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ANALYSIS OF ONLINE PRESSURE FOR RESILIENCE PHASE CHARACTERISATION OF LEAKAGE/BURST EVENTS

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Abstract

While operating a water distribution network (WDN), it is essential to prepare the system to face with intentional (*e.g.*, cyber-physical attack) or unintentional (*e.g.*, pipe leakage/burst) adverse events or other drivers such as the effects of climate change. Increasing the network's preparedness to deal with anomalous events is an effective manner to improve the system's resilience, reducing the negative impacts of events. In this paper, leakage/burst events, and ordinary network operation, are captured by both sensors and expert knowledge in a WDN in Spain. Event-driven and data-driven approaches are used to characterise the system behaviour, in particular when it is operating under the effects of an anomalous event, based on the resilience phases (*i.e.*, absorptive, adaptive, restorative) for the collected dataset. The relationship of clustering pressure head time series based on their potential state in a particular resilience phase, in three random cases of short-term leakage events, was explored. This paper focuses on capturing the behaviour of the system, through the exploration of the hydraulic parameters of WDNs (in particular the pressure head) before, during, and after a leakage event, by means of a spatial-temporal analysis. It was observed that the network behaviour could be categorised into 1) ordinary operation and 2) during the event, which would allow to characterise the system behaviour when influenced by leakage/burst event and also explore its adaptability to resilience phases. The results show that it is possible to extract relevant patterns (*i.e.*, feature maps) and generate an anomaly indicator from the pressure head heatmaps that facilitate the characterisation of anomalous events for WDNs.

Keywords
Three phases of resilience, Spatial-temporal analysis, Pressure sensors, Water distribution network, Preparedness, Protection of critical infrastructures, Intelligent data analysis, Leakage/burst events.

1 INTRODUCTION

Leakage and bursts are commonly known as minor (less severe) but more frequent than events such as flooding and cyber-physical attacks, widely known to be significant (more powerful) but less frequent events in water distribution networks (WDNs). Apart from these, the former category can intensify the latter's effects and make them more intense. One example is the possibility of a leakage/burst to increase the chance of causing a flood [1]. As a potential consequence of the effects of climate change, water shortage can become more severe if it leaks through the system's pipes. In addition, leakage points are potential sources of pollutant intrusion into the network and can increase the severity of flooding impacts. The balance between input and output water gets is further disturbed by wasted water, known as non-revenue water, from leakage points. Therefore, it is worth making efforts to prevent minor events to avoid more serious outcomes.

As mentioned, WDNs need to be prepared for such events not only to prevent their direct negative impacts on system objectives, but also to prevent significant events from having a wider impact. It should not be overlooked that leakage can cause flooding if they are not dealt with in time [2]. One manner to minimise the potential negative impacts due to the occurrence of these events is to improve the network's resilience through possible interventions (*e.g.*,) that can help restore system performance to near pre-event levels [3].

A WDN can performs at different levels (*e.g.*, ordinary, degraded, or failed operation) when it is under the influence of disruptive conditions, which can lead to a reduction in the network efficiency [3, 4]. In particular, whether the system as a whole or partially is working at degraded or failure performance levels, it can be increased by improving the resilience of the system. System resilience is commonly referred as the ability of the system to withstand disturbances, the ability to adapt more easily to changing conditions, and the ability to recover the system performance at the level prior to the occurrence of the anomalous event [5, 6, 7, 8]. Improving network preparedness for abnormal events is of great interest to water utilities as an effective manner to improve system resilience [9].

In this paper, we propose a strategy to characterise the behaviour of the network (in terms of pressure values) during both ordinary operation and event occurrence taking into account the resilience phases (*i.e.*, absorptive, adaptive, restorative), which will help improve the preparedness of networks.

2 PROPOSED FRAMEWORK

When the anomalous event (in this study leak/burst event) occurs and depending on the relevance of the affected component in the system, the network's performance may be lead in a decrease. In this sense, the start of the event may not be detected until the changes in the control parameters are representative or until, in the case of leak/burst events, it becomes visible on the surface. Given the uncertainty in the start time of this type of event, the start time of the event is assumed as the time at which the anomaly is detected. The end time of the event is referred to the time in which an acceptable or ordinary/regular level of performance is achieved for the system after the event occurs. The start and end times deploy a box whose area can represents the total resilience among the event. The capacities of system during an event can be divided to absorptive, adaptive and restorative capacities [10, 11]. These capacities are contained in boxed demarcated by no actions (absorptive capacity) or actions (adaptive and restorative) taken to remedy/mitigate the effects of the event (if any). However, some studies refer the adaptive and restorative capacity to an unique capacity (restorative). Due to both the nature of the system's behaviour and the actions to be implemented in each phase, in this work we refer to the three capacities of the system as each of the phases of the event. Resilience function captures the effect of the event in absorptive phase, adapts the system to the new temporarily disrupted conditions in the adaptative phase, and restores the system's performance in restorative phase if the adaptive capacity is not efficient [10]. Studies showed that one method to increase the resilience of critical infrastructures is to improve the resilience for each phase [12]. Figure 1 is a typical representation of changes in network performance in regular operation and during an event, considering resilience phases.

A potential action deployed in the system can significantly enhance network performance (see Figure 1, green area). For the case of leakage, isolation of the affected area is a temporary (palliative) action to prevent further pressure loss and volume of wasted water. Afterward, repairing the leakage or replacing the damaged component (e.g., pipe) are potential restorative actions. One means of improving preparedness is to capture the behaviour of the network during both ordinary operation and event occurrence. Identifying the network's behaviour to events could facilitate the decision-making process by supporting the implementation of preventive/responsive solutions to keep the network's resilience close to acceptable levels when such events occur.

