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Selecting the Best Location of Water Quality Sensors in Water Distribution Networks by Considering the Importance of Nodes and Contaminations using NSGA-III (Case Study: Zahedan Water Distribution Network, Iran)

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Abstract

Water quality sensors are one of the most effective ways to minimize the catastrophic consequences of pollution in water distribution networks (WDNs). The main challenge is arranging sensors properly in the network. In this study, the NSGA-III algorithm is developed to improve the optimal locations of sensors by balancing four conflicting objectives. 1. Detection likelihood, 2. Expected detection time, 3. Detection redundancy, and 4. The affected nodes before detection. The proposed procedure is based on chlorine concentration variation between defined upper and lower limits. The upper and lower bounds of chlorine concentration were determined utilizing the Monte Carlo simulator. To deal with the problem of a large size matrix of possible contaminants a heuristic method was utilized for selecting a representative collection of contaminations with the same characteristics and effects. Importance coefficients were introduced to avoid the same importance of contamination events and network nodes. The proposed simulation-optimization approach was tested on the benchmark and real water networks, then the optimal Pareto fronts were computed for each of the two sets of conflicting objectives. Moreover, the sensitivity analysis related to the number of sensors installed in the networks was conducted for the results obtained from different objective functions. According to the sensitivity analysis, the Pareto fronts became more efficient when the number of sensors increased. Also increasing the number of sensors to more than 10 and 15 in the benchmark and real systems, respectively, will provide little additional detection likelihood.

Keywords: Chlorine concentration, Contaminant detection, Contamination of important nodes, NSGA-III, Water distribution systems, Sensor placement strategy.

1. Introduction

The urban water distribution system (WDS) is one of an indispensable part of public infrastructure around the globe because of its relation to economic and social activities (Nafi 2018; Qian et al. 2021). WDS is a complex network, consisting of a collection of nodes, pumps, reservoirs, valves, storage tanks, treatment facilities, and numerous links (Adedoja et al. 2018a; de Winter et al. 2019; Nilsson et al. 2005; Palleti et al. 2016, 2018; Preis and Ostfeld 2008). The main function of WDS is to deliver fresh water at the standard quantity and quality levels from sources such as storage tanks, rivers, lakes, and reservoirs to commercial, industrial and residential users (de Winter et al. 2019; Mazumder et al. 2019; Priya et al. 2018).

Due to WDS large size, complex configurations, and many access points, they are highly vulnerable to different contamination events (radioactive, chemical, or biological contaminants) that can be accidental, resulting from cross-connections, pipe bursts, wastewater backflow, intrusion of contaminated water due to pressure reduction, polluted source, or deliberate (e.g., terrorist attacks) (Costa et al. 2013; De Sanctis Annamaria et al. 2010; Di Nardo et al. 2014; Huang and McBean 2009; Ostfeld et al. 2008).

A remarkable number of pollution incidents have been recorded in recent decades. examples of accidental pollutants include: Milwaukee, US (Mac Kenzie et al. 1994; Corso et al. 2003), Nokia, Finland (Laine et al. 2011), the United States (Adedoja et al. 2018a), Lanzhou, China (Chinadaily 2014), Walkerton, Ontario, Canada (Hrudey et al. 2003), Tuscany, Italy (Nuvolone et al. 2021), West Virginia (Rosen et al. 2014; Whelton et al. 2015; Cooper 2014), Ohio (Wilson 2014), Strasbourg, France (Deshayes et al. 2001) and recently two accidental events of waterborne diseases due to bacterial infection are recorded in California and Norway (Qiu et al. 2020;). Also, in recent years intentional contaminations have been reported, The United States is the most famous example of this, especially after 9/11 (Ostfeld et al. 2008). Other cases include: Moscow (Lambrou et al. 2015), Scotland (Gavriel et al. 1998), the united states, and Japan (Yokoyama 2007) events.

When the contaminants enter the network will distribute across the network through pipes and can cause irreparable damage to consumers' health (like cholera, diarrhea, paratyphoid, typhoid, hepatitis A, etc. (Butt and Iqbal 2007; Nabeela et al. 2014)) besides social and economic instability (Adedoja et al. 2018b; Liu et al. 2011; Sun et al. 2019; Xin et al. 2017). Several recent cases have demonstrated this, for example, the consumption of polluted water by Walkerton, Ontario residents caused approximately 2,300 hospitalizations (Hrudey et al. 2003) or accidental pollution of an industrial chemical in West Virginia WDS (USA) affected over 300,000 people (Cooper 2014; Rosen et al. 2014; Whelton et al. 2015). The spread of polluted water through the distribution network in Milwaukee polluted more than 400,000 users and hospitalized at a cost of about 96.2 million $ as well (Corso et al. 2003; Mac Kenzie et al. 1994).

Unfortunately, many of the intentional and accidental pollutions recorded in human history have not been identified until consumers have consumed the contaminated water for a long time, which has caused economic and public health losses and adverse social effects. In general, some contaminants, such as high concentrations of chlorine can be detected by consumers due to changes in the color and odor of water. But what happens if a contaminant enters the network, that has no color or odor for easy detection by consumers? What happens if a hazardous substance enters the network accidentally or negligently from areas where chemicals are used for agriculture or toxic waste is stored? Or even worse, what happens if someone deliberately injects a harmful pollutant into the water distribution network? Studies have confirmed that attacks on water distribution networks are real, as they have occurred previously and might happen again (Adedoja et al. 2018b). Thus, to prevent

significant disasters it is necessary to identify and warn about contamination events within the WDS, protect water quality against accidental and intentional contamination events and manage possible pollution events. The first step toward achieving this goal is improving the physical security of the system (e.g. fencing, guarding, additional alarms, surveillance instruments, locks, etc.) (Preis and Ostfeld 2008). The second step is utilizing monitoring sensors, a contamination warning system, (CWS) also known as an early warning system (EWS) to monitor water quality (Grayman et al. 2016). The third step is to develop effective response plans to neutralize or remove or minimize the impact of contaminants entering the network. It is possible to gain the maximum level of water safety by monitoring all nodes in the system, systematically (Adedoja et al. 2018b; Yazdi. 2018). But it is not feasible to install sensors at every node of the network due to the high cost, budget constraints, and maintenance issues (Adedoja et al. 2018a, b). To cope with these restrictions only a limited number of these sensors are required to be installed at specific key places in the water network. Therefore, to achieve efficient monitoring, it is necessary to develop optimal water quality sensor placement (WQSP) strategies for WDSs.

Sensor optimization investigation in the network started in the 1990s and has continued up to now. The issue based on the number of objective functions is classified as a single objective optimization problem (Al-Zahrani and Moeid 2001; Berry et al. 2006, 2009; Cheifetz et al. 2015; Comboul and Ghanem 2013; Hu et al. 2017; Kessler et al. 1998; Ohar et al. 2015; Ostfeld and Salomons 2004, 2005; Propato 2006; Propato and Piller 2006; Schwartz et al. 2014; Shastri and Diwekar 2006; Woo et al. 2001) and multiple objective optimization problems (Afshar and Miri Khombi 2015; Bazargan-Lari 2014; de Winter et al. 2019; Dorini et al. 2008; Eliades and Polycarpou 2006; Gueli 2008; He et al. 2018; Huang et al. 2008; Khorshidi et al. 2018, 2019; McKenna et al. 2006; Naserizade et al. 2018; Nazempour et al. 2018; Ostfeld et al. 2008; Ostfeld and Salomons 2008; Preis and Ostfeld 2008; Wu and Walski 2006).

Several objectives for the design of water quality sensor placement have been considered so far to detect pollution events as quickly as possible and minimize their effect, including the following: (1) Time of Detection (TD) (Kessler et al. 1998), (2) Demand Cover (DC) (Lee and Deininger 1992), (3) Detection Likelihood (DL)(Ostfeld and Salomons 2008), (4) Volume of Contaminated water consumed by users (VC)(Kessler et al. 1998), (5) Population Exposed to contamination (PE)(Berry et al. 2004), (6) Mass Consumed (MC)(Rathi and Gupta 2016), (7) Extent of Contamination (EC)(Rathi and Gupta 2016), (8) Number of Failed Detections (NFD)(Rathi and Gupta 2016), (9) Sensor Response Time (SRT)(Rathi and Gupta 2016), (10) Sensor Detection Redundancy (SDR)(Rathi and Gupta 2016) and (11) Total Length of polluted pipes (TL)(Watson et al. 2004).

Among the single objective methods: Lee and Deininger (1992) defined the total demands of nodes that are monitored by sensors as demand coverage (DC). They utilized mixed-integer linear programming (MILP) to optimally locate quality sensors in the network to maximize DC. Kumar et al (1997) developed the method used by Lee and Deininger. They calculated the residual chlorine concentration at each node and estimated the DC values based on it. Kessler et al (1998) defined the level of service as the maximum volume of contaminated water that is in a concentration more than the minimum danger level and consumed before the contamination is detected and introduced. They presented an algorithm to determine the optimal location of sensors based on the level of service. Kumar et al (1999) Defined time of detection as the time elapsed from the entry of the contaminant into the network to the time detected by the sensors. Al-Zahrani and Moeid (2001, 2003) modified the demand coverage using a Genetic Algorithm (GA). Ostfeld and Salomons (2004) used a genetic algorithm to find the optimal layout of sensors based on the level of service for accidental or deliberate events. Ostfeld and Salomons

(2005) developed their previous work by considering uncertainties for the demands and pollution events. Comboul and Ghanem (2013) described the analysis of uncertainty for the best sensor location to maximize the percentage of contamination detection. Rafi Schwartz et al. employed genetic algorithms to determine the optimal location of quality sensors to minimize the exposed consumers. Cheifetz et al (2015) introduced a greedy incremental sensor's placement method to be utilized for the optimization of quality sensors in a large real-world water distribution network. Rathi and Gupta (2016) considered maximizing the detection likelihood and water demand coverage as objective functions to determine the optimal location of sensors in water networks. They first normalized two objectives and then weighted them in a linear single objective function. Hu et al (2017) investigated the sensor placement in a large water network, utilizing a Spark-based genetic algorithm. In their study, the objective was minimizing the impact of contamination. They illustrated that the proposed model has a good performance by Comparing the results of the proposed model with the experimental results.

Simultaneous, In the context of multi-objective optimization, McKenna et al (2006) examined the ability of sensors to minimize the detection time of events, the population exposed to pollution, and the contamination extent within the network by considering the number and detection limits for sensors. They illustrated that the discovery of contamination events is reliant on the detection limits. Ami Preis and Avi Ostfeld (2008) utilized a multi-objective model for designing quality sensors to maximize two objectives of detection likelihood and sensor detection redundancy and minimize detection time. Dorrini et al (2008) employed the Noisy Cross-Entropy (nCE) algorithm for solving the optimization problem to minimize the detection time, the expected demand for polluted water, the affected population, and the maximization of detection likelihood. Aral et al. (2010) to optimally locate the sensors in network, four different objective functions: Detection time, affected population, consumed contaminated water, and detection likelihood using genetic algorithm were considered. Bazargan-Lari (2014) proposed a methodology, using NSGA-II four conflicting objectives of detection time, undetected contamination events, affected population before detection, and the number of sensors are minimized. Afshar and Miri Khombi (2015) presented two mathematical models for the best layout of sensors as dynamic double use benefit model (DDUBM) and the static double use benefit model (SDUBM) that provide a tradeoff between demand coverage and consumption of polluted water. They tested the validity of their proposed models utilizing two example problems with multi-objective ant colony optimization (ACO) algorithm. Antunes and Dolores (2016) employed the NSGA-II algorithm to determine the optimal locations for a set of sensors by considering four objective functions detection likelihood, detection time, consumption of contaminated water, and affected consumers before detection. Nazempour et al (2018) presented a new model applying complex network theory by considering that a WDS is a compound system. Two objective functions of maximizing the coverage of sensors and water demand coverage are studied by the authors. Naserizade et al (2018) presented a new model based on Conditional Value at Risk (CVaR) for best sensor placement in water systems. Four objective functions using the NSGA-II algorithm are developed to minimize detection time, affected population, cost, and the percentage of undetected events. Khorshidi et al (2019) used a decision support framework based on the game theory by considering the two goals of minimizing the detection time and the sensor cost for the optimal locations of quality sensors. Ponti et al (2021) proposed a novel evolutionary algorithm to estimate and analyze the optimal solutions of Pareto for sensor placement problems. Evaluation of the results of the new algorithm with the NSGA-II algorithm on a water distribution system through applying two objective functions demonstrated an improvement of this algorithm comparing with NSGA-II, especially for low iteration counts. Recently, Xu et al (2022) developed a new sensor

placement approach, integrating multi-objective optimization and a reduced order model, to minimize costs and maximize the performance of monitoring.

A review of previous studies on the CWS problem shows some simplifying assumptions as below: In many previous studies, sensors were designed for a fixed demand pattern. While in a real water network, owing to many consumers, the demand is not constant and fluctuates over time. Fluctuations in demand may cause significant variations in pipe flows and delay in contaminant propagation across the water network. Also, in most of the research, the pollutant entering the network has been considered conservative, which can affect the location of the sensor. The conservative assumption of pollutant may lead to an inaccurate impact approximation and spread of the pollutant, because a contaminant entering the network may decrease its concentration over time or produce a toxic substance with its products across the water network. For example, the results of Klosterman's investigation exhibited that in the case of employing adsorption models (reaction with the wall), the concentration of bulk arsenate and consumer exposure is significantly lower than the conservative assumption (Klosterman et al. 2014). Therefore, the optimal location of the sensors will be changed. Moreover, the type of pollutant detection sensor in previous studies has not been determined and it has been assumed that the sensor in the network detects the smallest concentration of conservative pollutants using a small and predetermined threshold in the network. Unfortunately, this assumption is unrealistic. Due to budget constraints, it is not possible to install sensors that detect a specific type of contamination with the smallest concentration fluctuations, as each network is exposed to different contaminants. It has been confirmed that chlorine has a significant reaction to both microbial and chemical contamination. Thus, in the present study, for a more realistic simulation, chlorine sensors have been utilized to detect contaminants entering the distribution network. In the proposed approach, chlorine concentration is compared to certain computed lower and upper periodic bounds for each node and various times. bounds are set, to record variations in chlorine concentration, by several Monte Carlo simulations considering uncertainty in demand patterns and roughness coefficients. Using chlorine sensors can be an inexpensive solution because they are currently used for monitoring water quality at many water stations.

