Battle of Postdisaster Response and Restoration

Diego Paez[1], Yves Filion[2], Mario Castro-Gama[3], Claudia Quintiliani[4], Simone Santopietro[5], Chris Sweetapple[6], Fanlin Meng[7], Raziyeh Farmani[8], Guangtao Fu[9], David Butler[10], Qingzhou Zhang[11], Feifei Zheng[12], Kegong Diao[13], Bogumil Ulanicki[14], Yuan Huang[15], Jochen Deuerlein[16], Denis Gilbert[17], Edo Abraham[18], Olivier Piller[19], Alicja Bałut[20], Rafał Brodziak[21], Jędrzej Bylka[22], Przemysław Zakrzewski[23], Yuanzhe Li[24], Jinliang Gao[25], Cai Jian[26], Chenhao Ou[27], Shiyuan Hu[28], Sophocles Sophocleous[29], Eirini Nikoloudi[30], Herman Mahmoud[31], Kevin Woodward[32], Michele Romano[33], Giovanni Francesco Santonastaso[34], Enrico Creaco[35], Armando Di Nardo[36], Michele Di Natale[37], Attila Bibok[38], Camilo Salcedo[39], Andrés Aguilar[40], Paula Cuero[41], Sebastián González[42], Sergio Muñoz[43], Jorge Pérez[44], Alejandra Posada[45], Juliana Robles[46], Kevin Vargas[47], Marco Franchini[48], Stefano Galelli[49], Joong Hoon Kim[50], Pedro Iglesias-Rey[51], Zoran Kapelan[52], Juan Saldarriaga[53], Dragan Savic[54], Thomas Walski[55]

[1] Queen's University. 58 University Ave., Kingston, Canada (corresponding author). E-mail: da.paez270@gmail.com

[2] Queen's University. 58 University Ave., Kingston, Canada.

[3] KWR Watercycle Research Institute. Groningenhaven 7, 3433 PE Nieuwegein, Netherlands.

[4] KWR Watercycle Research Institute. Groningenhaven 7, 3433 PE Nieuwegein, Netherlands.

[5] University of Cassino and Southern Lazio. Via Gaetano Di Biasio 43, 03043 Cassino, Italy.

[6] Centre for Water Systems. University of Exeter. North Park Rd., Exeter, EX4 4QF, UK.

[7] Centre for Water Systems. University of Exeter. North Park Rd., Exeter, EX4 4QF, UK.

[8] Centre for Water Systems. University of Exeter. North Park Rd., Exeter, EX4 4QF, UK.

[9] Centre for Water Systems. University of Exeter. North Park Rd., Exeter, EX4 4QF, UK.

[10] Centre for Water Systems. University of Exeter. North Park Rd., Exeter, EX4 4QF, UK.

[11] College of Civil Engineering and Architecture, Zhejiang University. 866 Yuhangtang Rd, Hangzhou, China.

[12] College of Civil Engineering and Architecture, Zhejiang University. 866 Yuhangtang Rd, Hangzhou, China.

[13] De Montfort University. Gateway House, Leicester, UK.

[14] De Montfort University. Gateway House, Leicester, UK.

[15] College of Civil Engineering and Architecture, Zhejiang University. 866 Yuhangtang Rd, Hangzhou, China.

[16] 3S Consult GmbH. Albtalstrasse 13, 76137 Karlsruhe, Germany.

[17] Irstea, UR ETBX, Water Department, Bordeaux regional centre. Cestas F-33612, France.

[18] Faculty of Civil Engineering and Geosciences, Delft University of Technology. Stevinweg 1, 2628 CN, Delft, Netherlands.

[19] Irstea, UR ETBX, Water Department, Bordeaux regional centre. Cestas F-33612, France.

[20] Poznań University of Technology. Berdychowo 4, 60-101 Poznań, Poland.

[21] Poznań University of Technology. Berdychowo 4, 60-101 Poznań, Poland.

[22] Poznań University of Technology. Berdychowo 4, 60-101 Poznań, Poland.

[23] Poznań University of Technology. Piotrowo 3A, 60-965 Poznań, Poland.
[24] Harbin Institute of Technology. Harbin, China.
[25] Harbin Institute of Technology. Harbin, China.
[26] Harbin Institute of Technology. Harbin, China.
[27] Harbin Institute of Technology. Harbin, China.
[28] Harbin Institute of Technology. Harbin, China.
[29] Centre for Water Systems. University of Exeter. North Park Rd., Exeter, EX4 4QF, UK.
[30] Centre for Water Systems. University of Exeter. North Park Rd., Exeter, EX4 4QF, UK.
[31] College of Engineering. University of Duhok. Zakho Street 38, 1006 AJ Duhok, Kurdistan Region-Iraq.
[32] United Utilities Group PLC. Lingley Green Avenue, Warrington, WA5 3LP, UK.
[33] United Utilities Group PLC. Lingley Green Avenue, Warrington, WA5 3LP, UK.
[34] Università della Campania “L. Vanvitelli”. Via Roma, 29, 81031 Aversa, Italy.
[35] Università di Pavia. Via Ferrata 3, 27100 Pavia, Italy.
[36] Università della Campania “L. Vanvitelli”. Via Roma, 29, 81031 Aversa, Italy.
[37] Università della Campania “L. Vanvitelli”. Via Roma, 29, 81031 Aversa, Italy.
[38] Budapest University of Technology and Economics. Műegyetem rkp. 3 Budapest, Hungary.
[39] Water Dist. and Sewer Systems Res. Center (CIACUA), Universidad de los Andes. Bogotá, Colombia.
[40] Water Dist. and Sewer Systems Res. Center (CIACUA), Universidad de los Andes. Bogotá, Colombia.
[41] Water Dist. and Sewer Systems Res. Center (CIACUA), Universidad de los Andes. Bogotá, Colombia.
[42] Water Dist. and Sewer Systems Res. Center (CIACUA), Universidad de los Andes. Bogotá, Colombia.
[43] Water Dist. and Sewer Systems Res. Center (CIACUA), Universidad de los Andes. Bogotá, Colombia.
[44] Water Dist. and Sewer Systems Res. Center (CIACUA), Universidad de los Andes. Bogotá, Colombia.
[45] Water Dist. and Sewer Systems Res. Center (CIACUA), Universidad de los Andes. Bogotá, Colombia.
[46] Water Dist. and Sewer Systems Res. Center (CIACUA), Universidad de los Andes. Bogotá, Colombia.
[47] Water Dist. and Sewer Systems Res. Center (CIACUA), Universidad de los Andes. Bogotá, Colombia.
[48] Università di Ferrara. Via Saragat, 1, 44122 Ferrara, Italy.
[49] Singapore University of Technology and Design, Pillar of Engineering Systems and Design. 8 Somapah Road, 487372, Singapore.
[50] Korea University. Seoul, South Korea , South Korea.
[51] Universidad Politécnica de Valencia. Camino de Vera s/n - 46022 (Valencia), Spain.
[52] Delft University of Technology. Stevinweg 1, 2628CN Delft, Netherlands.
[53] Universidad de los Andes. Carrera 1 Este No. 19A-40. Bogotá, Colombia.
[54] KWR Watercycle Research Institute. Groningenhaven 7, 3433 PE Nieuwegein, Netherlands.
[55] Bentley Systems. 3 Brians Place, Nanticoke, PA, USA.

Abstract: The paper presents the results of the Battle of Post-Disaster Response and Restoration (BPDRR), presented in a special session at the 1st International WDSA/CCWI Joint Conference, held in Kingston, Ontario, in July 2018. The BPDRR problem focused on how to respond and restore water service after the occurrence of five earthquake scenarios that cause structural damage in a water distribution system. Participants were required to propose a prioritization schedule to fix the damages of each scenario while following restrictions on visibility/non visibility of damages. Each team/approach was evaluated against six performance criteria that included: 1) Time without supply for hospital/firefighting, 2) Rapidity of recovery, 3) Resilience loss, 4) Average time of no user service, 5) Number of users without service for 8 consecutive hours, and 6) Water loss. Three main types of approaches were identified from the submissions: 1) General purpose metaheuristic algorithms, 2) Greedy algorithms, and 3) Ranking-based prioritizations. All three approaches showed potential to solve the challenge efficiently. The results of the participants showed that, for this network, the impact of a large-diameter pipe failure on the network is more significant than several smaller pipes failures. The location of isolation valves and the size of hydraulic segments influenced the resilience of the system during emergencies. On average, the interruptions to water supply (hospitals and firefighting) varied considerably between solutions and emergency scenarios, highlighting the importance of private water storage for emergencies. The effects of damages and repair work were more noticeable during the peak

demand periods (morning and noontime) than during the low-flow periods; and tank storage helped to preserve functionality of the network in the first few hours after a simulated event.

Introduction

A water distribution network (WDN) is one of the critical lifeline systems in a city. Its vulnerability to earthquakes, and other natural disasters, not only threatens residential, commercial, and industrial activities, but also can affect the capacity to attend to subsequent emergencies. Two of the most analysed examples in the literature are the 17 January 1994 Northridge earthquake (Los Angeles, California) and the 17 January 1995 Kobe earthquake (Japan). The first case resulted in more than 450,000 people losing water service and at least eight hospitals evacuated due to water and power damages, while for the second case, the earthquake affected the supply to more than 1.5 million people and required more than 30 hours to extinguish the fires due to water unavailability in many hydrants (PAHO, 1998).

Considering the potential vulnerability and key role played by WDN during seismic events, researchers have focused on three main topics: 1) How to assess the reliability of WDNs and other lifelines after extreme seismic events (e.g., Hwang, et al., 1998; Wang & O'Rourke, 2006; Shi & O'Rourke, 2006, Fragiadakis, et al., 2013; Liu et al., 2015); 2) How to reinforce the systems to minimize the impact of a given event (e.g., Cimellaro et al., 2015; Yoo et al., 2016); or 3) How to quickly restore the systems to normal/acceptable conditions after the event (e.g., Bonneau, & O'Rourke, 2009; Wang et al., 2010; Mahmoud et al., 2018). From these, the restoration problem has been the least studied, leaving the prioritization of resources to recover the functionality of the system to the expertise and criteria of utility operators. Considering that lives of people are at stake due to vitality of the supply for firefighting, or health care purposes, among other considerations, it is imperative to better characterize this problem and evaluate if current knowledge of WDNs can be of use in such circumstances.

