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OPTIMAL PLACEMENT OF METERING DEVICES FOR MULTIPLE PURPOSES

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Monitoring devices installed in a huge system like water distribution networks imply a high cost. This cost includes installation and maintenance. Thus, the placement of these devices must be optimal. The optimal sensor placement is an issue that comes up in many innovation projects involving water networks. The use of models is crucial in this process, even if the final application does not use them. Nevertheless, the optimality of the sensor placement may highly depend on the final use of these sensors. In general, a better sensor placement may be based in a more specific use of the information gathered by the sensors. This work studies the dependence of sensors placement on the functional orientation of the cost function. Two main applications for leak localisation and demand calibration are considered. These two applications are related since leaks and demands have a similar but not identical behaviour. In order to establish how sensors may be used for multiple purposes whilst keeping an optimal location, different optimisation strategies are tested here. The sensor distribution then becomes a multiobjective optimisation problem.

INTRODUCTION

A water distribution system (WDS) is constituted of three major components: pumps, distribution storage and distribution piping network. Most systems require pumps to supply lift to overcome differences in elevation and energy losses caused by friction. Pipes may contain flow-control devices, such as regulating or pressure-reducing valves [*2*]. The purpose of a distribution system is to supply users with the amount of water demanded under adequate pressure for various loading conditions. A loading condition is a spatial pattern of demands defining users' flow requirements.

Some models try to characterize transients in pipes, valves and pumps. Inverse transient models for leakage detection are used in [*4*]. Transient analysis is used in [*12*] for leakage detection and calibration of roughness, and may be also of interest in order to know the behaviour of a network in these transients [*5*]. This type of analysis and modelling approach needs a lot of data for calibration and is computationally expensive. Nevertheless, when the number of pipes, pumps and valves increases, the network tends to work steadier and the transients are less important. A first simplification considering this behaviour is related with time, so the dynamics of each element are compared with the sample time of the system. Most applications in computer supervision and control applied to huge networks work with steady-state models concatenated in an extended period simulation (EPS) [*2*], [*13*].

Once the WDS model is available, a demand model for the consumers is considered. The nodal demand in a junction is defined as

$$d_i(k) = bd_i \cdot p_{a,i}(k) \cdot D(k), \qquad (1)$$

where $d_i(k)$ is the demand of node i at time k, bd_i is the base demand of node i, $p_{a,i}(k)$ is the value of pattern a associated to node i at time k, and $D(k)$ is the sum of the supplied water to the system measured at the network inputs and storage units at time k.

Regarding leakage simulation using water network models, generally leaks are assumed to be located in the nodes of the network (see [*9*]). This assumption stands if the length of the pipes in the network is low compared with the maximum distance error on located leaks required by the company. Thus, this assumption reduces the complexity of the leakage model and does not affect the final result.

Proper flow and pressure measurement within a water network allows the calibration of the models and the correct supervision of the system. This supervision may use the models, but they are also useful for other purposes such as design. The organization of WDS in District Metering Areas (DMA is a common practice and the most accepted approach for leakage reduction. This geographic and topographic element includes the metering in its definition. Flows and pressures are measured at the connections with the transport network. Pressure can be often controlled depending on the available knowledge of the DMA. Billing purposes are using higher frequency of measurements each day and some samples are taken on real time. Pressure sensors in the DMA may be introduced for critical control purposes or supervision.

Sensor placement (flow and pressure) focusing different purposes is analysed here. The aim is to compare different sensor placement approaches that arise when considering different objectives, and try to find a compromise so that the sensor placement is as versatile as possible. In the following sections the telemetry for billing and the pressure sensors considered for leakage localization are studied. Also, a purpose-free methodology based on the use of the sensitivity matrix (SM) is described. Results of leakage location and demand calibration are compared and some conclusions and future work are proposed.

