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Research article

Sewer networks monitoring through a topological backtracking

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ABSTRACT

The interest in wastewater monitoring is always growing, with applications mainly aimed at detection of pollutants and at the environmental epidemiological surveillance. However, it often happens that the strategies proposed to manage these problems are inapplicable due to the lack of information on the hydraulics of the systems. To overcome this problem, the present paper develops and proposes a topological backtracking strategy for the optimal monitoring of sewer networks, which acts by subrogating the hydraulic information with the geometric ones, e.g., diameter and slope, thus not requiring any hydraulic simulation. The topological backtracking approach aims at evaluating an impact coefficient for each node of the network used to face with the problems of sensor location and network coverage for purposes related to the spread of contaminants and pathogens. Finally, the positioning of the sensors for each monitoring scheme is addressed by a priority rank, based on the efficiency of each sensor in terms of network coverage with respect to a specific weight (e.g., length, flow). The main goal is to design a monitoring scheme that provide the required coverage of the network by minimizing the number of sensors with respect to specific measurement threshold value.

The results show the effectiveness of the strategy in supporting the optimal design with the topological-based backtracking approach without the necessity of performing hydraulic simulations, with great advantage in terms of required data and computational time.

1. Introduction

Sewer networks (SNs) are critical infrastructures, inevitably interconnected with the needs of human society, often subject to dangerous and extreme events (e.g., accidental and intentional contamination, illegal spills, spread of pathogens, drunk and flooding due to climate change, etc.) that can have serious consequences both for human health (Hafeez et al., 2023; Iorember et al., 2022), for the economy and for the environment and practical issues related to water quality deterioration and its relative further use, such as desalinization (Panagopoulos and Giannika, 2022, 2023).

In order to control these events and mitigate their effects, various strategies have been proposed aimed at monitoring daily operations both in terms of hydraulic and quality attributes, at detecting the presence (Banik et al., 2015; Banik et al., 2017a; 2017b; De Vito et al., 2018; Simone et al., 2023) and the source (Pisa et al., 2019; Sambito et al., 2020, 2022; Shao et al., 2021) of contaminants and pathogènes (Nourinejad et al., 2021; Wang et al., 2023a,b), at the system maintenance (Draude et al., 2021) and management (Szeląg et al., 2021; Zhang et al., 2018), at the robustness (Hajiamoosha and Urich, 2020; Simone, 2023) and at anomaly detection (Garmaroodi et al., 2021) with implications, sometimes, also in terms of energy recovery (Shah et al., 2023).

While the control of contaminant in SNs is important for environmental aspects, the attention towards issues related to the spread of pathogens is also considerably increased. Many studies have been recently supported by projects on environmental epidemiological surveillance for the detection of the Sars-Covid2 virus in wastewater, both at international and national level (McMahan et al., 2021; La Rosa et al., 2021) and on the post-epidemic economic and social implications (Abbas, 2021; Abbas et al., 2023; Aqeel et al., 2022). The procedures adopted for the monitoring and detection of SARS-Covid2 in wastewater mainly refer to the Wastewater Based Epidemiology (WBE) approach (Daughton, 2001), aimed at the search for specific human excretion products in wastewater to individuate the presence of illicit drugs, alcohol, antibiotics etc. This approach generally involves collecting this information at the treatment plant, located downstream of the system.

To investigate flow path-dependent quality processes internal to the system, on the other hand, some studies proposed approaches based on

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the backtracking algorithm (Zierolf et al., 1998), a technique initially applied to water distribution systems to assess the presence and diffusion of contaminants, i.e., to evaluate the effects of decay and dilution in specific paths between input source and downstream nodes and their impact in terms of water quality. The first works on the subject have been proposed to evaluate the chlorine concentration in water distribution networks (Zierolf et al., 1998). In 2002, Shang et al. (2002) adopted the backtracking algorithm for sensors locations, including storage tanks, multiple water sources and quality inputs in the analysis. Later, Laird et al. (2005) proposed a tracking algorithm to identify both the time and location of potential contamination sources in water distribution systems. The authors presented an optimization design for this problem, estimating time-dependent contamination injections for every node to establish the sensors covering. De Sanctis et al. (2010) proposed a particle backtracking algorithm to identify the source of the contamination in a water distribution network, and the results showed that the method efficiently identified the area where contamination have been originated. Later on, Chachula et al. (2021) proposed the application of backtracking to SNs with a data fusion system, which transforms the time-series of sensor measurements into an array of localization of contamination events. The system (i) maps contaminant detection according to a priori knowledge, (ii) infers the propagation of the discharged contaminant downstream, (iii) groups the pollutant detections and (iv) inferred sensor observations to form tracks that are processed and propagated upstream to form the final list of probable events. The results of their localization strategy provided good results in terms of information on contaminant with a limited number of sensors. More recently, Guadagno et al. (2023) proposed a new sensor location methodology based on the backtracking approach to detect target substances in SNs. They computed an impact coefficient for all the nodes of the system, in steady-state conditions, for supporting the identification of the position for sensors. In particular, by varying specific threshold values, representing the sensitivity of the sensors used, they identify the corresponding monitoring systems that guarantee the network coverage. Furthermore, the promising comparison of the results obtained performing the analysis in unsteady and steady-state conditions, justified the adoption of the methodology for real practical applications.

The classic approaches designed for monitoring SNs generally require the knowledge of the hydraulic behaviour of the system, in terms of flow rates, decay times and concentrations of contaminants, through the implementation of numerical solutions (Ellis and Hvitved-Jacobsen, 1996; McGrane, 2016; Rauch et al., 2002; Sämann et al., 2019; Vaze and Chiew, 2004). These approaches become unusable when the hydraulic model is not available or not known, and in these cases, the need to resort to valid alternatives that do not require hydraulic data is increasingly urgent. From this point of view, topology-based approaches are gaining momentum. In recent years several researches proposed the use of Complex Network Theory (CNT) tools to evaluate the emergent behaviour of infrastructure systems, such as sewer networks, based only on their topology to address different specific tasks (Ganesan et al., 2020; Hesarkazzazi et al., 2022a,b; Hesarkazzazi et al., 2022; Meijer et al., 2018, 2022; Simone et al., 2020; Simone et al., 2022b). In order to design an optimal allocation and operation of sewer monitoring for wastewater-based disease surveillance, Kim et al. (2022) compared the performance of a genetic algorithm and a topological based spatial bisection method, showing that the latter is efficient despite its lower computational cost. Rodríguez-Alarcón and Lozano (2022) proposed an approach based on CNT tools to model and analyse structure and components of a whole river basin. They evaluated several CNT metrics in order to furnish indications about the system behaviour, both from a local and a global point of view and proposed an environmental impact centrality index based on a backtracking algorithm to evaluate potential spill or contaminant release on each node. Simone et al. (2022a,b) proposed a strategy based on the CNT concepts and backtracking algorithm to analyse and model the diffusion of pollutants along the SNs. They surrogated all information related to the flow rates of the sewer pipes with information obtained from the Horton's hierarchy of the system and evaluated a Contamination Index for each node, to inform about the effect that a contaminant spill originated in given nodes would have on the whole system.

Considering the potentiality of backtracking algorithms in studying contamination processes and the problem related to the lack of hydraulic information in planning and management activities in SNs, the present paper proposes a topological backtracking strategy for the optimal monitoring in wastewater. In particular, the strategy refers to the backtracking algorithm introduced in Guadagno et al. (2023), computed performing a steady state simulation, and aimed at the evaluation of the impact coefficient (*IC*) for planning a monitoring system.

The novelty of this work is the possibility of surrounding the hydraulic parameters (e.g., flow) of the model with the geometric ones (e.g., pipe diameter, slope) during the analysis, without performing any hydraulic simulation. This allows the strategy application to systems with the only knowledge of topology and geometry without the estimation of the input demands. It is crucial in studying complex system or in an early stage of the analysis. Moreover, the use of the only system geometry significantly reduces the computational cost of the strategy. The main goal is to indicate where to place sensors or collect samples in order to detect a target substance which can enter in each node of the system. The strategy consists of three main phases.

(i) The topological impact coefficient (IC^T) for the nodes of the network is evaluated using a new topological-based backtracking strategy, in which the hydraulic information are surrogated with the geometrical ones. The comparison between the impact coefficient values obtained through both the hydraulic simulation in steady-state conditions and the topological approach is used to validate the proposed methodology.