In most previous research, sensors have been designed for a series of random or specific scenarios with a limited number of contaminants. In other words, researchers have considered limitations for injection node, starting time, duration, and mass rate of pollutant entering to network. Then, based on these limitations, they designed the optimal location of the sensors. In a real network with a complex topology, contamination events can occur at any node and in any time with any mass rate and duration time. Therefore, the number of possible events is uncountable and considering a limited and specific number of pollutions is unrealistic. Considering all the different possible events makes the design of sensors impossible. So, a pollution matrix is employed in this study by utilizing genetic algorithm which represents the most representative contaminants entering the network. Unlike previous research, the importance of pollutants in the contamination matrix and the importance of nodes in the water network are not considered the same in this investigation. In other words, pollutants that have major influences on consumers are more important and nodes that, if infected, have a lot of harmful effects on consumers are more vital. So, with the presentation of two new coefficients, the sensors have been designed such that important contaminants are identified earlier than other contaminants and important nodes are not infected. Finally, a multi-objective optimization approach is applied to determine the optimal location of the sensors in the WDN to maximize sensor detection likelihood and detection redundancy, as well as minimize sensor expected detection time, and percentage of affected nodes.

2. Material and methods

2.1. EPANET

In this research for simulating the chlorine concentration and the effect of a contamination event distributed through the water network, the EPANET 2.0 and EPANET-MSX software were utilized. EPANET is a simulator performing an extended period simulation of hydraulic and water quality behavior (simulation of residual chlorine) within a drinking water distribution system. In the quality analysis, the concentration is calculated at each node and time step (Rossman 2000). The quality analysis in EPANET are advection, diffusion, and reactions that are expressed as follows:

$$\frac{\partial c_i}{\partial t} = -u_i \frac{\partial c_i}{\partial x} \pm R(c_i) \quad (1)$$

In this equation, c_i, u_i and $R(c_i)$ are the concentration of the contaminant in the ith pipe at time t and location x (mg/L), the velocity of water in the ith pipe (m/s) and the term for the reaction rate including the wall and bulk reactions, respectively.

2.2. EPANET-MSX

EPANET's limitation in simulating only a single chemical species makes it unsuitable for simulating the transport and the decay of chlorine in response to specific pollutants. An extended version of the original EPANET is developed that can model the transport and the decay of multi-chemical species. This software is referred to as EPANET-MSX (Multi-Species Extension) (Shang et al. 2008). In the quality analysis, the concentration is calculated at each node and time step. The quality analysis in EPANET-MSX is expressed as follows:

$$\frac{d[A]}{dt} = -k_1[A][D] - k_3[A][C] \quad (2)$$

$$\frac{d[D]}{dt} = -k_2[A][D] \quad (3)$$

$$\frac{d[C]}{dt} = -k_4[A][C] \quad (4)$$

In these equations, A, D and C represent chlorine, dissolved organic carbon (DOC), and contaminant concentration, respectively. K_1 and k_2 are reaction rate coefficients between chlorine and DOC. K_3 and K_4 are reaction rate coefficients between chlorine and contaminant.

In the present study arsenic, a cheap and available toxic heavy metal, was selected as the contaminant. In the water network arsenic reacts with chlorine and produces arsenate, then the adsorption of arsenate onto the exposed iron on the pipe wall surface occurs.

The EPANET and EPANET-MSX include Programmers Toolkit, a dynamic-link library, that allows users to customize the EPANET and EPANET-MSX computing engine according to their requirements (Rossman 2000). The output of this can be used as the input to MATLAB. Then this software is utilized for optimizing the location of sensors in distribution networks. The methods of evolutionary computation, such as genetic algorithms are beneficial and powerful tools in optimization problems, and solving searches for their unbiased nature allow them to perform very well in situations with little domain knowledge (Gong et al. 2014, 2015). The NSGA-III, an improved version of GA and NSGAII (Srinivas and Deb 1994), is one of the most efficient algorithms for many-objective evolutionary algorithms.

2.3. NSGA-III algorithm

In this study the objective functions conflict with each other; hence, no single answer can be obtained that optimizes all functions simultaneously. Therefore, multi-objective optimization or many-objective optimization methods should be used. Usually, multi-objective optimization problems (MOP) are defined for problems having

two or three objectives, while optimization problems with four or more objectives are categorized as many-objective optimization problems (MaOP) (Gu andWang 2020).

During the past decades, evolutionary algorithms (EAs) have been developed to solve multi and many-objective optimization problems. In this research, the evolutionary optimization algorithm known as the Non-dominated Sorting Genetic Algorithm (NSGA-III) has been used (Deb and Jain 2013). NSGA-III is designed for multi and many-objective optimizations. This algorithm has demonstrated its efficiency in solving optimization problems such as economic/environmental dispatch problems (Bhesdadiya et al. 2016), hydro-thermal-wind scheduling (Yuan et al. 2015), engineering design problems (Gaur et al. 2017), industrial symbiosis system (Cao et al. 2020), rush order insertion rescheduling (He et al. 2020), Feature Selection (Zhu et al. 2017), Biomedical Search Engines (Gupta et al. 2021), air quality in buildings (Martínez-Comesaña et al. 2022) and so on. The basic framework of NSGA-III is like the NSGA-II algorithm, But the method of selection in NSGA-III is different from the original NSGA-II (Deb and Jain 2013).

Let's consider the t-th generation of NSGA-III and NSGA-II algorithms. In both algorithms, the parent population is P_t with size N. Both use crossover and mutation operators to create an offspring population of Q_t having N members. Subsequently, the parent and offspring populations are combined $R_t = P_t \cup Q_t$ (of size 2N). Now, In the next step in both algorithms, based on the elite preservation approach, to select a new generation, the best N members of R_t must be chosen. To achieve this, they employ fast non-dominated sorting to sort R_t population according to different ranks (F1, F2 and so on). Then both select the top N members based on rank (the lower rank is better); But to choose between two members with the same rank, NSGA-II uses the crowding distance (any individual that has a large crowding distance is better). But NSGA-III Algorithm utilizes a selection method based on updating abundant reference points (a careful niching strategy) to provide diversity, and members with the least represented reference points are selected. So, NSGA-III easily generates the first solution, it is more efficient and faster than the original NSGA-II in solving multi and many optimization problems (Deb and Jain 2013; Jain and Deb 2013). Figures 1 and 2 illustrate the selection mechanisms in two algorithms and the Flowchart of NSGA-III, respectively.

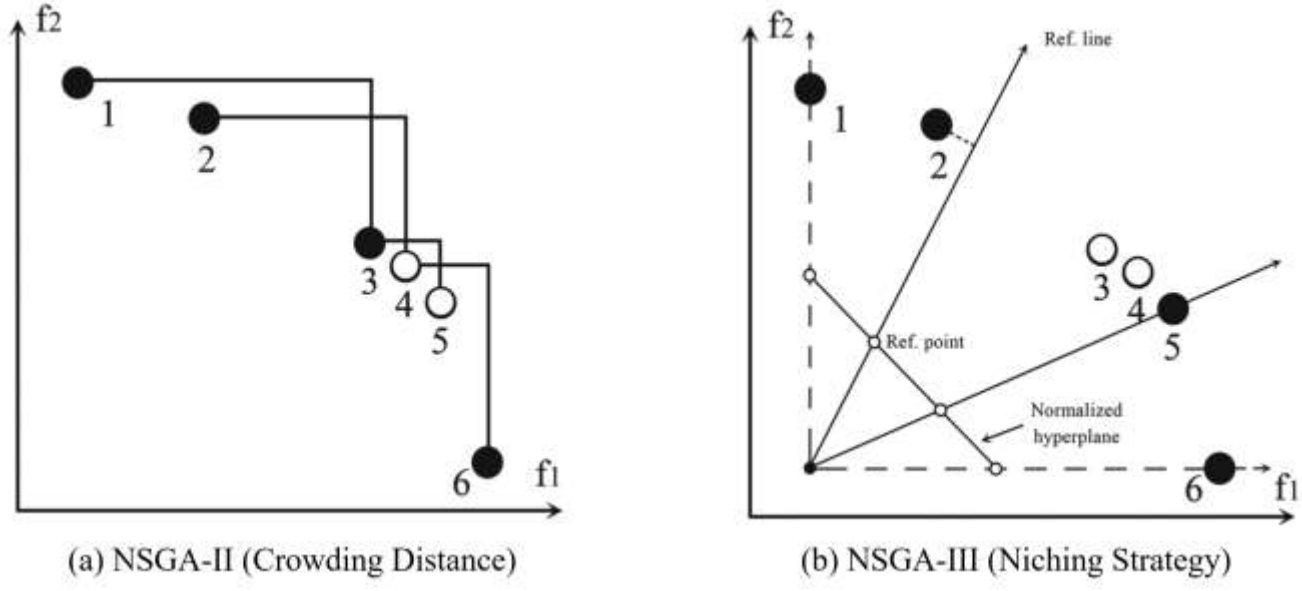

Fig.1 NSGA-II and NSGA-III Selection Methods

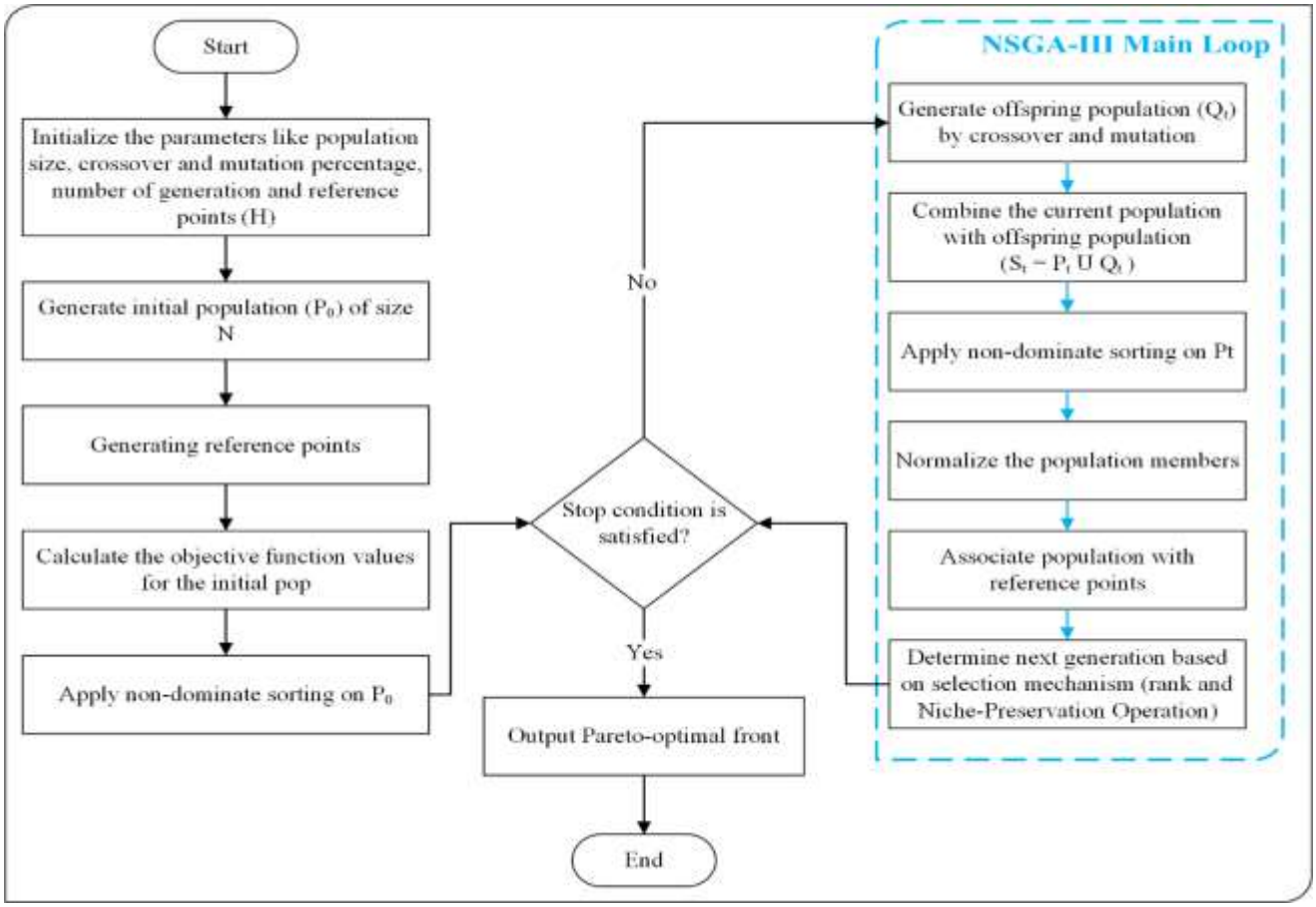

Fig. 2 Flowchart of NSGA-III Algorithm

2.4. Objective Functions

The aim of this research is to optimize the locations of quality sensors in the network as part of the battle of the water sensors networks (BWSN) utilizing the NSGA-III algorithm. The assumptions of the research are given below:

1- Contamination events can occur at any time of the day.

2- Each contamination event can occur at one point in the network.

3- pollutant reacts with other species like residual chlorine in the water network.

4- All nodes except booster nodes can be a possible location for the monitoring station.

5- Response time of the system is assumed to be 30 and 90 minutes for small and large networks, respectively. In the other words, when any of the sensors detect contamination, after 30 or 90 minutes the network is closed and during this time the monitoring station will record data.

6- Monitoring stations record concentrations every 10 minutes.

7- The sensors can record concentration fluctuations greater than 0. 01 mg/l without any errors.

Four specific objectives are considered for the optimal locations of water quality sensors in the network:

1- Sensor detection likelihood (f_1), 2- Sensor expected detection time (f_2), 3- Sensor detection redundancy (f_3), and 4- Percentage of affected consumer nodes (f_4).

2.4.1. Sensor detection likelihood (f_1)

In a specific layout of sensors, the probability of detection is described as below:

$$f_1 = \frac{1}{TS}\sum_{i=1}^{TS} d_i \quad (5)$$

In this equation, TS denotes the total number of contamination scenarios. d_i equal to one If the difference between the chlorine concentration and the lower bound of the allowable chlorine concentration in the candidate location of the sensor at three consecutive simulation time steps is more than 0.01 (the least assumed accuracy for the sensors), and d_i=0 otherwise.

It should be noted that in this study, unlike previous studies, to reduce the false-positive detection by sensors, it is assumed that if the sensor detects the presence of contamination for at least three consecutive time steps, contamination will be considered as detected contaminants. The optimal location of the sensors is where f_1 is maximized.

