Incremental Upgrading Sensor Placement Methodology: Application to the Leak Localization in Water Networks

Adrià Soldevila[a], Joaquim Blesa[a,b,c], Sebastian Tornil-Sin[a,b], Rosa M. Fernandez-Canti[a], Vicenç Puig[a,b,*]

[a]*Research Center for Supervision, Safety and Automatic Control (CS2AC). Edifici Gaia, Campus UPC Terrassa Rambla Sant Nebridi, 22, 08022 Terrassa (Spain).*
[b]*Institut de Robòtica i Informàtica Industrial (CSIC-UPC). Carrer Llorens Artigas, 4-6, 08028 Barcelona (Spain).*
[c]*Serra Húnter Fellow Automatic Control Department (ESAII), Universitat Politècnica de Catalunya (UPC), Pau Gargallo, 5, 08028 Barcelona, Spain*

Abstract

This paper presents a new methodology for sensor reallocation in large scale-systems considering fault isolation purposes. From an initial set consisting of a limited number of sensors already installed in certain locations of the system, the proposed methodology produces a new sensor placement where some of the sensors are strategically reallocated in different but available places of the system. The procedure is posed as an optimization problem where the performance index is specific of the fault isolation method to be used. The algorithm that solves the problem is an incremental upgrading approach based in the Sequential Forward Floating Search algorithm and it combines a forward phase (where sensors are added sequentially) with a backward phase (where sensors can be individually removed from the original sensor placement). The proposed methodology is illustrated by means of its application to the problem of leak localization in Water Distribution Networks (WDN), where the particular placement of the pressure sensors has a great impact in the ability to isolate the leaky node. Also, since only a limited number of pressure sensors can be installed in some nodes, space interpolation techniques must be used to estimate the pressure in the other network nodes. The performance of the localization process is measured in

*Corresponding author.
Email address: `vicenc.puig@upc.edu` (Vicenç Puig)

terms of pipe distance from the estimated leaky node candidate to the real leaky node. The proposed methodology is applied to two District Metered Areas from the WDN of a metropolitan area of Spain, using real measurements and leak scenarios.

Keywords: sensor placement, sensor reallocation, water distribution networks, leak localization

---

1. Introduction

The performance of fault diagnosis systems highly depends on the available measurements, i.e. on the number and location of installed sensors. Optimal sensor placement for fault diagnosis has been widely researched in the literature (see as e.g. [1], [2], [3],R1-C1:[4],[5]). The aim of the existing algorithms is to find the optimal location of the sensors in the system on the basis of a set of specifications related to detectability/isolabilty and/or reliability properties. These algorithms assume that there are no sensors already installed in the system. However, in systems in operation, sensors already exist and the problem is how to reallocate them or add some additional sensors to meet the desired specifications. This problem is known as the sensor reallocation problem [6]. The problem of sensor reallocation for fault diagnosis purposes has just been recently addressed in the literature (see as e.g. [7]).

In this paper, a new methodology is proposed for dealing with the sensor reallocation problem for fault diagnosis. In particular, the leak localization problem in Water Distribution Networks (WDNs) is considered. Water leaks are present to some extent in all WDNs. Leaks may imply important economic costs because of the amount of water loss, and the location and reparation efforts involved. In many WDNs, losses due to leaks are estimated to account up to 30 % of the total amount of extracted water [8]. This is a significant amount, taking into account that water is a precious resource and it has to satisfy the demand of a continuously growing human world population.

The traditional approach to leakage control is a passive one, whereby the leak is repaired only when it becomes visible. Acoustic devices recently developed [9] allow to locate invisible leaks too, but unfortunately, their application over a large-scale water network is very expensive and time-consuming. A feasible solution is to divide the network into District Metered

Areas (DMA), where the *flow* and the *pressure* at their input are measured [10, 8], and to maintain a continuous leakage monitoring taking into account that leakages increase the flow and decrease the pressure head at the DMA entrance. Various empirical studies [11, 12] propose mathematical models to describe the leakage flow with regard to the pressure at the leakage location. Best practice in the analysis of DMA flows consists in estimating the leakage when the demand is minimal. This situation typically occurs at night, when the customers demand is low and the leakage component represents a great percentage of the pipe flow [8]. Therefore, practitioners monitor the DMA or groups of DMAs for detecting and locating the leak, and estimating the leakage level, by analyzing the minimum night flow [8]. However, leakage detection may not be easy, because of unpredictable variations in consumer demands and measurement noise, as well as long-term consumption trends and seasonal effects.

Several works have been published dealing with leak detection and localization methods for WDNs (see [13] and references therein). For instance, in [14], a review of transient-based leak detection methods is offered as a summary of current and past work. In [15], a method is proposed to identify leaks using blind spots based on previously leak detection that uses the analysis of acoustic and vibration signals [16], and models of buried pipelines to predict wave velocities [17]. More recently, [18] have developed a method to locate leaks using Support Vector Machines (SVM) that analyzes data obtained by a set of pressure control sensors of a pipeline network to locate and calculate the size of the leak. The use of k-NN and neuro-fuzzy classifiers in leak localization has been recently proposed in [19], [20] and [21]. Another set of methods is based on the inverse transient analysis [22, 23]. The main idea of this methodology is to analyze the pressure data collected during the occurrence of transitory events by means of the minimization of the difference between the observed and the calculated parameters. In [24, 25], it is shown that unsteady-state tests can be used for pipe diagnosis and leak detection. The transient-test based methodologies use the equations for transient flow in pressurized pipes in frequency domain and the information about pressure waves.

Model-based leak detection and localization techniques using stationary models have also been studied, starting with the seminal paper [26] which formulates the leak detection and localization problem as a least-squares parameter estimation problem. However, the parameter estimation of water network models is not an easy task [27]. The difficulty relies on the non-linear nature of water network models and the few measurements usually available with respect to the large number of parameters to be estimated that lead to an under-determined problem. Alternatively, in [28], a model-based method that relies on pressure measurements in some internal network nodes[1] and leak sensitivity analysis is proposed. In this methodology, pressure residuals, i.e. differences between pressure measurements provided by sensors and the associated estimations obtained by using the hydraulic network model, are computed on-line and compared against associated thresholds that take into account the effects of modeling uncertainty and measurement noise. When some of the residuals exceed their thresholds, the residuals are matched against the binarized leak sensitivity matrix (Boolean reasoning) in order to identify which one of the possible leaks is present. Although this approach has good efficiency under ideal conditions, its performance decreases due to the nodal demand uncertainty and noise in the measurements. To improve the results, the direct analysis of the residuals and the sensitivity matrix (based on a geometrical reasoning without binarization) is proposed in [29] and [30]. Finally, the use of classifiers to analyze the residuals has been recently proposed in [31] and [32]. Sensor placement in WDNs is currently an active area of research. Initially it was focused on water quality monitoring [33, 34, 35] but, in the last years, sensor placement methodologies have been proposed for leak localization purposes by several researches. In order to cope with the combinatorial problem, different approaches have been proposed such as the entropy-based approach in [36] and the Genetic Algorithms used in [37, 38, 39, 40]. Clustering approaches combined with an efficient branch and bound search and sensitivity matrix analysis were proposed in [41] and in [42, 43]. More recently, feature selection techniques have been proposed in [44, 45] and a game theory approach has been proposed in [46] to solve the sensor placement problem.

This paper presents a new methodology for sensor reallocation in large scale-systems for fault isolation purposes. From an initial set consisting of a limited number of sensors already installed in certain locations of the system, the proposed methodology produces a new sensor placement where some of the sensors are strategically reallocated in different but available places of

[1]If flow measurements were available, leaks could be detected more easily since it would be possible to establish simple mass balance relations in the pipes. However, pressure sensors are cheaper and easier to install and maintain and this is the reason why they are preferred in practice.

the system. The procedure is posed as an optimization problem where the performance index is specific of the fault isolation method to be used. The algorithm that solves the problem is an incremental upgrading approach based in the Sequential Forward Floating Search (SFFS) algorithm and it combines a forward phase, where sensors can be added sequentially, with a backward phase, where sensors are individually removed from the previous sensor placement. The proposed sensor reallocation methodology is illustrated by means of its application to the problem of leak localization in WDNs, where the particular placement of the pressure sensors has a great impact in the ability to isolate the leaking node. Also, since only a limited number of pressure sensors can be installed in some nodes, space interpolation techniques must be used to estimate the pressure in the other network nodes. The goodness of the isolation process is measured in terms of pipe distance from the estimated leak node to the real leak node. The proposed methodology has been applied with real measurement data and leaks from two District Metered Areas (DMAs) from the WDN of a metropolitan area of Spain.