(ii) Once the IC^T has been computed for all nodes of the system, the strategy acts for defining the monitoring scheme according to sensor measurement threshold, i.e., to the sensitivity of the installed sensors. This is performed by reiterating the backtracking several times, choosing each time only the locations candidate to host sensors that not influence each other, i.e., that belong to separate branches, located further downstream in the system. By repeating the backtracking with respect to the new sensors installed, new candidate locations are indicated, for which the procedure is repeated. In this way the number of sensors to be installed is minimized. For a fixed measurement threshold, the obtained monitoring schemes represent the solution that minimize the number of sensors thus optimizing the network coverage.

(iii) The monitoring scheme previously designed also encloses an installation priority order for the sensors. The priority is expressed through the range P (P_1, …, P_M), with M number of sensors to install with the ordering which indicates the efficiency of each sensor in terms of network coverage, which can be evaluated considering different weights, e.g., number of covered nodes [%], topological flow ($Flow^T$) [l/s], length (L) [Km], etc.).

The paper is organized in the following way. The next section recalls the concept of backtracking algorithm. The third section presents all the phases of the proposed sensor location methodology using a small benchmark SN. The fourth section describe the results obtained applying the strategy to a literature case study. The first part of the section reports the calculation of the Topological Impact coefficients (IC^T) and the comparison with the ones obtained using the hydraulic approach in steady-state conditions, while the second part of the section shows the actions required to define the optimal monitoring schemes, also providing the priority range for the installation of the sensors. Concluding remarks are drawn in the last section.

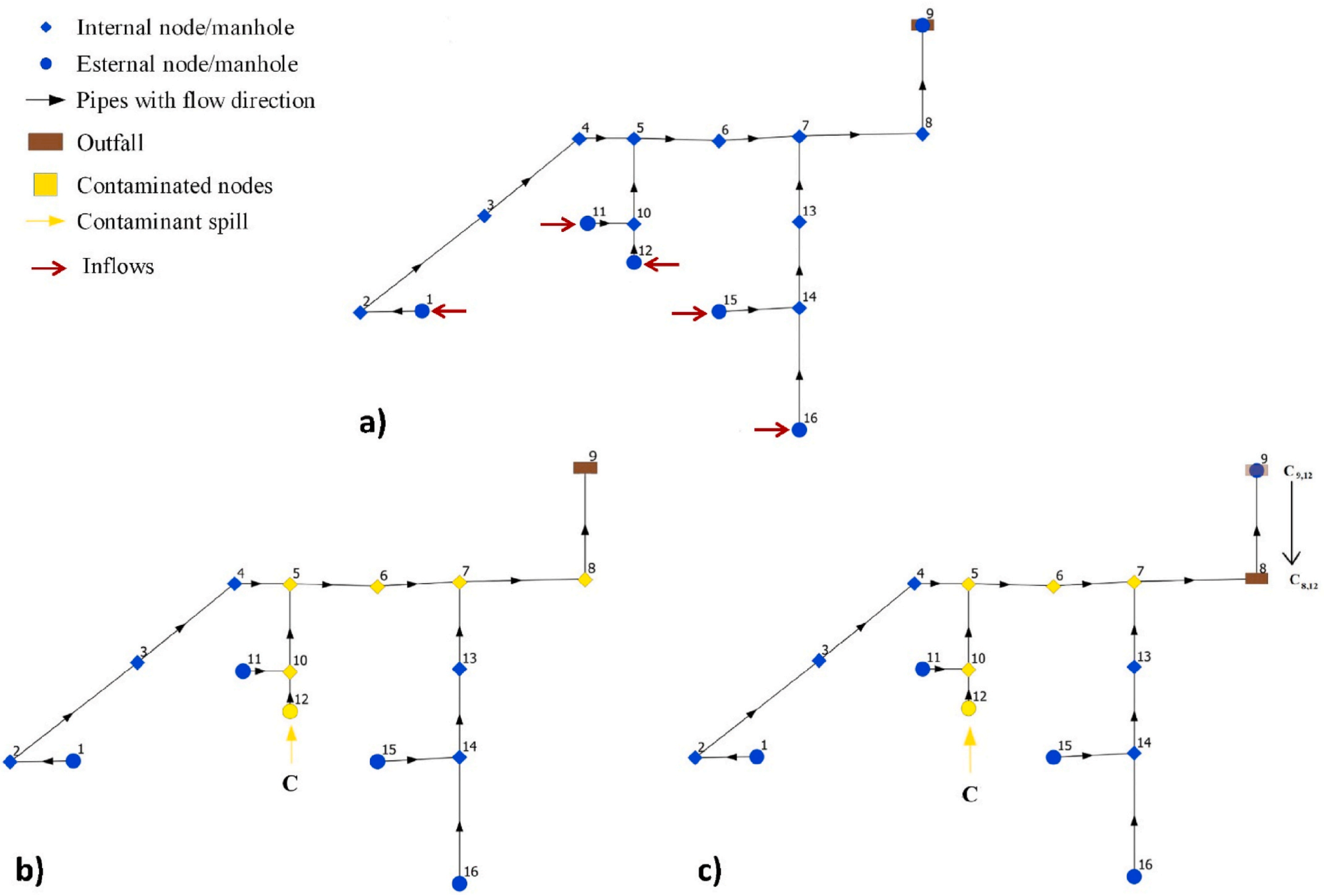


Fig. 1. Network layout (a). Contaminant input in node 12 defines a contamination path, highlighted in yellow (b). Example of backtracking from node 9 to node 8 (c) following back the path towards the node 12.

2. Backtracking algorithm

The spreading of contaminant in SNs is described with mass balance equations within pipes and nodes. The backtracking algorithm represent an approach that allows describing the variation of the contaminant concentration in the nodes of a system by measuring the value of the concentration at an output point. The approach uses the depth-first search method, i.e., a search algorithm on trees and graphs by the Complex Network Theory (CNT), which is developed to find the solution to a specific problem by building it step by step through recursive calling. Starting from an output node, the method allows to track the value of the contaminant concentration at a possible input nodes placed upstream, which in turn become output for the pipe placed immediately upstream. The process continues until the input node coincides with the source of the contamination for that specific path. This procedure, generally based on a search tree, where each branch represents a variable and each level a solution, applies very well to open networks such as sewer systems.

To understand the steps behind the backtracking process for SNs, Fig. 1-a shows the direct graph of an example scheme of portion of a sewer system composed of 16 nodes and 15 links, whose characteristics are given in the supplementary material (Tables A1 and A2). The direction of flow, imposed by the slope of the system, is indicated by arrows. The set of links *S* and the set of nodes *N* of the graph represent the sewer pipes and the manholes of the system, respectively. Node 9 represents the outfall.

Let us assume that a contaminant concentration is entered into node 12, as indicated in Fig. 1-b. The contamination path from node 12 towards the output (node 9) crosses nodes 10, 5, 6, 7 and 8, and in each node the concentration of contaminants varies according to the process of diffusion/dilution towards the pipes/nodes downstream of the source. In fact, once contaminated, the first target node of the path (node 10) is modelled as a new source of contamination and the process continues until the outfall is reached. Based on the concentration of contaminant arriving at the outfall (node 9), it is possible to go back at the concentration of contaminant in the upstream node (node 8), which becomes in turn the output of the pipe located further upstream, from which it is possible to go back at the concentration of its predecessor (node 7) (Fig. 1-c).

Proceeding recursively upstream, for all nodes of the contaminated path, it is possible to evaluate the variation in the concentration of contaminant. This recursive procedure is called backtracking (Zierolf et al., 1998). Repeating this procedure for all the nodes of the network allows to identify the contamination paths, and therefore, the variation in the concentration of contaminant for all nodes in the network.

To evaluate the dilution factor at the confluences and the decay factor of the contaminant along the pipes, the procedure requires the knowledge of the hydraulic (e.g., flow rate, speed, etc.) and topology (e.g., diameter, slope, length, etc.) of the system. The dilution process is expressed by the continuity equation at the generic node *n*, according to the relationship:

$$C_n(t) = \frac{\sum_{l \in S} q_l\,(t) C_{l,d}(t)}{\sum_{l \in S} q_l(t)} \tag{1}$$

where *S* is the set of pipes that converge in node *n*, $q_l\,(t)$ is the flow rate of the single pipe *l* that converges into node *n*, $C_{l,d}(t)$ is the concentration of contaminant in the section downstream pipe *l* entering in node *n*,

$\sum_{l \in S} q_l(t)$ is the sum of the flows entering in the same node.

The contaminant decay process occurring along the pipe l is calculated with a first order kinetics, according to the relationship:

$$C_{l,d}(t) = C_{l,u}(t) \exp\left(K_l T_l\right) \tag{2}$$

where $C_{l,u}$ is the concentration of contaminant in the upstream section of pipe l, K_l is the decay coefficient of the contaminant in the pipe l and T_l is the travel time of the pipe l, expressed by the relationship:

$$T_l = \frac{L_l}{v_l} \tag{3}$$

where L_l is the length and v_l the mean velocity of the pipe l.

