is measured by integrating the reliability and criticality of water segments. A deteriorated pipe segment, low reliability, is more susceptible to failure when subjected to various disruptions.

$$Я = w_1 \times \frac{\sum_{i=1}^{P} R_i \times C_i}{\sum_{i=1}^{n} C_i} + w_2 \times \frac{m-n-1}{2n-5} \quad (1)$$

Where Я is the resilience metric, R_i, C_i are the reliability and criticality index of segment i, P is the number of pipe segments, n and m are the network size and order, and w_1, and w_2 are relative weights of importance. This metric presents a measure of the network structural performance, structural reliability. The criticality index considers various economic, social, and environmental factors of pipe segments. These factors aim at assessing the expected economic, social, and environmental consequences of each pipe segment's failure. Stochastic modeling was employed to estimate the reliability and to establish deterioration curves for each water segment considering its age, material type, size, and previous number of failures. Redundancy is measured based on the intensity of loops available in the network, meshed-ness coefficient. More details about this metric and its practicality to be used in resilience assessments, enhancement, and restoration applications can be found at (Assad et al. 2019). This study focuses on enhancing resilience of water segments by improving its robustness. Rehabilitation of deteriorated segments can increase the reliability and robustness of water networks. The novelty of the employed metric is in its ability to dynamically update reliability of segments, and thus network resilience, based on their characteristics and the type of intervention actions they may undergo. For example, when a pipe segment is replaced, its reliability is increased to a value of 0.99. This value is less than a theoretical benchmark of 1.0 to account for factors that compromise the installation quality (Assad et al. 2020). In addition, its reliability along the subsequent years is calculated based on its age and the deterioration curve of newly installed segments that share the same size and material cohort. Similarly, major and minor actions increase the current reliability level of a segment and change its deterioration behavior along the following years. Resilience improvement realized due to major and minor interventions are assumed to be 0.5 and 0.25, respectively. Improvement values were elicited after analyzing the gathered maintenance reports of previous rehabilitation actions. These values match the expected improvement due to various rehabilitation types in other infrastructure systems (Elbehairy 2007). Subsequent deterioration of these segments is updated based on the deterioration curves of segments that were subjected to similar intervention actions and share the same characteristics. More details about the dynamic calculation and update of segments' reliabilities and deteriorations can be found at (Assad et al. 2019).

Weights in Equation 1 are user-defined values which allows decision makers to specify the relative weights of importance of each resilience quality: robustness and redundancy. In this analysis, they were set as at 0.75 and 0.25 for robustness and redundancy, respectively. Sensitivity analysis was performed and documented in a previous publication where the authors first introduced this metric (Ahmed et al. 2019).

Enhancement Module

This module investigates various types of interventions along with their associated costs, durations, and carbon emissions. Intervention actions can be broadly classified into four categories: do nothing, minor actions, major actions, and full replacement. In this analysis, two methods are considered under each intervention category, as shown in Table 1. As previously mentioned, reliability, and resilience, improvement is estimated based on the category of the intervention action. However, costs, durations, and associated CO_2 emissions are different for various methods within the same category. In addition, these methods are different in their range of applicability and suitability for various segment's characteristics.

Insert Table 1

For example, while both pipe bursting, PB, and pipe splitting, PS, are possible methods for full replacement, only PS is suitable for ductile iron segments as they do not easily fracture when utilizing classical PB (Atalah 2009). Also, epoxy lining, EL, is preferred over cement mortar lining, CML, as a minor action when the pipe segment is of a low thickness, less than 5mm (Yazdekhasti et al. 2014). Furthermore, slip lining, SL, is a more cost-effective option for major actions; however, it can be only be applied to segments that are made of PVC and polyethylene, PE, (Yazdekhasti et al. 2014). It shall be noted that other methods can be added based on the preference of the responsible municipality.

Costs and durations of intervention methods are then computed according to the method type and segment size. Unit costs and times were collected from different practitioners working in the water industry across Canada in 2019 and early 2020. The minimum, maximum, and average estimates were used to sample probability distribution functions for unit costs and durations. PERT distribution was selected to sample the associated uncertainties. Unlike uniform and triangular distribution, PERT distribution asserts more significance on the most probable estimate, which is better known with for decision makers. This fits the situation where municipalities constantly respond to failures and thus accumulate better experience in estimating the most probable values than the limit ones (Peters 2016; Assad et al. 2020). Furthermore, PERT distribution has a smoother shape than the angular shape of triangular distribution which offers a better fit for the limit values (Law et al. 2000). Cost and time inputs to the optimization model are thus stochastically sampled values rather than arbitrarily assumed estimates. The model also allows users to assign these values based on their preferences without effecting the proposed calculations. Carbon emissions were then calculated for each enhancement method utilizing a calculator tool initially developed by the North American Society of Trenchless Technology, NASTT, (O'Sullivan 2010). The calculator has been updated by the British Columbia chapter, NASTT-BC, and approved by the province of British Columbia, Canada (Beale et al. 2013; O'Sullivan 2010). This tool estimates the carbon emission profile associated with various pipeline replacement and renovation techniques based on the project dimensions, pipeline size, material, surface type, and others. The estimated emission profile considers site and transportation operations including mobilization, excavation, disposal, backfilling, and pipe installation or rehabilitation works. For example, the estimated CO_2 emissions resulting from replacing a pipe segment of 200mm in diameter, 200m in length, and buried at 2.5m depth utilizing PB technique is 2.5 (CO_2-e tonne). Similar results were calculated for all other segments and intervention methods. These results were used as inputs to the enhancement optimization model.

Enhancement Actions Optimization

As previously mentioned, the developed enhancement model aims at optimizing three conflicting objectives: 1) minimizing cost; 2) minimizing emissions; 3) and maximizing resilience after adopting all enhancement actions, as shown in Equations 2-4, respectively.

$$\textbf{Minimize}\ T.C. = \sum_{t\in T}\sum_{i\in P}\sum_{j\in M}\frac{1}{(1+r)^t}\left(x_{i,j}^t * C_{i,j}^t\right) \quad (2)$$

Where TC = total cost; $x_{i,j}^t$ = decision variable that takes a value of 1 when pipe segment i is enhanced using repair method j during year t and 0 otherwise; $C_{i,j}^t$ = enhancement cost of pipe segment *i* using method *j* during year *t*; *r* = discount rate; *P; M*; and *T* = the number of pipe segments, enhancement methods, and years respectively.

$$\textbf{Minimize}\ \ T.E. = \sum_{t\in T}\sum_{i\in P}\sum_{j\in M}\left(x_{i,j}^{t} * E_{i,j}^{t}\right) \tag{3}$$

