Uncertainty effect on leak localisation in a DMA

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***Abstract*— The leak localisation methodologies based on data and models are affected by both uncertainties in the model and in the measurements. This uncertainty should be quantified so that its effect on the localisation methods performance can be estimated. In this paper, a model-based leak localisation methodology is applied to a real District Metered Area using synthetic data. In the generation process of the data, uncertainty in demands is taken into account. This uncertainty was estimated so that it can justify the uncertainty observed in the real measurements. The leak localisation methodology consists, first, in generating the set of possible measurements, obtained by Monte Carlo Simulation under a certain leak assumption and considering uncertainty, and second, in falsifying sets of nodes using the correlation with a leak residual model in order to signal a set of possible leaky nodes. The assessment is done by means of generating the confusion matrix with a Monte Carlo approach.**

I. INTRODUCTION

A significant interest has been generated by leaks in water distribution networks (WDN), due to the financial cost borne by utilities, potential risks to public health and environmental burden associated with wasted water and energy. Thus, technologies for locating leaks have been developed. They range from ground-penetrating radar to acoustic listening devices [4]. [14] reviews the leakage assessment, detection, localisation and control methods. A review of transient-based leak detection methods is offered in [2] as a summary of current and past work. The use of sensor data from telemetry and mathematical models for real-time monitoring of water networks allows detecting and diagnosing possible abnormal situations, such as leakages. [16] proposes the use of sensitivity matrix for the leak location in WDN. Following this idea, a model-based leak location method was applied with satisfactory results in a District Metered Area (DMA) situated in Barcelona [11].

The accuracy of a leak localisation method is an important issue for the industry. This accuracy has to be assessed depending on the sensors available. [10] presents an accuracy assessment to be applied before the leak location. Some DMAs may only have measurements in the inputs. However, the lack of data is not the only handicap that a good accuracy in leak localisation faces. Actually, uncertainty in the model seems to be the main influence on accuracy. Uncertainty propagates through the use of these models to the decision taken. Key uncertainties in WDN modelling are considered in [6], where promising approaches for quantifying and reducing uncertainty are reviewed. Uncertainty in WDN modelling may be divided in two categories [5]: aleatory uncertainty and epistemic uncertainty. Aleatory uncertainty in demands is the main objection of the end users when using hydraulic models ([9]). Xu et al. [16] studies the reliability of a network based on the uncertainty in demands, roughness and tanks levels. The probability distribution of these parameters are estimated and validated by Monte Carlo (MC) simulation using a linear model. The normal distribution of the parameters generate, through the corresponding linearised model, a normal distribution of pressures. They alert of the difficulties of using the linearised model when the demand characteristics change and propose a modification creating different working points.

The paper is organized as follows: Section II presents the problem statement and the case study. The methodologies applied are described in Section III. In Section IV the results when applied to a real DMA with synthetic data are shown. Conclusions obtained are discussed in Section V.

II. PROBLEM STATEMENT

Given a model-based methodology for leak detection and localisation, the performance assessment must take into account the uncertainty both in the models and the measurements. Moreover, the resolution of the sensors may generate sets of undistinguishable leaks even in the absence of uncertainty.

In general, a DMA has its inputs monitored, both flows and pressures. This is the actual case in the Barcelona WDN where, in addition, some inner pressure measurements are used to set the model boundary conditions together with the demand distribution, based on registered water and the total demand provided by flow sensors at the network inputs. The pressure values obtained by sensors installed within the DMA present a relevant dispersion. This dispersion includes uncertainties from different sources. The main source of uncertainty is the demand distribution [9]. Thus, the reproduction of these uncertainties is done by means of introducing uncertainty in the demand model in the simulation [11].

Once the uncertainty can be reproduced, the expected residuals in different conditions are generated by MC simulations. This approach was compared with the analytical generation of the zonotopes in an academic example in [3]. Then, the leak localisation methodology is applied.