2.4.2. Sensor expected detection time (f_2)

For each pollution incident, the elapsed time from the start of the contamination event, to the first identified presence of contaminant by a sensor is defined as the time of detection by a sensor. t_i is the time of the first detection by ith sensor. The time of detection (t_d) is the minimum detection time among all sensors present in this design.

$$t_d = min\, t_i \tag{6}$$

The sensor expected detection time is computed by:

$$E(t_d) = \frac{1}{\sum_{i=1}^{TS} d_i} \sum_{i=1}^{TS} td_i \times I[t_d(i,t)] \tag{7}$$

where $E(t_d)$ represents the mathematical expectation of the minimum detection time t_d. As previously stated in this study the importance of contaminants in the contamination matrix is not considered the same. The contamination which is infected more nodes should be detected quickly than the others. This concept is considered in the present study for determining the optimal location of the sensors using modified sensor expected detection time as follow:

$$f_2 = Modified\ E(t_d) = \frac{1}{\sum_{i=1}^{TS} d_i} \sum_{i=1}^{TS} td_i \times I[t_d(i,t)] \times IF_i \tag{8}$$

$$I\,[t_d\,(i,\,t)] = \begin{cases} 1 & t_d(i,t) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

$$IF = \frac{1}{N} \sum_{i=1}^{N} PN_i \tag{10}$$

Where N is the total number of nodes in the network, PN_i = 1, If the difference between the chlorine concentration and the lower bound of the allowable chlorine concentration in the node at three consecutive simulation time steps is more than 0.01 (the minimum assumed accuracy for the sensors) e.g. the node is polluted and PN_i =0 otherwise. $I[t_d(i,t)]$ = 1, if the contamination identified by sensors and equal zero otherwise. IF is the impact factor, utilizing this coefficient the optimal location of the sensors is selected in such a way that the contaminants that infect more nodes of the network are detected earlier.

2.4.3. Sensor detection redundancy (f_3)

The development of sensors that detect the contamination in water distribution networks in real-time is still ongoing research, although there will be an uncertainty in sensor detections. Then, to avoid false-positive sensor detections and to increase the reliability of sensor detections it is necessary to increase redundancy among sensors. A triply redundant measure that three sensors were required at least to detect the presence of contaminant

concentration at a maximum time of 30 minutes between the first and third detections is considered. For each event, the redundancy of a sensor network design is equal to 1 if all the following conditions are true. Also, if at least one of them is false the redundancy is equal to 0.

1. $|t_1 - t_2| \leq 30$ min
2. $|t_1 - t_3| \leq 30$ min (11)
3. $|t_2 - t_3| \leq 30$ min

Where t_1, t_2, and t_3 are the detection times by sensor 1, sensor 2, and sensor 3 respectively.

The redundancy (f_3) for a sensor network design is:

$$f_3 = \frac{1}{\sum_{i=1}^{TS} d_i} \sum_{r=1}^{TS} R_r \quad (12)$$

$$R_r = \begin{cases} 1 & |t_1 - t_3| \leq 30 \text{ min} \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

2.4.4. Percentage of affected consumer nodes (f_4)

In previous research, the percentage of affected nodes is defined as follows:

$$PAF = \left(\frac{1}{N} \sum_{i=1}^{N} PN_i\right) \times 100 \quad (14)$$

Where $PN_i = 1$ if the node is polluted; otherwise $PN_i = 0$ and N denotes the total number of nodes in the water distribution network. As previously stated in this study the importance of contaminants and nodes in the contamination matrix are not considered the same. So, optimal sensor placement in the network should prevent infection of nodes with high demands.

For each water distribution network, several nodes have no demand. In other words, they do not have a consumer. These nodes are considered inactive nodes (internal nodes), and nodes that have demand are considered active nodes. Therefore, in this section, the percentage of nodes that have demand and have been infected before system response has been calculated. This objective function should be minimized and could be expressed as follows:

$$f_4 = \text{Modified PAF} = \left(\frac{1}{N} \sum_{i=1}^{N} PN_i\right) * D_i * IF_i \times 100 \quad (15)$$

$$IF = \frac{\sum_{t=0}^{t=t_d+t_r} D(i,t)}{\sum_{i=1}^{N} \sum_{t=0}^{t=t_d+t_r} D(i,t)} \quad (16)$$

D_i is the demand of nodes it equals one if the node demand is greater than zero, otherwise, it is equal to zero. $D(i,t)$, t_r and IF are the demand of node i at time t, the response time, and the impact factor respectively. According to this factor, the nodes that have more demands should be protected by sensors before being infected.

2.5. Case studies

In this study, to design water quality sensors by applying the proposed approach two different networks with different complexity and characteristics are considered: a small benchmark network (44 nodes) and a real water network of large size (916 nodes). Various types of analyses were conducted for every network, including a base run, contamination simulations, and sensitivity analyses.

2.5.1. Case study 1

Various researchers have used the southern region of Central Connecticut water distribution network to test and validate water quality models numerous times. Munavalli and Kumar (2003) modified the reaction coefficient (i.e. bulk and wall coefficients) and the location of booster stations of this network. In this study, the modified network of Munavalli and Kumar, shown in figure 3. a, was employed. This network consists of 37 nodes (consumer and internal nodes), 48 pipes linking the nodes, one elevated storage tank, one pump station, and six booster stations, represented by letters A to F. Time steps for water quality and hydraulic simulations were 10 minutes, and the demand flow patterns were 24 hr.

2.5.2. Case study 2

The proposed approach was applied to a real water distribution network in southeastern Iran (Zahedan city) which is shown in figure 3. b. This network is more complex and larger than case study 1. The topology of this network consists of 916 nodes (consumer and internal nodes), 1025 pipes linking the nodes, two pump stations, two reservoirs, and 10 booster stations. Time steps for water quality and hydraulic simulations were 10 minutes, and the demand flow patterns were 24 hr.

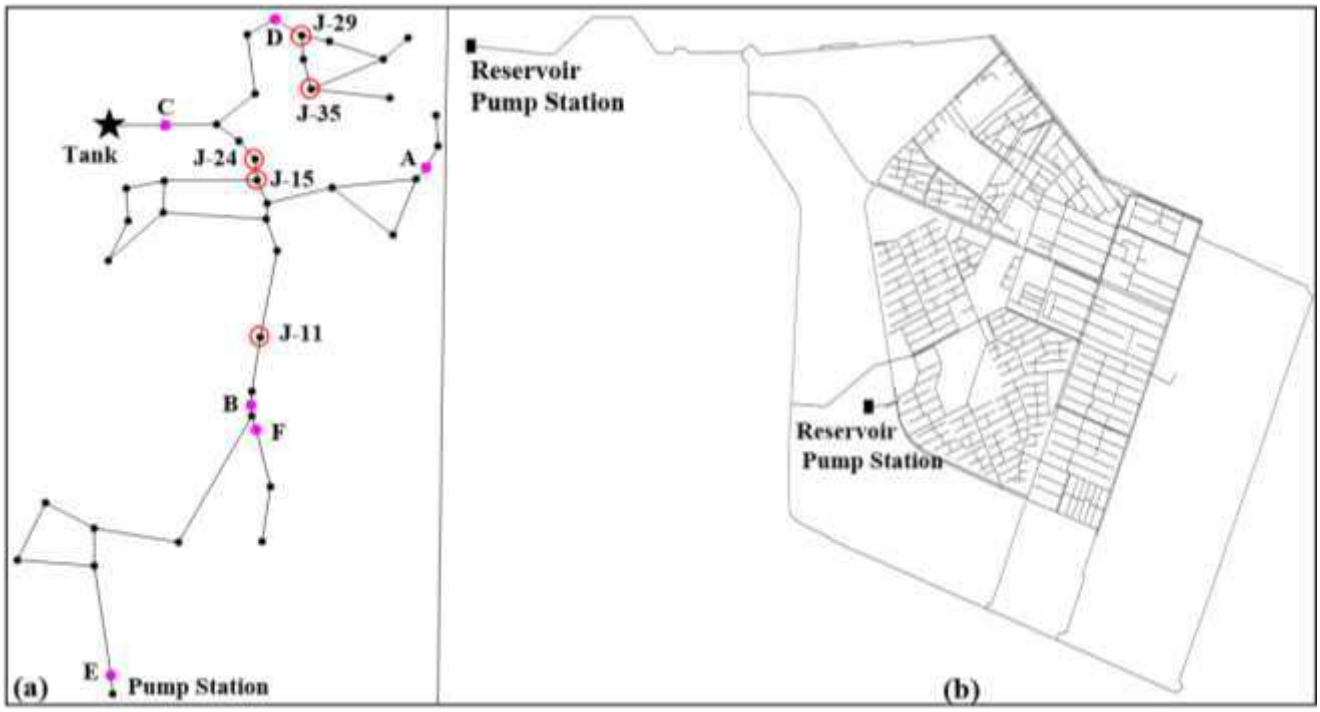

Fig. 3 (a) Benchmark WDN (b) Real WDN

2.6. Contamination Matrix

To evaluate the fitness function of the sensor network detection likelihood (f1), the sensor network detection redundancy (f3), and to evaluate the cost function of sensor expected detection time (f2), and percentage of affected consumer nodes (f4) a contamination matrix should be produced. To construct a contamination matrix, assumptions about the number, starting time, mass rate, duration of injection, and location of contaminations must be considered. In this study the following assumptions for networks are considered:

1- number of injections: one node

2- starting time of injection: randomly selected from the beginning to the end of the simulation.

3- mass rate of injection: randomly selected between 0.03 and 0.12 gr/min and between 0.05 to 0.2 gr/min for benchmark and real network, respectively.

4- duration of injection: randomly selected between 30 and 240 and between 10 to 100 min for benchmark and real network, respectively.

5- location of injection: randomly selected from all nodes excluding dead ends.

The contamination matrix in this research for benchmark network has 26112 contamination events, which is obtained as follows: injecting at 34 nodes (The number of dead-end nodes is 4, which is subtracted from the total number of network nodes as well as the tank is added), every 30 min for 24 hours, four mass injection rates of 0.03, 0.06, 0.09, and 0.12 gr/min, at four injection durations of 40, 80, 150, and 220 minutes (i.e. 34*48*4*4=26112 events). Also, the contamination matrix for the real network has 463872 contamination events. injecting at 604 nodes (The number of dead-ends and booster nodes is 312, which is subtracted from the total number of network nodes), every 30 min for 24 hours, four mass injection rates of 0.05, 0.1, 0.15, and 0.2 gr/min, at four injection durations of 10, 20, 60, and 90 minutes (i.e. 604*48*4*4=463872 events).

2.7. Construction of reduced contamination matrix

Contamination events can occur at any node and at any time with any mass rate and duration times. Therefore, as the size of the system increases, the number of possible contamination events increases and is uncountable. To deal with this problem, Preis and Ostfeld (2008), presented a heuristic process that utilized a small sample of contaminants that represented the total possible contaminants. Instead of employing the entire contamination matrix, they used a sampling approach able to select the most representative contaminations and obtained similar results to those achieved utilizing the full matrix. They developed the following formulas to create a set of contaminants that included a reduced contamination matrix:

$$\text{Minimize: } \sum_{i=1}^{5} |AS_i - AN_i| + |\sigma S_i - \sigma N_i| \quad (17)$$

$$\text{Subject to: } q_j > 0 \quad j = 1,2,\ldots,N \quad (18)$$

Where AS_i and S_i are average and standard deviation values of the geographical x coordinate of a sampled contamination events set. AN_i and N_i are average and standard deviation values of the geographical x coordinate of the water distribution system nodes. q_j is discharge flow from node j, and N is the total number of system nodes. In these equations, i=2 refers to the geographical y coordinate; i=3 represents the injection mass rate; i=4 expresses the injection starting time, and i=5 is the injection duration time.

Equation 18 states that when searching for the sample, the nodes located at the endpoints of the network should not be used because if the infection enters the network in these nodes, the infection will not spread in the network. By solving the optimization problem presented in Equations 17 and 18, we come to a sample of pollution, which represents the total pollution of the pollution matrix. This optimization problem is solved using a genetic algorithm. To create a reduced matrix by equations 17 and 18, 1000 contamination events were selected and these reduced matrices were utilized as contamination events that are injected into the two networks (case studies 1 and 2) and optimization is performed based on these contamination events. This study's general outline is presented in Figure 4.

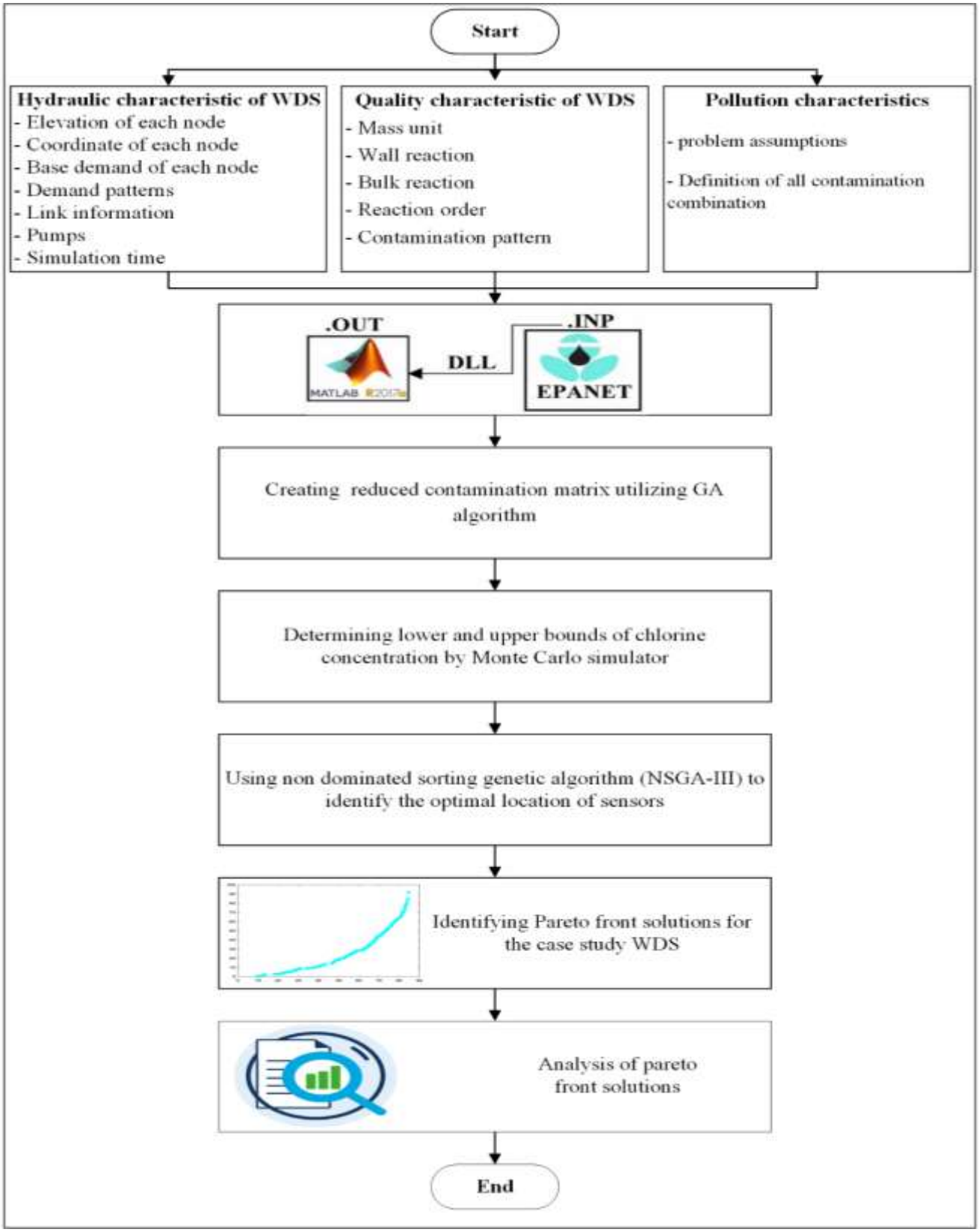

Fig. 4 Simulation–optimization flowchart of the research

2.8. Contamination detection with chlorine boundaries

As previously mentioned, in this study, the contamination event detection is based on chlorine concentration changes. Utilizing chlorine concentration sensors is more realistic and cost-effective. The chlorine concentration

in the water network must first be determined for all nodes at different times under normal conditions (conditions without contaminants in the network). In general, when chlorine is injected into the distribution network, after a period, the chlorine concentration reaches a steady condition in the network. Figure 5 illustrates the changes in chlorine concentration at node J-11 (see figure 3. a) during a 10-daysimulation of the benchmark network. As can be seen, the chlorine concentration is in a steady state from the fifth day. Therefore, pollutants can enter the network from the beginning to the end of the sixth day. Also, the effects of contaminant entry into the network up to 24 hours after injection have been evaluated in order to locate the sensors optimally. Therefore, the simulation period time for network 1 was considered 7 days with 10 min time steps and a response time of 60 min.

