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Identification of Suitable Locations in a Small Water Supply Network for the Placement of Water Quality Sensors Based on Different Criteria under Demand-Driven Conditions

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Abstract: Drinking water quality monitoring in real time is of utmost importance to ensure public health. Although water utilities, following the related legislative framework, monitor drinking water quality through samplings, the likelihood of detecting contaminants in consumers' taps is low, depending on the scale of the monitoring programme. Additionally, even if the monitoring frequency is high, there is a time delay since sampling and analysis processes take some time. The selection of suitable locations for the installation of online water quality sensors is a hard task for a water utility due to the complexity of the water distribution system, the limitations of certain network junctions which are not easily accessible, and the computational burden involved. This topic has been extensively studied in recent years and sophisticated methods have been developed using optimization techniques. However, small water utilities do not have the means to implement such tools. This paper applies a methodology to identify the suitable junctions for the installation of online water quality sensors based on different objectives and under demand-driven conditions. This paper utilizes the hydraulic simulation model of a standard network to set up the water quality simulation model. A thorough analysis of various contamination scenarios takes place with different injection nodes and at different starting injection times for 24 h. The latter relates to the contaminant's spread due to varying water demand. After a thorough analysis of 816 scenarios, a prioritized list of the most suitable nodes for the installation of the sensors is available for each optimization objective. Comparing the prioritized list of nodes achieved from each single or multi-objective function, the detection probability is almost the same. The analysis revealed that, due to varying water demand conditions, the ranking of the proposed nodes suitable for the installation of water quality monitoring sensors differs. Thus, varying hourly water demand should be part of analyses seeking to get reliable results.

Keywords: drinking water quality; online sensors; water quality simulation model; water demand

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1. Introduction

Drinking water distribution networks are complex infrastructure systems with high vulnerability to contamination events since contamination can happen at any time and at any point within the network [1]. Although most of the water supply system is buried, there are some vulnerable parts of it, such as manholes, customer connections, etc. Also, water supply vulnerability has to do with natural causes such as contamination due to flooding at the water abstraction area, growth of micro-organisms at the walls of pipes, etc. Moreover, the big variety of contaminants having different characteristics makes the detection of any contamination event extremely difficult. The common way to detect a contamination event is to use water quality monitoring to safeguard the consumers' health, to assess water quality and comply with the legislation. The water utilities are obliged, based on legislation, to monitor water quality characteristics at the consumers' taps and in some other cases at the water abstraction points or the treatment plants or both at the consumer and the treatment plant. The European Union's legislative framework requires the monitoring of several physical, chemical, microbiological and radiological parameters and determines the samplings' frequency based on the water volume consumed and the number of people supplied with water. Although the legislation strictly sets the necessary provisions to ensure drinking water safety, this is not always achieved due to the time needed for water sampling and analysis even if the monitoring network is well-established and the monitoring frequency is high. This means that, using conventional drinking water quality monitoring (using samplings and analyses at the laboratory), the detection of any contamination event will happen after a few hours or even days. It is obvious that this means that consumers are exposed to contamination. To overcome this obstacle, water utilities apply online water monitoring techniques. However, it is not possible to monitor each junction in the water supply system due to the high capital and operational costs of such a network of sensors. This is why it is important to identify the most strategic and suitable junctions for sensors' placement in order to monitor water quality as effectively as possible and at the same time detect the contamination as early as possible, minimizing all potential consequences, such as those on consumers' health.

This subject has been studied and analysed thoroughly by many researchers in the past, especially after the terrorist attacks of 11th of September 2001. The methods used for the identification of suitable sensor locations are based on expert opinion, the use of classification methods, and the use of optimization methods [2]. Expert opinion is very important for the design of an effective network of water quality monitoring sensors, but it can be affected by the expert's level of expertise, knowledge, and their judgment. Berry et al. [3] and Trachtman [4] evaluated cases where expert opinion was used for the site selection for monitoring stations. Experts used information and classification methods to rank possible locations by rating each potential location based on various factors, such as its proximity to critical installations. Using this methodology provided a prioritized list of potential locations. At the same time, the integration of a geographic information system and the network quality simulation model ensures adequate coverage of the water supply network [5–7]. The most advanced methods are the optimization ones that use a computational model to estimate the performance of a sensors' network. For example, a model can calculate the expected impact of a set of contamination events, given that the sensors are placed at strategic locations. Current methods use hydraulic simulation and water quality simulation software.

In the literature there are many research papers addressing the problem of sensor placement in drinking water supply networks in recent years. There are studies assuming a fixed or a variable number of sensors [8]. Other studies [9–12] assume a single-objective optimization methods in order to minimize the total cost. The single-objective methods try to minimize the total contaminated water volume consumed [13,14], to minimize the contamination detection time [15], to maximize the coverage and detection probability [11], or to minimize the population exposed to contaminants [3]. The aim of the studies of [13,15,16] was to determine the minimum number of stations required to ensure the total coverage of the water distribution system, assuming a variable number of sensors. Ghimire and Barkdoll [6] and Rathi and Gupta [8] proposed heuristic methods to simplify the optimization problem. In 2004, Watson et al. [17], used mixed-integer linear programming models for sensor placement in drinking water supply systems using several objectives. Based on two case studies, they showed that optimal solutions derived from a single objective (e.g., minimization of exposed population) are usually less optimal when using another optimization objective (e.g., minimization of detection time), which is a limitation of single-objective methods. Additionally, single objectives can be opposing, such as detection time and detection likelihood. For this reason, researchers have used multi-objective optimization methods. In the context of optimization, the "battle of the network of water sensors" took place where fifteen different approaches were compared [18]. Some researchers used multi-objective approaches where the objective functions remained distinct, and the results are expressed in the form of a Pareto curve [19–27]. Other studies used a single objective function to group distinct objectives and then optimization of the single objective function took place [28–33]. The objective most preferred is detection time as it leads to the early detection of contamination events. When a multi-objective function is used, the detection time is complemented by one or two complementary objectives that quantify the impact of the contamination event, such as the probability of detection or coverage [34]. Ostfeld et al. [18] compared solutions derived from different algorithms for four objectives: (a) detection time, (b) exposed population, (c) volume of contaminated water, and (d) probability of detection. The results from the different algorithms provide a different set of nodes for the placement of the sensors [8,18]. Other objectives include sensor response time, number of failed detections, probability of failed detection and sensor detection redundancy [35].

Another aspect in the context of optimizing the sensors' placement is the hydraulic conditions in the distribution network [33]. There are studies assuming a constant average daily nodal demand [3,9,16,17,36] while other studies assumed that the nodal demand varies with time [12,37,38] and in some cases is stochastic [39].