The Battle of Post-Disaster Response and Restoration (BPDRR) was the eighth call for academic and non-academic professionals to address a common problem in the water distribution field. Dating back to the first "Battle" in 1985, this series of competitions have focused on WDNs optimization (1985 and 2012), sensor placement for contaminant intrusion detection in WDNs (2006); WDNs model calibration (2010); leakage assessment in WDNs (2014); district-metered-area sectorization of WDNs (2016); and detection of cyber-attacks on WDNs (2017). For this version, the “Battle competition” focused on the how to respond and restore the service in an existing WDN after the occurrence of five different earthquake scenarios that damaged part of the distribution network. The results of the BPDRR were presented in a special session in the 1st WDSA/CCWI Joint Conference, held in Kingston, Ontario, in July 2018. This manuscript summarizes the challenge, the results, and makes recommendations for future research of the topic.

Problem formulation

The challenge addressed in the Battle is the one of identifying the best operational response in terms of restoration interventions to return a water distribution network to fully functioning pre-catastrophic event condition.

After an earthquake, damages to a WDN can degrade the water service in a city. There can be different approaches for prioritization of available resources in order to restore the water service. To evaluate the performance of the different approaches, a set of five post-disaster damage scenarios was generated on a model of the B-City water distribution network, and participants were invited to propose responses and restoration methods to return the system to pre-earthquake conditions. These damage scenarios, along with a calibrated EPANET model of the network, and a description of the performance criteria were provided to the participants. All data are included in the supplemental files of this manuscript and can be found with the problem description (Paez et al., 2018a) in the website: https://www.queensu.ca/wdsa-ccwi2018/problem-description-and-files.

B-City

B-City is a water distribution network model of a real system in an undisclosed location. The network consists of 4,909 junctions, 6,064 pipes, 1 reservoir, 4 pumps divided between two pump stations, and 5 district metered areas (DMA), each with one water tank (Figure 1). A total of 5,963 isolation valves are also distributed along the pipes of the network, delimiting 2,451 segments as defined by Walski (1993). The calibrated model also includes 24-hr demand patterns for residential and commercial/industrial consumers. The daily mean consumption on a typical day is 1,023.8 L/s.

For pre-catastrophic conditions, the minimum pressure during the day, amongst all demand nodes is 24.5 m, which means that the demand is fully supplied (the minimum required pressure is 20.0 m). Additionally, the tanks do not get emptied at any point, and their minimum levels vary from 0.62 m to 1.09 m.

Damage scenarios

One important assumption required to develop the problem was to consider that out of all network elements, only pipes were damaged during the events. In other words, facilities like pump stations, tanks, and the source reservoir were assumed to remain operational at all times. This assumption is consistent with remarks by Tabucchi et al. (2010), and even though PAHO (1998) mentions examples of tanks and pump stations structurally affected by earthquakes or disconnected temporally from the electric grid, they are significantly less common than damages in pipelines (Tabucchi et al., 2010).

To stochastically generate pipe damage scenarios, a Poisson process was used (Shi & O'Rourke, 2006). Therefore, the probability that a pipe was damaged during the earthquake was given by Eq. (1).

$$P(x_i) = 1 - e^{-\lambda_i L_i} \tag{1}$$

Where x_i is the event that pipe i is damaged ($i \in \{1, \dots, 6064\}$), L_i is the length of the pipe i in m, and λ_i is the average number of seismic-induced damages per m for that type of pipe. The values of λ_i were assumed as 0.0003 damages/m for pipes with diameter under 300 mm and as 0.00005 damages/m for larger diameter pipes, which is a simplification within the ranges presented by American Lifelines Alliance (2001). This means that the effect of other factors mentioned in the previous studies, like type of soil, pipe material, pipe age, and type of joints, on the probability of damage was assumed homogeneous for all pipes.

According to Ballantyne et al. (1990) and Hwang et al. (1998), the damages in pipes can be classified as *leaks*, which are minor damages that can be fixed by installing clamps or welding cracks, and *breaks*, which are more serious damages that require a replacement of entire pipe sections. The conditional probability that a damage was a break was taken as 0.20 for all pipes according to the assumption by HAZUS (NIBS, 1997) for damages generated by propagation of seismic waves:

$$P(y_i \mid x_i) = 0.20 \tag{2}$$

where y_i is the event that pipe i is broken. It is worth mentioning that according to HAZUS method, when the damages are caused by a permanent ground displacement, the probability of a break is considerably higher.

After an earthquake disaster, fires are also expected and, therefore, firefighting flows must also be supplied. To include them in the model, two nodes per scenario were randomly selected and assigned a fire flow demand of 35 L/s that would only stop until the delivered/supplied water reached 756 000 L (correspondent to a 6 hr-duration fire if the flow was fully supplied). The number of fire flow nodes was arbitrarily chosen, while the flow rate was suggested by members of the committee.

Using these assumptions, a set of five deterministic post-disaster damage scenarios was generated and provided to the participants, and a likelihood based on the probability of the state of each pipe was assigned to each scenario as a weight for the performance evaluation (computed as the logarithm of the normalized product of individual probabilities for the pipes). Figure 2 shows one of the five post-disaster damage scenarios as an example.

Damages modelling

To model the hydraulic effect of damages in the network, an emitter was located at the midpoint of the damaged pipe to simulate its water losses. In order to avoid reverse flows at the emitter (i.e. inflows) caused by negative pressures, a dummy check valve was also included upstream of the emitter. One additional assumption was that breaks in pipes with diameters under 150 mm were assumed to produce a full disconnection between the two ends of the pipe, and, therefore, the two halves of the pipe were modelled as check valves.

The emitters used to simulate water losses followed Eq. (3), with Eqs. (4) and (5) for the emitter coefficients (Shi & O'Rourke, 2006):

$$Q_i(t) = K_i \cdot \left(h_i(t)\right)^{0.5} \tag{3}$$

$$K_i = 0.5m \cdot 0.1° \cdot D_i \cdot \sqrt{2g} \quad \text{for leaks} \tag{4}$$

$$K_i = \frac{\pi}{2} \cdot 0.5° \cdot D_i^2 \cdot \sqrt{2g} \quad \text{for breaks} \tag{5}$$

where $Q_i(t)$ is the outflow from the emitter i at time t, $h_i(t)$ is the pressure head at the midpoint of pipe i at time t, D_i is the diameter of pipe i, and K_i is the emitter coefficient that represents a 0.5 m longitudinal crack with an angle of 0.1 °for leaks, and a 0.5 °round crack for breaks (Figure 3).

To consider that not all damages are immediately detected by the water utilities, some of them were considered *non-visible*, meaning that they could not be detected, and therefore fixed, only until some time after the event. Leaks in pipes with a diameter under 300 mm, and breaks in pipes with diameter under 150 mm were assumed non-visible unless they reached an outflow higher than 2.5 L/s (values based on the experience of some members of the committee). However, 48 hrs after the event it was assumed that some pressure tests and inspections would be carried out, making all damages visible after that time. Visibility of damages was important from the network restoration point of view (see next section).

Response and network restoration

After the occurrence of an earthquake, the water utility would require some reaction time (assumed 30 mins here) before the crews can be dispatched to begin the restoration works. There were assumed to be three crews able to work 24 hours independently of the turns of each worker, and they could perform four basic tasks: *Isolate*, *Repair*, *Replace*, and *Reopen*.

Both leaking and broken pipes could be *isolated* by sending a crew to the damage location (even though it is strictly necessary for broken pipes only). It was assumed that the water utility knows the location of all isolation valves in the network and, therefore, isolating a pipe consists of closing all the valves in the hydraulic segment that contains it. Isolation of pipes serves two main purposes: to stop water leaking from the network at a certain damage location, and to dry the pipes in the segment so they can be replaced if required.

Leaking pipes must be *repaired*. To repair a leaking pipe, a crew must be sent to the pipe location where they need to locate the leakage, excavate, repair the pipe either with a clamp or by welding, and restore trench conditions. Broken pipes must be *replaced*. To replace a broken pipe, it must first be isolated, excavated, replaced, and trench conditions must be restored (disinfection and pressure tests are assumed to be omitted in an emergency scenario). Finally, an isolation valve could be *reopened* to restore supply to the affected area, once damages were fixed.

The time each crew was assumed to take to isolate, repair and replace a pipe is shown in Table 1, where some simplified relations have been adjusted to the data presented in Porter (2016). Transportation times and times for reopening of valves are assumed to be included in the figures and expressions shown in Table 1.

Participants were required to propose a prioritization schedule for the three crews, for each scenario, indicating in which order to isolate, repair or replace damages in the network while following two restrictions: 1) Only visible damages could be fixed (details on visible/non-visible damages in the previous section), and 2) Only pipes whose hydraulic segment had been previously isolated could be replaced. Table 2 shows an example of the schedules given by participant teams.

Performance criteria

Since the system is working under low pressure conditions, the pressure driven method by Paez et al. (2018b) was used to compute nodal supplied flows (Q_i) and compare them with demand (QD_i) as follows:

$$Q_i(p_i) = \begin{cases} 0 & if\ p_i \leq 0 & \rightarrow \text{enforced by a Check Valve} \\ QD_i\left(\dfrac{p_i}{p_{req}}\right)^n & 0 < p_i \leq p_{req} & \rightarrow \text{enforced by a Throttle Control Valve} \\ QD_i & p_i > p_{req} & \rightarrow \text{enforced by a Flow Control Valve} \end{cases} \quad (6)$$

where p_i is the actual pressure head at node i, and p_{req} is the minimum required pressure head to ensure full supply (assumed 20 m here).