Where *TE* = total CO_2 emissions; $E_{i,j}^{t}$ = CO_2 emissions resulting from the enhancement of pipe segment *i* using method *j* during year *t*.

$$\textbf{Maximize}\ \ Я_{T} = \frac{\sum_{k\in S}(Я_{k}^{T} \times L_{k})}{\sum_{k\in S}(L_{k})} \tag{4}$$

$$Я_{k}^{t} = Я_{k}^{t-1} + ЯI_{k}^{t} - ЯD_{k}^{t} \tag{5}$$

$$ЯI_{k}^{t} = \sum_{i\in P}\sum_{j\in M}\left(x_{i,j}^{t} * ЯI_{i,j}^{t}\right) \tag{6}$$

Where $Я_{T}$ = resilience at year *T*, the end of the planning horizon. When several subnetworks are considered, their lengths, L_{k}, are used to get a weighted average resilience. $Я_{k}^{t}$ = resilience level of subnetwork *k* at year *t*; $ЯD_{k}^{t}$ = resilience deterioration of subnetwork *k* at year *t* due to aging; $ЯI_{k}^{t}$ = resilience improvement of subnetwork *k* at year *t* due to enhancement actions, $ЯI_{i,j}^{t}$ = resilience improvement resulting from the enhancement of pipe segment *i* using method *j* during year *t*; and *S* = the total number of subnetworks. Equation 5 suggests that resilience at any year equals the resilience of the previous year plus any resilience improvement realized by enhancement actions minus the resilience deterioration due to aging during that year. A budgetary constraint is added to guarantee that annual enhancement costs do not surpass the annual available budget, Equation 7. A constraint is also added in Equation 8 to ensure that any subnetwork's resilience along the planning horizon is always more than a minimum threshold value. This value can be specified individually for each subnetwork based on its importance. In addition, enhancement actions are usually accompanied by significant disruption. Hence, another constraint is added, Equation 9, to limit the number of visits for each specific segment along the planning horizon to a user-defined value. A visit is featured by each time a crew is dispatched to implement a particular rehabilitation action on a specific pipe segment.

Subject to

$$\sum_{i \in P} \sum_{j \in M} \left(C_{i,j}^{t} \right) \leq \; AB_t \quad (7)$$

$$\min_{t \in T} (\text{Я}_k^t) \; \geq \; \text{Я}_{\,k,Th} \; (8)$$

$$V_i \leq \; V_{max} \quad (9)$$

$$x_{i,j}^{t}, = \; \{0,1\} \; (10)$$

$$\forall \; i \; \in \; P, j \in M, k \in S, t \; \in T$$

Where AB_t = annual budget allocated for enhancement actions; $\text{Я}_{\,k,Th}$ = minimum resilience threshold for each subnetwork; and V_i = number of visits for segment i .

Once enhancement actions of individual segments are determined along with their implementation year, the framework proceeds with the scheduling process. A set of actions during a specific year is scheduled on two main stages: 1) Clustering the actions into work packages, and 2) Determining the optimal enhancement schedule. In the first stage, pipe segments are divided into work packages (WPs) based on their geographical location and intervention method. These WPs are formulated to facilitate monitoring and control of the enhancement process based on the number of pipe segments, type of enhancement work and its complexity, available budget, outsourcing versus in-house rehabilitation, and other factors. Different clustering techniques are utilized to cluster the pipe segments on groups based on their geographical location.

Clustering is the process of portioning a set of objects into homogenous groups based on shared similarities. In this analysis, clustering techniques are utilized to divide the selected network into a set of clusters based on the geographical location. K-means and K-medoid algorithms are investigated and compared to select the best performing algorithm to cluster the chosen network. The objective in K-means clustering is to minimize the squared error between the empirical mean of a cluster, clusters' centroids, and the cluster's points. In this algorithm, the cluster's centroid can, but do not have to, be one of the data points. This is the main distinction that differentiates K-means clustering algorithm from K-medoids, where the cluster's centroid is always one of the points in that cluster. The steps of K-means algorithms are shown below (Jain 2010):

1. Specify a certain number of clusters and a matching number random initial points, K, to serve as the preliminary clusters' centroids.
2. Compute the Euclidean distance between each data pint and the centroids. Euclidean distance is the square root of the sum of squared differences between components of two pattern vectors $X_i = X_{i1}; X_{i2}; \ldots, X_{id}$ and $X_j = X_{j1}; X_{j2}; \ldots X_{jd}$, as shown in Equation 11 (Sawant 2015):

$$d_{ij} = \sqrt{\sum_{k=1}^{d} \left(x_{ik} - x_{jk}\right)^2} \quad (11)$$

3. Assign data points to clusters based on the minimum distance between the data points and clusters' centroids, and recalculate the clusters' centroids.
4. Repeat steps 2-3 until convergence which is evidenced by no further observed changes regarding the centroid and data points.

The clustering algorithms were run using RapidMiner 9.6 platform (Rapid-Miner Inc. 2016). Since clustering is an unsupervised machine learning process, evaluating the generated clusters' quality may not be trivial. Clustering aims to minimize the intra-cluster distance, distance within the same cluster, and maximize the inter-cluster distance between clusters. To attain that, the Davies–Bouldin Index is employed to compare the clustering quality of K-means and K-medoids. Davies–Bouldin Index is a ratio between the sum of intra-cluster scatter to the inter-cluster separation, as shown in Equation 12 (Davies and Bouldin 1979):

$$DBI = \frac{1}{N}\sum_{i,j=1}^{N} \max_{i\neq j}\left(\frac{D_i + D_j}{d_{i,j}}\right) \quad (12)$$

Where *D* and *d* are the in the intra-cluster and the inter-cluster distances. The intra-cluster distance is measured as the average distance between the cluster centroid and data points, Equation 13. The inter-cluster distance is the distance between the centroids of the two clusters, Equations 11, by replacing X_i and X_j with C_i and C_j.

$$D = \frac{\sum_i \|X_a - C_i\|}{N_i} \quad (13)$$

Where X_a is an arbitrary point in cluster *i*; C_i and $N_i$are the centroid and is the total number of points in cluster *i*. A lower value of Davies–Bouldin index implies compact clusters with centroids far from each other, thus a better cluster (Sahani and Bhuyan 2017).

