Highlights:

1. Water quality sensors are located on pipes of water distribution system, as is in reality;
2. Weighted topology is used for reducing the computational burden of optimization phase;
3. Potential sensor locations are defined on the hydraulic/topological-wise most central pipes;
4. Detection performance, economic and logistic criteria are used to select the best solution;
5. A weighted multi-parametric Decision Support System for selecting the monitoring layout is proposed.

Multi-criteria method for the realistic placement of water quality sensors on pipes of water distribution systems

C. Giudicianni[1], M. Herrera[2], A. Di Nardo[3], E. Creaco[4], R. Greco[5]

Abstract

This paper aims to solve three issues frequently present in the optimal placement of water quality sensors for protecting water distribution systems (WDSs) from both accidental and intentional contamination, namely i) computational intractability of the optimization problem as the size of the WDS increases, ii) unrealistic assumption that sensors are positioned at nodes, rather than on system pipes, and iii) neglection of site-specific practical conditions. The three drawbacks were tackled by i) restraining the optimization to the hydraulic/topological-wise most important pipes, ii) introducing dummy nodes in the middle of these pipes as potential sensor locations, iii) applying a multi-criteria decision-making tool incorporating urbanistic and economic factors for selecting the most effective sensor locations. The method is tested on the WDS of the town of Parete (Italy), showing the manyfold benefits of the solution obtained.

[1] Dipartimento di Ingegneria, Università degli Studi della Campania "Luigi Vanvitelli", via Roma 29, Aversa, 81031, Italy; Action Group CTRL+SWAN of the European Innovation Partnership on Water, EU, Via Roma 29, 81031, Aversa, Italy; E-mail: carlo.giudicianni@unicampania.it (corresponding author)

[2] Institute for Manufacturing - Department of Engineering, University of Cambridge, 17 Charles Babbage Rd., CB3 0FS Cambridge, United Kingdom; E-mail: amh226@cam.ac.uk

[3] Dipartimento di Ingegneria, Università degli Studi della Campania "Luigi Vanvitelli", via Roma 29, Aversa, 81031, Italy; Action Group CTRL+SWAN of the European Innovation Partnership on Water, EU, Via Roma 29, 81031, Aversa, Italy; Institute for Complex Systems, Italian National Research Council, via dei Taurini 19, Roma 00185, Italy; E-mail: armando.dinardo@unicampania.it

[4] Dipartimento di Ingegneria Civile ed Architettura, Università degli Studi di Pavia, Via Ferrata 3, 27100 Pavia, Italy; Action Group CTRL+SWAN of the European Innovation Partnership on Water, EU, Via Roma 29, 81031, Aversa, Italy; E-mail: creaco@unipv.it

[5] Dipartimento di Ingegneria, Università degli Studi della Campania "Luigi Vanvitelli", via Roma 29, Aversa, 81031, Italy; Action Group CTRL+SWAN of the European Innovation Partnership on Water, EU, Via Roma 29, 81031, Aversa, Italy; E-mail: roberto.greco@unicampania.it

Keywords

contamination warning system; complex network theory; edge betweenness; sensor placement; water distribution system topology; water network protection.

1. INTRODUCTION

Water distribution systems (WDSs) are an essential part of the critical infrastructure of a city, since the availability of clean water affects both socio-economic prosperity and population safety. WDSs are considered inherently vulnerable to both intentional and accidental contaminations due to their large size (up to tens or hundreds of kilometres of pipes), complexity, large number of served users and access points (e.g. hydrants, consumer connections, tanks, reservoir and leak points) (Oliker et al. 2016). The assessment of contamination risk comes with an uncertainty related to the type of contaminant (and its consequences) and the characteristics of its intrusion (time, duration and location), making it one of the most difficult problems to address for WDS management. A widely used strategy for securing WDSs against contamination is the installation of a water quality sensor system (WQSS) (AWWA 2005). The aim is to quickly assess water quality, enabling early detection of potentially dangerous conditions. A WQSS provides indications on contamination events (Janke et al., 2006) and helps locating their source by using time and location of the actual detection (Ung et al., 2017). Considering that the first hours after contamination are crucial for mitigating its impacts (Zulkifli et al., 2018), the continuous monitoring of water quality parameters plays a key role for implementing and maximizing the benefits of an early warning system (Hu et al., 2017). To maximize the WQSS detection capability, water operators should address the issue of identifying the most suitable locations for sensor placement, by balancing both performance aspects and economic investment (Murray et al., 2008). Usually, securing the entire network is infeasible in practice, due to budget constraints that often limit the number of sensors a water utility can deploy. In this regard, sensors should be placed in strategic locations, at the same time easily accessible and assuring maximum capability of detecting and identifying contaminants in a short time. Since 1991

(Lee et al., 1991), researchers and practitioners have explored the optimal sensor placement problem in WDSs. Since the events of September 11th in the United States, protecting critical infrastructures from potential terrorist acts has become an absolute priority. Various methodologies have been proposed to define an optimal WQSS (Lee and Deininger, 1992; Uber et al., 2004; Chang et al., 2013). These are generally arranged in top-down decision support frameworks (Khorshidi et al., 2019), with the upper and lower decision levels related to public safety and operational costs, respectively. However, the optimal sensor placement challenge is still open from different viewpoints (e.g. identification of most suitable locations, performance evaluation, applicability to real-world scenarios) and there has not been found any general "optimality criteria". Rathi et al. (2015) divided models and algorithms for solving the sensor placement problem in two categories: a) *Single-Objective* approaches, such as the work of Kessler et al., (1998); Woo et al. (2001); Ostfeld and Salomons, (2005); Berry et al., (2009); b) *Multi-Objective* approaches, such as the methods proposed by Propato and Piller, (2006); Huang et al., (2006); Wu and Walski, (2006); Dorini et al., (2008). In the Battle of the Water Sensor Networks (BWSN), approaches of the two categories were compared and tested (Ostfeld et al., 2008). Overall, the objective functions developed in the literature are related to detection likelihood, expected contaminated water volume, detection time and exposed population. Extensive critical reviews of the topic can be found in Hu et al. (2018), as well as in Adedoja et al. (2019), who further classify the existing methods into four categories: opinion-based, rule-based, optimisation-based and theory-based. Generally, due to the huge number of potential contamination scenarios and to the WDS complexity, the problem of optimal WQSS layout comes with high computational costs, especially for large WDSs. As reported by Xu et al. (2013), the optimal sensor placement in a network represents a NP-hard combinatorial optimization problem. In this regard, together with the investigation of several objective functions, continuous efforts have been made to develop increasingly efficient numerical techniques (Hart and Murray, 2010; Diao and Rauch, 2013). In this regard, during the recent years, several aspects of the optimal water quality sensor placement have been addressed. Zhao et al. (2016) proposed a branch and bound sensor placement algorithm based on greedy heuristics and convex relaxation to minimize the consumption of contaminated water prior to contamination detection. Rathi and Gupta (2017) maximized the demand coverage and the detection probability with a time constraint for the early detection. Tinelli et al. (2018) discussed the impact of objective function selection on the optimal sensor placement problem. Ciaponi et al. (2019) proposed a combined management strategy for monitoring WDSs based on water network sectorization and installation of water quality sensors. Giudicianni et al. (2020) presented a topological approach for the case of limited information about the system, which relies on a priori clustering of the WDS, and on the installation of water quality sensors at the topologically most central nodes of each cluster. Hooshmand et al. (2020) addressed the sensor placement problem by minimizing the number of vulnerable nodes and assuming a limited sensor budget availability. Lee & Yoo (2020) suggested a methodology for defining water quality sensor locations considering the variability in water flow directions due to abnormal functioning conditions. Taha et al. (2021) considered the previously overlooked metric of state estimation and network-wide observability of the water quality dynamics to find optimal sensor placement with Kalman filtering. Fasaee et al. (2021) developed a new model to identify the optimal location of sensors, to effectively support hydrant flushing for ensuring an efficient discharge of contaminants. The variation in node contamination probability, due to population density and user properties, has been addressed in several works (He et al., 2018). In this regard, Hu et al. (2021) proposed a multi-objective approach based on the different characteristics of each node and the risk levels of contamination events, showing the effect of such variability on the selection of sensor locations. Naserizade et al. (2018) used the NSGA-II and included cost and probability of undetected events and uncertainties related to a contamination injection in the optimization process, while Cardoso et al. (2020) considered four contamination probability functions combined with a clustering-based post-processing method for a Pareto front analysis. The characteristics of sensors have been considered by Zeng et al. (2018), who maximized the quality-of-sensing and considered two types of sensors with different prices and communication capabilities. Sankary and Ostfeld

(2018) simultaneously minimized the affected population and the expected number of false positive detections, while de Winter et al. (2019) investigated the influence of sensor imperfection by means of two greedy algorithms and by considering multiple objective functions. Different techniques and algorithms have been explored and adopted for solving the problem of the optimal water quality sensor placement. For example, the information entropy theory was used by Khorshidi et al. (2018) and by Brentan et al. (2021), for reducing the computational burden of the problem and developing a multi-criteria decision-making technique for the selection of an optimal solution, respectively. Hu et al. (2020) and Jafari et al. (2021) adopted the NSGA-III algorithm to solve the multi-objective sensor placement problem, by considering the graph connectivity for the selection of individuals and the effect of contamination in important junctions in terms of social consequences, respectively. Finally, the resilience of water quality sensor placement strategies was investigated by Zhang et al. (2020) and Nikolopoulos et al. (2021). Zhang et al. (2020) considered all likely sensor failures and defined metrics for ranking alternatives. Nikolopoulos et al. (2021) developed a novel methodology to assess the resilience under cyber-physical attacks.

