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A Robust Decision Support Leader-Follower Framework for Design of Contamination Warning System in Water Distribution Network

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Abstract

In recent years, several models have been proposed to inoculate Water Distribution Systems (WDS) against impacts of accidental and/or intentional compromised water quality through optimal deployment of online monitoring sensors in the network, which is referred to as Contamination Warning Systems (CWS). Translating such modeling efforts to real-world practice is, however, a challenge as different involved parties may pursue conflicting goals and modeling-based recommendations may not justify all stakeholders' criteria. It is, hence, pivotal to develop conflict resolution methodologies to support engagement of different stakeholders in securing a safe water distribution. The decision making structure for CWS design is often of top-down nature, with the upper level decision maker concerned mainly about public safety and lower level stakeholders concerned about operational costs. In this study, a decision support framework based on Leader-Follower Game is proposed, given different power levels. Leader's objectives are focused on the CWS robustness, while followers have conflicting interests that are in turn resolved via Nash Bargaining method. Lamerd WDS (Fars, Iran) is selected to assess the proposed model's

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performance. The results show the proposed objective and parsimonious model provides a robust solution that complies with the leader's criteria and maximizes the followers' satisfaction. The proposed decision support system helps govern WDSs in a resilient and safe manner and warrants practical implementation of modeling-based security assurance policies to provide sustainable service to the society.

Keywords

Decision support system; Top-down decision making structure; Robust sensor placement optimization; Contamination warning system; Leader-follower game; Conditional Value-at-Risk

1. Introduction

Ever since the terrorist attack of 9/11, protecting critical infrastructures emerged as a top priority to decision and policy makers (Berry et al. 2005a). One of these infrastructures is Water Distribution Systems (WDS), which are designed to deliver safe drinking water to consumers (Preis and Ostfeld, 2008). However, WDSs are inherently vulnerable to accidental and intentional contamination because of their distributed geography and easy-to-access locations (Afshar and Khombi, 2015). Historical incidents corroborate the WDSs' vulnerability and their catastrophic impacts on public health (Forest et al. 2013). Contaminated drinking water delivered through WDSs in Scotland (Gavriel et al. 1998), Canada (Hrudey et al. 2003) and Japan (Yokoyama, 2007), leaving catastrophic societal impacts, intensifies concerns regarding the security of WDSs (Arad et al. 2013; Khorshidi et al. 2018). This has convinced the former United States president, George W. Bush, to issue a Presidential Directive, following the 9/11 terroristic attack, focused on addressing such critical concerns for homeland security (Janke et al. 2017).

The ideal scenario to minimize the impacts of compromised drinking water quality on public health is to equip every junction of WDS with online sensors with a centralized monitoring system, i.e. Contamination Warning System (CWS), to shut down the WDS upon detection of compromised water quality. However, installation and operational costs of such CWS are prohibitive (Zeng et al. 2016). For instance, one type of PSA analyzer that monitors real-time heavy metal concentration in potable water, with a 1 micro-grams per liter accuracy, costs between 3,000 to 5,000 USD (P. S. Analytical Co., 2018). Given the large number of junctions in a typical WDS, the required investment is impractical. Moreover, not every location in a WDS is technically feasible for placement of sensors (Berry et al. 2008).

From the early 2000s, multiple lines of study have contributed to the optimal deployment of CWS in WDSs (Hart and Murray, 2010). They can be clustered into three different categories: 1. rule-based, 2. opinion-based, and 3. optimization-based approaches (Hu et al. 2018). The optimization-based approach has shown not only superior performance to those of rule- and opinion-based approaches, but also has been recognized as being more objective (Berry et al. 2008; Hart and Murray, 2010; Khorshidi et al. 2018). Researchers have developed various single- or multi-objective optimization models for determining optimal layouts of CWS (e.g. Berry et al. 2005b; Shastri and Diwekar, 2006; Zhao et al., 2016). These objectives include impact on public health, time from injection to detection of contamination, extent of contamination, and likelihood of detecting contamination (Berry et al. 2012; Janke et al. 2017; Khorshidi et al. 2018).

Two main obstacles inhibited practical application of those models' results for real-world problems: 1. constrained budget, and, 2. lack of a decision support framework that could properly align with the decision making structure of the involved stakeholders (Hart and Murray, 2010). To address the first obstacle, some researchers have considered limited budget as a constraint in their proposed optimization model (e.g. Berry et al. 2005b). Also, with an assumption of monotonic relationship between the cost of deployment and maintenance of a CWS and the number of sensors used, some researchers fixed, a priori, the number of sensors to be placed in WDS to fix the associated costs (e.g. Berry et al. 2008; Weickgenannt et al., 2010; Tinelli et al., 2017), and others included minimizing number of sensors in a multi-objective optimization scheme (e.g. Afshar and Marino, 2012; Bazargan-Lari, 2014; Naserizade et al. 2018).

