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Influence of hourly water consumption in model calibration for leakage detection in a WDS

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Abstract

Leakage detection in hydraulic networks can be addressed through inverse analysis. However, the typical approaches found in literature have not been supported by experimental measurements, and no quantitative indication on the influence of the uncertainty of the hourly consumption patterns on efficiency of the objective function is available.
The water consumptions of two small towns were measured for over a year, thus allowing detailed analysis of the evolution of the consumption patterns. This information was used to improve the leakage identification by contextualizing the inverse analysis on small-sized hydraulic networks.

Keywords: Water consumption variability, model calibration, leakage, optimization, objective functions.

1. Introduction

The availability of drinking water has represented a key factor in the development of more advanced countries, and of the developing ones. Therefore efficiency and reliability of hydraulic networks are requirements sought by water networks administrators. Accordingly to the Kingdom et al. (2006), due to inefficient aqueduct systems every year more than 48 billions of cubic meters of water are lost all around the world, that correspond to an economic loss of more than 14 billions US-dollars. In the only United States of America, the American Water Works Association (AWWA) estimates that during the 2002 up to 10 billions kWh of electric energy were used to pump water that was lost in the leakages. The identification and localisation of water leakages is a challenging task due to the topographical complexity of the water systems to be analysed, that can be constituted by a large amount of users, ramifications of the pipes, and water tanks. Mutikanga et al. (2012) subdivided the managing of water losses into four actions: quantification, monitoring, localisation, and network management.

The leakages quantification is done through a water balance on a system-wide basis in a restricted District Metering Area (DMA). Monitoring of leakages allows the engineers to quantify the water flow into the DMA thus discrimi-

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nating when abnormal water consumptions can be associated to water losses. Flows and pressures are measured on different points on the DMAs usually constituted by up to 3,000 properties. During the data analysis only the information collected at night (between 02:00 *AM* and 04:00 *AM*) are considered because in this moment of the day it is registered the minimum flow (MNF), therefore the pressures and the effects of leakages on the water network are maximum. The water consumption monitoring can be done through many automatic methods, the most commons are: netbase (Burrows et al. (2000)), night flow characterisation together with leakage hydraulic analysis (Cheung and Girol (2009)), and flow statistical analysis (Buchberger and Nadimpalli (2004), Palau et al. (2012)).

Once it has been established the presence of leakages in the network, they must be localised and repaired. The former task can be addressed with different sensors, such as: acoustic devices that correlate the noise in the pipe to the leakage position (Clark (2012), Hamilton (2012)), multi parametric devices that gather information about flow and pressure (Koelbl et al. (2009), Farley (2012)), video cameras (Ong and Rodil (2012)), smart balls (Wu et al. (2011)), tracer gas, infrared imaging and ground penetrating radar (Fanner et al. (2007)). All the presented methodologies require however expensive and time-consuming in field measurements. For this reason, in the lasts years it has been increasing the number of research institutions that use network hydraulic models to predict the entity and the position of water losses. The reliability of numerical models depends strongly upon their calibration, that often is not a trivial task. Nevertheless these simulations allow the collection of a large amount of information, thus allowing different network analysis: network zoning (Sempewo et al. (2008), Awad et al. (2009)), pressure management planning for leakage control (Tabesh et al. (2009)), and leakage modelling as pressure-dependent demand (Almandoz et al. (2005), Giustolisi et al. (2008)). The latter is particularly interesting since it can be accomplished by exploiting data from water meters that are easily available. This methodology exploits optimisation algorithms to minimise excessive pressures in the network and to identify the position and entity of the leakages at MNF. The identification problem undergoes to constraints represented by energy conservation, mass balance, and minimum pressure in the network. Due to the dimensions of the modelled DMA, the number of parameters to be identified is usually high (up to 100 for a small network).

Wu et al. (2010) detected losses in hot spots at MNF, whose number was determined a priori based on the size of the network. The algorithm used by the authors exploited genetic algorithms to estimate the leakage coefficients by minimising the differences between calculated flows and pressures with the measured ones. The study here presented starts from this approach and overcomes it by relaxing the assumptions on MNF and on the number of leakages in the network. To analyse only the MNF is not suitable in systems with intermittent water supply, where the night flow is not enough reliable. The optimised target function was defined accordingly to a statistical analysis of water consumptions collected for two small italians municipalities during one year. The dimension of the identification problem was increased, and leakages were searched in all the network.

