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Improving the Resilience of Post-Disaster Water Distribution Systems Using Dynamic Optimization Framework

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Abstract

Improving the resilience of water distribution systems (WDSs) to handle natural disasters (e.g., earthquakes) is a critical step towards sustainable urban water management. This requires the water utility to be able to respond quickly to such disaster events and in an organized manner, to prioritize the use of available resources to restore service rapidly whilst minimizing the negative impacts. Many methods have been developed to evaluate the WDS resilience, but few efforts are made so far to improve resilience of a post-disaster WDS through identifying optimal sequencing of recovery actions. To address this gap, a new dynamic optimization framework is proposed here where the resilience of a post-disaster WDS is evaluated using six different metrics. A tailored Genetic Algorithm is developed to solve the complex optimization problem driven by these metrics. The proposed framework is demonstrated using a real-world WDS with 6,064 pipes. Results obtained show that the proposed framework successfully identifies near-optimal sequencing of recovery actions for this complex WDS. The gained insights, conditional on the specific attributes of the case study, include: (i) the near-optimal sequencing of recovery strategy heavily depends on the damage properties of the WDS, (ii) replacements of damaged elements tend to be scheduled at the intermediate-late stages of the recovery process due to their long operation time, and (iii) interventions to damaged pipe elements near critical facilities (e.g., hospitals) should not be necessarily the first priority to recover due to complex hydraulic interactions within the WDS.

Keywords: Resilience; post-disaster water distribution system; recovery actions; sequencing; genetic algorithm

Introduction

Natural disasters can cause widespread hydraulic damages and water quality impacts to water distribution systems (WDSs) as well as result in extensive water service interruptions that can last for days or even months (Tabucchi and Davidson 2006). In recognizing the vulnerability of WDSs under natural disasters, many researchers have started exploring how to minimize the impacts of these events to the WDSs, i.e., to improve the system resilience when dealing with natural disasters (Butler et al. 2017). In this context, resilience is usually defined as ability of a WDS to bounce back, i.e. absorb and recover from natural disasters (Diao et al. 2016). To this end, resilience has been increasingly pursued in the design and management of WDSs in face of a deeply uncertain and unpredictable future, especially in the context of climate change and urbanization (Ohar et al. 2015). This motivates a number of studies to investigate the resilience of the WDS over the past decade, mainly focusing on either the development of resilience metrics (Roach et al. 2018) or resilience analysis under various scenarios (Meng et al. 2018).

The resilience of the WDS was initially measured by the expected time that takes a WDS to fully recover its operational functionality (delivery capacity including flows and pressures under normal conditions) after a failure, with shorter recovery time representing greater resilience (Hashimoto et al. 1982). Such a resilience measure has been subsequently modified to improve its quantitative properties, with various metrics developed to quantitatively assess the recovery time of the WDS after a failure (Kjeldsen and Rosbjerg 2004; Chanda et al. 2014). In addition to using recovery speed to measure resilience of the WDS after a failure, the intrinsic capability of the looped WDS in dealing with potential stress or failure conditions has also been employed to indicate system resilience, which was referred as resilience index (Todini 2000; Prasad and Park 2004). In recent years, WDS resilience was alternatively measured from the system structure and connectivity characteristics with the aid of graph theory. These include, for example, the use of link-per-node ratio (Yazdani et al. 2011), diameter-sensitive flow entropy (Liu et al. 2014), critical link analysis (Wright et al. 2015), node degree (Farahmandfar et al. 2016), and topological attributes (Pandit and Crittenden 2016).

In parallel to the development of resilience measures, intensive studies have been also carried out to analyze resilience of WDSs under various scenarios. Originally, the WDS resilience analysis was undertaken using a single pipe failure at a time (Ostfeld et al. 2002). While being simple for analysis, the use of a single pipe failure might not be able to represent the realistic situation of the WDS resilience, especially in the context of natural disasters where a large number of pipes would be affected under such circumstances (Cimellaro et al. 2015). In recognizing this, the WDS resilience was subsequently assessed by the failures of multiple system components in a simultaneous or subsequent manner, such as multiple pipe-breaking scenarios (Gheisi and Naser 2014; Berardi et al. 2014), the concurrence of pipe failures, excess demand, substance intrusion and fire events (Kanta 2010; Bristow et al. 2007; Kanta and Brumbelow 2012), and cascaded component failures of the WDSs (Shuang et al. 2015). A recent outstanding study was Meng et al. (2018), where a novel framework was proposed to explore correlations between WDS resilience to pipe/pump failures and network topological attributes. In their work, resilience was comprehensively assessed with the aid of stress-strain tests which measure system performance using six metrics corresponding to system resistance, absorption and restoration capacities.

The above studies have made significant contributions in measuring or analyzing the WDS resilience. However, there have been few efforts so far made to improve the WDS resilience after natural disasters (e.g., earthquakes) and related events (e.g. major pipe bursts) through developing optimal sequencing of recovery actions (Cimellaro et al. 2015). Mahmoud et al (2018) have recently proposed a new methodology for optimizing the response to failures in WDS in near real-time by using multi-objective optimization, which trades-off the cost of recovery interventions against the corresponding reduction in negative impact on the WDS. This work, however, has been limited to more common failures such as pipe bursts and equipment failures and did not consider more catastrophic events such as earthquakes.

In a recent CCWI/WDSA 2018 conference in Kingston, Canada (Paez et al., 2018a; 2018b), a Battle of Post-Disaster Response and Restoration (BPDRR) was defined, where the objective was to identify optimal recovery strategies for a WDS damaged by different earthquake scenarios. This BPDRR highlights the great importance and urgent need to develop optimal recovery strategies to improve the resilience of post-disaster WDSs, and preparedness of emergency strategies should be a critical consideration for each water utility to minimize the impacts of WDS caused by unforeseeable natural disasters.

However, enhancing the resilience of a post-disaster WDS is challenged particularly for extreme events caused by natural disasters, such as earthquakes (Miles et al. 2006). This is because these natural disasters normally cause a large number of stresses (e.g., pipe breaks, leaks and pump failures) on the WDS due to their catastrophic consequences/impacts. Moreover, these stresses can be in different types or forms and may have complex behaviors ranging from occurring time and locations to occurring duration and magnitude (Shi et al. 2006). For example, some stresses may occur immediately after the disaster while some other stresses may occur after a certain period of time, and some stresses may be undetectable unless some inspections on the system are carried out.

In addition to the complex characteristics associated with the stresses applied to the WDS after disaster events, the recovery actions considered to restore the functionality of the damaged elements are often highly constrained. This is because (i) the emergency resources (e.g., the number of crews) that can be used to restore the water supply service are often very limited in the context of natural disasters and hence they need to optimally allocated; (ii) the priority levels of the water users can be varied, with critical customers (hospitals or firefighting stations) possessing a relatively higher priority relative to the normal residents; and (iii) the system components are hydraulically interdependent within the WDS and hence interventions to some system elements may significantly affect the hydraulic status of other system components (e.g., repairing a pipe may cause the breaking of another pipe or event breaks of many other pipes).

