A Pragmatic Approach for Leakage Detection Based on the Analysis of Observed Data and Hydraulic Simulations

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ABSTRACT

Introduction

Leakages in water distribution systems are an important environmental and economic issue and of major interest for water utilities. As a matter of fact, leakages can lead to economic losses, insufficient pressure and potential health risk [1]. From an operational standpoint, several methods aimed at detecting and localising leakages have been developed, consisting of data collection and their processing by means of different numerical approaches. Clearly, the aforementioned approaches for leak detection differ according with the kind of data collected: for example, in case of acoustic data, leakages can be directly located in field through leak noise loggers [2], while in case of pressure and flow data, leakages can be located by applying physical based methods such as inverse transient analysis [3] or a data-driven approach such as artificial neural networks [4].
Within this framework, the BattLeDIM 2020 is aimed at comparing different methods in their ability to detect and isolating various types of break and burst events occurred in a water distribution network (named L-Town) over one year. To this end, a hydraulic model of the water distribution system, including nominal base demands and weekly demand patterns are provided. Furthermore, pressure, flow, and demand data collected at several points within the network for two years, 2018 and 2019, are available. Finally, a historical dataset including information about leakages fixed in year 2018 is given.
In this work, a pragmatic approach is adopted to detect and localize leakage events occurred in L-Town in 2019. The approach is based on model calibration and the comparison between the observed pressure (i.e. pressure data recorded by the sensors placed on the network) and the pressure values obtained through the hydraulic simulation model. The approach adopted allows to locate leakages by minimizing the error given by the difference between the observed and the simulated pressure, thus enabling to define the evolution of the network leakage status in 2019.

Methods and Materials

The L-Town water distribution system has a total length of 42.6 km and is composed of two different DMAs (namely "Area A+B" and "Area C"). Specifically, the L-Town water utility owns an EPANET model of the water distribution system, including nominal base demands and weekly demand patterns, and monitors the network through a system of 33 pressure sensors and 3 flow sensors located within the system and 82 automated meters recording data at five-minute resolution located only in Area C. The corresponding, pressure, flow, and demand data are available for both years 2018 and 2019.
The developed, pragmatic approach for leakage detection consists of the use of the aforementioned data to: a) calibrate the model, in order to have a realistic representation of the hydraulic behaviour of the network; b) identify the total number of leakage occurred, their entity and period of occurrence and localize the leakage themselves by comparing the observed data against the results provided by the calibrated model.
Operatively, the model calibration phase was led by considering the 2018 dataset and followed the steps listed below:

1. evaluation of yearly demand pattern with seasonal variation;

2. creation of two separate hydraulic simulation models, one for Area A+B and one for Area C;
3. evaluation of the yearly leakage pattern for Area A+B and Area C;
4. calibration of Area A+B and Area C hydraulic simulation models.

The subsequent leakage detection phase was led by using the calibrated models and the 2019 dataset, following the steps listed below:

1. evaluation of the yearly leakage pattern for Area A+B and Area C;
2. identification of leakage start time and the pipe affected by the leakage.

Regarding the model calibration phase, a first step included the evaluation of yearly demand patterns with a seasonal variation, given that the water distribution system is located in the Northern hemisphere, thus water demand is expected to be higher at summer and lower at winter. From an operational standpoint, a set of 52 weekly demand multipliers was obtained based on water demand data measured by the automated meters placed in Area C, i.e. by calculating the mean water demand of the DMA for each week of 2018 and dividing it by the yearly mean water demand of the DMA. The 52 multipliers obtained were used to modulate the weekly demand patterns already included in the EPANET model for both Area A+B and Area C. Secondly, the EPANET hydraulic simulation model provided by the water utility was divided in two independent models, relying on the hydraulic discontinuity given by the tank. A model including only Area A+B was created, replacing the pumping station with a node, and assigning it an additional demand pattern based on the flow pumped. Besides, a model including only Area C was created, replacing the tank with a reservoir whose head pattern was calculated based on the observed water level within the tank. Thirdly, the yearly pattern of leakages was calculated for both Area A+B and Area C, by subtracting the total water demand of each area from the inflow of that area at each time step. It was observed that the obtained pattern included periods with almost no leakages, sudden increases (indicating bursts), slow increases (indicating increasing breaks) and abrupt decreases (indicating repairs), as confirmed by the information included in the 2018 leakage report. Fourthly, focusing on the periods without leakages, the model was calibrated by comparing the observed pressure and flow values against the ones resulting from the hydraulic simulation model. The observed inflows were compared against the simulated ones as well, in order not to alter the inflow contribution given by the reservoirs. Regarding pressures, the differences between observed and simulated data were minimized by adjusting roughness and diameter of some pipes. Specifically, the roughness of pipes with diameter of 200mm and 150mm was increased and the diameter of five pipes was increased from 150mm to 160mm in Area A+B, while it was not necessary to calibrate pipes roughness and diameter in Area C.
The calibrated EPANET models were then used to detect year 2019 leakages in space and time. The yearly time series of the leakage flows was calculated for both models, by subtracting the total water demand time series of each area from the measured inflow time series. The number of leakages (and repairs) occurred in 2019 was obtained through the identification with engineering judgment of the main positive (and negative) variations in the yearly time series of the leakage flows. Indeed, for each leakage, a time interval in which it kept steady or constantly increased was visually identified. The spatial localization and exact starting time were then defined in the following way.
The spatial localization, i.e. the detection of the pipe affected by the leakage, was led through an enumerative approach. Given the entity of the leakage to locate and its corresponding period of occurrence, all the network pipes were considered in turn. For each pipe, half of the leakage entity was assigned to the base demand of the two adjacent nodes and an error (E) was assessed as expressed in equation (1):

