Robustness analysis of sensor placement for leak detection and location under uncertain operating conditions

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Abstract

Some pressure sensor placement methods for leak detection and location in water distribution networks are based on the pressure sensitivity matrix analysis. This matrix depends on the network demands, which are nondeterministic, and the leak magnitudes, which are unknown. In this paper, the robustness of a sensor placement methodology against the fault sensitivity matrix uncertainty is studied. The robustness study is illustrated by means of a small academic network as well as a district metered area in the Barcelona water distribution network. Results reveal that this uncertainty should be taken into account in the sensor placement methodology.

Keywords: sensor placement; leak location; clustering; robustness analysis.

1. Introduction

Water loss due to leak in pipelines is one of the main challenges in efficient water distribution networks (WDN). Leaks in WDNs can happen due sometimes, to damages and defects in pipes, lack of maintenance or increase in pressure. Leaks can cause significant economic losses and must be detected and located as soon as possible to minimize their effects. The techniques and methods used to detect and locate the leaks are based on the sensor installed in the network. Ideally, a sensor network should be configured to facilitate leak detection and location and maximize diagnosis performance under a given sensor cost limit.

In WDNs, only a limited number of sensors can be installed due to budget constraints. Since improper selections may seriously hamper diagnosis performance, the development of sensor placement strategy has become an important research issue in recent years. In particular, leaks in WDNs are an issue of great concern for water utilities. Continuous improvements in water loss management are being applied, and new technologies are developed to achieve higher levels of efficiency [1].

In the last years, different works that deal with the topic of leak location in WDNs using pressure sensors have been published. Some of these last works tackle with the problem of leak location using the fault sensitivity matrix [2],

[3], which contains the information about how leaks affect the different node pressures. On the other hand, optimal pressure sensor placement algorithms that use the sensitivity matrix have been developed to determine which pressure sensors have to be installed among hundreds of possible locations in the WDN to carry out an optimal leak location as in [4] and [5]. The fault sensitivity matrix can be obtained by convenient manipulation of model equations as long as fault (leak) effects are included in them [6]. Alternatively, it can be obtained by sensitivity analysis through simulation [2]. The elements of this matrix depend on the operating point defined by the heads in reservoirs, the inflow, demand distribution, which is not constant, and the leak magnitudes, which are unknown.

This paper presents a robustness analysis of a sensor placement methodology based on the fault sensitivity matrix concept for WDNs. The study is based on the generation of different leak scenarios taking into account on one hand different leak magnitudes and on the other hand various operating points.

The robustness study is illustrated by means of a simple network with 12 nodes and a District Metered Area in the Barcelona WDN with 883 nodes. In this latter case a clustering technique is combined with the sensor placement methodology to reduce the size and the complexity of the problem.

2. Sensor placement for leak detection and location

2.1. Leak detection and location in WDNs

Model-based fault diagnosis techniques are applied to detect and locate leaks in WDNs. In model-based fault diagnosis [7] a set of residuals are designed based on a process model. Fault detection and isolation is achieved through the evaluation of residual expressions under available measurements. A threshold-based test is usually implemented in order to cope with noise and model uncertainty effects. At the absence of faults, all residuals remain below their given thresholds. Otherwise, when a fault is present, the model is no longer consistent with the observations (known process variables). Thus, some residuals will exceed their corresponding thresholds, signalling the occurrence of a fault. In model-based fault isolation, the number of residuals that are inconsistent and their magnitudes are compared against the different expected residual fault sensitivities, looking for the most probable fault that leads to model inconsistencies (residuals).