Consequently, developing optimal restauration plan for post-disaster WDSs is very complex, and how to ensure fast recovery and minimize different types of impacts simultaneously as much as possible (i.e., resilience improvement) is still an open question that needs systematic research. To this end, this paper proposes a dynamic optimization framework to identify near-optimal sequencing of recovery actions for the WDS taken from the BPDRR, aimed to improve the system resilience through restoring the functionality of damaged elements in a timely and effective manner. More specifically, the primary contributions of the present work include (i) the proposal of a combinatorial, variable-dynamic (both the number of the variables and the variables themselves can be varied over time) and sequential optimization framework to represent the resilience problem of the post-disaster WDSs, where six metrics are jointly used to quantitively measure the resilience; and (ii) the development of a tailored genetic algorithm to deal with this complex optimization problem.

Methodology

The proposed dynamic optimization framework

The aim of the proposed dynamic optimization framework is to maximize the resilience (denoted here as *RE*) of the post-disaster WDS by optimizing the sequencing of the recovery actions. In the context of disasters, the resilience of the WDS can be measured as a function of different metrics (Klise et al. 2017). Consequently, for a given disaster event, the maximization of the resilience for a post-disaster WDS can be mathematically defined as:

$$\max RE = f(M_1, M_2, ..., M_K) \tag{1}$$

$$M_k = F_k[S(\mathbf{D}(t), \mathbf{A}(t))], t \in [t_1, ..., t_N] \tag{2}$$

where M_k is the k^{th} (k=1, 2,…, K) metric used to measure a particular aspect of the resilience of WDS to a catastrophic event, and K is the total number of metrics considered; $\mathbf{D}(t)$ (t=t_1,…, t_N) is the set of the total damaged elements of the WDS at time t; N is the total number of recovery actions that are required to completely restore the functionality of the post-disaster WDS and t_N is the total required time for such actions; $\mathbf{A}(t)$ is the set of the recovery actions required for all damaged elements $\mathbf{D}(t)$; S is the optimal sequencing of these recovery actions; $F_k(\bullet)$ is a function to quantitively measure the resilience value of the recovery actions (i.e., $S(\mathbf{D}(t), \mathbf{A}(t))$) for the k^{th} metric.

The most important feature of the optimization problem defined in Equations (1) and (2) is that the total number of the decision variables (damaged elements) and the decision variables themselves (e.g., the pipes or tanks that need to be repaired) can both vary when the hydraulic status of the WDS is updated from t_j to t_{j+1}. Such an updating process is carried out at the completion of each intervention to the post-disaster WDS. This updating process is necessary and important to enable a global optimization to improve the resilience of the post-disaster WDS. This is because interventions to some damaged elements are likely to induce further serious damages to other elements that are originally only mildly impaired, due to the increase of pressure caused by recovery of supply capacity or water hammer (Cimellaro et al., 2015).

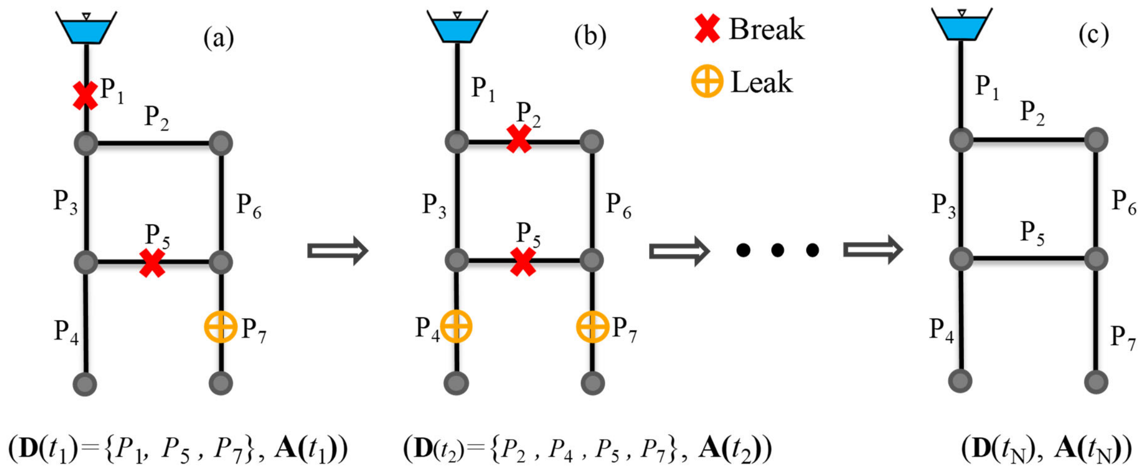


Fig. 1 Illustration of the dynamic updating process of the optimization problem

Fig. 1 is used to further illustrate the inherent dynamic characteristics of the optimization problem regarding resilience maximization for post-disaster WDSs. Let us assume that for this small WDS, the total number of the damaged pipes is three at time t_1 (Fig. 1(a)), i.e., $\mathbf{D}(t_1) = \{P_1, P_5, P_7\}$ after a catastrophic event. Assuming three actions ($\mathbf{A}(t_1) = \{R_1, R_2, R_3\}$) are required to recover this small system at time t_1 and the optimal sequence of these actions is $S(\mathbf{D}(t_1), \mathbf{A}(t_1)) = \{R_1, R_3, R_2\}$, where R_1 is the action to repair pipe P_1 with the first priority. It is likely that the completion of the first recovery action (R_1) can induce large hydraulic impacts to some pipes which are originally mildly damaged by the catastrophic event, resulting in visible leaks or even bursts that need urgent intervention. For this small example, let us assume pipes P_2 and P_4 are significantly affected by the completion of R_1, and hence the total number of the decision variables become 4 ($\mathbf{D}(t_2) = \{P_2, P_4, P_5, P_7\}$) at time t_2 as illustrated in Fig. 1(b). As a result, the status updating after the completion of R_1 leads to the removal of P_1 as a decision variable as well as the inclusion of P_2 and P_4 as the new decision variables. Such an updating process is performed after each recovery action until all pipes with visible damages are fixed as illustrated in Fig. 1(c). Therefore, the maximization of the resilience of post-disaster WDSs as defined in Equations (1) and (2) is a complex combinatorial, variable-dynamic and sequential problem, going beyond the capacity of many available optimization techniques.

Metrics used to indicate resilience of a post-disaster WDS

The CCWI/WDSA joint conference in Kingston 2018 (Paez et al., 2018a; 2018b) has proposed a number of metrics that can be used to measure the resilience of the post-disaster WDS during the recovery process in this study. This is because these metrics can represent the WDS's recovery efficiency of critical customers (e.g., hospitals) and the overall system as well as the functionality damages to the systems and consumers.

Restoration of critical customers (M_1)

Typically, the resilience of the post-disaster WDS can be measured by the time used to restore the functionality of critical customers (e.g., hospitals and firefighting stations):

$$M_1 = \sum_{i=1}^{NC} T(C_i) \tag{3}$$

$$T(C_i) = \{t_i^r \mid \frac{Q(C_i, t_i^r)}{DM(C_i)} \leq rc_i\} \tag{4}$$

where M_1 represents the total time used for all critical customers to recover their functionality to an acceptable level; C_i is the *i*-th critical customer and *NC* is the total number of critical customers; $T(C_i)$ is the time period used to recover the critical customer *i* to a service level of rc_i; $Q(C_i, t_i^r)$ are the received (supplied) water of *i-th* critical customer at time period of t_i^r; $DM(C_i)$ are the required water of critical customer *i*; for a critical customer with required water of $DM(C_i)$, t_i^r is the time period of the *i*-th critical customer without sufficient water. The service level of rc_i has to be specified by the users, which can be varied for different customers and for different cities.

