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Data-driven leak localization in WDN using pressure sensor and hydraulic information

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Abstract:
Maintaining a good quality of service under a wide range of operational management is challenging for water utilities. One of the significant challenges is the location of water leaks in the large-scale water distribution networks (WDN) due to limited data information throughout the system, generally having only flow sensors at the entrance of the system and some pressure sensors in some selected nodes. In addition, most systems do not have a hydraulic model of the network. Therefore, when using the hydraulic model, the presence of model errors such as nodal demand uncertainty and measurement noise can interfere with the performance of the leak location method. This work presents a fully data-driven technique to reduce the area of the leak localization in the WDN, using Graph theory to represent the network. To do so, we have developed a distance clustering with pre-defined centroids that are the sensor pressure information and some selected nodes. Furthermore, some extra pressure information of leaks events in the selected centroids is studied to develop a correlation between the pressure measurement and the event. Finally, the approach is evaluated in real-world water systems and discusses graphical results and key performance indicators.

Keywords: Water Distribution Network, Flow Analysis, Pressure Analysis, Graph theory, Data models

1. INTRODUCTION

WDNs are essential infrastructures in modern cities for several socioeconomic reasons. They are complex networks due to their size (thousands of pipes) and hydraulic behavior due to their nonlinearity. One of the concerns to be managed in these systems is water leakage, which may account for up to 30% of the total amount of distributed water (Puust et al., 2010), being significant because water is a limited resource. Leakage causes several problems such as difficulties with contamination, health problems (Ali and Choi, 2020), and the loss of water at a time when the world's demand for water is only increasing . Different factors can cause a leak in the system, such as weak joints, water hammers, utility construction or excavation, seasonal temperature changes, heavy traffic, and other things. Fault diagnosis and safety in water systems are vital challenges that will become even more crucial in the coming years (Eliades and Polycarpou, 2009).

Several works on leak localization were released by applying model-based approaches, commonly used demand-driven (DD) hydraulic simulators, like EPANET (Rossman, 2000). For example, in (Soldevila et al., 2016) the research is based on the analysis of pressure residues. Moreover, in (Javadiha et al., 2019), and (Wachla et al., 2015),the authors use hydraulic models with AI methods. The results based on hydraulic models are excellent. However, they require strong assumptions on the quality of the model, knowledge of the water demand, limitation of noise in the measurements to obtain good performances. When hydraulic models are not available, or these assumptions cannot be guaranteed, another line of research is to use data-driven methods where only information from the system and sensors is used. For example, the (Soldevila et al., 2016) research is hybridized using model-based and data-driven to locate leaks. Furthermore, the (Sun et al., 2020; Romero et al., 2021) use interpolation methods to do the leak location, demonstrating that the sensor data

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interpolation analyses in WDN are just starting and need a continuous and deep study.

For a large-scale network, the leak localisation is more complex and requires more time for the maintenance operator to solve the problem. For this purpose, this article proposes a new data-driven leak location method in large-scale WDNs. It is divided into two parts: the first part is the clustering of the WDN to minimize the area considering fault. One represents the system by using the Graph theory and defining the minimum path distance connecting the nodes to the pre-defined point in the network that will be the centroids of the clustering. The second part analyzes the correlation pressure residuals obtained simulating in the real WDN a leaky scenario in each pre-defined point set to be a cluster center, with the actual correlation pressure residual measurement. This study will provide the clustering with the highest chance of having the fault. The contributions of this paper are:

- **Network topology clustering:** a new clustering topology is proposed using the hydraulic information to define the distance between the pre-defined node and the centroids reference to each clustering. The clustering will reduce the fault location area and help the water utilities locate the correct place of the leak.
- **Leak localization method:** a new approach is presented fully data-driven that uses the study of pressure residual and the correlation of how they are affected in a different leaky scenarios.
- **Real-world water systems evaluation:** it is performed in a benchmark WDN with 268 nodes and four reservoirs. The Average Topological Distance in node and kilometer are applied. Discussions about the costs and benefits of the proposed approach are also presented.

2. METHODOLOGY

Water distribution networks worldwide have different structures, sizes, demand patterns, components, etc. In addition, the distribution, quantity, and properties of meters installed in networks vary from one location to another. Additionally, as already mentioned, some water networks do not have hydraulic models to represent them, or when they do, they lack measurements or demand estimates. Therefore, these networks must conduct a leak localization study that only needs sensors measurements and hydraulic information.

