KSCE Journal of Civil Engineering (2017) 21(6):2085-2096

DOI 10.1007/s12205-017-0447-7

Environmental Engineering

pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

Multi-objective Optimization Response Modeling to Contaminated Water Distribution Networks: Pressure Driven versus Demand Driven Analysis

Seyyed Nasser Bashi-Azghadi*, Mohammad Hadi Afshar**, and Abbas Afshar***

Received June 9, 2015/Revised August 25, 2016/Accepted September 25, 2016/Published Online January 13, 2017

Abstract

Implementation of management strategies following contamination detection in water distribution networks may extensively change operational mode of nominated valves and hydrants. The commonly used demand driven network solvers may fail to realistically represent system's performances of new topology due to possible pressure-deficient condition. Realizing their drawbacks, this paper integrates a Pressure Driven Network Solver (PDNS) with multi-objective Non-dominated Sorting Genetic Algorithm-II (NSGA-II) in a simulation-optimization scheme. It is illustrated that the two commonly used objective functions, namely minimization of consumed contamination mass and number of polluted nodes, may be in conflict when an operational strategy is implemented. A trade-off is developed to help decision-maker compromise between restraining spatial spread of contaminant and its risk to public health. Decision variables in this optimization model are valve closure and hydrant opening. Each trial solution developed by the NSGA-II addresses a new system topology by changing operational modes of the nominated valves and hydrants. The PDNS determines the nodal pressures and refines the nodal withdraw for trial solution. To illustrate the performance of the proposed methodology, Net3 from EPANET 2 is employed. The results show that the pressure-driven analysis is more realistic and appropriate in comparison with demand-driven analysis in operational conditions.

Keywords: *consequence management, water distribution networks, pressure-driven analysis, demand-driven analysis, pollution and remediation*

1. Introduction

Since the events of September 11, 2001 in the United States, great efforts globally have been made to improve the people awareness and security against different threats to public health and safety. Water Distribution Network (WDN) is one of the most important utilities which are highly vulnerable to accidental or deliberate contamination intrusion. In 2014, the US Environmental Protection Agency (EPA) presented a three-phase water security initiative emphasizing on (1) design of water quality surveillance and response system, (2) performance evaluation of the surveillance and response system, and (3) release of water quality surveillance and response system deployment. Important issues such as risk communication plans, operational strategy and consequence management plans have been addressed in a series of reports (USEPA, 2008; 2013a; 2013b). Specifically, the action that may be taken to minimize public health and economic consequences and the strategy to restore the system to normal operation condition is discussed (USEPA, 2008).

Minimizing the potential impact of any contamination threat to a WDN can be classified into three main steps, which is presented as follows: (1) sensor placement for efficient detection of contamination in both spatial and temporal terms (Zhao *et al*., 2014; Rathi and Gupta, 2015; Yoo *et al*., 2015), (2) pollution source identification (Liu *et al*., 2012) and (3) consequence management. This paper explores consequence management strategy for minimizing the harmful impacts and restoring the system to normal operation condition in a timely manner, once the source is identified.

Consequence management defines as measures to protect public health and safety, restore essential government services, and provide emergency relief to governments, businesses, and individuals following the contamination events (USEPA, 2004a). This step is a very vital part of response protocol and an appropriate implementation of remediation and recovery process can clearly reduce the affected people. Consequence management may consist of any combination of system isolation, public notification, flushing and finally providing short-term and long-term alternative

*Ph.D. Candidate, School of Civil Engineering, Iran University of Science and Technology, P.O. Box: 16765-163, Narmak, Tehran, Iran (Corresponding Author, E-mail: bashi@iust.ac.ir)
**Associate Professor, School of Civil Engineering, Iran University of Science and Technology, P.O. Box: 16765-163, Narmak, Tehran, Iran (E-mail: mhafshar@iust.ac.ir)
***Professor, School of Civil Engineering, Iran University of Science and Technology, P.O. Box: 16765-163, Narmak, Tehran, Iran (E-mail: a_afshar@iust.ac.ir)

domestic water supply (USEPA, 2004a; 2004b). Various methods to develop a consequence management plan in WDNs following the contamination detection have been proposed. Booster disinfection used for protecting a population against contamination and maintaining more stable chlorine residuals in a WDN (Propato and Uber, 2004; Poulin *et al.,* 2008).

Most researchers embedded optimization and simulation models in order to minimize different objectives such as: (1) the total network contaminant concentration, (2) number of field operations (i.e. valves closure and hydrants opening), (3) the total consumed contamination mass and (4) the extent of contamination. Baranowski and LeBoeuf (2008) coupled a demand-driven network solver (DDNS) namely EPANET (Rossman, 2000) with a single objective Genetic Algorithm (GA) to minimize contaminant concentrations in a network based on several scenarios while minimizing the cost of demand alteration. The results showed that closing pipes and altering the node demand might greatly reduce the total network concentration. Multi-objective optimization evolutionary models for developing sets of non-dominated consequence management responses against deliberate contamination intrusions have been reported (Preis and Ostfeld, 2008; Afshar and Marino, 2014). Relaxing the assumptions on static, homogenous, and stationary response in conventional engineering approaches, Rasekh *et al.* (2013) presented a sociotechnical risk assessment simulation framework for simulating the dynamics of a contamination event. They employed a GA approach to identify critical contamination events by maximizing risk, and a multi-objective approach to explore the trade-off between consequence and probabilities of occurrence. Afshar and Najafi (2014) incorporated minimize maximum regret and minimize total regret approaches with an ant colony optimization algorithm to present a robust method for consequence management under uncertainty. Injecting food-grade dye directly into WDN, Rasekh *et al.* (2014) developed a protective response action that minimizes the risk to life considering the uncertainties in threat observations and the imperfection in system understanding.

The main drawback of the existing literature is their inability to appropriately consider pressure-deficient conditions due to dynamic changes in the system's topology as different operational activities are imposed. In a new attempt, Rasekh and Brumbelow (2014) developed quantitative simulation-optimization models for planning emergency response management considering impacts on public health and system serviceability. They employed EPANET in an iterative procedure to handle the pressure deficiency and its effect on pollutant distribution throughout the WDN.

This paper, presents a multi-objective simulation-optimization framework to derive set of non-dominated optimum consequence management strategies under pressure-deficient conditions. Emphasizing on the drawbacks of the conventional DDNS in consequence management, this paper integrates the optimization module with a full scale pressure-driven network solver to account for possible changes in network topology during implementation of the strategies. It explicitly accounts for pressure-deficient conditions without significantly increasing the run time. The efficiency and applicability of these different analyses are evaluated using the network Net3 (USEPA, 2002). In order to illustrate the significance of Pressure-driven Analysis (PDA) in deriving the optimum strategy, the results of the methodologies based on Demand-driven Analysis (DDA) and PDA are compared. The results show that the PDA modeling approach more accurately accounts for dynamic variation of system topology. Therefore, a consequence management plans achieved by PDA may evidently be more realistic and reliable in pressure-deficient cases and may readily be used for operational conditions in WDNs. This paper is presented as follows: the next section describes the methodology including objective functions, optimization model, network simulation model and demand- and pressure-driven analysis; specific results obtained with the aid of a common application example are then evaluated and analyzed; finally, the significance of the results are discussed.