The functionality of the system, at a certain time t, is then defined as the percentage of the total demand that is supplied by the network according to the pressure driven model (based on the serviceability index discussed in Shi & O'Rourke, 2006):

$$Functionality(t) = 100\% \cdot \sum_{\substack{Demand\\nodes}} Q_i(t) \Bigg/ \sum_{\substack{Demand\\nodes}} DQ_i(t) \qquad (7)$$

Figure 4 shows the expected behaviour of the functionality as the network gets gradually fixed. Since the demand varies in time, it is likely that the system can fulfill a higher percentage of the demand during nights, while during mornings, when demand increases, the supplied percentage decreases, producing these peaks and troughs in the functionality trend.

For each scenario, the schedules proposed by the participants were evaluated according to six main criteria:

1) Time that the hospitals and the firefighting flows are without supply (*Fire & Hosp.*), calculated as the time-step of the simulation times the number of time steps in which the supply/demand ratio for the hospitals and firefighting flows was less than 0.5:

$$Fire \,\&\, Hosp. = \Delta\, t \cdot \sum_{\substack{Hospitals\ \ and \\ Firefighting\ nodes}} \operatorname*{count}_{t \in T} \{\, t \mid \, Q_i(t)/DQ_i(t) \leq 0.5\} \qquad [min] \tag{8}$$

where T is the set of all 15-minute time steps starting on Day 01 at 6:00am and ending at Day 07 at 6:00am and $\Delta\ t$ is 15 minutes.

2) Time until the system recovers permanently 95% of its functionality (*Rapidity of recovery – t_{95}*), calculated as the last (maximum) time-step in which the functionality is lower than 95% (see Figure 4):

$$t_{95} \ = \max_{t \in T} \{\, t \mid Functionality(t) \leq 95\%\} \qquad [min] \tag{9}$$

3) Accumulated loss of functionality from the occurrence of the disaster until full recovery (*Resilience Loss*), calculated as the area between the 100% line and the functionality time series (see Figure 4)

$$Res. Loss \ = \Delta\ t \cdot \sum_{t \in T} \big(100\% - Functionality(t)\big) \qquad [\% * min] \tag{10}$$

4) Average time, across demand nodes, each consumer (network node) is without service (*Time no serv.*), calculated by multiplying the time-step and the number of time steps in which the supply/demand ratio was less than 0.5 for each node, and then dividing by the total number of demand nodes ($DN = 4201$):

$$Time\ no\ serv. = \frac{\Delta\ t}{DN} \cdot \sum_{\substack{Demand \\ nodes}} \underset{t \in T}{\text{count}} \{\ t \mid Q_i(t)/DQ_i(t) \leq 0.5\} \quad [min] \tag{11}$$

5) Number of consumers (network nodes) without service for more than 8 consecutive hours (*Nodes no serv.*), calculated by counting the number of nodes with more than one time-step in which the next 8 hours had always a supply/demand ratio lower than 0.5:

$$Nodes\ no\ serv. = \underset{\substack{Demand \\ nodes}}{\text{count}} \left\{ i \mid \underset{t \in T}{\text{count}} \left\{ t \mid \frac{Q_i(t-\Delta t)}{DQ_i(t-\Delta t)} \leq 0.5 \ \ \forall \Delta t \in (0\,, 8hrs) \right\} \geq 1 \right\} \quad [nodes] \tag{12}$$

6) Volume of water lost during the 7 days after the event (*Water loss*), calculated as the sum of the outflows across all damages in the network times the time-step:

$$Water\ loss\ = \Delta\ t \cdot \sum_{i \in Damages} \sum_{t \in T} Q_i(t) \quad [L] \tag{13}$$

Since there were five scenarios, a total of 30 values had to be reported by each team. To assess an approach, each of the six criteria was averaged amongst the five scenarios using the likelihoods previously described in the section Damage Scenarios as weights, giving as a result one average performance per criteria per team.

For this version of the Battle, it was a deliberate decision not to provide a unified metric to rank the solutions. Instead, it was left to the participants' engineering judgment to prioritize the six criteria as they considered appropriate for the city. This decision was taken by the committee (Franchini, Galelli, Kim, Iglesias-Rey, Kapelan, Saldarriaga, Savic, and Walski) as a way to allow different approaches including non-optimization frameworks in the competition.

Post-disaster response and restoration algorithms

Ten teams participated in the BPDRR and submitted their approaches, prioritization schedules, results, and recommendations. This section briefly describes each approach:

• Castro-Gama et al. (2018) proposed an implementation based on a preliminary graph theory analysis of the network required to identify neighboring pipes. Second, an ε-MOEA algorithm (Deb et al., 2005) from an optimization library for Python: Platypus was used to obtain the Pareto front for the 6 criteria. Decision variables were set as a permutation of the possible interventions. The procedure took into account a constant time of displacement between locations (30 min), which increased the operation time of each crew from the values in Table 1. From the 6D Pareto front, a single solution per scenario was selected based on a Visual Analytics approach (Castro-Gama et al., 2017). The ε-MOEA solution was also compared with the one obtained using a greedy algorithm. Both methods showed similar outcomes with different prioritization of interventions, although the latter had the advantage of requiring only 30% of the computational time of the former. Finally, four engineering interventions (to increase/decrease the storage capacity or the pump flow) were evaluated for each selected solution and damage scenario.

• Sweetapple et al. (2018) developed an approach based upon graph theory and heuristic methodologies. First, graph theory was used to enable identification of hydraulic segments (Meng et al., 2018) and, subsequently, valve operations required to isolate each pipe break. Next, a single performance indicator incorporating all six objectives was developed to enable the problem to be reformulated as a single objective (assuming equal weights). Lastly, actions (i.e., isolations, replacements and repairs) were allocated to each crew using an adaptation of the 'nearest neighbour' algorithm (Cover and Hart, 1967), a 'greedy optimization heuristic. In this approach, performance was evaluated starting with no actions, and adding subsequent actions. Each new action was assigned to the first crew that finished the previously assigned actions. At each stage, the next action selected was the one that provided the greatest performance benefit (represented by the single objective value), given the specified prior actions and not accounting for future actions.

• Zhang et al. (2018) proposed a dynamic optimization framework with the objective function consisting of six different metrics summed by introducing weights. To identify an optimal sequencing of recovery actions for each post-earthquake scenario, a tailored Genetic Algorithms-based optimization algorithm was used, where the algorithm operators were modified to identify the optimal sequencing of recovery actions for post-disaster WDNs. The most important feature of the proposed method was that the total number of the decision variables (damaged segments) and the decision variables themselves (e.g., the pipes that need to be repaired) could both vary when the hydraulic status of the WDN was updated. That updating process was carried out at the completion of each intervention to the post-disaster WDN, and the final sequencing of recovery actions for each crew was identified. The results provided some insights on how to propose an optimal recovery plan. For instance, certain broken pipes were fixed between particular time stamps to avoid negative effects on the service level at some critical locations.

• Deuerlein et al. (2018) proposed greedy heuristics to schedule isolation, repairs and replacement by minimizing a weighted sum of the objectives. In the disaster response, the trade-off between water loss and the other criteria was explored. The method used graph decomposition techniques to identify the valves that isolated a hydraulic segment for replacement (Deuerlein 2008). The authors also analysed the network hydraulics and how the depletion of tanks affected service levels. Using these and systematic engineering judgement (Gilbert et al., 2017), recommendations were made for improving the capacity of the system and its absorptive and restorative resilience by design. This included the improvement of pumping stations, installation of control valves and some pipe reinforcement. The same greedy task scheduling algorithm was then used under these alternative network improvements, to evaluate the improvements with respect to all criteria.

• Balut et al. (2018) proposed a ranking-based approach where water network pipes' 'importance' was prioritized and applied in a pipe repair schedule. Several approaches to define the importance and create the rankings were proposed, based on hydraulic analyzes (using model under normal operating conditions). Expert knowledge was used, collected via conducted surveys, to define the 'rankings'. Authors surveyed 46 managers, consultants, IT specialists and water distribution modellers from utilities, asking them to list the main criteria that influenced the sequence of repair scheduling, in their opinion. For each disaster scenario, all types of 'rankings' developed (diameter, diameter and distance from the source, diameter and velocity, flow with and without strategic points, impact of pipes' closure on network's hydraulics) were applied to schedule tasks for all repair teams. Additionally, experts were also asked in the surveys to assign weights to four criteria that addressed the rapidity of recovery, number of nodes without service and volume of water lost. Results from the rankings were evaluated with use of Visual Promethee – a multicriteria decision aid software, and weights based on the recommendation by the experts. Calculation of hydraulic parameters and evaluation of the final solution based on the six predefined criteria were performed using the Epanet-Matlab toolkit (Eliades et al., 2016).

• Li et al. (2018) proposed a two-stage WDN restoration method based on Epanet-Matlab toolkit (Eliades et al., 2016). In the first stage, a shortest path algorithm and greedy algorithm were used to gain the top priority recovery action for a quick response to the disaster. Firstly, Dijkstra algorithm was used to calculate the shortest path from water source to hospital and fire point. The flow could be guaranteed to these locations by repairing the damaged point on the path and closing the valves of the damaged pipeline closest to the path. Then the greedy algorithm was used to obtain the restoration order of the remaining pipes. In the second stage, Particle Swarm Optimization algorithm was used to minimize the total amount of water loss during the restoration process.

- Sophocleous et al. (2018) developed a simulation-based response and restoration framework divided into three stages: 1) Pre-Processing, where the possible interventions for each crew were defined together with the time required to complete each intervention, 2) Optimisation, where an optimised schedule for fixing each damage was established using NSGA-II algorithm and a simplified version of weighting objectives, and 3) Restoration Planning, where an action plan (i.e., table of interventions ranked by priority) for each crew was identified using the optimum solution from stage 2. The proposed framework developed a methodology to identify the minimum number of links required to isolate a damaged pipe and enabled simplifying the complexity of the optimisation problem by: 1) solving two sub-problems in sequence (i.e., two-day and seven-day sub-problems, based on the visibility of the damages); and 2) allocating to each crew a particular part of the WDN and a specific number of interventions. This was done through the use of a K-means clustering-based approach (MacQueen, 1967) and engineering judgement (allowing the assumption that in real-life a crew would not be asked to deal with damages spread across the whole network). Simulations were run using the EPANET Programmer's Toolkit linked with the MATLAB optimisation tool.