The proposed leak location method is fully data-driven. It requires hydraulic information such as pipe diameter and length, measurements from pressure sensors installed in the system, and events simulated in the field by the water utilities of leak-free and leak scenarios in some selected nodes. First, the system is divided into k clusters using the graph theory, then the location of the leaks is determined by comparing the actual hydraulic state of the network and a reference without leaks indicating which zone is most probably to have the fault. The proposed method has the following features:

- It is applicable to measurements temporal information using Bayesian time reasoning.
- A clustering of k numbers is proposed, with the clustering centers being a predetermined nodes. In each k node, the water utilities must simulate leak events in the real system.
- Leak-free information can be obtained using historical data provided by the water company. In addition, nominal information can be used from the days prior to the appearance of the leak to deal with the uncertainty of water demand between different scenarios.
- It provides the cluster most likely where a leak is identified. It makes it easy to locate the leak in the real network.

2.1 Clustering

A water distribution network can be described by a directed graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, (Deo, 2017), where $\mathcal{V}$ is the set of n nodes (junctions, reservoirs, and tanks) and $\mathcal{E}$ is the set of m links (pipes, valves, and pumps). A node is referred to as $v_i \in \mathcal{V}$, and an edge $e_{ij} = (v_i, v_j) \in \mathcal{E}$ connects source node v_i with sink node v_j.

An edge e_{ij} is associated with a cost value, related in this case to the diameter and length of the pipe. Edge costs are exploited to generate weighted adjacency matrix $W(\mathcal{G}) \in \mathbb{R}^{n,n}$:

$$w_{ij} = \frac{l_{ij}}{D_{ij}^5} \tag{1}$$

where l_{ij} and D_{ij} are the length and diameter of the pipe, connecting nodes i and j, both in meters [m]. It refers to the friction loss in pipes of Hazen-Williams formula (see (Pérez and Sanz, 2017).

The network clustering process is divided into two phases: the first is the clustering study with k equal to the number of sensors s present in the system. The objective is to divide the n (nodes) observations into $s(\leq n)$ sets $C = \{C_1, C_2, \ldots, C_s\}$ concerning the hydraulic distance of the sensors. For this, the set of data points $x = [x_1, ..., x_s]$ is generated for each node with the minimum distance from the node to the sensors:

$$x_j = d^W(i, j) \tag{2}$$

where $i = 1, ..., n$ and $j = 1, ..., s$ and the distance $d^W(i, j)$ is the minimum sum of weights across all the paths connecting i and j.

The main objective of the clustering algorithm is to minimize the sum of distances between the points and their respective cluster centroid. The objective function is:

$$arg \min_C \sum_j^s \sum_{x \in C_j} ||x - \mu_j||^2 \tag{3}$$

where μ_j is the center of the clustering, which is the value of the distance from a sensor to the other sensors

$$\mu_j = [d^W(j, 1), ..., d^W(j, s)], \qquad j = 1, ..., s \tag{4}$$

This first clustering makes it possible to analyze how many nodes there are in each zone. Of course, the ideal is to have clusters with homogeneous numbers of nodes. However, in real cases where pressure sensors are already installed in the network, similar numbers of nodes in the clusterings may not be satisfied.

The second phase of clustering is designed to solve this problem. More q numbers of nodes are chosen to be a clustering center. So the goal is to divide n (nodes) observations into $s + q(\leq n)$ sets $C = \{C_1, C_2, \ldots, C_s, C_{(s+1)}, \ldots, C_{(s+q)}\}$. The extra q nodes are chosen on the frontier between one cluster and another in the first phase. The number of q nodes chosen has to be analyzed with the water company because the q selected in the most node containing sensors will need extra simulation information in the real network of events with leakage. Consequently, the exact number of q chosen will vary according to the water company's objective, as a previous cost-benefit study must be carried out, which will be explained better in the next section. The second clustering will be the same as Equation (3) with the new center:

$$\mu_j = [d^W(j,1), ..., d^W(j, s+q)], \qquad \forall j = 1, ..., s+q \quad (5)$$

2.2 Leak localization

The proposed leak location method aims to reduce the network area to the pre-defined regions with the highest chance of leaking. The method analyzes residuals from the pressure sensors already installed in the network. This process has an important role in maintaining easily the network and supporting the operator in its maintenance task.