Developing a decision support framework that warrants cooperation of different stakeholders can be even more complicated than the budget constraint (Hart and Murray, 2010). As mentioned earlier, different objectives and various stakeholders are involved in the CWS design and operation. While all objectives are obviously important, different decision makers may prioritize one (some) objective(s) over others (Janke et al. 2017). Despite the strives made in CWS deployment optimization models, providing decision support systems to facilitate the decision making process and resolve conflicts has received only little attention. Examples include Berry et al. (2008 and 2012) and Janke et al. (2017), in which a regret-analysis framework is incorporated in the TEVA-SPOT model. TEVA-SPOT is an optimization model, which uses a single-objective optimization module and can be recursively executed to perform multiple optimizations with various objectives (one at a time) and to include different fixed number of sensors (Khorshidi et al. 2018). Then, the user trades different CWS designs off in regret-analysis model to determine a comprise solution among different alternatives (Berry et al. 2008 and 2012; Janke et al. 2017). Also, Xu et al. (2010) and Chang et al. (2011 and 2012) developed decision support systems based on regret-analysis for design of a CWS. Xu et al. (2010) incorporated the concept of sensitivity region in their model, and Chang et al. (2011 and 2012) considered three rules of “intensity”, “accessibility” and “complexity” for near-optimal placement of sensors in WDS. Bazargan-Lari (2014) and Naserizade et al. (2018) used Multi-Criteria Decision-Making methods to choose from a set of Pareto-optimal CWS layouts. The importance of providing a comprehensive and robust decision support system for CWS design and operation has been further emphasized in recent years (Hart and Murray, 2010; Janke et al. 2017; Hu et al. 2018).

It is also worth mentioning that the sparse decision support studies in the field are based on the underlying assumption that the involved stakeholders are “willing to bargain” for their respective criteria. In real world, however, critical issues, such as protecting public health and confidence in the supply system, often receive a high-level governmental overlook that is actively involved in funding, designing and implementing procedures. Such organizations – which could be considered as leaders – set clear guidelines for related operations including specific criteria that could even lead to impasses at times. There are also other public and/or private sectors (followers) involved in such operations, but have no choice except to bargain with each other under the outlines of the leader (Gentile et al. 2018; Julien, 2017; Sedghamiz et al. 2018).

In this study, a decision support optimization framework based on Leader-Follower Game (LFG; Benchekroun and Van Long, 2001; Yang et al. 2015; Van Ackooija et al. 2018) is proposed, in which the leader funds the CWS deployment and sets clear guidelines on costs and robustness of CWS. The leader's criteria are (i) minimizing the CWS cost that could provide a certain level of Conditional Value-at-Risk (CVaR; Rockafellar and Uryasev, 2000 and 2002) of affected population (AP) and (ii) minimizing time to detection (TD). Note that CVaR is defined as expected value at the tale of loss distribution function at a certain level. The followers follow different interests, and they bargain to reach a compromise solution in form of the Nash equilibrium (Nash, 1953). The proposed model is a two-layer nested optimization model in which the first layer is leader's multi-objective optimization model, constrained in a lower level by the followers' single objective bargaining model. These will be discussed in details later. The model is applied to a real-world case study of CWS deployment in Lamerd WDS, Fars province, Iran. For this purpose, numerous possible contamination events are simulated via EPANET water quality model (Rossman, 2000) using Monte-Carlo Simulation (MCS). The simulation results are then used as the optimization model forcing. This offline simulation approach is widely used in the literature (e.g. Berry et al. 2012; Janke et al. 2017; Naserizade et al. 2018). The results show that the model is capable of providing optimal solutions, which could satisfy the stakeholders' criteria.

Novelty of the proposed decision support framework lies in incorporating the top-down approach in the decision making structure using the Leader-Follower Game, which replicates the distribution of power in CWS design and operation in the real-world. Moreover, robustness of the final design layouts is also considered as an important performance index in the decision making process. This framework is general and can be employed for resilient development of an important infrastructure, WDS, to provide sustainable service to the society. The objectives and power levels, among other parameters, in this framework can be adjusted to fit the real-world situations of any target study.

2. Case Study

The WDS of Lamerd City (Fig.1), Fars province, Iran, is designed and constructed to supply approximately 260 liters of potable water per capita per day to about 81,000 consumers. The hourly multipliers of the base demand are shown in Fig. 2. The WDS constitutes of 2 reservoirs, 1 tank, 185 pipes, 122 junctions and 23 hydrants.