This paper presents a novel method and a new perspective for the water quality sensor placement problem in a WDS. Compared to the previously developed methods, the major novelty lies in considering, more realistically, the placement of sensor on pipes, rather than in WDS nodes. Before carrying out the optimization, Complex Network Theory tools are applied to define the most important pipes on which subsequently locating dummy nodes as possible sensor locations. The graph of the WDS is weighted with a pipe hydraulic resistance surrogate parameter in order to consider also the hydraulics of the contaminant transport phenomenon. Accordingly, weighting the graph allows definition of the most important pipes from both topological and hydraulic viewpoints. As a result, the computational burden is significantly reduced, since a small subset of pipes is defined for the following optimization phase. Four different objective functions are investigated and optimised, to define the most suitable sensor placement layouts by exploring the new reduced solution space. In order to identify the most efficient and effective monitoring system, besides economic (incremental benefit) and detection performance criteria (detection time, detection likelihood, population exposed and extent of contamination), further logistic site-specific conditions are considered, such as surrogate metrics of accessibility and easiness of installation. Finally, this paper provides a general multi-criteria decision-making tool for supporting decisional processes in WQSS design.

2. METHODOLOGY

As mentioned before, optimal sensor placement in a water distribution network represents an NP-hard combinatorial optimization problem (Xu et al., 2013), as the computational complexity exponentially increases with the growth of WDS size. A constraint on the number of sensors should be added to this problem for obvious economic and practical reasons. The proposed methodology consists of five steps that progressively reduce the number of potentially adoptable solutions according to different criteria based on safety, logistic and economic viewpoints:

a) Modelling of the WDS as a weighted graph, calculation of the most central pipes and insertion of dummy nodes (*Topological step*);
b) Classification of locations through an accessibility criterion (*Logistic step*);
c) Heuristic optimization with four objective-functions (*Optimization step*);
d) Calculation of sensors placement cost and setting up of an incremental economic benefit threshold (*Economic step*);
e) Design of a decision support system based on a weighted normalised matrix of the detection criteria (*Decision step*).

The overall methodology adopted for the search of the most suitable WQSS is summarised in Figure 1. As subsequently described in detail, the Logistic step intervenes twice in the methodology, before the Optimization step and during the Economic one.

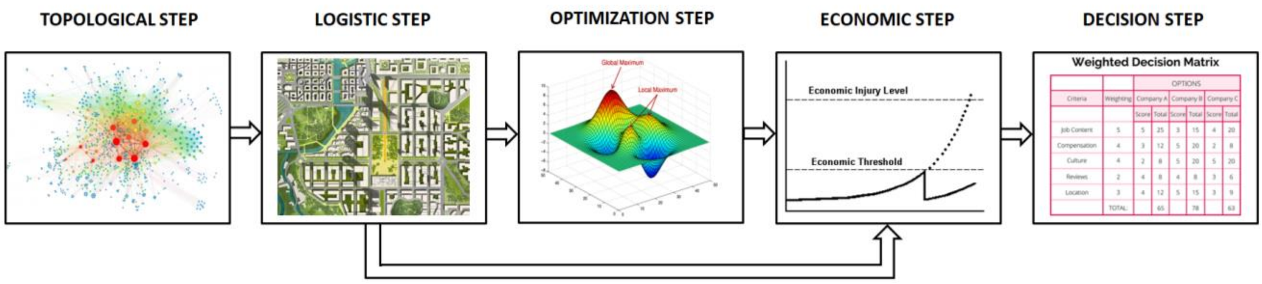

Figure 1: Flow-chart of the proposed multi-criteria method for the selection of the most suitable water quality sensor system (WQSS).

a. Topological step

The starting point of the method consists of modelling the WDS as an undirected weighted graph $G=(V,E,W)$, taking advantage of the topological properties of the WDS graph (Giudicianni et al., 2018). Indeed, (Perelman & Ostfeld, 2011) showed how adopting graph theory can help in gaining insight in to the WDS behaviour by simplifying its operation. (Sitzenfrei, 2021) showed graph theory's potential for assessing water quality of the WDS. Furthermore, (Giudicianni et al. 2021) identified the most critical contamination sources by means of topological metrics. In particular, V is the set of n nodes v_i (junctions, reservoirs and tanks), E is the set of m links $l_{ij}=(v_i, v_j)$ from node v_i to node v_j (pipes, valves and pumps), and $w_{ij}\in W$ is a weight characterising the physical characteristics of i-th link. The graph is considered weighted with a surrogate measure of pipe hydraulic resistance (Herrera et al. 2016). Specifically, the weight, $w_i=L_i/D_i$ has been assigned to each link (with L_i and D_i the length and diameter of pipes) to obtain a graph model that also considers the hydraulic behaviour of the WDS. The aim is to take into account the phenomenology of the system through a non-dimensional weight that is linearly dependent only on geometric characteristics of pipes, not related to a specific head-loss formula and not simulation-based, in such a way as to make it as general as possible. Subsequently, the application of Complex Network Theory algorithms allows considering simultaneously the topological structure and the hydraulic characteristics of the system. In this paper the NetworkX Python package is used for the topological analysis (Hagberg et al. 2022). ~~of~~ This aspect represents an improvement compared to previous works (Giudicianni et al. 2020) on the application of topological approaches to WQSS design, where the graph was considered unweighted. The second phase of the topological step is the search of "major" links through the *edge betweenness* $b_c(l)$, a centrality metric borrowed from Complex Network Theory. To this aim, the shortest path between two nodes is defined as the sequence of links connecting two nodes crossing the links associated with the minimum sum of weights (Dijikstra, 1959). The *edge betweenness* $b_c(l)$ of a link l (Newman and Girvan, 2004) is defined as the sum of the ratios of the number $\sigma_{vi,vj}(l)$ of shortest paths between pairs of nodes v_i and v_j that run through that link l and the total number $\sigma_{vi,vj}$ of shortest paths connecting pairs of nodes v_i and v_j. The edge betweenness centrality $b_c(l)$ of a link l is, then, mathematically defined by Equation (1):

$$b_c(l) = \sum_{v_i v_j \in V} \frac{\sigma_{v_i v_j(l)}}{\sigma_{v_i v_j}} \tag{1}$$

This metric allows identifying which links in a network appear more often along the shortest paths connecting pairs of nodes. Therefore, it can be used as a measure of the influence of a link over the information/water flow throughout the network. A link with a high value of the edge betweenness usually represents a bridge-like connector between two parts of a network, the removal of which may affect the communication between many pairs of nodes through the shortest paths between them (Lu and Zhang, 2013). After weighting the links of the graph with the weight $w_i=L_i/D_i$ defined above, the search for the highest "edge betweenness" links will enable identifying the links that have simultaneously a higher connectivity with pipes characterized by lower resistance, allowing to define the most central pipes from a topological/hydraulic viewpoint. Indeed, by weighting the graph, the shortest path between two nodes becomes the minimum weighted distance between two nodes (i.e. with the minimum sum of weights assigned to the corresponding pipes), which in the present study corresponds to the minimum sum of pipe surrogate resistances. Sensors located on these pipes are supposed to detect contamination intrusion and spreading in an easier and faster way. The solution space will be narrowed after selecting the most central pipes, using the edge betweenness criterion. Indeed, this phase allows focusing the following optimization step on a much smaller subset of pipes, strongly reducing the computational burden of the entire process. The last point of the topological step is the insertion of dummy nodes in the middle of the selected "major" pipes, characterised by null base demand and with elevation and coordinates based on a linear interpolation between the end points of the considered pipe. This point makes the current methodology closer to real-world applications, since sensors are installed on pipes and not at nodes, as it was assumed by all previous theoretical works on the topic. While being simple in its computational implementation, this assumption is infeasible from a practical point of view, especially in correspondence to a cross or tee junction, where the samples would be very different depending ~~on~~ which of the converging pipes is actually fitted with the sensor. By inserting dummy nodes on the most central pipes and narrowing the search of the possible sensor locations only to them, the aforementioned practical aspects are considered. Furthermore, the same computational simplicity as that associated with the search for optimal sensor locations at nodes is kept. It is worth highlighting that, though a single potential sensor location was considered in this work for each pipe, the methodology can be easily extended to consider more locations in the long pipes. As an example, after setting a threshold length value, the number of potential locations present in the generic pipe can be calculated as the ratio of the pipe length to the threshold length value, rounded to the closest integer.

