Resilience-Driven Multi-objective Restoration Planning for Water Distribution Networks

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Abstract

Sustaining functionality of water distribution networks (WDNs) following hazardous events is essential to public health and safety. Developing efficient restoration plans for rapid recovery is needed. This is because of several factors such as the ubiquitous nature of WDNs, severely deteriorated segments, increased level of urbanization, availability of various restoration methods, and possible uncertainties in time and cost estimates of such methods. This paper presents a multi-objective resilience-based optimization model that maximizes resilience of WDNs while minimizing the total time and cost of the selected restoration plans. A real WDN was utilized to demonstrate the practicality of the proposed model. The problem was solved deterministically and stochastically to generate a prioritized list of segments to be restored along with a schedule of their restoration that accounts for available work crews. When compared to current planning practices, the output plan achieved 4% cost saving, 48% duration reduction, and 4% resilience improvement. The model is expected to help City managers establish optimal restoration plans, especially in cases of limited budget and workforce.

Keywords: Resilience, Water distribution networks, Restoration scheduling, Multi-objective optimization.

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Introduction

The ubiquitous nature of water distribution networks (WDNs) has made them highly vulnerable to a broad spectrum of disruptions, whether natural or anthropogenic. The emphasis was lately shifted from classical reliability-based approaches of protection to resilience-based ones. Resilience of infrastructure systems is the ability to mitigate risks and rapidly recover services with minimum harm to the public (Ayyub 2014). Restoration capacity is one of the main three pillars, along with absorptive and adaptive capacities, of engineering systems resilience (Vugrin et al. 2011). Restorative capacity can be conceptualized by the degree of recovery and recovery time. Efficient recovery of WDNs after hazardous events poses a unique priority for asset managers because of their vital role in overall community recovery. As disruptive events are becoming more frequent and destructive, municipalities are expected to respond to an increasing number of simultaneous failures. These failures may cause significant consequences depending on the type of serviced facility (e.g., hospitals, power plants). Depending on accessibility, installation depth, and diameter of the pipe, repair activities may require extended periods and specialized equipment to get accomplished, which further worsen the extent of failure consequences. Municipalities are thus required to develop optimal restoration plans to affirm the resiliency of their WDNs. Development of such optimization models shall consider various available repair methods along with their suitability to different break types, pipes' characteristics, and the surrounding conditions. In Addition, recovery scheduling tools are required to cope up with the limited workforce and resources allocated for restoration actions. As such, this paper presents a holistic resilience-based model for optimal recovery of WDNs. The developed model suggests an optimal sequence of restoring failed segments along with the repair method of each considering the factors mentioned above.

Literature Review

In recent years, there have been several research studies proposing resilience-based asset management tools for WDNs. Most of these studies presented rehabilitation frameworks as means of enhancing resilience (Farahmandfar and Piratla 2017); Suribabu (2017). However, fewer researchers studied resilience-based restoration prioritization and scheduling of water networks. For example, Balut et al. (2019) utilized preference ranking organization method for enrichment evaluation (PROMETHEE) technique and hydraulic simulation to determine best restoration strategies following various hazard scenarios. PROMETHEE was used to rank the set of failed and pressure-driven hydraulic simulation was conducted to select the best ranking strategy based on several performance indicators such as rapidity of recovery and volume of water loss (Bałut et al. 2019). Mahmoud et al. (2018) developed an optimization model that minimizes both the impact of sudden failures on the performance of WDNs and the costs of intervention actions. The authors utilized GA and pressure-driven hydraulic simulation to select the optimal set of operational interventions such as resetting pressure reducing valves and installing temporary bypasses to respond to several sudden failures. Other researchers focused on the restoration of WDNs after seismic hazards such as Zhao et al. (2015). Zhao et al. (2015) compared the effects of two restoration strategies on improving the seismic resilience of WDNs. They analyzed the effects of ductile retrofitting strategy and meshed expansion strategy on seismic resilience of an actual WDN in China. The authors found that ductile retrofitting was a more effective strategy for resilience improvement in cases of fund scarcity. In addition, some scholars studied the role of interdependency in selecting the best restoration strategy. Almoghathawi et al. (2019) developed an optimization model to minimize the cost of restoring a fictitious system of interdependent networks, water, and power, following a disruptive event. The main focus of their study was to enhance the resilience of interdependent networks to retain their performance level before the disruption, which might leave some of the disrupted components not being restored. In a different effort, Osman et al. (2017) provided a tool to optimize the scheduling of repair crews in water networks using GA. The authors considered two repair methods to minimize the time and cost of repair actions as well as the cumulative pipeline criticality index. The authors applied their model on an actual network and were able to decrease the cost and time of the recovery by 0.78% and 21.7%, respectively. Earlier, Gay and Sinha (2014) developed a resilience assessment methodology for WDNs where resilience was not conceptualized as a system attribute, but rather as the result of a stochastic process. The authors studied a set of failure scenarios and compared the system performance to some performance targets. In addition to these studies, optimizing post-disaster restoration has been investigated by other authors across different fields such as community buildings (Lin and Wang 2016), bridges and transportation networks (Karamlou and Bocchini 2016), and electrical networks (Jun Wang et al. 2019).