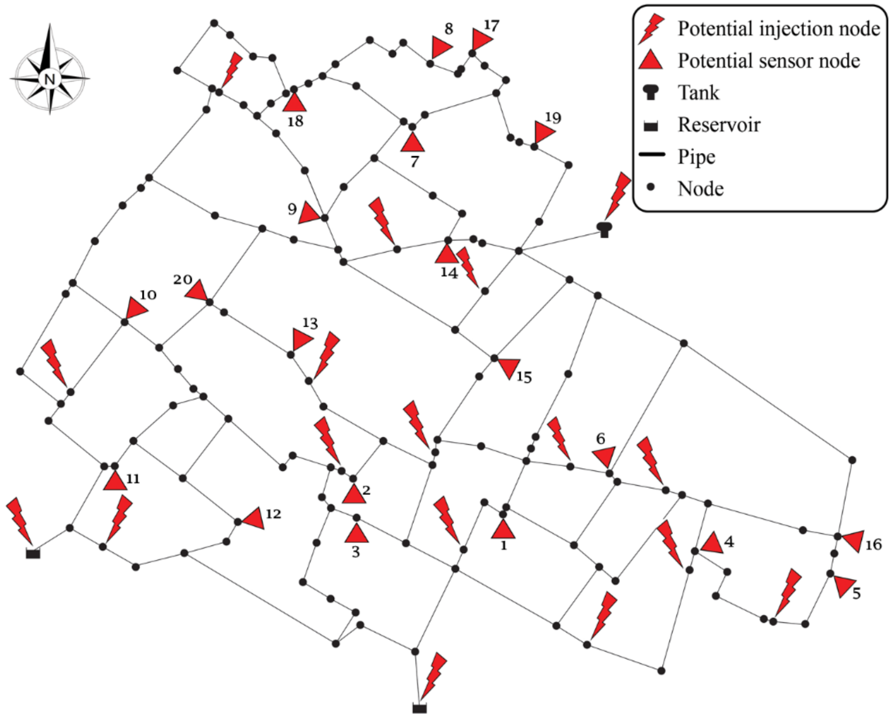

Fig. 1. Lamerd City's Water Distribution System. Potential locations for placement of sensors and injection of contamination are also marked.

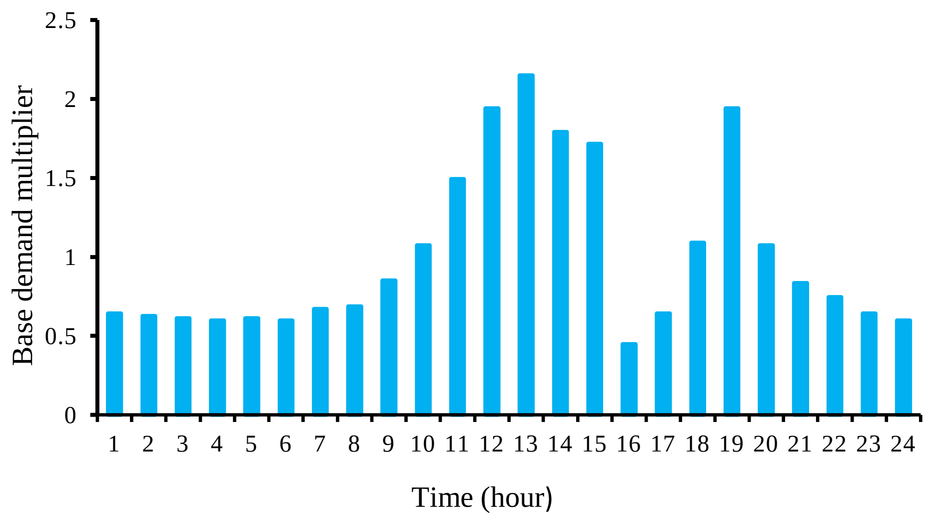

Fig. 2. Base demand's hourly multipliers during a day.

Arsenic is chosen in this study for scenario analysis and assessment of impacts of possible contamination intrusion on public health. Arsenic is deadly at low dosages, and is a cheap and accessible toxic heavy metal. This substance is, therefore, frequently used in the CWS design studies (e.g. Bazargan-Lari, 2014; Naserizade et al. 2018). A critical dose of Arsenic, CD (milligrams), is defined as the dose that could inflict harm depending on the exposed person's weight, WP (kg), and can be calculated as (Shafiee and Zechman, 2013),

$$CD = WP \times 5^{-8} \tag{1}$$

Assuming a person weights 70 kg on average, their health could be critically affected by ingesting 3.5 mg of Arsenic, according to Equation 1. In this study, it is assumed that (i) a person ingests contamination only through drinking contaminated water, and (ii) every person drinks 0.93 liters of water per day (similar to Shafiee and Zechman, 2013). The population who ingested 3.5 mg of Arsenic or more is considered as "Affected Population (AP)" throughout this study.

One of the challenges in sensor placement problems is the natural lack of knowledge about when, where and how contamination is introduced to the WDS. To address uncertainties associated with a contamination intrusion, Monte Carlo Simulation (MCS) is employed in this study. Various scenarios of contamination injection in WDS are defined with injection duration, time and location, as well as mass of Arsenic as uncertain input variables in MCS. Injection duration and mass of substance are considered in 40 to 80 minute intervals, and 200 to 700 mg/sec flux range. Also, 13 injection times in a day and 17 possible injection locations (including 14 hydrants, the tank and two reservoirs) are considered in MCS (Table 1).

Contamination injection from the remaining 9 hydrants has no or very low impact on population's health due to the hydraulic characteristics of the WDS, and hence are not considered in scenario analysis (Naserizade et al., 2018). Moreover, successive injection times have been chosen according to the base demand's hourly multipliers (Fig. 2). When the demand rate is at its highest, the time-gap between two successive injections is the smallest, and vice versa. The reason is to consider injection scenarios in which the contamination could be consumed at a higher rate and hence, the affected population is more compared to other injection scenarios. All combinations of the aforementioned variables define the contamination injection scenarios. A total of 48,100 contamination scenarios are generated and simulated in a MCS scheme using EPANET. It is worth mentioning that the tank is not always operational in WDS. In some scenarios, an injection may occur at the tank when it is not operational. Such scenarios are eliminated in the analysis. The hydraulic and water quality model of Lamerd WDS was previously calibrated by Bazargan-Lari (2014), and are used in this study. The simulation period for each contamination scenario is 48 hours with 60-second time-step for both hydraulic and water quality modules. Furthermore, wall reaction coefficient is not considered for quality simulations, as Arsenic does not react with the materials of pipe wall. However, bulk flow reaction is considered (-0.05 day^{-1}) in the water quality simulation. In this study, a detection limit of 0.01 mg per liter is considered for the sensors, similar to Naserizade et al. (2018) and Khorshidi et al. (2018). As defined by Janke et al. (2017), sensor's detection limit is a concentration threshold above which the used sensor is completely reliable for detection of contamination, and fully unreliable otherwise (binary performance). The results of MCS are then used for calculation affected population and time to detection at 20 potential locations for sensors (Fig.1).