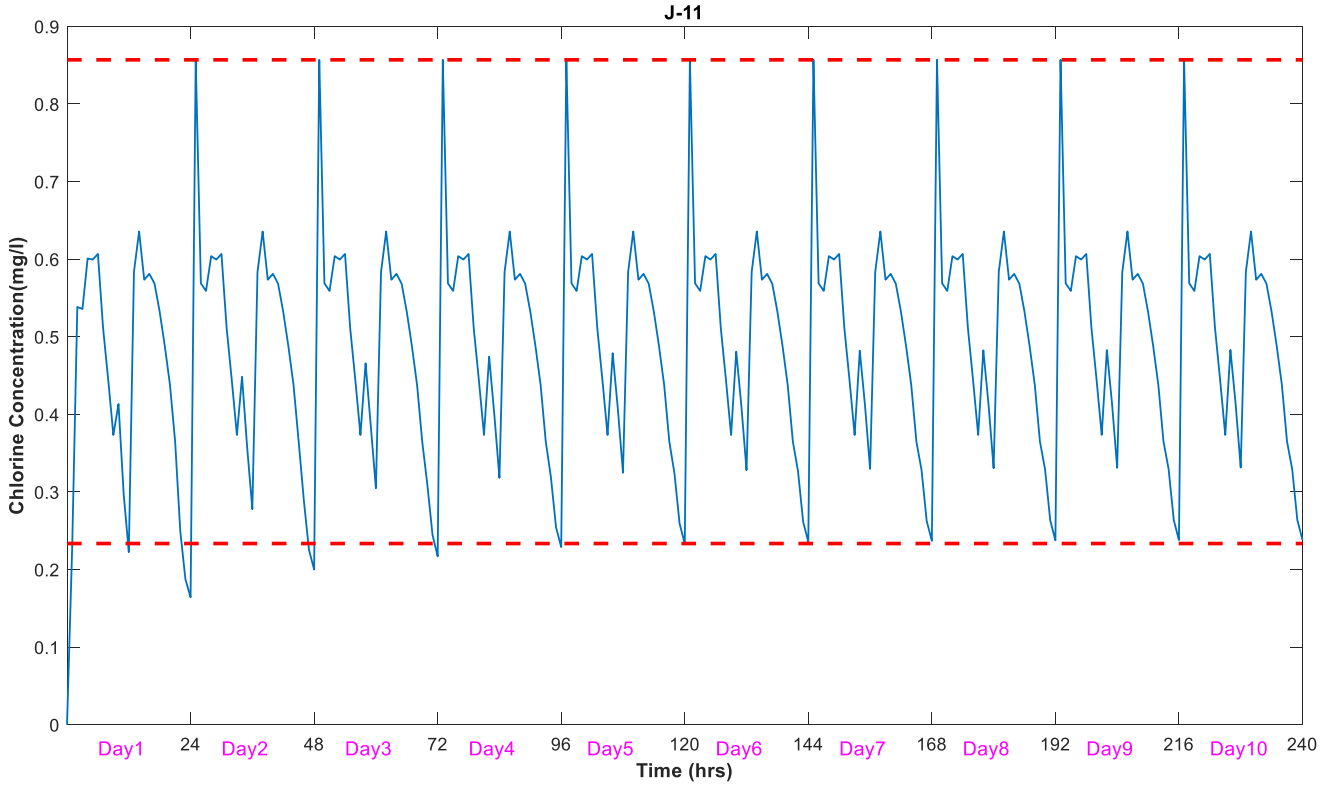

Fig. 5 Chlorine concentration at node J-11

In a real network, there are uncertainties in various parameters, such as demand patterns and roughness of pipes. Fluctuations in demand and roughness of pipes may cause significant variations in hydraulic (pipe flows) and water quality (delay in contaminant propagation) across the water network. To make the simulation conditions realistic, an uncertainty of ±20% for the demand patterns and ±10% for the pipe roughness coefficient with respect to normal values is considered. Then, due to these uncertainties, fluctuations in chlorine concentration were recorded for all nodes at different times employing the Monte Carlo simulator, and the upper and lower bounds of chlorine concentration for each node were determined. By injecting a contaminant into the network, the sensors detect the presence of a contaminant if the chlorine concentration in the network exceeds the defined boundaries for more than three-time steps of simulation (30 minutes).

To explain how the proposed method detects contamination events. We simulated node J-35 due to the entry of pollutants into network 1. Figure 6. a shows changes in chlorine concentration at node J-35 (see figure 3. a) during normal conditions. As can be seen, the chlorine concentration is between the upper and lower boundaries. But Figure 6. b demonstrates variations in chlorine concentration when contamination enters the network (injection at node J-29, starting at 20:00 of the 6-th simulated day (140 hours after simulation started) for 100 minutes with a

mass of 0.12 gr/min). The result indicates that, the concentration of chlorine in the time of 149 to 151 hours due to the reaction with the pollutant is less than the lower bound, which means that the contamination enters the distribution network, and then sensors can detect it.

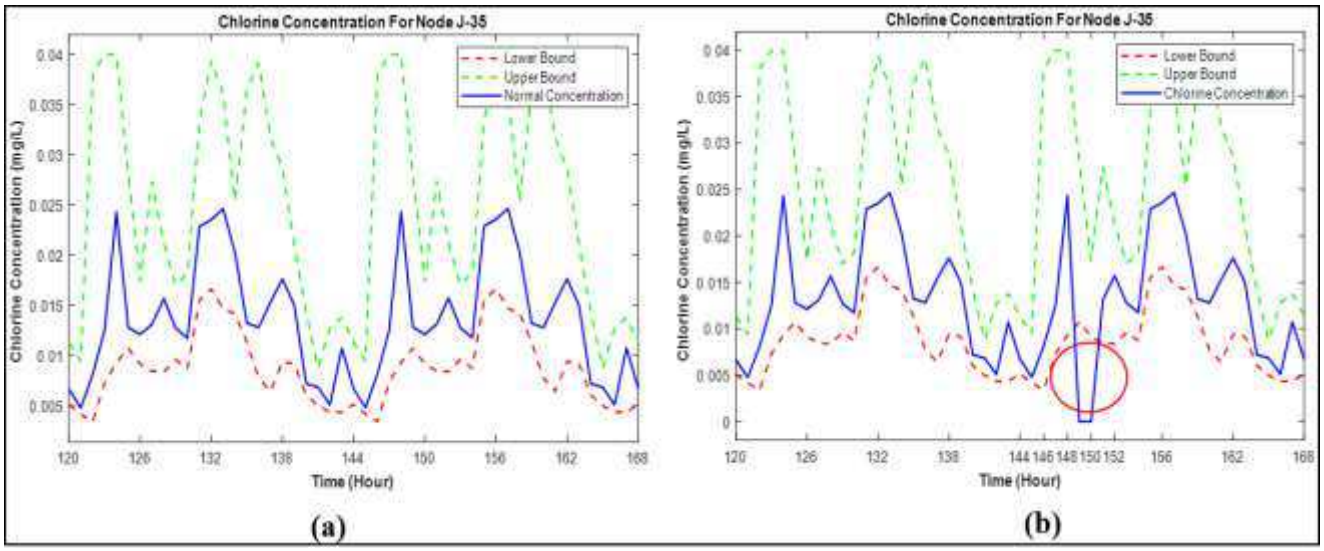

Fig. 6 Chlorine concentration at node J-35 during (a) normal conditions and (b) a contamination event

It should be noted that if a fixed boundary is set for detection, some contaminant events may not be detected in time and may take a longer time to detect. To understand more, figures 7 (a, b) illustrate changes in chlorine concentration at node J-24 during the normal condition and a contamination event, respectively (injection at node J-15, starting at 04:40 of the 6-th simulated day for 30 minutes with a mass of 0.03 gr/min). If we consider a fixed boundary for chlorine concentration such as 0.15 mg/L, the sensor installed in node 24 cannot detect the contamination. In summary, the larger the contaminant concentration, the faster the detection time. Due to more changes in chlorine concentration.

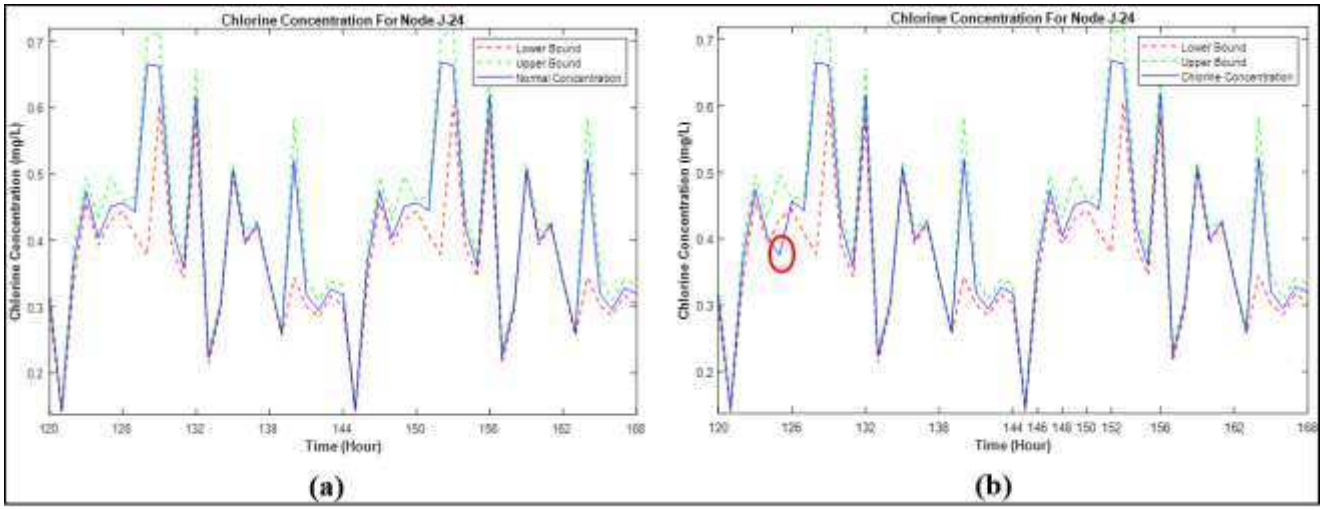

Fig. 7 Chlorine concentration at node J-24 during (a) normal conditions and (b) a contamination event

3. Results and Discussion

The NSGA-III algorithm was applied to solve a four plus one objective problem in determining the optimal location of sensors in two distribution systems to maximize the Sensor detection likelihood (f1), and Sensor detection redundancy (f3), and minimize the Modified Sensor expected detection time (f2), Modified Percentage of affected consumer nodes (f4), and the number of sensors. The objective functions conflict with each other;

hence, no single answer can be found that optimizes all functions simultaneously, and the optimal solutions will be a set of Pareto front rather than one specific solution.

Five sensors have been placed, and sensitivity analysis has been done for two networks. Since the description of the four-dimensional Pareto is hard and complicated, like Hu et al (2018), the four-dimensional Pareto has been interpreted in form of various two-dimensional diagrams. Genetic algorithm parameters in this study are as follows crossover probability is 0.75 and mutation probability is 0.1. The number of populations was 1000 and the maximum number of iterations was set to 300. There were two stop conditions for the NSGA-III algorithm: either if the number of iterations is equal to its maximum value of 300, or if at 20 successive generations, a new non-dominated solution was not found.

3.1. Benchmark WDN

3.1.1. Base run results

Figs. 8 to 13 show base run results for placing five sensors in water network 1. in figure 8.a an optimal Pareto front for maximizing sensor detection likelihood (f_1) versus minimizing modified sensor expected detection time (f_2) is summarized. The interaction between the two objective functions is such that in order to maximize sensor detection likelihood in the network, sensors should be installed in the downstream nodes of the network, Installing sensors downstream of the network increases detection time. On the other hand, in the second objective function, sensors should be installed in nodes close to the input point of infection to minimize the detection time of pollutants, especially pollutants that have a greater impact on the consumers, by using the introduced importance coefficient. So, the layout of sensors according to the two objective functions conflicts with each other.

Figure 8. b illustrates the selected locations of the sensors in the network for the three solutions from the Pareto front. To place the sensors in the network, three different solutions (locations) were selected based on the Pareto front points. The first solution has the best answer for objective function 1, and the worst one for objective function 2. The second solution has the best answer for objective function 2, and the worst one for objective function 1. Finally, the third solution is where both objective functions have an intermediate state. The sensor locations according to solution 1.2.1 indicate the best detection likelihood equal to 92.8% but the worst solution for the modified detection time (11.58 min). Solution 1.2.2 shows the location of the sensors according to the minimum contamination modified detection time (5.06 minutes), but the worst detection likelihood is 61.1%. In solution 1.2.3, the method presented by Young (1993) is used to select the optimal point of the Pareto front for locating the sensors in the distribution network. According to Young's method, the optimal point has a detection likelihood of 86.8% and a modified contamination detection time of 7.03 minutes.

