

Multiobjective Evolutionary Algorithms Applied to the Rehabilitation of a Water Distribution System: A Comparative Study

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Abstract. Recognising the multiobjective nature of the decision process for rehabilitation of water supply distribution systems, this paper presents a comparative study of two multiobjective evolutionary methods, namely, multiobjective genetic algorithm (MOGA) and strength Pareto evolutionary algorithm (SPEA). The analyses were conducted on a simple hypothetical network for cost minimisation and minimum pressure requirement, treated as a two-objective problem. For the application example studied, SPEA outperforms MOGA in terms of the Pareto fronts produced and processing time required.

1 Introduction

Most of the existing water supply distribution systems were developed to operate over a determined planning period. Along time, however, failures caused by the deterioration of pipes and hydraulic components become frequent in such systems. Besides, the increasing levels of urbanisation and demand for water lead to problems such as insufficient discharges to meet demand and low-pressure levels in the network. Thus, the decision process for rehabilitation and replacement of existing components to meet current and future demands constitutes a subject of great interest.

Improvements in a distribution system performance can be achieved through rehabilitation of some pipes or other components and/or adding new components to the existing network. Generally limited funding is available to modify the systems in order to guarantee a satisfactory level of the water supply service. Several researchers [1]–[5] have applied optimisation techniques in rehabilitation of water distribution systems, focusing on the economic considerations. Techniques such as linear, integer, non-linear and dynamic programming have been exhaustively used in water distribution system optimisation.

Many researchers [6]–[7] have pointed out the disadvantages of the conventional optimisation methods. The rehabilitation of water distribution systems is a complex and discontinuous problem with many local optima. Many conventional optimisation methods do not guarantee that the global optimum shall be found. Further, they are

based on single objectives, whereas many real situations require simultaneous optimisation of multiple objectives.

Optimisation has evolved over the last years by the introduction of a number of non-conventional algorithms as the Genetic Algorithms (GAs), which mimic the evolutionary principles of nature to drive the search towards optimal solutions. One of the most striking differences between classical search methods and GAs is the use of populations of solutions instead of only one solution [8].

In single objective optimisation, this algorithm attempts to obtain the best design or operational strategy, which is usually the global minimum or maximum, depending on the nature of the problem to be solved. Based on a very different concept, a typical multiobjective method seeks for a set of solutions that are superior to the remainder solutions in the search space. This set is denominated Pareto optimal front [8]. Because GAs work with populations of points, a number of optimal solutions can be captured during their iterative search process. Thus they are naturally well-suited to treat the multiobjective problems.

Evolutionary techniques for multiobjective optimisation can be classified into several classes [9]: objective reduction approaches, classified population approaches, weight-randomising approaches, preference relationship approaches and Pareto-based approaches. In Pareto-based approaches the objectives are dealt with simultaneously however in a different manner as compared to other cited classes which need some simplification process.

Three types of implementations based on non-dominance concept of Pareto [10] were first proposed as: multiobjective GA (MOGA) [11], niched Pareto GA (NPGA) [12] and non-dominated sorting GA (NSGA) [13]. Later, many others methods are being proposed, which can be classified as non-elitist and elitist [14]-[15] and still others based on tournament approaches [16]. In spite of such variety of methods, there are few comparisons available in literature for water resources engineering problems.

Many authors [17]-[20] have used GAs applied to the water engineering problem, focusing on sizing and layout of water distribution networks. However, few studies have applied multiobjective optimisation techniques in water distribution system problems. Halhal et al. [19] and Walters et al. [18] developed a structured messy genetic algorithm for a multiobjective approach. These studies incorporate the multiple objectives into the single objective formulation using weighting factors for each objective or constraint. More recently, MOGA was applied [20] to the problem of rehabilitation of a hypothetical network, considering economic and reliability criteria.

In order to compare the performance of the non-elitist (MOGA) and elitist (SPEA) methods, this paper uses a hypothetical network from literature. EPANET 2 [21] is used for the hydraulic evaluation in terms of nodal heads and pipe discharges.

2 The Problem of Water Distribution System Rehabilitation

The performance of water networks can be improved in terms of their hydraulic capacity by cleaning, relining, duplicating or replacing existing pipes; increasing their physical integrity by replacing structurally weak pipes; increasing system flexibility

by additional pipe links; improving water quality by removing or relining old pipes [19].

Generally, high costs are involved in remedial works and available economic resources are limited to implementation of such task. Thus, there is need for implementation and development of optimal rehabilitation plans since the funding must be optimally invested over the planning period.

3 Multiobjective Optimisation Model

Five objectives can be pointed out as regards the operation of water distribution networks, namely, hydraulic capacity, physical integrity, flexibility, water quality and economy, each of which can be expressed by means of several attributes, constituting a complex multiobjective problem.