Table 1. Variables used for Monte Carlo Simulation, and parameters used in EPANET water quality simulation.

Variable/Parameter	Values
Time of injection in day	1, 7, 9, 11, 12, 13, 14, 15, 16, 17, 18, 19, and 21.
Mass of injection	200 mg/sec to 700 mg/sec
Duration of injection	40 min to 80 min
Locations of injection	17 locations, including a tank, 2 reservoirs and 14 hydrants (Fig.1)
Number of injections	Simultaneous injection from 1, 2 and 3 points
Total number of scenarios	48100 scenarios

Iran's National Disaster Management Organization (NDMO) is a governmental agency that funds and supervises critical operations concerned with prevention and/or management of possible accidental or intentional hazards. NDMO is, hence, responsible to fund and supervise the design and operation of CWSs by other sectors including Lamerd Water and Wastewater Company (LWWC), Lamerd Environmental Protection Organization (LEPO), and Lamerd's branch of Ministry of Health and Medical Education (MOHME). The guidelines of NDMO instruct that the Conditional Value-at-Risk (CVaR; to be discussed later) of both affected population (AP) and time to detection (TD) at 95% confidence level should not exceed 5% of City's population and 6 hours, respectively. LWWC is responsible for design and implementation of CWS that maximizes the likelihood of detecting contamination (LD). According to the existing legislations, LWWC should also consider the criteria set by LEPO and MOHME in the CSW design. These criteria include minimization of average time to detection (TD_{ave}), and minimization of average affected population (AP_{ave}). In this setting, NDMO can be considered as leader whose utility has higher priority than other stakeholders, and LWWC, LEPO and MOHME can be considered as followers.

3. Methods

3.1. Conditional Value-at-Risk (CVaR)

A decision vector, x, is associated with an expected loss probability density function (pdf) in scenario-based analysis, and the confidence level, α, is defined as a certain cumulative probability; e.g. 0.8, 0.9 and 0.95. The minimum expected loss exceeding the confidence level α is defined as Value-at-Risk (VaR), and Conditional Value-at-Risk (CVaR) of the loss pdf at confidence level α is defined as the weighted average of losses exceeding VaR (Rockafellar and Uryasev, 2002). Let $z = f(x, y)$ represent loss pdf, which is a function of decision vector $x \in X$ and random vector $y \in Y$. The cumulative pdf of losses, $\Psi(x, z)$ would be defined as in eq. 2. Also, VaR and CVaR at the confidence level $\alpha \in [0,1]$ can be defined as in eq. 3 and eq. 4, respectively.

$$\Psi(x, z) = P\{y | f(x, y) \leq z\} \tag{2}$$

$$VaR(x) = \min\{z | \Psi(x, z) \geq \alpha\} \tag{3}$$

$$CVaR(x) = \mathrm{E}\{z | \Psi(x, z) \geq \alpha\} \tag{4}$$

where, P and E denote probability function and expected value operator, respectively. Rockafellar and Uryasev (2000) proved that when a finite number of scenarios (N) represent the random vector y, CVaR would be equal to minimized F_{α} over x and v in (Soltani et al. 2016),

$$F_\alpha(x, v) = v + \frac{1}{1-\alpha} \sum_{n=1}^{N} \max\{0, f(x, n) - v\} p(n), \tag{5}$$

where v represents VaR and $p(n)$ is probability of scenario n.

3.2. Leader-Follower Game (LFG)

Several governmental and public organizations, often with conflicting objectives, are involved in protecting infrastructure against terrorist attacks. Directly responsible organizations stand firm for their priorities (usually public safety) due to the critical nature of the problem, and other stakeholders compete in the restricted available space. Decision making structure is then of top-down type, resembling leader-follower game (LFG). In this game, an authority agent, a.k.a. the leader, has the power of determining general policies, and other stakeholders, a.k.a. the followers, bargain to maximize their utilities (objectives). Any design should comply with the outlines of the NDMO (leader). Furthermore, followers do not know about the leader's decision beforehand, but the leader knows how the followers would respond to its decision (Safari et al. 2013). While NDMO is the leader, LWWC, LEPO and MOHME are considered as followers with equal power in the bargaining process, because from management point of view they are regarded as organizations with the same level of importance in governmental hierarchy. However, as mentioned earlier, the model could be simply modified to account for different level of power for the followers. LFG is a two-layer nested optimization model. The first layer is the leader's and the second is the followers' optimization models, respectively.

