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Optimal placement of water quality monitoring stations in sewer systems: an information theory approach

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Abstract

A core problem associated with the water quality monitoring in the sewer system is the optimal placement of a limited number of monitoring sites. A methodology is provided for optimally design water quality monitoring stations in sewer networks. The methodology is based on information theory, formulated as a multi-objective optimization problem and solved using NSGA-II. Computer code is written to estimate two entropy quantities, namely Joint Entropy, a measure of information content, and Total Correlation, a measure of redundancy, which are maximized and minimized, respectively. The test on a real sewer network suggests the effectiveness of the proposed methodology.

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Keywords: Information theory; Sewer systems; Monitoring stations; Entropy; Optimization; NSGA-II.

1. Introduction

Improper management of wastewater could result in significant damage to the flora and fauna of the ecosystem, long term impacts on public health, distraction to commerce and economy, which in turns lead to the overall disruption of the nation's way of life. In past, the wastewater management has not got much attention to the stockholders mainly due to the lack of immediate and direct impact on public health. However, recently wastewater and storm water management is evolving from a simple sanitary and flood control to a whole environmental protection function. In many countries (such as, USA and EU members) operators usually require a permit from the regulatory authority in order to discharge their wastewater in the sewer systems (SSs). In this context, a very

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important aspect of the SSs management policy is to establish an early warning monitoring system to detect and eliminate an illicit intrusion [1], which can be intentional, such as unauthorized industrial effluent, or accidental spills. Ideally the most efficient monitoring network should have the number of monitoring stations equals to the number of nodes in the system. However, some practical limitations, such as budget constraints, force the manager to install only a limited number of monitoring stations. Therefore, assessing the wastewater quality in the SSs through a limited number of monitoring stations is an important engineering problem.

The design of an effective monitoring system has been addressed to various fields of water resource engineering, such as water distribution systems (WDSs), river systems, polder systems etc. Currently, after the terrorist attack on 2001, a lot of research is going on in the drinking water sector for optimal location of the monitoring stations in WDSs. Although the large number of methodologies available in this sector, there is no consensus amongst the researchers on the objectives and methodologies used [2]. The methodologies in WDSs can be broadly classified in two groups: i) methodologies with single objective ([3], [4], [5], [6] etc.) and ii) methodologies with multiple objectives ([7], [8], [9], [10], [11] etc.). The researchers have chosen different optimization parameters such as detection time, volume of contaminated water consumed, population exposed to contamination, extent of contamination, associated risk, detection likelihood, probability of failed detection, sensor response time, sensor detection redundancy. Other authors have used similar objectives to optimize operational responses, aiming at pollution flushing (e.g., [12]). GA, NSGA-II or heuristic algorithms have been adopted in solving the optimization problem by most of the researchers. A comprehensive review can be found in [2], while a comparison of 14 different methodologies presented during the WDSA 2006 symposium can be found in [11]. In the case of river systems monitoring among the used approaches there are statistical methods (e.g. [13]), direct survey (e.g. [14]), methods adopted from the WDSs (e.g. [15]) and information theory applications (e.g. [16]). A comprehensive review on the methods available for designing the monitoring networks in river system is presented by [17].

Although [18] used Information Theory to optimally locate pressure sensors in WDS, evidence of research done for finding the optimal location of monitoring stations in sewer networks is not found. The practical use suggests of placing monitoring stations early enough before the treatment process to allow mitigation steps or positioning them in order to minimize fouling ([19]).

This paper presents an original research to identify the optimal position of a limited number of monitoring stations in sewer networks based on information theory ([20]). The principle idea behind is to reduce the amount of uncertainty associated with the estimation of the variables of interest at the unmonitored locations of the network. Traditionally, the concept of uncertainty has been linked with the statistical variance. However, [21] have showed that the statistical variance is not an objective index of quality when comparing predicted values of a hydrologic model with the series of data records. They have introduced the information theory (IT) to the water resource field. The IT provides useful expressions to measure information, such as entropy, which can be denoted as the reduction of uncertainty. Entropy increases as the probability distribution of a variable approaches to the uniform distribution. In other words, theoretically maximum entropy value will be achieved when all the measurements of a variable are different from each other. In that case all the measurements have same probability which means all the information is known and therefore uncertainty is zero. Different researchers have used the concepts of IT in designing the monitoring network for different purposes. [22] has done a comprehensive review on the use of IT in water resources application.