Packaging and Scheduling Module

An optimization model is then formulated to determine the best distribution of enhancement actions into WPs. The aim is to efficiently cluster the rehabilitation actions into works packages. Adding as many segments as possible while respecting a set of constraints ensures maximizing each WP's resilience improvement. This approach avoids the generation of numerous packages that would need to be furtherly merged in subsequent steps. Th objective function is formulated to maximize the resilience improvement of the WP that has the minimum resilience improvement, as shown in Equation 14. A constraint is added in Equation 16 to specify the minimum size of WPs. Two more constraints are added in Equations 17 and 18 to determine the maximum size of WPs and to ensure that each WP consists of segments that share the same enhancement method. These are defined as soft constraints to account for exceptional solutions where segments of different enhancement methods, hybrid WP, or more actions than the maximum size, over-sized WP, need to be clustered in a WP. However, these solutions would imply penalties (α) and (β) in the objective function, Equation 14. Constraint 19 is included to ensure that segments in each WP share the same geographical zone.

$$\textbf{Maximize}\quad Я = \min_{v \in WP}(Я.\mathrm{I}_v) - \alpha - \beta \tag{14}$$

$$Я.\mathrm{I}_v = \sum_{v \in WP} \sum_{i \in P} \left(y_{i,v} * Я.I_i\right) \tag{15}$$

Subject to

$$\mathrm{C}_v \geq \mathrm{C}_{min} \ (16)$$

$$\mathrm{C}_v - \alpha \leq \mathrm{C}_{max} \ (17)$$

$$\mathrm{MT}_v - \beta = 1 \ (18)$$

$$\mathrm{Z}_v = 1 \ (19)$$

$$\alpha, \beta \geq 0 \ (20)$$

Where $y_{i,v}$ = decision variable that takes a value of 1 when pipe segment *i* is clustered in WP *v*; $Я.\mathrm{I}_v$= resilience improvement of work package *v*; C_v = cost of work package *v*, the summation of the individual enhancements actions' costs in work package *v*; C_{min} and C_{max}= minimum and maximum costs WPs representing the minimum and maximum possible size of a WP; MT_v =

number of different enhancement methods' types in WP *v*; Z_v = number of location zones in work package *v*; and *WP* is the number of work packages.

Finally, an optimization model is formulated to schedule the resulted WPs. Inputs include WPs, their total costs and durations, number of contractors, and maximum contract value. The objective of this scheduling model is to minimize the time of resilience enhancement process, as shown in Equation 21.

$$\textbf{Minimize} \quad T = \max_{w \in C}(T_w) \qquad (21)$$

$$TT_w = \sum_{w \in C} \sum_{v \in WP} \left(z_{v,w} * T_v\right) \qquad (22)$$

Where *T*= time of resilience enhancement; T_w = total time for contractor *w*; T_v = duration of work package *v*, the summation of the individual enhancements actions' durations in work package *v*; and $z_{v,w}$ = decision variable that takes a value of 1 when work package *v* is assigned to contractor *w*. A maximum contract price constraint is added to comply with the City's regulations, Equation 23.

$$\mathrm{C}_w \leq \mathrm{CP}_{max} \quad (23)$$

Where C_w= the total cost of work packages assigned to contractor *w;* and CP_{max} = the maximum allowable contract price to assure fair business practices.

It is worth mentioning that packaging and scheduling represent a preceding step before launching the bidding process. In this step, a municipality determines the size and type of each rehabilitation package before calling for technical and financial proposals. This would enhance the contractors' selection process since only those capable of executing the rehabilitation type of a specific package can apply. In addition, the maximum contract price assures fair business practices by allowing more contractors to receive works. The price calculated in this step, along with the suggested schedule, represents guidelines on the maximum expected cost and duration given the market conditions. This is essential in strategic planning and budgeting. The municipality may get better prices from the qualified contractors during the bidding process.

The resilience-driven sustainability-based rehabilitation planning model developed in this study was evaluated through a three-tire verification and validation process. Firstly, two optimization algorithms were assessed to compare their computational capabilities in solving the formulated problem. Secondly, the enhancement optimization results were compared to those determined by a heuristic model utilized by several cities in Canada. Finally, the solution quality and computational gains resulting from employing the proposed metric was demonstrated by a comparison with the performance a previous metric reported in literature. The remaining f this paper is arranges such that the utilized algorithms and decision-making techniques are briefly presented in the next section. Subsequently, implementation and validation of the proposed models are detailed. Concluding remarks and future extensions are finally elicited.

Optimization algorithms

Genetic algorithm, GA, and ant colony optimization, ACO are commonly utilized in asset management and resilience applications. In this paper, GA and a modified version of ACO are investigated to identify the best performing to solve the formulated optimization problem. GA is frequently utilized in asset management applications due to its efficiency and availability in many commercial packages (El-Ghandour and Elbeltagi 2017). The modified version of ACO utilized in this paper was not previously employed, at least to the authors' knowledge, in resilience-based asset management applications. Below is a brief description of each algorithm followed by an explanation of the metric used to compare their performances.

The first algorithm is an extension of the classical ant colony optimization proposed by (Schlüter et al. 2009). Initially, the basic idea of ACO is to mimic the biological behavior of ants trying to reach a food source. By using pheromone concentration, a substance that ants deposit while traveling, ants choose a path to the food source. The set of vertices on a path represent the solution components. Pheromone values, usually within a pheromone table, are continuously updated based on information gained during the search process. The procedure iteratively is repeated until meeting stopping criteria (Dorigo et al. 2006). Schlüter et al. (2009) exploit an aggregated weighted sum of several multi-kernel Gaussian probability density functions instead of pheromone tables to guide the search process. A discretization of this continuous function is introduced to allow intuitive handling of integer variables. Solution archive, SA, is suggested to continuously store and rank the most promising solutions investigated so far. In this extension, the mean and deviation of the Gaussian probability density functions, PDFs, are updated based on solutions stored in the SA. Each time a solution is created, its attractiveness is calculated and compared to those in the SA archive. A solution will be placed in the j^{th} position only if it has a better attractiveness than solution j. This way updating the SA implies updating the characteristics of the PDF, pheromone update, and thus the process of creating new solutions. The number of kernels within the multi-kernel Gauss PDF corresponds to the size of the SA, in this study taken as 40. In Addition, the algorithm is fortified with a robust penalty method for constraints handling and a local heuristic, sequential quadratic programming, to guide searching around the best-known solution (Exler and Schittkowski 2007). More details about this modified version of ACO and its implementation on real-world problems can be found at (Schlüter et al. 2009; Schlüter et al. 2012).

