Multiobjective Optimization to the Rehabilitation of a Water Distribution Network

P.B. Cheung, L. F. R. Reis & I.B. Carrijo
São Carlos School of Enginerring, University of São Paulo, São Carlos, São Paulo, Brazil

ABSTRACT: Many engineering problems involve optimization of multiple and competing objectives. Conventionally, analysts have treated these problems as single objective optimization problems instead of multiobjective ones. In multiobjective optimization, there is not a single optimum but a set of trade-off solutions known as Pareto-optimal, nondominated or non-inferior solutions. Recognizing the multiobjective nature of the rehabilitation problem of water supply distribution networks, this paper presents an application of an elitist multiobjective evolutionary algorithm, namely, Strength Pareto Evolutionary Algorithm (SPEA), to generate a series of nondominated solutions. The rehabilitation analyses were conducted on a simple hypothetical network for minimum cost, minimum pressure requirement and maximum hydraulic benefit, dealt with a three-objective problem. Analyses were performed to identify suitable crossover and mutation operators as well as parameters to this rehabilitation problem, for which SPEA presented high performance in producing Pareto fronts.

1 INTRODUCTION

Most of the existing water supply distribution systems were developed to operate over a determined planning period. Over time, however, failures caused by the deterioration of pipes and hydraulic components become frequent in such systems. In addition, the increasing demand for water caused by the urbanization has lead to problems such as insufficient discharges to meet demand and low-pressure levels in the network. Thus, the decision process of 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 specific pipes, other components and/or the addition of new components to the existing network. In general, limited funding is available to modify the systems in order to guarantee a satisfactory level of water supply service. Researchers (Kim & Mays 1994, Kleiner et al. 1998) have applied optimization techniques to 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 optimization.

Some researchers (Engelhardt et al. 2000, Walski 2001) have pointed out the disadvantages of the conventional optimization methods to treat the rehabilitation as a complex and discontinuous problem with many local optima. Many conventional optimization methods do not guarantee that a global optimum can be found. Further, they are based on a single objective, whereas many real situations require simultaneous optimization of multiple objectives.

Optimization has evolved over the recent years due to 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 a set of solutions instead of only one solution (Deb 2001).

In single objective optimization, the best (the global minimum or maximum) design or operational strategy is obtained depending on the nature of the problem to be solved. Based on a very different concept, a typical multiobjective method seeks a set of solutions that are superior to the remaining ones in the search space. This set is denominated Pareto optimal front. Because GAs work with populations of possible solutions, a number of optimal solutions can be captured during their iterative search process. Thus they are naturally well suited to treat multi-objective problems.

According to Fonseca & Fleming (1995) evolutionary techniques for multiobjective optimization can be classified into several classes: objective reduction approaches, classified population approaches, weight-randomizing approaches, preference relationship approaches and Pareto-based approaches. In Pareto-based approaches the objectives are dealt with simultaneously, and, differently when compared to other cited classes methods which require simplifications.

Deb (2001) classified the Pareto-based approaches on two main classes: non-elitist and elitist algorithms. Three types of non-elitist implementations were first proposed as: Multiobjective Genetic Algorithms (MOGA) (Fonseca & Fleming 1993), Niched Pareto Genetic Algorithms (NPGA) (Horn & Nafpliotis 1994) and Non-Dominated Sorting Genetic Algorithms (NSGA) (Srinivas & Deb 1995). Two elitist implementations stand out: Strength Pareto Evolutionary Algorithm (SPEA) (Zitzler 1999) and Non-Dominated Sorting Genetic Algorithms II (NSGAII) (Deb et al. 2000). In spite of such a variety of methods, there are few comparisons available in the literature (Cheung et al. 2003) for water resources problems.

Several researchers (Simpson et al. 1994, Dandy et al. 1996, Reis et al. 1997, Savic & Walters 1997) have applied GAs to the optimization of water distribution systems. However, some studies (Halhal et al. 1997, Walters et al. 1999, Dandy & Engelhardt 2001, Kapelan et al. 2002, Cheung et al. 2003, Formiga et al. 2003) have suggested the use of multiobjective optimization techniques in water distribution system problems. More recently, MOGA was applied (Dandy & Engelhardt 2001) to the problem of rehabilitation of a hypothetical network, considering cost and reliability criteria.

