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Evaluation of Different Formulations to Optimally Locate Sensors in Sewer Systems

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Abstract: Efficient management of a sewer system includes the control of the conveyed wastewater quality to adequately operate treatment plants and protect the receiving water bodies. Moreover, these systems are vulnerable to either accidental spills or intentional unauthorized discharges. To properly manage them, a limited number of sensors could be placed at different locations to monitor the water quality. In this paper, multiobjective and single-objective optimization procedures to optimally locate sensors in sewer systems are proposed, tested, and compared. The multiobjective procedures include objective functions related to information theory (IT procedure), detection time and reliability (DR procedure), and a combination of them (IT_DR procedure). The single-objective procedures include a greedy-based objective function (GR procedure) and a merged objective function (DR_IT_GR procedure). The procedures show a similar performance when applied on a small network, whereas in a real system, the results show that (1) the IT-based method can be effectively used as a filtering technique; (2) the DR_IT_GR procedure outperforms the other multiobjective ones; and (3) the GR procedure is very efficient in finding the Pareto extreme solutions. **DOI: 10.1061/(ASCE)WR.1943-5452.0000778.**

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Introduction

Efficient management of a sewer system includes the control of the conveyed wastewater quality to adequately operate treatment plants and protect the receiving water bodies. In fact, in combined systems, when discharge exceeds the treatment capacity, raw effluents are spilled directly into water bodies with possible acute effects on the environment (Gromaire et al. 2001; Diaz-Ferros et al. 2002; Even et al. 2004). In this context, the characterization of the collected wastewater is very important (Obropta and Kardos 2007), as differences in its usual composition can be identified. Moreover, sewer systems are vulnerable to both accidental spills and intentional inputs, such as unauthorized discharges, because the networks are geographically dispersed and have multiple access points. The development of online sensors for measuring wastewater quality, based on different technologies (Thomas et al. 1997; Bourgeois et al. 2001; Qin et al. 2012), enabled the identification of anomalous behaviors through event detection procedures (Arad et al. 2013; Campisano et al. 2016; Yang and Bocelli 2016) and the application of source identification methodologies in sewer systems (Banik et al. 2015d, 2017). Since the number of sensors is generally limited by budget and other constraints, an adequate monitoring network has to be adequately designed to efficiently detect anomalies.

The sensor placement problem has been widely studied for monitoring rivers (e.g., Telci et al. 2009; Alfonso et al. 2013; Lee et al. 2014) and for designing contamination warning systems in drinking water distribution networks. In this later research field, starting from the early contributions by Lee and Deininger (1992) and Kumar et al. (1997), many methodologies have been proposed (Hart and Murray 2010), which formulate the sensor location as an optimization problem. Generally, the selection of the objective function is difficult. Among the different proposed objective functions, the detection time (D), the volume consumed (VC), the population exposed (PE) (Rathi and Gupta 2014a, b) are commonly used. Optimization procedures may consider them either separately (in single-objective optimization) or simultaneously (in multiobjective optimization). Among the former group, Rathi and Gupta (2016) used a heuristic method to minimize detection time. More recently, Zhao et al. (2016) presented a branch and bound sensor placement algorithm with very good performances, based on greedy heuristics and convex relaxation.

The battle of the water sensor networks (BWSN) (Ostfeld et al. 2008), which compares 15 different approaches, showed that the sensor placement problem requires a multiobjective analysis, because a solution associated to one objective only is usually suboptimal. In some multiobjective approaches, different objectives are grouped together in a single function (e.g., Aral et al. 2010; Dorini et al. 2010; Rathi and Gupta 2016). In other formulations, the objective functions remain distinct and a group of solutions are reported in the form of a Pareto front (e.g., Preis and Ostfeld 2008; Weickgenannt et al. 2010; Shen and McBean 2011).

Sensor location methodologies can be computationally expensive, in particular when applied to real large-scale networks.

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Integer programming (e.g., Berry et al. 2005) and genetic algorithms (GA) (e.g., Guan et al. 2006) have been widely used as optimization problem solvers, but in complex schemes the computational time can be an important limitation. For these reasons, some methodologies have been developed to tackle the complexity of the network to reduce the computational runtime (e.g., Chang et al. 2012; Klise et al. 2013). For example, Krause et al. (2008) presented a multiobjective methodology, which uses the expected penalty reduction and the submodularity concepts. Comboul and Ghanem (2013), through the use of submodular cost functions, solved the optimization problem with a greedy algorithm, reducing computational effort. The same was achieved by Rathi et al. (2016), who presented a methodology for the selection of contamination events in intermittent water distribution networks, based on the identification of risk-prone areas.

Water quality sensors are often placed in sewer systems generally following practical aspects, such as the proximity of critical facilities, accessibility, and/or spatial density, and they are seldom based on optimization techniques. In a very recent contribution, Villez et al. (2016) proposed a methodology for sensor placement on a wastewater treatment plant for monitoring fault detection.

The novelty of the present research is to develop a methodology to optimally locate sensors for early warning in case of illicit water intrusion in sewer systems. In the proposed methodology, the sensor network design is formulated as an optimization problem, adopting five different procedures that use different objective functions. In particular, the approaches using multiobjective formulations are solved with the Nondominating Sorting Genetic Algorithm II (NSGA-II) and are compared with the single-objective optimization procedure. In order to evaluate the procedures, they are applied on a simplified network [Example 8 of the Storm Water Management Model 5 (SWMM) application manual (Gironás et al. 2009)] and on the sewer system of Massa Lubrense, a town located near Naples, Italy. The objective of the comparison is to highlight advantages and disadvantages of the different procedures, in order to identify those with the best performances.

Methodology for Sensor Location with Different Optimization Formulations

In the proposed methodology, sensor locations are optimized to detect any possible contamination scenario, represented by the intrusion of a conservative contaminant with a constant concentration at a single location in the system during a given period. The simplifying hypothesis of a conservative contaminant is assumed because the absence of decay is the most critical scenario. Any network node is considered as a possible intrusion point. The number of sensors to be placed is fixed, since it is usually constrained by limited budget. However, additional experiments have been performed with an increasing number of sensors, to investigate to what extent an additional sensor improves the performance of the monitoring network.

Different optimization problems are formulated, adopting the procedures listed in Table 1. The first procedure, called IT, considers a multiobjective approach, where joint entropy usually indicated as (JH) is maximized and total correlation (TC) is minimized. The second procedure, named DR, also considers a multiobjective approach, where detection time is minimized (D) and reliability (R) is maximized. The third procedure, named DR_IT, considers a combination of the previous two procedures, where IT is applied as a filtering tool prior the DR procedure. The fourth formulation, called GR, is a single-objective rank-based greedy algorithm that considers JH, D, and R as single objectives. In the fifth procedure, named DR_IT_GR, the DR_IT one is improved by incorporating the greedy solutions in the optimization process.

Table 1. Notation for Different Procedures

Procedures	Optimizer	Objectives
IT	NSGA-II	$\max(JH)$, $\min(TC)$
DR	NSGA-II	$\min(D)$, $\max(R)$
DR_IT	NSGA-II	$\min(D)$, $\max(R)$
GR	Greedy	$\max(JH)$
	Greedy	$\min(D)$
	Greedy	$\max(R)$
DR_IT_GR	NSGA-II	$\min(D)$, $\max(R)$

The multiobjective optimization procedures (IT, DR, DR_IT, and DR_IT_GR) are solved using the NSGA-II, developed by Deb et al. (2002). The NSGA-II was considered because it is a widely used optimization solver for global search problems, but other approaches could be adopted. NSGA-II is an elitist, nondominated sorting genetic algorithm which utilizes simulated binary crossover (SBN) and polynomial mutation as genetic operators. The output of NSGA-II consists of sets of quasioptimal nondominated solutions that define the Pareto front. The Pareto front plots a set of possible outcomes in terms of all objectives. The single-objective procedure (GR) is solved using a rank-based greedy algorithm.