The estimation pressure considering a leak-free scenario is done with the historical data analysis so that the network boundary conditions c are similar (e.g., reservoir pressures, flow, and consumer demands). A study of the pressure measurement of previous days or weeks where the system was considered without failures can be done. In this way, it can guarantee a better precision of the estimated measure of pressure. The study of residuals can be determined by the following:

$$r_i = \hat{p}_i(c) - p_i^f(c), \quad \forall i = 1, ..., s \qquad (6)$$

where $\hat{p}(c)$ is the pressure estimated with the boundary condition c in a leak-free scenario, and $p^f(c)$ the pressure measurement with the boundary condition c with a leak in node f. To minimize the effect of the leakage magnitude an offset can be calculated with a minimum value of r:

$$\bar{r}_i = r_i - \min(r_1, ..., r_s) \quad \forall i = 1, ..., s \qquad (7)$$

Then the likelihood index ∂_i is calculated as the normalization of the $\bar{r}$:

$$\partial_i = \frac{\bar{r}_i}{\sum_{j=1}^{s} \bar{r}_j} \quad \forall i = 1, ..., s \qquad (8)$$

A simple leak localization method can be defined only with residual analysis of Equation (6) (see (Jensen and Kallesoe, 2016; Romano et al., 2017)). In this case, only

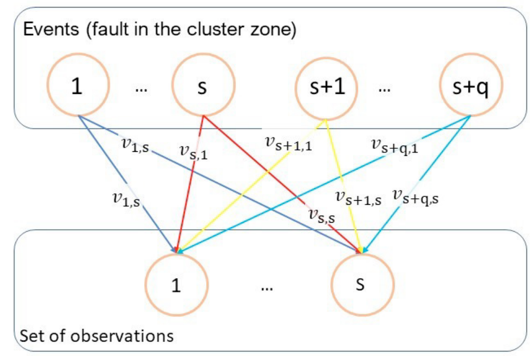

Fig. 1. Schema of the correlation between the sensor and the leak events

the first phase of clustering is utilized, with the center of the clustering expressed in Equation (4). The selected area with the leak is the one that presents the component with the maximum size, i.e.,

$$\hat{C} = \arg\max_{i \in 1,...,s} r_i \qquad (9)$$

This simple method only needs the information from the pressure sensors being a good reference point to analyze the improvement of the method. The dependency on the sensor's availability and its positioning in the network is a limitation to this simple method. For example, if the sensors are not well distributed in the system, a clustering one area may contain many nodes and others few. With that in mind, extra data information can balance the number of nodes in each cluster.

The effect of a leak on a node causes correlation factor between sensors (see. (Sun et al., 2020)), making it possible for objects within the same cluster to be as similar as possible (i.e., high intra-class similarity), while objects from different clusters are as different as possible (i.e., low inter-class similarity). Knowing this, it is possible to select q strategic points in the network (nodes) to be a new clustering center and thus balance the number of nodes in the cluster. Therefore, it is necessary to have leak-data scenarios in each node with sensors and selected centroids.

Figure 1 shows the sensor correlation scheme for each leak event generated with the signature vector of events $\nu^e \in \mathbb{R}^s$. Being $\nu^e = [\nu_1^e, ..., \nu_s^e]$ with ν_i^e normalized likelihood index (8) computed from normalized residual sensor $\bar{r}_i$ considering event (leak) in cluster $e \in 1, ..., s+q$.

For a given measured residual, the vector $\partial = [\partial_1, ..., \partial_s]$ is computed and the Euclidean distance is used to analyze the distance between the measurement and the centroids of each clustering:

$$\theta^e = \sqrt{(\partial_1 - \nu_1^e)^2 + ... + (\partial_s - \nu_s^e)^2} \qquad (10)$$

The most probable cluster is determined as the one that provided the minimum distance (10)

$$\hat{C} = \underset{e \in 1,\ldots,s+q}{\arg\min}\ \theta^e \tag{11}$$

Until now, only the single time instant analysis was studied, to improve the performance of the method and make it possible to analyze in time series the normalized θ^e information at different time instants t can be considered by applying Bayes' rule as:

$$P^e(t) = \frac{P^e(t-1)\theta^e(t)}{\sum_{l=1}^{s+q} P^l(t-1)\theta^l(t)} \tag{12}$$

where $P^e(t-1)$ is the prior probability whose initial value has to be determined (for example $P^e(0) = 1/(q+s)$). Then, the leak node localization can be estimated by using posterior leak correlation by:

$$\hat{C}(t) = \underset{e \in \{1,\ldots,s+q\}}{\arg\max}\ \{P^e(t)\} \tag{13}$$

2.3 Performance Indicators

The ATD in nodes and kilometers are the metrics being used to evaluate the performance in the dataset:

- Average topological distance (ATD): represents the distance in nodes or in kilometers between the centroid predicted as leaking with the true node that has the leak. The ATD index that presents minimum value is preferable. It is first necessary to create a matrix containing the minimum topological distance (in nodes or kilometers), $A \in \mathbb{R}^{n \times n}$. After it is necessary to create the confusion matrix $\Gamma_{i,j}$ depicted in Table 1 . The rows of this matrix correspond to the leak scenario and the columns to which the leak is located ($\hat{C}$) by the leak localization method.