2. Model Framework

In order to provide a consequence management plan following the contamination events in WDNs, an embedded framework including simulation and multi-objective optimization model is presented. In this approach, a simulation model namely EPNAET 2 is used to calculate the water quantity and quality distribution in the network. This model is free and open-source software and via its toolkit can easily be linked within different programming languages. It has successfully been used for developing consequence management strategies in WDNs (Preis and Ostfeld, 2008; Rasekh *et al*., 2013; Afshar and Marino, 2014). A modified version of the EPANET 2 is used here, which can easily handle the changes in network topology and Extended Period Simulation (EPS) for pressure-deficit distribution networks. This simulation model is incorporated with Non-dominated Sorting Genetic Algorithm-II (NSGA-II) multi-objective optimization model to develop a trade-off between selected objectives common in consequence management modeling. This framework is applied for two different hydraulic analyses namely DDA and PDA. The results are then presented and discussed to illustrate the significance of using PDA in comparison with DDA in operational conditions of WDNs such as consequence management.

2.1 Definition of the Objective Functions

This study considers three different objective functions in its modeling scheme. The first objective function, numbers of field operational actions, takes into account the technicality and expenses of the proposed solution; whereas the next two objectives, namely "consumed contamination mass" and "number of polluted nodes" account for public health and safety.

Z_1 is defined as the total number of operational response actions including valve(s) closing and hydrant(s) opening to isolate the contaminated zone and/or flush the contaminated water out of the network, respectively:

$$Z_1 = \sum_{i=1}^{V} VA_i + \sum_{j=1}^{H} HY_j \quad (1)$$

where, i is the valve index, VA_i is the ith valve, V is the total number of valves, j is the hydrant index, HY_j is the jth hydrant and H is the total number of hydrants in the system. Both VA_i and HY_j are binary variables and may accept either one or zero. If the value of VA_i is equal to one it means that the mode of operation for corresponding valve will change during the management implementation to help isolating some parts of the network, otherwise it remains open as in the normal operation mode. Likewise, if the value of HY_j is equal to one, the mode of operation of the associated hydrant in the network will be modified for flushing the contaminated water, otherwise it remains closed as of the normal operation mode. In real-life applications, however, this objective function may be replaced with appropriate cost functions to reflect the actual costs associated with the operational interventions including direct expenses (e.g., response implantation costs) and indirect costs (e.g., water outages).

The second objective function is selected to characterize a measure of damage to public health. It is assumed to measure the total cost imposed to the society by contamination event. Due to lack of real cost data on public health, it may be replaced by the total consumed contamination mass, Z_2, after starting consequence management:

$$Z_2 = \sum_{k=1}^{N} \sum_{t=t_c}^{EPS} C_{kt} \times V_{kt} \quad (2)$$

where, k is node index, N is total number of consumer nodes, t is time index and being considered after starting consequence management t_c until the entire simulation time namely EPS. C_{kt} and V_{kt} are defined as contamination concentration and consumed water volume of node k at time t, respectively.

Another objective may be used to represent temporal and spatial exposure of the network to contamination. A contaminated node in a given time step may or may not remain contaminated in the following time steps due to implementation of consequence management strategy. Therefore, total number of contaminated node times is selected to address the total number of contaminated nodes during the simulation process counted over all discrete time intervals. Mathematically Z_3 may be presented as:

$$Z_3 = \sum_{k=1}^{N} \sum_{t=t_c}^{EPS} PN_{kt} \quad (3)$$

Where, PN_{kt} has the value of 1 if C_{kt} at node k at time t has greater value than predefined threshold and 0 otherwise.

2.2 Non-dominated Sorted Genetic Algorithm-II (NSGA-II)

Most real-world engineering optimization problems have several conflicting objectives in nature that must be satisfied simultaneously. Although different versions of search-based optimization algorithms have successfully been applied to large number of water and environmental management problems (Bozorg Haddad *et al*., 2008; Rezaei *et al*., 2014), limited applications of multi-objective optimization of consequence management have been reported (Preis and Ostfeld, 2008; Rasekh and Brumbelow, 2014). In this study, NSGA-II is linked with modified version of EPANET simulation model to find a set of non-dominated solutions which optimizes the defined objectives. More details about the NSGA-II are available in Deb *et al*. (2002).

In this study, the optimal valves and hydrants for isolating and flushing the contamination out of the network should be selected among several potential valves and hydrants. Hence, the multi-objective optimization model has binary decision variables and total number of decision variables is equal to the total number of potential valves and hydrants in the network. Using the trade-off curve help decision-maker to select an appropriate number of operational response actions considering the desired level of the second and the third objective functions (Z_2, Z_3). Taking into consideration of total potential number of valves and hydrants in the network, the gene values in the corresponding chromosome in the final generation of NSGA-II present the optimal location of valves and hydrants. On the other hand, since the decision variables (genes) are binary in this study, a gene value equal to one indicates that the valve or hydrant in their corresponding potential locations should be closed or opened, respectively.

2.3 Network Simulator

Generally, there are two types of hydraulic analysis in WDNs namely DDA (Todini and Pilati, 1988) and head-driven or PDA (Bhave, 1981). In DDA approach, which is applicable for analyzing WDNs in normal condition, it is assumed that demands at all nodes are fully satisfied without considering the available hydraulic heads at those nodes. This method is not a realistic analysis for pressure-deficient conditions such as system rehabilitation or unplanned interruptions like pipe-failure, pump-failure and sudden changes in network topology (Babu and Mohan, 2012). EPANET 2, free and open-source software, same as the most available hydraulic simulators is basically a DDNS. In contrast, PDA approach tries to find a nodal relationship between head and discharge in pressure-deficient condition of WDNs. Efforts on computing the actual node demands under pressure-deficient conditions can be classified into two main groups. In the first group, researchers reform the network equations to establish a nodal pressure-discharge relationship. Implementing unmodified DDA hydraulic solvers, in particular that of EPANET 2, encourage the researches in the second group to indirectly apply DDA based solver for pressure-deficient analysis.