Cheung et al. (2003) compared the performance of the non-elitist (MOGA) and elitist (SPEA) methods in terms of Pareto front achieved, analyzed processing time and discussed population sizes from both methods in a water distribution network rehabilitation problem. The comparison of methods was based on a performance metric (Set Coverage Metric) proposed by Zitzler (1999), which evaluates the relative spread of solutions between two sets of solution vectors. The results showed that the Pareto fronts obtained through MOGA were entirely dominated by the fronts obtained through SPEA for the various population sizes. Besides, SPEA is faster than MOGA.

This paper presents an effort to identify suitable crossover and mutation operators to be considered in elitist multiobjective evolutionary algorithm (SPEA) applied to the rehabilitation of a hypothetical network (Gessler 1985).

2 THE PROBLEM OF WATER DISTRIBUTION NETWORK 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; and improving water quality by removing or relining old pipes (Halhal et al. 1997).

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

3 MULTIOBJECTIVE OPTIMIZATION MODEL

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

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 (Deb 2001)

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 (Fonseca & Fleming 1993, Veldhuizen 1999, Zitzler 1999, Deb 2001).

3.1 *Problem Formulation*

Water distribution systems frequently require rehabilitation (cleaning, lining, reinforcement, among others) to maintain the satisfactory services for the population. 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 skillful engineering judgment, and considerable capital resources. The examination and evaluation of design alternatives is a field in which optimization models can play an important role, particularly when economic resources are limited and the problems are of large size (Walters et al. 1999).

Many objectives can be incorporated in rehabilitation decision models. We prefer to formulate a three-objective network rehabilitation problem in order to compare our results with those reported in literature (Simpson et al. 1994, Cheung 2003) that consider single-objective and two-objective, respectively. Thus, the present paper formulates the rehabilitation problem as that of minimization of cost (Equation 1) and pressure deficit (Equation 2) as well as maximization of hydraulic benefit (Equation 3), considering various combinations of rehabilitation choices. The individual objectives are expressed as follows.

$$\text{Minimize Cost, } F_1 = \sum_{\ell \in \Im} c_\ell L_\ell + \sum_{k \in \pi} c_k L_k \qquad (1)$$

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); $\Im$ 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_ℓ 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.

$$\text{Minimize Pressure Deficit, } F_2 = \sum_{i=1}^{LC} \max\left(H_j - H_{j\min}\right)_i \quad j = 1,2,\ldots,nn \qquad (2)$$

where pressure deficit is the sum of maximum nodal deficits on the network for each demand pattern; j is the index of nodes; nn is the total number of nodes in the system; H_j is the energy and H_{jmin} 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.

Finally, the maximization of hydraulic benefit is based on formulation proposed by Halhal et al. (1997). However, in this paper it has been modified to give a physic characterization to the hydraulic benefit formulation. This objective function (Equation 3) is quantified as the difference between the pressure deficiencies in the network before improvement (DEFO) and after improvement (DEFP) represented by each solution found which is calculated by Equation 4.

$$\text{Maximize Hydraulic Benefit, } F_3 = \text{DEFO} - \text{DEFP} \qquad (3)$$

$$\text{DEFO}/\text{DEFP} = \gamma \sum_{j \in \Im} \left|H_{\min} - H\right|_j Q_j \qquad (4)$$

where γ represents the specific weight of water; $\Im$ is the set of nodes related to the energy below minimum required energy at node j; H is the energy and H_{min} is the required minimum energy at node j and Q is the demand at node j. Observe that this formulation (Equation 3) produces a benefit in terms of power and which differs from formulation proposed by Halhal et al. (1997).

3.2 *Multiobjective Evolutionary Algorithm*

Ziztler (1999) introduced elitism by explicitly maintaining an external population of possible solutions in the resolution of such multiobjective problem. This population stores a fixed number of the non-dominated solutions that are found until the beginning of iteration. In each iterate, 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 Algorithm (SPEA). It does more than just preserve the best solutions but 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.