This paper is organized as follows. It starts with a brief introduction about the IT, followed by the description of the methodology used, where data extraction procedure along with the description of a multi-objective optimization method is presented. In the application section the case-study, represented by the real sewer system Massa Lubrense, a town located near Napoli, Italy is described. Then, the design contamination scenario, generation of data and a screening procedure are shown .The result section analyzes the multi-objective optimization outcomes, the assessment of the existing monitoring network as well as two other possible configurations of monitoring stations. At the end of the result section, a sensitivity analysis respect to a parameter used in estimating the entropy is presented. Finally, some conclusions and recommendations are drawn.

1.1. Information theory

[20] has introduced the information theory to measure the information content, also known as entropy, of a variable X. The physical significance of entropy can be realized as the reduction of uncertainty. Mathematically, the entropy of a discrete random variable X, which comprise of the discrete values $x_1, x_2, ..., x_n$ with probabilities $p(x_1)$, $p(x_2), ..., p(x_n)$, where n is the number of elementary events, can be expressed as:

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

The amount of information that is available within two variables X_1, X_2 is given by the joint entropy,

$$H(X_1, X_2) = -\sum_{i=1}^{n}\sum_{j=1}^{m} p(x_{1i}, x_{2j}) \, logp(x_{1i}, x_{2j}) \tag{2}$$

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

However, a significant number of variables influence the natural processes. The relationship among the variables can be a good way to understand those processes. The concept of total correlation ([23], [24]) can be used to assess the dependencies among the N variables, which gives the amount of information shared by all those N variables at the same time, taking into account the dependencies between their partial combinations, is given by:

$$C(X_1, X_2, \ldots, X_N) = \left(\sum_{i=1}^{N} H(X_i)\right) - H(X_1, X_2, \ldots, X_N) \tag{3}$$

Although the term $H(X_1, X_2, ..., X_N)$ is difficult to compute as it requires the estimation of the joint distribution $p(x_1, x_2, ..., x_N)$, it can be solved by using the grouping property of mutual information ([25]) 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. A detailed explanation of the agglomeration procedure with an example can be found in [16]. The concept of total correlation has been widely used in the field of medicine, neurology, psychology, clustering, feature selection, genetics and recently in water resources ([16], [26], [27]).

2. Methodology

The proposed methodology is composed of two important steps: (i) Determination of the dynamic behavior of a contamination event in a sewer network. The data that are generated will be utilized in the second step; and (ii) determination of the optimal location of the monitoring stations based on an optimization model. Both steps are described below.

2.1. Data extraction through hydrodynamic and contaminant transport simulation

USEPA's Storm Water Management Model (SWMM) along with a SWMM toolkit developed by [28] has been used for the hydrodynamic and contaminant fate and transport analysis of a conservative contaminant. SWMM, a well documented and widely used public software, is a dynamic rainfall-runoff simulation model that computes runoff quantity and quality from, primarily, urban areas. It has been used in diverse sectors of water resource management. For instance, [15] have used this model to generate water quality data in introducing a methodology for the optimal placement of monitoring stations in a river system while [1] have introduced a pollution source identification methodology in the sewer system using this software. It uses the Manning's equation to calculate the depth of flow in conduits and in computing the flow within a conduit SWMM uses the conservation of mass and momentum equations. The contaminants are transported through the conduit link respecting the assumption that conduit behaves as a continuously stirred tank reactor (CSTR).