The rest of the paper is organized as follows. In Section 2, the sensor reallocation problem is introduced and an algorithm to determine the optimal reallocation of a set of sensors is proposed. In Section 3, the problem of leak localization in WDNs is presented as well as the optimal sensor placement and reallocation problems in WDNs. Section 4 illustrates the application of the whole methodology to two different DMAs. Finally, Section 5 draws the main conclusions of the work.

2. Sensor Reallocation

The performance of fault isolation methods strongly relies on the available measurements. In particular, in the fault localization problem, when different faults affecting different subsystems or locations have to be distinguished, then a set of sensors have to be strategically distributed along the system.

In this paper, it is assumed that an initial set of sensors is already installed in certain locations and that some of these sensors can be moved to other locations in order to improve the performance of the fault isolation. The set of all potential locations where sensors can be installed is represented by $\mathcal{S} = \{s_1, \ldots, s_{n_l}\}$, being n_l the total number of possible locations. The exact places where the initial sensors are installed is represented by the set $\mathcal{S}_I \subset \mathcal{S}$, being n_s the number of initially installed sensors. This number of sensors will remain at the end of the reallocation process. A maximum number of n_c

sensors can be reallocated, i.e. they can be moved from a location in $\mathcal{S}_I$ to a location in $\bar{\mathcal{S}}_I$ defined according to $\mathcal{S} = \mathcal{S}_I \cup \bar{\mathcal{S}}_I$. According to the previous definitions, the optimal sensor reallocation procedure searches for the set of sensor locations $\mathcal{S}_R \subset \mathcal{S}$ obtained as a solution of the following optimization problem

$$\begin{aligned} \min \quad & f^*(\mathcal{S}_R) && \text{(1a)} \\ \text{s.t.} \quad & && \\ & |\mathcal{S}_R| = |\mathcal{S}_I| = n_s && \text{(1b)} \\ & |\mathcal{S}_R \cap \bar{\mathcal{S}}_I| \leq n_c && \text{(1c)} \\ & f^*(\mathcal{S}_R) < f^*(\mathcal{S}_I) && \text{(1d)} \end{aligned}$$

where $f^*(\cdot)$ is a cost function that can be specific for the considered problem (particular system and type of faults) and/or the fault isolation method to be applied. It must be noticed that depending on the function definition $f^*(\cdot)$ a maximization problem can be considered. The constraint (1b) states that the final number of sensors placed inside the network will be the same as before the reallocation. The constraint (1c) defines the maximum number of sensors that can be reallocated. Finally, constraint (1d) implies that the reallocation must result in an improvement, if it is not, then the optimization problem has not a solution and the original sensor configuration must be kept.

The global solution of the optimization problem (1) would be trivial if all sensor combinations could be evaluated according to the selected fault isolation method with low computation cost. But this is far to be realistic in practical applications, especially in large-scale systems, where the number of potential sensor locations is large and the number of sensors that can be installed is kept limited to a much smaller number, thus leading to a really large number of possible combinations.

In this paper, a modification of the SFFS algorithm presented in [47] is proposed to solve the optimization problem (1) in a suboptimal but efficient way. Unlike the original algorithm, the selection of the next place to install each sensor can be restricted according to the sensors already installed by the algorithm and the number of reallocations allowed. In addition, a multi-step backward phase is proposed to obtain an algorithm more robust against the possibility of getting trapped in local optima.

The proposed algorithm is summarized in Algorithm 1. The algorithm requires: the set $\mathcal{S}$ with the n_l locations where sensors can be placed, the set $\mathcal{S}_I$ with the n_s initial sensor locations, the number n_c of sensors that can be reallocated, and the cost function $f^*(\cdot)$ to be minimized. The algorithm provides a suboptimal solution set $\mathcal{S}_R$ with a better placement for some of the sensors. It has a main loop (lines 2-29) that, starting from an empty set (initialization in line 1), it adds a new element to $\mathcal{S}_R$ at each iteration, finishing when the size of $\mathcal{S}_R$ equals the number of sensors that can be installed (n_s). Inside the loop, two main parts can be distinguished: the forward phase and backward phase.

The aim of the forward phase (lines 3-12) is to add a new sensor location to the current set of locations given by $\mathcal{S}_R$ in such a way the evaluation of the cost function over the updated set is minimized. This is done by first assigning a value to each possible sensor location (for loop in line 3). If the current sensor location s_i is not included in the current set $\mathcal{S}_R$ and if it belongs to the initial $\mathcal{S}_I$ or it does not belong to $\mathcal{S}_I$ but the number of already reallocated sensors in $\mathcal{S}_R$ is (strictly) smaller than the maximum allowed, then the current location is a candidate to be included in $\mathcal{S}_R$ and the cost function is evaluated for $\mathcal{S}_R \cup s_i$. If the previous condition is not satisfied this means that the current sensor is not a proper candidate to be included in $\mathcal{S}_R$ and the value assigned to it is ∞ (to prevent its election). After all these values are obtained, the candidate that presents the smallest associated value is selected and it is included in $\mathcal{S}_R$ (lines 10-11). Finally, the value of the cost function of the selected sensor configuration is stored in the component $|\mathcal{S}_R|^{th}$ of the vector $\boldsymbol{\epsilon}^{(H)}$ (variable $\epsilon^{(H)}_{|\mathcal{S}_R|}$ in line 12).

The main advantage of the forward part is that sensors are added sequentially. Therefore, the computational cost of each forward iteration is linear with the number of potential places to install the sensors n_l. However, it is not guaranteed that the obtained solution is the best solution among the all possible sensor combinations. In order to minimize the effect of the suboptimality solution of the forward part, a backward part is added.

Given the current sensor configuration $\mathcal{S}_R$, with $n = |\mathcal{S}_R|$ selected sensors, each step in the backward phase (each iteration of the while loop in line 13) starts with the evaluation of the cost function for all the different n sensor configurations of $n-1$ sensors obtained by not including one sensor of $\mathcal{S}_R$. If the smallest obtained value is smaller than the one stored in $\epsilon^{(H)}_{|\mathcal{S}_R|-1}$, this indicates that the selection of sensors obtained in a previous iteration of the algorithm main loop (while in line 2) was not optimal, and, consequently, it is changed by the current configuration. The backward steps are repeated until no improvement in the objective function is obtained or until the number of sensors becomes smaller or equal to 2. It must be highlighted that this multi-step strategy provides an algorithm more robust against the possibility of getting trapped in local optima.

3. Pressure Sensor Reallocation for Water Distribution Networks

Leak localization is an active area of research and in the last years several works dealing with the leak localization problem in WDNs have been published.

Some of the recent proposed leak localization methods assume that pressure sensors have been installed in some inner nodes of the WDN in addition to the inlet pressure and flow sensors that are usually installed in WDN for control and billing purposes. Since pressure sensors are cheaper and easier to install than flow sensors, these methods are of great interest to water companies.

3.1. Assumptions and basic operation

Let us consider the water distribution network as an undirected graph $\mathcal{G}$ composed by nodes as vertices $\mathcal{V}$ and pipes as edges $\mathcal{E}$. The set $\mathcal{V} = \{v_1, \ldots, v_{n_m}\}$ is composed by $n_m = n_n + n_r$ being n_n internal nodes and n_r reservoir nodes while the set $\mathcal{E} = \{e_1, \ldots, e_{n_p}\}$ contains the n_p pipes of the network. Then, we can define the incidence matrix $\boldsymbol{H}$ of the graph $\mathcal{G}$ with dimensions $n_m \times n_p$ whose elements are defined as

$$H_{i,j} = \begin{cases} 1 & \text{if the } j^{th} \text{ edge is entering or leaving } i^{th} \text{ vertex.} \\ 0 & \text{if the } j^{th} \text{ edge is not connected to the } i^{th} \text{ vertex.} \end{cases}$$

The n_n internal nodes are associated to user demands and pipe junctions, and it is assumed that leaks can only occur in these internal nodes of the network (as assumed in [28], [48], or [32]), which makes the number of potential leaks equal to n_n. This assumption is just a discretization of the network in order to reduce the infinite number of potential leak locations to a finite number. In addition, it is also usually assumed that only one leak can occur at a time.

