Heuristic-Based Approach for Near-Optimal Response to Water Distribution Network Failures in Near Real Time

Nikoloudi, Eirini; Romano, Michele; Memon, Fayyaz Ali; Kapelan, Zoran

DOI
10.1061/(ASCE)WR.1943-5452.0001582

Publication date
2022

Document Version
Final published version

Published in
Journal of Water Resources Planning and Management

Heuristic-Based Approach for Near-Optimal Response to Water Distribution Network Failures in Near Real Time

Eirini Nikoloudi[1]; Michele Romano[2]; Fayyaz Ali Memon[3]; and Zoran Kapelan[4]

Abstract: This paper proposes a new method to identify the near-optimal response to failures in water distribution networks in near real time. The response method is formulated as a two-objective optimization problem with objectives being the minimization of failure impacts and related operational costs. The new heuristics-based method is developed and used to solve this optimization problem. The method comprises three steps. In the first step, the initial list of available interventions is identified offline. In the second step (online), the narrowed-down list of interventions considered in the optimization is identified. Finally, in the last step (online), a novel heuristic algorithm is applied to identify near-optimal solutions in near real time. The new optimization method was validated and demonstrated in two case studies, a semireal case study based on a C-Town network and an assumed failure event (pipe burst), and a real UK case study involving a complex real pipe network and event caused by shutting down the Water Treatment Works. The Pareto front of response interventions identified by the new heuristics method approximates well the non-dominated sorting genetic algorithm II Pareto front in both cases with the largest differences measured in terms of end-impacts (between relevant solutions for the same cost) being 4% and 9%, respectively. In addition, the new heuristics method is able to identify near-optimal response solutions in a computationally fast manner (15 min and 1 h for the two cases). Therefore, the heuristics method can be used in near real time in real-life situations. **DOI:** 10.1061/(ASCE)WR.1943-5452.0001582. *© 2022 American Society of Civil Engineers.*

Author keywords: Near real-time optimization; Near real-time response; Water distribution network failures; Heuristic method; Multiobjective optimization problem.

Introduction

Uninterrupted water supply under sufficient pressure is of major importance. The water supply is uninterrupted only when the water distribution system (WDS) is under normal operation, i.e., without failure. However, nowadays, many WDSs, especially in old cities with aging water infrastructure, face different kinds of failures, such as leaks, bursts, pumps, or other equipment failures. In such WDSs, rehabilitation (i.e., pipe/equipment replacement) of the whole or part of the system is usually proposed as a long-term measure to permanently address the issue of WDS failures. In the literature, extensive investigation has been carried out on the best way to apply the WDS infrastructure rehabilitation. Several optimization techniques have been developed for this purpose (e.g., Alperovits and Shamir 1977; Su et al. 1987; Kim and Mays 1994; Kang and Lansey 2012; Zheng et al. 2016; Avila-Melgar et al. 2017), and WDS optimization (for the design and rehabilitation) has seen advancements over time.

However, in some cases, water utilities and municipalities prefer to apply more short-term measures and respond in real-time to the different WDS failures. In this case, extensive research is yet to progress. Additionally, it is not straightforward that the conventional optimization methods developed for the WDS design and rehabilitation can be used for real-time response. This is because each case covers a range of different aspects. For example, in WDS rehabilitation, utilities and municipalities are mainly concerned about the long-term (operational and capital) cost of their design/rehabilitation plan. On the opposite hand, in the real-time response, they aim to reduce the negative impact on the customers and properly allocate the technicians based on the resource availability and times/duration of intervention implementation.

The present work aims to address this challenge by proposing a new optimization method. The new method proposes a novel technique to identify in near real-time near-optimal response solutions but also solves a multiobjective optimization problem with realistic objective functions and decision variables. The proposed optimization method here is an extension of work found in Nikoloudi et al. (2020) where a novel response methodology was presented and implemented in a decision-support tool (i.e., the Interactive Response Planning Tool, IRPT). In Nikoloudi et al. (2020), the optimization problem was solved using the non-dominated sorting genetic algorithm II (NSGA II) which took approximately 2 days to be completed (i.e., not in real time). The heuristic-based optimization method presented here takes up to 1 h to solve the same optimization problem. The proposed novel method is regarded by the authors of great importance, as it could be potentially used in water utility practice due to its ability to identify accurately optimal solutions in near real time, unlike other optimization methods found in the literature (see the next section).

The paper is organized as follows. After the present Introduction Section, a brief background in the field of optimal response to WDS failures is presented. Later, the new optimization method is described in detail, including the optimization problem and the

[1]Ph.D. Candidate, Centre for Water Systems, Univ. of Exeter, North Park Rd., Exeter EX4 4QF, UK (corresponding author). ORCID: https://orcid.org/0000-0002-6482-184X. Email: eirininikoloudi@hotmail.gr

[2]Senior Engineer, United Utilities Group PLC, Lingley Green Ave., Warrington WA5 3LP, UK.

[3]Professor, Centre for Water Systems, Univ. of Exeter, North Park Rd., Exeter EX4 4QF, UK. ORCID: https://orcid.org/0000-0002-0779-083X

[4]Professor, Faculty of Civil Engineering and Geosciences, Delft Univ. of Technology, Stevinweg 1, Delft, CN 2628, Netherlands.

Note. This manuscript was submitted on January 12, 2021; approved on March 26, 2022; published online on May 27, 2022. Discussion period open until October 27, 2022; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Water Resources Planning and Management***, © ASCE, ISSN 0733-9496.

new optimization method (with the heuristic approach) description. Then, the first case study (i.e., the C-Town event) is presented, and in the context of which, a sensitivity analysis and a comparison with published related work are shown. Later, the second case study (i.e., the P-Town event) is described briefly, with more details explained in the Supplemental Materails. Finally, the conclusions of the present work are drawn.

Background

Several studies in the past have proposed different methods/advancements to address the optimal response to a WDS failure. However, none of the studies in the known literature so far has proposed a combination of these different advancements, e.g., optimization methods applied to complex real-life water networks, advanced optimization techniques (e.g., NSGA II, tailored genetic algorithms (TGA), and heuristics), multiobjective optimization problem formulation, and near real-time optimal response. In the following paragraphs of this section, some representative studies about the optimal response to failures in WDSs are reviewed.

Nikoloudi et al. (2020) developed a new interactive methodology and an interactive tool for the response to WDS failure events facilitating near real-time decision-making. In their method, they used the NSGA II to solve the two-objective optimization problem. Their method was also applied to a complex real-life network and event. However, the multiobjective nature of the problem as well as the application of the NSGA II to a complex network did not allow the identification of the optimal response solution(s) in near real time. The present paper expands on the application of Nikoloudi et al. (2020) by proposing an advanced, heuristic-based optimization technique. The new technique is used to solve the same optimization problem, i.e., on the same case study with the same objective functions (i.e., same impact indicators and cost function), decision variables, and constraints. By using the new heuristic-based method, the presented optimization problem is solved in near real time (i.e., up to 1 h after event localization). It is stressed here that event *localization* refers to the event management stage where the exact location of the event has been identified in the water network and precedes to the *response* stage (Nikoloudi et al. 2020).

Zhang et al. (2020) proposed a dynamic optimization methodology to improve the resilience of WDSs after the occurrence of natural disasters (e.g., earthquakes). The resilience of the affected WDS is improved through identifying optimal sequencing of recovery actions (i.e., interventions). A TGA was developed to solve the complex optimization problem. The proposed framework was tested on a real-world WDS. However, the authors in their method solve a single-objective optimization problem, with the objective being maximizing the resilience of the affected WDS. This implies that the optimization problem formulation is rather simple and alternative objectives usually required to be minimized under disaster scenarios (e.g., number/cost of interventions) are not considered. Furthermore, although an advanced optimization technique, the TGA makes use of initialization, crossover, and mutation processes, as usually/generally used in genetic algorithms. The presented processes, in contrast, require significant computational effort, especially when applied to complex water networks. Moreover, for a potential disaster scenario, the proposed dynamic TGA updates the number of decision variables (i.e., damaged pipes) in order to make the optimization problem more realistic. This process, however, increases the complexity of the optimization problem, and hence, the optimal solution might not be identified in near real time (as required by water utilities). The present work addresses the aforementioned challenges by developing a two-objective (i.e., more realistic) optimization problem. Additionally, the heuristic-based optimization method developed here enables quick (i.e., near real time) and accurate enough problem solving, even in real-life complex water systems.

