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Improving the resilience of post-disaster water distribution systems using a dynamic optimization framework --Manuscript Draft--

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Abstract:	<p>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.</p>	
Corresponding Author:	Feifei Zheng Zhejiang University Hangzhou, Zhejiang CHINA	
Corresponding Author E-Mail:	feifeizheng@zju.edu.cn	
Order of Authors:	Qingzhou Zhang	
	Feifei Zheng	
	Qiuwen Chen	
	Zoran Kapelan	
	Kegong Diao	
	Kejia Zhang	
	Yuan Huang	

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<p>If yes, please provide justification in the comments box below.</p> <p>as follow-up to "Authors are expected to present their papers within the page limitations described in Publishing in ASCE Journals: A Guide for Authors. Technical papers and Case Studies must not exceed 30 double-spaced manuscript pages,</p>	<p>The total number of words of the current paper (including abstract, main text and references) is 7800 and the page number is 38 in double space. While this exceeds the page limits, the authors believe all the information is highly necessary to enable the integrity of the entire paper, which is important to facilitate the paper review process. However, we will move some information, especially figures and tables, to the supplementary documents if this paper is luckily accepted.</p>

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<p>Papers published in ASCE Journals must make a contribution to the core body of knowledge and to the advancement of the field. Authors must consider how their new knowledge and/or innovations add value to the state of the art and/or state of the practice. Please outline the specific contributions of this research in the comments box.</p>	<p>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, specifically to prioritize the use of available resources to restore service rapidly and meanwhile minimize the negative impacts. Many methods have been developed to evaluate WDS resilience, but surprisingly few efforts have been made so far to improve resilience of post-disaster WDSs through identifying optimal sequencing of recovery actions. As pointed out by many WDS experts during the conference of Water Distribution System Analysis (WDSA) 2018, preparedness of emergency strategies should be a critical consideration for each water utility to minimize the impacts of WDS caused by unforeseeable natural disasters (https://www.queensu.ca/wdsa-ccwi2018/). This highlights the great importance and urgent need to develop optimal recovery strategies to improve the resilience of post-disaster WDSs, and the current paper is such an attempt to meet this demand. To address this gap, a dynamic optimization framework is proposed, in which a combinatorial, variable-dynamic, and sequential optimization formulation is developed to represent the resilience problem of the post-disaster WDSs, where six metrics are jointly used to quantitatively measure the resilience within the recovery process. Additionally, a tailored genetic algorithm is developed to solve this complex dynamic optimization problem. The proposed optimization framework is demonstrated using a real-world WDS with two different earthquake scenarios. Results obtained show that the proposed framework successfully identifies optimal sequencing of recovery actions for this complex WDS under two disaster scenarios. More importantly, the results build fundamental knowledge regarding the planning of recovery actions for post-disaster WDSs, including (i) the optimal sequencing of recovery strategy heavily depends on the damage characteristics of the post-disaster WDS, (ii) replacements of damaged segments (e.g., pipes) tend to be scheduled at the intermediate or late stages within the recovery process due to their long operation time, and (iii) interventions to damaged segments near the critical facilities (e.g., hospitals, pump stations, tanks) are not necessary the first priority due to the complex hydraulic interactions within the WDS. It is anticipated that the proposed framework can be practically very meaningful 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.</p>
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1 **Improving the resilience of post-disaster water distribution systems using a**
2 **dynamic optimization framework**

3 **Qingzhou Zhang¹, Feifei Zheng², Qiuwen Chen³, Zoran Kapelan⁴, Kegong Diao⁵, Kejia Zhang⁶ and**
4 **Yuan Huang⁷**

5 **¹Qingzhou Zhang:** Postdoctor, College of Civil Engineering and Architecture, Zhejiang
6 University, China. wdswater@gmail.com.

7 **²Feifei Zheng:** Corresponding author, Professor, College of Civil Engineering and Architecture,
8 Zhejiang University, China. feifeizheng@zju.edu.cn. Tel: +86-571-8820-6757. Postal address:
9 A501, Anzhong Building, Zijingang Campus, Zhejiang University, 866 Yuhangtang Rd,
10 Hangzhou, China 310058.

11 **³Qiuwen Chen,** Professor, Center for Eco-Environmental Research, Nanjing Hydraulic Research
12 Institute, qwchen@nhri.cn. Room 201, River and Harbour Building; Hujuguan 34, Nanjing
13 210029, China

14 **⁴Zoran Kapelan,** Professor, Delft University of Technology, Faculty of Civil Engineering and
15 Geosciences, Department of Water Management, Stevinweg 1, 2628 CN Delft, Netherlands.
16 z.kapelan@tudelft.nl

17 **⁵Kegong Diao:** Senior Lecturer, Faculty of Technology, De Montfort University, Mill Lane,
18 Leicester, LE2 7DR, UK. kegong.diao@dmu.ac.uk.

19 **⁶Kejia Zhang:** Associate Professor, College of Civil Engineering and Architecture, Zhejiang
20 University, China. zhangkj@zju.edu.cn.

21 **⁷Yuan Huang:** Postdoctor, College of Civil Engineering and Architecture, Zhejiang University,
22 China. huangyuanggg@163.com.

23

24

25 **Abstract**

26 Improving the resilience of water distribution systems (WDSs) to handle natural disasters (e.g.,
27 earthquakes) is a critical step towards sustainable urban water management. This requires the
28 water utility to be able to respond quickly to such disaster events and in an organized manner, to
29 prioritize the use of available resources to restore service rapidly whilst minimizing the negative
30 impacts. Many methods have been developed to evaluate the WDS resilience, but few efforts are
31 made so far to improve resilience of a post-disaster WDS through identifying optimal sequencing
32 of recovery actions. To address this gap, a new dynamic optimization framework is proposed
33 here where the resilience of a post-disaster WDS is evaluated using six different metrics. A
34 tailored Genetic Algorithm is developed to solve the complex optimization problem driven by
35 these metrics. The proposed framework is demonstrated using a real-world WDS with 6,064 pipes.
36 Results obtained show that the proposed framework successfully identifies near-optimal
37 sequencing of recovery actions for this complex WDS. The gained insights, conditional on the
38 specific attributes of the case study, include: (i) the near-optimal sequencing of recovery strategy
39 heavily depends on the damage properties of the WDS, (ii) replacements of damaged elements
40 tend to be scheduled at the intermediate-late stages of the recovery process due to their long
41 operation time, and (iii) interventions to damaged pipe elements near critical facilities (e.g.,

42 hospitals) should not be necessarily the first priority to recover due to complex hydraulic
43 interactions within the WDS.

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

46 **Introduction**

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

59 The resilience of the WDS was initially measured by the expected time that takes a WDS to fully
60 recover its operational functionality (delivery capacity including flows and pressures under
61 normal conditions) after a failure, with shorter recovery time representing greater resilience
62 (Hashimoto et al. 1982). Such a resilience measure has been subsequently modified to improve
63 its quantitative properties, with various metrics developed to quantitatively assess the recovery
64 time of the WDS after a failure (Kjeldsen and Rosbjerg 2004; Chanda et al. 2014). In addition to
65 using recovery speed to measure resilience of the WDS after a failure, the intrinsic capability of
66 the looped WDS in dealing with potential stress or failure conditions has also been employed to
67 indicate system resilience, which was referred as resilience index (Todini 2000; Prasad and Park
68 2004). In recent years, WDS resilience was alternatively measured from the system structure and
69 connectivity characteristics with the aid of graph theory. These include, for example, the use of
70 link-per-node ratio (Yazdani et al. 2011), diameter-sensitive flow entropy (Liu et al. 2014),
71 critical link analysis (Wright et al. 2015), node degree (Farahmandfar et al. 2016), and
72 topological attributes (Pandit and Crittenden 2016).

73 In parallel to the development of resilience measures, intensive studies have been also carried out
74 to analyze resilience of WDSs under various scenarios. Originally, the WDS resilience analysis
75 was undertaken using a single pipe failure at a time (Ostfeld et al. 2002). While being simple for
76 analysis, the use of a single pipe failure might not be able to represent the realistic situation of

77 the WDS resilience, especially in the context of natural disasters where a large number of pipes
78 would be affected under such circumstances (Cimellaro et al. 2015). In recognizing this, the
79 WDS resilience was subsequently assessed by the failures of multiple system components in a
80 simultaneous or subsequent manner, such as multiple pipe-breaking scenarios (Gheisi and Naser
81 2014; Berardi et al. 2014), the concurrence of pipe failures, excess demand, substance intrusion
82 and fire events (Kanta 2010; Bristow et al. 2007; Kanta and Brumbelow 2012), and cascaded
83 component failures of the WDSs (Shuang et al. 2015). A recent outstanding study was Meng et
84 al. (2018), where a novel framework was proposed to explore correlations between WDS
85 resilience to pipe/pump failures and network topological attributes. In their work, resilience was
86 comprehensively assessed with the aid of stress-strain tests which measure system performance
87 using six metrics corresponding to system resistance, absorption and restoration capacities.

88 The above studies have made significant contributions in measuring or analyzing the WDS
89 resilience. However, there have been few efforts so far made to improve the WDS resilience
90 after natural disasters (e.g., earthquakes) and related events (e.g. major pipe bursts) through
91 developing optimal sequencing of recovery actions (Cimellaro et al. 2015). Mahmoud et al (2018)
92 have recently proposed a new methodology for optimizing the response to failures in WDS in
93 near real-time by using multi-objective optimization, which trades-off the cost of recovery
94 interventions against the corresponding reduction in negative impact on the WDS. This work,

95 however, has been limited to more common failures such as pipe bursts and equipment failures
96 and did not consider more catastrophic events such as earthquakes.

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

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

111 period of time, and some stresses may be undetectable unless some inspections on the system are
112 carried out.

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

123 Consequently, developing optimal restoration plan for post-disaster WDSs is very complex, and
124 how to ensure fast recovery and minimize different types of impacts simultaneously as much as
125 possible (i.e., resilience improvement) is still an open question that needs systematic research. To
126 this end, this paper proposes a dynamic optimization framework to identify near-optimal
127 sequencing of recovery actions for the WDS taken from the BPDRR, aimed to improve the

128 system resilience through restoring the functionality of damaged elements in a timely and
129 effective manner. More specifically, the primary contributions of the present work include (i) the
130 proposal of a combinatorial, variable-dynamic (both the number of the variables and the
131 variables themselves can be varied over time) and sequential optimization framework to
132 represent the resilience problem of the post-disaster WDSs, where six metrics are jointly used to
133 quantitatively measure the resilience; and (ii) the development of a tailored genetic algorithm to
134 deal with this complex optimization problem.

135 **Methodology**

136 *The proposed dynamic optimization framework*

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

$$\max RE = f(M_1, M_2, \dots, M_K) \quad (1)$$

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

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

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

159 Fig. 1 is used to further illustrate the inherent dynamic characteristics of the optimization
160 problem regarding resilience maximization for post-disaster WDSs. Let us assume that for this
161 small WDS, the total number of the damaged pipes is three at time t_1 (Fig. 1(a)), i.e.,
162 $\mathbf{D}(t_1) = \{P_1, P_5, P_7\}$ after a catastrophic event. Assuming three actions ($\mathbf{A}(t_1) = \{R_1, R_2, R_3\}$) are
163 required to recover this small system at time t_1 and the optimal sequence of these actions is
164 $S(\mathbf{D}(t_1), \mathbf{A}(t_1)) = \{R_1, R_3, R_2\}$, where R_1 is the action to repair pipe P_1 with the first priority. It is
165 likely that the completion of the first recovery action (R_1) can induce large hydraulic impacts to
166 some pipes which are originally mildly damaged by the catastrophic event, resulting in visible
167 leaks or even bursts that need urgent intervention. For this small example, let us assume pipes P_2
168 and P_4 are significantly affected by the completion of R_1 , and hence the total number of the
169 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
170 result, the status updating after the completion of R_1 leads to the removal of P_1 as a decision
171 variable as well as the inclusion of P_2 and P_4 as the new decision variables. Such an updating
172 process is performed after each recovery action until all pipes with visible damages are fixed as
173 illustrated in Fig. 1(c). Therefore, the maximization of the resilience of post-disaster WDSs as
174 defined in Equations (1) and (2) is a complex combinatorial, variable-dynamic and sequential
175 problem, going beyond the capacity of many available optimization techniques.