It can be seen that most of the previous studies employed hydraulic simulation in analyzing restoration of WDNS. However, this may not be a feasible option, especially as the size and complexity of the network increase because of their extended computational time. Several key issues were also overlooked in models that investigated restoration of WDNs such as 1) considering various repair methods and their impacts on the objectives of the recovery process; 2) addressing the uncertainty that might arise in estimating repair time and cost; 3) taking into account the cost and time spent in relocation between failed components; 4) estimating the criticality of water mains as a way to quantify the consequence of failure on customers and other systems; 5) integrating the reliability of water mains within the recovery process. As such, the objective of this paper is to develop an optimization model for prioritizing and scheduling restoration actions of

WDNs. The model takes into consideration efficient resource allocation by minimizing both the time and cost of recovery and maximizing resilience. The output of this model is an optimal restoration plan that comprises two main components: 1) a prioritized sequence of water segments to be repaired, and 2) an optimal repair method for each. Additionally, a time schedule is generated to visualize the restoration activities and the overall restoration process.

Methodology

Generally, four main qualities are used to evaluate resilience of infrastructure systems, namely: robustness, redundancy, rapidity, and resourcefulness (Bruneau et al. 2003). This paper introduces a newly developed optimization framework that takes three sets of inputs to account for these qualities. The inputs represent the results of three modules: resilience assessment module, restoration module, and crew relocation module as shown in Fig. 1. The resilience assessment module integrates robustness and redundancy of WDNs. Restoration and crew relocation modules determine feasible recovery methods for pipe segments and the time and cost of crews relocation, respectively. The optimization framework considers the available resources to achieve the most rapid recovery. The details of the developed methodology are described subsequently.

Insert Figure 1

Resilience Assessment Module

The proposed resilience metric is formulated as a weighted sum of the robustness and redundancy of WDNs. Robustness is calculated as the sum of reliabilities of all the connected pipe segments. Criticalities of segments are employed as weights to prioritize critical ones. The formulation is normalized by the sum of criticalities. Redundancy is then added to quantify the extent to which a system is capable of satisfying functional requirements when significant degradation occurs. The developed resilience metric is given in equation 1 (Assad et al. 2019):

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

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, w_1, and w_2 are relative weights of importance. The criticality index considered various economic, social, and environmental factors. Fuzzy analytical network process (FANP) and multi-attribute utility theory (MAUT) were utilized to estimate the global weights of each factor. Probabilistic deterioration model was constructed using Weibull distribution functions (WDF) to estimate the reliability and deterioration of water segments. Segments were fist clustered into homogeneous cohorts based on material type and size. Inter-failure times were then calculated, and curve fitting was applied to obtain the distribution parameters for each transition state using the maximum likelihood estimate. Meshed-ness is one of the parameters that were studied to analyze their suitability in quantifying redundancy of WDNs. Meshed-ness was found to be the most relevant metric to estimate the intensity of loops in planar graphs such as WDNs. It is calculated as the ratio of the total number to the maximum number of independent loops in a planar graph, as shown in equation 2 (Yazdani and Jeffrey 2011):

$$R_m = \frac{m-n-1}{2n-5} \qquad (2)$$

Where R_m is the meshed-ness coefficient. Readers may refer to Assad et al. (2019) for more details about the underlying concepts and mathematical formulation of the developed resilience index.

Crew Relocation Module

Restoration crews spend time while travelling from one location to another to restore failed segments across the network. As these times and associated costs can significantly increase the time and cost of the recovery process, especially in sparse networks, they need to be considered in developing optimum restoration plans. This model is developed to accurately estimate the times and costs associated with crew's relocation. The coordinates of pipe segments were extracted from ArcGIS (ESRI, 2011) layers to create an origin-destination matrix from which the relocation time and cost can be determined. A Google application programming interface (API) was utilized to access Google Maps from which the distance and travel time between any two locations are determined. Utilizing the abilities of Google Maps, API allows for site routing and finding the shortest distance between the locations of failed segments. Additionally, travel times reported in Google Maps are adjusted to account for traffic conditions, which is crucial in dense urban cities and after massive disruptions. Relocation costs were then computed by multiplying the hourly rate of restoration crews by the relocation time. The final output of this model is the relocation time and cost between the locations of each pair of failed segments.

