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A DECISION SUPPORT SYSTEM FOR IDENTIFYING REAL LOSSES IN WATER DISTRIBUTION NETWORKS

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The investigation of real losses due to pipe aging is of paramount importance for water utility willing to control operational costs and environmental and social impacts of water supply. Real losses reduction could be achieved by continuous maintenance actions and occasional pipe substitutions. Maintenance activities in the distribution network represent one of the largest items in a water utility economic balance and, therefore, any approach aimed at maintenance optimization catches the interest of water managers. These strategies are constrained by the amount of funds, which are usually yearly available for maintenance. For this reason, a procedure is needed to prioritize maintenance tasks and focus the water manager on the most important leakages in the network. Several models have been developed for determining network components' optimal replacement time and rehabilitation planning by means of a Decision Support System (DSS). In the present paper, a procedure for leak detention in a water distribution network is proposed. The procedure is based on network flow and pressure monitoring, joined together with numerical dynamic modeling. The procedure was applied to a laboratory case study and the results obtained show that the proposed procedure has the potential to be a useful tool for rehabilitation scheduling.

Keywords: Decision Support System, hydraulic modelling, real losses, water distribution network

INTRODUCTION

In the last decades, one of the main concerns of the water system managers have been the minimisation of water losses, that frequently reach values of 30% or even 70% of the volume supplying the distribution network. The economic and social costs associated with water losses in modern water supply systems have been rapidly rising to unacceptably high levels.

In a water supply system, water losses are the difference between system input volumes and authorised consumptions, and consist of real losses and apparent losses, as reported in the IWA standard water balance [1].

Different approaches have been proposed in literature in order to cope with the leakage management. Puust et al. [2] distinguish between three approaches: i) the leakage assessment methods which focus on quantifying the water volume lost; ii) the leakage detection methods concerning with the bursts location and iii) the leakage control models focusing on the operational control of the leakage level. Once the water losses are quantified, leaks have to be detected and located and afterwards controlled.

With regards to the leakage detection several methodologies have been proposed, most of them require a well-calibrated hydraulic network model. The leakage detection problem was originally formulated as an optimization problem for computing the magnitudes and locations of leakages, based on some flow and pressure measurements; steady-state regime is often considered [3], although the use of hydraulic transient-based techniques has increased in the last decades (e.g. [4], [5]). In particular the optimization problem computes the pipe friction coefficients to calibrate the system model, as well as to compute the orifice area of the leakage models, based on the available data measurements. A review of the transient analysis solution methodologies is provided in [2].

Some methodologies consider the use of computational intelligence techniques for leakage detection such as fuzzy min-max neural network approach [6], artificial neural networks [7], genetic algorithms [4]. Furthermore, probabilistic and statistical methodologies [8] have been proposed as well as Bayesian inference [9] for this purpose.

Several models have been developed for determining network components' optimal replacement time and rehabilitation planning by means of a Decision Support System - DSS ([10], [11]). DSS actually provides highly valuable indications for infrastructure state and rehabilitation actions to undertake. DSS can also be used to address real losses investigation campaigns in order to focus monitoring efforts in those areas where real losses are probability higher.

In the present paper, a procedure for leak detention in a water distribution network is proposed. It is based on network flow and pressure monitoring, joined together with an homemade numerical dynamic modelling [12]. Due to spatial and temporal variability of leakages, the procedure was implemented with a dynamic model. The comparison between monitoring and modelling response is used to highlight network pipes where real losses are most probably present ([11], [13]). The decisional outputs are the selection of the pipes that have to be better investigated by means of active search methods. Considering the errors in monitoring data and the simplification in numerical modelling, the approach is coupled with uncertainty analysis in order to provide a probable leakage distribution with a specified level of reliability. The procedure is applied to a laboratory case study.

The paper is organized as follows. After a description of the case study, the main characteristics of the applied hydraulic network model and the procedure for the leakage detection are presented. The methodology is then applied to three different scenarios, and conclusions are drawn.

