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Raúl Baños, Consolacion Gil, Juan Reca, Julio Ortega. A Pareto-based Memetic Algorithm for Optimization of Looped Water Distribution Systems. *Engineering Optimization*, 2010, 42 (03), pp.223-240. 10.1080/03052150903110959 . hal-00567040

HAL Id: hal-00567040

<https://hal.science/hal-00567040>

Submitted on 18 Feb 2011

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Journal:	<i>Engineering Optimization</i>
Manuscript ID:	GENO-2009-0078.R1
Manuscript Type:	Review
Date Submitted by the Author:	20-May-2009
Complete List of Authors:	Baños, Raúl; University of Almería, Dept. Computer Architecture and Electronics Gil, Consolacion; University of Almería, Dept. Computer Architecture and Electronics Reca, Juan; University of Almería, Rural Engineering Ortega, Julio; University of Granada, Architecture and Computer Technology
Keywords:	water distribution systems, cost, reliability, multi-objective optimization, memetic algorithms
Note: The following files were submitted by the author for peer review, but cannot be converted to PDF. You must view these files (e.g. movies) online.	
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A Pareto-based Memetic Algorithm for Optimization of Looped Water Distribution Systems

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(Received 00 Month 200x; final version received 00 Month 200x)

Looped water distribution networks have traditionally been used in urban and industrial water supply. Nowadays, they are also being introduced in certain irrigation water distribution systems, such as in greenhouse horticultural systems. The design of looped networks is a much more complex problem than the design of branched ones, but their greater reliability can compensate for the increase in cost. Most papers found in the literature try to minimize the network investment cost, while other designing objectives are considered as constraints. This paper introduces a multi-objective memetic algorithm that simultaneously optimizes the total investment cost, and also the reliability of the network in terms of total surplus power at the demand nodes. This memetic algorithm uses the Pareto-dominance concept to determine the quality of the solutions. The results obtained in two small water supply networks, and a large irrigation water supply network denote the good performance of the memetic algorithm here proposed in comparison with other well known meta-heuristics.

Keywords: water distribution systems, cost, reliability, multi-objective optimization, memetic algorithms.

1. Introduction

In mathematics, optimization (Pardalos and Resende 2000) is the discipline which is concerned with finding inputs of a function that minimize or maximize its value, in most cases subject to constraints. Combinatorial optimization (Grotschel 1995) is a branch of optimization which is concerned with the optimization of functions with discrete variables. The optimal design of water distribution networks is a combinatorial optimization problem that consists of finding the best way of conveying water from the sources (reservoirs) to the users (demand nodes), satisfying some requirements. The typical single-objective constrained formulation of this problem aims to obtain a combination of pipe diameters (decision variables) that minimize the network investment cost, while pipe layout, connectivity and demands are imposed as constraints (Montesinos *et al.* 1999, Reca and Martinez

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2006). Mathematically, it is a non-linear, constrained and multi-modal problem included in the class of complex combinatorial problems known as NP-hard (Gupta *et al.* 1993), which implies that it is not feasible to obtain the optimal solution in a polynomial runtime. For this reason, an interesting, if not the best, way of treating this problem is to use computational optimization techniques, i.e. the design and implementation of algorithms for solving optimization problems. As a result of the research performed in the past, an important number of methods have been applied to solve this single-objective formulation, including non-linear optimization models (Varma *et al.* 1997), global optimization methods (Sherali *et al.* 1998), and heuristic approaches (Cunha and Sousa 1999, Maier *et al.* 2003, Reca and Martinez 2006). The main drawback of the single-objective constrained formulation is that it does not adequately incorporate the concept of reliability, understood as the capability of providing adequate supply under both normal and abnormal conditions (Farmani *et al.* 2005a). Todini (2000) references some previous studies that demonstrate that the choice of the minimum cost function does not incorporate the concept of reliability. This is the reason why, in recent years, some authors have coupled different multi-objective optimization methods considering network reliability. One difficulty that must be faced is finding an accurate way to express reliability analytically, and although different measures have been proposed, no single one is universally accepted (Xu and Goulter 1999). One of the most used reliability measures is the concept of resilience index proposed by Todini (2000), which is a measure of the capability of the network to cope with failures and is related indirectly to system reliability. Some authors have recently used this index in multi-objective formulations of this problem (Farmani *et al.* 2005a, Baños *et al.* 2009). In recent years, this resilience index has been improved in order to overcome some drawbacks (Prasad and Park 2004, Jayaram and Srinivasan 2008).

It is worth noting that heuristic approaches are suitable when solving NP-hard problems (Garey and Johnson 1979). Heuristic methods (Glover *et al.* 1993) can be seen as simple procedures that provide satisfactory, but not necessarily optimal, solutions to complex problems in a quick way. Meta-heuristics (Blum and Roli 2003) are generalizations of heuristics in the sense that they can be applied to a wide set of problems, needing few modifications to be adapted to a specific case. Over recent years, a number of independent researchers have shown that Memetic Algorithms (MA) (Moscato and Cotta 2003) is a very effective meta-heuristic to solve combinatorial optimization problems. MAs are population-based meta-heuristic search methods that are inspired by Darwinian principles of natural selection and Dawkins' notion of meme (Dawkins 1976). The aim of this work is to evaluate the performance of a new Pareto-based memetic algorithm to optimize water distribution networks using a multi-objective formulation. In order to achieve a strong comparison, two other multi-objective meta-heuristics (MOMHs) have also been implemented and evaluated in two small-sized water supply networks, and a larger irrigation water supply network.

2. Looped Water Distribution Networks: Multi-Objective Formulation

Typical single-objective formulation (Montesinos *et al.* 1999, Reca and Martinez 2006) of the optimal design of water distribution networks tries to minimize the cost with pipe diameters as decision variables, while pipe layout, connectivity and demands are imposed as constraints. Equation 1 shows the cost function that is typically used to solve the single-objective formulation of this problem (Reca and Martinez 2006), where C is the total cost of the network, c_i is the cost of the pipe with diameter i per unit length, L_i is the total length of pipe i in the network, and

$npipes$ is the number of available pipe diameters.

$$C = \sum_{i=1}^{npipes} c_i L_i \quad (1)$$

However, some authors (Todini 2000, Prasad and Park 2004, Farmani *et al.* 2005a, Baños *et al.* 2009) have extended the traditional single-objective formulation of the problem in order to consider not only the network investment cost, but also the reliability of the system. The reliability of a network can be understood as the capability of providing adequate supply under both normal and abnormal conditions (Farmani *et al.* 2005a). However, there are many different alternatives to consider reliability. In particular, two main research lines have been analysed in the past to include the concept of reliability (Farmani *et al.* 2005a): surrogate-based measures (deterministic modelling) and stochastic analysis of uncertainty (probabilistic modelling). One of the most used surrogate-based measures is the resilience index proposed by Todini (2000), which is strongly related to the intrinsic capability of the system to overcome failures, while still satisfying demands and pressures in nodes. Although most previous studies considering reliability in this problem have used the resilience index proposed by Todini, some authors (Prasad and Park 2004, Jayaram and Srinivasan 2008) have modified this in recent years. In particular, this paper uses the *modified resilience index* proposed by Jayaram and Srinivasan (2008), which overcomes the drawback of Todini's resilience index when evaluating networks with multiple sources. In contrast to Todini's resilience index, the value of the modified resilience index is directly proportional to the total surplus power at the demand nodes. Equation 2 shows this modified resilience index (MRI) where $nnodes$ is the number of demand nodes, q_j is demand at node j , $h_{a,j}$ is the pressure available at node j , $h_{r,j}$ is the pressure required at node j . It can be observed that are only considered those solutions with pressures equal to or higher than that required in all nodes.

$$MRI = \frac{\sum_{j=1}^{nnodes} q_j (h_{a,j} - h_{r,j})}{\sum_{j=1}^{nnodes} q_j h_{r,j}} \times 100 \quad (2)$$

subject to $h_{a,j} \geq h_{r,j} \quad \forall j$

Thus, the multi-objective formulation of the water distribution network design consists of finding the best diameter in each pipe so that the network investment cost (C) is minimized (Equation 1), while the modified resilience index (MRI) is simultaneously maximized (Equation 2). In the field of multi-objective optimization, there exist two different ways to consider all the objectives to be optimized. The first one is using *aggregating functions*, i.e. all the objectives to be optimized are included in a single function using a combination of mathematical operations (Hajela and Y-Lin 1992). However, the design of aggregating functions is very difficult when the objectives have different scales of values, e.g. cost and resilience. An interesting way to overcome this drawback is to apply Pareto-optimization (Goldberg 1989), which instead of giving a scalar value to each solution, establishes relationships between solutions according to Pareto-dominance relations. A solution s_1 is said to *dominate* another s_2 when s_1 is better in at least one objective, and not worse in the others. Two solutions are called *indifferent* or *incomparable* if neither one dominates the other. All the *non-dominated* solutions found in the search are usually stored in an external archive of solutions (ND). As all the objectives are equally important, the aim of multi-objective optimization is to find the Pareto-optimal set (or a representative sample of it). The practical advantage of using Pareto-based multi-objective algorithms is that the front of non-dominated solutions returned

can be used in a subsequent phase to select one of the solutions according to several criteria. In the case of water distribution networks, this selection process can be carried out according to several criteria (economic budget, supply requirements, etc). For instance, if the economic budget is not limited and/or the supply of water is critical, solutions with higher values of modified resilience index, but which are more expensive, should be selected. However, in other networks, where the supply requirements are not so critical, inexpensive solutions would be selected. Therefore, the multi-objective algorithm obtains a set (front) of non-dominated solutions, and later the solution is selected according to the particular circumstances.

