Leak Detection in Drinking Water Network using Pressure-based Classifier

Congcong Sun*, Benjamí Parellada*, Vicenç Puig*, and Gabriela Cembrano*,**

*Advanced Control Systems Group at the Institut de Robòtica i Informàtica Industrial (CSIC-UPC), Llorens i Artigas, 4-6, 08028 Barcelona, Spain, {csun, bparellada, vpuig, cembrano}@iri.upc.edu
**CETaqua, Water Technology Centre, Barcelona, 08904, Spain, gcembrano@cetaqua.com

Abstract: Water leakage in drinking water networks (DWN) is the main reason for water loss in water networks. Considering the worldwide problem of water scarcity added to the challenges that a growing population brings, minimizing the water losses through detection of water leakages in DWN using efficient techniques is an urgent humanitarian need. This paper proposes a new data-driven leak detection method of defining classifiers based on limit pressure measurements in DWNs. This can get rid of complexities and application constraints of the model-based approach. The end result is an average 60% detection accuracy with limited data requirements. The proposed approach is applied to Hanoi DWN.

Keywords: leak detection; data-driven; pressure-based classifier

Introduction

The literature is filled with works that contribute to the universal leakage detection problem in DWN. The most common approaches rely on estimating hydraulic dynamics using mathematical models (Savic et al., 2009; Puust et al., 2010). However, the high computation demand and the difficulty of parameter estimations hinder the usage of model-based approaches. To overcome these issues, (Pérez et al., 2014) proposes a mix hydraulic and data-based model which relies on pressure residual and leak sensitivity analysis, which consists in analyzing the difference between measurements and their estimation using a hydraulic network model. More recently, (Soldevila et al., 2018) presents a completely data-driven approach through analysing the pressure residual between a healthy DWN and a network with leakages, while using Kriging to interpolate the pressure in nodes without sensor information. However, due to the graph structure of DWN, the accuracy of this approach is affected by the distance between the leaking node and the inlet node.

In order to improve the results and avoid computing a reference model, this paper proposes a pressure-based classifier based on limit pressure measurements to deal with leak localization problem in DWN, or in partitioned zones called District Metered Areas (DMAs). Neural Networks (NN) are used to build a classifier, where all the parameters are estimated using a partitioned data set and afterwards validated. Afterwards, a Bayes reasoning is used to recalibrate the probabilities of each node being the leak candidate. As the benchmark, the Hanoi DWN is used as a case study.

Material and Methods

The basic ideas of the pressure-based classifier approach are: 1) Use historical data of the measured pressure at internal nodes, the pressure and flow at the inlets, as well as the true leak location to define the format of the dataset; 2) Use Kriging spatial interpolation to estimate the pressure at the nodes which are not equipped with sensors based on hydraulic proximity; 3) Use NN as the classifier to compute probabilities of each node being the leak location based on only the raw pressure without estimating a hydraulic model nor a reference; 4) Use Bayes rule to recalibrate the probabilities which the classifier provides to determine the leaky node; 5) Use the fitting accuracy and the Average Topological Distance (ATD) as performance indicators, where ATD is the average value of the minimum distance in nodes between node with the leak and candidate node proposed by the leak localization method.

The dataset analyzed contains (As example in Table 1.1):

- Response variable: **Leak**, label representing where the true leak is created.
- Pressure: **Press**, represents the head or pressure for each of the different nodes in DWN at each different time step.
- Flow from the inlet: **Flow**, flow which enters the DWN.

The steps to generate the pressure-based classifier using NN at step 3) are: a) split the matrix defined in advance into a training dataset and a validating dataset; b) NN is used to build the classifier using the statistical computing language R; c) train the classifiers on the training dataset with 10-fold cross-validation; d) use the resulting classifier (the one with better accuracy) using the validation dataset to obtain accurate estimations of the evaluation measures; e) use Bayes rule to recalculate the probabilities taking into account the linearity in time; f) when a signal is sent to inform that the leak is repaired, the Bayes calibration is performed again.

Results and Discussions

Figure 1 is the case study of Hanoi DWN. Real measurement data are read from the EPANET simulations. Possibility of a leak appearing in any of the nodes is considered. Assume different number of sensors are placed. Table 1.2 presents the accuracies and ATD performance using different quantity of sensor nodes in the network. Figure 1.2 and Figure 1.3 are the time evaluation plots corresponding to the accuracy and ATD performance when different quantities of nodes have sensors installed. These results prove that: 1) In the average case, the pressure-based classifier can obtain more than 60% accuracy with less than 2 nodes of ATD; 2) Number of sensors and location and their placements affect to a great extent the performance. More DMAs with different classifiers will be used for validation in the future.

References

A. Soldevila, T. N. Jensen, J. Blesa, S. Tornil-Sin, R. Femandez-Canti, and V. Puig, “Leak localization in water distribution networks using a kriging data-based approach,” in 2018 IEEE Conference on Control Technology and Applications (CCTA), IEEE, 2018, pp. 577

Puust, R. Z. Kapelan, D. A. Savic, and T. Koppel, “A review of methods for leakage management in pipe networks,” Urban Water Journal, vol. 7, no. 1, pp. 25, 2010.

Pérez, R., Sanz, G., Quevedo, J., Nejjari, F., Meseguer, J., Cembrano, G., Tur, J.M.M., and Sarrate, R., Leak Localization in Water Networks. IEEE Control Systems Magazine, Volume 34, Issue 4, August (2014), pp. 24.