Table 1. Confusion matrix $\mathbf{\Gamma}$.

	$\hat{l}_1$	$\cdots$	$\hat{l}_i$	$\cdots$	$\hat{l}_n$
l_1	$\Gamma_{1,1}$	$\cdots$	$\Gamma_{1,i}$	$\cdots$	$\Gamma_{1,n}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
l_i	$\Gamma_{i,1}$	$\cdots$	$\Gamma_{i,i}$	$\cdots$	$\Gamma_{i,n}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
l_n	$\Gamma_{n,1}$	$\cdots$	$\Gamma_{n,i}$	$\cdots$	$\Gamma_{n,n}$

The ATD is computed as follows:

$$ATD = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\Gamma_{i,j}A_{i,j}}{\sum_{i=1}^{n}\sum_{j=1}^{n}\Gamma_{i,j}} \tag{14}$$

3. CASE STUDY ANALYSIS

The Modena Network simplified version of the real WDN from the the Italian city Modena is represented in Figure 2. This large-scale network comprises 268 junctions (nodes) connected through 317 pipes and served by four reservoirs. There are no pumps in the network since it is entirely gravity-fed (Wang et al., 2015).

To test the evaluation of the proposed leak location method, artificial data were generated under different conditions using a hydraulic simulator Epanet 2 (see details in (Rossman, 2000)).

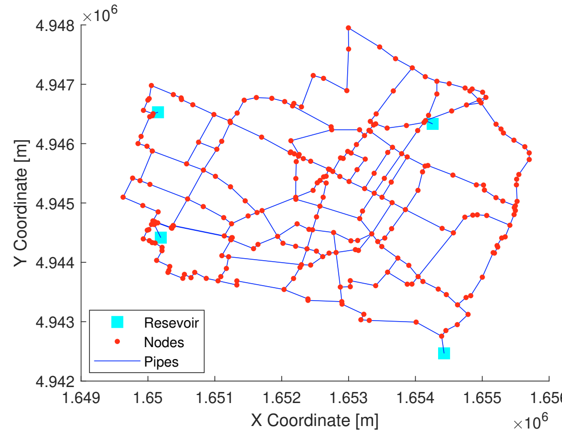

Fig. 2. Simplified Modena topological WDN.

Using the hydraulic simulator, data was generated with uncertainties related to the consumer's nodal demand created by applying Gaussian noise of 10[%] of the nominal demand value in the default value of the Modena benchmark in the Epanet repository and considering that the exact size of the leak is unknown, but is contained in the range of 5 and 50[l/s], representing 2% to 20% of the network consumption.

For each leak scenario, of the 268 nodes, a leak is simulated lasting 72h. The sampling rate is 10 min, but measurements are filtered hourly to reduce the impact of uncertainties in the diagnostic phase.

Six scenarios were generated with different sensors number to analyze the previously explained method. Table 2 displays the scenarios only with sensors installed on the network and the corresponding number of nodes in the clustering. Equation (3) and (4) were used to generate the clusterings. The number of sensors installed in the network is 3, 5, and 8, with two different cases to demonstrate the effect on the result concerning the positioning of the pressure sensors.

Table 2. Scenarios using only pressure sensors

Case	Nodes with sensors	Number of nodes in the clustering
1	**11 50 80**	64 109 95
2	**10 44 93**	83 74 111
3	**9 65 94 109 247**	63 103 45 23 34
4	**10 63 113 247 250**	55 45 90 45 33
5	**10 23 45 62 64 94 119 259**	19 24 48 28 25 53 47 24
6	**18 35 63 100 153 158 248 236**	45 32 31 27 30 30 34 39

Table 3 shows the scenarios demonstrated in Table 1 plus the extra nodes, q, which will be the additional center of clustering. The centroids are the s values of sensors installed in the s network, highlighted with the text in bold, and the q selected nodes are listed after the sensors, with $q + s$ being the centroids referred to in Equation (5). The value of q varies from one scenario to another to analyze how q affects the leak localization result. In addition, the number of nodes in the cluster is shown for each scenario. It is not always possible to balance the number of nodes in the areas, but the number of nodes in the areas is smaller.

