A high-resolution pressure-driven method for leakage identification and localization in water distribution networks

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ABSTRACT

Water losses are one of the main consequences of infrastructure failures in water distribution networks (WDNs). While background leakages and pipe bursts in well maintained systems generally amount to only 3-7% of the total water supplied, they can account for more than 50% for poorly maintained WDNs worldwide (Puust et al., 2010). Methods that support prompt detection and accurate localization of leakages are crucial to help water utilities implement timely mitigation measures and avoid unnecessary loss of water. Beyond the direct effect on reducing water losses, effective leakage management strategies can avoid revenue losses and other undesired effects, including contaminant infiltration, property damage, and WDN inefficiencies.

Several works in the literature proposed approaches for leakage detection and localization. However, the ongoing digitalization of urban water systems (Makropoulos and Savic, 2019; Stewart et al., 2018), along with the development of distributed sensor networks and improved real-time communication, are fostering the development of a new generation of on-line, data-driven leakage identification methods that process data stored in the supervisory control and data acquisition (SCADA) system in real-time. A lack of studies that comparatively analyze and benchmark different leak identification and localization methods has culminated in the organization of the Battle of the Leakage Detection and Isolation Methods (BattLeDIM 2020; Vrachimis et al., 2019). The BattLeDIM is an international competition organized for the purpose of comparing the performance of different leakage detection and localization methods based on time-to-detection and location accuracy.

This research develops a high-resolution pressure-driven method for leakage identification and localization in WDNs and tests the approach using the benchmark dataset provided as part of the BattLeDIM. Our method is composed of two modules that operate sequentially. The first module performs *leakage event identification*. Our leakage identification algorithm processes the pressure from SCADA data observed at different sensor nodes in a WDN and identifies time history of leakage events by analyzing pressure differences between pairs of nodes. The model is

trained using pressure data observed for a "normal" time period, i.e., a period without leak events occurring in the WDN. Leakages are then detected through the assessment of node pressure differences on a time series that potentially includes one or more simultaneous leak events. The reconstruction error from the model is analyzed to detect the anomalies, i.e., the leakages, in the observed WDN. The model can be recalibrated to include each newly detected leak into the "normal" situation, enabling it to detect overlapping leakage states. At the same time, conventional mass balance considerations are included where demand information is present to support leakage identification and characterization. This enables experts to identify leak occurrences on a 5 min resolution and monitor its development over time.

To demonstrate the functionality of the leakage identification algorithm, two examples are chosen to illustrate different scenarios (see Figures 1 and 2). For better visualization, the presented signals are denoised by moving average, considering an averaging period of 1 day. The first example, further referred to as *Burst*, represents a scenario where a pipe burst is detected. The state change observed in Figure 1 can be identified as a clear rupture in the reconstruction error signal which occurs at the time step indicated by the red dashed line. Considering the signal delay of 1 day due to the moving averaging, an immediate new and stable state is reached at a consistent level of the reconstruction error. Moreover, it can be observed that the leak is fixed at a later time (green dashed line), as the system returns to its previous state.

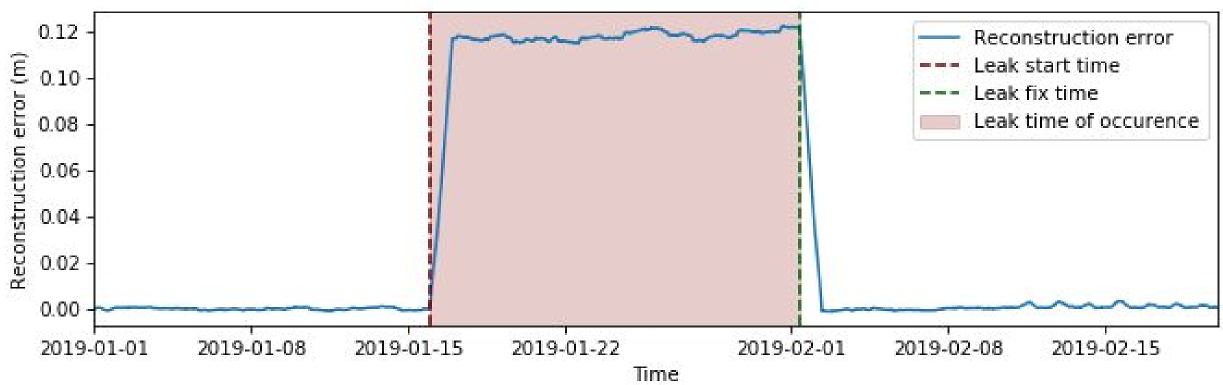

Figure 1: Model reconstruction error for the identification of a sample *Burst* (blue line). The shaded red area represents the time of occurrence of the leak. The estimated start and end of the leak are represented with dashed red and green lines, respectively.

