Consequence management of chemical intrusion in water distribution networks under inexact scenarios

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ABSTRACT

The US Environmental Protection Agency (EPA)'s Response Protocol Toolbox provides a list of recommendations on actions that may be taken to minimize the potential threats to public health following a contamination threat. This protocol comprises three steps: (1) detection of contaminant presence, (2) source identification and (3) consequence management. This paper intends to explore consequence management under source uncertainty, applying Minimize Maximum Regret (MMR) and Minimize Total Regret (MTR) approaches. An ant colony optimization algorithm is coupled with the EPANET network solver for structuring the MMR and MTR models to present a robust method for consequence management by selecting the best combination of hydrants and valves for isolation and contamination flushing out of the system. The proposed models are applied to network number 3 of EPANET to present its effectiveness and capabilities in developing effective consequence management strategies.

Key words | ant colony algorithm, consequence management, minimize maximum regret, water network contamination

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NOTATION

$G_{gb}^{k^*}$	objective function value for the ant with the best performance within the past total iterations
L	set of options $\{l_{ij}\}$
α, β	parameters which control the relative importance of the pheromone trail against heuristic value
η_{ij}	heuristic value representing the desirability of state transition ij
ρ	coefficient of pheromone evaporation
$\tau_{ij}(t)$	total pheromone deposited on path ij at iteration t
k_{gb}^*	ant with the best performance within the past total iterations
$P_{ij}(k, t)$	likelihood that ant k selects option l_{ij} for decision point i at iteration t
q	random variable uniformly distributed over [0, 1]
q_0	tunable parameter $\in$[0, 1]
Q	constant
$R(x, s)$	regret for solution x under scenario s
$Z(x, s)$	number of polluted consumer nodes with solution x under scenario s
$Z(x^*, s)$	number of polluted consumer nodes with optimal solution x^* under scenario s
F	number of polluted consumer nodes from the beginning of consequence management until the end of the simulation counted over all discrete time intervals
i	node index
n	total number of consumer nodes
S	set of scenarios
x	a solution composed of valves and hydrants
X	search space that is set of solutions composed of valves and hydrants
c_t	threshold value
t_{CM}	time of beginning the consequence management
x^*	an optimal solution composed of valves and hydrants
EPS	overall simulation duration

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INTRODUCTION

Water distribution networks are one of the most important infrastructures and highly vulnerable to deliberate contamination intrusions. Following the terrorism events of September 11, 2001 in the United States, the literature has been focused more on the possibility of intentional contamination intrusions within drinking water distribution systems. The US Environmental Protection Agency (EPA)'s Response Protocol Toolbox (US EPA 2003) provides a list of recommendations on actions that may be taken to minimize the potential threats to public health following a contamination threat. This protocol comprises three steps: (1) detection of contaminant presence, (2) source identification and (3) consequence management.

Addressing the contaminant detection, numerous researchers during the last decade have focused on the placement of online water quality monitoring sensors to effectively detect contamination incidents in shortest possible time to reduce potential public health and economic consequences (Ostfeld & Salomons 2004; Berry *et al.* 2006; Propato 2006). The locations of online sensors can be optimized to help achieve one goal or a combination of goals such as minimizing public exposure to contaminants, the spatial extent of contamination, sensor detection time, or costs. To address the second step (i.e. source identification) of the protocol a few other researchers have investigated different methods for identifying locations of contaminant injection after detection of pollution (De Sanctis *et al.* 2006; Laird *et al.* 2006; Preis & Ostfeld 2006). As the number of measurements increases over time, the problem is better defined but contaminant spread and public exposure also increase (Poulin *et al.* 2008), so source identification in a short time is a tricky task. Due to the sparseness of the sensor grid, this problem inherently has non-unique solutions (Laird *et al.* 2006). Thus solving the inverse problem of source identification leads to several probable injection locations.