Table 3. Scenarios using $s+q$ centroids

Case	Node set to be the cluster center	Number of nodes in the clustering
1	**11 50 80** 120 160	69 44 88 34 33
2	**10 44 93** 37 111 151 224	63 41 48 12 14 56 34
3	**9 65 94 109 247** 196 246	55 49 41 43 25 22 33
4	**10 63 113 247 250** 130 189 231 267	38 34 41 29 21 28 30 17 30
5	**10 23 45 62 64 94 119 259** 113 139 245 222	19 20 22 22 26 17 18 26 33 28 20 17
6	**18 35 63 100 153 158 248 236** 85 113 178 166 214 232	20 25 25 22 16 14 21 17 17 21 11 20 25 14

As noted before, the leak location method using the maximum residual variance seen in Equation (6) is a good point of comparison of method improvement. Therefore, the ATD was calculated applying the maximum residual method with the scenarios of Table 2. Then, the proposed leak localization method was applied to the scenarios in Table 3.

In the simplified WDN of Modena, in the example of Case 2 of Table 2 where three pressure sensors are considered, the computed clusters are depicted in Figure 3.(a). Following the clustering of the network in Case 2 of Table 3 contains the same pressure sensor position with four additional centroids. It is depicted in 3.(b). The nodes containing pressure sensors are highlighted with a red circle, and the q extra centroid is highlighted with a black circle. The clustering area with sensors is reduced by up to 56%, allowing a more homogeneous division of areas in the WDN.

Figure 4 shows the result of the ATD (node) of the two analyses, using the Bayes temporal reasoning in both cases with evolution of 48h. Figure 4.(a) is the result of the scenarios of Table 2 using the maximum residual approach, and Figure 4.(b) is the result of Table 3 scenarios applying the proposed method.

The analysis of the cases pairs that contain the same number of sensors, $\{1,2\}, \{3,4\}$, and $\{5,6\}$, (results in Figure 4.(a)) demonstrates the importance of a previous study for sensor placement. The ATD result improves with the same number of sensors in the network, which can reach up to one node difference. Moreover, cases $\{2,3\}$ have a similar result even though the two have a difference of 2 sensors installed in the network.

The results in Figure 4.(b) display the evolution of the ATD of the presented method. Comparing the correspondent Case in Figure 4. (a) an improvement in the ATD index is noticed in almost all cases. Only Case 1 presents better results using the maximum residual method due to the sensor placements on the network. Cases $\{1,2\}, \{3,4\}, \{5,6\}$ have the same number of sensors with only varying values of q. It is shown it is possible to obtain better results by increasing the value of q.

The same analysis was made analyzing the ATD with the distance in kilometers. This study is critical because as the distances between the pipes are not uniform, the

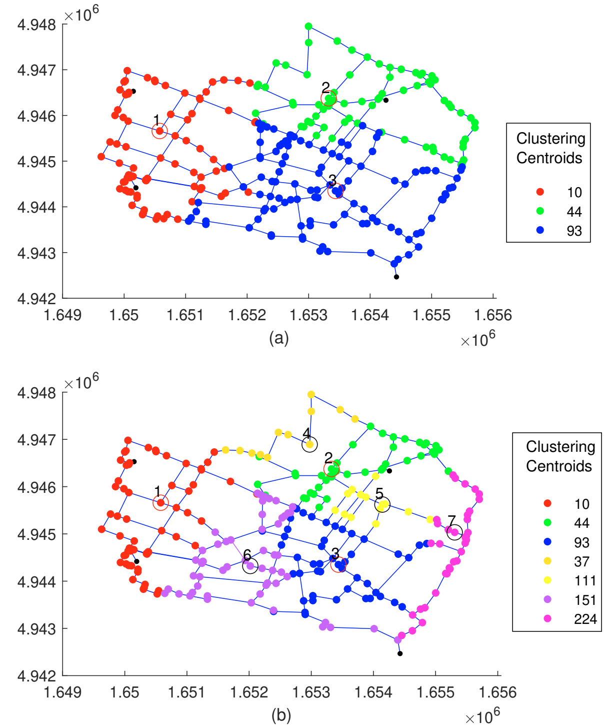

Fig. 3. Clustering of Case 2: (a) Table 2, with only pressure sensors highlighted with a red circle (b) Table 3, with sensors and 4 extra centroids, highlighted with a red and black circle