The goals that this work aims to achieve are:

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1) Obtain the undistinguishable leak models in the DMA given the sensor resolution.
2) Obtain the residual shape of the different leak models given the observed uncertainty.
3) The number of models/nodes that are signalled as leaky when the leak localisation methodology is applied.

A. *Case study*

In this work, a DMA located in the Barcelona area is used as a case study. In order to simulate the DMA isolated from the water transport network, the boundary conditions (i.e. pressure and flow measurements from the network) are fixed. Generally, pressure is fixed using a reservoir and the overall demand is obtained as the sum of the inflow distributed through the DMA. The total inflow is distributed using a constant coefficient (base demand) in each consumption node. Hence, all the consumptions are assumed to share the same profile, whilst the billing information is used to determine the base demand of each particular consumption. A good estimation of the demand model is paramount for the real case application.

The DMA considered here (Fig. 1) is called *Canyars* and is located at the pressure level 80 within the Barcelona water transport network. This DMA has $n_n = 694$ nodes and $n_l = 719$ links, and delivers water to the end consumers by means of a single input point.

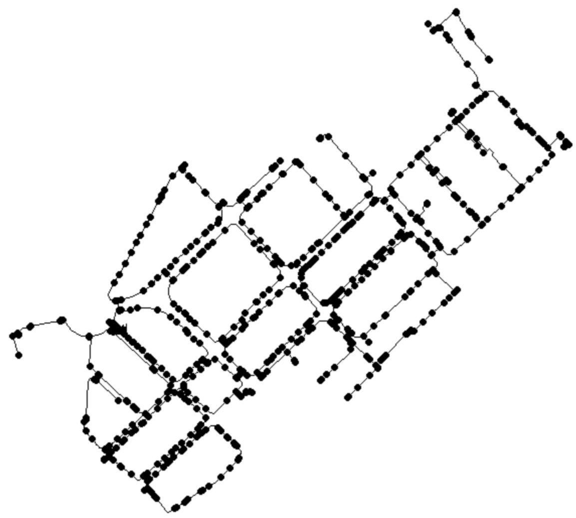

Fig. 1. Canyars DMA

Three sensors have been installed within the DMA [1]. The resolution is 0.1 mwc (meters of water column) for the pressure sensors. The simulated leak is of 10 l/s. The number of realisations for the MC simulatons is $N = 1000$.

III. METHODOLOGY

Synthetic data are generated by simulation of the real DMA model including the uncertainty. First the methodology to calibrate the demand distribution and its associated uncertainty is reviewed in this section and so is the leak localisation methodology. Finally, the assessment methodology is presented.

A. *Demand calibration and uncertainty simulation*

The demand components model [15] has been considered due to its capability of representing different demand behaviours depending on the pressure in the consumers area. This model uses a set of calibrated demand components to modulate the nodal demands in the network model. The representation of each of the n_d nodal demands is defined as:

$$d_i(q_{in}) = \frac{bd_i}{\sum_{j=1}^{n_d} bd_j} \cdot q_{in} \cdot \sum_{j=1}^{n_c} (\alpha_{i,j} \cdot c_j) \tag{1}$$

with

$$\alpha_{i,1} + \alpha_{i,2} + \cdots + \alpha_{i,n_c} = 1 \quad for \quad i = 1, ..., n_n \tag{2}$$

The memberships $\alpha_{i,j}$ of each nodal demand to each demand component are defined through the sensitivity analysis presented in [15] and bd_i is the weight of node i extracted from the quarterly users bills. The values of the n_c demand components can be calibrated through any optimization method with the objective of minimizing the errors in the calibrated model predicted variables. This calibration process assures implicitly that the total inflow is equal to the sum of demands:

$$q_{in} = \sum_{i=1}^{n_n} d_i \tag{3}$$

The resulting calibrated demand components include uncertainty boundaries that have been computed by means of the First-order Second-moment (FOSM) model. During the simulation tests, these uncertainty boundaries have been used to generate an equivalent predicted uncertainty in variables as in the real network measurements. Thus, the components c_j of equation (1) are modified in each simulation by a percentage ($\beta_j(k)$) randomly choosen within the uncertainty interval for that component (δc_j):

$$c_j(k) = (1 + \beta_j(k))c_j \quad -\delta c_j < \beta_j(k) < \delta c_j \tag{4}$$

The set of all demands produced with this uncertainty is $\mathcal{D} \subset \Re^{n_n}$ and the realisation generated for the MC simulation is $\hat{\mathcal{D}} = \{\mathbf{d}_j | \mathbf{d}_j \in \mathcal{D} \quad j = 1, ..., N\}$.