Restoration Module

Various repair methods can be utilized to restore a broken water segment. This model evaluates different alternatives for restoring failed segments and selects suitable methods based on a set of predefined criteria. The factors considered in this selection process include the pipe size, material type, location and accessibility, soil type under which the pipe is buried, the previous number of breaks, and defect characteristics. The repair methods that were considered in this study are mechanical clamps, pipe bursting (PB), pipe splitting (PS), and open-cut-method (OCM). Brief descriptions of these methods along with their applicability are shown in Table 1.

Insert Table 1

This module considers the criteria mentioned above in selecting the possible restoration methods for each pipe segment. For example, small breaks can be repaired using mechanical clamps and couplings while PB, splitting, and OCM are used to replace segments of bigger break sizes. A pipe segment might be nominated for replacement even if the break size is small when the total number of breaks reaches a certain threshold set by the municipality. The restoration time and cost are calculated based on the type of the repair method, diameter, and length of the pipe segment. Unit costs and times of the considered methods were gathered from different consultants and contractors in Canada. Resilience improvement realized from restoring a particular pipe segment depends on whether it was repaired or replaced. The theoretical value of reliability of newly replaced segments shall be 1.0. However, this value is usually reduced to account for mistakes and other factors that compromise the installation quality. This value can be fed to the model as an input that reflects the level of skills and qualification of the restoring crews. In this model, replacing a pipe segment is assumed to increase its reliability to a value of 0.95. On the other hand, when a pipe segment of a specific failure order is repaired, its reliability is found using the survivability function of the successive failure order as demonstrated by Assad et al. (2019). The final output of this model is the time, cost, and resilience improvement of all possible restoration options for each failed pipe segment.

Optimization Framework

The base of the formulated optimization in this study is a combination of the traditional knapsack and traveling salesman optimization problems (Lawler et al. 1985; Pisinger and Toth 1998). The proposed model aims at optimizing three conflicting objectives: 1) minimizing restoration cost; 2) minimizing restoration time; 3) and maximizing resilience level after adopting all restoration actions as shown in Equations 3, 4 and respectively.

Minimize

$$R.C. + z = \sum_{i\in P}\sum_{j\in C}\sum_{k\in M}\left(x_{j,k}^{i} * RC_{j,k}^{i}\right) + \sum_{t\in T}\sum_{j\in C}\sum_{i\in P}\sum_{l\in P}\left(x_{j}^{i,t} * x_{j}^{l,t+1}\right) * LC_{i,l} + z \quad (3)$$

Where *R.C.* = restoration cost; $x_{j,k}^{i}$ = decision variable that takes a value of 1 when pipe segment (*i*) is restored by crew (*j*) using repair method (*k*) and 0 otherwise; $RC_{j,k}^{i}$ = cost of restoring pipe segment (*i*) by crew (*j*) using restoration method (*k*); $LC_{i,l}$ = relocation cost between sites at which pipe segments (*i*) and (*l*) are located respectively; $x_{j}^{i,t}$ = decision variable that takes a value of 1 when pipe segment (*i*) is restored by crew (*j*) during restoration time step (*t*); *C; P; M*; and *T* = sets of the available number of crews, failed pipe segments, repair methods, and restoration time steps respectively. A restoration time step represents the order at which a particular segment is restored. Parameter (*z*) represents the penalty amount resulted from violating the budget constraint.

Minimize $R.T = \max_{j\in C} T.R.T_j$ (4)

$$T.R.T_j = \sum_{i\in P}\sum_{k\in M}\left(x_{j,k}^{i} * RT_{j,k}^{i}\right) + \sum_{t\in T}\sum_{i\in P}\sum_{l\in P}\left(x_{j}^{i,t} * x_{j}^{l,t+1}\right) * LT_{i,l} \quad (5)$$

Where *R.T* = the time of the restoration process; $T.R.T_j$ = total restoration time for crew (*j*); $RT_{j,k}^{i}$ = the time needed for restoring water pipe (*i*) by crew (*j*) using restoration method (*k*); $LT_{i,l}$ = relocation time between locations at which pipe segments (*i*) and (*l*) are located, respectively.

Maximize $T.Я.I. = \sum_{i\in P}\sum_{j\in C}\sum_{k\in M}\left(x_{j,k}^{i} * ЯI_{j,k}^{i}\right)$ (6)

Where T.Я.I. = total resilience improvement realized after restoring all failed segments, $ЯI_{j,k}^{i}$ = resilience improvement resulting from restoring pipe segment (*i*) by crew (*j*) using method (*k*). A constraint is added to guarantee that restoration costs will not exceed a specific allocated recovery budget, Equation 7. The budget constraint is considered as a soft constraint that might be violated by some solutions. However, such solutions would incur a penalty (z) in the objective function as shown in Equation 3. In addition, a constraint is added in Equation 8 to assure that no segment will be left unrestored. It limits the number of visits for each segment to exactly 1. Another constraint is also added to avoid assigning the same crew to more than one location at the same time step, Equation 9. The constraint shown in Equation 10 allows the user to specify a minimum resilience level that shall be achieved upon accomplishing all restoration actions.