In the absence of any preference information among the objectives, the goal of a multiobjective optimisation method is to arrive at a set of Pareto optimal designs. In addition to a number of Pareto optimal designs, a widely varying set of solutions is usually required to allow the decision-maker to choose from the set [22].

Classical methods are not efficient for multiobjective problems as they often lead to a single solution instead of a set of Pareto optimal solutions. Multiple runs cannot guarantee generation of different points on the Pareto front each time and some methods cannot even handle problems with multiple optimal solutions [8],[22].

Evolutionary methods, on the other hand, maintain a set of solutions as a population during the course of search and thus result in a set of Pareto optimal solutions in a single run. Widely differing Pareto optimal solutions can also be generated by using a diversification strategy within the evolutionary algorithms [8],[11].

3.1 Constraints

In GAs, one of the most important issues is the manner in which the constraints are incorporated into the fitness function to guide the search properly. In the last years, researchers [10],[23],[24] have proposed penalty functions to incorporate constraints into the fitness function. In many engineering problems this approach has been used and the results have demonstrated consistency. However, penalty functions have some known limitations of which the most significant is the difficulty of defining good penalty factors. These penalty factors are normally found by trial and error as their definition may affect the results produced by the GAs.

3.2 Problem Formulation

Water distribution systems frequently require rehabilitation (cleaning, lining, reinforcement among others) to maintain the satisfactory services for the society. However, the rehabilitation of an existing system is a complex task if it is to be

implemented in the most effective and economic manner. It necessitates a systematic and thorough approach, backed up by skilful engineering judgement, and significant capital resources. The examination and evaluation for design alternatives is a field in which optimisation models can play an important role, particularly when finances are limited and the problems are of a large size [18].

Many objectives can be incorporated in rehabilitation decision models. We prefer to formulate a two-objective network rehabilitation problem in order to compare our results with those of a similar one-objective problem [17] which dealt with the remaining objective as a constraint include in objective function. Thus the present paper formulates the rehabilitation problem as that of minimisation of cost (1) as well as pressure deficit (2) considering various combinations of rehabilitation choices. The individual objectives are:

$$\text{Minimise Cost, } F_1 = \sum_{\ell \in \mathfrak{S}} c_\ell L_\ell + \sum_{k \in \pi} c_k L_k \quad (1)$$

where ℓ is the index of the pipes to be rehabilitated (cleaned or left unaltered); k is the index of the new pipes (replaced or duplicated); \mathfrak{S} is the set of alternatives related to the pipes requiring rehabilitation; π is the set of alternatives for new pipes; L is length of the pipe; c_j are rehabilitation unit costs and c_k are unit costs of new pipes. The decision problem corresponds to the identification of pipes to be added in parallel or as a new pipe.

$$\text{Minimise Pressure Deficit, } F_2 = \sum_{i=1}^{LC} \max(H_j - H_{j_{\min}})_i \quad j=1,2,\dots,nn \quad (2)$$

where pressure deficit is the sum of maximum nodal deficits on the network for each demand pattern; j is the index that represents the nodes; nn is the total number of nodes in the system; H_j is the energy and $H_{j_{\min}}$ is the required minimum energy at node j . LC denotes the number of demand patterns considered. In this study three demand patterns shall be investigated: peak, average and minimum demands. One can observe that F_2 replaces a constraint of the rehabilitation problem.

3.3 Multiobjective Evolutionary Algorithms

Fonseca and Fleming [11] introduced multiobjective genetic algorithms where the ranking of a solution was based on non-dominated classification. The multiobjective genetic algorithm (MOGA) classifies each solution assigning a rank value that means the number of solutions that dominates it plus one. After the rank is assigned, the algorithm tries to distribute the points evenly over the Pareto optimal region using a sharing mechanism in the objective function domain. The solutions are proportionally selected and submitted to the crossover and mutation operators.

Zitzler and Thiele [14] introduced elitism by explicitly maintaining an external population. This population stores a fixed number of the non-dominated solutions that

are found until the beginning of a simulation. At every generation, newly found non-dominated solutions are compared with existing external population and the resulting non-dominated solutions are preserved. This algorithm is called strength Pareto evolutionary (SPEA). It does more than just preserve the best solutions, it also uses these elite solutions to participate in the genetic operations along with the current population in the hope of influencing the population to steer towards good regions in the search space.

In this paper, these two multiobjective evolutionary algorithm techniques (MOGA and SPEA) are applied to compare non-elitist and elitist methods in the rehabilitation water distribution system problem (2), whose details can be found in [8].

3.3.1 Evolutionary Algorithms Libraries

We implemented the MOGA algorithm through a C++ code supported by the GALib library [25] basic operators written by Matthew Wall at Massachusetts Institute of Technology.