When a leaky scenario is simulated a certain value of leak is assumed (f_0). Then the equation (3) becomes:

$$q_{in} = \sum_{i=1}^{n_n} d_i + f_0 \tag{5}$$

A new set of demands, assuming the leak f_0 is present and there is uncertainty in the demand distribution, $\mathcal{D}_{f_0} \subset \Re^{n_n}$ is defined and so is its sample set $\hat{\mathcal{D}}_{f_0} = \{\mathbf{d}_l | \mathbf{d}_l \in \mathcal{D}_{f_0} \quad l = 1, ..., N\}$. Equations (3) and (5) are fulfilled by means of normalisation.

B. Leak localisation review

We review the leak location methodology that is going to be assessed. This methodology is based on the one presented in [11]. Given the network boundary conditions $\mathbf{h_S}$ in the form of heads in some nodes, as well as the total inflow $q_{in} \in \Re$, the flows in the input pipes and the heads in the nodes of the network can be computed. A vector $\mathbf{y} = (y_1 \dots y_{n_y})$ of n_y additional measurements from the network is also available. In the absence of leakage, the total inflow q_{in} is distributed among the network nodes according to a given demand pattern. The demands of the nodes are represented by a vector $\mathbf{d} = (d_1, \dots d_{n_n})$ with n_n equal to the number of nodes in the network.

Given the boundary conditions, the computation of a prediction $\hat{\mathbf{y}}_{\mathbf{nf}}$ for a non-leakage scenario is denoted by

$$\hat{\mathbf{y}}_{\mathbf{nf}} = g_{nf}(q_{in}, \mathbf{h_S}, \mathbf{d}(q_{in})) \tag{6}$$

where $\hat{\mathbf{y}}_{\mathbf{nf}} \in \Re^{n_y}$, $g_{nf} : \Re \times \Re^{n_h} \times \Re^{n_d} \to \Re^{n_y}$, $\mathbf{h_S} \in \Re^{n_h}$ and $\mathbf{d} \in \Re^{n_d}$. Subscript nf indicates non-faulty, i.e. non-leakage scenario. The difference

$$\mathbf{r} = \mathbf{y} - \hat{\mathbf{y}}_{\mathbf{nf}} \tag{7}$$

that quantifies the consistency of the measurement with the model prediction is called a *residual*. We will also call it *observed residual* to distinguish it from *predicted residual* as it will be seen later. If there is no uncertainty in model (6), the absence of leakage implies $\mathbf{r} = 0$.

In a leakage scenario, only the possibility of one leak of nominal value f_0 in an unknown node of the network is considered. Consider the n_n predictions $\hat{\mathbf{y}}_{\mathbf{f_i}}$, each one corresponding to a leak of nominal value f_0 in node i

$$\hat{\mathbf{y}}_{\mathbf{f_i}} = g_{f_i}(q_{in}, \mathbf{h_S}, \mathbf{d}(\mathbf{q_{in}} - \mathbf{f_0}), f_0) \qquad i = 1 \dots n_n \tag{8}$$

where $\hat{\mathbf{y}}_{\mathbf{f_i}} \in \Re^{n_y}$, $g_{f_i} : \Re \times \Re^{n_h} \times \Re^{n_d} \times \Re \to \Re^{n_y}$, $\mathbf{h_S} \in \Re^{n_h}$, $\mathbf{d} \in \Re^{n_d}$ and $f_0 \in \Re$. Subscript f_i indicates a faulty scenario consisting of a leak in node i. The differences