This study employs the SPEA method based on elitism, implementing the code developed by Andrzej Jaszkiewicz in the Multiobjective Methods Metaheuristic Library for C++ (MOMHLib++). This library allows the user to build the genetic operators (recombination and mutation) most proper to the specific problem in hand. Three recombination operators (Linear, BLX-α and Uniform) and three mutation operators (Boundary, Random and Non-Uniform) were implemented whose details are presented here.

Recombination (crossover) and mutation aim at generating new solutions within the search space by the variation of existing ones. The recombination operator takes a certain number of parents and creates a certain number of offspring by recombining the parents features. To mimic the stochastic nature of evolution, a crossover probability is associated with this operator. By contrast, the mutation operator modifies individuals by changing small parts in the associated vectors according to a given mutation rate (Zitzler 1999).

3.2.1 Recombination Operator

Linear recombination: Wright (1991) proposed one of the earliest implementations where a linear operator creates three new solutions (Eqs. 5-7) from two parents solutions $x_i^{(1,t)}$ and $x_i^{(2,t)}$ at generation t, with the two best solutions being chosen as offspring. In this paper, the best solution of them was chosen utilizing the non-dominance concept.

$$x_i^{(1,t+1)} = 0.5x_i^{(1,t)} + 0.5x_i^{(2,t)} \tag{5}$$

$$x_i^{(1,t+1)} = 1.5x_i^{(1,t)} - 0.5x_i^{(2,t)} \tag{6}$$

$$x_i^{(1,t+1)} = -0.5x_i^{(1,t)} + 1.5x_i^{(2,t)} \tag{7}$$

where x is the decision variable; i is the index of the decision variable; t is the index of the generation; 1 and 2 are index of parents vectors

Blend recombination: Eshelman and Schaffer (1993) suggested this operator (BLX-α) for real-parameter GAs. Starting from parent solutions $x_i^{(1,t)}$ and $x_i^{(2,t)}$ (assuming $x_i^{(1,t)} < x_i^{(2,t)}$), the BLX-$\alpha$ randomly picks a solution in the range $[x_i^{(1,t)} - \alpha(x_i^{(2,t)} - x_i^{(1,t)}), x_i^{(2,t)} + \alpha(x_i^{(2,t)} - x_i^{(1,t)})]$. Thus, considering u_i a random number between 0 and 1, the BLX-α operator can be described in Equation 8.

$$x_i^{(1,t+1)} = (1-\gamma_i)x_i^{(1,t)} + \gamma_i x_i^{(2,t)} \tag{8}$$

where $\gamma_i = (1+2\alpha)u_i - \alpha$. Deb (2001) reported that α equals 0.5 performs better than BLX-α with another α values.

Uniform recombination: Goldberg (1989) and Michalewicz (1992) described the uniform recombination method which operates on individual genes of the selected chromosomes. They suggested this operator for the binary representation. However, in this study the uniform recombination operator was modified to the rehabilitation problem that was represented by real code (decision variables). Initially, a template vector (m_i) that assumes 0 or 1 value is randomly generated (the same size of solution vector) in each recombination operation. Equation 8 demonstrates it.

$$x_i^{(1,t+1)} = \begin{cases} x_i^{(1,t)} & \text{if} \quad m_i = 0 \\ x_i^{(2,t)} & \text{if} \quad m_i = 1 \end{cases} \tag{9}$$

3.2.2 Mutation Operator

Mutation is an important process that permits new genetic material to be introduced to a population during iterative process. The task of mutation operator is to disturb every solution in the parent population to create a new population.

Boundary mutation: Michalewicz (1992) reported that this operator (Equation 10) substitutes a selected gene by random gene which it is picked in $[x_i^{(L)}, x_i^{(U)}]$ interval where $x_i^{(L)}$ and $x_i^{(U)}$ are the lower limit and upper limit of decision variables, respectively.

$$y_i^{(t+1)} = \begin{cases} x_i^{L} & \text{if} \quad r < 0.5 \\ x_i^{u} & \text{if} \quad r > 0.5 \end{cases} \tag{10}$$

where y_i is the new solution and r is a random number in [0,1].

