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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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A Robust Decision Support Leader-Follower Framework for Design of Contamination	1
Warning System in Water Distribution Network	2
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Sadegh⁴

Abstract

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In recent years, several models have been proposed to inoculate Water Distribution 6 Systems (WDS) against impacts of accidental and/or intentional compromised water 7 8 quality through optimal deployment of online monitoring sensors in the network, which is referred to as Contamination Warning Systems (CWS). Translating such 9 modeling efforts to real-world practice is, however, a challenge as different involved 10 parties may pursue conflicting goals and modeling-based recommendations may not 11 justify all stakeholders' criteria. It is, hence, pivotal to develop conflict resolution 12 methodologies to support engagement of different stakeholders in securing a safe 13 water distribution. The decision making structure for CWS design is often of top-14 down nature, with the upper level decision maker concerned mainly about public 15 safety and lower level stakeholders concerned about operational costs. In this study, 16 a decision support framework based on Leader-Follower Game is proposed, given 17 different power levels. Leader's objectives are focused on the CWS robustness, while 18 followers have conflicting interests that are in turn resolved via Nash Bargaining 19 method. Lamerd WDS (Fars, Iran) is selected to assess the proposed model's 20

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performance. The results show the proposed objective and parsimonious model21provides a robust solution that complies with the leader's criteria and maximizes the22followers' satisfaction. The proposed decision support system helps govern WDSs in23a resilient and safe manner and warrants practical implementation of modeling-based24security assurance policies to provide sustainable service to the society.25

Keywords

Decision support system; Top-down decision making structure; Robust sensor 27 placement optimization; Contamination warning system; Leader-follower game; 28 Conditional Value-at-Risk 29

30

1. Introduction

Ever since the terrorist attack of 9/11, protecting critical infrastructures emerged as a 32 top priority to decision and policy makers (Berry et al. 2005a). One of these 33 infrastructures is Water Distribution Systems (WDS), which are designed to deliver 34 safe drinking water to consumers (Preis and Ostfeld, 2008). However, WDSs are 35 inherently vulnerable to accidental and intentional contamination because of their 36 distributed geography and easy-to-access locations (Afshar and Khombi, 2015). 37 Historical incidents corroborate the WDSs' vulnerability and their catastrophic 38 impacts on public health (Forest et al. 2013). Contaminated drinking water delivered 39 through WDSs in Scotland (Gavriel et al. 1998), Canada (Hrudey et al. 2003) and 40 Japan (Yokoyama, 2007), leaving catastrophic societal impacts, intensifies concerns 41 regarding the security of WDSs (Arad et al. 2013; Khorshidi et al. 2018). This has 42

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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 46 on public health is to equip every junction of WDS with online sensors with a 47 centralized monitoring system, i.e. Contamination Warning System (CWS), to shut 48 49 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, 50 one type of PSA analyzer that monitors real-time heavy metal concentration in 51 potable water, with a 1 micro-grams per liter accuracy, costs between 3,000 to 5,000 52 USD (P. S. Analytical Co., 2018). Given the large number of junctions in a typical 53 WDS, the required investment is impractical. Moreover, not every location in a WDS 54 is technically feasible for placement of sensors (Berry et al. 2008). 55

From the early 2000s, multiple lines of study have contributed to the optimal 56 deployment of CWS in WDSs (Hart and Murray, 2010). They can be clustered into 57 three different categories: 1. rule-based, 2. opinion-based, and 3. optimization-based 58 approaches (Hu et al. 2018). The optimization-based approach has shown not only 59 superior performance to those of rule- and opinion-based approaches, but also has 60 been recognized as being more objective (Berry et al. 2008; Hart and Murray, 2010; 61 Khorshidi et al. 2018). Researchers have developed various single- or multi-objective 62 optimization models for determining optimal layouts of CWS (e.g. Berry et al. 2005b; 63 Shastri and Diwekar, 2006; Zhao et al., 2016). These objectives include impact on 64 public health, time from injection to detection of contamination, extent of 65 contamination, and likelihood of detecting contamination (Berry et al. 2012; Janke et 66 al. 2017; Khorshidi et al. 2018). 67