The model generated data has been quantized prior to its use in the optimization procedure. The quantization is a process of compiling a continuous set of data to a discrete set. It rounds a value x to its nearest lowest integer multiple of a namely x_q, can be expressed as:

$$x_q = a \cdot floor\left(\frac{x}{a} + \frac{1}{2}\right) \tag{4}$$

In the result section a sensitivity analysis has been done on the parameter a, for verifying whether the entropy-related quantities are sensitive to it.

2.2. Optimization model

In this study the optimal placement of the monitoring stations have been done through evaluating two objectives: (i) maximum information content attain by a group of monitoring stations (ii) minimum dependency among the monitoring stations. The first objective can be achieved by maximizing the joint entropy of the selected monitoring stations (Eq. (2), in case of N variables) while the second one can be accomplished by minimizing the total correlation, in Eq. (3), among the monitoring stations of concern. Mathematically the optimization problem can be formulated as:

$$\begin{aligned} &max\{H(X_1, X_2, \ldots, X_N)\} \\ &min\{C(X_1, X_2, \ldots, X_N)\} \end{aligned} \tag{5}$$

Subject to: $H(X_1), H(X_2), \ldots, H(X_N) > H_{min}$.

where $H(X_i)$ is the marginal entropy of the node X_i and H_{min} is the minimum acceptable entropy value (i.e, information content of a single monitoring station). In this paper the optimization problem of Eq. (5) is solved by using NSGA-II ([29]). NSGA-II is an elitist, non-dominated sorting genetic algorithm which utilizes Simulated Binary Crossover (SBN) and Polynomial Mutation as genetic operators.

3. Application

The proposed methodology is applied to a real sewer network, located in Massa Lubrense a town near Naples, Italy. First of all the hydrodynamic setup of the real network has been made in SWMM and then by using the SWMM toolkit, time series of concentration data have been extracted. After performing the quantization, the extracted data have been screened based on the marginal entropy values. The screening is done simply to reduce the enormous search space associated in the optimization procedure.

3.1. Massa Lubrense sewer system

The sewer network of Massa Lubrense is schematically shown in Fig. 1. It is a combined sewer system, covering an area of 19.71 km^2 and serving a population of 14,087 (2011). The scheme consists of 1909 circular conduits connecting 1902 junctions, 14 pumps, 14 storage units and one treatment plants. The area is divided into 12 subcatchments. The dry weather flow (DWF) distribution is also depicted in Fig. 1. Among the 1916 nodes (junctions, storage units and treatment plant) 1866 nodes receives the DWF. Among the nodes which receive the DWF, the maximum, minimum and the average values are 0.0803 l/s, 0.0006 l/s and 0.0099 l/s respectively. As the network is not a pure dendritic one the hydrodynamic behaviour make the system more complex to be analyzed. A possible set of monitoring stations could be intuitively placed at the pumping stations. However, the authors demonstrate that this alternative is not optimal from the information content point of view.

3.2. Contaminant scenarios, data generation and screening

An automated 'C' code has been developed to run the SWMM simulations for different contaminant scenarios and to extract the relevant time series of the concentration data for using those in the optimization procedure. In this study, single conservative instantaneous events are considered for the contamination scenarios. The contamination scenario is chosen as a continuous injection of a conservative pollutant at one of the 1916 nodes, one at a time, with a concentration of 1.0 g/l starting from 9 AM with 5 hours duration. Eventually, all the nodes in the system have been contaminated. Six hours SWMM simulation time has been taken for the data extraction process, with a routing time step of two seconds and a reporting time step of five minutes, used for the concentration extraction. So, the size of the extracted time series is 137952 at each one of the 1916 nodes. The peak contaminant concentration profile obtained from one of these instantaneous events (intrusion at node 1) is shown as a typical outcome profile along one sewer path in Fig. 2.

