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# Demand pattern calibration in water distribution networks

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**Abstract**

Water distribution network models are widely used by water companies. Consumer demands are one of the main uncertainties in these models, but their calibration is not feasible due to the low number of sensors available in most real networks. However, the behaviour of these individual demands can be also calibrated if some *a priori* information is available. A methodology for calibrating demand patterns based on singular value decomposition (SVD) is presented. Demand stochastic nature is overcome by using multiple data samples. The methodology is applied to two water distribution systems: an academic network and a real network with synthetic data.



*Keywords:* Water distribution networks; demand models; demand patterns; calibration; singular value decomposition.

## 1. Introduction

Water distribution network models are used by water companies in a wide range of applications. A good calibration of these models is required in order to increase the confidence of the applications results, as seen in Pérez et al. (2011). Walski (1983) assessed that the major uncertainties in water distribution models are pipes' roughness and nodal consumptions. This work focuses on water demands due to their daily variability.

Generally, water distribution networks are formed by thousands of pipes and nodes; however, the number of measurements taken is reduced to a few selected locations. This makes unfeasible the problem of calibrating thousands of individual demands. A methodology based on SVD for solving the generalized inverse problem based on the approaches proposed by Wasantha Lal (1995) and Cheng and He (2011) is presented in this paper. The available consumers' information is included for reducing the number of unknowns of the system.

The structure of the paper is as follows. The literature on calibration of water distribution networks is reviewed in section 2. In section 3, one of the optimisation methods for solving the generalized inverse problem is exposed and adjusted for pattern calibration. Subsequently, the problem statement and the generated results for this particular case are presented in section 4 and 5. Finally, some conclusions are summarized in section 6.

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## 2. Literature Review

Water networks calibration has been thoroughly studied by researchers but almost evaded by practitioners. The high uncertainty in real networks together with the low number of measurements available make the calibration problem a challenge. Shamir and Howard (1977) state that calibration "consists of determining the physical and operational characteristics of an existing system and determining the data [that] when input to the computer model will yield realistic results". The calibration process typically alters system demands, fine-tunes pipes' roughness, and modifies pump operation characteristics until satisfactory matching is attained between measured and modelled data.

The global calibration state of the art is very well presented by Savic et al. (2009). Methods are classified depending on their dynamics (static/transient) and depending on the optimisation technique: (1) Iterative methods, based on trial and error procedures; (2) Explicit methods, which solve the extended set of steady-state mass balance and energy equations; and (3) Implicit methods, which are formulated and solved using an optimisation technique coupled with a hydraulic solver.

Walski (1983) proposed a trial and error methodology to adjust both demands and roughness in a pipe network using fire flow test. Bhave (1988) presented another iterative method where the network was divided in zones and the total demand in each zone was corrected while the resistances were adjusted too. Ormsbee and Wood (1986) formulated the calibration algorithm in terms of head loss coefficients, solving the basic network equations explicitly. However, implicit methods seem to be the most used. Datta and Sridharan (1994) described the direct problem that deals with the calculation of the pressure and flow distribution over the network, which corresponds to the given resistances and the consumptions and solves the inverse problem of determining resistances (Hazen-Williams coefficients) by means of weighted least squares (WLS) method using sensitivity analysis. Both consumptions and roughness were estimated by Reddy et al. (1996) using WLS method based on the Gauss-Newton minimization technique. Walters et al. (1998) used 90 pressure measurements for calibrating a 1000 pipes network by means of genetic algorithms. More references of calibration techniques are reviewed by Savic et al. (2009).

Due to the inaccuracy of the input data, it is important to calculate not only the estimated parameter values but also an indication of how reliable these estimations are. Bargiela and Hainsworth (1989) compared Monte Carlo simulation, an optimisation-based approach and a sensitivity-based approach for confidence limit analysis. However, most of the reviewed bibliography perform the quantification of the parameter and prediction uncertainties by means of the FOSM model (First-Order Second-Moment), based on linear regression theory.

### *2.1. The outgoing inputs: Demands*

In projects developed by the authors research group (PROFURED, RTNM, EFFINET) the experts assessed that nodal demands were one of the main sources of uncertainty in the models and consequently in results. Pérez et al. (2011) verified the effect of a bad demand calibration on a fault detection methodology.

Demands are not physically in the network like nodes or pipes. They are inputs because, as said by Walski et al. (2003), they are the driving force behind the hydraulic dynamics occurring in water distribution systems (WDS). Of course water is going out, thus common sense sees them as outputs of the system. They are estimated as parameters but very complex ones. Finally, from a control point of view they are nothing but disturbances that have to be rejected for a good service. Any place where water can leave the system represents a point of consumption, including a customer's faucet, a leaky main, or an open fire hydrant.