Subject to

$$Total\ Costs\ -\ z \leq\ B_{Total}\ (7)$$

$$V_i =\ \{1\}\ (8)$$

$$L_{it} =\ \{1\}\ (9)$$

$$\text{Я}_{F}\ \geq\ \text{Я}_{Threshold}\ \ (10)$$

$$x_{j,k}^{i}, x_{j}^{i,t}, x_{j}^{l,t+1} =\ \{0,1\}\ (11)$$

$$z\ \geq 0\ (12)$$

$$\forall\ \ i\ \in\ P, j \in C, k\ \in M, l\ \in P\ /\ \{i\}, t\ \in T$$

Where B_{Total} is the total restoration budget; V_i is the number of visits for segment (i); L_{jt} is the number of pipe locations that can be visited by crew (j) in a time step (t). $\text{Я}_{Threshold}$ is a benchmark value for network resilience at the recovered state as set by the decision-maker; and Я_{F} is the final resilience value.

Multi-objective Optimization

Weighted some method is utilized to solve the multi-objective optimization problem described in this paper. In this approach, the objectives are aggregated into a single weighted objective function. The weights here represent the relative importance of each objective. This approach is usually referred to as a prior preference approach. As with most methods that involve objective function weights, inputs from users are needed to reflect their preferences. These preferences can be exploited in two ways. Firstly, the decision-maker may directly assign the weights of each objective before the problem is solved. This allows the user to get a single solution. Alternatively, decision-makers may not be quite decisive about a specific set of relative weights and they may wish to investigate a possible trade-off between the considered objectives. In such cases, ranges of possible weights for each objective would be sought from the decision-makers. The problem would be iteratively solved for several times, specified by the user, while systematically altering the set of relative weights according to those ranges. This analysis yields several solutions from which users choose the one that best matches their preferences.

Minimize $Z = \alpha_1\, TRC + \alpha_2 RT + \alpha_3 TRI$ (11)

The search space of this problem is big. The number of possible solutions equals the factorial of the number of failed segments multiplied by the possible restoration methods raised to the number of failed segments. For example, if the number of failed segments is 15, and there are two different restoration methods to restore each segment, the search space will then be 4.28 $X10^{16}$ ($15!*2^{15}$). Several algorithms that are commonly used in asset management and resilience applications are investigated to identify the best performing optimization algorithm to be used to solve the formulated problem in this paper. These algorithms are Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Tabu Search (TS). Below is a brief description of each.

Genetic Algorithm (GA) is well-known for its ability to handle big search spaces. GA is a search heuristic that is inspired by the natural evolution theory. It was developed in the early 1970s by John Holland (Holland 1975). The algorithm starts by generating a set of random solutions representing different combinations of the decision variables. Solutions are then ranked based on their fitness, and the best solutions are selected to reproduce through the genetic operators of cross-over and mutation. In cross-over, two parents exchange genes until reaching the crossover point. This point was randomly chosen with a probability of 0.75. In mutation, genes are modified with low random probability (0.015 in this study) to maintain diversity and prevent premature convergence. These steps are repeated iteratively until meeting the stopping criteria to ensure convergence to the optimal/near-optimal set of solutions.

Ant Colony Optimization (ACO) is an evolutionary algorithm that is inspired by social behavior of ants trying to reach a source of food. It was first introduced by Dorigo (1996) has been used since then in many optimization problems involving graph routing and scheduling (Dorigo and Gambardella 1997; Maier et al. 2003; El-Ghandour and Elbeltagi 2017). The algorithm is based on the fact that ants deposit pheromone whenever they travel as a form of indirect communication. The shortest path is marked as the one that has the most deposited pheromone. The process starts by generating some random rants; each represents a possible solution. Ants are represented by several variables and pheromone concentration. Ants are first evaluated according to the objective function. Next, pheromone concentrations associated with each possible route (variable value) are updated in each iteration to reinforce good solutions, shorter paths. The variable values of each ant are then changed according to the updated pheromone concentration until meeting the termination criteria (Elbeltagi et al. 2005). A pheromone evaporation parameter (taken as 0.4) is introduced to prevent premature convergence by reducing the influence of the old pheromone. In this study, the number of iteration is 100 and the colony size is 40 ants.

