A Decision Support Too for a Sustainable Management of Water Distribution Networks

Luigi Berardi[1], Daniele B. Laucelli[1] and Orazio Giustolisi[1]

Abstract

Water distribution networks (WDN) are often described as arteries of urban and rural areas since they sustain all human activities. Unfortunately, after several decades of uninterrupted functioning, ageing and deterioration due to external and internal agents have caused a reduction in terms of pipe hydraulic capacity and, more importantly, an increased level of leakages. Traditionally WDN's maintenance was based on reactive replacement/repair of pipes after that failures occurred. In recent years the increasing of failures rates in many WDN worldwide have driven water managers to move towards a proactive approach in order to plan rehabilitation/maintenance of infrastructures before that major incidents would occur. This paper points out at the architecture of a decision support system (DSS) which integrates all information (both qualitative and quantitative) currently available on real WDN, recent advancements in ICT and management objectives for defining optimal medium-term rehabilitation plans. It consists of three main components: (1) a modeling tool including, besides other models, some utilities for automatic WDN hydraulic analysis; (2) a data-management tool allowing different types of information to be stored and the usage some artificial intelligence techniques in order to mine additional information from data and (3) an optimization tool aiming at searching optimal alternatives for decision makers. The main features of each component as well as their integration are further discussed and exemplified in a real-world case study.

---

[1]DICA, Technical University of Bari, 70125 Bari, Italy

Keywords
Water distribution networks, Rehabilitation, Planning

Introduction

Most of human activities in both developed and developing countries are concentrated in large urban areas. Therein water use is guaranteed by the correct functioning of water distribution networks which are necessary to carry water from sources (e.g. reservoirs connected to urban areas through large mains) to customers' taps (i.e. up to service connections). Although such infrastructures are likely to work without interruptions for years, they are subject to gradual deterioration along pipes and/or at joints and fittings. This phenomenon, in turns, results into many drawbacks for both water companies (or municipalities) and customers. In fact, the actual carrying capacity of pipe progressively reduces due to byproducts' encrustations/corrosion; this, would later affect service levels at delivery points where pressure can be insufficient for a correct water delivering. Moreover, uncontrolled deterioration would show several weakness points along the network which might lead to possible leakages that would at turn generate direct costs for repairing and indirect costs for urban community. Due to the above mentioned counter effects, water companies worldwide are gradually leaving the traditional reactive management approach in favor of a proactive planning of WDN surveys and rehabilitation works.

Today, the problem of planning interventions on such infrastructure pertains the wider issue of managing different utilities while planning the expansion of the existing urban areas. Such planning activities are usually based upon demographic analysis, as for instance, forecasting potential increase/decrease of cities' population in the future as well as provisional land uses in future urban scenarios. Moreover, the changes occurring in people lifestyles as well as the increasing impact of climate changes are some factors which need to be taken into account while trying planning interventions on such complex systems.

The main stakeholders of those plans are grouped within the target of final users/customers while decision makers are often find in the public/institutional sphere (i.e. municipalities) or private ones (i.e. companies) which should provide continuous service of utilities in urban area in order to guarantee acceptable lifestyle.

Along such a comprehensive perspective in terms of its rehabilitation and/or expansion, WDN management should be integrated with other interventions on urban utilities in order to avoid waste of money and to match future customers and final users' needs.

Nonetheless, the problem of acknowledging the actual network conditions is largely impaired since these infrastructures are mainly found in the underground. The impossibility of visual inspection severely reduces the diagnostic possibilities of such systems, thus, implying a considerable uncertainty in using any models on predicting failures. For this reason, water companies are improving their data collection practices as well as systematic surveys. Moreover, the advent of ICT for WDN management allows effective data management and visualization. In particular, the use of some new technologies (e.g., WEB 2.0 network) is being proposed to allow customers to communicate with water companies in order to report complaints due to malfunctioning or service information.

The need for taking proper courses of actions while planning intervention on a WDN is also motivated by two recently emerging community issues on water distribution analysis, namely water security and responses to climate changes. Water security refers to the level of alert and warning in giving prompt and right responses to potential contamination scenarios. This issue reflects the modern international relations' history signed by the threat of terrorist attacks and possible accidental contamination of WDN. On the other hand, climate changes are likely to affect customers' habits resulting, for example, into sharper patterns of daily demand. The knowledge of network behavior and the possible evaluation of different interventions may help identifying some strategies to reduce/annul possible network insufficiencies with respect to customer's demand variations.

Shamir and Howard (1979) and Walski and Pelliccia (1982) provided general guidelines for evaluating whether a pipe should be replaced/rehabilitated while mainly focusing on economic criteria. Successively, other criteria have been considered to select effective intervention plans: the reduction of pressure deficiencies (Walski, 1985), the improvement of water quality and system flexibility (Halhal et al., 1997) and the reduction of pumping costs (Kim and Mays, 1994). In some works the network reliability has been introduced to identify those pipes which need the most to be rehabilitated (Todini, 2000; Dandy and Engelhardt, 2006). A recent paper (Berardi et al., 2008) also took into account the reduction of leakages and the actual valve deployment while selecting pipes to be replaced.

A holistic approach to asset management should also be viewed as a business discipline for managing the life cycle of assets. Nonetheless, the so-called whole life cost models are likely affected by all uncertainties referring to discount rate, failure prediction and actual network service conditions (e.g., changes in demand patterns, network expansions, and so on). For these reasons long-term scheduling is often conceived in terms of a set of short planning phases (time steps).

In recent years, the problem of selecting optimal rehabilitation alternatives has been solved by using multi objective genetic algorithms (MOGA) (Goldberg, 1989; Savic, 2002), as it is given evidence in several papers (e.g., Halhal et al., 1997; Cheung et al., 2003, Dandy and Engelhardt, 2006). Only recently, some works (Giustolisi et al., 2006; Berardi et al., 2008; Giustolisi and Berardi, 2009) proposed a methodology to help decision makers in selecting the optimal intervention plans amongst a large amount of solutions provided by MOGA, especially when many objective functions are involved in the optimization process.