176

177 *Metrics used to indicate resilience of a post-disaster WDS*

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

183 *Restoration of critical customers (M_1)*

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

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

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

186 where M_1 represents the total time used for all critical customers to recover their functionality to
187 an acceptable level; C_i is the i -th critical customer and NC is the total number of critical
188 customers; $T(C_i)$ is the time period used to recover the critical customer i to a service level of
189 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 ;
190 $DM(C_i)$ are the required water of critical customer i ; for a critical customer with required water
191 of $DM(C_i)$, t_i^r is the time period of the i -th critical customer without sufficient water. The

192 service level of rc_i has to be specified by the users, which can be varied for different customers
 193 and for different cities.

194 *Rapidity of the system recovery (M_2)*

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

$$M_2 = t_{PA} = \max\{ t \mid Fun(t) \leq PA \} \quad (5)$$

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

199 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
 200 actual received water and required water of all nodes of the WDS at time t respectively.

201 *Functionality loss (M_3)*

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

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

205 *Average time of consumers without sufficient water service (M_4)*

206 Typically, the average time of customers without sufficient water service (M_4) can be considered

207 as an important aspect to enable resilience analysis of a post-disaster WDS, which is defined as

208 follows:

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

209 where m is the total number of customers (nodes) without sufficient water service. For a given

210 demand node i , when the actual received water $Q_i(t)$ are lower than a given percentage (rm_i) of

211 the required water $DM_i(t)$ at time t , this time is considered as the time without sufficient water

212 service for node i .

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

214 In addition to the average time that customers without sufficient water service, it is also

215 important to consider the number of customers without sufficient service for a consecutive time

216 period (PN). This metric (M_5) is defined as follows:

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

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

217 where N_{nodes} is the total number of demands nodes in the WDS; $I[\gamma(i)]$ is an indicator function,
 218 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
 219 consecutive time period for node i , otherwise $I[\gamma(i)] = 0$.

220 *Water loss (M_6)*

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

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

223 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)
 224 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
 225 pressure head at the i -th leak (or burst) at time t .

226 *Proposed method to weight different metrics*

227 In the proposed optimization framework, all the metrics are defined in a manner where a lower
 228 value represents great system resilience, which can facilitate the weighting process of different
 229 metrics. Typically, different metrics need to be simultaneously considered to improve the
 230 resilience of the post-disaster WDS within the recovery process (Shi et al. 2006). To handle this
 231 issue, two different methods are often used, that is (i) the multi-objective optimization method;
 232 and (ii) the weighting approach that aggregates all different metrics into a single one to enable

233 the identification of a final near-optimal solution. While the multi-objective optimization method
 234 has great merit in exploring the trade-offs among all considered metrics, the final Pareto fronts
 235 with many different solutions are often complex and the practitioners may be unable to identify
 236 the most appropriate recovery strategy, especially in the case that actions need to be taken in an
 237 urgent manner. To this end, a weighting method is proposed in this study to enable the joint
 238 consideration of all different metrics, which is similar to those used in Bibok (2018). This
 239 method is described as

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

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

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

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

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

252 *Hydraulic simulation of the post-disaster WDS*

253 As shown in above six metrics, hydraulic parameters including pressures, flows and leak rates
 254 need to be determined, which are used to update the decision variables (Fig. 1) and enable the
 255 calculations of the metric values. It has been widely acknowledged that a pressure-driven model
 256 is suitable to simulate the hydraulic parameter values under the post-disaster circumstances
 257 where the pressures are insufficient to supply the required water demands (e.g. Mahmoud et al
 258 2018). The pressure-driven model adopted here is (Wagner et al. 1988):

$$Q_i = \begin{cases} 0 & H_i \leq H_i^{\min} \\ DM_i \left(\frac{H_i - H_i^{\min}}{H_i^{req} - H_i^{\min}} \right)^{1/2} & H_i^{\min} < H_i \leq H_i^{req} \\ DM_i & H_i \geq H_i^{req} \end{cases} \quad (15)$$

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

263 *Decision variables and options*

264 Equation (3)-(11) have elaborated the calculation details for the overall optimization objective
265 (i.e., the resilience defined in Equation 1). This section describes the decision variables that are
266 subject to optimization. As shown in Equation (2), the decision variable at time t_i is denoted
267 here as $\mathbf{D}(t_i)$ and it represents all damaged WDS elements at time t_i . The decision options
268 available are different recovery actions $\mathbf{A}(t_i)$ that are required to restore the functionality of the
269 WDS post-disaster. These include isolations, repairs and replacements of the damaged elements.
270 The near-optimal solution is represented by the sequencing of these actions in time (i.e.,
271 $S(\mathbf{D}(t_i), \mathbf{A}(t_i))$ in Equation 2). It is noted that decision options for the replacement and isolation
272 actions of the same pipe have to be considered in a sequencing manner, as the damaged segments
273 of pipes have to be isolated first before they can be replaced. This further increases the
274 complexity of the optimization problem.

275

276 *The proposed GA-based dynamic optimization method*

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

289 Fortunately, evolutionary algorithms (EAs) combined with a WDS hydraulic simulation model
290 can be used to address the issue mentioned above (Maier et al., 2014). While many different EAs
291 are available, they cannot be directly used to identify the optimal sequencing of recovery actions
292 for the post-disaster WDS. This is because, as previously stated, some of recovery actions have

293 to be sequentially carried out. More specifically, isolations of the damaged elements (e.g., pipes)
294 have to be performed before replacements, and replacements may not be executed immediately
295 after isolations. However, such a sequence cannot be maintained by the majority of currently
296 available EAs due to the uses of the crossover and mutation operators, resulting in large
297 difficulties in identifying feasible solutions. To solve this particular issue, a Tailored Genetic
298 Algorithm (TGA) is developed with details given below.

299 *Coding of recovery actions*

300 In the proposed TGA, a string of integers is used to represent a potential sequencing of recovery
301 actions. Before coding, it is necessary to identify all necessary recovery actions (the set of A in
302 Equation (2)) to enable the functionality recovery for the post-disaster WDS. For the example of
303 WDS shown in Fig. 1(a), pipe P_1 is broken due to the impact of a disaster event, and hence the
304 required recovery actions for this pipe are isolation and replacement, which can be coded as $[P_1,$
305 $R_1, T(P_1, R_1)]$ and $[P_1, R_2, T(P_1, R_2)]$ respectively. Within the sub-string $[P_1, R_1, T(P_1, R_1)]$
306 representing first action (isolation), the first element (P_1) is the index of the damaged segment
307 being restored, the second element (R_1) is the particular action adopted and the third element $T(P,$
308 $R)$ is the duration required for this action. The sub-strings for all decision variables for the
309 example WDS shown in Fig. 1(a) are given in Table 1 with R_1, R_2 and R_3 representing recovery

310 actions of isolation, replacement and repair actions, respectively. The required time period $T(P,R)$
311 for each action is a function of the size of the damaged elements and the type of action adopted.
312 Symbols of ①,②,...,⑤ represents the first, second and the fifth sub-string respectively in Table 1,
313 and crews would follow this given schedule to begin the restoration.

314 *Modified operators*

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

322 The two-point crossover method is used in the proposed TGA and a checking process is
323 proposed to ensure each substring is included only once in each string after crossover. More
324 specifically, for two selected parent strings ST_1 and ST_2 , the substring Sub_1 in ST_1 swaps with
325 Sub_2 in ST_2 , followed by that the new substring Sub_2 in ST_1 is checked against with other
326 substrings in this string. If this new substring is identical to other substrings in ST_1 , Sub_2 in ST_1

327 and Sub_1 in ST_2 is swapped again. The performance of each population member in terms of
328 resilience (Equation 12) is evaluated by fitness values, and a pressure-driven hydraulic
329 simulation model is used to model the hydraulics of the post-disaster WDS, thereby enabling the
330 calculations of all metrics. The selection operator employed in the proposed TGA is the same as
331 that used in the traditional GAs (Zheng et al., 2011).

332 *Implementation procedures of the proposed dynamic optimization framework*

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

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

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

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

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

341 Step 5: Perform the pressure-driven hydraulic model at time $t=t+T(R_i)$ to update the decision
342 variables;

343 Step 6: If new decision variables are identified, the procedure goes back to Step 2, otherwise the
344 subsequent recovery action ($i=i+1$) is simulated (goes back to Step 4);
345 Step 7: The whole process is terminated after all the recovery actions are finished, and the final
346 near-optimal recovery strategy is consequently identified as the sequencing of these actions.

347 **Case study**

348 *Overview of the BPDRR*

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

355 Two damage scenarios with different spatial distribution of damaged elements after earthquake
356 events were provided by the local water utility based on the seismic conditions of B-city (Fig. 3).
357 For instance, in Scenario 1, many pipes in the surrounding region of the pump station are broken,
358 while for Scenario 2, many pipes near the reservoir and tanks are seriously affected by the
359 disaster event. The earthquake is assumed to occur at 6:00am in both scenarios. After the

360 occurrence of an earthquake, the water utility requires some reaction time (assumed 30 mins here)
361 before the crews can be dispatched to begin the restoration work. One important assumption
362 made by the BPDRR is that only pipes are damaged during the two disaster events. In other
363 words, facilities like pump stations, tanks, and the source reservoir are assumed to remain their
364 overall functionality after the earthquakes. The rationale behind this is that spatially distributed
365 pipelines are more vulnerable than tanks and pump stations within the WDS under a disaster
366 event (Tabucchi et al. 2006). Two different types of pipe damages are considered, which are pipe
367 breaks and leaks. As described within the BPDRR, the visible damages are considered as the
368 decision variables, where their leaking rates are greater than 2.5L/s calculated by a pressure-
369 driven hydraulic model (provided by the BPDRR organizer). It is noted that invisible damages
370 can become visible due to the operations of the recovery actions as well as the time-variant
371 stresses caused by disasters (Tabucchi et al. 2006), resulting in the variations in decision
372 variables.

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

376 Three crews are available to execute the recovery actions for this post-disaster WDS, and these
377 crews would follow its given schedule (the identified near-optimal strategy) to isolate, repair and
378 replace visible damages. The three crews are assumed to be able to work 24h (independently of
379 the turns of each worker). It was assumed in the BPDRR competition that all nonvisible damages
380 become visible 2 days (i.e. 48hrs) after the event and the total recovery time allowed is 7 days. A
381 pressure-driven model was provided by the organizer to enable the hydraulic simulations, with
382 the minimum pressure values that can provide required water demands at each node $H_i^{req}=20$ m
383 (Equation 15). The time required for pipe isolation, repair and replacement, i.e., $T(P,R)$ in Table
384 1 was provided by the competition organizer. The corresponding equation was obtained by
385 statistical analysis of historical records for the analyzed WDS, i.e. it is site specific. It is noted
386 that transportation time required by the crews to move from one location to another, as well as
387 and time required for reopening of valves are included in the following equation:

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

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

390 *Parameter settings*

391 Table 2 summarizes all the parameter values used in the six metrics considered for this case
392 study, which are all provided by the BPDRR organizer. For this case study, the weight settings
393 for the six metrics are determined using the following method: the metric of M_1 is only
394 considered at the first stage as these critical customers (hospitals and firefighting stations) are
395 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
396 these critical customers are restored to an acceptable level ($rc=0.5$), the remaining metrics are
397 jointly considered using Equation (14). More specifically, a ranking of the remaining five
398 metrics is $M_5 > M_4 > M_2 > M_3 > M_6$ after a discussion with the local water utility of this BWDS
399 and hence their weights are 0.44, 0.22, 0.14, 0.11, 0.09 respectively determined by Equation (14).
400 It is highlighted again that the choice of the ranking of these metrics is subjective to a certain
401 extent, but this does not affect the application of the proposed optimization framework. The
402 proposed TGA was applied to the BWDS with a population size of 100. A crossover probability
403 of 0.95 and a mutation probability of 0.05 were used for each of the two scenarios, and these
404 parameter values are typically used in many previous studies (Zheng et al.,2011). For each
405 optimization run, the TGA search is performed for 2000 generations, which take about 15 mins
406 using a parallel computer cluster with 4.4-GHz Intel Core i9-7980XE. Such a timeframe is
407 within the scale of time that a water utility would have to react after a disaster (30 mins are
408 considered as the reaction time after a disaster event as stated in the BPDRR). Five different runs

409 of the proposed TGA with different random number seeds were applied to each of the both
410 scenarios, and the results are overall similar across different runs.