b. Logistic step

Generally, the problem of water quality sensor placement is faced by using a single or multi-objective optimization approach according to the operators' choice, without considering practical aspects related to site-specific conditions and the spatial variability in logistic conditions (i.e., accessibility to the sensor placement solution areas as well as to the underground services nearby for the full functioning of the monitoring stations). All the locations are assumed to be equally good candidates for sensors and therefore they are considered equally desirable from a cost and accessibility standpoint. This constitutes a strong simplification compared to real-world applications

(Berry et al., 2005), and a field survey should be performed to ensure that the generic selected site is suitable for an easy installation of the sensor (i.e. protected room for housing the instrumentation, easy access for installation and maintenance activities, electric power supply, wired or wireless connection for transmitting acquired data (Giudicianni et al. 2020). In order to also consider economic and accessibility aspects, an analysis of the city map needs to be included to identify more/less desirable positions for locating sensors. Results of the analysis will be spatially visualised on the layout of the case study considered, thus identifying areas of interest that can be classified as follows:

- *Most desirable locations (green pipes):* water company sites and public buildings (i.e., fire or police stations), regularly visited by water utility maintenance personnel. These locations do not need construction works to install the monitoring station, to ensure power and SCADA connection;
- *Least desirable locations (red pipes):* highway, river, busy crossroads, for which there are issues with confined space entry, necessity of specific equipment and traffic control;
- *Neutral locations (blue pipes):* those not belonging to the previous two classes.

The number and typology of locations (as defined above) constitutes another parameter for the assessment of the most feasible WQSS. In particular, the least desirable locations are eliminated from the suitable sensor locations, in such a way as to further reduce the solution space.

c. Optimization step

After identifying the most central pipes and inserting the dummy nodes in their middle, and eliminating the least desirable locations, an optimization run is carried out by using the *Threat Ensemble Vulnerability Assessment and Sensor Placement Optimization Tool* (TEVA-SPOT), developed by the US Environmental Protection Agency (EPA) (Janke et al., 2012; US EPA, 2008). In this context, four objective functions (Detection time, Detection likelihood, Population exposed through ingestion, and Extent of contamination) are used. It is worth highlighting that, in this work, water demand (and therefore served population) is concentrated at nodes. Hence, to calculate the objective functions, reference is made to nodes and to the time when they are reached by the contaminant.

Let us denote with *S* the total number of considered contamination scenarios. In particular, the following assumptions have been made for the setting up of the set *S* of contamination events considered for the WQSS design:

- all the demand nodes and the reservoirs have been, one by one, considered as potential locations for contaminant injection;
- contamination starting time at the beginning of any of the 24 hours of a day;
- 1 single value of the mass injection rate;
- 1 single value of the injection duration.

Only one couple of values for mass injection rate and duration were sampled from those proposed by Preis and Ostfeld (2008), using the procedure of Tinelli et al. (2017), aiming to obtain a small, but still statistically significant, set of contamination events. The following objective functions are adopted:

1) *Detection time:*

$$T = mean(t_s) \tag{2}$$

where t_s, for each contamination scenario $s \in S$, represents the elapsed time from the start of the contamination to the first presence of a nonzero contaminant concentration identified by a sensor of the monitoring system (i.e., the time of the first contaminant detection). In this context, a perfect sensor for the generic contaminant is assumed. The characteristic detection time of a generic sensor layout is defined as the average of all t_s for all the contamination events considered. *T* is minimised, with the objective to reduce the time of detection for all contamination scenarios considered for the WQSS design;

2) *Detection likelihood:*

$$P_s = \frac{1}{S}\sum_{s=1}^{S} d_s \qquad (3)$$

where d_s=1 if contamination scenario s-th is detected, and d_s=0 otherwise; P_s represents the probability of detecting the contamination. P_s is maximised, so to detect as many contamination scenarios as possible;

3) Population exposed through ingestion:

$$P = mean(p_s) \qquad (4)$$

where p_s is the number of people that ingest contaminated water for the generic contamination scenario, s, before the first detection. The five-fixed-times ingestion model (Davis and Janke 2009) is considered for modelling the water consumption, according to which users use tap water at five fixed times during the day: 7:30 am, 10:30 am, 12:00 am, 3:00 pm, and 6:00 pm. The duration of the ingestion is considered instantaneous. Then, if any contamination reaches a consumption node at one of such five fixed times, the population allocated to the node is assumed to be exposed through ingestion. Then, P is minimised to lessen the impact of contamination on the population;

4) Extent of contamination:

$$EC = mean(L_{c,s}) \qquad (5)$$

where $L_{c,s}$ is the total length of the contaminated pipeline. The length of pipe contaminated during a contamination event, s, will be the sum of the length $l_{c,s}$ of all the contaminated pipes in the period t_s. EC is minimised to lessen the impact of contamination on the network.

d. Economic step

The proposed method offers the possibility of introducing an economic criterion for selecting the most cost-effective solutions among the set of configurations that satisfy topological/detection-performance criteria. For each of the four objective functions described above (Optimization step), 10 WQSS are defined with an increasing number of sensors (from 1 to 10 sensors), to define four Pareto fronts as a function of the number of sensors. Then, a simple economic analysis is performed to evaluate the installation, which includes only the purchase cost C_{sens} of the sensor, or C_{sens} + the civil work cost C_{cw}, for the desirable or neutral locations, respectively (Logistic step). According to the above-mentioned factors, the cost of a monitoring station is equal to:

$$C_{st} = \begin{cases} C_{sens}, & for\ the\ most\ desirable\ location \\ C_{sens} + C_{cw}, & for\ the\ neutral\ location \end{cases} \quad (6)$$

Accordingly, the total cost C_{tot} of each WQSS is defined as the sum of the costs of all its monitoring stations. This allows the Pareto fronts to be rearranged considering the costs associated with the installation of sensors based on their logistic features. Then, an incremental economic benefit threshold is defined and applied to the new Pareto fronts for further reducing the set of possible adoptable solutions.

e. Decision step

The last step consists of the design of a decision support system based on four detection performance metrics p (i.e., the same metrics as those used in the Optimisation step). It will result in a multi-criteria matrix for the selection of the most suitable WQSS. For each solution, the four parameters will be calculated and normalised with respect to the best value of the corresponding category (partial score S_p). In order to also consider the importance of the parameters, a weight $wt_p \in [0,1]$ is assigned to each of them, in such a way that $\sum wt_p = 1$. Finally, for each solution, a total quality score (S_q) is assigned, equal to the sum of all the weighted partial scores:

$$S_q = \sum S_p * wt_p \quad (7)$$

Theoretically, the values of S_q range between 0 (the worst monitoring option) and 1 (the best monitoring option).

The five-step method described above results in a tool for the decision-making process, to choose the most suitable/appropriate WQSS layout, which considers detection performance, logistic and economic aspects. It can be straightforwardly extended by also adding other criteria to lead the utility manager towards an even more informed choice.

3. CASE STUDY

The proposed method was tested on the real WDS serving the town of Parete, located in a densely populated area situated 20 km to the north of Naples (Italy), with a population of around 11,000 inhabitants (see Figure 2a, 2b, and 2c for the spatial distribution of pipe diameters, lengths and weights $w_i=L_i/D_i$, respectively). The WDS of Parete has 182 demand nodes (with ground elevation between 53 m a.s.l. and 79 m a.s.l.), 282 pipes (made of cast iron, with length ranging between 10.4 m and 542 m, and diameter ranging between 0.06m and 0.20m) and 2 reservoirs with fixed pressure head of 110 m a.s.l. Daily variation in the users' demand has been simulated through an hourly demand pattern, with multiplier values ranging from 0.2 to 3.1. Accordingly, the total demand at nodes ranges from 7.4 l/s at night to 113.9 l/s in the morning and midday peaks, with an average value of 54.6 l/s.