This paper describes the main feature of a system aimed at supporting decision on network maintenance/ rehabilitation/ renewal. From a decision theory perspective such work is likely to respond to a *decision aiding* problem since it points out the most effective intervention alternatives. On the contrary, the decision problem is still left to decision makers whose task is to select amongst available suggested (technically optimal) alternatives according to some additional criteria (which are not necessarily known to analysts). The aim of this work is to reduce the gap between the so-called domain experts (i.e., technicians of the

water companies) and methodology experts (i.e., analysts) by means of the suggested and recommended system.
Although this decision support system is clearly aimed at addressing WDN manager's need, the solutions that would be obtained can be profitably used as a pragmatic element for further analysis/discussion within the decision process by some other "city managers".

Operational decision support system for sustainable WDN management

Devising an operational decision support system (DSS) for water distribution network management means to be able to combine current available knowledge on infrastructure with a number of different objectives representing economic, management and service requirements. Although the main goal of using a DSS is the achievement of optimal maintenance/rehabilitation planning, its adoption in common practice for water utility management also results into many positive side effects:

1) it justifies the development of reliable hydraulic models to be used for assessing network functioning under different hypothetic scenarios (e.g., emergency response to malfunctioning and/or contaminant intrusion);

2)it helps water managers to acknowledge real management targets to be pursued in the near future, without overrating the marginal improvements that would otherwise be achieved in short-time planning;

3)it compels water utilities to improve the knowledge of real physical conditions of existing infrastructures;

4) it motivates the adoption of efficient data collection/ storage systems;

5)it encourages the adoption of some recent information and communication technologies (ICT) in order to enable interaction with customers. In fact, customers can be ultimately seen as "distributed sensors" which are essential for detecting unacceptable network functioning;

6)as a consequence, the pervasive use of DSS justifies regulatory bodies in defining stringent performance requirements to water utilities which, at turn, allows improving the efficiency of existing infrastructures;

7)further, it motivates city managers in discussing possible intervention scenarios with services utility managers (i.e., water managers, in this case) in order to take optimal decision from a global urban perspective;

8)it also encourages future efforts in developing some urban trends which could be easily included in future DSS.

The main architecture of the DSS reported herein consists of three main areas concerning *models*, *data management* and *optimization* as shown in Figure 1. Although they represent three separate cognitive aspects of the infrastructure management process, they are tightly linked to each other. In fact, *data management* should be designed in order to make promptly available inputs to models and, at turn, to accommodate model outputs. Moreover, the need for fast optimization procedure requires an extremely efficient data structure where information can be easily retrieved as well as a fast WDN simulation model. In particular, a computationally effective hydraulic model aims at speeding up multiple network simulations representing different hypothetic scenarios to be evaluated while searching for optimal intervention plans.
It is worth noting that the DSS is conceived herein to solve the so-called decision aiding problem (Tsoukiàs, 2007) rather than the decision problem itself. This means that the final purpose of using the DSS should be a set of optimal alternatives where decision makers (i.e., the water manager, or even the city manager) might choose the best ones according to their own criteria, which are not necessarily known when technicians/analysis set the DSS up.

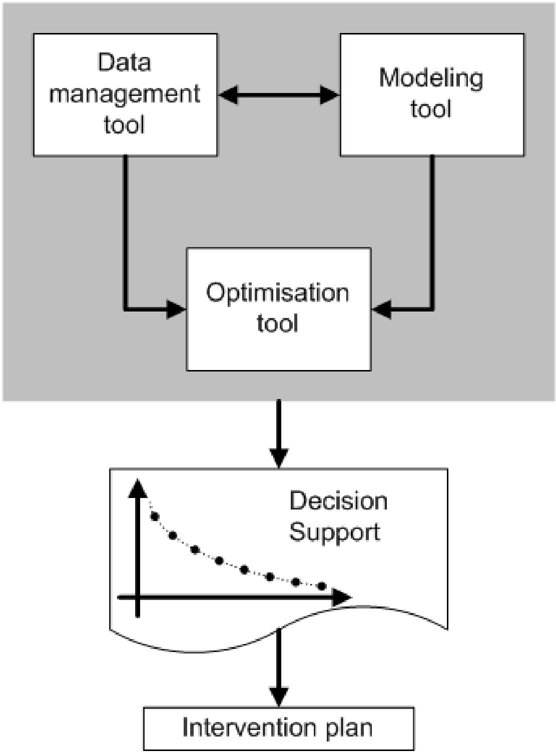

Figure 1. Main architecture of the decision support system for WDN management.

The main features of each area are included in the following figure along with some discussion about the key connections amongst each other.

Modeling tool

As it has been mentioned in the introduction, planning optimal interventions on WDN includes simulation of many aspects of separate systems in order to assess the impacts of each hypothetic intervention plan. In fact, acting on a given element of the WDN usually results into a temporary closure of isolation valves, service disruptions and temporary change of regular WDN functioning. In addition, setting intervention sites is also the cause of traffic disruptions, third party damages and different costs (e.g., interruption of some commercial activities, temporary shops closure, temporary interruption of urban roads nearby hospitals and so on). There is a number of models which are needed for simulating all these aspects, mostly concerning the particular application, thus, not easily to be generalized (e.g., the traffic model). In this work two types of models are mentioned by supporting brief details, namely hydraulic and cost models, since they have been traditionally considered in WDN rehabilitation planning. Nonetheless, the open architecture of the proposed DSS is able to accommodate other case-specific models.

Hydraulic model

The simulation of WDN hydraulic functioning is based on its topology in terms of *pipes* and *nodes*. Such a representation reflects two main conservation laws describing the physical behavior of the hydraulic system: the mass balance at each *node* and the energy conservation through each *pipe*.

