Optimal positioning of water quality sensors in water distribution networks: comparison of numerical and experimental results

Stefania Piazza[1], Mariacrocetta Sambito[2], Roberto Feo[3], Gabriele Freni[4], Valeria Puleo[5]
[1,2,3,4] School of Engineering and Architecture, University of Enna "Kore", Cittadella Universitaria, 94100 Enna, Italy.
[5] Department of Civil, Environmental, Aeronautic and Chemical Engineering, University of Palermo, Viale delle Scienze, Ed. 8, 90100 Palermo, Italy.
[2] *mariacrocetta.sambito@unikore.it; Tel.: +39-0935-536439*

ABSTRACT

In the water distribution networks, a deliberate or accidental contamination causes loss of water quality; the implementation of a real-time sensor network is essential to promptly detect the event of contamination. To achieve the optimum positioning of the probes, to reduce the cost of the instrumentation and maintenance, and obtaining, at the same time, a reliable monitoring of the system, optimization techniques are widely applied.
In the present study, a numerical optimisation approach was compared with the results of an experimental campaign. The optimization problem is formulated in accordance with literature state-of-the-art, using the genetic algorithm NSGA-II coupled with a hydraulic simulator. The results were tested and verified using a looped laboratory distribution network, equipped with a real-time monitoring water quality system, which allows to run contamination experiments in a controlled environment.

Keywords: genetic algorithm; optimal positioning of sensors; water distribution networks.

1 BACKGROUND

In recent years, the problem of water quality monitoring within the water distribution network (WDN) has been the subject of numerous studies by the scientific community, because the drinking water, inside the water supply system, could be altered as a result of accidental pollutants introduction or deliberate release of contaminants ([1], [2] among others). To better identify the occurrence of the contamination the optimal position of the probes in order to minimize the equipment costs and maximizing the detection efficiency is the fundamental importance [3]. The choice of a fixed or mobile monitoring system, affects differently on the effectiveness of measurements, since it has been notice that the use of implemented sensors inside the water supply, helps to monitor water in continue than a sampling mode [4]. Over time, many authors have ventured in the resolution of the optimization problem, proposing several methods with widely variable efficiencies [5-8]. From the first studies, several authors started to propose some of the simplistic hypotheses that are used to make the problem computationally feasible. Among others, Ostfeld et al. (2005) [1] took into account the randomness of the polluting injected flow, the randomness in consumer demands, the variability of sensor accuracy and response time [9]. In the work carried out by Grayman et al. (2006) [10], a simulation exercise was described, in which the "red team" simulates the contamination of a water distribution system and the "blue team" defends the system, by installing probes to detect the presence of the contaminant. This exercise has been useful to demonstrate the effectiveness of monitoring systems during the event of contamination [10]. Guan et al. (2006) have been involved in identifying the position of the sensors in order to determine the release history and the location of the contamination source. To do this, the authors have used the reduced gradient method (RGM) and by the use of a hydraulic simulator simulated concentrations in selected monitoring points. Afterwards the optimization model was used to estimate the release stories of contamination sources, based on the similarity between the simulated results and measured in the selected control points. To simplify the optimization mathematical model, the authors have focused only on correlation between the concentration values, not considering the topological structure of the system [11]. Antunes et al. (2016) have used the genetic algorithm NSGA-II to determine the optimum position of the sensors in the distribution networks, in order to detect the occurrence of the contamination and limit the potential adverse effects, using multiple objective functions [12]. The great majority of literature researches are based on hydraulic simulation tools, such as EPANET able to represent advective transport only and some simplified reaction kinetics. Even if such simplifications are adequate for many practical applications, the dispersive / diffusive transport simulation becomes relevant when flow velocity are low, like in urban water distribution networks during night [13]. Moreover, all the studies presented above were based on numerical and modelling analysis without any comparison with experimental data. As highlighted by Liu et al. (2016), the conventional detection methods fail to identify contamination events, they evaluated the performance of three contamination measurement methods, using data from a real contamination incident and two artificial data set, and realized as only one of the three methods used, the one in which real data were used, was able to identify the source and the magnitude of the contamination event [14]. The present study focused on two weak points of the state-of-the-art methods for the optimal positioning of water quality sensors: the use a simplified numerical transport model, not able to consider dispersion, and the absence of experimental validation. Many contamination experiments were run, using a conservative tracer, in the laboratory water distribution network of University of Enna “Kore” (Italy). Experiments were run with variable water demands at nodes and maintaining low flows in the network pipes. Results were then compared with numerical optimization approaches, based on NSGA-II and EPANET model, in its original version and in a modified one with the implementation of dispersion equations.