• Santonastaso et al. (2018) adopted a strategy to restore the water service after an earthquake following two phases: 1) identification of hydraulic segments, that provided which valves had to be closed to isolate the pipe that needed to be repaired (Creaco et al., 2010); 2) prioritization of the broken pipes according to a topological metric, based on the idea of primary network (Di Nardo et al., 2017) in order to organize the maintenance interventions after the earthquake. The proposed procedure to rank the pipes to be maintained was stated as follows: 1) compute the betweenness for all pipes in the network; 2) repair or replace leaking or broken pipes with high values of edge betweenness; 3) repeat step 2 until no pipes remain to be replaced or repaired.

• Bibok (2018) proposed a two-stage approach to the problem. A criticality analysis of network segments was carried out using Bentley System's WaterGEMS. It highlighted critical segments, of which size could be reduced by installing additional isolation valves. The visible leaks were determined by an initial hydraulic simulation considering the first 30 minutes. In the second stage, the optimization problem was reduced to a sorting task, which was carried out by a sorting genetic algorithm. The algorithm's genome was the ordered list of sequentially executed repair events. A swapping operator during mutation was utilized to preserve the consistency of the visible and non-visible leaks' list.

• Salcedo et al. (2018) proposed a decision support model based upon a prioritization methodology described as follows. Initially, a diagnosis of the network was done, including the assessment of the impact of each pipe within the network based on its reliability (Luong & Nagarur, 2005). Then, a prioritization list was developed considering the weighted sum of seven alternative criteria to assign the maintenance activities to each crew. These alternative criteria included the pressure head at hospitals and fire flow nodes, the functionality of the network after rehabilitating a pipe, water losses, and the time needed to rehabilitate each damaged pipe. The weighted list was evaluated at the end of each time step of the simulation using MATLAB and EPANET Programmer's toolkit. Finally, the final weights of the decision model were determined using a sensitivity analysis.

Results and discussion

Algorithm performance

Three main types of approaches can be identified from the submissions. The first type of approach was based on using general-purpose optimization methods, like Multi Objective Evolutionary Algorithm (MOEA), Non-Dominated Sorting Genetic Algorithms (NSGA-II) and Genetic Algorithms (Castro-Gama et al., 2018; Zhang et al., 2018; Sophocleous et al., 2018; Bibok, 2018). In these approaches, the problem was expressed as an optimal sorting task in which the decision variables were the order in which each damage on the network was fixed. The solution space was all possible permutations of the damages, and the objective functions were either the six criteria from Eqs.(8) to (13), a normalized sum of the six criteria (i.e., a single-objective optimization problem), or a combination of normalization and weighting of the six criteria. The normalization references were the computed range of each criterion (defined by the maximum and minimum values found), or a reference value based on an initial solution. The weights, on the other hand, were mostly based on engineering judgment and sense of importance of each criterion after a natural disaster.

The second type of approaches was ranking-based prioritizations, in which different metrics were used to define which pipes should be fixed first according to their “importance” (Balut et al., 2018; Santonastaso et al., 2018; Salcedo et al., 2018). In these approaches, one or various metrics to measure how important is a pipe with respect to the criteria were proposed and tested (the number of metrics tested is shown between square brackets in the second column of Table 3). The nature of proposed metrics included hydraulic properties of the pipes, hydraulic consequences of individual damages, and graph theory metrics. The objective functions used to evaluate a metric were: weighted and normalized sum of the six criteria for Balut et al. (2018); a weighted and normalized sum of scores, developed to simplify computation of the six criteria, for Salcedo et al. (2018); and the six given criteria for Santonastaso et al. (2018).

Finally, the third type of approaches was based on algorithms that made local optimum choices aiming to find near-optimal solutions (Sweetapple et al., 2018; Deuerlein et al., 2018; Li et al., 2018). In these approaches, that could be viewed as greedy algorithms, an objective function was defined either as a weighted and normalized sum of the six criteria, or as one of the six criteria depending on the stage of the optimization. Then, starting at the initial time of the simulation, all possible actions (damage fixing) were evaluated, and the one(s) that produced the highest marginal gain in the objective function were selected to be carried out. That process was repeated every time an action was completed until no more actions remained. It is worth noting that Li et al. (2018) used this third type of approach in a first stage of their optimization, followed by an application of a metaheuristic (Particle Swarm Optimization - PSO).

Table 3 summarizes the reported results for the six criteria, averaged amongst the five damage scenarios (using the likelihoods as weights), for each team. The top three performance values for each criterion are underlined, with the best performance highlighted with a double underline.

Figure 5 presents graphically the results of each team in each criterion compared with the average amongst all teams. Values outside the black dotted line (average), outperformed the average of the ten teams. It is important to note that three teams (Zhang et al., 2018; Deuerlein et al., 2018; Salcedo et al., 2018), one from each type of approach, had all six criteria outperforming against the average (all their areas are outside the average circle), showing that all three approaches have potential in solving the response and restoration challenge.

Participants' remarks

Participants were also encouraged to suggest some mitigation measures that the city could take in order to improve the response and restoration process for other possible scenarios. One factor that almost all participants seemed to agree, was that installing more isolation valves would reduce the size of the hydraulic segments, and therefore reduce the impact on the supply of the isolations required to replace a broken pipe.

Castro-Gama et al. (2018) also evaluated the effect of increasing or decreasing the storage and pumping capacity in the network, and found that increasing the storage and pumping capacity reduces the initial impact of the event (before the interventions), but once the fixing schedule is optimized, there is little improvement in the performance criteria. Sweetapple et al. (2018) evaluated the effect of the disconnection of all hydraulic segments in the network and suggested the separation of the most upstream segment to avoid having both the tank T1 and the reservoir isolated simultaneously in case pipe damage or a contaminant intrusion occurred in that segment. Li et al. (2018) used pipe damage statistics of the real Wenchuan earthquake in 2008 to suggest pipeline renewals to avoid concrete and gray iron pipes which seemed to be more vulnerable to this kind of events, while increasing the pipe burial depths to reduce pipe displacement. Finally, Bibok (2018) suggested running in advance combinations of simultaneous hydraulic segments isolation to reduce in advance search space and ease the computation of recommended schedules once the event occurs.

General observations

After analysing the results and recommendations of all participants, the main insights are summarized as follows:

• All six criteria used to evaluate performance of solutions (Eqs.(8) to (13)) were defined as desirable objectives of a response and restoration method, and as metrics that would contribute to better understand the consequences of extreme seismic events. However, the fact that only one out of ten teams used a multi-objective optimization approach using the six criteria, would suggest that it is necessary to prioritize some of them, with engineering judgment, according to the perspective and policies of the city, in order to make it a mathematically tractable problem that actually provides suitable solutions.

• Different types of approaches presented in this Battle have all potential to find satisfactory solutions to the problem. The use of metaheuristics requires in general more computational effort and, therefore, are useful to develop, in advance, plans to react in the moment a disaster occurs. Greedy algorithms are, in general, fast enough to be run at the moment a disaster occurs, making use of that reaction time mentioned before and adapting to new information on damages easily. Finally, ranking-based approaches are straightforward and quick to use, allowing an almost immediate reaction and an instantaneous reordering when given updated information but, unlike optimization-based approaches, rely on subjective, expert generated list of intervention options to consider.

•The run times for the participants' solutions were not reported as it was not a requirement for the submission (in order to allow the use of any available resource and technique), but the computational requirements of metaheuristic algorithms were mentioned by some participants as a drawback for this type of approach. As explained by Castro-Gama et al. (2018), the use of alternatives like greedy algorithms can reduce the computational time to a 30% of the time required by metaheuristics. However, the potential use of parallelization is expected to make the use of this type of optimization algorithms more suited and faster in future.

• Figure 6 shows the average *Res. Loss* among all participants versus the range of diameters of broken pipes in each scenario. It also shows how, for this particular network, the WDN gets more affected in its functionality by the size of the largest broken pipe, rather than by the number of breaks in the scenario. For example, Scenario 05 has ten more pipe breaks than Scenario 03, but since Scenario 03 has a 250mm pipe broken, it has on average higher resilience loss than Scenario 05 which has all its breaks in pipes with diameters under 200mm.

• One important factor that drives the resilience of the WDN to these emergency scenarios is the location of isolation valves and the size of hydraulic segments relative to affected areas. All participants agree that having more isolation valves would reduce the impact of repairs and replacement works in the supply.

• On average, the interruptions in the supply to emergencies (hospitals and firefighters) was 17.5 hrs, although considerable variability was seen between participants and scenarios (in some scenarios, some participants were able to maintain continuous water supply to the emergency nodes, while in other cases the interruption accumulated nearly 72 hrs). Since most of that demand occurred in hospitals, this suggests the need to install or increase their private storage to autonomously cope with their demand for longer periods of time.

• The Functionality time series follows a peaks-and- troughs shape driven by the highs and lows of diurnal water demand in the system. Figure 7 shows an example of a functionality time series (Scenario 01 by Zhang et al., 2018) as well as the demand time series. During evenings, the supplied water was more closely matched to the demands, while during mornings and noontime, the effects of the damages and the ongoing repair work were more noticeable. Additionally, water stored in the tanks offered an initial cushion on the functionality, which allowed full supply of the demand during the first few hours after the event.

• Regarding the criteria used to evaluate the performance of each team, a correlation analysis allowed to identify that only the pair t_{95} – *Res. Loss* has a strong positive correlation (0.92), suggesting that algorithms that minimize one, would indirectly minimize the other. This was difficult to know in advance, but it would indicate that in an optimization framework, only five objective functions were necessary to solve the challenge. All other computed correlations were below 0.55, with negative values for the four pairs between *Nodes no serv*. or *Water Loss*, and t_{95} or *Res. Loss*.