Random mutation: Deb (2001) reports this operator (Equation 11) as the simplest mutation scheme to create a solution randomly from entire search space.

$$y_i^{(t+1)} = r_i(x_i^{(U)} - x_i^{(L)}) \tag{11}$$

Non-uniform mutation: This operator depends on the current generation and the maximum number of allowed generations to create a new solution (Deb 2001). Equation 12 describes it.

$$y_i^{(t+1)} = x_i^{(1,t+1)} + \tau(x_i^{(U)} - x_i^{(L)})(1 - r_i^{(1-\frac{t}{t\max})^b}) \tag{12}$$

where τ takes a Boolean value, -1 or 1, each with a probability of 0.5; tmax is the maximum number of allowed generations and b is a user-defined parameter. In this study, the b parameter was chosen 6 (Michalewicz 1992).

3.3 *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, F_2 and F_3 using the EPANET 2 code (Rossman 2000) that 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.

3.4 *Performance Metric*

According to Deb (2001), performance measures should be used in the multiobjective analysis. In this study, the set coverage metric (Zitzler 1999) was adopted as performance index to compare the efficiency of genetic operators. 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 (Equation 13):

$$C(A,B) = \frac{\left|\left\{ b \in B \,|\, \exists a \in A : a \preceq b \right\}\right|}{|B|} \tag{13}$$

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.

4 APPLICATION EXAMPLE

The rehabilitation study of the hypothetical network in Figure 1 was initially proposed in Gessler (1985). Later various authors (Simpson et al. 1994, Wu & Simpson 2001, Cheung et al. 2003) used this problem as the basis for comparisons of their formulations. The network in Figure 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 hydraulic data can be found in the original paper (Gessler 1985) and several other papers (Simpson et al. 1994, Cheung et al. 2003).

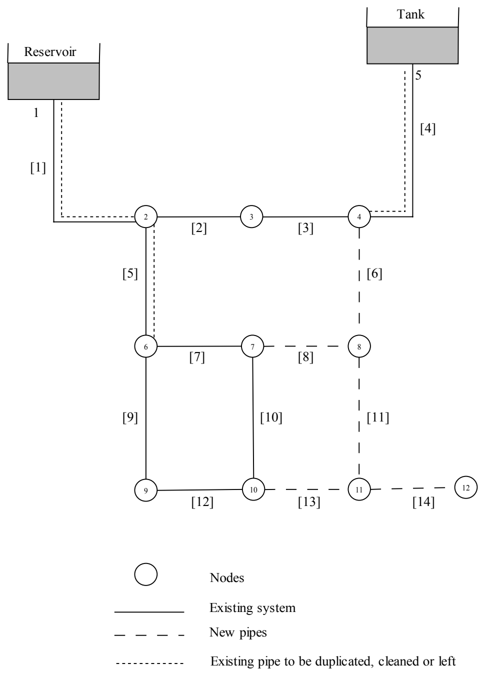

Figure 1. Hypothetical network

Table 1. Decision options (rehabilitation and design)

Rehabilitation Option	New Pipe Option mm	Real Code
Leave as existing	152	0
Clean existing pipe	203	1
Duplicate with 152 mm	254	2
Duplicate with 203 mm	305	3
Duplicate with 254 mm	356	4
Duplicate with 305 mm	407	5
Duplicate with 356 mm	458	6
Duplicate with 407 mm	509	7

The problem as posed in (Gessler 1985) 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 Table 1. The respective costs also can be found in (Gessler 1985, Simpson et al. 1994, Cheung et al. 2003).

4.1 Genetic Algorithm Implementation

GA applications are important to find the appropriate representation of decision variables through 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 (Michalewicz 1992, Goldberg 1991) have suggested the use of real code instead of the binary one in order to keep one gene-one variable correspondence. Hence, real code has been used in this study 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 1. 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 1.