For instance, Pathirana (2011) used standard emitter function of EPANET 2 for modeling the nodal demands. Yoo *et al.* (2012) presented a meta-heuristic harmony search algorithm that optimizes nodal water demands under nodal pressure requirement. The major limitation of the above-cited methods in the second group is their necessity of repetitive hydraulic simulations during

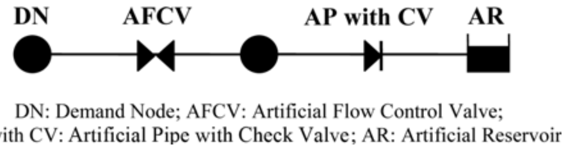

Fig. 1. The Required Links and Nodes for Each Demand Node

the successive simulations. For this reason, Babu and Mohan (2012) recently presented a new methodology that could be successfully used to find the nodal head-discharge in a single simulation run and suitable for EPS applications. In this approach, the pressure-dependent demand at any node is modeled as the flow in an artificial string connected to that node. As illustrated in Fig. 1, the artificial string consists of an Artificial Reservoir (AR), a pipe of negligible head loss with a Check Valve (CV), and an Artificial Flow Control Valve (AFCV). This methodology is comprised of the following steps:

(1) Connecting ARs to each Demand Node (DN): This is done with large diameter smooth pipes to ensure the negligible head-loss between ARs and DNs. The status of these pipes is defined as CV to let out the water only from DN to AR. Moreover, the elevation of the nth AR is set equal to the minimum hydraulic-head required at nth DN.
(2) Connecting AFCV with the pipes: The maximum flow through nth AFCV is set to demand at nth DN.
(3) Introducing each AR as a new demand-node: Setting the real nodal demand at zero causes to each AR act as a DN and the actual DN acts as dummy nodes with zero withdraws. Therefore, the nth AR will receive its required nodal demand based on the available hydraulic head. It is clear that there isn't any flow to the nth AR when its hydraulic head falls below the minimum required head.

This methodology will stop and print the results, if all nodes have hydraulic-heads greater than the related required levels. Despite of these modification proposed by Babu and Mohan (2012), this method can not consider the desired nodal pressure, H^{des}, and may have convergence difficulties in the vicinity of minimum pressure where the demand (q) changes from zero to required value (q^{req}) in a nearly stepwise manner. H^{des} is defined as desired pressure to satisfy the demand above which the nodal demand can be totally satisfied. In a new attempt and in order to resolve these problems, Gorev and Kodzhespirova (2013) assumed that the demand is satisfied in full above the value of H^{des}. They defined the desired nodal pressure in the network by the use of proper resistance for artificial pipes according to the demand time pattern. In their proposed approach, they specified the pipe resistance through minor loss coefficient for artificial pipes, which is convenient by choosing appropriate pipe length, diameter, and roughness. These modifications led to consider the transition range of DN between zero and the required demand with reasonable convergence. In present study, both PDA approaches proposed by Babu and Mohan, PDA-BM (2012) and Gorev and Kodzhespirova, PDA-GK (2013) are used to plan consequence management response in pressure-deficient conditions.

To compare the performance and drawback of the conventional DDA approach, the classical EPANET 2 is also used for deriving the management strategy.

3. Application of the Model

3.1 Model Setup

Application and performance of the proposed methodology for planning consequence management response is illustrated using EPANET Net3 (USEPA, 2002). This network is comprised of 92 junctions (59-consumer nodes), 117 pipes, two reservoirs (a lake and a river), three tanks and two pumps (Fig. 2). To apply non-iterative PDA proposed either by Babu and Mohan (2012) and/or Gorev and Kodzhespirova (2013), each DN must be connected to an AR through a pipe with CV and an AFCV, as illustrated in Fig. 1. Each AR behaves as a virtual DN the flow into which is controlled by the hydraulic head at the actual DN and the pre-set minimum required level in AR. Therefore, by setting the AFCVs, flow received by each AR will change according to the available hydraulic head and never exceed the demand at the associated node (Gorev and Kodzhespirova, 2013). In the approach proposed by Babu and Mohan (2012), flow to the AR will fall to zero, if the hydraulic head at the associated DN falls below the pre-set minimum pressure value. Gorev and Kodzhespirova (2013) considered H^{des} in their proposed methodology using the proper minor loss coefficient and illustrated that this modification satisfy full nodal demand above desired nodal pressure and provide reasonable convergence in calculating actual nodal demands. In this study, minor loss coefficient of the artificial pipes joined with zero required demands is assumed equal to 10^{10} and minimum and desired nodal pressure is set to zero and 4.3 psi, respectively. The ARs and AFCV's are accordingly setup to be applicable to both methods. In order to keep the network topology unchanged during EPS, artificial strings of reservoir, AFCV, and pipes with CV are connected to all DNs. The actual

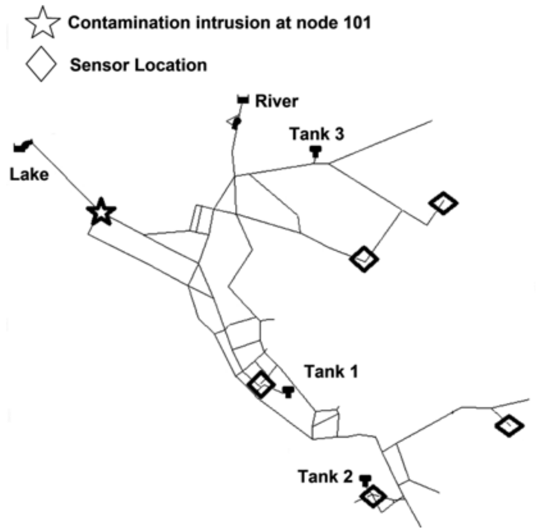

Fig. 2. EPANET Net3 Layout

water withdraw at each node will be addressed by the flow to the associated AR. This study employs both approaches to perform EPS under pressure-deficient conditions using modified EPANET 2 in an integrated scheme, which uses NSGA-II as the optimizer.

For evaluating the presented methodology to plan consequence management, it is assumed that a contaminant was deliberately injected into the network at node 101 during 08:00-12:00 with a mass rate of 0.00467 kg/s. Five sensors are assumed at nodes 15, 35, 145, 225 and 255 for early warning contamination detection. The sensor placement is based on the Ostfeld and Salomons (2004) study that maximizes the detection likelihood of a random intrusion. The sensor at node 35 detects the contamination intrusion at 10:55. This study assumes that 65 minutes is needed for source identification and stopping further contaminant injection.

