Optimal Pressure Sensor Placement for Leak Localisation Using a Relaxed Isolation Index: Application to the Barcelona Water Network [★]

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Abstract: Water distribution networks are large complex systems that are affected by leaks, which often entail high costs and may severely jeopardize the overall water distribution performance. Successful leak localisation is paramount in order to minimize the impact of these leaks when occurring. Sensor placement is a key issue in the leak localisation process, since the overall performance and success of the leak isolation method highly depends on the choice of the sensors gathering data from the network. Common problems when leak isolating in large scale highly-gridded real water distribution networks include leak mislabelling and large isolation areas obtention due to similarity of the measurements, which may be caused by topological issues and led to incomplete coverage of the whole network. The sensor placement strategy may minimize these undesired effects by setting the sensor placement optimisation problem with the appropriate assumptions e.g. geographically cluster alike leak behaviors, taking into account real aspects of the practical application such as the acceptable isolation distance. Here, a sensor placement methodology considering these assets and a general sensor distribution assessment method for leak diagnosis in water distribution systems is presented for a real District Metered Area (DMA) located within the Barcelona water distribution network.

Keywords: Sensor placement, fault detection and isolation, leak localisation, correlation coefficient, water distribution networks.

1. INTRODUCTION

An issue of great concern in water drinking networks is the existence of leaks at the distribution stage, highly related with water resource savings and management costs. Classic leakage management involves passive approaches, in which actions are taken after the leak is produced and noticeable, e.g. using acoustic instruments to locate non-visible leaks (Khulief et al., 2012), which are often unpractical in large-scale water networks. Alternatively, permanent leak control systems may be considered in District Metered Areas (DMAs) where some flows and pressure measurements are provided (Lambert et al., 2003), by monitoring network flows at night time, when the consumer demand decreases and hence the leak flow rate over the DMA measured flow increases. This is the approach used by practitioners, which also estimate the corresponding leakage flow by means of different techniques (Puust et al., 2010).

Several works in the literature address the leak location problem in DMAs. In Andrew F. Colombo and Karney (2009), a review of transient-based leak detection methods is summarized. In the seminal work Pudar and Liggett (1992), a model-based leak detection and isolation is solved by means of a least-squares estimation problem. The latter problem is, however, not easy to solve when considering the non-linear models involved. Alternatively, a method based on pressure measurements and leak sensitivity analysis is proposed in Pérez et al. (2011), where a set of residuals i.e. the difference between some pressure measurements and their estimations by the network hydraulic model, is analysed considering a certain threshold which takes into account practical factors e.g. the model uncertainty and the measurement noise. This approach shows satisfactory results under ideal conditions, but its performance degrades when considering nodal demand uncertainty and measurement noise. This technique is improved in Casillas et al. (2013), where an extended time horizon analysis is considered and a comparison of the performance under different metrics is detailed.

The performance of the leak localisation approach is highly dependent on the number of sensors considered and their allocation within the DMA. Hence, the sensor

placement strategy is a key issue to consider in the overall process. There is an important trade-off between the number of sensors and the subsequent cost which prevents the use of a high number of sensors for leak location purposes. Consequently, this number should be optimised at the sensor allocation stage in order to produce the highest possible benefit. According to these constraints, the sensors considered here are pressure sensors, but the methodology presented could also be applied to sensors of different nature (e.g. flow meters, chlorine meters) without loss of generality.

Regarding sensor placement for fault detection and isolation (FDI) purposes, several works may be found in the literature concerning this subject. Some approaches consider the study of structural matrices in order to locate sensors based on isolability criteria (Yassine et al., 2008). In Rosich et al. (2009), an optimal set of sensors for model-based FDI is sought by means of an optimisation method based on binary integer linear programming. These works are embraced in the general framework of FDI of dynamic systems. However, they are not specially suited to solve the non-explicit non-linear set of equations describing a water distribution network. Alternatively, several works treated the sensor placement problem when applied to water distribution networks, most of them addressing the water contamination monitoring (e.g. Krause et al. (2008); Aral et al. (2010)), where sensor allocation is considered in a large water distribution network in order to detect malicious introduction of contaminants. Regarding leak localisation, less contributions addressed the problem of sensor allocation. This problem is studied in Sarrate et al. (2012), where an strategy based on the leak isolability maximization is considered to optimally locate the sensors based on the water network structural model, and also in Pérez et al. (2011), where an optimal sensor placement is formulated as an integer programming problem, similarly as presented here. Also, an entropy-based approach for efficient water loss incident detection is introduced in Christodoulou et al. (2013).