Genetic Algorithm (GA) is a search heuristic that was introduced in the 1970s by John Holland (1975) inspired by the natural evolution theory. The first step in this algorithm is to initialize a set of random solutions; each represents a possible combination of the decision variables. Each solution's fitness is then calculated and used to rank each solution against other candidates in a population. Best solutions are selected utilizing specific selection strategies to reproduce by undergoing further genetic crossover and mutation genetic operators. Tournament selection is the parent selection strategy employed in this study. In crossover, genes in two parents are exchanged until reaching the randomly selected crossover point. In this study, the crossover point was randomly selected with a probability of 0.75. To prevent premature convergence, genes are randomly flipped with a low probability, taken as 0.015, in the mutation step. The process is iteratively repeated until meeting the stopping criteria (Whitley 1994). The two algorithms were run in a Matlab environment, and parameters' values were calibrated through trial and error.

Hypervolume indicator is the most common utilized metric to compare the performance of multi-objective optimization algorithms (Zitzler et al. 2003). It measures the m-dimensional volume of the region in objective space enclosed by the obtained non-dominated solutions and a reference point. Hypervolume indicator is the only indicator that can consider accuracy, cardinality, and diversity of the optimal solution (Riquelme et al. 2015). Accuracy is a closeness measure of the obtained solutions to the true non-dominated solutions. Cardinality is the number of points in the obtained solution. Diversity indicates the spread of the obtained solutions in the search space (Riquelme et al. 2015). Equation 24 is used to compute the hypervolume indicator (Nebro et al. 2013):

$$I_{HV} = \text{volume}\left(\bigcup_{i=1}^{|Q|} v_i\right) \quad (24)$$

Where I_{HV} is the hypervolume indicator; v_i is the hypercube of non-dominated solution i; and Q is the set of non-dominated solutions. A higher value of Hypervolume indicator suggests a larger distance between the obtained solution and the reference point, nadir point, hence a better solution.

Multi-criterion decision-making

The result of multi-objective optimization is a set of Pareto optimal solutions. Multi-criterion decision-making (MCDM) techniques can assist in selecting the most appropriate solution among the set of Pareto solutions. In this analysis, the Shannon Entropy and Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE II) are utilized to determine the best solution of the Pareto frontier points. Shannon entropy is based on the informational theory that assigns smaller weights to those attributes that assume similar values across various alternatives. In this work, weights of objectives are calculated based on the degree of index dispersion as detailed by (Akyene 2012). The PROMETHEE method is an interactive MCDM technique that can handle quantitative and qualitative criteria with discrete alternatives (Brans et al. 1986). Recently, the PROMETTE method has been successfully applied to real-life planning problems to rank alternatives which are difficult to be compared because of the conflicting trade-off relation between the evaluation criteria. (Abdullah et al. 2019). In this method, a preference function for each criterion is selected. A preference index for alternative “a” over “b” is computed based on this function. This index represents a measure to support the hypothesis that alternative “a” is preferred to “b”. The steps of applying the PROMETH II method can be reviewed at (Brans et al. 1986; Polat 2016)

Data Collection

Data needed for development and implementation purposes were gathered as geographic information systems, GIS, shapefiles of an actual WDN in the City London, Ontario. Different segments' characteristics, such as sizes, material types, ages, and installation depths were extracted. Street categories, traffic volume, and population density were also gathered from separate layers. These details were used along with data regarding each segment's installation date and failure history to assess the network resilience as per Equation 1. Coordinates of pipe segments were utilized to cluster the network into distinct geographical zones. Additionally, unit costs and durations of the considered rehabilitation methods were gathered to be utilized as inputs to the optimization model. Table 2 depicts the unit cost and times of the considered rehabilitation methods.

Insert Table 2

Optimization Model Implementation to a Case Study

The developed model was implemented on a section of the water network in London, Ontario. The selected section comprises 369 pipe segments of diameters ranging between 40mm and 450 mm that amount to approximately 34 km of length. The material types available are cast iron (CI), ductile iron (DI), and PVC. The selected section consists of three subnetworks covering a wide variation in land use, serviced facilities, and road types, as shown in Figures 2 and 3. Figure 2 shows the overall water network in the City of London with the land use zones superimposed. Distinct residential zones reflect variation in population size and tax base. Figure 3 depicts three subnetworks that form the selected case study of this paper. Each network is assigned a distinct minimum resilience threshold reflecting its importance to the decision-makers as previously explained.

Insert Figure 2

Insert Figure 3

Next, the multi-objective optimization problem was solved using the modified ACO and GA to determine their respective capabilities. To ensure the consistency of the algorithms' results, the problem was solved several times utilizing each algorithm (Dao et al. 2016). To provide a fair comparison, the number of iterations within each algorithm was set to 200, with a population size of 150. All optimization runs were performed on an 8GB 343 RAM, 3.60 GHz i7 core CPU, and Windows 7 with a 64-bit operating system. Table 3 illustrates the comparison between the modified ACO and GA. The modified ACO achieved the best values for the cost, resilience, and emissions objectives. Similarly, the worst values for the cost, resilience, and emissions objectives obtained by the modified ACO are better than those obtained GA. The modified ACO has a lower standard deviation regarding all the considered objective functions, indicating a higher stability of the algorithm. Additionally, modified ACO has a larger hypervolume indicator (78.68%) than GA. GA has a longer computational time (8.15 min) than the modified ACO (5.41 min).

Insert Table 3

Next, a two-tailed student's t-tests were performed to statistically assess the optimal solutions' significance level. The student's t-test investigates the null hypothesis (H_0) that assumes an insignificant difference between the optimal solutions achieved by the optimization algorithms. The alternative hypothesis (H_1) implies that there is a significant difference between the obtained optimal solutions. The P-value needs to be less than the significance level (alpha =0.05) to reject the null hypothesis in favor of the alternative hypothesis. The computed P-value was found to be $6.802 \text{ X } 10^{-6}$, which indicates that the modified ACO's performance is statistically significantly better than GA. From the previous analysis, the modified ACO is recommended to solve the formulated problem in this paper.

The model then proceeds with the MCDM process to determine the best solution among the Pareto frontier points obtained from the multi-objective optimization. First, the Shannon entropy method was exploited to compute the weights of the objective functions. The weights of the cost, resilience, and emissions attributes are 53.01%, 29.80%, and 17.19%, respectively, as shown in Table 4.

Insert Table 4

Once the objectives' weights are found, PROMETHEE II is utilized to determine the best solution. Figure 4 depicts a sample of the Pareto frontier points obtained by the modified ACO algorithm for one of the runs with the selected optimal solution highlighted in red. Table 5 illustrates some of these candidate solutions and their rankings based on the net outranking.

Insert Table 5

Solution number 23 in Table 5, encompasses interventions actions for around 58%, a total of 217, of the pipe segments to achieve the reported objective values while satisfying the set of defined constraints. Figure 5 illustrates the distribution of these segments based on their subnetwork, diameter, and age.