MATERIALS AND METHODS

Case study

The case study is the laboratory network at the Environmental Hydraulic Laboratory of the University of Enna (Italy). The network is a high-density polyethylene (HDPE 100 PN16) looped distribution network: it has three loops, nine nodes and eleven pipes DN 63 mm (Figure 1).

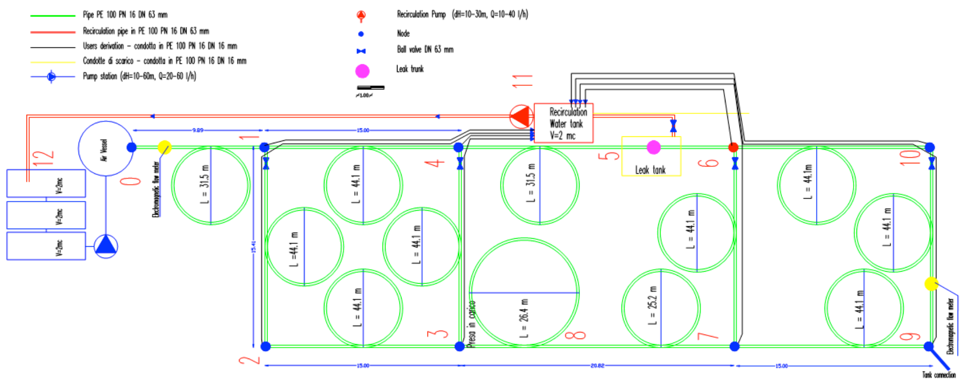

Figure 1. Layout of the laboratory network

Each pipe is about 45 m long and it is rolled up in nearly horizontal concentric circles with bending radius equal to 2.0 m; the form-resistance losses due to pipe bending can be neglected. The network is fed by three water tanks (they can store up to 6 m^3 overall). Four pumps lift up water volumes for supplying the network from the recycling tank to the upstream air vessel, which behaves as a constant head tank, keeping the pressure constant and equal to a value set by varying the speed of the pumps (total water head ranging from 10 to 60 m).

The system is monitored by: six electromagnetic flow meters, pressure cells and multi-jet water meters at each node positionat which user's demands are assumed to occur. Four hand operated sphere valves are installed in order to control the flow in each loop. The network is designed to model the effect of real losses as well as apparent losses.

The mathematical model

In water distribution networks, pipe may be filled by the start node or by the final node, with the result that two wave-fronts may be progressing within the same pipe in the opposite direction. The resulting collision overpressure propagates through the network with remarkable rapidity. Because of the complexity of the system, determined by the various possible filling conditions that may occur, it is necessary to make some simplifying assumptions. Based on the study conducted by Liou and Hunt [14], it is assumed that the air pressure at the water front is always atmospheric and the wave-fronts are always perpendicular to the pipe axis and coincident with the cross sections.

In this paper, the solution of hydraulic equations has been carried out by means of the Method of Characteristics (MOC), starting from the condition of empty network. The 1D unsteady flow of the compressible liquid in the elastic pipe is described in De Marchis et al. [12, 15] and later modified in Freni et al. [16].

The analysis of leakage discharge Q, in l/h, was carried out considering a power emitter law that can be expressed as:

$$Q_L = a_I \cdot H^b \tag{1}$$

The values of the coefficient *a* and of the exponent *b* describe the magnitude of the leakage and the dependence on network head H, in m H_2O. Eq. 1 was applied at network nodes as an additional network output, making the hypothesis to simulate the leakage at the nearest node with respect to the real leakage position.

The prioritization approach

The prioritization approach is based on a proactive application of modeling uncertainty analysis, extensively used to assess the reliability of modeling predictions subjected to data calibration. Uncertainty analysis techniques use the notion of probability to represent uncertainty or partial knowledge of a system that may be deterministic. In such approaches, model parameters are associated with a probability distribution stating the specific range within which the "real" (or calibrated) parameter value may be contained [17]. Several approaches use the concept of Bayesian inference to obtain conditioned probability distributions of model parameters; in the present application, the same approach is used to investigate the probability distribution of leakage parameters (Eq. 1) in different network nodes. In this way it is possible to identify the nodes where a leakage is more probable and the expected average leakage that should be present in that node.