The required data to evaluate the objective functions for the proposed procedures are obtained through hydrodynamic and quality simulations, performed using the well-known SWMM. For the hydraulic simulation, SWMM solves the conservation of mass and momentum equations (St. Venant equations). For the quality simulation, the contaminant is assumed to be discharged simultaneously with the wastewater, and it is considered conservative, without biochemical reaction. This contaminant is introduced at a source node with a fixed constant concentration during the release duration and is transported through the links. It is assumed that conduits behave as a continuously stirred tank reactor (CSTR) without considering the dispersion effect, which is usually kept negligible in water distribution and sewer systems (Rieckermann et al. 2005). To integrate the SWMM simulator within the methodology, the SWMM-Toolkit is used (Banik et al. 2014). In particular, the toolkit is applied to extract the time series of the concentration data for each node, which are required for the evaluation of the objective functions.

Information Theory Procedure (IT)

Information theory was developed by Shannon (1948), who introduced the concept of entropy (H) to measure the information content of a random variable, based on the probability distribution of its records. The higher the entropy value of a random variable, the higher is its amount of information. Considering a discrete random variable X, with values $x_1, x_2, \ldots, x_n$ with corresponding probabilities of occurrence $p(x_1), p(x_2), \ldots, p(x_n)$, the entropy is mathematically expressed as

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log p(x_i) \tag{1}$$

where n = number of distinct events or records in the random variable. In this study, n is the number of records related to a concentration value x_i at a particular node X. Depending on the base logarithm used, entropy takes different units: nats if the base is e and bits if the base is 2 [IEC 80000-13:2008 2013 (IEC 2013)].

In this paper, the base 2 is used. The probabilities $p(x_i)$ are estimated using a histogram-based method with a given bin size or number of classes as used by Markus et al. (2003), Mishra and Coulibaly (2009), and Alfonso et al. (2010b, c, 2013).

The amount of information that is jointly contained in two random variables X_1, X_2 is given by the joint entropy JH, defined as

$$JH(X_1, X_2) = -\sum_{i=1}^{n}\sum_{j=1}^{m} p(x_{1i}, x_{2j}) \log p(x_{1i}, x_{2j}) \quad (2)$$

in which $p(x_{1i}, x_{2j})$ = joint probability of the variables X_1 and X_2 and n and m = number of distinct events or records in X_1 and X_2, respectively.

The total correlation (McGill 1954; Watanabe 1960) TC represents the mutual information among N variables, and can be used to quantify the redundancy among multiple variables. This concept, widely used in the fields of medicine, neurology, psychology, clustering, feature selection, and genetics, has been recently applied in water resources (Alfonso et al. 2010a, b, 2013; Banik et al. 2015a; Ridolfi et al. 2016). Mathematically, the total correlation is given by

$$TC(X_1, X_2, \ldots, X_N) = \left[\sum_{i=1}^{N} H(X_i)\right] - JH(X_1, X_2, \ldots, X_N) \quad (3)$$

The computation of the term $JH(X_1, X_2, \ldots, X_N)$ requires the estimation of the joint probability distribution $p(x_1, x_2, \ldots, x_N)$. It is solved by using the grouping property of mutual information (Kraskov et al. 2005), in which the new variables are built up by agglomerating pairs of variables in such a way that the entropy of each new variable is equivalent to the joint entropy of the original pair (Alfonso et al. 2013).

In the presented IT procedure, the optimal placement of the monitoring sensors is formulated by evaluating the following two objectives: (1) maximum information content and (2) minimum correlation among the sensors. The first objective is achieved by maximizing the JH values [Eq. (2)] of the N selected monitoring sensors (variables), while the second can be accomplished by minimizing TC [Eq. (3)]. Mathematically the optimization problem is formulated as

$$\begin{aligned} f_1 &= \max\{JH(X_1, X_2, \ldots, X_N)\} \\ f_2 &= \min\{TC(X_1, X_2, \ldots, X_N)\} \\ &\quad \text{subject to } H(X_1), H(X_2), \ldots, H(X_N) > H_{\min} \end{aligned} \quad (4)$$

where N = number of sensors to be placed and $H(X_i)$ = entropy of the sensor X_i. The constraint is set by considering a minimum acceptable entropy value $H_{\min}$ in order to exclude nodes with low information content. The process of fixing the threshold value $H_{\min}$ is addressed in the IT Procedure section under Results and Discussion.

The concentration measurements in each node have to be quantized to convert all the records to integer values for computing JH and TC through the histogram-based probability method. The quantization is a process for compiling a continuous set of data to a discrete one (Alfonso et al. 2010b). A value z is quantized (z_q) by rounding it to its nearest lowest integer multiple of k. Mathematically

$$z_q = \text{floor}\left(kz + \frac{1}{2}\right) \quad (5)$$

where floor is a function that rounds down a decimal number to the nearest integer. The value of the parameter k is related to the threshold concentration detectable by a sensor, considering that their product has to be equal to 1.

Detection Time–Reliability Procedure (DR)

In this procedure the two considered objectives are detection time (D) and reliability (R), or detection likelihood, of the sensors [e.g., (Ostfeld and Solomon 2004; Telci et al. 2009)]. D is defined as the time between the beginning of a pollution event and the first nonzero concentration measurement by a sensor. R is related to the number of detected scenarios. In particular, for a given monitoring station displacement, a higher number of detected scenarios correspond to a higher Reliability. In this procedure, the purpose of the monitoring system is to detect the contamination event as quickly as possible with the smallest failure rate. To achieve this goal, average D has to be as small as possible and R has to be as high as possible.

Mathematically, M being the number of potential candidate nodes and N the number of sensors to install, with $M \geq N$, the solution vector is $Y = [y_1, y_2, \ldots, y_i, \ldots, y_N]$, where y_i is the original node index of the ith monitoring station. The overall detection time of the ith sensor for a contamination scenario s, indicated with $d_s^i(Y)$, is defined as the time (in minutes) elapsed between the starting time of the contamination and the time at which the measured concentration exceeds the threshold at y_i. The detection time of the monitoring network for the scenario $s\,[D_s(Y)]$ is defined as the smallest detection time of all monitoring sensors y_1 to y_N. It is expressed as follows:

$$D_s(Y) = \min\{d_s^1(Y), d_s^2(Y), \ldots, d_s^i(Y), \ldots .d_s^N(Y)\} \quad (6)$$

No penalty term is considered for the nondetected scenarios. Then, the average detection time of the monitoring network Y, $D(Y)$ is calculated as the average of $D_s(Y)$ over all detected scenarios:

$$D(Y) = \frac{1}{S_d}\sum_{s=1}^{S_d} D_s(Y) \quad (7)$$

where S_d = total number of detected scenarios.

The reliability of the solution Y, $R(Y)$ is defined as the ratio of detected contaminated scenarios to the total scenarios tested. R is expressed as a percentage, calculated as

$$R(Y) = \frac{1}{S}\sum_{s=1}^{S} \delta_s \quad (8)$$

where S = total number of considered scenarios. $\delta_s = 1$ if the scenario s is detected; otherwise $\delta_s = 0$.