Given a set of m target faults $f_j \in \mathbf{F}$ (i.e., m possible leak locations) and a set of n residuals $r_i \in \mathbf{R}$ (that compare measurements with model estimations), residual fault sensitivities are collected in the *Fault Sensitivity Matrix* (FSM) denoted by $\mathbf{\Omega}$

$$\mathbf{\Omega} = \begin{pmatrix} \frac{\partial r_1}{\partial f_1} & \cdots & \frac{\partial r_1}{\partial f_m} \\ \vdots & \ddots & \vdots \\ \frac{\partial r_n}{\partial f_1} & \cdots & \frac{\partial r_n}{\partial f_m} \end{pmatrix}. \tag{1}$$

In this work only pressure primary residuals will be considered. Primary residuals compare each actual pressure measurement vector $\mathbf{p}$ to the corresponding estimated value in the fault free case $\hat{\mathbf{p}}_{nf}$. The FSM can be approximately computed by means of the predicted residual vector $\hat{\mathbf{r}}_{f_j} \in \Re^n$ defined as

$$\hat{\mathbf{r}}_{f_j} = \hat{\mathbf{p}}_{f_j} - \hat{\mathbf{p}}_{nf}, \tag{2}$$

where $\hat{\mathbf{p}}_{f_j}$ is the estimated pressure vector under leak fault f_j. $\hat{\mathbf{p}}_{nf}$ and $\hat{\mathbf{p}}_{f_j}$ are the solutions of the following nonlinear equations

$$g_{nf}(\hat{\mathbf{p}}_{nf}, \boldsymbol{\theta}) = 0 \tag{3}$$

$$g_{f_j}(\hat{\mathbf{p}}_{f_j}, \boldsymbol{\theta}, f) = 0, \tag{4}$$

where $\boldsymbol{\theta}$ is a vector of dimension n_θ that defines the operating point in the *WDN* (heads in reservoirs, total inflow and demand distribution in nodes), f is the leak magnitude and $g_{nf} : \Re^n \times \Re^{n_\theta} \to \Re^{n_c}$ and $g_{f_j} : \Re^n \times \Re^{n_\theta} \times \Re \to \Re^{n_c}$ are nonlinear functions derived from n_c hydraulic relations that describe the WDN behavior.

The FSM can be approximated in a nominal operating point $\boldsymbol{\theta}^0$ and for a nominal leak magnitude f^0 by

$$\boldsymbol{\Omega}(\boldsymbol{\theta}^0, f^0) \simeq \frac{1}{f^0}(\hat{\mathbf{r}}_{f_1}(\boldsymbol{\theta}^0, f^0), \ldots, \hat{\mathbf{r}}_{f_m}(\boldsymbol{\theta}^0, f^0)), \tag{5}$$

where $\hat{\mathbf{r}}_{f_j}(\boldsymbol{\theta}^0, f^0) \in \Re^n$ can be obtained using (2) with $\hat{\mathbf{p}}_{f_j}$ and $\hat{\mathbf{p}}_{nf}$ being the solutions of (3) and (4) for $\boldsymbol{\theta} = \boldsymbol{\theta}^0$ and $f = f^0$, using a hydraulic simulator. In this work, (3) and (4) will be solved using the EPANET hydraulic simulator [8].

Thus, in general, the FSM defined in (1) is not constant but depends on the leak magnitude (f) and the operating point $\boldsymbol{\theta}$. i.e. $\boldsymbol{\Omega}(\boldsymbol{\theta}, f)$.

A fault can be detected as long as there exists at least a residual sensitive to it. Isolating faults requires more than one residual being sensitive to them, though. Fault isolation is achieved by matching the evaluated residual vector pattern to the closest residual fault sensitivity vector pattern (i.e., FSM column vector). In the present paper, a projection based method is considered. Let $\boldsymbol{\omega}_{\bullet j}$ be the column of $\boldsymbol{\Omega}$ corresponding to leak j and $\mathbf{r} = [r_1 \cdots r_n]^T$ be the actual residual vector corresponding to all n pressure measurement points

$$\mathbf{r} = \mathbf{p} - \hat{\mathbf{p}}_{nf} \tag{6}$$

Then, leak location can be achieved by solving the problem

$$\arg\max_j \frac{\boldsymbol{\omega}_{\bullet j}^T \cdot \mathbf{r}}{\|\boldsymbol{\omega}_{\bullet j}\|\|\mathbf{r}\|}, \tag{7}$$

where $\|\mathbf{v}\|$ stands for the Euclidean norm of vector $\mathbf{v}$. Thus, the biggest normalized projection of the actual residual vector on the fault sensitivity space is sought and the most probable leak j is obtained.

