Model-based leak detection and location in water distribution networks considering an extended-horizon analysis of pressure sensitivities

Myrna V. Casillas Ponce, Luis E. Garza Castañón and Vicenç Puig Cayuela

ABSTRACT

In this paper, we propose a new approach for model-based leak detection and location in water distribution networks (WDN), which considers an extended time-horizon analysis of pressure sensitivities. Five different ways of using the leak sensitivity matrix to isolate the leaks are described and compared. The first method is based on the binarization approach. The second, third and fourth methods are based on the comparison of the measured pressure vectors with the leak sensitivity matrix using different metrics: correlation, angle between vectors and Euclidean distance, respectively. The fifth method is based on the least square optimization method. The performance of these methods is compared when applied to two academic small networks (Hanoi and Quebra) widely used in the literature. Finally, the three methods with better performance are applied to a district metering area of the Barcelona WDN using real data.

Key words | leak detection, leak isolation, pressure measurements, sensitivity analysis, water leaks, water networks

INTRODUCTION

Water leaks in water distribution networks (WDN) can cause significant economic losses in fluid transportation and an increase in reparation costs that ultimately generate an extra cost for the final consumer. In many WDN, losses due to leaks are estimated to account up to 30% of the total amount of extracted water. Such a burden is a very important issue in a world struggling to satisfy the water demands of a growing population.

Several works have been published on leak detection and isolation methods for WDN (Wu et al. 2011). For example, in Colombo et al. (2009), a review of transient-based leak detection methods is offered as a summary of current and past work. In Yang et al. (2008), a method has been proposed to identify leaks using blind spots based on previous leak detection that uses the analysis of acoustic and vibrations signals (Fuchs & Riehle 1991), and models of buried pipelines to predict wave velocities (Muggleton et al. 2002). More recently, Mashford et al. (2009) have developed a method to locate leaks using support vector machines that analyzes data obtained by a set of pressure control sensors of a pipeline network to locate and calculate the size of the leak.

Another set of methods is based on the inverse transient analysis (Covas & Ramos 2001; Kepler et al. 2011). The main idea of this methodology is to analyze the pressure data collected during the occurrence of transitory events by means of minimization of the difference between the observed and the calculated parameters. In Ferrante & Brunone (2003a, b), it is shown that unsteady-state tests can be used in pipe diagnosis and leak detection. The transient test-based methodologies exploit the equations for transient flow in pressurized pipes in frequency domain and then information about pressure waves is taken into account as well.

Model-based leak detection and isolation techniques have also been studied starting with the seminal paper of Pudar & Ligget (1992) which formulates the leak detection and location problem as a least-squares estimation problem. However, the
parameter estimation of water network models is not an easy task (Savic et al. 2009). The difficulty lies in the non-linear nature of water network models and the few measurements usually available with respect to the large number of parameters to be estimated that leads to an underdetermined problem. Alternatively, in Pérez et al. (2011), a model-based method that relies on pressure measurements and leak sensitivity analysis is proposed. This methodology consists of analyzing the residuals (difference between the measurements and their estimation using the hydraulic network model) on-line regarding a given threshold that takes into account the modeling uncertainty and the noise. When some of the residuals violate their threshold, the residuals are compared against the leak sensitivity matrix in order to discover which of the possible leaks is present. Although this approach has good efficiency under ideal conditions, its performance decreases due to the nodal demand uncertainty and noise in the measurements. This methodology has been improved in Casillas et al. (2012) where an analysis along a time horizon has been taken into account and a comparison of several leak isolation methods is offered. In a case where the flow measurements are available, leaks could be detected more easily since it is possible to establish simple mass balance in the pipes. See for example the work of Ragot & Maquin (2006), where a methodology to isolate leaks is proposed using fuzzy analysis of the residuals. This method finds the residuals between the measurements with and without leaks. However, although the use of flow measurements is viable in large water transport networks, this is not the case in WDN where there is a dense mesh of pipes with only flow measurements at the entrance of each district metering area (DMA). In this situation, water companies consider as a feasible solution the possibility of installing some pressure sensors inside the DMAs, because they are cheaper and easy to install and maintain.

Recently, Goulet et al. (2013) proposed a model falsification leak detection and isolation approach as well as a sensor placement for leak detection and isolation technique. The central idea is to falsify model instances (parameter sets) for which the difference between predictions and measurements are larger than the maximal plausible error. Maximal plausible errors are determined through combining modeling and measurement uncertainties. However, this work is able to find leaks of large magnitudes and needs large instrumentation in the pipes.

The model calibration of a water distribution network is an important problem related to the leak detection task because the leakages are not all real (Wu et al. 2011, Chapter 6). In Koppel & Vassiljev (2012), an optimization procedure is proposed to obtain the proportion of real and apparent leakages. There are some works devoted to the prediction and correction of models. A hydraulic state estimation technique using statistical data to estimate future demands is proposed in Preis et al. (2011). This work uses genetic algorithms to calibrate the model with a modified least-squares fit method. Model calibration using genetic algorithms is also studied in Nicolini & Patriarca (2011) and Shu & Zhang (2010). Nodal demand calibration has been studied (Cheng & He 2011) using singular value decomposition in order to identify and understand the parameters of the model. However, for a limited number of monitoring sensors, this problem is underdetermined and the parameter estimation is too complex. Herrera et al. (2010) offer a description and comparison of predictive models for forecasting water demand where models are obtained using time series data for water consumption in an urban area of a city and applying predictive regression models, machine learning algorithms and Monte Carlo simulations. In Wu et al. (2010), a method for leakage detection and hydraulic model calibration is presented. This work shows that leak detection improves with the accuracy of the hydraulic model calibration and by identifying the unknown leakages and the non-revenue water consumptions. Moreover, this research demonstrates that water utilities can exploit the latest innovations of modeling technology to manage, detect, control and reduce water leakages. Wu et al. (2011) have found that velocities and head loss needs to be increased over normal values for the pressure-based leak detection methods work. Moreover, they have found that the effect of closed valves and model errors obscures leaks.