The optimization problem is mathematically formulated as

$$\begin{aligned} f_1 &= \min\{D(Y)\} \\ f_2 &= \max\{R(Y)\} \end{aligned} \quad (9)$$

Detection Time–Information Theory Procedure (DR_IT)

When the search space is big, the solutions may not converge fast to a Pareto front, which represents a concern for large networks. One possible way to cope with this situation is to reduce the search space. With this objective in mind, the DR procedure is modified by introducing a filtering method based on entropy. In this way, nodes having low marginal entropy (or insufficient information content) are removed from the candidate sensor location set. Then, in the filtering phase a fixed percentage of nodes having lower entropy are discarded from the potential candidates prior to the DR optimization. Mathematically the optimization problem is formulated as

$$
\begin{aligned}
f_1 &= \min\{D(Y)\} \\
f_2 &= \max\{R(Y)\} \\
&\text{subject to } H(y_1), H(y_2), \ldots, H(y_N) > H_{\min}
\end{aligned}
\tag{10}
$$

where $H(y_i)$ = marginal entropy of the node y_i and $H_{\min}$ is a fixed minimum entropy threshold. The $H_{\min}$ value is fixed as specified in the Procedure IT section under Results and Discussion.

Rank-Based Greedy Procedure (GR)

As a further alternative, a single-objective rank-based greedy algorithm is used to optimally place sensors, selecting one sensor location at a time. In this case the objectives JH, D, and R are considered independently. The first monitoring location in the GR procedure is chosen at the point with maximum JH, minimum D, or maximum R, in a similar fashion as that of Krstanovic and Singh (1992), depending on which objective is considered. After choosing the first location, the second one is selected based on the maximum marginal variation of the considered objective. The same procedure is repeated for the successive ones, evaluating the marginal variation considering the sensors already placed. When the single objective D is considered, a penalty term D_{sim} (total simulation time in minutes) is applied for the undetected scenarios. This is crucial to avoid dispositions with a high number of undetected cases. In fact, by minimizing D, all the peripheral (upstream) nodes having a low average time would be selected, furnishing a low reliable monitoring network. The average detection time of the monitoring network Y, $D(Y)$, is calculated as

$$D(Y) = \frac{1}{S}\sum_{s=1}^{S} D_s(Y) \tag{11}$$

with

$$D_s(Y) = \begin{cases} \min\{d_s^1(Y), d_s^2(Y), \ldots, d_s^i(Y), \ldots, d_s^N(Y)\} & \text{if scenario } s \text{ is detected} \\ D_{\text{sim}} & \text{otherwise} \end{cases} \tag{12}$$

where S = total number of scenarios considered in the analysis.

Detection Time–Information Theory–Rank-Based Greedy Procedure (DR_IT_GR)

Since the greedy algorithm is a good option to find the extremes of a Pareto front (Alfonso et al. 2013), the DR_IT procedure is modified with a manipulation of the initial population of NSGA-II. This is done by putting the solutions coming from the GR procedure (with objectives JH and D) into the randomly generated initial population of NSGA-II. The goal is to start from the extremes of the Pareto front to get trade-off solutions when adding the conflicting objectives D and R.

Case Studies

In order to compare the procedures, two different networks are used. One is a small example of the SWMM manual and the other one is a real network in Italy. Details of both networks are provided below. In the presented examples, only the dry weather condition is considered, since it represents the more impactful situation on the sewer functioning in the case of illicit intrusion.

An ad hoc developed C++ code, which integrates the SWMM simulator with its toolkit, is used to generate the contaminant scenarios and to extract the required concentration time series. Each contamination scenario consists of the continuous injection of a conservative pollutant at one node of the scheme, one at a time, with a concentration of 1.0 g/L for an assigned duration. In both cases the input concentration has been fixed as unitary (Cozzolino et al. 2011) because in this way the results can be easily scaled. The injection duration has been selected considering the time that the solute takes to move between the two most distant points of the scheme.

The minimum concentration value detectable from a sensor (threshold) is assumed equal to 0.0001 mg/L. However, additional tests for studying the effect of different threshold values on the methodology results are reported in presenting the Massa Lubrense test-case results.

Example 8 SWMM Manual

The procedures are applied first to the small network in the Example 8 of the SWMM application manual, depicted in Fig. 1. The network consists of 31 nodes (28 junctions, 2 outlets, and 1 storage unit) and 35 links (29 conduits, 1 pump, 1 orifice, and 4 weirs). All geometric data and the dry weather inflows, expressed as daily mean values, have been reported by Gironás et al. (2009) and Banik et al. (2017), respectively. For the contamination scenarios, the injection duration is 1 h. SWMM hydraulic and quality simulations are realized with a time step of 10 s, while the time series of the concentration values in each node are collected for 2 h, with a reporting time step of 5 min.

Massa Lubrense Case Study

Massa Lubrense is a small town near Naples, Italy, which has the sewer system, shown in Fig. 2, with a classical treelike network and some loops. It is a combined sewer system, covering an area of 19.71 km^2, divided into 12 subcatchments, serving a population of 14,087 (year 2011), with an approximate amount of yearly produced wastewater of 1.13×10^6 m^3. The scheme consists of 1,909 circular conduits connecting 1,902 junctions, 14 pumps, 14 storage units, and 1 treatment plant. The wastewater arrives at the treatment plant through two entry points (nodes 1901 and 1902). The daily mean values of the dry weather flows (DWF) in the 1866 nodes, depicted in Fig. 2, are assigned considering the population connected to each node. The Manning roughness coefficient is