1.1. Apulian Hydraulic Network

To validate the developed identification procedure, and to test its robustness in finding position, entity, and number of the leakages, a theoretical network was considered as a case study. This choice was made since none information were available about the position and characteristics of leakages in a real network. The chosen hydraulic network was the Apulian (Giustolisi et al. (2008)), because it was completely defined, simple, and relatively small. The latter is an interesting feature since in this study the novel target function was contextualised by using real data collected from two small municipalities: Cloz and Coredo. Therefore, during the leakages identification it was possible to use the weighed target function formulated through the experimental data collected from the two municipalities.

The Apulian network was constituted by 34 pipes, 23 nodes at the same elevation, a unique reservoir, and without losses. Co.Vi.R.I. (2009) estimated that the average percentage of lost water in the Italian network during 2011 was 36.2%. It was assumed that in the Apulian network only the 15% of water incoming from the reservoir was lost, since it is small and likely easily manageable. Known water losses were assigned to four nodes, Fig. 4. One of them was a big leakage, inserted to simulate a burst.

The resulting network needed too much water and node 23 reached negative pressure. To assure a correctly functionality of the network the diameter of pipe which connect node 23 to node 19 was doubled (from 100 *mm* to 200 *mm*). The leakage q_i, expressed in l/s, at the i-*th* node was calculated through:

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

were p_i was the hydrostatic pressure, γ was the pressure exponent chosen equal to 0.5 for nozzles and sprinkler heads, and k_i was the estimated emitter coefficient. Note that the unit of measurement for the latter was $l/(s\ m^{\gamma})$.

When modelling an hydraulic network its water consumption is described through a hourly pattern that is a-dimensional. The hourly consumption of costumers is obtained by multiplying the consumption pattern for the base demand. The consumption pattern assigned to the Apulian network was replaced with a virtual pattern calculated from the average water consumption of real patterns measured in Cloz and Coredo, as described in section 2.2. By doing so, during the leakage identification it was possible to utilise the new target function, contextualised on small alpine towns. This pattern was considered real because it represented the water consumptions of the users, without the effects of losses. To each node of the network was associated the same consumption pattern, that was then multiplied by the base demand factor known by the definition of the Apulian network. This pattern was used to obtain measurement representing in-field data. During the identification the latter was compared with the simulated data.

The programme required a pattern to estimate the evolution of the consumption. In a real application leakage investigation the pattern given as input in EPANET (Rossman (2000)) is unknown and need to be assessed starting from the measured incoming network volume. From the measurements of the flow outgoing the reservoir, it was known the total water volume entering the network V_{tot}. Thus the pattern given as input in EPANET was modified as follows:

1. the average network pressure$\widetilde{p_i}$ was calculated at each hour i
2. Eq.(2) was used to calculate a global emitter k_{glob}:

$$V_{tot} = \left(k_{glob} \sum_{i=1}^{T} \widetilde{p_i}^{\gamma} \right) T \tag{2}$$

3. k_{glob}, that was estimated equal to 10 $l/(s\ m^{\gamma})$, was used to determine the leakage flow of the entire network at each hour through the equation 1
4. the pattern consumption was calculated subtracting the hourly leakage to the reservoir outgoing flow

The measurements available from this case study network were supposed to be the reservoir outgoing flow and pressures at four nodes, Fig. 4. Three pressure sensors were positioned in nodes in the edge of the network. A fourth measuring point was placed on a central node, in order to have distributed measurements on the DMA.

2. Methodology

The identification analysis was addressed as a constrained multi objective optimisation problem in which the target function was defined by the difference in pressure and flow between the simulated model and the virtual measurements. The optimised variables were the leakage coefficients at each node. The identification was performed on a customised version of the Apulian network were the available measurements were assumed to be the reservoir outgoing flow and pressures at four nodes. It was verified that the performances of the identification procedures depended on two factors: the definition of the target function, and the first guess solution used to initialise the optimisation algorithm. Different target functions used in literature were tested. It was also presented an original procedure for weighting the terms of the objective function based on a statistical analysis of the hourly consumptions.