In this paper, a new approach for model-based leak detection and location in WDN is presented that considers an extended time horizon analysis of pressure measurements and sensor leak sensitivities. This approach has been combined with five leak location methods in order to find the best one. A first method, called Sensitivity Matrix Binarization, is based on the transformation of the real-valued leak sensitivity matrix to a binary matrix, according to a threshold suggested in Pérez et al. (2011a, b). Three methods are based on the comparison of measured pressure vectors with a leak sensitivity matrix using different metrics (correlation, angle between vectors and Euclidean distance, respectively). Finally, a method based on the least-square optimization
The method proposed in Pudar & Ligget (1992) is tested. In order to find the method with the best performance, the five methodologies are tested in simulation with two academic small WDN (named Hanoi and Quebra) assuming that the pressures in all the nodes are measured. Finally, the three methods with better performance are applied to a DMA of the Barcelona WDN, named Nova Icària, considering that only few sensors are available in practice, which implies more difficulties in determining the leakage area.

This paper is organized as follows: an overview of the proposed methodology; an explanation of the leak location strategies; presentation of the networks considered in the experiments including the Barcelona WDN; the experiments and results for the academic networks; the application and results obtained with the different methodologies in the real case are the presented, followed by the conclusions drawn.

OVERVIEW OF THE PROPOSED METHODOLOGY

Introduction

The main objective of the proposed methodology is to detect and isolate leaks in a water distribution network using pressure measurements and their estimation using the hydraulic network model. A leak will be considered as a water flow loss through a defect of a network element that is being monitored. The proposed approach assumes the existence of a single and continuous leak from the appearance time. Moreover, all the leaks are assumed to be located in the nodes of the network. This is a standard assumption in model-based leak detection and location literature (see, for example, Pudar & Ligget 1992).

The leak detection is based on computing the difference (residual) between the pressure measurements $p_i(k)$ against their estimation $\hat{p}_i(k)$ by means of the simulation of the hydraulic model

$$r_i(k) = p_i(k) - \hat{p}_i(k) \quad i = 1, \ldots, n$$

where $n$ is the number of pressure sensors available in the network. These residuals are evaluated against a threshold $\tau$ that is selected to take into account the measurement noise and model uncertainty. If for a given time window a residual violates its threshold (i.e., $|r_i(k)| > \tau$), then, the location process is initiated. The leak location is based on comparing the residual vector (obtained from the difference between measured and expected pressures of each sensor) against the leak sensitivity matrix that contains the effect of each possible leak in each residual. The candidate leaks are those whose effect matches the best in a time window when compared to the observer residual vector using some metric (see the following section for more details). Once the candidate leak has been isolated, an estimation of the leak could even be provided by means of the residual leak sensitivity. Figure 1 summarizes graphically the proposed
methodology including the leak detection, location and estimation processes.

As with any model-based approach, the results of the proposed methodology rely on the quality of the model. Thus, leaks will not be detected if their effect on pressure is masked by the cumulative effect of model errors (e.g. connectivity, closed valves) and demand variations not accounted for by the model.

Unexpected demands changes due to special days/events or some test/changes in the network could induce the methodology to indicate a leak when in fact there is not (false positives). For this reason, the proposed methodology should be used in combination with the DMA monitoring methodology proposed in Quevedo et al. (2012) that analyses the night flows altogether with the supplied/billed amount of water. When a leak is detected with the methodology, then proposed leak location could be safely used to approximately locate the leak. Finally, technicians will go into the field using acoustic-based leak location equipment to precisely locate the point where the leak is and repair it.

**Leak sensitivity matrix**

As discussed above, leak location is based on the evaluation of the effect of all possible leaks in the available pressure measurement sensors using a sensitivity analysis. As a result of this analysis the sensitivity matrix (Pérez et al. 2009a) is obtained as follows:

\[
S = \begin{bmatrix}
\frac{\partial p_1}{\partial f_1} & \frac{\partial p_1}{\partial f_m} \\
\vdots & \vdots \\
\frac{\partial p_n}{\partial f_1} & \frac{\partial p_n}{\partial f_m}
\end{bmatrix}
\]

(2)

where each element \(s_{ij}\) of the sensitivity matrix \(S\) measures the effect of a leak \(f_j\) in the pressure of sensor \(p_i\) (i.e. the difference of pressure between the expected pressure and that measured when a leak of magnitude \(f\) occurs in the node \(j\)). Each element is normalized according to the leak magnitude. The sensitivity matrix \(S\) has as many rows as sensors and as many columns as considered leaks. It is extremely complex to calculate \(S\) analytically in a real network since the model is based on a huge set of implicit non-linear equations. Instead, this work proposes to generate the sensitivity matrix by simulation thanks to a hydraulic simulator (as EPANET) and using increments of pressure while maintaining constant the leakage flow. First, the computation of the sensitivity matrix needs the construction of the non-faulty operation scenario of the network in a 24 h time horizon, which allows the user to obtain the vector \(p(k)\) for the non-faulty pressure of each node of the network

\[
p(k) = \begin{bmatrix}
p_1(k) \\
\vdots \\
p_n(k)
\end{bmatrix}
\]

(3)

where \(p_i(k)\) represents the pressure of node \(i\) at time \(k\) without the presence of leak and \(n\) is the number of sensors in the network.

Then, leak scenarios are considered in simulation by introducing a leak at a time in each node of the network. The pressures of the sensors in the case of each considered leak scenario are stored in the matrix

\[
P_f(k) = \begin{bmatrix}
p_1^l(k) & \ldots & p_n^l(k) \\
\vdots & \ddots & \vdots \\
p_1^m(k) & \ldots & p_n^m(k)
\end{bmatrix}
\]

(4)

where \(p_i^l(k)\) is the pressure of the sensor \(i\) at time instant \(k\) when a leak is present at node \(j\), \(m\) is the number of nodes in the network (possible leaks) and \(n\) is the number of sensors in the network.

Finally, using vector (3) and matrix (4), the sensitivity matrix \(S\) for each time instant of the horizon considered is computed as follows:

\[
S(k) = \begin{bmatrix}
\frac{p_1^l(k) - p_1(k)}{f_1} & \ldots & \frac{p_n^l(k) - p_1(k)}{f_m} \\
\vdots & \ddots & \vdots \\
\frac{p_1^m(k) - p_n(k)}{f_1} & \ldots & \frac{p_n^m(k) - p_n(k)}{f_m}
\end{bmatrix}
\]

(5)

where each element \(s_{ij}(k)\) measures the effect of leak \(f_j\) in the pressure of sensor \(p_i\) at the instant \(k\). Thus, the
The sensitivity matrix is composed of \((n \times m)\) elements where each element is determined by computing the difference between the non-leaky and the leaky pressure obtained by simulation normalized with respect to the magnitude of the leak used to obtain the sensitivity matrix.

