A DUAL MODEL FOR LEAK DETECTION AND LOCALIZATION

BattLeDIM 2020 - Battle of the Leakage Detection and Isolation Methods

Team: Under Pressure

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ABSTRACT

In this work, we employ a hierarchical approach for leak diagnosis, where time series analysis of AMR data, demand models and measured flows is first used for demand calibration. In the next step, efficient mathematical optimisation is used to calibrate the pipe roughnesses and valve statuses and update the network data. Finally, the calibrated water network model is employed to first build a dual hydraulic network representation for the combined sensor & water systems, simulation of which provide a first estimate for the leak's size and location. This dual network is then used to (i) detect the start time of the leaks as well as (ii) to compute analytical sensitivities and the Pearson correlation for pressure residuals, which allow further localisation of leaks. This whole process of leak diagnosis and localisation scales well as the dual network size is of the same order as the original network, analytical derivations are used for computing sensitivities, and a fast and stable least squares method is used for calibration and valve status assessment.

Demand calibration

Data from the 82 AMRs in Area C was used to develop a demand model for the unmeasured customers within the L-town network. Additionally, a virtual inflow measurement of Area C has been constructed from the pump flow measurements and the tank's water level. This virtual inflow was used to (i) validate the demand model and to (ii) estimate the leak outflow in Area C. Various time series models were tested on the AMRs aiming to extract daily and weekly seasonalities and trend components for the different customer types (Residential, Commercial). For both customer types, best performance was achieved with a rather simple model, consisting of a multiplicative superposition of weekly seasonalities (S(t)), a time varying trend (T(t)) and a random component (R(t)) accounting for stochastic variations and measurement noise:

$$Q(t) = \overline{q} \cdot T(t) \cdot S(t) \cdot R(t)$$

where $\overline{q}$ is the base demand for the corresponding customer type at the measurement node. Subsequently, the time varying demand at each unmeasured location is inferred with this model according to the base demand in the EPANET file. The seasonal and the trend components are shown in Figure 1.

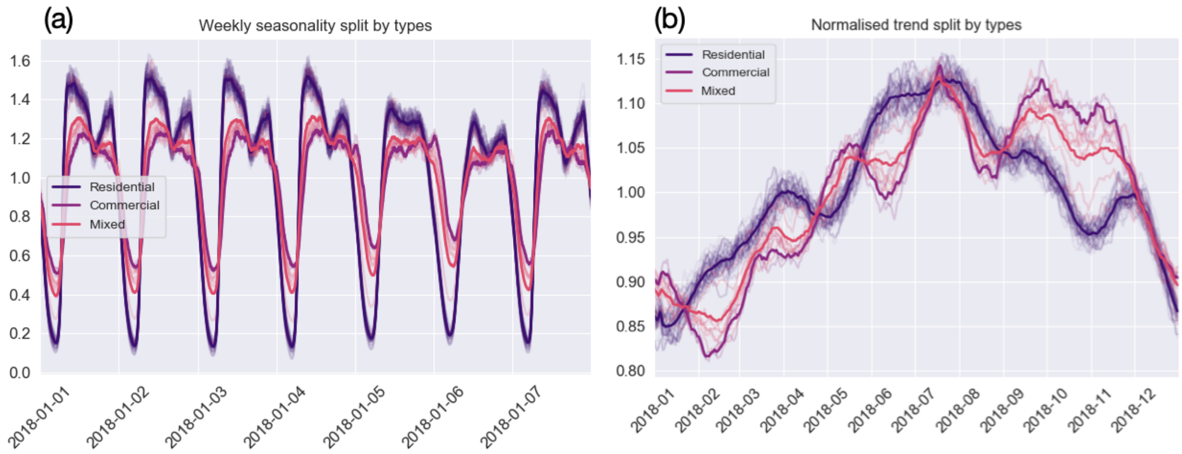

Figure 1: Weekly seasonality (a) and yearly trend (b) extracted from the AMR measurements for the different customer types (Residential and Commercial) and nodes consisting of a mix of them (Mixed)

Roughness calibration and valve status identification

The network calibration was done using the first week of 2018 measurements and the solving of a least-squares problem with a Levenberg-Marquardt method as in Piller (2019). The pipes were categorized in six different roughness clusters according to their diameter, material, initial roughness values and managing zones in which they are located. Figure 2 shows an overview of the roughness groups and the statistics node by node of the residuals. The MSE (green curve in Figure 2b) is around 6 cm H2O. Additionally, closed valves were identified during the roughness calibration.