The MOMHLib++ library [26] was used to obtain the results for the SPEA algorithm developed by Andrzej Jaszkiewicz at Poznan University of Technology.

3.4 Hydraulic Simulator Model

A steady-state hydraulic analysis was used to evaluate the consequences of a rehabilitation plan in terms of the objectives, F_1 and F_2 using the EPANET 2 [21] which was linked to our C++ code. It should be noted that EPANET 2 represents an efficient code for hydraulic calculations related to water distribution networks.

3.5 Comparative Study

The set coverage metric [8] was adopted as performance index to compare the applied methods (MOGA and SPEA). The metric is used to get an idea of the relative spread of solutions between two sets of solution vectors A and B. The set coverage metric $C(A,B)$ calculates the proportion of solutions in B, which are weakly dominated by solutions of A (3):

$$C(A, B) = \frac{|\{b \in B | \exists a \in A : a \preceq b\}|}{|B|} \quad (3)$$

The expression $a \preceq b$ denotes that a dominates b. The metric value $C(A,B) = 1$ means that all the members of B are weakly dominated by A. On the other hand, $C(A,B) = 0$ expresses that no member of B is weakly dominated by A. Since the domination operator is not a symmetric operator, $C(A,B)$ is not necessarily equal to $1 - C(B,A)$. Thus, one must calculate both $C(A,B)$ and $C(B,A)$ to understand how many solutions of A are covered by B and vice versa [8].

4 Application Example

The rehabilitation study of the hypothetical network in Fig.1 was initially proposed in [27]. The network in Fig.1 has 14 pipes, 2 constant level reservoirs (nodes 1 and 5) and 9 demand nodes (2, 3, 6, 7, 8, 9, 10, 11 and 12), where the solid lines represent the existing system and dashed lines depict new pipes. The pipe and node data are presented in Tables 1 and 2.

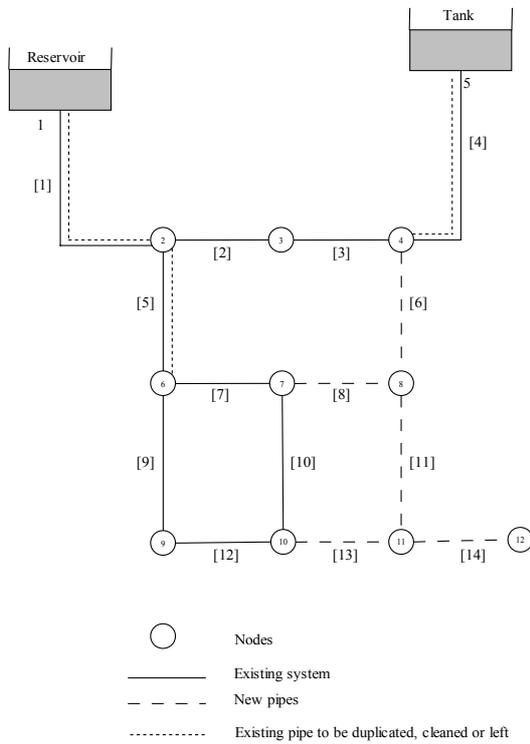


Table 1. Pipe characteristics

Pipe	Diameter (mm)	Length (m)	C_{hw}
1	356	4828	75
2	254	1609	80
3	254	1609	80
4	254	6437	80
5	254	1609	80
6	New	1609	120
7	203	1609	100
8	New	1609	120
9	254	1609	80
10	102	1609	100
11	New	1609	120
12	203	1609	100
13	New	1609	120
14	New	1609	120

Fig. 1. Hypothetical Network [27]

The problem as posed in [27] has some interesting features that include: selection of diameters for five new pipes; three existing pipes may be cleaned, duplicated, or may remain unaltered; three demand patterns are considered; and two supply sources are available, whose options are described in Tables 3 and 4. The respective costs are presented in Tables 5 and 6.

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Table 2. Demand patterns, associated minimum pressures and node elevation for example network

Node	Elevation (m)	Demand Pattern 1		Demand Pattern 2		Demand Pattern 3	
		Demand (L/s)	Minimum Pressure (m)	Demand (L/s)	Minimum Pressure (m)	Demand (L/s)	Minimum Pressure (m)
1	365.76	Reservoir	-	Reservoir	-	Reservoir	-
2	320.40	12.62	28.18	12.62	14.09	12.62	14.09
3	326.14	12.62	17.61	12.62	14.09	12.62	14.09
4	323.23	0	17.61	0	14.09	0	14.09
5	371.86	Tank	-	Tank	-	Tank	-
6	298.70	18.93	35.22	18.93	14.09	18.93	14.09
7	295.66	18.93	35.22	82.03	10.57	18.93	14.09
8	292.61	18.93	35.22	18.93	14.09	18.93	14.09
9	289.56	12.62	35.22	12.62	14.09	12.62	14.09
10	289.56	18.93	35.22	18.93	14.09	18.93	14.09
11	292.61	18.93	35.22	18.93	14.09	18.93	14.09
12	289.56	12.62	35.22	12.62	14.09	50.48	10.57