Regarding the subsequent successful detection of a contamination event via a contamination warning system, consequence management strategies must be implemented. These consequence management strategies would include the following factors: (1) public notification; (2) isolation of a contaminant through valve operations (US EPA 2004a); (3) flushing the contaminated water out of the system through hydrants (US EPA 2004b); and (4) any combinations of public notification, valve operations, and system flushing. Flushing is the purging of water from the distribution network via fire hydrants or blow-off ports to address water quality concerns (Baranowski *et al.* 2008). Consequence management strategies which could best minimize public health hazard and economic impacts to remediate contaminated systems must then be evaluated. Limited researches have systematically focused on the development and application of the most effective consequence management strategies in response to contamination which leaves it in its early stages of development. Baranowski & LeBoeuf (2006) investigated consequence management in order to identify demands which were most appropriate to minimize the concentration of contaminants in a water distribution network. They employed three different gradient-based optimization techniques in order to find out the near-optimal demand necessary and requisite for minimizing total network contaminant concentration after detection of pollution presence by warning sensors. In another attempt, Baranowski & LeBoeuf (2008) employed a genetic algorithm to minimize contaminant concentrations in a water network along with minimizing the cost of hydrant flushing. EPANET as a hydraulic simulator was employed in their study, and the genetic algorithm was utilized to identify the following items: (1) the nodes at which to alter the demand; (2) the new demands for these nodes; and (3) pipe closure locations essential to decrease the contaminant concentration during an incident. Regarding their assumption, flushing could be done at any nodes and every pipe could be closed as desired. Preis & Ostfeld (2008) utilized Non-Dominated Sorted Genetic Algorithm II (NSGAII) as an optimizer in order to enhance the response against intentional contamination intrusions into water networks. They explored two conflicting objectives: (1) contaminant mass consumed minimization following detection, versus (2) minimization of the number of operational activities requisite for isolation and flushing the contaminant out of the network. They defined the first objective as the total mass of contamination in the consumed water following detection until the end of the simulation period. In their system simulation, occurrence of negative pressures was disregarded. Poulin *et al.* (2008) introduced a simple topological method to organize the isolation of polluted zones within the drinking water supply networks. Their approach is based on closing proper valves and leaving one pipe to let clean water go through the isolated area. Following the previous study which addressed isolation of the contaminated area, in another study, Poulin *et al.* (2010) defined unidirectional flushing strategies through a heuristic set of rules in a well-organized and efficient way. Alfonso *et al.* (2010) presented a methodology for finding sets of operational activities in a water distribution network in order to flush the pollution out of the system to minimize the impact on the population. They explored the situation as two aspects: single-objective and multi-objective optimization problem, which were investigated by using optimization techniques, in combination with EPANET.

Although different strategies have been defined and a few methodologies developed to effectively manage the consequences of the contamination after potential source identification, very few attempts have been made to explicitly or implicitly deal with the uncertain location of the intrusion as an important issue which should be addressed following the second step. In fact, inverse solutions for source identification may not result in a single solution, implying that more than one source may be nominated as a possible polluted node. Each polluted node will call for a different optimal consequence management and operational strategy. All previous studies have developed consequence management strategies assuming predefined intrusion location. Disregarding the uncertainties involved in the assumed polluted node may result in a solution strategy very far away from the optimal one. In a most recent work, Haxton & Uber (2010) utilized a source location algorithm according to an event backtracking analysis to determine feasible and likely injection nodes. In their study, the source locations were considered as inputs to the flushing approach, which made the average impact least across all of the injection locations. Based on their results, knowing the contaminant source location would influence the efficiency of the flushing significantly and if the number of potential and feasible source locations was smaller, the decrease in impacts would be greater. Realizing that there might be no priority in selecting any of the nominated nodes for consequence management, a well-established approach is lacking. In this study, consequence management is explored under source uncertainty applying Minimize Maximum Regret (MMR) and Minimize Total Regret (MTR) approaches. Although the min-max regret model has been applied to several optimization cases under uncertainties (Averbakh 2004; Chang & Davila 2007; Afshar & Amiri 2010), utilization of these methods in consequence management has not been reported.