Rapidity of the system recovery (M_2)

In addition to the efficiency in restoring the critical customers, the time used to enable the functionality of the entire WDS to reach an acceptable level *PA* (i.e., rapidity of the system recovery) is another important indicator to represent the resilience of post-disaster WDSs during the recovery process. This metric (M_2) can be described as follows:

$$M_2 = t_{PA} = \max\{t \mid Fun(t) \le PA\} \tag{5}$$

$$Fun(t) = \frac{\sum_{i=1}^{nodes} Q_i(t)}{\sum_{i=1}^{nodes} DM_i(t)} \tag{6}$$

where $Fun(t)$ is the functionality recovery level at time *t*; $\sum_{i=1}^{nodes} Q_i(t)$ and $\sum_{i=1}^{nodes} DM_i(t)$ are the actual received water and required water of all nodes of the WDS at time *t* respectively.

Functionality loss (M_3)

The metric of functionality loss (M_3) is defined as the accumulated loss of functionality from the occurrence of the disaster to the full recovery (100% recovery after the time of t_N), which is defined as follows:

$$M_3 = \int_{t_1}^{t_N} (100\% - Fun(t))\, dt \tag{7}$$

Average time of consumers without sufficient water service (M_4)

Typically, the average time of customers without sufficient water service (M_4) can be considered as an important aspect to enable resilience analysis of a post-disaster WDS, which is defined as follows:

$$M_4 = \frac{1}{m}\sum_{i=1}^{m}\{\sum_{t_1}^{t_N}(t \mid \frac{Q_i(t)}{DM_i(t)} < rm_i)\} \tag{8}$$

where m is the total number of customers (nodes) without sufficient water service. For a given demand node i, when the actual received water $Q_i(t)$ are lower than a given percentage (rm_i) of the required water $DM_i(t)$ at time t, this time is considered as the time without sufficient water service for node i.

Number of consumers without sufficient service for a given consecutive time period (M_5)

In addition to the average time that customers without sufficient water service, it is also important to consider the number of customers without sufficient service for a consecutive time period (PN). This metric (M_5) is defined as follows:

$$M_5 = \sum I[\gamma(i)],\ \forall i \in Nodes \tag{9}$$

$$I[\gamma(i)] = \begin{cases} 1, & if\ \dfrac{Q_i(t)}{DQ_i(t)} < rm_i \text{ is true over a consecutive time period } PN \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where *Nodes* is the total number of demands nodes in the WDS; $I[\gamma(i)]$ is an indicator function, with $I[\gamma(i)]=1$ if the insufficient water service (i.e., $\frac{Q_i(t)}{DQ_i(t)} < rm_i$) consistently occurs over *PN* consecutive time period for node *i*, otherwise $I[\gamma(i)]=0$.

Water loss (M_6)

Typically, the water loss caused by the damages to the pipes is also considered within the resilience analysis of the post-disaster WDS, which is

$$M_6 = \sum_{i=1}^{N_L} \sum_{t=t_1}^{t_N} L_i(t) \tag{11}$$

where N_L is the total number of leaks (bursts); $L_i(t) = k_i(h_i(t))^{0.5}$ is the water discharge rate (m^3/s) from the *i-th* leak (or burst) at time *t*; k_i is the emitter coefficient at leak(or burst) *i*; $h_i(t)$ is the pressure head at the *i-th* leak (or burst) at time *t*.

Proposed method to weight different metrics

In the proposed optimization framework, all the metrics are defined in a manner where a lower value represents great system resilience, which can facilitate the weighting process of different metrics. Typically, different metrics need to be simultaneously considered to improve the resilience of the post-disaster WDS within the recovery process (Shi et al. 2006). To handle this issue, two different methods are often used, that is (i) the multi-objective optimization method; and (ii) the weighting approach that aggregates all different metrics into a single one to enable the identification of a final near-optimal solution. While the multi-objective optimization method has great merit in exploring the trade-offs among all considered metrics, the final Pareto fronts with many different solutions are often complex and the practitioners may be unable to identify the most appropriate recovery strategy, especially in the case that actions need to be taken in an urgent manner. To this end, a weighting method is proposed in this study to enable the joint consideration of all different metrics, which is similar to those used in Bibok (2018). This method is described as

$$RE = f(M_1, M_2, \ldots, M_K) = \frac{1}{\sum_{i=1}^{K} w_i \times D(M_i)} \tag{12}$$

$$D(M_i) = \frac{M_i - M_i^{\min}}{M_i^{\max} - M_i^{\min}} \tag{13}$$

where w_i is the weight of metric i=1,2,…,K; $D(M_i)$ is a function to normalize the metric values within the range of [0, 1]; $M_i^{\min}$ and $M_i^{\max}$ are the minimum and maximum values of metric i respectively, which remain constant at each iteration. These two values can be determined by engineering experience or optimization runs with objective being the single metric i. As part of the proposed weighting method, the weight of each metric is determined using:

$$w_i = \frac{\frac{1}{Rank(M_i)}}{\sum_{i=1}^{K} \frac{1}{Rank(M_i)}} \tag{14}$$

where $Rank\,(M_i)$ is the priority rank of metric M_i. The ranking is often determined by the relevant government departments and water utilities. For instance, the priority of the restoration of critical customers (M_1) is often higher than the other five metrics, in order to save lives and properties. A larger value of w_i in Equation (12) indicates a higher priority of the corresponding metric M_i. It is noted that the ranking of each metric can be subjective, as it may vary for different cities or even different disaster events at the same city. However, the choice of the ranking of the metrics does not affect the application of the proposed optimization framework.

Hydraulic simulation of the post-disaster WDS

As shown in above six metrics, hydraulic parameters including pressures, flows and leak rates need to be determined, which are used to update the decision variables (Fig. 1) and enable the calculations of the metric values. It has been widely acknowledged that a pressure-driven model is suitable to simulate the hydraulic parameter values under the post-disaster circumstances where the pressures are insufficient to supply the required water demands (e.g. Mahmoud et al 2018). The pressure-driven model adopted here is (Wagner et al. 1988):

$$Q_i = \begin{cases} 0 & H_i \le H_i^{\min} \\ DM_i \left(\dfrac{H_i - H_i^{\min}}{H_i^{req} - H_i^{\min}} \right)^{1/2} & H_i^{\min} < H_i \le H_i^{req} \\ DM_i & H_i \ge H_i^{req} \end{cases} \tag{15}$$

where Q_i and DM_i are actual received water and required water at node i, H_i is the pressure at node i after the disaster event; $H_i^{\min}$ is the minimum required pressure at node i that can receive water demands (typically $H_i^{\min} = 0$); and H_i^{req} is the required pressure value that can supply the required demands DM_i to node i.

Decision variables and options

Equation (3)-(11) have elaborated the calculation details for the overall optimization objective (i.e., the resilience defined in Equation 1). This section describes the decision variables that are subject to optimization. As shown in Equation (2), the decision variable at time t_i is denoted here as $\mathbf{D}(t_i)$ and it represents all damaged WDS elements at time t_i. The decision options available are different recovery actions $\mathbf{A}(t_i)$ that are required to restore the functionality of the WDS post-disaster. These include isolations, repairs and replacements of the damaged elements. The near-optimal solution is represented by the sequencing of these actions in time (i.e., $S(\mathbf{D}(t_i), \mathbf{A}(t_i))$ in Equation 2). It is noted that decision options for the replacement and isolation actions of the same pipe have to be considered in a sequencing manner, as the damaged segments of pipes have to be isolated first before they can be replaced. This further increases the complexity of the optimization problem.