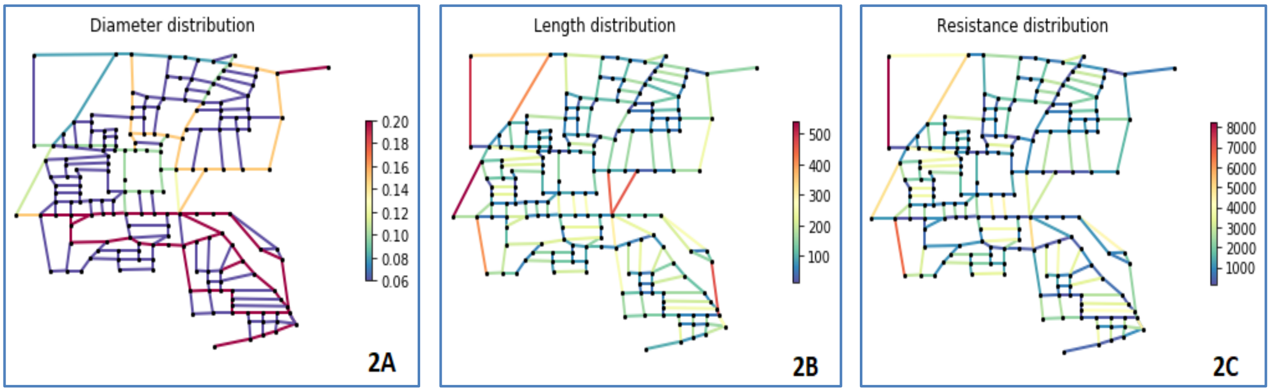

Figure 2: Spatial distribution of pipe geometric characteristics represented on the WDS layout of Parete: a) diameters [m]; b) lengths [m]; c) hydraulic resistance surrogate weight $w_i=L_i/D_i$ [m/m].

Regarding the set S of contamination events considered for the WQSS design, all the 182 demand nodes and the 2 reservoirs were considered as potential locations for contaminant injection. The value of the mass injection rate and the injection duration are set equal to 100 gr/min and 60 min, respectively. The total number of considered contamination events was S = 184×24×1×1= 4416. In the context of the optimization, the hydraulic and quality simulations were carried out using the hydraulic simulation software EPANET (Rossman, 2000) embedded in the TEVA-SPOT Software, assuming a conservative contaminant, a water quality time step of 5 minutes and a reporting time step of 5 minutes. Regarding the logistic analysis, the location classification is shown on the map of the WDS serving the city of Parete in Figure 3. Five least desirable locations were defined (around the middle of the WDS) and disregarded in the subsequent steps. Accordingly, the investment cost assessment concerned only neutral and most desirable locations. In particular, the preliminary financial analysis assumed the cost of a multiple-parameters and continuous monitoring sensor to be C_{sens}=10000 €. Civil work cost C_{cw} was estimated at 30% of sensor costs C_{sens}, then C_{cw}=3000 €. Therefore, the cost of a monitoring station for neutral locations is $C_{st} = C_{sens} + C_{cw}$ = 13000 €. It is worth highlighting the generalizability of this step. Indeed, the financial analysis can be carried out by further detailing the costs associated with the installation of the monitoring station, as well as by considering a different cost of sensors.

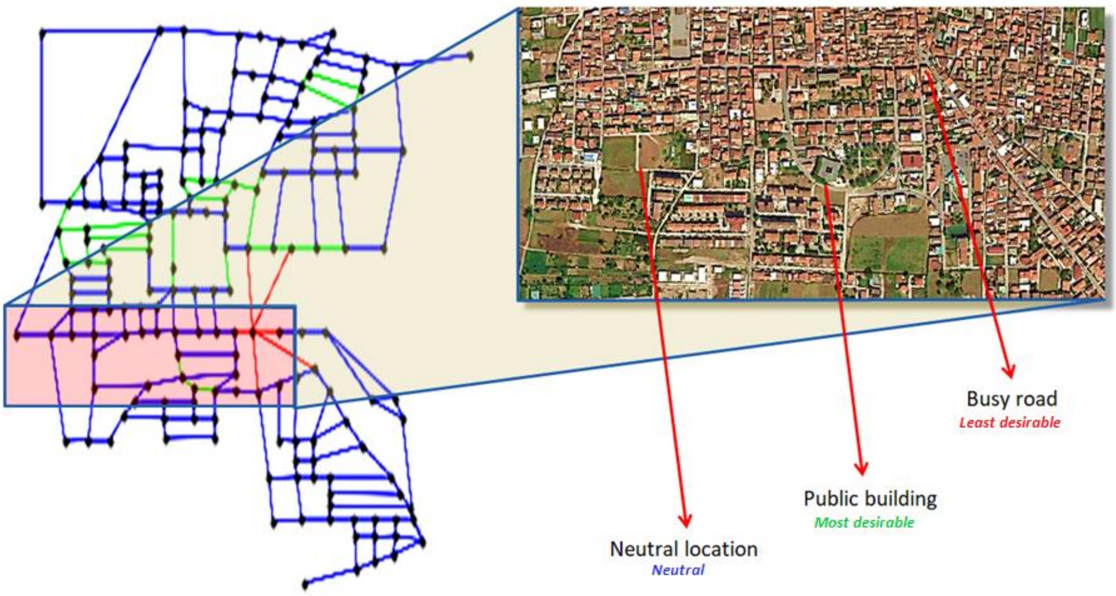

Figure 3: Location classification: Most desirable (green); Least desirable (red); Neutral (blue).

4. RESULTS AND DISCUSSION

The first step was the calculation of the most central pipes according to the values of the edge betweenness centrality. Figure 4 shows the results of the weighted topological analysis. Figure 4a is a scatter plot of the weighted edge betweenness (EB_w) of pipes sorted in descending order, in which it is possible to spot a knee in the distribution in correspondence to the first 50 pipes.

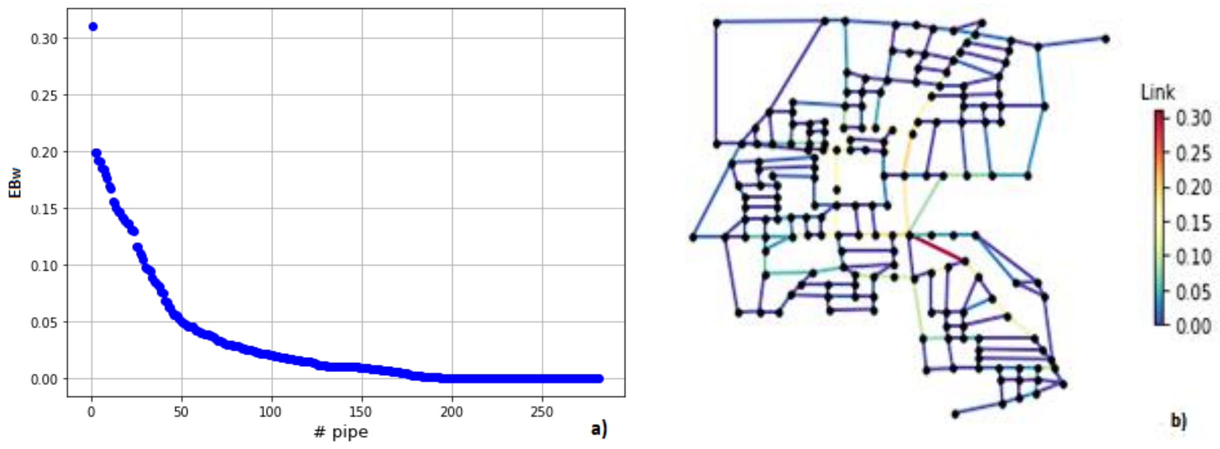

Figure 4: a) pipes sorted by EB_w in descending order; b) Spatial distribution of the EB_w on the WDS graph of Parete.