DEMAND ESTIMATION WITH TELEMETRY

Generally, in WDS delivered water is real-time monitored using a SCADA system that allows monitoring and control of the DMA inputs every certain period, while billing is generated less frequently (quarterly). Reducing consumed water estimation time has a big impact on the improvement of the demand modelling. Telemetry may give the consumption of a finite number of consumers. If the consumers can be grouped in segments and the mean consumption of each segment is estimated the estimation of the water consumed in each DMA can be calculated from this estimation. Segmentation of consumers consists in clustering the consumers in groups with similar behaviour so that a minimal telemetry gives best accuracy in consumption estimation on real time for each group. In [6] a first study on demand groups is defined by means of contract type. Nevertheless clustering using artificial intelligence is proposed for the consumption classification. The annual profile of each consumption is its descriptor. The likelihood with another consumption defines whether both consumptions belong to the same group. Software SALSA based on algorithm LAMDA (Learning Algorithm for Multivariable Analysis) is used [1]. LAMDA is a fuzzy methodology of conceptual clustering and classification. It is based on the *adequacy* concept. The idea is to determine the adequacy degree of an object (or individual) to each of the existing classes. This adequacy is obtained from the analysis of a relation between each characteristic of a given object and the respective parameter of each class. The descriptors used are the monthly consumption through one year. The selection of these descriptors takes into account the intended use of the classification, which is demand estimation.

The histograms of the consumptions for each class are shown in figure 1. In the latter, the statistical characteristics of these distributions did not encourage the sampling. In figure 2, the prediction error of each consumption appears with a normal distribution, with the exception of class 6, which contains six great consumers. The sampling is decided on basis of confidence in estimation of this prediction error.

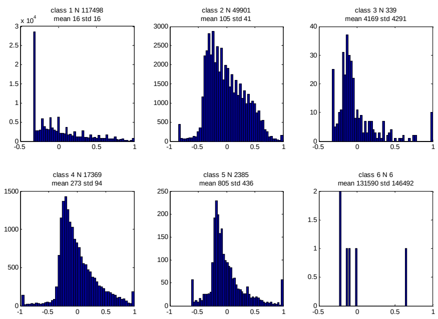


Fig. 1: histogram of the consumptions may 2007, for the 6 segments N=number of elements in each class

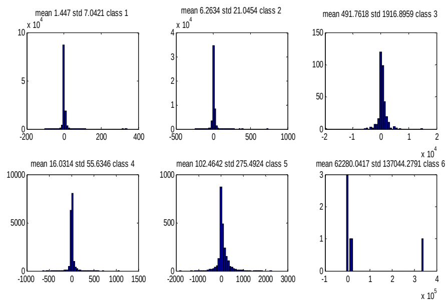


Fig. 2: histograms of prediction errors (may 2007) for the 6 segments

The predicted consumption is generated by historical data. The estimation error with a confidence degree *C* of the mean is quantified by equation 3.

$$error = t^* \frac{\sigma}{\sqrt{n}} \tag{3}$$

Where t* is the superior critical value *(1-C)/2* for the Student distribution *t(n-1)*. With the estimation error, the number of samples can be decided. The estimation error used in the previous work [6] was of $0.005m^3/day$, here same value is used so that results provided in both works may be compared. figure 3 shows the estimation process. The number of telemetries needed for each segment depends both on the estimation error and on the confidence interval defined. In table 1 the number of samples needed and the cost in terms of *number of samples/litres of consumption* is presented both for a direct mean demand estimation and when the error is estimated and the demand is generated combining it with the prediction algorithm. This estimation is general for all the network and the mean allows an estimation of each DMA consumption for a comparison with delivered water that is measured in the input. Leakage detection is improved and then a search in the less efficient DMA is carried out.

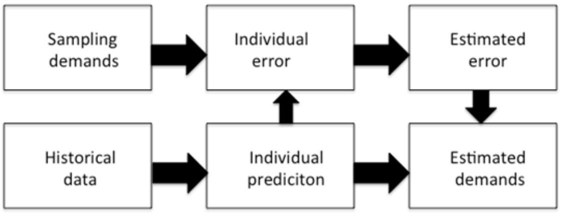


Fig. 3: Estimation of demands combining demand prediction and error estimation

Table 1: sampling of the 6 segments generated by classification in water network in Barcelona