Water usage in municipal WDS is inherently unsteady due to continuously varying demands. To be effective a real-time modelling technique must acknowledge and accommodate the disconnection between mean demand estimates that change gradually and real demands. These two objectives (the time and spatial distribution) that have been described by Davidson and Bouchart (2006) are the aim of this work. Hence, the calibration of demands will use both information coming from outside (billing records) and inside (installed sensors) the network.

The adjustment of demands is a typical inverse problem based on optimisation. Aksela and Aksela (2011) used the measured weekly consumption for classification of different types of households. This classification allowed an estimation of the demand curves using Gibbs sampling and combination of Gaussians. Davidson and Bouchart (2006) and Cheng and He (2011) described how to estimate demands using head and flow measurements by means of implicit methods based on least squares (LS) and SVD.

## 3. Calibration Methodologies

An implicit calibration methodology that uses SVD for solving the inverse problem is presented in this work. The optimisation problem finds the minimum of the following objective function:

$$minJ(D) = \sum_{i=1}^{nh}(W_i^h)^2[h_i^m - h_i^p(D)]^2 + \sum_{j=1}^{nq}(W_j^q)^2[q_j^m - q_j^p(D)]^2 \tag{1}$$

subject to

$$G(H, D, R) = 0 \tag{2}$$

Where $J$ is the objective function; $D$ is the vector of nodal demand; $h_i^m$ and $h_i^p$ are the measured and predicted heads at node $i$, respectively; $q_j^m$ and $q_j^p$ are the measured and predicted pipe flows at pipe $j$, respectively; $W^h$ and $W^q$ are the weighting factors applied to the different terms to ensure that they are of similar magnitude and unit; $nh$ and $nq$ are the number of observed nodal heads and pipe flows, respectively; $H$ is the vector of nodal heads; R is the vector of pipes' roughness; and $G$ is the system of nonlinear equations describing the hydraulic steady state of flows and pressures in a water distribution network, which includes mass continuity and energy conservation equations.

### 3.1. Generalized inverse problem

The method used by Wiggins (1972) and Uhrhammer (1980) for seismographic networks, Wasantha Lal (1995) for riverbed roughness calibration and Cheng and He (2011) for WDS is used and adapted in the current study. The objective of the calibration problem is to find the parameter vector $x$ that minimizes the errors $\varepsilon = y_m - y_p$, where $y_m$ and $y_p$ are the vectors of measured and predicted values, respectively. The corrections in parameters ($\Delta x$) that make $\varepsilon = 0$ can be obtained by solving the system of equations:

$$S \cdot \Delta x = \varepsilon \tag{3}$$

where $S$ is the sensitivity matrix that relates errors in predictions with errors in the models' parameters. In non-linear problems, $\Delta x$ is calculated iteratively and used to correct the parameter vector $x$:

$$x_{r+1} = x_r + \rho \Delta x_r \tag{4}$$

where $r$ is the iteration number and $\rho$ is a parameter to control the step size. The iterative scheme is continued until a termination criterion is achieved.

The system in Eq. 3 can be solved using methods such as Gaussian elimination (evendetermined), least squares method (overdetermined) or Penrose inverse solution (underdetermined). However, none of these solution techniques can be used with rank-deficient or ill-conditioned $S$ matrices. The SVD is capable of solving under-, over-, even- or mixed-determined problems with no rank conditions in $S$, as explained by Menke (1982). The SVD of matrix $S$ in Eq. 3 is:

$$\underset{(m\times n)}{S} = \underset{(m\times n)}{U} \cdot \underset{(n\times n)}{\Lambda} \cdot \underset{(n\times n)}{V^T} \tag{5}$$

where $U$ is a matrix of orthonormal singular vectors associated with the observed data, $V$ is a matrix of orthonormal singular vectors associated with the calibrated parameters; and $\Lambda$ is a diagonal matrix of the singular values of $S$. Eq. 3 can be solved by SVD as:

$$\Delta x = V \frac{1}{\Lambda} U^T \varepsilon \tag{6}$$

where $1/\lambda_i$ is $ith$ diagonal element of $1/\Lambda$, and $\lambda_i$ is the $ith$ diagonal element of $\Lambda$ (for $\lambda_i = 0$, the corresponding element of $1/\Lambda$ is set to 0). SVD determines the optimisation direction $\Delta x$ for a problem that minimizes $\|\Delta x\|$ and $\|\varepsilon\|$. A cut-off level for small $\lambda$ is set to avoid $1/\lambda$ becoming too large. Uhrhammer (1980) and Wiggins (1972) used the SVD matrices for the estimation of the covariance matrix for the parameter space:

$$\Upsilon^2 = V \frac{\sigma^2}{\Lambda^2} V^T \tag{7}$$

where $\sigma^2$ is the variance of the measurements, considered the same for all sensors. The diagonal elements of $\Upsilon$ are estimates of the uncertainty (standard error) of the estimated parameters.