The value of EB_w corresponding to the knee was assumed as a threshold to select the most central pipes for the subsequent steps of the proposed method, thus strongly reducing the set of potential sensor locations. Figure 4b shows the EB_w for each pipe of the WDS of Parete (in red, higher values of the centrality and therefore the most central pipes). From Figure 4b it is also clear that the most central pipe (EB_w=0.31) is around the middle of the WDS. The last point of the topological step is the insertion of dummy nodes in the middle of the 50 most central pipes selected. In Figure 5 a new sketch of Parete' WDS is reported introducing the dummy nodes (red circles) to be considered as potential installation locations for the optimization, after the further elimination of the least desirable locations.

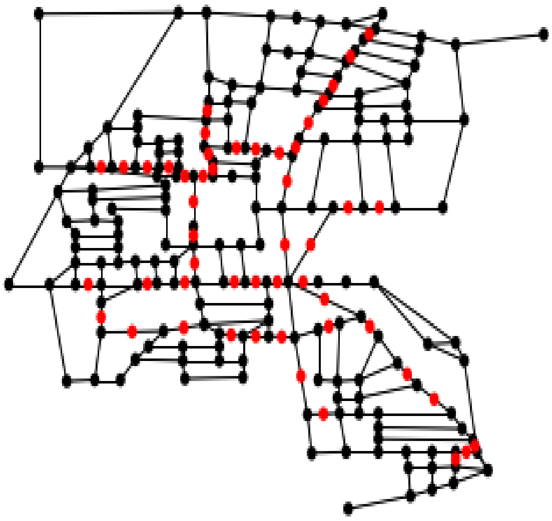

Figure 5: Dummy nodes (red circles) in correspondence to the middle of the 50 most central pipes according to the EB_w.

It is evident that the most central pipes selected are spread throughout the entire network. A visual analysis of the location of the dummy nodes (Figure 5) indicates that the topological step ensures a uniform spatial distribution of the potential locations of the sensors, by covering all the geographical extension of the WDS. This is in agreement with Nazempour et al. (2018)'s statement "since a water distribution system is a geographically distributed network, so should be the sensors". The merging of information in Figure 5 and Figure 2 points out that the pipes with the largest diameters are preferred candidates for locating sensors. The longest pipes at the border of the system are instead penalized. In fact, the betweenness centrality tends to favour more linked and internal pipes, by considering the position of each pipe with respect to the rest of the network. An additional benefit of this step is the possibility to significantly reduce the solution space by narrowing the set of possible sensor locations to only the pipes characterised by high values of EB_w. Indeed, to allocate N_{sens} sensors within a network of m pipes, the total number of possible WQSS combinations is expressed in Equation (6):

$$\binom{m}{N_{sens}} = \frac{m!}{N_{sens}!(m-N_{sens})!} \tag{6}$$

If a number N_{sens}=6 of sensors is assumed for the case study of Parete, it would give $6.62\text{x}10^{11}$ combinations. The selection of the 50 most central pipes, from which the 5 least desirable locations are removed, would give 8.15x10^6 combinations, with an almost 1/10000 reduction of the solution space.

Simulation results are reported in Table 1 in terms of detection quality performance, for the WQSS layouts obtained by adopting one by one the four objective functions defined above and for an increasing number of sensors (from 0 to 10). The maximum number of ten sensors is reasonable for a small/medium-sized WDS like that tested in this work (Giudicianni et al., 2020).

Table 1: Simulation results for all the WQSS (number of sensors from 0 to 10) obtained by optimizing one at a time the four objective functions defined in the Methodology section.

n° sensors	OBJECTIVE FUNCTION							
	T_{mean}-*based*		P_s-*based*		P-*based*		EC-*based*	
	Impact [min]	Benefit [%]	Impact [%]	Benefit [%]	Impact [-]	Benefit [%]	Impact [m]	Benefit [%]
0	750	0.0	100.0	0.0	462	0.0	6375	0.0
1	302	59.7	30.7	69.3	210	54.5	3913	38.6
2	260	65.3	24.7	75.3	151	67.3	2997	53.0
3	243	67.6	23.3	76.7	106	77.0	2504	60.7
4	226	69.8	22.4	77.6	90	80.6	2070	67.5
5	220	70.7	21.8	78.2	74	83.9	1833	71.3
6*	**213**	**72.1**	**21.4**	**78.6**	**61**	**86.8**	**1623**	**74.5**
7	209	72.3	21.2	78.9	57	87.5	1461	77.1
8	207	72.4	20.9	79.1	44	90.5	1348	78.8
9	204	72.8	20.7	79.3	38	91.7	1257	80.3
10	202	73.0	20.5	79.5	35	92.4	1179	81.5

*** in bold the performance of the WQSS layouts for a number of sensors equal to 6, which is selected according to the assumed incremental economic benefit threshold**

Specifically, *Impact* represents the value of the objective function corresponding to the WQSS (detection time, detection likelihood, exposed population and extent of contamination) while *Benefit* represents the percentage reduction (for the detection time, the exposed population and the extent of contamination) or percentage increase (for the detection likelihood) of the *Impact* in comparison with the no sensor scenario, as a result of the installation of an increasing number of sensors. Figure 6a reports the graphs of *Benefit* for the four objective functions for an increasing number of sensors. The fronts show increasing values of *Benefit* as the number of sensors increases up to 10, with the additional *Benefit* due to the installation of a further sensor progressively decreasing for all the four objective functions.

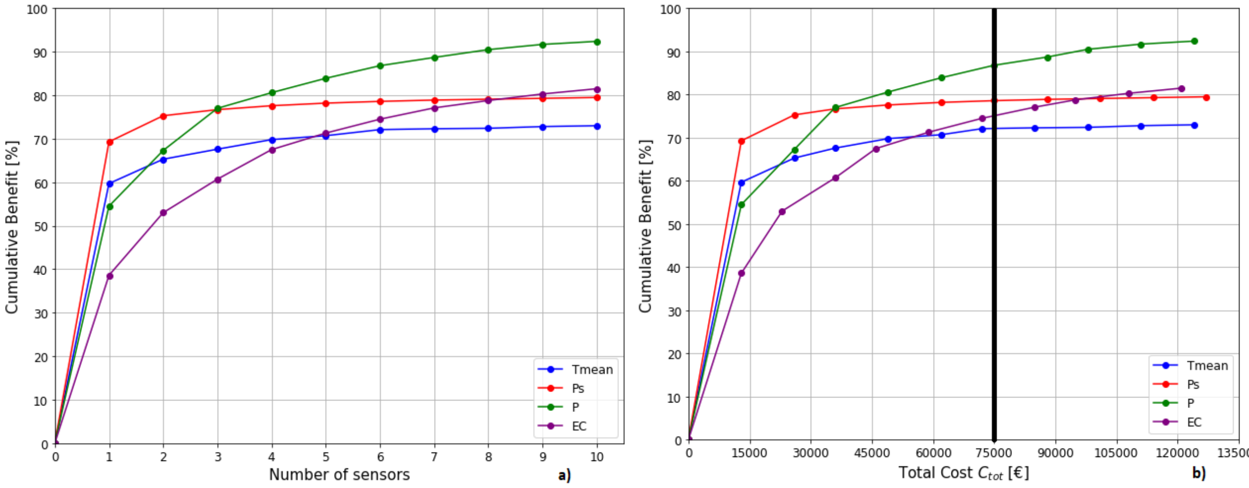

Figure 6: Cumulative Benefit of WQSS layouts defined with the four objective functions: a) for increasing number of sensors (from 0 to 10); b) as a function of the total cost C_{tot}

This suggests the possibility to set a threshold of profitability (Economic step) for the choice of the most suitable number of sensors to install in the network, especially in the presence of budget constraints. In this regard, the total cost C_{tot} associated with each WQSS was calculated, and the Pareto fronts were rearranged, as shown in Figure 6b. The incremental economic benefit was defined as the ratio of the total cost C_{tot} of the WQSS to the corresponding cumulative *Benefit* (Table 2). It can be interpreted as the average cost of each percentage point of *Benefit* provided by that WQSS. The threshold is the maximum acceptable value and represents the highest price the water utility is willing to pay for each percentage point. In this case study was assumed equal to 1000€.