2 METHODS

The laboratory network is a closed water supply distribution network, made up of 3 loops, 10 nodes and 11 pipes of DN 63 mm, thickness 5.8 mm and about 45 m long, arranged in almost horizontal concentric circles with curves having radius 2.0 m and supplied by four tanks of the 8 m^3 capacity.

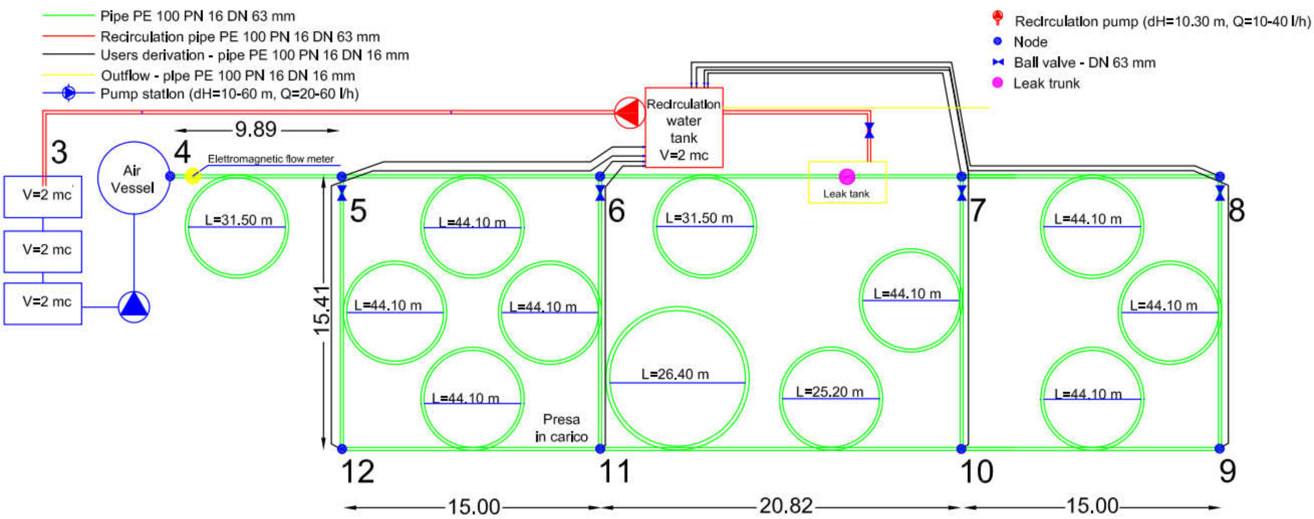

Figure 1. Layout of the water distribution network.

The supply tanks are connected to a group of four pumps and then to an air vessel in order to stabilize pressure. The pumping system behaves like a constant load tank, keeping the pressure constant and equal to a pre-set value, between 1 and 6 bar, with a tolerance of 0.05 bar, varying the speed of the pumps.

System flows in pipes are monitored by 4 electromagnetic flow meters installed in some sections. Pressure cells and multi-jets water meters are present in each node. Additionally, WiFi real time remote controlled conductivity probes (Figure 2) were positioned at each node and connected with all the monitoring appliances to a central computer also able to regulate flows supplied to the users by means of remotely controlled valves. Further details about the laboratory network can be found in *De Marchis et al.* [15].

Figure 2. Overview of the water distribution network and placement of conductivity sensors.