METHODOLOGY

In this paper, an ant colony optimization (ACO) algorithm for solving MMR and MTR models, considering a constraint for technical operational capacity, is presented. A water distribution network is considered in which some of the pipes represent valves and some of the nodes represent hydrants. To deal with uncertainties, five nodes are assumed as probable locations of intrusion. The strategy that has been used consists of three steps. The first step finds the optimal solution employing the ACO algorithm. The objective function in the optimization model seeks to minimize the total number of polluted consumer nodes for each scenario. The second step finds the solution that minimizes the maximum regret over all potential scenarios, as will be defined in the next section (Minimizing Maximum Regret). The third step finds the solution which minimizes the total regret over all potential scenarios (Minimizing Total Regret).

MMR AND MTR APPROACHES IN CONSEQUENCE MANAGEMENT STRATEGIES

Many problems are associated with the degree of uncertainty. In these situations, the decision maker tries to find a solution that performs relatively well across uncertainties. Regret criterion is a useful tool for decision making under uncertainty. Regret is a sense of loss which is felt by the decision maker knowing an alternative action would be more profitable than the one that was taken (Mausser & Laguna 1998). For instance, in finance, an investor may observe not only his own portfolio performance but also returns on other stocks or portfolios in which he was able to invest but decided not to. Therefore, it seems very natural to assume that the investor may feel joy/disappointment if his own portfolio outperformed/underperformed some benchmark portfolio or portfolios (Aissi *et al.* 2009). MMR and MTR approaches are among the most reliable criteria for decision making under uncertainties when the likelihood of the possible outcomes cannot be predicted with a satisfying accuracy (Loulou & Kanudia 1999). In other words, the MMR and MTR approaches are suitable in situations where the decision maker may feel regret if a wrong decision has been made, so when he/she decides which results will be more satisfying if this regret were taken into account. The objective of the MMR approach is to address a decision which minimizes the maximum deviation between that decision and the optimum decision for each scenario over all possible (or identified) scenarios. In fact this model intends to make a decision with the best possible performance in the worst case (Aissi *et al.* 2009). In this study, alternative actions or scenarios are defined as probable injection locations. The decision maker in this problem is an authority governing and running the city's water distribution network. He/she is the one who bears the responsibility of making a decision and may make that decision based on MMR or MTR when analyzing the consequences and the harmful impact of the harmful effects of intrusion on public health.

Let $Z(x, s)$ be the number of polluted consumer nodes under scenario s and solution x where x is a solution that consists of valves and hydrants used to isolate and remove contaminant out of the system and s is a probable node of intrusion. In this definition $x \in X$ and $s \in S$ where X is decision space and S contains all of the probable nodes of intrusion (scenarios). For a solution $x \in X$, the regret under scenario $s \in S$ is defined as follows:

$$R(x, s) = Z(x, s) - Z(x^*, s) \tag{1}$$

where $Z(x^*, s)$ is the total number of polluted consumer nodes with optimal solution x^* under scenario s. In order to determine x^*, the number of polluted consumer nodes should be calculated for each scenario individually by the optimizer. Therefore regret for a scenario is defined as the difference of polluted consumer nodes counted for applying a solution $x \in X$ and the number of polluted consumer nodes according to the optimal solution for that scenario. The MMR model may now be formulated as:

$$r = \min\{\max R(x, s)\} \tag{2}$$

The aim of Equation (2) is finding a solution by ACO to minimize the maximum regret over all the possible scenarios. The approach of MTR is very similar to MMR while minimization of total regret is considered as the objective function. The structure of the model is as follows:

$$r = \min \sum_{S} R(x, s) \tag{3}$$

In order to illustrate the previous definitions, the problem of sensor placement, as contaminant warning systems for a water distribution system, is considered. Suppose that three different layouts (installations) of water quality monitoring stations have been proposed and intrusion could occur in one of the nodes with labels i, j and k (scenarios). Table 1 shows the time of contaminant detection in minutes for each of the three scenarios.