The proposed GA-based dynamic optimization method

The problem defined above can be considered as a multi-agent job sequencing problem (Agnetis et al., 2007). However, a major difference between the problem defined in this paper and the traditional multi-agent job sequencing problem is that the former needs to call a hydraulic simulation model in order to calculate the objective functions as well as to update the hydraulic status after each time step. Within this simulation model, conversations of mass equations and conversations of energy equations for each basic loop of the WDS have to be satisfied and hence this model involves a large number of linear and nonlinear equations (Rossman, 2002). Such a simulation becomes more complex when the flow-pressure relationship needs to be considered to model the leaks. Therefore, it is difficult, if not impossible, to explicitly write all these equations as constraints within the traditional multi-agent job sequencing. Meanwhile, solving this problem with so many constraints can be computationally very inefficient and/or likely to lead to convergence issues, as discussed in Zheng et al. (2011).

Fortunately, evolutionary algorithms (EAs) combined with a WDS hydraulic simulation model can be used to address the issue mentioned above (Maier et al., 2014). While many different EAs are available, they cannot be directly used to identify the optimal sequencing of recovery actions for the post-disaster WDS. This is because, as previously stated, some of recovery actions have to be sequentially carried out. More specifically, isolations of the damaged elements (e.g., pipes) have to be performed before replacements, and replacements may not be executed immediately after isolations. However, such a sequence cannot be maintained by the majority of currently available EAs due to the uses of the crossover and mutation operators, resulting in large difficulties in identifying feasible solutions. To solve this particular issue, a Tailored Genetic Algorithm (TGA) is developed with details given below.

Coding of recovery actions

In the proposed TGA, a string of integers is used to represent a potential sequencing of recovery actions. Before coding, it is necessary to identify all necessary recovery actions (the set of $\boldsymbol{A}$ in Equation (2)) to enable the functionality recovery for the post-disaster WDS. For the example of WDS shown in Fig. 1(a), pipe P_1 is broken due to the impact of a disaster event, and hence the required recovery actions for this pipe are isolation and replacement, which can be coded as [P_1, R_1, $T(P_1,R_1)$] and [P_1, R_2, $T(P_1,R_2)$] respectively. Within the sub-string [P_1, R_1, $T(P_1,R_1)$] representing first action (isolation), the first element (P_1) is the index of the damaged segment being restored, the second element (R_1) is the particular action adopted and the third element $T(P, R)$ is the duration required for this action. The sub-strings for all decision variables for the example WDS shown in Fig. 1(a) are given in Table 1 with R_1, R_2 and R_3 representing recovery actions of isolation, replacement and repair actions, respectively. The required time period $T(P,R)$ for each action is a function of the size of the damaged elements and the type of action adopted. Symbols of [1],[2],…,[5] represents the first, second and the fifth sub-string respectively in Table 1, and crews would follow this given schedule to begin the restoration.

Table 1 Coded substrings for the recovery actions of the exampled WDS in Fig.1(a)

Symbols	Substring	Recovery actions
[1]	$[P_1, R_1, T(P_1, R_1)]$	Isolate P_1
[2]	$[P_1, R_2, T(P_1, R_2)]$	Replace P_1
[3]	$[P_5, R_1, T(P_5, R_1)]$	Isolate P_5
[4]	$[P_5, R_2, T(P_5, R_2)]$	Replace P_5
[5]	$[P_7, R_3, T(P_7, R_3)]$	Repair P_7

Modified operators

As the same with the traditional GAs, the proposed TGA also includes the initialization, crossover and mutation operators. In the initialization process, each of the total substrings is randomly selected to constitute a string, representing a potential sequencing of recovery actions. However, each substring must be selected only once in the proposed TGA, which differs to the traditional GAs. In addition, a scanning process is proposed to ensure the isolation is always executed before the replacement for each broken pipe for the initial population as well as the population after the mutation operator, thereby guaranteeing the practicality of these solutions.

The two-point crossover method is used in the proposed TGA and a checking process is proposed to ensure each substring is included only once in each string after crossover. More specifically, for two selected parent strings ST_1 and ST_2, the substring Sub_1 in ST_1 swaps with Sub_2 in ST_2, followed by that the new substring Sub_2 in ST_1 is checked against with other substrings in this string. If this new substring is identical to other substrings in ST_1, Sub_2 in ST_1 and Sub_1 in ST_2 is swapped again. The performance of each population member in terms of resilience (Equation 12) is evaluated by fitness values, and a pressure-driven hydraulic simulation model is used to model the hydraulics of the post-disaster WDS, thereby enabling the calculations of all metrics. The selection operator employed in the proposed TGA is the same as that used in the traditional GAs (Zheng et al., 2011).

Implementation procedures of the proposed dynamic optimization framework

Fig. 2 presents the implementation procedures of the proposed dynamic optimization framework, with main steps given below,

Step 1: Identify the decision variables $\mathbf{D}(t)$ (the set of the damaged elements) at time $t=t_1$;

Step 2: Identify the total required recovery actions at time t ($\mathbf{A}(t)$) as illustrated in Table 1;

Step 3: Find the near-optimal sequencing of these recovery actions at time t using the proposed TGA;

Step 4: Simulate the i^{th} (i=1) recovery action (R_{i}) using a pressure-driven hydraulic model (Paez et al., 2018);

Step 5: Perform the pressure-driven hydraulic model at time $t=t+T(R_{\text{i}})$ to update the decision variables;

Step 6: If new decision variables are identified, the procedure goes back to Step 2, otherwise the subsequent recovery action (i=i+1) is simulated (goes back to Step 4);

Step 7: The whole process is terminated after all the recovery actions are finished, and the final near-optimal recovery strategy is consequently identified as the sequencing of these actions.