3. Multi-Objective Memetic Algorithm (MOMA)

The population-based approach called Memetic Algorithm (MA) was first introduced by Moscato (1989). Memetic Algorithms are optimization techniques inspired by Darwinian principles of natural evolution and Dawkins' notion of a meme (Dawkins 1976), defined as a unit of cultural evolution that can exhibit local refinement. In practice, MAs apply the operators of the evolutionary algorithms (EAs) while also applying a separate local search process to refine individuals (Moscato and Cotta 2003). Many different implementations of memetic algorithms have been reported across a wide range of applications (Hart *et al.* 2004, Knowles and Corne 2004, Eusuff *et al.* 2006).

In the last decade, some authors have proposed MAs for multi-objective optimization. Ishibuchi *et al.* (1997), proposed the so called Multi-Objective Genetic Local Search (MOGLS), which is a genetic algorithm for multi-objective optimization that employs local search to each individual of the population using a weighted sum of multiple objectives as a fitness function. Authors demonstrated the high performance of MOGLS in the flowshop scheduling problems in comparison with VEGA (Shaffer 1984). Knowles and Corne proposed the memetic-PAES (M-PAES) (Knowles and Corne 2000), which is an extension of PAES (Knowles and Corne 1999) using a population of agents (solutions) and a crossover operator which recombines agents found by the PAES procedure. Promising agents found in the search are also stored in an external set of agents (external archive). Results obtained in the 0/1 knapsack problem outperformed PAES and were similar to those obtained by SPEA (Zitzler and Thiele 1999). Later, Jaszkiewicz (2002) presented an extension of the method proposed by Ishibuchi *et al.*, whose main difference is the way the agents are selected for recombination. In particular, Jaszkiewicz proposed that the parents were selected from a temporary population that contains a certain number of agents as the best agents found in the search.

This paper evaluates the performance of a multi-objective memetic algorithm (MOMA) for solving the multi-objective formulation described in Section 2. The multi-objective memetic algorithm presented here uses evolutionary operators and local search. Procedure 1 shows the basic description of MOMA, where: P is the main population composed of P_{size} agents. $emphParents_{rate}$ is the percentage of agents taken from P that are used to generate the offspring, and n_e is the number of evaluations that determine the stop criterion. The algorithm starts by initialising the population of agents (P). Let us notice that as the agents are randomly generated some of them have a negative value of the modified resilience index. In order to avoid these unfeasible solutions, the `FeasibleSolution()` procedure is called, which improves the solution in terms of resilience (increasing the pipe sizes) until the modified resilience index becomes positive or zero and all the minimum demand pressures are fulfilled. The main loop is then repeated until the number of evaluations of the fitness function exceeds n_e . This loop consists of dividing the

population into two subpopulations of the same size in order to apply local optimizers in each one, as described below. In each iteration of the main loop some agents of the same subpopulation are combined to generate an offspring, i.e. a new agent (network configuration) which takes some pipe diameters from each parent. In this combination process only the best agents of the main population in terms of Pareto-dominance can participate as parents. In particular, the agents are sorted based on a ranking of Pareto-dominance, such that the agent that dominates most agents in the population has the highest ranking, while the one dominating fewest has the lowest ranking. Thus, agents are selected from best to worst rankings, such that when generating offspring, a given percentage of parents ($Parents_{rate}$) are selected according to this score. After that, the offspring is improved using one of the three local optimizers. When all the offspring have been generated and improved with the local search optimizer, the population P is updated taking into account this new factor. In particular, the previous population and the offspring are sorted according to their Pareto-dominance ranking, where the agent which is dominated by the lowest number of agents (of the population and the offspring) has the highest rank, and the most dominated agent has the lowest rank. Thus, the new population is composed of the P_{size} agents with highest Pareto-dominance ranking. It is generally required that the individuals/agents of evolutionary/memetic algorithms should maintain diversity over the entire search process to avoid the premature convergence of agents. The diversity of the population of agents can be measured by various means. One of the most used strategies is Shannon's information entropy concept (Davidor and Ben-Kiki 1992). This strategy in the single-objective constrained formulation would be equivalent to saying that the algorithm has converged when a large percentage of agents have the same fitness values (Baños *et al.* 2007). As in the multi-objective case there is not a single objective function to optimize, this strategy must be adapted to consider several objectives. In particular, our implementation considers that the population has converged in a given iteration of the main loop when none of the offspring agents have been included in the new population P , in which case a restart procedure is called, which consists of re-initialising the main population with new agents.

Procedure 1 : Multi-Objective Memetic Algorithm (MOMA).

Input: P_{size} , n_e , $Parents_{rate}$, LO_1 , LO_2 ;

Output: P ;

For $i=1$ To P_{size}

$P(i) \leftarrow$ Generate randomly an agent();

$P(i) \leftarrow$ FeasibleSolution($P(i)$);

Repeat

 For $i=1$ To P_{size}

 If $i \leq P_{size}/2$ Then

$parent1 \leftarrow$ SelectParents($P(1)$, $P(P_{size}/2)$, $Parents_{rate}$);

$parent2 \leftarrow$ SelectParents($P(1)$, $P(P_{size}/2)$, $Parents_{rate}$, $parent1$);

$offspring \leftarrow$ Recombine($parent1$, $parent2$);

 LocalOptimizer(LO_1 , $offspring$);

 Else If $i > P_{size}/2$ Then

$parent1 \leftarrow$ SelectParents($P((P_{size}/2)+1)$, $P(P_{size})$, $Parents_{rate}$);

$parent2 \leftarrow$ SelectParents($P((P_{size}/2)+1)$, $P(P_{size})$, $Parents_{rate}$, $parent1$);

$offspring \leftarrow$ Recombine($parent1$, $parent2$);

 LocalOptimizer(LO_2 , $offspring$);

$P \leftarrow$ UpdatePopulation(P , $offspring$);

 If Convergence(P)=1 Then

 Re-startPopulation(P);

Until (number_evaluations $\geq n_e$);

Return (ND(P));

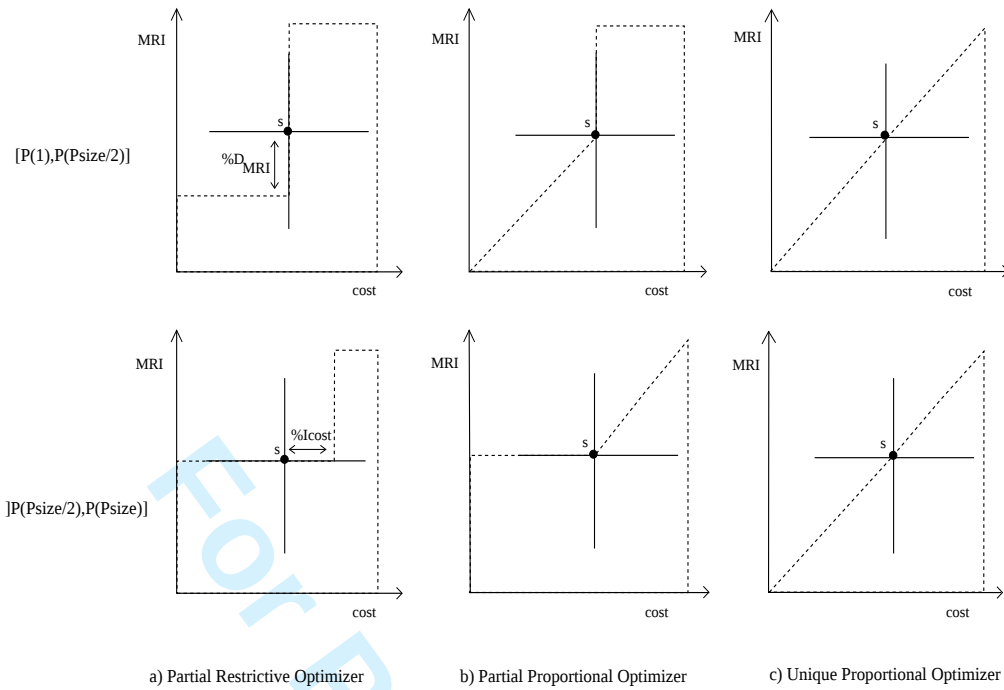


Figure 1. (a) Partial Restricted Optimizer, (b) Partial Proportional Optimizer, (c) Unique Proportional Optimizer.