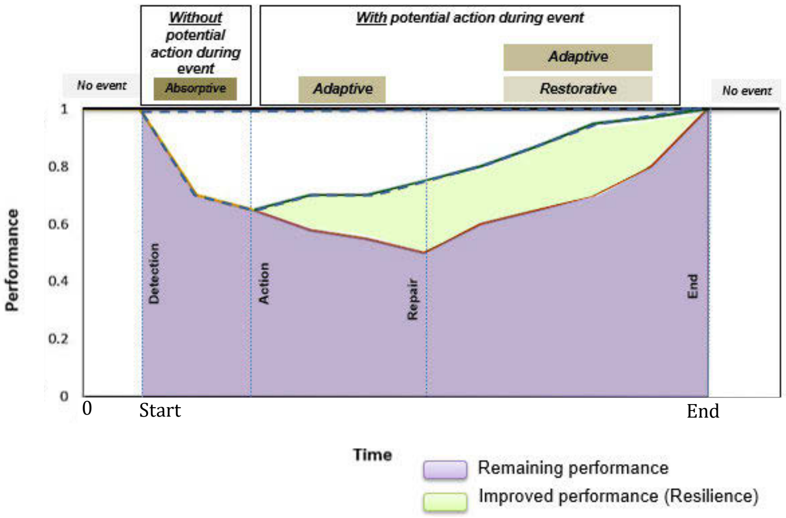

Figure 1. Resilience curve for a disruptive event in WDNs.

The purpose of this paper is to capture the behavioural patterns of the network under normal condition, and during leakage event (pre and post actions) at the pressure heads (which will be called pressure in this paper) through spatial-temporal analysis. It is proposed that extraction of these patterns will allow the network to adapt to each resilience phase. Three random cases of short-term leakage events were selected to implement how effective is the recognition of patterns of pressure values in the whole network.

3 CASE STUDY

In this section, a real WDN, working under abnormal/degraded operating conditions has been selected to apply the proposed methodology. The reason for choosing this network was the availability of data from both sensors and company records by operators, including information on the leak detection and repair process. This medium-size utility network (Figure 2) is located in Spain. The model consists of 146 demand nodes, each node responsible for delivering water to a large number of consumers (mainly houses), 212 links (40 km), two pumping stations, two reservoirs, and four tanks. There were 23 pressure sensors (recording pressure values every 15 minutes) in the network with different working conditions at different times (Table 1).

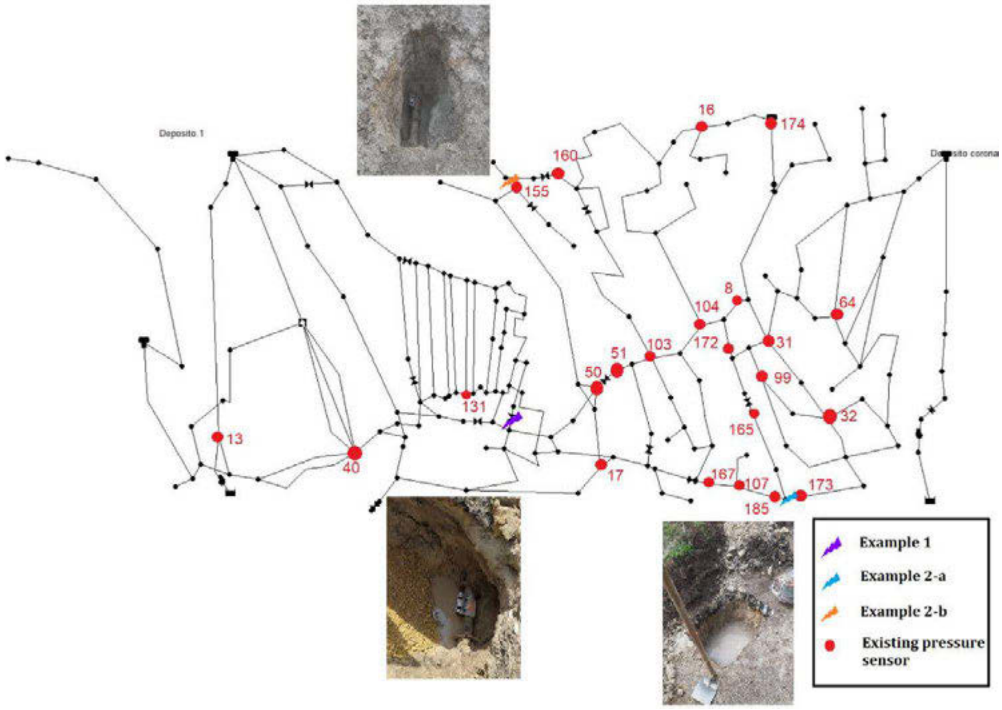

Figure 2. Case study network with the location of pressure sensors.

Table 1. Status of pressure sensors. No operative -, and Operative ✔ .

Number	ID	Working status		Number	ID	Working status		Number	ID	Working status	
		Example 1	Example 2			Example 1	Example 2			Example 1	Example 2
1	103	-	-	9	165	-	-	17	173	-	-
2	104	✔	✔	10	17	✔	✔	18	167	-	-
3	185	✔	✔	11	155	✔	✔	19	32	-	-
4	16	✔	✔	12	131	✔	✔	20	99	-	-
5	50	✔	✔	13	160	-	✔	21	64	-	-
6	51	✔	✔	14	174	-	-	22	13	-	-
7	172	✔	✔	15	107	✔	✔	23	31	-	-
8	8	✔	✔	16	40	-	✔				

4 DATASET

The dataset includes: 1) historical data from pressure sensors (dataset 1) and 2) utility expert knowledge (dataset 2), including information about the type of leakage, causes, detecting and repairing each leakage, among others. Analysis of leakage was initially conducted through a data-driven method from sensors' time-series data. Then leakages were temporally labelled by an event-driven approach from the records by utility expert knowledge. The removal of outliers in the data was conducted by means of manual inspection and in collaboration with the system operator.