**LEAK LOCATION SCHEMES**

Leak location is based on analyzing the residuals (1) along the proposed time horizon, trying to find some inconsistency between the pressure measurement and their estimated value in order to establish which node is the most affected and thus has the highest probability of presenting leakage. In this paper, a comparison of five different methods to isolate leaks that use the sensitivity matrix (5) is performed. The proposed methods can be divided into ‘direct’ and ‘indirect’ methods. The direct methods can be classified as binary or non-binary. The non-binary direct methods considered are based on residual correlation, Euclidean distance and the angle of the residual vector with the leak signature vectors stored in the sensitivity matrix. On the other hand, the indirect method is based on a least-square optimization method. In all these methods, a sensitivity matrix (2) that quantifies the effect of all possible leaks in all nodes and pressure sensors in the network is needed to initiate the detection of the leak. The five approaches are described below.

**Binarized sensitivity method**

The binarized sensitivity method works as follows (see Pérez et al. 2013):

(a) The sensitivity matrices (5) are binarized according to an established threshold

\[
s_{ij}^{\text{bin}}(k) = \begin{cases} 1 & \text{if } s_{ij}(k) > \rho \\ 0 & \text{otherwise} \end{cases}
\]

where \(s_{ij}^{\text{bin}}(k)\) represents the element of the \(S^{\text{bin}}(k)\) sensitivity.

(b) The current residual vector \(r(k)\) defined in (1) is computed and binarized in a similar way than the sensitivity matrix in the previous step

\[
r_{i}^{\text{bin}}(k) = \begin{cases} 1 & \text{if } r_{i}(k) > \beta \\ 0 & \text{otherwise} \end{cases}
\]

where \(r_{i}^{\text{bin}}(k)\) are the elements of the actual residual vector \(r^{\text{bin}}(k)\).

(c) The residual vector is compared against each column of the sensitivity matrix. When the algorithm finds a match at a given time instant, i.e. \(r^{\text{bin}}(k) = s_{ij}^{\text{bin}}(k)\), then the leak \(f_{j}\) associated to the column \(j\) that matches is indicated as a candidate leak.

(d) Because the leaks are analyzed for a time horizon of 24 h, it is necessary to count the coincidences found on a previous step in order to find the leak with the maximum number of coincidences. As result of this comparison, a matrix \(\Phi\) is created in which the binary indicators of the existence or absence of the leak will be saved

\[
\phi_{jk} = \begin{cases} 1 & \text{if } r^{\text{bin}}(k) = s_{ij}^{\text{bin}}(k) \\ 0 & \text{otherwise} \end{cases} \quad j = 1, \ldots, m
\]

and where \(k\) is the time instant. To calculate the leak in the time horizon, we look for the index that appears the most through the time horizon \(L\) and this index is assigned as the leak index during the considered time. This is formulated as follows:

\[
\gamma_{j} = \sum_{k=1}^{L} \phi_{jk}(k)
\]

where \(\gamma\) is a vector that contains the number of fault indications for the possible leaks according to the row that it is occupying. Thus, if the maximum of this vector is found, then the index of the node that contains the leak in the desired time horizon is obtained by

\[
\text{leak index} = \arg \max_{j \in \{1, \ldots, m\}} \left( \gamma_{j} \right).
\]

(e) Finally, the leak magnitude can be estimated using the residual vector (1) and the sensitivity matrix column
corresponding to the candidate leak \( f_i \) identified using (10)

\[
\min_{f_i} \sum_{k=1}^{L} |r(k) - s_{-j}(k)f_i|^2
\]  

(11)

**Angle between vectors method**

The angle method is based on evaluating the angle between the current residual vector \( r(k) \) and each column of the leak sensitivity matrix as follows:

\[
a_j(k) = \arccos \left( \frac{r^T(k)s_{-j}(k)}{|r(k)||s_{-j}(k)|} \right) \quad j = 1, \ldots, m
\]

(12)

Then, the mean angle in the selected time horizon \( L \) is computed as

\[
\bar{a}_j = \frac{1}{L} \sum_{k=1}^{L} a_j(k) \quad j = 1, \ldots, m
\]

(13)

and the candidate leak proposed is the one that presents the smallest mean angle:

\[
\text{leak}_{\text{index}} = \arg \min_{j \in \{1, \ldots, m\}} (\bar{a}_j)
\]

(14)

After locating the leak, its magnitude can be estimated using the residual vector and the leak sensitivity matrix using (11).

**Correlation method**

The correlation method is based on correlating the current residual vector \( r(k) \) with each column of the leak sensitivity matrix as follows:

\[
c_{jk} = \frac{\sum_{i=1}^{n} \left( r_i(k) - \bar{r}(k) \right) \left( s_{ij}(k) - \bar{s}_j(k) \right)}{\sqrt{\sum_{i=1}^{n} \left( r_i(k) - \bar{r}(k) \right)^2} \sqrt{\sum_{i=1}^{n} \left( s_{ij}(k) - \bar{s}_j(k) \right)^2}}
\]

(15)

where \( \bar{r}(k) \) is the mean of the \( k \) residual vector and \( \bar{s}_j(k) \) represents the average along the \( j \) vector of the \( k \) sensitivity matrix.

Then, the mean correlation in the selected time horizon \( L \) is computed and the candidate leak proposed is the one with the smallest value:

\[
\hat{c}_j = \frac{1}{L} \sum_{k=1}^{L} c_j(k) \quad j = 1, \ldots, m.
\]

(16)

Then, looking at the maximum correlation along the time horizon, we can find the leaky node as follows:

\[
\text{leak}_{\text{index}} = \arg \min_{j \in \{1, \ldots, m\}} (\hat{c}_j)
\]

(17)

As in the previous method, after locating the leak, its magnitude can be estimated using the residual vector and the leak sensitivity matrix using (11).