Furthermore, leak localisation in real water networks involves discrimination among a high number of possible leak locations (nodes here) which tend to mislabel the right one due to the limited number of sensors available. However, in practice it is not needed to locate the leak at the exact place since final on-the-ground leak localisation techniques (e.g. ground-penetrating radar, acoustic listening devices (Farley and Trow, 2003)) may locate leaks in a precise way starting from an area close to where the actual leak is occurring. Hence, this calls for a methodology of sensor placement trying to cluster similar leak behaviors geographically in order to minimize the number of installed sensors and locate the leak within a certain cluster distance precision.

Having all this into account, here a new approach for leak localisation focused on sensor allocation in DMAs is proposed, based on the leak localisation method introduced in Quevedo et al. (2011). Alternatively to Pérez et al. (2011), the approach presented here does not binarize the sensitivity matrix, hence the complete numerical precision of the latter is used, leading to better leak isolation performance as pointed out in (Quevedo et al., 2011; Casillas et al., 2013)). This approach requires the reformulation

of the optimisation problem introduced in Pérez et al. (2011), since even both approaches are formulated as an integer optimization problem, isolability conditions considered in the former do not apply here. Furthermore, the non-linear integer nature and large dimension of the resulting optimization problem calls for the use of a well-suited optimisation solver such as one based on genetic algorithms (GA). The methodology presented is evaluated in a real DMA, located in the Barcelona network.

The paper is organized as follows: the leak localisation methodology used as basis for this work is introduced in Section 2. The sensor placement methodology is presented in Section 3. The application case study, a real DMA of the water distribution network within the Barcelona area, is shown in Section 4, and the results obtained applying the methodology proposed are detailed in Section 5. Finally, in Section 6, some concluding remarks and future work are given.

2. LEAK ISOLATION PROBLEM

The leak isolation problem may be separated in two different levels, which include the sensor placement stage and the leak isolation itself, given a set of sensors. The leak localisation approach is summarised in this section since it is the basis of the sensor placement algorithm formulation proposed in this work.

The leak location methodology considered here aims to detect and isolate leaks within a DMA by means of some pressure measurements gathered from the network and their estimations obtained by a network hydraulic model. For a given DMA with N demand nodes and M pressure sensors, the leak detection methodology relies on the computation of the residuals $\mathbf{r} = [r_1 \ \ldots \ r_M]^T$, where $r_i \in \mathbf{r}$ is the difference between the pressure measurement p_i and its corresponding estimation $\hat{p}_i$ obtained from a leakless simulation using the network hydraulic model as follows

$$r_i = p_i - \hat{p}_i, \quad i = 1, \ldots, M \tag{1}$$

having one residual per each available pressure measurement within the DMA.

On the other hand, the leak isolation method relies on the study of the residual vector in (1) by means of sensitivity analysis, aiming to determine the effect of each particular leak on every available pressure sensor measurement at a certain time (Pudar and Liggett, 1992)

$$S = \begin{pmatrix} s_{11} & \cdots & s_{1N} \\ \vdots & \ddots & \vdots \\ s_{M1} & \cdots & s_{MN} \end{pmatrix} \tag{2}$$

given $M \leq N$ sensors within the network and N possible faults (leaks in nodes) with

$$s_{ij} = \frac{\hat{p}_{ij} - \hat{p}_i}{f_j}, \quad i = 1 \ldots M; j = 1 \ldots N \tag{3}$$

where $\hat{p}_i$ is the leakless scenario pressure estimation in node i and $\hat{p}_{ij}$ is the pressure estimation in node i due to leak f_j scenario occurring in node j.

To perform the sensitivity analysis, the leak scenarios are generated by numerical simulation using EPANET hydraulic solver (Rossman, 2000), obtaining the sensitivity vector in (4)

$$\mathbf{s}_j = \begin{bmatrix} s_{1j} \\ \vdots \\ s_{Mj} \end{bmatrix}, \quad j = 1, \cdots, N \tag{4}$$

Each simulated fault scenario is performed by setting a leak of magnitude f_j in the jth DMA network node, for all the N existing network nodes. Then, analysing both residual vector in (1) and sensitivity vectors in (4), leak isolation may be performed by checking which node has the highest potential to present a leakage. This analysis may be performed by using different metrics (Rokach and Maimon, 2005). Here, a method presented in (Quevedo et al., 2011; Pérez et al., 2013), based on correlation between residual and sensitivity vectors, is considered. According to the study in Casillas et al. (2013), the latter method presents the best performance for leak location, even it should be remarked that the sensor allocation method presented here could be applied with alternative leak localisation methods exploiting sensitivity analysis.