Rathi and Gupta [8], Rathi et al. [40] and Adedoja et al. [35] published reviews of the methods used to optimize the placement of water quality monitoring sensors. The algorithms used in the case of multiple criteria are genetic algorithms [21,32,41,42], including the NSGA-II algorithm [24,25,33,43,44] and NSGA-III algorithm [34] and heuristic algorithms [20,45,46]. The literature review revealed that genetic algorithms and in particular NSGA-II are the most preferred algorithms for multi-objective optimization problems. Recent studies have combined multi-criteria approaches with other techniques. Cardoso et al. [27] addressed the sensors' placement problem using a multi-objective approach combined with post-processing methods and genetic algorithms. Brentan et al. [47] combined NSGA-II algorithm for the optimization problem, and the ELECTRE TRI (ELimination Et Choix Traduisant la REalite) method to cluster the optimal solutions. Other studies examined specific contaminants such as organophosphates [48] to predict the number of affected consumers. The study of Zhang et al. [49] used an evolutionary algorithm-based method to investigate the resilience of the sensors' placement strategy due to sensors' failures. The problem of imperfect sensors has been also addressed [50–53]. The computational requirements of using genetic algorithms increases with the size of the network and the number of contamination scenarios considered, which limits their application to large network problems. Heuristic algorithms have other limitations as they may not offer the optimal solution [8]. Although the research work already done in the field of optimization algorithms can solve large-scale problems, water utilities, which are the end-users, find them difficult to implement due to the sophisticated algorithms used and the computational burden involved. In addition, Giudicianni et al. [26] have reported the problem of a lack of hydraulic data for some water utilities resulting in the formation of hydraulic simulation models which are not well established and calibrated. On the other hand, Ciaponi et al. [54] proposed a management strategy that takes into consideration water network partitioning and the formation of district metered areas to be used to decide the placement of sensors. This management strategy reduces the computation burden and offers cost benefits. An important aspect is that the operators in small water utilities are not experienced or educated enough to use such advanced tools for everyday operations.

The present study aims to apply a simple methodology in a small water supply network based on the objectives already used, taking into consideration water demand variability to prioritize the nodes that are more suitable for sensors' placement. In this context a single objective and a multi-objective function that groups two objectives are both proposed and used in the analysis.

2. Materials and Methods

The present paper presents a methodology based on the optimization objectives approach and can be easily used by the operators of small water utilities. Initially, the contamination scenarios are set inserting a predefined contaminant's concentration at a specific junction, for a given time period. Then, using a water quality simulation model (with time step up to 15 min) and assuming the time for contamination detection after the initial injection, the calculation of the concentrations of the contaminant at all nodes in the water distribution network (WDN) takes place. The analysis of various objectives leads to a prioritized list of the nodes to locate the sensors. The expected contaminated population, P_a, is calculated as follows [18,55]:

$$P_a = \sum_{i=1}^{m} R_i P_i \tag{1}$$

where P_i is the population supplied with water from the node i; m is the total nodes' number; R_i is the probability [0,1] that a person that consumed a mass of the contaminant would be infected or symptomatic. The objective function O_1 shows the expected population contaminated before the contamination detection [18,55]:

$$O_1 = E(P_a) \tag{2}$$

where E (·) is the expected value estimated by Monte Carlo simulation.

Another optimization objective is the expected water volume consumed before the contamination detection, O_2 [18,55,56]:

$$O_2 = E(V_d) \tag{3}$$

$$V_d = \sum_{k=1}^{N} \sum_{i=1}^{m} \delta_{k,i} q_{k,i} \Delta t_k \tag{4}$$

$$\delta_{k,i} = \begin{cases} 0, C_{k,i} < DL \\ 1, C_{k,i} \geq DL \end{cases} \tag{5}$$

where V_d is the total water demand with a contaminant concentration higher than a determined value; N is the number of the calculation time steps between the starting time (that is the contaminant's injection time) and the time when the contaminant has been removed from the WDN at the contamination scenario s; m is the number of the water demand nodes in the network; $q_{k,i}$ is the water demand at node i at the time step k; Δt_k is the k-th time step; $\delta_{k,i}$ is a variable taking into consideration the contamination status at the node i during the time step k; DL is the death concentration limit for the contaminant; and $C_{k,i}$ is the contaminant's concentration at the node i during the time step k.

The reliability of detection optimization objective O_3 is the detection probability, calculated using [18,55]:

$$O_3 = \frac{1}{S} \sum_{j=1}^{S} d_j \tag{6}$$

where d_j gets the value 1 if the contamination scenario j is detected and 0 if it is not detected and S is the total number of the contamination scenarios analysed. The aim is to minimize the optimization objectives O_1 and O_2 and maximize the optimization objective O_3.

Trying to estimate the population infected in a simple way, a fixed water consumption rate per consumer is used. Thus, assuming that the consumption of any contaminated water volume causes health problems, the population infected is calculated dividing the contaminated water volume with the fixed water consumption per consumer. The assumption that consumers consume only the amount of water for a specific time period and then they stop consuming still stands. In this case, minimizing the objectives O_1 and O_2 provides the same nodes for the location of the sensors. However, the level of the contaminant mass ingested by the consumer is crucial for the impacts to the consumers' health. Therefore, the present study proposes a new objective, the contaminant mass ingested at a specific node, O_4:

$$O_4 = E(M) \tag{7}$$

$$M = \sum_{i=1}^{m} M_i \tag{8}$$

$$M_i = \sum_{k=1}^{N} c_{ik}\rho_{ik} \tag{9}$$

$$\rho_{ik} = \frac{q_{ik}}{\overline{q_i}} \tag{10}$$

where M_i is the contaminant mass consumed by the consumers at node i (mg); m is the total number of the nodes; c_{ik} is the concentration of the contaminant in node i at time step k (mg/L); N is the number of time steps before the detection; ρ_{ik} is the multiplier of the dose rate in node i at time step k; $\overline{q_i}$ is the average water demand at the node i; and q_{ik} is the water demand at the node i. The contaminant mass M_i consumed before the detection by a consumer in a network's node, for a specific contamination scenario, is calculated based on [18,55]. The aim is to minimize the objective O_4.

Water is not only used for drinking purposes, but we assume that all the contaminant mass consumed affects the consumers [57]. It is known that contaminants can also enter the organism by respiration and dermal routes. Still, there are water uses that do not affect consumers, such as clothes washing, etc. We assume the worst-case scenario, that all contaminant mass affects the population. In the case of intermittent water supply, the water networks suffer from water quality problems due to the non-continuous water supply. Also, there is an increase of consumer complaints in these cases. The contaminant mass is also used in the TEVA-SPOT toolkit [3,58] taking into consideration the water volume ingested or inhaled by a consumer.

As already discussed, the single objective approach does not provide the optimum solution, because applying another objective derives to another optimum solution. As the problem of sensors' placement is a multi-objective one, the use of a single multi-objective function that groups several single objectives is preferred. Aral et al. [55] suggested a multi-objective function combining four single objectives: the detection time, the population exposed, the water volume contaminated and the detection probability. Wu and Walski [32] have suggested another multi-objective function grouping the four objectives mentioned before. Since the population exposed to the contaminant is related to the water volume contaminated, the authors proposed a new multi-objective function O, grouping the objectives O_2 (contaminated water volume) and O_3 (detection probability). Since these objectives contradict (minimization of O_2 and maximization of O_3), the multi-objective function O can be calculated as follows:

$$O_i = (1 - O_{3i})\frac{O_{2i}}{\sum_{i=1}^{m} O_{2i}} \tag{11}$$

This multi-objective function is based on the work done by Kanakoudis and Tolikas [59] and Kanakoudis [60]. The aim is to reduce the people affected by the contaminant, minimizing the contaminated water volume. Higher detection reliability is necessary in order for the sensors network to be effective.