Initially, the optimization problem was solved by using the genetic algorithm NSGA-II (implemented within Matlab) and the EPANET model in its standard version. Considering that the adopted network has 10 nodes, a set of three sensors was considered for the optimisation. In the study, a conservative soluble tracer was adopted in order to reduce the complexity of the following experimental campaign. Considering that the position, the magnitude and the duration of contamination can be uncertain, each individual in the GA is given by a set of 200 simulations in which contamination parameters are randomly setup (contaminant mass, contamination duration and contamination node). User demands in all nodes were fixed and equal to 2.5 l/min. Inlet head was fixed as well to 3.5 bar.

Three objective functions were used:

- F_1: Detection likelihood, i.e. the probability of a sensor configuration to detect the contamination;
- F_2: Detection time, i.e. the average time passed between contamination and detection in the 200 simulations constituting each individual;
- F_3: Detection redundancy, i.e. the probability that the contamination is detected by two sensors within 20 minutes

The objective functions were slightly adapted from those presented in *Preis et al.* [2] in order to comply with the smaller dimension of the analysed network. The optimization problem was run with 200 generations, each made by 50 individuals, mutation and cross-over probability are equally set to 20%. The network numerical model was calibrated against experimental hydraulic data (pressures and flows) only and EPANET water quality parameter were set up at default values in the conservative form (no reactions).

Although, EPANET can solve advective transport, dispersive and diffusive transport is not implemented. Some recent literature [16-17] demonstrated that such processes are relevant if flow velocity is low and flow regime oscillates between laminar and turbulent, as may be the case in WDN during night. Axworthy and Karney [13] proposed the implementation of diffusive/dispersive equation in EPANET. Romero-Gomez and Choi [17] proposed the implementation of two different equations to take into account the effect of flow direction on dispersion. This last approach was used in the study, as it is able to highlight the difference between mass flows, backward and forward in a specific position, resulting from the different dispersion velocities leading to the transport of the solute (*eq. 1*).

$$\frac{\partial C}{\partial t} = \frac{1}{\Delta x}\left(\phi_b - \phi_f\right) - u_m \frac{\partial C}{\partial x} \tag{1}$$

in which

$$\phi_b = -E_b \left.\frac{\partial C}{\partial x}\right|_b \qquad and \qquad \phi_f = -E_f \left.\frac{\partial C}{\partial x}\right|_f \tag{2}$$

where E_b *and* E_f are the dispersion parameters backward and forward with the respect to the flow direction and u_m is the flow average velocity.

In order to calibrate the upgraded EPANET model, which consider the dispersion, 200 contamination experiments were carried out on the laboratory network. Hydraulic conditions were maintained constant in all the experiments and contamination was randomly performed, using sodium chloride, and changing contaminant mass (between 10 and 500 grams), contamination duration (between 5 min and 30 min) and contamination node. The contamination was performed by means of a 100 lt tank and an injection pump connected to any of the network node randomly picked (Figure 3). Once the EPANET model was calibrated, the two optimisation exercises were performed in Matlab using Matlab – EPANET toolkit and results were compared with the experiments.

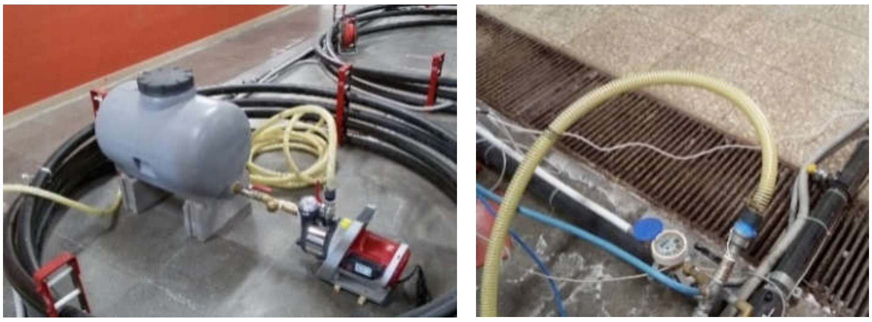

Figure 3. Installation of the pump-reservoir system (left) and connection to node (right).