Consider the WDN working under some operating conditions $\mathbf{c}$ given by the positions of internal valves, reservoirs pressures and flows, and users demands. Consider the presence of a leak l_j with magnitude l and acting on

Algorithm 1 Sequential forward floating search for sensor reallocation.

Require: The number of initial sensors placed n_s, the set of potential places where the sensors can be installed $\mathcal{S}$, $\mathcal{S}_I \subset \mathcal{S}$ is the set of sensors currently installed, the number of sensors allowed to be reallocated n_c and the expression of the cost function f^*.

Ensure: Suboptimal sensor reallocation $\mathcal{S}_R$ starting from an initial sensor placement $\mathcal{S}_I$ with n_c allowed sensor reallocations.

$\mathcal{S}_R = \emptyset$
while $|\mathcal{S}_R| < n_s$ **do**
 for each $s_i \in \mathcal{S}$ **do**
  if $s_i \notin \mathcal{S}_R$ and $(s_i \in \mathcal{S}_I$ or $(s_i \in \bar{\mathcal{S}}_I$ and $|\mathcal{S}_R \cap \bar{\mathcal{S}}_I| < n_c))$ **then**
   $\epsilon_{s_i} = f^*(\mathcal{S}_R \cup s_i)$
  else
   $\epsilon_{s_i} = \infty$
  end if
 end for
 $s_{\min} = \arg\min\{\epsilon_{s_1}, \ldots, \epsilon_{s_{n_l}}\}$
 $\mathcal{S}_R = \mathcal{S}_R \cup s_{\min}$
 $\epsilon^{(H)}_{|\mathcal{S}_R|} = \epsilon_{s_{\min}}$
 while $|\mathcal{S}_R| > 2$ **do**
  for each $s_i \in \mathcal{S}$ **do**
   if $s_i \in \mathcal{S}_R$ **then**
    $\epsilon_{s_i} = f^*(\mathcal{S}_R \setminus s_i)$
   else
    $\epsilon_{s_i} = \infty$
   end if
  end for
  $s_{\min} = \arg\min\{\epsilon_{s_1}, \ldots, \epsilon_{s_{n_l}}\}$
  if $\epsilon^{(H)}_{|\mathcal{S}_R|-1} > \epsilon_{s_{\min}}$ **then**
   $\mathcal{S}_R = \mathcal{S}_R \setminus s_{\min}$
   $\epsilon^{(H)}_{|\mathcal{S}_R|-1} = \epsilon_{s_{\min}}$
  else
   Break inner while.
  end if
 end while
end while

node j. If pressure measurements are available in all the nodes of the WDN and historical data of these sensors are available for the same operating conditions in a leak-free scenario, or an accurate model is available to compute these leak-free pressures, then a residual vector can be computed as

$$\mathbf{r} = \mathbf{p}(\mathbf{c}) - \mathbf{p}^{(l_j)}(\mathbf{c}) \tag{2}$$

where

- $\mathbf{p}(\mathbf{c}) = (p_1(\mathbf{c}), \ldots, p_{n_n}(\mathbf{c}))$ is the vector that defines the pressure map in the WDN under operating conditions $\mathbf{c}$ and leak-free scenario.
- $\mathbf{p}^{(l_j)}(\mathbf{c}) = (p_1^{(l_j)}(\mathbf{c}), \ldots, p_{n_n}^{(l_j)}(\mathbf{c}))$ is the vector that defines the pressure map in the WDN under operating conditions $\mathbf{c}$ and leak scenario given by a leak of magnitude l in node j.

Once a leak has been detected in a WDN, usually by means of the analysis of the inlet flow, the maximum difference between the pressure maps in leak-free and leak scenarios will be around the leaky node (see [49], [50] and [51]). Therefore, the leaky node localization can be estimated as the one with the biggest pressure residual component, i.e.

$$\hat{j} = \arg\max_{i \in \{1,\ldots,n_n\}} \{r_i\} \tag{3}$$

where $r_i \quad i = 1, \ldots, n_n$ are the components of the residual vector $\mathbf{r}$ defined in (2).

In practice, there are two limitations. Firstly, a limited number of sensors n_s, much more smaller than n_n, are installed in the network. A second limitation comes from the fact that experimental data for leak-free operation are limited. Let $\mathcal{S}_R$ with $|\mathcal{S}_R| = n_s$ be the set that describes the associated pressure sensor locations, pressure residuals can only be computed for the n_s available pressure sensors.

Model-based leak localization methods [52, 53] compute the n_s residuals $(r_{s1}, \ldots, r_{sn_s})$ using (2) with pressure measurements $(p_{s1}^{(l_j)}(\mathbf{c}), \ldots, p_{sn_n}^{(l_j)}(\mathbf{c}))$ in the unknown leak scenario l_j and expected leak-free pressure values at the same operating conditions $(p_{s1}(\mathbf{c}), \ldots, p_{sn_s}(\mathbf{c}))$ estimated by means of an hydraulic model of the WDN. Leak localization in model-based approaches is based on the leak sensitivity matrix $\mathbf{\Omega}(\mathbf{c})$

$$\Omega(\mathbf{c}) = \begin{pmatrix} \frac{\partial r_{s1}}{\partial l_1}(\mathbf{c}) & \cdots & \frac{\partial r_{s1}}{\partial l_{n_n}}(\mathbf{c}) \\ \vdots & \ddots & \vdots \\ \frac{\partial r_{sns}}{\partial l_1}(\mathbf{c}) & \cdots & \frac{\partial r_{sns}}{\partial l_{n_n}}(\mathbf{c}) \end{pmatrix}. \tag{4}$$

that can be approximated by [54]

$$\Omega(\mathbf{c}) \simeq \frac{1}{f^0}(\hat{\mathbf{r}}_{\mathbf{l_1}}(\mathbf{c}), \ldots, \hat{\mathbf{r}}_{\mathbf{l_{n_n}}}(\mathbf{c})) \tag{5}$$

where $\hat{\mathbf{r}}_{\mathbf{l_i}}(\mathbf{c})$ $\forall i = 1, ..., n_n$ is the residual vector computed considering the n_s pressure sensor locations in (2) and with both no-leak and leaky pressures (leak of magnitude f_0 at node i) estimated by the hydraulic simulator.

Another way to tackle the two limitations aforementioned has been proposed in [55, 51, 56] and it consist in the following two steps. First, the use spatial interpolation techniques which, starting from the available pressure measurements in the n_s inner nodes, are able to estimate the pressure in the other nodes. Second, the calibration of a reduced order model proposed in [57] that considers the current operating conditions $\hat{\mathbf{c}}$ and historical data data, allows the extrapolation of a pressure map in the leak-free scenario. In this way, the ideal residual vector defined in (2) can be approximated by

$$\hat{\mathbf{r}} = \hat{\mathbf{p}}(\mathbf{c}, \mathcal{S}_R) - \hat{\mathbf{p}}^{(l_j)}(\mathbf{c}, \mathcal{S}_R) \tag{6}$$

where

- $\hat{\mathbf{p}}(\mathbf{c}, \mathcal{S}_R)$ is the vector that approximates the pressure map in the WDN under operating conditions $\mathbf{c}$ and no-leak scenario. If $\hat{p}_i(\mathbf{c}, \mathcal{S}_R)$ corresponds to a node i where a sensor is installed, it is computed by using pressure values $p_i(\mathbf{c})$; otherwise it is computed by interpolation techniques that allow the estimation of the pressure values for the unmeasured nodes.

- $\hat{\mathbf{p}}^{(l_j)}(\mathbf{c}, \mathcal{S}_R)$ is the vector that approximates the pressure map in the WDN under operating conditions $\mathbf{c}$ and leak scenario of magnitude l in node j. It is computed using actual measurement values $\hat{p}_i^{(l_j)}(\mathbf{c})$ if pressure node i is measured; otherwise the pressure values for the unmeasured nodes are estimated by interpolation techniques.