The additional information given by matrices $U$ and $V$ can be used for analysing the parameter resolution and the information density. Parameter reduction can be achieved from these analyses, but generally it causes a loss of physical meaning of the new parameters. In this work, re-parametrization is performed by means of *a priori* information.

### 3.2. Application to water distribution networks

One of the main difficulties in applying the previous methodology to WDS is the calculation of the sensitivity matrix $S$. The elements of this matrix can be calculated using the influence coefficient method:

$$s_{ij} = \frac{\delta y_i}{\delta x_j} = \lim_{\Delta x_i \to 0} \frac{y_i(x_i + \Delta x_i) - y_i(x_i)}{\Delta x_i} \tag{8}$$

However, using this method for huge (real-life) networks with n elements (nodes, links or a combination), the calculation of $S$ requires $n + 1$ simulations, which is highly time consuming. Nevertheless, matrix analysis of the WDS equations can simplify this calculations as explained by Cheng and He (2011). Eq. 2 can be expressed as:

$$BCB'H^* = D^* \to BCB'(H^p + \Delta H) = D^p + \Delta D \to BCB'\Delta H = \Delta D \to A\Delta H = \Delta D \to \Delta H = A^{-1}\Delta D \tag{9}$$

where $B$ is the incidence matrix; $C$ is the non-linear matrix depending on the pipes' roughness, lengths, diameters and hydraulic gradient; $D^*$ and $H^*$ are the real nodal demands and heads, respectively; $D^P$ and $H^P$ are the predicted nodal demands and heads, respectively; $\Delta D$ and $\Delta H$ are the differences between real and predicted nodal demands and heads; and $A^{-1}$ is the sensitivity matrix relating nodal demands and heads. The same process can be applied to the flow matrix equation:

$$Q^* = CB'H^* \to \Delta Q = CB'\Delta H \to \Delta Q = CB'A^{-1}\Delta D \tag{10}$$

where $Q^*$ is the vector with real flows; and $\Delta Q$ is the difference between real and predicted flows. This time the sensitivity matrix is represented by $CB'A^{-1}$, relating nodal demands and pipes' flows. Finally, a constraint defining that the sum of consumptions can not vary is defined:

$$\mathbf{1}\Delta D = 0 \tag{11}$$

where $\mathbf{1} = [11...1]$.

Matrix $A_{mh}$ and vector $\Delta H_{mh}$ can be extracted from matrix $A^{-1}$ and vector $\Delta H$ respectively, which are related to measured nodal heads. In the same way, matrix $A_{mf}$ and vector $\Delta Q_{mf}$ can be extracted from matrix $CB'A^{-1}$ and vector $\Delta Q$ respectively, which are related to measured pipes' flows. Assembling these matrices with Eq. 11, Eq. 12 is obtained, and can be solved as explained in section3.1. Weights $W$ are added in order to unify units.

$$W \begin{vmatrix} A_{mh} \\ A_{mf} \\ \mathbf{1} \end{vmatrix} \Delta D = W \begin{vmatrix} \Delta H_{mh} \\ \Delta Q_{mf} \\ 0 \end{vmatrix} \tag{12}$$

Calibration of nodal demands in a real life network is an underdetermined problem due to the low number of available sensors. However, the lack of sensors can be overcome with the addition of known information, like quarterly billing and type of consumer. The first gives information about the average consumption of each node, i.e. the weight of this consumption over the whole network, while the second allows to discern among different types of behaviours, e.g. commercial, industrial or residential demand. It is assumed that demands of the same type share the same pattern behaviour, individually weighted depending on the average consumption (base demand) of each node obtained from billing. This definition of demands can be represented as follows:

$$d_i(k) = bd_i \cdot p_{a\to i}(t \to k) \cdot totalDemand(k) \tag{13}$$

where $d_i(k)$ is the demand of node $i$ at sample $k$; $bd_i$ is the base demand of node $i$; $p_{a\to i}(t \to k)$ is the value of the pattern $p_a$ associated to node $i$ at time $t$ associated to sample $k$, with no units; and $totalDemand(k)$ is the total consumed demand measured at the inputs at sample $k$. The time $t$ refers to a period of the pattern, meanwhile the sample $k$ refers to the real time, i.e. if working with 24 samples per day, the value $t = 1$ of the patterns is the same for samples $k = 1, 25, 49...$, what means that the behaviour at 1am is the same on monday, tuesday, etc.