Insert Figure 4

It can be observed from Figure 5 that most of the segments selected for enhancements are in subnetwork 3. This is because subnetwork 3 has the most deteriorated segments, as evidenced by the average age of its segments. The segments' average ages in subnetworks 1, 2, and 3 are 24, 34, and 50 years, respectively. The attained resilience improvement with CAD 1.57 Million investment represents around 24% increase in resilience compared to the case where no enhancement actions are taken over the five subsequent years.

Insert Figure 5

A comparison between the obtained results and an in-house portfolio management plan followed by some cities in Canada, referred herein as City's approach, was then performed to assess the quality of the obtained results. The optimization objectives: resilience, cost, and emissions, were calculated using the same unit cost, expected CO_2 emission, and expected improvement detailed in this paper. Table 6 shows that the developed model resulted in a 33% cost savings, a 6% increase in resilience improvement, and a 7% carbon emissions reduction. The plans differ in the selection criteria of individual segments set to be enhanced. While the City's approach focuses on the age and reliability of segments, the developed method integrates segments' criticality in the selection process. Thus, asserting more weights to the most critical segments. In addition, the dynamic nature of reliability computation yields a more accurate deterioration estimation of various segments.

Insert Table 6

The optimization problem was then solved again utilizing a previously developed resilience metric. This topology-based metric also integrates robustness and redundancy of water networks in estimating their resilience; however, the formulation is different. Readers may refer to Farahmandfar et al. (2016) for the mathematical formulation and underlying concepts of this metric. In a later study, this metric's performance was compared against another flow-based resilience metric's performance. The authors reported 55% less computational time when utilizing the topology-based metric in rehabilitation planning problems. This benefit in computational time was accompanied by resilience improvement underestimating by around 20% (Farahmandfar and Piratla 2018). In this step, a two-tier comparison between this metric's performance and the utilized one's was carried out. Firstly, the multi-objective optimization problem was solved utilizing the resilience metric developed by Farahmandfar et al. (2016). Table 7 illustrates the results of this comparison. The proposed metric in Equation 1 showed superiority in solution quality, as evidenced by the three objective functions' values. Additionally, the computational time required for utilizing the proposed metric is 20% less than the previously developed topology-based metric for rehabilitation planning.

Insert Table 7

Secondly, the resilience improvement due to applying the enhancement actions resulted from utilizing the metric in Equation 1 was estimated again using the previously developed metric. While these actions resulted in around 24% resilience improvement over the five subsequent years, this increase was only 19% using the previously developed metric. This suggests another superiority of the newly developed resilience metric, Equation 1, in estimating resilience improvement due to rehabilitation actions. The observed superior performance can be attributed to the deterioration and improvement estimation model integrated within the metric in Equation 1. The obtained superior performance justifies the practicality of utilizing this metric in strategic rehabilitation planning of WDNs.

Next, resilience enhancement actions of year one are selected to be scheduled. The first step is to cluster them into work packages based on the intervention method and geographical location. The area of the considered networks has been divided into two zones to speed up the travel time. K-means yielded a lower Davies–Bouldin index, 0.850, than K-medoids. Thus, it was selected for the geographical clustering. Enhancement actions were then clustered into work packages as per Equation 14. Table 8 illustrates the output of this clustering process. It shows nine packages, each composed of segments that share the same geographical zone and intervention method except for package two, which is a mixed one. These work packages were then scheduled, assuming three contractors will perform enhancements actions along three time steps. A time step denotes the order at which a work package is being performed. The scheduling process aims to minimize the cumulative time of the resilience enhancement process while satisfying each contractor's maximum contract price. Figure 6 depicts the incremental increase of resilience with time. According to this plan, it is possible to achieve a total of 0.0334 resilience enhancement from the first year's actions during a period of 25.58 days. The assignments of contractors among the different time steps are also shown in Table 8. The total price values for contractors 1, 2, and 3 are CAD $236,851, $209,670, and $141,520 respectively.

Insert Table 8

Cities in Canada and US employ an in-house model to determine the importance of each section of their WDNs. Factors that usually influence such estimation include land use, type of serviced facilities, population density, tax base, and others. Specifying the exact importance of each section within a network is beyond the scope of this work. However, this important parameter, and widely implemented practice, does affect the enhancement decisions. As such, users are given the option to specify minimum resilience thresholds that sought to be satisfied upon realizing all the enhancement actions for each section. These thresholds values are estimated based on of the importance metric of each section. A sensitivity analysis was conducted to investigate the effects of these resilience thresholds on the overall optimization objectives. Due to the space limitation, a sample of this analysis is illustrated in Figure 7. In this analysis, the optimization problem was iteratively solved while repetitively changing the minimum resilience threshold of subnetwork 3 from 0.55 to 0.75, with an increment of 0.05. Optimal solutions were determined and plotted against the minimum resilience threshold. Figure 7 shows that the cost and resilience improvement objectives change by around 13% and 24%, respectively, with a 36% change in the resilience threshold of subnetwork 3. This analysis provides a thorough understanding of resilience threshold impacts on the optimization objectives. Thus, it helps in determining the optimal set of enhancement actions that best fit the preferences of the decision-makers.

Insert Figure 6

Insert Figure 7

Summary and Conclusions

Maintaining sustainable functionality of WDNs after events is rather challenging. This paper presented a multi-objective resilience-driven enhancement model to optimize three competing objectives: resilience improvement, life cycle cost, and carbon emissions. The model encompasses two phases where the intervention actions are fist determined along with their timing before being clustered into work packages and scheduled. The final output is an optimal schedule of rehabilitation work packages, with each work package consists of segments sharing the same enhancement type and geographical location. The model considers pipe segments' reliability and criticality, variant objectives target for different network zones, contract size, and planning horizon. The formulated optimization model was solved using modified ACO, which outperformed GA. An actual WDN in the City of London, Ontario was leveraged to demonstrate the practicality of the developed model . The obtained plan resulted in a 24% resilience improvement with around 1. 57$ million investment. The plan also resulted in a 33% cost savings, a 6% increase in resilience improvement, and a 7% reduction in carbon emissions compared to a plan suggested by the City. This developed framework is expected to help city managers and other governmental agencies better manage WDNs by preparing more efficiently for hazardous events. The model can determine the optimal type and sequence of mitigation actions that maximize resilience and sustainability of WDNs while respecting managerial and operational constraints. Main contributions of this work include:

- Integrating resilience and sustainability of WDNs in a single holistic rehabilitation planning model.
- Developing a dynamic reliability model to estimate the level of improvement due to various intervention actions.
- Developing an optimization model to enhance the resilience absorptive capacity for WDNs considering uncertainty and distinct zones requirements.
- Developing a novel optimization-based model to cluster the set of optimal enhancement actions into homogeneous work packages based on a set of defined commonalities.