Table 3. Decision options - rehabilitation

Rehabilitation Option	Real Code
Leave as existing	0
Clean existing pipe	1
Duplicate with 152 mm	2
Duplicate with 203 mm	3
Duplicate with 254 mm	4
Duplicate with 305 mm	5
Duplicate with 356 mm	6
Duplicate with 407 mm	7

Table 4. Decision options - new pipes

New Pipe Diameter (mm)	Real Code
152	0
203	1
254	2
305	3
356	4
407	5
458	6
509	7

Table 5. Rehabilitation Costs [12]

Diameter (mm)	Cleaning of Pipe (\$/m)
152	47.57
203	51.51
254	55.12
305	58.07
356	60.70
407	63.00
458	-
509	-

Table 6. Costs of new pipes [12]

Diameter (mm)	New Pipe Cost (\$/m)
152	49.54
203	63.32
254	94.82
305	132.87
356	170.93
407	194.88
458	232.94
509	264.10

4.1 Genetic Algorithm Implementation

It is important in GA applications to find the appropriate representation of decision variables by strings of fixed length. While many coding schemes are possible, it is convenient to avoid the decoding phase in order to reduce processing time. Several authors [23], [28] have suggested the use of real code instead of the binary one in

order to keep one gene-one variable correspondence. Hence, this study has preferred the use of real code for decision variables representing the rehabilitation options to be implemented in the network to improve its hydraulic performance. The first three variables in the string refers to the decision in pipes 1, 4 and 5, for which values in the range from 0 to 7 have to be determined, according to the options defined in Table 3. The next five variables in the string refer to the decision for pipes 6, 8, 11, 13 and 14, for which values in the range from 0 to 7 have to be determined according to the options defined in Table 4.

4.1.1 Genetic Algorithm Parameters

For this application example, three population sizes were considered: 100, 300 and 500; crossover probability of 1.0 and mutation probability of 0.1, following [17], although a check of other values is desirable. In MOGA algorithm, the sharing parameter value of was assumed to be 0.5. The algorithms were permitted to run for 50,100 and 200 generations, starting from thirty different initial populations [14] of solutions (random seeds) for each population size.

5 Results and Discussions

The results obtained from the application of MOGA and SPEA methods to the example problem (Fig.1) are presented in this section.

Firstly, we performed a sensitivity analysis on the number of generations, in order to identify the consequences of this parameter in the final Pareto fronts. Several simulations were developed for both methods starting from 30 distinct initial populations, producing similar final Pareto fronts. To illustrate this behavior, Fig. 2 presents some results found for population size of 300 solutions. The analysis suggests that no premature convergence was detected. Thus, only the results obtained for 200 generations are shown in this paper for reasons of limited space.

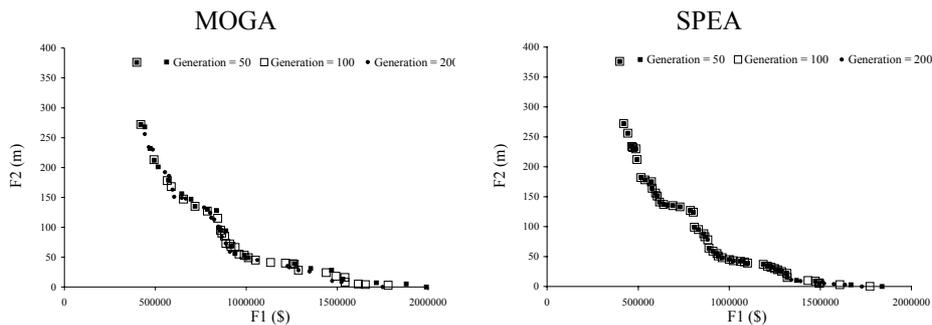


Fig. 2. Sensitivity analysis for the number of generations

Fig. 3, 4 and 5 show Pareto fronts obtained using the population sizes of 100, 300 and 500, where one can observe that SPEA produces solutions (represented by points)

better defining the fronts than those met by MOGA. Considering the points in Pareto front corresponding to values for F_2 near zero as a region of special interest for our purposes, SPEA algorithm appears more efficient in defining such points.