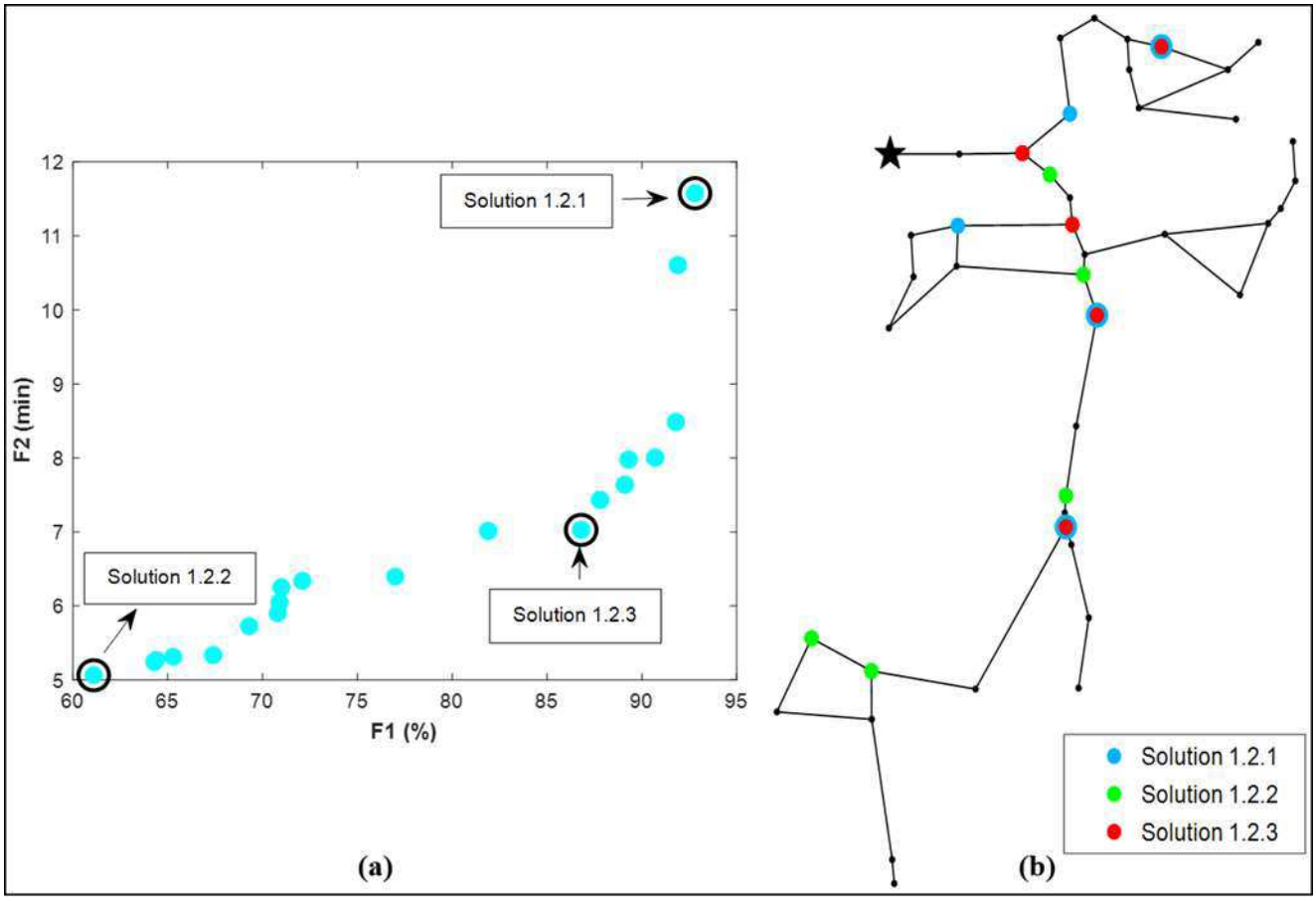

Fig. 8 (a) Optimal Pareto front for detection likelihood versus sensor expected detection time, and (b) selected locations of the sensors according to Pareto front

As expected, the optimal location of the sensors according to solution 1.2.1 is the downstream points of the network, and based on solution 1.2.2, the points are close to the injection areas.

In figure. 9.a an optimal Pareto front for maximizing sensor detection likelihood (f_1) versus maximizing sensor detection redundancy (f_3) is summarized. The interaction between the two objective functions is such that to achieve the maximum detection likelihood, the sensors must be spread in the downstream nodes of the network to cover more nodes, while in objective function 3, to achieve maximum redundancy, the sensors must have a short distance from each other. Therefore, the location of the sensors in two objective functions conflicts with each other.

Figure 9. b describes the selected locations of the sensors in the network for the three solutions from the Pareto front. Solution 1.3.1 indicates that the best percentage of detection likelihood is 92.8%, but the worst value of redundancy (1.19%). Solution 1.3.2 shows the location of the sensors according to the best redundancy value of 80.51%, but the worst detection likelihood (23.6%). In solution 1.3.3, the method presented by Young (1993) is used to select the optimal point of the Pareto front for locating the sensors in the distribution network. According to Young's method, the optimal point has a detection likelihood of 68.2% and a redundancy value of 38.12%.

Figure. 10. a. depicts an optimal Pareto front for maximizing sensor detection likelihood (f_1) versus minimizing the modified percentage of affected active nodes (f_4). To achieve the maximum detection likelihood, the sensors must be spread across the downstream nodes of the network, which cause to infect many network nodes. However, in the objective function 4, to achieve the minimum number of infected nodes, especially nodes that have more demands by using the introduced importance coefficient, sensors must be installed in locations close to where the

pollution enters the network. Therefore, the optimal location of the sensors in the two objective functions conflicts with each other.

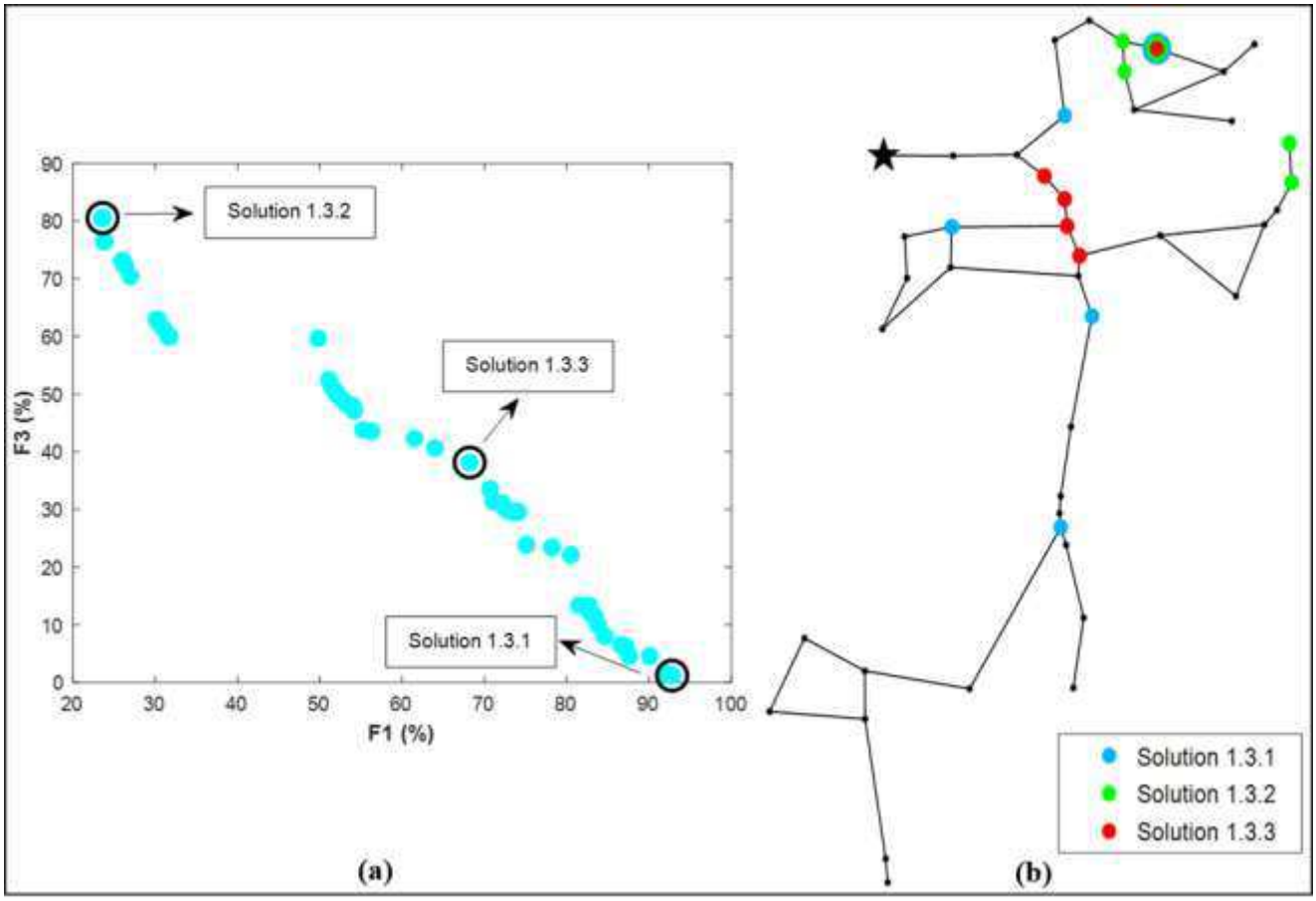

Fig. 9 (a) Optimal Pareto front for detection likelihood versus sensor redundancy, and (b) selected locations of the sensors according to Pareto front

Figure 10. b. illustrates the selected locations of the sensors in the network for the three solutions from the Pareto front. The location of the sensors according to solution 1.4.1 indicates the best percentage of detection likelihood equal to 92.8% but shows the worst modified percentage of infected nodes (15.34%). Solution 1.4.2 shows the location of the sensors according to the minimum (the best) modified percentage of infected nodes equal to 11.59%, but the percentage of detection is the lowest (64.3%). In solution 1.4.3, according to Young's method, the optimal point has a detection likelihood equal to 90.7% and the modified percentage of affected nodes of 12.78%.

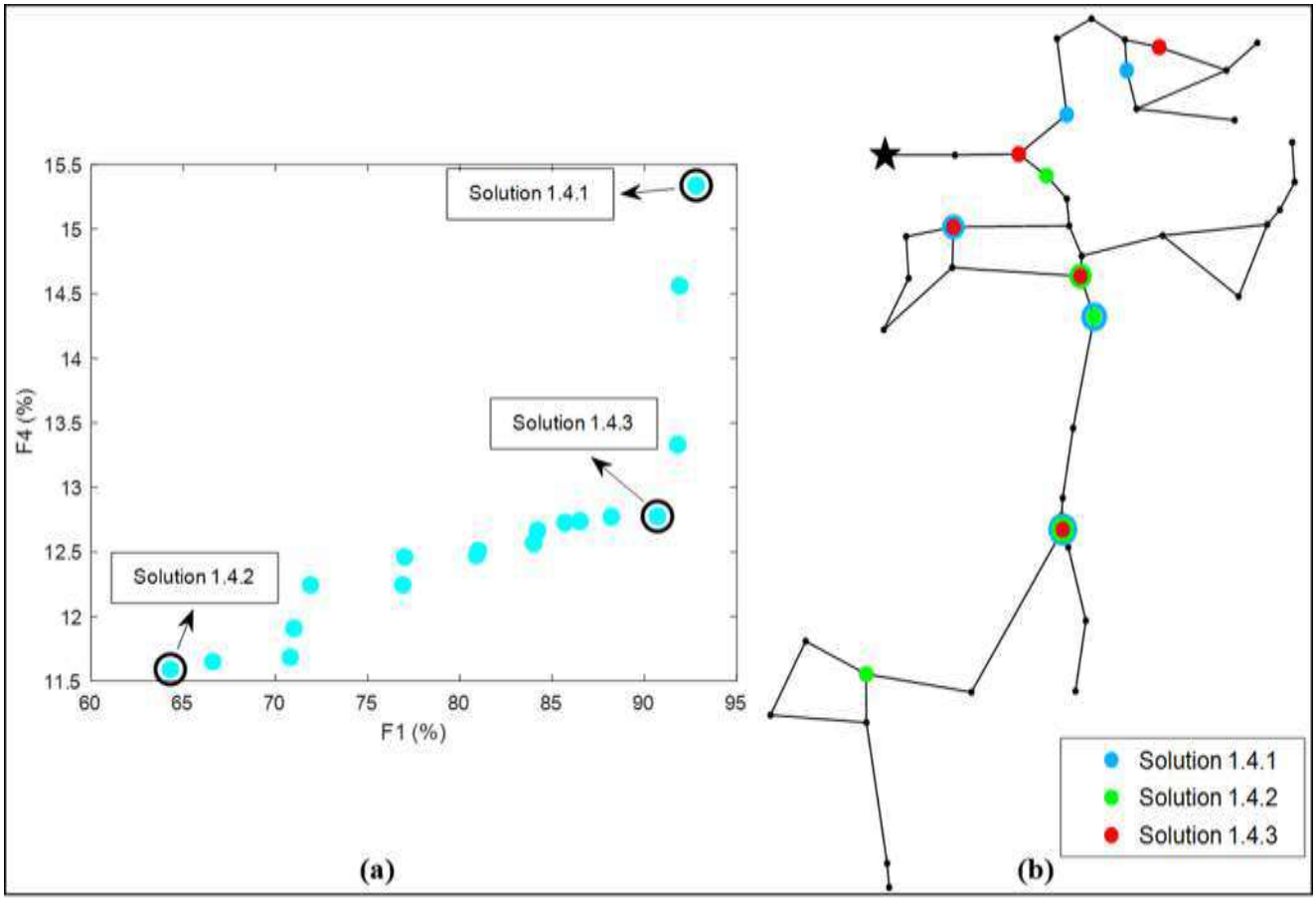

Fig. 10 (a) Optimal Pareto front for detection likelihood versus percentage of active polluted nodes, and (b) selected locations of the sensors according to Pareto front

Figure 11. a. demonstrates an optimal Pareto front for minimizing modified sensor expected detection time (f_2) versus maximizing sensor detection redundancy (f_3). To achieve the minimum sensor expected detection time in the distribution network, the sensors should be located in areas close to the input point of contamination, especially pollutants that have a greater impact on the consumers, and in different parts of the network, but to achieve the optimal value according to objective function 3, the sensors should be located close to each other. Therefore, the optimal location of the sensors in two objective functions conflicts with each other.

Figure 11. b. displays the selected locations of the sensors in the network for the three solutions from the Pareto front. The location of the sensors according to solution 2.3.1 indicates the location of the sensors according to the minimum modified contamination detection time equal to 5.88 minutes, but the worst sensor detection redundancy (15.32 %). Solution 2.3.2 shows the location of the sensors according to the best redundancy value of 59.64%, but the worst modified expected detection time (14.14 min). In solution 2.3.3, according to Young's method, the optimal point has a modified contamination detection time equal to 8.94 minutes and a redundancy of 43.33%.