Tabu Search is a local-based metaheuristic algorithm that has been used to solve many combinatorial problems such as water network optimization, traveling salesman problem and routing problems (da Conceicao Cunha and Ribeiro 2004; Brandão 2009; Basu 2012) The process starts by an initial solution represented as a combination of the decision variables. The algorithm then iteratively explores the possible neighborhood of that solution. A neighborhood to a solution is any other solution that can be obtained by altering the values of the decision variables. To prevent cycling within a small set of solutions, certain moves that lead to recently visited solutions are forbidden for a limited time, stored in the Tabu List. Occasionally, certain moves would be allowed even if they are Tabu when they lead to a solution better than the current best-known solution; this is called aspiration criteria. A diversification procedure is added to avoid getting trapped in a local optimum by encouraging moves to regions in the search space that were not previously investigated. The algorithm terminates if a pre-specified number of iterations is reached (100 iterations in this study). More information about Tabu Search can be found in Glover and Laguna (1997).

Deterministic Versus Stochastic optimization

As previously mentioned, the model asks the users to provide three sets of inputs regarding the considered repair methods. These inputs are the unit cost, time, and resilience improvement of each repair method. In case the values of these parameters are known to decision-makers with reasonable certainty, they can be directly assigned. For example, when the City calls for estimates about the unit time and cost of specific repair methods from contractors along with their technical profiles to choose one of them. The problem, in this case, would be solved deterministically. However, when estimates about these parameters are rather uncertain, which is the case when decision-makers plan for long-term resilience, these uncertainties that need to be addressed. Estimates about costs, durations, and resilience improvements are subjected to change in these cases due to several factors such as material availability, skills of restoration crews, surrounding conditions, and other risks. In order to provide decision-makers with a comprehensive analysis that includes the worst and best possible estimates regarding the restoration objectives, the problem would be solved stochastically. Here, the objective of the optimization is modified such that the mean of the original objective function is minimized. In this type of optimization, a predefined number of trials, sets of distinct values of the decision variables, are generated and the simulation runs several iterations for each specific trial. In each iteration, probability distribution functions of the uncertain variables are sampled, and the objective function is computed. Upon completing the iterations, the result of the trial is the statistic of the objective function that is sought to be optimized. This value is then used by the optimization algorithm to guide generating new better trial solutions until some termination criterion is met.

Data Collection

Different data were gathered and analyzed to develop the previously described model. Data collected are comprised of GIS shapefiles of an actual WDN in the City London, Ontario. Different segments' characteristics, such as ages, lengths, diameters, material types, and installation depths were extracted from these shapefiles. Street categories, traffic volume, and types of serviced facilities were also collected from distinct layers. These data were used to estimate the criticality of each pipe segment utilizing FANP technique as mentioned earlier. Additionally, data regarding installation dates and failure history for each segment were obtained to predict its reliability and expected deterioration. Information about the connectivity of the network were leveraged to quantify its redundancy. Also, estimates of the unit costs and times of various restoration methods were fetched to be used in developing the restoration model.

Optimization Model Implementation to a Case Study

The model was implemented on a WDN in London, Ontario. The chosen subnetwork is composed of 186 pipe segments of diameters ranging between 40mm and 450 mm that amount approximately 13.1 km of length. The material types include cast iron (CI), ductile iron (DI), copper, and PVC. Fig. 2 shows the distribution of the pipe segments in the considered network grouped by material type and size. The portion of the network was selected such that it offers variability in overall land use, road types, and serviced facilities. To demonstrate the practicality of the developed model, a disruption scenario that caused a failure of 30 pipe segments in the form of small and big breaks was assumed. It was assumed that five repair crews would be available to respond to this event. Table 2 illustrates a sample of the input data to the optimization model. As previously mentioned, several factors are considered in choosing the set of possible restoration methods. For example, open-cut and splitting methods are the possible options for replacing DI pipes since they do not fracture using regular PB. Also, existing of rocks, densely compacted soils, or expansive soils can cause difficulties for PB. All the data in Table 2 are extracted from the database provided by the City of London, Ontario.

Insert Figure 2

Insert Figure 3

Insert Table 2

Next, the multi-objective optimization problem was solved as per equation 11. In this analysis, the relative weights for the cost, time, and resilience objectives are suggested as 0.3,0.5,0.2 respectively. Three optimization algorithms, GA, ACO, and TS, are tested in this study to determine their respective capabilities in achieving a near-optimal solution of the three considered objectives. Table 3 presents the results obtained from solving the problem using the three different algorithms. It is observed that the three algorithms were able to provide similar solutions in terms of restoration cost and resilience improvement. However, there are some variations when it comes to the restoration time. GA provided a 12% and 14% shorter restoration time than ACO and TS respectively. Consequently, it is chosen to be used in the developed optimization model.