Accordingly, *nodes* are usually related to outflows and pressure control points (e.g., water tanks), while *pipes* are likely referred to any kind of energy balance elements (including some elements like pumps and minor head losses which are actually punctual entities). Such a topological representation also accommodates isolation *valves* considered to be as special elements located near nodes and upon pipes allowing interruption of some potential water paths and, as a consequence, of the whole network layout.

Attempts made in modeling the hydraulic behavior of a WDN means to have an interesting attempt at predicting its status in terms of pipe water flows and nodal pressures, once boundary conditions which represent the current network topology (as it results from the isolation of valves' status), proper characteristics of assets and service conditions (i.e., the basis of nodal demands, water level in tanks, status of pumps and minor losses) have been provided. Moreover, in order to achieve a realistic prediction of pipes status, simulation should be performed by considering pressure-dependent nodal demands (i.e., pressure-driven

simulation) (Giustolisi et al., 2008a). Such a modeling approach also leads to the introduction of water leakages from pipes and joints as pressure-dependent water outflows whose pressure-discharge relation can be modeled by using some pipe leakage parameters (Germanopoulos, 1985).
Once the hydraulic model has been built and calibrated, actual pressures and supplied demands can be assessed whatever would be the boundary conditions (i.e., actual topology, demand pattern, pump status and so on). In addition, it would be also possible to estimate the amount of water lost from joints and fittings.
It is worth noting that developing/calibrating a reliable pressure-driven hydraulic model is likely to realistically reproduce actual network functioning. This, in turn, means avoiding false misgivings about future system insufficiencies due to future expected increases of water demand. As a consequence, this leads to a more cost-effective planning of system expansion works.
The hydraulic model to be used in a DSS for WDN maintenance should be coupled with the following ancillary analysis utilities:

- the automatic identification of *pipe segments* related to isolation valve shutdowns (Giustolisi and Savic, 2010);

- the automatic detection of some portions of the WDN currently connected with water sources (Giustolisi et al., 2008b).

The former utility can be used right after defining the WDN topology and locating isolation valves. The latter should precede the hydraulic simulation in order to detect the current network topology to be simulated. The combination of both utilities with the WDN hydraulic simulator permits assessing system reliability in case of abnormal functioning conditions due to planned/emergency interventions as well as the simulation of responses after the contaminant intrusion from any possible location.

Cost model

Maintenance/rehabilitation/expansion interventions require capital expenditure, thus investments should be carefully assessed based on actual costs and management practices. In fact, the economic impact of rehabilitation interventions has to be evaluated in terms of both direct costs (e.g., crew, materials, excavation, repaving) and indirect costs (e.g., service interruption, traffic disruption) (Clark et al., 2002). Usually, the latter are tremendously difficult to be quantified since they include customers' dissatisfaction, eventual/potential traffic congestion, third party damages. The easiest way to estimate indirect costs is the use of some multiplier of direct costs (Walski, 1985; Dandy and Engelhardt, 2006) which take into account different land uses in the supplied areas. Some more refined models can be obtained by using detailed information on real activities which might be available on a GIS platform. Coupling such information with a traffic model may help quantifying the impact of emergency/planned interventions from a global urban service perspective.

Another issue which should be taken into account considers the possible savings on both materials and crew when some quantities of the same material are used or interventions are close to each other. Such aspects dealing with scale economies depend on specific management practices and cannot be easily coded into a mathematical expression of general validity.

Finally, according medium-long term planning it is essential to take into account the interest rate which should be carefully predicted during DSS settings. Overestimating or underestimating interest rate might result into misleading alternatives for any decision makers. Such a predictive uncertainty together with the uncertainty about future network conditions (i.e., leakage level, pipe deterioration, demand increase) led some authors (e.g., Dandy and Engelhardt, 2006) to plan medium-long term interventions considering multiple time steps. Each time step for planning usually span from one up to five years since most of the WDN working conditions can be approximately kept constant.

Data management tool

As mentioned above, the data structure to be used in a DSS is conceived to facilitate data retrieving whenever required during network analysis and simulation. As a consequence, the database adopted in the present DSS reflects the main distinction between *pipes* and *nodes* which has been outlined in the previous section. The reason for such a choice is twofold. On one hand, the *pipes-nodes* data structure does not need any further manipulation to be used as input for hydraulic model, which is usually the most computationally required component out of the whole analysis and optimization procedure. On the other hand, it reflects the two main entities the WDN management information is related to. In fact, all data about infrastructure assets (e.g., age, material, length and so on) as well as costs for their rehabilitation, replacement or maintenance are usually attributed to *pipes*. Conversely, all information concerning customers (e.g., demand, domestic/commercial/industrial type of customers) and service levels (e.g., water supplied, service pressure) refer to *nodes*. Information on *pipe segments* associated with valve shutdowns (as well as the segment each pipe/node belong to) is included as an additional field in both tables.

Finally, it is worth noting that even outputs of models discussed in previous section (i.e., hydraulic simulator and cost assessment) refers to *pipes* and *nodes* or, if this is not straightforward the case, they can be easily associated to *pipes* or *nodes*.

Besides existing information available to water managers (e.g.., asset features, costs and so on) and deriving from models (e.g., WDN hydraulic simulation), the *data management tool* suggested herein allows users (i.e., technicians/analysts) to exploit such information in order to gain additional knowledge about the system which can be used for setting up the DSS. Apart from classical statistic inference functions (e.g., mean, standard deviation and statistical tests to check if data belong to a given PDF) the *data management tool* is linked to external utilities that affect artificial intelligence (AI) techniques. This extension aims at discovering existing patterns in available data. The resulting analysis might help reproducing system behavior and/or estimating the likelihood of a given phenomenon to occur.