2.1. Target function

In this section there are reported the target functions used in literature for the leakages identification. At each t-*th* time instant and for each i-*th* node, these functions compare the measured hydraulic grades $H_{t,i}$ and pipe flows $Q_{t,i}$ with the calculated ones. Three are the used formulations (Wu et al. (2010)):

- sum of difference squares:

$$f_{sds} = \frac{1}{N_H + N_Q} \sum_{t=1}^{T} \left[\sum_{i=1}^{N_H} w_i \left(\frac{Hs_{i,t} - Hm_{i,t}}{Hm_{i,t}} \right)^2 + \sum_{j=1}^{N_Q} w_j \left(\frac{Qs_{j,t} - Qm_{j,t}}{Qm_{j,t}} \right)^2 \right] \quad (3)$$

- sum of absolute differences:

$$f_{sad} = \frac{1}{N_H + N_Q} \sum_{t=1}^{T} \left[\sum_{i=1}^{N_H} w_i \left| \frac{Hs_{i,t} - Hm_{i,t}}{Hm_{i,t}} \right| + \sum_{j=1}^{N_Q} w_j \left| \frac{Qs_{j,t} - Qm_{j,t}}{Qm_{j,t}} \right| \right] \quad (4)$$

- maximum absolute difference:

$$f_{mad} = arg_{t,i,j} \max \left\{ \left| \frac{Hs_{i,t} - Ho_{i,t}}{Hm_{i,t}} \right|, \left| \frac{Qs_{j,t} - Qm_{j,t}}{Qm_{j,t}} \right| \right\} \quad \text{with } i = 1, .., N_H \text{ and } j = 1, .., N_Q \quad (5)$$

where the subscripts m and s were referred to the measured and simulated data respectively, T was the number of analysed hours, N_H and N_Q were the number of nodes at which the hydraulic grades and the pipe discharges were measured. w_i and w_j were the user-defined weighting factors that were used to penalise the observed hydraulic grades and pipe flows.

The formulation of the fitness adopted in this paper was the sum of absolute differences, Eq.(4). It was chosen because its was linear and continuous with respect to the estimation error of flows and pressures. These two properties eased the convergence of the optimisation algorithm when the fitness was close to its minimum value.

Three strategies were adopted for the definition of the weighting factors w_i and w_j, thus generating three different formulations of Eq.(4):

- $f_{sad,5}$: the weighting factors were constant at each hour of the night, and equal to the inverse of T, the number of hours of the night ($T = 5$, measurements were taken from 0:00 to 4:00).

- $f_{sad,25}$: the weighting factors were constant at each hour of the day, and equal to the inverse of T, the number of hours of the day ($T = 25$, measurement were taken from 0:00 to 24:00).

- $f_{sad,a}$: the weighting factors were different at each hour of the day, and calibrated through the procedure reported in the section 2.2. This definition of the target function allowed the identification to be more precise at the hours when the effect of the water leakages was preponderant to the user water consumption. The target function was thus contextualised to the analysed network.

Constraints were applied to the maximum value of each emitter coefficient and to theirs sum K, in order to limit the maximum global water leakage. The latter should have been imposed as a equality constraint and equal to k_{glob}, if the pressures at each node of the network had been equal to the average pressure of the network, i.e. if the global water losses had been known. Nevertheless, the total looses were not known with full accuracy, due to measurements noise, limited measurement accuracy and precision. To take into account these source of uncertainty, the value of k_{glob}, related to the total water losses, was limited to an interval rather to a single value. The extremes of such interval were chosen as the 10% of k_{glob}. The constraints on K were applied through a system of penalty functions:

$$p_1 = \begin{cases} \frac{|K-9|}{9} & if\ K < 9 \\ 0 & if\ 9 \le K < 11 \\ \frac{|K-11|}{11} & if\ K \ge 11 \end{cases} \quad (6)$$

Each emitter coefficient assumed values that were greater than zero but limited by physical constraints to a maximum value. From equation 1 it was possible to estimate a maximum value k_{max} of the emitter coefficients equal to about 6 l/sm^{γ}, supposing that in the worst scenario more than half of total leakage of the network (referring to the global emitter coefficient k_{glob}) was concentrated in one node. The two constraints on minimum and maximum values of k_i were:

$$p_2 = [\max(0, -k_i)]^2 \tag{7}$$

$$p_3 = [\max(0, k_i - k_{max})]^2 \tag{8}$$

The final objective function that was used during the identifications was the sum of f_{sad} and the penalties:

$$f_{ob} = f_{sad} + p_1 + p_2 + p_3 \tag{9}$$

2.2. Measurements

No data are in general available for hourly consumption of hydraulic network, but only information about the flows exiting the tanks and the pressure in few points of the network, obtained through in-field measurements. The weights of the target function $f_{sad,a}$ were calculated by analysing the hourly water consumptions collected from two different small municipalities that had equivalent demographical, geographical, and topological characteristics. The two town were Cloz and Coredo.