3. Case Study

3.1. Description of the Case Study

The WDN from WaterGEMS lesson "Water Quality" was used for the application of the methodology described (WaterGEMs is a hydraulic simulation software from Bentley Systems, Incorporated, Exton, PA, USA and has been extensively used [61]). The network is a typical one, supplied with water from two reservoirs, R-1 and R-3. The network consists of two water tanks, one pump near reservoir R-3, 50 pipes of total length 11,269 m and 32 nodes. The pipes' material is cast iron (40.15%) and ductile iron (59.85%) and their diameters range from 101.6 mm to 337.26 mm. Representing the hydraulic behaviour of the network, daily water demand (domestic and commercial) varies over 24 h. The water demand over 24 h fluctuates from 5.05 to 10.54 m^3/h and the average daily water demand is 191.23 m^3/day.

3.2. The Methodology Applied—Assumptions

The methodology is based on various assumptions. The first assumption refers to the use of "perfect sensors", as they accurately and continuously measure any concentration of the contaminant at a node. The contaminant concentration, injected one node at a time, is 10 mg/L and the injection duration is 3 h. The time until the first detection is 3 h, meaning that after this time period there is no consumption of contaminated water due to water supply interruption. The time of 3 h was selected in order to incorporate the time to detection minimization objective. The contaminant is injected at the 32 nodes of the network and at the two reservoirs, for a total of 34 nodes. Thus, the present study analyses 34 contamination scenarios, for a specific starting injection time. The present study does not consider multiple injections over space or time at the beginning. Then, multiple injection times are considered and examined. The contaminant is assumed conservative, not reacting with water or the pipes' walls and is modelled in WaterGEMS. The molecular diffusivity coefficient is set to 1.208×10^{-9} m^2/sec, as proposed by the software guidelines. To estimate the population affected at each node, the fixed water consumption is assumed as 200 L per consumer per day. Since the contaminant is considered dangerous for public health at any concentration, water is infected when the contaminant's concentration is greater than zero at any node.

The aim of the present study is to get a prioritized list of nodes for the placement of water quality sensors, minimizing health impacts and maximizing the detection reliability (probability of detection). Thus, the methodology applied consists of the setup of contamination scenarios. Initially the contaminant is injected at a specific concentration at one node at a time for a given stable starting time (the same for all scenarios). The period from the injection time to the time the contaminant was detected is assumed to be 3 h. In general, the contaminant is not detected right away and even if this happens, it takes time to apply emergency response measures (e.g., water interruption). Real cases show that this time period is sometimes long. This assumption is used to incorporate the time to detection objective (which should be minimized). Based on this assumption, water quality simulation takes place using WaterGEMS for each contamination scenario separately. From the simulation, the contaminant's concentration at each node of the network after 3 h is estimated. The construction of a binary matrix takes place, where the columns refer to contamination scenario (the contaminant is injected at each node of the network at the same time). The rows refer to the nodes of the network that could serve as potential sensor locations. The j^{th} column lists the concentrations at all nodes due to a specific contamination scenario. The i^{th} row lists the concentrations of the contaminant of all contaminant scenarios that can be detected by a sensor located to the specific node i. This matrix provides a stochastic representation of the consequences of a set of contamination events, imposed at the system nodes. Based on this matrix and the water demand data for the specific 3 h-period derived from WaterGEMS, the calculation of the contaminated water volume takes place. Thus, objective O_2 is calculated using the Equations (3)–(5). Objective O_1 is calculated assuming that the water consumption per consumer is a fixed number (200 L per consumer per day). Equation (6) is used for the calculation of objective O_3, and Equations (7)–(10) are used to calculate objective O_4. Finally, the multi-objective O is calculated using Equation (11). Using the numerical results of the objectives and classifying the nodes starting from the minimum values of each objective, a prioritized list of nodes is formed for each objective O_1, O_2, O_4 and O. The same happens when classifying the O_3 values starting from the maximum ones. Then, using the four first nodes of each list, the formation of the final list took place for each objective.

Since water demand varies over 24 h, it is necessary to apply the same methodology for different injection starting times. As water demand varies on an hourly basis, the starting time is set at every hour over the course of a day. Thus, a total of 24 binary matrices of the contaminant concentrations at each node are taken, for 34 contamination scenarios each. Each matrix represents the same starting injection time, from 0 h up to 23 h, at time steps of 1 h. Thus, 816 scenarios are formed (34 contamination scenarios for 24 h). Using this methodology, the present paper analyses how the spread of the contaminant to the network's nodes affects the selection of the nodes for sensor placement. The equations described above are used for the calculation of all objectives. The application of the methodology resulted in a list where each node takes a value for each of the objectives O_1, O_2, O_4 and O. The aim is to minimize or maximize the objective's values to get the optimum solution. Thus, a list of the nodes with the lowest or highest values for each objective is formed. In order to form a prioritized list of the nodes that have the highest frequency of appearance for each injection time (0 to 23 h), we assume that we can use the four nodes with the lowest or the highest value for each objective. Although this is an assumption, it seems, from the results obtained, that the prioritized list of nodes convincingly represents the nodes that optimize the objective function. When two or more nodes have the same frequency of appearance, they are ranked based on their position, i.e., the first node is the one ranked in higher positions. Finally, assuming that the sensors are placed at the specific nodes, the calculation of the probability of detection takes place. For the analysis below, only the objectives O_2, O_4 and O are used, as the population affected (O_1) is based on the water volume contaminated (objective O_2), giving the same results.

4. Results and Discussion

4.1. Contaminant Injected at Time t = 0

The application of the methodology resulted in a matrix showing the contaminant's concentrations at each node for each contamination scenario when the injection started at 0 h (Table 1). The ranking of the objectives' values from the lowest to the highest (for the objectives O_1, O_2, O_4 and O) provided a prioritized list of the suitable nodes for water quality sensors' placement. The same happened for the objective O_3 but the ranking was done from the highest to the lowest value. The four nodes with lowest values for the objectives O_1, O_2 and O are J-32, J-22, J-23 and J-16 (Figure 1a and Table 2), respectively. As expected, the same nodes have the lowest values for both objectives O_1 and O_2, as the population exposed to contamination (objective O_1) derived from the water volume contaminated (objective O_2). As the four nodes with the lowest O and O_2 values are the same, the use of the objective O_3 for the estimation of the multi-objective O does not affect the classification of the nodes. The nodes with the highest values of the objective O_3 are J-11, J-29, J-2 and J-28 (Figure 1b and Table 2). The nodes with the lowest values for the objective O_4 are J-22, J-32, J-23 and J-25 (Figure 1c and Table 2). Only the last node is different compared with the nodes derived from objective O_2.