Table 2: Total cost C_{tot} and incremental economic benefit for all the WQSS (number of sensors from 0 to 10).

n° sensors	OBJECTIVE FUNCTION							
	T_{mean}-*based*		P_s-*based*		P-*based*		EC-*based*	
	C_{tot} [€]	C_{tot}/Benefit [€/%]	C_{tot} [€]	C_{tot}/Benefit [€/%]	C_{tot} [€]	C_{tot}/Benefit [€/%]	C_{tot} [€]	C_{tot}/Benefit [€/%]
0	0	0	0	0	0	0	0	0
1	13000	218	13000	187	13000	238	13000	337
2	26000	398	26000	345	26000	386	23000	434
3	36000	533	36000	469	36000	467	36000	593
4	49000	703	49000	632	49000	608	46000	681
5	62000	877	62000	793	62000	739	59000	828
6*	**72000**	**998**	**75000**	**955**	**75000**	**864**	**72000**	**966**
7	85000	1176	88000	1116	88000	1005	85000	1103
8	98000	1355	101000	1276	98000	1083	95000	1205
9	111000	1526	114000	1437	111000	1210	108000	1345
10	124000	1698	127000	1598	124000	1342	121000	1485

*** in bold the total costs of the WQSS layouts for a number of sensors equal to 6, which is selected according to the assumed incremental economic benefit threshold**

Therefore, N_{sens}=6 was chosen, and the corresponding four WQSS layouts were selected as possible/feasible monitoring solutions for the water system of Parete (highlighted in bold in Table 1 and 2). The total cost associated with these four WQSS (see Figure 6b) is 72000€ for the T_{mean}-based and *EC*-based layouts (with two of the sensors being located in the most desirable locations) and 75000€ for the P_s-based and *P*-based layouts (with one sensor being located in one of the most desirable locations). These investment costs are acceptable for protecting the served population for a medium size water utility, also considering that the *per-capita* cost of this investment would correspond to roughly 7€ for each inhabitant. The small difference in terms of costs between the solutions is due to the accessibility feature of the locations and to the fact that the least desirable locations, to which much higher investment cost would have been associated, were preliminarily disregarded from the simulations.

After that, the four selected solutions are reprocessed in terms of all the four quality criteria and globally compared. The results of the postprocessing are reported in Table 3, highlighting that none of the sensor layouts is capable of simultaneously getting the best values of all the performance indices.

Table 3: Quality performance for the four selected solutions (with a number of sensors N_{sens}=6).

		SENSOR LAYOUT			
		T_{mean}-*based*	P_s-*based*	P-*based*	EC-*based*
PERFORMANCE	T_{mean} [min]	**213**	214	219	407
	P_s [%]	78.4	**78.6**	78.0	49.2
	P [-]	65	72	**61**	130
	EC [m]	2293	2070	2238	**1623**

However, as expected, each of them respectively optimizes the performance used for the optimization (highlighted in bold). Moreover, the T_{mean}-based, P_s-based and P-based layouts get very similar performance in terms of detection time (T_{mean}=213min, 214min, and 219min, respectively), and detection likelihood (P_s=78.4%, 78.6%, and 78.0%, respectively). Instead, these three layouts have slightly different values of exposed population, (P=65, 72, and 61, respectively), and extent of contamination (EC=2293m, 2070m, and 2238m, respectively). On the other way around, the EC-based layout, shows completely different (and generally worse) values of all the performance indices, and generally worse, obviously except for the extent of contamination with a value of EC=1623m.

A criterion for ranking the solutions is proposed. This is based on the normalization of the quality parameters with respect to the best one (partial score S_p in Table 4 as discussed in the Decision step). Without loss of generality, the same importance was considered for the four criteria, by assigning them a weight wt_p=0.25 (equidistribution of weights). Note that different weights can be assigned based on the most appealing criterion to target, according to the specific monitoring priority and opinion of operators. For each solution, in Table 4, a total quality score (S_q last row in bold) is attributed, equal to the sum of all the weighted partial scores (wt_p*S_p in bold in Table 4). This last step allows the operators to select the most feasible solution as a suitable trade-off between all the selected monitoring criteria.

Table 4: Total quality score S_q for the four selected possible solutions.

			SENSOR LAYOUT			
			T_{mean}-based	P_s-based	*P*-based	*EC*-based
PERFORMANCE	T_{mean}	S_p	1.00	0.99	0.97	0.52
		wt_p* S_p	**0.250**	**0.248**	**0.243**	**0.131**
	P_s	S_p	1.00	1.00	0.99	0.63
		wt_p* S_p	**0.249**	**0.250**	**0.248**	**0.156**
	P	S_p	0.94	0.85	1.00	0.47
		wt_p* S_p	**0.235**	**0.212**	**0.250**	**0.117**
	EC	S_p	0.71	0.78	0.73	1.00
		wt_p* S_p	**0.177**	**0.196**	**0.181**	**0.250**
	TOT	**S_q**	**0.911**	**0.906**	**0.923**	**0.654**

The highest value is reached by the *P*-based solution (S_q=0.923), which makes this layout the most desirable one, well balancing 3 out of the 4 quality detection performance parameters (T_{mean}, P_s and obviously *P*) while featuring a slightly worse, but still acceptable, value for the extent of contamination *EC*. The corresponding WQSS layout is shown on the map of the Parete WDS (colour pipes according to the accessibility of the site) in Figure 7. The final solution selected represents a suitable compromise between all the defined detection criteria, yielding managerial and economic benefits (because of considering logistic aspects) and guaranteeing an efficient monitoring and warning system.

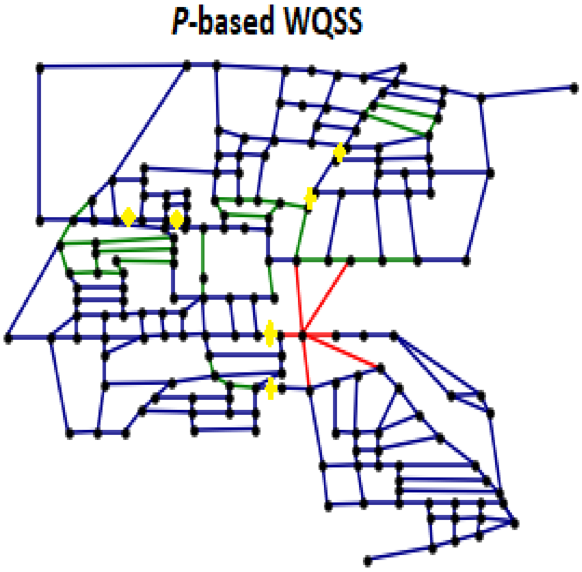

Figure 7: Final solution of WQSS with N_{sens}=6 (yellow stars) shown on the map of the Parete WDS with colour pipes according to the accessibility of the site.

It is worth highlighting that, even if the first steps allow for keeping the possible sensor locations uniformly spread throughout the WDS (as it is indeed desirable), the final WQSS solution selected presents some quite close sensors. This is due to the objective function, i.e. the population exposed through ingestion. Indeed, since most of the population is concentrated in some areas, the optimization step tends to locate sensors there. The selection of a higher number of sensors would have yielded sensors more spread over the entire system.

The main advantage of the multi-criteria method proposed in this paper, besides the significant computational reduction thanks to the preliminary topological step, is the possibility to select at each stage the most desirable solutions by combining several criteria and balancing the power of the heuristic tools (optimisation step) with the opinion of the experts (urbanistic, economic, decision steps), resulting in a well-balanced compromise between different viewpoints. Furthermore, the topological step allows us to switch to a different perspective regarding the management and the monitoring of water systems in general. Indeed, in this first stage, besides considering the hydraulics and therefore the physics of the system, the problem of sensor placement is shifted from the nodes to the links (through the insertion of dummy nodes on the most central links). This makes the approach more realistic since the devices are installed on the pipes, which are real asset. Accordingly, this allows addressing a generally disregarded but crucial aspect: from a practical point of view, on which pipe must the sensor be installed considering that the samples would be very different depending on which pipe is tapped? In this work, the sensor layouts are directly optimised by considering the actual position on pipes, therefore making the proposed multi-criteria method even more appealing for the water utilities. Finally, it should be admitted that the choice of the ultimate solution is sensitive to the change of the experts' opinion. In this regard, a sensitivity analysis can be carried out to assess the dependence of the final selection on the variability in the weights assigned to the detection parameters during the decision-making process. The main goal hereto is to show the potential of this general framework for helping water utility managers in selecting objectively the most feasible solution for the WQSS during the decision-making process, by considering several aspects.