The current metric considered here for leak isolation is based on the correlation function, given by the inner product of the regressor vector in (1) and the sensitivity vector in (4), for each particular fault in node j

$$\gamma_j = \frac{\mathbf{s}_j^T \mathbf{r}}{|\mathbf{s}_j||\mathbf{r}|} \tag{5}$$

Then, the highest correlation determines the candidate leaky node k

$$\gamma_k = \max(\gamma_1, \cdots, \gamma_N). \tag{6}$$

The objective here is to develop a methodology to allocate a given number of sensors, M, within a DMA in order to obtain a sensor set maximizing leak isolability under realistic conditions (e.g. signature mislabelling in large DMAs) considering the leak isolation scheme presented in this section. This is the first stage of the twofold leak localisation problem, where leaks are isolated given a set of sensors at the second stage. The methodology to obtain this sensor set, based on the correlation-based method presented here, is introduced in the next section.

3. SENSOR PLACEMENT METHODOLOGY

3.1 Sensor Placement as an Optimisation Problem

The goal here is to place the best sensor set in order to achieve the maximum number of isolable faults (i.e. leaks) within the considered water network. The sensor distribution method is based on the system sensitivity matrix (2). As discussed in the introduction, a former methodology is presented in Pérez et al. (2011), where the residuals are binarized by a certain threshold value. In the approach presented here, the complete information of the residual is used in order to avoid data loss and hence to increase leakage discriminability (Quevedo et al., 2011). Also, the sensor localisation method uses a relaxed isolation index to better handle some real-world effects affecting water network systems, such as system

non-linearity, sensor measurements resolution and model inaccuracy in e.g. demands or network element parameters. These real-world effects cause deviation between the modelled and the actual system behavior, which may lead to mislabel the latter, and confusion between different leak scenarios (sensitivity vectors in (4)). However, if the confusion involves geographically close behaviors, this undesired effects do not impact on the final leak isolation. Hence, the optimal sensor distribution takes into account that the leak isolation distance may be relaxed and places the sensors accordingly in order to geographically cluster leaks with similar signature (4). In order to perform the sensor allocation of M sensors, let us define the binary vector

$$\mathbf{x} = (\, x_1 \, \cdots \, x_N \,) \tag{7}$$

where $x_i = 1$ if the pressure sensor in node i is available and 0 otherwise, hence $\mathbf{x}$ represents the selected sensors. Defining

$$X(\mathbf{x}) = diag(x_1, \cdots, x_N) \tag{8}$$

the corresponding sensitivity vectors can be represented as follows

$$\mathbf{s}_j(\mathbf{x}) = X(\mathbf{x})\mathbf{s}_j, \quad j = 1, \cdots, N \tag{9}$$

where $\mathbf{s}_j$ is the sensitivity matrix obtained when all the N sensors are available, i.e. $M = N$. Hence, the projection between two different predicted classes (leaks in nodes) a and b for a given subset of sensors $\mathbf{x}$ is introduced by their inner product as follows

$$\gamma_{ab}(\mathbf{x}) = \frac{\mathbf{s}_a^T X(\mathbf{x})\mathbf{s}_b}{|X(\mathbf{x})\mathbf{s}_a||X(\mathbf{x})\mathbf{s}_b|}, \quad a, b = 1, \cdots, N \tag{10}$$

where $\mathbf{s}_a, \mathbf{s}_b$ are vectors corresponding to two different fault signatures (columns) for each (class) fault in the sensitivity matrix in (2) and γ_{ab} is a measure of similarity between these two classes. From (10), the projection matrix may be stated

$$\Gamma(\mathbf{x}) = \begin{pmatrix} \gamma_{11}(\mathbf{x}) & \cdots & \gamma_{1N}(\mathbf{x}) \\ \vdots & \ddots & \vdots \\ \gamma_{N1}(\mathbf{x}) & \cdots & \gamma_{NN}(\mathbf{x}) \end{pmatrix} \tag{11}$$

Regarding the nature of its elements, the matrix derived in (11) is called cross-correlation matrix. It may be noted that the latter is symmetric, so $\Gamma = \Gamma^{\top}$.