An important aspect concerns the local search strategies used. MOMA improves the population by modifying the pipe diameters of the agents using three different local search strategies: partial restrictive optimizer (PRO); partial proportional optimizer (PPO), and unique proportional optimizer (UPO). All the local optimizers work selecting randomly a pipe from a given network (agent) which is substituted with another pipe of different diameter. The difference among local optimizers arises in the criterion of accepting the new solutions after the pipe change, as Figure 1 shows. In this figure, the dotted lines enclose the area of the objective space where a given agent s cannot be located after a movement (e.g. after a pipe change).

- The *partial restrictive optimizer* (PRO) has two variants, PRO_1 and PRO_2 , which are applied to each half of population P . In particular, PRO_1 tries to improve (minimize) the cost by means of reducing the pipe diameter by one degree, accepting this change if and only if the cost decreases and the modified resilience index decreases less than a given percentage ($\%D_{MRI}$). PRO_2 tries to improve (maximize) the modified resilience index by means of increasing the diameters by one degree, accepting this change if and only if the modified resilience index increases and the cost increases less than a given percentage ($\%I_{cost}$).
- The *partial proportional optimizer* (PPO) has two variants, PPO_1 and PPO_2 , which are also applied to each half of the population P . PPO_1 tries to improve (minimize) the cost by means of reducing the pipe diameter by one degree, accepting this change if and only if the cost decreases more than the modified resilience index decrement. PPO_2 tries to improve (maximize) the resilience by means of increasing the diameters by one degree, accepting this change if and only if the modified resilience index increases more than the cost increment.
- The *unique proportional optimizer* (UPO) is applied to the entire population, and consists of randomly increasing or decreasing the pipe diameter by one

degree of random pipes, accepting only these solutions where the cost reduction is higher than the modified resilience index reduction or the modified resilience index increment is higher than the cost increment.

It can be observed that all the local optimizers avoid premature convergence and guarantee population diversity, since none of the local optimizers are hill climbing methods where only new improved (dominating) agents are accepted, but they do also accept new agents which are indifferent or incomparable to the original ones, whenever they do not increase/decrease a given pre-established cost/resilience, respectively.

4. Empirical Analysis

4.1. Test Problems

The performance of the multi-objective memetic algorithm proposed and of the other two MOMHs are evaluated in three gravity-fed looped water distribution networks. The main characteristics of each network are summarised below. A detailed description of these networks can be found in Reca and Martinez (2006).

- Alperovits and Shamir network (Alperovits and Shamir 1977) is a simple two-loop network, with seven nodes and eight pipes arranged in two loops. A total of 14 commercial pipe diameters can be selected, i.e. there exist $14^8 = 1,4758 * 10^9$ possible configurations;
- Hanoi network (Fujiwara and Khang 1990) consists of 32 nodes, 34 pipes, and 3 loops. A set of 6 available commercial-diameter pipes is used, which implies a total of $6^{34} = 2,8651 * 10^{26}$ possible configurations;
- Balerna network (Reca and Martinez 2006) is a greenhouse irrigation network that consists of a multi-source network, containing a total of 443 demand nodes (hydrants), fed by 4 reservoirs. It has 454 pipes and 8 loops. The pipeline database is composed of ten commercial PVC pipes, i.e. there exist 10^{454} possible configurations.

A minimum pressure limitation is 30 meters above ground level for each node ($h_{r,j}=30$) in Alperovits-Shamir and Hanoi networks, while Balerna has a pressure limitation of 20 meters ($h_{r,j}=20$). The interface of the program and the memetic algorithm have been programmed in the Visual-Basic programming language. Database management system has been implemented using a relational database and the ActiveX Data Objects (ADO) model. EPANET network solver (Version 2.00.07) (Rossman 2000) has been used considering its default values.

4.2. Parameter Settings

To compare the results of different executions, the stop criterion in the experiments cannot be fixed to a number of iterations, since each MOMH has particular characteristics that could result in considerable differences in their runtimes. Given this circumstance, the best way to guarantee the equality of conditions is that all the methods perform the same number of evaluations of the fitness function. That number of evaluations, n_e , should depend on the complexity of the network. The size of the search space is a function of the number of links n_l and the number of possible pipe diameters n_d . Equation 3 has been adopted to establish a ratio between the number of evaluations in two different networks (α and β). The resulting fitness function evaluations are 91690, 264570, and 4540000 for the Alperovits-Shamir,

Hanoi and Balerna networks, respectively. These values have been obtained taking as reference that the number of evaluations of the fitness function in Balerna is $n_e = 10000 \times n_l$.

$$\frac{n_e^\beta}{n_e^\alpha} = \frac{n_l^\beta * \ln(n_d^\beta)}{n_l^\alpha * \ln(n_d^\alpha)} \quad (3)$$

When applying heuristic methods to optimization problems it is advisable to perform a sensitivity analysis, i.e. to determine to what extent the output of the model depends upon the inputs. One aspect to determine when applying population-based meta-heuristics in general, and memetics algorithms in particular, is the population size (P_{size}). This empirical study has been performed using different population sizes ($P_{size} = \{50, 200, 500\}$ agents) in order to analyse the effect of modifying this factor. Another important input is the parameter that determines the degree of elitism, i.e. the percentage of best agents taken from the population P that are used to generate offspring (Parks *et al.* 2001). Our empirical study uses $Parents_{rate} = \{10\%, 25\%, 50\%, 100\%\}$, where low values mean that only best solutions (in terms of Pareto-dominance ranking) are used in the offspring generation (high elitism), while using the highest value means that all the agents can participate in this process (without elitism). Another important aspect to determine is the local optimizer to be applied. In particular, it is analysed which of the three local optimizers described in Section 3 obtains the best median non-dominated front of eleven independent runs, using fixed values of $P_{size}=200$ and $Parents_{rate}=50\%$. It is important to note that while in single-objective optimization it is straightforward to determine the median value of several runs, in Pareto-based multi-objective optimization it is not possible, because it is obtained not one single solution, but rather several non-dominated solutions as an approximation to the (unknown) Pareto-optimal front. Thus, each parametric configuration is run eleven times, and that execution which has the median value in terms of set coverage (SC) and hyper-volume (HV) is then selected. While PPO and UPO do not use any parameters, each run of PRO uses different parameters (Run1:%Icost=%Dresilience=0%; Run2:%Icost=%Dresilience=10%; ..., Run11:%Icost=%Dresilience=100%). Once the local optimizers have been evaluated, a second sensitivity analysis is performed to determine accurate values of P_{size} and $Parents_{rate}$, as Table 1 shows.

Table 1. Parameters used in the empirical executions.

	A	B	C	D	E	F	G	H	I	J	K	L
P_{size}	50	50	50	50	200	200	200	200	500	500	500	500
$Parents_{rate}$	10%	25%	50%	100%	10%	25%	50%	100%	10%	25%	50%	100%

4.3. Performance Measures

The quality of the sets of non-dominated solutions is evaluated using two metrics: set coverage, and hyper-volume. Both are based on ideas taken from the metrics proposed by Zitzler and Thiele (Zitzler and Thiele 1999). A more detailed description of the adaptation of both metrics to this problem can be found in (Baños *et al.* 2009).

Set Coverage (SC). Given two subsets of non-dominated solutions, X , X' , function SC maps the ordered pair (X, X') to a value z within the interval $[0, 1]$. The value z represents the percentage of solutions of X' dominated by at least one solution of X . The value $SC(X, X')=1$ means that all solutions in X' are *dominated* by any solution of X . It should be noted that SC is not a symmetric metric, i.e.