Then, in (3), the leak node localization in a realistic case can be estimated by using the approximated residual vector (6) instead of the ideal residual vector (2), i.e.

$$\hat{j} = \arg\max_{i \in \{1,\ldots,n_n\}} \{\hat{r}_i\} \tag{7}$$

The accuracy when using the realistic leak localization defined in (7) instead of the ideal one defined in (3) will depend on the number of sensors, their localization in the WDN, the amount of historical data available from these sensors and the interpolation method.

Recent works have shown that the Kriging method, a well-known interpolation method in the area of geostatistics [58], is suitable to estimate the pressure values for the unmeasured nodes $\hat{p}_i^{(l_j)}(\mathbf{c}, \mathcal{S}_R)$ by means of

$$\hat{p}_i^{(l_j)}(\mathbf{c}, \mathcal{S}_R) = \mu(\mathbf{c}) + \varepsilon(\boldsymbol{\chi}(\mathbf{c}), \boldsymbol{\theta}(\mathbf{c}), \mathbf{d}_i(\mathcal{S}_R)) \tag{8}$$

where $\mu(\mathbf{c})$ provides a value that represents the constant part of the interpolation given a particular operating condition $\mathbf{c}$. Function $\varepsilon(\boldsymbol{\chi}(\mathbf{c}), \boldsymbol{\phi}(\mathbf{c}), \mathcal{D}_{i,:}(\mathcal{S}_R))$ is the spatially correlated part of the variation where $\boldsymbol{\chi}(\mathbf{c})$ is a polynomial function, $\boldsymbol{\phi}(\mathbf{c})$ is the correlation function and $\mathcal{D}_{i,:}$ is the i^{th} row of a symmetric matrix $\mathcal{D} \in \Re^{n_n \times n_n}$ whose components $\mathcal{D}_{i,j}$ are the minimum weighted distance in pipe from node i to node j and $\mathcal{S}_R$ indicates that only the components of $\mathcal{D}_{i,:}$ associated to the measured nodes are considered. The constant term $\mu(\mathbf{c})$ and function $\varepsilon(\cdot)$ are obtained in the fitting process as well as the functions $\boldsymbol{\chi}(\mathbf{c})$ and $\boldsymbol{\phi}(\mathbf{c})$.

From the incidence matrix H defined in (2) we can define a path $\mathcal{P}$ as a sequence $\{x_i\}_{i=1}^{\ell}$ being $x_i \in \mathcal{V}$, $x_i x_{i+1} \in \mathcal{E}$ and $x_i \neq x_j$ for every pair $i, j \in \{1, 2, \ldots, \ell\}$. Also, we only consider that the edge e_j is part of $\mathcal{P}$ only if fulfills $e_j = x_k x_{k+1}$ with $x_k \in \mathcal{P}$ and $x_{k+1} \in \mathcal{P}$. Since different paths can connect j^{th} and i^{th} vertices such as $\mathcal{P}_{i,j} = \{\mathcal{P}_{i,j}^{(1)}, \ldots, \mathcal{P}_{i,j}^{(n)}\}$, we can find the minimum weight pipe distance between nodes i and j using

$$\bar{\mathcal{D}}_{i,j} = \arg\min_{\mathcal{P}_{i,j}^k \in \mathcal{P}_{i,j}} \sum_{e_z \in \mathcal{P}_{i,j}^k} \frac{L_z}{D_z^5} \tag{9}$$

where L_z and D_z are the length and the diameter of the edge (pipe) e_z respectively, both in [m].

3.2. Sensor Placement and Reallocation

The methods for solving the problem of sensor placement for leak localization purposes presented above aim to determine which are the optimal locations of pressure sensors among all inner nodes where it is possible to install a sensor in order to maximize the performance of the leak localization with a minimum number of installed sensors.

To assess the performance of a leak localization method, different scenarios for every leak l_i, with different operating points, nodal demand uncertainty [59], measurement noise [60], and other uncertainties, should be considered. As it is not possible to have real data for all the leaks and different scenarios, realistic simulators can be used to generate synthetic data. Then, applying the leak localization method to all the different scenarios for every leak l_i with a particular sensor configuration, the accuracy of the leak localization method can be evaluated. However, in order to reduce the computational cost in the sensor placement optimization problem, the nominal sensitivity matrix and some indirect indicators computed from this matrix have been proposed as the cost functions $f^*(\cdot)$ to minimize in the optimal sensor placement problem.

In general, for any network, there is not a unique optimal set of sensors because it depends on the particular leak localization method that is going to be used. A set of sensors can be optimal for a given leak localization method but not for a different one. So, consider a WDN that is supervised by means of a set of n_s pressure sensors that have been installed to optimize the performance according to a particular leak localization method. If the leak localization method is replaced for another one, Algorithm 1 can be used to determine the changes in the sensor configuration that increase the performance of the new localization method. It is enough to determine the number of sensors allowed to be reallocated n_c and a cost function $f^*(\cdot)$ to characterize the error of the new leak localization method.

In the leak localization methods that use the Kriging interpolation approach [55, 51, 56] described previously, the performance depends on the accuracy of the interpolation. Therefore, the sum of square relative errors of the Kriging interpolation in pressure values considering no-leak and leak scenarios under different boundary conditions[2] $\mathbf{c}(k_j)$ can be used as the cost

[2]The boundary conditions are the flow (demand) and pressure at the entrance of the DMA plus the position of the internal valves.

function $f^*(\cdot)$ in Algorithm 1 and it can be computed as

$$f^*(\mathcal{S}_R) = \sum_{j=0}^{|\mathcal{S}|} \sum_{k_j=1}^{N_j} \sum_{i=1}^{|\mathcal{S}|} \left(\frac{p_i^{(l_j)}(\mathbf{c}(k_j)) - \hat{p}_i^{(l_j)}(\mathbf{c}(k_j), \mathcal{S}_R)}{p_i^{(l_j)}(\mathbf{c}(k_j))} \right)^2 \tag{10}$$

where l_0 denotes no-leak scenario, N_j denotes the number of data samples in the no-leak scenario (N_0) and in the different leak scenarios ($N_j \quad j \neq 0$), and $\hat{p}_i^{(l_j)}(\mathbf{c}(k_j), \mathcal{S}_R)$ denotes pressure estimations using the sensor configuration $\mathcal{S}_R$ and the topology of the network. A sensor placement strategy is required before sensors are installed in the WDN, because only a limited number of sensors can be installed in the network. In this case, since data from other sensor locations would be necessary, a hydraulic simulator of the WDN can be used to generate data in all the nodes for the different leak scenarios (including the no-leak case) and different boundary conditions ($\mathbf{c}(k_j)$). In this paper, we will consider the same number of data (boundary conditions) for the no-leak scenario and for all the different leak scenarios $N_j = N \quad \forall j = 0, ..., n_n$. As a remark, the accuracy of the hydraulic simulator necessary to generate the data for the sensor placement problem is not as critical as if the hydraulic simulator was used in a model-based leak localization scheme. The purpose of the hydraulic simulator that generates pressure values in (10) is to have an idea about the pressure map in the WDN in order to determine the optimal placement of the pressure sensors by means of the optimization problem (1).

4. Case Studies

The proposed sensor reallocation as an incremental sensor upgrading has been tested in two DMAs from the WDN of a metropolitan area of Spain to reconfigure the current sensor placement for the leak localization technique presented in [55] that is based in Kriging interpolation. To validate the performance of the proposed method, in addition to the sensor reallocation, hydraulic models have been used to generate a synthetic validation data set for each DMA. Furthermore, a real water leak case study is available for each DMA through engineered events (opening fire hydrants) by the water company in charge of this WDN. At each network a total of ten sensors where initially installed with the aim of maximize the performance of the leak localization technique presented in [28]. Using the proposed method described in the Algorithm 1 and the objective function (10), five sensors were considered static and five new sensor locations where considered. Instead of removing the sensors to be reallocated to the new place, new sensors were installed additionally allowing us to compare both, original and new, sensor placements according to the new leak localization technique tested.