By measuring the concentration at the output node, it is possible to follow the spread of contaminant along each path considering the upstream node as a potential input source. As reported in Guadagno et al. (2023), the ratio between the value of the concentration measured at the output node n and those at the input node j defines the Impact Coefficient IC of node j, expressed by the dimensionless relationship:

$$IC_{j,n}(t) = \prod_{l \epsilon p} \frac{q_l(t) \exp\left(K_l T_l\right)}{\sum_{l \in S} q_l(t)} \tag{4}$$

where p is the path between nodes j and n. The backtracking proceeds until it reaches all the nodes of the path, evaluating for each of them the IC value.

3. Material and methods

3.1. The topological backtracking algorithm

The potentialities of the backtracking algorithms above described are often limited by the lack/inaccuracy of information on the systems to be analysed. In the specific case of SNs, the lack of information mainly refers to the hydraulic parameters/models, especially for large urban systems, thus limiting their analysis.

To overcome this drawback, a topological backtracking algorithm is here proposed as first phase of the monitoring design strategy. Obviously, using only topologic and geometric information, instead of hydraulic ones, requires the adoption of simplifying hypotheses. In particular, the only use of topologic and geometric information implies a steady-state analysis, without considering the time variability of the input demands.

3.1.1. Geometric parameters at the basis of the analysis

Hydraulic information is surrogated with geometric and topological ones. For each pipe the following topological flow and mean velocity, function of only geometric parameters, are defined as:

$$\begin{cases} q_l = A K_s R_h^{\frac{2}{3}} i^{\frac{1}{2}} \\ v_l = K_s R_h^{\frac{2}{3}} i^{\frac{1}{2}} \end{cases} \tag{5}$$

where q_l and v_l represent flow and mean velocity along the specific pipe l, respectively. Furthermore, A is the cross section, K_s is the roughness coefficient, R_h is the hydraulic radius and i is the slope. In the hypothesis of full pipe flow, the formulations (5) can be rewrite as function of the diameter and simplified, obtaining:

$$\begin{cases} q_l = \pi \frac{D^2}{4} K_s \left(\frac{D}{4}\right)^{\frac{2}{3}} i^{\frac{1}{2}} \\ v_l = K_s \left(\frac{D}{4}\right)^{\frac{2}{3}} i^{\frac{1}{2}} \end{cases} = \begin{cases} q_l = b K_s D^{\frac{8}{3}} i^{\frac{1}{2}} \\ v_l = c K_s D^{\frac{2}{3}} i^{\frac{1}{2}} \end{cases} \tag{6}$$

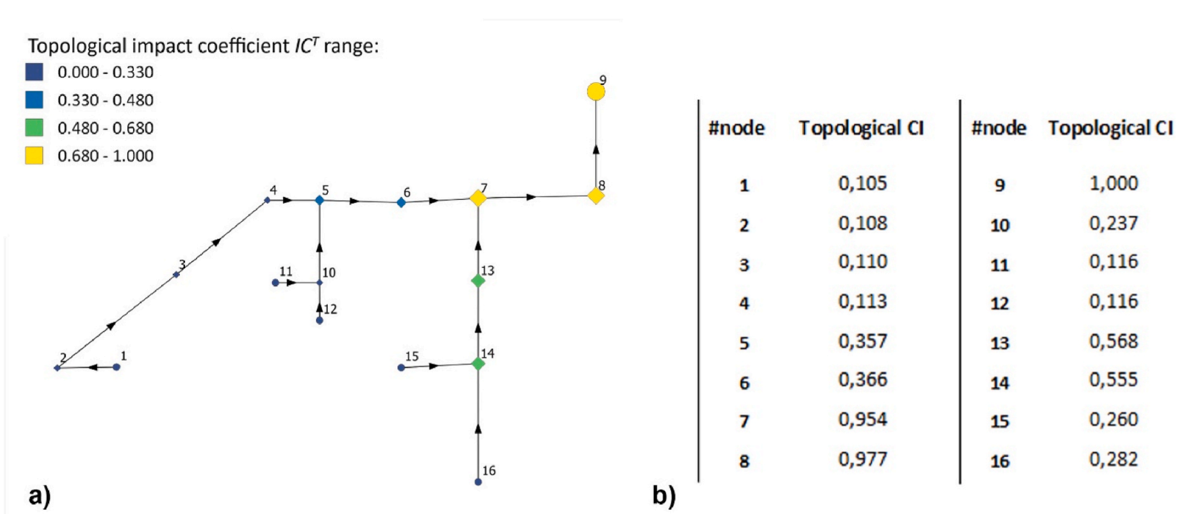
where the terms b and c represent constants equal to:

$$b = \frac{\pi}{4^{\frac{2}{3}} \bullet 4} = 0.31; \quad c = \frac{1}{4^{\frac{2}{3}}} = 0.40; \tag{7}$$

The strategy allows to assign different value of K_s to the pipes, thus making the analysis much closer to the reality. It worth of noting that the use of Eq. (6) implies the assumption of pipe filled, which does not generally happen in a SN with a correct functioning. However, this assumption, necessary for the use of the topological backtracking, is accepted because at security advantage for the present application. Hence, Eqs. (1) and (2) can be reformulated considering topological parameters as:

$$\begin{cases} C_n = \frac{\sum_{l \in S} q_l\, C_{l,d}}{\sum_{l \in S} q_l} = \frac{\sum_{l \in S} \left(b K_s D^{\frac{8}{3}} i^{\frac{1}{2}}\right) \bullet C_{l,d}}{\sum \left(b K_s D^{\frac{8}{3}} i^{\frac{1}{2}}\right)} \\ C_{l,d} = C_{l,u} \exp(K_l T_l) = C_{l,u} \exp\left(K_l \cdot \left(\frac{L_l}{c K_s D^{\frac{2}{3}} i^{\frac{1}{2}}}\right)\right) \end{cases} \tag{8}$$

Then, the topological Impact Coefficient IC^T is expressed by the relationship:



#node	Topological CI	#node	Topological CI
1	0,105	9	1,000
2	0,108	10	0,237
3	0,110	11	0,116
4	0,113	12	0,116
5	0,357	13	0,568
6	0,366	14	0,555
7	0,954	15	0,260
8	0,977	16	0,282

Fig. 2. Network layout with graphical representation of the topological impact coefficient IC^T (a). Topological impact coefficient IC^T values for all nodes of the network (b).

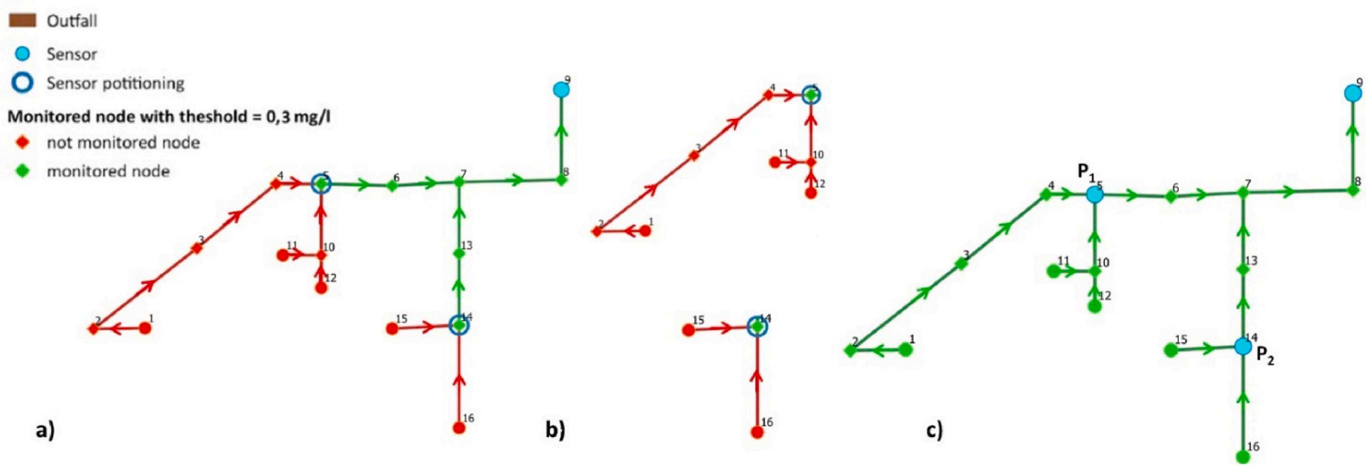


Fig. 3. Network coverage (monitored green part) guaranteed by the sensor placed at the outfall (node 9) by setting a threshold value of 0.3 mg/l (a). Two subsystems for which the backtracking is again performed considering sensors installed in nodes 5 and 14 (b). Network full covered with three sensors (c).

$$IC_{j,n}^{T} = \prod\nolimits_{l\epsilon p} \frac{q_l \exp\left(K_l T_l\right)}{\sum\limits_{l\in S} q_l} = \prod\nolimits_{l\epsilon p} \frac{\left(bK_s D^{\frac{8}{3}}\ i^{\frac{1}{2}}\right)_l}{\sum\left(bK_s D^{\frac{8}{3}}\ i^{\frac{1}{2}}\right)_l} \exp\left(K_l \cdot \left(\frac{L_l}{cK_s D^{\frac{2}{3}}\ i^{\frac{1}{2}}}\right)\right) \tag{9}$$

The IC^{T} assumes values in the range [0; 1].