Considering nodal demands as defined in Eq. 13, the demand vector $D = [d_1\ d_2\ ...\ d_n]'$ can be expressed as a set of matrices representing the same nodal demand but defined using patterns. Then, for an example with four nodal demands, where $d_1$ and $d_3$ belong to pattern $A$, and $d_2$ and $d_4$ belong to pattern $B$, the set of equivalent matrices is:

$$\begin{vmatrix} d_1(k) \\ d_2(k) \\ d_3(k) \\ d_4(k) \end{vmatrix} = \begin{vmatrix} bd_1 \cdot p_A(t \to k) \cdot totalDemand(k) \\ bd_2 \cdot p_B(t \to k) \cdot totalDemand(k) \\ bd_3 \cdot p_A(t \to k) \cdot totalDemand(k) \\ bd_4 \cdot p_B(t \to k) \cdot totalDemand(k) \end{vmatrix} = \begin{vmatrix} bd_1 & 0 & 0 & 0 \\ 0 & bd_2 & 0 & 0 \\ 0 & 0 & bd_3 & 0 \\ 0 & 0 & 0 & bd_4 \end{vmatrix} \cdot \begin{vmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 0 \\ 0 & 1 \end{vmatrix} \cdot \begin{vmatrix} p_A(t \to k) \\ p_B(t \to k) \end{vmatrix} \cdot totalDemand(k) \quad (14)$$

Hence, the demand matrix $D$ is decomposed into the base demand matrix $BDM$, the pattern matching matrix $PMM$ and the pattern matrix $P$. This modification reduces the network variables (individual nodal demands) to a few unknown parameters (patterns of behaviour). The new matrices fulfill Eq.15, so the same pattern value can be used independently of the consumed total demand.

$$\sum BDM \cdot PMM \cdot P = 1 \quad (15)$$

Subsequently, the sensitivity matrix used for calculation of the optimal search vector is defined as the effect of pattern changes on measurements. Defining $\Delta P$ as the difference between the real pattern values and the predicted ones, and considering that $BDM$ and $PMM$ matrices are known and fixed during time, it can be deduced that variations on demands at sample $k$ are produced by variations in patterns at the same sample:

$$\Delta D = BDM \cdot PMM \cdot \Delta P \cdot totalDemand \quad (16)$$

Consequently, Eq. 12 can be redefined as:

$$W \begin{vmatrix} A_{mh}(k) \\ A_{mf}(k) \\ \mathbf{1} \end{vmatrix} \cdot BDM \cdot PMM \cdot \Delta P(t \to k) \cdot totalDemand(k) = W \begin{vmatrix} \Delta H_{mh}(k) \\ \Delta Q_{mf}(k) \\ 0 \end{vmatrix} \quad (17)$$

The singular value decomposition determines $\Delta P$ for a problem that minimizes both $\|\Delta P\|_2$ and $\|\varepsilon\|_2$. Solving iteratively Eq. 17 leads to a set of patterns values for the pattern period $t$.

The stochastic nature of the nodal demands and the noise in measurements cause the calibrated patterns to differ from the real ones. The effect of both uncertainties can be reduced if data from multiple samples with the same boundary conditions and same expected demand patterns behaviours are used. The rank of the system is not increased, though it becomes more overdetermined, and the solution minimizes the error of all samples simultaneously. The system represented in Eq. 17 is extended including the extra data samples:

$$W \begin{vmatrix} A_{mh}(k_1) \cdot totalDemand(k_1) \\ A_{mh}(k_2) \cdot totalDemandalD(k_2) \\ \cdots \\ A_{mh}(k_n) \cdot totalDemand(k_n) \\ A_{mf}(k_1) \cdot totalDemand(k_1) \\ A_{mf}(k_2) \cdot totalDemand(k_2) \\ \cdots \\ A_{mf}(k_n) \cdot totalDemand(k_n) \\ \mathbf{1} \end{vmatrix} \cdot BDM \cdot PMM \cdot \Delta P(t \to k_1 \dots k_n) = W \begin{vmatrix} \Delta H_{mh}(k_1) \\ \Delta H_{mh}(k_2) \\ \cdots \\ \Delta H_{mh}(k_n) \\ \Delta Q_{mf}(k_1) \\ \Delta Q_{mf}(k_2) \\ \cdots \\ \Delta Q_{mf}(k_n) \\ 0 \end{vmatrix} \quad (18)$$

The inclusion of the extra samples do not increase the rank of the sensitivity matrix, so it does not overcome the lack of sensors problem mentioned before. Nevertheless, these extra information filters the noise in both demands and sensors.