MATLAB's interp2 function was used to construct the pressure matrix, P (of size $m \times n$), for each evaluated time. Where m with $i = 1, \dots, m$ and n with $j = 1, \dots, n$ represent the resolution for the x-axis and y-axis of the spatial coordinates, respectively. The matrix P was built from the nodes with sensors that were operational at the specific time evaluated. A homogeneous mesh was created for both the x and y coordinates. Each of these meshes contained all the nodes of the network. These meshes were used to infer the spatial relationship between the different available sensors presented in P. As a result of multiple iterations, the selected mesh size corresponded to a 100×100 resolution mesh. It should be mentioned that the matrix P can be easily visualised through the use of heatmaps (and this is done as a visual example in some sections below). However, all the calculations are conducted directly in the P matrix for each evaluated time.

A preliminary temporal analysis of the pressures, for the sensors, available in dataset 1 was conducted in order to contrast the information recorded in dataset 2. In a case where the leakage was not observable through Dataset 1, the second dataset source was used to track the location and the information that was not possible to get from sensors, such as time of detection, visit, isolation, repair, and corresponding data. Taking advantage of two data resources, we recognised resilience phases for each of the examples explained in the next section.

5 PRELIMINARY RESULTS

The first example corresponds to a leakage event recorded on 22 August 2021. The location of the leakage point is presented in Figure 2 (violet lightning flash in the bottom middle). Figure 3 shows changes in pressure values recorded by sensors from 20 August to 24 August 2021. Figure 3 shows the effect of the leak event on the pressure values, which was recorded in most of the sensors that were working at that time. This information was confirmed by the utility operator who conducted interviews. The operators' records show that people observation reported the leakage area one day before intervention to solve the problem. As the leak was not repaired on the same day as the detection, further pressure drops occurred and affected almost the entire network at around 7:30-10 am on 23 August (Figure 3). This result shows the crucial role of resilience phases in avoiding severe impacts in time.

The second example includes two overlapping leakage events, which were reported on 24 and 25 October 2021 (locations are shown in Figure 2, blue and orange lightning flashes in the bottom right, and top middle, respectively). Example 2-a was a leakage reported 24 hours before the visit, and the leakage of Example 2-b was reported 6 hours before visiting. Oscillating and high pressure caused leakages in two parts of the network; both were seen, isolated, and repaired on 25 October. This example is a more complex case, compared to Example 1, as the behaviour of the network could be affected by overlapping events, which in some cases might need a more advanced type of analysis. The interesting point about this example is that it is almost impossible to track the first leakage through sensors' records. The pressure curves extracted from most sensors before, during, and after leakage, shown in Figure 4, confirm this.

The pressure drops of sensors 155, 160, and 16 for Example 2-b indicate that the effect of the leak in the surrounding area occurs over a short period. This pressure drop could not have been more severe as the isolation action was conducted quickly and prevented the rest of the network from being affected. But in some cases, isolation might reduce pressure in some areas based on the network's characteristics. It is necessary to mention that the effect of demand on pressure values has been ignored. In both cases observed, the pressure variations due to leakage were much larger than the demand fluctuations.