3.1.2. Lateral inflow

In the proposed methodology lateral inflows are also assumed not known and estimated through topological parameters. For the external/head nodes, the topological lateral inflow is assumed equal to the topological flow belonging the pipe immediately downstream of it (e.g., considering Fig. 1-a, the lateral inflow entering in node 1 is equal to the flow along the pipe 1–2). For the internal nodes, such as nodes 2 and 10, the lateral inflow is differently evaluated depending on.

(i) if the node is not a confluence and the upstream and the downstream pipes have the same diameter, the topological lateral inflow is assumed equal to zero. This approximation is acceptable considering that the lateral inflow, when present, should already be contained in the downstream pipe which works at full filling;
(ii) if the node is not a confluence and the upstream and the downstream pipes have different diameters, the topological lateral inflow is equal to the difference between the two topological flows;
(iii) if the node is a confluence, the topological lateral inflow is evaluated as the difference between the topological flow of the pipe downstream the node and of the sum of topological flows of the pipes upstream of the node.

3.1.3. Topological impact coefficient IC^T

To compute the IC^T, it is assumed that the introduction of contaminant may occur though all nodes characterized by a lateral inflow with a unitary input concentration ($c_0 = 1$ mg/l). In this case, the IC^T of the node coincides with the concentration measured at the sensor due to the input in this node. Then, an IC^T equal or larger than the sensitivity of the sensor means that the input of the substance in the node is detected (Guadagno et al., 2023).

In this prelaminar test, the lateral inflows are only assumed at the head-nodes for simplicity, as reported in Fig. 1-a. The decay coefficient has been set equal to 0.146 h^{-1}, which refers to Sars-COVID2 as target substance (Hart and Halden, 2020).

The obtained IC^T values are graphically shown in Fig. 2-a and reported in the table of Fig. 2-b. It is possible noting that the values of the IC^T, consistently with the diffusion/decay processes, increase from the upstream to the downstream nodes, i.e., from the smallest to the largest rhombuses in terms of size. Particularly, nodes with high value of IC^T (from green to yellow) represent the points in which any contaminant input is easily detected at the outfall, while nodes with a very low IC^T (blue) represent the points in which any contaminant input is difficult to detect at the outfall, because of the dilution and decay phenomena that occur along the paths.

3.2. Optimal sampling design of monitoring system

The last step of the proposed strategy involves the identification of the monitoring schemes as function of a measurement threshold value (TV) of the sensor, which represents the minimum concentration detectable. A higher threshold value indicates low quality and requires a greater number of sensors. For each monitoring scheme (number of sensors and their different locations), the strategy acts for providing the minimum number of sensors to guarantee the fixed coverage of the network by reiterating the backtracking several times.

Considering the first sensor placed at the outfall and its threshold, the coverage of the network is evaluated on the base of the IC^T values previously computed within the backtracking phase. IC^T equal or larger than TV means that the introduction of unitary input concentration produces a concentration detectable by the sensor, i.e., the node is covered, while with IC^T smaller than TV, the node is not covered. Then, the procedure acts for installing sensors in the nodes located at the extremities of the area covered by the existing sensor with the new devices that do not interfere each other, i.e., they belong on distinct branches. By repeating the backtracking with respect to the new sensors, new points are suggested where to install sensors, and the procedure is successively repeated until the fixed coverage is reached. In this way, the monitoring scheme, i.e., number and positions of the sensors, is defined.

Each monitoring scheme is enriched with an installation priority order for the sensors. The priority is expressed through the range P (P_1, …, P_M), with M number of sensors, where the ordering indicates the efficiency of each sensor in terms of network coverage, here expressed as length L [Km]. The priority order is increasing, i.e., P_1 represents the most efficient sensor and P_M the least efficient one. The order of priority is provided only for the planned sensors, considering those located at the outfall as a prior.

For example, Fig. 3-a shows the coverage of the network based on the IC^T of Fig. 2-a, by setting a threshold value of 0.3 mg/l. The analysis starts only considering the sensor placed at the outfall (node 9), which guarantees a coverage of the network of 43,8% (1.957 Km), represented by the green part. The results of the analysis suggest of positioning other two sensors, in nodes 5 and 14, to cover the remaining part of the system. It is possible noting that the candidate locations do not interfere

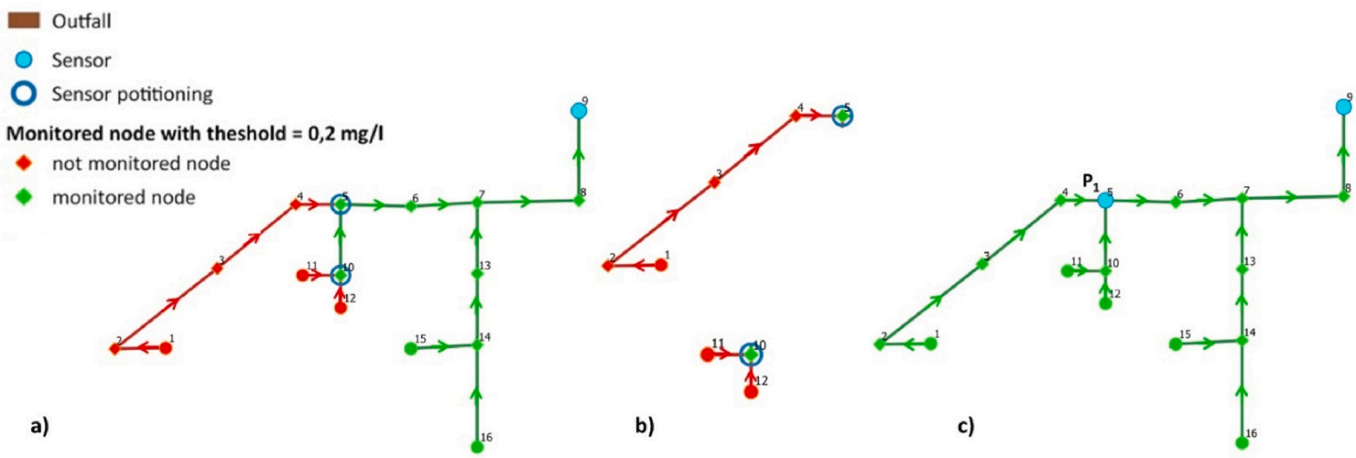


Fig. 4. Network coverage (green part) guaranteed by the sensor placed at the outfall (node 9) by setting a threshold value of 0.2 mg/l (a). Two subsystems for which the backtracking should be again performed (b). Network full covered with only two sensors (c).

with each other, belonging to two distinct branches, and therefore both sensors have to be installed and considered in the next step.

By setting nodes 5 and 14 as new output nodes, the backtracking is performed only for the two subsystems represented in Fig. 3-b, for which the contaminant concentrations were not detected at node 9. Finally, Fig. 3-c reports the system with the three sensors and the network full covered. The order of priority in the installation of the sensors is indicated in Fig. 3-c, evaluated considering the length L [in Km] that each sensor covers. Installing only one additional sensor, P_1 in node 5 is selected, i.e., the first in the order of priority, that guaranteeing a network coverage of 87,5% (3.397 Km), which passes to 100% (4.263 Km) by also installing the sensor P_2 in node 14.

The situation that arises by setting a threshold value of 0.2 mg/l is different. The sole sensor placed at the outfall (node 9) guarantees a greater coverage of the network than in the previous case (Fig. 4-a), i.e., equal to 50% of the network in terms of nodes (2550 Km), due to the greater sensitivity of the instrument used. Also in this case, the analysis suggests of positioning other two sensors, in nodes 5 and 10, to cover the remaining part of the system (Fig. 4-b). It is possible noting that the two candidate locations belong to the same path toward the outfall, i.e., they are influenced by each other because node 5 is in the path from node 10 toward the outfall. In this case the strategy proceeds by performing the backtracking only with respect to the node located further downstream, i.e., node 5. Fig. 4-c shows that a sensor installed in node 5 covers the remaining part of the network, i.e., the total coverage is guaranteed with only 2 sensors.