The quality of a leak diagnosis system can be determined through the evaluation of leak detectability and locatability properties.

Definition 1 (Detectable leak set)**.** Given a set of residuals $r_i \in \mathbf{R}$, a set of leaks $f_j \in \mathbf{F}$ and the corresponding leak (fault) sensitivity matrix $\boldsymbol{\Omega}$, the set of detectable leaks $\mathbf{F}_D$ is defined as

$$\mathbf{F}_D = \{f_j \in \mathbf{F} : \exists r_i \in \mathbf{R} : |\omega_{ij}| \geq \epsilon\}, \tag{8}$$

where ϵ is a threshold to account for noise and model uncertainty.

Definition 2 (Leak locatability index)**.** Given a set of residuals $r_i \in \mathbf{R}$, a set of leaks $f_j \in \mathbf{F}$ and the corresponding leak (fault) sensitivity matrix $\mathbf{\Omega}$, the leak locatability index I is defined as

$$I = \sum_{(f_k, f_l) \in \mathbb{F}} 1 - \frac{\boldsymbol{\omega}_{\bullet k}^T \cdot \boldsymbol{\omega}_{\bullet l}}{\|\boldsymbol{\omega}_{\bullet k}\| \|\boldsymbol{\omega}_{\bullet l}\|}, \tag{9}$$

where $\mathbb{F} = \{(f_k, f_l) \in \mathbf{F} \times \mathbf{F} : k < l\}$.

Following the leak location criteria defined in Eq. (7), the leak locatability index aggregates the normalized projection degree between the residual fault sensitivity vectors for all combinations of two faults. Since a minimal normalized projection is desired, the greater the index is, the better it is.

2.2. Sensor placement methodology

Usually, the sensor placement problem is presented as an optimization problem where the cheaper sensor configuration fulfilling some given diagnosis specifications is sought [9, 10]. Nevertheless, a baseline budget is usually assigned to instrumentation by water distribution companies which constraints the cost of the sought sensor configuration. Thus, in the water distribution domain, companies are not interested in achieving a given diagnosis performance but in the best diagnosis performance that can be reached by installing a specific number of sensors that satisfy the budget constraint.

Let $\mathbf{S}$ be the candidate pressure sensor set and m_p the number of pressure sensors that will be installed in the system. Then, the problem can be roughly stated as the choice of a configuration of m_p pressure sensors in $\mathbf{S}$ such that the diagnosis performance is maximized. This diagnosis performance depends on the set of sensors installed in the network $S \subseteq \mathbf{S}$ and it will be stated in terms of the detectable leak set and the leak locatability index, i.e., $\mathbf{F}_D(S)$ and $I(S)$.

To solve the sensor placement problem, a network model is also required. The leak sensitivity matrix $\mathbf{\Omega}$ corresponding to the complete set of candidate sensors is assumed to have been previously computed in a nominal operating point $\boldsymbol{\theta}^0$ and for a nominal leak magnitude f^0, as described in Section 2.1. Hence, the sensor placement for leak diagnosis can be formally stated as follows:

GIVEN a candidate sensor set $\mathbf{S}$, a leak sensitivity matrix $\mathbf{\Omega}$, a leak set $\mathbf{F}$, and the number m_p of pressure sensors to be installed.

FIND the m_p-pressure sensor configuration $S \subseteq \mathbf{S}$ such that:

1. all leaks in $\mathbf{F}$ are detectable, $\mathbf{F}_D(S) = \mathbf{F}$, and
2. the leak locatability index is maximized, i.e. $I(S) \geq I(S^\star)$ for any $S^\star \subseteq \mathbf{S}$ such that $|S^\star| = m_p$.

This optimization problem can not be solved by efficient branch and bound search strategies. Thus, a suboptimal search algorithm based on clustering techniques will be applied. However, in order to alleviate the suboptimality drawback of clustering techniques a two-step hybrid methodology that combines them with an exhaustive search is proposed:

Step 1 Clustering techniques are applied to reduce the initial set of candidate sensors $\mathbf{S}$ to $\mathbf{S}'$, such that next step is tractable. Step 1 will be described below.