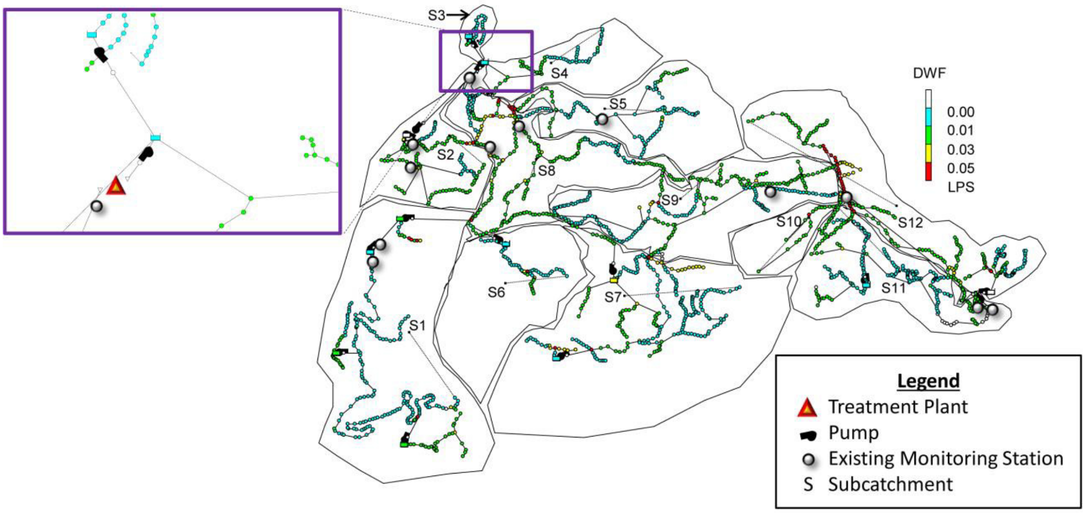

Fig. 1. Scheme of Massa Lubrense Sewer System

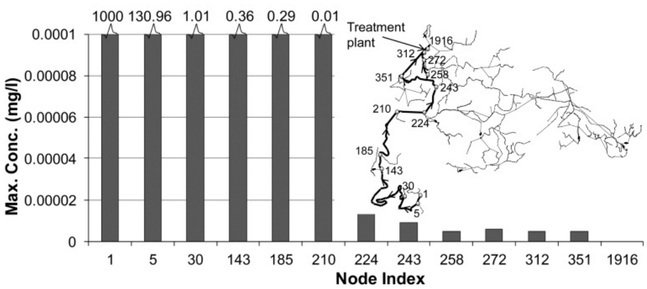

Fig. 2. Typical transport and dilution of a contaminant event along a sewer path of Massa Lubrense (Intrusion at Node 1)

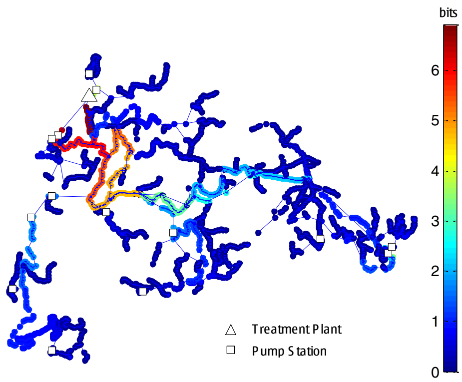

Fig. 3. Entropy map in bits (a = 0.0001 mg/l)

In Fig. 2 the horizontal axis consists of all the confluence (where branches are met) nodes in the considered path (with the exception of two entry nodes to treatment plant at 312 and 1916), while the vertical axis represents the maximum concentration detected at those nodes during the entire simulation period. Although conservative pollutants are considered in this study the dilution effect is clearly evident as the contaminant travel towards the downstream of the network (node 1916 in Fig. 2). It is worth mentioning that a drastic change has been noticed at node 224 where the concentration decreases with an order of magnitude of 1000 while before that point it is almost 10. This significant reduction has happened due to the fact that a huge amount of wastewater, produced from the subcatchments 6–12, passes through the node 224 on the way to the treatment plant. Based on this observation, it is important to note that the detection threshold or quantization parameter, the parameter a in Eq. (4), can play a significant role. So, a detection threshold value less than 0.00001 mg/l would have been a practical choice. However, as the entropy calculation is extremely sensitive to the higher number of digits in a measurement, the detection threshold is kept as 0.0001 mg/l in this paper.