The Bayesian method uses parameter probability distributions for representing the operator knowledge before and after the application of the model to a specific data set. The prior probability distribution $P(\theta)$ of the model parameter θ is defined as the historical or expert information before collecting any new data. The Bayes' theorem on conditional probabilities is used to update a prior probability distribution of model parameters to the posterior distribution that should include the additional information provided by measurements (D) and by the model application to the analyzed system. The Bayesian update can be carried out by means of the definition of conditional probability as:

$$P(\theta \mid D) = \frac{P(D \mid \theta)P(\theta)}{\int P(D \mid \theta)P(\theta)d\theta} \qquad (2)$$

where the posterior parameter distribution is computed as a function of the prior distribution, $P(\theta)$, and the conditional probability for the measured data given the parameter vector θ, $P(D \mid \theta)$. The distribution function $P(D \mid \theta)$ is often referred to as the *likelihood function* of the model. Eq. (2) cannot be generally evaluated by analytical approach. This is mainly due to the complexity of the integral at the denominator. For this reason a numerical estimation has been carried out in the present study considering that a discrete number of parameter sets was investigated in the Monte Carlo Analysis.

In common applications, the hypothesis is made regarding the normal distribution of the residuals between the model and observations assuming the null average and variance σ_e^2. According to such hypothesis, $P(D \mid \theta)$ can be written in the multiplicative form as:

$$P(D \mid \theta) = \prod_{i=1}^{m} \frac{1}{\sqrt{2\pi\sigma_e^2}} \exp\left(\frac{(D_i - Y_i)^2}{-2\sigma_e^2} \right) \qquad (3)$$

where Y_i are the modelling responses that correspond to the m available measurements D_i of a specific variable (i.e., discharges, concentrations, loads, etc.) at a specific system cross-section. The hypothesis of residuals homoscedasticity should be verified or imposed by a residual transformation. In the present study, the Box – Cox transformation was used for forcing the residuals to be homoscedastic [18].The posterior distribution may be used directly to calculate probability distributions for model predictions, thus contributing to the estimation of model uncertainty or to refine the estimation of model parameters, like in the present case. Pressure data measured in the network (in presence of unknown leakages) are used to run

Bayesian inference and obtain the most probable position and parameters of leakage formula (Eq. 1)

The present application may be summarized in the following steps:

1. Pressure data are collected in a condition in which one or more leakages are present in the network in a unknown condition.
2. Prior distributions of leakages parameters are obtained from all available knowledge. Empirical distributions may be obtained from direct measurements (if the parameter is measurable) or by calibration on available data. Theoretical distributions may be assumed by literature or prior knowledge [19]. In this case, common uniform distributions are used.
3. Posterior distributions may be populated by applying Eq. 2 and Eq. 3 to model outputs provided by Monte Carlo analysis, that can be obtained by totally random sampling or by guided sampling (Latin Hypercube, Marcov Chain, etc.).
4. The cumulated probability of leakage parameters and their most probable values are considered as the probability of leakage presence near a specific node and to estimate its magnitude based on pressure.

Steps 2 to 4 can be iterated each time new data are available.

SIMULATIONS AND RESULTS

In the present paper, the above presented approach was applied to the laboratory network of the University of Enna “Kore”. The numerical model was initially calibrated in order to represent the behavior of the network; the only parameter subjected to calibration was the pipe roughness that was set equal to 0.023 mm that is consistent with HDPE pipes.