$$\hat{\mathbf{r}}_{\mathbf{f_i}} = \hat{\mathbf{y}}_{\mathbf{f_i}} - \hat{\mathbf{y}}_{\mathbf{nf}} \tag{9}$$

are the predicted residuals for the nominal leak f_0. If there is no uncertainty in model (8) and the value of the unknown leak to be located is small enough, then the dependency of the observed residual $\mathbf{r}$ can be supposed to be approximately linear with the leak magnitude f

$$\mathbf{r} = \hat{\mathbf{r}}_{\mathbf{f_i}} \cdot \frac{f}{f_0} + \mathbf{e} \qquad i = 1 \dots n_n \tag{10}$$

where $\mathbf{e}$ represents the error due to the uncertainties and the linear approximation. Because of linearity of $\mathbf{r}$ in f, if vectors $\hat{\mathbf{r}}_{\mathbf{f_i}}$ are linearly independent, then each $\hat{\mathbf{r}}_{\mathbf{f_i}}$ characterizes a different leak. Therefore a correlation measure to test linear dependency between $\mathbf{r}$ and $\hat{\mathbf{r}}_{\mathbf{f_i}}$ can be used to select the most consistent leak with $\mathbf{r}$. Thus the selected leak is the one maximizing the correlation measure

$$\rho(\mathbf{r}, \hat{\mathbf{r}}_{\mathbf{f_i}}) = \frac{\mathbf{r}^T \cdot \hat{\mathbf{r}}_{\mathbf{f_i}}}{\parallel \mathbf{r} \parallel \parallel \hat{} \mathbf{r}_{\mathbf{f_i}} \parallel} \tag{11}$$

where $\parallel . \parallel$ denotes the norm associated to the vector dot product. In this work the 2 norm is used. Note that if (10) has additive uncertainty, then the selection of $\hat{\mathbf{r}}_{\mathbf{f_i}}$ by maximizing the correlation measure ρ gives the least squares solution of (10).

Given that there is a leak in node i of nominal value f_0, uncertainty in demands means that we only know that:

$$\mathbf{d}(q_{in} - f_0) \in \mathcal{D}_{f_0}. \tag{12}$$

We use (9) with $\hat{\mathbf{y}}_{\mathbf{f_i}}$ generated by (8) and considering (12) to bound the residual with the set

$$\mathbf{r} \in \mathcal{R}_{f_i} \qquad i = 1 \dots n_n$$

where $\mathcal{R}_{f_i} \subset \Re^{n_y}$ is the set of possible residuals in leak scenario i considering uncertainty in demands. In particular $\hat{\mathbf{r}}_{\mathbf{f_i}} \in \mathcal{R}_{f_i}$.

To see the effect of this uncertainty on the location procedure, we restrict ourselves to the case when there is a leak of nominal value f_0. The evaluation of the correlation measures in (11) for all the residuals $\mathbf{r}$ in a set $\mathcal{R}$ gives a collection of intervals $[\rho](\mathcal{R}, \hat{\mathbf{r}}_{\mathbf{f_i}})$

$$[\rho](\mathcal{R}, \hat{\mathbf{r}}_{\mathbf{f_i}}) = \left\{ \frac{\mathbf{r}^T \cdot \hat{\mathbf{r}}_{\mathbf{f_i}}}{\parallel \mathbf{r} \parallel \ \|\hat{\mathbf{r}}_{\mathbf{f_i}}\|} : \mathbf{r} \in \mathcal{R} \right\} \tag{13}$$

As was proposed in [3] a straightforward way to transmit the uncertainty from demands to the residuals through the pressures is to generate a set of possible demand realisations $\hat{\mathcal{D}}_{f_0}$. As the cardinal N of this set increases, the coverage of the set $\mathcal{D}_{f_0} \subset \Re^{n_n}$ improves. Once the sampled set of possible demands $\hat{\mathcal{D}}_{f_0}$ is generated, sets $\hat{\mathcal{R}}_{f_i} \subset \Re^{n_y} \quad i = 1, ..., n_n$ that are sampled sets of $\mathcal{R}_{f_i}$ are obtained applying (7) to leak pressure samples obtained by non-linear models (8) considering demand values of $\hat{\mathcal{D}}_{f_0}$.