3.2.1. Leader’s CVaR-based multi-objective optimization model

It is assumed that the costs associated with placement and maintenance of CWS have a monotonic relationship with its number of sensors. Hence, the leader’s objectives are: 1. Minimizing number of sensor (Z_1), 2. Minimizing CVaR of TD (Z_2), and, 3. Minimizing CVaR of AP (Z_3), as represented in,

$$minimize: Z_1 = NS,$$

$$minimize: Z_2 = CVaR_{\alpha}^{TD} = VaR_{\alpha}^{TD} + \tfrac{1}{1-\alpha}\textstyle\sum_{n=1}^{N} \tfrac{1}{N} \min\{b_i.TD_i^n\} - VaR_{\alpha}^{TD}, \forall i,$$

$$minimize: Z_2 = CVaR_{\alpha}^{AP}$$
$$= VaR_{\alpha}^{PA} + \frac{1}{1-\alpha}\sum_{n=1}^{N}\frac{1}{N}\{b_i.PA_i^n - VaR_{\alpha}^{AP} | b_i.TD_i^n = \min\{b_i.TD_i^n\}, \forall i\},$$

where, NS is the number of sensors (leader’s decision variable), and b_i is a binary variable equal to 0 if a sensor is not placed at node i, and 1 otherwise. TD for scenario n (TD^n) is the minimum time elapsed before contamination becomes detectable at nodes that are equipped with a sensor; hence, TD^n is equal to $\min\{b_i.TD_i^n\}$ (eq. 6.b). Affected population for scenario n (AP^n) corresponds to TD^n (eq. 6.c). VaR and CVaR represent value at risk and conditional value at risk, respectively. As mentioned earlier, the leader’s model has two constraints:

$$CVaR_{\alpha}^{TD} \leq 360\ minutes \quad (7.a)$$

$$CVaR_{\alpha}^{AP} \leq 0.05\ POP \quad (7.b)$$

where, POP is the total population of the City (about 81,000). The leader's multi-objective optimization model is handled by the Non-dominated Sorting Genetic Algorithm II (NSGA-II; Deb et al. 2000 and 2002, Alizadeh et al. 2017).

3.2.2. Followers' bargaining model

In the first layer of the LFG model (leader's model), the leader only decide how many sensors should be placed in WDS, while the layout of CWS is determined by the followers. Therefore, b_i is the decision variable of followers' model. As mentioned earlier, LWWC, LEPO and MOHME are the followers and their objective functions are maximizing LD (likelihood of detection), minimization of TD_{ave} (time to detection), and minimization of AP_{ave} (affected population), respectively. The Nash Bargaining (NB) method is used to resolve the followers' bargaining process. NB is a single-objective optimization problem (eq. 8), which can find a fair compromise solution when bargainers make decisions simultaneously.

$$Maximize: Z = \prod_s (g_s - d_s) \tag{8}$$

Subject to:

$$g_s \geq d_s \ \forall s \tag{9}$$

$$g_s \in H \ \forall s \tag{10}$$

where g_s and d_s represent objective function's value and non-cooperative point for stakeholder s, respectively. Eqs. 9 and 10 are the model's constraints, ensuring that stakeholders objective functions are greater than their non-cooperative thresholds, and objective functions fall in the criteria set H. Since NB maximizes the objective functions of bargainers, the utilities of LWWC (eq. 11.a), LEPO (eq. 11.b) and MOHME (eq. 11.c) can be defined in [0, 1] interval, as follows,

$$(g_1 - d_1) = LD \tag{11.a}$$

$$(g_2 - d_2) = 1 - \frac{1}{2880}\frac{1}{N}\sum_{n=1}^{N} \min\{b_i.TD_i^n\},\ \forall i \tag{11.b}$$

$$(g_3 - d_3) = 1 - \frac{1}{POP}\frac{1}{N}\sum_{n=1}^{N}\{b_i.PA_i^n - VaR_\alpha^{AP} | b_i.TD_i^n = \min\{b_i.TD_i^n\},\ \forall i\}. \tag{11.c}$$

The value of NS represents a constraint for followers' bargaining model, so that, $\sum_{\forall i} b_i = NS$. Eqs. 7 pose a checkpoint for the followers' model, so that if the compromise solution (from eq. 8) does not satisfy eqs. 7, the leader would eliminate the solution from further consideration. This single-objective optimization model is solved by the Genetic Algorithm (GA; Holland, 1992). GA is a heuristic search optimization algorithm, inspired by Charles Darwin's theory of natural evolution.

3.4. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

The multi-objective optimization model returns a tradeoff curve containing a set of optimal points, referred to as Pareto-points. Multi Criteria Decision Making (MCDM) methods can then be applied to select the most desired alternative among the Pareto-points based on the decision maker's priorities. In this study, we employ TOPSIS to select such scenario. In simple words, TOPSIS ranks the available alternatives based on their similarity to the ideal solution. If rows and columns of matrix AL represent different alternatives and criteria, respectively, the first step is to assign weights to each alternative and construct a matrix V according to:

$$V_{a,c} = \frac{AL_{a,c}}{\sqrt{\sum_a AL_{a,c}^2}} \times W_c \ \ \forall a, c, \tag{12}$$

where, a and c denote alternative and criterion, respectively, and W_c is the weight of criterion c. Next step is to find ideal and anti-ideal solutions for different criteria. Note that, if a criterion is of minimization type, eq. 13, and otherwise eq. 14, should be used to estimate ideal solution, A^+, and anti-ideal solution, A^-, respectively.