Based on the previously generated time-series of concentrations and after quantization, entropy of each node of the network has been calculated, as shown in Fig. 3. It can be noted that the entropy increases at points where the branches meet. If the entropy of a node is relatively high it will be regarded as an informative node. In other words, if a monitoring station is placed in that node, it will provide information that can reduce uncertainty. It is observed that 50% of the nodes have an entropy value less than 0.12 (<1.5% of the maximum value) while the maximum entropy in the network is 6.89. Therefore, based on the entropy values, two least informative quartiles (50%) have been eliminated. In this way, the constraint of the optimisation problem posed in Eq (5) is accounted for.

4. Result

4.1. Multi-objective optimization approach

The formulated multi-objective optimization procedure in Eq. (5) is solved using the Non-Dominated Sorting Genetic Algorithm, NSGA-II ([29]), for which the number of populations (P), number of generations (G) as well as the number of decision variables have to be specified. To reduce the impact of those (population and generation) GA parameters in the optimization procedure, a number of experiments have been carried out, in which three different combinations of P and G are tested, namely (P, G): (100,100), (100,200), (200,200). The experiments are carried out varying the number of monitoring stations from 7 to 14. The crossover and mutation probabilities have been fixed to 0.9 and 0.1 respectively. The final solutions for each configuration of monitoring stations are determined from three Pareto fronts considering high joint entropy and less total correlations (Fig. 4).

Fig. 4 reflects that the increment of monitoring stations provides a small increment in joint entropy but in expense of a significant amount of redundant information, especially after 12 monitoring stations. This implies that addition of new monitoring stations after 12 will not add much information content which is also shown in Fig. 5, where the scores of two objectives are drawn against the number of monitoring stations in case of most informative solution (solution having maximum joint entropy) in the Pareto front.

4.2. Comparison with existing monitoring stations

In the Massa Lubrense network there are currently 12 monitoring stations installed. It must be noted that they have been temporarily placed for the testing purpose of an ongoing project and their location is decided on the basis of consideration on the availability of electrical power supply in nodes as well as of the needed GSM coverage for transmitting the recorded data. The performance of this set of placement has been evaluated from the perspective of information theory, obtaining a value of joint entropy = 12.81 bits and a value of total correlation = 12.12 bits. This performance is compared with the outcomes from the multi-objective optimization procedure where 12 monitoring stations are considered (Fig. 6). It is evident that the existing set of monitoring stations is only a sub-optimal solution and there exist better solutions. The placement of the existing monitoring stations along with the proposed optimal solution is presented in Fig. 7.

4.3. Comparison with monitoring stations before and after pump stations

To date, the authors have found no evidence of mathematical models or methodology for optimal location of monitoring stations in a sewer network. The current practice is to place them in pumping stations, wet wells and at the key facilities, but no guidance or explanatory information is available on the optimal selection of these locations ([19]). There are 14 pump stations available in the Massa Lubrense network. Considering this suggestion, the placement of the monitoring stations before and after a pump station is also evaluated from an information theory perspective. From Fig. 6 it is clear that those sets again produce a sub-optimal solution. Although both sets are outperformed by the multi-objective solutions, it is interesting to note that the guided set of solution (placement at pumping stations) has performed at least better than the existing one. And also if there is no methodology or model exists it might be better to place the monitoring stations before the pumping stations. The placement of two guided sets of monitoring stations along with the most informative solution, in terms of joint entropy in the Pareto front, obtained from the multi-objective optimization is shown in Fig. 8.