4. Results and discussion

4.1. Topological impact coefficient IC^T

The proposed strategy is here applied to a benchmark sewer system (Simone et al., 2023) whose layout is reported in Fig. 5. The system model is composed of 77 nodes, 79 edges and 1 outfall (node 78), whose topological characteristics are given in of the supplementary material (Tables A3 and A4). Fig. 5 reports the network with the modelled topological lateral inflow (red arrows). It is possible noting that the lateral inflow is present in the head nodes and at the confluences, since for the serial nodes the diameter generally does not change between upstream and downstream pipes, and therefore the topological inflow is null.

The IC^T is then computed for each node of the system only considering the sensor positioned at the outfall (node 78). As in the previous test case, it is assumed a unitary input concentration and a decay coefficient equal to 0.146 h^{-1} (Hart and Halden, 2020).

Fig. 6-a shows the IC^T values, classified in four ranges, differentiated both in size and colour. Small blue nodes indicate low values of the coefficient, while large nodes (from green to yellow) indicate high values. The nodes with low values of the coefficient are those strongly conditioned by the dilution process, or in any case located far from the outfall. Conversely, high values of the coefficient occur mainly for nodes located close to the outfall, for which any contaminant input should be easily detectable.

The lower range of values [0–0.009] affects mainly the head nodes, subject to important dilution processes during the contamination paths. The most part of the nodes of the network assume values belonging to the second and third range, and the remaining part of the nodes, instead, have coefficient values belonging to the last two ranges, i.e., the highest one. This situation is clearly visible in the figure, where the most important nodes define paths from points inside the network up to the outfall.

In order to validate the effectiveness of the topological backtracking, Fig. 6 shows the comparison between the IC^T and the impact coefficients IC calculated using the hydraulic approach considering steady-state conditions, as in Guadagno et al. (2023). The comparison shows the same system behaviour in the contaminant diffusion process in both cases.

The topological impact coefficients are, globally, slightly lower than the hydraulic ones, probably attributable to the different lateral inflow configuration between the two systems, which inevitably affects the dilution process. This means that, for the specific system, the topological approach guarantees a lower network coverage, thus going to the safety advantage. However, Fig. 7 shows the correlation between the coefficients for the two approaches. The high correlation, equal to 99%, confirms the effectiveness of the topological approaches in identifying the emergent behaviour of SNs, also in terms of diffusion of contaminant, i.e., the topological approach reflects very well the trend of the hydraulic one considering steady-state conditions.

4.2. Monitoring schemes

Once the IC^T is computed for all nodes of the system, it is possible to evaluate the coverage of the network fixing the sensor threshold value and, therefore, to define number and position of further sensors to add. All monitoring schemes are designed to provide optimal solutions, obtained by minimizing the number of sensors to cover the network. As said, the procedure is reiterated several times, choosing at each step the candidate locations at the last monitored nodes that not influence each other. With respect to these new sensors the backtracking procedure is repeated to indicate new candidate locations to host sensors. The first step of the procedure with respect to the network of Fig. 5-b starts only

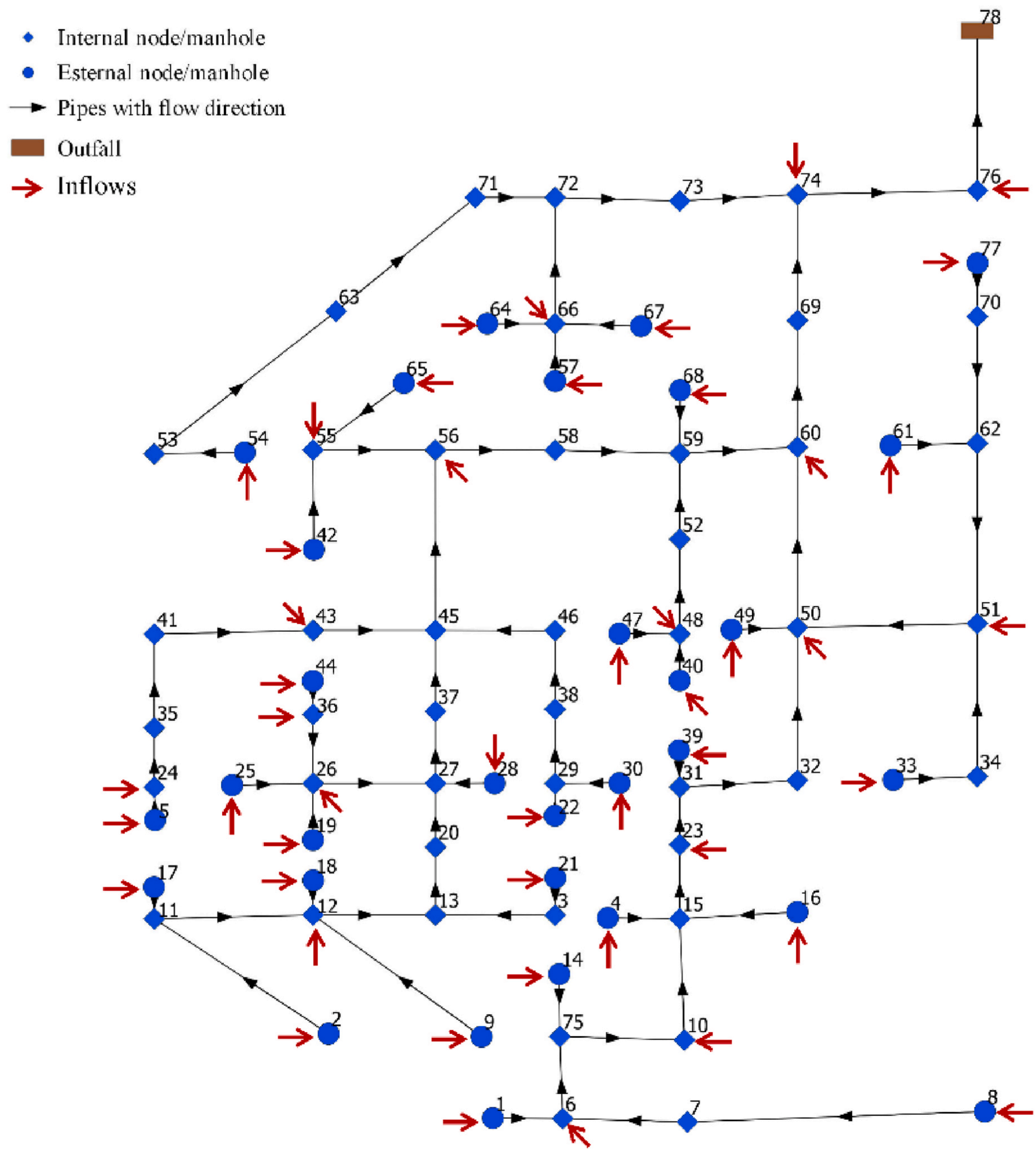


Fig. 5. Sewer network layout with topological lateral inflow.

considering the sensor located at the outfall, i.e., at node 78. The analysis is performed assuming a threshold value of 0.05 mg/l and the resulting covered nodes (in green) are shown in Fig. 8-a. The nodes detected by the sensor correspond mainly both with those closest to the outfall and the most hydraulically relevant, because their important flows reduce the influence of dilution processes due to the flows coming from other pipes. Conversely, most of the nodes not covered by the sensor (in red) are those distant from the outfall, for which the impact coefficient values are very low, due to the dilution at the confluences along the path to reach the sensor. It is evident that the installation of other sensors is necessary to increase the coverage of the network.

In particular, the results of this first step suggest of placing additional sensors in correspondence of the last monitored nodes. The candidate positions for sensors are nine, corresponding to nodes 23, 27, 31, 45, 50, 51, 56, 59 and 72, highlighted in Fig. 8-a.

Since the strategy plans to consider only the nodes not belonging to the same paths forward the outfall and positioned further downstream in the network, only nodes 50, 59 and 72, highlighted in Fig. 8-a with filled blue circles, are selected to place sensors. In fact, the selected nodes are crossed by the other candidate nodes along their path toward the outfall, i.e., these latter, most likely, are automatically covered guaranteed by the three selected sensors.