Balut et al. (2018) presented their proposition for the restoration of a WDS that has been damaged by an earthquake in the context of the Battle of Postdisaster Response and Restoration (BPDRR) (see Paez et al. 2020). They developed a ranking-based prioritization method to solve the optimization problem. Their method included rankings of pipes, each based on some criteria. The ranking criteria determined the importance of each pipe in the network and were defined after a survey of different utilities. The aim of ranking was to facilitate the planning of repair works (i.e., order of response actions). The proposed ranking method (similarly to all ranking-based methodologies) obtains the advantage that does not require a calibrated model to run the hydraulic simulations. However, such methods are rather practical/industrial in nature and do not always guarantee the identification of an optimal, or even near-optimal solution (although the solution is feasible and is identified in near real time). Furthermore, ranking-based solutions are based on rather subjective criteria (i.e., each utility makes use of different criteria). In that way, the ranking-based methods are not generic in their use. This challenge is addressed here by proposing a method that identifies near-optimal solutions in near real time, hence making the new optimization method generic in use for water utilities. It is stressed that the rest of the papers/propositions of the BPDRR are not reviewed here due to their relevance with the rest of the literature presented in this section.

Mahmoud et al. (2018) developed a methodology for near real-time response to WDS failure events (e.g., pipe bursts or equipment failures). The optimal combination of interventions is identified by using a multiobjective optimization approach with objectives being the minimization of the negative impact on the consumers and the minimization of the corresponding number of operational interventions. The NSGA II was used for the solution of the optimization problem. Their methodology was tested on the simple, real-world WDS of C-Town. It is observed that although the advanced optimization method of NSGA II was used, the methodology proposed by Mahmoud et al. (2018) might be inappropriate to propose an optimal response solution under real-life circumstances in near real time due to the following inadequacies: (1) The second objective of the optimization problem is minimizing the number of recovery interventions, which acts as a surrogate to the more realistic objective of minimizing the operational cost of the recovery interventions; (2) During the offline process of the proposed methodology, hydraulic simulations are conducted to identify the affected district metered areas (DMAs) (required to the following online process). However, when offline (i.e., before the event occurs), operators are unable to be aware of the details of the real event. This leads operators to make different assumptions of the event that may not correspond to the real event (when this happens); and (3) The authors make use of the advanced NSGA II, which is applied to a simple water network. NSGA II is a computationally demanding optimization technique, and it is expected that when applied to a real-life, complex network, it will propose optimal solutions after a significant period of time, i.e., not near real time (as also observed in Nikoloudi et al. 2020). The present paper addresses the first challenge by using the minimization of the operational cost of interventions as the second optimization objective. The second challenge is addressed by running all the hydraulic simulations online simulating only the real-life event. Finally, the third challenge is addressed by proposing a novel, heuristic-based optimization technique tested on a real-life complex network that identifies optimal responses in near real time.

Vamvakeridou-Lyroudia et al. (2010) presented an intervention management model (IMM) for the near real-time response to WDS failure events (i.e., pipe bursts and leaks). A multiobjective problem was formulated with two objective functions: (1) minimizing impacts on customers, and (2) minimizing the number of interventions. Optimization was carried out using a heuristic algorithm based on the discrete dynamic dimensioned search method. The method was tested on a real-life case study in the Harrogate area of North Yorkshire, UK. Although the aforementioned advanced optimization technique was used to solve the optimization problem, the use of the number of interventions as the second objective (as in Mahmoud et al. 2018) does not allow a realistic approach to the real optimization problem (e.g., the operational cost of interventions, as used in the present study, could be a more realistic approach). Furthermore, the authors make use of an offline preprocessor (similarly to Mahmoud et al. 2018) to simulate (through hydraulic simulations) different pipe failure scenarios and store the resulted response of each scenario in an offline database. However, an offline preprocessor is unable to predict and simulate all the possible failure scenarios, i.e., all the combinations of failure pipe(s), time of failure, magnitude of failure, and pipes to be isolated for repair. The present paper addresses the presented challenge by making all the hydraulic simulations online, i.e., after the failure event has happened.

From the presented literature review, it can be seen that among the different optimization methods used to optimize the response to WDS failures, the use of genetic algorithms (GAs), e.g., TGA and NSGA, dominates. The review of Mala-Jetmarova et al. (2018) mentions that stochastic methods including GAs that have been used for the optimal WDS design/rehabilitation and more lately for optimal WDS failure responses have proven to be able to successfully deal with these problems, accurate (in optimization problems of varying complexity), and time-efficient (in noncomplex optimization problems). Therefore, in this study, the results of the proposed heuristic-based method have been compared with the results of the widely used NSGA II method. Having said this, other mathematical optimization methods could have been used for the comparison instead of the NSGA II, as these methods have also proven to be effective in dealing with the issues of nonlinearity and discrete nature of decision variables present in the control and operation of water supply systems (e.g., Pecci et al. 2019, 2021; Ulusoy et al. 2021). However, this is beyond the scope of present work, and a robust comparison of different mathematical and other optimization methods with the heuristic-based method proposed here is recommended for future work.

As mentioned earlier, the NSGA II is conducted in the context of this work (i.e., in the case studies) in order to compare the optimal solutions (generated by the NSGA II) with the near-optimal ones (generated by the heuristic). The aim of this comparison is to point out the benefit of the new method regarding the reliability of solutions and the time for them to be identified compared to more conventional methods used in past studies. The NSGA II method used in this work considers as objective functions the minimization of the total end-impact of an identified response solution to customers and the minimization of the total cost of this response solution, i.e., the same objectives as in the heuristics-based method. The NSGA II decision variables are the different combinations of interventions (like in the heuristics method), as well as the start time of each intervention considered in the response solution. It is observed that more decision variables are used in the NSGA II method compared to the heuristics method because it has been proven that NSGA II can better deal with multiple variables, although it might be time-inefficient in complex networks (Nikoloudi et al. 2020). This makes the NSGA II results in the present work more reliable, i.e., NSGA II identifies optimal solutions, whereas the heuristics method identifies near-optimal solutions.

Heuristics-Based Optimization Methodology

Optimization Problem

In this section, the new optimization method is described and formulated. As mentioned in the Background Section, the same optimization problem (i.e., same objective function, decision variables, and constraints) as in Nikoloudi et al. (2020) has been used here. Later in this paper, the new optimization approach to solve the optimization problem (i.e., to identify optimum solutions in near real time) is discussed. The presented optimization problem is two-objective. The two objectives are the minimization of the total end-impact (of a response solution) and the minimization of the total cost associated with this solution.

More specifically, the first objective function is the minimization of the total (i.e., aggregated) end-impact, i.e., impact after interventions are implemented. This is estimated by normalizing and then adding up the values of the individual impact indicators, as follows:

$$Total\_impact = \sum_{i=1}^{4}(w_i f'_i) \quad (1)$$

where i = index of each impact indicator with $i\epsilon[1,4]$; f'_i = normalized impact indicator i; and w_i = weight of impact indicator i with $\sum w_i = 1$. Further details for calculating the first objective are presented in the Supplemental Materials.

The impact indicators used here cover the impact aspects of supply interruption, low pressure, and discoloration risk increase. They are the following: (1) customer minutes lost (CML) in minutes/customer; (2) average minutes low pressure (AMLP) in minutes/customer; (3) unaccounted for water (UW) in cubic meters; and (4) discoloration risk increase (DRI) in the number of pipes that face a high risk of discoloration increase. AMLP and UW are calculated for different customer types, namely: residential, industrial, and sensitive (i.e., schools and hospitals). The impact horizon in the new response methodology is the period of time for which the end-impact is assessed. It starts from the localization time of an event and lasts until the repair is completed (i.e., the time period over which restoration interventions can be implemented). The definitions of impact indicators used in this work are presented in the Supplemental Materials for this paper, but more details can be found in Nikoloudi et al. (2020).

