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Methodology for Leakage Isolation Using Pressure Sensitivity and Correlation Analysis in Water Distribution Systems.

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Abstract

In this paper is presented a novel leakage localization approach that is calibrated on real networks. Leakage positions are usually inferred by measuring pressure in a certain number of the nodes of the network. Since pressure sensors are quite expensive, only a few number of them is available. As a consequence, the effective arrangement of them turns out to be a not trivial problem. The study is devoted in performing an analysis of the sensitivity and correlation of the network in order to extract the best measurement points (i.e. nodes).

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1. Introduction

Water Distribution Systems are complicate networks to analyze since they might be constituted by large amount of nodes (i.e. users), ramifications of the pipes, water tanks, pumps and valves. Due to such topological complexity, the managing of water leakages is still a challenging task and open research topic. According to the definition given by [17], the managing of water leakages can be classified into four actions:

1. quantification: the quantification of leakages is done by means of a water balance, that is carried out on a system-wide basis in restricted District Metering Areas (DMAs). The subdivision of a network in DMAs can is done as instance by [32] by exploiting the complex network theory.
2. monitoring: flows and pressures are measured at different positions in the DMAs, thus quantifying the water flowing into the hydraulic network. This operation allows the identification of abnormal water consumptions which might be associated to unpredicted user demands, or water losses. In order to discriminate between these two events, only the data collected from flow and pressure meters during nocturnal hours (from 02:00 *AM* to 04:00 *AM*) are considered. It is indeed assumed that at night time the water demand is at its minimum, and it is registered the Minimum Night Flow (MNF). To a minimum flow corresponds a maximum pressure, therefore the

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effect of leakages (which are proportional to the pressure in the pipe) is maximum. The monitoring of the water consumption can be carried out through with several approaches, the most commons are: net-base ([6]), night flow characterization together with leakage hydraulic analysis ([7]), and flow statistical analysis ([5], [20]).

3. localization: once it has been established the presence of leakages in the network, they must be localized and repaired. The localization of leakages requires on-field analysis of the network, through devices that allow to evaluate the structural integrity of the pipes, such as: acoustic devices that correlate the noise in the pipe to the leakage position ([8], [14]), multi-parametric devices that gather information about flows and pressures ([16], [11]), video cameras ([19]), smart balls ([26]), tracer gas, infrared imaging and ground penetrating radar ([10]), as well as microwave reflectometry ([42]). In the last years a number of mathematical methods are employed to accomplish the leakage localization: Inverse Transient Analysis ([41]), Wavelets ([39], [40]), Frequency Analysis ([37]), Genetic Algorithm ([38]), Fuzzy logic ([46], [45]), Neural Network ([43]) and hybrid approach ([47]), Bayesian inference ([34],[35],[36]).
4. network management: water losses have an economical impact on the management of the hydraulic network. However, a correct districtualization of the network, and a calibrated policy for managing the water supply system can be utilized to ease the localization of water leakages [33].

The approaches followed nowadays by network managers require however expensive and time-consuming on-filed measurements. For these reasons, led by the increasing in power computing of personal computers, in the last years research institutions have started to develop model-based water leakages identifications. These approaches rely on a numerical model of the hydraulic network, and on measurements performed on the real network. By comparing the data collected from flow and pressure meters, with the predictions coming from the simulations it is possible to identify the entity of the leakage and the most probable area of the network in which the leakage can be found. The reliability of numerical models however depends upon their calibration, that is not a simple task due to the laking of structural and hydraulic data about the pipes constituting the network [33]. Nevertheless, when those data are available, the information provided by simulations allow a wide spectrum of analysis, such as: network zoning ([23], [3]), pressure management planning for leakage control ([24]), and leakage modeling as pressure-dependent demand ([2,13]).

When simulating the effect of leakages on the water demand, data coming from water meters are used to calibrate the numerical model, through optimization algorithms aimed at minimizing the discrepancies between measurements and simulations. The calibration is handled as a minimization, in which constraints are imposed on the conservation of energy, mass balance, and minimum pressure in the network. An example of this approach was given by [28]. The author identified losses in hot spots at MNF, and the number of leaking nodes was defined a priori, based on the size of the network. A genetic algorithm was utilized to estimate the value and the position of the leakages, by minimizing the differences between simulated flows and pressures with the measured ones.

[4] have relaxed the assumptions on the number of leaking nodes, and on the MNF which is not suitable in systems with intermittent water supply, where the night flow is not enough reliable. A water-consumption driven contextualization of the optimization procedure was performed with real data acquired from two small municipalities. The target function was defined in order to consider measurements carried out all day long, and it was weighted accordingly to a statistical analysis of water consumption. The effectiveness of the new methodology was assessed by comparing it with the results given by the state-of-art. However, few points remained to be addressed, including the identification of robust measurement nodes across the network, which is tackled in this work.