Two main obstacles inhibited practical application of those models' results for real-68 world problems: 1. constrained budget, and, 2. lack of a decision support framework 69 that could properly align with the decision making structure of the involved 70 stakeholders (Hart and Murray, 2010). To address the first obstacle, some researchers 71 have considered limited budget as a constraint in their proposed optimization model 72 (e.g. Berry et al. 2005b). Also, with an assumption of monotonic relationship between 73 the cost of deployment and maintenance of a CWS and the number of sensors used, 74 some researchers fixed, a priori, the number of sensors to be placed in WDS to fix 75 the associated costs (e.g. Berry et al. 2008; Weickgenannt et al., 2010; Tinelli et al., 76 2017), and others included minimizing number of sensors in a multi-objective 77 optimization scheme (e.g. Afshar and Marino, 2012; Bazargan-Lari, 2014; 78 Naserizade et al. 2018). 79

Developing a decision support framework that warrants cooperation of different 80 stakeholders can be even more complicated than the budget constraint (Hart and 81 Murray, 2010). As mentioned earlier, different objectives and various stakeholders 82 are involved in the CWS design and operation. While all objectives are obviously 83 important, different decision makers may prioritize one (some) objective(s) over 84 others (Janke et al. 2017). Despite the strives made in CWS deployment optimization 85 models, providing decision support systems to facilitate the decision making process 86 and resolve conflicts has received only little attention. Examples include Berry et al. 87 (2008 and 2012) and Janke et al. (2017), in which a regret-analysis framework is 88

incorporated in the TEVA-SPOT model. TEVA-SPOT is an optimization model, 89 which uses a single-objective optimization module and can be recursively executed 90 to perform multiple optimizations with various objectives (one at a time) and to 91 include different fixed number of sensors (Khorshidi et al. 2018). Then, the user 92 trades different CWS designs off in regret-analysis model to determine a comprise 93 solution among different alternatives (Berry et al. 2008 and 2012; Janke et al. 2017). 94 95 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 96 the concept of sensitivity region in their model, and Chang et al. (2011 and 2012) 97 98 considered three rules of "intensity", "accessibility" and "complexity" for near-99 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-100 optimal CWS layouts. The importance of providing a comprehensive and robust 101 decision support system for CWS design and operation has been further emphasized 102 in recent years (Hart and Murray, 2010; Janke et al. 2017; Hu et al. 2018). 103

104 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 105 bargain" for their respective criteria. In real world, however, critical issues, such as 106 107 protecting public health and confidence in the supply system, often receive a highlevel governmental overlook that is actively involved in funding, designing and 108 implementing procedures. Such organizations - which could be considered as leaders 109 - set clear guidelines for related operations including specific criteria that could even 110 lead to impasses at times. There are also other public and/or private sectors 111

(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 115 Game (LFG; Benchekroun and Van Long, 2001; Yang et al. 2015; Van Ackooija et 116 al. 2018) is proposed, in which the leader funds the CWS deployment and sets clear 117 guidelines on costs and robustness of CWS. The leader's criteria are (i) minimizing 118 the CWS cost that could provide a certain level of Conditional Value-at-Risk (CVaR; 119 Rockafellar and Uryasev, 2000 and 2002) of affected population (AP) and (ii) 120 minimizing time to detection (TD). Note that CVaR is defined as expected value at 121 the tale of loss distribution function at a certain level. The followers follow different 122 interests, and they bargain to reach a compromise solution in form of the Nash 123 equilibrium (Nash, 1953). The proposed model is a two-layer nested optimization 124 model in which the first layer is leader's multi-objective optimization model, 125 constrained in a lower level by the followers' single objective bargaining model. 126 These will be discussed in details later. The model is applied to a real-world case 127 study of CWS deployment in Lamerd WDS, Fars province, Iran. For this purpose, 128 numerous possible contamination events are simulated via EPANET water quality 129 model (Rossman, 2000) using Monte-Carlo Simulation (MCS). The simulation 130 results are then used as the optimization model forcing. This offline simulation 131 approach is widely used in the literature (e.g. Berry et al. 2012; Janke et al. 2017; 132 Naserizade et al. 2018). The results show that the model is capable of providing 133 optimal solutions, which could satisfy the stakeholders' criteria. 134 Novelty of the proposed decision support framework lies in incorporating the top-135 down approach in the decision making structure using the Leader-Follower Game, 136 which replicates the distribution of power in CWS design and operation in the real-137 world. Moreover, robustness of the final design layouts is also considered as an 138 important performance index in the decision making process. This framework is 139 general and can be employed for resilient development of an important infrastructure, 140 WDS, to provide sustainable service to the society. The objectives and power levels, 141 among other parameters, in this framework can be adjusted to fit the real-world 142 143 situations of any target study.