3 RESULTS AND DISCUSSION

Preliminarily, a direct comparison was made between the results of the two models (EPANET with and without the dispersion equations) and the experimental data. In order to explain the impact of diffusion and dispersion processes, a single experiment was compared and solute concentrations in different nodes were reported in Figure 4. In the presented experiment, contamination was performed in node 6 with duration of 12 minutes and mass equal to 370 grams (leading to a constant concentration of 3700 mg/l).

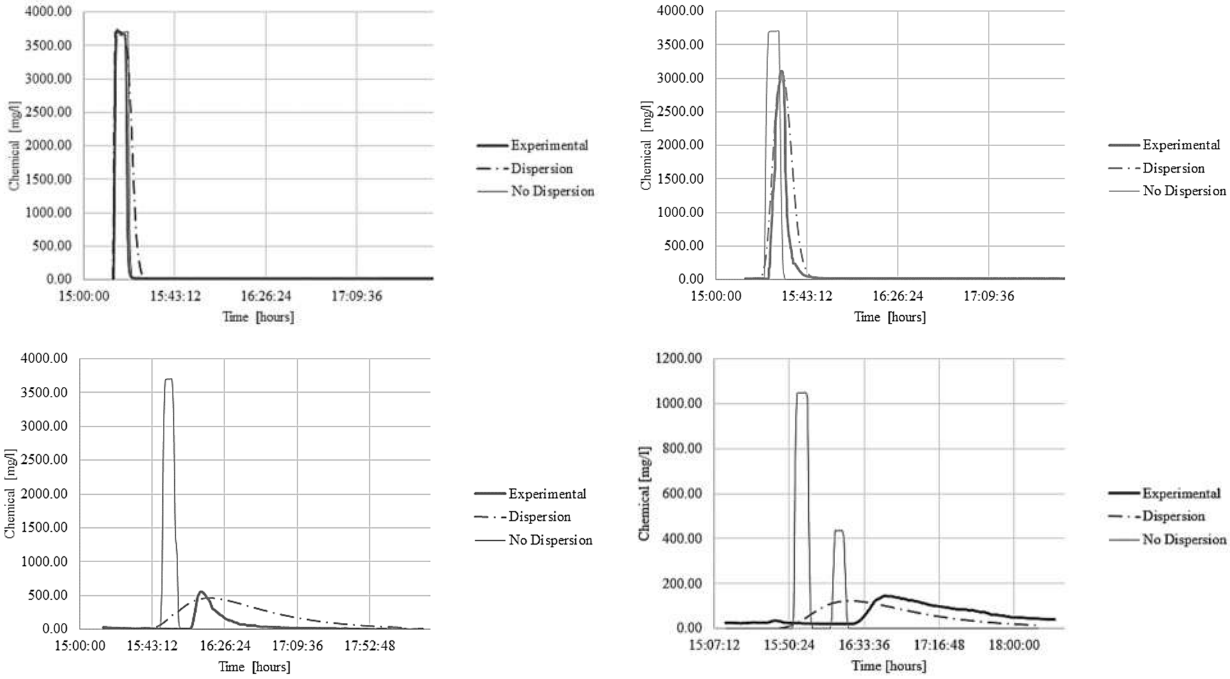

Figure 4. Comparison of experimental data, simulated data in EPANET with or without dispersion: contamination in node 6 (top left), nodes 7 (top right), 8 (bottom left) and 10 (bottom right).

The comparison of the models results clearly shows the limitation of the simple advective approach:

- Maximum concentration remains as high as in the contamination node in the nodes nearby and lowers only in the nodes far from the contamination;
- The advective model (no dispersion) shows a double peak in node 9 that is due to two different paths (path 6-7-8-9-10 and path 6-7-10) taking the contaminant from the source to the node; the experimental data and the dispersive model do not show such phenomenon due to the impact of dispersion;
- Dispersion effect is clear in the experimental data as demonstrated by the typical bell shaped graphs and dispersion seems to be more relevant backward then forward in the direction of the flow;
- The dispersive model represents better the real phenomena especially with regards to the reduction of maximum concentration at nodes;
- Still some issues may be found in dispersive/diffusive approach with respect to travel time that is underestimated in both modelling approaches and in the correspondence of the pollutograph shape in nodes that are far from the contamination origin.