In order to evaluate the quality of a sensor allocation setup, $\rho_{ab}(\mathbf{x})$ is defined

$$\rho_{ab}(\mathbf{x}) = \left(\gamma_{ab}(\mathbf{x}) \left(1 - \frac{d_{ab}}{d_{\max}} \right) \right)^{d_c} \\ + \left((1 - \gamma_{ab}(\mathbf{x})) \frac{d_{ab}}{d_{\max}} \right)^{d_f}, \quad a, b = 1 \ldots N \tag{12}$$

where γ_{ab} is the cross-correlation value of the node a leak signature vector with the node b leak signature vector, d_{ab} is the topological (pipe) distance between node a and node b, $d_{\max}$ is the maximum pipe distance for the whole

network and d_c and d_f are weight parameters related with the included high-correlated close leaks cluster and the excluded high-correlated far nodes for a certain leak, respectively. This particular cost function aims to obtain the best sensor set in order to isolate the maximum number of faults, grouping faults with similar signature as geographically close as possible, whilst discarding sensor sets promoting faults with similar signature in distant locations. The cost function is depicted in Fig. 1 for a particular set of threshold parameters. As also depicted in the latter, the use of this cost function aims to achieve sensor distribution obtaining high-cost/low-distance (first term) and low-cost/high-distance (second term) combinations.
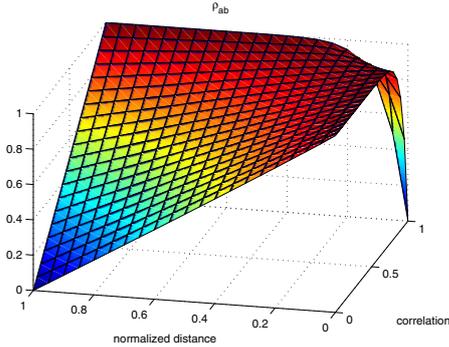

Fig. 1. cost for a given $a - b$ node pair

Considering (10), the sensor allocation may be stated as an optimisation problem, with the following cost function

$$\rho(\mathbf{x}) = 1 - \frac{1}{N^2} \sum_{a=1}^{N} \sum_{b=1}^{N} \rho_{ab}(\mathbf{x}) \qquad (13)$$

so the optimisation problem may be formulated as follows

$$\begin{aligned} \underset{\mathbf{x}}{\text{minimize}} \quad & \rho(\mathbf{x}) \\ \text{subject to} \quad & \sum_{i=1}^{N} \mathbf{x}_i = M \end{aligned} \qquad (14)$$

where $\rho(\mathbf{x})$ is to be optimised over the full N sensors set available, and M is a predefined restriction on the number of the solution sensor set members. The sensor placement optimisation problem (14) is solved using GA, which is a suitable approach for large-scale non-linear problems as the one considered here (Gallagher and Sambridge, 1994).

3.2 Isolability Assessment

In order to assess the fault isolability capabilities of a fault isolation method, for a particular set of measurement points and a given topology, a metric based on the confusion matrix is used (Fawcett, 2006). The confusion matrix is a specific table layout which allows visualisation of the performance achieved by a certain fault diagnosis layout, i.e. a certain sensor set and its corresponding sensitivity model here. Each column of this matrix represents instances in a predicted class/fault, whilst each row stands for instances in an actual class/fault. The name stems from the fact that this representation allows to check when the fault diagnosis method is confusing two

different classes, commonly by mislabelling one as another. A confusion matrix displays the number of correct and incorrect predictions made by the fault isolation model compared with the actual class occurring in the test data. Here, the confusion matrix is determined comparing the predicted classes against themselves

$$C = \begin{pmatrix} \kappa_{11} & \cdots & \kappa_{1N} \\ \vdots & \ddots & \vdots \\ \kappa_{N1} & \cdots & \kappa_{NN} \end{pmatrix} \qquad (15)$$

where $\kappa_{ab} \in [0,1]$ for $a,b = 1 \ldots N$. Matrix in (15) shows how the fault isolation model obtained by a certain sensor set is mislabelling different faults between two different nodes a and b, which could be confused according to the considered metric. Hence, the number of correctly isolated faults is given by $\zeta = \text{tr}(C)$, so the correct isolated faults are those which are just assigned to its own class and not to any other possible fault occurring in the system. The values of κ_{ab} depend on each particular isolation criterion used. Here, a criterion based on the cross-correlation (11) is used to obtain the maximum correlation for each actual fault