The response solution includes a series of operational interventions whose application allows the restoration of supply while the repair is been conducted. The interventions considered here are: (1) rezoning by valve manipulations (i.e., opening initially closed boundary valves); (2) water injection at different network locations; (3) overland bypasses; and (4) combination of these. Water injection, which is a novel type of intervention considered in this study, is carried out through the alternative supply vehicles (ASVs). It is important to stress that rezoning is assumed to last until the repair is complete (i.e., as in utility's general practice), i.e., its duration is not considered a decision variable. ASV injection, on the other hand, is carried out until the tank (modeled at each injection point) gets empty. This may happen before the repair is complete depending on the water demand (under normal conditions) of the affected area. Injection takes place from specific hydrant locations in the network.

It should be stressed that the isolation of the failure pipeline was not included in the optimization. This is because this isolation is assumed to have already been conducted before the application of interventions considered here in order to isolate the failure. The interventions optimized here are assumed to be applied after isolation to restore the interrupted supply.

The second objective function is formulated as follows (with more details being presented in the Supplemental Materials):

$$Total\_cost = c_{rez}d_{rez}N_{rez} + c_{PRV}d_{PRV}N_{PRV} + c_{ASV}h_{ASV} + c_{OLB}h_{OLB} \quad (2)$$

where c_{rez}, c_{PRV} = costs (£) per hour of manipulating (i.e., opening, closing, or adjusting) a single rezoning valve or pressure reduction valve (PRV); c_{ASV}, c_{OLB} = costs (£) per hour of ASV and overland bypass (OLB) injection; d_{rez}, d_{PRV} are the time periods it takes to open, close, or adjust a single rezoning valve or PRV, in hours; h_{ASV}, h_{OLB} = total time periods of ASV and OLB injection (i.e., hours of injection from all the ASVs and OLBs sent to the site); and N_{rez}, N_{PRV} = numbers of rezoning valves and PRVs to open, close, or adjust in the specific response solution.

Heuristic-Based Optimization Method

The new optimization method developed here consists of three main steps, the offline step 0 and the online steps 1 and 2. The offline step is conducted under normal (i.e., business as usual) operation of the system (i.e., no event has been detected/localized). It contains all the (offline) actions required by the utilities to identify their available intervention options (i.e., types and locations) in their system. The online steps (steps 1 and 2) include manual/human decisions and automatic calculations for the preparation of the optimization and the optimization through a heuristic algorithm, respectively. In Fig. 1, the new optimization steps and the heuristic algorithm are shown.

The proposed optimization method has been developed in the programming environment of MATLAB R2016b (Higham and Higham 2016). More specifically, step 0 of the method is applied manually by utility operators who update/make use of the utility systems. Step 1 of the method is conducted manually in Matlab to prepare for the heuristics optimization in step 2. Step 2 of the method is the execution of the heuristics optimization, and it is applied automatically in Matlab (implementing the pseudocode presented in Fig. 1). Matlab also links to EPANET 2.0 (Rossman 2000) for the execution of the hydraulic simulations. Pressure-driven network modeling is used based on the methodology developed by Paez et al. (2018).

The new optimization method's steps are described in detail in the following text. Step 0 includes the offline preparation for the optimization. Here, the initial list of all the interventions is identified. This database of interventions should be updated periodically by the utility to reflect reality. The offline process here, unlike the process in Mahmoud et al. (2018), does not consider any event scenario, i.e., no hydraulic simulation is conducted for the identification of affected DMAs/nodes. This is because when offline, it is hard to predict/evaluate all the possible event scenarios, including start time of the event, start time of isolation, magnitude of leak/burst, and location of the event.

In step 1, the online preparation for optimization takes place. Specifically, in step 1a, the initial list of interventions from step 0 is narrowed down in the following way: (1) the overland bypasses and rezoning valves located in areas that link affected with unaffected DMAs are considered, (2) the OLBs and ASV points located in the affected DMAs are considered, and (3) the (pressure reduction valves) PRVs located upstream of affected nodes are considered. It is implied that at this step, the affected DMAs/nodes of the specific event have to be identified after hydraulic analysis. In this step, a DMA is considered affected when at least one node has a pressure less than 15 m (i.e., low pressure or no supply impact) for at least one time step (i.e., 15 mins).

Step 0: Offline: Update database with available interventions

Step 1: Online: Preparation for optimisation

a. Initial narrowing-down of interventions

b. Individual evaluation of end-impact/cost of single interventions

c. Selection of the final number of interventions

Step 2: Online: Optimisation (heuristic algorithm):

a. Assess end-impact/cost of the initial solution m (i.e. IM_m, C_m). Go to step 2b.

b. Assess end-impact/cost of the subsequent solution i (i.e. IM_i, C_i). Go to step 2c.

While $i \leq i_{max}$

*c. **If** $IM_m \leq IM_i$ **and** $C_m \leq C_i$, then go to step 2h, otherwise go to step 2d.*

*d. **If** $IM_m > IM_i$ **or** $C_m > C_i$, then go to step 2i, otherwise go to step 2h.*

e. Assess end-impact/cost of the subsequent solution i+1 (i.e. IM_{i+1}, C_{i+1}). Go to step 2f.

*f. **If** $IM_i \leq IM_{i+1}$ **and** $C_i \leq C_{i+1}$, then go to step 2h, otherwise go to step 2g.*

*g. **If** $IM_i > IM_{i+1}$ **or** $C_i > C_{i+1}$, then go to step 2i, otherwise go to step 2h.*

*h. Reject solution, **i = i +1** and go to step 2e.*

*i. Accept solution, **i = i +1** and go to step 2e.*

End of iterations

j. Identification of the final Pareto front of near optimal solutions.

Fig. 1. New optimization strategy steps and heuristic algorithm.

In step 1b, individual evaluation of end-impact and cost for the identified interventions (i.e., types and locations identified in step 1a) for a selected (by an operator) start time is conducted. In that way, the individual interventions that do not further reduce end-impact are rejected and not considered anymore in the next step. The start time is selected by the operator due to time limitations to evaluate every single start time. This means that all the interventions will be implemented at the same time. This is a significant limitation of the new optimization method, but when online, the time to identify the best solutions is limited. The selection of start time by operators compensates for this limitation though, as engineering judgment makes this selection more realistic (e.g., time to reach the site and availability/accessibility of recourses). In Mahmoud et al. (2018), the start time of interventions is not a variable either (e.g., for the burst on pipe P307 in their paper they consider a start time 8 h after localization for all the interventions). It is stressed that the heuristic proposed in step 2 (i.e., optimization step) can be also applied considering the start time of each intervention type as a decision variable.

In step 1c, a number (hereafter equal to x) of interventions with the lowest end-impact is selected, and these interventions are nominated to the optimization stage. This number depends on the time it takes for each evaluation to be completed (i.e., in simple networks, it takes some seconds, whereas in more complex real-life networks, it takes some minutes).

In step 2, the optimization via a heuristic takes place online. The heuristic algorithm's steps are described hereafter. In step 2a, in real time, the initial solution is identified (from the identified list of x interventions in step 1c) by the heuristic algorithm as the single intervention with the lowest cost. If multiple solutions with the same lowest cost exist, then the solution with the lowest end-impact for this cost is selected by the algorithm. Then, the heuristic identifies the subsequent solution i in step 2b as the single intervention from step 1 with the lowest end-impact. If multiple solutions with the same lowest end-impact exist, then the solution with the lowest cost for this end-impact is selected by the algorithm. This is done in order to account for the other extreme point, i.e., the solution with the lowest end-impact. Solution i is accepted if at least one of the two objectives is better (i.e., lower) compared to the initial solution. In step 2e, new solutions are identified by combining single interventions. At every iteration, the single intervention with the next lowest end-impact is added to the previous solution. If the new solution is rejected, then the last single intervention that was added is removed and the next best (i.e., with the lowest end-impact) single intervention is added. Iterations (i.e., new solutions generation) end when all the available single interventions identified in step 1 have been added/used.