**Euclidean distance method**

Alternatively to the previous methods, the Euclidean distance between the current residual vector \( r(k) \) and each column of the leak sensitivity matrix can be used to isolate the leaks at a given instant in time

\[
d_{ji}(k) = \sqrt{\sum_{i=1}^{n} \left( \frac{r_i(k)}{f_i} - s_{ij}(k) \right)^2} \quad j = 1, \ldots, m
\]

(18)

where \( f_i \) is the nominal leak used to compute \( s_{ij} \). Then, the distance vector for the time horizon is calculated as

\[
\bar{d}_j = \frac{1}{L} \sum_{k=1}^{L} d_{ji}(k) \quad j = 1, \ldots, m
\]

(19)

Since each element of this vector represents the Euclidean distance to every possible leak, we conclude that the candidate leak can be found determining the minimum value of that vector

\[
\text{leak}_{\text{index}} = \arg \min_{j \in \{1, \ldots, m\}} (\bar{d}_j)
\]

(20)

This method works well only when the leak has the same magnitude as the one used to compute the sensitivity.
matrix. If this is not the case, it does not provide good results.

Similar to the previous methods, after the leak is located, its magnitude can be estimated using the residual vector and the leak sensitivity matrix using (11).

Least-square optimization method

This method works in an opposite way to the other methods, i.e. it computes an inverse optimization problem in order to find an appropriate leak size that explains the pressure measurements present in every node. Then, it performs an analysis of the minimum error in order to find the node affected by a leak.

This method also uses the leak sensitivity matrix and solves the following optimization problem for each candidate leak:

\[
J_q = \min_{j} \sum_{k=1}^{L} |r(k) - s_j(k)f_j|^2 \quad j = 1, \ldots, m
\]  

(21)

Then, the leaky node is found as the one that produces the smallest index:

\[
\text{leak\_index} = \arg \min_{j=1, \ldots, m} (J_q)
\]  

(22)

As one can see, this method allows obtaining more information about the leak since it provides the leak size that fits the best for the observed pressure data. The leak that provides the smallest value in (22) is the candidate leak.

**DESCRIPTION OF THE WATER NETWORKS USED IN THE EXPERIMENTS**

To test the aforementioned methodologies, two academic networks were used. The Hanoi network (from Fujiwara & Khang 1993), and the Quebra network (provided as an example within the EPANET software). As discussed above, all the leaks are located in the nodes of the network. In simulation, this can be performed in two ways. The first way is to add an extra demand for water at a specific node and to use two patterns of water demands: one to simulate the non-leaky water demand and the other to simulate the leak. The second way is to find the corresponding emitter coefficient that provides the desired leak magnitude in the network. In Rossman (2000), it is shown that in EPANET the emitter coefficient is specified for individual leaks according to the equation

\[
EC = Q/F_p^{P_{\exp}}
\]  

(23)

where \(EC\) (in \(lps/m^{0.5}\)) is the emitter coefficient, \(Q\) is the flow rate, \(F_p\) is the fluid pressure and \(P_{\exp}\) is the pressure exponent.

In the academic networks used in this paper, the leak is simulated as an extra demand with a unitary pattern along the time horizon considered, i.e. we will take into account that the leak is single and continuous along a determinate time window. On the contrary, in the real case application of the Barcelona network, the leak is simulated using an emitter coefficient approach described previously. This allows us to consider that leaks also depend on the pressure in the node where they appear.

To compare the efficiency of each location method presented above, changes in the leak magnitude, noise in the measurements and nodal demands were simulated. A time horizon window of 24 h was considered for the simulations. Matlab® and EPANET were combined to simulate the leaks and to obtain and analyze the network data using the algorithms proposed in the paper.

**Hanoi network**

This network is presented in Figure 2. It will allow us to analyze the effectiveness of the proposed methods in a network with big flows.

The demand pattern is designed according to Fujiwara & Khang (1990). A simulation of 24 h with a sampling time of 15 min is carried out. This is because the demand is measured each 15 min. This gives a total of 97 samples.

This network has 31 demand nodes with indices from 2 to 32. A leak with a magnitude of 50 l per second is used to compute the sensitivity matrices shown in Figure 3.
Quebra network

This network is presented in Figure 4. It will allow analysis of the performance of the proposed methods using a network of greater size than the Hanoi network. Quebra is a network designed according to the method presented in the EPANET webpage.

In this network, the demand is measured with a sampling time of 1 hour. The simulation is carried out for 24 h giving a total of 25 samples (0–24 h). The following parameters used in the simulation of the network are established: The network is composed of 55 nodes and the samples are taken every hour. The sensitivity matrices are calculated with a leak magnitude of 0.01 liters per second. Figure 5 shows the values of the sensitivity matrix for node 34 at the sample instant of maximum consumption (left) and with a leak (right).

In Hanoi and Quebra academic networks, the leak magnitude used to compute the sensitivity matrix and those magnitudes for the simulated leaks are chosen according to the observed demands along the time horizon. The idea is to introduce leaks that, based on the considered, will affect the pressure in order to probe that the methodology can be applied. Later we will see what happens when we apply the methods in a real case.

Barcelona network

Finally, the proposed approach is applied to a real network simulated in EPANET that corresponds to a DMA located in Nova Icaria area in Barcelona, Spain. It is composed of 3,320 nodes, where 1,900 are demand nodes and the rest are used to simulate street or junction nodes. In our case, we propose to simulate the possible leaks for all 3,320 nodes. Using the method presented in Pérez et al. (2009b), a first optimal sensor placement of 15 sensors was considered (see Figure 6). Later, taking into account the budget restrictions of the Barcelona water company, six sensors were installed, optimally located using the same method proposed in Pérez et al. (2009b) (see Figure 7).

Once we know the localization of the sensors, we can establish the parameters to compute the sensitivity matrices. When 15 sensors are used, sensitivity matrices are evaluated with a nominal leak of 3 l s⁻¹ which corresponds to an
emitter coefficient of $EC = 0.48$ and in the case of the six sensors, we propose an $EC = 0.25$. The reason for using these values comes from the fact that in a first trial we took 15 sensors within our experimentation, trying to isolate leaks whose magnitudes were between 0.7 and $6.3 \text{l s}^{-1}$. Then, when the first part of the work was done, we decided to change the size of the nominal leak, knowing that the leak sizes to be located, according to the water company, are between 0.7 and $3 \text{l s}^{-1}$. In the same way, we noticed from the results obtained in the first part of the experimentation that when the real leak is close to the value of the nominal leak, it can be located more easily.

