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Optimal placement of quality sensors in water distribution systems

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1 Introduction

Water supply infrastructures are crucial for the sustainable existence and development of modern cities [1, 2]. Water distribution systems (WDSs) are complex structures formed by many elements designed and erected to transport water of sufficient quality from water sources to consumers. The amount of the above elements, which can reach up to tens of thousands of links and junctions, their frequently wide spatial dispersion and the WDS characteristic of being very dynamic structures make the management of real WDSs a complex problem [3–5]. Moreover, although the main objective is to supply water in the quantity and quality required, other requirements are essential, namely maintaining conditions far from failure scenarios [6, 7], ability to quickly detect sources of contamination intrusion [8, 9], minimization of leaks [10–12], etc.

Most of these objectives may be achieved through suitable location of sensors along the network and, currently, an increasing number of efforts are carried out in this direction [12–14]. The identification of potential contaminant intrusion in water networks is a crucial point to fully guarantee water quality in WDSs. As a consequence, water utilities are bound to measure water quality parameters continuously, so that quality can be adequately monitored. To this end, an optimal lattice of sensors should be designed that covers strategical points of the water network [15]. It is a matter of safety and security arrangement in WDS management, and sensors cannot be randomly placed along the network. Placing sensors may seem simple at the beginning, but considering sensor station costs and the extension of the network that should

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be covered, it turns out to be a challenging problem.

The plurality of potential contaminants, the identification of the contaminant sources in the network, and the reaction time of the utilities to deal with a contamination event are also important elements to consider. This work is not intended to cover all the aspects related to network protection against potential contaminant intrusion. It will rather concentrate on proposing a solution just for the sensor placement problem, namely, optimally determining the number of sensors and their locations. And we address this optimization problem from a multi-objective perspective.

Several goals should be taken into account when placing water quality sensors. Optimal sensor placement aims to achieve early contaminant detection and seclusion of affected areas so that the public exposure to contamination be minimum. First, it is desired to identify quality problems as soon as possible, it means, to minimize the detection time. Second, irrespective of the location of the contaminant source, at least one sensor should always be able to identify a quality problem; this amounts to maximizing the coverage of protection. Additionally, the bulk of poor or bad quality water consumed should be minimized; this, specifically, involves that high population density areas have to receive special attention compared to other areas with much lower consumption rate. And, importantly, the cost, which is directly proportional to the number of installed sensors, should be kept to a minimum.

These objectives are mutually conflicting and improving one of them will probably result in a detriment for another. The rationale is clear. For example, maximizing the protection coverage in the network will require either to increase the number of sensors (it means the cost) or to probably be bound to accept larger detection times. Consequently, the final solution will result from a compromise among objectives rather than from a unique “best alternative”. Suitably solving problems of this nature requires the use of a multi-objective approach. Such an approach is able, for example, to answer marginal cost questions, such as if it is worth buying an additional sensor to get a reasonable improvement in another objective, because there is no way to know how much improvement in protection coverage and detection time will bring that additional sensor. Those are the kinds of questions that a multi-objective approach helps to answer. We claim that those are the kind of questions and answers needed to eventually find a sensor placement solution that represents a good trade-off among all the objectives involved.

In this contribution we present the necessary materials and methods. Then, we develop contaminations scenarios and evaluate the considered objectives based on the so-called contamination matrix concept. Next, we develop a multi-objective solution using a well-known multi-objective optimization algorithm [16]. A use case corresponding to a medium-size water distribution network is presented together with the obtained results and a thorough discussion.

2 Contamination scenarios and evaluation of objectives

WDSs are vulnerable against various sources of accidental and intentional contaminations. The US EPA [17] considers three protocol steps: (i) detection of contaminant presence, (ii) source identification and (iii) consequence management. To develop suitable Early Warning Systems (EWSs) for alerting the consumers and isolating contaminated areas, optimal location of measurement devices is paramount to accurately identify the source of contamination. Hart and Murray [18] describe EWSs and conclude that sensor placement is one of the critical aspects of the design of EWSs.

2.1 The objectives

The objectives we consider to solve the sensor location problem are: detection time, coverage of protection, affected population and implementation costs.

- Detection time: First we consider the time elapsed since the contamination is introduced through one node till one sensor is reached by the contaminant. The detection time is the average of those times calculated for all the nodes. For the case that no sensor detects the contaminant we use a null detection time. This circumstance will heavily penalized by other objectives in charge of evaluating the amount of contaminated water and the detection failure.