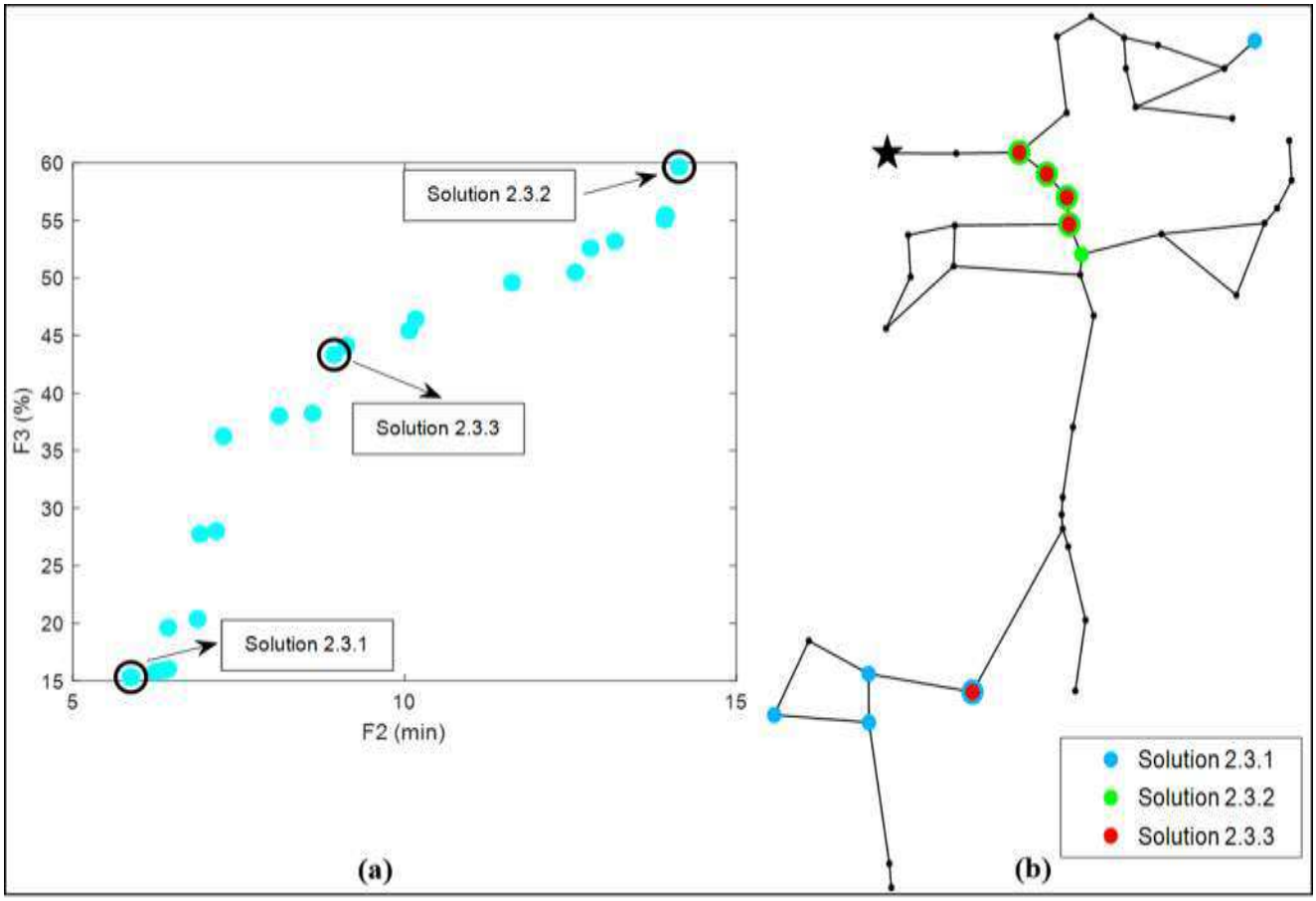

Fig. 11 (a) Optimal Pareto front for modified detection time versus sensor redundancy, and (b) selected locations of the sensors according to Pareto front

As shown in figure12. a. optimal Pareto front for minimizing modified sensor expected detection time (f_2) versus minimizing the modified percentage of affected consumer nodes (f_4) is summarized. As can be seen, there is not a lot of conflict between the two objective functions.

Figure 12. b. shows the selected locations of the sensors in the network for the three solutions from the Pareto front. The location of the sensors according to solution 2.4.1 indicates the location of the sensors according to the minimum modified contamination detection time equal to 3.21 minutes, but the worst modified percentage of active (consumer) nodes affected (27.45 %). Solution 2.4.2 shows the location of the sensors according to the best-modified percentage of active (consumer) nodes affected 11.59%, but the worst modified expected detection time (5.47 min). In solution 2.4.3, according to Young's method, the optimal point has a contamination detection time equal to 5.06 minutes and a percentage of affected nodes of 12.79%.

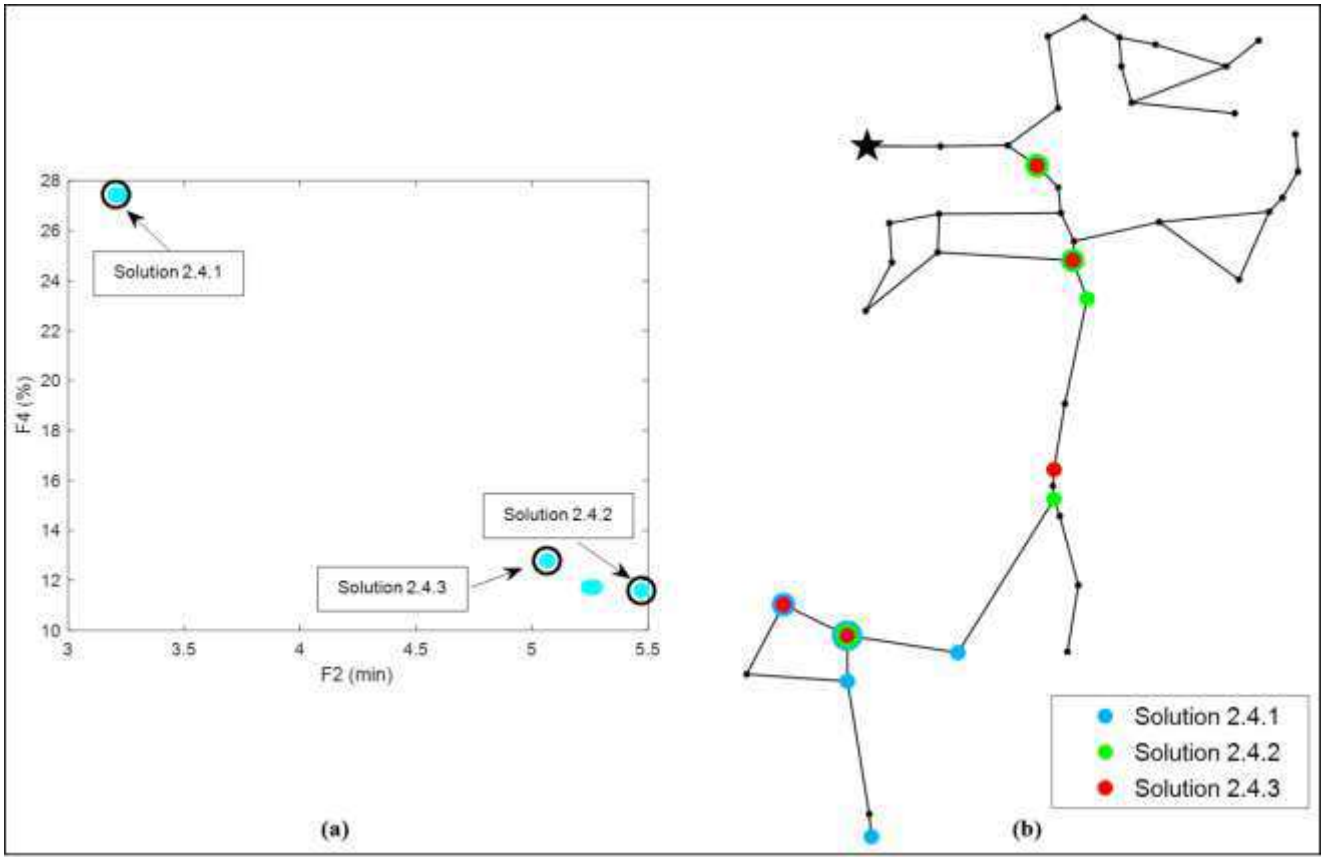

Fig. 12 (a) Optimal Pareto front for modified detection time versus percentage of active polluted nodes, and (b) selected locations of the sensors according to Pareto front

Figure 13. a. illustrates the optimal Pareto front for maximizing sensor detection redundancy (f_3) versus minimizing the modified percentage of affected active (consumer) nodes (f_4). To achieve maximum redundancy, the sensors should be located close to each other, but to minimize the number of infected nodes, especially nodes that have more demands, the sensors should be spread across different parts of the network and close to the entry point of contamination. Therefore, the optimal location of the sensors according to these two objective functions conflict with each other.

Figure 13. b. presents the selected locations of the sensors in the network for the three solutions from the Pareto front. The location of the sensors according to solution 3.4.1 indicates the location of the sensors according to the best redundancy value of 80.51%, but the worst modified percentage of active (consumer) nodes affected (30.69 %). Solution 3.4.2 shows the location of the sensors according to the best-modified percentage of active (consumer) nodes affected 11.59%, but the worst redundancy (0 %). In solution 3.4.3, according to Young's method, the optimal point has a redundancy equal to 52.45% and the modified percentage of affected nodes of 16.61%.

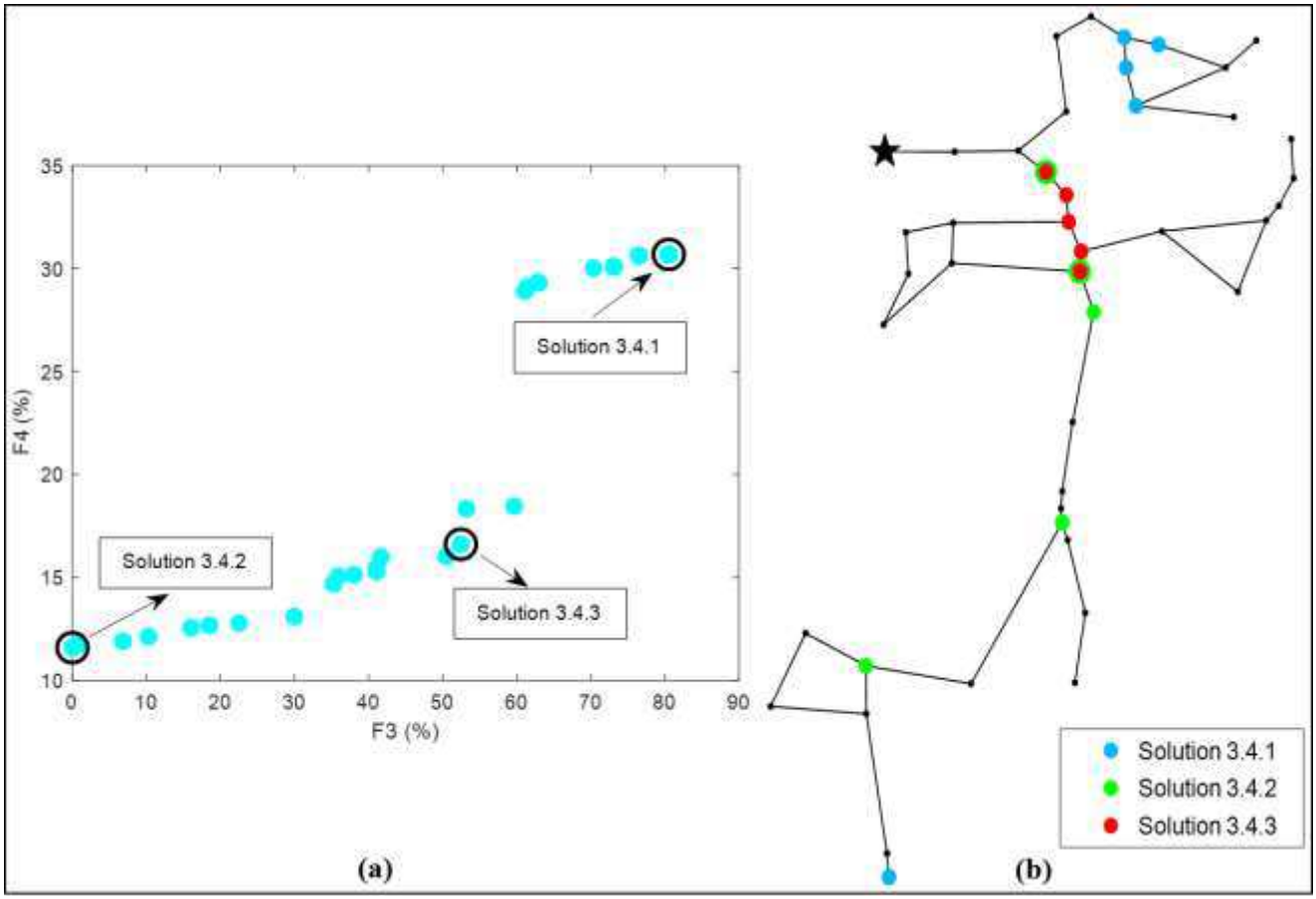

Fig. 13 (a) Optimal Pareto front for sensor redundancy versus percentage of active polluted nodes, and (b) selected locations of the sensors according to Pareto front

3.1.2. Sensitivity analysis results

This section investigates the effect of the number of sensors utilized in the network on the objective functions. The purpose is to check whether the increase in the number of sensors improves the optimal Pareto fronts. For this purpose, the number of sensors was increased from five to seven and ten sensors. Figure 14 (a to f) demonstrates the comparison among the optimal Pareto fronts for the five, seven, and ten sensors applied in the base and sensitivity analysis runs. As presented in figures 14. a to 14. f, the Pareto fronts for 7 sensors dominate the Pareto fronts of 5 sensors, and the Pareto fronts for 10 sensors dominate the Pareto fronts of 5 and 7 sensors. For example, according to figure 14. a. When employing five sensors, the best detection likelihood is 92.8%, and the worst solution for the modified detection time is 11.58 minutes. But with the increase in the number of sensors to seven, the best detection likelihood by sensors increased by 4.85 % and reached 97.3%, on the other hand, the worst solution for the modified detection time decreased by 4.15 minutes (35. 9%) and reached 7.43 minutes, which has improved the two objective functions. Then, with the increase in the number of sensors to ten, the best detection likelihood compared to five and seven sensors increased by 7.65 and 2.67 percent, respectively, and reached 99.9 percent. Also, the worst solution for the modified detection time compared to five and seven sensors decreased by 55.35 and 30.42 percent and reached 5.17 minutes.