Once the sampled sets of possible residuals for each leak are generated, the correlation interval bounds $\underline{\rho}_{i,i}$ and $\overline{\rho}_{i,i}$ between the uncertain set $\mathcal{R}_{f_i}$ and nominal hypothesis f_i

$$[\rho](\mathcal{R}_{f_i}, \hat{\mathbf{r}}_{\mathbf{f_i}}) = [\underline{\rho}_{i,i}, \overline{\rho}_{i,i}] \tag{14}$$

can be approximated using (13) and $\hat{\mathcal{R}}_{f_i}$ as

$$\begin{aligned} \underline{\rho}_{i,i} = & \min_{\mathbf{r}} \quad \rho(\mathbf{r}, \hat{\mathbf{r}}_{\mathbf{f_i}}) \\ & \text{subject to} \quad \mathbf{r} \in \hat{\mathcal{R}}_{f_i} \end{aligned} \tag{15}$$

Bound $\overline{\rho}_{i,i}$ can be obtained using (15) but replacing min by max. If we assume that the actual leak is f_i the correlation of the residual $\mathbf{r}$ with $\hat{\mathbf{r}}_{\mathbf{f_i}}$ must be inside this interval.

C. Leak localisation algorithm

A new location algorithm based on a falsification process is proposed. Given the n_n nominal leak hypothesis $\hat{\mathbf{r}}_{\mathbf{f_i}}$, correlation boundaries $\underline{\rho}_{i,i}, \overline{\rho}_{i,i}$ and actual residual $\mathbf{r}$, Algorithm 1 uses a falsification process to provide the possible leak locations consistent with the considered demand uncertainty.

As a result of Algorithm 1, vector **leak** contains 1 for those leak hypothesis assigned with leak.

Algorithm 1 Leak localisation algorithm

Require: $\hat{\mathbf{r}}_{\mathbf{f_i}}$, $\underline{\rho}_{i,i}$, $\overline{\rho}_{i,i}$ $\quad i = 1, ..., n_n$ and $\mathbf{r}$
  leak=ones
    for $i = 1...n_n$
      compute $\rho(\mathbf{r}, \hat{\mathbf{r}}_{\mathbf{f_i}})$
      if $\rho(\mathbf{r}, \hat{\mathbf{r}}_{\mathbf{f_i}}) < \underline{\rho}_{i,i}$ or $\rho(\mathbf{r}, \hat{\mathbf{r}}_{\mathbf{f_i}}) > \overline{\rho}_{i,i}$
        leak(i)=0
      end
    end
  return leak

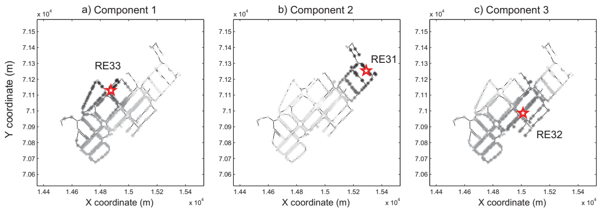

Fig. 2. Memberships of nodes to each demand component in Canyars network considering the three available sensors. Each representation of the network depicts a grayscale map with the membership of each node to a particular demand component: the darker the node in the map, the higher the membership of the node to the demand component. The sensor with the highest sensitivity to variations in each demand component is also depicted in each map

D. Performance assessment

The assessment of the leak localisation methodology under the demand uncertainty is performed creating a confusion matrix for N realisations of each leak (row). The matrix is created applying the leak localisation methodology and counting the number of assignations to each leak hypothesis (column). If no confusion is present the matrix should be diagonal full of N values. In order to keep the characteristics of a confusion matrix when more than one model matches one is taken randomly so that the sum of the rows of the matrix is N. The numbers that appear in the diagonal and their comparison with the maximum number in each row are studied in order to acknowledge whether the algorithm may give good results in a real scenario.