$$\gamma_{ab_{\max}} = \max_{b \in 1 \ldots N} \gamma_{ab}, \quad a = 1 \ldots N \qquad (16)$$

being κ_{ab} as follows,

$$\kappa_{ab} = \begin{cases} 1 & \gamma_{ab} = \gamma_{ab_{\max}} \\ 0 & \text{otherwise} \end{cases}, \quad a,b = 1 \ldots N \qquad (17)$$

Hence, the matrix in (15) is called confusion cross-correlation matrix here. In order to provide less conservative isolation results while still realistic and well suited to the optimisation criterion stated in (12), the isolation condition in (17) may be relaxed by a certain fault isolation cluster distance d_{cluster} as follows

$$\kappa_{ab} = \begin{cases} 1 & d_{ab_{\max}} < d_{\text{cluster}} \\ 0 & \text{otherwise} \end{cases}, \quad a,b = 1 \ldots N \qquad (18)$$

where $d_{ab_{\max}}$ is the distance between the node with higher correlation $\gamma_{ab_{\max}}$ and the actual faulty node a, and d_{cluster} is a given parameter corresponding to the maximum allowed distance between the actual faulty node a and the predicted faulty node in order to determine the predicted fault is well isolated.

On the other hand, the best isolation rate (ζ_{best}) for a given d_{cluster} is obtained when sensors in all nodes are available i.e. when $M = N$, which states a topological limit $0 \leq \zeta_{opt} \leq \zeta_{best} \leq N$, where ζ_{opt} is the isolation index obtained with the corresponding optimal sensor placement, for a given d_{cluster}.

4. CASE STUDY: BARCELONA DRINKING WATER NETWORK

Here, a DMA located in the Barcelona area is used as a case study. In order to simulate the DMA isolated from the water transport network, the boundary conditions (i.e. pressure and flow measurements from the network) are

fixed. Generally, pressure is fixed using a reservoir and the overall demand is obtained as the sum of the inflow distributed through the DMA using a demand pattern model. The total inflow is distributed using a constant co-efficient (base demand) in each consumption node. Hence, all the consumptions are assumed to share the same profile, whilst the billing information is used to determine the base demand of each particular consumption. A good estimation of the demand model is paramount for the real case application.

The DMA considered here (Fig. 2) is called *Canyars* and is located at the pressure level 80 within the Barcelona water transport network. This DMA has 694 nodes and 719 links, and delivers water to the end consumers by means of a single input point.
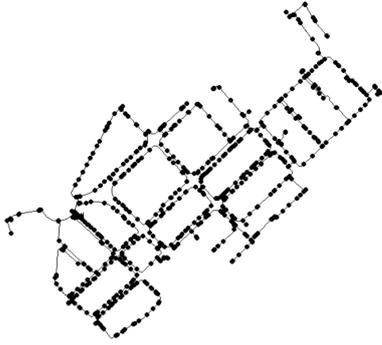

Fig. 3. Two sensors placement in Canyars DMA
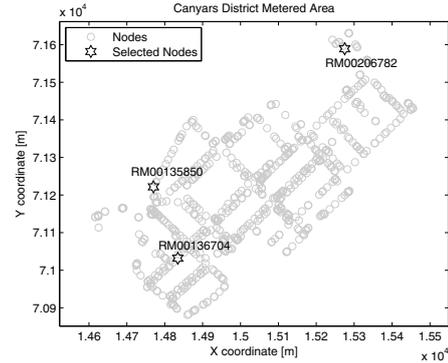
Fig. 2. Canyars DMA

Fig. 4. Three sensors placement in Canyars DMA

5. RESULTS

The sensors considered here are pressure sensors which may be installed in any node of the network. The maximum isolation distance d_{cluster}, which is a parameter given by the company managing the network, is assumed of 200 m for this particular problem (for distances below d_{cluster}, there exist alternative more precise methods to isolate the leak e.g. ground penetrating radar).