2. Case Study

The WDS of Lamerd City (Fig.1), Fars province, Iran, is designed and constructed to145supply approximately 260 liters of potable water per capita per day to about 81,000146consumers. The hourly multipliers of the base demand are shown in Fig. 2. The WDS147constitutes of 2 reservoirs, 1 tank, 185 pipes, 122 junctions and 23 hydrants.148



Fig. 1. Lamerd City's Water Distribution System. Potential locations for placement150

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 of156possible contamination intrusion on public health. Arsenic is deadly at low dosages,157and is a cheap and accessible toxic heavy metal. This substance is, therefore,158frequently used in the CWS design studies (e.g. Bazargan-Lari, 2014; Naserizade et159al. 2018). A critical dose of Arsenic, *CD* (milligrams), is defined as the dose that160could inflict harm depending on the exposed person's weight, *WP* (kg), and can be161calculated as (Shafiee and Zechman, 2013),162

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

Assuming a person weights 70 kg on average, their health could be critically affected 163 by ingesting 3.5 mg of Arsenic, according to Equation 1. In this study, it is assumed 164 that (i) a person ingests contamination only through drinking contaminated water, 165 and (ii) every person drinks 0.93 liters of water per day (similar to Shafiee and 166 Zechman, 2013). The population who ingested 3.5 mg of Arsenic or more is 167 considered as "Affected Population (AP)" throughout this study. 168

One of the challenges in sensor placement problems is the natural lack of knowledge 169 170 about when, where and how contamination is introduced to the WDS. To address uncertainties associated with a contamination intrusion, Monte Carlo Simulation 171 (MCS) is employed in this study. Various scenarios of contamination injection in 172 WDS are defined with injection duration, time and location, as well as mass of 173 Arsenic as uncertain input variables in MCS. Injection duration and mass of 174 substance are considered in 40 to 80 minute intervals, and 200 to 700 mg/sec flux 175 range. Also, 13 injection times in a day and 17 possible injection locations (including 176 14 hydrants, the tank and two reservoirs) are considered in MCS (Table 1). 177

Contamination injection from the remaining 9 hydrants has no or very low impact on 178 population's health due to the hydraulic characteristics of the WDS, and hence are 179 not considered in scenario analysis (Naserizade et al., 2018). Moreover, successive 180 injection times have been chosen according to the base demand's hourly multipliers 181 (Fig. 2). When the demand rate is at its highest, the time-gap between two successive 182 injections is the smallest, and vice versa. The reason is to consider injection scenarios 183 in which the contamination could be consumed at a higher rate and hence, the affected 184 population is more compared to other injection scenarios. All combinations of the 185 aforementioned variables define the contamination injection scenarios. A total of 186 48,100 contamination scenarios are generated and simulated in a MCS scheme using 187 188 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 189 scenarios are eliminated in the analysis. The hydraulic and water quality model of 190 191 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 192 60-second time-step for both hydraulic and water quality modules. Furthermore, wall 193 reaction coefficient is not considered for quality simulations, as Arsenic does not 194 react with the materials of pipe wall. However, bulk flow reaction is considered 195 (-0.05 day^{-1}) in the water quality simulation. In this study, a detection limit of 0.01 196 mg per liter is considered for the sensors, similar to Naserizade et al. (2018) and 197 Khorshidi et al. (2018). As defined by Janke et al. (2017), sensor's detection limit is 198 a concentration threshold above which the used sensor is completely reliable for 199 detection of contamination, and fully unreliable otherwise (binary performance). The 200

results of MCS are then used for calculation affected population and time to detection				
at 20 potential locations for sensors (Fig.1).	202			

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Table 1. Variables used for Monte Carlo Simulation, and parameters used in EPANET204water quality simulation.205