Up to date, a number of techniques which are available mainly come from operational research and computer science. Although there are not explicit restrictions about the use of any type of technique in the main DSS architecture, some of them are readily linked to the *data-management tool* of the DSS described herein. Their main features are summarized in the following paragraph.

- Evolutionary Polynomial Regression (EPR) (Giustolisi and Savic, 2006; 2009): this is a hybrid stepwise regression which integrates the effectiveness of genetic programming and search strategies with the advantages of numerical regression for estimating model parameters. EPR has been widely adopted in many application areas including water distribution networks, sewers, hydrology and structural engineering. The versatility of EPR modeling paradigm as well as the easiness of interaction with the user from data preparation to model selection justify its increased use in recent years.
- Artificial Neural Networks (ANN) (Haykin, 1999): ANN are based on the mechanisms underlying the behavior of neurons. They can be roughly defined as general purpose regression techniques. Nowadays there are innumerable applications of ANN in many scientific fields. ANN main feature is the capability of fitting any data so that they are also known as *universal regressors*.
- Evidence Theory (ET): it was introduced by Dampster and Shafer (e.g., Shafer, 1976) and is based on the so-called theory of evidence. It consists of combining evidence from different sources until reaching a degree of belief (represented by a belief function) which takes into account all the available evidences. Although ET results might be in conflict with the classical Bayesian theory of probability, it also suggests to consider independent sources of information, as it is the case of data coming from customers or remote sensors within a WDN.
- Case Based Reasoning (CBR) (Agnar and Plaza, 1994): it is generally considered as the process of solving new problems based on the solutions of similar past problems. It has been also considered as a particular class of machine learning such as rules induction. Decision trees are typical example of such artificial intelligence strategies.

Figure 2: it summarizes both *pipes-nodes* database' structure adopted in the *data management tool* and the interaction between data, artificial intelligence utilities and the *modeling* tool.
The DSS user is allowed to select data of interest (e.g., field in the *pipes* table) and then, to call one of the AI utilities. Data are manipulated (through a guided procedure) in order to match the data format that has to be used as an input for the specific AI utility.
As known, such AI techniques may provide simple data (i.e. numeric values which might be added in the main data base as an additional information) or even models to be included into the modeling tool. In the latter case, models can be symbolic mathematical expressions (e.g., as from EPR), trained networks (e.g., from ANN), probability density functions (e.g., from ET), decision trees (e.g., from CBR) and so on.

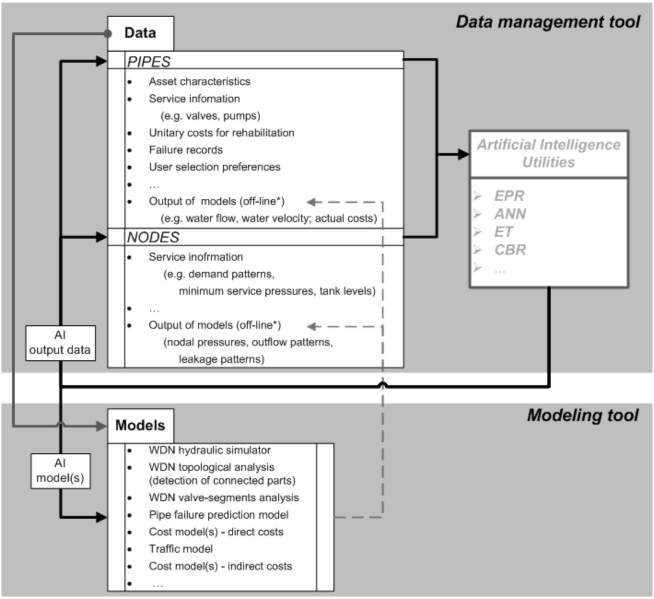

Figure 2. Interaction between data management, modeling tools and artificial intelligence techniques.

Optimization tool

A pragmatic DSS for sustainable management of WDN should include the preservation of water resources for future generations by proposing effective solutions for present managers. If the former goal fails, sustainability would be mismatched; if the latter requisite lacked, water managers may would not be enough motivated in pursuing such interventions. In such a multi-objective decision framework there is not a unique "best" solution but rather a set of "optimal" tradeoffs between different objectives. As a consequence, the DSS should provide the best compromise solutions among a set of different (and conflicting) aims. Afterwards, the decision maker should be able to evaluate each of these solutions from both technical standpoint and using additional (that analysts would not yet know) criteria. Optimal solutions, to be provided to final user, should be:

- easy to understand (*what* actions to undertake, *where* and *when* to intervene);
- able to contain a limited number of viable alternatives (it is preferable to simply provide the *priority* of intervention on each network element);
- easy to be evaluated in terms of marginal improvement of objective functions achievable by shifting between different optimal alternatives.

The present DSS exploits a Multi-Objective Genetic Algorithm (MOGA) named OPTIMOGA (Giustolisi et al., 2004). MOGAs are known as *population based* search and optimization techniques are optimal solutions that are obtained by mimicking the evolution mechanisms in nature. As it happens as mammalian reproduction, each new solution is obtained from two parent solutions by using *crossover* and *mutation* operators. In multi-objective decision contexts the fitness of each solution is evaluated in terms of Pareto-dominance within the space of objective functions. Once the search is completed (i.e. a fixed number of generations is reached) OPTIMOGA returns a population of the best fit solutions.

Nonetheless, due to a number of decision variables involved (e.g., multiple types of alternative interventions for each WDN element) and multiple objective functions used to drive the research, the

size of resulting population is usually quite large. The DSS proposed herein exploits these solutions to obtain a priority of intervention per each element proper of the water distribution network (Berardi and Giustolisi, 2009). In this way, OPTIMOGA solutions are used as a knowledge base for devising operational intervention plans. In particular, based on specific types of interventions which are coded amongst decision variables, a priority of action is assigned to each pipe that is based upon the frequency of selection among the Pareto front of OPTIMOGA solutions. In the case of binary decision (e.g., replace/do-nothing or survey/not-survey problems) such a priority reflects, also, the action to undertake. Otherwise, when multiple alternatives are considered, such a priority can be used to support the analyst further in the aim of refining the range of feasible options (i.e. candidate pipes and actions to consider).
The *optimization tool* requires two essential issues to be defined, namely decision variables and the objective functions.