Nivell 1 (Gauss2,Prob.,Exig.=0.1,GNIC=0.5,2iteracions)						
Elements in each class	117498	49901	339	17369	2385	6
number of samples						
confidence 0,05						
estimating demands	29503	4442	339	3359	2385	6
cost=nº of samples/consumption	0,01627	0,00085	0,00024	0,00071	0,00124	7,6E-06
estimating prediction error	4758	3430	339	3940	2385	6
cost=nº of samples/consumption	0,00262	0,00066	0,00024	0,00083	0,00124	7,6E-06
Confidence 0.025						
estimating demands	41883	6306	339	4768	2385	6
cost=nº of samples/consumption	0,02310	0,00121	0,00024	0,00101	0,00124	7,6E-06
estimating prediction error	6754	4870	339	5593	2385	6
cost=nº of samples/consumption	0,00372	0,00094	0,00024	0,00118	0,00124	7,6E-06
Confidence 0,005						
estimating demands	72346	10892	339	8236	2385	6
cost=nº of samples/consumption	0,03990	0,00210	0,00024	0,00174	0,00124	7,6E-06
estimating prediction error	11666	8411	339	9660	2385	6
cost=nº of samples/consumption	0,00643	0,00162	0,00024	0,00204	0,00124	7,6E-06

PRESSURE SENSORS PLACEMENT

Once the global demand is estimated, the DMA structure of the network allows the evaluation of the leakages in each area. The leak localisation within the DMA requires more information than the global demand of each DMA estimation. Pressures and flows highly depend on demands and leaks. Pressure sensors are more affordable and less invasive than flow sensors. Optimal sensor placement is often focused on the final application. First, a leak localisation approach is proposed [*7*]. Nevertheless, the sensors give information that should be further exploited. Demand calibration provides a network model that can be used for precise control or quality supervision. A sensor distribution methodology based on the pressure sensitivity matrix is proposed. This second methodology is generated for demand calibration [*3*] but does not include the demand evaluation in the cost function. Both sensor distributions are applied to a real DMA located in the Barcelona area and the results for leak localisation and demand calibration are compared.

Optimal sensor distribution for leak localisation

The problem of where a small number of sensors may give the best discriminability in the leakage localisation process is posed as an optimisation problem. Optimisation variables are the localisation of a finite number of sensors and the number of sensors itself. Here, the number of sensors is increased one by one and the optimisation problem for each number of sensors is solved. The cost used is the maximum number of leakages *mk* that have the same signature *k*. It has to be minimised for it means that when such signature appears the leakage will be in any of this nodes. The problem is a MinMax problem with a constraint in the number of sensors.

$$\begin{gathered}\min_{\{i,j,....\}}\left(\max_k (m_k)\right)\\ card(\{i,j,....\}) = n\end{gathered} \quad (4)$$

The formulation of the possible solutions makes Genetic Algorithms very suitable for solving it [*10*]. Stabilised results have been obtained using the Matlab GA toolbox, setting different initial populations in each execution. This algorithm is then used for sensor placement in the network, thus the obtained sensors are called real sensors from now.

Sensor distribution by sensitivity matrix

This methodology selects the k most sensitive sensors that have to be installed depending on the sensitivity matrix S relating heads variations with demand patterns variations. The generation of matrix S is detailed in [*3*].

The information density matrix I_d in Eq. 5 can be computed using matrix U, which is generated by means of the Singular Value Decomposition (SVD) of the sensitivity matrix S. Matrix U is an m x m matrix of orthonormal singular vectors associated with the m potential measurements.

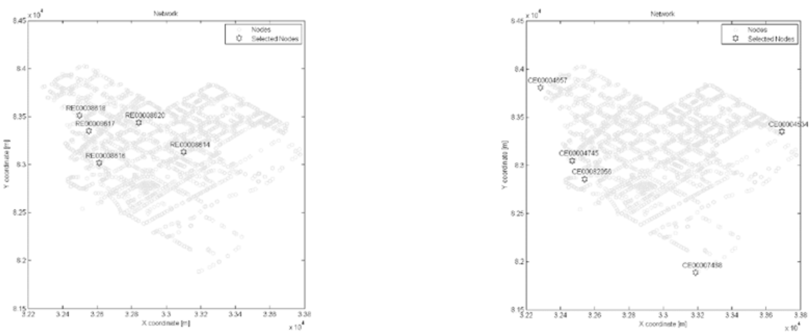
$$I_d = U_r(U_r)^T \qquad (5)$$

where U_r is a reduced form of U, where only the first k columns associated to the k highest singular values have been considered.