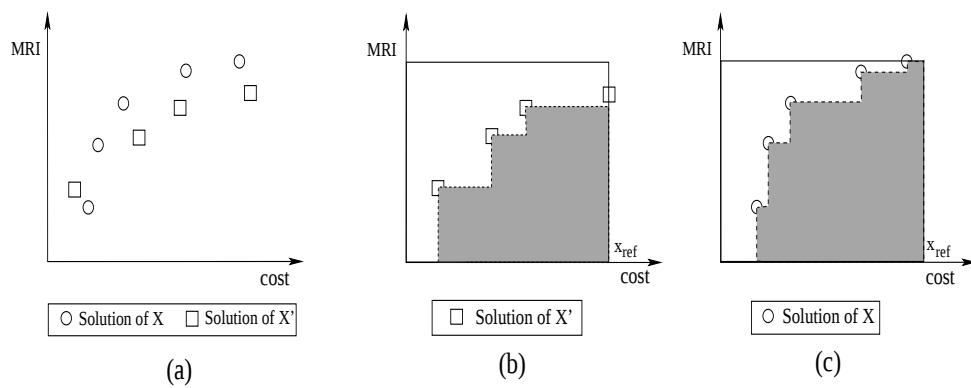


Figure 2. Graphical explanation of the metrics used over two non-dominated sets.

$SC(X, X') = z$ does not imply that $SC(X', X) = 1 - z$. For instance, if the solutions of Figure 2(a) are considered, $SC(X, X') = 0.75$, and $SC(X', X) = 0.20$, i.e. 75% of solutions of non-dominated front X' are dominated by at least one solution of X , and 20% of solutions of X are dominated by at least one solution of X' .

Hyper-volume (HV). Let $X = (x_1, x_2, \dots, x_n)$ be a set of non-dominated solutions. The function $HV(X)$ returns the area of the objective space (bounded by a reference point) dominated by at least one of the members of X . The reference point is $x_{ref} = (\max(C(x_i)), 0)$, i.e. the maximum cost, and the minimum resilience allowed (0). Figures 2(b) and 2(c) show that $HV(X) > HV(X')$.

4.4. Results and Discussion

As commented above, the first empirical study here performed aims to determine the performance of the three local optimizers described in Section 2 (PRO, PPO, UPO) using fixed values of $P_{size} = 200$ and $Parents_{rate} = 50\%$. In all cases, the comparison has been performed using the median non-dominated front of eleven runs in terms of set coverage and hyper-volume metrics. For instance, the median front obtained by MOMA using PRO in Alperovits-Shamir network was obtained using $\%Icost = \%Dresilience = 30\%$. Table 2 shows a comparison of the three local optimizers in Alperovits-Shamir network. It can be observed that only few solutions of PPO or UPO are dominated by at least one solution of PRO, while PPO dominates 56.3% and 35.7% of the solutions found by PRO and UPO, respectively. UPO dominates 43.8% and 53.0% of the solutions of PRO and PPO, respectively. In terms of set coverage, UPO obtains the best average result and best ranking, while PPO is the best in terms of hyper-volume. Therefore, it can be concluded that PPO and UPO could be ranked with the same value. Similar analysis is made in the Hanoi network, as displayed in Table 3. In this network, PRO ($\%Icost = \%Dresilience = 40\%$), PPO, and UPO obtain the same final ranking. The reason for the good performance of PRO in terms of hypervolume is due to the fact that the front of non-dominated solutions obtained by this local optimizer obtains extreme solutions (low cost), and therefore dominates a greater area of the objective space (see Figure 3). Finally, Table 4 shows that when comparing the three local optimizers in Balerna network, UPO obtains a higher final ranking than UPO and PRO ($\%Icost = \%Dresilience = 50\%$).

Figures 3, 4 and 5 show the non-dominated fronts obtained by these optimizers in Hanoi, Alperovits-Shamir, and Balerna networks, respectively. These figures confirm that non-dominated solutions obtained by UPO and PPO are very similar, outperforming the results obtained by the restrictive approach (PRO). The reason

Table 2. Sensitivity analysis of local optimizers in Alperovits-Shamir network.

	PRO	PPO	UPO	AVG_SC (RANK)	HV (RANK)	Σ _RANK	FINAL_RANK
PRO		0.0606	0.0804	0.0705 (3)	0.8226 (3)	6	2
PPO	0.5625		0.3571	0.4598 (2)	0.8494 (1)	3	=1
UPO	0.4375	0.5303		0.4839 (1)	0.8465 (2)	3	=1

Table 3. Sensitivity analysis of local optimizers in Hanoi network.

	PRO	PPO	UPO	AVG_SC (RANK)	HV (RANK)	Σ _RANK	FINAL_RANK
PRO		0.1458	0.0659	0.1059 (3)	0.3901 (1)	4	=1
PPO	0.4255		0.1264	0.2760 (2)	0.3828 (2)	4	=1
UPO	0.3511	0.5347	0.000	0.4429 (1)	0.3792 (3)	4	=1

Table 4. Sensitivity analysis of local optimizers in Balerma network.

	PRO	PPO	UPO	AVG_SC (RANK)	HV (RANK)	Σ _RANK	FINAL_RANK
PRO		0.0119	0.0066	0.0093 (3)	0.6469 (3)	6	3
PPO	0.5429		0.0199	0.2814 (2)	0.8266 (2)	4	2
UPO	0.4571	0.4071		0.4321 (1)	0.8291 (1)	2	1

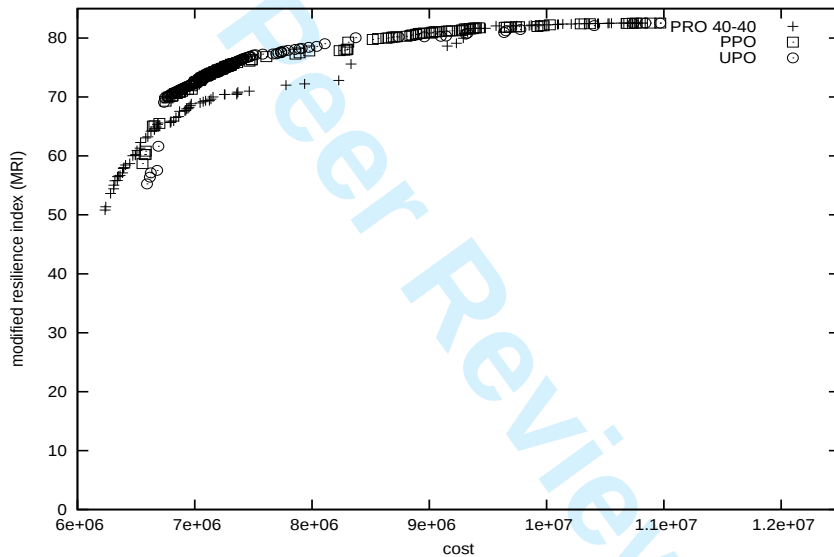


Figure 3. Comparison of median fronts obtained by local optimizers in Hanoi network.

for the poor performance of PRO is the difficulty of establishing adequate values of %Icost and %Dresilience. On the other hand, it can be observed that the effect of dividing the population into two subpopulations in an attempt to optimize each objective separately (PRO and PPO) does not have a clear advantage in comparison with using a unique proportional optimizer in the entire population (UPO). Considering that UPO obtains the highest final ranking in all the networks, and that it also obtains the best ranking in terms of set coverage, the unique proportional optimizer (UPO) will be used as local optimizer in MOMA.

Once it has been evaluated the performance of the three local optimizers, a second sensitivity analysis is performed to determine accurate values of P_{size} and $Parents_{rate}$, using the values described in Table 1. Firstly, let us analyse the results obtained by these configurations from the point of view of the set coverage metric (Metric SC). Table 5 shows the set coverage values in Alperovits-Shamir network. In particular, numerical values located in row i , column j indicate the set coverage between both executions ($SC(i,j)$). For instance, the value 0.475 in row D, column

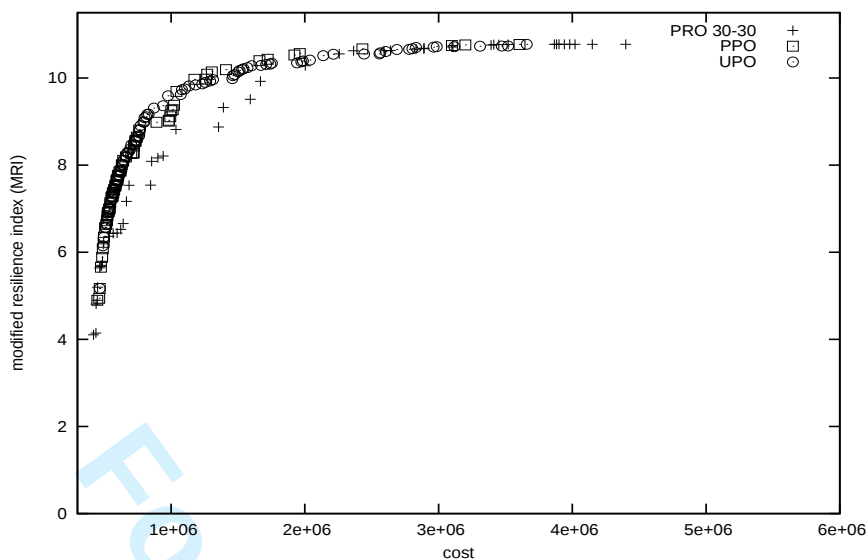


Figure 4. Comparison of median fronts obtained by local optimizers in Alperovits-Shamir network.