The crude choice to minimize the longest duration detection time would be selection of layout 2, ensuring the time of detection does not exceed 320 min. However, based on Table 2 if intrusion at node j occurred, the regret associated with this choice would be 300, which is the difference between the 320 and 20 min which is too large and could have been avoided if the exact scenario had been known. In addition the total regret of this choice is 620 which is too big (the summation of 65, 300 and 255 min). Therefore, in this example, according to the maximum and the total regret the best choice would be to select layout 1,

Table 1 | Time of contaminant detection for different layouts of monitoring stations (minute)

Scenario Layout	Intrusion at node *i*	Intrusion at node *j*	Intrusion at node *k*	Worst time of detection
Layout 1	385	20	40	385
Layout 2	305	320	295	320
Layout 3	240	280	330	330
Best time of detection	240	20	40	

Table 2 | Maximum and total regret of each scenario for each layout of monitoring stations (minute)

	Intrusion at node *i*	Intrusion at node *j*	Intrusion at node *k*	Maximum regret	Total regret
Layout 1	145	0	0	145	145
Layout 2	65	300	255	300	620
Layout 3	0	260	290	290	550

ensuring maximum and total regret of no worse than 145 min.

In this study, the fitness value is calculated as the total number of polluted consumer nodes from the beginning of consequence management until the end of the simulation counted over all discrete time intervals:

$$F = \sum_{i=1}^{n} \sum_{t=t_{\mathrm{CM}}}^{\mathrm{EPS}} N(i, t) \tag{4}$$

Please note that the number of polluted nodes may vary from one computational time step to another. In other words, due to dynamics of the system, a given node may be recognized as a polluted node in one time step and unpolluted in the next one. Summation of the total polluted nodes in the entire computational time steps will often result in a fitness value exceeding the total number of network nodes. In Equation (4), i is the node index, n is the total number of consumer nodes, t_{CM} represents the time of beginning the consequence management and EPS (Extended Period Simulation) is the overall simulation duration. The value of N depends on the existence of certain pollutant concentrations in the nodes. A node is considered polluted when its concentration exceeds the threshold value c_t. Depending on the nature of the contaminant and its impact on public health, different residual concentrations may be set for the consequence management strategy. Without loss of generality, a lower threshold of 0.01 mg/l has been used here to observe and assess the consequences if the management period extends for a longer time. If the pollution concentration in node i at time t is more than 0.01 mg/l, it is assumed polluted and hence $N(i, t)$ denoted as 1, otherwise it is assigned 0. The polluted consumer nodes are added together every 15 min after beginning the consequence management. Although shorter and/or longer time steps could be used, it is a more rational time step for consequence management both from computational and plan implementational points of view. When minimizing F, indirectly two key issues are addressed: first, reducing the pollution extent (contaminated area) in the network and second, reducing the time of exposure of concentrations above the threshold (Alfonso *et al.* 2010). In this article regardless of the differences in total nodal demands, it is assumed that the density of population over the nodes is equally distributed; therefore, all nodes in terms of impact are similarly significant. Note that this is crude because EPANET example 3 consists of nodes with different demands. In addition, in reality some nodes of a water distribution network such as supply nodes for hospitals and schools are more important than others if they become polluted. So it would be more precise if nodes were weighted according to their demands and importance which needs to be considered in future studies.

ACO ALGORITHM; GENERAL ASPECTS

ACO algorithms, using principles of communicative behavior occurring in real ant colonies, have successfully been applied to solve various combinatorial optimization problems (Abbasi *et al.* 2010).

In general, the kth ant at iteration t moves from state i to state j with probability (Dorigo *et al.* 1996):

$$P_{ij}(k, t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}}{\sum_{j=1}^{J}\left[\tau_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}} & \text{if } j \in N_k(i) \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where $\tau_{ij}(t)$ is the total pheromone deposited on path ij at iteration t, η_{ij} is the heuristic value representing the desirability of state transition ij, $N_k(i)$ is the possible neighborhood of ant k when located at decision point i, and α and β are two parameters to control the relative importance of the pheromone trail against the heuristic value.

Let q be a random variable uniformly distributed over [0, 1] and $q_0 \in [0, 1]$ be a tunable parameter. The next option, j, that ant k chooses is (Dorigo & Gambardella 1997):

$$j = \begin{cases} \arg_{l \in N_k(t)} \max\left\{[\tau_{il}(t)]^{\alpha}[\eta_{il}(t)]^{\beta}\right\} & q \leq q_0 \\ J & \text{otherwise} \end{cases} \quad (6)$$

where J is a random variable value selected based on the probability distribution of $P_{ij}(k, t)$ (Equation (6)).