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

206

207 Iran's National Disaster Management Organization (NDMO) is a governmental agency that funds and supervises critical operations concerned with prevention and/or 208 209 management of possible accidental or intentional hazards. NDMO is, hence, responsible to fund and supervise the design and operation of CWSs by other sectors 210 211 including Lamerd Water and Wastewater Company (LWWC), Lamerd Environmental Protection Organization (LEPO), and Lamerd's branch of Ministry of 212 Health and Medical Education (MOHME). The guidelines of NDMO instruct that the 213 Conditional Value-at-Risk (CVaR; to be discussed later) of both affected population 214 (AP) and time to detection (TD) at 95% confidence level should not exceed 5% of 215 216 City's population and 6 hours, respectively. LWWC is responsible for design and 217 implementation of CWS that maximizes the likelihood of detecting contamination (LD). According to the existing legislations, LWWC should also consider the criteria 218 set by LEPO and MOHME in the CSW design. These criteria include minimization 219

of average time to detection (TD_{ave}) , and minimization of average affected 220 population (AP_{ave}) . In this setting, NDMO can be considered as leader whose utility 221 has higher priority than other stakeholders, and LWWC, LEPO and MOHME can be 222 considered as followers. 223

224

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3. Methods

3.1. Conditional Value-at-Risk (CVaR)

A decision vector, x, is associated with an expected loss probability density function 226 (pdf) in scenario-based analysis, and the confidence level, α , is defined as a certain 227 cumulative probability; e.g. 0.8, 0.9 and 0.95. The minimum expected loss exceeding 228 the confidence level α is defined as Value-at-Risk (VaR), and Conditional Value-at-229 Risk (CVaR) of the loss pdf at confidence level α is defined as the weighted average 230 of losses exceeding VaR (Rockafellar and Uryasev, 2002). Let z = f(x, y) represent 231 loss pdf, which is a function of decision vector $x \in X$ and random vector $y \in Y$. The 232 cumulative pdf of losses, $\Psi(x, z)$ would be defined as in eq. 2. Also, VaR and CVaR 233 at the confidence level $\alpha \in [0,1]$ can be defined as in eq. 3 and eq. 4, respectively. 234

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

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

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

where, *P* and *E* denote probability function and expected value operator, 235 respectively. Rockafellar and Uryasev (2000) proved that when a finite number of 236 scenarios (*N*) represent the random vector *y*, CVaR would be equal to minimized F_{α} 237 over *x* and *v* in (Soltani et al. 2016), 238

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

where v represents VaR and p(n) is probability of scenario n. 239

240

3.2. Leader-Follower Game (LFG)

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Several governmental and public organizations, often with conflicting objectives, are 242 involved in protecting infrastructure against terrorist attacks. Directly responsible 243 organizations stand firm for their priorities (usually public safety) due to the critical 244 nature of the problem, and other stakeholders compete in the restricted available 245 space. Decision making structure is then of top-down type, resembling leader-246 247 follower game (LFG). In this game, an authority agent, a.k.a. the leader, has the 248 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 249 250 outlines of the NDMO (leader). Furthermore, followers do not know about the 251 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 252 MOHME are considered as followers with equal power in the bargaining process, 253 because from management point of view they are regarded as organizations with the 254 same level of importance in governmental hierarchy. However, as mentioned earlier, 255 the model could be simply modified to account for different level of power for the 256 followers, LFG is a two-layer nested optimization model. The first layer is the 257 leader's and the second is the followers' optimization models, respectively. 258

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 261 a monotonic relationship with its number of sensors. Hence, the leader's objectives 262 are: 1. Minimizing number of sensor (Z_1) , 2. Minimizing CVaR of TD (Z_2) , and, 3. 263 Minimizing CVaR of AP (Z_3) , as represented in, 264

minimize: $Z_1 = NS$,

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

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 265 variable equal to 0 if a sensor is not placed at node *i*, and 1 otherwise. TD for scenario 266 $n (TD^n)$ is the minimum time elapsed before contamination becomes detectable at 267 nodes that are equipped with a sensor; hence, TD^n is equal to min $\{b_i, TD_i^n\}$ (eq. 6.b). 268 Affected population for scenario $n (AP^n)$ corresponds to TD^n (eq. 6.c). VaR and 269 CVaR represent value at risk and conditional value at risk, respectively. As 270 mentioned earlier, the leader's model has two constraints: 271

$$CVaR_{\alpha}^{TD} \le 360 \text{ minutes}$$
 (7.a)

$$CVaR^{AP}_{\alpha} \le 0.05 \ POP$$
 (7.b)

where, *POP* is the total population of the City (about 81,000). The leader's multi-272objective optimization model is handled by the Non-dominated Sorting Genetic273Algorithm II (NSGA-II; Deb et al. 2000 and 2002, Alizadeh et al. 2017).274