411 **Results and discussions**

412 *Summary of resilience results*

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

419 Fig. 4(b) outlines the variations of the number of the decision variables (visible damaged pipes)
420 over time. Overall, the number of the decision variables decreases over time due to the
421 interventions (i.e., application the recovery actions). However, at some time periods, the number
422 of decision variables is stable or even increases because some new damaged pipes become
423 visible as observed in Fig. 4(b). A sudden increase in the number of decision variables after 48
424 hours of the earthquake is because all small invisible leaks become visible after two days of the

425 earthquake through the use of online sensors or other detection equipment, as described in the
426 BPDRR.

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

433 Table 3 presents the metric values of the final near-optimal solutions for the post-disaster BWDS
434 with two different disaster scenarios. The total recovery time for Scenario 1 and 2 are 137 and
435 114 hours respectively. The values of near-optimal solution for Scenario 1 are significantly
436 larger than that that for Scenario 2, implying that the severity of the disaster Scenario 1 is larger
437 than Scenario 2 in terms of impacts to the BWDS. As outlined in Table 3, the near-optimal
438 sequencing of recovery actions for Scenario 1 needs 675 minutes for the restoration of the four
439 critical customers (M_1) and 53.5 hours for the system recovery (M_2) to an acceptable level (95%).
440 Within the recovery process, the total functionality loss is 25,545 [% × min] (M_3 , see Table 3), the
441 averaged time for consumers without sufficient water supply is 172.6 minutes (M_4), the number

442 of consumers without sufficient service over eight consecutive hours is 103 (number of nodes,
443 M_5), and the total water loss is 77,276 m³ (M_6). Interestingly, the near-optimal solution identified
444 for Scenario 2 can ensure the functionality of the four critical customers at an acceptable level
445 throughout the recovery process, i.e., $M_1=0$.

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

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

459 disaster event (Fig. 5(g)), the system functionality is not actually seriously affected as measured
460 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
461 with the occurrence of disaster event (morning) are low. It is noted that the variation of m_1 over
462 time is caused by the varying hydraulic conditions in the network which, in turn, is a
463 consequence of recovery actions implemented and demand variations with time.

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

472 *Sequencing analysis of the results*

473 Fig. 6 outlines the sequencing of the first ten recovery actions of the final near-optimal solutions
474 for each of the two scenarios executed by the three crews. The yellow arrow indicates the overall
475 flow direction of the BWDS, with the starting point at the reservoir. The assignments of the first

476 three actions to the three crews can be random, and each crew is assigned subsequent
477 assignments at the completion of the previous assignment (i.e., the new assignment is
478 immediately given to the crew who has completed its assigned action). For Scenario 1 (Fig. 6(a)),
479 the majority of the first ten actions are pipe repairs. More specifically, the three crews are first
480 assigned to repair three important pipes with relatively large leaking rates as indicated by the (C1,
481 1), (C2, 1), and (C3, 1) in Fig. 6(a). This is because the repairs of these pipes can significantly
482 increase the overall pressure values of the BWDS, which are subsequently beneficial to improve
483 the water service level for the four critical important customers. After the completion of the first
484 three actions, C1 and C2 are assigned to continuously repair pipes with relatively large leaks, as
485 indicated by (C1, 2), (C1,3), (C2, 2), (C2,3) and (C2,4), while C3 is assigned to isolate broken
486 pipes, i.e., (C3,2) and (C3,3).

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

493 pipe isolations in a short time period. C3 is assigned to isolate a broken pipe, followed by the
494 repair of a pipe that requires a relatively long time.

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

505 **Summary and Conclusions**

506 A new, dynamic, optimization based framework is proposed in this paper with the aim to identify
507 the near-optimal sequencing of recovery actions for a WDS that experienced a disaster type
508 event (e.g. an earthquake). Within the proposed framework, a combinatorial, variable-dynamic,
509 and sequential optimization problem is defined maximizing the WDS resilience during the

510 recovery process. Six different metrics were used simultaneously to quantify different aspects of
511 this resilience. A tailored genetic algorithm was developed to solve this complex optimization
512 problem. The proposed dynamic optimization framework is applied to solve the BPDRR
513 problem, where a WDS with 4915 nodes and 6064 pipes is damaged under two different
514 earthquake scenarios. The main findings and implications based on the results, conditioned on
515 the site-specific attributes of repair/replacement times as well as the case study properties, can be
516 summarized as follows:

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

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

525 (iii) Pipe isolations and repairs are the primary actions selected by the TGA at the initial stage
526 of the recovery process in this case study. The rationale behind this is that these two types of
527 interventions can be implemented relatively quickly hence can be beneficial in reducing the

528 overall disaster event impact in a short time period. However, note that this conclusion is
529 conditional on the site-specific attributes of isolation/repair/replacement times shown in Equation
530 (16), i.e. if these times change, the optimal interventions selected may change too.

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

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

545 departments in the context of frequent occurrences of natural disasters in a changing climate,
546 such as earthquakes, floods, and typhoons.

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

554 **Data Availability Statement**

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

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

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

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662 **Table 2 Parameter values of the metrics**

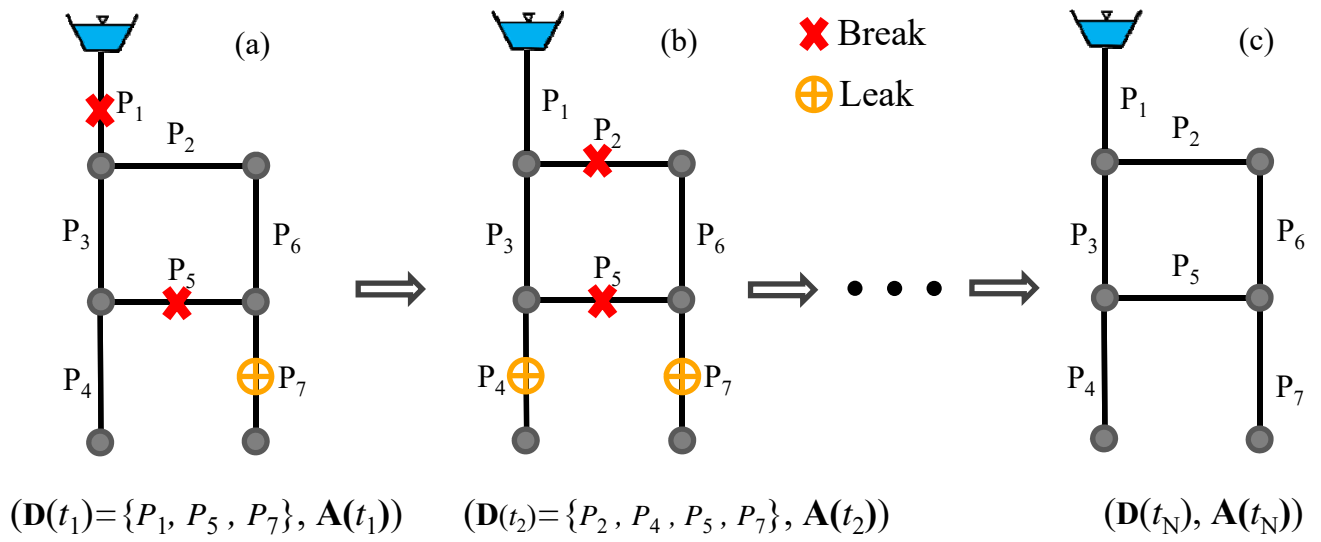
Parameters	rc of M_1	PA of M_2	rm of M_4	PN of M_5
Equations	(4)	(5)	(8)	(10)
Values	0.5	0.95	0.5	8 hours
Comments	rc is the same for all critical customers	-	rm is the same for all resident demand nodes	-

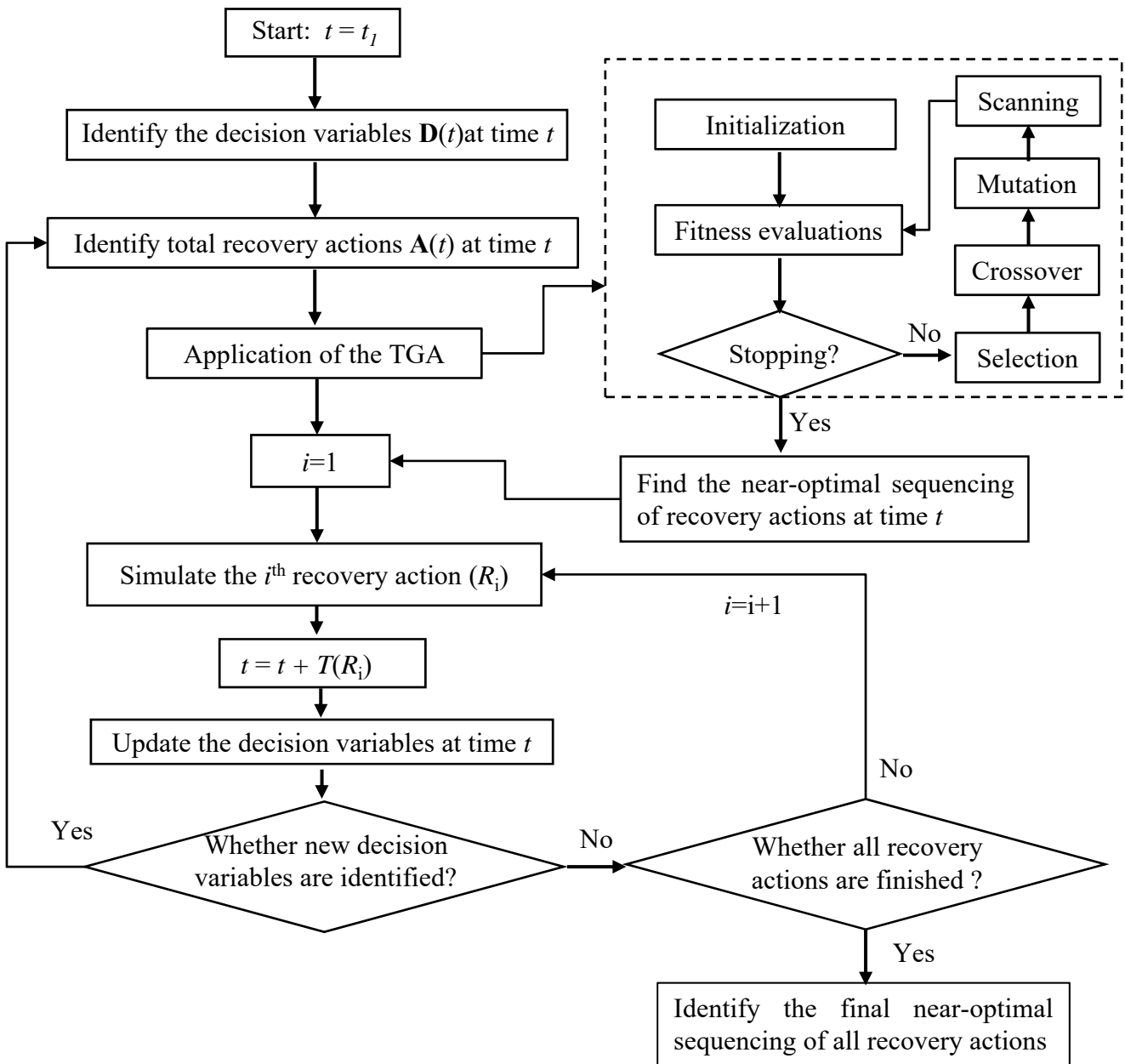
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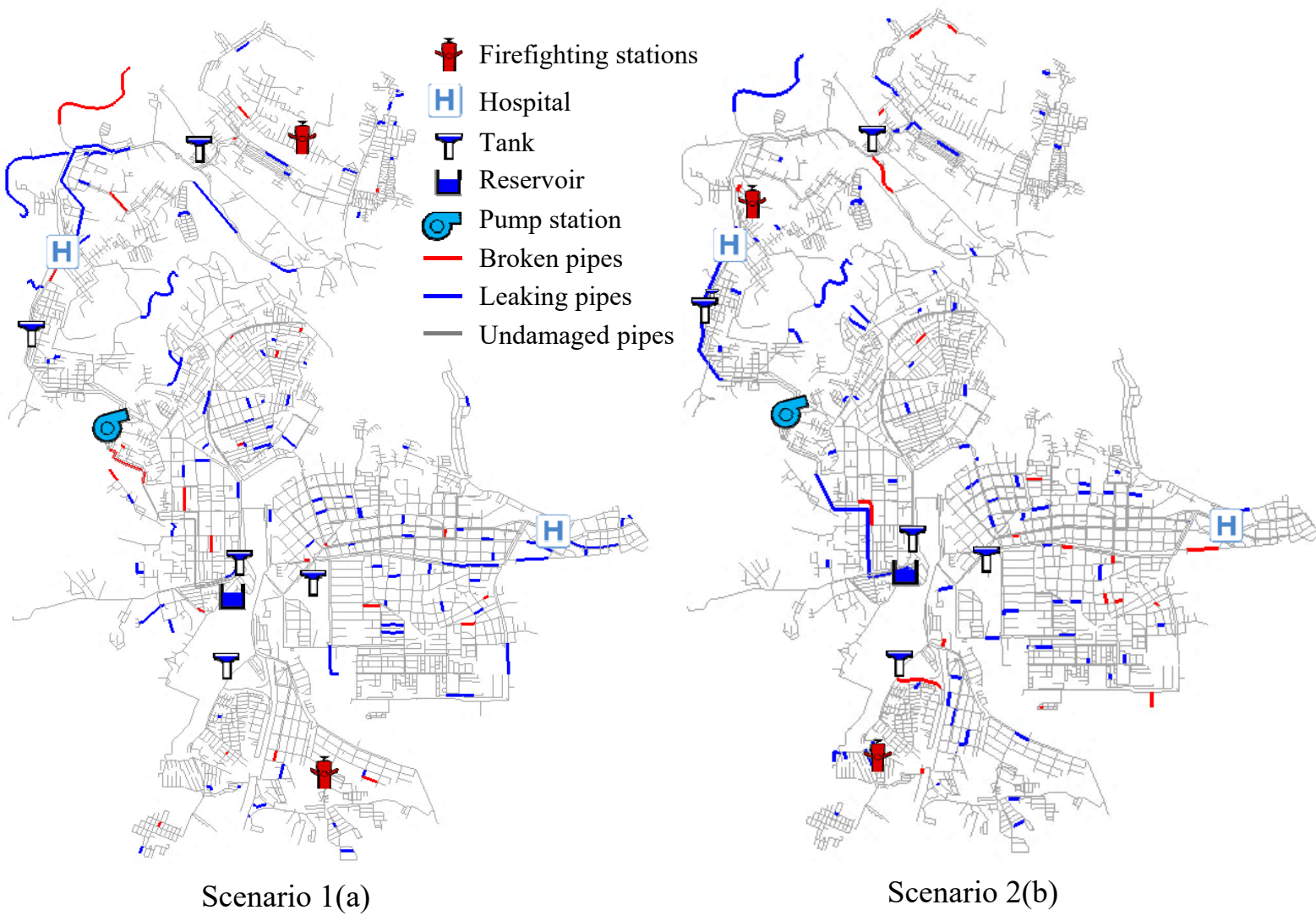
664 **Table 3 Values of the six metrics and the objective function (RE) of the near-optimal**665 **solutions for the post-disaster BWDS with two earthquake scenarios**