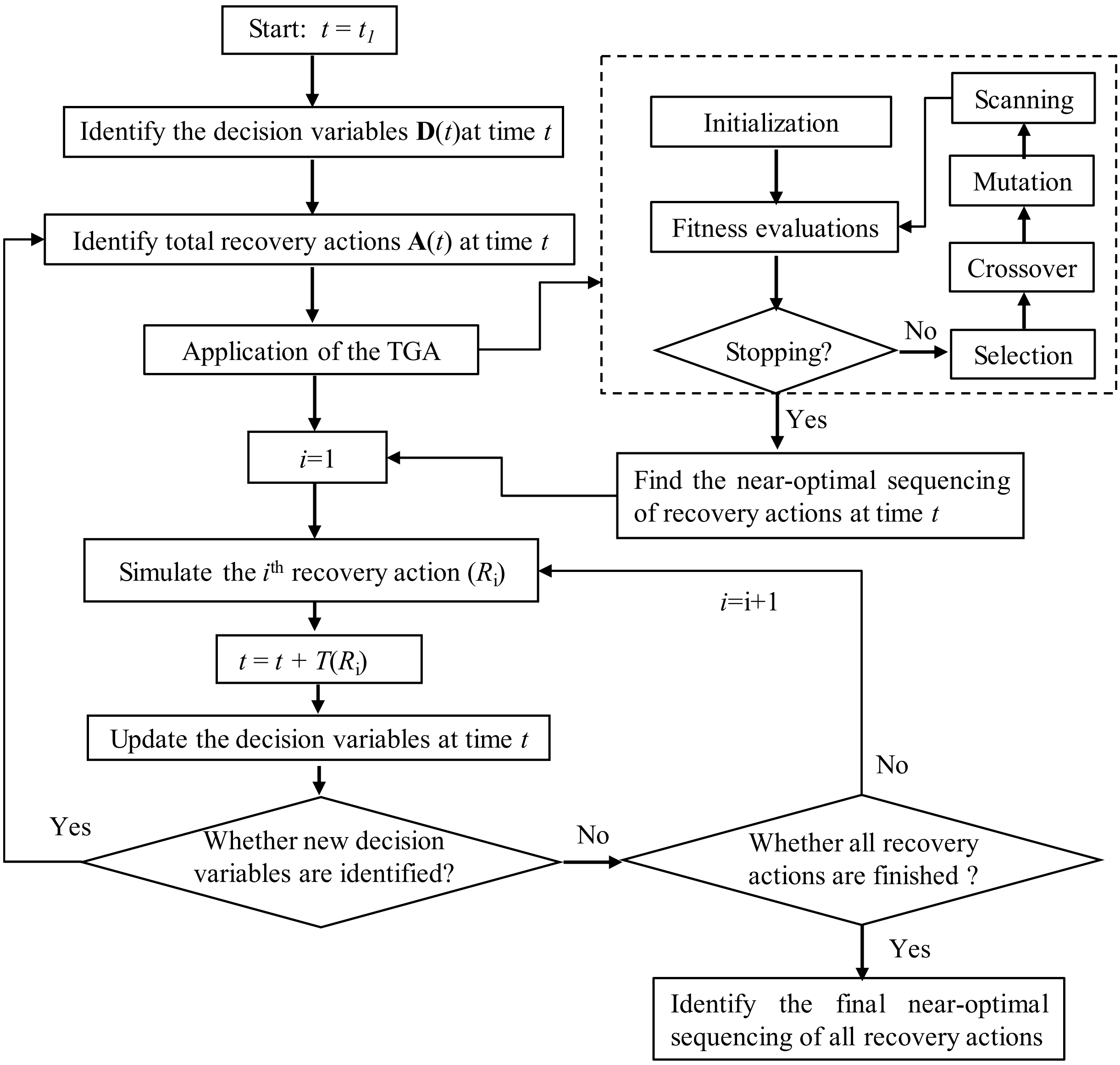
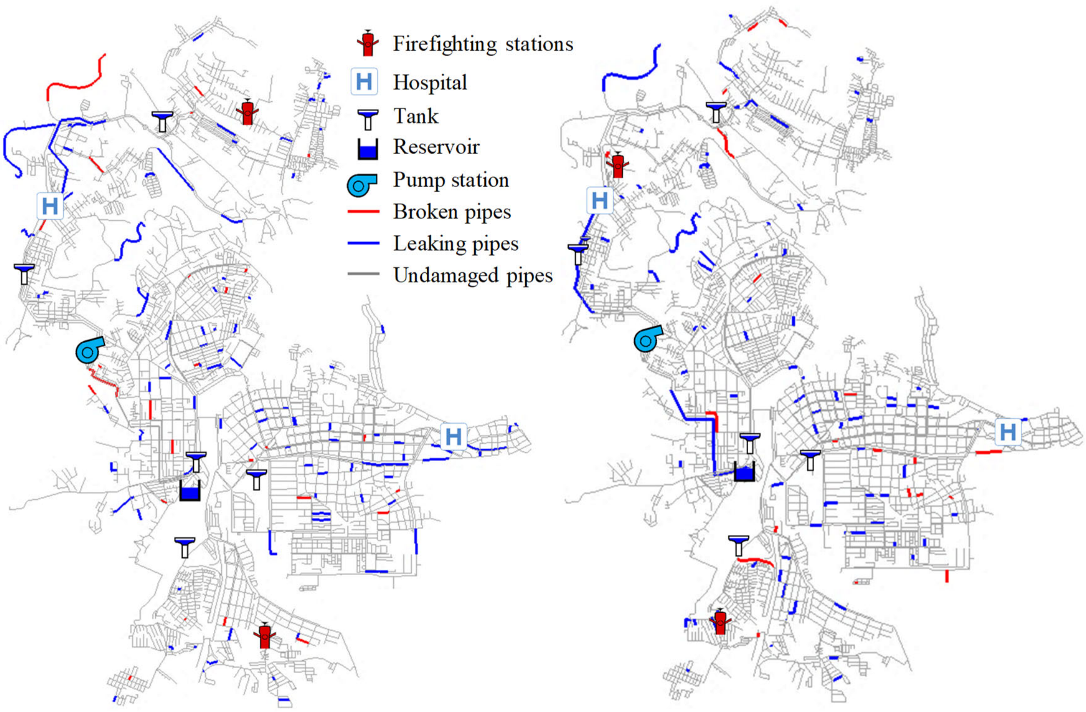


Fig. 2. Implementation procedures of the proposed dynamic optimization framework.

Case study

Overview of the BPDRR

The BPDRR case study (Paez et al., 2018a; 2018b) is designed to identify the optimal recovery strategy using the limited available resources for the restoration of a damaged WDSs following a major disaster (e.g., an earthquake). The WDS used within the BPDRR was taken from the B-city (referred as BWDS). It consists of 4,915 nodes, 6,064 pipes with a total length of approximately 400 km, one reservoir, five tanks, and one pump station with four pumps, as shown in Fig. 3.



(a) (b)

Fig. 3 Two damaged scenarios of BWDS after earthquakes: (a) Scenario 1; and (b) Scenario 2.

Two damage scenarios with different spatial distribution of damaged elements after earthquake events were provided by the local water utility based on the seismic conditions of B-city (Fig. 3). For instance, in Scenario 1, many pipes in the surrounding region of the pump station are broken, while for Scenario 2, many pipes near the reservoir and tanks are seriously affected by the disaster event. The earthquake is assumed to occur at 6:00am in both scenarios. After the occurrence of an earthquake, the water utility requires some reaction time (assumed 30 mins here) before the crews can be dispatched to begin the restoration work. One important assumption made by the BPDRR is that only pipes are damaged during the two disaster events. In other words, facilities like pump stations, tanks, and the source reservoir are assumed to remain their overall functionality after the earthquakes. The rationale behind this is that spatially distributed pipelines are more vulnerable than tanks and pump stations within the WDS under a disaster event (Tabucchi et al. 2006). Two different types of pipe damages are considered, which are pipe breaks and leaks. As described within the BPDRR, the visible damages are considered as the decision variables, where their leaking rates are greater than 2.5L/s calculated by a pressure-driven hydraulic model (provided by the BPDRR organizer). It is noted that invisible damages can become visible due to the operations of the recovery actions as well as the time-variant stresses caused by disasters (Tabucchi et al. 2006), resulting in the variations in decision variables.

Four critical customers including two hospitals and two firefighting stations are included in the BWDS and they should be prioritized for each scenario (Fig. 3). The locations of the two firefighting stations are different for the two different scenarios.