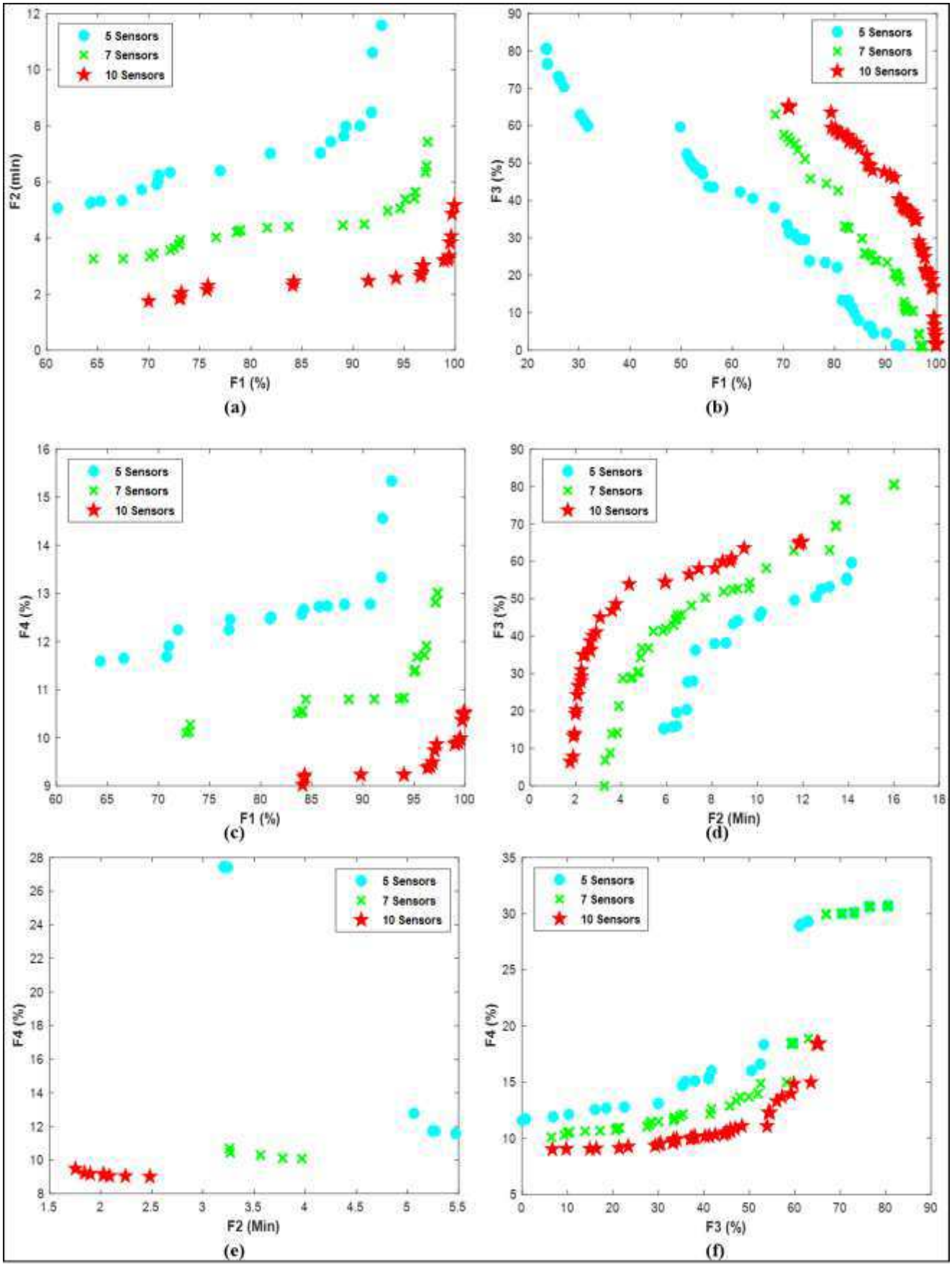

Fig. 14 Comparing the optimal Pareto fronts for 5 sensors with 7 and 10 sensors utilized in the base and sensitivity analysis runs for different objective functions of benchmark network

As observed, with increasing the number of sensors, the solutions of different objective functions have improved compared to the base run (5 sensors). Figure 15. shows the optimal Pareto front for the number of sensors utilized in the distribution network 1 versus the best detection likelihood. Results express that by installing only one or two sensors in the network, 36.4 and 63.2% of pollutants can be detected. As can be seen, Initially, when the number of sensors is small, the percentage of detection changes rapidly as the number of sensors increases. But, as the number of sensors increases, the detection percentage changes at a slower rate. So increasing the number of sensors to more than 9 sensors in this small system will provide little additional detection likelihood. For example, by increasing the number of sensors from 1 to 2, the detection likelihood increased by 73.6%, but by increasing the number of sensors from 3 to 4, the detection likelihood just increased by 12.7%. The maximum detection likelihood corresponds to 11 sensors, which means that increasing the number of sensors to more than 11 sensors will provide any additional detection likelihood of pollutants entering the network.

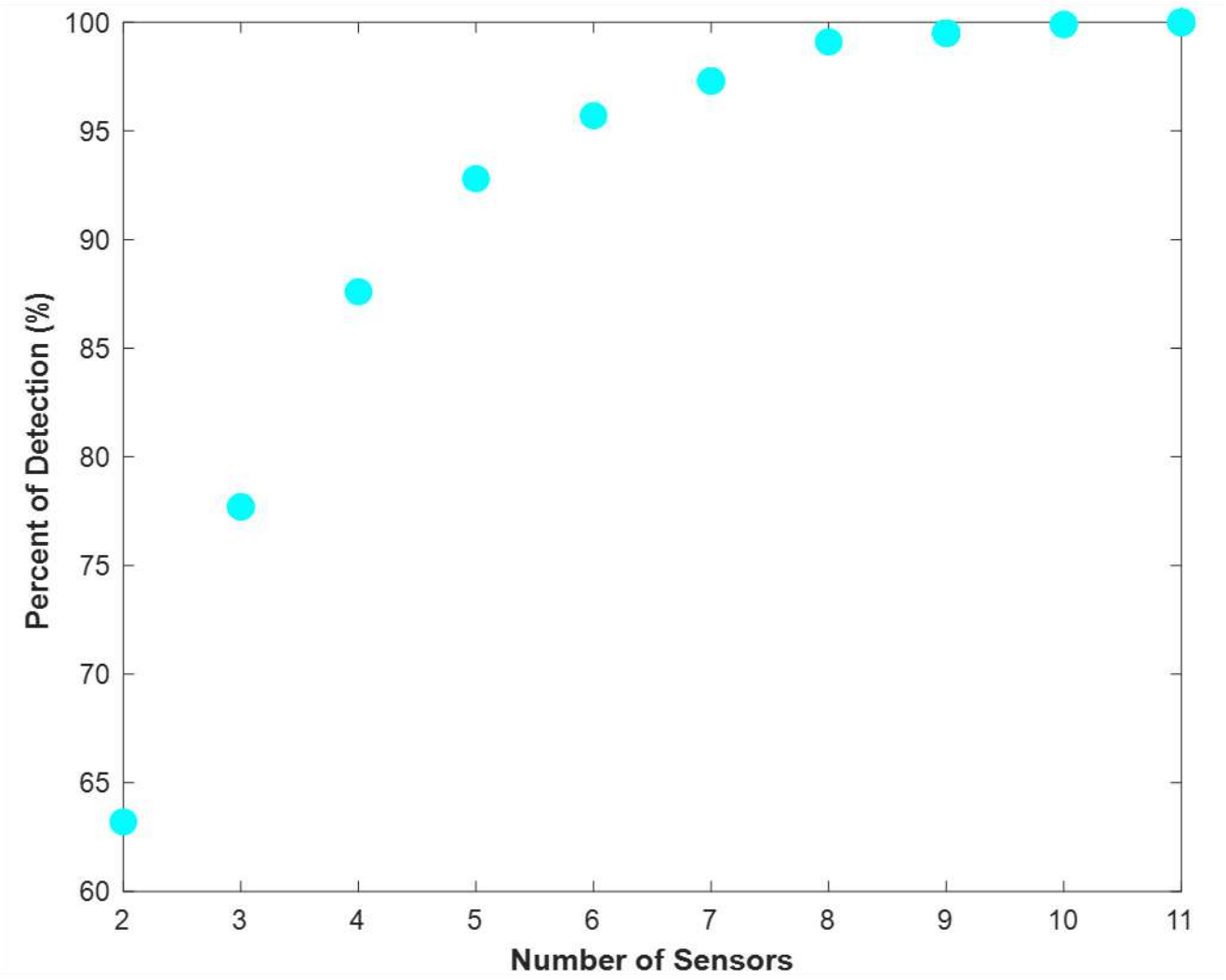

Fig. 15 Optimal Pareto front for the number of sensors versus detection likelihood for benchmark network

3.2. Real WDN

To evaluate the effectiveness of the proposed method in large networks, a real water distribution network in southeastern Iran (Zahedan city) is used (Figure 3. b). Figure 16 illustrates the optimal Pareto front for the number of sensors utilized in the distribution network 2 versus the best detection likelihood. Results represent installing only one or two sensors in the network, 24.5 and 45.2% of pollutants can be detected. As can be seen, the

maximum detection likelihood corresponds to 20 sensors, which means that increasing the number of sensors to more than 20 sensors will provide any additional detection likelihood of pollutants entering the network. Also increasing the number of sensors to more than 15 sensors in this large system will provide little additional detection likelihood. Therefore, in this study, to analyze the sensitivity of the number of sensors, the effect of 5, 10, and 15 sensors on the network has been investigated.

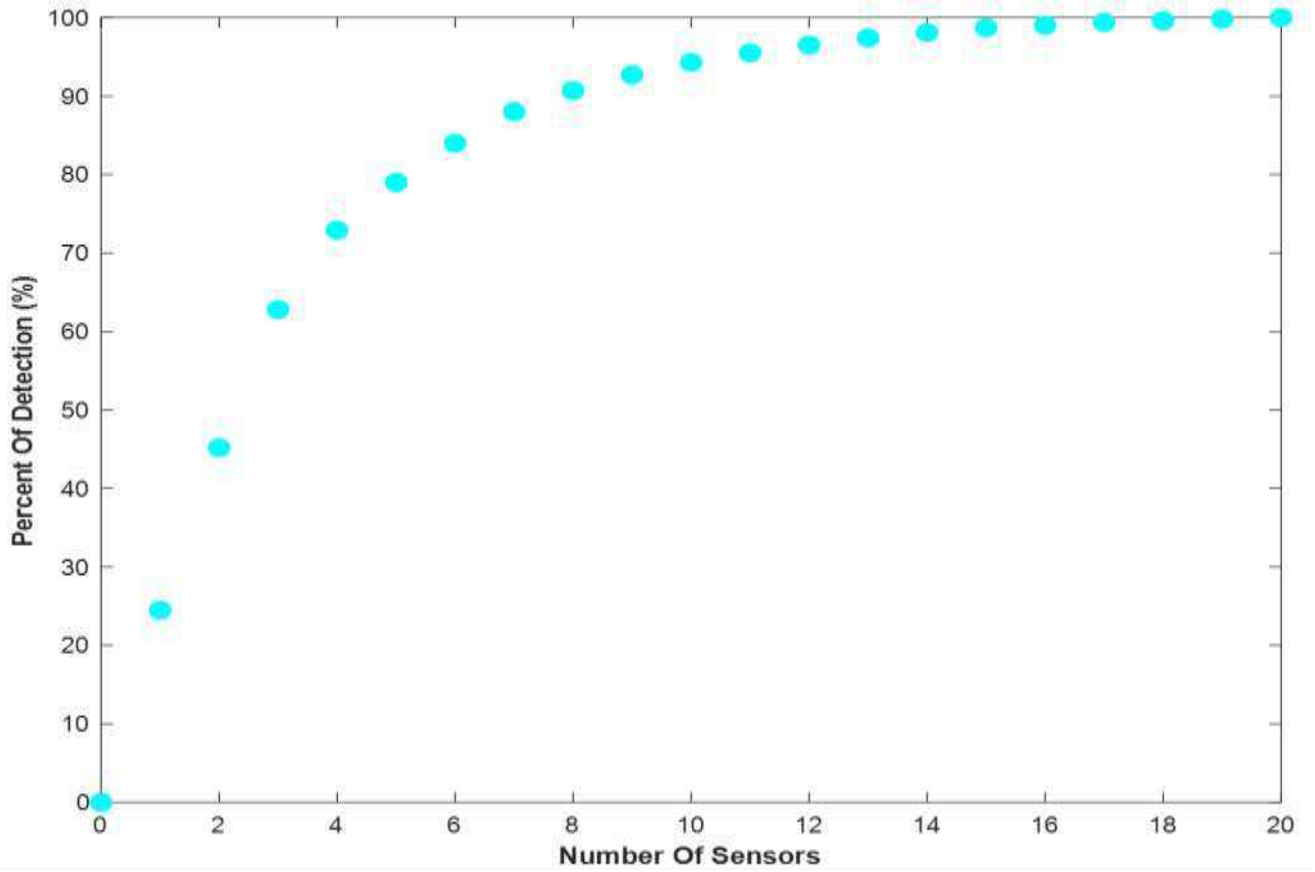

Fig. 16 Optimal Pareto front for the number of sensors versus detection likelihood for real network

Figures 17,18 (a to f) demonstrate optimal Pareto front and sensor locations for placing five sensors in water network 2 according to base run results. Optimal Pareto fronts for the four conflict objective functions are plotted in the form of various two-dimensional diagrams. According to figure17.a, The more the modified detection time, the more the detection percentage, Because when the detection percentage is maximum, it means that the sensors are installed at the end areas of the network, which causes them to be far from the entry point of the pollutant, thus detection time increase. Figure 17.b exhibits that increasing the detection percentage reduces redundancy. In order to achieve the maximum detection percentage, the sensors must be installed across the network and far from each other, which reduces redundancy. Also, the more detection likelihood, leads to the more the modified percentage of polluted nodes (figure 17.c). The results of figure 17.d represent that with increasing redundancy, the detection time increases. Because the sensors are located close to each other and far from the input nodes. Finally figures 17.e and 17.f present that decreasing the modified percentage of infected nodes increases the redundancy and detection time.