$$A_c^+ = \min_a\{V_{a,c}\} \ \ and\ A_c^- = \max_a\{V_{a,c}\}\ \forall a \tag{13}$$

$$A_c^+ = \max_a\{V_{a,c}\} \ \ and\ A_c^- = \min_a\{V_{a,c}\}\ \forall a \tag{14}$$

Then, the Euclidian distance of alternatives from the ideal solution, S_a^+, and anti-ideal solutions, S_a^-, should be calculated as,

$$S_a^+ = \sqrt{\sum_c \left(V_{a,c} - A_c^+\right)^2}\ \forall a, \tag{15}$$

$$S_a^- = \sqrt{\sum_c \left(V_{a,c} - A_c^-\right)^2}\ \ \forall a. \tag{16}$$

The final step is to calculate a score for each alternative, C_a^*. The ranking of alternatives is based on proximity to the ideal solution, with those closer to the ideal solution ranked higher.

$$C_a^* = \frac{S_a^-}{S_a^- + S_a^+},\ \forall a \tag{17}$$

Interested reader can find detailed discussion about TOPSIS in Yoon and Hwang (1981).

4. Results and discussion

Monte Carlo simulation (MCS) is used to generate 48,100 scenarios that cover different uncertain parameters of when, where and how contamination is introduced to the water distribution system (WDS) (Table 1). These scenarios are in turn used to force the EPANET model to simulate water quality in the Lamerd WDS. The collective run-time of scenario simulations is 2,110 seconds on a PC (CPU: Intel® Core™ i7-4500U; RAM: 12GB DDR3). Then, the time elapsed before contamination becomes detectable at the 20 potential locations for placement of sensors, as well as the population that are affected before contamination detection in every scenario are calculated. The results are two matrices of time to detection (TD) and affected population (AP) with columns and rows corresponding to the number of potential locations of sensors and the number of contamination scenarios, respectively. The minimum, average and maximum TD for the 20 potential locations of sensors, and minimum, average and maximum AP in all scenarios are depicted in Fig. 3.

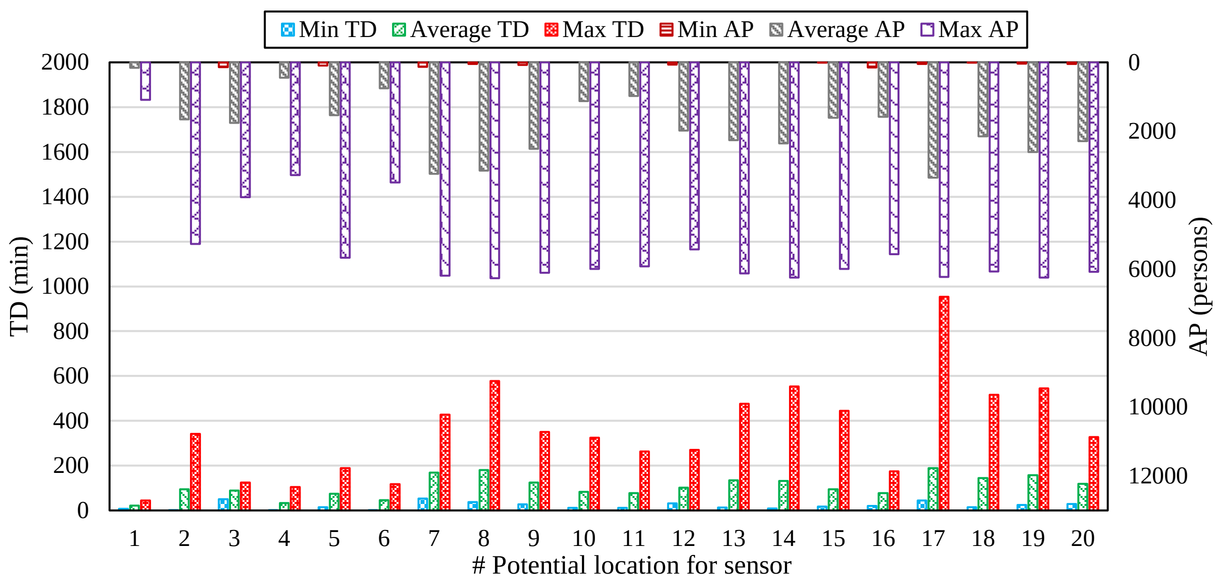

Fig. 3. Minimum, average and maximum time to detection (TD) at potential locations for sensor placement; and minimum, average and maximum affected

population (AP) in all scenarios. The locations are shown in Fig.1. The undetected scenarios are not included in calculations.

The two matrices of TD and AP are subsequently used as forcing for the leader-follower game (LFG) model. As mentioned earlier, the LFG model is a two-layer nested optimization model. Briefly, when the optimal number of sensors, NS (leader's objective at the upper level), is determined by NSGA-II, a single-objective optimization algorithm (GA) is employed to determine Nash equilibrium for the followers (lower level). The number of decision variables for NSGA-II is 1 and its population size is set to 20, while the maximum number of generations is set to 50. Since there is only one decision variable for NSGA-II, it is expected that the algorithm converges after a few generations. Furthermore, the number of binary decision variables for GA, which is used to find Nash equilibrium for the followers, is 20 (number of potential locations for placement of sensors). The population size for GA is set to 200 and maximum number of generations is set to 400. Other parameters used in the optimization algorithms are provided in Table 2.