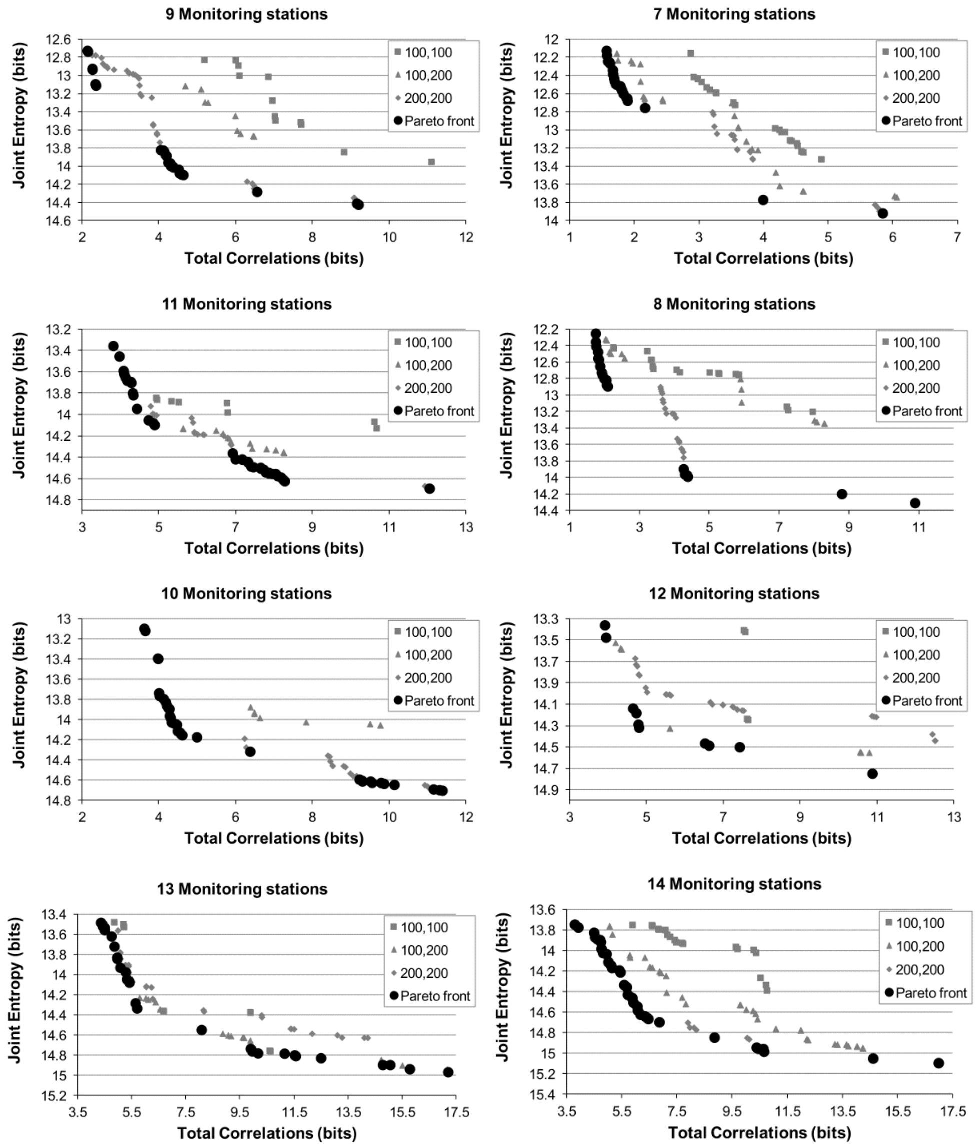

Fig. 4. Solutions from multi-objective optimization approach

4.4. Sensitivity analysis on the parameter 'a'

The parameter a may changes the outcome of an entropy-related quantity. In order to see if any significant change in the entropy has encounter due to the change in parameter a, the entropy map is redrawn for three other values of a. Fig. 9 shows that the entropy values decrease with increasing a. This is expected as the bin size reduces with the increase of a, which in turns implies less number of sums to assess the Eq. (1). However, the relative value of any point with respect to the others in the same map is remained same in all four cases. That means, although the Eq. (2) and (3) will produce different values during the optimization process, the sensor locations will remain the same. This concludes that the resultant monitoring networks obtained using the presented methodology do not change with different value of *a*.