Three crews are available to execute the recovery actions for this post-disaster WDS, and these crews would follow its given schedule (the identified near-optimal strategy) to isolate, repair and replace visible damages. The three crews are assumed to be able to work 24h (independently of the turns of each worker). It was assumed in the BPDRR competition that all nonvisible damages become visible 2 days (i.e. 48hrs) after the event and the total recovery time allowed is 7 days. A pressure-driven model was provided by the organizer to enable the hydraulic simulations, with the minimum pressure values that can provide required water demands at each node H_i^{req} =20 m (Equation 15). The time required for pipe isolation, repair and replacement, i.e., $T(P,R)$ in Table 1 was provided by the competition organizer. The corresponding equation was obtained by statistical analysis of historical records for the analyzed WDS, i.e. it is site specific. It is noted that transportation time requred by the crews to move from one location to another, as well as and time required for reopening of valves are included in the following equation:

$$T(R) = \begin{cases} 0.25 \times VP, & R = isolation \\ 0.233 \times d^{0.577}, R = repair \\ 0.156 \times d^{0.719}, R = replacment \end{cases} \tag{16}$$

where $T(R)$ is the time (hours) used for different recovery actions; VP is the number of valves for the pipe being considered for isolation; d is the pipe diameter (mm).

Parameter settings

Table 2 Parameter values of the metrics

Parameters	rc of M_1	PA of M_2	rm of M_4	PN of M_5
Equations	(4)	(5)	(8)	(10)
Values	0.5	0.95	0.5	8 hours
Comments	rc is the same for all critical customers	-	rm is the same for all resident demand nodes	-

Table 2 summarizes all the parameter values used in the six metrics considered for this case study, which are all provided by the BPDRR organizer. For this case study, the weight settings for the six metrics are determined using the following method: the metric of M_1 is only considered at the first stage as these critical customers (hospitals and firefighting stations) are important to save lives and properties, i.e., w_1=1, w_2= w_3= w_4= w_5= w_6=0; after the functioning of these critical customers are restored to an acceptable level (rc=0.5), the remaining metrics are jointly considered using Equation (14). More specifically, a ranking of the remaining five metrics is $M_5 > M_4 > M_2 > M_3 > M_6$ after a discussion with the local water utility of this BWDS and hence their weights are 0.44, 0.22, 0.14, 0.11, 0.09 respectively determined by Equation (14). It is highlighted again that the choice of the ranking of these metrics is subjective to a certain extent, but this does not affect the application of the proposed optimization framework. The proposed TGA was applied to the BWDS with a population size of 100. A crossover probability of 0.95 and a mutation probability of 0.05 were used for each of the two scenarios, and these parameter values are typically used in many previous studies (Zheng et al.,2011). For each optimization run, the TGA search is performed for 2000 generations, which take about 15 mins using a parallel computer cluster with 4.4-GHz Intel Core i9-7980XE. Such a timeframe is within the scale of time that a water utility would have to react after a disaster (30 mins are considered as the reaction time after a disaster event as stated in the BPDRR). Five different runs of the proposed TGA with different random number seeds were applied to each of the both scenarios, and the results are overall similar across different runs.

Results and discussions

Summary of resilience results

Fig. 4(a) shows the objective function values (resilience *RE*) over different generations for a typical TGA optimization run applied to the post-disaster BWDS under two earthquake scenarios. As shown from this figure, the values of *RE* increase over the optimization process. This implies that the resilience of the post-disaster BWDS is enhancing through the identification of near-optimal sequencing of recovery actions, demonstrating that the proposed optimization method is able to identify near-optimal solutions.

Fig. 4(b) outlines the variations of the number of the decision variables (visible damaged pipes) over time. Overall, the number of the decision variables decreases over time due to the interventions (i.e., application the recovery actions). However, at some time periods, the number of decision variables is stable or even increases because some new damaged pipes become visible as observed in Fig. 4(b). A sudden increase in the number of decision variables after 48 hours of the earthquake is because all small invisible leaks become visible after two days of the earthquake through the use of online sensors or other detection equipment, as described in the BPDRR.

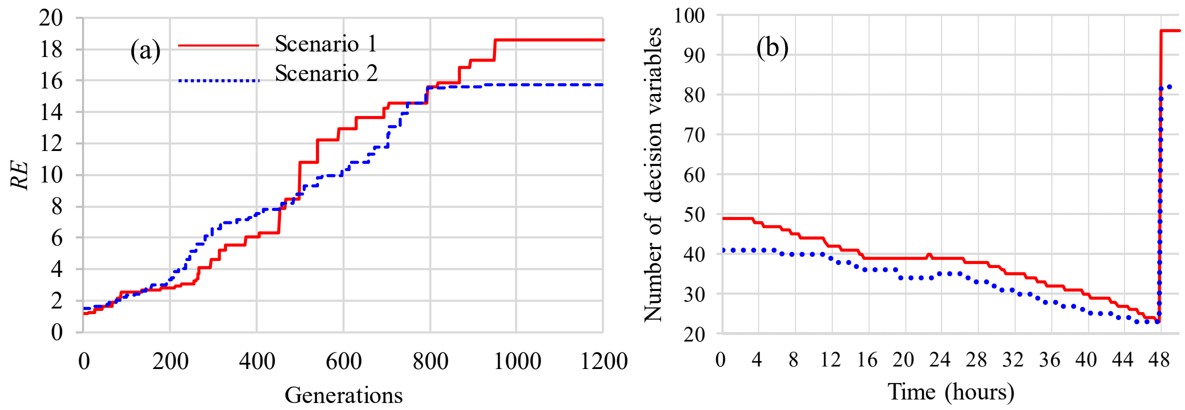


Fig. 4. (a) Values of RE versus generations; and (b) the number of decision variables (visible damaged pipes) versus time.

When comparing the severity of the two earthquake scenarios, Scenario 1 caused larger damages to the BWDS than Scenario 2 as the former consistently had a larger number of decision variables than the latter across the recovery process (Fig. 4(b)). For example, a total of 49 damaged pipes was visible immediately after the earthquake in Scenario 1, while this number was 41 for Scenario 2. After 48 hours of the earthquake, Scenario 1 still had 96 pipes that needed intervention, which was larger than Scenario 2 with 82 pipes that required recovery actions.

Table 3. Values of the six metrics and the objective function (*RE*) of the near-optimal solutions for the post-disaster BWDS with two earthquake scenarios

Metrics	Scenario1	Scenario2	Unit
M_1	675	0	[mins]
M_2	53.5	36.7	[hours]
M_3	25,545	4,329	[% $\times$ min]
M_4	172.6	29.7	[mins]
M_5	103	8	[No. of nodes]
M_6	77,276	49,971	[m^3]
Objective function values (RE)	18.684	15.795	--
Total required time for complete system recovery	137	114	[hours]

Table 3 presents the metric values of the final near-optimal solutions for the post-disaster BWDS with two different disaster scenarios. The total recovery time for Scenario 1 and 2 are 137 and 114 hours respectively. The values of near-optimal solution for Scenario 1 are significantly larger than that that for Scenario 2, implying that the severity of the disaster Scenario 1 is larger than Scenario 2 in terms of impacts to the BWDS. As outlined in Table 3, the near-optimal sequencing of recovery actions for Scenario 1 needs 675 minutes for the restoration of the four critical customers (M_1) and 53.5 hours for the system recovery (M_2) to an acceptable level (95%). Within the recovery process, the total functionality loss is 25,545 [% $\times$ min] (M_3, see Table 3), the averaged time for consumers without sufficient water supply is 172.6 minutes (M_4), the number of consumers without sufficient service over eight consecutive hours is 103 (number of nodes, M_5), and the total water loss is 77,276 m^3 (M_6). Interestingly, the near-optimal solution identified for Scenario 2 can ensure the functionality of the four critical customers at an acceptable level throughout the recovery process, i.e., M_1=0.