Table 2. Parameters and run-time of the LFG model.

Parameter	NSGA-II	GA
Number of decision variables	1	20
Population size	20	200
Maximum number of generations	50	400
Population type	Mixed integer	Binary
Selection method	Tournament	Tournament
Crossover	Scattered	Scattered
Mutation	Adaptive Feasible	Adaptive Feasible
Crossover coefficient	0.2	0.2
Mutation coefficient	0.8	0.8
Function tolerance	10^{-6}	10^{-6}

LFG model returns a Pareto-front consisting of 14 Pareto-optimal points on the trade-off curve (Table 3) and the run-time of the model is 1,780 seconds on a PC (CPU: Intel® Core™ i7-4500U; RAM: 12GB DDR3). The short total run-time of both simulation and optimization model shows the efficiency of the proposed decision support LFG model. Roughly one hour is enough to obtain the optimal layouts that simultaneously satisfy the followers' objectives and comply with the leader's requirements. Moreover, this is an objective and straightforward algorithm, without any need to iteratively modify CWS designs as traditionally done.

The leader only determines the number of sensors (NS), while the followers design their compromise CWS layout from hundreds to thousands of possible CWS layouts. The obtained values of Nash equilibrium lie in the [0, 1] interval, where 0 and 1 represent minimum and maximum satisfaction of the followers, respectively. The maximum obtained value of Nash equilibrium is 0.99, when NS for design of CWS is more than 7 sensors. This shows that the followers are most satisfied when any CWS layout with more than 7 sensors is chosen.

Likelihood of detection (LD) is 100% for the CWS layouts with more than 7 sensors. Furthermore, best values for $CVaR_{0.95}^{TD}$, $CVaR_{0.95}^{AP}$, TD_{ave}, and AP_{ave} are 57.87 minutes, 627 persons, 15.33 minutes, and 86 persons, respectively, derived from the Pareto-point # 14. Worst results for these functions are obtained from the Pareto-point # 1, which are 2879.5 minutes, 5327 persons, 180.4 minutes, and 3136 persons, respectively. This shows that all the obtained layouts could not be considered as safe from security point of view. Note that about 5,000 scenarios could not be detected with a CWS layout with 1 sensor, and all scenarios can be detected by CWSs with more than 7 sensors. Obviously, all the CWSs with more than 7 sensors would be perfect choices from the detection likelihood point of view. Moreover, average affected population (AP) in all contamination scenarios for CWSs with less than 4 sensors is more than 1,000 people. This could be reduced to less than 100 people if CWSs with more than 12 sensors is chosen. Average time to detection (TD) has a wide range between 15 minutes to about 3 hours over all contamination scenarios. CWSs with more than 6 sensors can provide average TD below 30 minutes, while the difference of average TDs between CWSs with more than 6 sensors are only a few minutes. This implies that increasing number of sensors above 6 may not help with significantly reduce TD. Finally, the strength of the proposed decision support system is explicitly considering the robustness of the designed CWSs in form of CVaR. While the obtained $CVaR_{0.95}^{TD}$ ranges between less than an hour and about two days, the differences between the CWSs' $CVaR_{0.95}^{TD}$ with more than 7 sensors are only a few minutes. Similar conclusions can be drawn for CWSs' $CVaR_{0.95}^{Ap}$ with more than 10 sensors.

Table 3. Pareto-optimal solutions from the LFG multi-objective optimization model. The obtained values of $CVaR_{0.95}^{TD}$, $CVaR_{0.95}^{AP}$, Nash equilibrium, TD_{ave}, AP_{ave}, and LD are enlisted.

NS	Selected potential nodes for sensors	$CVaR_{0.95}^{TD}$ (min)	$CVaR_{0.95}^{AP}$ (persons)	Nash	TD_{ave} (min)	AP_{ave} (persons)	LD (%)
1	{8}	2879.5	5326.72	0.71	180.4	3136.39	88.82
2	{5,8}	1189.06	4191.3	0.91	98.52	1795.7	98.16
3	{5,8,14}	538.42	3582.06	0.95	76.5	1301.83	99.4
4	{5,6,8,14}	303.88	2863.47	0.97	57.09	850.93	99.85
5	{5,6,14,18,20}	223.33	2033.45	0.97	45.7	599.72	99.83

6	{4,5,6,8,13,14}	205.35	1893.55	0.98	37.39	381.57	99.93
7	{1,4,5,6,13,14,18}	250.23	1438.26	0.98	28.53	235.18	99.83
8	{1,4,5,6,8,13,14,19}	145.86	1658.83	0.99	28.88	265.4	100
9	{1,5,6,13,14,15,16,18,19}	123.05	1341.66	0.99	28.89	256.83	100
10	{1,4,5,6,7,10,14,15,18,19}	98.06	1178.03	0.99	21.95	167.41	100
11	{2,4,5,6,10,11,13,14,15,18,19}	72.7	681.74	0.99	18.36	115.08	100
12	{1,2,4,5,6,8,10,11,13,14,15,19}	66.3	722.06	0.99	15.99	101.94	100
13	{1,2,4,5,6,8,10,11,13,14,15,18,19}	62.16	654.85	0.99	15.54	89.38	100
14	{1,2,4,5,6,10,11,12,13,14,15,16,18,19}	57.87	627.07	0.99	15.33	86.42	100