$$E = \left(\sum_{j=1}^{m} \sqrt{\frac{\sum_{i=1}^{n} \left(p_{sim,i}^{j} - p_{i}^{j} \right)^2}{n}} \right) \Big/ m \qquad (1)$$

In the above equation, $p_{sim,i}^{j}$ is the pressure simulated in node j at time i, p_i^j is the pressure observed in node j at time i, n is the length of the selected time period (i.e. the abovementioned period of leakage occurrence) and m is the number of sensors placed in the network ($n = 30$ and $n = 3$ for Area A+B and Area C, respectively). The leakage was then located in the pipe related to the minimum value of E.

As far as the leakage start time is concerned, two different approaches were adopted based on the kind of leakage. In case of bursts, the start time was identified by analysing the 2019 leakage pattern and selecting the instant of abrupt increase. In case of leakages including a slower evolution, the start time was obtained iteratively, by modelling leakage development and growth in the EPANET model and comparing the simulated and the observed pressure values, as in the case of leakage spatial localisation.

Results and Discussion

The application of the pragmatic approach for leakage spatial and temporal detection allowed to obtain the evolution of the L-Town leakage status in 2019. Specifically, the ID of pipes affected by leakages and the start time of each leakage are shown in Table 1, where leakages are marked with letters "ab" if detected in Area A+B and letter "c" if observed in Area C. In addition, Figure 2 shows the map of L-Town water distribution system, where all the detected leakages and their locations are marked in red.

Given the very nature of the chosen approach for leakage detection, an optimal solution was always obtained in terms of spatial localisation, that is the pipe related to the minimum error in terms of difference between simulated and observed pressure values. However, it is worth noting that the "leakage history" was built gradually and iteratively, sometimes by also considering the pipelines adjacent to the optimal one, as they often presented an error that was close to the lowest one. Thus, especially in the case of more than one leakage occurring simultaneously, several scenarios were conducted by taking the adjacent pipes into account and the history related to the global lowest error was selected in the end.

Leak	Start time	Pipe ID
ab1	15 Jan 2019, 23:10	p523
ab2	24 Jan 2019, 18:45	p826
c1	10 Feb 2019, 12:15	p265
ab3	24 Mar 2019, 14:05	p209
ab4	2 Apr 2019, 21:00	p87
ab5	16 Apr 2019, 00:00	p392
c2	8 Jun 2019, 00:00	p263
ab6	12 Jun 2019, 20:10	p661
ab7	10 Jul 2019, 11:00	p72
ab8	1 Aug 2019, 00:00	p838
ab9	13 Aug 2019, 00:00	p562
ab10	25 Oct 2019, 14:00	p611
ab11	3 Nov 2019, 00:00	p890
ab12	10 Nov 2019, 00:00	p109