Decision variables
Planning interventions on water pipe networks means to decide *when* starting works (timing of interventions), *where* allocating interventions (location) and *what* actions to undertake (type of intervention). Rehabilitating a water distribution pipe basically means improving its hydraulic conveyance capacity, structural resilience or both. A typical intervention for improving pipe hydraulic capacity merely consists of reducing the internal roughness by cleaning and/or relining pipe wall. Unless it is obtained by inserting a new pipe into the old one, pipe re-lining does not improve pipe structural performance. Vice versa, pipe replacement allows for complete renewing of structural and hydraulic performance, although it is the more drastic and expensive option. A further alternative type of intervention refers to the replacing of a pipe by selecting amongst a set of commercial diameters. In all cases both pipe hydraulic resistance is changed.
Moreover, it is reasonable to assume that possible water losses through joints or fittings in those pipes that had been selected for interventions would also be repaired during inspections,

irrespectively on the type of a specific action. This means that the pipes' expected propensity to leak after interventions is drastically reduced.

Based on interventions that have afore considered, decision variables might be coded in different ways, thus resulting into even different search space (Dandy and Engelhardt, 2006).

Objective functions

The search for optimal interventions through OPTIMOGA is mainly driven by the fitness of solutions in terms of objective functions. They represent different aims to be pursued in order to fulfill economic effectiveness, system performance improvement and/or some management strategies, potentially involving some other city management aspects. It is evident that these objectives vary among different WDNs even if they are managed by the same water company. For this reason, the architecture of the proposed DSS is conceived to allow the user (i.e. the technician/analyst working for the water company) formulating specific objective functions based on data and models available from *data management* and *modeling* tools, respectively.

It is worth noting that this is a crucial improvement over previously existing works on DSS construction for WDN management. In fact, differently from a general purpose decision aiding approach (Tsoukìas, 2007), both analysts and customers share the same cognitive background which conjugates the engineering and the economic aspect of the problem. In addition, it often happens that technicians/analysts of water companies themselves are called up to find viable intervention plans. Based on such as positive working situation, the present DSS is suited to fill the gap further (between the domain expert and the analyst). A gap which originates from coding client expectations into formal objectives.

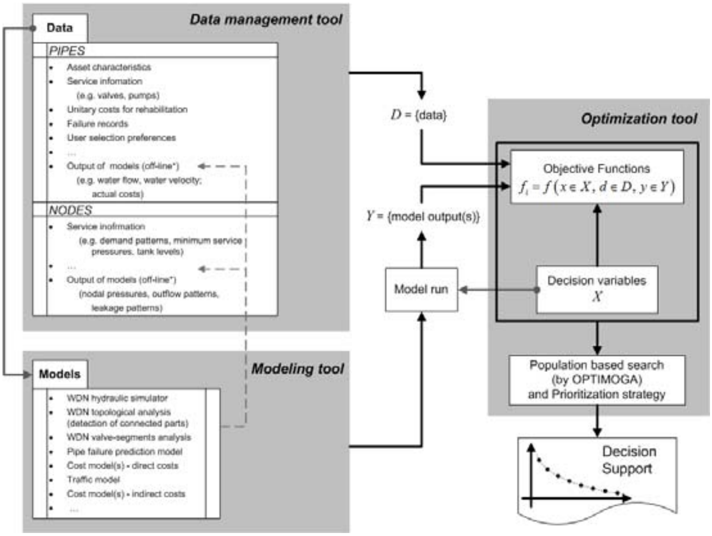

Figure 3. Conceptual scheme for interaction among the DSS tools.

As reported in Figure 3, the generic objective f_i is a function of data, decision variables and, if the case, outputs from model(s). In more details, decision variables X (i.e. intervention works and timing) are likely to affect expected network behavior as simulated by model(s). This means that the search for optimal solutions requires multiple model(s) runs, each of them using different sets of decision variables. The user is allowed to combine all possible model outputs Y with data (i.e., fields in the main database D) and/or current decision variables X into simple mathematical expressions that are used to drive the search for optimal solutions (i.e., by using OPTIMOGA). Such an open architecture allows the user to combine together results from hydraulic, economic and city management models. Thus, for example, a possible objective could be to concentrate as many interventions as possible in shopping areas or city center in order to minimize the probability of pipe failure and multiple emergency interventions on the same zone in the near future. On the other hand, interventions on residential areas may be planned not necessarily closer in terms of time and space due to their limited economic impact.

In addition, DSS user is also provided with an archive of readily selectable objective functions which are of general applicability on WDN. They are briefly described below:

- *Minimization of the investment required*: it is the sum of costs for planned interventions based on cost data stored in the *pipes* database.
- *Minimization of the expected cost of pipe breaks*: pipe rehabilitation campaign is aimed at curtailing the risk of future incidents due to pipe failures. Usually, such risks are evaluated in terms of costs related to such incidents and on the likelihood of pipes' future failures. The assessment of potential risks is based on the analysis of incident data records which are available to water companies and might come out from the application of some data-driven modeling (Berardi et al., 2008) or probability (Watson, 2005) techniques.
- *Preferential selection of some pipes*: this objective function encompasses different preferences of selection for WDN elements which might reflect some management strategies (e.g., the use of some types of pipes for stock control) or the concomitance with other works on underground service utilities in the same streets. Although evaluating such preferences might be related to proper models, this default objective function simply maximize the sum of some numeric preference values to be attributed at each network element (i.e., each pipe) a priori.
- *System reliability*: it is based on the minimization of number of customers who are affected by insufficient pressure or who are no longer supplied with water due to a system's failure. The assessment of deficiently supplied customers requires the application of both topological analysis (in order to detect customers who are actually connected to water sources) and pressure-driven hydraulic simulation.
- *Expected leakage reduction*: rehabilitating a WDN pipe implies that inspection and, in specific cases, repair of some leakages are made. From a hydraulic modeling perspective this means changing the relevant leakage parameters to be used in the pressure-driven hydraulic simulator. Along such a hypothesis, it is possible to assess the expected level of leakages after each

intervention. It is worth noting that, even a complete system's renewal would not reset water leakages to zero. Moreover, the use of pressure-driven hydraulic simulation is an essential prerequisite to evaluate actual effects, after each intervention, into a looped system in terms of pressure regime variations and, as a consequence, in terms of leakage outflows.