As mentioned earlier, while the leader would like to minimize the number of sensors, $CVaR_{0.95}^{TD}$ and $CVaR_{0.95}^{AP}$, it also has infallible constraints of $CVaR_{0.95}^{TD} \leq 360$ minutes and $CVaR_{0.95}^{AP} \leq 0.05 \times POP$ (4050 people). These constraints are regarded as the robustness indices of the CWS designs by the leader. From Table 3, it can be seen that Pareto-optimal solutions with less than 4 sensors do not satisfy $CVaR_{0.95}^{TD} \leq 360$ minutes, while those with less than 3 sensors do not also satisfy $CVaR_{0.95}^{AP} \leq 4050$ people. Hence, Pareto-points #1, 2, and 3 will be eliminated from further consideration by the leader. The leader then chooses from the Pareto-optimal solutions using TOPSIS, which is a Multi Criteria Decision Making (MCDM) method. The leader considers similar weights for its criteria, including NS, which represents the costs of CWS, $CVaR_{0.95}^{TD}$, and $CVaR_{0.95}^{AP}$ which are robustness indices of CWS, respectively. The values of weighted dimensionless criteria, the ideal and anti-ideal solutions, the Euclidian distances of alternatives to ideal and anti-ideal solutions, their score, and alternative ranks are presented in Table 4.

Table 4. TOPSIS results, including values of weighted dimensionless criteria, V_1, V_2, and V_3, ideal and anti-ideal solutions, A^+, and A^-, Euclidian distances of alternatives to ideal and anti-ideal solutions, S^+, and S^-, their score, C^*, and ranks.

NS	V_1	V_2	V_3	S^-	S^+	C^*	Rank
4	-0.102	0.106	0.109	0.076	0.112	0.406	7
5	-0.101	0.074	0.095	0.111	0.078	0.589	6
6	-0.099	0.044	0.076	0.147	0.043	0.775	3
7	-0.093	0.015	0.045	0.187	0.011	0.945	1
8	-0.1	0.061	0.087	0.127	0.062	0.672	5
9	-0.103	0.139	0.123	0.041	0.147	0.22	9
10	-0.1	0.051	0.081	0.138	0.052	0.727	4
11	-0.103	0.112	0.112	0.07	0.118	0.373	8
12	-0.104	0.175	0.14	0.011	0.187	0.055	11
13	-0.097	0.031	0.064	0.163	0.026	0.86	2
14	-0.103	0.149	0.129	0.03	0.158	0.161	10
A^+	-0.104	0.015	0.045	-	-	-	-
A^-	-0.093	0.175	0.14	-	-	-	-

The Pareto-point with 7 sensors for design of CWS is selected as the most preferred alternative by the TOPSIS method. The scores of the set of Pareto-optimal solutions (Table 4) range between 0.055 and 0.945, indicating that the alternatives are widely distributed in the Euclidian space from the ideal point. The selected Pareto-point with a score of 0.945, however, is very similar to the ideal solution. In more detail, the selected point's distances from ideal and anti-ideal solutions are 0.011 and 0.187, respectively, which are the minimum (from ideal solution) and maximum distances (from anti-ideal solution) among all alternatives. Furthermore, the values of $CVaR_{0.95}^{TD}$ and $CVaR_{0.95}^{AP}$, are 250.23 min and 1,438 people. The value of Nash equilibrium for this alternative is 0.98, which is very close to the ideal value of 1, indicating that the followers are generally very satisfied with this alternative. The selected layout by the followers for this number of sensors ($NS = 7$) can detect 99.83% of simulated scenarios, which is near to perfection for any CWS design. The values of TD_{ave} and AP_{ave} are 28.53 min and 235 people, which correspond to less than 30 minutes and 0.3% of City's population, satisfying the leader's constraints.

5. Conclusions

Failure of critical infrastructure, due to sabotage or accidental events, could significantly harm public health and institutional confidence. Hence, several authority entities are involved in design and maintenance of public facilities aiming to secure sustainable and resilient service to the society. There often exists a direct responsible governmental organization that funds the process and is not willing to bargain for its criteria and/or priorities with other involved parties. Hence, other stakeholders have to bargain at a lower level to maximize their utilities, while satisfying the upper level authority's criteria. Such top-down decision making structure resembles the Leader-Follower Game (LFG) method.

One infrastructure prone to accidental and/or deliberate compromise is Water Distribution System (WDS). In recent years, several researchers have contributed to the field of deploying Contamination Warning Systems (CWS) in WDS to reduce the impacts of compromised water quality on the public. However, lack of a robust decision support system for deployment of CWS in WDS has been widely acknowledged. Such decision support systems should properly model the decision making structure and provide a solution capable of complying with the criteria of the involved parties. In this study, we propose a robust decision support framework for deployment of CWS in WDS based on LFG. To assess its efficacy, we successfully applied the proposed model for design of CWS in Lamerd City's WDS, in Fars province, Iran. The results show that the framework is capable of providing a solution that not only guarantees safety of the WDS against possible contamination events, but also provides a solution that is economically justifiable. The solution maximizes utilities of the involved parties, including the leader and the followers.

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