Measurements of the flows exiting the tanks of the towns were collected for almost all the days of year 2011, with except of some days randomly distributed across the year were the acquisitions were corrupted by short-time failures of the water meters. In total 260 days were acquired for Cloz and 328 for Coredo. The data were characterised by a high variance, especially during daylight hours. This issue was due do the fact that the water demand were user driven, and it was maximum during the day when the habitants of the towns were more active. Wu et al. (2010) addressed the leakage identification problem by analysing only the nocturnal hours, the moment of the day when the pressures at the nodes were higher. Nevertheless, daylight consumptions are important in water networks with an intermittent water demand.

By exploiting the available consumption data, it was possible to define a procedure to adaptively weight the terms of the fitness function $f_{sad,a}$ at each hour of the day. The followed steps were:

1. For both Cloz and Coredo, the total hourly water consumptions were obtained by integrating the consumptions at each water meter.
2. The results obtained at each day were then normalised on the average daily consumption. These ratios were called consumption coefficients.
3. At a given hour, it was calculated the mean and variance of the relative consumption coefficient across the whole year. In Fig. 1 are reported the average hourly consumptions and the box plot of the measurements for Cloz and Coredo.
4. The weight for the t-*th* hour, of the i-*th* town, was calculated as the inverse of the standard deviation of the corresponding consumption $\sigma_{t,i}$, Table 1:

$$w_{t,i} = \frac{1}{\sigma_{t,i}} \tag{10}$$

5. The sum of absolute differences in f_{sad}, Eq.(4), was weighed by the corresponding w_t. The latter was the average value between $w_{t,Cloz}$ and $w_{t,Coredo}$. This new target function was called $f_{sad,a}$.

2.3. Optimization Algorithm

Many optimization algorithms have been exploited in water management system. Due to the complexity and to the high dimension of the problem, different evolutive approaches were studied: genetic algorithm, ant colony optimisation, honey-bee mating optimisation, PSO, and differential evolution. Genetic algorithm has been applied to leakage identification due to ease of implementation and to its capability of spanning across wide domains. A

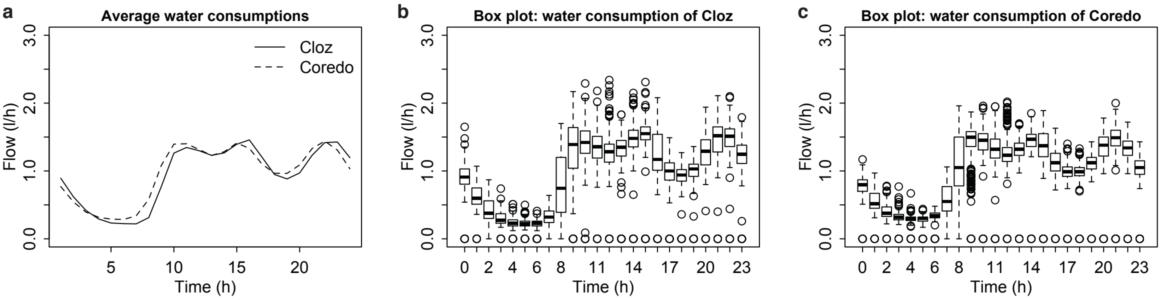

Fig. 1. Measured total water consumptions: (a) hourly average, (b) box plot of measurements collected in Cloz, (c) box plot of measurements collected in Coredo.

Table 1. Hourly weights assigned to the target function.

Hour	0	1	2	3	4	5	6	7	8	9	10	11
w_t (/)	0.9	1.3	1.8	2.4	2.9	1.8	0.5	0.3	0.5	0.6	0.5	0.7
Hour	12	13	14	15	16	17	18	19	20	21	22	23
w_t (/)	0.8	0.9	0.5	0.7	1.1	1.1	0.8	0.6	0.7	0.8	0.8	1.0

comparison between GA and PSO was given by Eberhart and Shi (1998). With respect to GA, PSO tends to explore a smaller portion of the domain of the target function, but it tends to converges more quickly to the minimum. Shi and Eberhart (1999) tested the PSO with different functions, concluding that the desirable features of this algorithm are its scalability and its low sensibility to the population size. These characteristic are interesting since they state that the computational cost of the PSO remains limited even for high dimensional target functions. For these reasons the PSO was chosen in this study.