It is stressed that the heuristic's checks of end-impact/cost of the subsequent solutions (i.e., steps 2c, 2d, 2f, and 2g) do not always generate nondominated solutions. For example, when both objectives of the subsequent solution are lower than the ones in the previous solution, then the subsequent solution dominates the previous one. This issue is addressed at the end of iterations (in step 2j) by identifying the nondominated solutions. The nondominated solutions then form the final Pareto front of near-optimal solutions proposed to operators.

It is also highlighted that the focus of this new optimization method is not on selecting the initial population, but on the improvement of the optimization method for the generation of near-optimal solutions in near real time. Hence, the new heuristic algorithm proposed here (in step 2) can be easily linked to any preferred method for selecting the initial population (i.e., step 1 can be substituted with any desired initial population selection method).

Case Study

The new optimization method is tested/validated on two real-life networks: (1) C-Town (i.e., a simple real-life network); and (2) a more complicated real-life network obtained by the water industry (located in northwest England), hereafter called P-Town. The first network has been extensively used in the literature to demonstrate different optimization methods, e.g., in Mahmoud et al. (2018). In the context of the first case study, a sensitivity analysis is conducted in order to investigate the sensitivity of the new method to the start time of intervention implementation. For the first case study, a comparison is also conducted between the NSGA II solutions obtained in Mahmoud et al. (2018) (i.e., for the same network and event) and the new method's solutions. The second network (also found in Nikoloudi et al. 2020) is used here in order to validate the new method on a more complicated real-life network and demonstrate its benefit (i.e., near-optimal solutions in near real time) under a real-life scenario (i.e., network and event). The real-life event used in the second case is the same as the one used in Nikoloudi et al. (2020). As mentioned at the beginning of the paper, in both case studies, the NSGA II is also conducted in the context of this work in order to compare the optimal solutions (generated by the NSGA II) with the near-optimal ones (generated by the heuristic).

C-Town

The assumed failure event considered here is a burst on pipe P307 localized at 1 a.m. and isolated at 2 a.m. (i.e., 1 h after localization). Fig. 2 shows the C-Town network layout as well as the network elements. It is highlighted that the isolation start time considered here is the same as the one used in Mahmoud et al. (2018) to allow for the comparison between the aforementioned study and the present one. The initial system condition here (that needs to be restored/recovered via optimized recovery interventions) is the system with the leaking pipe (at 1 a.m.) and isolated main (at 2 a.m.) (i.e., the same as in Mahmoud et al. 2018). Selecting a later isolation start time could reduce the end-impact even more, as proposed in Nikoloudi et al. (2020). However, selecting the isolation scenario is part of a more effective overall response methodology and is not the focus of the present study.

The impact horizon starts from the localization time (i.e., 1 a.m.) and lasts until the end of isolation duration 25 h later (i.e., at 2 a.m. of the next day), similar to Mahmoud et al. (2018). Other assumptions made here that are the same as the ones used in the aforementioned work (to facilitate the comparison) are the following: (1) location of hydrant points (shown in Fig. 2); (2) location of isolation valves (shown in Fig. 2); (3) diameter, Hazen–Williams roughness coefficient and the maximum length of overland bypasses (linking pairs of hydrants) equal to 200 mm, 100 m, and 300 m, respectively; (4) $P_{req} = 15$ m (pressure under which low-pressure impact is introduced and hence undelivered volume of water); (5) same intervention types, i.e., PRVs setting adjustment and overland bypasses. (Rezoning valves and water injection are not considered here as intervention types because there are no real-life data about them for the C-Town network and they are not used in Mahmoud et al. 2018); (6) PRV settings allowed to change are: no increase, 5% increase, 10% increase, 15% increase, 20% increase, or 25% increase, all relative to the original PRV setting; and (7) assumption of recovery initialization (i.e., start time of all interventions) at 9 a.m. (i.e., 8 h after event localization). It is stressed that the same assumption/limitation is used in the heuristic to facilitate the comparison between the two studies. However, this is not the case with the NSGA II conducted for the same case study

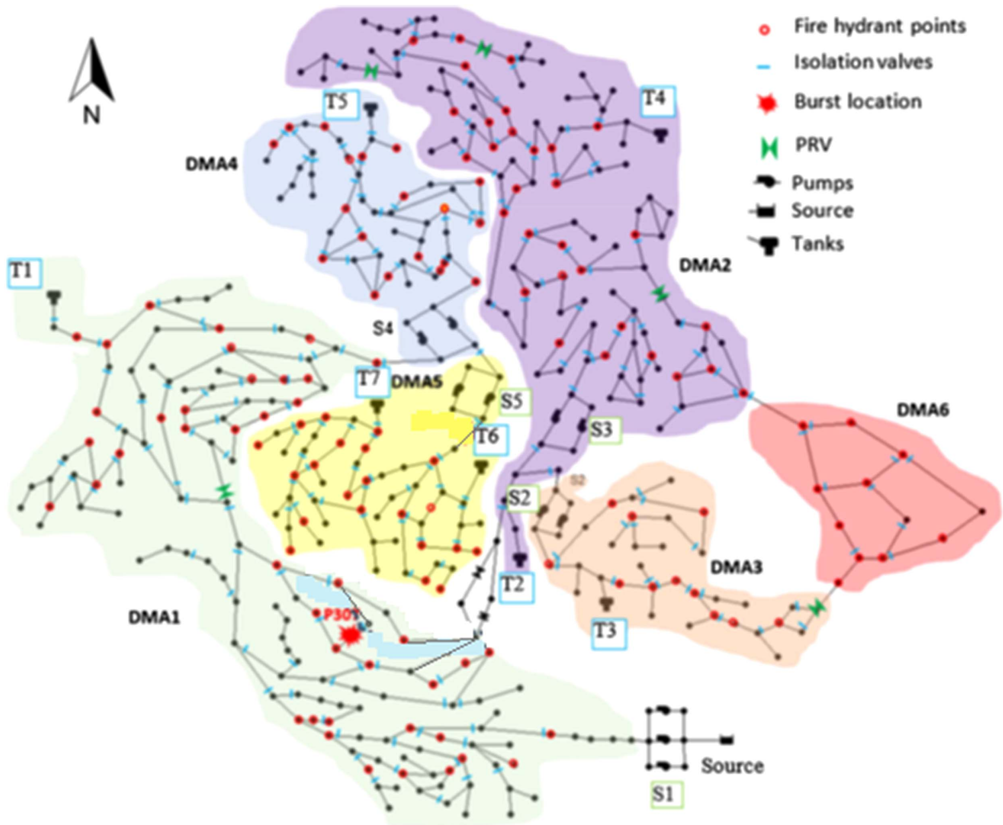

Fig. 2. C-Town network layout with the simulated event (burst) on pipe P307. (Reprinted from Mahmoud et al. 2018, © ASCE.)

where each intervention is allowed to start at a different time on the horizon.

One significant discrepancy between the previous work and the present one is the impact assessment. Mahmoud et al. (2018) assess end-impact in a more conventional way, i.e., by considering only the volume of water undelivered to the customers. Here, end-impact is calculated by taking into account different impact aspects (see impact assessment method in Nikoloudi et al. 2020), including supply interruption (CML index), low pressure (AMLP index), undelivered water (UW index), and discoloration risk increase (DRI index). The same weight factors for all impact indicators have been used [see Eq. (S1)]. Additionally, the second optimization objective differs between the two studies. Mahmoud et al. (2018) optimize the number of interventions (i.e., again in a more conventional way), whereas here the cost of the recovery interventions is used. It is stressed that a smaller number of interventions does not always imply lower cost due to particular hydraulic network requirements (e.g., the use of only one ASV injection point might be quite expensive when injecting many hours to meet the required demand). Finally, the opening/closing of isolation valves is not considered here as a possible intervention type, as done in the previous work. This is because manipulation of isolation valves is not a common means to intervene in the network when a failure occurs. Notwithstanding the presented discrepancies, it is assumed here that it is still worth comparing the results between the two studies. In that way, the difference in optimal solutions will be demonstrated when different aspects of impact and selection of interventions (number of interventions vs cost), i.e., different optimization conditions, are considered. It is worth mentioning here that in order to directly compare the results of the two studies, the identified optimal solutions by Mahmoud et al. (2018) were regenerated in the present paper, i.e., under the optimal conditions of our study. Due to the aforementioned differences between the optimization conditions of the two studies, some of the optimal solutions by Mahmoud et al. (2018) turned into dominated solutions in our work.