The DMAs are equipped with flow and pressure sensors at the inlet, and pressure sensors inside the network. Also, a flowmeter at the leak point is installed to measure the size of the leak. The pressure sensors used in this sensor placement belong to the family of IMP-S-004-020S, which is able to work up to 20 bars of pressure. In all the cases, the installed sensors have a sampling rate of two minutes and they have a resolution of 0.1 [mwc] in the case of pressure sensors and a resolution of 0.1 [l/s] in the case of flow sensors. The sensor measurements are registered by a LoLog 450 device which has a battery that allows it to work five years until the next recharge.

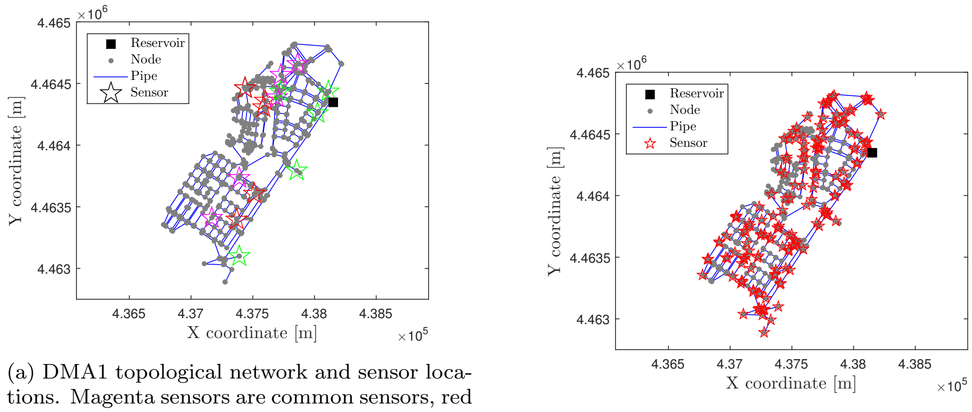
To generate the data for the sensor placement and for the synthetic validation data sets, the Epanet 2.0 hydraulic simulator [61] has been used. The Kriging interpolation technique used in this work to estimate the pressure in the inner nodes which do not have pressure sensors installed has been implemented by means of the DACE Matlab toolbox [62], and to solve the equation (9), the Dijkstra's Algorithm [63] has been used.

To assess the leak localization performance in the case studies, two metrics are used. On the one hand, the linear distance between the node candidate pointed by the leak localization algorithm and the real leaky node, in meters [m]. On the other hand, the minimum pipe distance between the node candidate and the real leaky node, also in meters. This last indicator can be computed using (9) but instead of using the weighted distance $\sum_{e_z \in \mathcal{P}_{i,j}^k} \frac{L_z}{D_z^5}$ it is used the pipe distance $\sum_{e_z \in \mathcal{P}_{i,j}^k} L_z$ for each possible path between nodes i and j. Finally, point out that the results of the synthetic test are given through the mean and the median of these two indicators.

4.1. DMA1

DMA1 is a large network is composed of one reservoir that feds the network with water by elevation, 954 consumer nodes and 1071 pipes. Ten pressure sensors where initially placed placed inside at nodes with indexes 823, 809, 858, 844, 923, 799, 853, 897, 939 and 869.

The topology and the location of the sensors installed are depicted in Figure 1a. Also, the total potential places in the network where pressure sensors can be installed, $|\mathcal{S}| = 158$, are depicted in Figure 1b.



(a) DMA1 topological network and sensor locations. Magenta sensors are common sensors, red sensors are part of the original sensor placement and green sensors are part of the new sensor placement.

(b) DMA1 potential sensor locations.

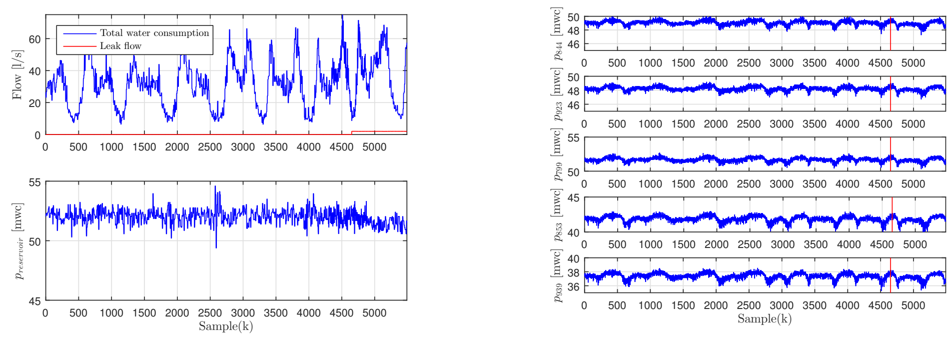
Figure 1: DMA1 network topology and sensor location.

Synthetic data is generated using a hydraulic model based on the Epanet software [61]. Using this model, the measured total consumption pattern with added noise, with an amplitude of ±20% of the nominal value, and the estimated nodal consumer demands (obtained form historical billing records), also with added noise of ±10% of the nominal measurement value, are used to generate one day of artificial measurements for a day without leak and one day for a leak of magnitude of 2 [l/s] at each node, with a sampling time of 2 minutes. As a result of the proposed sensor reallocation method, the new nodes with installed sensors are 922, 841, 867, 807 and 833, which are also depicted in Figure 1a while maintaining sensors 807, 833, 841, 867 and 922 and removing sensors 809, 823, 858, 869 and 897. The indicators obtained using the cost function (10) are $5.54 \cdot 10^{-8}$ for the initial sensor placement and $4.48 \cdot 10^{-8}$ for the new sensor placement. The validation data set has been generated under the same conditions but with a sampling rate of 1 hour in order to reduce the computational load. The day without leak has been used to calibrate the reference model of the leak localization method, see [55] for more details, and the day of measurements has been used to perform the leak localization. The results are summarized in Table 1.

Two data records, with and without leak respectively, were obtained for the engineered real leak test. Measurements without leak were recorded starting the 11^{th} of October of 2017 at 02:00 pm until the 18^{th} of October of 2017 at 00:58 am, whereas the leak event was recorded from the 18^{th} of

Table 1: Leak localization results for the synthetic validation data set in DMA1 for the original and new sensor placements.

Indicator	Original Configuration	New Configuration
Mean linear dis. [m]	903.24	686.50
Median linear dis. [m]	807.13	582.48
Mean pipe dis. [m]	1282.90	879.09
Median pipe dis. [m]	1211.40	894.17



(a) DMA1 inlet and leak measurements.

(b) DMA1 common sensor measurements.

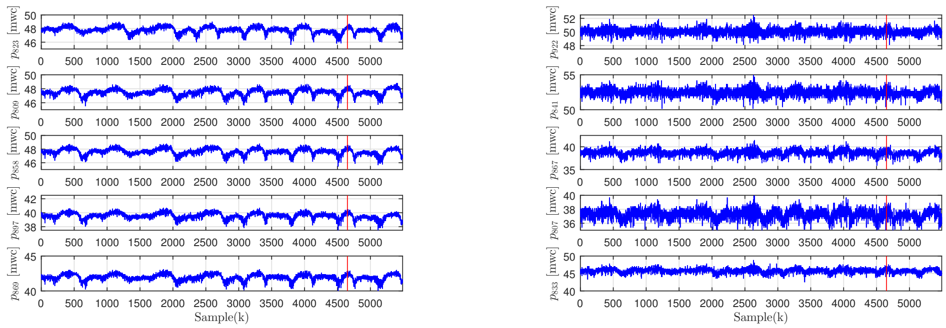
Figure 2: DMA1 leak, inlet and shared sensor measurements.

October of 2017 at 04:00 am until the 19^{th} of December of 2017 at 07:58 am. The leak had a size of 2 [l/s] approximately. The leak and the inlet measurements are depicted in Figure 2a.

The measurements recorded inside the network are depicted in Figure 2b in the case of the no sensors reallocated, in Figure 3a for the sensors in the original location location, and in Figure 3b for the measurements of the new sensor locations for both time periods.