- Detection Failure: It is an index related to the amount of contamination cases happening downstream of all sensor locations, and where no detection is possible considering the current sensor placement solution.

- Contaminated water consumption: It refers to the amount of contaminated water consumed in the network before the contaminant has reached at least one of the sensor locations.

- Implementation costs: It is the cost of the solution expressed as a function of the number of sensors to be installed in the network multiplied by an estimated global cost per sensor.

2.2 The contamination matrix

The first step for solving a sensor placement problem is the generation of a contamination matrix. This matrix (of size number of nodes times number of nodes) stores, for every single contamination alternative in a given node, how long it takes to reach each of the other network nodes. Once all the contamination alternatives have been calculated, the search of Pareto dominant solution can be started.

3 Algorithm and software for calculations

Many approaches may be used to find the Pareto front in a multi-objective optimization problem. Here, we use Agent Swarm Optimization (ASO) [19]. ASO combines multi-objective evolutionary algorithms, rule-based agents and data analytics, intelligently integrating problem-domain knowledge within the optimization process and learning engineer's preferences to achieve more real results.

In this research we introduce basic rules for reducing the decision space. A “normal” agent could locate a sensor at virtually any node of the network. However, based on the experience of the authors on solving several use cases it was found that: (i) locating sensors too downstream of the network will probably guarantee a good coverage of the network but will result in big detection time; (ii) locating sensors too much upstream of the network will help to detect events faster but the coverage of the network will be compromised.

These two ideas suggest drawing boundaries that help the algorithm delimit nodes of bigger interest to host sensors. These nodes should be neither too close to the water sources nor at the very end of the piping network. One issue is the reaction, which is the time until operation actions are enforced. This is used by the rule-based agents to define a border so that nodes downstream of that border cannot host a water quality sensor. Another issue is the distance to the water sources. Another boundary should be drawn to discard too upstream nodes as eligible for sensor location. Incidentally, these boundaries help reduce the search space.

Another key aspect from the computational point of view is the size of the contamination matrix. Such a matrix cannot be fully hosted in RAM for large WDSs. An MS SQL database is used to hold that matrix in this research. Then, calculations have been suitable encoded.

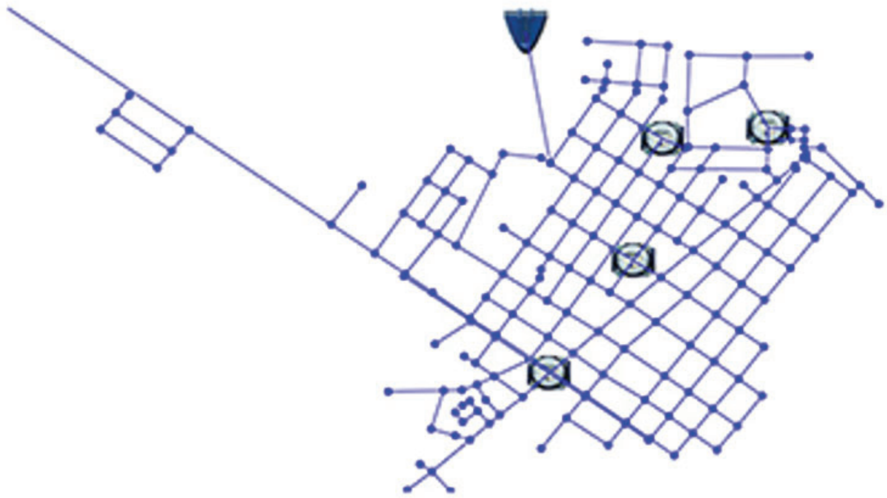

Figure 1: Network model of San José with 4 water quality sensors.

4 Case study

We consider a modified version of the water network of San José de las Lajas, a small town in Cuba, closed to Havana, with more than 24 km of pipes and one single entry point. Fig. 1 represents the network with a solution for placing 4 water quality sensors. This solution will be specially marked in red in Fig. 2-4 for a better interpretation of results. The execution of sensor placement results in the charts represented in fig. 2 to 4.

In Fig. 2 it can be seen what happens with the contaminated water that is consumed if the average detection time changes. For very low detection times we are not standing at solutions that can detect a significant number of contamination event. Note that the detection time is assumed equal to zero for those non-detected events.