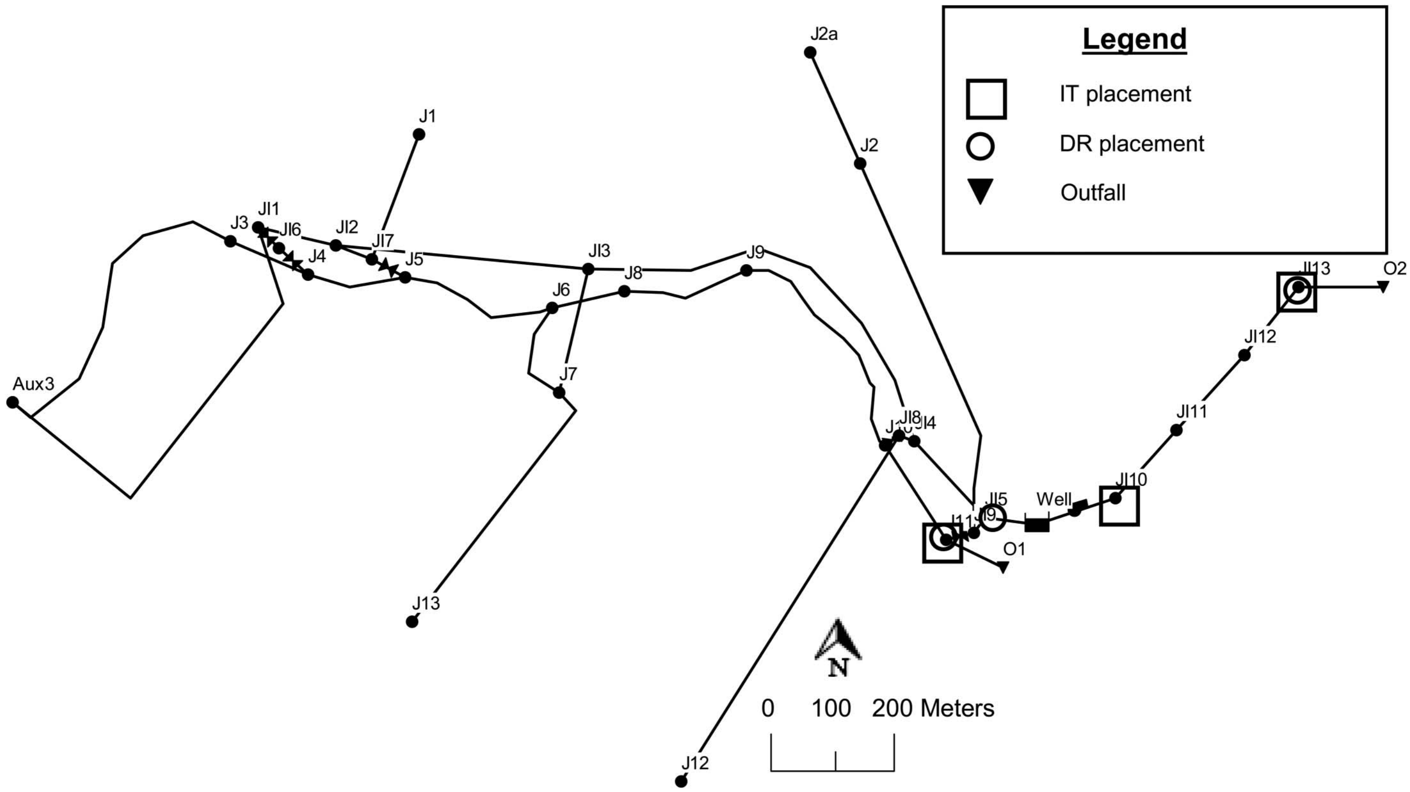

Fig. 1. Scheme of SWMM Example 8 system; placement of the optimal solution corresponding to three sensors

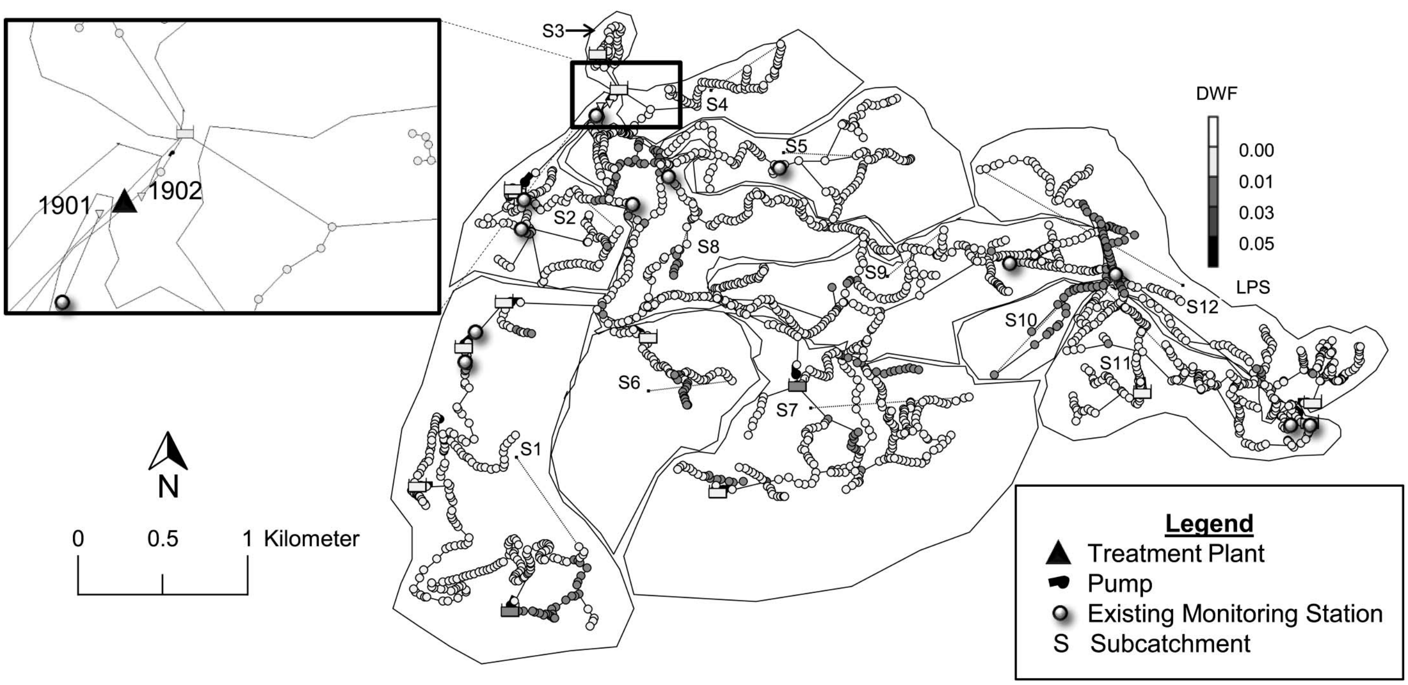

Fig. 2. Scheme of Massa Lubrense system

assumed to be 0.016 $m^{-1/3}$ s. Other geometric data are available on the website http://www.progettosimona.it. The system has 12 monitoring stations that were installed as part of the ongoing Simona project. The actual sensor locations have been decided on the basis of practical considerations, primarily related to the availability of the electrical power supply and to the need for the global system for mobiles (GSM) coverage for transmitting the recorded data.

In the contamination scenarios, the injection duration is 5 h. The time series of the concentration values in each node are collected for 6 h. The SWMM hydraulic and quality simulations are run with a time step of 2 s. Considering a reporting time step of 5 min, the

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size of the extracted time series is 137,952 at each of the 1,916 nodes.

Results and Discussion

The general performances of the procedures are reported first for the small network and further expanded in detail for the real network, where more comprehensive experiments are run and reported.

Example 8 SWMM

In this application, the number of considered sensors is varied between 2 and 7. For this small network, the results for the IT procedure reveal that after three monitoring stations, any additional sensor fails to increment JH, while the total correlation increases significantly. Fig. 1 shows the resulting sensor placement obtained for the solution with the maximum JH value in the Pareto front. For the DR procedure, the maximum redundancy is reached at a detection time of 5 min, with six sensors. The solution for the placement of three sensors with maximum reliability is also reported in Fig. 1. Regarding the GR procedure, the maximum redundancy is achieved with only two sensors, using R as objective; when considering D and JH as objectives, no further improvement is obtained after three sensors. The first two cases of the GR procedure produce a similar network configuration than the one obtained with DR, while the GR with JH as its objective generates the same output as the IT procedure (Fig. 1). In conclusion, this simple example confirms a consistency between the results obtained with the different procedures. This point is further expanded in the discussion section.

Massa Lubrense Case Study

For the multiobjective optimization procedures (IT, DR, DR_IT, and DR_IT_GR), the NSGA-II is applied with the following parameters: crossover probability equal to 90% and mutation probability equal to 10%. Moreover, after a sensitivity analysis, the population and generation values are fixed to 200 and 2,000, respectively. Increasing those values does not improve significantly the optimization outcome, with an increase of the computational burden, especially for the IT-based approaches where the entropy calculation is very computationally intensive. For this case, the experiments consider a number of sensors between 7 and 14. This interval has been selected in order to have the number of monitoring stations already installed (12) in the range, so that the existing locations can be compared with those obtained with the proposed methodologies. In this way, it is possible to understand the advantages or disadvantages of reducing or adding sensors, having the existing ones as a reference.

For better readability, some intermediate points have been eliminated from the graphs, including Pareto fronts.