Insert Table 3

While the time objective would usually pose the most significant concern in restoration applications, there are cases where the fund and other resources could be scarce. In others, achieving a certain level of resilience after accomplishing the recovery process might be required. For such cases, decision-makers will be asked to define a range of possible weights for each objective instead of assigning a specific value. The problem would then be solved several times to investigate the part of the Petro front enclosed within the defined ranges. This will yield a set of various near-optimal solutions from which decision-makers may choose the one that best matches their preferences. For illustration purposes, it was assumed that the range of weights for the time objective is (0.3-0.5) and for the cost objective (0.1-0.4). The values of weights for resilience objective were calculated as the complement of the corresponding values to 1. The problem was then solved using several combinations of the possible weights between these ranges (15 sets). Table 4 shows a sample of the different runs of the multi-objective optimization problem that were solved using different combinations of weights. The optimization problems were run on an 8GB

RAM, 3.60 GHz i7 core CPU, and Windows 7 with a 64-bit operating system. The computational time of the different optimization runs ranged between 125 s and 179 s. This performance allows utility managers to obtain real-time near-optimal restoration plans to respond to different hazard events.

Insert Table 4

The solution resulting from the optimization model was then used to create a restoration work plan. A typical restoration work plan encompasses the sequence of segments restoration, the methods of restoration, start and end dates, and the crew assignment. Detailing the steps of each restoration method is beyond the scope of this work. Readers can refer to (Yazdekhasti et al. 2014; Weaver and Woodcock 2014; Simicevic and Sterling 2001) for more about major activates and best practices regarding the various possible restoration methods. Table 5 depicts a restoration work plan for one solution to the optimization problem.

Insert Table 5

To evaluate the performance of the developed optimization model, the obtained results were compared to a restoration plan suggested by the City of London. Municipalities in Canada develop in-house portfolio management heuristics to guide investment planning and obtain such restoration plans. The total restoration time, cost, and resilience improvement resulting from the City's plan were calculated. The suggested optimization model resulted in a significant improvement over the City's plan concerning the restoration time and cost, as shown in Table 6. The obtained restoration plan by the optimization model is around 13 days shorter and CAD 63,000 less expensive. The realized improvement in network resilience as suggested by the optimization model is around 4% more than its corresponding value following the city's approach. The two plans are different in the sequence of restoring the failed segments and in the individual segments that are suggested to be replaced despite having a small break because of exceeding a certain number of breaks. While respecting the available budget, the segment that was selected for replacement by the optimization model is more critical, and thus resulted in a bigger resilience improvement, than the corresponding segment suggested based on the City's plan. This is because criticality of each segment is explicitly considered in the utilized resilience metric as shown in Equation 1 (Assad et al. 2019).

Insert Table 6

Stochastic Analysis

When decision-makers are not able to give certain estimates about the unit time, cost, and resilience improvement of the various considered repair methods, stochastic optimization can be utilized to provide a range of expected values of the considered objectives. Decision-makers would be asked to provide some minimum, maximum, and most probable estimates about the uncertain values. In this analysis, minimum, maximum, and average values of the gathered restoration costs and durations are assumed to be the limits and most probable estimates that will be fed to the Monte Carlo simulation. PERT distribution was selected as the type of probability distribution to sample the associated uncertainties. Different than triangular distribution, PERT distribution places more emphasis on the most probable estimate which is usually more-well known than the extreme values. This suits the case of utility managers who constantly respond to segments' failures and, consequently, accumulate historical experience allowing them to better estimate the most probable values compared to the limit values. In addition, PERT distribution has a smoother shape compared to the angular shape of triangular distribution which offers a better fit for the subjective estimates of the limit values (Law et al. 2000). Stochastic optimization was then run as per the steps explained in the previous section. Fig. 3 illustrates the probability density functions and the cumulative distribution functions for the total cost, time, and resilience improvement of the restoration plan obtained using GA algorithm. Fig. 3 (a) shows that the minimum and maximum values of the total restoration cost are 1.513 Million CAD and 1.623 Million CAD, respectively. Similarly, the minimum and maximum total restoration durations are 16.40 days and 18.91 days, respectively [Fig. 3(b)], and the minimum and maximum resilience improvement are 0.1058 and 0.1070, respectively [Fig. 3(c)]. The mean values of restoration cost, time, resilience improvement are 1,570 Million CAD, 17.54 days, and 0.106 respectively. Table 7 depicts a comparison between the results of the deterministic and stochastics solutions of the formulated problem. As evidenced by the observable variations, utility managers shall consider utilizing a stochastic approach in cases where the input estimates are highly uncertain. In stochastic analysis, different statistics can be optimized instead of the mean of the original objective such as the 95th percentile which can be used by utility managers in planning and risk management. However, when decision-makers have reasonable certainty about the used estimates, deterministic approach is preferred due to the significant decrease in the computational time and effort.

Insert Figure 4

Insert Table 7

Several sensitivity analyses were conducted to determine the input variables whose impacts on the mean values of the objective functions are the highest. Fig. 4 depicts a tornado graph showing the sensitivities of total restoration cost to different inputs. Restoring pipe segments #10 and #27 were found to impact the restoration cost the most. Segments 10 and 27 are two of the largest segments in this studied network with diameters of 450mm and 300mm, respectively. Additionally, the restoration methods suggested for these two segments are pipe bursting and open-cut-method. Similar analyses were performed to highlight critical segments based on restoration time and resilience improvement. This kind of analysis is essential to determine the crucial segments whose restoration needs to be carefully reviewed and implemented.