4.1.1 Genetic Algorithm Parameters

For this application example, a population size (n) of 300 strings was considered following suggestions of Cheung et al. (2003). A probability of recombination (p_r) of 0.9 and a mutation probability (p_m) of 0.1 ($1/n < p_m \leq 1/\ell$, where ℓ represents string length) were chosen following Simpson et al. (1994). The SPEA was permitted to run for 1000 generations, starting from three different initial populations of solutions (random seeds).

5 RESULTS AND DISCUSSIONS

The results obtained from application of SPEA method to the example problem (Fig. 1) are presented in this section in order to identify the influence of different recombination and mutation operators on the Pareto fronts produced. Three recombination and mutation operators have been considered. Table 2 presents the computational simulation design which was performed in this work. All simulations were run in an AMD Athlon (TM) XP 1800+.

Table 2. Computational simulation design and average processing time

Configuration	Recombination operator	Mutation operator	Random seeds	Average run time (minutes)
1	BLX-α	Boundary	0, 1000 and 2000	11.12
2	Linear	Boundary	0, 1000 and 2000	20.13
3	Uniform	Boundary	0, 1000 and 2000	11.30
4	BLX-α	Random	0, 1000 and 2000	10.18
5	Linear	Random	0, 1000 and 2000	17.61
6	Uniform	Random	0, 1000 and 2000	10.3
7	BLX-α	Non-uniform	0, 1000 and 2000	11.8
8	Linear	Non-uniform	0, 1000 and 2000	20.8
9	Uniform	Non-uniform	0, 1000 and 2000	10.9

Table 2 presents the average processing time for each type of considered configuration (genetic operators) in this study. Observe that the configurations #2, #5 and #8 presented the highest processing time. In common, these configurations used the linear recombination operator. The difference in the behavior of linear recombination operator is due to search algorithm of nondominated solutions. This recombination operator takes more processing time than other operators because it always creates three new individuals in each evaluation and the best individual is chosen according to the Pareto dominance concept (search algorithm of nondominated solutions). It can be observed that the mutation operator does not significantly change the processing time.

As mentioned before (item 1), the multiobjective optimization methods always look for a set of optimal solutions. The visualization of final solutions is very difficult, mainly when the problem has more than two objectives. In some studies, researches still get to plot (Halhal et al. 1997, Walters et al. 1999) and to perform sensitivity analysis (Cheung et al. 2003) to infer about genetic parameters (generations, population size). However, for three-objective problems comparison studies the performance metric (Equation 13) should be used and the visual analyses should be used as complement. Inasmuch as, the main objective of this paper was to investigate the relative merit of different genetic operators (recombination and mutation) in a three-objective problem, the performance metric (3.5) was used to evaluate the different simulation configurations (Table 3).

Three runs were made for each configuration starting from distinct initial populations (random seeds) and the comparisons were performed considering the combinations between all possible pairs of configurations. The metric in (Equation 13) was used and the results presented in matrix box plot form in Figure 2, where each rectangle contain a box plot representing the distribution of the C values for all combinations (nine) of pairs of two configurations. Each graph presents distribution of C calculated from results (A) obtained from the configuration indicated in the row in combination with those (B) from the configuration indicated in the column through definition in (Equation 13) for C (A, B).