IT Procedure

Eq. (4) is used to constrain the minimum allowed information content, $H_{\min}$, to filter out low-entropy nodes. In particular, the two least informative quartiles (50%) of nodes are eliminated. The maximum entropy in the network is 6.89 bits, while in 50% of the nodes it is less than 0.12 bits (<1.5% of the maximum value), which is the value assigned to $H_{\min}$. The total joint entropy of the system is $JH_{\text{sys}} = H(X_1, X_2, \ldots, X_{1916}) = 16.71$ bits, which represents the amount of information provided if all nodes were monitored. After filtering 50% of the nodes, the JH value reduces to $JH_{\text{filter}} = H(X_1, X_2, \ldots, X_{958}) = 16.65$ bits, which means that the

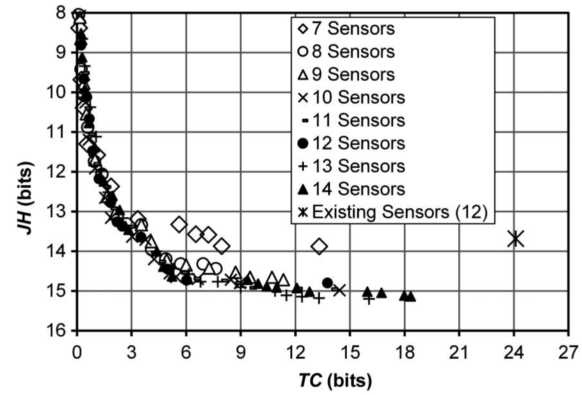

Fig. 3. Procedure IT: Pareto fronts corresponding to different sensor numbers

eliminated points provide only 0.35% of the total joint entropy of the system. This suggests that the filtering process provides a reduction of the computational cost with a marginal loss in information content.

The optimal solutions obtained by solving the optimization problem of Eq. (4) with a different number of sensors are reported in Fig. 3. After 10 monitoring stations, additional sensors do not produce a notable increment of the JH while the total correlation either remains constant or increases because of the effect of sensor redundancy. Moreover, for all cases, the Pareto fronts near the y-axis (up to 3 bits of total correlation) follow almost the same pattern, whereas differences are evident near the x-axis. In fact, during the optimization process, the objective TC plays only a subordinate role, just to avoid redundancy, while the JH plays the primary role. This implies that TC as a single objective does not produce a good optimization outcome. Fig. 3 shows that the network of the existing sensors is suboptimal, as better objective functions are achieved with fewer sensors.

It is extremely difficult to choose one particular solution from multiple optimal solutions given by the Pareto fronts. The trade-off between information content and redundancy implies that the ideal network configuration would be located at the origin of any Pareto graph, called the utopia point (Pandey et al. 2013). In the considered test case, the utopia point is (0, 16.71), representing an imaginary solution with the maximum JH value ($JH_{\text{sys}} = 16.71$ bits) and zero redundancy. Therefore, in order to analyze the results, two Pareto points are analyzed in depth, namely the one with the maximum JH value [most informative solution (MIS)] and the one closest to the utopia point (CUP). Fig. 4 shows the values of the two IT objective functions for such MIS and CUP points. Regarding MIS, an increase in redundancy is observed after 9 sensors, while JH has just a mild increment. The increment of JH observed when going from 10 to 14 sensors is just 1% (from 14.99 to 15.14 bits), while TC increases by more than 27% (from 14.43 to 18.34 bits). In fact, 10 sensors provide about 90% of the information content of the whole system. Regarding CUP, both JH and TC show almost a constant trend. For all considered numbers of sensors, the JH is around 13 bits, which represents 78% of the total information of the system, with a TC slightly larger than 2 bits.

Fig. 5 shows the monitoring network configurations for the MIS solutions for 8, 10, 12, and 14 sensors. A regular distribution of the measurements is evident for the solutions with 8 and 10 sensors, while for the solutions with 12 and 14 sensors redundancy is important. For instance, node 703 and nodes 892 and 1,372 are redundant in the cases with 12 and 14 sensors, respectively. In all

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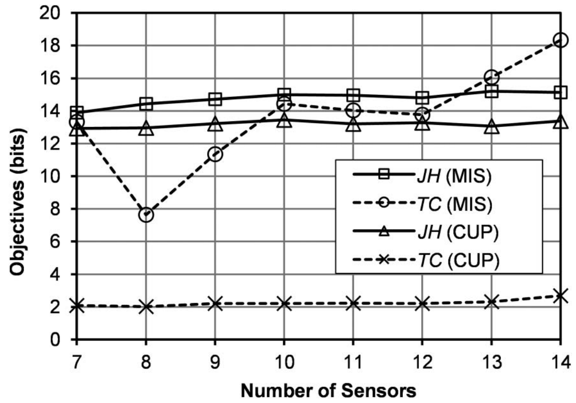

Fig. 4. Procedure IT: objective values for the optimal solutions selected from the Pareto fronts using the MIS and CUP methods for different sensor numbers

solutions, two of the selected points are the entry points to the treatment plant (1,901 and 1,902) or their immediate upstream nodes (719 and 1,915). Furthermore, with 10, 12, and 14 sensors, eight selected nodes are in all cases essentially near 1,901; 1,902; 766; 94; 794; 266; 1,335; and 1,911.

In Fig. 6, the monitoring network configuration obtained in MIS and CUP, using 12 sensors, is compared with the existing monitoring network. The majority of sensors in the CUP solution are located in the upstream part of the scheme, where the information content is relatively low, which produces less redundancy. The existing sensor placement is partially supported by the locations obtained in the MIS solution. In fact, 7 (1,902; 772; 92; 1,335; 668; 1,069; and 1,911) out of 12 sensors are very close to the existing monitoring stations. In the remainder of the paper, only the MIS point of each Pareto front will be analyzed.

DR Procedure

Reliability [Eq. (8)] is computed using a total of 1,916 contamination scenarios, considering as possible intrusion point all nodes and storage units of the scheme. However, the maximum reliability of the system is 97.39%, because only 1,866 nodes receive inflows (DWF) while the remaining 50 (2.61% of total nodes) are connecting nodes. In other words, contamination events generated at such nodes always remain undetected.

The Pareto fronts shown in Fig. 7 are generated and obtained for a number of sensors varying from 7 to 14. After 9 sensors, the differences among the Pareto fronts are reduced. A comparison with the existing sensor network demonstrates that it is suboptimal. The most reliable solution of the obtained Pareto front is further analyzed in Fig. 8, where the values of D and R are plotted against the number of sensors. From 9 to 14 sensors, R increases by only 0.2%, while the decrement of D is less than 25%. Moreover, none of the sensor configurations achieves the maximum R value (97.39%).

DR_IT Procedure

Fig. 9 shows the optimization results from 7 to 14 sensors using the DR_IT procedure. It can be deduced that the optimization results are much better than the ones obtained using the DR procedure (Fig. 7). Indeed, using the DR procedure with 14 sensors, the maximum reliability achieved is less than 60% for a detection time of 10 min and less than 80% for a detection time of 15 min (Fig. 7). In contrast, running the DR_IT procedure with the same number of