Table 1. Leakage report for year 2019

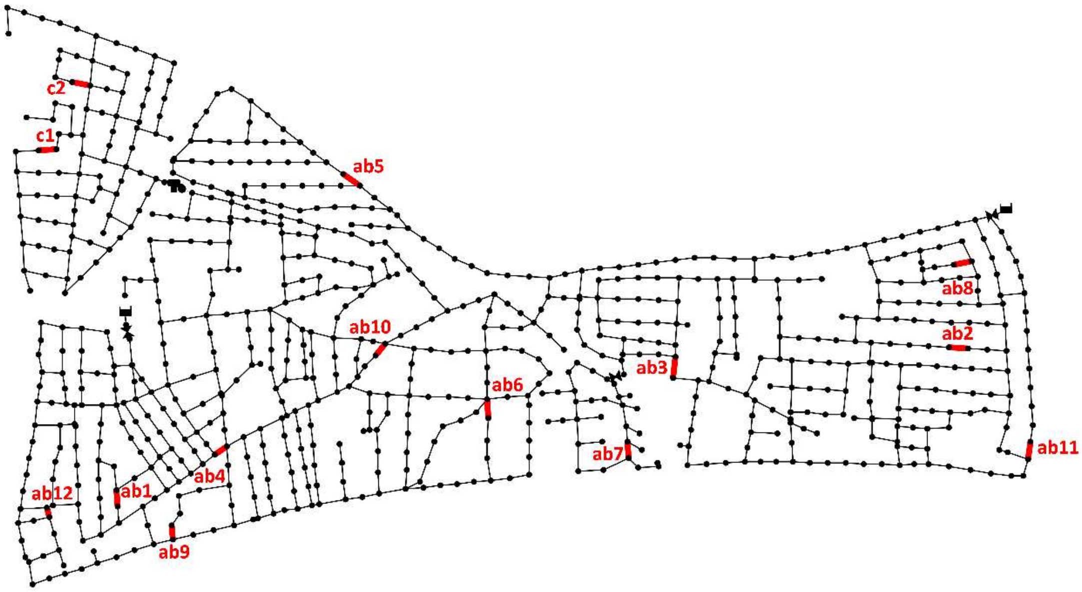

Figure 1. L-Town network map including the detected leakages and their corresponding pipes.

Figure 2 and 3 show the leakage pattern for year 2019 for Area A+B and Area C, respectively. Start and repair time of each leakage are marked in red and green respectively, while residual leakages are marked in black. It is worth noting the presence at the beginning of 2019 of two leakage started in 2018 and unrepaired located one in Area A+B and one in Area C, namely ab0 and c0.

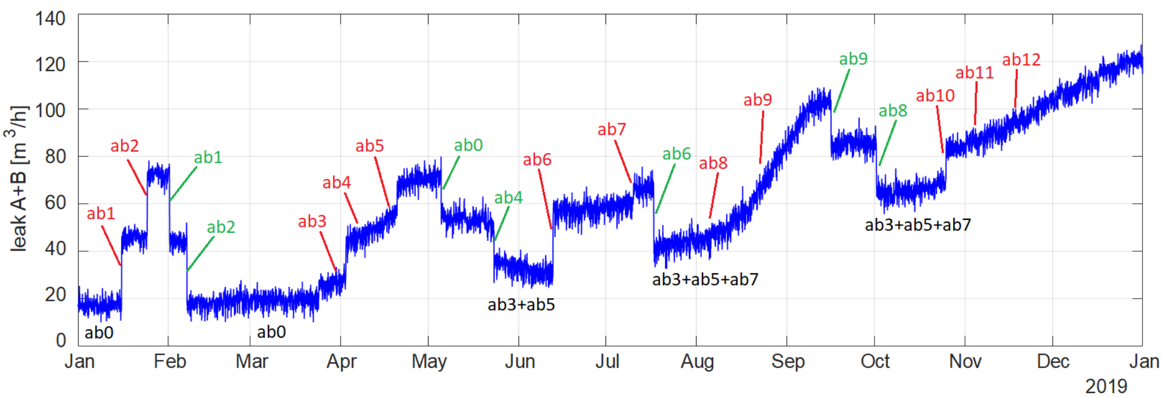

Figure 2. Leakage pattern for Area A+B (at one-hour temporal resolution) for year 2019. Start and repair time of each leakage are marked in red and green respectively, while residual leakages are marked in black.