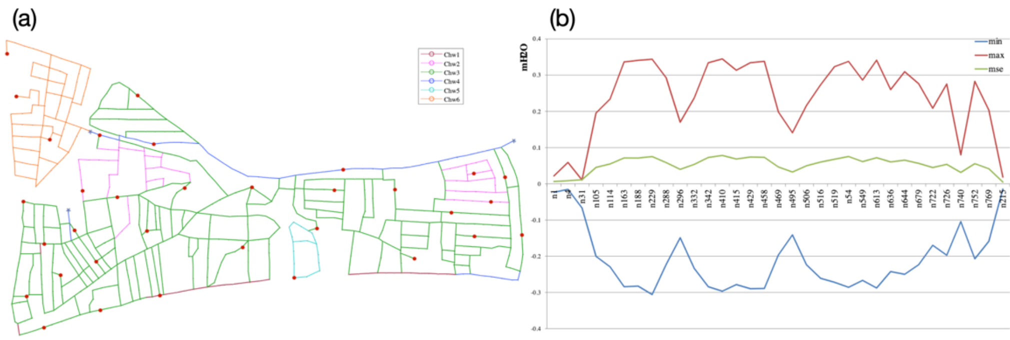

Figure 2: Network coloured by cluster of roughness (a) and residuals statistics for each measurement node (b).

Dual modeling approach

For the localization of the leaks the so-called "Dual Approach (DA)" is introduced. In the DA the pressure measurement nodes are connected by a valve with virtual reservoirs. The origin of the name "dual" stems from the fact that, instead of using the fixed demand boundary condition ("primal"), the dual fixed heads are used. Consequently, the DA heads are equivalent to the measurements and imbalances in the system that lead to flows to the virtual reservoirs. If a new leak appears in the primal approach the residuals between measured and calculated pressures are increasing. The pressure drop caused by higher flow velocities towards the leak in the real system is not observed in the model that is still based on the leak free system. In the dual approach the measured pressure drop is applied to the fixed head reservoirs and, as a consequence, an additional outflow is calculated. This outflow can be understood as outflow residual. The advantage of the dual method is that the calculated outflows act as amplifiers that deliver significant and localised signals even for small pressure drops. In addition, the outflows at the virtual reservoirs are a good first estimate for the leak's size and location.

Leak Detection

Two different signals are used for leak detection; (i) the flow residual between the measured inflow and total demand in an area, (ii) the dual model's outflows to the virtual reservoirs (see Figure 3). Two different types of leaks were found in the data – instant bursts and leaks that are growing over time. Growing leakage flows are modelled with a quadratic function that saturates at a certain point of time to a constant value. Additionally, leaks are evolving simultaneously in the system, making the detection more difficult.
Data from the dual model is used to identify the leak start times and their shapes (i.e. instant or growing). For that reason, thresholds are extracted from the DA flows at each sensor using the leak free case. If the DA signal exceeds the threshold, a leak is detected in the system. The detection time is the start time of the leak. To estimate the leakage outflow, the start times and the shapes of the leaks are used to fit the leak shape on the flow residuals. If a single leak evolves over time, a Bayesian inference approach is used (e.g. in Area C). In the case of multiple evolving leaks (Area A&B), a heuristic method using differential evolution is used to identify the best combination of leak outflows over time. The shapes were then checked again with the outcomes of the DA and subsequently used for the leak localisation.

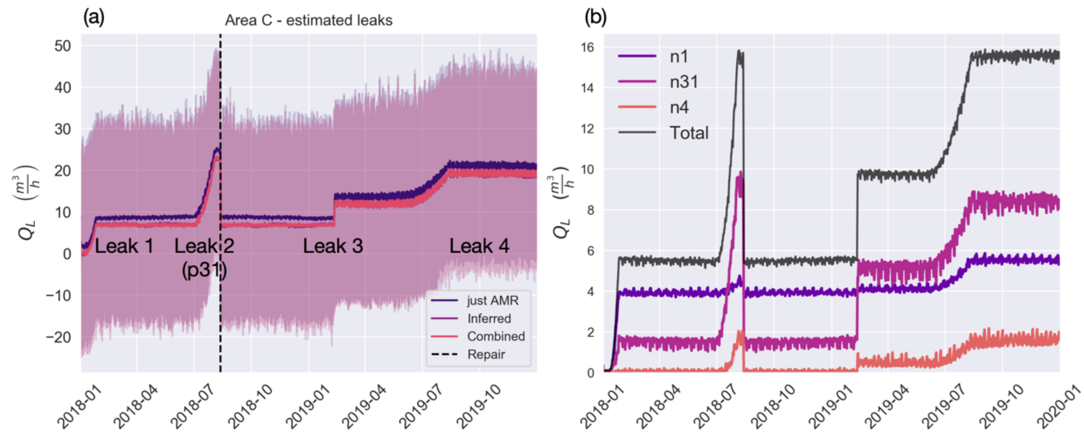

Figure 3: Leakage outflow in Area C (a) estimated by comparing the 'virtual' inflow measurement and the demand model and (b) as provided by the dual model.