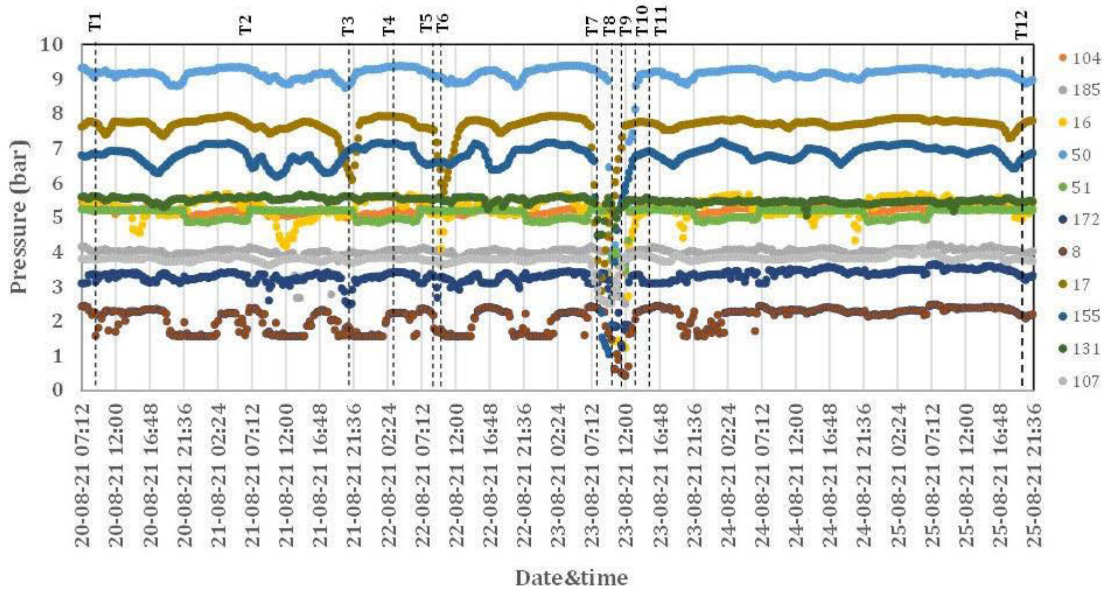

Figure 3. Pressure history from the working sensors for Example 1

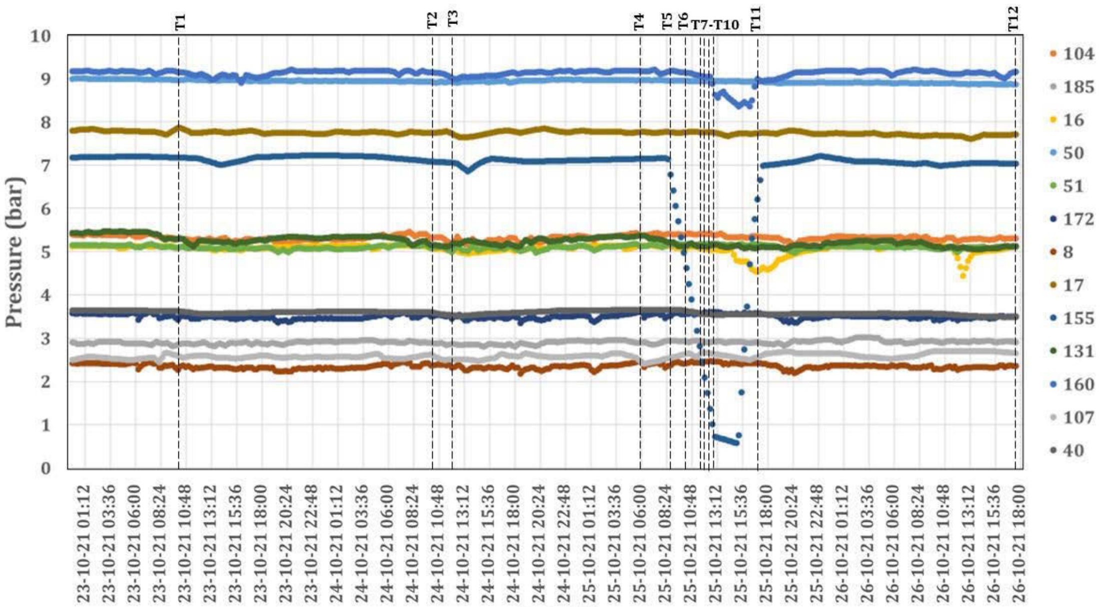

Figure 4. Pressure history from the working sensors for Example 2.

The spatial-temporal distribution of pressure for a selection of 12 timesteps from 20 to 25 August in Example 1 (Figure 5) and from 22 to 26 October in Example 2 (Figure 6) reflects the changes in pressures over time at different points of the network. It should be noted that 12 timesteps were selected to be representative of the leakage behaviour of the network in terms of pressure. In this sense, all the data of every 15-minute record was involved in the calculations. Timesteps were chosen according to historical data records and modified with interviews with the operator. Details are provided in Table 2 and Table 3.

Table 2. Timesteps for Example 1

ID	Date/Time	Description	Resilience phase
T1	20/08/2021 09:00	Time before the start of leakage	Pre-event
T2	21/08/2021 07:00	Random time	Pre-event
T3	21/08/2021 21:15	Pressure drop time	Pre-event
T4	22/08/2021 03:00	Pressure drop time	Pre-event
T5	22/08/2021 09:00	Detection time	Start
T6	22/08/2021 10:15	Random time	Absorptive
T7	23/08/2021 08:00	Visit time	Absorptive
T8	23/08/2021 10:00	Isolation time	Adaptive
T9	23/08/2021 11:00	Repair time	Restorative
T10	23/08/2021 13:00	End of leakage	End
T11	23/08/2021 15:00	A few hours later	Post-event
T12	25/08/2021 20:30	Hours after event	Post-event

Table 3. Timesteps for Example 2

ID	Date/Time	Example 2-a		Example 2-b	
		Description	Resilience phase	Description	Resilience phase
T1	23/10/2021 10:00	Time before the start of leakage	Pre-event	Time before the start of leakage	Pre-event
T2	24/10/2021 10:00	Detection time	Start	Random time	Pre-event
T3	24/10/2021 12:00	Random time	Absorptive	Random time	Pre-event
T4	25/10/2021 06:00	Random time	Absorptive	Detection time	Start
T5	25/10/2021 08:30	Random time	Absorptive	Start of pressure drop time	Absorptive
T6	25/10/2021 10:00	Visit time	Absorptive	Random time	Absorptive
T7	25/10/2021 11:30	Random time	Absorptive	Visit time	Absorptive
T8	25/10/2021 12:00	Isolation time	Adaptive	Isolation time	Adaptive
T9	25/10/2021 12:30	Repair time	Restorative	Random time	Adaptive
T10	25/10/2021 13:00	End of leakage	End	Repair time	Restorative
T11	25/10/2021 17:30	A few hours later	Post-event	End of leakage	End
T12	26/10/2021 17:30	Hours after event	Post-event	Hours after event	Post-event

The changes in the behaviour of the network as a function of the values of pressure (shown in Figure 5 for the first leak example and Figure 6 for the second leak example) can be obtained in the specific parts of the network in the effective times. The pressure maps show that changes in pressure are around the affected area and in the areas that have strong dependencies to this point.