The developed model has some limitations that can be enhanced in upcoming studies. This model tackled resilience enhancement through robustness improvement exclusively. However, considering redundancy improvement can noticeably contribute to resilience enhancement. Estimating resilience improvement due to various rehabilitation actions can be further enhanced by analyzing more previous rehabilitation events. The model can also be modified to include more sustainability objectives such as energy requirements. This paper considered exclusively pipe segments as they constitute the largest components of WDNs. This analysis be extended to incorporate more assets such as pumps and water tanks. Moreover, estimates about the segment's criticality can be fortified by capturing dependencies with other critical infrastructure systems. Finally, automating the developed optimization model to make more user-friendly is recommended before being utilized by municipalities.

Data Availability Statement

Data analyzed during the study were provided by a third party. Requests for data should be directed to the provider indicated in the Acknowledgments.

Acknowledgment

The authors would like to thank Dr. Khaled Shahata, Manager, Corporate Asset Management in the City of London, Ontario, for securing the data needed for the development and implementation of the proposed model. Dr. Khaled’s insights and valuable feedback during the implementation and validation of the developed model are highly appreciated. The authors would also like to extend their appreciation for all consultants and contractors across Canada who contributed to filling the rehabilitation actions survey.

References

Abdullah, L., Chan, W., and Afshari, A. (2019). "Application of PROMETHEE method for green supplier selection: a comparative result based on preference functions." *Journal of Industrial Engineering International,* 15(2), 271-285.

Akyene, T. (2012). "Cell phone evaluation base on entropy and TOPSIS". I*nterdisciplinary Journal of Research in Business,* 1(12), 9-15.

Alan Atalah. (2009). "*Pipe Bursting"*. Plastics Pipe Institute, Irving, TX.

Alsadi, A. A., and Matthews, J. C. (2020). "Evaluation of Carbon Footprint of Pipeline Materials during Installation, Operation, and Disposal Phases." *Journal of Pipeline Systems Engineering and Practice*, 11(2), 04020005.

Aşchilean, I., and Giurca, I. (2018). "Choosing a water distribution pipe rehabilitation solution using the analytical network process method." *Water,* 10(4), 484.

Assad, A., Moselhi, O., and Zayed, T. (2020). "Resilience-Driven Multi-objective Restoration Planning for Water Distribution Networks." *J.Perform.Constr.Facil.,* 34(4), 04020072.

Assad, A., Moselhi, O., and Zayed, T. (2019). "A New Metric for Assessing Resilience of Water Distribution Networks." *Water,* 11(8), 1701.

Ayyub, B. M. (2014). "Systems resilience for multihazard environments: Definition, metrics, and valuation for decision making." *Risk Analysis,* 34(2), 340-355.

Bałut, A., Brodziak, R., Bylka, J., and Zakrzewski, P. (2019). "Ranking Approach to Scheduling Repairs of a Water Distribution System for the Post-Disaster Response and Restoration Service." *Water,* 11(8), 1591.

Beale, D. J., Marlow, D. R., and Cook, S. (2013). "Estimating the cost and carbon impact of a long term water main rehabilitation strategy." *Water Resour.Manage.,* 27(11), 3899-3910.

Brans, J., Vincke, P., and Mareschal, B. (1986). "How to select and how to rank projects: The PROMETHEE method." *Eur.J.Oper.Res.,* 24(2), 228-238.

Cimorelli, L., Morlando, F., Cozzolino, L., D'Aniello, A., and Pianese, D. (2018). "Comparison among resilience and entropy index in the optimal rehabilitation of water distribution networks under limited-budgets." *Water Resour.Manage.,* 32(12), 3997-4011.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). "A place-based model for understanding community resilience to natural disasters." *Global Environmental Change*, 18(4), 598-606.

D’Ercole, M., Righetti, M., Raspati, G. S., Bertola, P., and Maria Ugarelli, R. (2018). "Rehabilitation Planning of Water Distribution Network through a Reliability—Based Risk Assessment." *Water*, 10(3), 277.

Dandy, G. C., Bogdanowicz, A., Craven, J., Maywald, A., and Liu, P. (2008). "Optimizing the sustainability of water distribution systems." Kruger National Park, South Africa, 267–277.

Dandy, G. C., and Engelhardt, M. O. (2006). "Multi-objective Trade-Offs between Cost and Reliability in the Replacement of Water Mains." *Journal of Water Resources Planning and Management*, 132(2), 79-88.

Dao, S. D., Abhary, K., & Marian, R. (2016). "Maximizing Performance of Genetic Algorithm Solver in Matlab." *Engineering Letters*, 24(1).

Davies, D. L., and Bouldin, D. W. (1979). "A cluster separation measure." *IEEE Trans.Pattern Anal.Mach.Intell.*, (2), 224-227.

Dessavre, D. G., Ramirez-Marquez, J. E., & Barker, K. (2016). "Multidimensional approach to complex system resilience analysis." *Reliability Engineering & System Safety*, 149, 34-43.

Dorigo, M., Birattari, M., and Stutzle, T. (2006). "Ant colony optimization." *IEEE Computational Intelligence Magazine*, 1(4), 28-39.

Elbehairy, H. (2007) "Bridge management system with integrated life cycle cost optimization" Ph.D. thesis, Univ. of Waterloo, Waterloo, Ont., Canada.

El-Ghandour, H. A., & Elbeltagi, E. (2017). "Comparison of five evolutionary algorithms for optimization of water distribution networks." *Journal of Computing in Civil Engineering*, 32(1), 04017066.

Elshaboury, N., Attia, T., & Marzouk, M. (2020). "Application of Evolutionary Optimization Algorithms for Rehabilitation of Water Distribution Networks." J*ournal of Construction Engineering and Management*, 146(7), 04020069.

Exler, O., and Schittkowski, K. (2007). "A trust region SQP algorithm for mixed-integer nonlinear programming." *Optimization Letters*, 1(3), 269-280.

Farahmandfar, Z., and Piratla, K. R. (2017). "Resilience-based water main rehabilitation planning in a multi-hazard context." *Journal of Water Supply: Research and Technology-Aqua*, 66(8), 651-664.

Farahmandfar, Z., & Piratla, K. R. (2018). "Comparative evaluation of topological and flow-based seismic resilience metrics for rehabilitation of water pipeline systems." Journal of Pipeline Systems Engineering and Practice, 9(1), 04017027.