Once all ants have built a tour, the pheromone trail intensity will be updated. This is done according to following equations:

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \Delta\tau_{ij}(t) \quad (7)$$

where $\tau_{ij}(t+1)$ is the amount of pheromone deposited for a state transition ij at iteration $t+1$, $0 \leq \rho \leq 1$ is the pheromone evaporation coefficient and $\Delta\tau_{ij}(t)$ is the amount of pheromone deposited on path ij at iteration t:

$$\Delta\tau_{ij}(t) = \begin{cases} \dfrac{Q}{G^{k^*_{gb}}} & \text{if } (i,j) \in \text{tour done by ant } k^*_{gb} \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

where, Q is a constant and $G^{k^*_{gb}}$ is the objective function value for ant k^*_{gb} which is the ant with the best performance within the past total iterations.

MODEL SETUP

The water system utilized is the EPANET example 3 network (Rossman 2000). It comprises two constant head sources, a lake and a river, three elevated storage tanks, two pumping stations, 117 pipes, 59 consumer nodes and 35 internal nodes (Figure 1). In EPANET, a hydraulic and constituent time step of 15 min was used for a 24 hour simulation period.

Today accounting for uncertainty without accounting for the certain errors coming from wrong water distribution network modeling is unacceptable. Thus, here, realizing the deficiency of the EPANET software in handling the pressure driven condition, an extension of EPANET was prepared to directly include the pressure driven issue in the modeling approach. In pressure driven analysis, the relationship

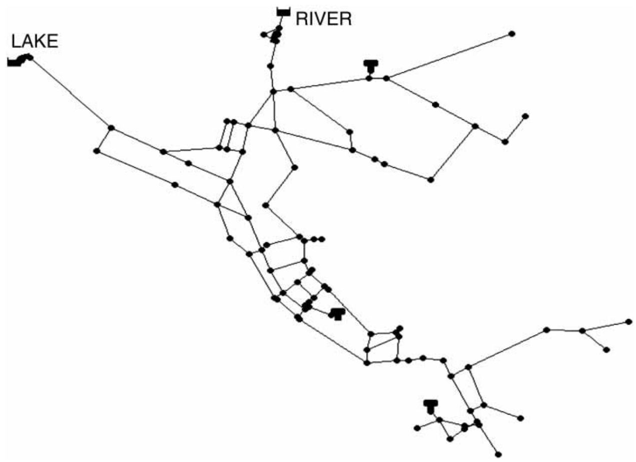

Figure 1 | Schematic of EPANET's example 3.

between pressure and demand is incorporated. In this type of analysis, functions assume fixed demand above a given critical pressure, zero demand below a given minimum pressure and some relationship between pressure and demand for intermediate pressures (Cheung *et al.* 2005). In this study, minimum and desired pressure limits are assumed to be 0 and 25 m, respectively. Flow of an open hydrant was modeled as an emitter by $Q = K\sqrt{P}$, where P is the pressure drop across the emitter and K is the emitter coefficient. K for all of the simulations was considered $1\ \mathrm{l/s/m^{0.5}}$. In this research, the hydrants and valves that are selected for consequence management are similar to those that Preis & Ostfeld (2008) utilized in their research (Table 3). The total numbers of decision variables are equal to 51 which consider the modes of operation for 20 valves and 31 hydrants. The decision variables are coded as binary numbers (0, 1) which determines whether the valve and hydrants are open or closed. Initially all valves are assumed 'open' and hydrants are 'closed'. The mode of operation for open valves and closed hydrants are identified

Table 3 | Valve and hydrant locations employed in consequence management

Valve locations (links number)	111, 175, 105, 116, 177, 215, 204, 237, 269, 173, 123, 107, 229, 311, 155, 309, 221, 231, 317, 301
Hydrant locations (nodes number)	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

by 0, whereas the decision variable for closed valves and open hydrants is represented by 1 in the proposed binary coding. In any trial solution, decision variables are free to take either 0 or 1 to redefine the operational mode of the valves and/or hydrants. Each trial solution will have its own consequences with its own regret, if implemented. It should be noted that in EPANET example 3 there are no valves, but each pipe can be closed or opened at any time and this option was used to overcome this issue. Contaminant injection takes place with a mass rate of 0.006 kg/s at 09:00 am for a duration of 7 hours.