Here, the new optimization method (described in the previous section) is implemented step by step for the C-Town network and event. In the offline step 0, all the intervention types (i.e., overland bypasses and PRVs) and possible locations are identified for the C-Town network. The initial list of interventions includes 352 OLBs and 5 PRVs. In the online step 1a, the initial list is narrowed down by identifying: (1) the OLBs that link affected with unaffected DMAs, (2) the OLBs located in the affected DMAs, and (3) the PRVs upstream affected nodes. In that way, 247 OLBs are nominated to the online step 1b, and out of which: 35 OLBs link (affected) DMA1 with (unaffected) DMA5, 20 bypasses link (affected) DMA2 with (unaffected) DMA4, and 192 OLBs are located in the affected DMA1 and DMA2. No PRV was identified to be upstream affected nodes, i.e., no PRV is nominated for the next step. Fig. 3 shows the affected nodes/DMAs for the 'No intervention' case, the PRVs, and some OLBs (i.e., the ones used in the intervention plans proposed by the optimization as shown later, for clarity reasons).

In the online step 1b (i.e., individual evaluation step), the 247 bypasses are assessed individually (for their total aggregated end-impact and cost) for a fixed start time in the impact horizon. Here, it is assumed that operators decide the interventions start at 9 a.m. (i.e., 8 h after localization), i.e., similar to Mahmoud et al. (2018). This start time is a realistic decision, as it assumes that interventions start when there is peak in demand, as well as it allows plenty of time for the technicians to reach the site and start implementation. In the online step 1c, a number of interventions with the lowest

J. Water Resour. Plann. Manage., 2022, 148(8): 04022039

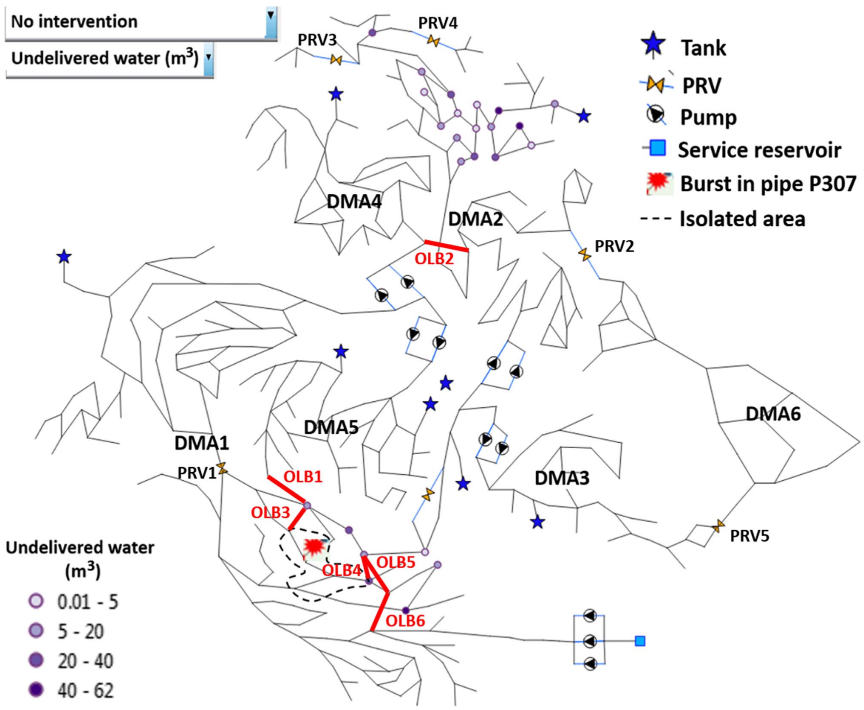

Fig. 3. Location of affected nodes for the 'No intervention' case (i.e., with burst on pipe P307 and isolation in place), isolated area, PRVs, and overland bypasses OLB1, OLB2, OLB3, OLB4, OLB5, and OLB6 in the C-Town network.

end-impact (identified in step 1b) are selected and nominated for the optimization step (i.e., step 2). Here, 10 interventions are selected because this number is considered adequate to provide a sufficient response plan for a small network such as that of C-Town, as well as the total time required for evaluation can be conducted in near real time. This is because a single impact evaluation takes approximately 3 s to take place for the simple network of C-Town. Hence, step 1b, which includes 247 single impact evaluations (see above), lasts for 247 (interventions) × 3 s (time of a single impact evaluation) = 741 s. Considering that steps 1a and 1c take approximately 1 min each (because they do not require hydraulic simulation), then the overall preparation in step 1 takes approximately 14 min.

The end-impact (in %) and cost (in £) of the 10 candidate interventions (i.e., overland bypasses in 10 different locations) for a start time of 9 a.m. are shown in Table 1. It is stressed that in the cost function in Eq. (2), only the cost of the overland bypasses has been used (assuming $c_{OLB} = 30£/h$, obtained by the utility) because this is the only intervention type nominated for the next step of optimization. In Table 1, it is observed that all interventions obtain the same cost because they are of the same type and applied for the same duration.

In step 2a of the heuristic, the initial solution is identified by the algorithm as the single intervention with the lowest cost. In Table 1, it can be observed that the cost of all interventions is equal to £540 because they all start at the same time. The single solution OLB3 that obtains the lowest end-impact (i.e., equal to 6.63%) is selected as the initial solution (i.e., Solution 1).

Then, in step 2b of the heuristic algorithm, the subsequent solution is identified as the single solution with the lowest end-impact among all interventions. In this example, the solution with the lowest end-impact has already been used. In this case, the lowest end-impact of the rest of the solutions is identified. In Table 1, it is shown that the next lowest end-impact is equal to 7.44% obtained by OLB1 (Solution 2). This solution does not reduce the end-impact (i.e., at least one of the two objectives), and it is rejected. In the subsequent solution (i.e., Solution 3), the single intervention with the next lowest end-impact is added to Solution 1 (i.e., the last accepted solution). As noticed in Table 1, OLB2 obtains the next lowest end-impact (equal to 7.45%) and is added to Solution 1. Hence, Solution 3 is the combination of OLB3 and OLB2. Table 2 shows the end-impact and cost of all the solutions (i.e., intervention combinations) identified by the heuristic. It is observed that Solution 3 with an end-impact equal to 6.77% and a cost of £1,080 does not further reduce end-impact or cost compared to Solution 1, and it is rejected. Because Solution 3 is rejected, in subsequent Solution 4, OLB2 is not considered and the single intervention with the next lowest end-impact is added. In Table 2, it is observed that OLB6 obtains the next lowest end-impact, and is combined with

Table 1. End-impact (%) and cost (£) of single interventions for the C-Town event

Intervention type	End-impact (%) Start time 2 a.m.	End-impact (%) Start time 9 a.m.	Cost (£) Start time 2 a.m.	Cost (£) Start time 9 a.m.
No intervention	8.63	—	0	—
OLB1	—	7.44	—	540
OLB2	—	7.45	—	540
OLB3	—	6.63	—	540
OLB4	—	8.56	—	540
OLB5	—	8.38	—	540
OLB6	—	8.09	—	540
OLB7	—	8.14	—	540
OLB8	—	8.62	—	540
OLB9	—	8.62	—	540
OLB10	—	8.62	—	540

J. Water Resour. Plann. Manage., 2022, 148(8): 04022039

Table 2. Solutions identified by the heuristic algorithm for the C-Town event compared to the 'No intervention' case and optimal solutions proposed by Mahmoud et al. (2018)

Solutions	Evaluations	End-impact (%)	Cost (£)	Outcome
No intervention	—	8.63	0	—
Solution 1	(OLB3, t = 9 a.m.)	6.63	540	Accept
Solution 2	(OLB1, t = 9 a.m.)	7.44	540	Reject
Solution 3	(OLB3/OLB2, t = 9 a.m.)	6.77	1,080	Reject
Solution 4	(OLB3/OLB6, t = 9 a.m.)	6.08	1,080	Accept
Solution 5	(OLB3/OLB6/OLB7, t = 9 a.m.)	6.08	1,620	Reject
Solution 6	(OLB3/OLB6/OLB5, t = 9 a.m.)	6.07	1,620	Accept
Solution 7	(OLB3/OLB6/OLB5/OLB4, t = 9 a.m.)	5.98	2,160	Accept
Solution 8	(OLB3/OLB6/OLB5/OLB4/OLB8, t = 9 a.m.)	5.98	2,700	Reject
Solution 9	(OLB3/OLB6/OLB5/OLB4/OLB9, t = 9 a.m.)	5.98	2,700	Reject
Solution 10	(OLB3/OLB6/OLB5/OLB4/OLB10, t = 9 a.m.)	5.98	2,700	Reject
Solution A[a]	(OLB3, t = 9 a.m.)	6.63	540	—
Solution B[a]	(OLB3/OLB1, t = 9 a.m.)	6.84	1,080	—

[a]Mahmoud et al. (2018).