Insert Figure 5

Summary and Conclusions

Restoring functionality of WDNs after disruptive events is a challenging process. This paper presented a multi-objective resilience-driven restoration model to optimize three conflicting objectives: total restoration time, total restoration cost, and total resilience improvement. The decision variables include the sequence of restoring failed segments along with the restoration method of each. The time and cost of crew relocation were calculated using API for Google Maps. In order to determine the optimal restoration plan, the formulated optimization model was solved using GA, which outperformed ACO and TS. The developed model was implemented on actual WDN in the City of London, Ontario. The obtained plan resulted in 4% cost savings, 48% duration reduction, and 4% resilience improvement when compared to a plan suggested by the city. Simulation optimization was also utilized to account for uncertainties that might arise in estimating the time, cost, and resilience improvement associated with the restoration actions. Decision-makers shall determine to solve the problem deterministically or stochastically based on the level of confidence in the used estimated. This model is expected to help city managers and other governmental agencies in better managing WDNs by responding more efficiently to hazardous events. The model can determine the optimum sequence and type of restoration activities while respecting a set of performance and managerial constraints.

The proposed model has some limitations that could be enhanced in future studies. This model assumed that the available crews could do all types of restoration methods. However, some restoration tasks might require specialized crews and equipment. The model can be modified such that different crews will be entitled to different restoration tasks. This work focused on pipe segments as they constitute the largest portion of WDNs. The analysis can be extended to include other assets such as pumps and water tanks. Moreover, models that capture dependencies between WDNs and other critical infrastructure systems can be utilized to provide a more accurate estimate of each segment's criticality. Before being utilized by municipalities, it is recommended to automate the proposed optimization model to make it more user-friendly.

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. Information about the Journal's data sharing policy can be found here: https://ascelibrary.org/doi/10.1061/(ASCE)CO.1943-7862.0001263

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Table 1. Set of Considered Repair Methods

Method	Description
Mechanical Clamps and Couplings	Repair techniques that are used to fix small breaks, leaks, and circumferential cracks. Clamps allow conducting repair actions without full depressurization of the pipe segment (Weaver and Woodcock 2014).
Pipe Bursting (PB)	A replacement technique that involves insertion of a bursting head into the host pipe to break it and pull along a new pipe of the same or larger diameter. The most preferred trenchless technique to replace pipes of different materials and sizes. Rocks and densely compacted soils are not favorable (Yazdekhasti et al. 2014).
Pipe Splitting (PS)	A method for replacing an existing pipe by longitudinal splitting and drawing in a new pipe of the similar or larger diameter behind. A special variant of PB to replace ductile iron pipes that do not fracture using regular PB (Alan Atalah 2009).
Open Cut Method (OCM)	The most commonly used method for water mains renewal with no restrictions on the size or material type of pipes that can be replaced using OCM. A lengthy process and much more expensive than PB. OCM may not be feasible in case of low accessibility and congested urban areas (Yazdekhasti et al. 2014).

Table 2. Sample of the Data Used in the Optimization Model

Pipe ID	X (Easting)	Y (Northing)	R_i	C_i	Diameter (mm)	Length (m)	Soil Type	NOPB[a]	Age	Material	Break Type
1	480,086	4,758,960	0.375	0.402	150	116.38	Sand	0	28	CI	Small
2	479,268	4,758,590	0.383	0.394	450	107.55	Clay	4	19	CI	Small
3	478,790	4,759,090	0.695	0.321	150	82.97	Sand	1	21	CI	Big
4	478,850	4,759,650	0.769	0.333	200	152.92	Clay	0	17	PVC	Small
5	479,833	4,759,070	0.514	0.368	250	64.58	Clay	1	25	CI	Big
—	—	—	—	—	—	—	—	—	—	—	—
30	479790	4758790	0.446	0.422	450	57.06	Sand	0	30	CI	small

[a]NOPB = Number of previous Breaks

Table 3. Comparison of Optimization Results Using GA, ACO, and TS

Criterion	GA	ACO	TS
Time (days)	13.9	15.8	16.2
Cost ($x10^3$ CAD)	1,557	1,557	1,557
Resilience Improvement	0.106	0.106	0.106

Table 4. Different Optimal Solution Sets Resulting from Different Iterations

Iteration	W_1	W_2	W_3	Cost ($x10^3$ CAD)	Time (days)	Resilience Improvement	Weighted Objective Function
1	0.3	0.3	0.4	1,588	14.45	0.110	0.471
2	0.4	0.3	0.3	1,557	14.26	0.106	0.734
3	0.1	0.5	0.4	1,587	14.30	0.110	0.435
4	0.4	0.4	0.2	1,557	13.84	0.106	0.965
5	**0.3**	**0.5**	**0.2**	**1,557**	**13.86**	**0.106**	**0.949**
—	—	—	—	—	—	—	—
15	0.2	0.5	0.3	1,557	14.26	0.106	0.707

Note: The bold row represents the combination of weights that was assumed in solving the optimization problem.