In this study we assume that: (1) the water system is equipped with some sensors for detection of contaminant presence; (2) nodes 103, 111, 125, 113 and 259 are probable nodes of intrusion (Table 4); and (3) the necessary time for detection of contaminant presence in the network by monitoring stations and delay in the response time (including: (1) contamination source identification; (2) isolation and containment by valve closures; (3) flushing by hydrant opening; and (4) public notification (Preis & Ostfeld 2008)) is 4 hours; thus consequence management will begin at 13:00 pm. In addition, the constraint 'technical operational capacity to implement response' is considered. Based on this constraint, the total number of operational response activities is restricted to 20. In some real cases, however, the number of operational responses may far exceed this number if a large number of valves and hydrants are selected by the optimizer to be re-operated.

Table 4 | Probable nodes of intrusion (scenarios)

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Node number	103	111	125	113	259

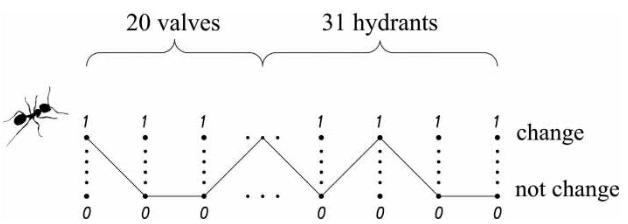

Figure 2 | Decision graph of ACO algorithm for consequence management strategies.

In order to apply ACO algorithms to a specific problem, the problem should be represented on a graph or a similar structure easily covered by ants (Afshar *et al*. 2009). Solutions that are produced by ants are combinations of valves and hydrants which are closed and opened by operators at 13:00 simultaneously and remain unchanged until 24:00. In Figure 2, each column represents a valve or hydrant utilized in consequence management. As an example, if an ant selects number 1, it means that the status of that valve or hydrant will be changed in the proposed management alternative. Otherwise, the situation of the valve or hydrant will remain unchanged.

As mentioned above, in order to obtain optimal solutions for MMR and MTR models, the ACO algorithm should be solved for each scenario individually. The function evaluations for all of the ACO algorithms are 90,000 and the metaheuristic parameters are: $\beta = 0$, $\alpha = 1$, $\rho = 0.05$ and $q_0 = 0.4$. To control the amount of pheromone deposited for a state transition ij, the proper value of Q must be selected by sensitivity analysis. The values of Q for each sub-problem consisting of different inexact scenarios and MMR and MTR are selected through sensitivity analysis as displayed in Table 5.

RESULTS AND DISCUSSION

The number of polluted consumer nodes without performing consequence management for each scenario is shown in Table 6. As presented in Table 6, the total number of polluted consumer nodes for the identified scenarios ranges from 753 to 1,307 for scenario numbers 4 and 3, respectively. Numbers of operational activities along with identification number of valves and hydrants to be re-operated under optimal solutions for different scenarios are

Table 5 | Q values for ACO algorithms in order to find optimum solutions

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	MMR Model	MTR Model
Q	40	50	115	60	45	70	180

Table 6 | Number of polluted consumer nodes without performing response actions

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Polluted consumer nodes	914	906	1,307	753	1,153

presented in Table 7. As presented, for scenario number 1, a total of 18 operational activities are identified with nine valves and nine hydrants. The number of polluted consumer nodes based on the occurrence of each scenario while employing the optimal solutions are shown in Table 8. In this table, dark cells are optimal solutions under given consequence management scenarios. Compared to the number of polluted consumer nodes with no consequence management, a significant reduction in the number of polluted consumer nodes may be achieved for scenario numbers 1 to 5. Specifically speaking, assuming that the polluted node is fully identified, the total number of polluted consumer nodes may be reduced by 82, 80, 69, 79 and 84% for scenario numbers 1 to 5, respectively. As an example, for the first scenario, implementation of the consequence management may reduce the total number of polluted nodes from 914 to 164 (Table 8). Please note that even if the right scenario is not correctly identified, the management strategy will still reduce the number of polluted consumer nodes by 42% (from 914 to 533) or more. The second column of Table 8 illustrates that if the decision maker implements the optimum solution associated with scenario number 1, the total number of polluted consumed nodes will reach 164, whereas this number may increase to 699 nodes if the third scenario prevails. The results obtained from the optimization scheme demonstrate that the use of the number of polluted nodes in consequence management helps in reducing both exposure time and consumed pollutant concentrations. Given a scenario, results also illustrate the usefulness of ACO to provide optimal solutions in order to minimize the number of polluted nodes in water distribution network.