Table 1. Contaminant concentrations (mg/L) at each node for all contamination scenarios at injection time 0.

	Contamination Scenarios																																	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**
Nodes	J-1	J-2	J-3	J-4	J-5	J-6	J-7	J-8	J-9	J-10	J-11	J-12	J-13	J-14	J-15	J-16	J-17	J-18	J-19	J-20	J-21	J-22	J-23	J-24	J-25	J-26	J-27	J-28	J-29	J-30	J-31	J-32	R-1	R-3
J-1	10	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J-2	0	10	0	0	0	0	0	0	0	0	0	0	0	0.1	2.1	0	0	0	0	0	0	0	0	0	0	0	0	0	1.7	0	7.9	7.9	0	0
J-3	2.4	0	10	0	0	0	0	0	0	0	0	0	0	0	0	7.6	7.1	0	0	0	0	0	0	0	0	2.9	0	0	0	0	0	0	0	0
J-4	0	0	0	10	0	0	0	0	0	4.3	10	0	0	0	0	0	0	0	0	0	0	2.4	3.3	0	0	0	0	0	0	0	0	0	0	0
J-5	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0
J-6	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0
J-7	0	0	0	0	10	10	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J-8	0	0	3	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0
J-9	4.9	0	4.1	0	0	0	0	0	10	0	0	0	0	0	0	3.5	0	0	0	0	0	0	0	0	0	6.9	0	0	0	0	0	0	0	0
J-10	0	0	2.3	0	0	0	0	0	0	10	0	0	0	0	0	9.2	7.6	0	0	0	0	0	0	0	0	0.7	0	0	0	0	0	0	0	0
J-11	0	0	1	0	0	0	0	0	0	4.2	10	0	0	0	0	3.2	0	0	0	3.3	2.4	2.4	3.3	0	0	0	0	0	0	0	0	0	0	0
J-12	10	0	0	0	0	0	10	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J-13	5.6	0	0	0	0	0	0	0	0	0	0	5.6	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.4	0	4.4	0	0
J-14	10	0	0	0	0	0	10	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J-15	0.7	0	0	0	0	0	0	0	0	0	0	0	0	1.7	10	0	0	0	0	0	0	0	0	0	0	0	2.2	6	8.3	0	0	0	0	0
J-16	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J-17	0	0	0	0	0	0	0	0	0	0	0	5.6	10	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	4.4	0	0	0	0
J-18	0	0	0	8.6	0	0	0	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J-19	0	0	0	10	0	0	0	0	0	0	10	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J-20	0	0	6.8	0	0	0	0	0	0	0	0	0	0	0	0	4.8	0	0	0	10	0	0	0	3.2	3.2	2	0	0	0	0	0	0	0	0
J-21	0	0	2.4	0	0	0	0	0	0	10	0	0	0	0	0	7.5	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0
J-22	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0
J-23	0	0	6.9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	10	3.1	0	0	0	0	0	0	0	0	0	0
J-24	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0
J-25	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	7.1	0	0	0	0	0	0	0	0	10	2.9	0	0	0	0	0	0	0	0
J-26	8	0	0	0	0	0	8	0	0	0	0	0	0	0	0	2.0	2.0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0
J-27	10	0	0	0	0	0	0	0	0	0	0	7.4	0	2.6	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0
J-28	1.2	0	0	0	0	0	0	0	0	0	0	1.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	6.7	2.1	8	0	0
J-29	0	0	0	0	0	0	0	0	0	0	0	2.9	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0	2.2	7.8	10	5.2	0.4	0	0	0
J-30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	10	0	0
J-31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	10	0	0
J-32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0
R-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0
R-3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10
T-1	0	0	0	0	0	0	0	0.7	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T-2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

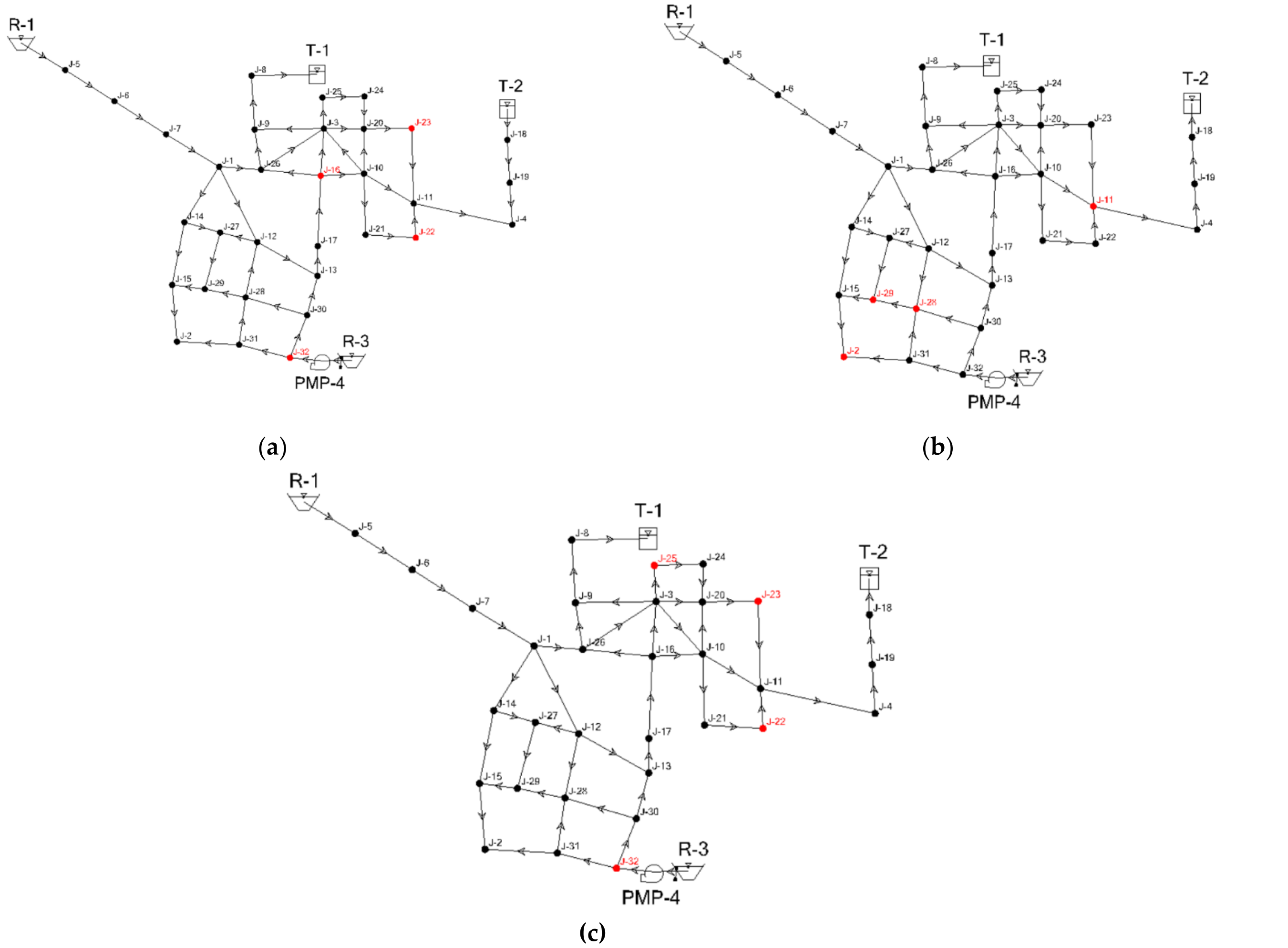

Figure 1. The nodes (marked as red) with: (**a**) the lowest values for objectives O_1, O_2 and O; (**b**) the highest values for the objective O_3; and (**c**) the lowest values for the objective O_4.