5. CONCLUSIONS

This paper proposes a multi-criteria methodology for the design of water quality sensor system. The topological characteristics of the water distribution system were exploited for the identification of the most central topologically weighted pipes. The results shown were useful to define dummy nodes on those pipes, which were considered as decisional variables for optimal sensor placement, thus resulting in the reduction of the solution space and computational burden. A further reduction was provided by disregarding from the analysis the dummy nodes located in the least desirable locations, from an accessibility viewpoint. Solutions were searched for in the trade-off between number of installed sensors and four quality parameters for an assigned set of contamination events. Subsequently, the logistic/economic criteria (in order to consider the accessibility of the locations, engineering experience, domain knowledge and investment cost) were included to further narrow the solution space to the most desirable solution. Indeed, the aim was to provide a general tool for the decision-making process, particularly tailored to the frequent constraint of limited budget, by considering simultaneously several quality assessment criteria and the practical aspect that monitoring devices are installed on pipes, instead of at nodes. Indeed, the exclusive use of complex optimization procedures based on thousands of hydraulic/water quality simulations is often worthless, since the choice of number and locations of water quality sensors should be a trade-off between economic/operational aspects and the aim of protecting populations by quickly detecting contamination events.

It is worth pointing out that some of the future research directions identified by Ostfeld et al. (2008) during the Battle of the Water Sensor Networks and later confirmed in Hart and Murray (2010) were addressed in the present study, highlighting the opportunities offered by the methodology proposed. Specific reference was made to:

- *aggregation:* the possibility of using a reduced but still significant sample of locations as potential sensor placement, by focussing only on the most topologically central pipes and by eliminating uneasily accessible locations. This is particularly advantageous in the case of big-sized WDSs, for which the problem of optimal sensor placement may become computationally untreatable;
- *selection of number of sensors:* the possibility to identify the marginal returns, in terms of protection and costs, for additional sensors for establishing the profitable number of sensors especially in the case of limited budgets. A novel approach was proposed for the selection of the most desirable solution, based on the urbanistic features of sites which has the advantage of reducing the subjectivity of the choice without disregarding the know-how of the operators;
- *multiobjective analysis*: the possibility to guide water utility operators in the decision-making process by means of different protection objectives, a multi-criteria method and leaning on the design of a weighted normalised decision matrix.

All the issues addressed contribute to reduce the computational complexity of the methods for optimal sensor placement. Furthermore, by considering the practical and operational aspects of the problem, they contribute to fill the knowledge gap that was identified as responsible for limiting the widespread application of sensor placement technologies in drinking water distribution systems. Future work will investigate the possibility of including the dynamic behaviour of the system by considering the temporal variability in operating conditions (normal and abnormal situations) by directly implementing them in the graph of the WDS and assessing the impact on the sensor layout. Another potential avenue to explore is the sensitivity analysis of the central pipes selected to the weights attributed to the graph. Finally, the possibility to formalise the shift of the modelling paradigm from nodes to pipes will also be investigated, and the decision-making step will be enriched by adding other managerial criteria.

CONFLICT OF INTEREST STATEMENT

Conflict of Interest – None

ACKNOWLEDGEMENT

The research was conducted as part of the activities financed with the awarding of the V:ALERE:2019 project of the Università degli Studi della Campania 'L. Vanvitelli'

REFERENCES

Adedoja, O. S., Hamam, Y., Khalaf, B., & Sadiku, R. (2019). A state-of-the-art review of an optimal sensor placement for contaminant warning system in a water distribution network. Urban Water Journal, 1-16.

Hagberg, A., Schult, D., Swart, P. (2022). NetworkX Reference Release 2.7rc1.dev0.

AWWA, 2005. Contamination Warning Systems for Water: An Approach for Providing Actionable Information to Decision-Makers. AWWA, Denver.

Berry, J., Carr, R. D., Hart, W. E., Leung, V. J., Phillips, C. A., & Watson, J. P. (2009). Designing contamination warning systems for municipal water networks using imperfect sensors. Journal of Water Resources Planning and Management, 135(4), 253-263.

Berry, J., Hart, W. E., Phillips, C. A., Uber, J. G., & Walski, T. M. (2005). Water quality sensor placement in water networks with budget constraints. In Proc. ASCE/EWRI (Environmental & Water Resources Institute) Conf., Anchorage, Alaska.

Brentan, B., Carpitella, S., Barros, D., Meirelles, G., Certa, A., Izquierdo, J. (2021). Water Quality Sensor Placement: A Multi-Objective and Multi-Criteria Approach. Water Resour Manage, https://doi.org/10.1007/s11269-020-02720-3.

Cardoso, S. M., Barros, D. B., Oliveira, E., Brentan, B., & Ribeiro, L. (2020). Optimal sensor placement for contamination detection: A multi-objective and probabilistic approach. Environmental Modelling & Software, 135, 104896.

Chang, N. B., Pongsanone, N. P., & Ernest, A. (2013). A rule-based decision support system for sensor deployment in small drinking water networks. Journal of cleaner production, 60, 152-162.

Ciaponi, C., Creaco, E., Di Nardo, A., Di Natale, M., Giudicianni, C., Musmarra, D., & Santonastaso, G. F. (2019). Reducing impacts of contamination in water distribution networks: a combined strategy based on network partitioning and installation of water quality sensors. Water, 11(6), 1315.

Davis, M. J., & Janke, R. (2009). Development of a probabilistic timing model for the ingestion of tap water. Journal of Water Resources Planning and Management, 135(5), 397-405.

de Winter, C., Palleti, V. R., Worm, D., & Kooij, R. (2019). Optimal placement of imperfect water quality sensors in water distribution networks. Computers & Chemical Engineering, 121, 200-211.

Diao, K., & Rauch, W. (2013). Controllability analysis as a pre-selection method for sensor placement in water distribution systems. Water research, 47(16), 6097-6108.

Dijikstra, E. W. (1959). A note on two problems in connexion with graphs. Numerische Mathematik, 1(1), 269-271.

Dorini, G., Jonkergouw, P., Kapelan, Z., Di Pierro, F., Khu, S. T., & Savic, D. (2008). An efficient algorithm for sensor placement in water distribution systems. In Water Distribution Systems Analysis Symposium 2006 (pp. 1-13).

Fasaee, M. A. K., Monghasemi, S., Nikoo, M. R., Shafiee, M. E., Berglund, E. Z., & Bakhtiari, P. H. (2021). A K-Sensor correlation-based evolutionary optimization algorithm to cluster contamination events and place sensors in water distribution systems. Journal of Cleaner Production, 319, 128763.

Giudicianni, C., Di Nardo, A., Di Natale, M., Greco, R., Santonastaso, G. F., Scala, A. (2018) Topological taxonomy of water distribution networks. Water, 10(4), 444.

Giudicianni, C., Herrera, M., Di Nardo, A., Greco, R., Creaco, E., & Scala, A. (2020). Topological placement of quality sensors in water-distribution networks without the recourse to hydraulic modeling. Journal of Water Resources Planning and Management, 146(6), 04020030.

Giudicianni, C., Herrera, M., Di Nardo, A., Oliva, G., & Scala, A. (2021). The faster the better: On the shortest paths role for near real-time decision making of water utilities. Reliability Engineering & System Safety, 212, 107589.

Hart, W. E., & Murray, R. (2010). Review of sensor placement strategies for contamination warning systems in drinking water distribution systems. Journal of Water Resources Planning and Management, 136(6), 611-619.

He, G., Zhang, T., Zheng, F., & Zhang, Q. (2018). An efficient multi-objective optimization method for water quality sensor placement within water distribution systems considering contamination probability variations. Water research, 143, 165-175.

Herrera, M., Abraham, E., & Stoianov, I. (2016). A graph-theoretic framework for assessing the resilience of sectorised water distribution networks. Water Resources Management, 30(5), 1685-1699.

Hooshmand, F., Amerehi, F., & MirHassani, S. A. (2020). Logic-based benders decomposition algorithm for contamination detection problem in water networks. Computers & Operations Research, 115, 104840.

Huang, J., McBean, E. A., and James, W. (2006). Multiobjective optimization for monitoring sensor placement in water distribution systems., Proc., 8th Annual Water Distribution System Analysis Symp., Cincinnati.

Hu, C., Dai, L., Yan, X., Gong, W., Liu, X., & Wang, L. (2020). Modified NSGA-III for sensor placement in water distribution system. Information Sciences, 509, 488-500.

Hu, C., Li, M., Zeng, D., & Guo, S. (2018). A survey on sensor placement for contamination detection in water distribution systems. Wireless Networks, 24(2), 647-661.

Hu, C., Ren, G., Liu, C., Li, M., & Jie, W. (2017). A Spark-based genetic algorithm for sensor placement in large scale drinking water distribution systems. Cluster Computing, 20(2), 1089-1099.

Hu, Z., Chen, W., Shen, D., Chen, B., Ye, S., & Tan, D. (2021). Optimal Sensor Placement for Contamination Identification in Water Distribution System Considering Contamination Probability Variations. Computers & Chemical Engineering, 107404.