By the analysis of the modelling responses, a reduced detectability of contamination should be expected taking dispersion into account and lower redundancy, due to the fact that concentrations drop rapidly in the system when moving from the contamination node to the others.

The optimisation problem using advective model provides two possible configurations for the sensors positioning, presented in Table 1 shows the characteristics and performance of the optimal configurations. A single configuration (based on sensors in nodes 6, 7 and 10) is able to maximise two objective functions (F_1 and F_2). To maximise function F_3, node 8 should be included in the monitoring campaign. With the use of three sensors in the optimal positions, 92% of the contamination episodes may be averagely detected (maximum value of function F_1) and 56% may be detected by at least 2 sensors within 20 minutes (maximum value of function F_3). Average detection time is optimally equal to more than 10 minutes. Figure 5 shows the Pareto fronts obtained for the three objective functions.

Table 1 Numerical analysis: Results of Optimization Problem.

Advection					Dispersion				
Objective Functions	**Optim. Values**	**Sensor node index**			**Objective Functions**	**Optim. Values**	**Sensor node index**		
Detection likelihood (F_1)	0.92	6	7	10	Detection likelihood (F_1)	0.866	6	8	11
Detection time (F_2)	633.40	6	7	10	Detection time (F_2)	673.00	6	7	9
Redundancy (F_3)	0.56	6	7	8	Redundancy (F_3)	0.51	6	9	12

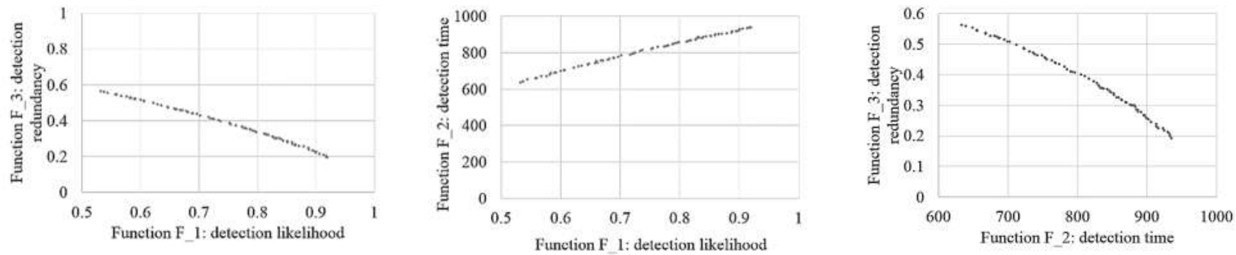

Figure 5. Pareto Front including only advection respectively F_1-F_3 (left), F_1-F_2 (center), F_2-F_3 (right).

The optimal solutions considering dispersion differ from the simple advective case both considering the location of optimal sensors and objective function values (Table 1). Each objective function is optimised by a different sensor configuration and only node 6 is present in all of them. Generally, the optimal configurations do not privilege central nodes of the system (like in the advective case) probably because concentrations decrease rapidly moving from the contamination node to the others, requiring the sensors to be widely distributed to increase detection likelihood. Pareto fronts are presented in Figure 6. The maximum detection likelihood (F_1) is provided by a configuration containing one external node and two internal ones (Figure 7). The nodes are not contiguous and this is probably related with the sharp attenuation of concentrations moving from the contamination node, requiring the sensors to be more distributed in the network. The detection time (F_2) does not change significantly in the two optimisation exercises and the two optimal configurations are superimposed with the exception of one node. Also, the optimisation of redundancy function (F_3) shows different results in the two exercises: including dispersion, the nodes providing the best result are widely distributed in the network showing the importance of contaminant attenuation in its detection.