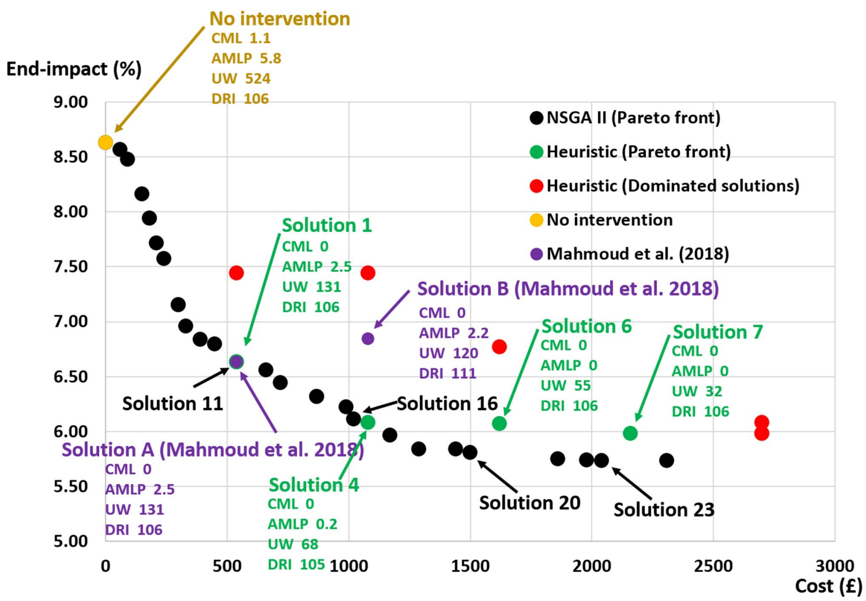

Fig. 4. End-impact versus the cost of the solutions for the C-Town event identified by NSGA II (Pareto front), the Heuristic (Pareto front and dominated solutions), and the NSGA II by Mahmoud et al. (2018)–CML in mins/cust, AMPL in mins/cust, UW in m^3 and DRI in no. of pipes.

OLB3 in Solution 4. Now, Solution 4 does further reduce end-impact compared to Solution 1, and it is accepted, as shown in Table 2. The same process is followed until all the single interventions have been added (i.e., after 10 evaluations, as shown in Table 2).

The 10 solutions proposed by the heuristic algorithm (shown in Table 2) are finally checked for optimality in step 2j online. This implies that each proposed solution should not be better than another solution (i.e., Pareto front). It is noticed that the accepted solutions in Table 2 are already the optimal ones and are the final solutions included in the Pareto front. Finally, step 2 includes 10 more impact evaluations, i.e., it lasts for 10 (evaluations) × 3 s (time of a single impact evaluation) = 30 s. This means that the total duration of the application of the optimization method for the C-Town network is approximately 15 min (i.e., 14 min from step 1 and 30 s from step 2).

After the implementation of the new optimization method proposed here, the NSGA II is conducted for the same event. The considered interventions, the impact horizon, and optimization objectives are the same as used in the heuristic. More specifically, the decision variables of the heuristic are the 10 OLBs identified in step 1 of the new optimization method. However, NSGA II here considers the start time of each intervention a variable too (i.e., in the range of 1 and 24 h after localization). This is done in order to indicate the error introduced by the limitation of the heuristic (i.e., where a fixed start time is assumed). Additionally, the optimal solutions (i.e., combinations of overland bypasses) identified by Mahmoud et al. (2018) are assessed here (i.e., in the environment of IRPT) for their total end-impact (i.e., considering all aforementioned impact aspects) and for their cost. It is reminded here that Mahmoud et al. (2018) identified these optimal solutions by assessing the impact of undelivered water (only) and the number of interventions (i.e., not cost). Fig. 4 compares the results obtained by the NSGA II (Pareto front) of the present optimization problem, the heuristic Pareto front of near-optimal solutions, the heuristic dominated (i.e., rejected) solutions, the 'No intervention' case, and the solutions obtained by Mahmoud et al. (2018).

Based on the results shown in Table 2 and Fig. 4, the following observations are made:

- The Pareto front identified by the heuristic sufficiently approximates the NSGA II Pareto front, as the maximum discrepancy (i.e., error) of end-impact between an NSGA II and a heuristic solution with similar costs (e.g., Solution 6 of heuristic compared to Solution 20 of NSGA II and Solution 7 of heuristic compared to Solution 23 of NSGA II) is equal to 4%.
- The Pareto optimal front identified by the heuristic is less dense than the Pareto front proposed by the NSGA II. This is because only four near-optimal solutions are proposed by the heuristic compared to the 24 solutions proposed by the NSGA II. However, this is not deemed a significant drawback of the new optimization method because all the proposed solutions are near-optimal. Additionally, it is believed here that in near real time in a control room, there is limited time available to check a large number of optimal solutions.
- In Table 2 and Fig. 4, it is observed that all the overland bypasses identified in the accepted solutions (i.e., OLB3, OLB4, OLB5, and OLB6) are located in the affected DMA1, close to the affected nodes and isolated area (i.e., burst event). With this observation, it is confirmed the obvious point that bypassing affected nodes with unaffected nodes in the affected DMA and close to the isolated area can significantly reduce end-impact.
- The NSGA II Solution B conducted by Mahmoud et al. (2018) managed to reduce the undelivered water (i.e., their sole impact indicator) to 120 m^3. However, the new heuristic method identified a solution (i.e., Solution 7) where the undelivered water was reduced to 32 m^3. This is due to the fact that the heuristic optimized not only the undelivered volume of water but also additional impact aspects (e.g., CML, AMLP) whose reduction facilitates the reduction of undelivered water.
- In Mahmoud et al. (2018), Solution A and Solution B are the nondominated solutions in their proposed NSGA II Pareto front. In their study, Solution B obtains lower end-impact (i.e., undelivered water volume, first objective) and a larger number of interventions (i.e., second objective) than Solution A. However, in Fig. 4, it is shown that when end-impact with more than one impact aspect is considered (i.e., 1st objective function) and when cost instead of the number of interventions is used (i.e., 2nd objective function), the Pareto front can change. Here, Solution B is dominated by Solution A. This is because while UW was reduced to 120 m^3 in Solution B (compared to 131 m^3 in Solution A) and AMLP was reduced to 2.2 mins/cust in Solution B (compared to 2.5 mins/cust in Solution A), the number of DRI interventions was increased (from 106 in Solution A to 111 in Solution B). This ultimately led to the increase of the total aggregated end-impact of Solution B (instead of decreasing it as anticipated in a Pareto front).

In the context of the present case study, a sensitivity analysis is also conducted in order to test different start times of interventions. This sensitivity analysis aims to investigate the sensitivity of the new optimization method to the interventions' start time. As was mentioned earlier, the new optimization method proposes a (selected by the operator) fixed start time (here assumed as 9 a.m.) due to time limitations to test different start times in near real time. In the context of this analysis, five more start times close to the selected one here (i.e., 9 a.m.) are tested, i.e., at 6 a.m., 7 a.m., 8 a.m., 10 a.m., and 11 a.m. The mentioned additional start times are considered here to be adequate to conduct the sensitivity analysis. This is due to the fact that they are all morning hours (i.e., with similar demands) close to the initially selected one (i.e., some start times earlier than 9 a.m. and some start times later than 9 a.m.). Considering much later hours (i.e., after 12 p.m.) might produce results substantially deviated from the original start time due to different demand levels. The results are shown in Fig. 5 and are compared with the NSGA II results.