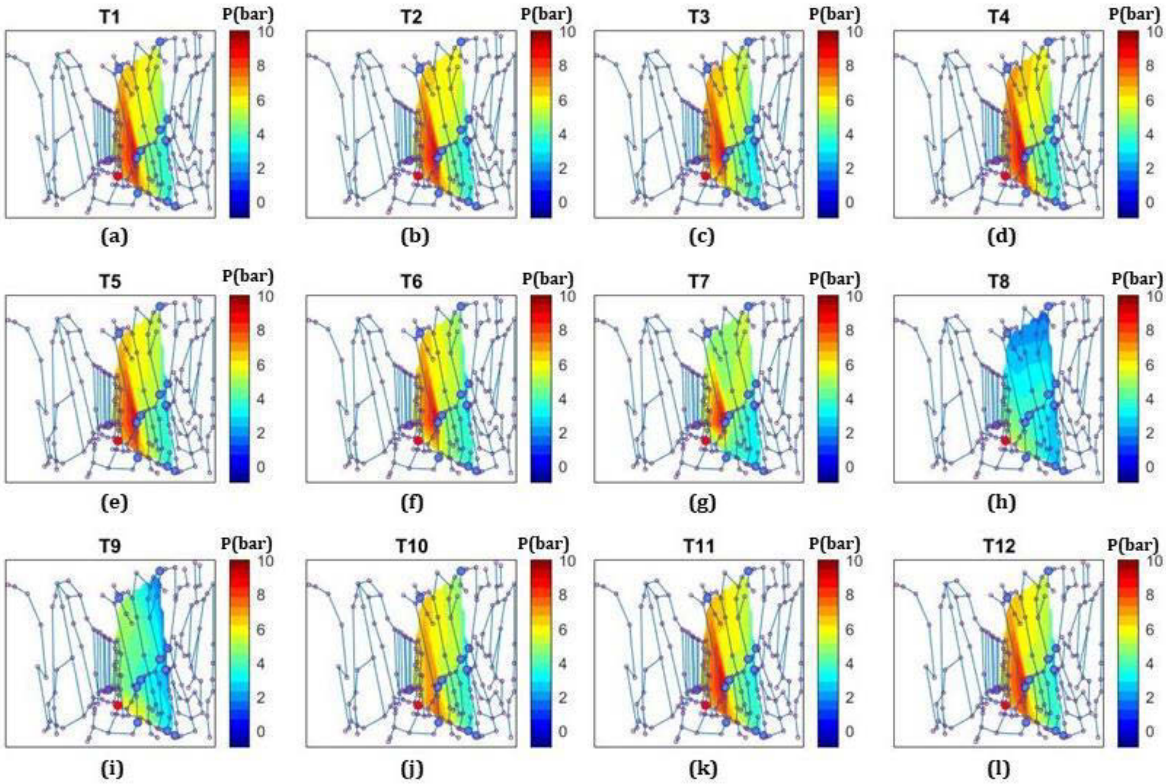

Figure 5. Spatial-temporal distribution of pressure for Example 1. (a)-(d); before, (e)-(j) during, and (k)-(l) after the leakage event.

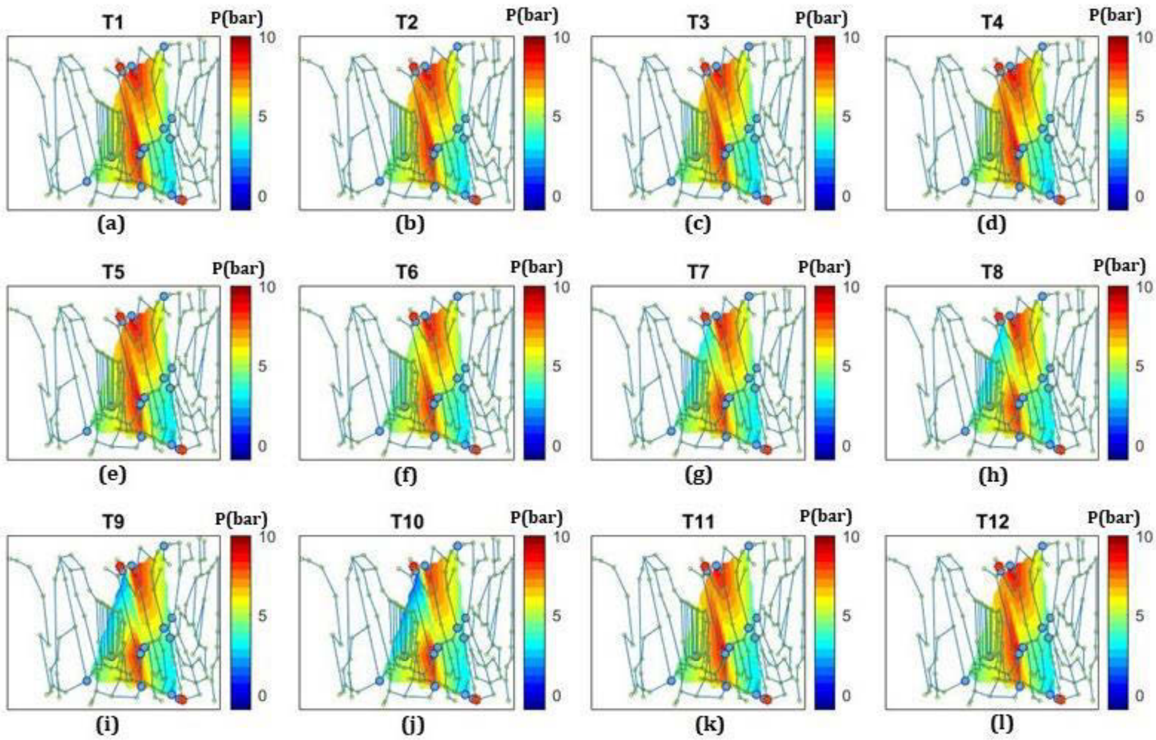

Figure 6. Spatial-temporal distribution of pressure for Example 2-a. (a); before, (b)-(j) during, and (k)-(l) after the leakage, and Example 2-b. (a)-(c); before, (d)-(k) during, and (l) after the leakage