To perform the leak localization task, the data is firstly filtered hourly by computing the average of the measurements inside that hour. Then, the 155 hours of data without leak are used to fit the data models for each node equipped with a sensor by means of the least squares fitting technique, which, in this case, leads to ten pressure models (one for each inlet sensor) to estimate the internal pressure under no-leak conditions through the inlet operational conditions.

The application of the described leak localization method to the DMA1 real case with the new sensor placement obtained after the proposed sensor



(a) DMA1 original sensor measurements.

(b) DMA1 new sensor measurements.

Figure 3: DMA1 original and new sensor measurements.

Table 2: Leak localization results for the real leak case in DMA1 for the original and new sensor placements.

Indicator	Original Configuration	New Configuration
Linear dis. [m]	848.39	320.84
Pipe dis. [m]	1097.86	406.17

placement reallocation, at the end of the 28 hours that the leak lasted, gives the 73. The node candidate obtained using the original sensor placement is 897 node as candidate to be the leaking node, whereas the leak is actually in node 856. The leak localization results for the original sensor placement and the new one are summarized in Table 2 where the geometrical and pipe distance from the real leak to the candidate leak node are provided. The results are depicted in Figure 4.

From the results obtained with the synthetic validation data set showed in Table 1 and validated with the real case summarized in Table 2 can be seen an improvement of the performance from the employed metrics for the leak localization technique based on the Kriging interpolation with the reallocation. It can be expected a larger improvement if more sensors were allowed to be reallocated but in any case a performance as good as it was a new sensor placement. Also, since the error metric used in this case studies, the new sensor placement should perform better than the original sensor placement for any other technique that is based on Kriging interpolation such as the one presented in [56].

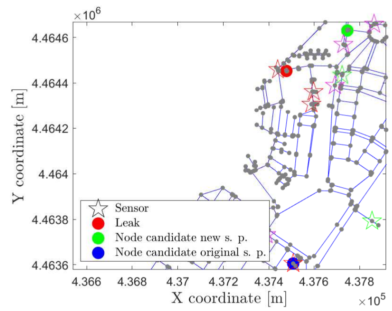
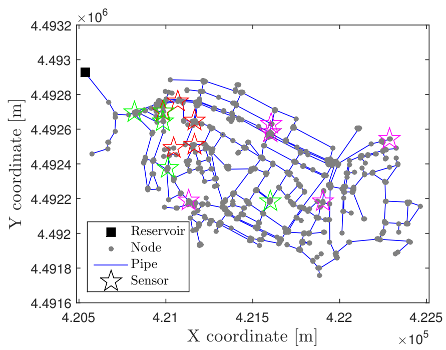
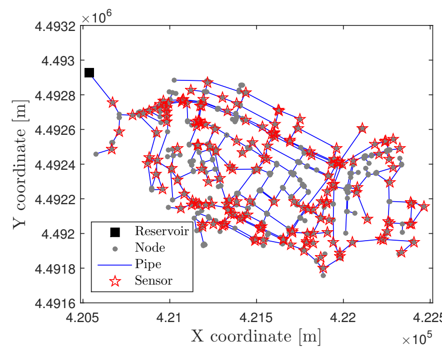


Figure 4: Leak localization results in DMA1 real case.



(a) DMA2 topological network and sensor placements. Magenta sensors are common sensors, red sensors are part of the original sensor placement and green sensors are part of the new sensor placement.



(b) DMA2 potential sensor locations.

Figure 5: DMA2 network topology and sensor location.

4.2. DMA2

DMA2 is a medium to large network formed by one reservoir that also feds the network by elevation, 1031 consumer nodes and 1100 pipes. Ten pressure sensors where originally placed inside the DMA at nodes with indexes 886, 877, 864, 971, 880, 898, 917, 933, 943 and 948. The new sensor placement maintains the sensors at 886, 877, 948, 943 and 933 nodes while adds the new sensors at nodes 895, 905, 981, 942 and 968. The topology and the location of both sensor placements are depicted in Figure 5a. The total number of locations where it is suitable to install sensors sums up to $|\mathcal{S}| = 169$, and their locations inside the network are depicted in Figure 5b.

The application of the sensor placement reallocation was done over one

Table 3: Leak localization results for the synthetic validation data set in DMA2 for the original and new sensor placements.

Indicator	Original Configuration	New Configuration
Mean linear dis. [m]	725.99	585.53
Median linear dis. [m]	707.18	589.61
Mean pipe dis. [m]	969.82	882.65
Median pipe dis. [m]	935.35	806.35

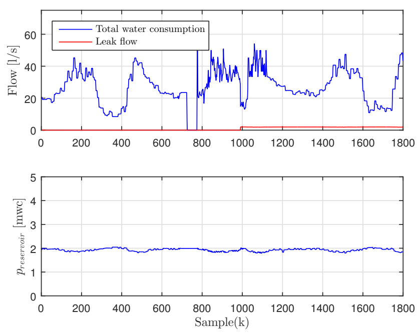
day of synthetic data generated through the use of the Epanet model of the network using the same uncertainty bounds as in the previous case study. Then, the Kriging interpolation was applied using the shortest weighted pipe distance contained in the $\mathbf{D}$ matrix and the cost function (10). This procedure provides the sensor placement reallocation for Kriging-based leak localization methods which can be seen in Figure 5b. The original sensor placement has a value of $1.62 \cdot 10^{-7}$ according to the indicator (10) while the new sensor placement after the reallocation has improved this indicator up to $2.47 \cdot 10^{-8}$.

The process of generating synthetic data also has been done as in the previous case considering a leak of magnitude of 2 [l/s]. The results are summarized in Table 3.

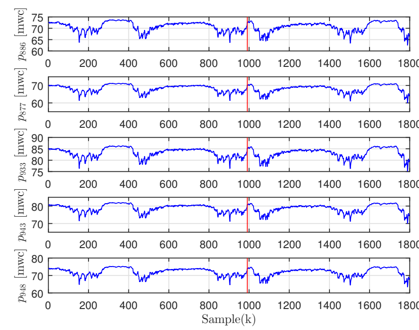
As in the previous case study, here a real leak scenario was engineered through a fire hydrant capturing data under leaky conditions, with a leak size of 2 [l/s], and no-leaky conditions. Sensor recordings under non-leaky conditions for all pressure sensors, inlet flow and leak flow have been registered from the 2^{nd} of November of 2017 at 05:00 am until the 4^{th} of November of 2017 at 00:58 am (a total amount of 33 hours). The leak event took place the 4^{th} of November of 2017 at 04:00 pm until the 5^{th} of November of 2017 at 07:58 am (27 hours). The inlet measurements (pressure and flow) and the leak flow for both time periods are depicted in Figure 6a.

The measurements recorded for both periods for the sensors that were not reallocated from the original sensor placement by the proposed sensor placement reallocation are depicted in Figure 6b. Measurements from sensors installed in the original sensor placement but reallocated due to the sensor placement reallocation are depicted in Figure 7a. Measurements from pressure sensors installed in the new locations are depicted in Figure 7b.

The place in the network where the leak was engineered was at node 882. The application of the data-driven leak localization approach described earlier to both original and new sensor placements before and after the appli-

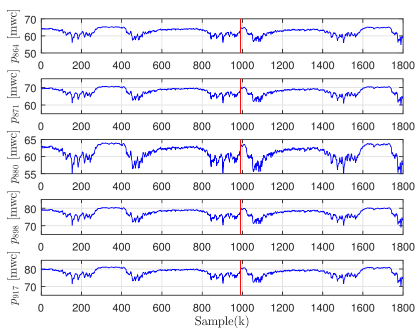


(a) DMA2 inlet and leak measurements.

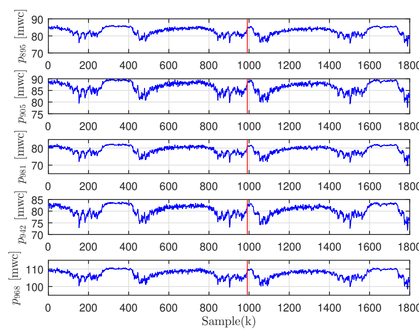


(b) DMA2 common sensor measurements.

Figure 6: DMA2 leak, inlet and shared sensor measurements.



(a) DMA2 original sensor measurements.