**APPLICATION TO THE ACADEMIC NETWORKS**

**Experiments**

In the case of the academic networks, the following experiments were developed to test the proposed methodologies:

1. Impact analysis of the leak magnitude.
2. Application of random demand noise between $\pm 2\%$ and $\pm 4\%$ of the medium demand along the time horizon.
3. A study of the effect of the measurement noise, applying Gaussian white noise of around ±2% of the pressure measurements.
4. Application of both uncertainties introduced in Steps 2 and 3.
5. Finally, both effects were tested with 200 random leaks location with and without noise whose size depends on the network, i.e., with sizes around 20 to 80 l s⁻¹ for the Hanoi network, and from 0.01 to 11 l s⁻¹ for the Quebra network.
In all the experiments performed, the proposed angle method is compared first with the least-square optimization method and then with the correlation method. In all the cases, the efficiency achieved by each method is evaluated and compared with that achieved when all the network pressures are fully accessible.

Results

The results of tests 1, 2, 3 and 4 are shown in Tables 1 and 3. It can be observed that each method delivers very good results. The results of test 5 are shown in Tables 2 and 4 where it can be observed that best method is the proposed angle between vectors.

In all the tables, the effectiveness is shown in percentage obtained according to the number of leaks detected satisfactorily divided by the number of tests realized. It is important to mention that the network structure has an important impact on the results. It means that introducing appropriate structural changes in the network, even better performance of the methods could be achieved.

Looking at the tables presented above, we are able to conclude that binarization and Euclidean distance methods are not efficient enough at locating leaks. In the case of the binarization method, this may be due to the fact that we have to establish a threshold in order to binarize the vectors and in several cases it is not possible to know the correct value. In the case of the Euclidean distance, noise factors and demand pattern changes tend to decrease the similarity between corresponding vectors and the location becomes difficult. However, we have seen that correlation, optimization and the proposed angle method can be efficient techniques in the leak location task. After analyzing the result of the tests, it can be concluded that methods based on optimization and vector angle provide excellent results.

Table 1 | Efficiency (%) in tests applied to the Hanoi network

<table>
<thead>
<tr>
<th>Leak size</th>
<th>Test of effect of 2% noise on demand and measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Binarization</td>
</tr>
<tr>
<td>50</td>
<td>51.61</td>
</tr>
<tr>
<td>10</td>
<td>38.71</td>
</tr>
<tr>
<td>20</td>
<td>38.71</td>
</tr>
<tr>
<td>30</td>
<td>38.71</td>
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<tr>
<td>40</td>
<td>51.61</td>
</tr>
<tr>
<td>60</td>
<td>58.06</td>
</tr>
<tr>
<td>70</td>
<td>58.06</td>
</tr>
<tr>
<td>80</td>
<td>61.29</td>
</tr>
<tr>
<td>Average efficiency</td>
<td>48.76</td>
</tr>
</tbody>
</table>

Table 2 | Efficiency (%) in random tests for the Hanoi network

<table>
<thead>
<tr>
<th>Test</th>
<th>Binarization method</th>
<th>Correlation method</th>
<th>Angle method</th>
<th>Distance method</th>
<th>Optimization method</th>
</tr>
</thead>
<tbody>
<tr>
<td>No noise</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>33.33</td>
<td>100</td>
</tr>
<tr>
<td>Demand noise</td>
<td>86</td>
<td>90</td>
<td>98</td>
<td>46.67</td>
<td>94</td>
</tr>
<tr>
<td>Measure noise</td>
<td>60</td>
<td>70</td>
<td>98</td>
<td>60</td>
<td>98</td>
</tr>
<tr>
<td>Noise in both</td>
<td>48</td>
<td>60</td>
<td>98</td>
<td>46.67</td>
<td>96</td>
</tr>
</tbody>
</table>
APPLICATION TO THE BARCELONA WATER NETWORK

Experimental scenarios

From the tests performed in the academic networks, we noticed that the angle, optimization and correlation methods have a better efficiency regarding the localization task when all the pressure measurements are available. In order to test the performance of the considered methods in the real case where not all pressure measurements are available, several scenarios have been proposed in this paper. In these scenarios, we test the location of: a nominal leak without noise; a non-nominal leak without noise, and a non-nominal leak with noise. In the previous scenarios nominal means that the leak has the same magnitude as the one used to compute the sensitivity matrices, while non-nominal means that the leak has a different magnitude.

This section shows the results obtained when considering only one of the leaky nodes, subject to different conditions corresponding to the scenarios described below and for the methods considered in the network. In the figures showing leak location results, the nomenclature presented in Figure 8 will be used.

Fifteen sensors case

The first scenario involves the presence of a nominal leak affecting the network. In this case, the three methods find the exact node where the leak is present. Figure 9 presents the location of a nominal leak without noise applying the angle method. In that case, the correct location of the leak

<table>
<thead>
<tr>
<th>Test</th>
<th>Binarization method</th>
<th>Correlation method</th>
<th>Angle method</th>
<th>Distance method</th>
<th>Optimization method</th>
</tr>
</thead>
<tbody>
<tr>
<td>No noise</td>
<td>98</td>
<td>100</td>
<td>100</td>
<td>26.67</td>
<td>100</td>
</tr>
<tr>
<td>Demand noise</td>
<td>98</td>
<td>100</td>
<td>100</td>
<td>33.33</td>
<td>100</td>
</tr>
<tr>
<td>Measure noise</td>
<td>72</td>
<td>94.5</td>
<td>97.5</td>
<td>40.00</td>
<td>98</td>
</tr>
<tr>
<td>Noise in both</td>
<td>71.5</td>
<td>94.5</td>
<td>98.5</td>
<td>13.33</td>
<td>98.25</td>
</tr>
</tbody>
</table>

Average efficiency

<table>
<thead>
<tr>
<th>Leak size</th>
<th>Binarization</th>
<th>Correlation</th>
<th>Angle</th>
<th>Distance</th>
<th>Optimization</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>62.96</td>
<td>88.89</td>
<td>92.59</td>
<td>98.15</td>
<td>88.89</td>
</tr>
<tr>
<td>0.03</td>
<td>46.3</td>
<td>79.63</td>
<td>81.48</td>
<td>1.85</td>
<td>85.19</td>
</tr>
<tr>
<td>0.02</td>
<td>66.67</td>
<td>94.44</td>
<td>94.44</td>
<td>46.30</td>
<td>94.44</td>
</tr>
<tr>
<td>0.08</td>
<td>79.63</td>
<td>98.15</td>
<td>98.15</td>
<td>20.37</td>
<td>98.15</td>
</tr>
<tr>
<td>0.15</td>
<td>83.33</td>
<td>96.3</td>
<td>98.15</td>
<td>16.67</td>
<td>98.15</td>
</tr>
<tr>
<td>0.2</td>
<td>85.19</td>
<td>96.3</td>
<td>98.15</td>
<td>16.67</td>
<td>98.15</td>
</tr>
</tbody>
</table>

Table 3: Efficiency (%) in tests applied to Quebra network

Table 4: Efficiency (%) in random tests for Quebra network
node is achieved, as noticed, the absence of noise and nominal leak magnitude tested, facilitate the location of the leak.