3.2.2. Followers' bargaining model

275

(0)

285

In the first layer of the LFG model (leader's model), the leader only decide how many 276 sensors should be placed in WDS, while the layout of CWS is determined by the 277 278 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 279 are maximizing LD (likelihood of detection), minimization of TD_{ave} (time to 280 detection), and minimization of AP_{ave} (affected population), respectively. The Nash 281 Bargaining (NB) method is used to resolve the followers' bargaining process. NB is 282 a single-objective optimization problem (eq. 8), which can find a fair compromise 283 solution when bargainers make decisions simultaneously. 284

$$Maximize: Z = \prod_{s} (g_s - d_s)$$
⁽⁸⁾

Subject to:

 $g_s \ge d_s \,\forall s \tag{9}$

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

where g_s and d_s represent objective function's value and non-cooperative point for 286 stakeholder *s*, respectively. Eqs. 9 and 10 are the model's constraints, ensuring that 287 stakeholders objective functions are greater than their non-cooperative thresholds, 288 and objective functions fall in the criteria set *H*. Since NB maximizes the objective 289 functions of bargainers, the utilities of LWWC (eq. 11.a), LEPO (eq. 11.b) and 290 MOHME (eq. 11.c) can be defined in [0, 1] interval, as follows, 291

$$(g_1 - d_1) = LD$$
 (11.a)

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

$$(g_3 - d_3) = 1 - \frac{1}{POP} \frac{1}{N} \sum_{n=1}^{N} \{b_i \cdot PA_i^n - VaR_{\alpha}^{AP} | b_i \cdot TD_i^n = \min\{b_i \cdot TD_i^n\},$$

$$\forall i\}.$$
(11.c)

292

The value of *NS* represents a constraint for followers' bargaining model, so that, 293 $\sum_{\forall i} b_i = NS$. Eqs. 7 pose a checkpoint for the followers' model, so that if the 294 compromise solution (from eq. 8) does not satisfy eqs. 7, the leader would eliminate 295 the solution from further consideration. This single-objective optimization model is 296 solved by the Genetic Algorithm (GA; Holland, 1992). GA is a heuristic search 297 optimization algorithm, inspired by Charles Darwin's theory of natural evolution. 298

3.4. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) 299

The multi-objective optimization model returns a tradeoff curve containing a set of 300 optimal points, referred to as Pareto-points. Multi Criteria Decision Making 301 302 (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 303 TOPSIS to select such scenario. In simple words, TOPSIS ranks the available 304 alternatives based on their similarity to the ideal solution. If rows and columns of 305 matrix AL represent different alternatives and criteria, respectively, the first step is to 306 assign weights to each alternative and construct a matrix V according to: 307

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

where, *a* and *c* denote alternative and criterion, respectively, and W_c is the weight of 308 criterion *c*. Next step is to find ideal and anti-ideal solutions for different criteria. 309 Note that, if a criterion is of minimization type, eq. 13, and otherwise eq. 14, should 310 be used to estimate ideal solution, A^+ , and anti-ideal solution, A^- , respectively. 311

$$A_{c}^{+} = \min_{a} \{ V_{a,c} \} \text{ and } A_{c}^{-} = \max_{a} \{ V_{a,c} \} \forall a$$
(13)

$$A_{c}^{+} = \max_{a} \{ V_{a,c} \} \text{ and } A_{c}^{-} = \min_{a} \{ V_{a,c} \} \forall a$$
(14)