Moreover, it is assumed that two hours is required for deriving optimal response actions and initiating the response actions through deploying the operational teams to handle the contamination risk. Thus, the optimal consequence management response actions including closure of valves and opening the hydrants are assumed to start at 14:00. It is assumed that the active operations are remained unchanged until the end of EPS. In other words, the network topology is assumed to remain unchanged, after we changed operation mode of the selected valves and hydrants at the start of response management operation. Therefore, distribution of pollution within the network has two phases. In phase one it will be controlled by the normal condition and existing topology. This condition will last until 14:00 where the management response action initiates. Thereafter (second phase), the distribution of pollution is controlled by the new operational strategy and network topology. The total potential locations of 20 valves and 31 hydrants are presented in Table 1. The maximum discharge rate of each hydrant is set to 0.003154 m^3/s which may not be fully satisfied in pressure-deficient condition. The hydrants are modelled as emitters.

The optimum strategy must be selected from the total of 51 decision variables (Table 1). In this study, a multi-objective optimization model (NSGA-II) is used to find optimal strategies after starting consequence management. For this reason, EPANET simulation model is embedded in the optimization model to plan the best consequence management actions. It is assumed that for each response action including valve closure or hydrant opening, one reaction team is needed. In this study, at most 15 reaction teams can simultaneously used to handle the contamination event. Tuning the GA optimization parameters were performed through different sensitivity analyses and final values are determined. The NSGA-II population size consists of 50 chromosomes and the optimization model is stopped when the stopping criteria is met. The GA may be coded to use variety of stopping conditions .The most common criteria consist of (1) generation limit, (2) fitness limit and (3) time limit. This study employs the first and second criteria to terminate the search process. The algorithm stops as soon as anyone of these conditions is met. Constraint tolerance is another criteria used to determine feasibility of the solution. In the meantime, the constraint tolerance criteria are used to guarantee the feasibility of the solutions. Sensitivity analysis revealed that considerable improvement on Pareto fronts may not be obtained by increasing the population size and generation number, however; the computational time may introduce a new challenge. Moreover, crossover and mutation probabilities are obtained 0.8 and 0.1, respectively. Altering the crossover and mutation probabilities has not provided a significant influence on performance of the optimization model.

Table 1. Potential Valves and Hydrants Location in EPANET Example 3

Potential valves location	Potential hydrants location
105, 107, 111, 116, 123, 155, 173, 175, 177, 204, 215, 221, 229, 231, 237, 269, 301, 309, 311, 317	40, 50, 60, 601, 61, 120, 129, 164, 169, 173, 179, 181, 183, 184, 187, 195, 204, 206, 208, 241, 249, 257, 259, 261, 263, 265, 267, 269, 271, 273, 275

3.2 Solution Methodology

In this study, the network solver is linked with the optimizer in an online operation mode. The solution methodology starts with generation of initial trial solutions. Each random generated trial solution consists of a binary decision variables set which defines the nominated valves and hydrants operation modes. Before implementing consequence management plan, it is assumed that all decision variables are in normal mode (valves are open and hydrants are close). To address this normal mode of operation, the value of zero is assigned for all valves and hydrants. As the solution proceeds, change in mode of operation for valves and/or hydrant will be presented by value of one for the associated gene in the chromosome structure. In other words, value of one for a gene means that the state of the associated valve or hydrant in the network is changed to close or open mode, respectively. Having generated the trial solutions, the NSGA-II algorithm is called to determine the optimal response which simultaneously minimizes the number of field activities and either the total mass of consumed pollutant (Eq. (2)) or a measure of temporal and spatial distribution of the pollutant (Eq. (3)). In this study, the number of contaminated nodes is evaluated using EPANET simulation model for all chromosome sets with 30-minute intervals after starting consequence management up to the total EPS time of 24:00 hr. In other words, in a 30-minute discrete time interval, nodes with contamination concentration exceeding the given threshold are identified and summed up for the entire simulation run. The number of identified contaminated nodes may vary from one discrete time step to another due to dynamic nature of the network and management strategy. In fact, one node may be identified as contaminated in one discrete time step and uncontaminated in the following one. Consumed contamination mass is also computed as the total multiplication of actual nodal demand and contaminant concentration of water quality whereas the number of polluted nodes is calculated as the total number of

DNs with contaminant concentration above 0.01 mg/L.

For this problem, the decision variables will refer to the change of mode of operation for the nominated valves and hydrants in the management policy. Different operators of GA such as selection, crossover and mutation parameters are used to generate new solution until the process is reached to stopping criteria. Finally, the obtained Pareto front helps decision-maker to select the appropriate number of operational response actions considering the number of polluted nodes or consumed contamination mass.

4. Results and Discussion

Besides the values of the objective functions, solutions to the models address the valves and hydrants whose modes of operation have to be modified and kept unchanged until the end of the process. In other words, the solution reported in this study is a static solution and does not account for possible changes during the consequence management implementation. Fig. 3(a) shows the optimal trade-off between the number of operational response actions and the consumed contamination mass based on DDA, PDA-BM and PDA-GK. As expected, by increasing the number of field operations following the contaminant detection, the consumed contaminant is decreased drastically. As presented, without any consequence management program, the total consumed contaminant would approach to 16.7 kg, if node 101 were attacked as outlined earlier. In this study, consumed contamination mass following consequence management plan implementation considers all possible water uses for demand nodes. With 15 operational response actions, the consumed contaminant would drop to 10.7 kg, 9.1 kg and 9.0 kg for DDA, PDA-BM and PDA-GK, respectively. All three network solvers show that the first four sets of activities have great impacts on reducing the total consumed mass of pollutant during the management implementation. The results imply that the first four sets of operational activities may reduce the total consumed contaminant by more than 35%, when either PDA-BM or PDA-GK is employed. The optimal solution of the first four sets of activities for all hydraulic solvers are comprised of only valve closure that show its better performance on reducing the consumed contamination mass in comparison with hydrant opening.

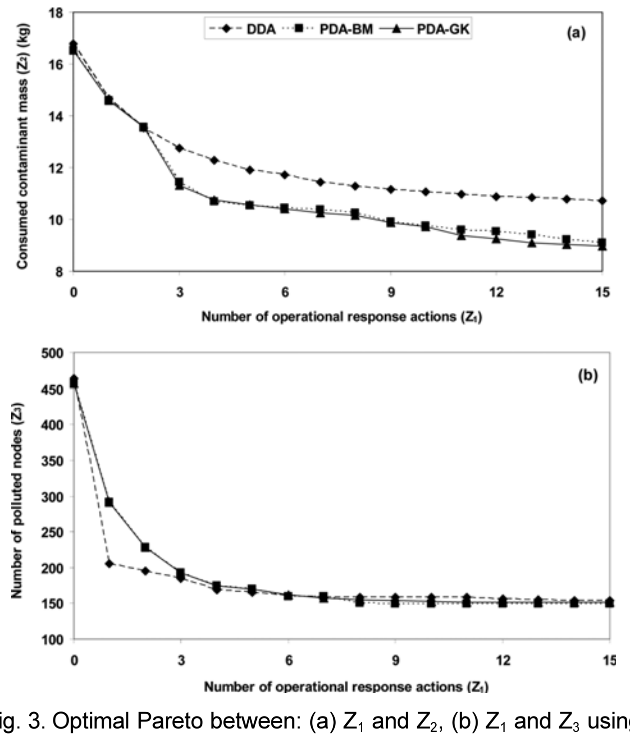

Fig. 3. Optimal Pareto between: (a) Z_1 and Z_2, (b) Z_1 and Z_3 using Different Hydraulic Methods