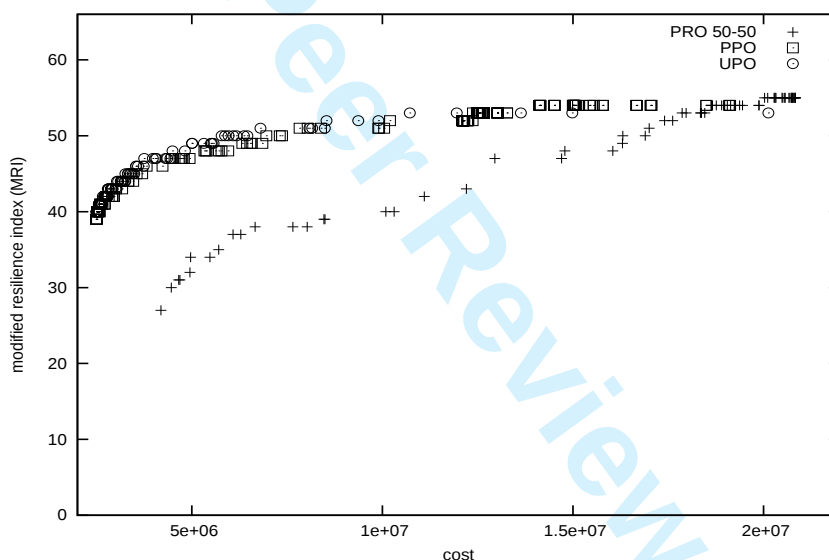


Figure 5. Comparison of median fronts obtained by local optimizers in Balerma network.

B means that 47.5% agents (solutions) of B are dominated by at least one agent of D. The last column displays the average (AVG) of all the coverage values. From this table some conclusions can be drawn about the impact of parametric settings of these MOMHs for this problem. When analysing this table it can be perceived that configuration F ($P_{size}=200$; $Parents_{rate}=25\%$) obtains the best average coverage. In general, runs using 200 agents often obtain higher set coverage values than using 50 or 500 agents. However, it is not possible to obtain clear conclusions about the best value of $Parents_{rate}$, although rates of 25% obtain good results. The same analysis is performed on the Hanoi network. As Table 6 displays, once again configuration F obtains the highest set coverage. In this case, the use of populations of 200 agents also often improves the results obtained using 50 or 500 agents. As in Alperovits-Shamir network, it is very difficult to obtain a clear conclusion about the best values of $Parents_{rate}$. Finally, Table 6 shows the results

obtained in Balerna network, and it is observed that configuration F also obtains the highest average coverage. Therefore, it is possible to conclude that the best parametric configuration to be used in terms of coverage is F.

Table 5. Set Coverage (metric SC) of MOMA in Alperovits-Shamir network.

	A	B	C	D	E	F	G	H	I	J	K	L	AVG
A	—	0.425	0.132	0.356	0.083	0.058	0.071	0.067	0.078	0.067	0.067	0.089	0.136
B	0.220	—	0.132	0.254	0.095	0.039	0.054	0.112	0.052	0.076	0.122	0.144	0.118
C	0.561	0.650	—	0.492	0.191	0.175	0.080	0.146	0.198	0.124	0.167	0.289	0.279
D	0.293	0.475	0.283	—	0.083	0.107	0.089	0.124	0.095	0.095	0.144	0.211	0.182
E	0.634	0.625	0.585	0.712	—	0.340	0.357	0.371	0.345	0.267	0.367	0.500	0.464
F	0.781	0.825	0.755	0.763	0.548	—	0.500	0.584	0.517	0.410	0.533	0.622	0.622
G	0.756	0.775	0.698	0.729	0.476	0.369	—	0.416	0.397	0.381	0.456	0.544	0.545
H	0.732	0.650	0.642	0.695	0.429	0.291	0.393	—	0.379	0.257	0.367	0.489	0.484
I	0.732	0.775	0.623	0.712	0.512	0.359	0.464	0.449	—	0.305	0.500	0.533	0.542
J	0.707	0.750	0.660	0.763	0.548	0.418	0.518	0.483	0.474	—	0.533	0.567	0.584
K	0.707	0.625	0.547	0.661	0.488	0.359	0.366	0.405	0.328	0.267	—	0.489	0.477
L	0.683	0.550	0.377	0.509	0.357	0.282	0.357	0.315	0.336	0.219	0.267	—	0.387

Table 6. Set Coverage (metric SC) of MOMA in the Hanoi network.

	A	B	C	D	E	F	G	H	I	J	K	L	AVG
A	—	0.265	0.349	0.516	0.105	0.104	0.110	0.122	0.235	0.326	0.302	0.340	0.252
B	0.310	—	0.258	0.375	0.105	0.055	0.088	0.085	0.333	0.348	0.460	0.383	0.255
C	0.250	0.279	—	0.359	0.099	0.071	0.071	0.116	0.177	0.304	0.302	0.319	0.213
D	0.179	0.250	0.288	—	0.072	0.060	0.082	0.098	0.177	0.326	0.302	0.340	0.198
E	0.655	0.632	0.652	0.719	—	0.368	0.401	0.384	0.549	0.435	0.492	0.426	0.519
F	0.655	0.750	0.682	0.688	0.454	—	0.462	0.500	0.451	0.435	0.492	0.426	0.545
G	0.643	0.735	0.667	0.719	0.368	0.352	—	0.457	0.451	0.435	0.508	0.426	0.524
H	0.595	0.721	0.621	0.656	0.382	0.280	0.335	—	0.510	0.478	0.492	0.468	0.504
I	0.000	0.000	0.000	0.000	0.079	0.060	0.050	0.049	—	0.087	0.127	0.128	0.053
J	0.000	0.000	0.000	0.000	0.092	0.066	0.066	0.061	0.784	—	0.365	0.170	0.146
K	0.000	0.000	0.000	0.000	0.099	0.077	0.066	0.073	0.706	0.587	—	0.298	0.173
L	0.000	0.000	0.000	0.000	0.099	0.077	0.071	0.073	0.804	0.478	0.587	—	0.199

Table 7. Set Coverage (metric SC) of MOMA in the Balerna network.

	A	B	C	D	E	F	G	H	I	J	K	L	AVG
A	—	0.129	0.000	0.090	0.004	0.034	0.033	0.058	0.008	0.010	0.000	0.000	0.033
B	0.054	—	0.055	0.135	0.013	0.063	0.073	0.068	0.031	0.020	0.000	0.000	0.047
C	0.609	0.247	—	0.416	0.113	0.093	0.080	0.068	0.008	0.010	0.000	0.000	0.149
D	0.239	0.400	0.044	—	0.026	0.144	0.113	0.068	0.008	0.020	0.000	0.000	0.099
E	0.489	0.541	0.055	0.315	—	0.211	0.291	0.408	0.450	0.330	0.390	0.521	0.364
F	0.000	0.400	0.000	0.000	0.322	—	0.431	0.796	0.626	0.700	0.878	0.833	0.453
G	0.000	0.271	0.000	0.000	0.322	0.317	—	0.806	0.733	0.820	0.842	0.833	0.449
H	0.000	0.000	0.000	0.000	0.222	0.131	0.066	—	0.176	0.440	0.671	0.729	0.221
I	0.000	0.000	0.000	0.000	0.217	0.228	0.139	0.670	—	0.690	0.866	0.792	0.327
J	0.000	0.000	0.000	0.000	0.183	0.084	0.060	0.408	0.183	—	0.793	0.896	0.237
K	0.000	0.000	0.000	0.000	0.139	0.030	0.046	0.243	0.099	0.210	—	0.667	0.130
L	0.000	0.000	0.000	0.000	0.048	0.017	0.020	0.087	0.038	0.030	0.281	—	0.047

Table 8 shows the results obtained by MOMA considering the hypervolume metric (Metric HV) in Alperovits-Shamir, Hanoi, and Balerna networks. The hypervol-

ume obtained using 200 (configurations E, F, G, H) and 500 agents (configurations I, J, K, L) is often higher than using 50 (configurations A, B, C, D) in all the networks, especially in Balerma. As regards the $Parents_{rate}$, using intermediate rates higher than 25% often obtains slightly better results than using low rates (10%), which denotes that applying a high elitism pressure does not imply an increase in the quality of the sets of non-dominated solutions.

