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LEAK LOCALISATION METHOD USING A DETAILED HYDRAULIC MODEL COMBINED WITH HIGH RESOLUTION PRESSURE SENSORS APPLIED TO A REAL NETWORK

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Abstract

The objective has been the elaboration of a method of locating specific and background leaks in hydraulic models. We have worked with high-resolution hydraulic models with high resolution pressure sensors. The method has been applied to a real network. To execute an agile adjustment of the models, it is essential to link the hydraulic model with the data of the SCADA. The tool developed by the GISWATER ASSOCIATION, QGIS on POSGRESQL allows exporting networks to EPANET with the demanded resolution. This Work has used three levels of definition regarding the nodes introduced. As instrumentation, three pressure sensors have been used with a resolution of 1 centimetre. The situation of sensors in the network has been defined by using algorithms based on the sensitivity matrix.

Background leakage has been modelled using EPANET emitter coefficients. The value of these coefficients has been calculated based on the overall performance of the sector. They have been calculated individually for each node weighted by the lengths of the pipes linking to each node. The combination of a network with a high density of nodes, a distribution of background leakage balancing the emitting coefficients has allowed to adjust the model with errors in the pressures in the three control nodes of the order of 17 centimetres. A previous macrocalibration phase [3] was required because the sensitivity of the model became high enough to detect the existence of a tank that had not been considered due to its little effects.

To obtain the flow attributed to punctual leak, a fictional reservoir has been used [4] to subsequently calculate the most likely area where it is located from a thorough search on all nodes. At points where the leak situation is most likely, the average error of the three pressure sensors has been below 11.5 cm

Keywords
Sampling design, Macrocalibration, Leak localisation.

1 INTRODUCTION

The objective has been the elaboration of a method of locating specific and background leaks in hydraulic models. We have worked with high-resolution hydraulic models with high resolution pressure sensors. The method has been applied to a real network.

To execute an agile adjustment of the models, it is essential to link the hydraulic model with the data of the SCADA. The integration of POSGRESQL with QGIS through PYTHON executables such as WNRT or R with functions that use EPANET TOOLKIT provides this link. The tool developed by the GISWATER ASSOCIATION, QGIS on POSGRESQL [1] allows exporting networks to EPANET with the demanded resolution. This Work has used three levels of definition regarding the nodes introduced: node by change of material or diameter; nodes by subscriber; nodes according to a fixed distance. These are three of the four criteria allowed by the tool. The main water network of Manresa has 5,121 nodes the first level of definition. It increases to 10,495 nodes for the second and 38,788 nodes for the third, with an average distance between nodes of 2.98 meters. This will allow to observe the behaviour of the hydraulic model obtained according to the density of nodes.

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2 MATERIALS AND METHODS

2.1 Case study

In order to choose the case study network the project stablished the following criteria:

- Urban network with at least 1.000 consumption meters.
- Both residential and industrial activity.
- With a source tank.
- Electromagnetic flowmeter.
- Chlorine analyser at the source.
- Time series of flow data at least for 10 years.

From all the networks managed by the company the hugest one District Metered Area (DMA) was chosen as it fulfilled all the criteria and its study was of high interest. It includes 39.000 consumers, its mean flow is 373 m^3/h. Its model (Figure 1) includes 5123 nodes and 5285 pipes. It is fed by gravity from a tank where an electromagnetic flowmeter provides the global consumption on-line.

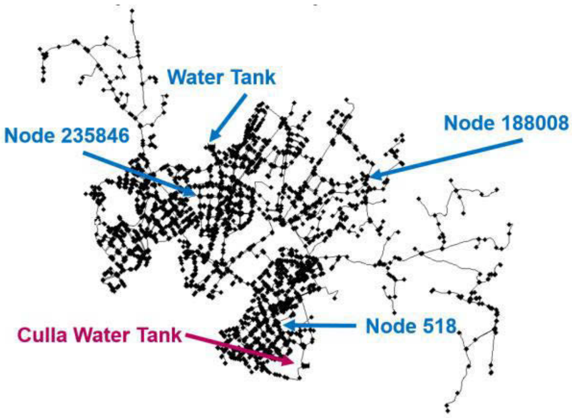

Figure 1: EPANET model for the case study network.

2.2 Sensor placement

One of the objectives of the project was to provide the network with new sensors. These sensors should be able to provide hydraulic and quality information from the network. Pressure, temperature, and chlorine sensors were installed and connected to the big data platform Zeus.

For this work only hydraulic information was used. The tank had a level sensor and an electromagnetic flow sensor at the output. Three pressure sensors were added. They are able to work between 0-10 mca and their precision is of 0.01 mca.