Jafari, H., Nazif, S., & Rajaee, T. (2021). A multi-objective optimization method based on NSGA-III for water quality sensor placement with the aim of reducing potential of important nodes contamination. Water Supply.

Janke, R., Murray, R., Uber, J., and Taxon, T. (2006). Comparison of Physical Sampling and Real-Time Monitoring Strategies for Designing a Contamination Warning System in a Drinking Water Distribution System. Journal of Water Resources Planning and Management, 132 (4), 310-313.

Janke, R., Murray, R., Haxton, T. M., Taxon, T., Bahadur, R., Samuels, W., & Uber, J. (2012). Threat ensemble vulnerability assessment-sensor placement optimization tool (TEVA-SPOT) graphical user interface user’s manual. US EPA National Homeland Security Research Center (NHSRC), 1-109.

Kessler, A., Ostfeld, A., & Sinai, G. (1998). Detecting accidental contaminations in municipal water networks. Journal of Water Resources Planning and Management, 124(4), 192-198.

Khorshidi, M. S., Nikoo, M. R., & Sadegh, M. (2018). Optimal and objective placement of sensors in water distribution systems using information theory. Water research, 143, 218-228.

Khorshidi, M. S., Nikoo, M. R., Ebrahimi, E., & Sadegh, M. (2019). A Robust Decision Support Leader-Follower Framework for Design of Contamination Warning System in Water Distribution Network. Journal of Cleaner Production, 124, 666-673.

Lee, B. H., and Deininger, R. A. (1992). Optimal locations of monitoring stations in water distribution system. Journal of Environmental Engineering, 118(1), 4-16.

Lee, B.H., Deininger, R.A., Clark, R.M., (1991). Locating monitoring stations in water distribution systems. J. AWWA (Am. Water Works Assoc.) 83, 60–66.

Lee, C. W., & Yoo, D. G. (2020). Decision of Water Quality Measurement Locations for the Identification of Water Quality Problems under Emergency Link Pipe Operation. Applied Sciences, 10(8), 2707.

Lu, L., & Zhang, M. (2013). Edge betweenness centrality. Encyclopedia of systems biology, 647-648.

Murray, R., Baranowski, T., Hart, W. E., & Janke, R. (2008). Risk reduction and sensor network design. US Environmental Protection Agency.

Naserizade, S. S., Nikoo, M. R., & Montaseri, H. (2018). A risk-based multi-objective model for optimal placement of sensors in water distribution system. Journal of Hydrology, 557, 147-159.

Nazempour, R., Monfared, M. A. S., & Zio, E. (2018). A complex network theory approach for optimizing contamination warning sensor location in water distribution networks. International Journal of Disaster Risk Reduction.

Newman, M. E., & Girvan, M. (2004). Finding and evaluating community structure in networks. Physical review E, 69(2), 026113.

Nikolopoulos, D., Ostfeld, A., Salomons, E., & Makropoulos, C. (2021). Resilience Assessment of Water Quality Sensor Designs under Cyber-Physical Attacks. Water, 13(5), 647.

Oliker, N., Ohar, Z., & Ostfeld, A. (2016). Spatial event classification using simulated water quality data. Environmental Modelling & Software, 77, 71-80.

Ostfeld, A., & Salomons, E. (2005). Securing water distribution systems using online contamination monitoring. Journal of Water Resources Planning and Management, 131(5), 402-405.

Ostfeld, A., Uber, J. G., Salomons, E., Berry, J. W., Hart, W. E., Phillips, C. A., Watson, J. P., Dorini, G., Jonkergouw P., Kapelan, Z., Di Pierro, F., Khu, S. T., Savic, D., Eliades, D., Polycarpou, M., Ghimire S. R., Barkdoll B. D., Gueli, R., Huang, J. J., McBean, E. A., James, W., Krause, A., Leskovec, J., Isovitsch, S., Xu, J., Guestrin, C., VanBriesen, J., Small, M., Fischbeck, P., Preis, A., Propato, M., Piller, O., Trachtman, G. B., Wu, Z. Y., and Walski, T. (2008). "The battle of the water sensor networks (BWSN): a design challenge for engineers and algorithms." J. Water Resour. Plann. Manag. 134 (6), 556-568.

Perelman, L., & Ostfeld, A. (2011). Topological clustering for water distribution systems analysis. Environmental Modelling & Software, 26(7), 969-972.

Preis A, and Ostfeld A (2008) Multiobjective contaminant sensor network design for water distribution systems. J. Water Resour. Plann.Manage. 134:4(366):366–377.

Propato M, and Piller O (2006) Battle of the water sensor networks. Proc., 8th Annual Water Distribution System Analysis Symp., Cincinnati.

Rathi, S., & Gupta, R. (2017). Optimal sensor locations for contamination detection in pressure-deficient water distribution networks using genetic algorithm. Urban Water Journal, 14(2), 160-172.

Rathi, S., Gupta, R., & Ormsbee, L. (2015). A review of sensor placement objective metrics for contamination detection in water distribution networks. Water Science and Technology: Water Supply, 15(5), 898-917.

Rossman LA (2000). EPANET2 Users Manual. US EPA, Cincinnati, Ohio.

Sankary, N., & Ostfeld, A. (2018). Analyzing multi-variate water quality signals for water quality monitoring station placement in water distribution systems. Journal of Hydroinformatics, 20(6), 1323-1342.

Sitzenfrei, R. (2021). Using complex network analysis for water quality assessment in large water distribution systems. Water Research, 117359.

Taha, A. F., Wang, S., Guo, Y., Summers, T. H., Gatsis, N., Giacomoni, M. H., & Abokifa, A. A. (2021). Revisiting the Water Quality Sensor Placement Problem: Optimizing Network Observability and State Estimation Metrics. Journal of Water Resources Planning and Management, 147(7), 04021040.

Tinelli S, Creaco E, Ciaponi C (2017) Sampling significant contamination events for optimal sensor placement in water distribution systems. Journal of Water Resources Planning and Management, doi: 10.1061/(ASCE)WR.1943-5452.0000814.

Tinelli S, Creaco E, Ciaponi C (2018). Impact of objective function selection on optimal placement of sensors in water distribution networks. Italian Journal of Engineering Geology and Environment, Special Issue 1, DOI: 10.4408/IJEGE.2018-01.S-16.

Uber, J., Janke, R., Murray, R., & Meyer, P. (2004). Greedy heuristic methods for locating water quality sensors in distribution systems. In Critical transitions in water and environmental resources management, 1-9.

Ung, H., Piller, O., Gilbert, D., & Mortazavi, I. (2017). Accurate and Optimal Sensor Placement for Source Identification of Water Distribution Networks. Journal of Water Resources Planning and Management, 143(8), 04017032.

U. S. Environmental Protection Agency (2008) User’s Manual: TEVA-SPOT Toolkit. EPA 600/R-08/041, April 2008.

Woo, H. M., Yoon, J. H., & Choi, D. Y. (2001). Optimal monitoring sites based on water quality and quantity in water distribution systems. In Bridging the Gap: Meeting the World's Water and Environmental Resources Challenges, 1-9.

Wu, Z. Y., and Walski, T. (2006). Multiobjective optimization of sensor placement in water distribution systems. Proc., 8th Annual Water Distribution System Analysis Symp., Cincinnati.

Xu, X., Lu, Y., Huang, S., Xiao, Y., & Wang, W. (2013, September). Incremental sensor placement optimization on water network. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases (pp. 467-482). Springer, Berlin, Heidelberg.

Zhang, Q., Zheng, F., Kapelan, Z., Savic, D., He, G., & Ma, Y. (2020). Assessing the global resilience of water quality sensor placement strategies within water distribution systems. Water Research, 172, 115527.

Zhao, Y., Schwartz, R., Salomons, E., Ostfeld, A., & Poor, H. V. (2016). New formulation and optimization methods for water sensor placement. Environmental Modelling & Software, 76, 128-136.

Zeng, D., Zhang, S., Gu, L., Yu, S., & Fu, Z. (2018). Quality-of-sensing aware budget constrained contaminant detection sensor deployment in water distribution system. Journal of Network and Computer Applications, 103, 274-279.

Zulkifli, S. N., Rahim, H. A., & Lau, W. J. (2018). Detection of contaminants in water supply: A review on state-of-the-art monitoring technologies and their applications. Sensors and Actuators B: Chemical, 255, 2657-2689.