Then, the Euclidian distance of alternatives from the ideal solution, S_a^+ , and anti-ideal 312 solutions, S_a^- , should be calculated as, 313

$$S_{a}^{+} = \sqrt{\sum_{c} \left(V_{a,c} - A_{c}^{+} \right)^{2}} \,\,\forall a,$$
(15)

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

The final step is to calculate a score for each alternative, C_a^* . The ranking of 314 alternatives is based on proximity to the ideal solution, with those closer to the ideal 315 solution ranked higher. 316

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

Interested reader can find detailed discussion about TOPSIS in Yoon and Hwang317(1981).318

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320

4. **Results and discussion**

Monte Carlo simulation (MCS) is used to generate 48,100 scenarios that cover 321 different uncertain parameters of when, where and how contamination is introduced 322

to the water distribution system (WDS) (Table 1). These scenarios are in turn used to 323 324 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® 325 CoreTM i7-4500U; RAM: 12GB DDR3). Then, the time elapsed before contamination 326 becomes detectable at the 20 potential locations for placement of sensors, as well as 327 the population that are affected before contamination detection in every scenario are 328 329 calculated. The results are two matrices of time to detection (TD) and affected 330 population (AP) with columns and rows corresponding to the number of potential locations of sensors and the number of contamination scenarios, respectively. The 331 minimum, average and maximum TD for the 20 potential locations of sensors, and 332 minimum, average and maximum AP in all scenarios are depicted in Fig. 3. 333



Fig. 3. Minimum, average and maximum time to detection (TD) at potential335locations for sensor placement; and minimum, average and maximum affected336

population (AP) in all scenarios. The	e locations are shown in Fig.1	. The undetected	337
scenarios are no	t included in calculations.		338

The two matrices of TD and AP are subsequently used as forcing for the leader-339 follower game (LFG) model. As mentioned earlier, the LFG model is a two-layer 340 nested optimization model. Briefly, when the optimal number of sensors, NS 341 (leader's objective at the upper level), is determined by NSGA-II, a single-objective 342 optimization algorithm (GA) is employed to determine Nash equilibrium for the 343 followers (lower level). The number of decision variables for NSGA-II is 1 and its 344 population size is set to 20, while the maximum number of generations is set to 50. 345 Since there is only one decision variable for NSGA-II, it is expected that the 346 347 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, 348 is 20 (number of potential locations for placement of sensors). The population size 349 for GA is set to 200 and maximum number of generations is set to 400. Other 350 parameters used in the optimization algorithms are provided in Table 2. 351

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}

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

LFG model returns a Pareto-front consisting of 14 Pareto-optimal points on the trade-354 off curve (Table 3) and the run-time of the model is 1,780 seconds on a PC (CPU: 355 Intel® CoreTM i7-4500U; RAM: 12GB DDR3). The short total run-time of both 356 simulation and optimization model shows the efficiency of the proposed decision 357 support LFG model. Roughly one hour is enough to obtain the optimal layouts that 358 simultaneously satisfy the followers' objectives and comply with the leader's 359 requirements. Moreover, this is an objective and straightforward algorithm, without 360 any need to iteratively modify CWS designs as traditionally done. 361

The leader only determines the number of sensors (*NS*), while the followers design 362 their compromise CWS layout from hundreds to thousands of possible CWS layouts. 363 The obtained values of Nash equilibrium lie in the [0, 1] interval, where 0 and 1 364 represent minimum and maximum satisfaction of the followers, respectively. The 365 maximum obtained value of Nash equilibrium is 0.99, when *NS* for design of CWS 366 is more than 7 sensors. This shows that the followers are most satisfied when any 367 CWS layout with more than 7 sensors is chosen. 368

Likelihood of detection (LD) is 100% for the CWS layouts with more than 7 sensors. 369 Furthermore, best values for $CVaR_{0.95}^{TD}$, $CVaR_{0.95}^{AP}$, TD_{ave} , and AP_{ave} are 57.87 370 minutes, 627 persons, 15.33 minutes, and 86 persons, respectively, derived from the 371 Pareto-point # 14. Worst results for these functions are obtained from the Pareto-372 point # 1, which are 2879.5 minutes, 5327 persons, 180.4 minutes, and 3136 persons, 373 374 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 375 with a CWS layout with 1 sensor, and all scenarios can be detected by CWSs with 376