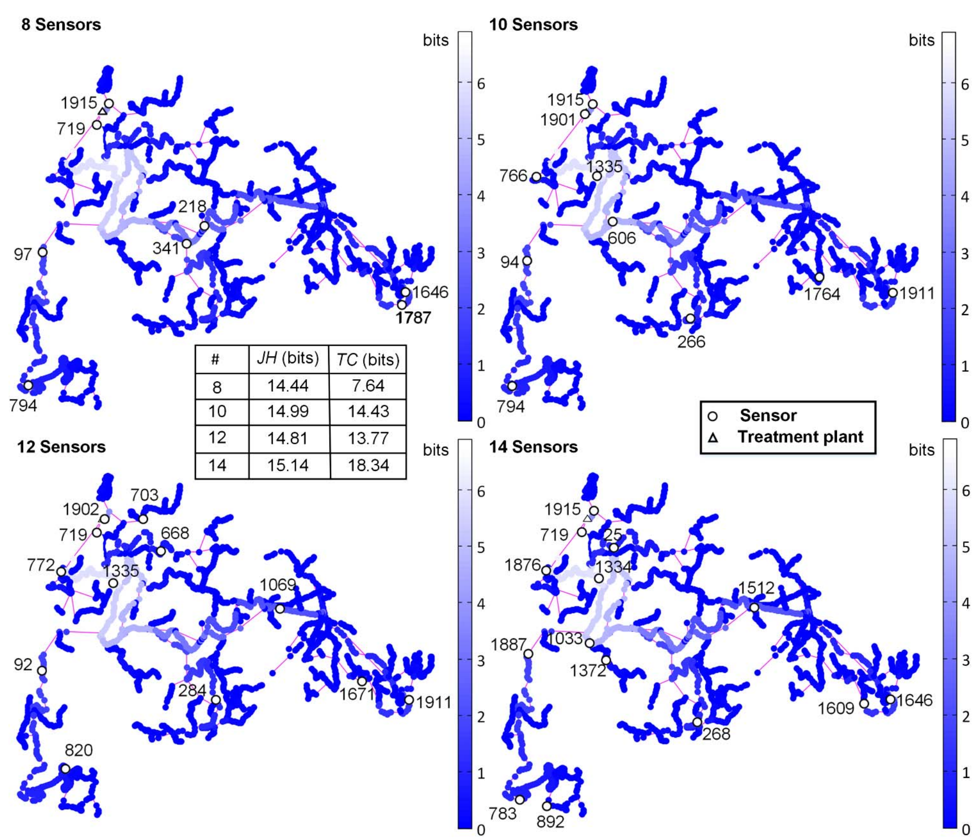

Fig. 5. Procedure IT: placements of the optimal solutions selected from the Pareto fronts using the MIS method corresponding to 8, 10, 12, and 14 sensors

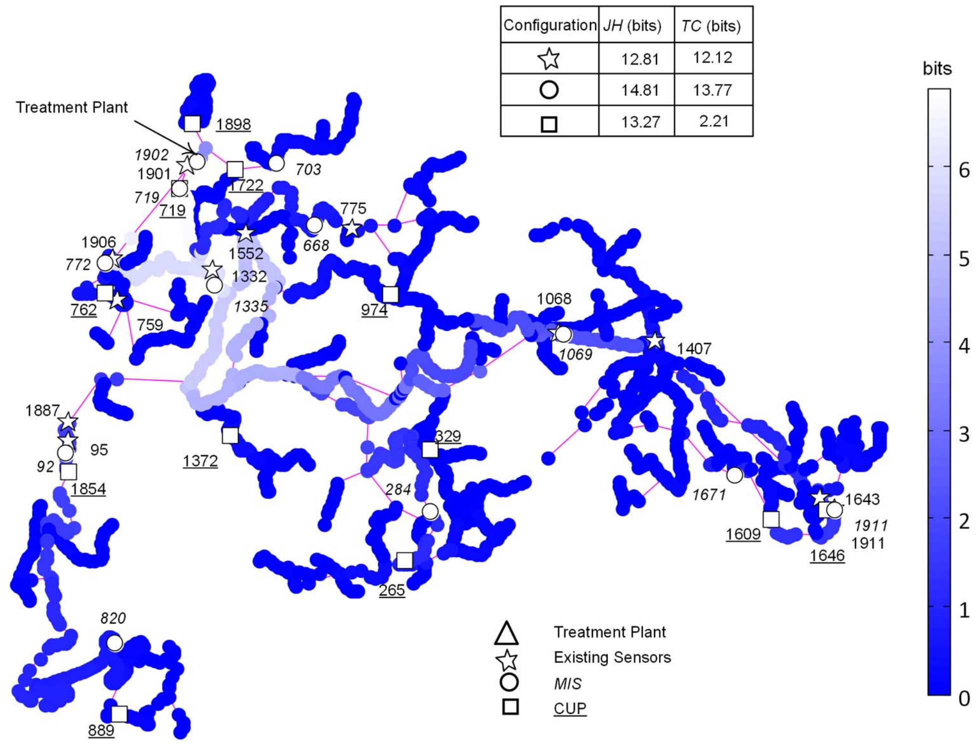

Fig. 6. Procedure IT: placement of 12 sensors using the MIS and the CUP solution methods along with the existing network

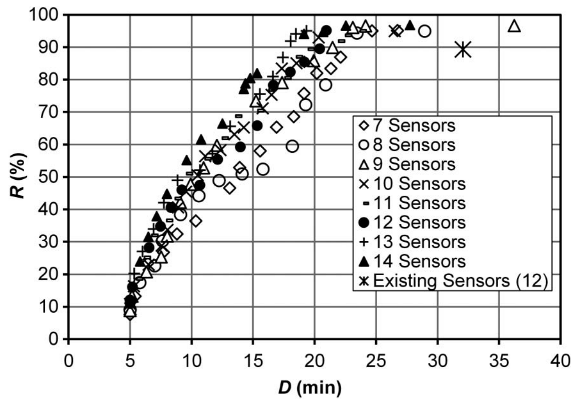

Fig. 7. Procedure DR: Pareto fronts corresponding to different sensor numbers

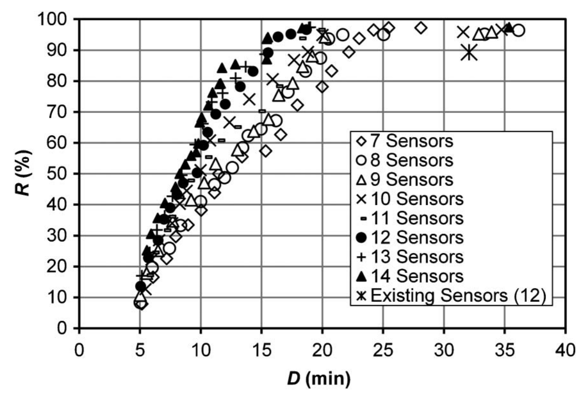

Fig. 9. Procedure DR_IT: Pareto fronts corresponding to different sensor numbers

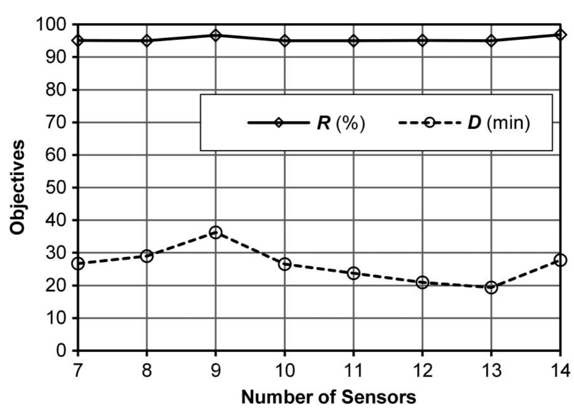

Fig. 8. Procedure DR: objectives values for the most reliable solution selected from the Pareto fronts for different sensor numbers

sensors gives a maximum reliability of 70 and 90% for the respective detection times (Fig. 9).

In addition, the Pareto fronts obtained using the DR_IT procedure with 12 sensors indicate that the existing sensor network is suboptimal. The most reliable solution of the Pareto front shows that the theoretical maximum reliability (97.39%) is achieved with 13 sensors.

GR Procedure

The same numbers of sensors (7–14) are considered for the GR procedure. Single-objective optimization is considered using the three different objectives, namely JH, D, and R.

Fig. 10 shows the JH, D, and R values for the different considered numbers of sensors. From 9 to 14 sensors JH increases by only 6%, while D shows a decrease of 28%. With 6 sensors R achieves the maximum possible reliability (97.39%), while using the DR_IT procedure the same R is achieved with 13 sensors.