Step 2 An exhaustive search is applied to the reduced candidate sensor set $\mathbf{S}'$. This search implies that the diagnosis performance must be evaluated $\binom{|\mathbf{S}'|}{m_p}$ times. The most time demanding test concerns the evaluation of the leak locatability index for every pair of leaks which involves computing $\binom{|\mathbf{F}|}{2}$ times the normalized projection of the leak sensitivity vectors. Thus, in all, an exhaustive search is of exponential complexity, but an optimal solution is guaranteed.

In [11], a reduction in the number of candidate sensors has been proposed by grouping the n initial sensors candidate into ℓ groups (clusters) applying the Evidential c-means (ECM) algorithm [12]. Then N representative sensors will be selected for each cluster, setting up the new candidate sensor set of $N\ell$ elements ($N\ell \leq n$). The number of groups ℓ will be determined by means of a study of the evolution of the validity index provided by the ECM algorithm for different number of groups. Finally, the number N ($N \geq 1$) will be given by

$$N = \left\lceil \frac{n_r}{\ell} \right\rceil \tag{10}$$

where n_r is the expected cardinality of the reduced candidate sensor set and $\lceil \ \rceil$ denotes the nearest integer in the direction of positive infinity.

In this case, the criterion used for determining the similitude between the n sensor candidates is the sensitivity pattern of their primary residuals to faults. This is provided by the n normalized rows of the fault sensitivity matrix $\mathbf{\Omega}$ defined in (1) that is approximated in a nominal operating point $\boldsymbol{\theta}^0$ and for a nominal leak magnitude f^0.

3. Robustness analysis methodology

The robustness analysis will concern the leak magnitude uncertainty and the operating point variation. Both analyses will be done separately.

On the one hand, the study concerning leak magnitude uncertainty will involve, for a given nominal operating point $\boldsymbol{\theta}^0$, evaluating the effect of possible uncertain values of the leak magnitude f^i within a given interval $f^i \in [f_{min}, f_{max}]$ on the sensor placement methodology. This analysis considers a finite number sf of scenarios that lead to sf different FSMs $\mathbf{\Omega}(\boldsymbol{\theta}^0, f^1), \cdots, \mathbf{\Omega}(\boldsymbol{\theta}^0, f^{sf})$, where $f^1 = f_{min}$ and $f^{sf} = f_{max}$.

On the other hand, the study concerning the operating point variation will involve, for a given nominal leak magnitude f^0, evaluating the effect of the operating point $\boldsymbol{\theta}^j$ variation (total inflow, demand distribution, etc...) on the sensor placement methodology. This analysis considers a finite number $s\theta$ of representative operating point scenarios in the network that lead to $s\theta$ different FSMs $\mathbf{\Omega}(\boldsymbol{\theta}^1, f^0), \cdots, \mathbf{\Omega}(\boldsymbol{\theta}^{s\theta}, f^0)$.

The sensor placement methodology proposed in Section 2.2 will be applied to every scenario. The optimal solution obtained for each scenario is expected to be different. Let S_j be the optimal sensor configuration obtained for scenario j and let $I_i(S)$ be the locatability index that corresponds to scenario i when sensor configuration S is installed. Then, the *leak locatability matrix*, LLM, with as many rows and columns as scenarios, is defined, whose elements llm_{ij} correspond to $I_i(S_j)$. Based on this matrix, robustness will be evaluated through the *robustness percentage index* ρ defined as

$$\rho = 100 \max_i \left(\frac{\max_j llm_{ij} - \min_j llm_{ij}}{\max_j llm_{ij}} \right). \tag{11}$$

In order to gain robustness under uncertain operating conditions, the following extended FSM will be used by the clustering procedure proposed in [11] to reduce the number of candidate sensors:

$$\overline{\boldsymbol{\Omega}} = (\boldsymbol{\Omega}(\boldsymbol{\theta}^0, f^1), \cdots, \boldsymbol{\Omega}(\boldsymbol{\theta}^0, f^{sf}), \boldsymbol{\Omega}(\boldsymbol{\theta}^1, f^0), \cdots, \boldsymbol{\Omega}(\boldsymbol{\theta}^{s\theta}, f^0)). \tag{12}$$