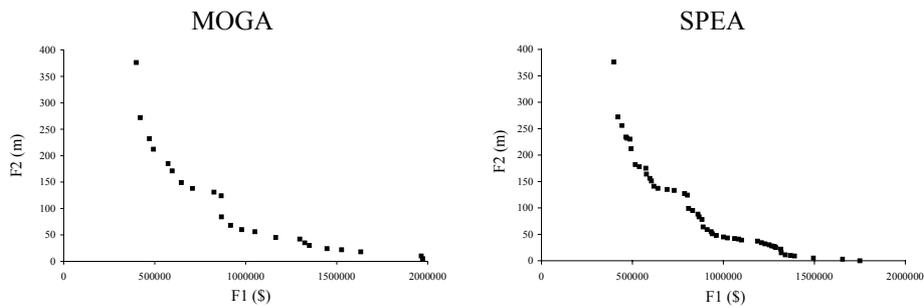


Fig. 3. Pareto fronts of population size 100 and generation number 200 of both methods

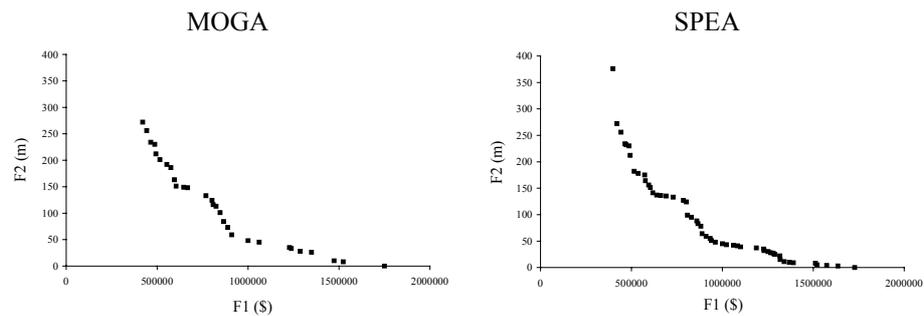


Fig. 4. Pareto fronts of population size 300 and generation number 200 of both methods

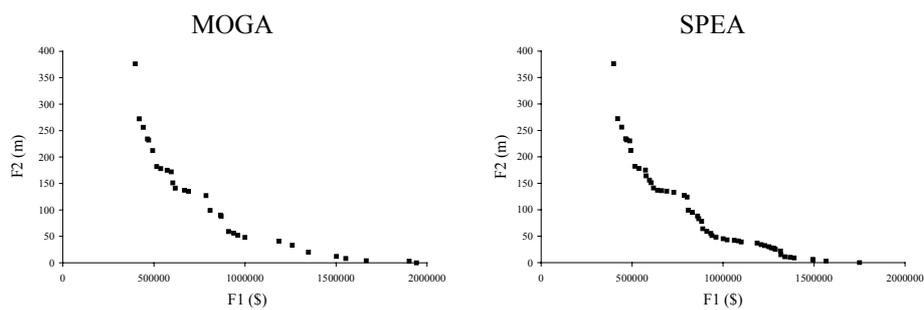


Fig. 5. Pareto fronts of population size 500 and generation number 200 of both methods

Fig. 6 presents the individual MOGA and SPEA solutions randomly chosen among thirty (30) final solutions produced for population sizes of 500 and 200 generations.

These fronts were chosen for visual comparison effect, as they were obtained starting from different initial populations for both methods.

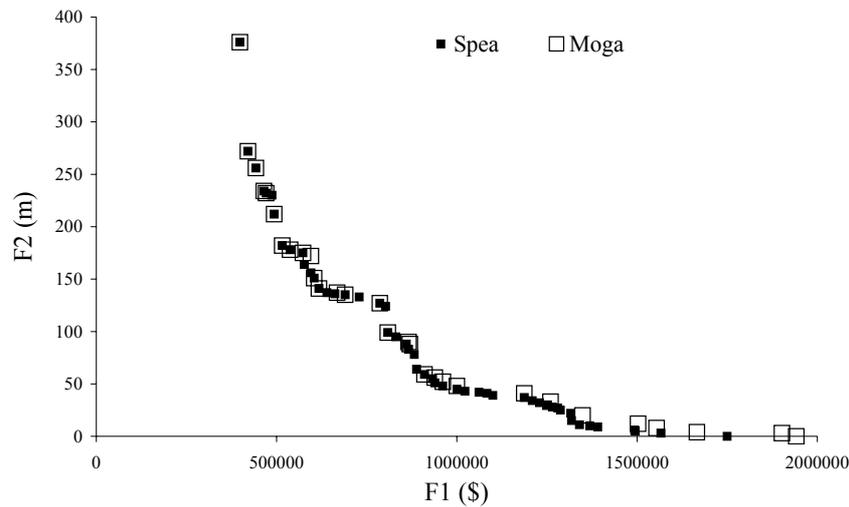


Fig. 6. Comparison of the methods for a run case

Even in this simple example of two objectives functions, the visual comparison is difficult, requiring a comprehensive metric to evaluate the relative merit of both algorithms. Once 30 runs were made for each algorithm starting from distinct initial populations, the comparisons were performed considering the combinations between all possible pairs of solutions obtained from both algorithms. The metric in (3) was used and the results presented in matrix box plot form in Fig.7, where each rectangle contain a box plot representing the distribution of the C values for all combinations (900) of pairs of two algorithms. The scale is 0 at the bottom and 1 at the top in each box plot. Each graph presents distribution of C calculated from results (A) obtained from the algorithm indicated in the row in combination with those (B) from the algorithm indicated in the column through definition in (3) for $C(A,B)$.