- *Optimal work allocation*: such objective is based on the relationship between *pipe segments* and isolation valves which need to be necessarily closed to each other in order to let crews work on pipes. It is aimed at minimizing the number of different *pipe segments* that need to be isolated in order to accomplish a given intervention plan.

Once both decision variables and objective functions are defined, a final decision support, which contain all viable intervention alternatives water managers can make use of, is obtained after that search and the prioritization procedure is taken place.

Example application

Figure n. 4 portrays the layout of a real network named "Apulian_1". All the asset data, assumed nodal demands and cost information about all diameters in the network can be found in Berardi et al.(2009). The work also contains further information on network elements and available data that are used in order to predict the extent of pipe bursts' propensity per each year.

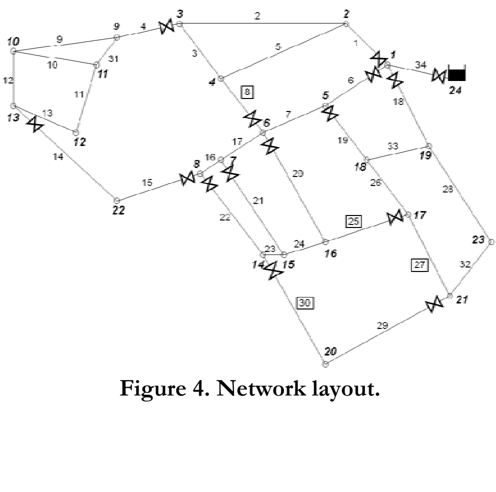

Figure 4. Network layout.

Table 1 portrays expressions representing objective functions. Relevant meanings are clarified in the following. Pipes 8, 25, 27 and 30m, seem to be *preferred* for selection and relevant numerical preferences and are deliberately set $w_p = 0.5$ (in a scale from 0 to 1) for these pipes and $w_p = 0$ for the others. Such values are used to evaluate objective f_3 in Table 1.

Table 1. Objective functions in example application

Description	*Objective function*
Investment required	$f_1 = \underset{R}{Min}\left(\sum_{p \in R} C_{repl} \cdot L_p\right)$
Expected cost of pipe breaks	$f_2 = \underset{R}{Min}\left(\frac{\sum_{p \in G} d_p \cdot C_{repair} \cdot BR_p}{\sum_{p \in Net} d_p \cdot C_{repair} \cdot BR_p}\right)$
Preferential selection	$f_3 = \underset{R}{Min}\left(\frac{\sum_{p \in H} w_p}{\lvert H \rvert}\right)$
System reliability	$f_4 = \underset{R}{Min}\left(\frac{\sum_{p \in G}\left[\left(d \cdot Pr\right)_i + \left(d \cdot Pr\right)_d\right]_p \cdot BR_p}{\sum_{p \in Net}\left[\left(d \cdot Pr\right)_i + \left(d \cdot Pr\right)_d\right]_p \cdot BR_p}\right)$
Work allocation	$f_5 = \underset{R}{Min}\left(\lvert S_R \rvert\right)$
Expected leakage reduction	$f_6 = \underset{R}{Min}\left(Q_R^L\right)$
Economies of scale	$f_7 = \underset{R}{Min}\left(\lvert D_R \rvert\right)$

$\lvert H \rvert$ represents the number of pipes which are not selected for rehabilitation works. Two extreme demand scenarios are assumed at 8.00 a.m. (peak demand) and 1.00 a.m. (lowest demand - equal to about 10% of peak demand). The former scenario is used for assessing system reliability (f_4) and the latter for estimating the leakage level (f_6). In Table 1, BR_p is the number of pipe bursts which are predicted by the use of an EPR based model (Giustolisi and Berardi, 2007; Berardi et al., 2009); Pr_p is the number of connections to private properties; subscripts i and d refers to

isolated and deficiently supplied properties due to pipe p failing. To put it simple, all properties are assumed to be domestic, thus the cost multiplier has been defined as $d = 1.5$ for all pipes (Berardi et al., 2008). In order to estimate the leakage level (f_6) the pressure-driven leakage model proposed by Giustolisi et al. (2008a) is used since it allows a pipe level reduction of leakages in terms of reduced leakage coefficients. In this case it is assumed that leakage coefficient $□_p$ reduces from $2.35 \cdot 10^{-7}$ (for existing pipes) to $2.71 \cdot 10^{-8}$ for new pipes, as resulting from the assumption that complete network renewal would reduce water losses from 25% to 5% of the peak hour demand. Leakage exponent $□_p$ is assumed to be 1.2 in both cases. Moreover, new pipes are assumed to have a Bazin's roughness coefficient $□_N = 0.10 m^{1/2}$, lower than $□_O = 0.20 m^{1/2}$ of old pipes. Thus hydraulic simulator accounts for changes in both pipe which carry capacity and leakage reduction.
In Table 1: C_{repair} represents the repair cost of each pipe; $|S_R|$ is the number of pipe isolated district which allows rehabilitation works; $|D_R|$ is the number of different types of interventions (e.g. new diameters of renewed pipes) selected for rehabilitation. Thus, objectives f_5 and f_7 are used as a measure for evaluating optimal work allocation (by reducing the number of required pipe segments' isolation) and the fulfillment of scale economies (Nafi and Kleiner, 2009) (by selecting the minimum number of different types of works).