Fault sensitivity matrices $\boldsymbol{\Omega}(\boldsymbol{\theta}^0, f^i)$ and $\boldsymbol{\Omega}(\boldsymbol{\theta}^j, f^0)$ will be obtained using the EPANET hydraulic simulator. Leaks are simulated in EPANET through the corresponding emitter coefficient, which is designed to model fire hydrants and fire sprinklers, and it can be adapted to provide the desired leak magnitude in the network, according to the equation:

$$Q = EC \cdot P^{P_{exp}} \tag{13}$$

where EC is the emitter coefficient, Q is the flow rate, P is the available pressure at the considered node and P_{exp} is the pressure exponent. EPANET permits the value of the emitter coefficient to be specified for individual leak sites, but the pressure exponent can only be specified for the entire network.

Concerning the operating point robustness study, scenarios are generated with EPANET by specifying several values for the network total inflow.

4. Application to a small WDN benchmark

4.1. Case study 1 description

The robustness analysis will be firstly performed on a small network (see Fig. 1). The network has 12 nodes and 17 pipes, with two inflow inputs modeled as reservoir nodes. Thus, 10 potential leaks and 10 candidate pressure sensor locations will be considered at the network nodes (excluding reservoir nodes).

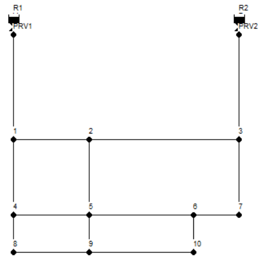
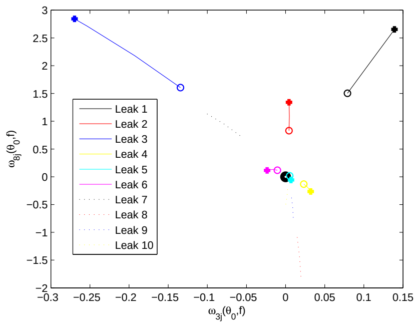
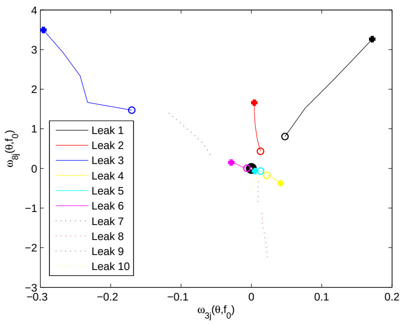


Figure 1: Case study 1 network map.



(a) Leak magnitude dependency.



(b) Operating point dependency.

Figure 2: Evolution of $\mathbf{\Omega}$ row vector components 3 and 8 in case study 1 for the 10 possible leaks.

Five scenarios are defined concerning leak magnitude uncertainty ($\boldsymbol{\theta}^0 = 15.84$ lps, $\mathbf{f} = \{0.5, 0.7, 0.9, 0.93, 0.95\}$) and five others related to operating point variation ($\boldsymbol{\theta} = \{5, 10, 15, 20, 25\}$ lps, $f^0 = 0.92$). Remark that the operating point $\boldsymbol{\theta}$ is defined here by the network inflow and leaks are characterized through the emitter coefficient i.e. $f = EC$.

Assume that a sensor placement problem with $m_p = 2$ is to be solved.