Savic, D., Kapelan, Z., Jonkergouw, P. Quo vadis water distribution model calibration? Urban Water Journal, Vol. 6, No. 1 (2009). pp. 3

Van den Berg, C. “Drivers of non-revenue water: A cross-national analysis,” Utilities Policy, vol. 36 (2015), pp. 71

Figures and Tables

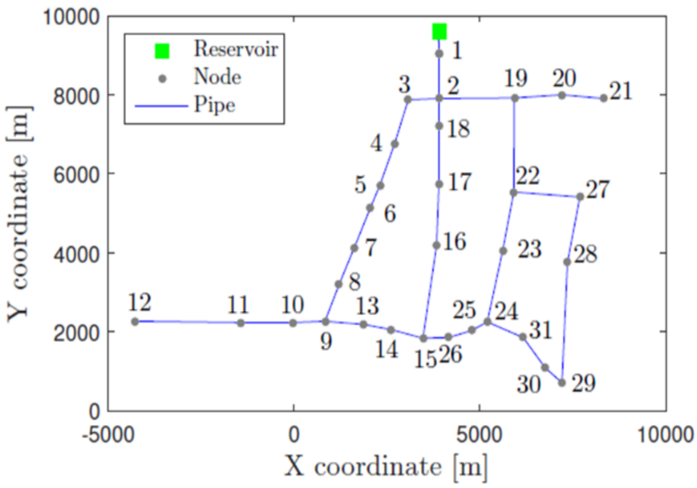

Figure 1.1 The Hanoi DWN.

Table 1.1 The dataset format

Leak	Pres 1	Pres 2	…	Pres n	Flow
1	12.46	11.12	…	12.50	211
1	12.64	11.53	…	12.66	195
1	12.72	11.17	…	12.73	141
…	…	…	…	…	…

Table 1.2 Application and results with different quantity of nodes with sensors

Number of sensors	Accuracy (%)	ATD
2	65.32	0.48
3	86.98	0.18
4	96.31	0.03
5	16.82	2.17
6	44.12	1.02
7.1	51.38	0.92
7.2	70.62	0.41
8	75.69	0.29
6	79.61	0.31
12	70.16	0.36
31	75.35	0.32

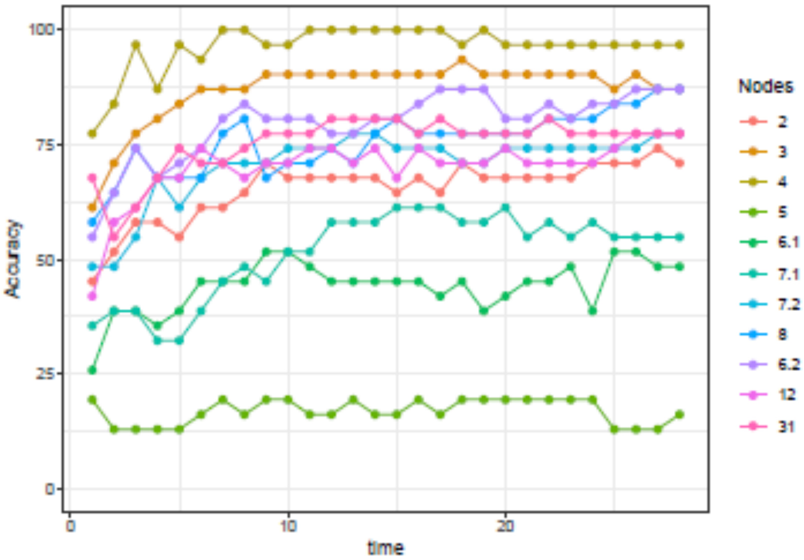

Figure 1.2 Accuracy of the application results.

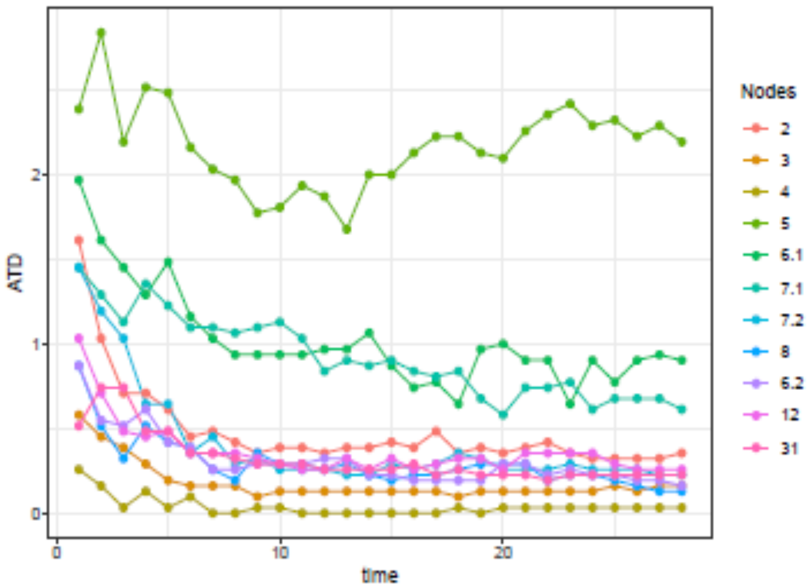

Figure 1.3 ATD of the application results.