Figure 19 describes comparison between the optimal Pareto fronts for five, ten, and fifteen sensors utilized in the base and the sensitivity analysis runs. As confirmed in figures 19.a to 19.f, the Pareto fronts for 10 sensors dominate the Pareto fronts of 5 sensors, and the Pareto fronts for 15 sensors dominate the Pareto fronts of 5 and

10 sensors. For example, in figure 19.b, When five sensors in the network are exist, the best detection likelihood is equal to 78.7%, and the best solution for redundancy is 98.87 percent. But with increasing the number of sensors to ten, the best detection likelihood by sensors increased by 18.93 % and reached 93.6%. Moreover, the best solution for redundancy increased to 98.94%, which has improved the two objective functions. Then, with increasing the number of sensors to fifteen, the best detection likelihood compared to five and ten sensors increased by 24.66 and 4.8 percent, respectively, and reached 98.1 percent. Also, the best solution for the modified detection time related to five and fifteen sensors increased to 99.1 percent.

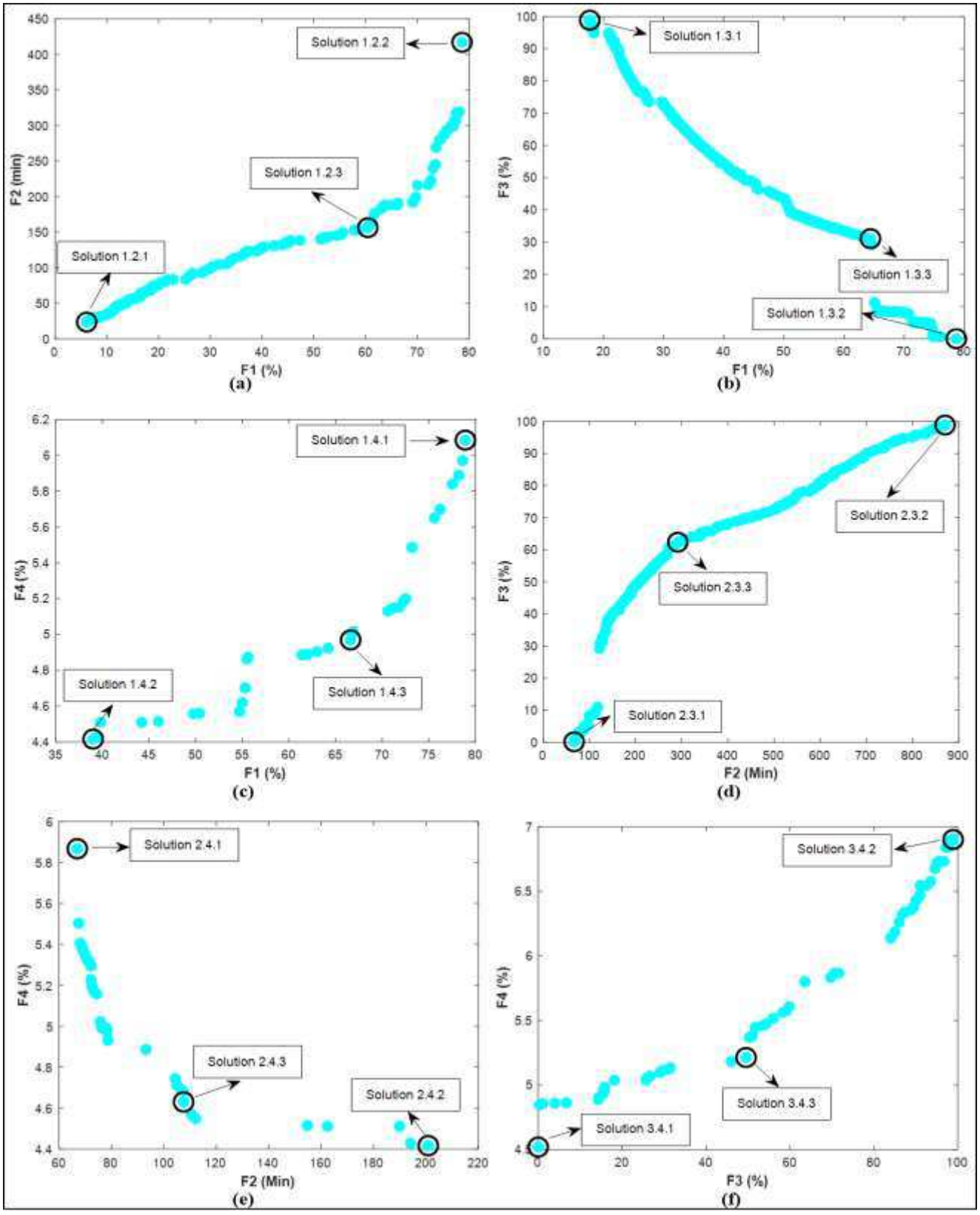

Fig. 17 Optimal Pareto front for a base run of real network for different objective functions

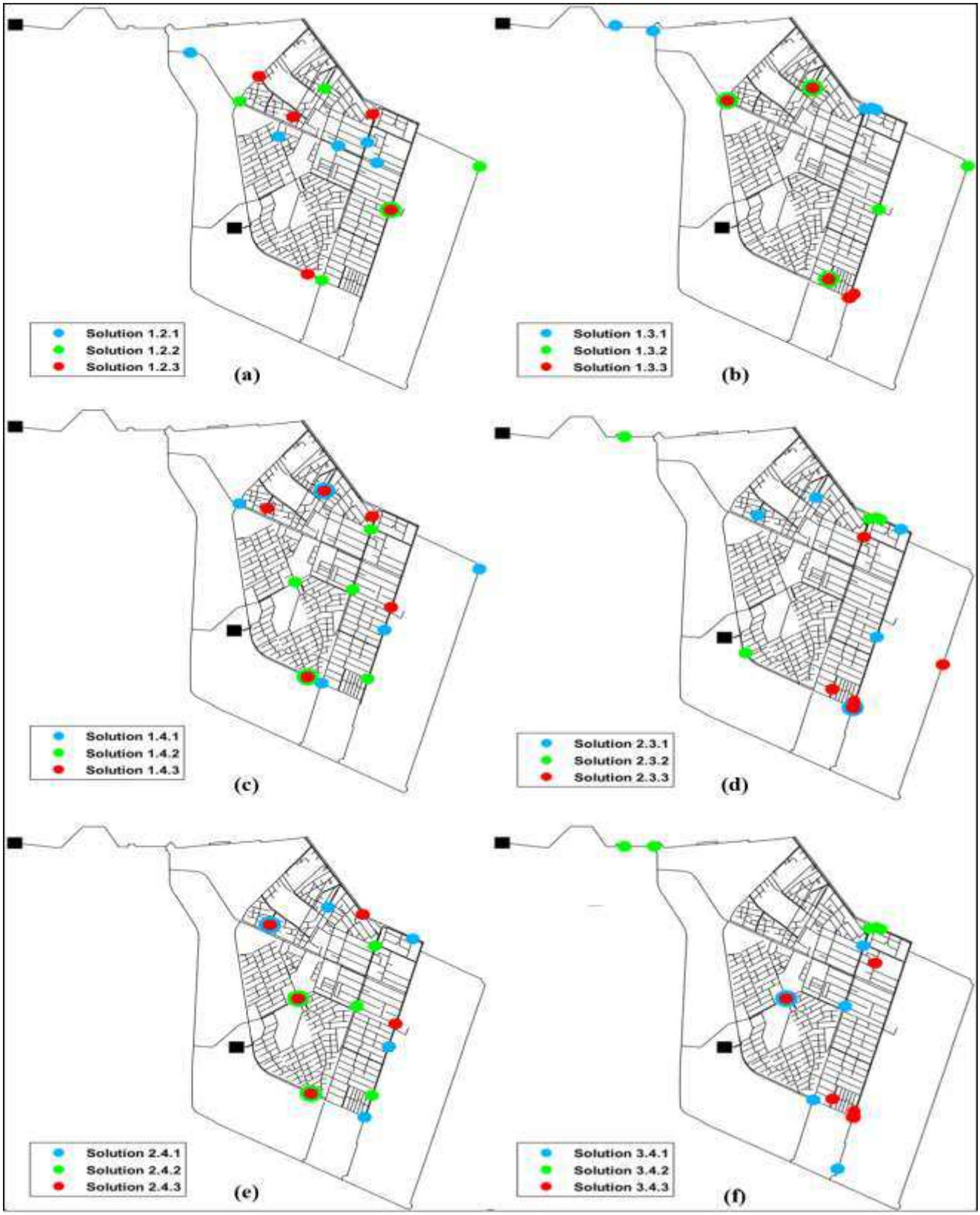

Fig. 18 selected locations of the sensors according to Pareto fronts for a base run of real network for different objective functions

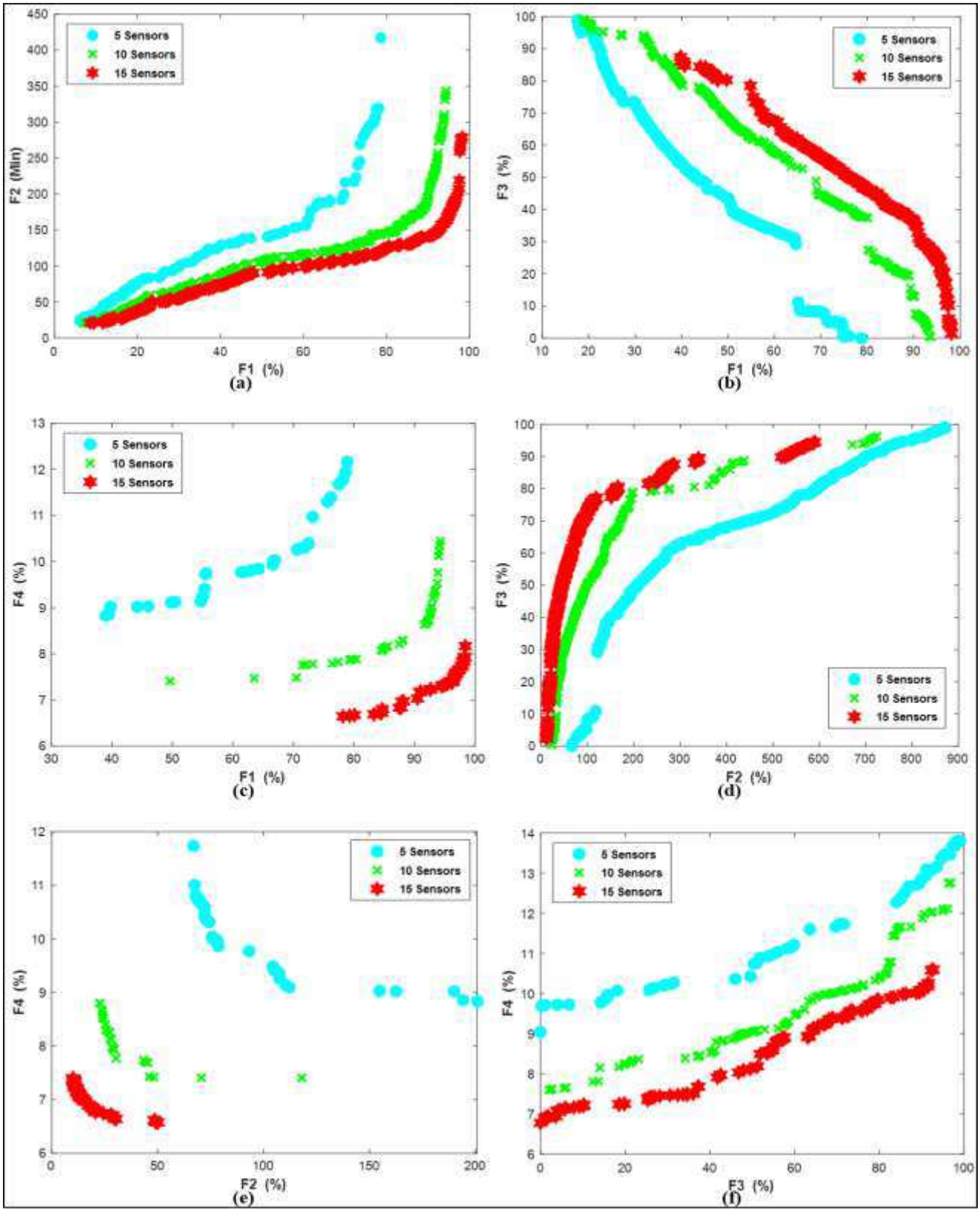

Fig. 19 Comparing the optimal Pareto fronts for 5 sensors with 10 and 15 sensors utilized in the base and sensitivity analysis runs for different objective functions of real network

4. Conclusions

Water distribution Networks (WDNs) are one of the main components of public infrastructure that distribute safe drinking water to billions of customers worldwide. WDNs are vulnerable to intentional or accidental

contamination events due to the complexity of their structures and several access points. When contamination enters WDNs, it spreads through the system and harms the customer health and the local economy. Therefore, WDNs protection is crucial, and water security needs to be improved. This led utilizing of sensors for identifying the pollutants in water distribution systems. This study proposes a multi-objective approach for sensor network design to improve the optimal locations of sensors. For this purpose, two networks (benchmark and real water network) with different complexity and characteristics have been selected to test the proposed approach.

As the size of the system increases, the number of possible contamination events increases. Contamination events are a potential risk, they can occur at any node, at any time with any mass rate, and duration times. For this reason, a heuristic method was employed for selecting a representative sample of contaminations that had similar characteristics and effects. A contamination matrix based on 1000 pollutant events was created for benchmark and real water networks. The developed contamination event detection procedure is based on chlorine concentration measurements relative to defined upper and lower limits. The upper and lower bounds of chlorine concentration for each node were determined utilizing the Monte Carlo simulator. The optimal placement of five sensors in two networks was analyzed utilizing a simulation-optimization approach. EPANET, EPANET-MSX, and NSGA-III were applied as a hydraulic-quality simulator and an optimizer approach, respectively. Sensor locations have been selected based on the following four objectives: 1- sensor detection likelihood, 2- sensor expected detection time, 3- sensor detection redundancy, and 4- the affected nodes before detection. The importance of contaminations and the importance of network nodes are not considered the same by developing two important coefficients based on the amount of damage caused by contamination events. According to the important coefficient 1, the contaminations that cause more damage to the distribution network (affect more nodes) are more important and should be identified quickly also according to the important coefficient 2, nodes with more demands are more important, and sensors must be installed in places to detect contaminations before infecting these nodes. Then, in the second step, the sensitivity analysis related to the number of sensors on different objective functions was investigated so that the number of sensors increased from five to seven and ten for the benchmark system and increased from five to ten and fifteen for a real system. The results illustrated that as the number of sensors increased, the Pareto fronts became more efficient. Finally, the optimal Pareto front for the number of sensors versus the best detection likelihood was depicted. The results demonstrated that increasing the number of sensors to more than 10 and 15 sensors in benchmark and real systems respectively, will provide little additional detection likelihood. Also, the maximum detection likelihood corresponds to 11 and 20 sensors for benchmark and real water systems.

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