4.2. Sensor placement analysis and results

Fig. 2 (a) shows the evolution of row vector components 3 and 8 of $\mathbf{\Omega}(\boldsymbol{\theta}^0, f)$ considering $f = f_{min}, \cdots, f = f_{max}$ for the 10 possible leaks *i.e.* $\omega_{3j}(\boldsymbol{\theta}^0, f)$ and $\omega_{8j}(\boldsymbol{\theta}^0, f)$ for $j = 1, \cdots, 10$.
Notice that the normalized vector $\|[\omega_{3j}(\boldsymbol{\theta}^0, f), \omega_{8j}(\boldsymbol{\theta}^0, f)]\|$ for all the considered leaks is almost the same. Thus, nonsignificant variation in the locatability index (9) is expected for the different leak scenarios. Fig. 2 (b) shows the evolution of the same components of $\mathbf{\Omega}(\boldsymbol{\theta}, f^0)$ for different operating points $\boldsymbol{\theta}^1, \cdots, \boldsymbol{\theta}^{s\theta}$, considering the same leak magnitude f^0 in all the leak scenarios. In this case, the variation that the normalized vector exhibits is remarkable. Thus, some variation in the locatability index (9) is expected for the different operating point scenarios.

Due to the network size being small, the clustering procedure is not needed to solve the sensor placement problem. Thus, just step 2 of the methodology outlined in Section 2.2 has been directly applied. Table 1 provides the resulting leak locatability matrices. At the top row, the optimal sensor locations for each scenario are provided.

Table 1: Leak locatability matrices for case study 1.

(a) Leak magnitude uncertainty analysis.

	$\{1,4\}$	$\{1,4\}$	$\{3,8\}$	$\{1,4\}$	$\{1,4\}$
$Scn1$	50.00	50.00	48.03	50.00	50.00
$Scn2$	50.00	50.00	49.24	50.00	50.00
$Scn3$	50.00	50.00	50.00	50.00	50.00
$Scn4$	50.00	50.00	50.00	50.00	50.00
$Scn5$	50.00	50.00	50.00	50.00	50.00

(b) Operating point variation analysis.

	$\{1,9\}$	$\{3,8\}$	$\{3,8\}$	$\{1,4\}$	$\{1,4\}$
$Scn1$	50.00	49.57	49.57	47.73	47.73
$Scn2$	49.63	49.97	49.97	48.03	48.03
$Scn3$	43.50	50.00	50.00	50.00	50.00
$Scn4$	42.79	50.00	50.00	50.00	50.00
$Scn5$	43.03	50.00	50.00	50.00	50.00

The robustness percentage index for leak magnitude uncertainty is 3.94%, which means that the sensor placement results are very robust against this kind of uncertainty. However, the robustness percentage index for operating point variation is 14.43%, which proves some dependency of the sensor placement results on this kind of variation.

5. Application to a real WDN in Barcelona

5.1. Case study 2 description

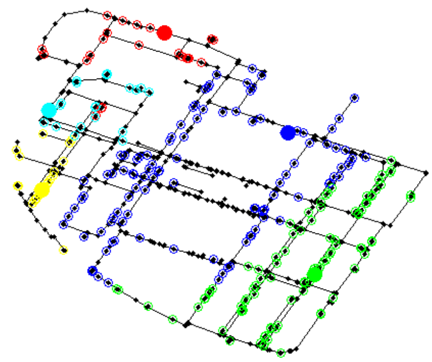
The robustness analysis is performed on a bigger real network. The DMA is located in Barcelona (see Fig. 3) and has 883 nodes and 927 pipes. The network consists of 311 nodes with demand (RM type), 60 terminal nodes with no demand (EC type), 48 nodes hydrants without demand (HI type) and 448 dummy nodes without demand (XX type). Only dummy nodes can have leaks. Thus, since there are 448 dummy nodes (XX type) in the network, there are 448 potential leaks to be detected and isolated. The network has two inflow inputs modeled as reservoir nodes.

The same scenarios defined for case study 1 are considered for case study 2.

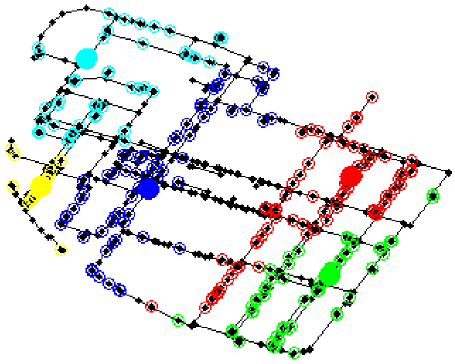
Pressure sensors at RM nodes set up the candidate sensor set. Assume that a sensor placement problem with $m_p = 5$ has to be solved.