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]
<i>Objective function values (RE)</i>	18.684	15.795	--
<i>Total required time for complete system recovery</i>	137	114	[hours]

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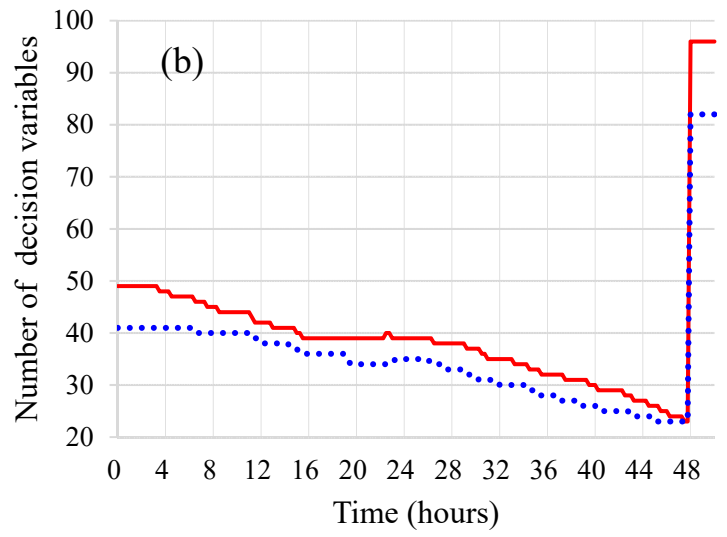
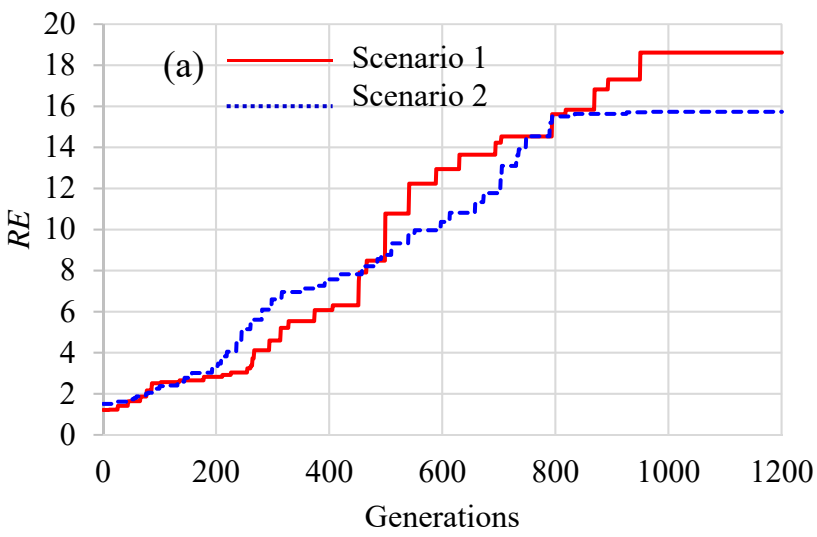


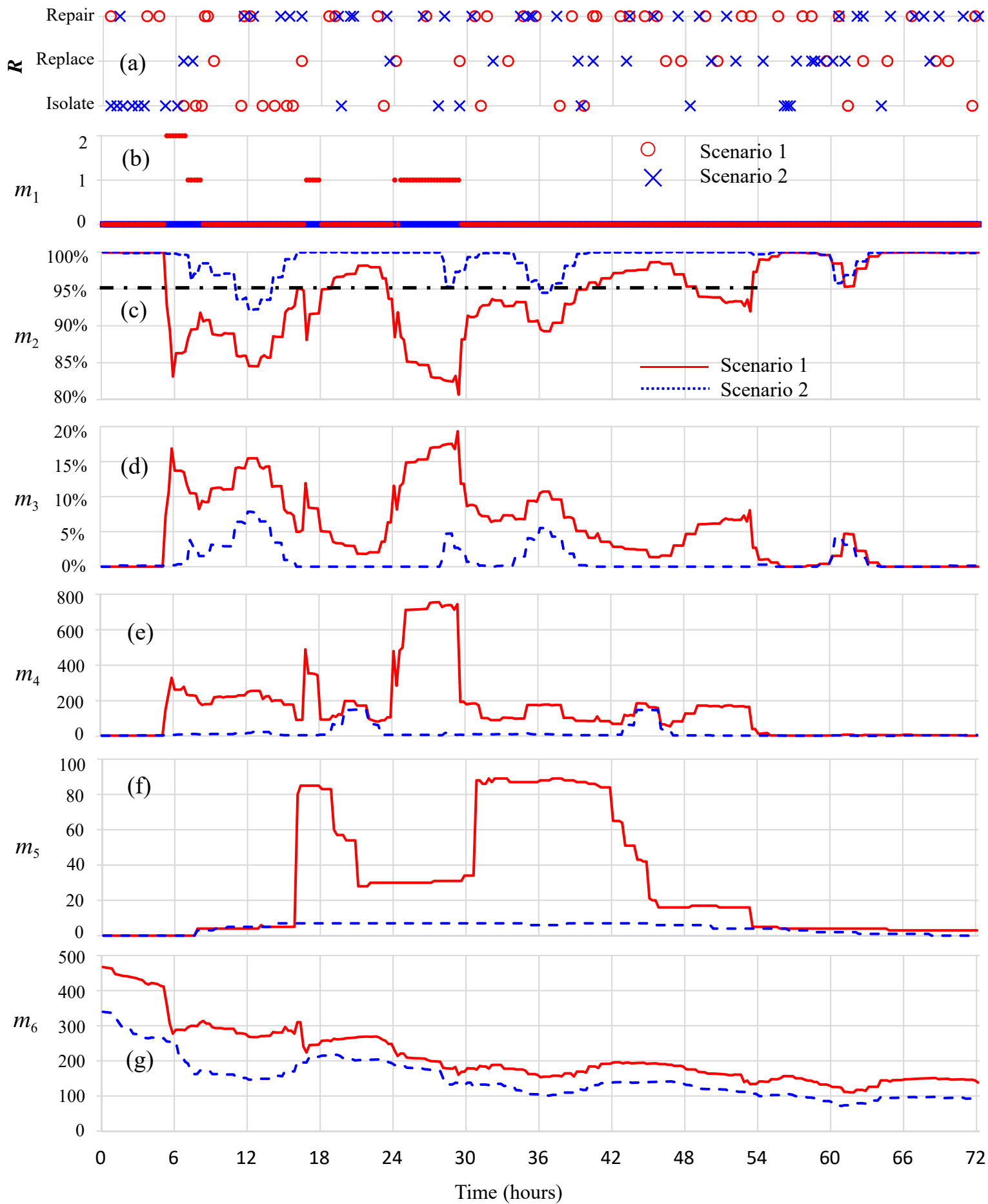




Scenario 1(a)

Scenario 2(b)