The second scenario involves the presence of a nominal leak also taking into account noise in the measurements and in the demands. In this case, the method efficiency is reduced. In Figure 10, we can see how the angle method locates the leak near to the real leak, while in Figure 11 we see that using the optimization method, the distance is slightly higher than using the angle method.

The third scenario corresponds to the case where there is a non-nominal leak present in the network and where the noise can be taken into account or not. In the experiments,
we took the example of leaks whose magnitude varies from 0.7 and 6.3 l s$^{-1}$. Figure 12 shows the behavior of the angle method when a non-nominal leak occurs, despite the presence of noise, a leak is found near the correct leak. Figure 13 shows the same experiment using the optimization method, where the distance found is higher than with the angle method. Finally, in Figure 14, we show the case of a non-nominal leak when random noise is added using the correlation method. In that case, the behavior is very similar to that obtained with the optimization method.
Six sensors case

Similar to the experiments where 15 sensors are involved, we performed the analysis for the case where six sensors are installed. Below, we detail the behavior of the methods for the same type of scenarios as the ones previously presented. When a nominal leak without noise affects the network, the three methods find the exact leak location. The behavior of the methods in the case of a non-nominal leak and taking into account the

![Figure 13](https://iwaponline.com/jh/article-pdf/16/3/649/387279/649.pdf)  
**Figure 13** | Leak location of $0.7 \text{ s}^{-1}$ magnitude leak in the case of random noise using the optimization method. The leakage node was located 142.52 m from the real leak.

![Figure 14](https://iwaponline.com/jh/article-pdf/16/3/649/387279/649.pdf)  
**Figure 14** | Non-nominal leak location using the correlation method. The leakage node is found at 151.44 m from the real leak node.
presence of random noise is shown in the following. In Figure 15, we observe that using the angle method, even when only six sensors are present within the network, the potential leak is located about only 82 m from the real leak. Figure 16 shows the behavior of the optimization method taking into account the same case. As we can see, the leak is located further than using the angle method. Finally, using the correlation method to locate the same leak, the distance obtained is farther than the one obtained with the angle method but nearer than that obtained using the optimization method as can be seen in Figure 17.
Another important case is when a leak begins during the process of simulation in a given point of the time horizon. Such a situation is shown in Figure 18 where the pressure and the demand change when a leak appears at the eighth hour. Pressure is measured in meters water column (mwc) and demand in liters per second (l s\(^{-1}\)).

As one can see, the difficulty in this case is that when the leak appears at a given instant of the time horizon, it may be

Figure 17 | Location of a non-nominal leak of 6.3 l s\(^{-1}\) magnitude in the case of random noise using the correlation method. The leakage node was located 149.72 m from the real leak.

Figure 18 | Behavior of the demand and the pressure in the case of a single leak appearing at the eighth hour in the time horizon. It shows that the pressure varies only slightly and that noise may affect the detection and location.
difficult to discriminate between measurement noise and a significant variation, i.e. the very small pressure change can lead to some confusion in the location process.

Results

In the previous section, we have seen examples of results obtained for different types of scenarios. Here, we give a brief summary of the results obtained for each experiment performed and also a result discussion is provided. Presented here are the tables that sum up the efficiencies for each experiment.

Angle method

We first present the results in the case of 15 sensors and then the results in the case of six sensors. With 15 sensors, by computing a test where every possible leak was considered (i.e. we have simulated one by one all the possible leaks in the network); we observe how many have been found at the correct location which gives us the corresponding efficiency percentage of location. After performing this test, we found that the angle method is able to find the exact leakage node for 83.04% of the nodes, while almost 90% are localizable within a distance lower than 2 m from the real leak. According to the results of this test, we can say that 230 of the 3,220 nodes are non-localizable in the network or have a low level of confidence. In Table 5, we can see the efficiency for a test where 100 leak simulations have been performed using the angle method and 15 sensors. We observe that the mean distance even in cases with noise is lower than 200 m.

With six sensors and performing the mentioned location ability test, the ability to find the exact node is now 80.06%, 88% of possible leaks are located within a distance less than 2 m and there are 266 non-localizable nodes. In Table 6 we can see the efficiency of the angle method when only six sensors are installed.

These experiments show that the angle method is able to detect and isolate single leaks in a real network even in the worst case with a maximum distance of approximately 700 m. However, it is remarkable to note that the mean distance for each experiment is close to 100 m in the presence of random noise. It is important to note that even when the number of sensors is reduced, the efficiency of the method is not severely affected. This means that we may reduce significantly the instrumentation on the network without greatly affecting the efficiency of the location.

Optimization method

Similar to the angle method, the ‘leak location test’ was performed for the optimization method. In the case of 15 sensors, by computing the mentioned test, we found that the method is able to find the exact leakage node for 81.08% of the nodes, while 89% are localizable within a distance less than 2 m from the real leak. According to the results of this test, we can say that 230 of the 3,220 nodes are non-localizable in the network or have a low level of confidence. In Table 5, we can see the efficiency for a test where 100 leak simulations have been performed using the angle method and 15 sensors. We observe that the mean distance even in cases with noise is lower than 200 m.

With six sensors and performing the mentioned location ability test, the ability to find the exact node is now 80.06%, 88% of possible leaks are located within a distance less than 2 m and there are 266 non-localizable nodes. In Table 6 we can see the efficiency of the angle method when only six sensors are installed.

These experiments show that the angle method is able to detect and isolate single leaks in a real network even in the worst case with a maximum distance of approximately 700 m. However, it is remarkable to note that the mean distance for each experiment is close to 100 m in the presence of random noise. It is important to note that even when the number of sensors is reduced, the efficiency of the method is not severely affected. This means that we may reduce significantly the instrumentation on the network without greatly affecting the efficiency of the location.