Figure 5 lays out a snapshot of one of the tables resulting from the DSS which contains the incremental variations or simply the values of objective functions corresponding to those obtained after the implementation of the above mentioned procedure to Apulian_1. $□f_1$ is pipe replacement cost; $□f_2$ is the reduction of breakage risk; $□f_3$ is the fulfilment of preferential selection (it decreases at preferential pipes only); $□f_4$ is the reduction of system unreliability; f_5 is the number of pipe segments to be isolated; $□f_6$ is the reduction of leakage flow (in percentage) with respect of the do-nothing option at the peak-pressure hour (i.e. 1.00 a.m.); f_7 is the number of different diameters required to be chosen among a set of 9 alternatives.

	A	B	C	D	E	F	G	H	I
1	Pipe ID	Δf_1 [$]	Δf_2 [$]	Δf_3	Δf_4	f_5	Δf_6 [%]	f_7	
2	8	29903	-62	-0.0134	-81.04	1	-1.54	1	
3	5	49098	-101	0.0014	-133.06	1	-3.53	1	
4	3	29946	-62	0.0015	-81.16	1	-2.12	1	
5	25	20553	-42	-0.0151	-48.35	2	-0.84	1	
6	28	52254	-108	0.0011	-130.85	3	-2.30	1	
7	27	42451	-51	-0.0166	-55.03	3	-2.24	1	
8	20	49271	-102	0.0007	-115.91	3	-3.05	1	
9	9	57933	-120	0.0007	-91.90	4	-3.00	1	
10	21	44497	-92	0.0008	-104.68	4	-2.87	1	
11	18	42744	-51	0.0008	-55.41	4	-4.53	1	
12	33	23510	-49	0.0009	-58.88	4	-1.65	1	
13	32	26530	-55	0.0010	-66.44	4	-1.17	1	
14	11	31812	-66	0.0011	-50.47	4	-1.60	1	
15	6	55763	-29	0.0012	-41.25	5	-39.34	1	
16	24	15630	-32	0.0013	-36.77	5	-0.04	1	
17	13	25978	-54	0.0015	-41.21	5	-1.07	1	
18	1	43806	-23	0.0016	-19.41	5	-16.03	2	
19	23	10261	-21	0.0018	-24.14	5	-0.02	2	
20	14	63432	-131	0.0021	-97.88	6	-0.68	2	
21	29	49141	-102	0.0024	-62.86	7	-0.02	2	
22	2	112994	-56	0.0027	-53.22	7	-5.67	2	
23	30	68307	-67	-0.0385	-36.48	7	0.01	2	
24	19	43941	-31	0	-30.65	7	-0.20	2	

Table Manager

Figure 5 portrays a snapshot of the manager table showing the marginal objective improvements corresponding to progressive pipe replacing.

Note that in the first column of Figure 5 pipes are sorted according to decreasing priority. Based on such a order managers may repeat the search of optimal solutions on a smaller pipes' number (10 pipes is the most number) and possible alternatives (i.e. set of diameters) based, for example, on either available budget or expected pressure conditions. Otherwise, such a solution can be used straightforward to replace old pipes with new diameters that result from the prioritization's procedure.

The suggested DSS is a way that would actually help technicians in formulating selection criteria (as objective functions), analyzing the decision context, refining the search of space and, finally getting a set of optimal alternatives.

Discussion and conclusions

The decision support system introduced herein is structured into three main tools allowing *data management*, system *modeling* and *search for optimal solutions*.

The *data management* tool is based on the main *pipes-nodes* architecture so that different types of information can be easily stored and retrieved. Such module is linked to some external utilities that leverage as many as different artificial intelligence techniques to mine patterns in data and gain additional information on system behavior. Outputs of such an external AI utilities can be either based on numerical values to be stored in the main database or based on models (e.g., symbolic formulas, trained artificial neural networks, decision trees and so on) to be included in the modeling tool.

The *modeling* tool represents a collection of models which can be used to simulate different aspects of network behavior. It includes a WDN hydraulic simulator including a realistic pressure-driven leakage model based upon some topological analysis utilities. In addition, this work introduces an essential feature of a cost model which exemplifies other model's possible inclusion (e.g. traffic model, failure prediction model) aimed at assessing network functioning during the search for optimal solutions.

The *optimization* tool exploits a Multi Objective Genetic Algorithm (named OPTIMOGA) as the main search and optimization techniques. The user has to define the optimization problem in terms of decision variables and objective function formulation. This latter can be directly formulated by the user as simple expressions by retrieving both data, that has been stored in the main database, and model outputs.

From an operational standpoint, technicians of water companies as well as urban planners are, then, allowed to clearly evaluate the consequences of each intervention by looking at the marginal variation of each objective function. Moreover, the analysis that's been performed, could be repeated per each year (or even after a given time lag) in order to both accommodate changes in the system and introducing additional criteria (i.e. objectives). This basically allows a dynamic planning of maintenance works on the

WDN which can be also tailored to match city management/planning needs.

It is noteworthy that the open architecture suggested by the DSS aims at filling the gap between analysts (referring to a methodology expert) and customers (referring to a domain/utility expert) by using an intuitive formalization of objective which can be easily reported to stakeholders as well as city managers. This circumstance is expected to gain credibility from customers as well as to reduce discrepancies between different urban utilities' management objectives and urban planning.

References

Agnar A., and Plaza E. (1994), Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches, *Artificial Intelligence Communications*, 7(1), 39-52.