It is also observed that the calculated consumed mass with DDA for more than two operational activities is significantly higher than those calculated with either PDA approaches. Operating the network with DDA solver for all operational activities sets except one and two resulted in pressure-deficient condition. Under these circumstances, compared to DDA, the PDA modeling approach more realistically represented the changes in topology of the network and resulted pressure distribution. In fact, unrealistic assumption of meeting full demands in DDA method, regardless of any pressure drop due to topological changes in the network, may have caused the overestimation on consumed contaminant. Although the general trend of the trade-off curves for both non-iterative PDA models are the same, small deviations at some points are observed. There variations are mainly due to the differences in the actual nodal demands resulting from application of PDA-BM or PDA-GK.

Employing PDA methods and four optimal operational activities, the actual nodal demand and pressure at DNs before and after the consequence management are presented in Table 2. As presented, employing DDNS during the consequence management period may result in negative pressure at some nodes while withdrawing the nominated nodal demands. This is addressed in Table 2 where 21 nodes suffer from negative pressure ($H <= 0$). This problem is fully resolved in both PDA methods by employing one or another kind of PDA approach. Operating the network with each PDA method under pressure-deficient conditions enables the hydraulic solver to determine the nodal demand based on the available nodal pressure. For example, without occurring negative pressure in the network, PDA-BM and PDA-GK approaches at 15:00 decrease 59 nodes with full demand satisfaction to 56 and 50, respectively. Moreover, the computed demand and pressure for node 203 with the highest amount of base demand are also presented in Table 2. As it is presented in this table, PDA-GK approach provides a reasonable demand satisfaction under pressure-deficient conditions in comparison with PDA-BM. Allocating more than 1034 Gallon Per Minute (GPM) at a nodal pressure of 0.0002 psi do not seem to be realistic for PDA-BM.

As an instance, Fig. 4 represents the demand and pressure time series during consequence management period when each of DDA and two PDA are employed. This figure is obtained based on four optimal operational response actions of minimizing

Table 2. Network Conditions before and after the Consequence Management with Four Actions

Time	Number of demand nodes with:					Node 203			
	DDA		PDA-BM (PDA-GK)			DDA		PDA-BM (PDA-GK)	
	H>0	H<=0	$q=q^{req}$	q=0	$0<q<q^{req}$	q^{req}–*GPM*	q–*GPM*	q–*GPM*	H–psi
12:00:00	59	0	59 (59)	0 (0)	0 (0)	4531	4531	4531 (4531)	62.9 (62.9)
13:00:00	59	0	56 (49)	0 (0)	0 (0)	4521	4521	4521 (4521)	62.9 (62.9)
14:00:00	38	21	56 (49)	2 (2)	1 (8)	4449	4449	1018 (1076)	2e-4 (0.25)
15:00:00	38	21	56 (50)	2 (2)	1 (7)	4439	4439	1034 (1085)	2e-4 (0.26)
16:00:00	38	21	55 (48)	3 (3)	1 (8)	4449	4449	1014 (1066)	2e-4 (0.25)
17:00:00	38	21	55 (48)	3 (3)	1 (8)	4460	4460	998 (1050)	2e-4 (0.25)
18:00:00	38	21	55 (48)	3 (3)	1 (8)	4439	4439	1030 (1072)	2e-4 (0.25)
19:00:00	38	21	55 (48)	3 (3)	1 (8)	4419	4419	1030 (1072)	2e-4 (0.25)
20:00:00	38	21	55 (48)	3 (3)	1 (8)	4368	4368	945 (1009)	2e-4 (0.23)
21:00:00	38	21	55 (48)	3 (3)	1 (8)	4399	4399	901 (978)	2e-4 (0.21)
22:00:00	38	21	56 (48)	2 (2)	1 (9)	4470	4470	786 (903)	1e-4 (0.18)
23:00:00	38	21	56 (48)	2 (2)	1 (9)	4480	4480	609 (797)	8e-5 (0.14)
24:00:00	38	21	55 (48)	3 (3)	1 (8)	4439	4439	610 (797)	8e-4 (0.14)

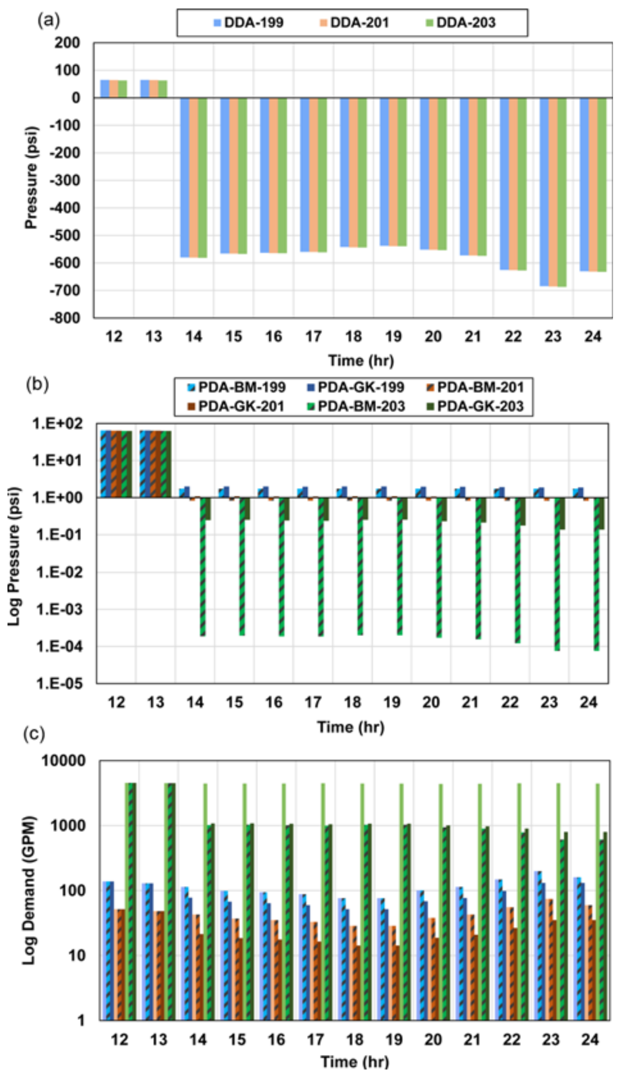

Fig. 4. Demand and Pressure Time-series for Three Nodes During Consequence Management Period when Each of DDA and PDA Approaches are applied with Four Operational Response Actions

consumed contamination mass for nodes 199, 201 and 203. Operating the network based on these four response actions causes negative pressure due to assumption of full demand satisfaction in DDA method after starting consequence management (Fig. 4(a)). Variation of pressure using PDA-BM and PDA-GK methods is presented in Fig. 4(b). Moreover, actual nodal demand considering both DDA and PDA methods is shown in Fig. 4(c). It can be seen from this figure that the demands at these pressure-deficient nodes cannot be fully satisfied. Besides, the computed results based on PDA-BM do not seem to be realistic. For example, actual demand at node 203 is provided near required demand at very low pressure. This figure demonstrates the realistic demand satisfaction in the network based on PDA-GK method.