A second backtracking step is executed considering the three new sensors (cyan filled circles) as output nodes for monitoring the remaining part of the system, and the results are shown in Fig. 8-b. The sensor installed in node 72 covers all the upstream nodes, and therefore does not require the installation of further sensors in the underlying portion of the network. The sensor installed in node 50 covers most of the nodes located upstream, including nodes 23, 31 and 51, indicated as candidate locations in the first step, thus avoiding the installation of sensors in those nodes. At the same time, with respect to node 50, the second backtracking step indicates of integrating the sensor scheme with

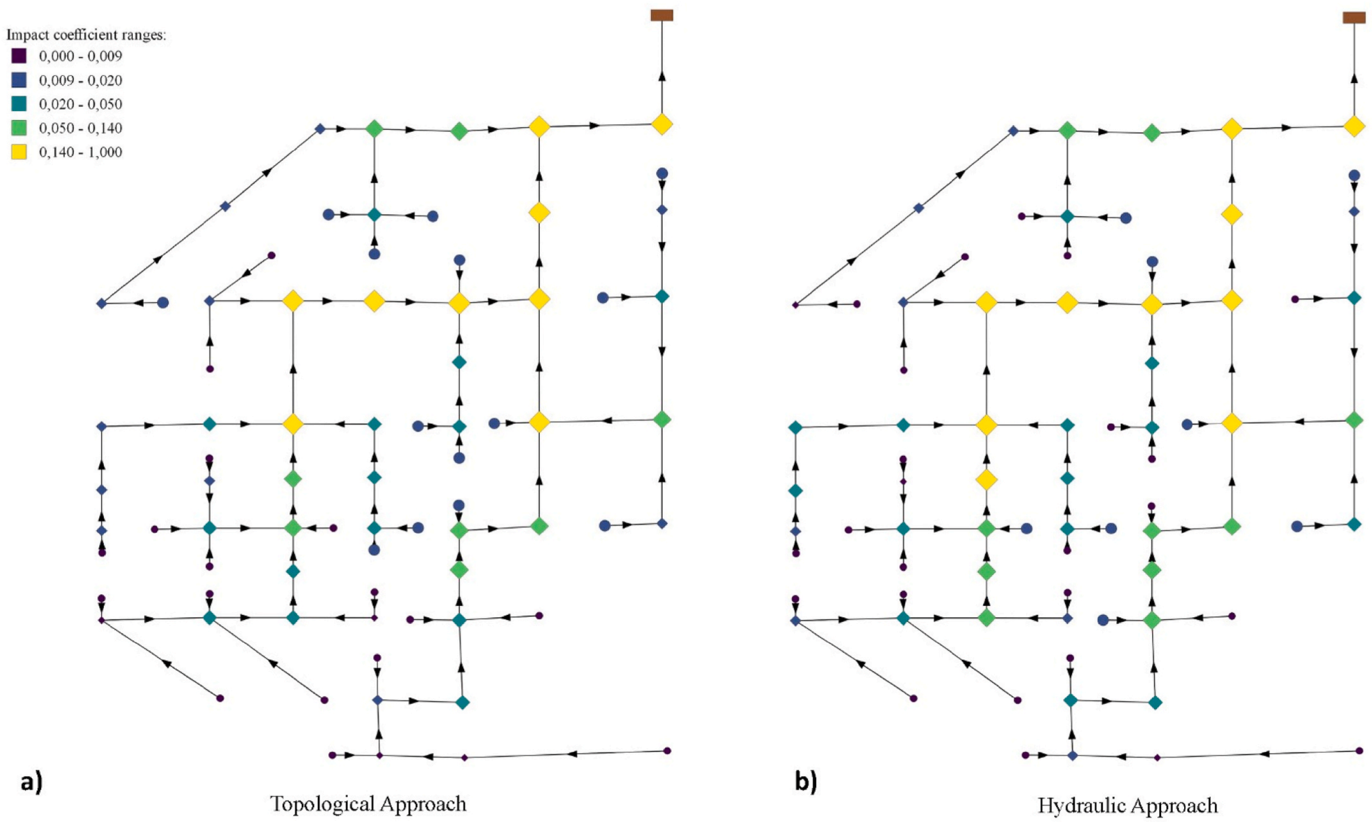


Fig. 6. Impact Coefficient values computed considering the topological (a) and the hydraulic (b) approaches.

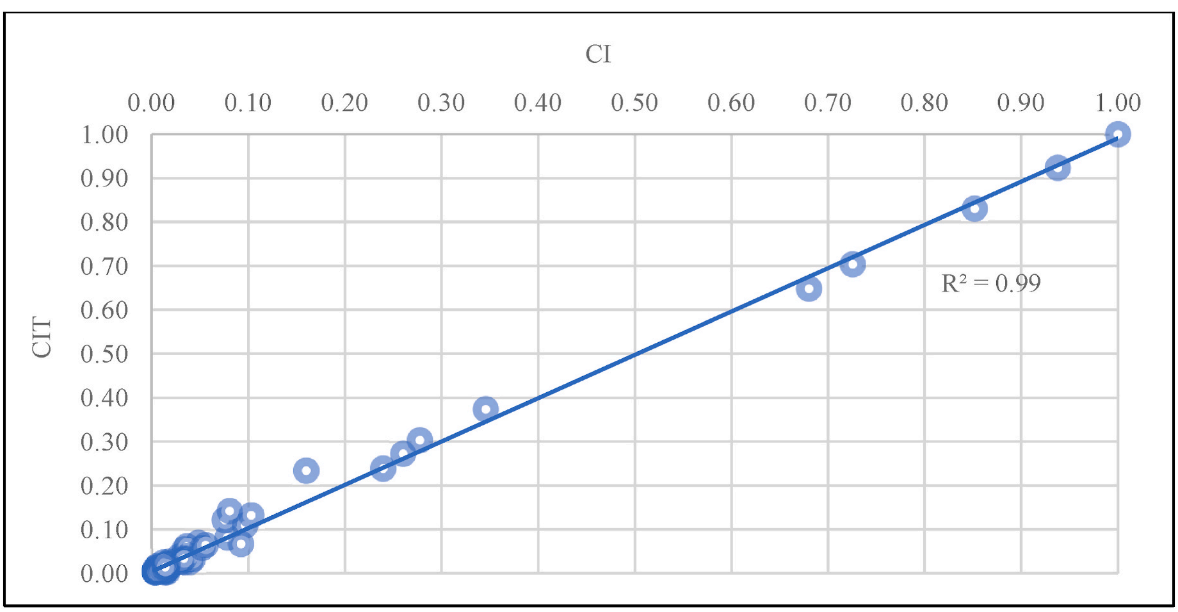


Fig. 7. Topological Impact Coefficient *vs*. Hydraulic Impact Coefficient. Correlation index.

two other devices in the last monitored nodes, suggesting nodes 15 and 75 as candidate sensors (empty blue circles). These two nodes influence each other, being node 15 located along the path from node 75 toward the outfall. It follows that only node 15 is selected to host sensor (filled blue circle), being, of the two, the one positioned further downstream in the network.

The sensor installed in the node 59, on the other hand, covers the node 56 (previously indicated as candidate locations) and requires integrating the monitoring scheme with sensors in nodes 45 and 27, which are, however, connected to each other. Once again, the one located further downstream is selected between the two, i.e., node 45.

The third step repeats the backtracking procedure with respect to the new two sensors, installed in nodes 45 and 15 (Fig. 9-a). The sensor installed in node 15 manages to cover the entire portion of the network that underlies and indicates the uselessness of the sensor in node 75, as expected in the previous step. Conversely, the sensor installed in node 45