---

### Table 5 | Efficiency in the random leaks location with the angle method using 15 sensors

<table>
<thead>
<tr>
<th>Leak size ( (\text{L s}^{-1}) )</th>
<th>Maximum distance (m)</th>
<th>Mean distance (m)</th>
<th>Distance between ranges(^a) (%)</th>
<th>Random noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 (Nominal)</td>
<td>7.85</td>
<td>2.49</td>
<td>96</td>
<td>No</td>
</tr>
<tr>
<td>0.7</td>
<td>504.86</td>
<td>75.46</td>
<td>61</td>
<td>No</td>
</tr>
<tr>
<td>1.7</td>
<td>602.52</td>
<td>72.79</td>
<td>59</td>
<td>No</td>
</tr>
<tr>
<td>6.3</td>
<td>728.11</td>
<td>75.95</td>
<td>60</td>
<td>No</td>
</tr>
<tr>
<td>3 (Nominal)</td>
<td>331.44</td>
<td>109.66</td>
<td>60</td>
<td>Yes</td>
</tr>
<tr>
<td>0.7</td>
<td>706.32</td>
<td>191.82</td>
<td>36</td>
<td>Yes</td>
</tr>
<tr>
<td>1.7</td>
<td>723</td>
<td>135.88</td>
<td>51</td>
<td>Yes</td>
</tr>
<tr>
<td>6.3</td>
<td>564.4</td>
<td>86.91</td>
<td>71</td>
<td>Yes</td>
</tr>
</tbody>
</table>

\(^a\)Ranges are: 3 m for nominal leak without noise; 50 m for non-nominal leak without noise; 100 m for leak with noise.

### Table 6 | Efficiency in the random leaks location with the angle method using 6 sensors

<table>
<thead>
<tr>
<th>Leak size ( (\text{L s}^{-1}) )</th>
<th>Maximum distance (m)</th>
<th>Mean distance (m)</th>
<th>Distance between ranges(^a) (%)</th>
<th>Random noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.67 (Nominal)</td>
<td>383.37</td>
<td>17.50</td>
<td>82</td>
<td>No</td>
</tr>
<tr>
<td>0.7</td>
<td>471.19</td>
<td>74.44</td>
<td>58</td>
<td>No</td>
</tr>
<tr>
<td>3</td>
<td>284.22</td>
<td>53.03</td>
<td>64</td>
<td>No</td>
</tr>
<tr>
<td>6.3</td>
<td>444.71</td>
<td>129.11</td>
<td>34</td>
<td>No</td>
</tr>
<tr>
<td>1.67 (Nominal)</td>
<td>479.41</td>
<td>101.95</td>
<td>66</td>
<td>Yes</td>
</tr>
<tr>
<td>0.7</td>
<td>449.15</td>
<td>119.88</td>
<td>58</td>
<td>Yes</td>
</tr>
<tr>
<td>3</td>
<td>523.97</td>
<td>135.88</td>
<td>51</td>
<td>Yes</td>
</tr>
<tr>
<td>6.3</td>
<td>554.85</td>
<td>112.27</td>
<td>58</td>
<td>Yes</td>
</tr>
</tbody>
</table>

\(^a\)Ranges are: 3 m for nominal leak without noise; 50 m for non-nominal leak without noise; 100 m for leak with noise.
are non-localizable in the network or have a low level of confidence. With six sensors and according to the leak location test, the capacity of finding the exact node is 74.25% in the case of the optimization method, while the percentage of finding a node within a distance of less than 2 m is 84.78%. In Tables 7 and 8, we can see the efficiency of the optimization method in the case of 15 and six sensors installed, respectively.

We have to highlight that even when the optimization method behavior is not as good as the angle method; it has the advantage that it provides an approximate leak magnitude and an error in the optimization that can be exploited as extra information in order to improve the leak detection and location process.

As we can see from the result tables of the optimization method, the location process is affected when we have a low number of pressure sensors in a network with a large number of nodes. Moreover, this method is strongly affected when the difference between the nominal and the real leak is large. Nevertheless, these results proved that the method can be applied to a real network.

**Correlation method**

Finally, the results obtained with the angle and least square optimization methods are compared with the behavior of the correlation method that has been applied already to a real network in Pérez *et al.* (2014). We performed the same experiments with and without noise using the correlation method. Using the leak location test, we found that the correlation method is able to find the exact leakage location for 81.58% of the nodes when using 15 sensors and 71.67% when using six sensors. The method locates 87 and 80%, respectively, within a distance less than 2 m from the real leak. Also, with this approach, there are 242 and 408 non-localizable nodes in the case of 15 and six sensors, respectively. Results obtained with the exhaustive tests in the 15 sensors case are shown in Table 9 while the results for the case of six sensors installed are shown in Table 10.

---

**Table 7**  Efficiency in the random leaks location with the optimization method using 15 sensors

<table>
<thead>
<tr>
<th>Leak size (l s⁻¹)</th>
<th>Maximum distance (m)</th>
<th>Mean distance (m)</th>
<th>Distance between ranges (%)</th>
<th>Random noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 (Nominal)</td>
<td>1.04</td>
<td>0.04</td>
<td>100</td>
<td>No</td>
</tr>
<tr>
<td>0.7</td>
<td>476.19</td>
<td>84.34</td>
<td>52</td>
<td>No</td>
</tr>
<tr>
<td>1.7</td>
<td>1250.9</td>
<td>55.12</td>
<td>72</td>
<td>No</td>
</tr>
<tr>
<td>6.3</td>
<td>551.56</td>
<td>66.07</td>
<td>61</td>
<td>No</td>
</tr>
<tr>
<td>3 (Nominal)</td>
<td>331.44</td>
<td>109.66</td>
<td>56</td>
<td>Yes</td>
</tr>
<tr>
<td>0.7</td>
<td>1218.6</td>
<td>188.41</td>
<td>37</td>
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</tr>
<tr>
<td>1.7</td>
<td>1046.4</td>
<td>146.07</td>
<td>56</td>
<td>Yes</td>
</tr>
<tr>
<td>6.3</td>
<td>760.63</td>
<td>99.18</td>
<td>68</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*Ranges are: 3 m for nominal leak without noise; 50 m for non-nominal leak without noise; 100 m for leak with noise.