Wiggins [*14*] presented an approach for extracting k orthonormal vectors from the resolution matrix that enhance the delta-like behavior of that matrix. A similar approach is used in order to select the best sensors depending on their sensitivity [*3*]. From each generated delta vector, the node with the highest value is chosen as sensor. Ideally, each chosen sensor would have the highest sensitivity to one of the new k parameters while being little sensitive to the rest.

Leak localisation and demand calibration results

The two sensors sets used for leak localisation and demand calibration are depicted in Figure 4. The methodology presented here is applied to Nova Icària DMA in the Barcelona Water Network.



(a) (b)

Figure 4. Pressure sensors in Nova Icària DMA, (a) Installed sensors; (b) Suggested demand sensitivity-based sensors

Regarding leak localization results, three figures of merit are given: the mean distance (over the localization horizon) from the real leakage to the node with maximum correlation d_{pl_t} the mean distance to the gravity center of nodes with correlation over 99 % of the maximum correlation d_{gc_t} and the area covered by this 99 % set of nodes. The use of the gravity center instead of the potential fault introduces stability to the indicator. The comparison of these two sensor distribution approaches is shown in Figure 5. Here, results obtained at the end of the scenario considered (i.e. at hour 72) are presented. These results accumulate residuals information of the last 10 hours.

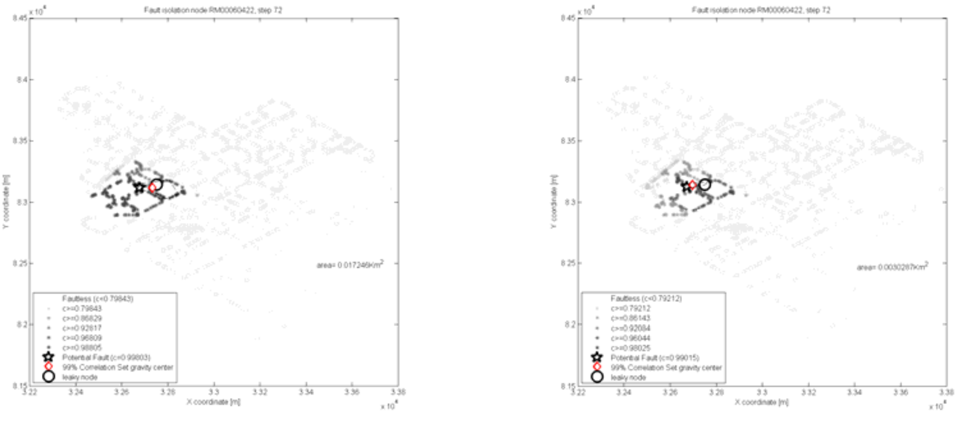


Figure 5. Leak localization results in Nova Icària DMA, (a) Installed sensors; (b) Suggested demand-based sensors

In Figure 5, it may be observed how both approaches achieve good leak localization results for this particular scenario. In the first approach (i.e. installed sensors), $\overline{d}_{pl_1} = 13.24\,\mathrm{m}$, $\overline{d}_{gc_1} = 53.34\,\mathrm{m}$ and the area covered by the 99 % correlation set is about 0.017 Km2 (Figure 5a), whereas in the second approach (i.e. proposed demand-based sensors), $\overline{d}_{pl_2} = 42.75\,\mathrm{m}$, $\overline{d}_{gc_1} = 43.71\,\mathrm{m}$ and the area covered by the 99 % correlation set is about 0.003 Km2 (Figure 5b).

Regarding demand calibration, five different groups of nodes are generated considering each sensor configuration (the real ones and the sensors placed by SM). Synthetic data is generated with a demand model where 10 different patterns are distributed all over the network. In Figure 6, the total demand of each nodes set using the calibrated patterns and the assumed data (i.e. synthetic data emulating reality), are compared. The results are good in both cases considered, similarly as with the predicted pressures of the sensors.