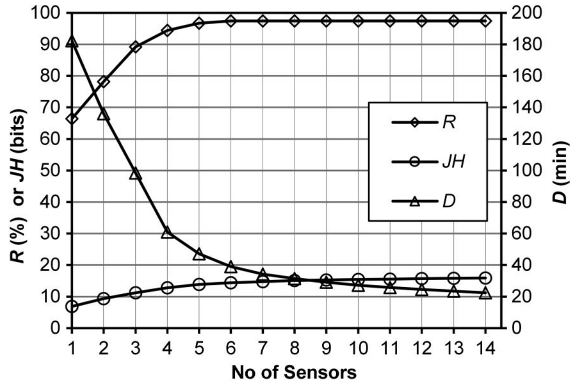

Fig. 10. Procedure GR: objective values for the optimal solutions for different sensor numbers

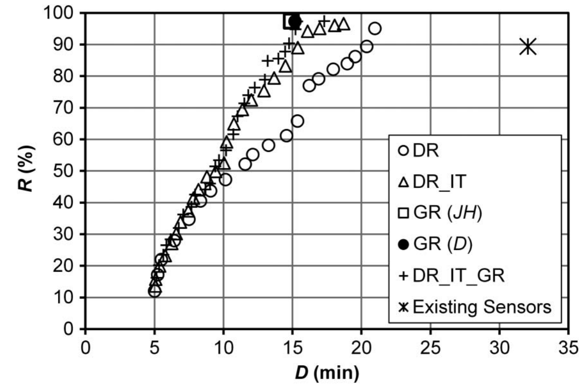

Fig. 12. Comparison of the Pareto fronts obtained from all procedures with 12 sensors

In particular, the maximum JH achieved with 14 sensors using the IT procedure is 91% of the total JH_{sys} (15.14 bits), whereas using the GR procedure it is about 95% (15.85 bits) of JH_{sys} (16.71 bits). These results confirm that the greedy algorithm is a useful alternative to find the extreme solutions in the Pareto front (Alfonso et al. 2013).

DR_IT_GR Procedure

This procedure is a combination of the previous procedures. It consists of using the GR solutions derived from the two objectives JH and D, placing them into the initial population of NSGA-II, and then running the DR_IT procedure. The solution obtained using R as an objective function is not considered in the initial population because the maximum R is achieved by using only six sensors. So, in the initial populations of 200 individuals, 198 are randomly chosen while the other two come from the GR procedure. The intention is to get a better Pareto front near the extreme ends.

The new Pareto fronts obtained for the different numbers of sensors are reported in Fig. 11, which shows an improvement in the extremes of R with respect to the DR and DR_IT procedures. For instance, with 12 sensors and $D = 15$ min, the value of R is about 65% if the DR procedure is used, while it is 97.39% if the DR_IT_GR procedure is used. These results are more clearly shown in Fig. 12, where the solutions with 12 sensors of all procedures considering the D objective are compared. The improvement attributable to the incorporation of the two greedy solutions into the initial population of the DR_IT is evident, with the DR_IT_GR outperforming all the previous multiobjective procedures, in particular to the extreme of R. Fig 13 shows the D and R values for the most reliable solutions are taken from all the Pareto fronts (case 0.0001). As in the case of Fig. 12, R is almost constant after 7 sensors, while D is halved.

To investigate the effect of dilution on the results, the whole DR_IT_GR procedure is repeated for four other threshold values (0.001, 0.01, 0.1, and 1 mg/L) and a number of sensors from 4 to 14. Fig. 13 reports the objective values for different numbers of sensors and different detection thresholds, taken from the Pareto solutions with the maximum reliability. The results show that the effect of the threshold value is important. As expected, a decrease of the threshold value produces an increase of R and a decrease of D. However, the increase of R is important when moving from a threshold value 0.1 to 1 mg/L. The 1 mg/L threshold is unrealistic; in fact, a reliability of 93% can only be achieved with more than 100 sensors.

Fig. 14 reports the sensor placements for the cases of 4, 8, 12, and 14 sensors, selecting in each Pareto front the solution with the maximum reliability, for the four considered threshold values. For 4 and 8 sensors the optimal configurations are very close, while for 10 and 12 sensors they are quite different. In particular, for 4 sensors the optimal sensor placements obtained with 0.0001, 0.001, and 0.01 mg/L are almost equivalent. At 0.1 mg/L, there are some differences, with one isolated sensor placed in a different position with respect to the other cases. For 14 sensors, the number of isolated sensors is 3, 2, 4, and 8 for 0.0001, 0.001, 0.01, and 0.1 mg/L, respectively. This reveals that, with a smaller number

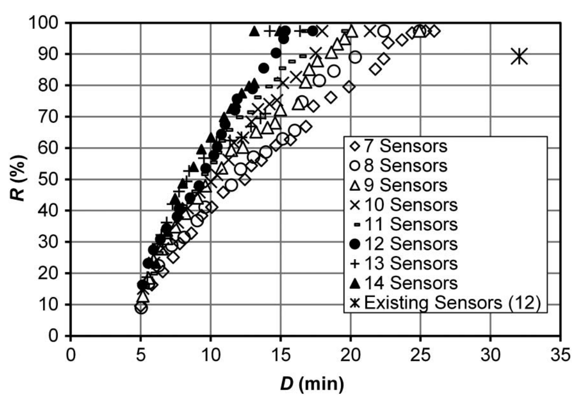

Fig. 11. Procedure DR_IT_GR: Pareto fronts corresponding to different sensor numbers

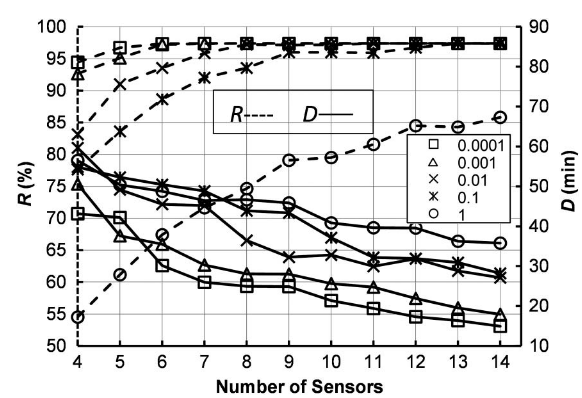

Fig. 13. Procedure DR_IT_GR: objective values for the most reliable solutions for different sensor numbers and considering different detection thresholds