**Table 8**  Efficiency in the random leaks location with the optimization method using 6 sensors

<table>
<thead>
<tr>
<th>Leak size (l s⁻¹)</th>
<th>Maximum distance (m)</th>
<th>Mean distance (m)</th>
<th>Distance between ranges (%)</th>
<th>Random noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.67 (Nominal)</td>
<td>15.04</td>
<td>1.34</td>
<td>88</td>
<td>No</td>
</tr>
<tr>
<td>0.7</td>
<td>754.06</td>
<td>89.48</td>
<td>56</td>
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</tr>
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<td>1251.8</td>
<td>123.85</td>
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</tr>
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<td>6.3</td>
<td>768.85</td>
<td>181.1</td>
<td>26</td>
<td>No</td>
</tr>
<tr>
<td>1.67 (Nominal)</td>
<td>794.52</td>
<td>143.95</td>
<td>56</td>
<td>Yes</td>
</tr>
<tr>
<td>0.7</td>
<td>595.56</td>
<td>150.27</td>
<td>48</td>
<td>Yes</td>
</tr>
<tr>
<td>3</td>
<td>684.16</td>
<td>155.86</td>
<td>56</td>
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</tr>
<tr>
<td>6.3</td>
<td>769.16</td>
<td>209.92</td>
<td>44</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*Ranges are: 3 m for nominal leak without noise; 50 m for non-nominal leak without noise; 100 m for leak with noise.

**Table 9**  Efficiency in the random leaks location with the correlation method using 15 sensors

<table>
<thead>
<tr>
<th>Leak size (l s⁻¹)</th>
<th>Maximum distance (m)</th>
<th>Mean distance (m)</th>
<th>Distance between ranges (%)</th>
<th>Random noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 (Nominal)</td>
<td>11.82</td>
<td>0.55</td>
<td>92</td>
<td>No</td>
</tr>
<tr>
<td>0.7</td>
<td>204</td>
<td>46.37</td>
<td>64</td>
<td>No</td>
</tr>
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<td>1.67</td>
<td>292.43</td>
<td>41.74</td>
<td>74</td>
<td>No</td>
</tr>
<tr>
<td>6.3</td>
<td>216.71</td>
<td>49.29</td>
<td>64</td>
<td>No</td>
</tr>
<tr>
<td>3 (Nominal)</td>
<td>646.21</td>
<td>161.07</td>
<td>42</td>
<td>Yes</td>
</tr>
<tr>
<td>0.7</td>
<td>1223.9</td>
<td>368.68</td>
<td>20</td>
<td>Yes</td>
</tr>
<tr>
<td>1.67</td>
<td>982.49</td>
<td>223.59</td>
<td>46</td>
<td>Yes</td>
</tr>
<tr>
<td>6.3</td>
<td>585.25</td>
<td>94.03</td>
<td>70</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*Ranges are: 3 m for nominal leak without noise; 50 m for non-nominal leak without noise; 100 m for leak with noise.
As we can see, both the mean distance and the distance between expected ranges reach higher values when using the correlation method than with the two other leakage location strategies. It means that even when the correlation methods can be applied to a real network with clearly efficient results, we have seen that the leak localization can be improved using other available methods that can be compatible with the leak sensitivity approach.

**Test in a real leak scenario**

To test our proposed methodology in a real leak scenario, the water company provided us with data of a real leak which occurred between 00:00 hours on December 20, 2012 and 6:30 hours on December 21, 2012, i.e. 30 h and 30 min of a continuous leak. Then, in our case, we use a time horizon of 30 h taking into account data from 00:00 hours until 6:00 hours of the next day.

The first stage prior to the methodology application is to detect the occurrence of a new leakage scenario in the DMA. In general, a detection procedure followed by water utilities is based on the analysis of the difference between night flows. Although leakage is pressure dependent, and at night-time pressure is lower, the reduction of the demand uncertainty makes it more reliable to analyze the night flows instead of the day flows. As shown in Figure 19 (upper plot), the total DMA inflow suffered a meaningful increase on December 20th when the leakage was provoked with respect to the previous day. The difference between these two flows (Figure 19, bottom plot) and its average value allows estimation of the size of the leakage. In this case, the estimated value of this increase (the leakage size) is 5.6 l s\(^{-1}\) on average.

The resolution of the sensors strongly affects the performance of the leak location. In our case, the sensors installed were benefiting of a 10 cm resolution. In order to improve the resolution, the sensors measured the pressure every 10 min along the time horizon, while the residuals were computed with an hourly scheme such that each hourly measure is obtained as

\[
p_{hr} = \frac{1}{6} \sum_{k=1}^{6} p_{10 \text{ min}}
\]

where \(p_{hr}\) represents the pressure obtained after 6 measurements in an hour and \(p_{10 \text{ min}}\) represents each measurement obtained with the sensors at a time step of 10 min.

In a real application, some practical problems are quite common. In particular, one of the six sensors installed in the network was not working, and so the leak location was performed using only five sensors. An emitter coefficient of 0.92 has been chosen to compute the sensitivity matrices.

In Figure 20, we can see the probability of the leak represented with the same nomenclature as the one proposed previously in the experimental scenarios. The leakage node was located at 93.204 m from the real leak. It is an important result that demonstrates the efficiency of the methodology proposed when using real data.
CONCLUSION

In this paper, a new approach for model-based leak detection and location in WDN, which considers an extended time-horizon analysis of pressure sensitivities, has been proposed. Five different ways of using the leak sensitivity matrix to isolate the leaks have been described. The performance of these methods has been compared when applied to two academic small networks (Hanoi and Quebra). Finally, the three methods with better performance are applied to a DMA of the Barcelona WDN. Results have shown that the angle method increases the capability of isolating leaks in a great number of cases. Moreover, distances between the estimation of the leak position and its real location are reduced by 200 m in the presence of noise. Another interesting point is that we observed how reducing the number of sensors does not seriously affect the performance of the methods. A final important achievement of this work is the test of the proposed angle method when a real leak scenario occurred in the network. In this test, we achieved close to the real leak location and demonstrated that the method is already applicable in real leak scenarios.

As future work, we would like to perform an improved demand calibration and better sensor placement based on the same principle as our location method in order to investigate the relationship between sensor placement and the method used for leak location.

ACKNOWLEDGEMENTS

The authors would like to thank Gerard Sanz, PhD student, for sharing with us the data necessary to perform the real test presented.

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