(b) DMA2 new sensor measurements.

Figure 7: DMA2 original and new sensor measurements.

Table 4: Leak localization results for the real leak case in DMA2 for the original and new sensor placements.

Indicator	Original Configuration	New Configuration
Linear dis. [m]	400.67	148.68
Pipe dis. [m]	455.21	403.69

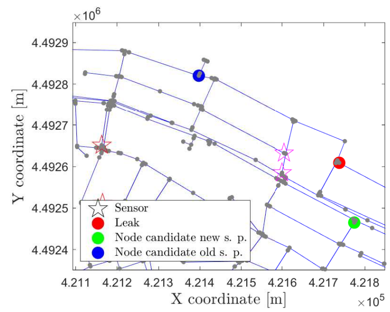


Figure 8: Leak localization results in DMA2 real case.

cation of the sensor reallocation presented in this paper provides the nodes candidates 282 and 505 for the new and the original sensor placement respectively. Both leak localization results are depicted in Figure 8. Leak localization of both original and new sensor placements results are summarized in Table 4 where the geometrical and pipe distance from the real leak to the candidate leak node are provided.

Similar to the previous case study, the leak localization with a technique based on Kriging interpolation results obtained using the the new sensor placement outperform the ones obtained with the previous sensor placement in both synthetic case and the real case scenario.

5. Conclusions

In large-scale systems, the performance of any fault diagnosis method strongly relies on the available measurements, therefore a set of sensors must be strategically distributed through the system. In practical systems the number of sensors is usually too small compared to the system dimension, so there exist a great number of different sensor configurations than can be taken. Obtaining the sensor configuration that best performs in a fault isolation procedure is not an easy task due to the computational resources required.

In this paper, a new methodology for sensor reallocation has been presented and developed. From an initial set of existing sensors, an optimization algorithm produces a new sensor configuration where some of the original sensors are placed to different locations of the system. The algorithm optimizes a performance index specific of the fault isolation method to be used and combines forward and backward computations to add and substract sensors to the set.

The methodology has been illustrated by means of its application to the problem of leak localization in WDNs. In this application the new pressure sensors configuration is designed to perform better than the original one in terms of distance to the real leak.

The proposed methodology has been successfully tested in two real DMAs from the WDN of a metropolitan area of Spain.

Acknowledgment

This work has been partially funded by L-BEST Project (PID2020-115905–RB-C21) funded by MCIN/ AEI /10.13039/501100011033, by the European Commission through contract EFFINET (ref. FP7-ICT2011-8-318556), and by the Catalan Agency for Management of University and Research Grants (AGAUR), the European Social Fund (ESF) and the Secretary of University and Research of the Department of Companies and Knowledge of the Government of Catalonia through the grant FI-DGR 2015 (ref. 2015 FI_B 00591).

References

[1] M. Krysander, E. Frisk, Sensor placement for fault diagnosis, IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans 38 (6) (2008) 1398–1410.

[2] O. Prakash, M. Bhushan, S. Narasimhan, R. Rengaswamy, Sensor network design based on system-wide reliability criteria. Part I: Objectives, Journal of Process Control 93 (2020) 66–82.

[3] O. Prakash, M. Bhushan, S. Narasimhan, R. Rengaswamy, Sensor network design based on system-wide reliability criteria. part ii: Formulations and applications, Journal of Process Control 93 (2020) 14–27.

[4] M. Serpas, G. Hackebeil, C. Laird, J. Hahn, Sensor location for nonlinear dynamic systems via observability analysis and max-det optimization, Computers & Chemical Engineering 48 (2013) 105–112.

[5] A. Seth, K. A. Klise, J. D. Siirola, T. Haxton, C. D. Laird, Testing contamination source identification methods for water distribution networks, Journal of Water Resources Planning and Management 142 (4) (2016) 04016001.

[6] M. Bagajewicz, M. Sánchez, Reallocation and upgrade of instrumentation in process plants, Computers and Chemical Engineering 24 (8) (2000) 1945–1959.

[7] S. Kolluri, M. Bhushan, Reallocation index based sensor network design, Journal of Loss Prevention in the Process Industries 53 (2018) 89–102.

[8] R. Puust, Z. Kapelan, D. A. Savic, T. Koppel, A review of methods for leakage management in pipe networks, Urban Water Journal 7 (1) (2010) 25–45.

[9] Y. Khulief, A. Khalifa, R. Mansour, M. Habib, Acoustic detection of leaks in water pipelines using measurements inside pipe, Journal of Pipeline Systems Engineering and Practice 3 (2) (2012) 47–54.

[10] M. Lambert, A. Simpson, J. Vítkovský, X.-J. Wang, P. Lee, A review of leading-edge leak detection techniques for water distribution systems, in: 20th AWA Convention, Perth, Australia, 2003.

[11] A. Lambert, What do we know about pressure:leakage relationships in distribution systems?, in: IWA Conference System Approach to leakage control and water distribution system management. Brno, Czech Rebublic., 2001.

[12] J. Thornton, A. Lambert, Progress in practical prediction of pressure: leakage, pressure: Burst frequency and pressure: Consumption relationships, in: eakage 2005 Conference Proceedings. Halifax, Canada., 2005.

[13] Z. Y. Wu, P. Sage, Water loss detection via genetic algorithm optimization-based model calibration, in: Systems Analysis Symposium, ASCE, 2006, pp. 1–11.

[14] A. Colombo, P. Lee, B. Karney, A selective literature review of transient-based leak detection methods, Journal of Hydro-environment Research (2009) 212–227.

[15] J. Yang, Y. Wen, P. Li, Leak location using blind system identification in water distribution pipeline, Journal of Sound and Vibration 310 (1-2) (2008) 134–148.

[16] H. Fuchs, R. Riehle, Ten years of experience with leak detection by acoustic signal analysis, Applied Acoustics 33 (1) (1991) 1–19.

[17] J. Muggleton, M. Brennan, R. Pinnington, Wavenumber prediction of waves in buried pipes for water leak detection, Journal of Sound and Vibration 249 (5) (2002) 939–954.

[18] J. Mashford, D. D. Silva, D. Marney, S. Burn, An approach to leak detection in pipe networks using analysis of monitored pressure values by support vector machine, in: Third International Conference on Network and System Security, Gold Coast, Australia, 2009, pp. 534–539.

[19] L. Ferrandez-Gamot, P. Busson, J. Blesa, S. Tornil-Sin, V. Puig, E. Duviella, A. Soldevila, Leak localization in water distribution networks using pressure residuals and classifiers, IFAC-PapersOnLine 48 (21) (2015) 220 – 225.

[20] D. Wachla, P. Przystalka, W. Moczulski, A method of leakage location in water distribution networks using artificial neuro-fuzzy system, IFAC-PapersOnLine 48 (21) (2015) 1216 – 1223.

[21] C. Verde, L. Torres, Modeling and Monitoring of Pipelines and Networks: Advanced Tools for Automatic Monitoring and Supervision of Pipelines, Springer, 2017.

[22] D. Covas, H. Ramos, Hydraulic transients used for leak detection in water distribution systems, in: 4th International Conference on Water Pipeline Systems, Cranfield, UK., 2001, pp. 227–241.

[23] A. Kepler, D. Covas, L. Reis, Leak detection by inverse transient analysis in an experimental *pvc* pipe system, Journal of Hydroinformatics 13 (2) (2011) 153–166.

[24] M. Ferrante, B. Brunone, Pipe system diagnosis and leak detection by unsteady-state tests. 1. harmonic analysis, Advances in Water Resources 26 (1) (2003) 95–105.

[25] M. Ferrante, B. Brunone, Pipe system diagnosis and leak detection by unsteady-state tests. 2. wavelet analysis, Advances in Water Resources 26 (1) (2003) 107–116.

[26] R. S. Pudar, J. A. Liggett, Leaks in pipe networks, Journal of Hydraulic Engineering 118 (7) (1992) 1031–1046.

[27] D. Savić, Z. Z. Kapelan, P. Jonkergouw, Quo vadis water distribution model calibration?, Urban Water Journal 6 (1) (2009) 3–22.