The Pareto front displaying the number of operational response actions versus number of polluted nodes, counted over 30-minute intervals, is presented in Fig. 3(b). For a total EPS of 24 hours with 30-minute time intervals, 458 times nodes would have been identified as contaminated if no operational activities had been performed. Utilizing 15 response actions can reduce the number of polluted nodes to about 150 under different hydraulic analysis methods. With only one operational activity almost 40 percent reduction in total number of polluted nodes, counted over 30-minute time interval, is observed. The rate of reduction of number of contaminated nodes sharply decreases for number of operational activities exceeding one. Although the fronts for the first few operational response activities differ from each other for DDA and PDA solvers, they almost coincide for larger number of operational activities. Minimizing the number of polluted nodes can only be achieved by minimizing the spread of contamination throughout the network. This objective function does not force to reduce water and contaminant consumption at polluted nodes. Relaxing the value of consumed contamination mass in objective function of minimizing the number of polluted nodes encourages the optimization model to satisfy the actual demand in PDA as of DDA method. In other words, minimizing the number of polluted nodes based on PDA methods tries to satisfy full nodal demand nearby DDA. This leads to both DDA and PDA methods has almost the same value for the third objective function.

Each run of DDA, PDA-BM and PDA-GK required about 0.27, 1.55 and 1.33 seconds of CPU time in a personal computer with 3.80 GHz CPU and 8 GB RAM, respectively. Reported optimization results are obtained approximately after 5000 function evaluations including 50 chromosomes within 100 generations. Therefore, about 23, 129 and 111 minutes required for optimizing operational response actions based on DDA, PDA-BM and PDA-GK methods, respectively. Convergence history of optimization model for DDA for minimizing consumed contamination mass and number of polluted nodes is presented in Fig. 5. As it is shown in this figure, significant improvements are obtained in the initial phase of optimization process.

Using PDA-GK, spatial extensions of the contamination measured by the third objective function at 17:00 for 5 and 10 operational activities are graphically displayed in Fig 6. Fig. 6(a) presents the locations of the 59 DNs for the EPANET Net3. The spatial distribution of the contaminated nodes following the contamination intrusion at node 101 in the absence of any consequence management plan is presented in Fig. 6(b). As expected, operation of the network based on the optimal solution, which minimizes the number of total polluted nodes, would successfully limit the spatial distribution of the injected

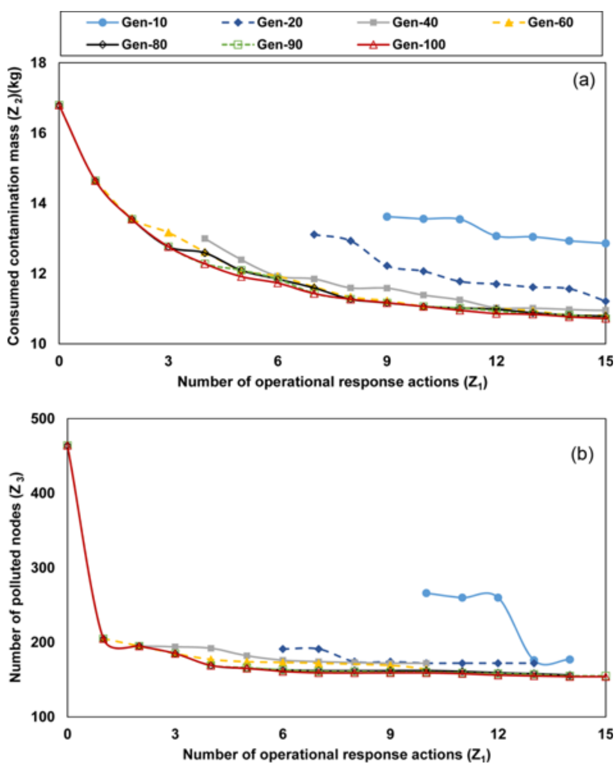

Fig. 5. Non-dominated Solutions for DDA at Different Generations between: (a) Z_1 and Z_2, (b) Z_1 and Z_3. Gen-10 Corresponds to 10th Generation

contaminant. Figs. 6(c,d) display the nodes which are identified as contaminated at 17:00 for 5 and 10 operational activities, respectively. As presented, by increasing the number of response actions, the number of polluted nodes has significantly decreased.

Besides minimizing a measure of total cost incurred to modify the network operation mode for isolating contaminated zone and/or flushing out the contaminant, it is common to minimize a measure of risk to public health simultaneously. As addressed by Eqs. (2) and (3), functions Z_2 and Z_3 are often used to measure harm and associated risk to the public health. The former one replaces the risk to public health with the mass of contaminant consumed; whereas the latter one addresses the issue by a measure of temporal and spatial exposure of the network to the contaminant. As presented in Table 3, the third objective function has more tendencies to use valve closure in comparison with hydrant opening to limit contaminant distribution within the network. For example, when Z_3 is minimized for 5 operational activities, no hydrant is nominated for change in its mode of operation. All 5 activities, which are attributed to valve closure, can significantly reduce the network exposure to contamination (i.e., 170 times nodes would have been identified as contaminated following the contamination detection). In this case, no contaminant is flushed out of the network.

As presented in Table 3, strategies which follow minimization of the second objective (i.e., minimizing the pollutant mass consumption), reduces the total consumed mass of contaminant as the number of operational activities increases. These strategies, however, increase the number of contaminated nodes as measured by the third objective function (Z_3). As an example, when the number of operational activities increases from 5 to 15, the total consumed mass of contaminant decreases by 1.5 kg (from 10.5 to 9.0 kg), whereas the number of polluted nodes increases by 66 times nodes (from 317 to 383). The same sort of observation can be made when the selected strategy follows minimization of the third objective (i.e., Min Z_3).