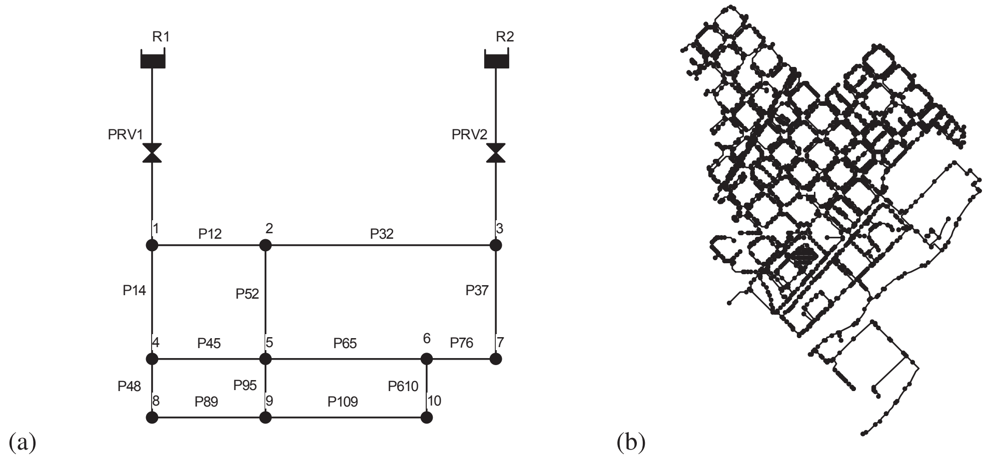


Fig. 1. (a) Academic network; (b) Icària network

## 4. Problem Statement

### *4.1. Used networks*

In order to evaluate the methodology presented in section 3, two networks with synthetic data have been used. The first one (Fig. 1.a) is an academic network consisting of 10 consumptions and 13 pipes. It has been designed for testing and understanding calibration and sampling design methodologies, identifiability studies, etc., as its simplicity allows to work manually with the small set of equations that forms the network model. On the other hand, the second network depicted in Fig. 1.b is a real network situated in a Barcelona neighbourhood called Nova Icària. It is composed by 3455 pipes and 3377 junctions, 1371 of which are consumers.

### *4.2. Assumptions*

Some assumptions are considered for the application of the methodologies. First, the inner network measurements consist in pressure sensors, as the company experts assessed that this type of sensors are the most used in water distribution networks for their lower cost and greater confidence in measurements when compared with flow sensors, although the latter may give more information about demands. Additionally, the monitoring system also registers the total inflow of the network. The second assumption is that no unaccounted for water (Lambert (1994)) exists in the network, so the measured inflow is fully consumed by the users. However, irregularities in the calibrated demand patterns when compared with the expected ones may signal unaccounted for water (leakages, fraudulent consumptions, etc.). This is actually one of the objectives of the author thesis, but beyond the scope of this paper.

The used methodology requires a seed for the parameters to be calibrated. In this work all initial parameters are set to the same value. Since then, the resulting parameters from the calibration at time $t$ are the initial values for the next sample. In a real case this seed would be obtained from studies of the consumptions that analyse the automated metered readings of representative members of each type of contract, probably improving the optimisation results.

### *4.3. Sensor distribution*

The sensors election is done basing on the information density matrix mentioned in section 3.1, computed as $I_d = UU'$. The diagonal elements of this matrix rate the information distribution among the observations. Starting from the information density matrix containing all network nodes, the one with the lower diagonal value is deleted at each iteration. Subsequently, $I_d$ matrix is recalculated and the previous step is repeated until $I_d$ becomes the identity matrix. The remaining nodes are the selected sensors.