The PSO emulates the behaviour of social groups such as birds, fishes, bees and humans (Abraham et al. (2006)). The method tries to emulate the fact that the experience of a group of people influences its own behaviour while trying to address a task with an optimum approach. The individuals of a population are represented as particles described by a position x and a velocity v, and the task to be optimised is the research of the minimum of a target function called fitness. The algorithm is initialised by randomly generating the particles of the first population, from a predetermined domain, and the fitness is evaluated for each individual. Given a p-*th* particle, its best position is stored in the vector $\hat{x_p}$, while best particle among all the particles in the population is represented by $\tilde{x}$. Note that each vector has dimension $\mathbb{R}^N$, where N is the number of nodes of the network (23 for Apulian's model). At the new iteration $i + 1$, the velocity vector of the p-*th* particle projected along the j-*th* direction is determined as the sum between the old velocity, and two terms measuring the distance from the particle to its best position, and to the position of the best individual in the population:

$$v_{i+1,p,j} = w\ v_{i,p,j} + c_1 r_1 \left(\hat{x}_{i,p,j} - x_{i,p,j}\right) + c_2 r_2 \left(\tilde{x}_{i,j} - x_{i,p,j}\right) \tag{11}$$

r_1 and r_2 are random numbers generated from a uniform unitary distribution, w is the inertial weight, c_1 and c_2 are positive constant parameters called acceleration coefficients. These parameters were set according to what reported by Abraham et al. (2006): the inertial weight was $w = 0.95$ and the acceleration coefficients were $c_1 = c_2 = 2$. Once all the N components of the velocity vector $v_{i+1,p}$ of the p-*th* particle at the $i + 1$ iteration has been calculated, the next position of the individual is given by the sum of its previous position $x_{i,p}$ with its current velocity:

$$x_{i+1,p} = x_{i,p} + v_{i+1,p} \tag{12}$$

These iterations are repeated until a convergence is reached. In this study two convergence criteria were applied: the first one is on the maximum number of iterations, while the second one is on the residual of the target function.

2.4. Procedure

During the identification procedure, the optimised variables were the emitter coefficients of each node in the network, therefore. The target function was defined as: $f : \mathbb{R}^{23} \rightarrow \mathbb{R}$. The architecture of the identification procedure is schematised in Fig. 2. The program started by generating random population of 69 particles, that was three times the number of unknowns. Each particles was a vector with 23 elements, i.e. the emitter coefficients at the nodes of the network. The initial emitters were sampled from a uniform distribution defined in the interval $[0; 6]\ l/(s\ m^{\gamma})$. An EPANET model was generated and run for each particle, thus the flow rates at pipes, pressures at nodes, and flows at the reservoir were calculated. The latter was used together with measured pressures of four selected nodes during the evaluation of the target function in Eq.(9). Three formulations of the fitness were considered: $f_{sad,a}$ with adaptive weights, $f_{sad,25}$ where all the hours of the day were equally weighted, $f_{sad,5}$ that considered only 5 nocturnal hours. When all the individuals of the population were evaluated, the convergence criteria was checked. If the output of this phase was positive, the algorithm was stopped, otherwise the population was modified to the next iteration. Two convergence criteria were used: the maximum number of iterations (set to 200), and the residual R of the target function. The latter was calculated by considering a percentage error $\epsilon_{\%}$ of 5% in the estimation of each observable quantity:

$$R = T\,(N_H + N_Q)\,\epsilon_{\%} \tag{13}$$

where N_H and N_Q are the numbers of points of measurement (respectively 4 pressure and 1 flow measurements) and T is the number of hours considered in the target function (5 for $f_{sad,5}$ and 25 for $f_{sad,25}$ and $f_{sad,a}$). It was thus calculated a residual threshold of 1.25 for $f_{sad,5}$ and 6.25 for the other two fitnesses.