IV. RESULTS

The results presented in this work has been generated by synthetic data with a real DMA model. Three demand components have been defined as indicated in Section III-A. Figure 2 depicts, in each of the network maps, the membership of each node to a particular demand component: the darker the node, the higher the membership to that component. Each map in Figure 2 also includes the location of the sensor with the highest sensitivity to the component drawn.

A. Nominal Residuals, distinguishable leaks

Residuals generated by simulation showed that there were only 169 distinguishable nominal leak hypothesis due to the sensors' resolution. Even though the oversampling (10 minutes samples are merged each hour) enhances their

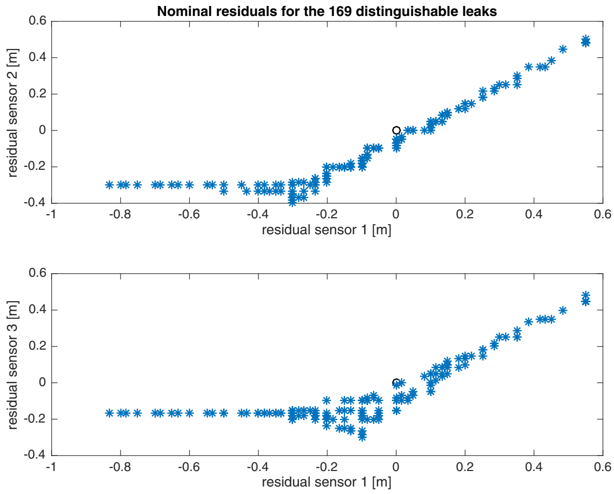

Fig. 3. Projection of the three residuals for the nominal leak hypothesis $\hat{\mathbf{r}}_{\mathbf{f_i}}$ $i = 1...169$ in Canyars

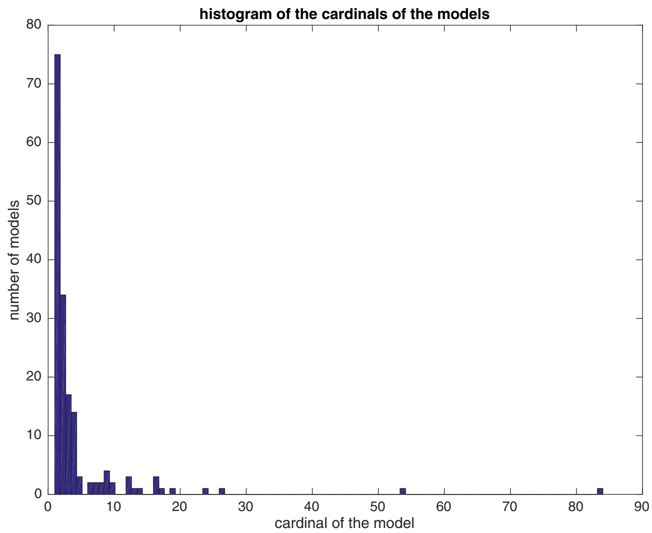

Fig. 4. Histogram of the cardinals of the models

resolution [7]. Figure 3 shows the projection of the three residuals for all the $n_n = 694$ nodes. Only $n_m = 169$ are different. Hereinafter only the distinguishable nodes/leak hypothesis are taken into account.

Figure 4 shows the Histogram of cardinality of the new leak hypothesis. All they have cardinal below 30 nodes except hypothesis 4 and 20 which will further be analyzed.

B. Uncertainty propagation

Including the uncertainty in the demand model the residuals are no more deterministic. The propagation of the uncertainty using the MC simulations produce a discrete (due to the sensor resolution) set of residuals. They are generated for the $n_m = 169$ possible leaky scenarios.