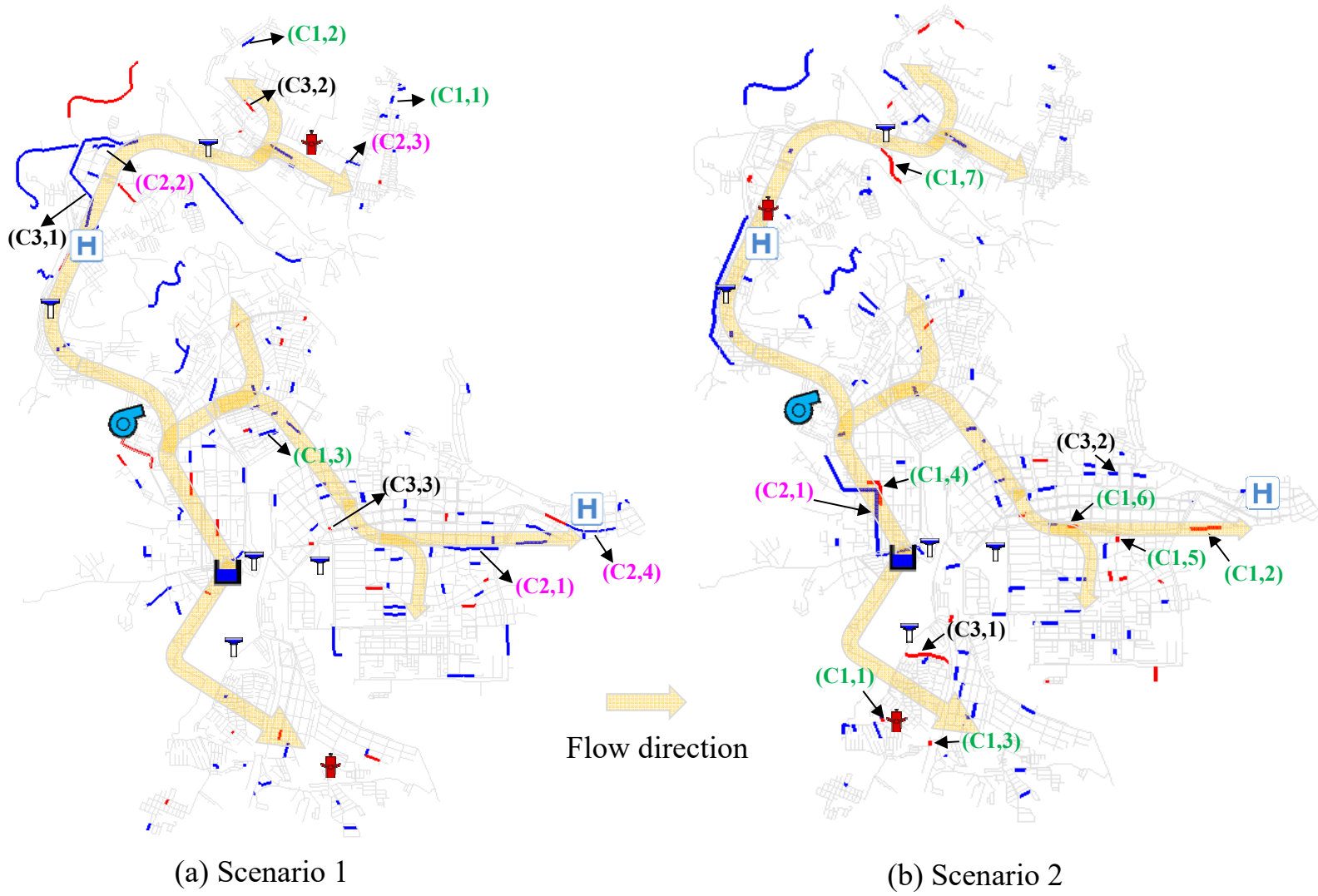


Figure captions

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

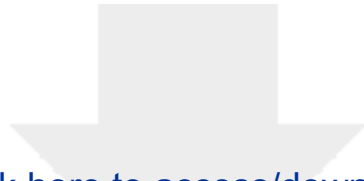
Fig. 2 Implenmentation procedures of the propsoed dynamic optimization framework

Fig. 3 Two damaged scenarios of the BWDS after earthquakes

Fig. 4 (a) values of RE versus generations, (b) the number of decision variables (visible damaged pipes) versus time

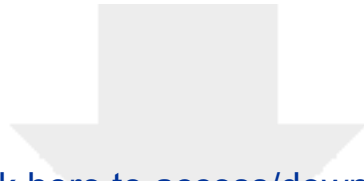
Fig. 5 (a) the sequencing of recovery actions (R) of the two near-optimal solutions for the two scenarios; m_1 (b) and m_4 (e) is the number of critical customers without sufficient water over time and the number of consumers without sufficient water supply over time respectively. m_2 (c), m_3 (d), m_5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

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

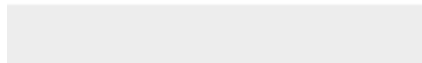


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Author(s) – Names, postal addresses, and e-mail addresses of all authors

Qingzhou Zhang: Postdoctor, College of Civil Engineering and Architecture, Zhejiang University, China. wdswater@gmail.com

Feifei Zheng: Corresponding author, Professor, College of Civil Engineering and Architecture, Zhejiang University, China. feifeizheng@zju.edu.cn

Qiuwen Chen, Professor, Center for Eco-Environmental Research, Nanjing Hydraulic Research Institute, qwchen@nhri.cn

Zoran Kapelan, Professor, Delft University of Technology, Faculty of Civil Engineering and Geosciences, Department of Water Management, Stevinweg 1, 2628 CN Delft, Netherlands. z.kapelan@tudelft.nl

Kegong Diao: Senior Lecturer, Faculty of Technology, De Montfort University, Mill Lane, Leicester, LE

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Paper Title: Improving the resilience of post-disaster water distribution systems using a dynamic optimization framework

Corresponding Author: Professor Feifei Zheng

Contributing Authors: Qingzhou Zhang, Feifei Zheng, Qiuwen Chen, Zoran Kapelan, Kegong Diao, Kejia Zhang and Yuan Huang

The authors would like to thank the reviewers for their comments, which have helped to improve the quality of this paper significantly.

Response to Editors

Comment 1 from Editor

Your Technical Paper, listed above, has completed a review for publication in ASCE's Journal of Water Resources Planning and Management. The editor has requested that a revised manuscript be prepared based on the reviewers' evaluations (shown at the end of this email) and submitted for re-review by 06-17-2019. When preparing the revised manuscript in accordance with the reviewers' concerns and suggestions, be sure to address the following additional requirements, if not already completed:

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Authors' Response: The authors appreciate the significant efforts made by all reviewers, the Associate Editor and Editors in providing excellent and well thought out comments. As suggested by the Editor, we have submitted the documents following the instructions as shown above.

Comment 2 from Editor

Based on the reviews, it is recommended that the author should revise and resubmit the manuscript. The author is encouraged to review the past JWRM publications on this subject and to take the reviewer comments into consideration in improving the paper. However, please submit a list of changes or a rebuttal against each point raised by the reviewer with your revised manuscript. Please note that the earlier we receive your revised manuscript, the earlier we can process it. Thanks for your interest in the Journal of Water Resources Planning & Management. We look forward to receiving the revised manuscript from you. The reviewer comments are listed below.

Authors' Response: We have carefully addressed all comments raised by the reviewers, and made corresponding changes in the manuscript (for details please see the responses to comments below).

Comment 3 from Editor

The paper addresses an important topic, and reviews are generally positive. However, one reviewer recommends to decline (based on the optimization algorithm), and all reviewers express a number of concerns and offer suggestions for improving the paper. The decision on publication is thus deferred until the authors are able to revise and resubmit. The revisions should carefully address the concerns and suggestions made by the reviewers, and a detailed description of how review comments have been addressed in the revision should be submitted with the revised paper. The authors should pay careful attention to the length of their revised paper and ensure that it complies with the ASCE guidelines for length of Technical Papers. The authors are also requested to review the recent research literature (including web-published papers: In Press, Just Released, and Posted Ahead of Print) and include relevant citations in their revised submission.

Authors' Response: Thanks for the Editor's comments. All the comments of the reviewers have been carefully addressed with details given below in this document.

Response to the Associate Editor

Comment from the Associate Editor

A number of fundamental questions were raised in the four reviews received for this paper. I agree with the reviewers that the paper should be revised to address the following comments including the use of GA instead of other mathematical algorithms, the selection of indicators, generalisation of the conclusions, and justification of the main conclusions, and clarification of the key contributions. The presentation of this paper should also be improved as suggested by reviewers.

Author's Response: We would like to thank the AE for these comments. In the revision we have carefully addressed all comments from the reviewers. Additionally, we have significantly improved this paper following the suggestions/comments made by the reviewers. The responses to the AE's specific concerns are also presented below.

(i) The use of GA instead of other mathematical algorithms

Responses: We agree with the reviewer 2 in that the optimization problem defined in this paper is a problem of multi-agent job sequencing (at each time step). However, it should be noted that 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 (e.g., the leaking rate or the total loss of the water) as well as to update the hydraulic status after each time step. Within this simulation model, the conversations of mass equations and conversations of energy equations for each basic loop of the WDS have to be satisfied (a large number of linear and nonlinear equations). Such a simulation becomes more complex when the flow-pressure relationship needs to be considered to model the leaks (see Section of *Hydraulic simulation of the post-disaster WDS* in the paper). Therefore, it is difficult, if not impossible, to explicitly write all these equations (can be up to a few thousands for this WDS) as constraints within the traditional multi-agent job sequencing (then solved by the ϵ -constrained algorithm). Meanwhile, solving this problem with so many constraints is virtually impossible as it can be computationally very inefficient and/or likely to lead to convergence issues, as discussed in Zheng et al. (2011). Fortunately, heuristic approaches (e.g., the GA used in this paper) combined with a WDS hydraulic simulation model can be used to address this issue, which is exactly the reason why heuristic approaches have been widely used to handle WDS design or operation problems (Maier et al., 2014). To address this issue, the following text has been added in the revised manuscript with tracked changes (Lines 320-336)

“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.”

Zheng, F., Simpson, A. R., and Zecchin, A. C. (2011). "A combined NLP-differential evolution algorithm approach for the optimization of looped water distribution systems." *Water Resources Research*, 47(8), 2924-2930.

Maier, H., et al. (2014). "Evolutionary algorithms and other metaheuristics in water resources: current status, research challenges and future directions." *Environmental Modelling & Software* 62: 271-299.

(ii) The selection of indicators

Responses: The use of the six metrics is suggested by the BPDRR organizers in the consideration of 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 after a catastrophic event. This has now been explicitly stated in the revised paper (Lines 187-195)

“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.”

(iii) Generalisation, Justification and clarification of the conclusions

Responses: The authors agree with the reviewers in that the results are conditioned on the case study properties as well as the parameters/assumptions made. This has now been explicitly stated in the Abstract and Conclusion sections in the revised paper, with text given below.

(Lines 37-39)

“The gained insights, conditional on the specific attributes of the case study, include ……”

(Lines 636-667)

“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.”

The authors believe the final results can be dependent on the case study properties (e.g., the distribution of the tanks and pumps) as well as the parameters used. Therefore, it is necessary to run the proposed method for each analyzed case. This is exactly the contribution of this paper as it provides an efficient and effective and generic methodology and tool to identify near-optimal recovery strategies for a post-disaster WDS. Given this as well as that the paper at the current form is already very long, the sensitivity analysis is not performed. This is explicitly stated in the revised paper (Lines 668-670):

“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.”

(vi) Presentation of this paper should also be improved as suggested by reviewers

Responses: Following the suggestions from Reviewers #2, #3 and #4, the description of the proposed TGA has been significantly extended with additional details provided in the revised paper. The relevant text is also shown here 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 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 P1 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 [P1, R1, T(P1,R1)] and [P1, R2, T(P1,R2)] respectively. Within the sub-string [P1, R1, T(P1,R1)] representing first action (isolation), the first element (P1) is the index of the damaged segment being restored, the second element (R1) 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 R1, R2 and R3 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.

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 ST1 and ST2, the substring Sub1 in ST1 swaps with Sub2 in ST2, followed by that the new substring Sub2 in ST1 is checked against with other substrings in this string. If this new substring is identical to other substrings in ST1, Sub2 in ST1 and Sub1 in ST2 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 $D(t)$ (the set of the damaged elements) at time $t=t1$;

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

Step 3: Find the 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 $t=t+T(R_i)$ 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 optimal recovery strategy is consequently identified as the sequencing of these actions.”

Response to Reviewer 1

Comment 1

This paper offers a tool capable of providing an optimal sequencing of recovery actions for post-disaster WDS using a dynamic optimization framework. The optimization is resolved using a Tailored Genetic Algorithm (TGA). Even though the topic is important and of use by the relevant water departments and worth publishing, three conclusions made by the authors need to be supported and better addressed.

Authors' Response: The authors thanks for the reviewer's positive feedback and constructive comments. Following the reviewer's comments, we have revisited the three conclusions questioned by the reviewer in this paper. The details of our responses are given below.