Box plots are used to visualise the distribution of these samples. The upper and lower ends of the box are the upper and lower quartiles, while a thick line within the box encodes the median. Dashed appendages summarise the spread and shape of the distribution.

Fig.7 shows the direct comparison based on the measure C (3) for MOGA and SPEA methods. The Pareto fronts achieved by MOGA (population size 100, 300 and 500) are entirely dominated by fronts identified by SPEA for all the population sizes. The elitist method (SPEA) seems to perform better than the non-elitist multiobjective evolutionary algorithm (MOGA). However, there is no clear evidence of superior performance when the results obtained for several population sizes are compared among themselves for a given algorithm.

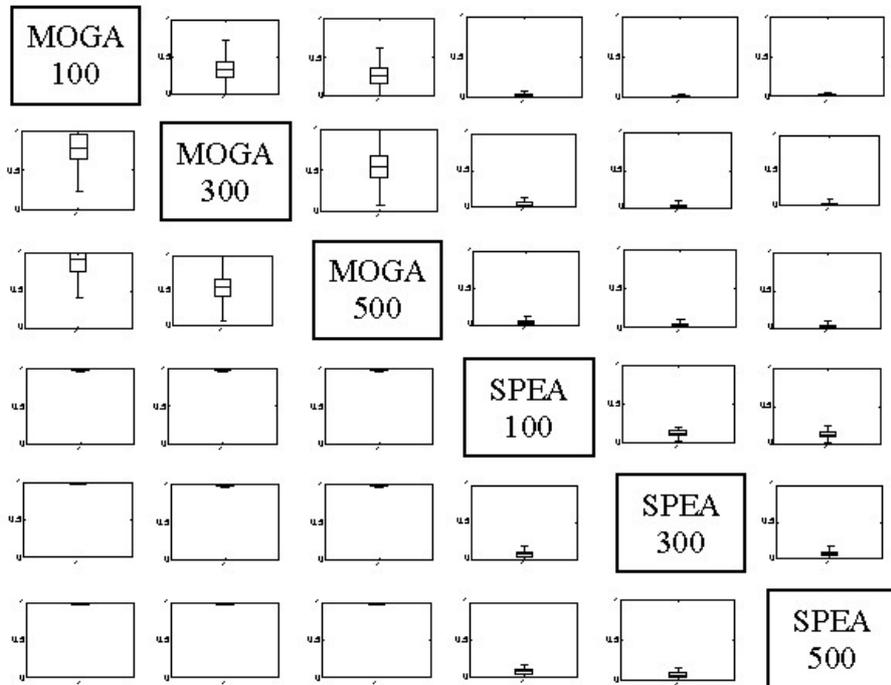


Fig. 7. Box plot based on measure C defined in (3)

Table 7 presents the average processing times for MOGA and SPEA on Athlon XP 1.8 GHz with 512 MB RAM computer. Note that SPEA is faster than MOGA for all cases investigated.

Table 7. Average processing time

Population Size	Average Processing Time (Seconds)		
	Generation	MOGA	SPEA
100	50	12.4	7.6
	100	20.6	17.4
	200	47.3	30.1
300	50	36.5	26.3
	100	74.2	43.4
	200	249.6	86.5
500	50	65.2	44.2
	100	127.6	87.3
	200	249.6	165.1

Table 8 presents ten combinations of least cost alternatives with zero pressure deficit found by the SPEA algorithm. In this table, we can see the lowest value of \$1,666,760 whereas [27], using selective enumeration to optimise this problem found a least cost network of \$1,833,700. Simpson et al. [17] accomplished complete enumeration of all alternative solutions for each of the three demand patterns finding two least cost networks at a cost of \$1,750,000. We attribute the difference in results obtained to the hydraulic simulator used by [17] based on Newton-Raphson solver. In this paper EPANET 2 was used as hydraulic simulator which is based on gradient method solver.