Figures 5 and 6 compared the projections for the three residuals for two distinguishable leak hypothesis (40 mwc

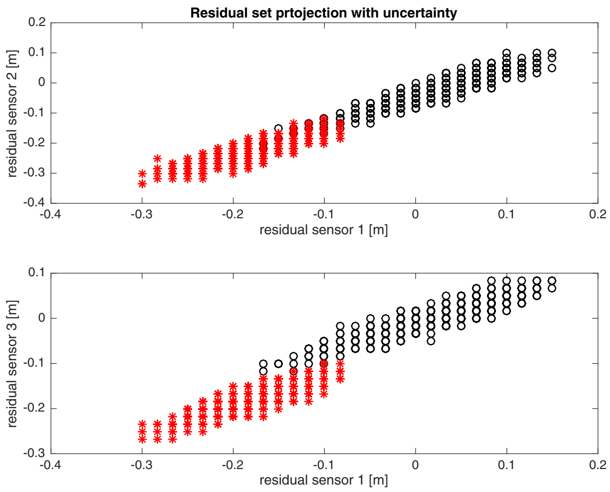

Fig. 5. Projection of the three residuals for the non-leaky scenario (o) and leak hypothesis 40 $\hat{\mathcal{R}}_{f_{40}}$ (*) with uncertainty in Canyars

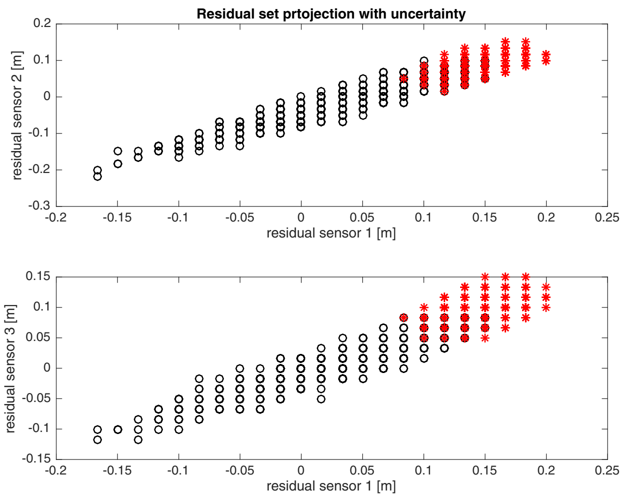

Fig. 6. Projection of the three residuals for the non-leaky scenario (o) and leak hypothesis 150 $\hat{\mathcal{R}}_{f_{150}}$ (*) with uncertainty in Canyars

and 150 mwc) and the projections of the non-leak scenario.

Once all the 169 sets of residuals are generated the lower and upper bounds for the correlation with equation (15) and its equivalent for the upper bound. Then, Algorithm 1 can be used to assign the consistent leak hypothesis.

C. Confusion Matrix

The confusion matrix is generated with 1000 new MC simulations for each leak scenarios. The representation of such matrix is impossible and useless. Therefore the diagonal of the confusion matrix compared with the maximum value in the corresponding row is presented in figures 7.

The number of leak hypothesis that get 80% or more assignments than the actual leak hypothesis and the corresponding number of nodes are presented in figure 8 and equivalently in figure 9 for the 50% of assignments.

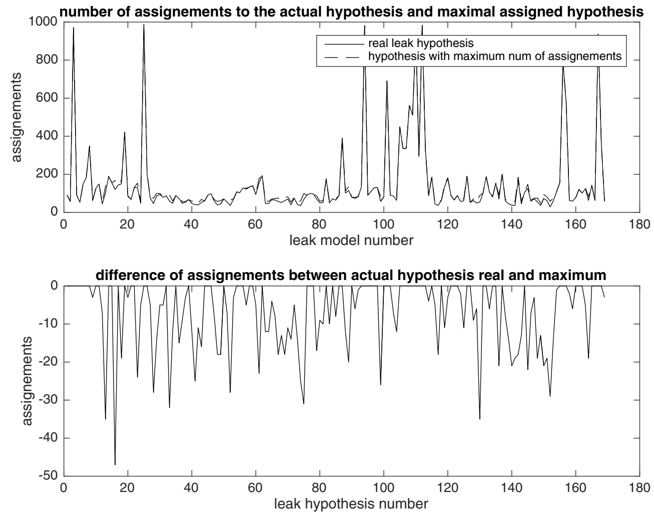

Fig. 7. Diagonal of Confusion Matrix and maximum value in the corresponding row and difference of these values for falsification