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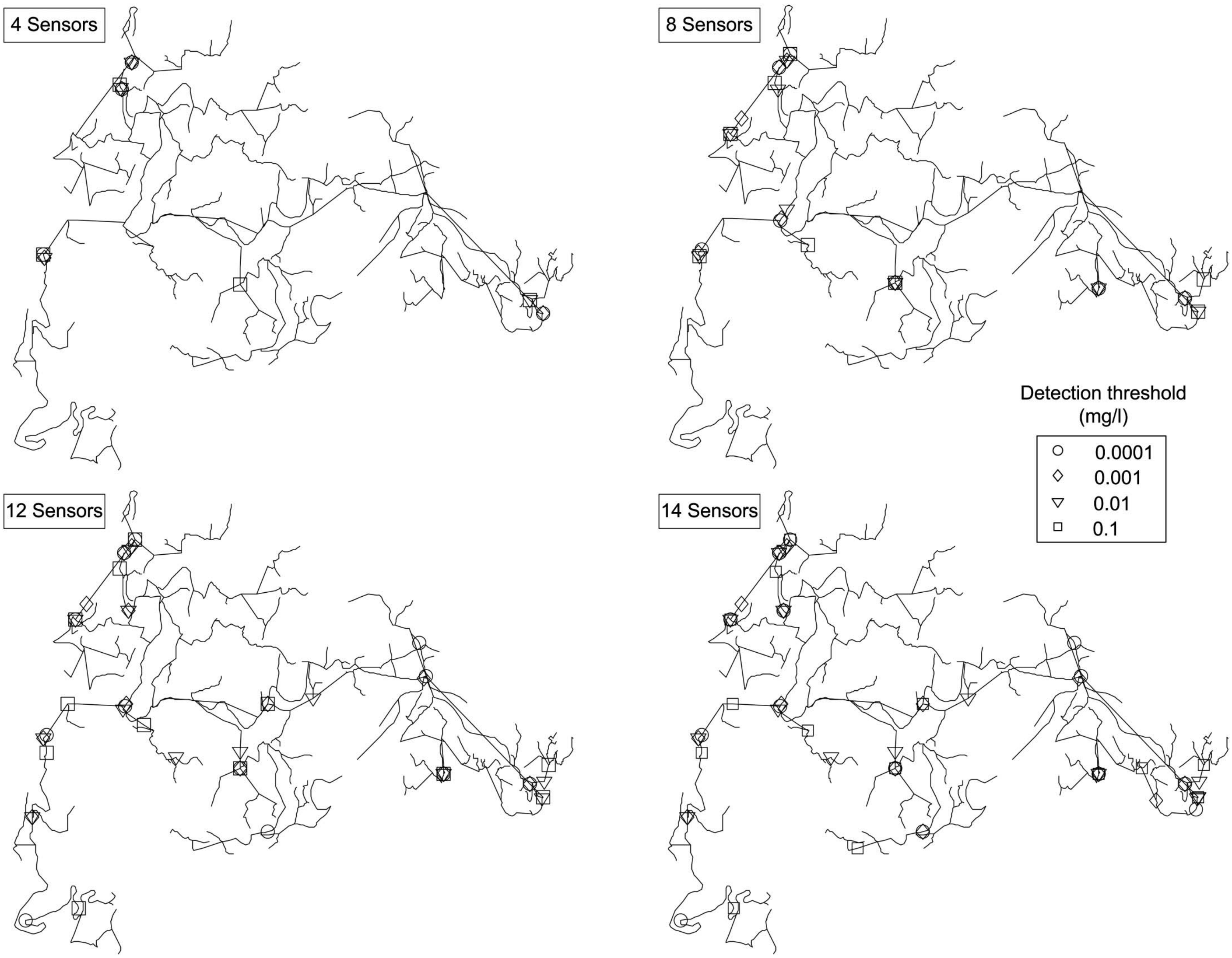

Fig. 14. Procedure DR_IT_GR: placement of the optimal solutions selected from the Pareto fronts using most reliable method corresponding to 8, 10, 12, and 14 sensors and with different detection thresholds

of monitoring stations, sensor characteristics in terms of minimum detectable concentration have limited influence on the optimization procedure. The differences denoted with more sensors may derive from the fact that in such cases the search space of the optimization problem becomes larger. Another interesting observation is that with a fixed threshold there is consistency of the locations obtained when increasing the number of sensors. In particular, Fig. 14 evidences that the same sensor location obtained for 4 sensors is found in the solution for 8 sensors. In general, the monitoring network configuration obtained with fewer sensors is almost the same as the configurations with more sensors. This is attributable to the incorporation of the greedy solutions in the initial population of the NSGA-II.

Performance of the Proposed Procedures

It is not fair to compare different multiobjective approaches, as well as single-objective and multiobjective procedures. However, for practical applications, the researchers have to indicate only one procedure to use; then a way for making the comparison is necessary. In this work, to compare the performances of the presented procedures, a weighted average index (PI), considering all the four objective functions (JH, TC, R, and D) is adopted. The JH, TC, R, and D values are computed from the optimal solution obtained for each approach, for a fixed number of sensors. For the procedures involving multiobjective optimization, the solution with the maximum JH value for the IT is selected, while for the remaining procedures (DR, DR_IT, and DR_IT_GR) the solutions with maximum R are considered. A normalized version of the objective functions is used, and for each of them the following score W_i is calculated:

$$W_i = \begin{cases} \dfrac{(O_{i\_\max} - O_i)}{(O_{i\_\max} - O_{i\_\min})} & \text{if objective } O_i \text{ has to be minimized} \\ \dfrac{(O_i - O_{i\_\min})}{(O_{i\_\max} - O_{i\_\min})} & \text{if objective } O_i \text{ has to be minimized} \end{cases} \tag{13}$$

where $i = 1.4$ is the number of the considered objective, and $O_{i\_\max}$ and $O_{i\_\min}$ are the maximum and minimum objective function values, respectively.

The performance index (PI) is then calculated as the arithmetic average of the four objective scores equally weighted:

Table 2. Performance of All Procedures [Eq. (14)]

Procedures	Number of sensors 8	10	12	14
IT	0.59	0.64	0.20	0.57
DR	0.38	0.40	0.20	0.60
DR_IT	0.40	0.42	0.57	0.48
$GR(JH)$	0.70	0.69	0.67	0.75
GR(D)	0.90	0.80	0.79	0.91
DR_IT_GR	0.70	0.79	0.67	0.75

$$\mathrm{PI} = (W_1 + W_2 + W_3 + W_4)/4 \tag{14}$$

A higher PI indicates a better overall performance.

Considering the Massa Lumbrense system, the obtained PI values for the six different procedures with 8, 10, 12, and 14 sensors are reported in Table 2. In all cases, the greedy approach using the detection time as single objective ranks first. In fact, considering that the selected solutions are extreme on the Pareto front, the greedy algorithm is very effective in searching such extremes.

The IT procedure has better performances with respect to DR and DR_IT. The DR_IT_GR procedure ranked second, because of the improvement of DR_IT by the incorporation of the greedy solutions in the initial population of NSGA-II. The DR_IT_GR procedure not only outperforms the other multiobjective approaches, but its performance is also comparable with the extreme solutions obtained from the greedy approach.

Regarding the Example 8 test case, the IT_DR and IT_DR_GR procedures do not produce any improvement with respect to the DR. The other procedures (IT, DR, and GR with D and JH as objectives) result in very similar sensor locations and therefore they have the same PI value. This suggests that while the procedures have different performances when applied to a large and complex system, they give equal results on simpler schemes.

Conclusions

In this paper, different procedures for designing optimal monitoring networks in sewer systems were presented and tested in a simplified case, SWMM Example 8, and in a real case, Massa Lubrense. Four of these procedures (IT, DR, DR_IT, and DR_IT_GR) used a multiobjective optimization approach, while one used a single-objective approach (GR).

While very similar results were obtained from the different procedures when applied on the small scheme of SWMM Example 8, different performances were observed on the complex system of the Massa Lubrense. In this test case with a limited number of sensors (less than 12), the overall performance of the DR procedure was worse with respect to the IT procedure. As a large search domain can deteriorate the optimization outcomes, the proposed IT-based screening approach significantly improves the DR procedure.

The greedy-based GR procedure, applied with three different independent objective functions, was efficient at finding the extreme Pareto solutions. In particular, the GR with objective R reaches the optimal solution with fewer sensors, with respect to the applications with the other objectives.

A further comparison among the procedures was performed by adopting a multiobjective index and considering all the four objectives (JH, TC, R, and D). For a fixed number of sensors, solutions with maximum JH for IT and maximum R for the DR, DR_IT, and DR_IT_GR were compared. The GR procedure with objective D is the most effective, except for the objective function R. The DR_IT_GR procedure outperforms all the multiobjective optimization formulations, especially at the extreme values of reliability.

The existing monitoring network in Massa Lubrense is found to be suboptimal for all the procedures. However, 7 out of 12 existing sensors are found to be very close to the solution obtained by the IT procedure. This observation suggests that a lesser number of sensors can be used if they are optimally located.

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