Leak Localization

For the localization, the Pearson correlation for pressure residuals and the first-order estimates using sensitivities is calculated (Perez et al. 2014). Since the measurement nodes are connected to the fixed head reservoirs the residuals and the sensitivity coefficients are very small. However, in our test this didn't show any negative impact in the allocation. In contrast, the system seems to be stabilized by the additional pressure boundary conditions which makes the correlation more stable. One important requirement that is immanent to the procedure of applying the correlation method is that the leak to be localized must be isolated in time from other leaks. The method does not work for two or more leaks appearing at the same time. Therefore, the leakage curves that have been calculated for detection served as a basis for choosing the best time for allocation. The network was divided into two separate parts. The pump has been removed by the flow measurement for Zone A and B.

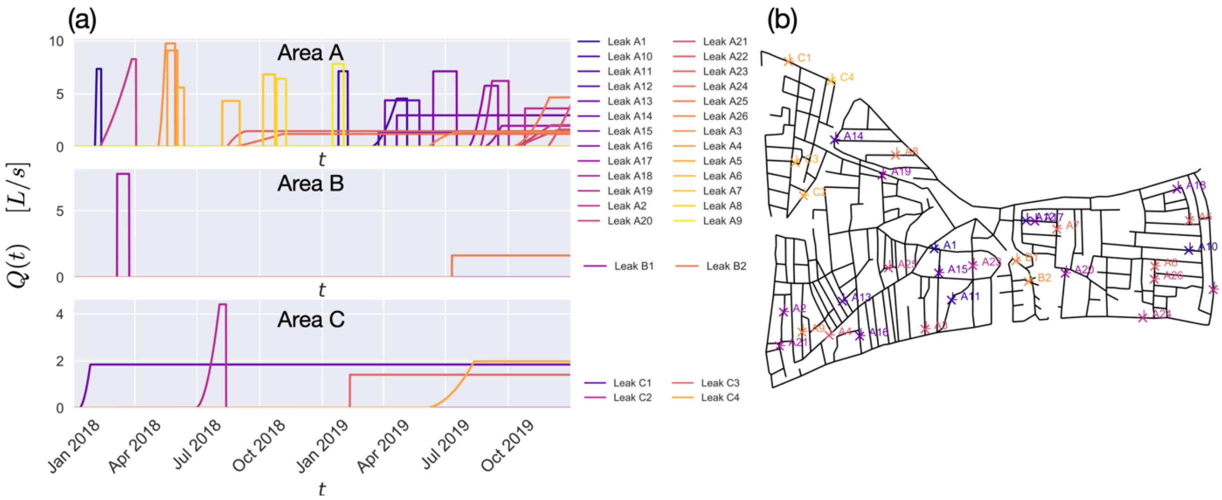

Figure 4: Results of leak detection and localisation: (a) Identified leakage outflows over time and (b) estimated locations of the leaks.

Keywords: dual network representation; time series analysis of demand; pressure residuals; Pearson correlation; calibration; sensitivity matrix

SUMMARY

We have proposed a hierarchical approach that first derives better prediction models for the demand at network nodes and the pressures at logger locations. For the demand, a time series analysis is tailored to understand the main effects of seasonality (i.e. over seasons, days, and diurnally). A multiplicative model was used to stabilize the variance for the different customer types. Then, based on the nodal demand prediction, the pipe roughness coefficients were calibrated in the first week of 2018 (assumed to be the least leaky period) and nominal internal diameters were checked. This calibrated model was then used to compute the sensitivities of pressures at nodes *with respect to* additional nodal demands. The latter will drive the leakage localization. Second, once model predictions are derived, a two-tier model-based fault diagnosis approach is used for leak detection and identification. First level is to partition leaks with the demand model. This gives an approximation of the starting time of leaks and the order of magnitude. Then a correlation method between pressure residuals and the first-order sensitivities is employed to identify the potential node candidates. It was found that transforming the water network model to a dual network model, which includes the pressure sensors using virtual reservoirs, makes the localisation more robust.

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