6 ANOMALY INDICATOR

According to the observations, it is possible to construct an anomaly indicator based on pressure to characterise the leakage/burst events. To better understand the pressure response of the network leakage, a matrix of maximum pressure was created for the given period according to equation (1) as a basis for the anomaly indicator. The highest pressure values are assumed to be desired. The maximum pressure map is shown in Figure 7. This map does not correspond to a single timestep, but represents the maximum pressure achieved for each element of P during the study period. Comparing Figure 7a and Figure 7b, we observe that in Example 1, maximum pressure distribution is less abrupt (smoother) than in Example 2. These different trends underline the importance of considering the maximum pressure values as a basis for the analysis of pattern extraction.

$$P_{max_{i,j}} = \max\left(p_{t_{1\,i,j}}, p_{t_{2\,i,j}}, \ldots, p_{t_{12\,i,j}}\right) \tag{1}$$

where, $p_{t_{i,j}}$ is the pressure value in the i_{th} row and j_{th} column in the matrix at time t. It should be mentioned that the process includes all the timesteps that were set every 15 minutes.

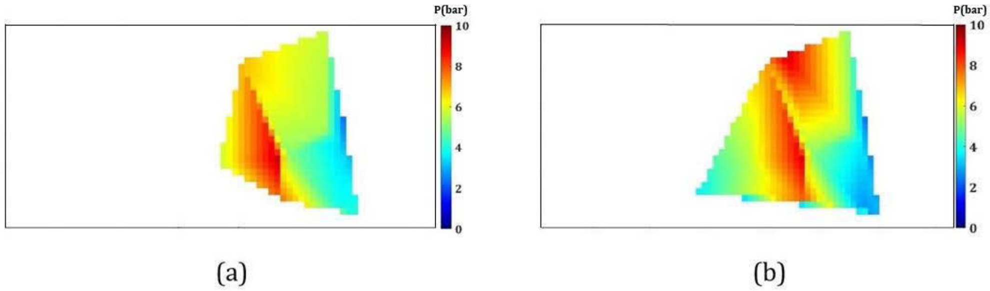

Figure 7. Maximum pressure during the given period for (a) Example 1 and (b) Example 2.

The maps in Figure 7 facilitate the analysis of the behaviour of the network via an anomaly indicator (equation 2) in terms of pressure. The relative pressure resulting from dividing the pressure by the maximum pressure (individually for each element of P) over the whole period was calculated for all the points in the network. Figure 8 and Figure 9 show the spatial-temporal representation of the relative pressure maps for the selected timesteps. These values range between 0 and 1.

$$R_{t_{i,j}} = \frac{P_{t_{i,j}}}{P_{max_{i,j}}} \tag{2}$$

where, $R_{t_{i,j}}$ refers to anomaly indicator in the i-th row and j-th column in the matrix at time t.

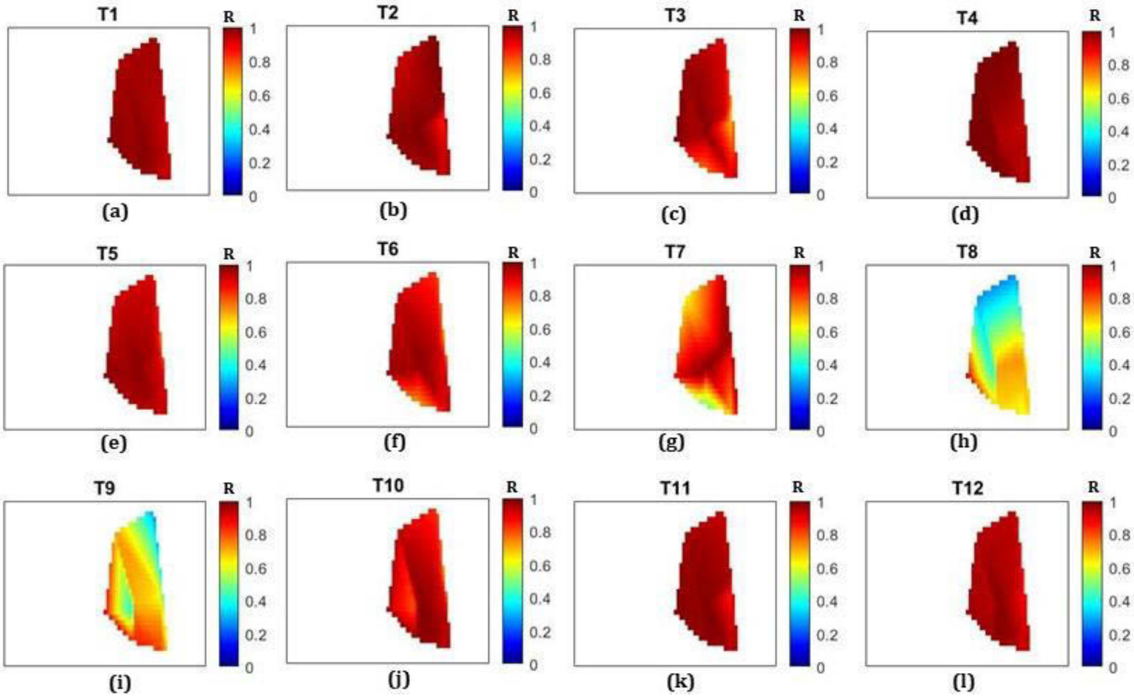

Figure 8. Spatial-temporal distribution of relative pressure for the Example 1. (a)-(d); before, (e)-(j) during, and (k)-(l) after the leakage.