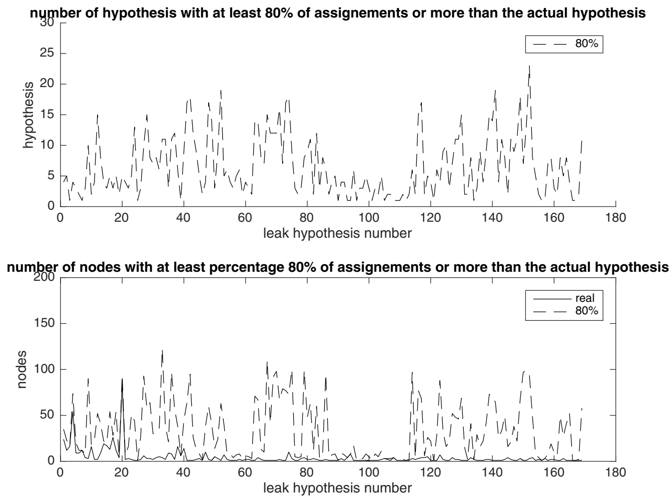

Fig. 8. Number of distinguishable leak hypothesis with 80% or more assignements of the actual hypothesis

V. CONCLUSIONS

In this paper, a new leak localisation method in WDN using pressure measurements and models has been proposed. The leak localisation method is based on a falsification algorithm that provides the leak hypothesis consistent with actual pressure measurements. Leak hypothesis consider the uncertainty in node demands using Monte Carlo simulations. In order to assess the performance of this Algorithm, a confusion matrix is generated. This matrix contains the number of assignments out of the realisations (using MC) of each leak scenario for each leak hypothesis. When the algorithm is applied to a real DMA, the resolution of the sensors implies that not all leaks are distinguishable leaks. Nevertheless the number of

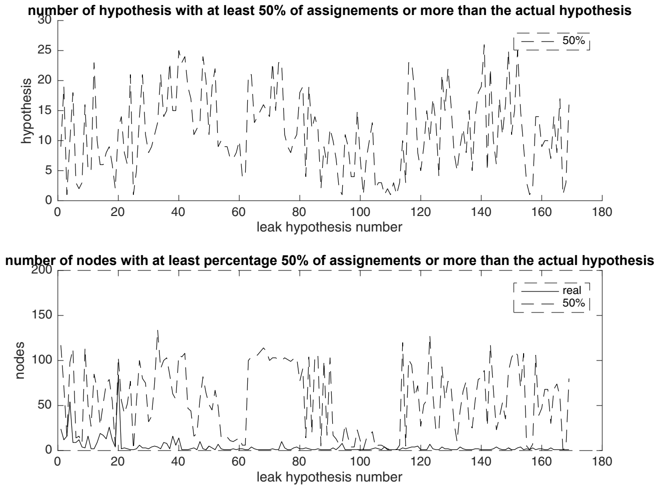

Fig. 9. Number of distinguishable leak hypothesis with 50% or more assignements of the actual hypothesis

distinguishable leak hypothesis implies a reasonable cardinal in each set. When the confusion matrix is generated the diagonal that corresponds to the actual leak hypothesis has the maximum number of assignments. If the number of assignments is relaxed, i.e. taking those leak hypothesis with 80% or more of the assignments of the actual one, the number of nodes included does not overcome 120 nodes out of 690. Thus, the localisation process reduces in these cases the search region in 83%. If the threshold of number of assignments is set to 50% the number of nodes involved is the same because the rest of the hypothesis are never assigned. It stands even for the two leak hypothesis with greatest cardinal that are not confused with other leak hypothesis. This results shows that the one step algorithm may not assign to the actual hypothesis but a multiple step algorithm may provide a reasonable search region that includes the actual leak. As a future work, this multiple step algorithm will be developed and applied to real date.

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