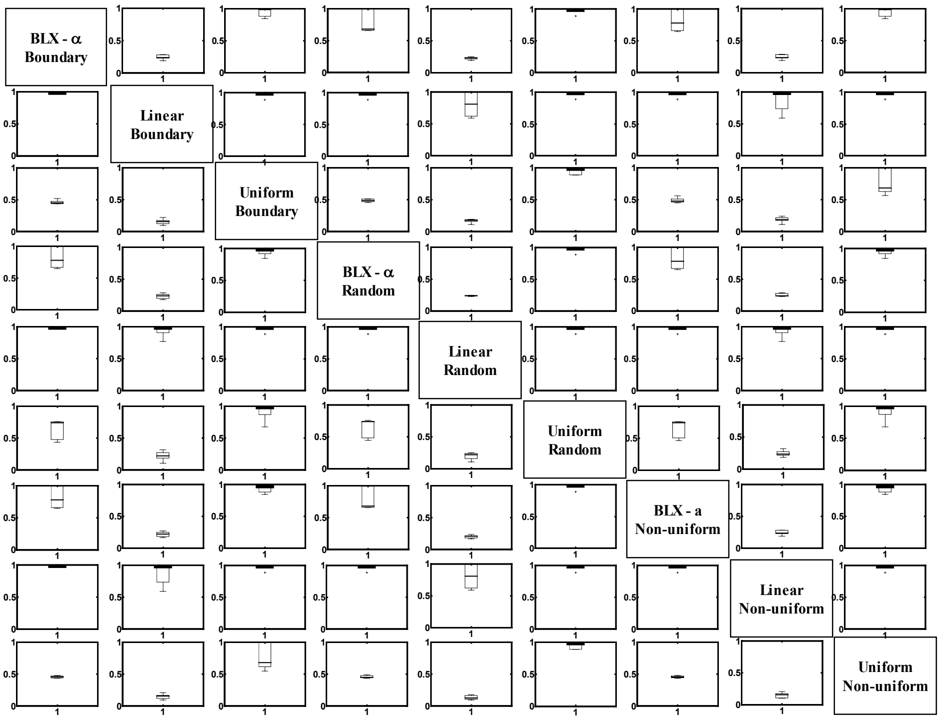

Figure 2. Box plot based on measure C defined (3.5)

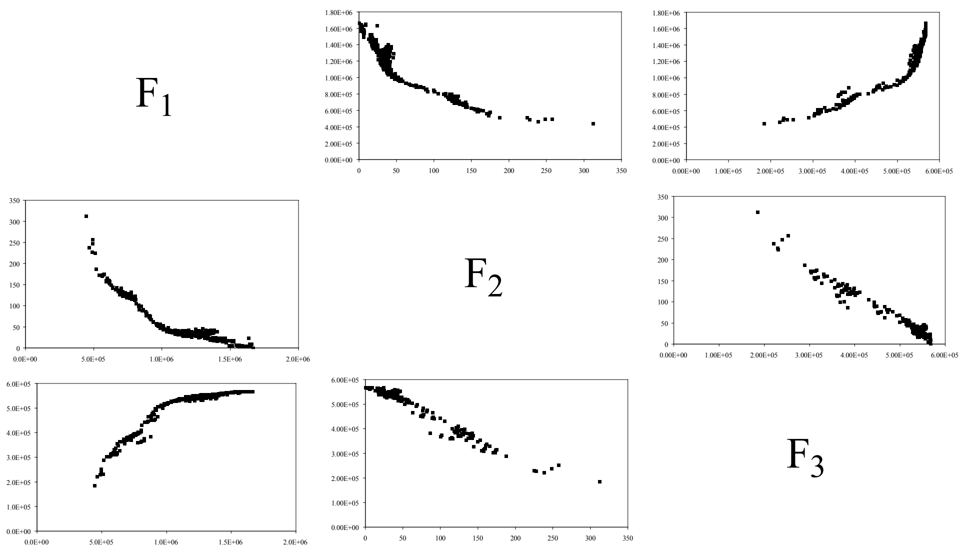

Figure 3. Scatter-matrix of a set of nondominated solutions at #9 configuration (random seed 1000)

Box plots are used to visualize the distribution of these samples. The upper and lower ends of the box are the upper and lower quartiles, while the line within the box encodes the median. According to this figure (Figure 2) the box summarize the spread and shape of the distribution.

Figure 2 shows the direct comparison based on the measure C (3.5) for both configurations. The Pareto fronts achieved by configuration that utilizes linear recombination operator configuration are entirely dominated. The configurations that contain BLX-α operator are dominated by the configurations that contain uniform operator. It is seen that the configurations that contain uniform recombination operator dominate all other configurations that not contain it. There is not clear evidence of superior performance when the results obtained for several configurations are compared among themselves for a given case. In general, it seems that the recombination operators have more influence on the Pareto front than mutation operator.

Figure 3 presents a set of nondominated solutions for configuration #9, among which a solution (F_1 = \$ 1.67E+06, F_2 = 0 m and F_3 = 567359 kW) can be identified as similar to the one that has already been pointed out by Simpson et al. (1994), considering a single objective problem, and Cheung et al. (2003) considering a two-objective problem.