Contrary to the rupture caused in the *Burst* scenario, holes in pipe walls might grow in size slowly and entail a rather smooth transition to a leakage state. This may be observed for the following scenario, further referred to as *Transient leak* (Figure 2).

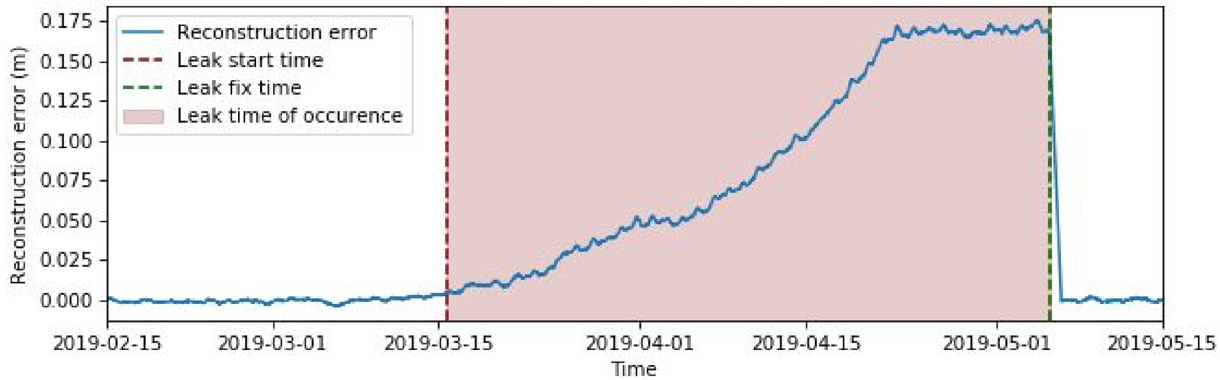

Figure 2: Model reconstruction error for the identification of a sample *Transient leak* (blue line). The shaded red area represents the time of occurrence of the leak. The estimated start and end of the leak are represented with dashed red and green lines, respectively.

The model reconstruction error in Figure 2 shows this transition as a transient growth process. Consequently, the start of the growth process is not as evident as for a *Burst*. In this case, an expert-based analysis of the reconstruction error is needed in our method to estimate the start time of the leak. The growth process reaches a final state at which growth stops. This final state indicates that the considered hole in the pipe wall has stopped growing, possibly due to reaching the size of the pipe diameter. Finally, a fix is also visible for this example (dashed green line), after which the system returns to its normal state.

The leakage annotations from the leakage identification module are then used by the second module of our proposed method, which performs *leakage localization*. The simulation-optimization framework developed in Berglund et al. (2017) is adapted to locate leakages by the application of an iterative mixed-integer linear programming (MILP), which minimizes the absolute differences between observed (SCADA) and hydraulic model simulated pressure values reported at the sensors. To incorporate seasonal demand variation in the hydraulic model, the base demands and demand patterns (for one full year) are updated in the input file based on AMR readings present in DMA C. Figure 3 shows the annual consumption reported by AMR data and the modeled demand before and after editing the base demands and the consumption pattern multipliers. The framework relies on the pressure response of a set of candidate pipes when a fixed leak value is inserted at the center of each candidate pipe. The candidate pipes are selected based on the pressure drop reported by the sensors, and candidate pipes are included in a search area located around the most affected sensor. In case the selection of candidate pipes does not include the real pipe, the output of the model reports the pipe closest to the true leaking pipe. Figure 4 shows, as an example, the candidate pipes location for the *Burst* and *Transient leak* events identified on the first stage of the procedure. The set of candidate pipes does not vary across each simulation-optimization run. A series of linear constraints are applied to ensure that a solution is identified that yields the estimated leak magnitudes that minimize the pressure error reported from the set of candidate pipes.