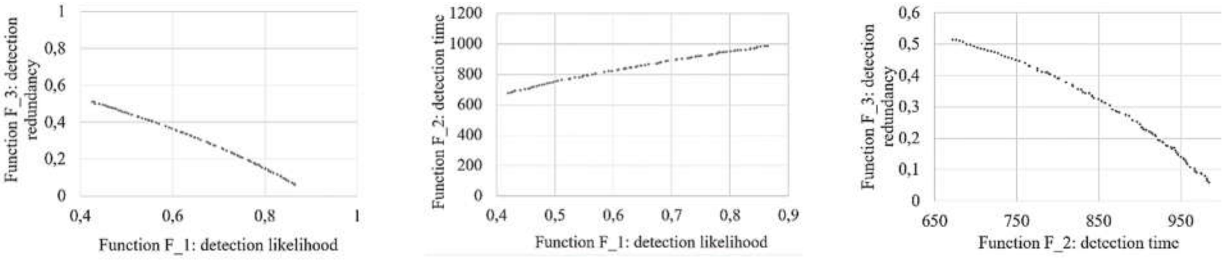

Figure 6. Pareto Front including dispersion respectively F_1-F_3 (left), F_1-F_2 (center), F_2-F_3 (right).

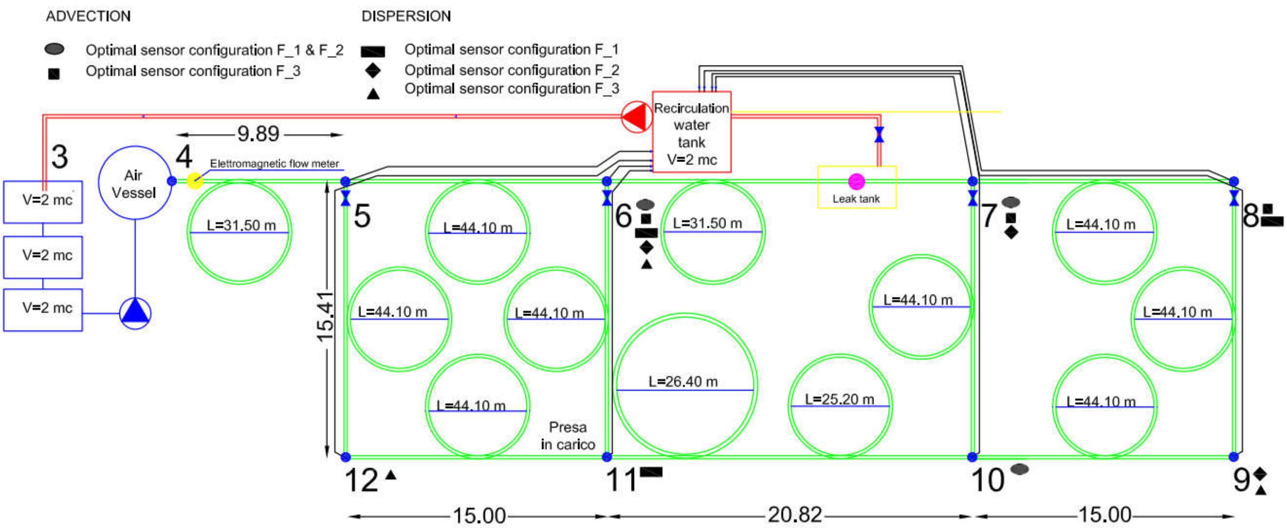

Figure 7. Optimal positioning of sensors for the UNIKORE Laboratory Network.

4 CONCLUSIONS

The results show a very strong dependency of water quality sensors optimal positioning to dispersion of a conservative contaminant. It is observed that the Detection Likelihood (F_1) and Redundancy (F_3) objective functions show smaller values if compared to the advective case. This is mainly due to the attenuation of the contaminant concentration when dispersion is considered. Moreover, the objective function Detection Time (F_2) is anticipated with respect to the experimental data, while remaining unaltered by comparing the obtained results considering advection only and advection - dispersion.

This is also evident in the configuration obtained for the sensors positioning as those maximizing the function F_1 and minimizing the function F_3 are positioned in the central area of the network, while those that maximize the function F_3 include external nodes.

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