From Fig. 5, it is observed that:

- The Pareto front obtained using the heuristics algorithm approximates the NSGA II front reasonably well, especially for the most important part with lower-cost solutions. Indeed, for lower costs (i.e., lower than £1,500) and for all the start times the heuristic approach identifies solutions that are almost identical to the NSGA II. For higher costs (i.e., higher than £1,500), heuristic solutions are dominated by the NSGA II solutions but not by much, i.e., the distance between the two Pareto fronts is

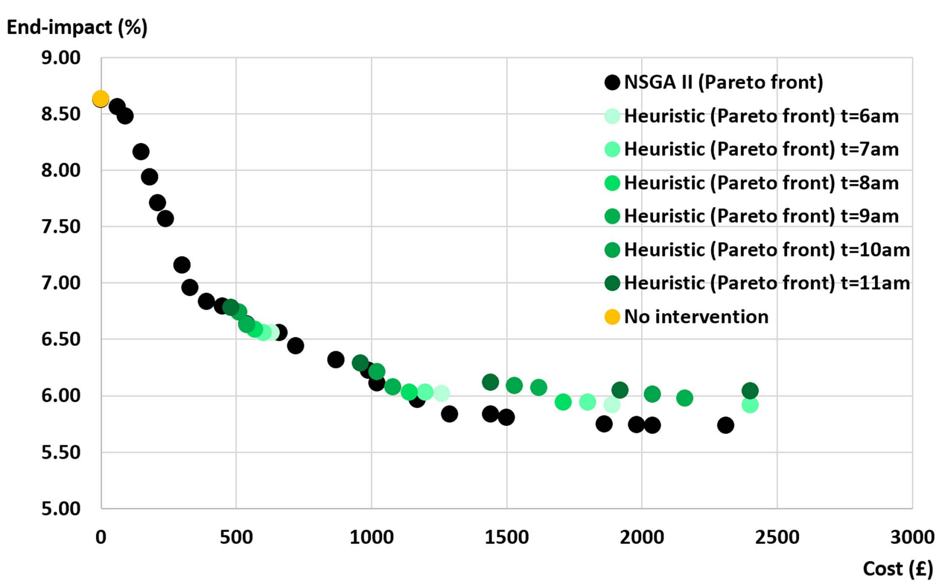

Fig. 5. Solutions of different start times identified by the heuristic for the C-Town event.

J. Water Resour. Plann. Manage., 2022, 148(8): 04022039

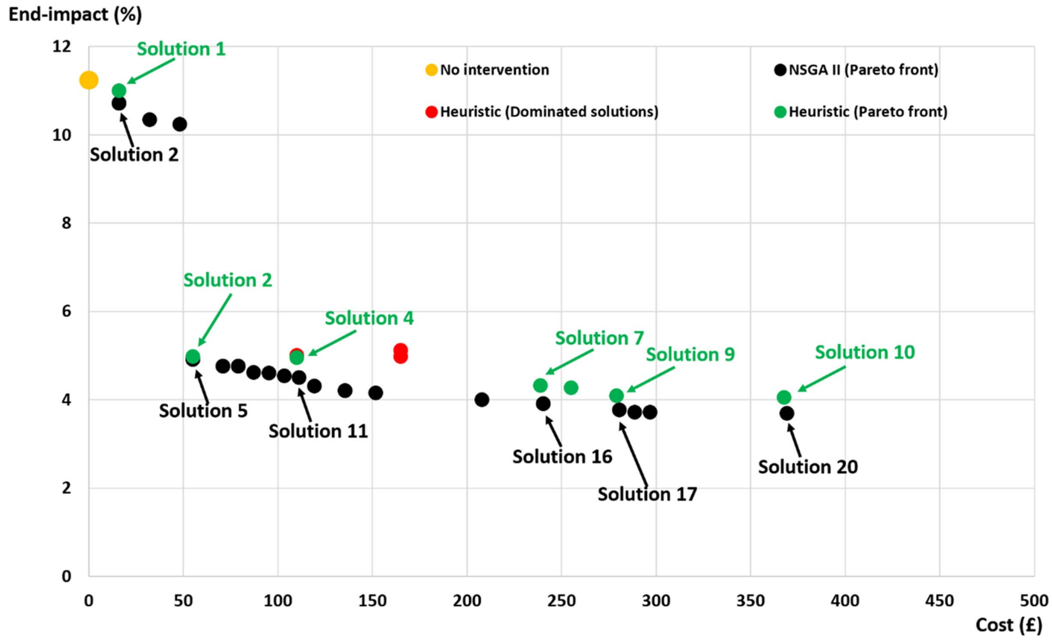

Fig. 6. End-impact versus the cost of the solutions for the P-Town event identified by NSGA II (Pareto front) and the heuristic (Pareto front and dominated solutions).

rather small with heuristic solutions with the earliest start times (i.e., 6 a.m. and 7 a.m.) being closer to the NSGA II solutions.

- The following overland bypasses exist in all heuristic solutions, regardless of the start time used: OLB3, OLB4, and OLB6. This is good news as these overland bypasses are the most important ones, as confirmed by the NSGA II solutions.

P-Town

Here, the steps of the new optimization method are followed for the P-Town network and event and are also compared with the NSGA II results (conducted in the context of this case study, similar to the C-Town case study). The P-Town network serves approximately 100,000 customers via water treatment work (WTW). The customers are separated into 24 DMAs, and among them, there are 16 schools, 11 industrial users, and 1 hospital. The P-Town real-life event is a shutdown at the WTW of the network, localized at 2 p.m. on 2nd November 2019. The shutdown lasted for 24 h (i.e., until 2 p.m. the next day). The impact horizon considered here lasts from the localization time (i.e., 2 p.m. the first day) until the end of shutdown/isolation (i.e., 2 p.m. the next day), i.e., 24 h horizon. More details about the event description and timeline can be found in Nikoloudi et al. (2020). The heuristic-based optimization method is applied here too step by step (as described in the previous section), but the details of this implementation are shown only in the Supplemetal Materials due to the space limitation of this paper.

Fig. 6 compares the results obtained by the NSGA II (Pareto front) of the present optimization problem, Heuristic Pareto front of near-optimal solutions, heuristic dominated (i.e., rejected) solutions, and 'No intervention' case. In Fig. 6, it is observed:

- The Pareto front identified by the heuristic approximates the NSGA II Pareto front well, as the maximum discrepancy (i.e., error) of end-impact between an NSGA II and a heuristic solution with similar costs (e.g., Solution 7 of heuristic compared to Solution 16 of NSGA II) is equal to 9%. It is noticed that the error in the P-Town case study is higher than the error in the C-Town (i.e., 4%). However, it is deemed low considering the significant limitation of the fixed start time for the present complex real-life network.
- The new method also identified the 'jump' from a solution with high end-impact (i.e., Solution 1) to a solution with much lower end-impact (i.e., Solution 2) with the minimum cost increase. Solutions like these (i.e., Solution 2) are likely to be selected by decision makers. It is also observed that Solution 2 seems identical to the solution proposed by NSGA II.
- Similar to the C-Town case study, the Pareto optimal front identified by the heuristic is less dense than the Pareto front proposed by the NSGA II. Here only seven (nondominated) near-optimal solutions are proposed by the heuristic compared to the 20 solutions proposed by the NSGA II. However, as mentioned earlier, this is not deemed a significant drawback of the new optimization method because the front coverage is good, and in near real time, in a control room, there is limited time available to check a large number of optimal solutions.
- NSGA II was conducted here and took approximately 2 days to be completed, while the new optimization process (i.e., online selection of population and heuristic) took approximately 1 h. It is noticed that the time the proposed heuristic optimization was completed here is much lower than the NSGA II.