• A Pareto ranking of the ten teams showed that six solutions were non-dominated (Castro-Gama et al., 2018; Zhang et al., 2018; Deuerlein et al., 2018; Li et al., 2018; Bibok, 2018; and Salcedo et al., 2018), with Salcedo et al. (2018) dominating three of the four other solutions, followed by Zheng et al. (2018) dominating two, and Deuerlein et al. (2018) and Castro-Gama et al. (2018) dominating one.

• To evaluate the robustness of the approaches, the standard deviation across the five scenarios was computed for each criterion and each team. Figure 8 compares the standard deviations with the averages (an ideal approach would be closer to the bottom-left corner indicating good average performance and low variability in its results). It can be seen that generally, teams with good performance in a criterion (small average value) also had a small standard deviation in that criterion, indicating that their approaches are also robust (with consistently good results for all five scenarios). Exceptions to this remark are mostly in the Resilience Loss criteria, where teams a), f) and c) (Castro-Gama et al., 2018; Li et al., 2018; and Zhang et al., 2018), in that order, had comparatively good average performances, but with high variation between scenarios.

• The coefficients of variation for the six criteria were computed (across the ten teams). The *Nodes no serv.*, the *Fire & Hosp.*, and the *Time no serv.* were, in that order, the criteria with highest variability, which would suggest that these might be criteria more difficult to attain.

Conclusions

The paper summarizes the competition challenge and the results of the Battle of Post-Disaster Response and Restoration (BPDRR) held in Kingston, Ontario in July 2018, as part of the 1st International WDSA/CCWI Joint Conference. Participants in the BPDRR were tasked with identifying the best strategies to respond and restore water service following five hypothetical earthquake scenarios. A total of ten teams developed approaches that fell into three broad categories of metaheuristic methods, ranking-based prioritization methods, and near-optimal optimization methods. Six performance criteria were used to evaluate the solutions of the ten teams and they included: 1) Time without supply for hospital/firefighting, 2) Rapidity of recovery, 3) Resilience loss, 4) Average time of no user service, 5) Number of users without service for 8 consecutive hours, and 6) Water loss.

The key findings from the Battle are summarized as follows:

• Even though, the six performance measures taken together were used to characterize the appropriateness of the response and restoration solutions, the positive correlation found between some of the criteria suggests that in an optimization framework it might not be necessary to include all of them.

• All three categories of approaches proved to be appropriate to find satisfactory response and restoration solutions despite important differences in computational requirements between approaches. Metaheuristics, on one hand, seem to be suitable to develop plans beforehand the occurrence of the event, as their computational cost limits their application during reaction times. Greedy algorithms, on the other hand, are faster to compute and can also adapt easily to new available information, making them more applicable in the case of an emergency. Finally, ranking-based approaches condense expert knowledge and intuitive criteria to suggest swiftly the recommended interventions to follow.

• The location of isolation valves and the size of hydraulic segments relative to areas affected was found to drive the operational resilience of the system. This highlights the importance of having an adequate location and mapping of isolation valves, as well as a regular maintenance to keep them operational in this disaster scenarios.

• The average period of interruption to water supply for hospitals and firefighting flows was 17.5 hrs and varied considerably between participants and emergency scenarios. This highlights the importance of private water storage for emergency response entities.

• Tank storage helped to preserve functionality in the network but only in the first few hours after an emergency event. This may be specific for the system analysed, i.e. other WDN may be able to provide water for longer periods of time.

One important point to mention is that extending the results and conclusions of this Battle to practise requires that the list of assumptions remains valid in the specific systems. This implies that utilities need to have updated models of their networks, with good mapping of their isolation valves, and with trained crews that can perform the required tasks in periods close to the assumed. Moreover, they need to keep sufficient resources and parts to fix the damages and communicate efficiently with their crews. Only then, a risk assessment and evaluation of alternatives based on the methods presented in this competition should be performed.

Future research

• One aspect that was not explored further was the demand variation that can occur after an earthquake. Depending on the magnitude of the event, commercial and industrial demands can be affected since some businesses would close temporarily while normal conditions are re-established.

• Similarly to the previous point, other important simplification for the problem was not to consider damages to other network elements (e.g., pumps, tanks). Power grids energizing the pumping stations and generators may also be damaged during an earthquake. Communication networks that might be used for monitoring and control operations can also be affected in such scenarios. The effect of this type of damages, as well as their probability of occurrence, and the times to fix them, are worth further investigation.

• The relationship between demand and functionality (Figure 7) suggests that there can be better and worst times to fix damages, specially breaks that require isolation, and therefore might be good to explore idle times for crews where they do not fix anything and wait until a low demand time, as noted by Bibok (2018).

• The impact of catastrophic events such as an earthquake may have a more profound impact on the water quality which needs to be explored further. If this is the case, then partial water supply during the restoration may be of use for specific water uses only (e.g. toilet flushing) and additional measures may have to be considered (e.g. supply of bottled water).

• Usually, important earthquakes produce collapse of buildings and roads, making some streets unfit due to rubbles. These aspects affect mobility and possibility of working of the crews activated for repairing water pipes. These aspects were not considered in the current Battle but might have a significant impact on actual restoring and repairing actions.

• The simplification of transportation times in Table 1 can not apply in many real cases, specially large cities, as fixing two close damages can be less time consuming than fixing two very separate damages. Future studies could attempt to discard this simplification.

• Other practical assumptions made in the competition included the full availability of spare parts and resources to conduct the interventions to all damages. However, this might not be the case in many cities, and therefore, the impact of limited/unavailable resources on the problem could be explored in future.

• Smart water technologies, such as pressure sensors, hydrophones and flow meters (Hill et al., 2014), provide a large amount of information on the state of a WDN. Going forward, it would be interesting to understand how these data could aid water utilities in the design of response solutions to earthquakes as well as other catastrophic events.

• Recent Battles have focussed on various events that strongly threaten the performance of a WDN, such as contamination events (Ostfeld et al., 2008), cyber-physical attacks (Taormina et al., 2018), or earthquakes (BPDRR). While these Battles provide enhanced understanding on the performance of engineering solutions to specific events, there seems to be a lack of knowledge on how these solutions should be merged and implemented into joint contingency plans.

• Due to organizational limitations, this Battle used a disclosed/open set of five scenarios used by the participant teams to develop, adjust and evaluate their approaches, instead of a bigger, concealed set of predefined scenarios to be tested after the submission of their methods/algorithms. This implies that some methodologies might not have been oriented to a generic solution of the problem, but to the specific solution of these five scenarios. Future research in the topic could benefit from using *training scenarios* to feedback and adjust the approaches, and *test scenarios* to evaluate the approaches' actual performance.

Data Availability Statement

Some or all data, models, or code generated or used during the study, including the EPANET models and the results for each team, are available from the corresponding author by request (da.paez270@gmail.com). Additionally, requests regarding code used by the participants to solve the problem will be directed by the corresponding author to the developers of the code.

References

American Lifelines Alliance. (2001). *Seismic Fragility Formulations for Water Systems: Guideline*. American Lifelines Alliance.

Ballantyne, D. B., Berg, E., Kennedy, J., Reneau, R., and Wu, D. (1990). *Earthquake loss estimation modeling of the Seattle water system*. Tech. Rep., Kennedy/Jenks/Chilton, Federal Way, Wash.

Balut, A., Brodziak, R., Bylka, J., Zakrzewski, P. (2018). Battle of Post-Disaster Response and Restauration (BPDRR). *1st International WDSA / CCWI 2018 Joint Conference*, 23/07/2018 - 25/07/2018, Kingston, CAN, 14.

Bibok, A. (2018). Near-optimal restoration scheduling of damaged drinking water distribution systems using machine learning. *1st International WDSA / CCWI 2018 Joint Conference*, 23/07/2018 - 25/07/2018, Kingston, CAN, 14.

Bonneau, A. L., & O'Rourke, T. D. (2009). *Water supply performance during earthquakes and extreme events* (Vol. 234). Mceer.

Castro-Gama, M. (2017) *Visual Analytics for Multi-Objective Optimization Solutions (VAMOS)*. A Matlab open library. ZENODO doi: 10.5281/zenodo.437872

Castro-Gama, M., Quintiliani, C., Santopietro, S. (2018). After earthquake Post-Disaster Response using a Many-Objective approach, a Greedy and engineering interventions. *1st International WDSA / CCWI 2018 Joint Conference*, 23/07/2018 - 25/07/2018, Kingston, CAN, 14.

Cimellaro, G. P., Tinebra, A., Renschler, C., & Fragiadakis, M. (2015). New resilience index for urban water distribution networks. *Journal of Structural Engineering*, 142(8), C4015014.

Cover, T.M., Hart, P.E. (1967). Nearest neighbour pattern classification, *IEEE Transactions on Information Theory*, vol. 13, no. 1, pp. 21-27.

Creaco, E., Franchini, M., & Alvisi, S. (2010). Optimal placement of isolation valves in water distribution systems based on valve cost and weighted average demand shortfall. *Water resources management*, 24(15), 4317-4338.

Deb, K., Mohan, M., & Mishra, S. (2005). Evaluating the ε-domination based multi-objective evolutionary algorithm for a quick computation of Pareto-optimal solutions. *Evolutionary computation*, 13(4), 501-525.

Deuerlein, J., Gilbert, D., Abraham, E., and Piller, O. (2018). A Greedy Scheduling of Post-Disaster Response and Restoration using Pressure-Driven Models and Graph Segment Analysis. *1st International WDSA / CCWI 2018 Joint Conference*, 23/07/2018 - 25/07/2018, Kingston, CAN, 14.

Deuerlein, Jochen W. (2008) Decomposition model of a general water supply network graph. *Journal of Hydraulic Engineering* 134, no. 6: 822-832.

Di Nardo, A., Di Natale, M., Giudicianni, C., Santonastaso, G. F., & Savic, D. (2017). Simplified approach to water distribution system management via identification of a primary network. *Journal of Water Resources Planning and Management*, 144(2), 04017089.