Table 2. The four nodes with the lowest values for objectives O_1, O_2, O_4 and O and the highest values for objective O_3.

Objective	Node ID	Value	Node ID	Value	Node ID	Value	Node ID	Value
O_1 (people)	J-32	17	J-22	20	J-23	22	J-16	29
O_2 (m^3)	J-32	3.3	J-22	3.9	J-23	4.4	J-16	5.7
O_3 (%)	J-11	23.53	J-29	20.59	J-2	17.65	J-28	17.65
O_4 (g)	J-22	22.2	J-32	28.6	J-23	31.1	J-25	46.3
O	J-32	0.014	J-22	0.016	J-23	0.017	J-16	0.023

4.2. Contaminant Injected at Every One Hour for 24 h

As water demand varies over the day, the contaminant spreads in a different way within the network. The variation of the demand results in different scenarios for the contaminant injection time. Twenty-four different scenarios were set up and applied to all contamination scenarios (totally 816 scenarios). For every objective, the four nodes are identified with the lowest (or highest) values for each injection time. The application of the methodology already described results in a matrix composed of the nodes (Table 3). The columns list the 4 nodes for each injection time, from 0 to 23 h.

Table 3. The four nodes with the lowest values for O_1, O_2, O_4 and O and the highest values for O_3, for all injection times (from 0 h to 23 h).

Criterion	Injection Time (Hours)																						
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
O_1	J-32	J-32	R-3	J-32	J-22	J-22	J-22	J-22	J-32	J-32	J-32	J-32	J-32	J-32	J-1	J-22	J-22	J-22	J-22	J-22	J-32	R-3	J-32	J-32
	J-22	J-30	J-32	J-22	J-23	J-23	J-23	J-16	J-22	J-22	J-22	J-22	J-30	J-22	J-22	J-23	J-23	J-23	J-23	J-23	J-30	J-32	R3	J-30
	J-23	J-31	J-31	J-1	J-17	J-17	J-17	J-23	J-30	J-30	J-30	J-30	J-31	J-23	J-23	J-17	J-32	J-32	J-17	J-17	J-31	J-30	J-30	J-31
	J-16	R-3	J-1	J-23	J-29	J-29	J-29	J-17	J-31	J-23	J-31	J-23	J-22	J-1	J-9	J-1	J-17	J-30	J-29	J-29	J-1	J-31	J-31	R-3
O_2	J-32	J-32	R-3	J-32	J-22	J-22	J-22	J-22	J-32	J-32	J-32	J-32	J-32	J-32	J-1	J-22	J-22	J-22	J-22	J-22	J-32	R-3	J-32	J-32
	J-22	J-30	J-32	J-22	J-23	J-23	J-23	J-16	J-22	J-22	J-22	J-22	J-30	J-22	J-22	J-23	J-23	J-23	J-23	J-23	J-30	J-32	R3	J-30
	J-23	J-31	J-31	J-1	J-17	J-17	J-17	J-23	J-30	J-30	J-30	J-30	J-31	J-23	J-23	J-17	J-32	J-32	J-17	J-17	J-31	J-30	J-30	J-31
	J-16	R-3	J-1	J-23	J-29	J-29	J-29	J-17	J-31	J-23	J-31	J-23	J-22	J-1	J-9	J-1	J-17	J-30	J-29	J-29	J-1	J-31	J-31	R-3
O_4	J-22	J-32	J-32	J-23	J-22	J-22	J-22	J-22	J-22	J-22	J-22	J-22	J-32	J-32	J-23	J-22	J-22	J-22	J-22	J-22	J-22	J-32	J-32	J-32
	J-32	J-30	R-3	J-22	J-23	J-23	J-23	J-32	J-32	J-32	J-32	J-32	J-30	J-23	J-22	J-23	J-23	J-23	J-23	J-23	J-23	R-3	J-23	J-22
	J-23	J-31	J-23	J-32	J-29	J-29	J-29	J-23	J-31	J-23	J-23	J-23	J-31	J-22	J-9	J-25	J-29	J-29	J-29	J-29	J-29	J-22	R-3	J-30
	J-25	J-23	J-31	J-9	J-25	J-25	J-25	J-30	J-30	J-31	J-30	J-30	J-29	J-31	J-32	J-29	J-25	J-32	J-32	J-32	J-32	J-23	J-30	J-31
O_3	J-11	J-11	J-11	J-11	J-10	J-10	J-10	J-11	J-11	J-11	J-11	J-11	J-11	J-11	J-11	J-10	J-10	J-10	J-10	J-10	J-11	J-11	J-11	J-11
	J-29	J-4	J-10	J-10	J-11	J-11	J-11	J-29	J-29	J-29	J-29	J-13	J-4	J-10	J-10	J-11	J-11	J-11	J-11	J-11	J-10	J-4	J-4	J-29
	J-2	J-2	J-4	J-4	J-2	J-2	J-2	J-28	J-2	J-2	J-2	J-12	J-27	J-4	J-4	J-20	J-2	J-2	J-2	J-2	J-2	J-2	J-10	J-4
	J-28	J-23	J-28	J-2	J-3	J-3	J-3	J-23	J-28	J-20	J-12	J-2	J-3	J-3	J-3	J-3	J-3	J-3	J-3	J-3	J-3	J-23	J-2	J-2
O	J-32	J-32	R-3	J-32	J-22	J-22	J-22	J-22	J-32	J-32	J-32	J-32	J-32	J-32	J-23	J-22	J-22	J-22	J-22	J-22	J-32	R-3	J-32	J-32
	J-22	J-30	J-32	J-23	J-23	J-23	J-23	J-16	J-22	J-22	J-22	J-22	J-30	J-23	J-22	J-23	J-23	J-23	J-23	J-23	J-30	J-32	R-3	J-30
	J-23	J-31	J-31	J-22	J-17	J-17	J-17	J-23	J-30	J-23	J-30	J-23	J-31	J-22	J-1	J-17	J-32	J-32	J-17	J-17	J-31	J-31	J-30	J-31
	J-16	J-23	J-23	J-1	J-29	J-29	J-29	J-17	J-31	J-30	J-23	J-30	J-22	J-4	J-9	J-1	J-17	J-30	J-29	J-29	J-1	J-30	J-31	R-3

The nodes with the lowest O_2 values for all injection time scenarios ranked as described are J-22, J-32, J-23, J-30, J-31, J-17, J-1, R-3, J-29, J-16 and J-9 (Table 3 and Figure 2). Then, the estimation of the detection probability took place. Initially one sensor was placed at the first node (J-22) and the detection probability ranged from 5.88% to 17.65% depending on the injection time. By adding another sensor at the second node (J-23) the detection probability ranged from 8.82% to 29.41%. Following the same process eleven sensors were placed at the nodes indicated above, and the detection probability ranges from 64.71% to 79.41% (with an average value of 71.81%) (Figure 3). Figure 3 shows the detection probabilities when each node was added at the monitoring network (MN) (Table 4). The detection probability per MN achieved a maximum and minimum value depending on the injection time within the 24-h day. Figure 3 also shows the average detection probability for the 24 h.