Pressure is measured in each node with 10 seconds time step and real leakages were introduced in the nodes in order to investigate if the prioritization approach is able to identify them. Initially, only one leakage was considered (Scenario 1) and then two other scenarios were considered with two (Scenario 2) and three (Scenario 3) leakages respectively. For each experimental scenario, pressure at the network inlet was set constantly to 30 m and constant leakage discharge were simulated at the network nodes as better described in the following.

Initially, each network node was supposed to have equal probability to present a leakage (prior assumption of uniform distribution). Leakage parameters, according to Eq. 1, were varied uniformly in the ranges presented in Table 1 and 10.000 Monte Carlo Simulations were run for each scenario. The likelihood function (Eq. 3) was computed comparing simulated and measured pressure in each node and posterior probability distributions were obtained for leakage parameters in each node and for the leakage location.

Table 1. Leakage parameter ranges

Parameter	Units	Min	Max	Distribution
a	[-]	0.00	10	Uniform
b	[-]	0.5	1.5	Uniform

In scenario 1, a single leakage was put in node 3 by means of a constant discharge equal to 70 l/h. After the Monte Carlo Simulations, simulated leakage posterior probability is presented in Figure 2. The model was able to clearly identify node 3 as a leaking node and the most probable values of the parameters of leakage equation were a = 5.02 and b = 0.786, creating a simulated leakage equal to 68.91 l/h in node 3.

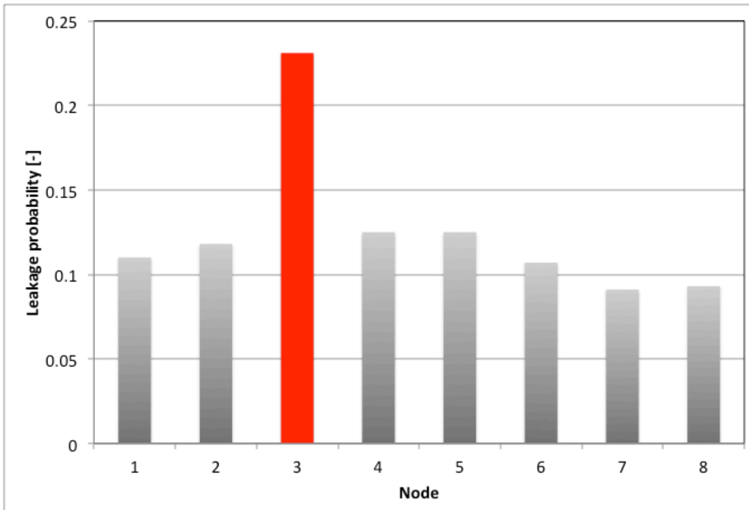

Figure 2. Posterior distribution of leakage probability in Scenario 1 (leaking node is in red)

The prioritization tool was thus able to clearly identify the leaking node and it was also able to correctly estimate the magnitude of the leakage in the analyzed network conditions.

Subsequently, in Scenario 2, two leakages were experimentally set in node 6, by means of a constant discharge equal to 60 l/h, and in node 2, with a discharge of 40 l/h. Figure 3 shows the distribution of leakage probability among nodes.

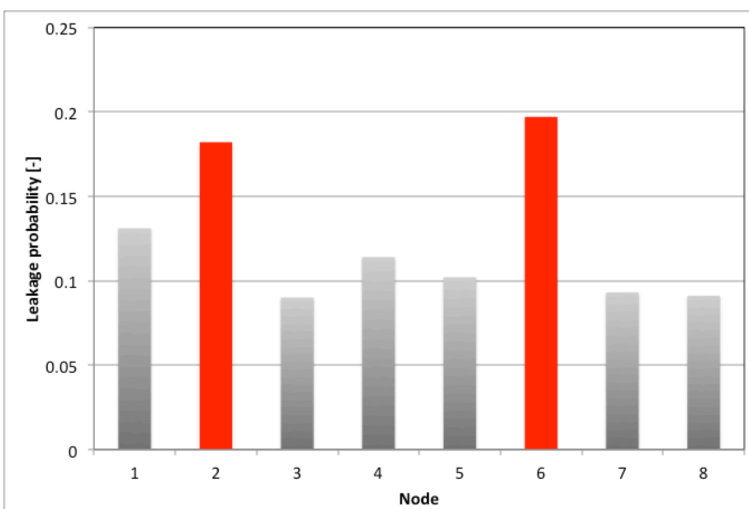

Figure 3. Posterior distribution of leakage probability in Scenario 2 (leaking nodes are in red)