The sensor placement procedure methodology was based on the sensitivity matrix of pressures to demands. The objective of these pressure measurement is to detect changes in the demands that eventually can be associated to leaks.

Given the sensitivity matrix $\boldsymbol{S}$, its singular value decomposition provides the matrix $\boldsymbol{U}$. This matrix $\boldsymbol{U}$ corresponds to a base of orthonormal vectors of the measurement space (pressure). The first n (three in our case) are the maximum singular values and are related to the most relevant directions both in the pressure and demand spaces. Using the first three columns of $\boldsymbol{U}$ we obtain the Information Density Matrix that allow to find the nodes where the pressure is most sensible to changes in the demands. This methodology is explained in detail in [2].

2.3 Macrocalibration

Before using the model for supervision purposes, as leak localisation, it has to be calibrated. This calibration was carried out in a progressive improvement of the pressure estimation at the nodes where sensors had been installed. The process included 3 steps:

1. Simulation and analysis of the original model. For step one, we simulate the model considering the tank level as a boundary condition and the water flow as a global demand, but with no leaks.
2. Background leakage simulation. For step two, we introduce minor leaks to every node assuming that the water balance was due to background leakages. The assignment of the emitter coefficient is homogeneous, all the nodes have the same.

The model obtained in step 2 highlighted a sharp change in the pressure, specially in one node, that was not seen in the measurements. The analysis of the inflow showed that there was a sharp increase of the demand that could not be imputed to a domestic demand.

3. Introduction of the secondary tank. The feedback of the company acknowledged that for simplicity they had omitted the presence of a secondary tank (10 meter below of the source) that is usually closed but when in-flow valve opens it takes around 140 l/s. The

lowest tank was included. We also updated the emitter coefficients so that they are proportional to the length of the pipes connected to each node.

2.4 Leak estimation

To estimate the magnitude of the leak, we introduce a virtual reservoir at the node where the pressure is measured. This virtual reservoir behaves as a source sink of water in order to maintain the known pressure at the node [4]. In our case we simulated the three possible scenarios given three pressure sensors. The water consumed by the reservoir is the estimation of the leak.

2.5 Leak localisation

With the calibrated model, the leak estimated will be introduced to every of the 5124. For each scenario we simulate and compared the predicted pressures with the measured ones. We use the mean absolute error (MAE) as a metric for evaluating the probability of having a leak in a node.

3 RESULTS

The results of the five methodologies applied to our case study are presented in this section. The starting point is a network illustrated by the map of Figure 1 where we installed three sensors. The evolution of the estimation of the pressure is illustrated graphically and with the average value for each step of the macrocalibration. Finally the result is another map where we provide the probability of having a leak in any of the nodes.

3.1 Sensors placement

The number of sensors to be introduced in the network was a trade-off between the budget and the information required as it often happens. In Figure 2 the first 10 singular values of the sensitivity matrix show how they decrease.

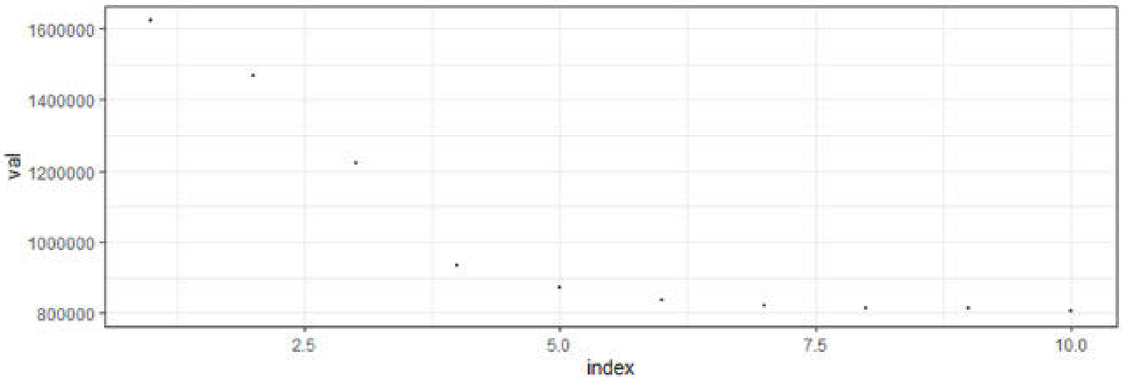

Figure 2:10 first singular values of the Sensitivity Matrix.

The Information Density Matrix was evaluated in different demand conditions. The most pressure sensible nodes were not always the same, but they appeared to be in the same three regions. One of the possible configurations was chosen. The exact location is presented in Figure 1.