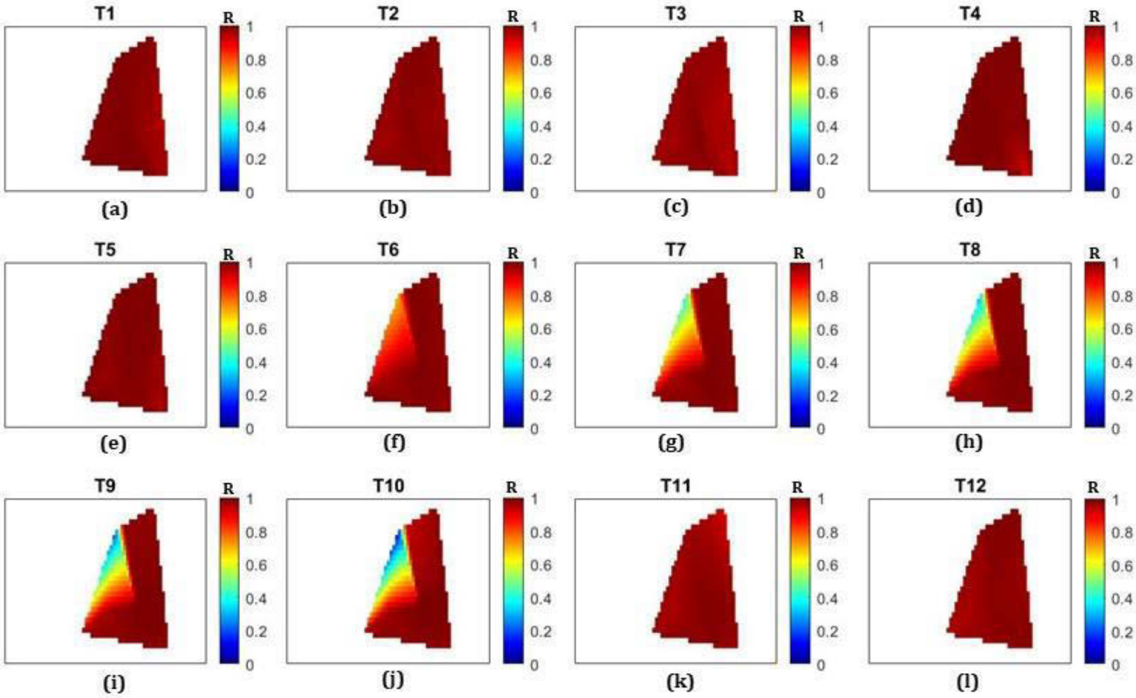

Figure 9. Spatial-temporal distribution of relative pressure for the Example 2.

$$R_t = \frac{\sum_{j=1}^{n} \sum_{i=1}^{m} R_{t_{i,j}}}{m \times n} \tag{3}$$

where R_t is the anomaly indicator, representative of pressure behaviour of the entire network (study area) at timestep t.

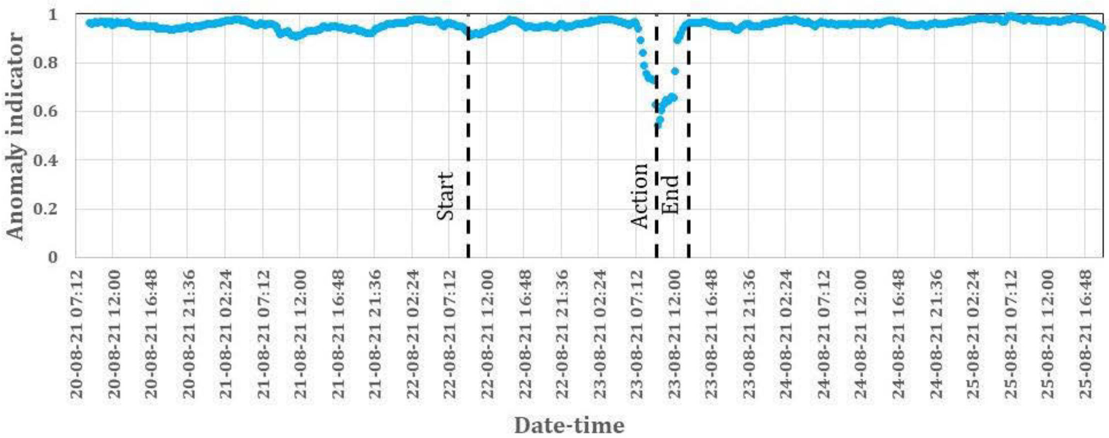

Figure 10. Anomaly indicator curve for the Example 1.