Both leaking node were identified as the most probable location for a leakage and the expected values of leakage parameters were:

- a = 3.96 and b = 0.803 for node 6, leading to a leakage equal to 57.1 l/h
- a = 2.45 and b = 0.881 for node 2, leading to a leakage equal to 45.8 l/h

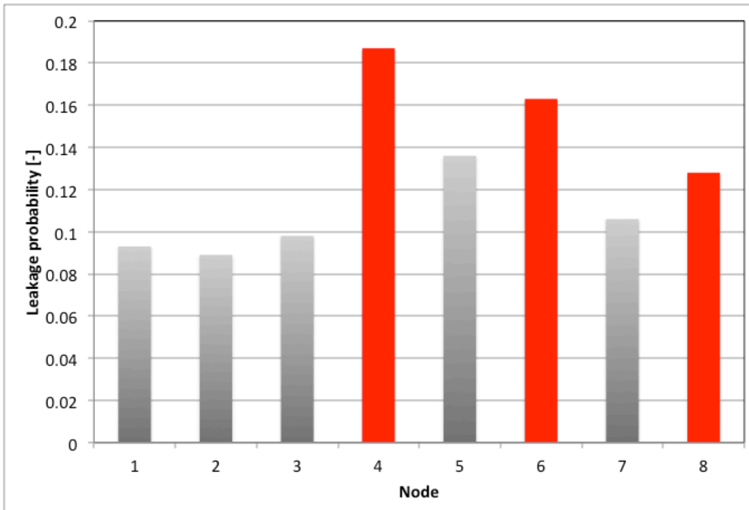

Figure 4. Posterior distribution of leakage probability in Scenario 3 (leaking nodes are in red)

Finally, in Scenario 3, three leakages were experimentally set in node 4, by means of a constant discharge equal to 70 l/h, in node 6, with a discharge of 50 l/h, and in node 8, 30 l/h. Figure 4 shows the distribution of leakage probability among nodes.

The prioritization tool was able to identify leakages in node 4 and 6 but it was not able to identify the smallest leakage in node 8, suggesting an higher probability to find a leakage in node 5. Also leakage parameters in node 8 presented significant differences with the experiments:

- a = 4.21 and b = 0.822 for node 4, leading to a leakage equal to 64.7 l/h
- a = 2.37 and b = 0.875 for node 6, leading to a leakage equal to 43.5 l/h
- a = 1.21 and b = 0.811 for node 8, leading to a leakage equal to 17.9 l/h

Similar results were obtained considering more than three leaking nodes with the tool always able to identify the most important leakages but missing the smaller ones.

CONCLUSIONS

The paper presented a tool for leakage search prioritization based on Bayesian probability analysis. The tool is based on numerical modeling and Monte Carlo Analysis with the aim of simulating different possible leakage distributions. Monitored pressure data and simulation results were compared to compute the most likely position of the leakage and the most probable parameters related to its emitter law.

The approach demonstrated to be efficient in identifying leaking nodes when 1 or 2 leakages are present in the system. The analysis of scenarios with higher number of leakages in the system showed that the tool is only able to find the most important leaking nodes but it usually is unable to identify the smallest ones. This is probably due to modeling equifinality problems considering that several leakage configurations may lead to similar pressure levels at the network nodes thus masking the presence of small leakages in the system.

This tool showed to be efficient in providing the initial knowledge to orienting the decision in leakage search programs, addressing the attention of the water manager to the nodes / areas in which most probably a leakage is present.

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