The solutions of SPEA permits to the decisor-maker to visualize trade-offs (costs, pressure deficit and hydraulic benefit) and can choose a satisfactory solution that meets the needs of his system. For example, if the decision-maker accepts the solution of Figure 3, he is aware of that the cost is not minimum value and that the benefit is not obtained maximum value. It demonstrates that the multiobjective optimization technique has become a great interest area to the decision making of water distribution systems problems.

6 CONCLUSION

This paper employs an elitist multiobjective evolutionary algorithm (SPEA) to the rehabilitation problem of a water distribution network, considering the objectives of minimization of costs and pressure deficit and maximization of hydraulic benefit of network to meet water demand. It represents an effort to compare the performance of the recombination and mutation operators applied to the problem that suggests the uniform recombination operator as suitable operator to the rehabilitation problem using SPEA. Another contribution presented in this paper refers the hydraulic benefit formulation that transforms the deficiency of nodal pressures to power (kW).

Direct comparison based on set coverage metric (Equation 13) shows the poor performance of the linear recombination operator in terms of the proximity of the calculated solution to the Pareto region as in terms of processing time. However, the uniform recombination operator presents the highest performance in relation to the others considered recombination operators. These analyses also demonstrates that recombination operator has more influence on the Pareto solution than the mutation operator.

In order to obtain satisfactory results using multiobjective evolutionary algorithms for water distribution networks, it is important to choose appropriated recombination and mutation operators for reading a stable Pareto front. Finally, the potentialities of the elitist multiobjective evolutionary algorithm SPEA are demonstrated, and several future possibilities are open for resolution of water resources problems including the treatment of more realistic and complex objectives than those dealt with here.

7 ACKNOWLEDGEMENTS

The present paper has resulted from a current research grant “Tools for the Rational and Optimised Use of Urban Water (CT-HIDRO 01/2001 – 550070/2002-8)” funded by Brazilian National Research Council (CNPq). The authors wish to express their gratitude to CAPES for concession of scholarships to the first author of this work.

REFERENCES

Cheung, P.B. & Reis, L.F.R. & Formiga, K.T.M. & Chaudhry, F.H. & Ticona, W.G.C. 2003. Multiobjective evolutionary algorithms applied to the rehabilitation of a water distribution system: a comparative study. *Evolutionary Multi-Criterion Optimization.* Springer, Heidelberg. LNCS 2632: 662-676.

Dandy, G.C. & Simpson, A.R. & Murphy, L.J. 1996. An improved genetic algorithm for pipe network optimisation. *Water Resources Research,* 32(2): 449-458.

Dandy, G.C. & Engelhardt, M.O. 2001. Optimum rehabilitation of water distribution system considering cost and reliability. *Proceedings of the World Water and Environmental Resources Congress, Orlando, Florida, 2001*

Deb, K. 2001. *Multi-Objective Using Evolutionary Algorithms*. John Wiley & Sons, Ltd.

Deb, K. & Pratap, A. & Agarwal, S. & Meyarivan, T. 2000. A fast and elitist multi-objective genetic algorithm – NSGAII. *KanGAL Report Number 2000001*.

Engelhardt, M.O. & Skipworth, P.J. & Savic, D.A. & Saul, A.J. & Walters, G.A. 2000. Rehabilitation strategies for water distribution networks: a literature review with a UK perspective. *Urban Water* (2): 153-170.

Eshelman, L.J. & Schaffer, J.D. 1993. Real-coded genetic algorithms and interval-schemata. In *Foundations of Genetic Algorithms 2 (FOGA-2)*: 187-202.

Fonseca, C.M. & Fleming, P. J. 1993. Genetic algorithms for multiobjective optimization: formulation, discussion and generalization. *Proceedings of the Fifth International Conference, San Mateo 1993.*

Fonseca, C.M. & Fleming, P. J. 1995. An overview of evolutionary in multiobjective optimization. *Evolutionary Computation* 3 (1): 1-16.