Conclusions

The paper presents a novel optimization methodology to identify near-optimal response solutions to water network failures in near real time. The optimization problem is multiobjective, and the decision variables are the interventions in the network to restore supply as long as the repair is being conducted. Unlike other conventional optimization problems, the present problem minimizes the total aggregated end-impact to the customers (i.e., considering different impact aspects) and the cost of a response solution (i.e., instead of the conventional number of interventions). The new optimization method includes three main steps, one offline and two

J. Water Resour. Plann. Manage., 2022, 148(8): 04022039

online. In the offline step, the initial list of available interventions is identified. In the first online step, the narrowed-down set of interventions considered in the optimization is found. In the second online step, a novel heuristic algorithm is applied in order to identify near-optimal solutions in near real time. The new optimization method was validated in two semireal case studies.

Based on the case study results obtained, the following results are concluded:

1. The new, heuristics-based method is able to identify near-optimal response solutions in an effective (i.e., accurate) and efficient (i.e., computationally fast) manner. The effectiveness is confirmed by running the full, NSGA II-based optimization runs and comparing the resulting Pareto fronts that match well. The computational efficiency achieved enables its application in near real time for larger, more complex WDS.
2. The Pareto optimal front identified by the heuristics method has good coverage, but it is less dense than the corresponding front obtained by the NSGA II. This, however, is not deemed as a significant drawback because all solutions proposed by the heuristics method are near-optimal and the set of solutions identified represents well the trade-off between the impact reduction and associated costs of responses. Therefore, the solutions identified provide a good starting point for consideration by control room operators who have a final say anyway.
3. When compared to the solutions obtained by Mahmoud et al. (2018), the heuristics method managed to improve the quality of some solutions (e.g., reduced the volume of undelivered water) despite the fact that its impact reduction is driven by other criteria as well.
4. The potential limitation of the method is its inability to optimize for the start time of interventions that therefore needs to be set by the control room operator. Having said this, as demonstrated in both case studies, the solutions generated by the heuristics method are robust enough, i.e., rather insensitive to this start time.

Future work on further improvement of the proposed method includes: (1) consideration of the start time of interventions as a decision variable (i.e., each intervention should be able to start at a different time on the horizon); (2) consideration of more impact aspects in the calculation of the first objective (e.g., environmental aspect and 3rd party damage); (3) development of a more advanced (i.e., more automatic) process for selection of the initial population (i.e., step 1 of the new method); (4) application of the methodology in cases of multiple pipeline failures occurring at the same time; and (5) reduction of computational time required to identify the near-optimal response solution, ideally to less than 1 h even in the case of complex water networks. Mathematical optimization methods should be considered for this, in addition to heuristic-based methods.

Data Availability Statement

All data, models, and code that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

This work was funded as part of the Water Informatics Science and Engineering Centre for Doctoral Training (WISE CDT) under a grant from the Engineering and Physical Sciences Research Council (EPSRC) (Grant No. EP/L016214/1), as well as from United Utilities. The present work has made use of resources, data, and information provided by United Utilities.

Supplemental Materials

Eqs. (S1)–(S15), Figs. S1–S3, and Tables S1–S3 are available online in the ASCE Library (www.ascelibrary.org).

References

Alperovits, E., and U. Shamir. 1977. "Design of optimal water distribution systems." *Water Resour. Res.* 13 (6): 885–900. https://doi.org/10.1029/WR013i006p00885.

Avila-Melgar, E. Y., M. A. Cruz-Chávez, and B. Martinez-Bahena. 2017. "General methodology for using Epanet as an optimization element in evolutionary algorithms in a grid computing environment for water distribution network design." *Water Sci. Technol.* 17 (1): 39–51. https://doi.org/10.2166/ws.2016.101.

Balut, A., R. Brodziak, J. Bylka, and P. Zakrzewski. 2018. "Battle of postdisaster response and restauration (BPDRR)." In *Proc., 1st Int. WDSA/CCWI 2018 Joint Conf., 14*. Kingston, ON: Queen's Univ.

Higham, D. J., and N. J. Higham. 2016. *MATLAB guide*. Philadelphia: Society of Industrial and Applied Mathematics (SIAM).

Kang, D. S., and K. Lansey. 2012. "Revisiting optimal water-distribution system design: Issues and a heuristic hierarchical approach." *J. Water Resour. Plann. Manage.* 138 (3): 208–217. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000165.

Kim, J. H., and L. W. Mays. 1994. "Optimal rehabilitation model for water-distribution systems." *J. Water Resour. Plann. Manage.* 120 (5): 674–692. https://doi.org/10.1061/(ASCE)0733-9496(1994)120:5(674).

Mahmoud, H. A., Z. Kapelan, and D. Savić. 2018. "Real-time operational response methodology for reducing failure impacts in water distribution systems." *J. Water Resour. Plan. Manage.* 144 (7): 04018029. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000956.

Mala-Jetmarova, H., N. Sultanova, and D. Savic. 2018. "Lost in optimisation of water distribution systems? A literature review of system design." *Water* 10 (3): 307. https://doi.org/10.3390/w10030307.

Nikoloudi, E., M. Romano, F. A. Memon, and Z. Kapelan. 2020. "Interactive decision support methodology for near real-time response to failure events in a water distribution network." *J. Hydroinf.* 22 (6): 483–499. https://doi.org/10.2166/hydro.2020.101.

Paez, D., et al. 2020. "The battle of post-disaster response and restoration." *J. Water Resour. Plann. Manage.* 146 (8): 04020067. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001239.

Paez, D., C. R. Suribabu, and Y. Filion. 2018. "Method for extended period simulation of water distribution networks with pressure driven demands." *Water Resour. Manage.* 32 (8): 2837–2846. https://doi.org/10.1007/s11269-018-1961-1.

Pecci, F., E. Abraham, and I. Stoianov. 2019. "Model reduction and outer approximation for optimizing the placement of control valves in complex water networks." *J. Water Resour. Plann. Manage.* 145 (5): 04019014. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001055.

Pecci, F., I. Stoianov, and A. Ostfeld. 2021. "Relax-tighten-round algorithm for optimal placement and control of valves and chlorine boosters in water networks." *Eur. J. Oper. Res.* 295 (2): 690–698. https://doi.org/10.1016/j.ejor.2021.03.004.

Rossman, L. A. 2000. "EPANET 2: Users manual." Accessed May 11, 2022. https://epanet.es/wp-content/uploads/2012/10/EPANET_User_Guide.pdf.

Su, Y. C., L. W. Mays, N. Duan, and K. E. Lansey. 1987. "Reliability-based optimization model for water distribution systems." *J. Hydraul. Eng.* 113 (12): 1539–1556. https://doi.org/10.1061/(ASCE)0733-9429(1987)113:12(1539).

Ulusoy, A. J., F. Pecci, and I. Stoianov. 2021. "Bi-objective design-for-control of water distribution networks with global bounds." *Optim. Eng.* 23 (1): 527–577. https://doi.org/10.1007/s11081-021-09598-z.

Vamvakeridou-Lyroudia, L. S., J. Bicik, M. Morley, D. Savic, and Z. Kapelan. 2010. "A real-time intervention management model for reducing impacts due to pipe isolation in water distribution systems." In *Proc., 12th Annual Water Distribution Systems Analysis Conf. WDSA2010*, edited by K. E. Lansey, C. Y. Choi, A. Ostfeld, and I. L. Pepper, 209–221. Reston, VA: ASCE.

J. Water Resour. Plann. Manage., 2022, 148(8): 04022039

Zhang, Q., F. Zheng, Q. Chen, Z. Kapelan, K. Diao, K. Zhang, and Y. Huang. 2020. "Improving the resilience of postdisaster water distribution systems using dynamic optimization framework." *J. Water Resour. Plann. Manage.* 146 (2): 04019075. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001164.

Zheng, F., A. C. Zecchin, H. R. Maier, and A. R. Simpson. 2016. "Comparison of the searching behavior of NSGA-II, SAMODE, and Borg MOEAS applied to water distribution system design problems." *J. Water Resour. Plann. Manage.* 142 (7): 04016017. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000650.