Table 8. Hypervolume of MOMA in Alperovits-Shamir, Hanoi and Balerma Networks.

	A	B	C	D	E	F	G	H	I	J	K	L
HV _{Alperovits}	0.793	0.759	0.821	0.796	0.844	0.846	0.847	0.844	0.848	0.845	0.846	0.849
HV _{Hanoi}	0.352	0.339	0.354	0.353	0.369	0.370	0.379	0.370	0.290	0.311	0.323	0.320
HV _{Balerma}	0.661	0.665	0.622	0.664	0.843	0.849	0.847	0.846	0.846	0.845	0.838	0.824

Having considered the results obtained by the implemented MOMA in both metrics, it must be decided which is the best parametric configuration. To this end it is established a ranking among configurations according to both metrics. Table 9 summarizes these results for Alperovits-Shamir network. The first column shows the configurations, the second one the average set coverage and their respective rankings. The third column shows the hypervolumes and the corresponding rankings. Finally, the last two columns display the sum of rankings of coverage and hypervolume, and the relative order among methods. Taking into account the last column, it can be deduced that the best configurations are F, G, and I. Table 10 shows the same ranking analysis but for the Hanoi network. In this case, the best configuration is G. In the case of Balerma, Table 11 shows that the best parametric configuration is F. This indicates that it is more advisable, especially in Hanoi, to perform an in-depth search, i.e. using few agents ($P_{size}=\{50,200\}$), which means that each agent perform more evaluations of the fitness function than using larger populations ($P_{size}=500$), where the diversity is higher, but each agent performs a shorter search.

Table 9. Ranking of parametric configurations in Alperovits-Shamir network.

Config.	AVG.SC (RANK)	HV (RANK HV)	Σ_RANK	FINAL RANK
A	0.1358 (11)	0.7925 (11)	22	9
B	0.1182 (12)	0.7594 (12)	24	10
C	0.2793 (9)	0.8214 (9)	18	7
D	0.1817 (10)	0.7959 (10)	20	8
E	0.4638 (7)	0.8437 (8)	15	6
F	0.6215 (1)	0.8455 (5)	6	1=
G	0.5451 (3)	0.8465 (3)	6	1=
H	0.4839 (5)	0.8438 (7)	12	5
I	0.5422 (4)	0.8479 (2)	6	1=
J	0.5837 (2)	0.8452 (6)	8	2
K	0.4765 (6)	0.8460 (4)	10	4
L	0.3865 (8)	0.8486 (1)	9	3

Having performed the parametric analysis of the proposed MOMA in the water distribution networks, and having obtained the best parametric configurations, the next step is to compare the results with those obtained by the other two well known MOMHs that use the concept of Pareto-dominance: SPEA2 (Zitzler *et al.* 2001) and PESA (Corne and Knowles 2000). The performance of SPEA2 in this problem was evaluated by Farmani *et al.* (Farmani *et al.* 2005b). Baños *et al.* (2009) applied SPEA2, PESA and other MOMHs to this problem using Todini's resilience index and admitting solutions with positive values of the resilience index. However,

Table 10. Ranking of parametric configurations in the Hanoi network.

Config.	AVG_SC (RANK)	HV (RANK HV)	$\sum$ _RANK	FINAL RANK
A	0.2522 (6)	0.3519 (7)	13	6=
B	0.2545 (5)	0.3394 (8)	13	6=
C	0.2134 (7)	0.3535 (5)	12	5
D	0.1976 (9)	0.3528 (6)	15	7
E	0.5193 (3)	0.3693 (4)	7	4
F	0.5448 (1)	0.3695 (3)	4	2
G	0.5237 (2)	0.3792 (1)	3	1
H	0.5035 (4)	0.3698 (2)	6	3
I	0.0527 (12)	0.2897 (12)	24	11
J	0.1459 (11)	0.3109 (11)	22	10
K	0.1732 (10)	0.3233 (9)	19	9
L	0.1991 (8)	0.3204 (10)	18	8

Table 11. Ranking of parametric configurations in the Balerma network.

Config.	AVG_SC (RANK)	HV (RANK HV)	$\sum$ _RANK	FINAL RANK
A	0.0333 (12)	0.6613 (12)	24	10
B	0.0465 (11)	0.6645 (9)	20	9
C	0.1493 (7)	0.6621 (11)	18	7=
D	0.0992 (9)	0.6639 (10)	19	8
E	0.3638 (3)	0.8433 (6)	9	4
F	0.4532 (1)	0.8490 (1)	2	1
G	0.4493 (2)	0.8474 (2)	4	2
H	0.2213 (6)	0.8456 (4)	10	5=
I	0.3274 (4)	0.8458 (3)	7	3
J	0.2369 (5)	0.8445 (5)	10	5=
K	0.1303 (8)	0.8377 (7)	15	6
L	0.0473 (10)	0.8235 (8)	18	7=

these methods have been adapted to this study using now the modified resilience index and obliging solutions to have not only positive values of resilience, but also pressure higher than that required in all the demand nodes. Parameter settings of SPEA2 and PESA obtained in a previous work (Baños *et al.* 2009) are used in the comparison with the memetic algorithm, but always considering the same number of evaluations of the fitness function according to Equation 3.

In reference to Alperovits-Shamir network, the results shown in Table 12 indicate that agents obtained by MOMA dominate 36.1%, and 28.6% of those obtained by SPEA2 and PESA, respectively, while fewer than 21.4% of the agents of MOMA are dominated by the solutions obtained on the other fronts. Figure 6 compares these MOMHs in Alperovits-Shamir network. It can be seen that although all the methods are very close, MOMA is able to dominate many agents of the other MOMHs.

Table 12. Set Coverage (SC) among MOMHs using their best run in Alperovits-Shamir network.

	SPEA2	PESA	MOMA
SPEA2		0.5714	0.2136
PESA	0.0164		0.0583
MOMA	0.3607	0.2857	

Table 13 shows the same analysis performed on the Hanoi network. Here again, MOMA is clearly the best method. In fact, fewer than 10.5% of the agents of MOMA are dominated by the solutions obtained on the other fronts, while MOMA

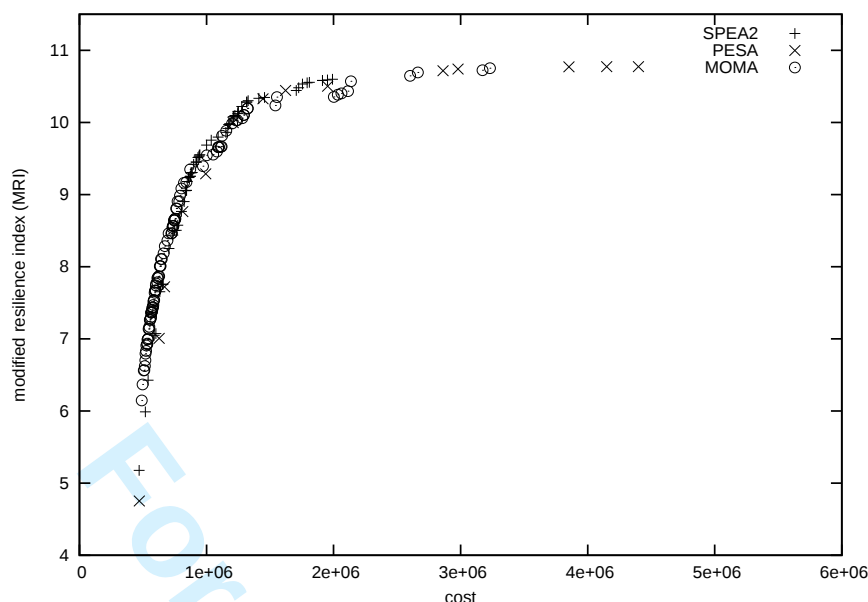


Figure 6. Non-dominated agents obtained by the MOMHs in Alperovits-Shamir network.

dominates over 59.1% of the solutions of the remaining MOMHs. These conclusions can be graphically corroborated in Figure 7.

Table 13. Set Coverage (SC) among MOMHs using their best run in the Hanoi network.

	SPEA2	PESA	MOMA
SPEA2		0.5000	0.1044
PESA	0.0000		0.0110
MOMA	0.5915	0.6667	

Finally, it is evaluated the performance of all the MOMHs in the large-scale irrigation network (Balerna) using their best parameter settings. Let us note that this irrigation network has several branches, and so the results could be improved by increasing the local search process in these links. However, with a view to comparing the performance of the method with the other meta-heuristics, MOMA operators have been used without particular adaptations, i.e. the local optimizers evaluate not only branch pipes, but also random ones. Table 14 shows the coverage ratios obtained by the executions performed in the Balerna network. Once again, MOMA outperforms the remaining MOMHs, dominating over 59.1% of the solutions of the remaining MOMHs. These results can be graphically observed in Figure 8.