2. Hydraulic Network

The method presented in this paper uses the Apulian hydraulic network ([12]). It is a theoretical network that is completely defined, simple, relatively small, and it was chosen also in a previous study ([4]) due to the laking of information on hydraulic parameters and positions of leakages in a real network.

The model of the Apulian network is defined by 34 pipes, 23 nodes all at the same elevation, a unique reservoir, and zero losses (Fig. 1). The leakages are modeled as emitter nodes, placed halfway in the pipes. The water flow q_i of the leakage at the i-*th* node, expressed in l/s, can be calculated:

$$q_i = k_i p_i^{\gamma} \tag{1}$$

where p_i is the hydrostatic pressure in m, γ is the pressure exponent chosen equal to 0.5 for nozzles and sprinkler heads, and k_i is the emitter coefficient expressed in $l/(s\ m^{\gamma})$ that has to be identified.

In a numerical model of a hydraulic network, the hourly total water consumption is given by the arithmetical sum of the measured hourly consumptions of each customer. The latter is obtained by the multiplication of the hourly consumption pattern for the base demand. The consumption pattern associated to each of the 13 nodes (i.e. customers) of the Apulian network is the pattern adopted by [4], that is defined from experimental measurements carried out on two real networks, which are analogous to the Apulian network from a topological and hydraulic point of view.

3. WDS monitoring strategy

In this section, we present the approach followed to position the pressure sensors in the network with the aim of enhancing the effectivity of the leakage identification algorithm. Up to nowadays the authors have not found in literature a study that addresses this problem yet.

The only assumption made by the procedure here proposed is on the number of pressure sensors available to monitor the hydraulic network. For the Apulian network, that is a small-sized network, the number of available transducers is four. Such choice is made by considering the cost of each sensor which is in the range of 100-300 €. When positioning the pressure sensors in the network it should be avoided any configuration which might correspond

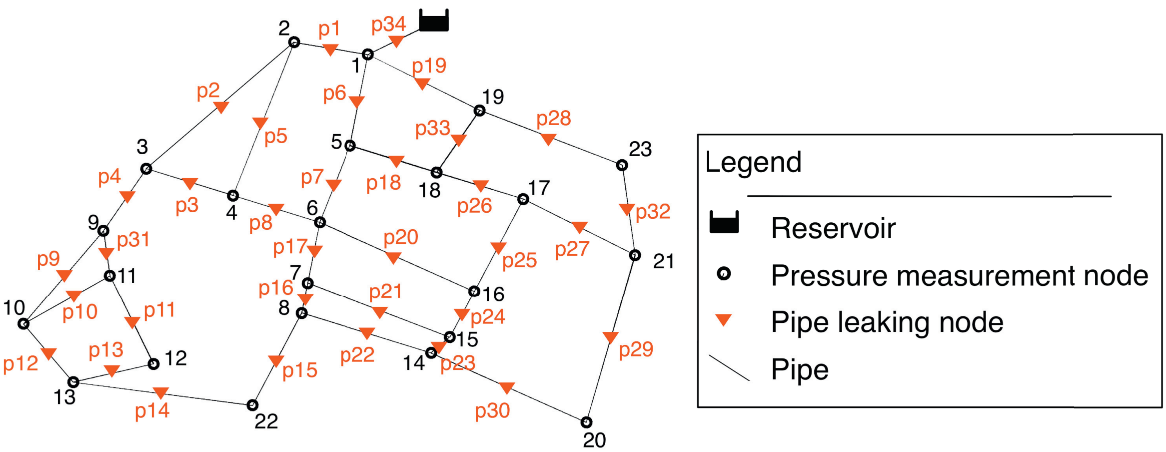

Fig. 1: Apulian hydraulic network, the nodes placed in the halfway of pipes are named with "*p*".

with a symmetry plane or center-of-mass of the network. Indeed, in those conditions the measurements made by pressure sensors might be affected with the same entity for different positions of the leakages. In other words, the variation in flow pressure associated to leakages will be the same no matter what is the position of the leaking pipe in the network ([30]). What is instead desired, is a configuration of the pressure sensors whose sensibility is maximum with respect to different positions of the leakages.

Two different procedures for choosing the best configuration of pressure sensors are studied and compared. Both proposed strategies are driven by two considerations:

1. the best nodes where to position the pressure sensors are those that exhibit the largest sensitivity in measuring the pressures with respect to different positions of leaking pipes;
2. the measurement nodes should be uncorrelated from each other in order to avoid duplicate information.