Comment 2

Conclusion (ii): It is concluded that the optimal recovery strategy is affected by the damage properties including the spatial distribution of the damaged segments and occurrence time of a disaster event (day or night). This conclusion wasn't supported in the results' section. The model description didn't also indicate how the location of the damaged segments and the occurrence time of the disaster was considered. The case study mentioned that three crews are available to mitigate the damage and the sequencing analysis (Sec 4.2) showed the sequence of mitigation undertaken by each crew in the first initial stages at different locations distant from each other without elaborating on the time taken to transport from one location to another. The framework seems not considering the time taken in transporting form one location to another no matter what such distance is! Same thing about the occurrence time of the disaster as nothing in the model description nor on the results address that! Not considering these issues in the proposed framework; contrary to the conclusions, makes the results of no use from practical point of view.

Authors' Response: Thanks for the reviewer's constructive comments. Regarding the damage properties of the WDS, we agree with the reviewer in that the previous version of the paper relevant details were not presented in the model description. The following text has been added in the revised paper to address this issue:

(Lines 442-448 in the Case study section of the submitted version with tracked changes)

“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.”

(Lines 604-606 in the Results and Discussions Section)

“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...

(Lines 616-619 in the Results and Discussions Section)

“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.”

Based on the results, we found that the identified optimal strategy is dependent on the damage properties of the WDS, and hence the results can support this conclusion. However, regarding the occurrence time of a disaster event (day or night), the reviewer is correct that we did not explicitly consider this within the model. The rationale behind the corresponding conclusions’ statement is that the nodal demands can significantly change over time (high demands at day time and low demands at night time), and hence this will affect the identification of the optimal recovery strategy. Having said this, given that the two earthquake scenarios provided by the BPDRR are assumed to occur at a specific day time (6:00 am), the words “occurrence time of a disaster event (day or night)” have been removed in Conclusion (ii), as shown below (Lines 642-644). In addition, we have also significantly softened the tone in generalizing these results based on the case study considered in this paper.

“(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.”

Regarding the transportation time, this time was already included in Equation (16) that is used to compute the time used for pipe isolation, repair and replacement, as explicitly stated by the organizers of the BPDRR (Queen’s university in Canada, <http://www.queensu.ca/wdsa-ccwi2018>). This is now explicitly stated in the revised paper as follows (Lines 479-482):

“It is noted that transportation time required 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:

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

For the competition the organizers suggested to ignore the time differences used by the crews to transport from one location to another. This is based on the assumption that the spatial scale of the B-city is rather small. However, the authors entirely agree with the reviewer in that transportation time from one location to another should be incorporated within the optimization framework as it may affect the identification of the optimal recovery strategy, especially for the larger cities. This has now been explicitly stated in the Conclusion of the paper (Lines 683-685),

“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”

Comment 3

Conclusion (iii): It is concluded that pipe isolations and repairs are the primary actions selected by the TGA at the initial stage of the recovery process. This was explained by the fact that these two types of interventions require a relatively low amount of time, and hence these operations can be quickly finalized to reduce the overall impacts of the disaster events in a short time period. Beforehand and according to Equations 16, the repair times are slightly less than the replacement time for diameters greater than 16 inches (if D in these equations are defined in inches since where no units were not given). The opposite is true for diameters less than 16 inches.

Authors’ Response: Thank you for the observation. The diameter d in Equation 16 is defined in millimeters (mm), and the range of diameter in this case study is from 75 mm to 1200 mm. Consequently, the repair time for a pipe will be always less than the replacement time. The following text has been added (Line 484):

“ d is the pipe diameter (mm)”

Comment 4

Yet, the authors mentioned that Equations 16 were provided by the organizer and apparently they are site specific and driven from statistical correlations of historical records (this needs explanation). So this conclusion can’t be generalized and needs to be rephrased to better explain the results and reflects the site-specific attributes of repair/replacement times. It can be also improved by conducting new runs exploring the effect of these equations (if different for another system and/or conditions) on the results (resilience, optimal sequencing, and total mitigation times).

Authors’ Response: Yes, Equation (16) was provided by the organizer based on statistical correlations of historical records in this specific site of the WDS being considered. This has been now explicitly stated in the revised paper (Lines 476-478):

“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.

Following the reviewer’s suggestion, we have rephrased the relevant statements to highlight the results are conditioned on the site-specific attributes of repair/replacement times (Lines 636-638):

“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:

(Lines 649-654)

“(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.”

Thanks for the reviewer’s suggestion in conducting additional runs to explore the effect of above equation on the results. With all due respect we prefer not to conduct additional runs as equation (16) already provides the best estimate of times required for isolation, repair and replacement for the analyzed WDS. Also, applying this equation to another system would not be the right thing to do as Equation (16) is site specific, i.e. it is valid for the analyzed WDS only. In addition, the paper is already very long and hence there is really no space for reporting additional analyses. Finally, we have already acknowledged with above text changes that if aforementioned times change this may have an impact on the optimal interventions selected.

Comment 5

A similar observation for Conclusion (iv) regarding the recovery sequencing of the damaged pipes near the critical customers, this should be rephrased to reflect the site-specific aspect of such results.

Authors’ Response: We agree and have modified conclusion (iv) to address the reviewer’s comment (Lines 661-664):

“(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).”

In addition, the following text has been added in the Abstract to reflect the site-specific aspect of the results (Lines 38-39)

“The gained insights, conditional on the specific attributes of the case study, include:”

Comment 6

$Q(C_i, t_i)$ in equation 4 should be defined as “actual received (supplied) water” and can’t be “actual demands”. Similarly, remove the word “demand” from the definitions of $Q(t_i)$ in equations 6, 8 and 15.

Authors’ Response: Thanks for the reviewer’s comments. We have made corresponding modifications in the revised paper as follows:

“ $Q(C_i, t_i^r)$ are the received (supplied) water of i -th critical customer after time period of t_i^r ” (Line 207)

“ $\sum_{i=1}^{nodes} Q_i(t)$ and $\sum_{i=1}^{nodes} DM_i(t)$ are the actual received and required water of all nodes of the WDS at time t respectively.” (Line 221)

“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 ” (Line 240)

“where Q_i and DM_i are actual received water and required water at node i ” (Line 298)

Comment 7

In Equation 11, the units of $L_i(t)$ is not given. How it is defined here as water discharge rate even though it is reported in Table 3 (M_6) as volume in m^3 ?

Authors’ Response: We have made corresponding changes in the revised paper as follows (Lines 262-264):

“ $L_i(t) = k_i(h_i(t))^{0.5}$ 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 (Shi & O’Rourke, 2006); $h_i(t)$ is the pressure head at the i -th leak (or burst) at time t .”

Comment 8

Line 274, add “be” after “need to”

Authors’ Response: This sentence has been changed to following sentence in the revised manuscript (Lin 292).

“As shown in above six metrics, hydraulic parameters including pressures, flows and leak rates need to be determined”

Comment 9

Section 3.1 (Overview of the BRDRR), need to provide a more detailed description of the two damage scenarios introduced in line 343.

Authors’ Response: Thanks for the reviewer’s comments. We have made a more detailed description in the revised manuscript (Lines 442- 448).

“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 for Scenario 2. 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”

Comment 10

As mentioned above, need to define units of D in Equations 16 and elaborate on how these equations are driven by the organizer.

Authors’ Response: We have made corresponding changes in the revised manuscript according to the reviewer’s comments (Lines 476-484):

“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 required 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:

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

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).”

Comment 12

Section 2.6: Need to provide a better description of the TGA and as mentioned above, if (and how) the disaster occurrence time and the transport time between damaged segments were considered

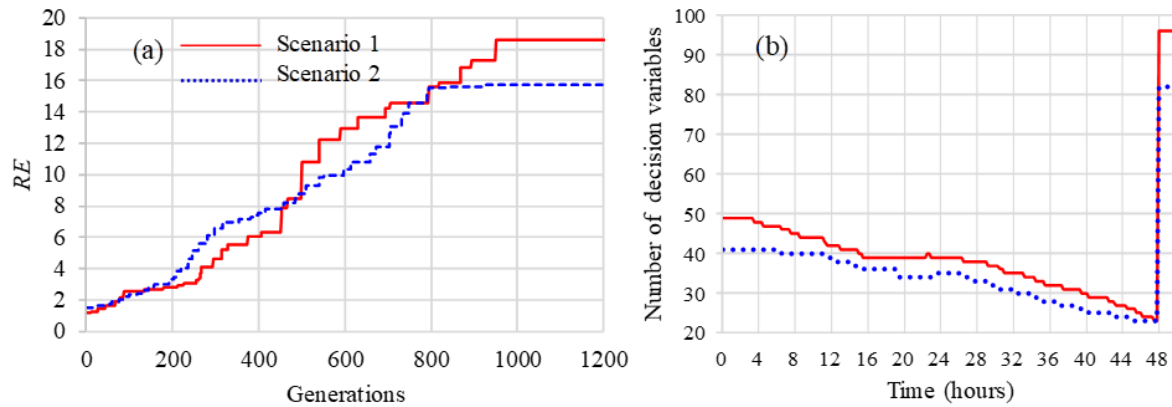
Authors’ Response: As shown in the responses to Comment 2, the transportation time is already included in Equation (16), as explicitly stated by the organizers of the BPDRR competition (Queen’s university in Canada, <http://www.queensu.ca/wdsa-ccwi2018>). However, the organizers suggested to ignore the time differences used by the crews when transporting from one location to another, due to that the spatial scale of the B-city being rather small. Therefore, the transport time between damaged segments is not considered within the optimization framework for this particular case study.

Comment 13

Fig 3(a), need to run the TGA for more than 1000 generations till RE stabilizes especially for Scenario 1.

Authors’ Response: We apologize that we did not explain this case study in details in the original version of the paper. For each optimization process, the TGA was actually

run for 2000 generations, and we found that results were not improved after 1000 generations (converged to a maximum of RE). To better present the results, Fig 4(a) now shows the objective function values up to 1200 generations, i.e. 200 generations more than before.



Comment 14

Line 390, remove “is” after “It”

Authors’ Response: The word ‘is’ has been removed after “It”.

Comment 15

Line 410: replace “Scenario 1” by “Scenario 2”

Authors’ Response: The words “Scenario 1” has been replaced by “Scenario 2”.

Comment 16

Line 415: the statement “This matches well with the findings made based on Fig.3” is redundant and may be removed since the both the results on Table 3 and on Figure 3 are both produced as one set of results from the same model for the same inputs.

Authors’ Response: The sentence has been deleted in the revised manuscript.

Comment 17

Figure 4: Need to include a plot on M_3 results

Authors’ Response: The M_3 results have now been added in Figure 5 in the revised manuscript.

Comment 18

Need proofreading the paper and improve its English Style

Authors’ Response: Thanks for the reviewer’s comments. We have made our best efforts to improve the readability of this paper.

Response to Reviewer 2

Comment 1

Essentially the optimization problem described here, for each time step t , is the classical problem of multi-agent job sequencing with limited resources (see for example [Baker and Smith 2003, Hoogeveen 2002, A., Mirchandani, Pacciarelli and Pacifici 2004, A., De Pascale and Pacciarelli 2009, Sourd 2008, Leung, Pinedo and Wan 2010, Yuan, Shan and Feng 2005, Cheng, Ng and Yuan 2006]). This problem is optimally solved by the ε (epsilon) - constrained algorithm. For a set of conditions (see [A., Pacciarelli and Pacifici 2007]), the ε - constrained algorithm is solvable in poly-time. If the problem in hand fulfills these conditions (which to the best of this reviewer's judgement is the case), the authors must explain their choice to overlook the poly-time option and go with GA. If the authors claim that the Pacciarelli-Pacifici conditions do not apply - they must state and explain this as well. Thus, the decision to go with a heuristic approach must be justified.

Authors' Response: Thanks for the reviewer's constructive comments. We agree with the reviewer in that the optimization problem defined in this paper is a problem of multi-agent job sequencing (at each time step). However, it should be noted that 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 (e.g., the leaking rate or the total loss of the water) as well as to update the hydraulic status after each time step. Within this simulation model, the conversations of mass equations and conversations of energy equations for each basic loop of the WDS have to be satisfied (a large number of linear and nonlinear equations). Such a simulation becomes more complex when the flow-pressure relationship needs to be considered to model the leaks (see Section of *Hydraulic simulation of the post-disaster WDS* in the paper). Therefore, it is difficult, if not impossible, to explicitly write all these equations (can be up to a few thousands for this WDS) as constraints within the traditional multi-agent job sequencing (then solved by the ε - constrained algorithm). Meanwhile, solving this problem with so many constraints is virtually impossible as it can be computationally very inefficient and/or likely to lead to even not cannot be convergence issues, d as discussed in Zheng et al. (2011).