Table 8. Some solutions of lower costs found by SPEA algorithm

Solution	DECISION VECTOR								Objective Function	
	Pipes								F1 (\$)	F2 (m)
	1	4	5	6	8	11	13	14		
1	1	4	4	2	1	1	1	2	1,666,760	0
2	1	4	4	2	1	2	0	2	1,695,270	0
3	1	4	3	2	2	2	0	2	1,695,270	0
4	1	4	4	2	1	3	0	1	1,705,810	0
5	1	4	4	3	1	2	0	1	1,705,810	0
6	1	4	4	2	1	1	2	2	1,717,440	0
7	7	0	5	2	0	1	0	2	1,721,100	0
8	1	4	3	2	2	1	1	3	1,727,980	0
9	0	6	0	3	1	1	0	2	1,750,100	0
10	0	6	0	3	1	2	0	1	1,750,100	0

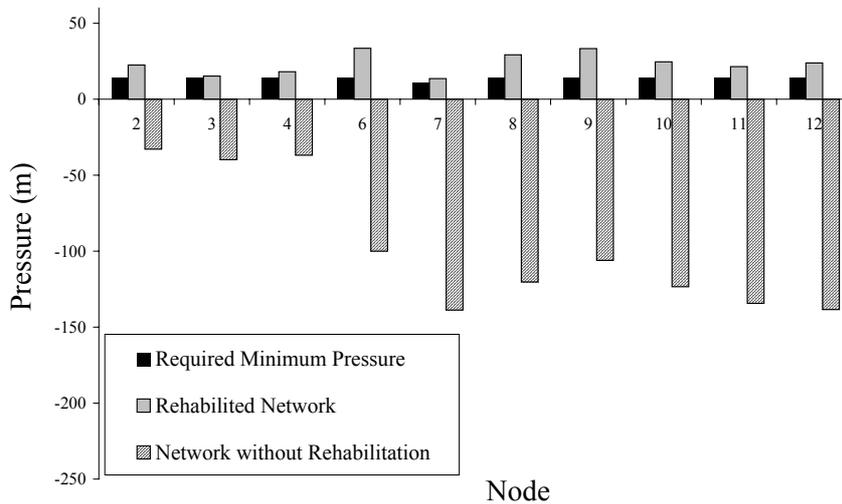


Fig. 8. Pressures in the example network considering demand pattern 2 (average)

As mentioned above, the points on Pareto front region which are of special interest, were analysed in detail from the hydraulic point of view in terms of nodal pressures. Fig. 8 reproduces the solution vector in terms of pressures corresponding to the alternative solution 1 in Table 8. The minimum pressures in Fig. 8 are the values stipulated in Table 2. The pressures in the rehabilitated network are the values obtained from the hydraulic simulations applying the decision vector of solution 1 (Table 8). The pressures in the network without rehabilitation refer to the values resulting from the hydraulic simulations assuming minimum diameters for pipes (6, 8, 11, 13 and 14) besides the existing pipes according to Table 1. One can observe that the network rehabilitation improved the hydraulic performance, making the nodal pressures acceptable for the demand patterns considered (peak, average and minimum).

6 Conclusions

This paper represents an effort to compare the performance of two approaches known as multiobjective genetic algorithm (MOGA) and strength Pareto evolutionary algorithm (SPEA) applied to the water supply network rehabilitation problem. The same problem was studied before [17] through the conventional approach that includes a penalty function in the single objective formulation.

A sensitivity analysis of the number of generations with respect to the final solutions defined in terms of Pareto fronts was conducted. Several simulations were made for both methods starting from distinct initial populations, producing similar final Pareto fronts. Direct comparison based on set coverage metric [8] shows that the Pareto fronts achieved by MOGA are entirely dominated by indicated by SPEA for various population sizes. Further, SPEA is faster than MOGA, requiring smaller processing time.

A least cost solution of \$1,666,760 could be identified, whereas [17], using complete enumeration for each of the three demands, found two networks with a least cost of \$1,750,000. It is presumed that this difference results from the use of a hydraulic simulator inferior to EPANET 2.

Finally, once the potentialities of the elitist multiobjective evolutionary algorithm SPEA are demonstrated, several future possibilities open for solution of engineering problems. Such possibilities include the treatment of more realistic and complex objectives than those dealt with here and comparative studies between more recent elitist methods and SPEA.