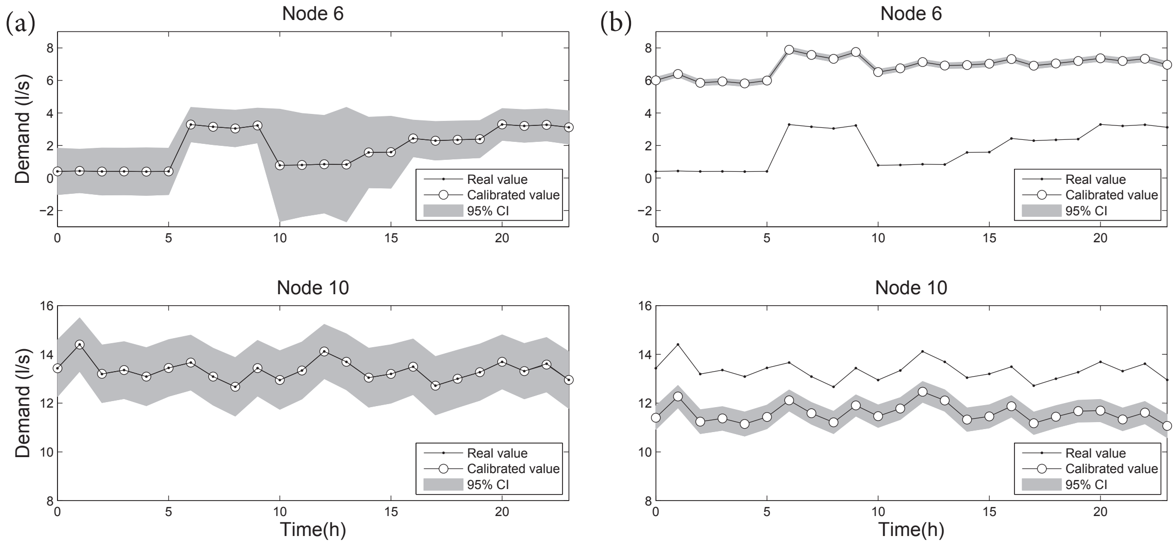


Fig. 2. Academic nodal demand calibration using: (a) 10 sensors (b) 4 sensors

### 4.4. Synthetic demand generation

Synthetic nodal demands of the academic and real networks have been generated with a random noise $N(0, 0.1d_i(k))$ applied to each demand at each sample, where $d_i(k)$ is the consumption of node $i$ at sample $k$ without noise. Four different patterns have been defined for the academic network and ten for the real one, representing different types of contracts: industrial, restaurant, commercial and household. All patterns and consequently all nodal demands have different behaviours during weekdays and weekends. The average consumption of each node has been calculated with the mean of the three months synthetic demands, thus the base demand assumed for each node will not be accurate as the calibration for weekdays and weekend is performed separately.

## 5. Results

### 5.1. Academic network: Demand calibration

Initially, nodal demand calibration is performed, reproducing the results in Cheng and He (2011), adding a random noise $N(0, 0.1)$ in pressure measurements. When using a pressure sensor in each of the network junctions, the generated results are perfect and all the demands are correctly calibrated. The synthetic and calibrated demands, and the 95% confidence intervals (CI) for nodes 6 and 10 are represented in Fig.2.a. However, when reducing the number of sensors to four, the system becomes underdetermined and one of the possible solutions that fit the model is obtained, as seen in Fig. 2.b. Also notice that using less sensors introduces less uncertainty to the solution.

### 5.2. Academic network: Pattern calibration

It has been seen that when decreasing the number of sensors, the calibration of nodal demands individually is unfeasible. Therefore, the *a priori* information of average consumptions and type of contract is introduced to the methodology to generate the BDM and PMM matrices, and patterns are defined as the new calibration parameters. Fig. 3 depicts the calibrated patterns and the 95 % CI in light grey. Now, although only four sensors (chosen as explained in section 4.3) were used, all patterns have been correctly calibrated. Consequently, the resulting nodal demands generated from the calibrated patterns are also well calibrated.