The first procedure selects the nodes which, are more sensitive to the position of the leakages, while the second procedure does a subsequent refinement by choosing those measurement nodes which are also as much uncorrelated as possible.

It is worth noting that an issue to be addressed in leakage identification is to have a good knowledge of hourly consumptions in the network and of the hydraulics parameters of the network (e.g. the roughness of the pipes). As a consequence, methods which provide both leakages detection and calibration of pipe internal roughnesses can be carried out ([44]), although, for sake of simplicity, now the roughness of the pipes is assumed well-known.

3.1. Network sensitivity

The leakages in the Apulian network are modeled as emitter nodes, positioned at the half-way of the pipes, therefore in total the network has 33 potential leaking pipes. In order to study the sensibility of the network to the position of the leakages, simulations are run by setting an emitter coefficient different from zero in one pipe node at time. The number of run simulations is 33, thus matching the number of pipes in the hydraulic network. The leakages are defined as a ratio of the water flowing through the network in absence of leakages. Three multiplication factors are tested: 0.5, 1, and 2. The use of different factors corresponds to the necessity of having a network sensitivity analysis as general as possible, namely not strictly related to the leakage magnitude. Once the value of the leaking flow has been chosen, the emitter coefficient of the node is calculated from the Eq. (1).

For each run simulation are recorded the pressures in all the 23 nodes of the network that correspond to possible positions of the pressure measurement sensors. Downstream of the 33 simulations, it is available a sensitivity matrix $\mathbb{S}$ ([31]) of the network that has as many rows as pressure measurement nodes (i.e. 23 rows), and as many columns as pipe leaking nodes (i.e. 33 columns). Each entry in the sensitivity matrix is the percentage variations of pressures with respect to the nominal case in which no leakage is affecting the network. $\mathbb{S}_h$ is computed for each h-*th* hour of the day.

A feature reduction is made on the data collected from the 24 sensitivity matrices in order to extract a ranking index of the measurement nodes. Given that the sensibility matrix at the h-*th* hour is $\mathbb{S}_h$, and that its entries are the percentage pressure variations $p\%_{m,l,h}$, measured at node m-*th* for the leakage in the pipe l-*th* at the h-*h* hour, four features are defined:

1. the mean percentage pressure variation for different positions of leakages is:
$$\bar{p}\%_{m,h} = \frac{\sum_{l=1}^{33} p\%_{m,l,h}}{33} \tag{2}$$
   and then the first feature is calculated as the mean of $\bar{p}\%_{m,h}$ across the whole day:
$$f_{1,m} = \frac{\sum_{h=1}^{24} \bar{p}\%_{m,h}}{24} \tag{3}$$
2. the second feature is the variance of $\bar{p}\%_{m,h}$ across the whole day
$$f_{2,m} = \frac{\sum_{h=1}^{24} (\bar{p}\%_{m,h} - f_{1,m})^2}{24} \tag{4}$$

3. the variance of the percentage pressure variation for different positions of leakages is:

$$\sigma^2_{m,h} = \frac{\sum_{l=1}^{33}(p\%_{m,l,h} - \bar{p}\%_{m,h})^2}{33} \tag{5}$$

The third feature is calculated as the mean of $\sigma^2_{m,h}$ across the whole day:

$$f_{3,m} = \frac{\sum_{h=1}^{24}\sigma^2_{m,h}}{24} \tag{6}$$

4. finally, the fourth feature is the variance of $\sigma^2_{m,h}$ across the whole day:

$$f_{4,m} = \frac{\sum_{h=1}^{24}(\sigma^2_{m,h} - f_{3,m})^2}{24} \tag{7}$$

The four features for every measurement node is organized in the $\mathbb{F}$: 23×4 matrix. A further feature reduction is performed on $\mathbb{F}$ through a Principal Component Analysis (PCA) analysis, in order to rank the measurement nodes according to the most significative feature. In table 1 nodes are ranked according first principal component of the feature matrix $\mathbb{F}$. It is possible to observe that the most sensitive nodes are the more peripheral ones. This is in agreement with the fact that the pressure of a node far from the reservoir will be more affected by leakages in the network than the pressure of a node close to the water source (e.g. node number 1).
According to the analysis here proposed, the best four nodes in which measure the pressure are the number 23, 12, 13 and 21.

Table 1: Nodes ranked according to the first principal component of the feature matrix $\mathbb{F}$.