The sensor placement results obtained considering Canyars network (Fig. 2) are depicted in Figs. 3 to 5. The sensitivity matrix S is obtained for a fixed leak of 6 LPS, in an hourly sampled scenario comprised between 24/02/2014 09:00h and 25/02/2014 09:00h, so the sensitivity S is concatenated for the 24 hours available leading to a dimension of 16656×694. Also, the information in this matrix considers sensor resolution of 0.1 m to add realism to the simulated scenario. In the next steps of this work, further realistic assumptions which may impact on the performance of the method are to be considered, such sensor measurements and (demand) model uncertainty. The distance used here is the topological distance among nodes, i.e. minimum pipe distance between these elements. For this particular network, the maximum number of isolable faults considering all the sensors available (ζ_{best}) is 398 (57 % of $N = 694$ nodes conforming the network).

Isolation assessment results concerning sensor distribution for different number of sensors (from two to four) are detailed in Table 1. From the latter, it may be observed how the results obtained between three and four sensors do not improve in terms of ζ_{opt}, even a better ρ is achieved
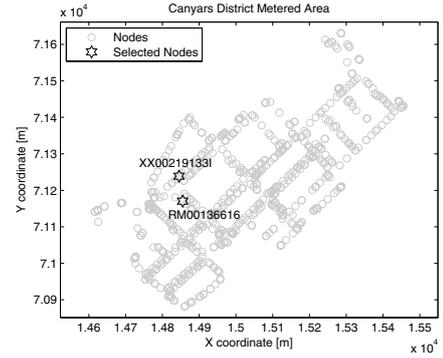
for four sensors at the optimisation stage. In this case, the benefit of installing extra sensors may obtain reduced isolation clusters, but still bigger than d_{cluster}. Hence, since the coverage of the network is high (97 % of ζ_{best}) the optimal sensor distribution is obtained for three sensors (Fig. 4) since is the one achieving best ζ_{opt} with the minimum number of sensors. In future steps of this work, the optimal number of sensors to install in the network is to be included as part of the optimisation problem.

The impact of sensors resolution is also worth to be noted. Although it does not have impact on the maximum number of isolable faults $\zeta_{\text{best}} = 398$ (hence, the maximum achievable coverage is not limited by the sensors resolution but by the topological network setup, when sufficient number of sensors are available) it does have impact on ζ_{opt} for different sensor setups (hence, for limited information gathered from the network, sensors resolution effect is noticeable). For example, considering five full-resolution sensors setup, almost complete coverage of the network is achieved ($\zeta_{\text{opt}} = 395$), against the 388 isolable faults achieved by the five limited-resolution (0.1 m) sensors setup counterpart.

6. CONCLUSIONS

In this paper, a successful sensor placement and leak localisation assessment methodologies are proposed in order to improve the performance of leak isolation in water distribution networks, which may have severe impact on maintenance cost and performance of water distribution along DMAs. Common problems arising on the leak diagnosis in large real water networks are confronted at the sensor

Table 1. Isolation assessment results, Canyars DMA ($d_{\text{cluster}} = 200$ m)

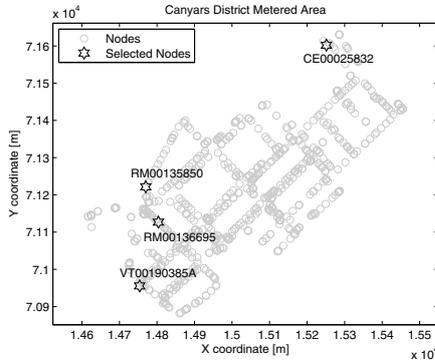| Number of sensors	2	3	4
ζ_{opt}	267	388	388
% of N	38	56	56
% of ζ_{best}	67	97	97
ρ	0.7375	0.7342	0.7321

Fig. 5. Four sensors placement in Canyars DMA

placement stage, e.g. leak discriminability and large isolation areas, when taking into account real world leak diagnosis trade-offs related with geographic isolation precision. Hence, a general method of sensor placement is proposed, taking into account these trade-offs by clustering similar leaks geographically within an acceptable isolation area from the application point of view. The proposed method achieved promising leak isolation results, evaluated by an also proposed general assessment method for leak diagnosis in water distribution systems, in a DMA situated in the Barcelona urban area. These results motivate the use of the proposed methodology in the actual and similar water networks. Further work involves the inclusion of the number of sensors to install as part of the optimisation problem, as well as the consideration of uncertainty (e.g. in sensor measurements and demand model) in the scenarios to cope with more realistic assumptions.

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