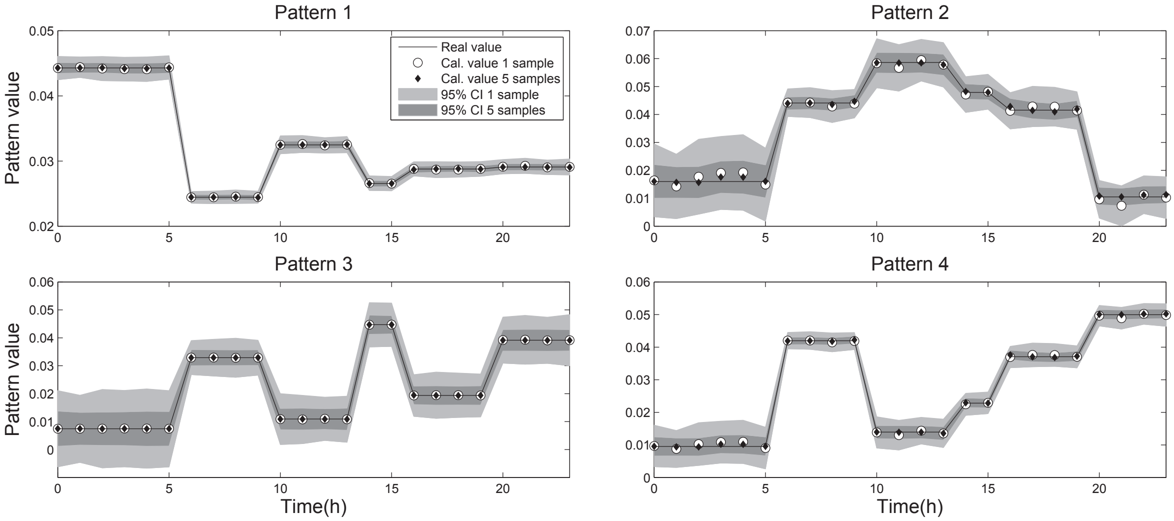


Fig. 3. Academic demand pattern calibration results with four sensors

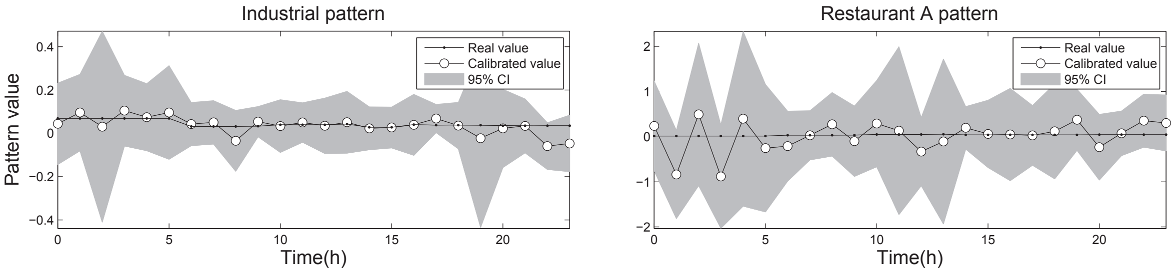


Fig. 4. Icària demand pattern calibration results with sensors noise $N(0, 0.1)$

## 5.3. Reducing uncertainty: Multiple sample calibration

The stochastic nature of the network demands, together with the pressure sensors lack of precision, lead to calibration results with high uncertainty in some cases (Fig. 3 patterns 2 and 3 boundaries in light grey). To reduce this uncertainty, multiple samples with the same boundary conditions can be used, as explained in section 3.2. The calibrated patterns using five samples (weekdays), as well as the resulting CI (dark grey) are depicted in Fig. 3 too.

## 5.4. Real network with synthetic data

The results obtained with the small academic network show that nodal demand calibration is not reliable if a low number of sensors is used, but the pattern calibration overcomes this problem. Besides, the use of multiple samples with same boundary conditions helps to reduce the results uncertainty. However, further studies should be done in order to assess the effectiveness of the methodology in real networks, so the multiple sample pattern calibration approach is evaluated with the Nova Icària network. A sensor distribution as explained in section 4.3 is performed, locating 10 sensors all over the network.

Fig. 4 depicts the pattern calibration and 95% confidence intervals for patterns 1 and 2, considering a random noise $N(0, 0.1)$ in the sensors. It can be seen that the noise in the measurements generates a bad calibration, as indicated by the large confidence intervals.

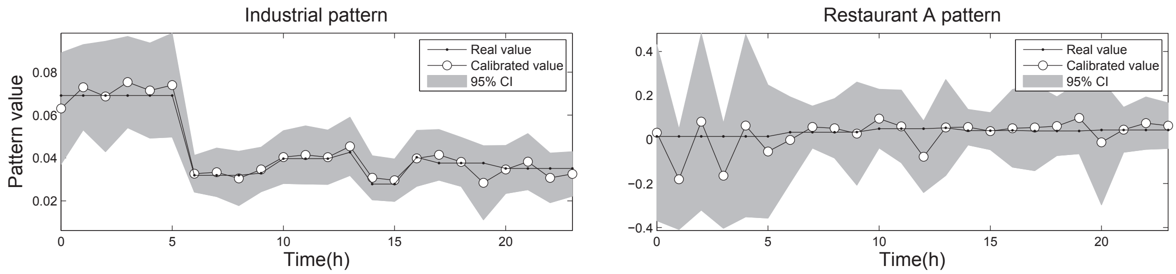


Fig. 5. Icària demand pattern calibration results with sensors noise $N(0, 0.01)$