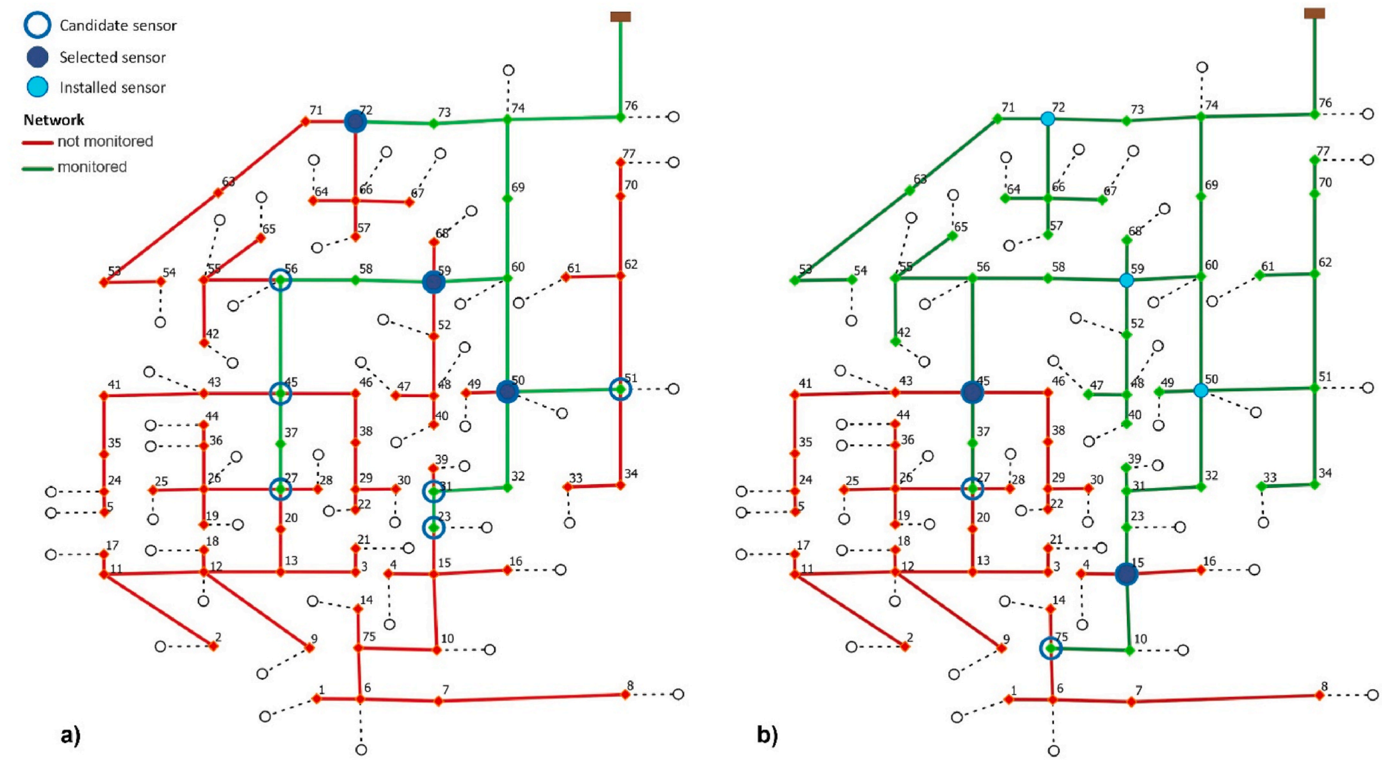


Fig. 8. First (a) and second (b) steps of backtracking with highlighted candidate nodes, selected nodes, and installed sensors.

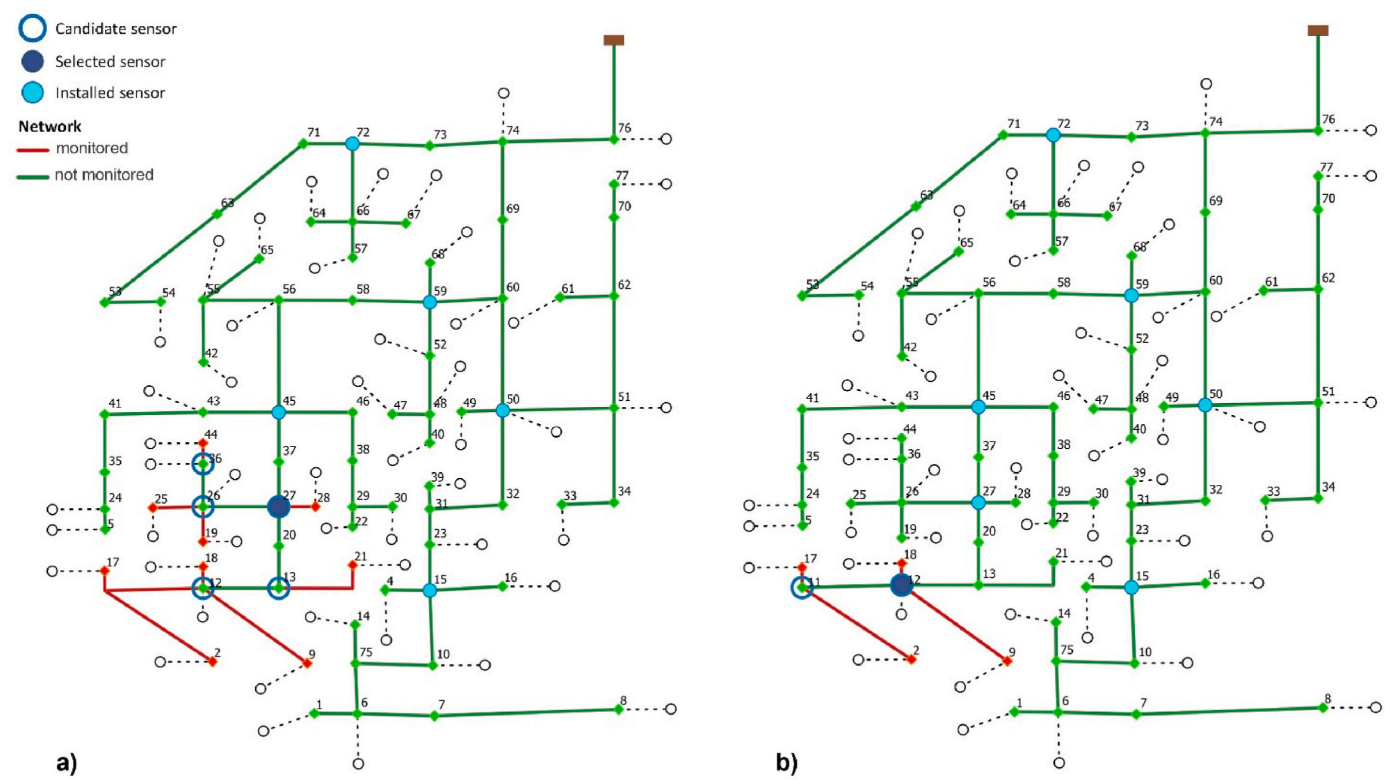


Fig. 9. Third (a) and fourth (b) steps of backtracking with highlighted candidate nodes, selected nodes, and installed sensors.

covers a large part of the upstream nodes, especially those coming from small branches external to the main body of the system, from right and left sides, because they are characterized by small flow rates and less influenced by dilution processes. At the same time, however, it fails to cover the portion of the network coming from the central part, with respect to which the algorithm indicates five other candidate positions to host sensors. Among the candidate positions, as stated above, only one is selected, i.e., node 27. Finally, the backtracking procedure with

Table 1
Priority in terms of percentage of nodes, flow and length covered by each sensor sorted with respect to the covered flow, along with cumulative values of flow and the length covered by the installed sensors.

Priority	ID sensor	Nodes covered [%]	$Flow^T$ [l/s]	$Flow^T_{cum}$ [l/s]	Lc [Km]	L_{cum} [Km]
Prior	n78	11,54	724,42	724,42	2,55	2,55
1	n59	14,10	369,86	1094,28	2,54	5,09
2	n45	15,38	248,93	1343,20	2,41	7,50
3	n27	14,10	228,37	1571,57	2,79	13,91
4	n50	16,67	197,99	1769,56	3,62	11,12
5	n15	11,54	102,46	1872,02	2,73	16,64
6	n12	6,41	62,86	1934,87	1,47	20,10
7	n72	10,26	50,96	1985,84	1,99	18,63

respect to the sensor installed in node 27 indicates two further candidates to host sensors (Fig. 9-b), even if the installation of the sensor only in node 12, the one selected since further downstream, manages to guarantee coverage of the remaining part of the system. The total number of sensors installed is equal to eight, one placed at the outfall and more additional seven.

4.3. Installation priority order

The number of sensors defined by the previous procedure is here characterized by an order of priority in the installation. In fact, it may happen that the sewer utilities do not have sufficient funds to support a total monitoring campaign and, therefore, additional information regarding the priority, in terms of efficiency of each sensor to be installed, could be useful. The priority is here expressed through the range P (P_1, …, P_M), with M number of sensors. The order of priority is provided only for the planned sensors, considering the one at the outfall as a prior.

Table 1 reports the information about the priority order for the sensors of the previously defined monitoring schemes. The topological flows, $\mathbf{Flow^T}$, covered by each sensor has been considered as a measure of efficiency, even if information about number of covered nodes [%] and covered length, **L** [Km], are also provided. In particular, Table 1 shows the IDs of the nodes where to install the sensors, the percentage of nodes, the flow and the length covered by each sensor. The first sensor, installed in node 59, covers the most significant $\mathbf{Flow^T}$. From the second to the fourth sensor in order of priority, it is possible noting that the flows covered increases more than the lasts tree, because they are upstream nodes.