Eliades, D. G., Kyriakou, M., Vrachimis, S., & Polycarpou, M. M. (2016). *EPANET-MATLAB toolkit: An open-source software for interfacing EPANET with MATLAB*.

Fragiadakis, M., Christodoulou, S. E., & Vamvatsikos, D. (2013). Reliability assessment of urban water distribution networks under seismic loads. *Water resources management*, 27(10), 3739-3764.

Gilbert, Denis, Edo Abraham, Idel Montalvo, and Olivier Piller. Iterative Multistage Method for a Large Water Network Sectorization into DMAs under Multiple Design Objectives. *Journal of Water Resources Planning and Management* 143, no. 11 (2017): 04017067.

Hill, D., B. Kerkez, A. Rasekh, A. Ostfeld, B. Minsker, and M. K. Banks. (2014). Sensing and cyberinfrastructure for smarter water management: The promise and challenge of ubiquity. *Journal of Water Resources Planning and Management* 140 (7): 01814002.

Hwang, H. H., Lin, H., & Shinozuka, M. (1998). Seismic performance assessment of water delivery systems. *Journal of Infrastructure Systems*, 4(3), 118-125.

Li, Y., Gao, J., Jian, C., Ou, C., Hu, S. (2018). A Two-stage Post-Disaster Response and Restoration method for the Water Distribution System. *1st International WDSA / CCWI 2018 Joint Conference*, 23/07/2018 - 25/07/2018, Kingston, CAN, 14.

Liu, W., Zhao, Y., & Li, J. (2015). Seismic functional reliability analysis of water distribution networks. *Structure and Infrastructure Engineering*, 11(3), 363-375.

Luong, H. T., & Nagarur, N. N. (2005). Optimal maintenance policy and fund allocation in water distribution networks. *Journal of water resources planning and management*, 131(4), 299-306.

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability* (Vol. 1, No. 14, pp. 281-297).

Mahmoud, H., Kapelan, Z. and Savic, D., (2018), "Real-time Operational Response Methodology for Reducing Failure Impacts in Water Distribution Systems", *Journal of Water Resources Planning and Management*, 144(7).

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

National Institute of Building Sciences (NIBS, 1997). *Earthquake loss estimation methodology HAZUS 97: Technical Manual*. Prepared for Federal Emergency Management Agency, Washington D.C.

Ostfeld, A., et al. (2008). The battle of the water sensor networks (BWSN): A design challenge for engineers and algorithms. *Journal of Water Resources Planning and Management* 134 (6): 556–568.

Paez, D., Filion, Y., & Hulley, M. (2018a). *Battle of Post-Disaster Response and Restoration (BPDRR) - Problem Description and Rules*. Available at: https://www.queensu.ca/wdsa-ccwi2018/problem-description-and-files

Paez, D., Suribabu, C. R., & Filion, Y. (2018b). Method for Extended Period Simulation of Water Distribution Networks with Pressure Driven Demands. *Water Resources Management*, 32(8), 2837-2846.

Pan American Health Organization - PAHO (1998). *Natural Disaster Mitigation in Drinking Water and Sewerage Systems*. Washington, D.C. ISBN 92 75 12250 4

Porter, K.A. (2016*) Damage and restoration of water supply systems in an earthquake sequence*. Structural Engineering and Structural Mechanics Program, University of Colorado, Boulder, Colorado 80309

Salcedo, C., Aguilar, A., Cuero, P., Gonzalez, S., Muñoz, S., Pérez, J., Posada, A., Robles, J., Vargas, K. (2018). Determination of the Hydraulic Restoration Capacity of B-City Involving a Multi-Criteria Decision Support Model. *1st International WDSA / CCWI 2018 Joint Conference*, 23/07/2018 - 25/07/2018, Kingston, CAN, 14.

Santonastaso, G.F., Creaco, E., Di Nardo, A., Di Natale, M. (2018). Post-Disaster Response and Restauration of B-Town Network Based on Primary Network. In *WDSA/CCWI 2018 Joint Conference Proceedings* (Vol. 1).

Shi, P., & O'Rourke, T. D. (2006). *Seismic response modeling of water supply systems*. Technical Report MCEER-08-0016. ISSN 1520-295X

Sophocleous, S., Nikoloudi, E., Mahmoud, H.A., Woodward, K., Romano, M. (2018). Simulation-Based Framework for the Restoration of Earthquake-Damaged Water Distribution Networks using a Genetic Algorithm. *1st International WDSA / CCWI 2018 Joint Conference*, 23/07/2018 - 25/07/2018, Kingston, CAN, 14.

Sweetapple, C., Meng, F., Farmani, R., Fu, G., Butler, D. (2018). A Heuristic Approach to Water Network Post-Disaster Response and Restoration. *1st International WDSA / CCWI 2018 Joint Conference*, 23/07/2018 - 25/07/2018, Kingston, CAN, 14.

Tabucchi, T., Davidson, R., & Brink, S. (2010). Simulation of post-earthquake water supply system restoration. *Civil Engineering and Environmental Systems*, 27(4), 263-279.

Taormina et al. (2018) The battle of the attack detection algorithms: disclosing cyber attacks on water distribution networks. *Journal of Water Resources Planning and Management*, 144(8), 04018048.

Walski, T. M. (1993). Water distribution valve topology for reliability analysis. *Reliability engineering & system safety*, 42(1), 21-27.

Wang, Y., Au, S. K., & Fu, Q. (2010). Seismic risk assessment and mitigation of water supply systems. *Earthquake Spectra*, 26(1), 257-274.

Wang, Y., & O'Rourke, T. D. (2006). *Seismic performance evaluation of water supply systems*. Mceer

Yoo, D. G., Kang, D., & Kim, J. H. (2016). Optimal design of water supply networks for enhancing seismic reliability. *Reliability Engineering & System Safety*, 146, 79-88.

Zhang, Q., Zheng, F., Diao, K., Ulanicki, B., Huang, Y. (2018). Solving the battle of post-disaster response and restauration (BPDRR) problem with the aid of multi-phase optimization framework. *1st International WDSA / CCWI 2018 Joint Conference*, 23/07/2018 - 25/07/2018, Kingston, CAN, 14.

Table 1. Tasks duration times per pipe

Task	Duration time per pipe
Isolate	15 min/valve
Repair*	$0.223 \cdot D_i^{0.577}$
Replace*	$0.156 \cdot D_i^{0.719}$

*D_i in mm and resulting times in hours (rounded to the lowest hour)

Table 2. Example of prioritization schedule

Crew	**List of tasks (ordered chronologically)**
Crew 01	Isolate P136
	Isolate P283
	Repair P206
	Replace P152
	Repair P242
	⋮
Crew 02	Isolate P367
	Isolate P152
	Replace P367
	Replace P136
	Repair P154
	⋮
Crew 03	Isolate P105
	Replace P105
	Repair P254
	Repair P221
	Isolate P133
	⋮

Table 3. Performance of participant teams in the six defined criteria

Team	**Algorithm**	**Optimization / Ranking criteria**	**Fire & Hosp. (min)**	**t_{95} (min)**	**Res. Loss (%*min)**	**Time no serv. (min)**	**Nodes no serv. (nodes)**	**Water Loss. (ML)**
Castro-Gama et al. (2018)	Platypus ε-MOEA	6 (Original criteria)	1411	4094	13271	38.8	17.9	67 760
Sweetapple et al. (2018)	Nearest Neighbor Search	1 (Weighted and normalized original criteria)	365	5154	15472	49.6	90.0	79 982
Zhang et al. (2018)	Improved Genetic Algorithm	1 (Weighted and normalized original criteria)	147	3106	10195	64.1	28.6	60 380
Deuerlein et al. (2018)	Greedy Alg.	1 (Weighted relative increase of 5 original criteria)	301	3918	13250	54.4	140.3	57 278
Balut et al. (2018)	Pipe/Damage rankings [x 6] + Expert survey	1 (Weighted and normalized original criteria)	3396	5184	25988	79.4	212.1	66 580
Li et al. (2018)	Greedy Alg. + PSO	1 (*Fire & Hosp*. for stage 1 and *Res. Loss* for stage 2)	1532	3902	13574	364.7	818.0	56 624
Sophocleous et al. (2018)	NSGA-II	1 (Normalized original criteria)	2528	9510	42129	86.5	37.6	94 116
Santonastaso et al. (2018)	Pipe/Damage ranking [x 1]	6 (Original criteria)	315	4845	16958	50.0	104.9	77 881
Bibok (2018)	Genetic Algorithm	1 (Normalized original criteria)	234	4638	15944	216.6	8.4	73 923
Salcedo et al. (2018)	Pipe/Damage rankings [x 5+]	1 (Weighted and normalized modified criteria)	270	4471	14235	46.0	35.6	66 799
	AVERAGE		1050	4882	18102	105.0	149.3	70 132

Note: Entries underlined represent the top three values for each criterion. MOEA: Multi Objective Evolutionary Algorithm. PSO: Particle Swarm Optimization. NSGA-II: Non-Sorted Genetic Algorithm.

Figure 1. B-City water distribution network. Dotted lines delimit DMAs and “H” represents the hospitals.

Figure 2. Damage scenario 01. Breaks highlighted in red, leaks highlighted in yellow, and fire-flows marked with an “F”.

Figure 3. Schematic representation of breaks and leaks.