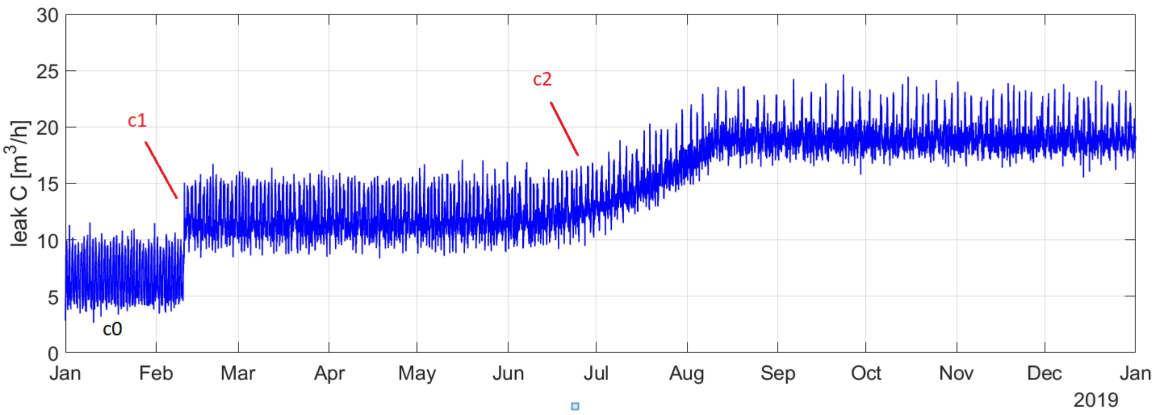

Figure 3. Leakage pattern for Area C (at one-hour temporal resolution) for year 2019. The start time of each leakage is marked in red, while residual leakages are marked in black.

As far as it regards Area A+B, 12 leakages were detected in year 2019. The first two of them (namely ab1 and ab2) occurred over the month of January and were right after repaired, so that only the residual one (i.e. ab0) remained. Between the end of March and April, three additional leakages occurred, (namely ab3, ab4 and ab5). In the subsequent period, one of them (i.e. ab4) and the residual leakage (i.e. ab0) were repaired. Between June and July, two new leakages occurred (namely ab6 and ab7), the first of which was later repaired. In August, two further leakages occurred (namely ab8 and b9), increasing over time along with the other leakages in the network. The hypothesis of only one leakage was excluded because it led to a large difference between the simulated and observed inflows from the reservoirs. Both ab8 and ab9 were repaired within early October. In the last two months of 2019, three additional leakages occurred (namely ab10, ab11 and ab12) and none of them was repaired within the end of the year. The assumption of three separate leakages instead of one was again supported by lower errors, i.e. lower differences between observed and simulated pressures. As far as it regards Area C, two leakages were detected for year 2019: a former burst (i.e. c1) occurred in mid-February, and a latter leakage (i.e. c2) gradually developed over the month of June. None of them was repaired within the end of the year.

Conclusions

The aim of the BattLeDIM 2020 was to detect and localize in space and time the leakages affecting the water distribution network of L-Town over year 2019. A pragmatic approach was used, including the iterative use of the EPANET hydraulic model to assign each leakage to the pipe minimizing the difference between observed and simulated pressure at each sensor. The approach is simple and transparent and it allowed to identify the history of leakages for year 2019 only by relying on data observed at each sensor. However, it is worth noting that the characterization of leakage entity and pattern and the subsequent visual evaluation of the number of leakages significantly depends on the estimated water consumptions, thus an accurate estimation of the water demand patterns, both at daily, weekly and seasonal level is very important. Furthermore, since observed and simulated pressures are compared in order to identify the pipe associated with the lowest error, a well-calibrated hydraulic model is essential to avoid misclassifications.

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Keywords: leakage detection, model calibration, water consumptions.

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SUMMARY

Leakages in water distribution system is an important issue that can led to economic losses for the water utilities, insufficient pressure and potential health risk. Operatively, various methods for leakage detection and localization have been developed based on data collection and the application of numerical models. The BattLeDIM goal is to develop methods to detect and localize leakages occurred over a year in the L-Town network and to compare them in their ability to detect various types of break and burst events in space and time.
In this work, a pragmatic approach is adopted to detect and localize leakage events, based on the analysis of the observed pressures and flows and the use of a hydraulic model of the network. The developed approach consists of a first phase in which the hydraulic model is calibrated in order to have a realistic representation of the hydraulic behaviour of the network. Secondly, the observed inflows and water demands are analysed to obtain the yearly time series of leakage flow and visually identify leakage number, entity and time of occurrence with engineering judgment. Each identified leakage is spatially localised through an enumerative procedure: it is assigned to the extreme nodes of each pipe of the network in turn and the error in terms of sum of differences between observed and simulated pressures at all the sensors is computed. The pipe featuring the lowest error is thus selected. The approach is simple and transparent and it allows to identify the history of leakages occurred only by relying on data observed and the iterative use of the network model.