Amounts of regret under different scenarios are shown in Table 9. Suppose that the decision maker implements the optimal solution for scenario number 3, for which 402 nodes are expected to be polluted. Let's assume that, in reality, scenario number 4 occurs. In this case, as a result of incorrect scenario identification, the decision maker must pay for a regret of 238 extra polluted nodes (399–161). This issue is reflected in the fifth column and fourth row of Table 9. According to Table 9, if the decision maker employs optimal solutions, the maximum regret would range from 298 to 996 and total regret from 676 to 1,835 for different scenarios.

MMR approach

Minimizing the total or maximum regret may eventually lead to a more robust solution for cases of inexact scenarios. The objective of the MMR approach is to address a decision which minimizes the maximum deviation between the alternative taken and the optimum one for each scenario over all possible (or identified) scenarios. In fact this model intends to make a decision with the best possible performance in the worst case. In order to minimize the maximum regrets under different scenarios, the MMR

Table 7 | Optimal solutions for each scenario

	Number of operational activities	Valve numbers	Hydrant numbers
Scenario 1	18	107, 111, 155, 204, 221, 231, 269, 309, 311	601, 120, 179, 183, 184, 187, 195, 204, 267
Scenario 2	18	107, 111, 116, 204, 215, 221, 231, 269, 309	179, 183, 184, 187, 195, 204, 263, 267, 269
Scenario 3	20	155, 175, 237	40, 601, 61, 120, 129, 164, 169, 173, 179, 181, 183, 195, 204, 265, 269, 271, 273
Scenario 4	18	116, 204, 231, 269, 309, 311	60, 129, 179, 183, 184, 187, 195, 204, 257, 261, 267, 269
Scenario 5	20	107, 111, 123, 221, 269, 301, 309	164, 169, 173, 179, 181, 183, 257, 259, 261, 263, 265, 269, 273

Table 8 | Number of polluted consumer nodes based on occurrence of each scenario and employing optimal solutions

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
$x^*(\mathrm{sc}=1)$	164	226	699	195	477
$x^*(\mathrm{sc}=2)$	183	179	1,396	204	731
$x^*(\mathrm{sc}=3)$	533	475	402	399	671
$x^*(\mathrm{sc}=4)$	346	336	1,398	161	679
$x^*(\mathrm{sc}=5)$	382	552	589	444	179

approach is applied. The results are shown in Tables 10 and 11. By minimizing maximum regret, it is intended to re-operate the valves and hydrants in such a way that, for all possible scenarios, the maximum deviation of the number of polluted consumer nodes from the optimum value is minimized. In this case, the maximum amount of regret under different scenarios will be reduced. Table 10 provides the valves and hydrants which minimize the maximum regret over all identified scenarios. For valves and hydrants proposed in Table 10, the values of regret for different scenarios are presented in Table 11. As presented, for the proposed valves and hydrants re-operation, the maximum regret will result when scenario number 3 occurs. By comparing the maximum regret associated with single scenario-based optimum number of polluted consumer nodes, the solution to the MMR model has decreased the maximum regret. To be pleased about the drops in maximum regret, one may compare the regret values in Table 11 with those in column 7 of Table 9. Table 11 implies that no matter which scenario is going to happen, the decision maker's regret will not exceed 157 polluted consumer nodes. Whereas the maximum regret for the single scenario-based solution ranges from 298 to 996 for different scenarios (Table 9).