Operating the network by the use of valve closure or hydrant opening in consequence management period may possibly cause pressure-deficient conditions. In these conditions, water consumption and spatiotemporal distribution of contamination may vary for each optimal solution of the second or the third objective function. Fig. 7 presents the cumulative water consumption and contaminated nodes for 5 and 15 operational activities where either second or third objective function is minimized. Fig. 7(a) presents the cumulative water consumption during the consequence management period with optimum utilization of 5 and 15 operational activities under second and third objective functions. As presented, actual water consumption significantly drops when the strategy which minimizes the second objective function is employed. This is basically due to the fact that the second objective function, besides redistribution of the contaminant concentration, tries to minimize the contaminant consumption through reducing the actual water consumption. In contrast, the total water consumption under the third objective function approaches that of DDNS as

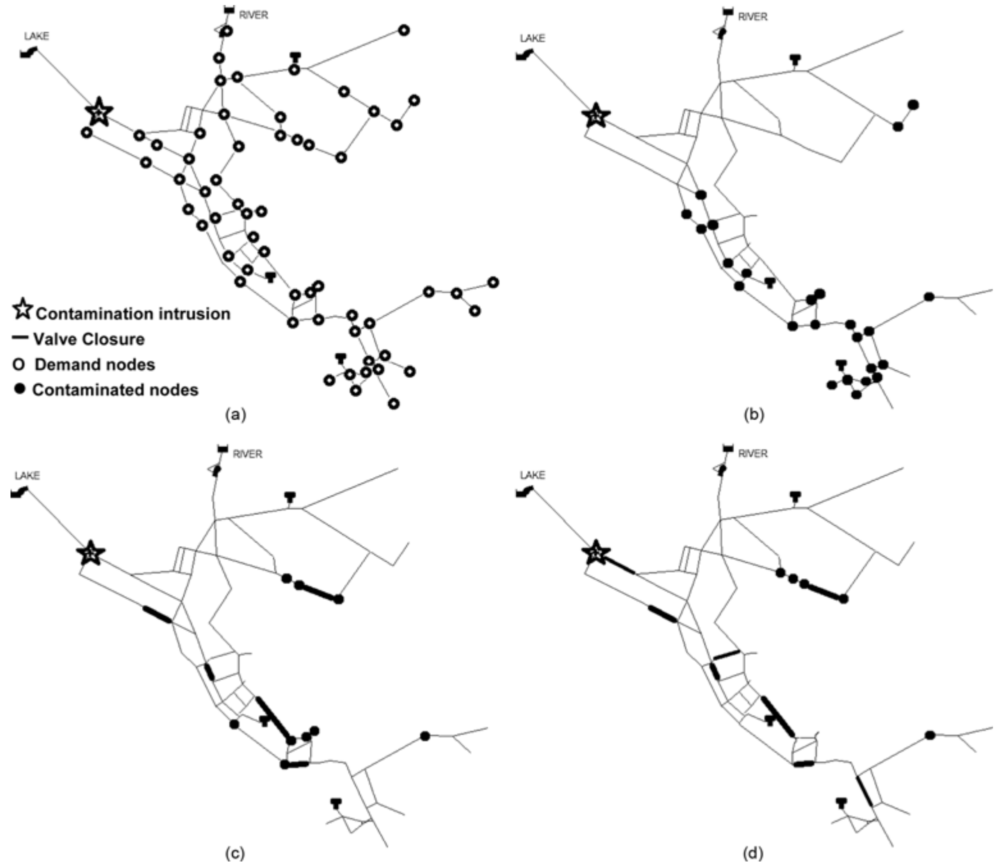

Fig. 6. Distribution of Contamination in Demand Nodes under Different Actions using PDA-GK at Time 17:00: (a) Demand Nodes, (b) Contaminated Nodes without Response Action, (c) Contaminated Nodes with 5 Actions while Minimizing Z_3, (d) Contaminated Nodes with 10 Actions while Minimizing Z_3

Table 3. A Comparison between the Results of the Second and the Third Objective Function

Objective function	Z_1	ΣHY	Z_2—*kg*	Z_3	TFCM—*kg*
	0	0	16.7	458	0
Min Z_2	5	1	10.5	317	0.28
	10	3	9.7	358	0.75
	15	6	9.0	383	1.3
Min Z_3	5	0	14.5	170	0
	10	2	14.8	153	0.15
	15	5	15.1	152	0.46

TFCM: total flushed contamination mass

the number of operational activities increases. On the other hand, the third objective function attempts to discharge the residual contamination from the network via approaching the actual demand to required value. Cumulative water consumption with full demand satisfaction (DDNS) during the consequence management period is equal to 8.7e+5 ft^3. Optimally utilizing 5 and 15 operational activities under the second objective function decrease the cumulative water consumption to 6.3e+5 and 5.9e+5 ft^3, respectively. Fig. 7(b) presents the cumulative number of contaminated nodes for 5 and 15 operational activities during the consequence management period, counted over 30-minute time interval. As presented, the number of contaminated nodes increases as the number of operational activities increases from 5 to 10, provided that the total contaminant mass consumption is minimized. In other words, the optimal management strategies are highly dependent on the objective function employed for the management implementation.

In brief, the consequences of the management implementation on public health as well as spatial and /or temporal exposure of the network to contaminant may vary with the definition of the objective function. Although the second objective function reduces the consumed mass of contaminant by cutting the actual demand, it may accumulate the contaminant within the network. The third objective function, however, restrains contaminants temporal and spatial distribution by minimizing the number of contaminated nodes. This may keep the actual water consumption close to the nominal demand regardless of its effect on public health and consumed pollutant (Table 3 and Fig. 7). Similarly, minimizing the second objective function can effectively reduce consumed contamination mass regardless of remaining contamination in the network. These observations led us believe that there might be some sort of tangible trade-off between the number of contaminated nodes and total contaminant consumption. If so, it will emphasize on the rational selection of the objective function on any consequence management strategy development. This issue will be discussed and explored as follows.