Two challenges were identified for the localization step. The first one is related to the candidate pipes selection, which is a key input of the optimization model. To address this issue, we relied on the assumption that the most affected pressure sensor should be located closest to the leak. Based on that, we explore several options for the pipes surrounding the most affected pressure sensor. Second, as pointed out by Berglund et al. (2017), the iterative MILP method is suitable for error-free data, and for this application, we needed to match the output of the hydraulic model with the SCADA data. However, as data at the node-level is available only for one district of the network, we are assuming that the rest of the nodes have a similar consumption pattern to that observed in DMA C.

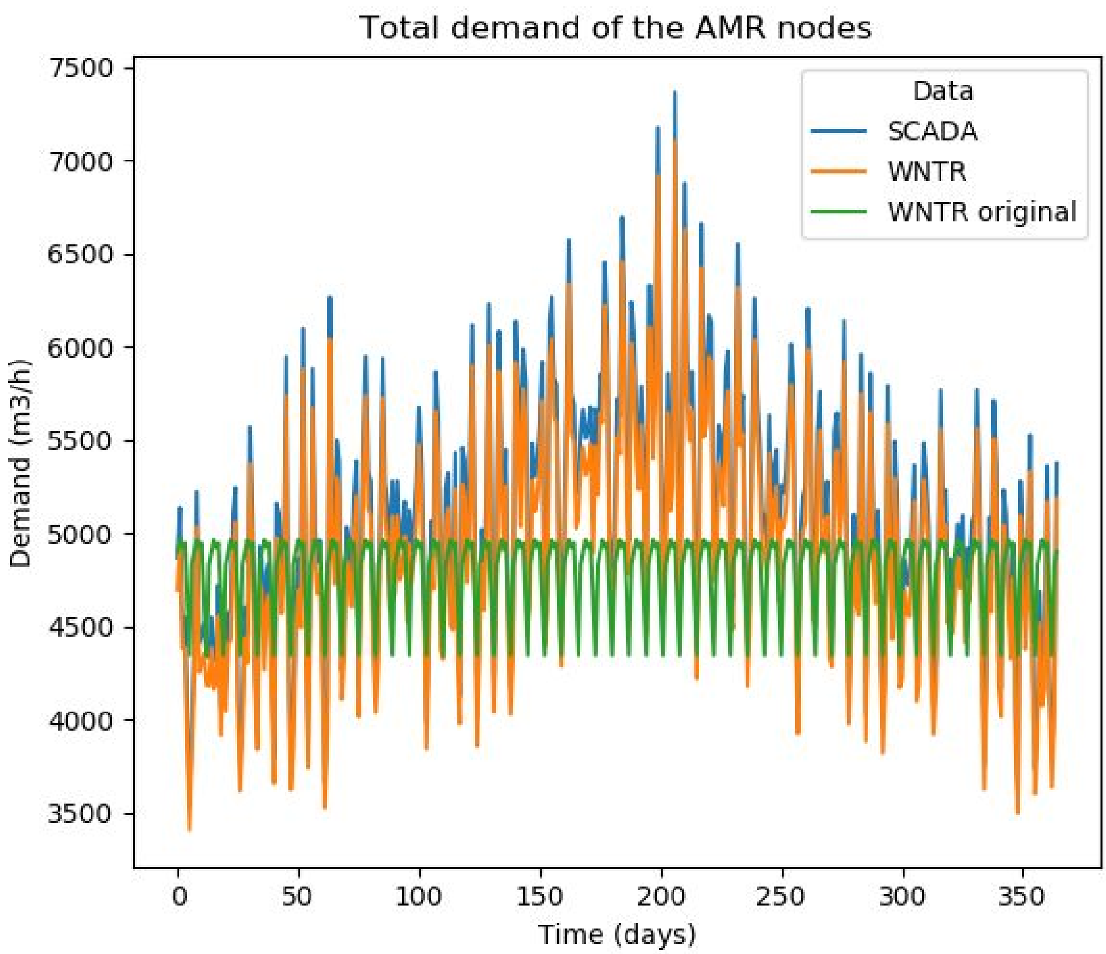

Figure 3: Daily water demand reported by AMR data aggregated at the district level over a year. (Blue) Original demand from SCADA data. (Orange) Updated demand of the WNTR hydraulic model, with edited base demand and pattern multipliers for a time horizon of one year. (Green) Original demand of the WNTR hydraulic model.