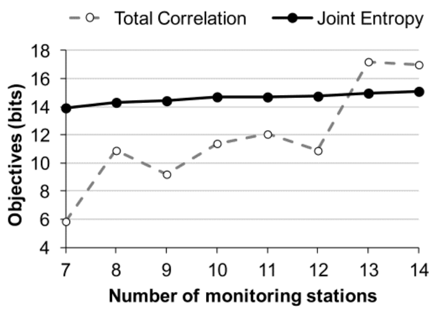

Fig. 5. Change of two objectives with the number of monitoring stations for most informative solution

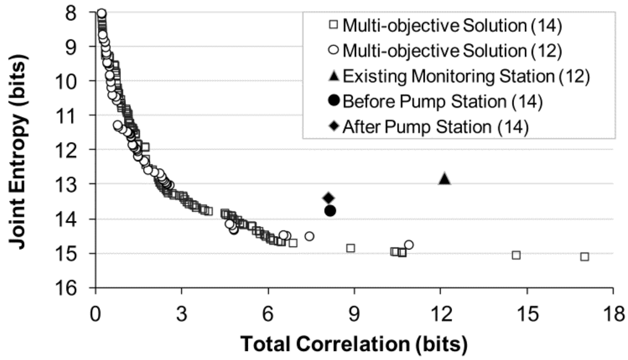

Fig. 6. Comparison of multi-objective solutions with different configuration of monitoring stations

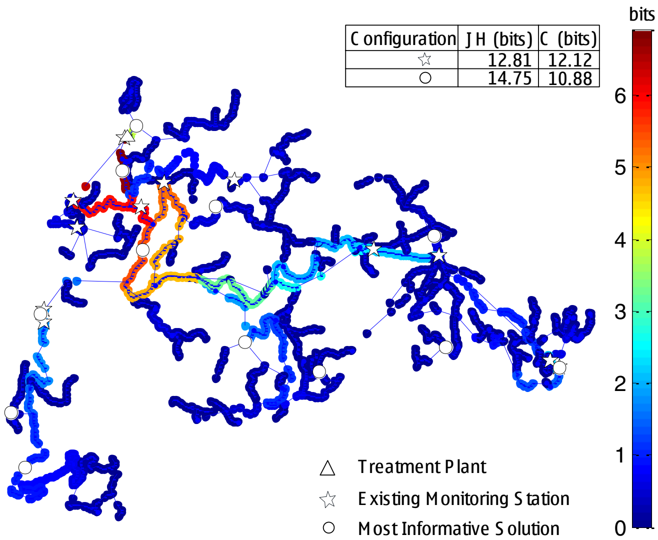

Fig. 7. Location of existing monitoring stations and corresponding optimized location

5. Conclusions

An Information theory based approach is introduced in this paper to design the optimal placement of a set of monitoring stations in a real sewer network Massa Lubrense. The first decision on selecting the potential locations of setting a monitoring station comes from the analysis of the entropy map of the network. It is observed that the entropy values change where the new branches meet. The selection of high entropy points leads to redundant information, whereas the selection of lower entropy points will produce less information. This dilemma leads to use the multi-objective optimization approach. The decision on the final network configuration from the Pareto front is, however, not a straightforward task. To do so, the decision maker has to take into consideration some other constraints, such as geographical convenience, accessibility, safety etc, to assess the relative importance of the joint entropy and total correlation.

The methodology is compared with the existing monitoring stations and two other guided configurations (before and after the pump stations). All three scenarios are sub-optimal solutions of the multi-objective optimization. However, in absence of any methodology or model to assess the optimality, it is a good idea to place the monitoring stations before the pumping stations. Moreover, it has been also noticed that although the quantization parameter *a* is not sensitive to the optimization results, an extreme or illogical value (such as 1000 mg/l or 0.0000001 mg/l) of *a* will produce a useless constant entropy map.