Farahmandfar, Z., Piratla, K. R., & Andrus, R. D. (2016). "Resilience evaluation of water supply networks against seismic hazards." *Journal of Pipeline Systems Engineering and Practice,* 8(1), 04016014.

Faust, K. M., & Kaminsky, J. A. (2017). "Building water and wastewater system resilience to disaster migration: utility perspectives." *Journal of construction engineering and management*, 143(8), 04017058.

Fiksel J, Goodman I, Hecht A. (2014). "Resilience: Navigating a sustainable future." *Solutions*, 5(5), 38-47.

Holland, J. H. (1975). "Adaptation in natural and artificial systems. An introductory analysis with application to biology, control, and artificial intelligence." *Ann Arbor, MI: University of Michigan Press*, 439-444.

Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). "A review of definitions and measures of system resilience." *Reliability Engineering & System Safety,* 145, 47-61.

Jain, A. K. (2010). "Data clustering: 50 years beyond K-means." *Pattern Recog.Lett.,* 31(8), 651-666.

Jayaram, N., and Srinivasan, K. (2008). "Performance-based optimal design and rehabilitation of water distribution networks using life cycle costing." *Water Resour.Res.,* 44(1).

Klise, K. A., Murray, R., & Walker, L. T. N. (2015). "Systems measures of water distribution system resilience (No. SAND2015-20746R)." *Sandia National Lab*. (SNL-NM), Albuquerque, NM (United States).

Law, A. M., Kelton, W. D., and Kelton, W. D. (2000). *Simulation modeling and analysis.*500 McGraw-Hill, New York, USA.

Lueke, J. S., Matthews, J. C., Stowe, R., and Lamont, C. (2015). "Comparing carbon footprints of trenchless water main renewal technologies." *Proc,* Denver, Colorado, USA.

Meng, F., Fu, G., Farmani, R., Sweetapple, C., & Butler, D. (2018). "Topological attributes of network resilience: A study in water distribution systems." *Water Research*, 143, 376-386.

Meng, J., Yan, J., & Xue, B. (2018). "Exploring relationships between national culture and infrastructure sustainability using QCA." *Journal of Construction Engineering and Management*, 144(9), 04018082.

Muhammed, K., Farmani, R., Behzadian, K., Diao, K., and Butler, D. (2017). "Optimal rehabilitation of water distribution systems using a cluster-based technique." *J.Water Resour.Plann.Manage.,* 143(7), 04017022.

Nebro, A. J., Durillo, J. J., and Coello, C. A. C. (2013). "Analysis of leader selection strategies in a multi-objective particle swarm optimizer." *2013 IEEE Congress on Evolutionary Computation*, IEEE, 3153-3160.

O’Sullivan D (2010). "Reduce your carbon footprint using trenchless." *No Dig Show 2010*, Chicago, Illinois, USA, North American Society for Trenchless Technology.

Pant, R., Barker, K., Ramirez-Marquez, J. E., & Rocco, C. M. (2014). "Stochastic measures of resilience and their application to container terminals." *Computers & Industrial Engineering*, 70, 183-194.

Peters, L. (2016). "Impact of probability distributions on real options valuation." *Journal of Infrastructure Systems*, 22(3), 04016005.

Polat, G. (2016). "Subcontractor selection using the integration of the AHP and PROMETHEE methods." *Journal of Civil Engineering and Management*, 22(8), 1042-1054.

RapidMiner Inc. (2016) RapidMiner 9.6 software. https://rapidminer.com/products/studio/. Accessed 01 June 2020.

Riquelme, N., Von Lücken, C., and Baran, B. (2015). "Performance metrics in multi-objective optimization." *2015 Latin American Computing Conference (CLEI)*, IEEE, 1-11.

Roshani, E., and Filion, Y. R. (2015). "Water distribution system rehabilitation under climate change mitigation scenarios in Canada." *Journal of Water Resources Planning and Management*, 141(4), 04014066.

Roshani, E., MacLeod, S. P., and Filion, Y. R. (2012). "Evaluating the impact of climate change mitigation strategies on the optimal design and expansion of the Amherstview, Ontario, water network: Canadian case study." *J.Water Resour.Plann.Manage.*, 138(2), 100-110.

Sahani, R., and Bhuyan, P. K. (2017). "Pedestrian level of service criteria for urban off-street facilities in mid-sized cities." *Transport*, 32(2), 221-232.

Sawant, K. B. (2015). "Efficient determination of clusters in K-mean algorithm using neighborhood distance." *The International Journal of Emerging Engineering Research and Technology*, 3(1), 22-27.

Schlüter, M., Egea, J. A., and Banga, J. R. (2009). "Extended ant colony optimization for non-convex mixed integer nonlinear programming." *Comput.Oper.Res.*, 36(7), 2217-2229.

Schlüter, M., Gerdts, M., and Rückmann, J. (2012). "A numerical study of MIDACO on 100 MINLP benchmarks." *Optimization*, 61(7), 873-900.

Shuang, Q., Liu, H. J., & Porse, E. (2019). "Review of the quantitative resilience methods in water distribution networks." *Water*, 11(6), 1189.

Suribabu, C. R. (2017). "Resilience-based optimal design of water distribution network". *Applied Water Science*, 7(7), 4055-4066.

Suribabu, C. R., Prashanth, K., Vignesh Kumar, S., and Ganesh, N. S. (2016). "Resilience enhancement methods for water distribution networks." *Jordan Journal of Civil Engineering*, 10(2).

Tavakoli, R., Najafi, M., Tabesh, A., and Ashoori, T. (2017). "Comparison of Carbon Footprint of Trenchless and Open-Cut Methods for Underground Freight Transportation." American Society of Civil Engineers, Phoenix, Arizona, USA, 45-55.

Todini, E. (2000). "Looped water distribution networks design using a resilience index based heuristic approach." *Urban Water*, 2(2), 115-122.

WCED (World Commission on Environment and Development). (1987). "Our common future", Oxford University Press, New York.

Whitley, D. (1994). A genetic algorithm tutorial. *Statistics and Computing*, 4(2), 65-85.

Wu, W., Maier, H. R., and Simpson, A. R. (2010y). "Single-objective versus multi-objective optimization of water distribution systems accounting for greenhouse gas emissions by carbon pricing." *Journal Water Resources Planning Management.*, 136(5), 555-565.

Yazdani, A., & Jeffrey, P. (2011). "Complex network analysis of water distribution systems." C*haos: An Interdisciplinary Journal of Nonlinear Science*, 21(1), 016111-10.

Yazdekhasti, S., Piratla, K. R., Khan, A., and Atamturktur, S. (2014). "Analysis of Factors Influencing the Selection of Water Main Rehabilitation Methods." *North American Society for Trenchless Technology (NASTT) * Orlando, Florida, USA.