Table 5. Restoration Schedule Based on a Sample Output of the Restoration Model

Objective	Tasks	Restoration Method	Responsible	Start Date	Target Date
Restoring the failed water subnetwork to the agreed resilience level within the minimum possible time and respecting the allowed budget and available resources. Tasks shall be performed based on the listed sequence and specified restoration method.	Restoring Seg. 18	Clamp	Crew #1	3/1/2020	3/1/2020
	Restoring Seg. 10	Pipe Bursting	Crew #2	3/1/2020	3/4/2020
	Restoring Seg. 29	Open-Cut	Crew #3	3/1/2020	3/9/2020
	Restoring Seg. 28	Pipe Splitting	Crew #4	3/1/2020	3/3/2020
	Restoring Seg. 30	Clamp	Crew #5	3/1/2020	3/1/2020
	Restoring Seg. 21	Pipe Bursting	Crew #1	3/1/2020	3/3/2020
	Restoring Seg. 19	Pipe Bursting	Crew #5	3/1/2020	3/2/2020
	Restoring Seg. 17	Clamp	Crew #5	3/2/2020	3/3/2020
	Restoring Seg. 12	Clamp	Crew #5	3/3/2020	3/3/2020
	Restoring Seg. 2	Pipe Bursting	Crew #1	3/3/2020	3/5/2020
	Restoring Seg. 5	Pipe Bursting	Crew #5	3/3/2020	3/4/2020
	Restoring Seg. 20	Clamp	Crew #4	3/3/2020	3/3/2020
	Restoring Seg. 8	Pipe Bursting	Crew #4	3/3/2020	3/7/2020
	Restoring Seg. 27	Open-Cut	Crew #5	3/4/2020	3/14/2020
	Restoring Seg. 13	Clamp	Crew #2	3/4/2020	3/5/2020
	Restoring Seg. 4	Clamp	Crew #2	3/5/2020	3/5/2020
	Restoring Seg. 9	Pipe Bursting	Crew #1	3/5/2020	3/6/2020
	Restoring Seg. 15	Pipe Bursting	Crew #2	3/5/2020	3/7/2020
	Restoring Seg. 26	Pipe Splitting	Crew #1	3/6/2020	3/9/2020
	Restoring Seg. 24	Pipe Bursting	Crew #2	3/7/2020	3/11/2020
	Restoring Seg. 11	Clamp	Crew #4	3/7/2020	3/7/2020
	Restoring Seg. 14	Pipe Bursting	Crew #4	3/7/2020	3/12/2020
	Restoring Seg. 6	Pipe Splitting	Crew #1	3/9/2020	3/13/2020
	Restoring Seg. 22	Clamp	Crew #3	3/9/2020	3/10/2020
	Restoring Seg. 16	Pipe Bursting	Crew #3	3/10/2020	3/12/2020
	Restoring Seg. 3	Clamp	Crew #2	3/11/2020	3/11/2020
	Restoring Seg. 25	Pipe Splitting	Crew #3	3/12/2020	3/16/2020
	Restoring Seg. 7	Pipe Bursting	Crew #4	3/12/2020	3/16/2020
	Restoring Seg. 1	Clamp	Crew #3	3/16/2020	3/16/2020
	Restoring Seg. 23	Pipe Splitting	Crew #3	3/16/2020	3/18/2020

Table 6. Comparison between City’s Approach and Suggested Optimization Model

Criterion	Optimization Model	City’s Approach	Enhancement
Time (days)	13.86	26.95	48.5%
Cost (x10^3 CAD)	1,557	1,620	3.9%
Resilience Improvement	0.1056	0.1018	3.7%

Table 7. Comparison between Deterministic and Stochastic Solutions of the Optimization Model

Criterion	**Deterministic Results**	**Deterministic Results (Mean Values)**
Time (days)	13.86	17.54
Cost (x10^3 CAD)	1,557	1,570
Resilience Improvement	0.106	0.106
Computational Time (min.)	2.1 – 3.0	10.5 - 14.1

Figure Captions:

Fig. 1. Methodology framework

Fig. 2. Layout of the selected sub-network in the City of London, Ontario.

Fig. 3. Distribution of water pipe segments grouped by (a) material (b) diameter

Fig. 4. Distributions of the optimal solution resulting from stochastic optimization (a) cost (b) time (c) resilience improvement

Fig. 5. Tornado graph ranking inputs by effect on the mean of the restoration cost