Table 10 | Optimal solution obtained from MMR approach

Number of operational activities	Valve numbers	Hydrant numbers
19	105, 111, 116, 155, 204, 215, 229, 269, 301, 309, 311, 317	40, 173, 195, 204, 259, 267, 271

MTR approach

To test the performance of the MTR model in handling injection location uncertainty in consequence management, the same case example and the same five scenarios are used. The final results of the model application are provided in Tables 12 and 13. Similarly to Table 10, Table 12 provides the optimum solution which minimizes the total regret over all possible scenarios. For valves and hydrants proposed in Table 12, the total values of regrets for different scenarios are presented in Table 13. As presented, for the proposed valves and hydrants re-operation, maximum regret will result when scenario number 3 occurs. Table 13 shows that the decision maker should implement valves and hydrants provided in Table 12, for which the total regret for the fifth scenario will be 18. In this case if other scenarios take place, the decision maker will feel regrets ranging from 82 to 183 polluted consumer nodes. For the proposed solution the total regret over all identified scenarios will be equal to 576 polluted consumer nodes (Table 13). Compared to the MMR model, the total regret resulting from the MTR model has been reduced (i.e. from 639 in Table 11 to 576 in Table 13). In this model, compared to the MMR model, total regret is reduced by almost 10 percent and maximum regret is increased by 14 percent. As a result, it seems that MMR and MTR models nearly eventuate

Table 9 | Regret under different scenarios

Assumed scenario	Reality Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Maximum regret	Total regret
Scenario 1	0	47	297	34	298	298	676
Scenario 2	19	0	994	43	552	994	1,608
Scenario 3	369	296	0	238	492	492	1,395
Scenario 4	182	157	996	0	500	996	1,835
Scenario 5	218	373	187	283	0	373	1,061

Table 11 | Number of polluted consumer nodes and amounts of regret with optimal solutions under different scenarios obtained from MMR approach

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	
Number of polluted consumer nodes	294	319	559	272	280	
Regret	130	140	157	111	101	Total = 639

Table 12 | Optimal solution obtained from MTR approach

Number of operational activities	Valve numbers	Hydrant numbers
16	107, 111, 116, 123, 215, 221, 237, 269, 309, 317	129, 173, 195, 267, 269, 271

in the same results and both are suitable in consequence management.

CONCLUSIONS

Efficient consequence management in an intentionally contaminated water distribution network is only possible if the source of the contamination is known. Complete knowledge on the contaminant source location will lead to great reduction in the polluted consumer nodes and greatly influence the effectiveness of the consequence management. However, inverse solutions for source identification may identify multiple inexact sources of contamination and polluted nodes, each one demanding different optimal consequence management and operational strategy. This study proposed and tested a systematic approach based on MMR and MTR in connection with the well-established ACO approach to develop a set of robust consequence management strategies with known impacts on alternating strategies. It was illustrated that the approach is mathematically sound, computationally feasible and the proposed method can be used to analyze the regrets associated with any employed consequence management strategy. In addition it was shown that knowing the exact location of contaminant intrusion will strongly influence the effectiveness of the response activities.

Contamination detection, source identification, and consequence management strategy implementation are all time consuming and may demand relatively considerable time. To minimize the time lag and overcome the computational shortcomings, it is recommended to set up and calibrate the models for detection, source identification, and consequence management in advance and have them in 'ready to be used' condition. It was shown that both MTR and MMR models are suitable for design and analysis of consequence management strategies. Realizing the discrete nature of the decision space in the consequence management problem, the ACO algorithm performed quite satisfactorily and is recommended for similar studies. Although not providing the water network governor and authorities with a single solution, results of the proposed models may provide the decision maker with a reasonable level of awareness and impacts of the alternating decisions considering the uncertainties involved in exact identification of the contaminated node. In addition, the proposed methodology disregards other uncertainties, such as type of injected contaminant and injection time, which need to be investigated in future works. The testing of more networks with different topological structures is recommended for improving the confidence in the proposed approach.

Table 13 | Number of polluted consumer nodes and amounts of regret with optimal solutions under different scenarios obtained from MTR approach

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	
Number of polluted consumer nodes	246	350	585	283	197	
Regret	82	171	183	122	18	Total = 576

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