Nodes	23	12	13	21	10	16	4	15	20	11	17	9
First PCA component	0.37	0.19	0.13	0.10	0.08	0.06	0.04	0.03	0.03	-0.02	-0.03	-0.03

Nodes	22	14	3	8	19	7	18	6	5	2	1
First PCA component	-0.04	-0.04	-0.06	-0.07	-0.08	-0.08	-0.09	-0.10	-0.12	-0.12	-0.13

3.2. *Correlation of measurement nodes*

In the previous section has been derived a method that allows the hydraulic network managers to make a reasonable choice for the positioning of pressure sensors. The analysis here proposed shows that the candidate nodes for measuring the pressure might be close to each other since they might lay on a region of the network that is highly sensitive to the effect of leakages. In such case, the information measured from the nodes might be redundant. In order to tackle this issue, a correlation analysis between the measurement nodes is carried out.
It is defined a 23×33 matrix $\mathbb{P}$ that has the same structure as the $\mathbb{S}$ matrix. Each element of $\mathbb{P}$ is the value of the percentage variation of pressure $\bar{p}\%_{m,l}$ averaged on the daily hours for the m-*th* measurement node and l-*th* position of the leakage.

Only some rows (i.e. pressure measurement nodes) of this matrix are considered in the following analysis, those related with strictly positive values of the correspondent first principal component (there are nine nodes: see table 1). Indeed, a negative value is meaningless from a statistical point of view. The correlation matrix C is derived as follow: it is a square matrix, whose number of elements is the square of the number of the potential nodes.

Assume $\mathscr{U}$ as the set of the potential candidate nodes. The elements of $\mathscr{U}$ set are ranked according to a decreasing order of "importance", namely, the value of their own correspondent first principal component. It is defined the decisional variable X_j, $j \in \mathscr{U}$, as follows:

$$X_j := \begin{cases} 1, & \text{if at the } j-th \text{ node we install a sensor,} \\ 0, & \text{otherwise.} \end{cases}$$

It is solved the least squares optimization problem:

$$\min X^T |C| X \tag{8}$$

under the following constraints:

$$\sum_j X_j = 4 \tag{9}$$

$$X_1 = 1 \tag{10}$$

The Eq. (9) is related to the number of the available sensors, while Eq. (10) forces the choice of the first (best) candidate node, thus taking into account the results obtained from the sensitivity analysis.
Note that Eq. 8 requires to solve a nonlinear optimization problem. That problem is very sensitive to the cardinality of $\mathscr{U}$, as it is shown in figure 2: the value of the target function dramatically decreases as the number of considered measurement nodes goes from 6 to 7. As a consequence, we decide to pick the nodes coming out solving the problem with 7 possible candidate nodes (4-10-12-13-16-21-23), among the nine ones previously identified. This fact is because, as the cardinality of $\mathscr{U}$ becomes greater than 7, the objective function levels off, while less and less sensitive nodes are chosen.

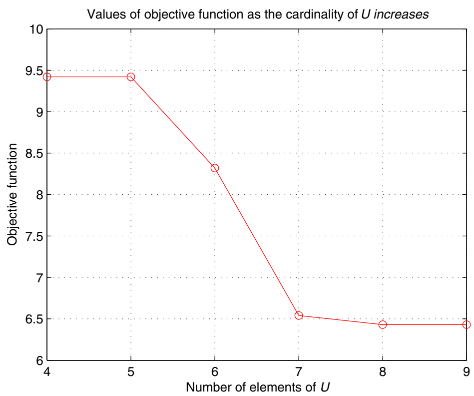

Fig. 2: The different values of the objective function (8) as the cardinality of $\mathscr{U}$ increases.

4. Results

In this section are discussed the results obtained by applying the analysis described in the previous section 3. The water leakage identification is carried out in three different situations:

Scenario 0 no sensitivity analysis is performed: the measurement nodes are those chosen by [4];

Scenario 1 the measurement nodes are chosen according to the sole analysis of the network sensibility;

Scenario 2 the measurement nodes are chosen according to the sensitivity and correlation analysis.

In table 2 are summarized, for each scenario, the nodes in which the four pressure sensors are placed.

Table 2: The sets of chosen nodes for the different scenarios.

Scenario	Measurement nodes
0	3,8,18,21
1	12,13,21,23
2	4,13,16,23

5. Conclusions

A leakage localization method based on the pressure measurements and sensitivity-correlation analysis of nodes in a network has been proposed.

The efficiency of the leakage identification procedure is particularly sensitive to the quality of information available from the real network. For these reason, it has been developed a methodology to efficiently position pressure sensors into the hydraulic network. Three different scenarios ae proposed: a condition in which the pressure sensors are displayed according to empirical considerations, a case in which only sensitivity analysis of the network on the position of the leakage is made, and a condition in which a correlation analysis of the pressure measurement nodes is done afterwards the sensitivity analysis of the network.

The next step will be comparing these three scenarios by means of a reliable statistical tool.

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