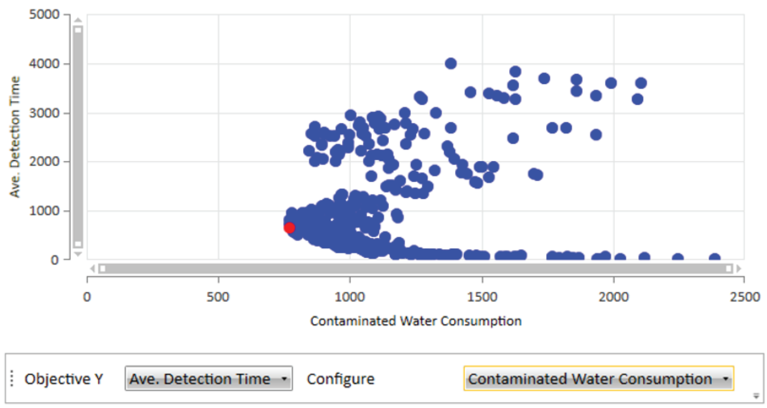

Figure 2: Average detection time vs contaminated water consumption.

Fig. 3 relates the amount of detection failure with the contaminant detection time. Using solutions with very high detection time means that sensors will be located at nodes very downstream in the network. In these cases, it takes a little longer to detect a contaminant (as average considering all possible contamination) but the detection failure is much lower. Again, from fig. 3 it can be seen that for higher values of detection time, the detection failure is relative lower.

Fig. 3 relates the amount of detection failure with the contaminant detection time. Using solutions with very high detection time means that sensors will be located at nodes very downstream in the network. In these cases, it takes a little longer to detect a contaminant (as average considering all possible contamination) but the detection failure is much lower. Again, from fig. 3 it can be seen that for higher values of detection time, the detection failure is relative lower.

Fig. 4, on the other hand, shows that the average volume consumed of contaminated water can be increased because of two main reasons: either we are standing at solutions with higher detection failure in average (sensors located too close to the sources that cannot detect contamination downstream) or we are standing at solutions where sensors are located at nodes in very downstream positions, which requires longer in average to receive the contamination effects. The relation between detection time and detection failure was previously mentioned and can be seen in Fig. 3.

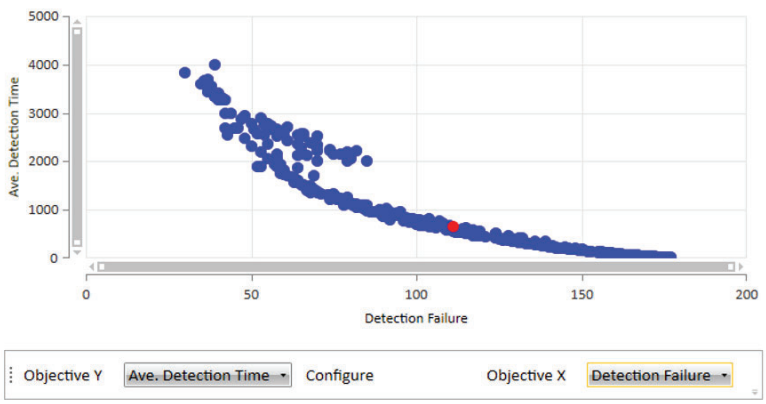

Figure 3: Average detection time vs detection failure.

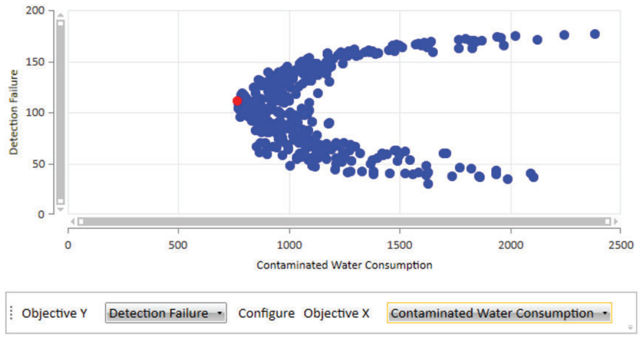

Figure 4: Average detection failure vs average contaminated water consumed.

5 Conclusions

Two important questions have to be answered in order to properly protect a water network against accidental or provoked contamination events and water quality problems: how many sensors are needed and where to place them. Answering these questions requires a decision about the criteria and requirements to be considered for achieving a good solution combined with a multi-objective approach for solving the problem. The final solution should be based on a trade-off among the objectives involved and the tolerance to "fail" that we could have in each of them. An improvement in all the objectives analyzed can be done by adding new sensors but this, of course, has the consequence of increasing the costs which can be a constraint for the implementation of the solution.

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