Yoo, D. G., Kang, D., Jun, H., and Kim, J. H. (2014). "Rehabilitation priority determination of water pipes based on hydraulic importance." *Water*, 6(12), 3864-3887.

Zhao, X., Chen, Z., and Gong, H. (2015). "Effects comparison of different resilience enhancing strategies for municipal water distribution network: A multidimensional approach." *Mathematical Problems in Engineering*, 2015.

Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C. M., and Da Fonseca, V. G. (2003). "Performance assessment of multi-objective optimizers: An analysis and review." *IEEE Transactions on Evolutionary Computation*, 7(2), 117-132.

Table 1. Set of Considered Rehabilitation Methods

Intervention Category	Method	Description
Minor	Epoxy lining (EL)	A non-structural renewal method for rehabilitation aging yet structurally strong segments through spraying a thin coating of liquid epoxy on the pipe's internal wall. A smoother surface that is easier to be maintained, faster curing, and applicability on smaller pipes are some advantages of EL over regular cement mortar lining (Yazdekhasti et al. 2014).
	Cement Mortar lining (EL)	A non-structural renewal method in which a smooth placing cement mortar is placed on a structurally sound segment's inner surface. Minimum thickness required is 5mm to avoid significant reduction in hydraulic capacity (Yazdekhasti et al. 2014).
Major	Cured in Place Pipe (CIPP)	A structural rehabilitation method in which a resin-coated fiber tube, liner, is inserted into a structurally deteriorated host pipe. This method results in the least diameter reduction with significant smoother surface among other structural rehabilitation techniques (Yazdekhasti et al. 2014).
	Close-fit- Slip lining (SL)	A structural rehabilitation method in which a new pipe is inserted by pulling or pushing into an existing pipe. Diameter of the new pipe is temporarily reduced to facilitate its insertion. The original diameter is then retrieved by pressurization (Yazdekhasti et al. 2014).
Full Replacement	Pipe Bursting (PB)	A replacement method in which a bursting head is inserted to break a host pipe and pull along a new pipe of a similar or larger diameter. The most common trenchless technique utilized to replace segments of various sizes and material types (Yazdekhasti et al. 2014).
	Pipe Splitting	A replacement method in which longitudinal splitting and drawing in a new pipe of a similar or larger diameter occur. A special variation of PB to replace segments that do not fracture using regular PB such as ductile iron pipes (Alan Atalah 2009).

Table 2. Costs and Durations of Rehabilitation Methods

Intervention Method	Unit Cost (CAD/mm^2/m)	Unit time (days/m)
Cement Mortar Lining (CML)	59.75*	0.0100
Epoxy lining (EL)	66.39*	0.0103
Cured in Place Pipe (CIPP)	2.04	0.0162
Close-fit Slip Lining (SL)	1.88	0.0155
Pipe Bursting (PB)	3.02	0.0202
Pipe Splitting (PS)	3.17	0. 0216

* Cost is in CAD/m.

Table 3. Comparison between results of the modified ACO and GA

	Objective function	**Modified ACO**	**GA**
Minimum	Cost (Million CAD)	1.5504	1.6709
	Resilience	0.6533	0.6290
	Emissions (CO_2-e tonne)	134.25	137.37
Maximum	Cost (Million CAD)	1.7878	2.1314
	Resilience	0.6657	0.6368
	Emissions	142.14	144.56
Mean	Cost (Million CAD)	1.6153	1.957
	Resilience	0.6628	0.6321
	Emissions (CO_2-e tonne)	138.74	141.38
Standard deviation	Cost (Million)	0.0418	0.1841
	Resilience	0.0028	0.0053
	Emissions (CO_2-e tonne)	2.09	3.98
Hypervolume indicator (HV)		78.68%	59.97%
Computational time (min)		5.41	8.16

Table 4. Calculation of Objectives' Weights based on Shannon Entropy

Criterion	**Cost**	**Resilience**	**Emissions**
Entropy value (e_j)	0.232	0.5682	0.751
Variation coefficient (d_j)	0.768	0.4318	0.249
Weight (w_j)	53.01%	29.80%	17.19%

Table 5. Different Optimal Solution Resulting from the modified ACO

Solution	Cost ($x10^6$ CAD)	Resilience	Emissions (CO2-e tonne)	ϕ (a)	Rank
1	1.596	0.6537	142.1	-0.1181	24
2	1.617	0.6643	142.0	-0.3489	32
3	1.564	0.6572	141.7	0.0571	14
:	:	:	:	:	:
23	**1.572**	**0.6648**	**135.2**	**0.5241**	**1**
:	:	:	:	:	:
35	1.663	0.6654	134.25	0.0022	18

Note: The bold row represents the selected optimal solution for the optimization problem.

Table 6. Comparison between the Obtained Results

Criterion	Optimization Model	City's Approach	Enhancement
Cost ($x10^6$ CAD)	1,572	2,351	33.13%
Resilience	0.6648	0.6297	5.57%
Emissions (CO2-e tonne)	135.2	145.3	6.95%

Table 7. Comparison between the Performance of Resilience Metrics

Criterion	Proposed Metric, Eq 1	Previous Metric	Enhancement
Cost ($x10^6$ CAD)	1,572	2,081	24.44%
Resilience	0.6648	0.6317	5.24%
Emissions (CO2-e tonne)	135.2	142.2	4.95%

Table 8. Packaging and Scheduling of Enhancement Actions of Year 1

Package No.	Cost ($x10^3$ CAD)	Resilience	Time (day)	Enhancement Action	Time Step	Contractor
1	96.39	0.0034	6.78	PB	1	C1
2	80.10	0.0038	5.47	PS & SL	1	C2
3	88.48	0.0054	9.59	CIPP	1	C3
4	46.33	0.0041	13.56	CML	2	C2
5	93.01	0.0036	4.46	SL	2	C1
6	83.24	0.0030	6.04	CIPP	3	C2
7	47.45	0.0046	14.35	EL	3	C1
8	53.04	0.0055	15.96	CML	2	C3

Figure Captions:

Figure 1. Methodology framework

Figure 2. Layout of the water network in the City of London, Ontario.

Figure 3. Layout of the selected subnetworks.

Figure 4. Pareto Frontier Points of the modified ACO algorithm

Figure 5. Distribution of Rehabilitated Segments based on a) sub-network; b) age; and c) size.

Figure 6. Optimum scheduling Results

Figure 7. Sensitivity of Total Cost and Resilience Improvement to Variation in Minimum Resilience Threshold of Sub-Network 3.