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References

1. Shamir, U., Howard, C.D.D.: An Analytic Approach to Scheduling Pipe Replacement. *Journal American Water Works Association*, Vol. 71, No. 5 (1979) 248-258
2. Walski, T.M.: Economic Analysis of Rehabilitation of Water Mains. *Journal of Water Resources Planning and Management*, ASCE, Vol. 108, No. 3 (1982) 296-308
3. Clark, R.M., Stafford, C.L., Goodrich, J.A.: Water Distribution Systems: A Spatial Cost Evaluation. *Journal of Water Resources Planning and Management*, ASCE, Vol. 108 WR 3 (1982) 243-255
4. Kleiner, Y., Adams B. J., Rogers, J. S.: Long-Term Planning Metodology for Water Distribution System Rehabilitation. *Water Resources Research*, Vol. 34, No. 8 (1998) 2039-2051
5. Kim, J.H., Mays, L.W.: Optimal Rehabilitation Model for Water Distribution Systems. *Journal of Water Resources Planning and Management*, ASCE, Vol. 120, No. 5 (1994) 674-692
6. Walski, T.M.: The Wrong Paradigm, Why Water Distribution Optimization Doesn't Work. *Journal of Water Resources Planning and Management* (Editorial), ASCE, Vol. 123, No. 3 (2001) 203-205
7. Engelhardt, M.O., Skipworth, P.J., Savic, D.A., Saul, A.J., Walters, G.A.: Rehabilitation Strategies for Water Distribution Networks: a Literature Review with a UK Perspective. *Urban Water*, No. 2 (2000) 153-170
8. Deb, K.: *Multi-Objective Using Evolutionary Algorithms*. John Wiley & Sons, Ltd (2001)
9. Fonseca, C.M., Fleming, P. J.: An Overview of Evolutionary in Multiobjective Optimization. *Evolutionary Computation*, Vol. 3, No. 1 (1995) 1-16
10. Goldberg, D.E.: *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison-Wesley, Reading, Massachusetts (1989)
11. Fonseca, C.M., Fleming, P. J.: Genetic Algorithms for Multiobjective Optimization: Formulation, Discussion and Generalization. *Proceedings of the Fifth International Conference, San Mateo* (1993)
12. Horn, J., Nafpliotis, N.: Multiobjective Optimization using the Niche Pareto Genetic Algorithm. *Proceedings of the First IEEE Conference on Evolutionary Computation, IEEE World Congress on Computational Intelligence*, Vol. 1 (1994) 1-32
13. Srinivas, N., Deb, K.: Multiobjective Optimization using Nondominated Sorting in Genetic Algorithms. *Evolutionary Computation*, Massachusetts Institute of Technology, Vol. 2, No 3 (1995) 221-248
14. Zitzler, E., Thiele, L.: Multiobjective Evolutionary Algorithms: A Comparative Case Study and the Strength Pareto Approach. *IEEE Transactions on Evolutionary Computation*, Vol. 3, No 4 (1999) 257-271

15. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: A Fast and Elitist Multi-Objective Genetic Algorithm – NSGAI. KanGAL Report Number 2000001 (2000)
16. Veldhuizen, D. V.: Multiobjective Evolutionary Algorithms: Classifications, Analyses, and New Innovations. Ph. D. Thesis, Dayton, OH: Air Force Institute of Technology (1999)
17. Simpson, A. R., Dandy, G.C., Murphy, L. J.: Genetic Algorithms Compared to Other Techniques for Pipe Optimization. *Journal of Water Resources Planning and Management*, ASCE, Vol. 120, No. 4 (1994) 423-443
18. Walters, G.A., Halhal, D., Savic, D.A., Ouazar, D.: Improved Design of Anytown Distribution Network using Structured Messy Genetic Algorithms. *Urban Water*, Vol. 1 (1999) 23-38
19. Halhal, D., Walters, G.A., Savic, D.A., Ouazar, D.: Scheduling of Water Distribution System Rehabilitation using Structured Messy Genetic Algorithms. *Evolutionary Computation*, Vol. 7, No. 3 (1999) 311-329
20. Dandy, G.C., Engelhardt, M.O.: Optimum Rehabilitation of Water Distribution System considering Cost and Reliability. *Proceedings of the World Water and Environmental Resources Congress*, Orlando, Florida, (2001)
21. Rossman, L. A.: EPANET 2, USERS MANUAL. U. S. Environmental Protection Agency, Cincinnati, Ohio, (2000)
22. Ray, T., Tai K., Seow, K.C.: Multiobjective Design Optimization by an Evolutionary Algorithm. *Engineering Optimization*, Vol. 33 (2001) 399-424
23. Michalewicz, Z.: *Genetic Algorithms + Data Structures = Evolution Programs*. Springer-Verlag, New York, N.Y., (1992)
24. Gen e Cheng: *Genetic Algorithms and Engineering Design*. John Wiley & Sons, INC, (1996)
25. Wall, M.: Galib: A C++ Library of Genetic Algorithm Components (version 2.4). Mechanical Engineering Department, Massachusetts Institute of Technology, (1996)
26. Jaskiewicz, A.: MOMHLIB++: Multiple Objective Metaheuristics Library in C++. <http://www-idss.cs.put.poznan.pl/~jaskiewicz/MOMHLIB>.
27. Gessler, J.: Pipe Network Optimization by Enumeration. *Proceedings Computer Applications for Water Resources*, ASCE, New York, N.Y., (1985) 572-581
28. Goldberg, D.E.: Real-Coded Genetic Algorithm, Virtual Alphabets, and Blocking. *Complex Systems*, Vol. 5, No. 2 (1991) 139-168