3.2 Macrocalibration

The model was run introducing the real level of the input Tank as head of the reservoir in the model and adapting the demand to the measured inflow. Figure 1*Figure 3* presents the comparison between the measured pressure and its prediction in each sensor. We can observe two behaviours. For the nodes 518 and 188008 the discrepancies depend on the time instant being lower during the day while in node 235846 the discrepancies are much more constant. It is obvious that demand/leakages are responsible of part of the discrepancies due to this time dependence.

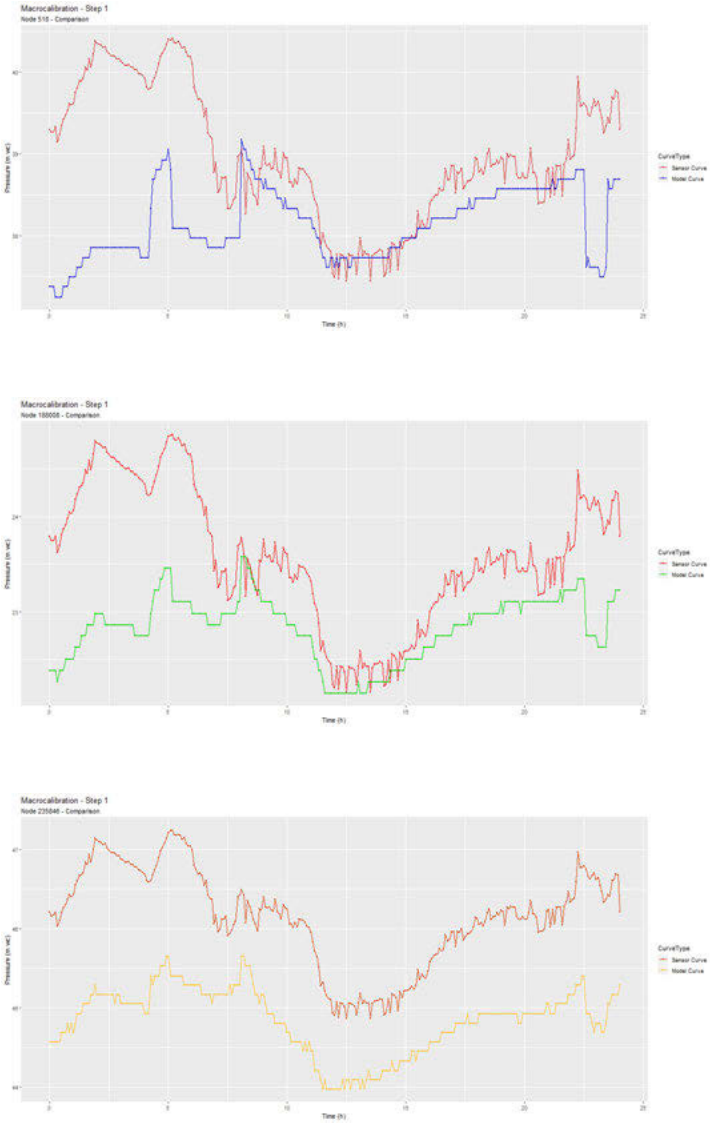

Figure 3. Comparison of measured (in red) and predicted (with the original model) pressure at the three sensors installed. From above to bellow nodes: 518, 188008 and 235846

Table 1 presents the average of the pressure errors. As was evident from *Figure 3* the maximum eror appears in node 235846.

Table 1. Average pressure absolute error (MAE) for the original model

Average Error for 24 hours	Data (m wc)
Node 518 Pressure	0,876533
Node 188008 Pressure	0,757516
Node 235846 Pressure	1,312204
Average from the three nodes	0,982084

The hydraulic balance of this DMA is around 80%. This has been stablished from billing data and the SCADA data for inflow. To adjust the demand behaviour we distributed 20% of the mean inflow as background leakages using a identical emitter coefficient at all the nodes. *Figure 4* presents the comparison between the measured pressure and its prediction in each sensor. *Table 2* presents the average of the pressure errors. The performance of the model has improved for each measurement. The maximum error still corresponds to node 235846. Nevertheless, we could not pass over the sharp changes in predicted pressure at node 518 and more subtle in node 188008 that was not present in measurement at all. We presented these results and received feedback from the company.