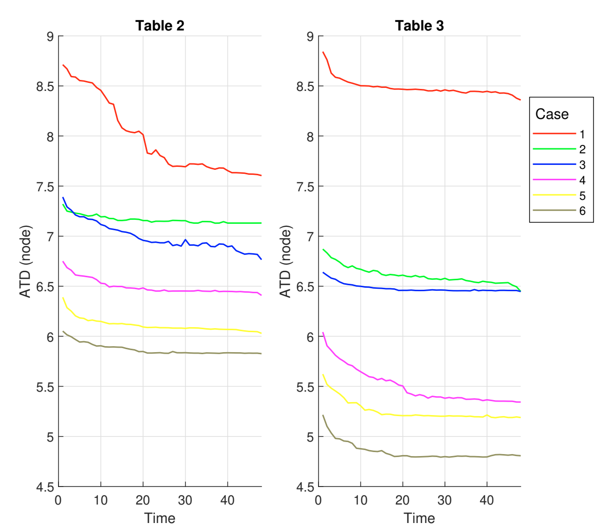

Fig. 4. Evolution of ATD (node) when using the Bayes temporal reasoning (a) scenarios of Table 2 using the maximum residual approach (b) scenarios of Table 3 using the proposed method

variation of the ATD in the node may not indicate the actual improvement. Figure 5.(a) shows the result of the scenarios of Table 2 using the maximum residual approach. It demonstrates the importance of comparing the ATD in nodes and kilometers. The cases [5, 6] have a similar value when they are compared in kilometers and in nodes, the case 6 has a slight improvement. Figure 5.(b) is the result of Table 3 scenarios applying the proposed method. This result shows that in Case 1, even with similar results compared to the maximum residual, it remains more constant with a better result in the time series. In the cases $\{2, 3\}$ that has an improvement in kilometers distance present a similar value in the comparison of the ATD in node.

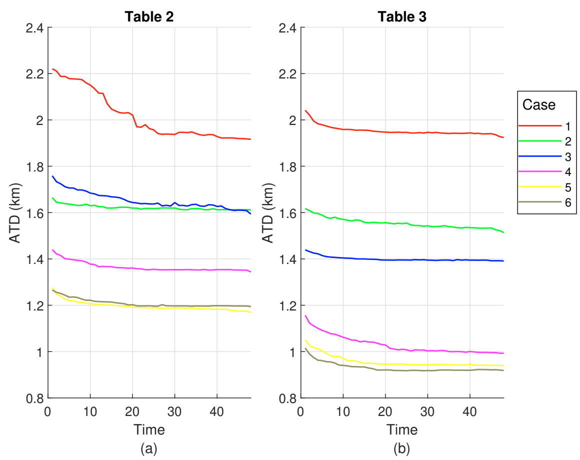

Fig. 5. Evolution of ATD (km) when using the Bayes temporal reasoning (a) scenarios of Table 2 using the maximum residual approach (b) scenarios of Table 3 using the proposed method

As remarked, the positioning of the pressure sensors in the network affects the results dramatically. Therefore, a pre-analysis of the sensor placement, setting the best nodes to contain sensors and the best node to be the clustering centroids, can improve the results illustrated.

4. CONCLUSION

A new full data-driven method to leak localization problem in WDN based on distance clustering in association with the residual analysis distance of pressure sensor has been presented in this study. The proposed approach has been explained, and an example is presented using the Modena Network simplified version of the real WDN as a case study.

The distance clustering approach has been introduced using the Euclidean distance with the centroids set to be the pressures sensor's location and additional q strategical nodes in the network. An extra data collection needs to be done in the real WDN, simulating a leak event in the network in each location set to be a cluster center. Following the leak localization approach founded in analyzing the residual correlation simulated in the leak events and the actual residual measurements.

A simple leak localization approach has been demonstrated that utilizes only the residual of pressure measurement, applying the maximum residual to set the highest chance of clustering has a fault, to serve as a basis for comparison with the method explained. The case study applying both approaches demonstrates that the proposed method has improved the ATD compared to the maximum residual approach.

In this work, we see the sensors' placement may affect the performance of the leak localization apporach. Hence, in the future, we plan to study sensor and centroid optimal location to improve the result of the method.

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