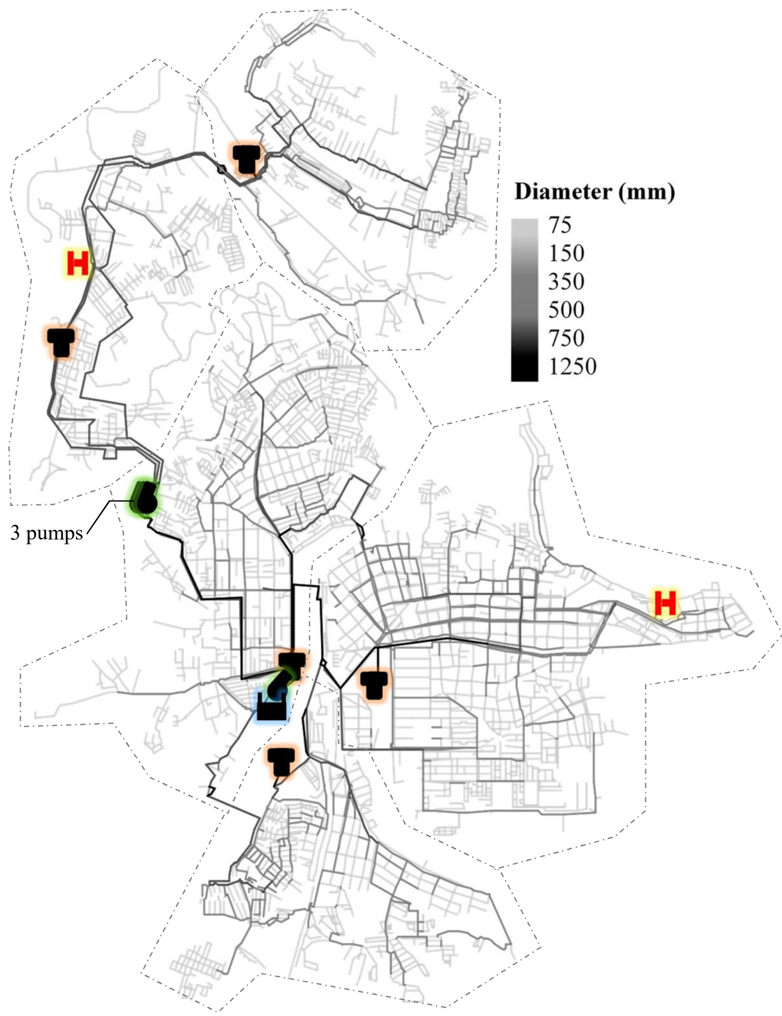
Figure 4. Time variation of Functionality as the system is gradually fixed.

Figure 5. Performance comparison of each team with respect to the average (black dotted line). Better performance indicated by larger green areas. a) Results from Castro-Gama et al. (2018); b) Results from Sweetapple et al. (2018); c) Results from Zhang et al. (2018); d) Results from Deuerlein et al. (2018); e) Results from Balut et al. (2018); f) Results from Li et al. (2018); g) Results from Sophocleous et al. (2018); h) Results from Santonastaso et al. (2018); i) Results from Bibok (2018); j) Results from Salcedo et al. (2018).

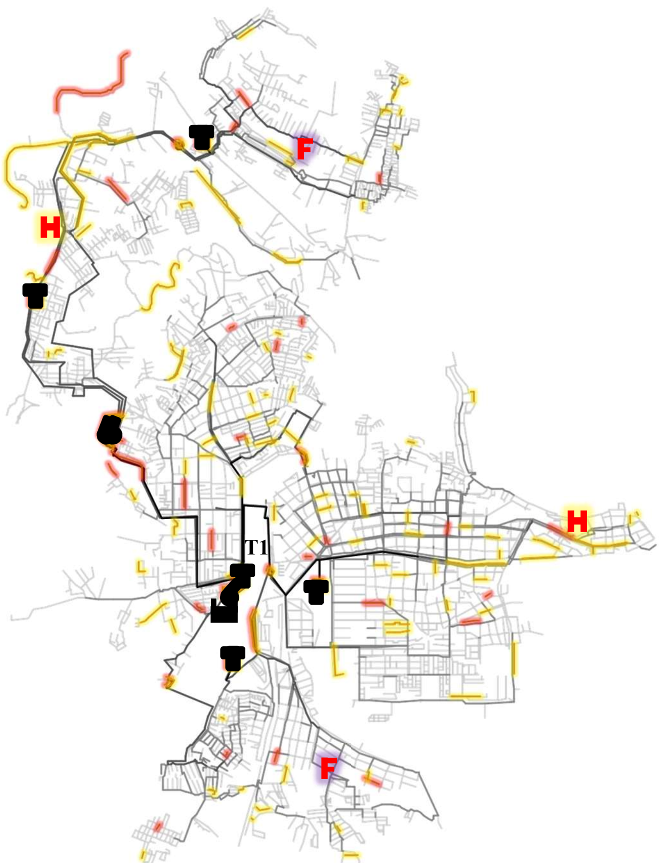
Figure 6. Average Resilience Loss vs. Pipe breaks range per damage scenario

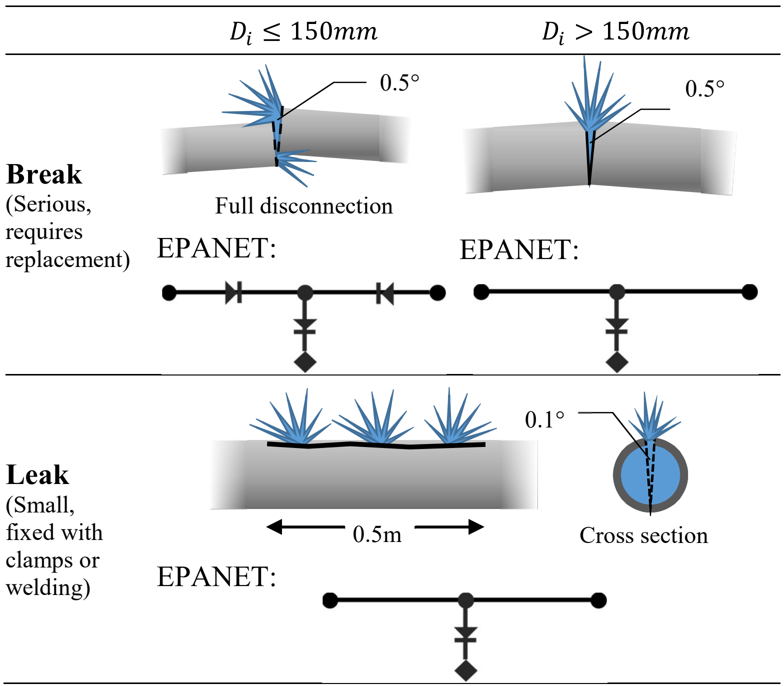
Figure 7. Functionality time series for Scenario 01 by Zhang et al. (2018)

Figure 8. Average and Standard Deviation per criteria per team.

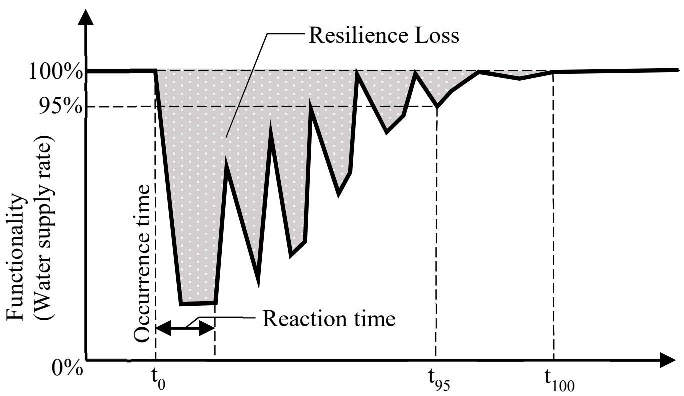


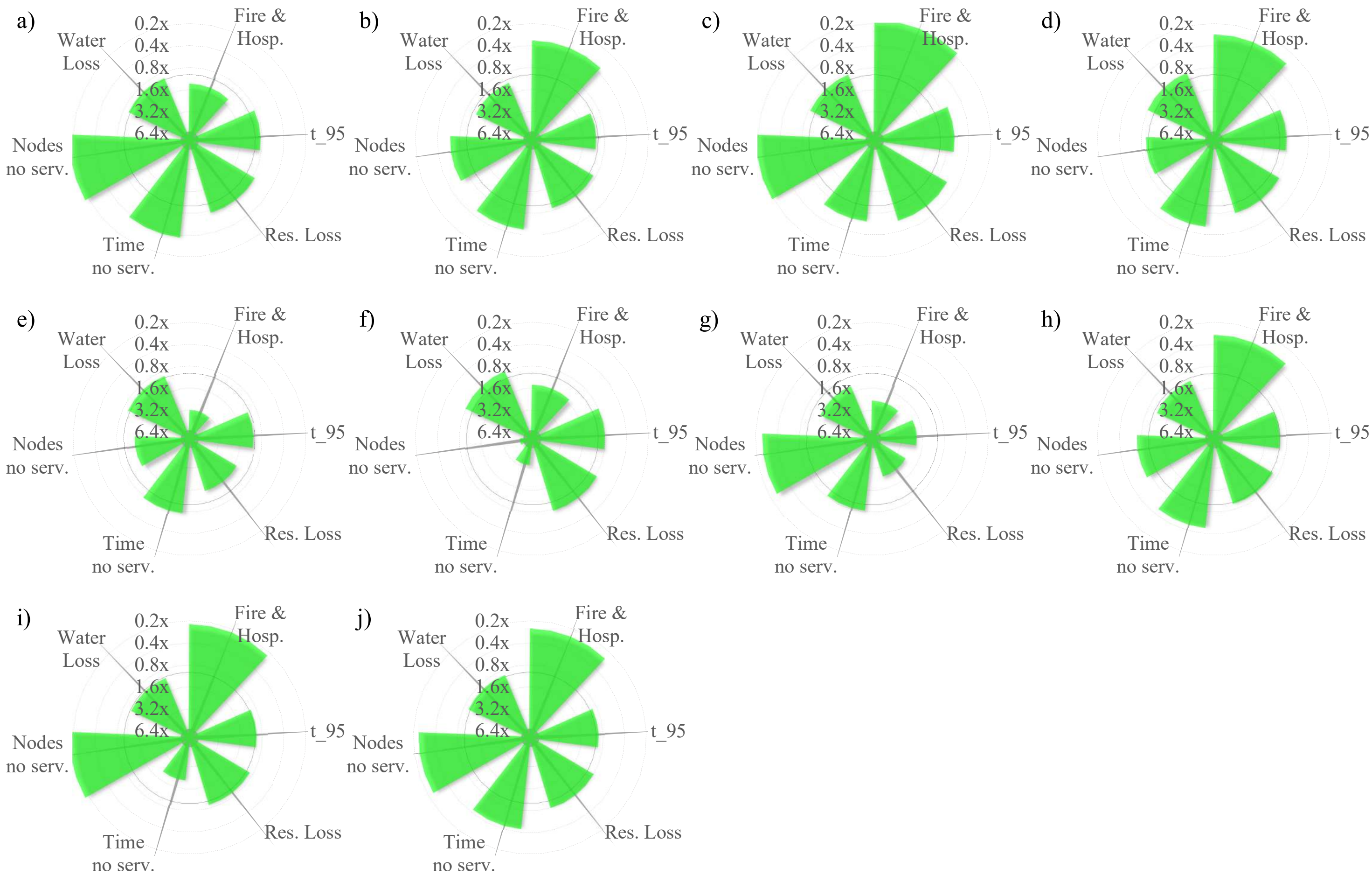
Diameter (mm)
75
150
350
500
750
1250
3 pumps
H
H