Table 4. The monitoring networks and the selected nodes for sensor placement for each monitoring network for three cases based on different objectives: O_2, O_4 and O.

Monitoring Network (MN)	Selected Nodes for Sensor Placement		
	Analysis Based on O_2	**Analysis Based on O_4**	**Analysis Based on O**
MN1	J-22	J-23	J-22
MN2	J-22, J-32	J-23, J-22	J-22, J-32
MN3	J-22, J-32, J-23	J-23, J-22, J-32	J-22, J-32, J-23
MN4	J-22, J-32, J-23, J-30	J-23, J-22, J-32, J-29	J-22, J-32, J-23, J-30
MN5	J-22, J-32, J-23, J-30, J-31	J-23, J-22, J-32, J-29, J-30	J-22, J-32, J-23, J-30, J-31
MN6	J-22, J-32, J-23, J-30, J-31, J-17	J-23, J-22, J-32, J-29, J-30, J-31	J-22, J-32, J-23, J-30, J-31, J-17
MN7	J-22, J-32, J-23, J-30, J-31, J-17, J-1	J-23, J-22, J-32, J-29, J-30, J-31, J-25	J-22, J-32, J-23, J-30, J-31, J-17, J-29
MN8	J-22, J-32, J-23, J-30, J-31, J-17, J-1, R-3	J-23, J-22, J-32, J-29, J-30, J-31, J-25, R-3	J-22, J-32, J-23, J-30, J-31, J-17, J-29, R-3
MN9	J-22, J-32, J-23, J-30, J-31, J-17, J-1, R-3, J-29	J-23, J-22, J-32, J-29, J-30, J-31, J-25, R-3, J-9	J-22, J-32, J-23, J-30, J-31, J-17, J-29, R-3, J-1
MN10	J-22, J-32, J-23, J-30, J-31, J-17, J-1, R-3, J-29, J-16		J-22, J-32, J-23, J-30, J-31, J-17, J-29, R-3, J-1, J-16
MN11	J-22, J-32, J-23, J-30, J-31, J-17, J-1, R-3, J-29, J-16, J-9		J-22, J-32, J-23, J-30, J-31, J-17, J-29, R-3, J-1, J-16, J-9
MN12			J-22, J-32, J-23, J-30, J-31, J-17, J-29, R-3, J-1, J-16, J-9, J-4

The application of the same methodology for the objective O_4 leads to a prioritized list of nodes with a high frequency of appearance when all 816 scenarios are analysed. The nodes included in the list are J-23, J-22, J-32, J-29, J-30, J-31, J-25, R-3 and J-9 (Table 3). When only one sensor was place at node J-23, the detection probability ranged from 11.76% to 23.53% (Figure 4). Adding sensors to the nodes one-by-one (forming a different monitoring network shown in Table 4), the detection probability increased. The detection probability values ranged from 52.94% to 73.53% (average 64.58%) when nine sensors were placed at the above-mentioned nodes (Figure 4). Figure 4 shows the detection probabilities when each node was added at the monitoring network (MN) (Table 4).

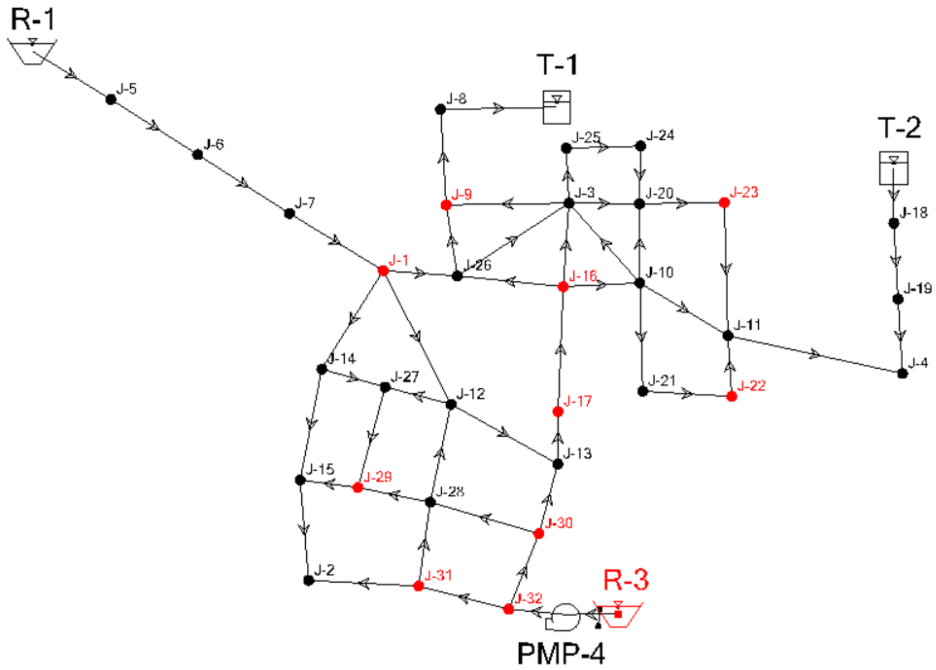

Figure 2. The eleven nodes (marked as red) with the highest frequency of appearance in the 24 scenarios for O_2.