Fortunately, heuristic approaches (e.g., the GA used in this paper) combined with a WDS hydraulic simulation model can be used to address this issue, which is exactly the reason why heuristic approaches have been widely used to handle WDS design or operation problems (Maier et al., 2014). To address this issue, the following text has been added in the revised manuscript (Lines 320-336)

“The problem defined above can be considered as a multi-agent job sequencing problem (Agnētis 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, 2000). 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 or even not cannot be converged 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.”

Zheng, F., Simpson, A. R., and Zecchin, A. C. (2011). "A combined NLP-differential evolution algorithm approach for the optimization of looped water distribution systems." *Water Resources Research*, 47(8), 2924-2930.

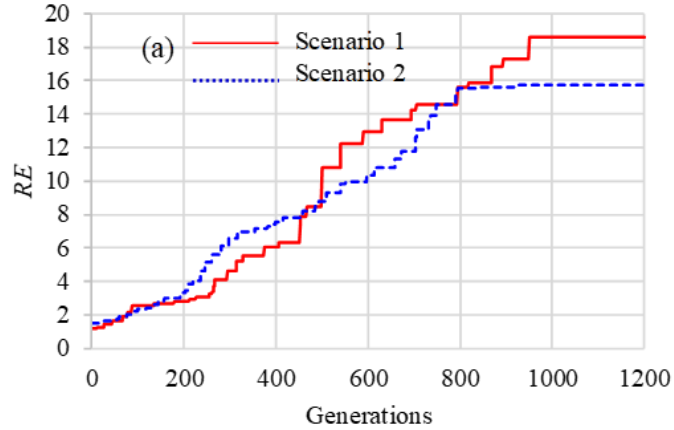
Maier, H., et al. (2014). "Evolutionary algorithms and other metaheuristics in water resources: current status, research challenges and future directions." *Environmental Modelling & Software* 62: 271-299.

Comment 2

The heuristic approach does not guarantee local nor global optimality. Thus, while the authors claim this several times in the manuscript, the provided solutions to the two case studies are not shown to be optimal. The authors do provide some logic why the provided solutions make sense, but in no circumstances, these should be considered as proofs for optimality. Further, the application on two case studies in the same network is limited and cannot be generalized as easily as is insinuated in the paper. Therefore, this reviewer believes that the claims of the manuscript must be limited accordingly.

Authors' Response: The reviewer is correct in observing that a heuristic approach cannot guarantee local nor global optimality. However, the provided solutions can be considered as near-optimal solutions due to the following two reasons (it is also noted that “optimal” regarding the proposed method has been changed to “near-optimal” throughout the revised paper):

- (1) The value of the objective function (resilience value) is consistently increased over the searching time as shown in Figure 4(a), which is presented below as well. This implies that the final identified solutions are significantly better than the random solutions at the first generation in terms of the objective function values, indicating that our provided solutions can be considered as the near-optimal solutions.



- (2) Within the BPDOR, our results obtained using the proposed method overall outperformed the results provided by other participants (e.g., Bibok, 2018, Sweetapple et al. 2018). This can also support that the results presented in this paper are near-optimal solutions.

It is also noted that WDS problem defined in this paper is very complex and is often featured by complex, rough fitness landscapes (Maier et al., 2014). Therefore, even though ideal, it is not necessary to identify the global optimal solution(s) for such a complex problem, it is equally good to find the near-optimal solution(s) using the limited computational resources. This is especially the case for the problem defined in this paper as it is vital to make decision for the recovery actions in a time efficient manner. The following text has been added in the revised manuscript to address this issue (Lines 512-518):

“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 optimal sequencing of recovery actions, demonstrating that the proposed optimization method is able to identify near-optimal solutions.”

Regarding the comment about the application on two case studies in the same network being limited and that this cannot be generalized as easily as is insinuated in the paper, we believe that the overall methodology presented (the 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. We have added this observation to the paper as follows (Lines 674-676):

“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.”

Comment 3

The mathematical formulation is superfluous. There is no need to index t nor D . The time, t , is the index. Thus, $D(t)$, $A(t)$ and $t \in [0, N]$. Using these notations, also eliminates the need for the symbols of table 1.

Authors' Response: Thanks for the reviewer's suggestion. We have used $D(t)$, $A(t)$ throughout the revised paper, and the changes are given below

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

where M_k is the k^{th} ($k=1, 2, \dots, K$) 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; $\mathbf{D}(t)$ ($t=t_1, \dots, t_N$) 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 quantitatively measure the resilience value of the recovery actions (i.e., $S(\mathbf{D}(t), \mathbf{A}(t))$) for the k^{th} metric.

In terms of the symbols in Table 1, we believe it is necessary to have all these details to enable a better understanding of the proposed TGA method. This is also required by Reviewers #4.

Comment 4

While the authors can define the optimization problem as they wish, the problem can be simplified by maintaining the same set of decision variables, with the exception that the fixing utility (or the mitigation of the disaster impact on the network) of undamaged components is zero.

Authors' Response: Thanks for this observation. Fundamentally, our dynamic approach only handles the damaged components (which is 1 following the reviewer's method), which can be variable after each recovery action based on the simulation results of the pressure-driven model. However, if all the undamaged components (which is zero) are also considered within the optimization process, in addition to damaged components, this will significantly increase the complexity of the proposed TGA in terms of the implementation as well as the efficiency. This is especially the case for the WDS considered this paper as the proportion of the damaged pipes is very low (125 damaged pipes out of a total of 6064 pipes).

Comment 5

The authors do not provide any reasoning for the use of the six resilience measures in the manuscript out of the myriad of resilience measures in the literature.

Authors' Response: The use of the six metrics is suggested by the BPDRR organizers in the consideration of 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 after a catastrophic event. This has now been explicitly stated in the revised paper (Lines 187-195)

“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.”

Comment 6

The reasoning for the various weights, w_i , is not provided. Even if determined elsewhere, for the sake of completeness, the reasoning should be briefly provided.

Authors' Response: The weights are computed using Equation (14), which is a function of the ranks of the relative importance of the six metrics considered. 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. This has now been explicitly stated in the revised paper (Lines 284-290)

“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.”

For this case study, the rationale behind the use of the various weights is also stated in the revised paper (Lines 487-496)

“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.”

Comment 7

Eq. (13) - are $M^{\{max\}}$ and $M^{\{min\}}$ heuristically or analytically determined. Do they change in each iteration?

Authors’ Response: The parameters M_i^{\min} and M_i^{\max} are constant, i.e. they do not change with iterations. This has been explicitly stated in the revised manuscript (Lines 280-283):

“ 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 . ”

Comment 8

The authors use interchangeably BRDRR and BPDRR (see for example the heading of Section 3.1.

Authors’ Response: Thank you for spotting this, this spelling mistake was corrected throughout the revised manuscript.

Response to Reviewer 3

Comment 1

Comprehensive and well written manuscript, thank you very much. I would suggest that sections describing the applied metrics (M1 to M6) could be shortened.

Authors' Response: Thanks for the positive feedback of our paper. Following the reviewer's suggestion, we have significantly shortened the description of the metrics M1 to M6. The text is also given below

“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 (M₁)

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):

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

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

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 after 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 (M₂)

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:

$$M_2 = t_{PA} = \max\{ t \mid Fun(t) \leq PA \} \quad (5)$$

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

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:

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

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:

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

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:

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

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

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

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

where N_L is 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 leak (or burst) at time t .

Comment 2

The description of the proposed Tailored Genetic Algorithm (TGA) (section 2.6 onwards) could be extended and described in more detail as I think this is the core of your work.

Authors' Response: Thanks for this suggestion. The description of the proposed TGA has been extended with more details in the revised paper. The text is also 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 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 P1 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 [P1, R1, T(P1,R1)] and [P1, R2, T(P1,R2)] respectively. Within the sub-string [P1, R1, T(P1,R1)] representing first action (isolation),

the first element (P1) is the index of the damaged segment being restored, the second element (R1) 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 R1, R2 and R3 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.

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 ST1 and ST2, the substring Sub1 in ST1 swaps with Sub2 in ST2, followed by that the new substring Sub2 in ST1 is checked against with other substrings in this string. If this new substring is identical to other substrings in ST1, Sub2 in ST1 and Sub1 in ST2 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 $D(t)$ (the set of the damaged elements) at time $t=t1$;

Step 2: Identify the total required recovery actions at time t ($A(t)$) 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

Step 5: Perform the pressure-driven hydraulic model at time $t=t+T(R_i)$ 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.

Response to Reviewer 4

Comment 1

I think that the research and the work done by the authors are valuable and potentially worth to publish. However, there are some aspects that the authors need to develop further in the paper before it can be of publishing quality.

Authors' Response: Thanks for the reviewer's constructive comments, which helped us significantly improve the paper quality of our paper. We have carefully addressed all comments from the reviewer, with details given below.

Comment 2

The main contribution from this paper seems to be the application of the "Tailored Genetic Algorithms" to the problem described in the battle of post-disaster response and restoration. In that sense, I believe Fig. S1. should be included in the main manuscript and not in the supplementary material. Moreover, I think it is necessary that the authors elaborate on the steps of mutation and crossover, as the same difficulties pointed out for the initialization step would exist in these steps.

Authors' Response: As suggested by the reviewer, the implementation procedures of the proposed dynamic optimization framework (Fig. S1) has now been included in the revised manuscript (Fig. 2). Meanwhile, the steps of mutation and crossover have been detailed description in the revised manuscript. The text is also 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 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 P1 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 [P1, R1, T(P1,R1)] and [P1, R2, T(P1,R2)] respectively. Within the sub-string [P1, R1, T(P1,R1)] representing first action (isolation), the first element (P1) is the index of the damaged segment being restored, the second element (R1) 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 R1, R2 and R3 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.

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 $ST1$ and $ST2$, the substring $Sub1$ in $ST1$ swaps with $Sub2$ in $ST2$, followed by that the new substring $Sub2$ in $ST1$ is checked against with other substrings in this string. If this new substring is identical to other substrings in $ST1$, $Sub2$ in $ST1$ and $Sub1$ in $ST2$ 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).

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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

Step 5: Perform the pressure-driven hydraulic model at time $t=t+T(R_i)$ 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.

Comment 3

Given that the point of this research seems to be finding optimal ways to restore the water service on a city given a set of damages produced after a disaster, the computational time to solve the optimization problem, and therefore find the restoring tasks, is a critical factor that should be analyzed deeper. Currently the paper does not state if the time used for solving the optimization problem is within the scale of time that a water utility would have to react after such a disaster.

Authors' Response: This is a very good comment. Details of the time used for solving this paper have been added in the revised paper (Lines 501-507)

“For each optimization run, the TGA search is performed for 2000 generations, which takes 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).”

Comment 4

Many of the observations/conclusions reached can be case specific or highly dependent on the parameters adopted for the problem. I suggest the authors to conduct sensitivity analyses on parameters/assumptions like the 48hrs period to make damages visible, or the times required to perform the recovery tasks.

Authors' Response: Thanks for this comments. The authors completely agree with the reviewer in that the results are conditioned on the case study properties as well as the parameters/assumptions made. This has now been explicitly stated in the Abstract and Conclusion sections in the revised paper, with text given below.

(Lines 37-39)

“The gained insights, conditional on the specific attributes of the case study, include.....”

(Lines 636-667)

“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.”

The authors believe the final results can be dependent on the case study properties (e.g., the distribution of the tanks and pumps) as well as the parameters used. Therefore, it is necessary to run this algorithm for a particular case, which is exactly the contribution of this paper as it provides an efficient and effective tool to identify optimal recovery strategies for a post-disaster WDS. Given this as well as that the paper at the current form is already very long, the sensitivity analysis is not performed. This has explicitly stated in the revised paper (Lines 668-670)

“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.”