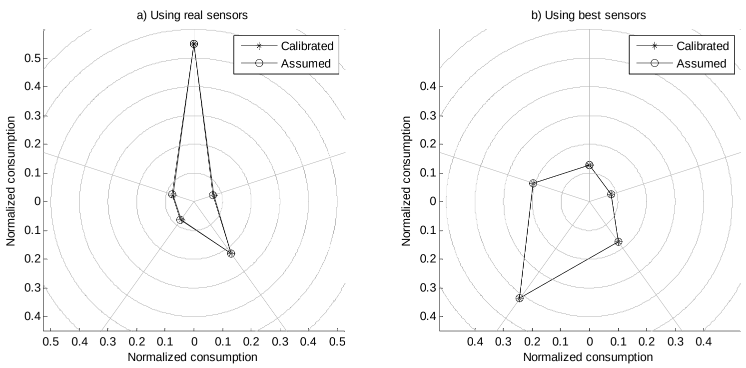


Fig. 6: Global demand for the calibrated sets compared with the assumed consumption using synthetic data.

The calibrated patterns are presented in Figure 7. In the latter, a slight improvement can be observed in the sensor configuration produced using the Sensitivity Matrix.

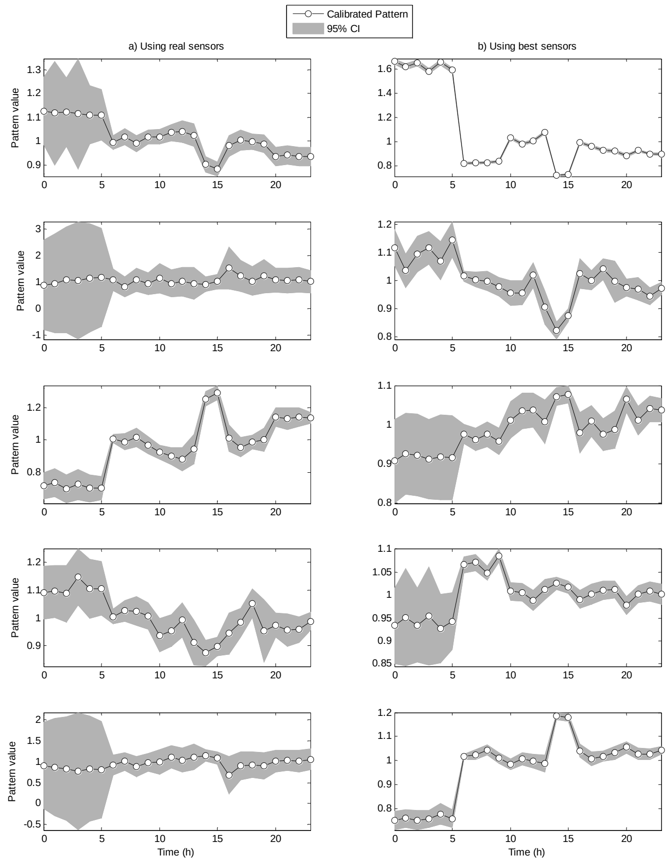


Fig. 7: demand patterns for the two sensor sets.

CONCLUSIONS

Here the sensors placement problem applied to a WDS is treated, considering the two main concerns affecting such systems management, which are demand estimation and leak localisation. Regarding demand estimation, two different approaches are studied. Demand telemetry can help estimating the consumed water. A reduced number of telemetries combined with a correct sampling for a group of demands with similar characteristics provides a good estimation of the mean consumption of this group. It requires the classification of demands and the definition of the sampling depending on how the estimation will be carried out. The combination of prediction and prediction error estimation decreased the exigency of telemetry.

The second approach uses hydraulic information and the dependence of the pressure on demands and leakages. Two sensor placement methodologies are compared: the first is leak-localization oriented while the second is based on the use of the sensitivity matrix. The results of demand calibration and leak localization are rather similar with a slight advantage for the sensors placed using the sensitivity matrix. This encourages to place sensors independently of the final application.

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