[28] R. Pérez, V. Puig, J. Pascual, J. Quevedo, E. Landeros, A. Peralta, Methodology for leakage isolation using pressure sensitivity analysis in water distribution networks, Control Engineering Practice 19 (10) (2011) 1157–1167.

[29] M. V. Casillas, L. Garza-Castañón, V. Puig, Extended-horizon analysis of pressure sensitivities for leak detection in water distribution networks, in: 8th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, Elsevier, 2012, pp. 570–575.

[30] R. Pérez, G. Sanz, V. Puig, J. Quevedo, F. Nejjari, J. Meseguer, G. Cembrano, J. Mirats, R. Sarrate, Leak localization in water networks, IEEE Control Systems Magazine August (2014) 24–36.

[31] A. Soldevila, J. Blesa, S. Tornil-Sin, E. Duviella, R. M. Fernandez-Canti, V. Puig, Leak localization in water distribution networks using a mixed model-based/data-driven approach, Control Engineering Practice 55 (2016) 162 – 173.

[32] A. Soldevila, R. M. Fernandez-Canti, J. Blesa, S. Tornil-Sin, V. Puig, Leak localization in water distribution networks using Bayesian classifiers, Journal of Process Control 55 (2017) 1–9.

[33] V. Rico-Ramirez, S. Frausto-Hernandez, U. M. Diwekar, S. Hernandez-Castro, Water networks security: A two-stage mixed-integer stochastic program for sensor placement under uncertainty, Computers & Chemical Engineering 31 (5–6) (2007) 565 – 573.

[34] D. G. Eliades, M. M. Polycarpou, B. Charalambous, A security-oriented manual quality sampling methodology for water systems, Water Resources Management 25 (4) (2011) 1219–1228.

[35] S. Rathi, R. Gupta, S. Kamble, A. Sargaonkar, Risk based analysis for contamination event selection and optimal sensor placement for intermittent water distribution network security, Water Resources Management 30 (8) (2016) 2671–2685.

[36] S. E. Christodoulou, A. Gagatsis, S. Xanthos, S. Kranioti, A. Agathokleous, M. Fragiadakis, Entropy-based sensor placement optimization for waterloss detection in water distribution networks, Water Resources Management 27 (13) (2013) 4443–4468.

[37] M. V. Casillas, V. Puig, L. E. Garza-Castañón, A. Rosich, Optimal Sensor Placement for Leak Location in Water Distribution Networks Using Genetic Algorithms, Sensors 13 (11) (2013) 14984–15005.

[38] M. Casillas, L. Garza-Castañón, V. Puig, A. Vargas-Martinez, Leak Signature Space: An Original Representation for Robust Leak Location in Water Distribution Networks, Water 7 (3) (2015) 1129–1148.

[39] D. B. Steffelbauer, D. Fuchs-Hanusch, Efficient sensor placement for leak localization considering uncertainties, Water Resources Management 30 (14) (2016) 5517–5533.

[40] M. A. Cugueró-Escofet, V. Puig, J. Quevedo, Optimal pressure sensor placement and assessment for leak location using a relaxed isolation index: Application to the barcelona water network, Control Engineering Practice 63 (2017) 1 – 12.

[41] R. Sarrate, J. Blesa, F. Nejjari, J. Quevedo, Sensor placement for leak detection and location in water distribution networks, Water Science and Technology: Water Supply 14 (5) (2014) 795–803.

[42] F. Nejjari, R. Sarrate, J. Blesa, Optimal pressure sensor placement in water distribution networks minimizing leak location uncertainty, Procedia Engineering 119 (2015) 953–962, computing and Control for the Water Industry (CCWI2015), Leicester, UK.

[43] J. Blesa, F. Nejjari, R. Sarrate, Robust sensor placement for leak location: analysis and design, Journal of Hydroinformatics 18 (1) (2016) 136–148.

[44] A. Soldevila, J. Blesa, S. Tornil-Sin, R. M. Fernandez-Canti, V. Puig, Sensor placement for classifier-based leak localization in water distribution networks using hybrid feature selection, Computers & Chemical Engineering 108 (Supplement C) (2018) 152 – 162.

[45] J. Li, C. Wang, Z. Qian, C. Lu, Optimal sensor placement for leak localization in water distribution networks based on a novel semi-supervised strategy, Journal of Process Control 82 (2019) 13–21.

[46] G. Arbesser-Rastburg, D. Fuchs-Hanusch, Serious sensor placement—optimal sensor placement as a serious game, Water 12 (1) (2020).

[47] P. Pudil, J. Novovičová, J. Kittler, Floating search methods in feature selection, Pattern recognition letters 15 (11) (1994) 1119–1125.

[48] M. V. Casillas, L. E. Garza-Castañón, V. Puig, Extended-horizon analysis of pressure sensitivities for leak detection in water distribution networks: Application to the Barcelona network, in: European Control Conference (ECC'2013), Zurich, Switzerland, 2013, pp. 401–409.

[49] T. Jensen, C. Kallesøe, Application of a Novel Leakage Detection Framework for Municipal Water Supply on AAU Water Supply Lab, in: 3rd Conference on Control and Fault-Tolerant Systems (SysTol'2016), Barcelona, Spain, 2016, pp. 428–433.

[50] M. Romano, K. Woodward, Z. Kapelan, Statistical Process Control Based System for Approximate Location of Pipe Bursts and Leaks in Water Distribution Systems, Procedia Engineering 186 (2017) 236–243.

[51] A. Soldevila, J. Blesa, R. M. Fernandez-Canti, S. Tornil-Sin, V. Puig, Data-driven approach for leak localization in water distribution networks using pressure sensors and spatial interpolation, Water 11 (7) (2019).

[52] R. Pérez, V. Puig, J. Pascual, J. Quevedo, E. Landeros, A. Peralta, Methodology for leakage isolation using pressure sensitivity analysis in water distribution networks, Control Engineering Practice 19 (10) (2011) 1157 – 1167.

[53] V. Puig, C. Ocampo-Martínez, R. Pérez, G. Cembrano, J. Quevedo, T. Escobet, Real-time monitoring and operational control of drinking-water systems, Springer International Publishing, 2017.

[54] R. Pudar, J. Liggett, Leaks in Pipe Networks, Journal of Hydraulic Engineering 118 (7) (1992) 1031–1046.

[55] A. Soldevila, T. N. Jensen, J. Blesa, S. Tornil-Sin, R. Femandez-Canti, V. Puig, Leak localization in water distribution networks using a kriging data-based approach, in: IEEE Conference on Control Technology and Applications (CCTA'2018), Copenhagen, Denmark, IEEE, 2018, pp. 577–582.

[56] A. Soldevila, J. Blesa, T. N. Jensen, S. Tornil-Sin, R. M. Fernández-Cantí, V. Puig, Leak localization method for water-distribution networks using a data-driven model and dempster-shafer reasoning, IEEE Transactions on Control Systems Technology 29 (3) (2021) 937–948.

[57] T. Jensen, C. Kallesøe, J. Bendtsen, R. Wisniewski, Plug-and-play commissionable models for water supply networks with multiple inlets, in: Proc. 16th EUCA European Control Conference, 2018.

[58] J. P. Kleijnen, Regression and kriging metamodels with their experimental designs in simulation: A review, European Journal of Operational Research 256 (1) (2017) 1 – 16.

[59] P. Cugueró-Escofet, J. Blesa, R. Pérez, M. A. Cugueró-Escofet, G. Sanz, Assessment of a leak localization algorithm in water networks under demand uncertainty, IFAC-PapersOnLine 48 (21) (2015) 226 – 231.

[60] J. Blesa, R. Pérez, Modelling uncertainty for leak localization in water networks, IFAC-PapersOnLine 51 (24) (2018) 730 – 735, 10th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes SAFEPROCESS 2018.

[61] L. Rossman, Epanet 2 user's manual, United States Envionmental Protection Agency (2000).

[62] H. B. Nielsen, S. N. Lophaven, J. Søndergaard, DACE - a matlab kriging toolbox, in: Informatics and Mathematical Modelling, Technical University of Denmark, DTU, 2002.

[63] E. W. Dijkstra, A note on two problems in connexion with graphs, Numerische mathematik 1 (1) (1959) 269–271.