Comment 5

In the introduction the authors mention elements like tanks and pumps as vulnerable to potential damages after an earthquake, but then in the methods they are not considered in the damage scenarios. I think the authors need to include a deeper discussion on this assumption/simplification.

Authors’ Response: Following the reviewer’s suggestion, the authors have made an in-depth discussion on this assumption/simplification in the methodology (Section of *The proposed dynamic optimization framework*) of the revised paper (Lines 450-454).

“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 retain their functionality after the earthquake. 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. 2010).”

Comment 6

According to their webpage, the battle of postdisaster response and restoration should be cited as "(Paez et al., 2018a; 2018b)" and not "(Zakrzewski et al., 2018)". Please correct throughout the document.

Authors' Response: Thanks for the reviewer's observation. The error has been corrected throughout the revised manuscript.

Comment 7

Eq. (1) and (2) are not clear. Why do you use the word "segments" instead of "elements" in line 142. Is "N" the number of damaged elements or the number of recovery actions required? Are these two numbers different? Please improve the description.

Authors' Response: Thanks for the reviewer's comments. The word "segments" has been replaced with "elements" throughout the revised paper. The descriptions of Equations (1) and (2) were improved following the reviewer's suggestion as well as suggestions from Reviewer #2, with details given below (Lines 144-153):

$$\max RE = f(M_1, M_2, \dots, M_K) \quad (1)$$

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

where M_k is the k^{th} ($k=1, 2, \dots, K$) 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; $\mathbf{D}(t)$ ($t=t_1, \dots, t_N$) 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 quantitatively measure the resilience value of the recovery actions (i.e., $S(\mathbf{D}(t), \mathbf{A}(t))$) for the k^{th} metric.

As shown in the above statement, N is the total number of recovery actions that are required to completely restore the functionality of the post-disaster WDS, which is different to the total number of damaged elements. This is because some damaged pipes require multiple actions, such as isolation and replacement.

Comment 8

Line 152-155: Can you give a small explanation on why? Is it because of water hammer?

Authors' Response: As suggested by the reviewer, the following text has been added in the revised paper (Lines 158-162).

"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., 2016)."

Comment 9

Line 176: The conference name is CCWI/WDSA. Please fix.

Authors' Response: The spelling mistake has been corrected in the revised manuscript (Lines 187-189)

"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."

Comment 10

It is not clear what the authors understand by "functionality". Please clarify before mentioning it.

Authors' Response: Thanks for the reviewer's comments. The word "functionality" has been clarified in the revised manuscript (Lines 60-63).

"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)"

Comment 11

Is Eq. (14) developed by the authors, or based on a reference? Please include the reference if required.

Authors' Response: The Eq. (14) is developed by the authors hence no reference is required.

Comment 12

It seems from the supplementary material that the method used to implement the pressure driven model is Paez et al. (2018b). Please reference it.

Authors' Response: The sentence has been revised by adding the reference.

"Step 4: Simulate the i th ($i=1$) recovery action (R_i) using a pressure-driven hydraulic model (Paez et al., 2018);"

Comment 13

Line 290-295 is not very clear. Please improve.

Authors' Response: The authors have rephrased these sentences, with details given below (Lines 310-313)

"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.”

Comment 14

Eq. (16): Please indicate the units of the diameter.

Authors’ Response: Thanks for the reviewer’s observation, Eq. (16) has been indicated the units of the diameter.

“d is the pipe diameter (mm).” (Line 484)

Comment 15

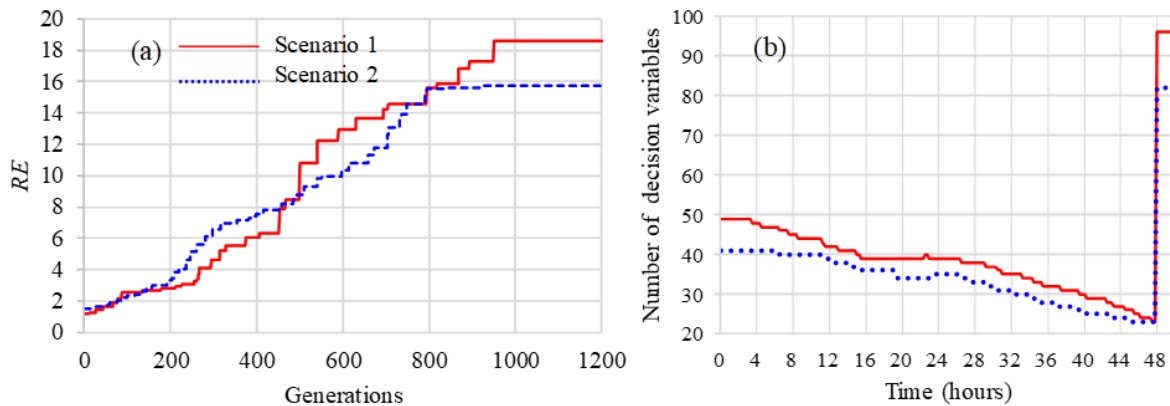
In the introduction the authors mention damages in "segments" and mention tanks and pumps. However, throughout the paper, tanks and pumps are not considered in the analysis.

Authors’ Response: Please refer to the responses to comment 5 for details.

Comment 16

It seems from Figure 3 that at least one scenario has not converged to a maximum of RE after 1000 generations. Authors should increase the number of generations until no considerable improvement is achieved.

Authors’ Response: We apology that we did not explain this case study in details in the original version of the paper. For each optimization process, the TGA was actually run for 2000 generations, and we found that results were not improved (converged to a maximum of RE) after 1000 generations (converged to a maximum of RE). To better present the results, Fig 4(a) now shows the objective function values up to 1200 generations, i.e. 200 generations more than before. We have now changed this figure by extending the results from 1000 to 1200 generations and the new figure is given below.



Comment 17

Given the importance of the 48hr assumption for the number of decision variables, authors should elaborate on the nature of this assumption and the sensitivity of their results to it.

Authors' Response: This assumption was taken from the competition organizers (Paez et al., 2018a; 2018b). The rationale behind this assumption is that pressure tests and inspections would be carried out to ensure identifying all visible damages within 48 hours of the occurrence of two disaster events. This has been explicitly stated in the revised paper (Lines 470-471):

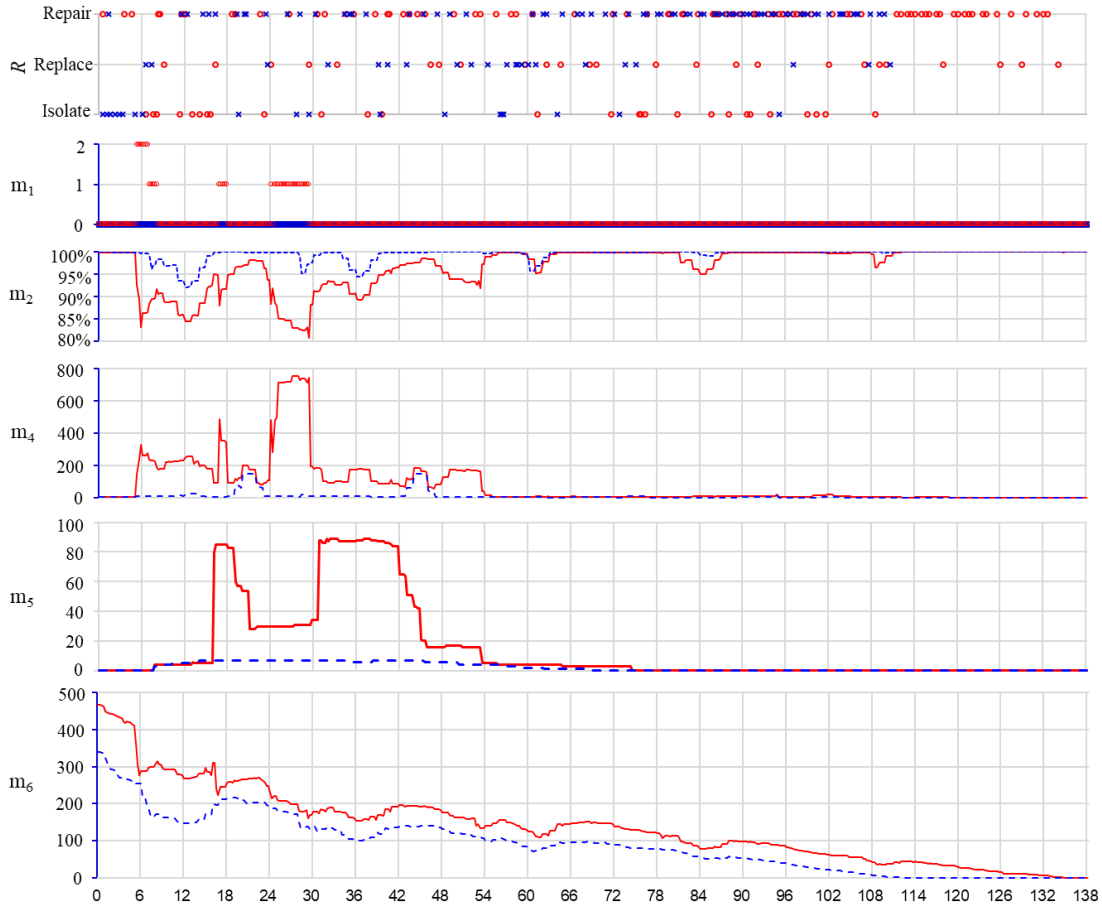
“It was assumed in the BPDRR competition that all nonvisible damages become visible 2 days (i.e. 48hrs) after the event and the total recovery time allowed is 7 days.”

We believe that the final results can be affected by this assumption, in addition to other parameters used for this case study. Therefore, it is necessary to run proposed algorithm for different WDSs or the same WDS with different assumptions. This highlights the importance of the contribution of this paper as it provides an efficient and effective methodology and tool to identify optimal recovery strategies for a post-disaster WDS. Given this as well as that the paper in the current form is already very long, the sensitivity analysis was not performed.

Comment 18

From Fig. (4) it is not clear why M6 does not finish in zero at the end of the simulation. Please clarify.

Authors' Response: The total recovery times for Scenarios 1 and 2 are 137 and 114 hours, respectively (Table 3). Fig. 5 in the original version of the paper shows the results of the initial 72 hours. The results for the entire time have been now added to the Supplemental data. It can be seen from this that M_6 is zero at the end of the simulation, i.e. as noted by the reviewer.



Comment 19

From Fig. (4), can you elaborate on why M_1 jumps from 0 to 1 and 2? It is not clear from Eq. (3) how this behavior can happen.

Authors’ Response: In Fig. (4), m_1 is the number of critical customers without sufficient water over time and the value of M_1 (Eq. 3) is the total time of critical customers without sufficient water within the entire recovery period. The following text has been added in the revised paper to elaborate the variation of m_1 (Lines 571-573)

“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.”

Comment 20

Line 487-489: This is a very interesting observation indeed. However, it seems to be driven by the time functions used in Eq. (16). Therefore, authors should mention this is case specific, and perhaps conduct a sensitivity analysis to verify if this is true for other time functions.

Authors’ Response: Thanks for this suggestion. The following text has been added in the revised paper (Lines 622-626).

“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”

Comment 21

There are missing references in the text (e.g. Bibok, 2018) and wrongly cited papers (Zakrzewski et al., 2018 should be Balut et al., 2018). Please double check.

Balut, A. , Brodziak, R., Bylka, J. & Zakrzewski, P. (2018). Battle of Post-Disaster Response and Restauration (BPDRR). In WDSA/CCWI Joint Conference Proceedings (Vol. 1).

Bibok, A. (2018). Near-optimal restoration scheduling of damaged drinking water distribution systems using machine learning. In WDSA/CCWI Joint Conference Proceedings (Vol. 1).

Paez, D., Fillion, Y., & Hulley, M. (2018a). Battle of post-disaster response and restauration (BPDRR): problem description and rules. In 1st International Water Distribution System Analysis / Computing and Control in the Water Industry Joint Conference, Kingston, Canada, July 23-25, 2018.

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Authors' Response: Thanks for the reviewer's comments. We have carefully checked the references, and made corresponding changes in the revised manuscript.



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