Due to the intrinsic stochasticity of the PSO, the optimal solution changed at every run of the procedure. To limit this effect, 10 runs were launched for each one of the three fitness functions tested. The final set of leaking nodes were those found by the identification run with the lowest residual.

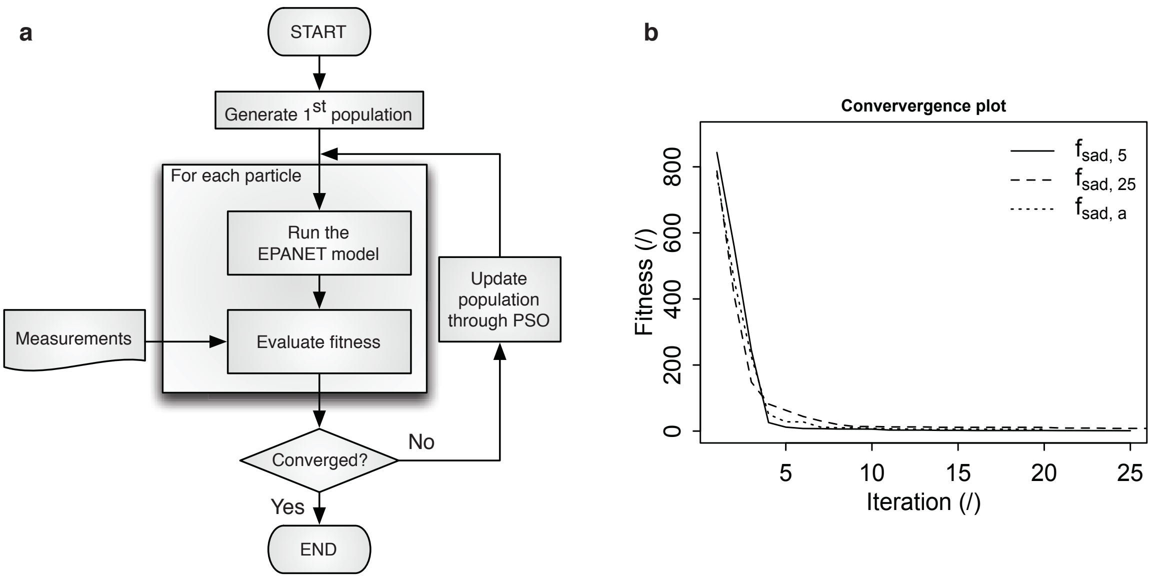

Fig. 2. (a) architecture of the identification scheme; (b) convergence results obtained with the three formulations of the fitness.

3. Results

The convergence of $f_{sad,5}$ and $f_{sad,a}$ was achieved on the value of the residual, while $f_{sad,25}$ converged on the maximum number iterations, Table 2. The comparison between the results obtained with the different formulations of f_{sad} were made by considering: the speed of the convergence, and the accuracy in predicting both the flow outgoing the reservoir, and the positions of the four a-priori defined leakages.

In Fig. 2 it is reported the convergence plot of the three target functions. All the identifications converged to a small value, and the new formulation of the objective function $f_{sad,a}$ showed convergence speed comparable to the one achieved with the state of the art $f_{sad,5}$.

An efficiency parameter η was defined to compare the performance of the identifications in finding the correct position and value of the leakages through each one of the f_{sad} utilised. Given N_{pn} leaking nodes, η was obtained by multiplying three terms: the number of leakage nodes estimated N_{pc}, a term related to the hydraulic distance d between the known leakage node j and the calculated one i, and a third contribute used to take into account the absolute difference $\Delta k_{i,j}$ between the set and calculated values of the emitter k. The equation of the efficiency was:

$$\eta = e^{\frac{-(N_{pn}-N_{pc})^2}{N_{pn}^2}} \sum_{i=1}^{N_{pn}} \left(\frac{1}{\beta}^{\Delta k_{i,j} + \frac{d_{i,j}}{1{,}000}} \right) \tag{14}$$

β was set equal to 10, and it was the parameter used to tune the sensitivity of the efficiency with respect to nodes calculated far away with respect to the set ones. A high efficiency was reached when all the calculated leaking nodes were close to the leakages a priori defined in terms of: value, distance, and number. The best identification was obtained with $f_{sad,a}$, Table 2.