Fig. 10 plots the number of sensors versus the cumulative topological flow $\mathbf{Flow^T_{cum}}$, clearly showing the added value of each sensor in terms of network coverage. It is possible noting the presence of an inflection point in the curve, which represents an optimum of the solution. Analysing the solution in terms of Costs (Sensor) and Benefits (Covered Flow), the Benefits/Cost ratio tends to decrease after this point, and therefore the insertion of any other sensor becomes no longer cost-effective. Overall, the diagram represents a useful tool to support sewer monitoring planning and management because it provides useful information for both scheduled planning and sporadic monitoring campaigns. Furthermore, with respect to the spread of epidemics and the tracking of contaminants in sewer networks, this procedure also envisages the possibility of passing from a network to a district scale, by activating through the backtracking procedure, additional sensors, also in step-test mode, which make it possible to identify the points of spillage/diffusion with ever greater accuracy.

Finally, Fig. 11 reports the network with the seven sensors placed by applying the strategy and the corresponding order of priority P (P_1, …, P_7) in the installation.

5. Conclusions

The strategy here proposed aims at developing a promising approach for SNs monitoring, with optimal solutions in terms of sensor location and network coverage. The first part of the strategy concerns in the used of the backtracking method based on the evaluation of the impact coefficient through a topological approach, which envisages to substitute the hydraulic information with the geometric ones.

The second part of the strategy involves determining optimal monitoring schemes with respect to specific threshold values, which indicate the sensitivity of the sensors to be installed. Monitoring schemes are designed to provide optimal solutions, which minimize the number of sensors to ensure the network coverage, by repeating the backtracking procedure several times, from downstream to upstream, choosing at each step the candidate locations that do not influence each other. An order of priority in the installation of the sensors, as indicator of their efficiency, is given according to the portion of network covered by each device with respect to the monitored flow.

The results indicate that the topological impact coefficient, IC^T values are comparable with those obtained using the hydraulic approach in steady-state conditions, with a correlation of 99%. The obtained sensor location demonstrates that, although the strategy is only based on the network topology, without implementing the hydraulic analysis, it manages to identify the process of diffusion of contaminants. Furthermore, the presented application shows its effectiveness in supporting the optimal design of the sewer network monitoring with the advantages of

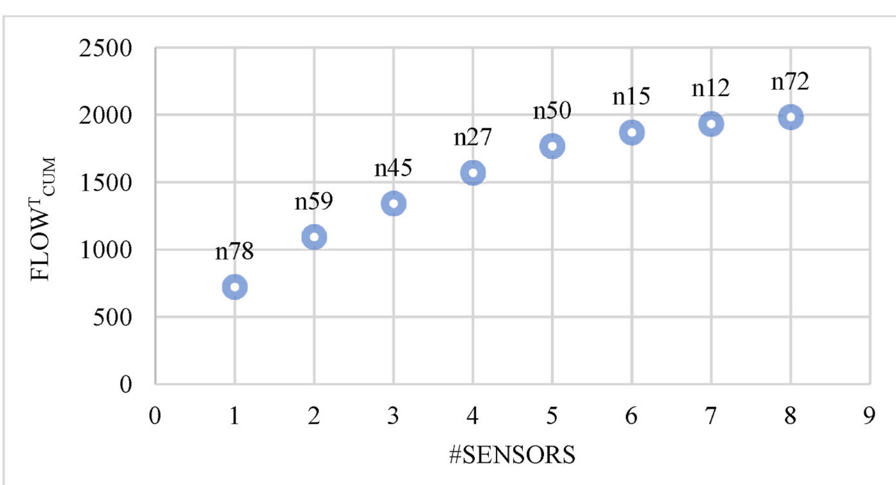


Fig. 10. Installation priority order for sensors. Cumulative topological flow *vs* number of sensors.

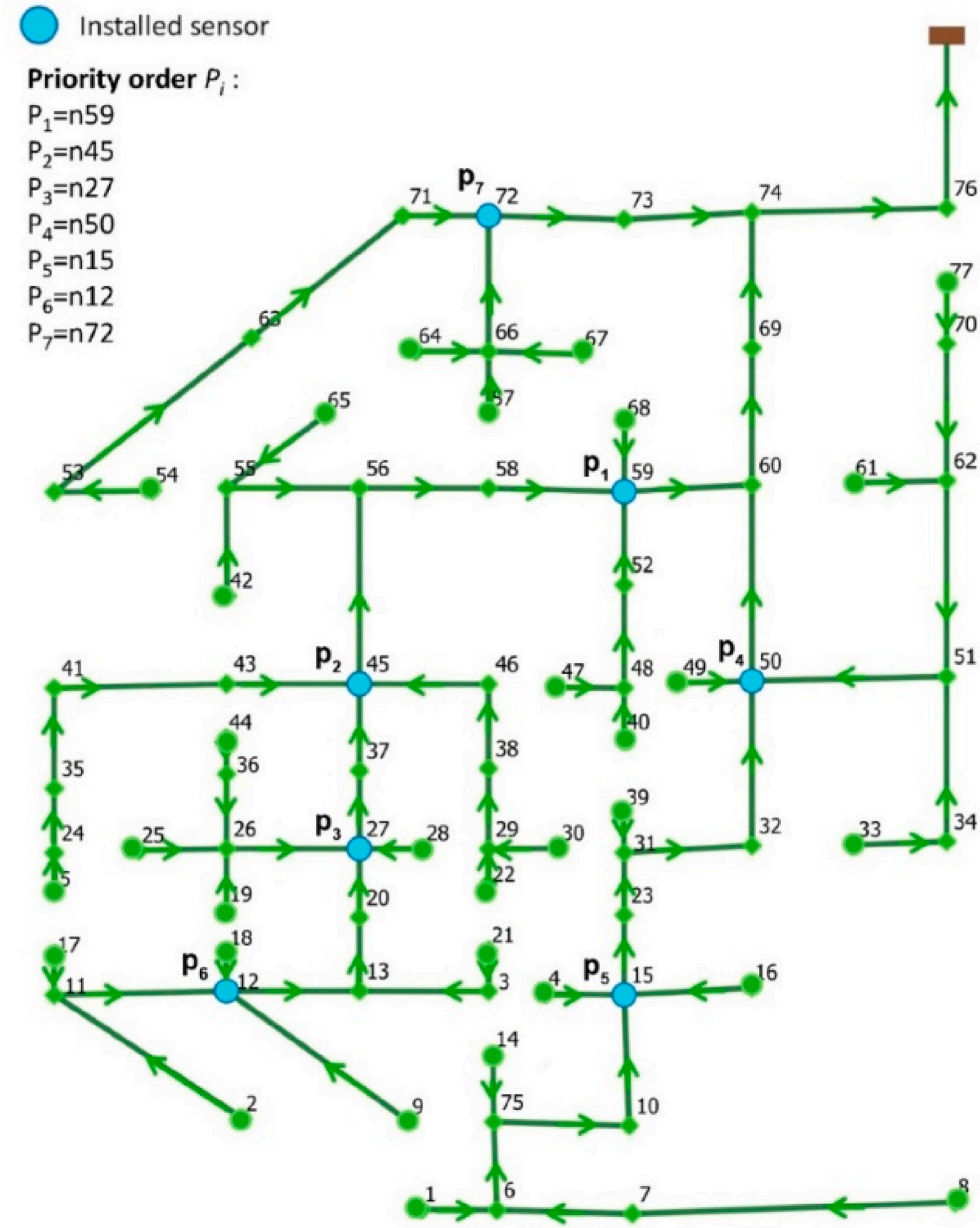


Fig. 11. Monitoring scheme with the priority order for sensors.

a topology-based backtracking approach, which doesn't require the knowledge of the hydraulics of the system. It brings as an added value, compared to the hydraulic approach, a low computational burden, thus simplifying the analysis.

Furthermore, the information relative to the installation priority order permits an analysis in terms of Benefits/Cost ratio about the number of sensors to instal.

Overall, the strategy represents a useful tool to support sewer monitoring for both scheduled planning and periodic monitoring campaigns from the preliminary phase of the analysis regardless of the system's hydraulic information. However, it is possible embedding any information about the hydraulic behaviour of the system acquired over time for refining the model and validate the previous results.

In perspective, future works will be devoted to the use of the methodology to applications in river basin motoring for detection of pollutant substances. It could also be adapted to face with source detection problems.

Code availability

The codes used are available by request.

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Ethics declarations

The authors have no Conflicts of Interest/competing interests to declare that are relevant to the content of this article.

CRediT authorship contribution statement

Antonietta Simone: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Visualization, Writing – original draft, Writing – review & editing, Supervision. **Cristiana Di Cristo:** Conceptualization, Methodology, Validation, Visualization, Writing – review & editing, Supervision, Funding acquisition. **Valeria Guadagno:** Conceptualization, Methodology, Validation, Visualization, Writing – review & editing. **Giuseppe Del Giudice:** Conceptualization, Methodology, Validation, Visualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.119015.

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