Table 14. Set Coverage (SC) among MOMHs using their best run in the Balerna network.

	SPEA2	PESA	MOMA
SPEA2		0.3810	0.1224
PESA	0.0000		0.0211
MOMA	0.5294	0.8095	

Table 15 shows the results obtained by the best run of each MOMH in all the networks, considering the hyper-volume (HV). It can be seen that, although all the methods obtain approximate hyper-volumes in most cases, MOMA is the best in Alperovits-Shamir, and Balerna networks, while SPEA2 slightly outperforms MOMA in Hanoi. These results reinforce the previous conclusions obtained using the set coverage (SC).

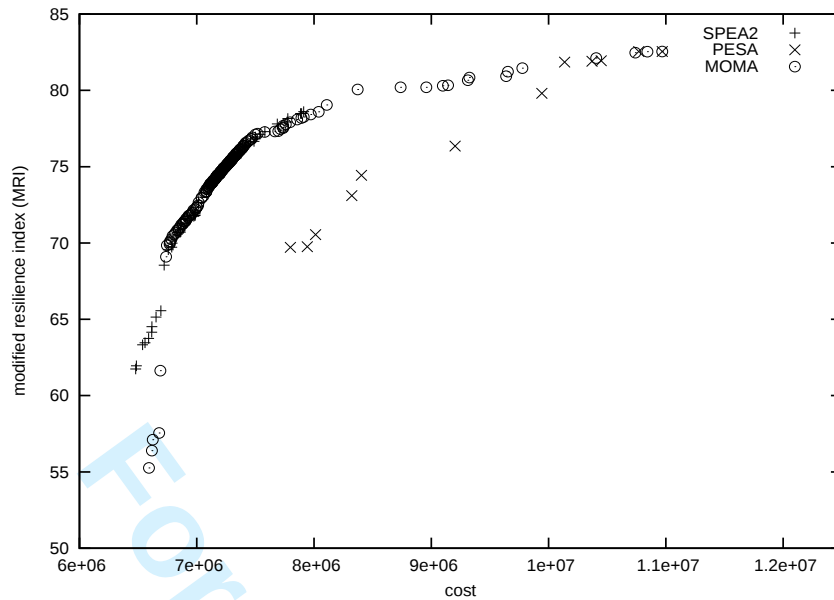


Figure 7. Non-dominated solutions obtained by the MOMHs in the Hanoi network.

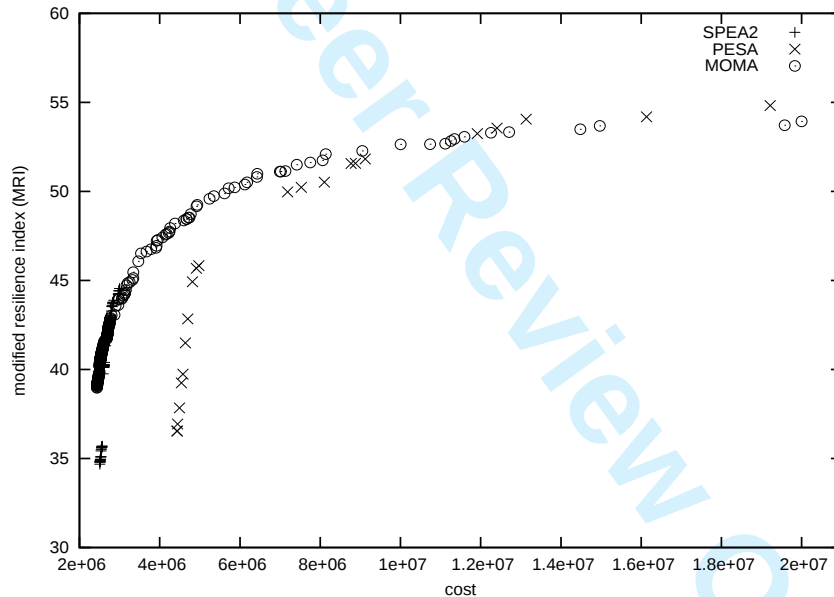


Figure 8. Non-dominated solutions obtained by the MOMHs in the Balerna network.

The better performance of MOMA in comparison with SPEA2 and PESA would be explained by the use of the local optimizers. While SPEA2 and PESA apply recombination and mutation operators to improve the quality of the solutions, MOMA also substitutes the random mutation of SPEA2 and PESA with a local optimizer. The main difference between the mutation operator of SPEA2 and PESA and the local optimizer of MOMA is that, although in all cases a pipe diameter is modified, in MOMA it is modified only one degree in a pre-established direction (i.e. increasing or reducing the pipe diameter by one degree depending on whether the aim is to reduce the cost or increase the resilience). Therefore, MOMA makes a better use of the number of evaluations than SPEA2 and PESA.

Table 15. Hyper-volume (HV) obtained by all the MOMHs in all three networks.

	SPEA2	PESA	MOMA
Hyper-volume (ALP)	0.8423	0.8323	0.8455
Hyper-volume (HAN)	0.3808	0.2678	0.3792
Hyper-volume (BAL)	0.7157	0.7412	0.8377

5. Conclusions

This paper presents and evaluates the performance of a new memetic algorithm to solve a multi-objective formulation of the water distribution network design problem. This formulation tries to reduce the total investment cost, while increasing the reliability of the network by modifying the pipe diameters, which are the decision variables. The reliability of the network has been measured by using the recently proposed modified resilience index, whose values are directly proportional to the total surplus power at the demand nodes. Unlike single-objective optimization, where a numerical value is enough to determine the quality of the solutions, in Pareto-based multi-objective optimization this process is more complicated. With the aim of overcoming this drawback, two metrics have been used when comparing non-dominated fronts, and these, together with the graphical plotting of the non-dominated fronts, provide the reader with information about the performance of each method. Three different local search optimizers have been proposed and empirically evaluated, concluding that the so-called unique proportional optimizer obtains the best results. On the other hand, the parameters of the memetic algorithm have been set under the condition that all the runs perform the same number of evaluations. It has been observed that modifying the percentage of parents used to generate offspring does not have a clear impact on the results obtained, but these results also show that intermediate-sized populations obtain the best results in almost all runs. The results obtained by the memetic algorithm here proposed are compared with two other meta-heuristics in order to establish a strong comparison. In general, all the methods here evaluated have obtained good results when applied to three benchmark water distribution networks, but especially the memetic algorithm, which is closer to the Pareto-optimal front, particularly in the largest network (Balerna). The reason for this better performance of MOMA is the advantage of using a local search optimizer that increases or reduces the pipe diameter by one degree depending on whether the aim is to reduce the cost or increase the resilience. These conclusions can offer very useful guidelines for solving larger realistic loop water distribution networks. Furthermore, this study helps researchers to optimize other design objectives for this problem.

Acknowledgements

This work was partially supported by grants P2007-TIC-02988 (CICE, Junta de Andalucía) and CTM2007-66639/TECNO (MEC).