The flow outgoing the reservoir was estimated with a low error with the three target functions, Fig. 3. In particular, $f_{sad,25}$ and $f_{sad,a}$ allowed a good estimation of the flow also during the daily hours. Fig. 4 shows the known leakage nodes and the calculated ones for the three different fitness. The exact position of the leaking nodes have not been identified exactly. Nevertheless the identifications localised correctly the areas of the network in which the leakages are located. Note also that by using $f_{sad,a}$ it was possible to estimate the value of the set emitter coefficients with the highest accuracy.

Table 2. Summary of the performances of the identifications performed.

Fitness	Best run	Iterations	Convergence threshold	Residual	η
$f_{sad,5}$	7	25	1.25	1.07	2.55
$f_{sad,25}$	4	200	6.25	7.26	3.89
$f_{sad,a}$	4	20	6.25	4.78	4.31

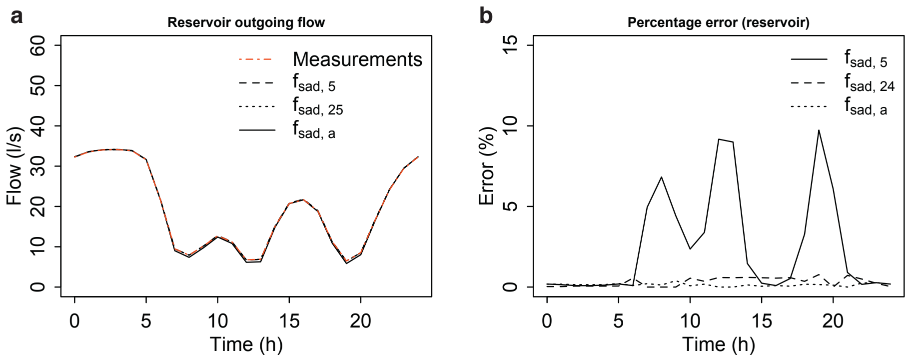

Fig. 3. (a) calculated and a priori flow outgoing the reservoir; (b) percentage error in estimating the outgoing flow.

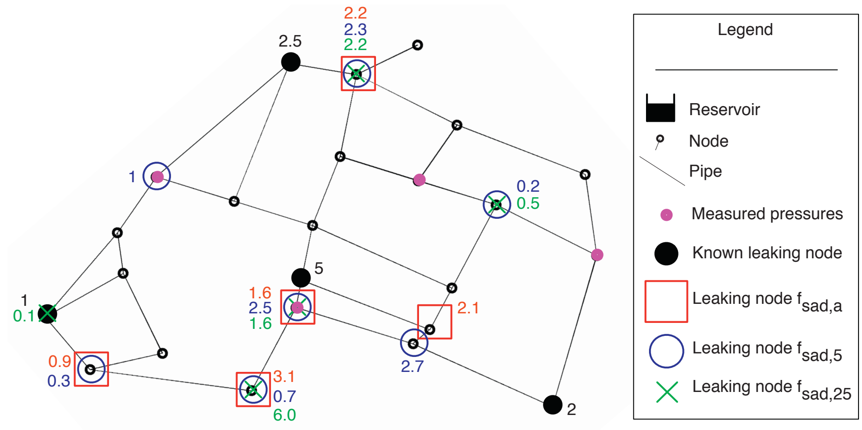

Fig. 4. Apulian network in which are highlighted: measurement points of pressures, leaking nodes, and identified leaking nodes.

4. Conclusions

An original approach to the formulation of the water leakages identification problem has been presented. The study exploited an optimisation procedure to determine the emitter coefficients, i.e. the leakages, of a hydraulic model of a customised Apulian hydraulic network. A new procedure to define the target function by contextualising it to small size hydraulic networks has been proposed. The new objective function was defined by taking into account the relative error between the simulated and measured hourly flows at the reservoir, and the pressures at four nodes of the network. At each hour, different weights were assigned to the target, in order to discriminate robustly the hours characterised by more stable consumptions during the year. The hourly weights of target function were calibrated with a statistical analysis of water consumptions of two small italian towns, Cloz and Coredo.

The performance of the novel objective function were compared with the ones achieved by exploiting two target definitions used in literature. It has been shown that even if the identification procedure was not able to calculate exactly the positions of leaking nodes, the areas of the network in which the leakages were positioned a priori were correctly localised. Moreover, the new target function allowed to estimate the values of the emitter coefficients with the highest accuracy.

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