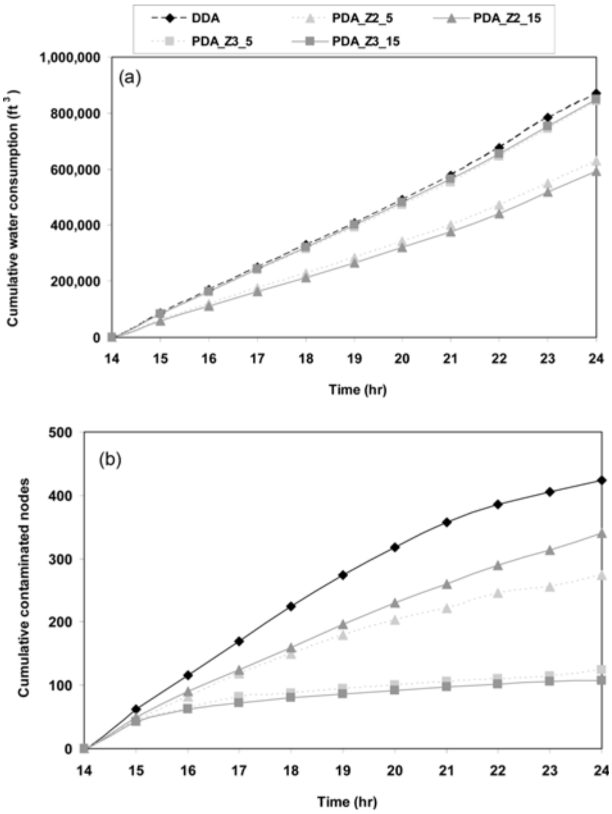

Fig. 7. Comparing the Results of Z_2 and Z_3 in Consequence Management Period using Different Hydraulic Analysis

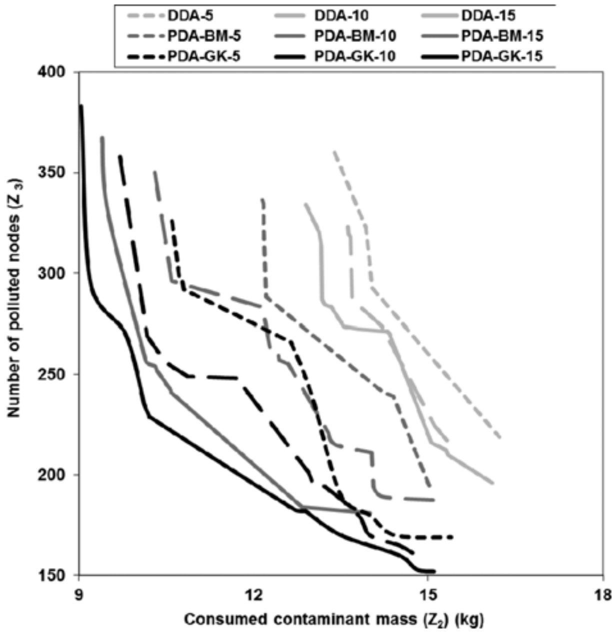

Fig. 8. Trade-off between Consumed Contamination Mass (Z_2) and Number of Polluted Nodes (Z_3)

Consumed contamination mass minimization is an appropriate goal for decreasing the contamination effects on public health via flushing out the contaminant as well as keeping the pollution in the network, whereas minimizing the number of polluted nodes focuses on decreasing the spread of contamination regardless of consumer's health. Therefore, the decision-maker may will to compromise between the pollutant mass consumption and the temporal and spatial spread of the contaminant throughout the network. In order to provide a Pareto front between the objective functions addressing the contaminant consumption and a measure of network exposure to contamination (Z_2 and Z_3 in this study), the NSGA-II multi-objective function is employed. Fig. 8 shows the trade-off between the second and the third objective functions based on DDA and PDA hydraulic solver for 5, 10 and 15 operational activities. As illustrated, for all cases the DDA approach overestimates the values of the objective functions. In fact, disregarding the possibility of negative pressure and reduction on actual demand due to changes in system topology may lead to quite unrealistic results. The results show that the two objective functions are in conflict and any decrease (improvement) in one of them is only possible by sacrificing the other one. It is also clear how both objectives may improve as the number of operational activities increases. The results indicate that the reduction rate of both objective functions is evidently decreased by increasing the number of response actions. Implementing PDA with square root relationship between the nodal demand and the nodal pressure (PDA-GK), which is suitable for operational conditions of the network such as pressure-deficient, can realistically estimate the consumed contaminant and the number of polluted nodes.

5. Conclusions

Implementation of a consequence management strategy by changing modes of operation for nominated valves and hydrants may modify the topology of the network. Any change in topology may cause pressure-deficient condition in the network, thereby reducing the actual water withdraw. It was shown how a DDA solver may fail to realistically represent system's hydraulic performances in a simulation-optimization scheme for optimal development of consequence management strategy. For the tested cases, it was illustrated that the DDA approach unrealistically overestimates the values of the objective functions. It was also illustrated how different objective functions may result in conflicting strategies. By developing the Pareto front, it was shown that two commonly used objective functions, which minimizes the spatial and temporal spread of the contaminant or the total mass consumption, are in conflict. The set of optimal non-dominated solutions forming the Pareto front may help the decision-maker to compromise between the achievements in limiting the temporal and spatial spread of the contaminant and real risk to public health by consuming contaminated water. The application of the methodology was evaluated using Net3 EPANET. In this study, for planning consequence management in operational conditions and reducing the computational time of traditional PDA, a simple technique is implemented to solve a water distribution network with pressure-dependent demands in a single run without modifying the snapshot hydraulic analysis engine of in EPANET 2. Hence, the results of optimal consequence management strategies based on PDA can be implemented and observed on graphical user interface of EPANET. The results show that the modified PDA-GK may be more appropriate and realistic for emergency response actions.

In this study, a medium scale network is used for developing consequence management strategies. Implementing this framework may be time consuming in very large networks. Therefore either improving the computational efficiency by parallel or cloud computing or reducing the size of the system through techniques such as clustering is recommended. The latter approach is the subject of an ongoing research with the authors. In this research, only potential valves and hydrants are used as decision variables for developing consequence management strategies. The use of pumps in contaminated water distribution networks can influence the optimal operational response actions. Considering the effects of switching on/off pumps on consumed contamination mass and number of polluted nodes is recommended for future research.

Notations

AFCV = Artificial flow control valve
AR = Artificial reservoir
C_{kt}, V_{kt} = Contamination concentration and consumed water volume of node k at time t, respectively
CV = Check valve
DDA = Demand-driven analysis
DDNS = Demand-driven network solver
DN = Demand node
EPA = Environmental Protection Agency
EPS = Extended period simulation
GA = Genetic algorithm
GPM = Gallon per minute
H^{des} = Desired nodal pressure
i, j, k = Valve, hydrant and node index, respectively
NSGA-II = Non-dominated sorting genetic algorithm-II
PDA = Pressure-driven analysis
PDA-BM, PDA-GK = PDA approaches of Babu and Mohan, Gorev and Kodzhespirova, respectively
PDNS = Pressure driven network solver
PN_{kt} = 1 if C_{kt} at node k at time t has greater value than threshold and 0 otherwise
Psi = Pounds per square inch
q, q^{req} = Actual and required demand, respectively
t = Time index and being considered after starting consequence management (t_c)
V, H, N = Total number of valves, hydrants and consumer nodes
VA_i, HY_j = ith valve, jth hydrant, respectively
WDN = Water distribution network
Z_1 = Total number of operational response actions
Z_2 = Total consumed contamination mass
Z_3 = Total number of contaminated nodes

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