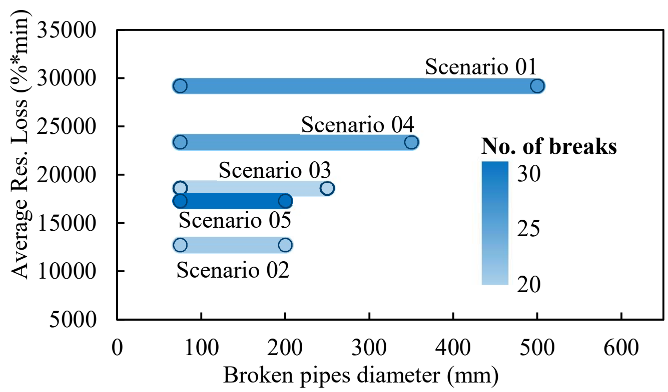

F
H
T1
H
F



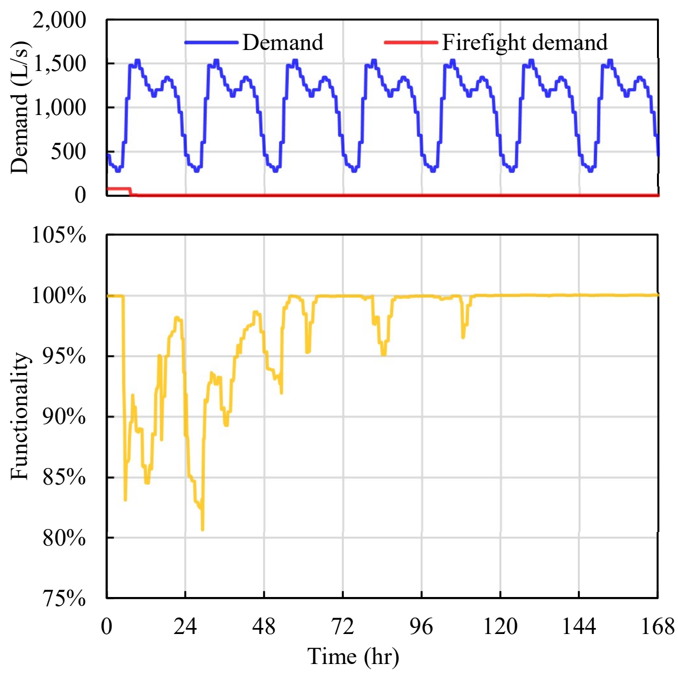
$D_i \leq 150mm$
$D_i > 150mm$
0.5°
0.5°
Break
(Serious, requires replacement)
Full disconnection
EPANET:
EPANET:
0.1°
Leak
(Small, fixed with clamps or welding)
0.5m
Cross section
EPANET:


Resilience Loss
100%
95%
Functionality
(Water supply rate)
Occurrence time
Reaction time
0%
t0
t95
t100

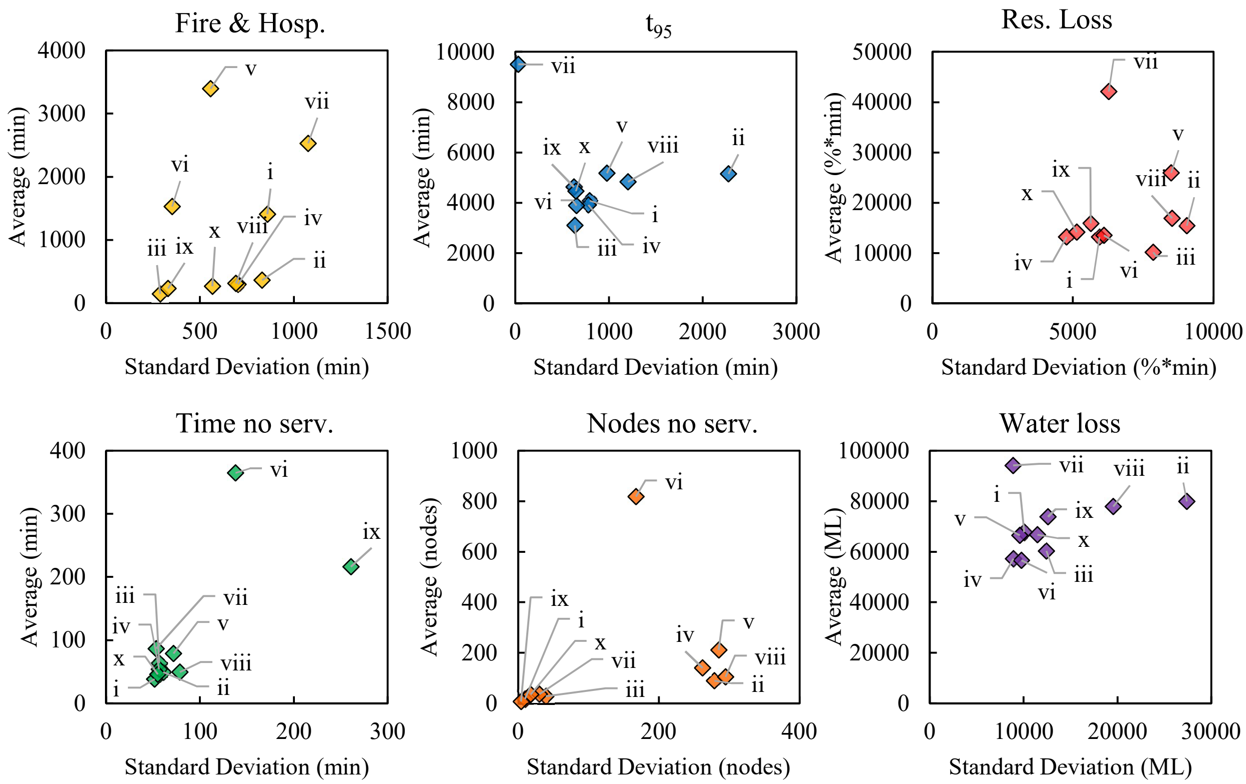

a)
Water Loss
0.2x
0.4x
0.8x
1.6x
3.2x
6.4x
Fire & Hosp.
t_95
Res. Loss
Time no serv.
Nodes no serv.
b)
Water Loss
0.2x
0.4x
0.8x
1.6x
3.2x
6.4x
Fire & Hosp.
t_95
Res. Loss
Time no serv.
Nodes no serv.
c)
Water Loss
0.2x
0.4x
0.8x
1.6x
3.2x
6.4x
Fire & Hosp.
t_95
Res. Loss
Time no serv.
Nodes no serv.
d)
Water Loss
0.2x
0.4x
0.8x
1.6x
3.2x
6.4x
Fire & Hosp.
t_95
Res. Loss
Time no serv.
Nodes no serv.
e)
Water Loss
0.2x
0.4x
0.8x
1.6x
3.2x
6.4x
Fire & Hosp.
t_95
Res. Loss
Time no serv.
Nodes no serv.
f)
Water Loss
0.2x
0.4x
0.8x
1.6x
3.2x
6.4x
Fire & Hosp.
t_95
Res. Loss
Time no serv.
Nodes no serv.
g)
Water Loss
0.2x
0.4x
0.8x
1.6x
3.2x
6.4x
Fire & Hosp.
t_95
Res. Loss
Time no serv.
Nodes no serv.
h)
Water Loss
0.2x
0.4x
0.8x
1.6x
3.2x
6.4x
Fire & Hosp.
t_95
Res. Loss
Time no serv.
Nodes no serv.
i)
Water Loss
0.2x
0.4x
0.8x
1.6x
3.2x
6.4x
Fire & Hosp.
t_95
Res. Loss
Time no serv.
Nodes no serv.
j)
Water Loss
0.2x
0.4x
0.8x
1.6x
3.2x
6.4x
Fire & Hosp.
t_95
Res. Loss
Time no serv.
Nodes no serv.



Average Res. Loss (%*min)
35000
30000
25000
20000
15000
10000
5000
0
100
200
300
400
500
600
Broken pipes diameter (mm)
Scenario 01
Scenario 04
Scenario 03
Scenario 05
Scenario 02
No. of breaks
30
25
20



Demand
Firefight demand
Demand (L/s)
2,000
1,500
1,000
500
0
105%
100%
95%
90%
85%
80%
75%
Functionality
0
24
48
72
96
120
144
168
Time (hr)



i. Castro-Gama et al. (2018) **ii**. Sweetapple et al. (2018) **iii**. Zhang et al. (2018) **iv**. Deuerlein et al. (2018) **v**. Balut et al. (2018) **vi**. Li et al. (2018) **vii**. Sophocleous et al. (2018) **viii**. Santonastaso et al. (2018) **ix**. Bibok (2018) **x**. Salcedo et al. (2018).