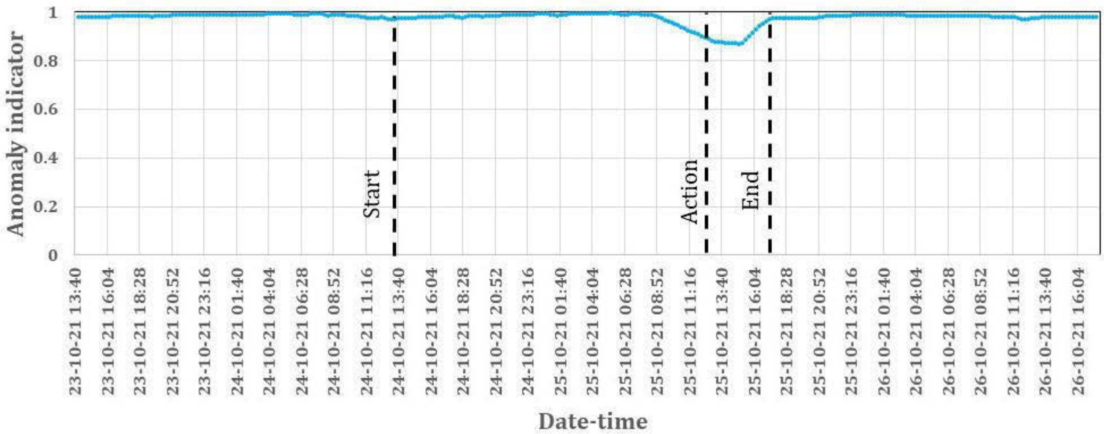

Figure 11. Anomaly indicator curve for Example 2.

Analysis of Example 1. As we can see in Figure 8, the leak becomes detectable at T7 (drops in pressure values), then changed significantly (huge reduction in pressures) in the adaptive and restorative phases, and gradually returns to normal operation (leakage was fully repaired). The classification of this behaviour also represents the phases of resilience. In other words, the behaviour of the network is classified as follow: no leakage, during the leakage with no action (absorptive phase), and with action (adaptive/restorative phases).

Analysis of Example 2. Observing the maps in Figure 8, the first overlapping leakage (Example 2-a) is not considerable, probably due to the more significant impacts of the second overlapping leakage (Example 2-b) in the pressure of the whole network. For this reason, the latter will have the central role in this example. Focusing on Example2-b, the network behaviour started to change significantly (drops in pressure values) at T6 and T7, and pressures gradually drop in the adaptive and restorative phases (T8 to T10), and return to the normal operating condition (T11 and T12). As with Example 1, for Example 2 the behaviour of the network is classified as follow: no leakage, during the leakage with no action (absorptive phase), and with action (adaptive/restorative phases).

The anomality indicator curves for both examples are shown in Figure 10 and Figure 11. These values result from the average relative pressure values of the whole network for each time. This curve is at its highest level during the regular operation (close to or equal to 1) and at its lowest level, when the pressure drop is at its lowest state. These curves can be representative of resilience curves. So, these curves allow the water utility to characterise the network in terms of its resilience phase and to better prepare for leakage by focusing on the points where there are gaps. For instance, in Example 1, the impact of leakage (both before and after action) can be seen in more areas of the network than in Example 2. This analysis shows which parts of the network are most sensitive to leakage according to high-pressure zones and the relevant changes in pressure in some specific regions. Comparing the adaptive/restorative phases for the two examples (shown in Figure 10 and Figure 11), it can be concluded that being prepared to respond to the event as quickly as possible would avoid huge pressure drops.

7 CONCLUSIONS

In this paper, we explored a dataset including two examples of leakage events and the ordinary operation of a real WDN in Spain. The data was provided by sensor records and expert knowledge. The resilience phases (i.e., absorptive, adaptive, restorative) within the collected dataset were rebuilt using event-driven and data-driven approaches. The results illustrated the importance of clustering the pressure head time series according to the phases of resilience. Capturing the behaviour of the pressure head as a determining hydraulic parameter before, during, and after the leakage was achieved by means of a spatial-temporal analysis. The results were promising, recognising the patterns of pressure head values throughout the network. It was observed that the network behaviour could be categorised into 1) ordinary operation and 2) during the event, which would allow to characterise the system behaviour when influenced by leakage/burst event and also explore its adaptability to resilience phases.

The approach was based on the available information from sensors and expert knowledge in a WDN. One of the benefits of this form of analysis is that if any sensor fails or is relocated, it is still possible to identify an abnormal incident in the network by spatial-temporal analysis. It means that the reflection of an event would be independent of only one specific sensor and will be obtained through the extracted patterns. In other words, events can be traced even when there is a lack of either historical data from sensors or records of utility experts. On the other hand, the information given by sensors is useful for checking if the analysis is correct. If the history of an event is missed, temporal-spatial analysis of pressures (and other parameters) can be practical.

The output of this preliminary study would be advantageous to develop research studies in many aspects, such as:

- The ability to extract relevant patterns (i.e., feature maps) from the preliminary results of the pressure head heatmaps allows for appropriate characterisation of these events.
- Increase the capacity of the network to learn from events by anticipating the potential reaction of the network (in this study, pressure head change) to a similar type of event.
- Pressure distribution maps during an event make it possible to recognise the critical areas in the network to a specific parameter before and after action. Many factors can be considered to make the best decisions to improve the preparedness of WDN. For example, a delay in pipe isolation (as an adaptive action) might negatively impact the pressure of the entire network depending on the affected part. Developing this approach will help identify the potential landmarks, the following purpose for our future study.
- This type of analysis with spatial-temporal dimension can be improved by including other hydraulic/non-hydraulic parameters such as flow, weather temperature, and factors causing the leakage (for example, pipe age, human/environmental interventions., etc.).
- The anomaly indicator could serve as a basis for further characterisation processes and support the decision-making process in terms of the implementation/deployment of actions likely to mitigate the effects of the event. In future research, we will investigate how to anticipate future events by increasing the network preparedness, being proactive in preventing the occurrence of an event, and/or responding more quickly to events.
- Intelligent data analysis tools are recommended for a comprehensive study of influencing parameters for this approach, taking into account diversities in the event types, causes of events, network types., etc.

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