more than 7 sensors. Obviously, all the CWSs with more than 7 sensors would be 377 perfect choices from the detection likelihood point of view. Moreover, average 378 affected population (AP) in all contamination scenarios for CWSs with less than 4 379 sensors is more than 1,000 people. This could be reduced to less than 100 people if 380 CWSs with more than 12 sensors is chosen. Average time to detection (TD) has a 381 wide range between 15 minutes to about 3 hours over all contamination scenarios. 382 CWSs with more than 6 sensors can provide average TD below 30 minutes, while the 383 384 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 385 significantly reduce TD. Finally, the strength of the proposed decision support system 386 is explicitly considering the robustness of the designed CWSs in form of CVaR. 387 While the obtained $CVaR_{0.95}^{TD}$ ranges between less than an hour and about two days, 388 the differences between the CWSs' $CVaR_{0.95}^{TD}$ with more than 7 sensors are only a 389 few minutes. Similar conclusions can be drawn for CWSs' $CVaR_{0.95}^{Ap}$ with more than 390 10 sensors. 391

Table 3. Pareto-optimal solutions from the LFG multi-objective optimization392model. The obtained values of $CVaR_{0.95}^{TD}$, $CVaR_{0.95}^{AP}$, Nash equilibrium, TD_{ave} ,393

AP_{ave} , and LL	are enlisted.
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	$CVaR_{0.95}^{TD}$	$CVaR_{0.95}^{AP}$		TD_{ave}	AP _{ave}	LD
Selected potential nodes for sensors	(min)	(persons)	Nash	(min)	(persons)	(%)
{8}	2879.5	5326.72	0.71	180.4	3136.39	88.82
{5,8}	1189.06	4191.3	0.91	98.52	1795.7	98.16
{5,8,14}	538.42	3582.06	0.95	76.5	1301.83	99.4
{5,6,8,14}	303.88	2863.47	0.97	57.09	850.93	99.85
{5,6,14,18,20}	223.33	2033.45	0.97	45.7	599.72	99.83
	Selected potential nodes for sensors {8} {5,8} {5,8,14} {5,6,8,14} {5,6,14,18,20}	$CVaR_{0.95}^{TD}$ Selected potential nodes for sensors(min) $\{8\}$ 2879.5 $\{5,8\}$ 1189.06 $\{5,8,14\}$ 538.42 $\{5,6,8,14\}$ 303.88 $\{5,6,14,18,20\}$ 223.33	CVaR ^{TD} _{0.95} CVaR ^{AP} _{0.95} Selected potential nodes for sensors (min) (persons) {8} 2879.5 5326.72 {5,8} 1189.06 4191.3 {5,8,14} 538.42 3582.06 {5,6,8,14} 303.88 2863.47 {5,6,14,18,20} 223.33 2033.45	CVaR ^{TD} _{0.95} CVaR ^{AP} _{0.95} Selected potential nodes for sensors (min) (persons) Nash {8} 2879.5 5326.72 0.71 {5,8} 1189.06 4191.3 0.91 {5,8,14} 538.42 3582.06 0.95 {5,6,8,14} 303.88 2863.47 0.97 {5,6,14,18,20} 223.33 2033.45 0.97	$CVaR_{0.95}^{TD}$ $CVaR_{0.95}^{AP}$ TD_{ave} Selected potential nodes for sensors(min)(persons)Nash(min) $\{8\}$ 2879.55326.720.71180.4 $\{5,8\}$ 1189.064191.30.9198.52 $\{5,8,14\}$ 538.423582.060.9576.5 $\{5,6,8,14\}$ 303.882863.470.9757.09 $\{5,6,14,18,20\}$ 223.332033.450.9745.7	$CVaR_{0.95}^{TD}$ $CVaR_{0.95}^{AP}$ TD_{ave} AP_{ave} Selected potential nodes for sensors(min)(persons)Nash(min)(persons){8}2879.55326.720.71180.43136.39{5,8}1189.064191.30.9198.521795.7{5,8,14}538.423582.060.9576.51301.83{5,6,8,14}303.882863.470.9757.09850.93{5,6,14,18,20}223.332033.450.9745.7599.72