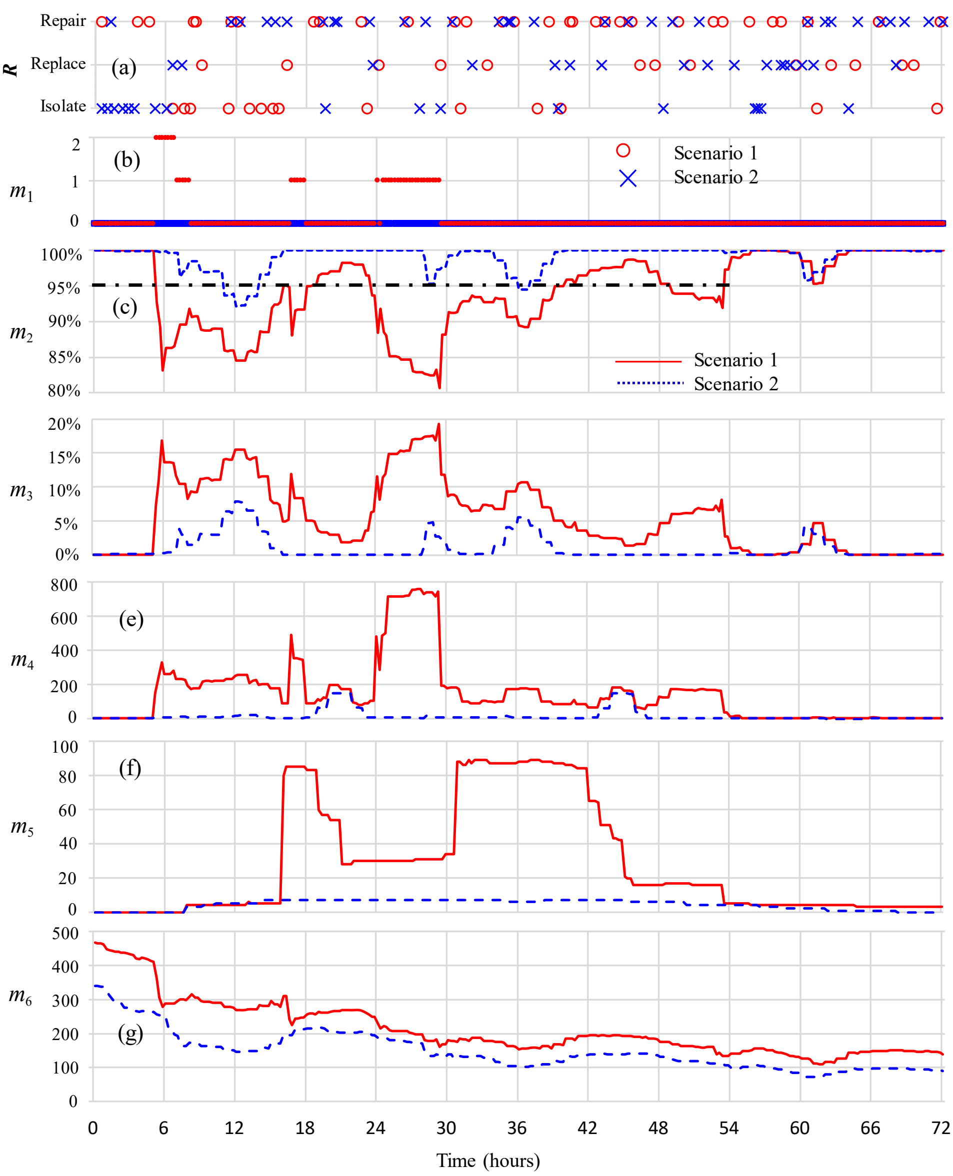
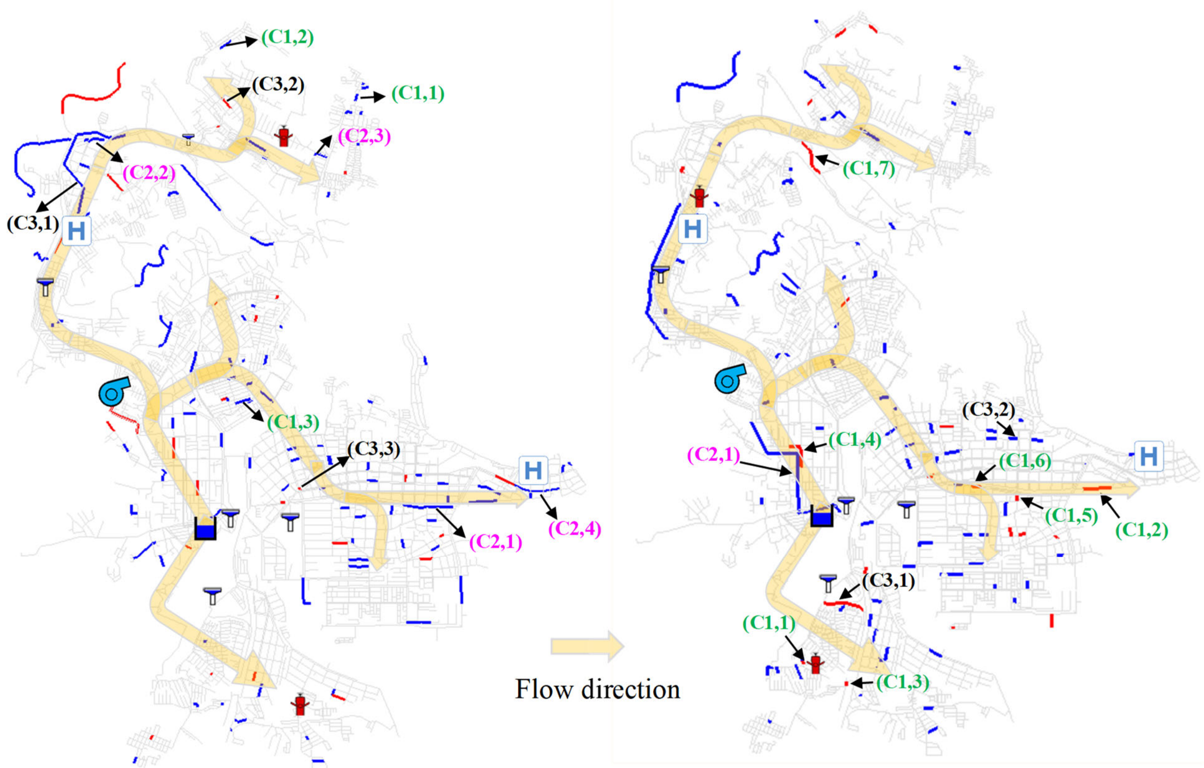


Fig. 5 (a) the sequencing of recovery actions (R) of the two near-optimal solutions for the two scenarios; m_1 (b) and m_4 (e) is the number of critical customers without sufficient water over time and the number of consumers without sufficient water supply over time respectively. m_2 (c), m_3 (d), m_5 (f), m_6 (g) represent the metrics of M_2, M_3, M_5 and M_6 at each time respectively.

The sequencing of the recovery actions (R) are shown in Fig. 5(a) with recovery actions adopted for the initial 72 hours being presented for clarity (The results for the entire time have been added to the Supplemental data). Fig. 5(a) shows that many isolation actions are adopted at the very initial stage for Scenario 2, while the pipe repairs are the main focus for Scenario 1 during this time period. In Fig. 5(b, e), m_1 and m_4 represent the number of critical customers without sufficient water and the number of consumers without sufficient water respectively while m_2, m_5, and m_6 in Fig.6 (c, f, g) represent values of metrics of M_2, M_5 and M_6.