5.2. Sensor placement analysis and results

In order to reduce the complexity of the exhaustive algorithm, the number of candidate pressure sensors has been reduced from 311 to $n_r = 25$ using clustering techniques as has been proposed in [11]. Clustering techniques have been applied to the 311 normalized rows of the nominal sensitivity matrix $\boldsymbol{\Omega}(\boldsymbol{\theta}^0, f^0)$ to classify the data set in 5 different clusters. The same procedure has been



(a) Based on the nominal FSM.



(b) Based on the extended FSM.

Figure 3: Case study 2 network map and clustering results.

carried out with the extended FSM $\overline{\mathbf{\Omega}}$ defined in (12). Figs. 3 (a)- 3 (b) depict in different colors the 5 different network node clusters obtained with the nominal and extended FSM respectively, where the closest node to the centroid has been highlighted in every cluster. Remark that there is an appreciable variation between the clustering obtained considering the nominal FSM and the one obtained considering the extended FSM.

Finally, the most N representative sensors of every cluster have been chosen as has been proposed in [11] with $N = 5$ given by Eq. (10).

The exhaustive search is next applied to the reduced candidate sensor set provided by the clustering algorithm based on the extended FSM. Table 2 provides the resulting leak locatability matrices.

Results are similar to case study 1 concerning robustness analysis. The robustness percentage index for leak magnitude uncertainty is 0.94%, which means that the sensor placement results are very robust against this kind of uncertainty. However, the robustness percentage index for operating point variation is 25.26%, which proves some significative dependency of the sensor placement results on this kind of variation.

Table 2: Leak locatability matrices for case study 2.

(a) Leak magnitude uncertainty analysis.

	$\{2, 8, 9,$ $138, 285\}$	$\{2, 8, 9,$ $138, 285\}$	$\{2, 8, 9$ $138, 285\}$	$\{2, 8, 9$ $138, 171\}$	$\{2, 8, 9$ $138, 171\}$
$Scn1$	88985	88985	88985	88152	88152
$Scn2$	94127	94127	94127	93938	93938
$Scn3$	95150	95150	95150	95027	95027
$Scn4$	95053	95053	95053	95194	95194
$Scn5$	95020	95020	95020	95221	95221

(b) Operating point variation analysis.

	$\{171, 244,$ $245, 250, 285\}$	$\{171, 244,$ $245, 250, 285\}$	$\{2, 8, 9,$ $138, 171\}$	$\{9, 171, 206,$ $244, 285\}$	$\{2, 8, 9,$ $138, 171\}$
$Scn1$	96599	96599	74824	82401	74824
$Scn2$	96036	96036	79437	80969	79437
$Scn3$	87622	87622	95164	80855	95164
$Scn4$	41944	41944	45783	48209	45783
$Scn5$	36659	36659	49047	45347	49047

6. Conclusions

The robustness analysis of the sensor placement problem in WDNs has been addressed in this paper. A distribution network usually describes a mesh topology involving hundreds of interconnected nodes whose behavior follows nonlinear physical laws. Such complexity requires the development of tools applicable to large-scale systems. Leak location in WDN using the pressure sensitivity matrix has been demonstrated to be efficient and different sensor placement strategies based on sensitivity matrix for a nominal scenario have been developed in the literature.

A first contribution of the paper is the definition of the robustness percentage index to evaluate the variation of the leak locatability index achieved by optimal sensor placement strategies for different leak magnitudes and DMA operating points. A second contribution is the use of an extended sensitivity matrix that considers all possible leak scenarios and operating point scenarios by the clustering analysis to reduce the number of candidate sensors.

The use of the robustness analysis has been applied to an academic network and to a DMA in the Barcelona WDN. Results show that there is not a significative variation of the leak locatability index when different leak scenarios are considered, but the variation can be significative when different operating point scenarios are considered. Therefore, this variation should be considered in future optimal sensor placement strategies.

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