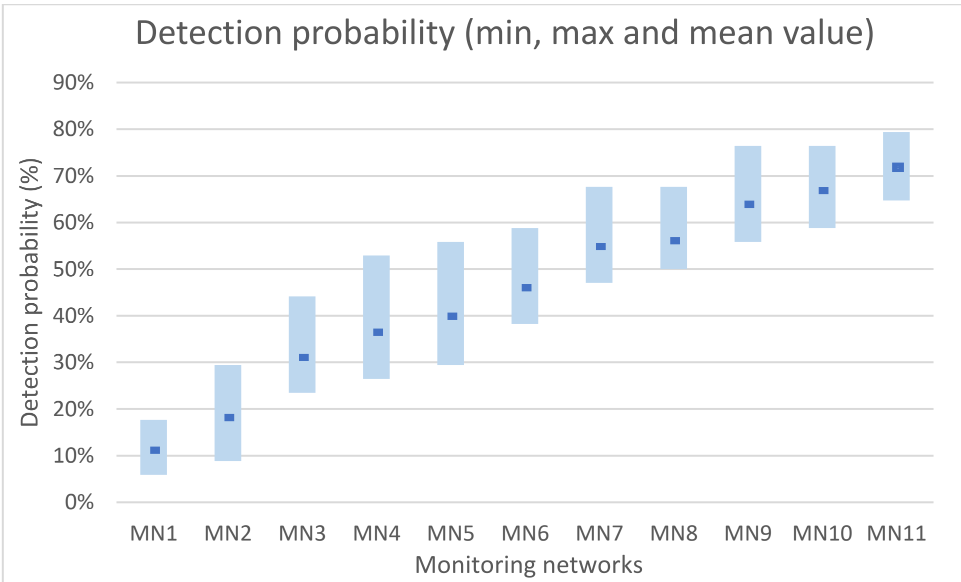

Figure 3. Detection probability minimum, maximum and mean values for monitoring networks (consisting of nodes for installation of sensors based on O_2 objective).

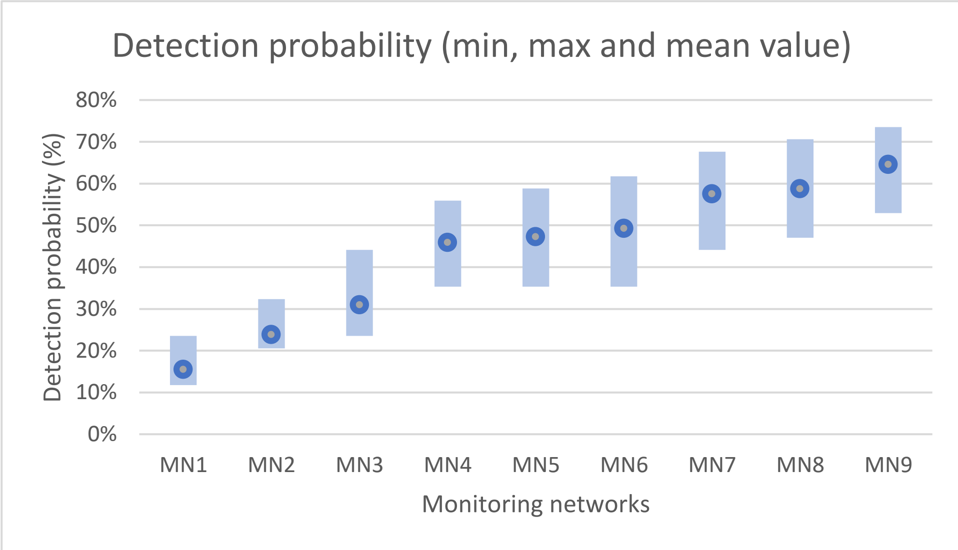

Figure 4. Detection probability minimum, maximum and mean values for monitoring networks (consisting of nodes for installation of sensors based on O_4 objective).

The application of the objective O for all scenarios leads to the list of the nodes with a high frequency of appearance for the lowest O values for the 24 scenarios. These nodes are J-22, J-32, J-23, J-30, J-31, J-17, J-29, R-3, J-1, J-16, J-9 and J-4 (Table 3). The detection probability was estimated by setting one sensor at node J-22 and adding sensors one-by-one to each node forming a different monitoring network (Table 4). If only one sensor was placed in node J-22, the detection probability ranged from 5.88% to 17.65% depending on the injection time (Figure 5). When twelve sensors were placed at the nodes indicated above, then the detection probability ranged from 70.59% to 91.18% (with an average value of 78.92%) (Figure 5).

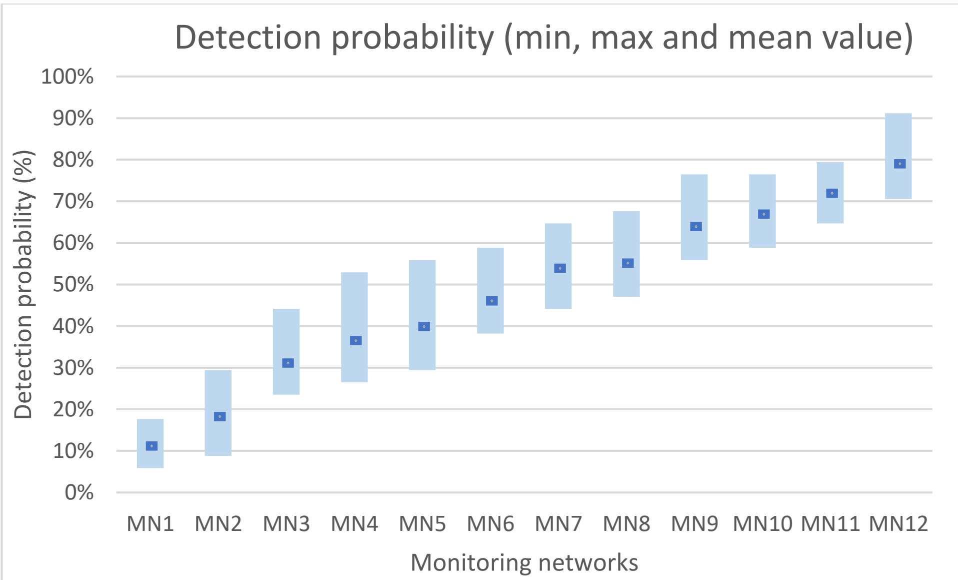

Figure 5. Detection probability minimum, maximum and mean values for monitoring networks (consisting of nodes for installation of sensors based on O objective).

4.3. Discussion

Comparing the results from the application of the methodology for the three objectives, three different scenarios including different nodes for sensor placement are identified. The nodes included in the scenarios obtained from the application of the objectives O_2 and O are almost the same. The difference is the ranking order for nodes J-29 and J-1, where node J-1 is ranked seventh in order with a detection probability ranging from 47.06% to 67.65% (average 54.78%) when using objective O_2, whereas node J-29 is ranked seventh in order with a lower detection probability ranging from 44.12% to 64.71% (average 53.8%), when using objective O. Regardless of the objective used (O_2 or O) if only eleven sensors are placed, the detection probability is the same, because the first eleven nodes are the same for each objective. Another difference is the number of nodes included in the scenario: twelve nodes using objective O and eleven nodes using objective O_2. The additional node is J-4, achieving a higher mean detection probability of 78.92%. The results from the use of the objective O_4 result in nine nodes. The first node is different compared with the other two scenarios and node J-25 is included. However, even if only nine nodes are used to install the sensors, the detection probability values are higher when using the objective O_4 (Figure 6).