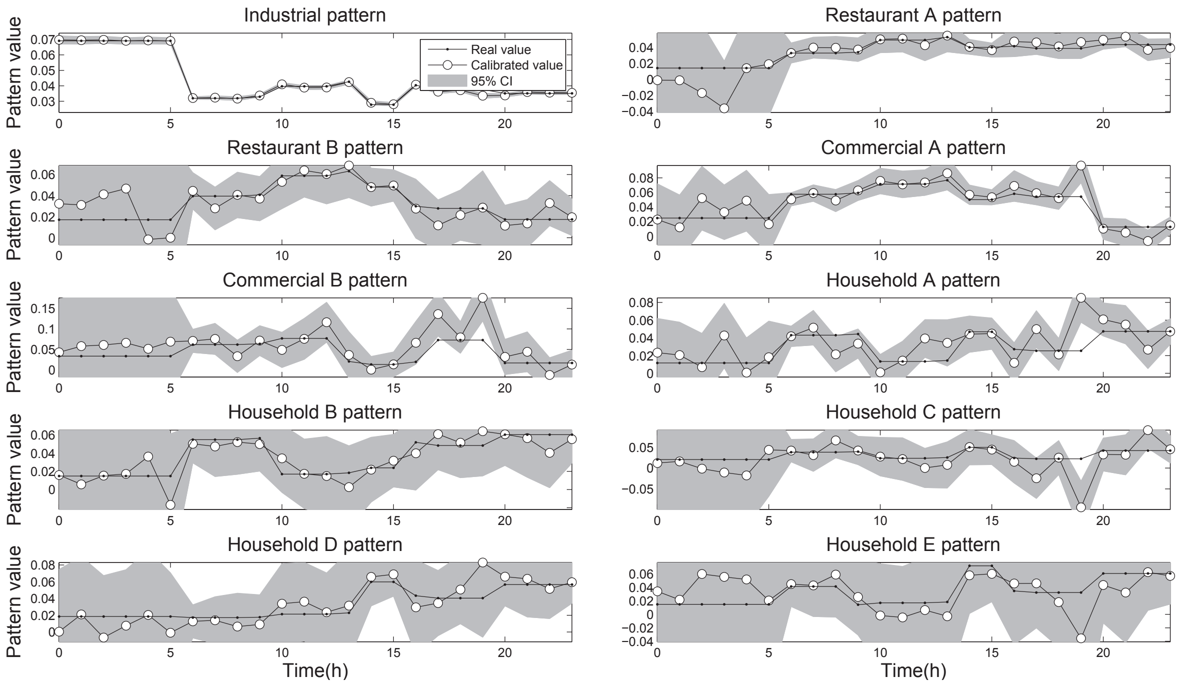


Fig. 6. Icària demand pattern calibration results with sensors noise $N(0, 0.001)$

Reducing the sensors noise to $N(0, 0.01)$ the results improve. Fig. 5 shows a good calibration in the first pattern (industrial), with more narrow confidence intervals. However, the rest of the nine patterns remain with a bad calibration with large boundaries (example of pattern 2 in the same figure). This may be due to the high (25%) water consumption of the industrial pattern over the rest.

Finally, when applying the pattern calibration algorithm with sensors noise $N(0, 0.001)$ all patterns are better calibrated, as represented in Fig. 6. Notice that the industrial pattern is perfectly resolved, with even tighter confidence intervals, due to its high consumption. For the same reason, nocturnal confidence intervals are wider due to the low night consumption of commercial, restaurant and household patterns.

The reduction of the sensors noise can be achieved by filtering several measurements along a period of time, so the standard deviation of the averaged measurement is decreased: $\sigma_{mean} = (1/\sqrt{N}) \cdot \sigma_{measurement}$. This filter together with the multiple sample calibration can reduce considerably the uncertainty in the calibrated patterns.

The same tests have been performed considering a demand model without noise, obtaining very similar results. Consequently, it seems that the calibrated parameters are more affected by noise in measurements than by noise in demands, as the calibration with noisy demands and no noise in measurements generates a nearly perfect result.

## 6. Conclusions

This work presents a methodology for demand pattern calibration in water distribution networks which solves the generalized inverse problem by means of the SVD. The methodology is tested in two networks with synthetic data.

Using the academic network, it has been shown that the use of a limited number of sensors makes a good calibration of individual demands unfeasible, as the problem becomes underdetermined. However, the addition of *a priori* information (quarterly billing and type of contract) for reducing the number of unknown parameters generates good results even with a low number of sensors. The use of multiple samples sharing similar working points allows to reduce the uncertainty of the calibrated parameters. This uncertainty derives from the noise of the network sensors and from the stochastic nature of demands. Additionally, the used average demands do not represent exactly the mean consumptions as the calibration results presented are performed only using weekdays.

The application of the multiple sample demand pattern calibration approach to the real network generates acceptable results, considering the existing uncertainty and the meshed topology of this huge network with mixed demand patterns. It is important to see that the demand pattern with highest consumption is always the best calibrated, so a high percentage of the consumed water and consequently, a great amount of the demand model is correctly identified.

During the author's thesis a graphical interface is being developed. The results presented in this work can be reproduced with a first version of this software, available at the authors research group website[1].

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