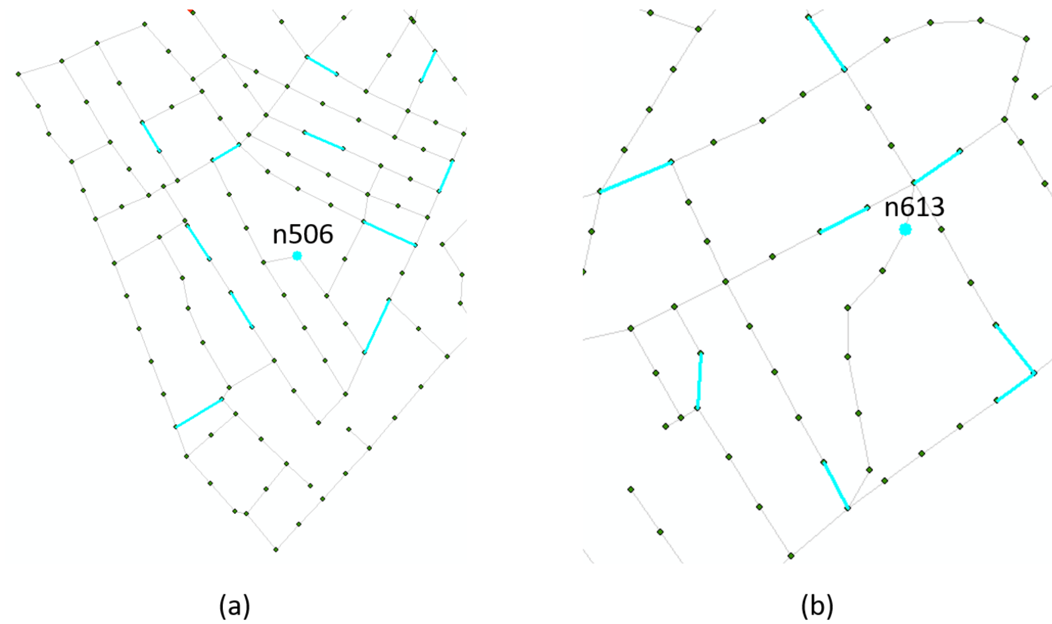

Figure 4: Candidate pipes (cyan) shown for the identified (a) *Burst* and (b) *Transient leak* events based on the most affected pressure sensor.

Our pressure-driven method for leakage identification and localization is tested on the SCADA data provided for the benchmark WDN of L-Town (BattLeDIM, 2020). L-Town is a medium-sized network featuring two reservoirs that supply water to a network with pipes developing for a length of 42.6 km, 782 junctions, 1 water tank, 1 pump, and 3 pressure reduction valves. Thirty-three pressure sensors and 82 Automated Meter Reading (AMR) sensors provide demand and pressure information to the SCADA system with a sampling frequency of 5 minutes. SCADA data for the L-Town WDN are provided for 2018 and 2019, along with ground-truth labeled leakage locations and fixes for 2018. Preliminary experiments show that our pressure-driven method can promptly detect and localize most of the labeled leakages for 2018. The absence of minimum requirements regarding the temporal frequency of pressure and demand data sampling makes it suitable for real-time applications.

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SUMMARY

Water losses are one of the main consequences of infrastructure failures in water distribution networks (WDNs), accounting for more than 50% in some WDNs worldwide. Methods that support prompt detection and accurate localization of leakages are crucial to help water utilities implement timely mitigation measures and avoid unnecessary losses of water and revenues. This research develops a high-resolution pressure-driven method for leakage identification and localization in WDNs and tests it using the benchmark dataset provided as part of the "BattLeDIM", an international competition on leakage detection and localization. Our method is composed of two modules that operate sequentially. The first module performs leakage identification by processing pressure data observed at different sensor nodes in a WDN and by analyzing pressure differences between pairs of nodes. The model is trained using pressure data observed for a “normal” time period, i.e., without leak events occurring in the WDN. The reconstruction error from the model is then analyzed to detect the anomalies on a time series that potentially includes one or more simultaneous leak events. The leakage annotations from the leakage identification module are then used by the second module, which performs leakage localization. A simulation-optimization framework is adapted to locate leakages by iterative mixed-integer linear programming. The framework relies on the pressure response of a set of candidate pipes when a fixed leak value is inserted there. The candidate pipes are selected based on the pressure drop reported by the sensors, and candidate pipes are included in a search area located around the most affected sensor. Our proposed method is tested on the SCADA data provided with a 5-minute sampling frequency for the benchmark medium-sized WDN of L-Town. Preliminary experiments show that our pressure-driven method can promptly detect and localize most of the labeled leakages and it is suitable for real-time applications.