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
1							

As mentioned earlier, while the leader would like to minimize the number of sensors, 396 $CVaR_{0.95}^{TD}$ and $CVaR_{0.95}^{AP}$, it also has infallible constraints of $CVaR_{0.95}^{TD} \leq 360$ minutes 397 and $CVaR_{0.95}^{AP} \leq 0.05 \times POP$ (4050 people). These constraints are regarded as the 398 robustness indices of the CWS designs by the leader. From Table 3, it can be seen 399 that Pareto-optimal solutions with less than 4 sensors do not satisfy $CVaR_{0.95}^{TD} \leq 360$ 400 minutes, while those with less than 3 sensors do not also satisfy $CVaR_{0.95}^{AP} \leq 4050$ 401 people. Hence, Pareto-points #1, 2, and 3 will be eliminated from further 402 consideration by the leader. The leader then chooses from the Pareto-optimal 403 solutions using TOPSIS, which is a Multi Criteria Decision Making (MCDM) 404 method. The leader considers similar weights for its criteria, including NS, which 405 represents the costs of CWS, $CVaR_{0.95}^{TD}$, and $CVaR_{0.95}^{AP}$ which are robustness indices 406 of CWS, respectively. The values of weighted dimensionless criteria, the ideal and 407 anti-ideal solutions, the Euclidian distances of alternatives to ideal and anti-ideal 408 409 solutions, their score, and alternative ranks are presented in Table 4.

395

Table 4. TOPSIS results, including values of weighted dimensionless criteria, V_1 , 410

 V_2 , and V_3 , ideal and anti-ideal solutions, A^+ , and A^- , Euclidian distances of 411 alternatives to ideal and anti-ideal solutions, S^+ , and S^- , their score, C^* , and ranks. 412

NS	<i>V</i> ₁	V_2	V_3	<i>S</i> ⁻	<i>S</i> +	С*	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	-	-	-	-

413

The Pareto-point with 7 sensors for design of CWS is selected as the most preferred 414 alternative by the TOPSIS method. The scores of the set of Pareto-optimal solutions 415 (Table 4) range between 0.055 and 0.945, indicating that the alternatives are widely 416 417 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 418 selected point's distances from ideal and anti-ideal solutions are 0.011 and 0.187, 419 420 respectively, which are the minimum (from ideal solution) and maximum distances (from anti-ideal solution) among all alternatives. Furthermore, the values of 421 $CVaR_{0.95}^{TD}$ and $CVaR_{0.95}^{AP}$, are 250.23 min and 1,438 people. The value of Nash 422 equilibrium for this alternative is 0.98, which is very close to the ideal value of 1, 423 indicating that the followers are generally very satisfied with this alternative. The 424 selected layout by the followers for this number of sensors (NS = 7) can detect 425 99.83% of simulated scenarios, which is near to perfection for any CWS design. The 426 values of TD_{ave} and AP_{ave} are 28.53 min and 235 people, which correspond to less 427 than 30 minutes and 0.3% of City's population, satisfying the leader's constraints. 428

5. Conclusions

429

Failure of critical infrastructure, due to sabotage or accidental events, could 430 significantly harm public health and institutional confidence. Hence, several 431 432 authority entities are involved in design and maintenance of public facilities aiming 433 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 434 bargain for its criteria and/or priorities with other involved parties. Hence, other 435 stakeholders have to bargain at a lower level to maximize their utilities, while 436 satisfying the upper level authority's criteria. Such top-down decision making 437 structure resembles the Leader-Follower Game (LFG) method. 438

One infrastructure prone to accidental and/or deliberate compromise is Water 439 440 Distribution System (WDS). In recent years, several researchers have contributed to the field of deploying Contamination Warning Systems (CWS) in WDS to reduce the 441 impacts of compromised water quality on the public. However, lack of a robust 442 decision support system for deployment of CWS in WDS has been widely 443 444 acknowledged. Such decision support systems should properly model the decision making structure and provide a solution capable of complying with the criteria of the 445 involved parties. In this study, we propose a robust decision support framework for 446 deployment of CWS in WDS based on LFG. To assess its efficacy, we successfully 447 applied the proposed model for design of CWS in Lamerd City's WDS, in Fars 448 449 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,	450
but also provides a solution that is economically justifiable. The solution maximizes	451
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