Berardi L., Giustolisi O. and Savic D. (2009), An operative approach to water distribution system rehabilitation *Proc. of the World Environmental & Water Resources Congress 2009 - Great Rivers*, Kansas City, Missouri, USA, ASCE Publisher, S. Starrett Editor, (CD-ROM), 238-250.

Berardi L., Colombo A. and Giustolisi O., (2008), Optimal pipe replacement accounting for leakage reduction and isolation valves, *Proc. of 10th Water Distribution Systems Analysis*, Kruger National Park, (CDROM), 348-360.

Berardi, L., Kapelan, Z., Giustolisi, O. and Savic, D. (2008), Development of Pipe Deterioration Models for Water Distribution Systems using EPR,"*Journal of Hydroinformatics*, 10(2) 113-126.

Cheung P.B., Reis L. F. R., Formiga K.T.M., Chaundhry F.H. and Ticona W.C. (2003), Multiobjective Evolutionary Algorithms applied to the rehabilitation of a water distribution system: a comparative study, *Proc. of Evolutionary Multi-Criterion Optimization: Second International Conference*, Faro, Springer Berlin/Heidelberg, publisher, 2632, 662-676.

Clark, R.M., Sivaganesan, M., Selvakumar, A. and Sethi, V. (2002), Cost Models for Water Supply Distribution Systems, *J. of Water Resour. Plan. and Manag.*, 128(5), 312-321.

Dandy, G.C. and Engelhardt, M.O. (2006), Multi-Objective Trade-Offs between Cost and Reliability in the Replacement of Water Mains, *J. Water Resour. Plan. and Manag.*, 132(2), 79-88.

Economou, T., Kapelan, Z. and Bailey, T. (2007), An aggregated hierarchical Bayesian model for the prediction of pipe failures, *Proc. 9th International Conference on Computing and Control for the Water Industry*, 13-16, Taylor and Francis, Leicester, UK.

Germanopoulos, G. (1985), A technical note on the inclusion of pressure dependent demand and leakage terms in water supply network models, *Civil Engineering Systems*, 2(September), 171-179.

Giustolisi, O., Doglioni, A., Savic, D.A. and Laucelli, D. (2004), A proposal for an effective multi-objective non-dominated genetic algorithm: the OPTimised Multi-Objective Genetic Algorithm: OPTIMOGA. Tech. Rep. 2004/07, Centre for Water Systems, University of Exeter, Exeter, UK.

Giustolisi O., Laucelli D., and Savic D.A., (2006), Development of rehabilitation plans for water mains replacement considering risk and cost-benefit assessment.. *Civil Eng. and Env. Syst. J.*, 23(3), 175-190.

Giustolisi, O., Savic, D.A., and Kapelan, Z. (2008a), Pressure-driven demand and leakage simulation for water distribution networks. *J. of Hydr. Eng.*, 134(5), 626-635.

Giustolisi, O., Kapelan, Z. and Savic, D. (2008b), An algorithm for automatic detection of topological changes in water distribution networks, *J. Hydr. Eng.*, ASCE, 134(4), 221-233.

Giustolisi, O. and Berardi, L. (2009) Prioritizing pipe replacement: from multi-objective genetic algorithms to operational Decision Support, *J. Water Resour. Plan. and Manag.*, ASCE, USA. 135 (6), 484-492.

Giustolisi, O. and Savic, D. (2010), Identification of segments and optimal isolation valve system design in water distribution networks, *Urban Water J.*, Elsevier, 7(1), 1-15.

Giustolisi, O., Savic, D.A. (2009), Advances in Data-Driven Analyses and Modelling Using EPR-MOGA. Special Issue on Advances in Hydroinformatics, *Journal of Hydroinformatics*, 11(3), 225-236.

Goldberg, D.E. (1989), *Genetic Algorithms in Search, Optimization and Machine Learning.* Addison-Wesley, Reading, Massachusetts.

Halhal, D., Walters, G.A., Ouzar, D., and Savic, D.A. (1997), Water network rehabilitation with a structured messy genetic algorithm, *J. Water Resour. Plan. and Manag.*, 123(3), 137-146.
Haykin, S. (1999), *Neural Networks: A Comprehensive Foundation (2nd edn).* Prentice-Hall Inc., Upper Saddle River, New Jersey, USA.
Kim, J.H., and Mays, L.W. (1994), Optimal rehabilitation model for water distribution systems. *J. Water Resour. Plan. and Manag.*, 120(5), 674-692.
Nafi, A. and Kleiner, Y. (2009), Scheduling Renewal of Water Pipes While Considering Adjacency of Infrastructure Works and Economies of Scale. *J. Water Resour. Plan. and Manag.*, 136**(**5), 519-530
Savic, D.A. (2002), Single-objective vs. multiobjective optimisation for integrated decision support. *First Biennial Meeting of the International Environmental Modelling and Software Society*, Lugano, Switzerland, Vol. 1, 7-12.
Shafer, G. (1976), *A Mathematical Theory of Evidence, Princeton University Press*, Princeton, New Jersey, USA.
Shamir, U., and Howard, C.D.D. (1979), An analytic approach to scheduling pipe replacement. *Journal American Water Works Association*, 117(5), 248-258.
Tsoukiàs A. (2007), On the concept of decision aiding process, *Annals of Operations Research*, vol. 154, 3-27.
Todini, E., (2000), Looped water distribution networks design using a resilience index based heuristic approach, *Urban Water*, 2, 115-122.
Walski, T.M.,and Pelliccia, A. (1982), Economic analysis of water main brakes, *Journal American Water Works Association*, 74(3), 140-147.
Walski, T. M. (1985), Cleaning and lining versus parallel mains, *J. Water Resour. Plan. and Manag. Division*, ASCE, 111(1), 43-53.
Watson, T.G. (2005), *A hierarchical Bayesian model and simulation software for water pipe networks*, Phd thesis, Dept of Civil and Resources Engineering, The University of Auckland, Auckland, New Zeland.