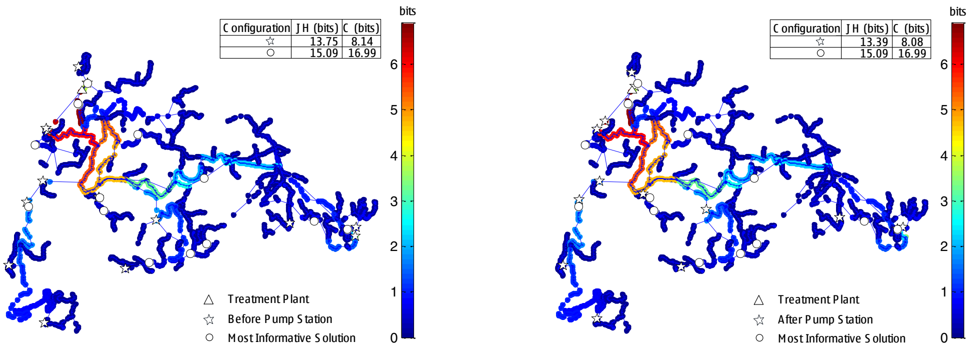

Fig. 8. Location of nodes before (left) and after (right) the pump station and corresponding optimized location

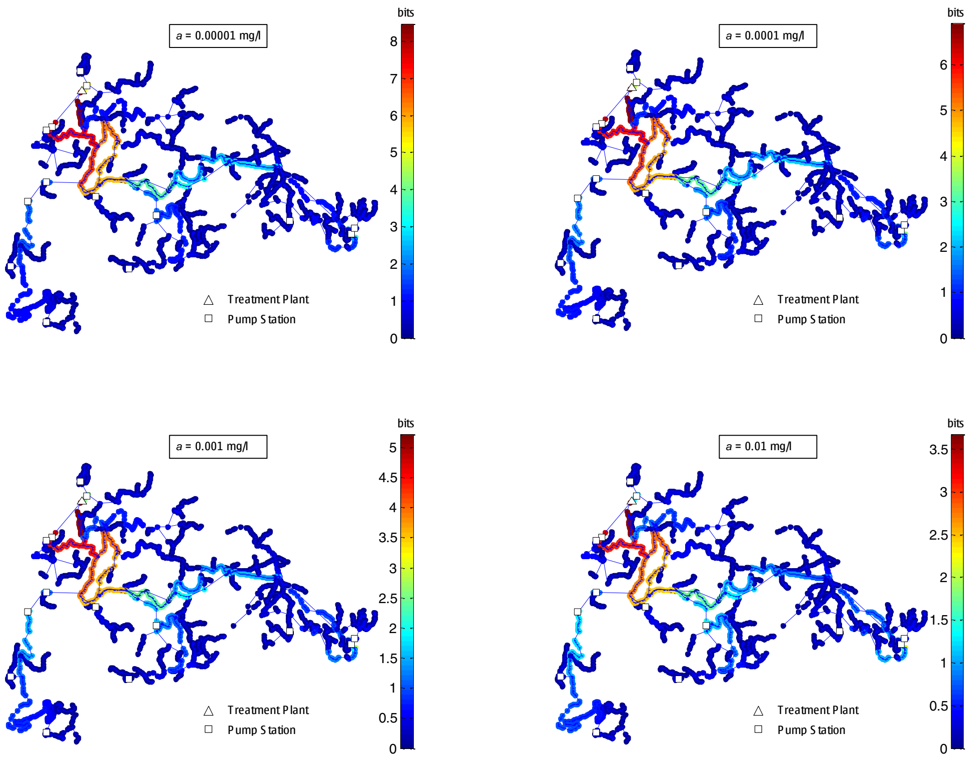

Fig. 9. Sensitivity analysis for different value of *a* (quantization parameter)

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