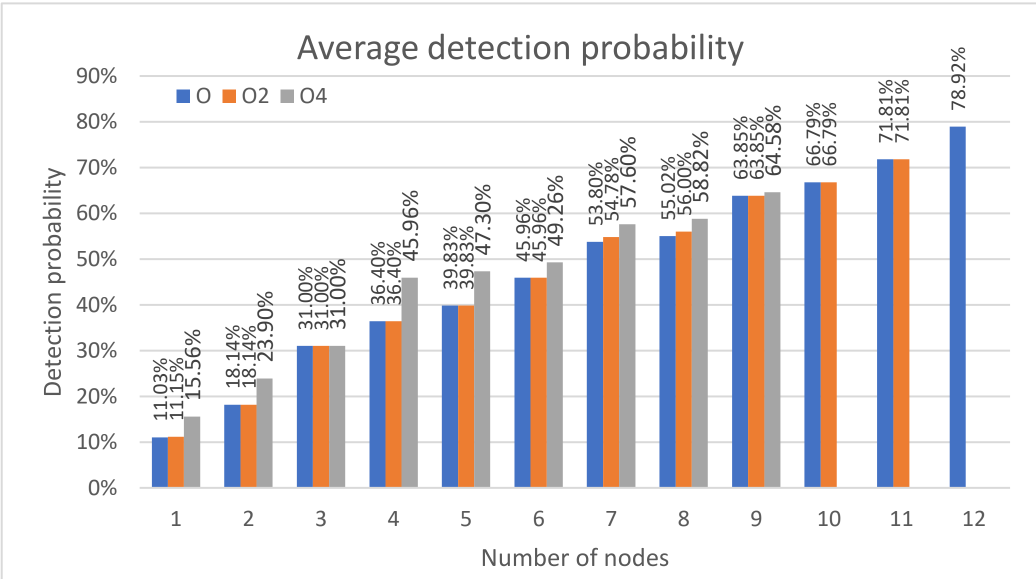

Figure 6. Comparing mean detection probability from the objectives O_2, O_4 and O.

Comparing the number of nodes and the detection probability, when the objective O is used for twelve nodes the detection probability is higher. Comparing the results when the objectives O_2 and O are used, the detection probabilities are almost the same, except for the seventh and the eighth node. In conclusion, if the number of nodes cannot be higher than nine (for example due to cost constraints), then the application of the objective O_4 gives higher detection probabilities. If the cost is not the decisive factor and any number of sensors can be placed, the application of the objective O results in a higher number of total nodes and consequently higher probability of detection.

Several assumptions are made to estimate the population affected by the contamination, the water consumed and the contamination mass ingested. This study considered the worst-case scenario where all water consumed affects the population's health, even if there is water use that does not affect people (e.g., clothes' washing). Also, we assumed that the contaminant causes health problems to the people upon consumption at its lowest concentration. In reality, the water volume and the contaminant mass consumed gets lower values due to other water uses. Also, there is a safe concentration of the contaminant that does not cause any harm. Thus, as the study actually aims at locating the appropriate nodes for the installation of sensors, it considers the worst-case scenario. A more thorough analysis should consider different kinds of contaminants such as toxins or microbiological factors.

The simulation time was assumed to be 3 h from the injection time, starting at a different time during the day. This assumption was selected to take into consideration the time to detection objective. Usually, the time to detection and the issuing of appropriate measures (such as a water supply interruption) is long. To find the appropriate nodes for the location of the sensors, the authors used two single objectives and one multi-objective function. Using this simple methodology, a list of nodes with the lowest (or highest depending on the optimization target of each objective function) objective value is formed. Then, we formed a list with the nodes having the highest frequency of appearance, based on the first nodes with the lowest or highest objective values. Although a small number of nodes with the lowest (or highest value) were selected, we examined a higher number of nodes that provided the same results. Based on these assumptions, and on this simple methodology, the water utility operators can take a preliminary list of appropriate nodes for the location of the sensors. The nodes derived from this methodology can be used to install portable sensors and then, using the monitoring results and advance algorithms, arrive at the optimum number and locations for the sensors.

The problem for the selection of the optimal locations for the installation of water quality sensors has been addressed for many years and many advanced tools have been developed. However, operators in small water utilities are not keen on using such tools. Using a simple methodology and given that contamination can happen at any time and at any place in the network (as contamination also can be accidental), water utility operators can spot the suitable nodes with an acceptable detection probability. The application of the proposed methodology can be useful to water operators. The steps they need to take are to firstly develop a hydraulic model of the WDN that needs to be calibrated and then to choose the contamination scenarios based on their experience and on the vulnerable parts of the network. The choice of the single or multi objective function is also important. Multi-objective functions have proven to be more efficient. The final results of the proposed methodology will be a list of locations (nodes) where the sensors will be installed. However, as not all locations are proper (due to difficulties in reaching the specific node) and some of the locations are more important (for example a node supplying water to the local hospital or other critical organization), the water operators can select the most important locations.

The novelty of the proposed approach is based mainly on the simple methodology used which can be applied by the operators in small water utilities who do not have the means to apply advanced algorithms. The proposed approach requires a well calibrated hydraulic model of the distribution network and the setup of proper contamination scenarios. Using the appropriate objectives, and preferably a multi-objective function, provides the water operators with several locations for the installation of sensors. Water operators will use their experience at interpreting the results to select the proper locations.

5. Conclusions

The standard water distribution network from the WaterGEMs "Water quality" lesson was used for the application of a simple methodology for sensor placement. Contamination scenarios in which the same contaminant concentration was injected at all nodes in the WDN at different starting times provided a list of nodes with the lowest values for the objectives population affected (O_1), water volume contaminated (O_2), contaminant mass (O_4) and the highest values for the probability of detection objective (O_3). As the problem of sensor placement is a multi-objective problem, a multi-objective function O was proposed. This is based on the water volume contaminated and the detection probability, which are contradictory objectives. A thorough analysis of 816 scenarios resulted in five scenarios consisting of nodes for each starting injection time. The five scenarios contain nodes ranked in order based on lowest values for the objectives O_1, O_2, O_4 and O and highest values for the O_3 objective. Taking into consideration the frequency of appearance of the nodes to the different scenarios, a final list with prioritized nodes was obtained after the application of each objective.

The final obtained lists based on the objectives O_2, O_4 and O contain almost the same nodes with small variations in ranking. The list obtained from the application of objective O_4 includes less sensors and gives higher detection probabilities. If cost is not a decisive factor, then the multi-objective O gives better results, detecting 78.92% of the possible contamination events on average, using twelve sensors. The analysis undertaken took into consideration various starting times of injection over the 24-h day, as the hydrodynamic behaviour of the network affects the contaminant's spread. The contamination is a random phenomenon and can happen at any time. Additionally, it is crucial for the water utility to identify which are the time periods of injection resulting in larger contaminated areas of the network. This will help the water utility to apply measures during these time periods, such as more frequent samplings.

As the problem of sensor placement in water distribution networks to monitor water quality is a difficult task [62,63], this simple methodology can be useful to operators in small water utilities to identify a preliminary list of junctions to install portable water quality sensors. In terms of future work, the authors will test this simple methodology followed by a more thorough analysis using advanced algorithms and tools to be able to provide an optimal list of locations for sensor placement.

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