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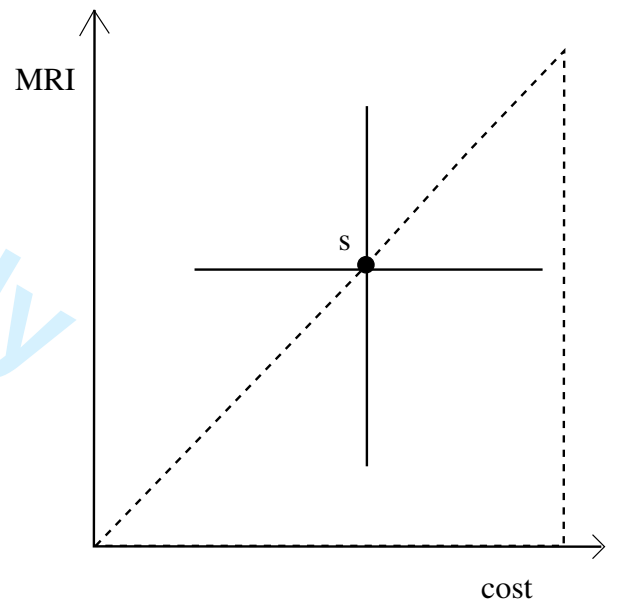
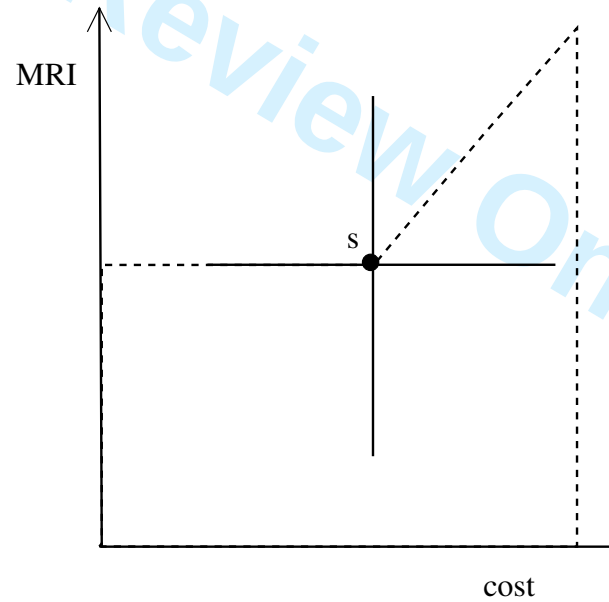
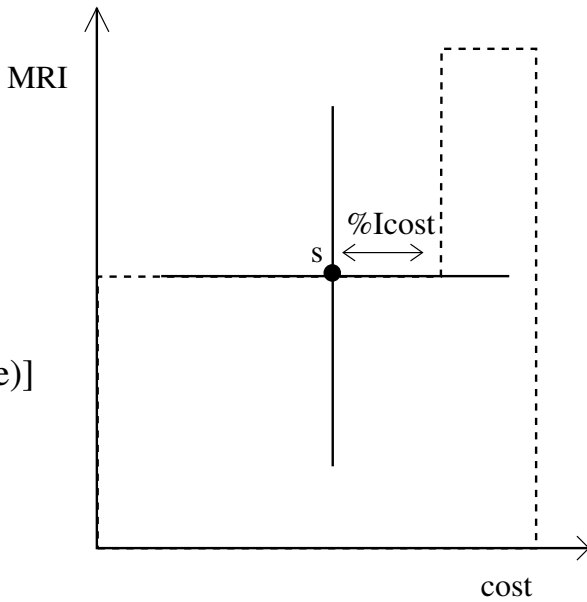
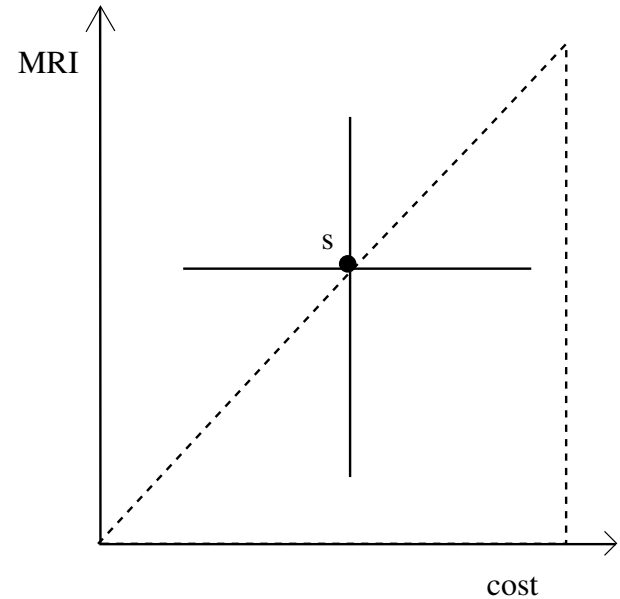
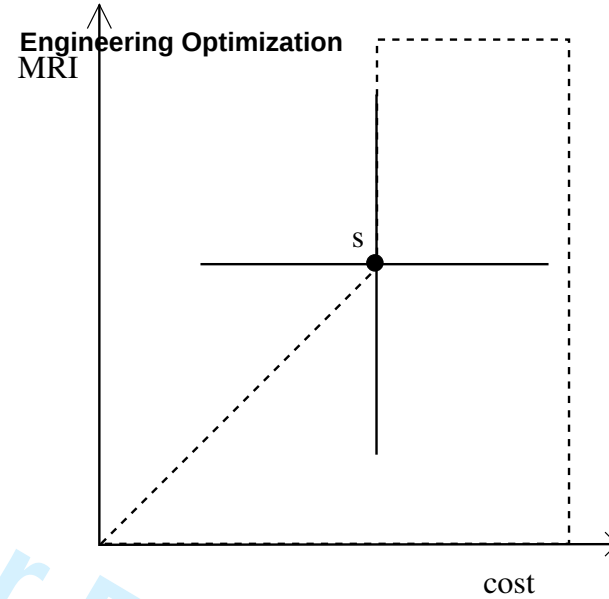
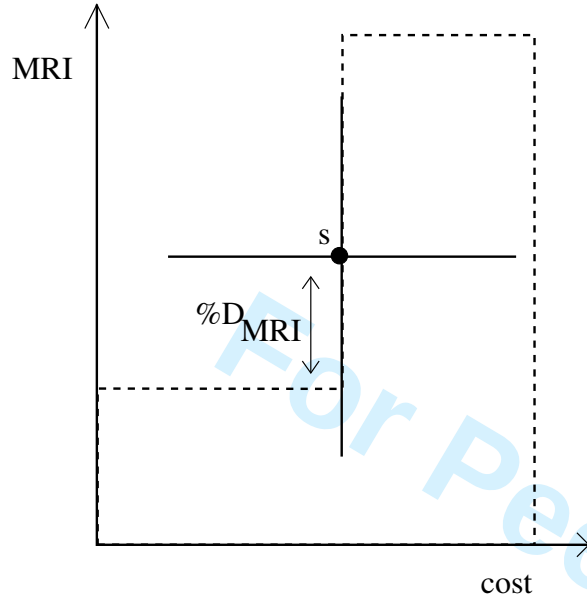
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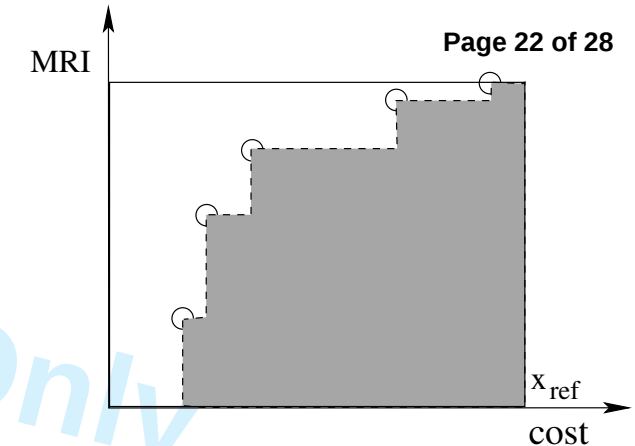
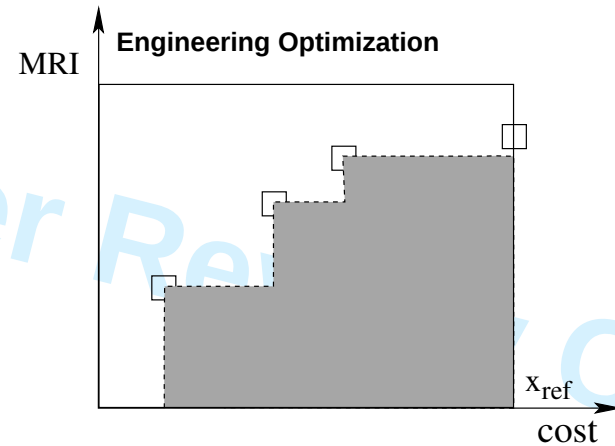
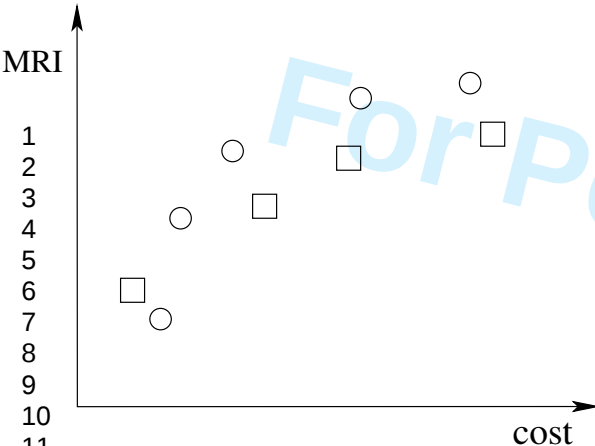
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a) Partial Restrictive Optimizer

b) Partial Proportional Optimizer

c) Unique Proportional Optimizer



○ Solution of X □ Solution of X'

□ Solution of X'

○ Solution of X

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(a)

(b)

(c)