Formiga, K.T.M. & Chaudhry, F.H & Cheung, P.B. & Reis, L.F.R. 2003. Optimal design of water distribution system by multiobjective evolutionary methods. *Evolutionary Multi-Criterion Optimization.* Springer, Heidelberg. LNCS 2632: 677-691.

Gessler, J. 1985. Pipe network optimization by enumeration. *Proceedings Computer Applications for Water Resources, ASCE, New York, N.Y.,* 572-581.

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

Goldberg, D.E. 1991. Real-coded genetic algorithm, virtual alphabets, and blocking. *Complex Systems*, 5 (2): 139-168.

Halhal, D. & Walters, G.A. & Ouazar, D. & Savic, D.A. 1999. Water network rehabilitation with structured messy genetic algorithm. *Journal of Water Resources Planning and Management* 123(3): 137-146.

Horn, J. & Nafpliotis, N. 1994. Multiobjective optimization using the niched pareto genetic algorithm. *Proceedings of the First IEEE Conference on Evolutionary Computation, IEEE World Congress on Computational Intelligence,* 1: 1-32.

Jaskiewicz, A. MOMHLIB++: Multiple Objective Metaheuristics Library in C++. *http://www-idss.cs.put.poznan.pl/~jaszkiewicz/MOMHLIB.*

Kapelan, Z. S. & Savic, D. A. & Walters, G. A. 2002. Multi-objective sampling design for water distribution model calibration. *Proceedings 3rd International Conference on Environmental Management*, Johannesburg, RSA.

Kim, J.H. & Mays, L.W. 1994. Optimal rehabilitation model for water distribution systems. *Journal of Water Resources Planning and Management*, ASCE, 120(5): 674-692.

Kleiner, Y. & Adams B. J. & Rogers, J. S. 1998. Long-term planning metodology for water distribution system rehabilitation. *Water Resources Research*, 34(8): 2039-2051.

Michalewicz, Z. 1992. *Genetic Algorithms + Data Structures = Evolution Programs*. Springer-Verlag, New York, N.Y.

Reis, L.F.R. & Porto, R.M. & Chaudhry, F.H. 1997. Optimal location of control valves in pipe networks by genetic algorithm. *Journal of Water Resources Planning and Management.* 123(6): 317-326.

Rossman, L. A. 2000. *EPANET 2, USERS MANUAL*. U. S. Environmental Protection Agency, Cincinnati, Ohio.

Savic, D.A. & Walters, G.A. 1997. Genetic algorithms for least-cost of water distribution networks. *Journal of Water Resources Planning and Management*, ASCE, 123(2): 67-77.

Simpson, A. R. & Dandy, G.C. & Murphy, L. J. 1994. Genetic algorithms compared to other techniques for pipe optimization. *Journal of Water Resources Planning and Management*, ASCE, 120 (4): 423-443.

Srinivas, N. & Deb, K. 1995. Multiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary Computation*. Massachusetts Institute of Technology, 2(3): 221-248

Veldhuizen, D. V. 1999. *Multiobjective Evolutionary Algorithms: Classifications, Analyses, and New Innovations*. Ph. D. Thesis, Dayton, OH: Air Force Institute of Technology.

Walski, T.M. 2001. The wrong paradigm, why water distribution optimization doesn't work. *Journal of Water Resources Planning and Management* (Editorial), ASCE, 123(3): 203-205.

Walters, G.A. & Halhal, D. & Savic, D.A. & Ouazar, D. 1999. Improved design of anytown distribution network using structured messy genetic algorithms. *Urban Water*, 1: 23-38.

Wright, A. 1991. Genetic algorithms for real parameter optimization. In *Foundations of Genetic Algorithms 2 (FOGA-1)*: 205-218.

Wu, Z.Y. & Simpson A.R. 2001. Competent genetic-evolutionary optimization of water distribution systems. *Journal of Water Resources Planning and Management*, ASCE, 15(2): 89-101.

Zitzler, E. 1999. Evolutionary algorithms for multiobjective optimization: methods and applications. Ph. D. Thesis, Switzerland, Swiss Federal Institute of Technology Zurich.