Figure 4. Comparison of measured (in red) and predicted (adding background leakage) pressure at the three sensors installed. From above to bellow nodes: 518, 188008 and 235846

Table 2. Average pressure absolute error (MAE) adding background leakage

Average Error for 24 hours	Data (m wc)
Node 518 Pressure	0,830616
Node 188008 Pressure	0,559142
Node 235846 Pressure	1,020405
Average from the three nodes	0,803388

The company clarified that for simplicity the model omitted a tank that is generally closed and gives service to another DMA. The relevance of this tank is that at some times during the day, when its valve opens, it takes water from our DMA. As this tank (Culla in Figure 1) is 10 m bellow the feeding tank a great amount of water flows by gravity. Using the data of the inflow measured at Culla tank we introduced it in the model. Figure 5 presents the comparison between the measured pressure and its prediction in each sensor. Table 3 presents the average of the pressure errors. From the behaviour of sensors at nodes 188008 and 235846 we deduced that demand distribution geographically may not be the same throughout the day. Such phenomenon can be imputed to a leak that has a constant behaviour compared to domestic consumers.

Figure 5. Comparison of measured (in red) and predicted (with the final model) pressure at the three sensors installed. From above to bellow nodes: 518, 188008 and 235846

Table 3. Average pressure absolute error (MAE) for the final model

Average Error for 24 hours	Data (m wc)
Node 518 Pressure	0,077114
Node 188008 Pressure	0,249073
Node 235846 Pressure	0,197529
Average from the three nodes	0,174572

3.3 Leak estimation

We introduced a fictional reservoir in each node provided with a pressure sensor. The head of the reservoir became the input and as output of the simulation we obtained the flow coming or leaving the reservoir. We carried out three simulations moving the fictional reservoir among the three nodes. Table 5 presents the results. Only at node 188008 the reservoir behaved as a sink (expected behaviour of a close leak). In Table 3 we had already observed that the node with worst adjustment in the prediction was this. The average inflow in this scenario is taken as an estimation of the leak.

Table 4. Average extra flow for the fictional reservoir

Node which has been added an additional water tank	Average extra flow (l/s)	Flow direction
Node 518	1,04	The water tank provide water to the network
Node 188008	4,34	The water tank absorb water from the network
Node 235846	7,01	The water tank provide water to the network

3.4 Leak localisation

Once the leak is estimated the emitter coefficients are recalculated. The proportion of leakage associated to background leakage has been reduced. In this process the emitter coefficient is not constant anymore. It has been calculated proportional to the length of the pipes connected with the node.

To locate the leak we simulate the same scenario as many times as nodes in the network (5123) introducing the leak in each node. The average absolute error (MAE) is evaluated in each scenario. Figure 6 presents these results. The colour represents the average error obtained when the leak was supposed in that node. Those nodes with lowest error are those more likely to have a leak.

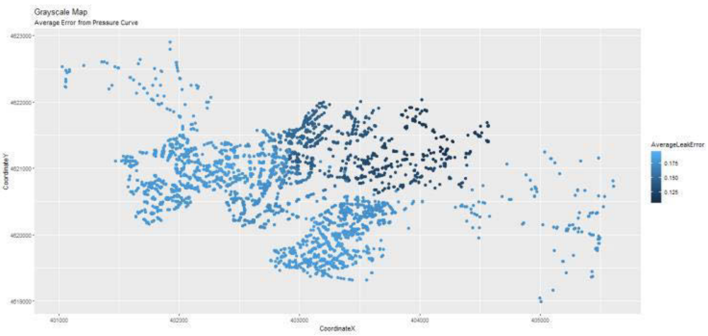

Figure 6. Average error of the measurements depending on where the leak is located.

Finally Figure 7 presents the same results but discretised. It seemed useful for the company when they wanted to plan the search campaign.

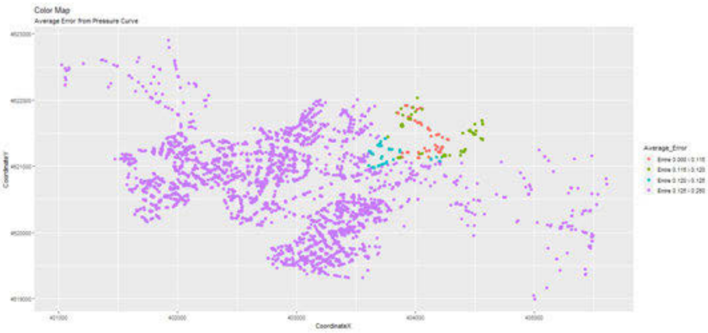

Figure 7. Discretised Average error of the measurements depending on where the leak is located.

4 CONCLUSIONS

The work presented applies in a real network methodologies of the literature for sensor placement, calibration and leak estimation and localisation. The model obtained has improved it performance arriving to errors in pressure prediction between 10 and 20 cm.

The leak localisation results encouraged the company a search campaign on those nodes with highest probability. Although no leak was finally found on the field they agree in the fact that the area signalled can have higher rate of background leakage.

Future projects will be focused in connecting the probability of leakage calculated on data available on pipes and economical assessment for the invest to do in a network.

5 ACKNOWLEDGEMENTS

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