An interesting observation made from Fig. 5 is that the most serious impacts induced by a disaster event (e.g., earthquake) may not be necessarily at the time immediately after the event occurrence. This is because water demands required by the residents are significantly varied over time and the interventions adopted within the recovery process can appreciably affect the hydraulic status of the post-disaster WDS. For the example BWDS, both earthquake scenarios occur during the morning and hence, while the water loss is substantial immediately after the disaster event (Fig.

5(g)), the system functionality is not actually seriously affected as measured by m_1, m_2, m_3, m_4, and m_5 until later on. This is because the required water demands at the time with the occurrence of disaster event (morning) are low. It is noted that the variation of m_1 over time is caused by the varying hydraulic conditions in the network which, in turn, is a consequence of recovery actions implemented and demand variations with time.



(a) Scenario 1

(b) Scenario 2

Fig. 6. The sequencing of recovery actions executed by the three crews (C1, C2 and C3) for the BWDS under two earthquake scenarios, where the number in the bracket representing the order of this action being performed

The impacts of the disaster event to the BWDS are most serious between 6-54 hours after the occurrence of the event. This is reflected by the long time period of the critical customers without sufficient water supply (m_1), low system functionality performance (m_2), long average time of consumers without sufficient water service (m_4), and a larger number of consumers without sufficient water service over eight consecutive hours (m_5) between 6-54 hours as shown in Fig. 5. After 54 hours of the start of the recovery actions, the post-disaster BWDS can recovery its functionality performance at a 95% level for both earthquake scenarios as shown in Table 3 (M_2) and indicated by the black dotted line in Fig. 5(c).

Sequencing analysis of the results

Fig. 6 outlines the sequencing of the first ten recovery actions of the final near-optimal solutions for each of the two scenarios executed by the three crews. The yellow arrow indicates the overall flow direction of the BWDS, with the starting point at the reservoir. The assignments of the first three actions to the three crews can be random, and each crew is assigned subsequent assignments at the completion of the previous assignment (i.e., the new assignment is immediately given to the crew who has completed its assigned action). For Scenario 1 (Fig. 6(a)), the majority of the first ten actions are pipe repairs. More specifically, the three crews are first assigned to repair three important pipes with relatively large leaking rates as indicated by the (C1, 1), (C2, 1), and (C3, 1) in Fig. 6(a). This is because the repairs of these pipes can significantly increase the overall pressure values of the BWDS, which are subsequently beneficial to improve the water service level for the four critical important customers. After the completion of the first three actions, C1 and C2 are assigned to continuously repair pipes with relatively large leaks, as indicated by (C1, 2), (C1,3), (C2, 2), (C2,3) and (C2,4), while C3 is assigned to isolate broken pipes, i.e., (C3,2) and (C3,3).

In contrast to Scenario 1 with many pipe repairs at the initial stage of the recovery process, the majority of the actions identified by the near-optimal recovery strategy for Scenario 2 are isolations of broken pipes. As shown in Fig. 6(b), C1 is consistently assigned to isolate broken pipes, and seven pipes are isolated during the time period that C2 is assigned to repair a pipe (C2,1) near the reservoir with a larger diameter (350 mm). This is because a pipe isolation is significantly faster than a pipe repair or a pipe replacement and hence C1 can complete seven pipe isolations in a short time period. C3 is assigned to isolate a broken pipe, followed by the repair of a pipe that requires a relatively long time.

From Fig. 6, it can be seen that significantly different strategies are identified during the initial stage of the system recovery for the two disaster scenarios. This emphasizes the near-optimal recovery strategy is significantly affected by the spatial distribution of the damaged elements. This also highlights the great importance and necessity to develop an optimization framework (the aim of the present study) that can be used to identify the effective sequencing of recovery actions based on the damage characteristics of the WDS induced by disaster events. An interesting observation for this case is that no replacement is adopted at the initial recovery stage for both scenarios, and this is because such an action is very time consuming based on Eq. 16 and hence it is scheduled at the intermediate-late stages of the recovery process. This finding may vary when different time functions are used, which can be one focus of future study.

Summary and Conclusions

A new, dynamic, optimization based framework is proposed in this paper with the aim to identify the near-optimal sequencing of recovery actions for a WDS that experienced a disaster type event (e.g. an earthquake). Within the proposed framework, a combinatorial, variable-dynamic, and sequential optimization problem is defined maximizing the WDS resilience during the recovery process. Six different metrics were used simultaneously to quantify different aspects of this resilience. A tailored genetic algorithm was developed to solve this complex optimization problem. The proposed dynamic optimization framework is applied to solve the BPDRR problem, where a WDS with 4915 nodes and 6064 pipes is damaged under two different earthquake scenarios. The main findings and implications based on the results, conditioned on the site-specific attributes of repair/replacement times as well as the case study properties, can be summarized as follows:

(i) The proposed method successfully identifies near-optimal sequencing of recovery actions for both scenarios, demonstrating the great utility of the proposed optimization framework in handling such a complex optimization problem.

(ii) The near-optimal recovery strategy can be affected by the damage properties (i.e., spatial distribution of the damaged elements) of the WDS induced by disaster events as observed in this case study. This implies that it is important to have an effective optimization tool as the one proposed in this paper to identify the near-optimal sequencing of recovery actions according to the damage characteristics of the post-disaster WDS.

(iii) Pipe isolations and repairs are the primary actions selected by the TGA at the initial stage of the recovery process in this case study. The rationale behind this is that these two types of interventions can be implemented relatively quickly hence can be beneficial in reducing the overall disaster event impact in a short time period. However, note that this conclusion is conditional on the site-specific attributes of isolation/repair/replacement times shown in Equation (16), i.e. if these times change, the optimal interventions selected may change too.

(iv) Based on the site-specific attributes of repair/replacement times (Equation 16) and the case study properties, it is found that the damaged pipes near the critical customers (e.g., hospitals) or the important hydraulic facilities are not always the first priority in terms of recovery sequencing as observed in this study (e.g., Scenario 1). This is because the functionality recovery of some other pipes, such as the pipes located downstream of the critical customers, can also potentially improve the hydraulic performance (e.g., pressure) for these important customers due to the strong hydraulic interactions between different WDS elements.

In closing, the key contribution of this paper is the generic, dynamic optimization framework that is able to identify near-optimal sequencing of recovery actions for a post-disaster WDS, thereby improving the system resilience through prioritizing the use of available emergency resources. It is believed that the presented optimization framework is generic enough to be transferred to other case studies. Of course, any case study specific details such as interventions considered, impact assessment, etc. would need to be adjusted accordingly. It is also anticipated that such a framework can be practically useful to practitioners, water utilities, and relevant government departments in the context of frequent occurrences of natural disasters in a changing climate, such as earthquakes, floods, and typhoons.

It is noted that this paper focuses on improving the resilience of the post-disaster WDS in considering water delivery ability and hydraulic safety. Future studies along this research line should include (i) the consideration of water quality safety within the framework, (ii) the incorporation of the transportation time used by the crews to move from one location to other (to conduct restoring and repairing actions) into the proposed optimization framework, especially for the WDSs with large spatial scales, (iii) the extension of the proposed methodology to involve other sections (e.g., electricity section), in addition to the water section considered in this paper.

Data Availability Statement

All data and models used during the study appear in the submitted article, and the codes generated during the study are available from the corresponding author by request.

Acknowledgments

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Supplemental Data

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