15th Triennial World Congress, Barcelona, Spain

MULTIOBJECTIVE OPTIMIZATION OF DYNAMIC PROCESSES BY EVOLUTIONARY METHODS

B. Andrés-Toro, E. Besada-Portas, P. Fernández-Blanco, J. A. López-Orozco, J. M. Girón-Sierra

Departamento de Arquitectura de Computadores y Automática
Universidad Complutense de Madrid
28040 Madrid, España
deandres@dacya.sim.ucm.es

Abstract: The real-world optimisation of dynamic processes, such as batch processes, space applications and robotic problems, is usually a matter of several objectives and constraints. In many cases it is difficult to deal with such problems with conventional methods. Evolutionary methods provide an interesting alternative, with less programming and computational efforts. This paper presents four Evolutionary methods for solving complex multiobjective problems applied to an illustrative example: the optimisation and control of the industrial beer fermentation. The first method is based on aggregating functions, and the others adopt a Pareto set approach. *Copyright © 2002 IFAC*

Keywords: Multiobjective Optimisation, Genetic Algorithms, Industrial Control, Optimal Control, Multivariable Control Systems, Fermentation Processes, Batch Control.

1. INTRODUCTION

As an alternative to conventional optimisation methods, Genetic Algorithms (GAs) offer the opportunity of getting satisfactory results with less computational cost and with simple programming. Their multiobjective variants, Multiobjective Evolutionary Algorithms (MOEAs) can be used to deal with the multiobjective nature of many real-life problems.

In this work a combined problem is considered: to get an optimal trajectory for a dynamic system and, at the same time, to get a dynamic control effort (to drive the system along the optimal trajectory) with good properties. This is a multiobjective problem.

An example of such problems is beer fermentation, a multivariable problem that can be solved using eight different objectives. The fermentation is a batch process controlled along time by a temperature profile (Ramirez, 1994). To achieve the temperature trajectory, sometimes heat must be extracted from the system and sometimes added. The industry wants to get good beer in less time: this is a goal of this research. But the control efforts to make the process follow the temperature profile must be feasible: this is another goal of the research. The quality of the beer is ensured if certain constraints concerning ethanol and by-products are fulfilled.

The optimisation objectives and constraints have been handled in different ways during this investigation. The first approach was to joint five objectives and constraints in a single aggregating function. A second stage of the research was to use MOEAs based on Pareto sets, to be able to include more complex scenarios of optimisation objectives. During this stage, first the dimension of the problem was expanded by considering what happens with the heat. Second, the objective of minimizing the total process time was also considered. And finally a new individual representation with variable time intervals designed for the problem was introduced.

The GAs have been implemented with EVOCOM, a Matlab Toolbox for Evolutionary Algorithms developed in the Department during the last two years (Besada-Portas *et al.*, 2001a,b).

The paper begins introducing the process example. Afterwards, the different multiobjective evolutionary optimisation methods are described, using the example. Finally, some conclusions are presented.

2. PROBLEM FORMULATION

The beer fermentation starts after mixing yeast and wort. At the beginning the biomass (yeast) is in a latent state, and after a lag phase of some hours, it becomes active. Active biomass is the main responsible of the fermentation process. During the fermentation, ethanol, diacethyl and ethyl acetate are produced. The temperature profile followed during the process determines the final quantities of these products, which are used by the industry to measure the quality of the beer. Besides, all the process can be spoiled by *Lactobacillus plantarum*.

The process has been analysed in a pilot plant fermenter in compliance with industrial conditions (avoiding stirring and using industrial materials) to obtain realistic results. After more than 200 fermentations for acquiring the necessary knowledge and data, a mathematical model of the process (Andrés-Toro *et al*., 1198b) was obtained.

The final goal of the study is to obtain a temperature profile, which can be implemented by the industry (that is with a feasible external heat profile), that minimises the time of process and contamination risk, while fulfilling the ethanol, diacethyl and ethyl acetate final concentration constraints. Taking into account all these goals, eight different optimisation objectives are used in the different implemented MOEAs (fig.1). Three of them are considered constraints and the others, objective functions to be optimised. Constraints are understood as high-priority (hard) objectives, which must be satisfied before optimising the remaining objectives (soft).

Table 1 shows the specifications of the objectives and constraints. The constraint J_1 is the final ethanol concentration: it must be at least 60g/l. The other two constraints are the final concentrations of diacethyl (J_2) and ethyl acetate (J_3). The industry imposes limits of 0.2ppm and 15ppm in the diacethyl and acetate final concentrations respectively.

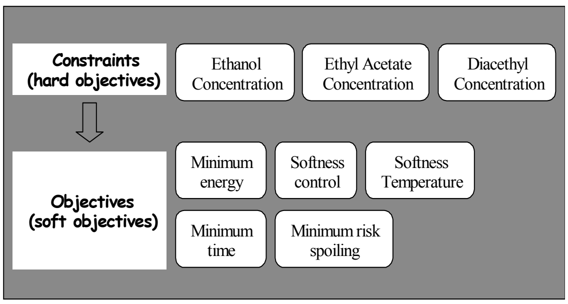

Fig. 1. Beer Fermentation Multiobjective Problem.

The first soft objective (J_4) to be minimised measures the risk of beer spoiling by *Lactobacillus plantarum*. This risk increases a lot with temperatures over 16ºC.

The temperature profiles obtained based only on J_1, J_2, J_3 and J_4 are too jagged, and therefore the industry cannot implement them. So, a new objective (J_5) for minimising abrupt changes of temperatures is added to the optimisation. To further improve the smoothness of the temperature profile hill climbing procedures were added, as a final local optimisation step, to the GAs (Andrés-Toro *et al.*, 1998a), obtaining better profiles.

Table 1. Objectives of the Problem

Obj	Function	Meaning	T_1	T_2	T_3
J_1	$ethanol_{end}$	Ethanol final concentration	H0	o	Q
J_2	$diacethyl_{end}$	Diacethyl final concentration	H0	u	Q
J_3	$acetate_{end}$	Acetate final concentration	H0	u	Q
J_4	$\int_0^t \mu_{LB} \cdot dt$	Spoiling Risk	S0	m	R
J_5	$\sum_{i=1}^{time} abs(T_{i+1}-T_i)$	Temperature Smoothness	S0	m	C
J_6	$\sum_{i=1}^{time} Q_i^2$	Total and Instant Heat	S0	m	C
J_7	$\max\left\|Q_{i+1}-Q_i\right\|$	Heat Smoothness	S0	m	C
J_8	*Time*	Process Time	S0	m	T

However, the control efforts (adding or extracting heat) to get the optimal temperature profile were not smooth enough to make them applicable. So, new soft objectives (J_6 and J_7) were incorporated to improve the control. J_6, implemented as a summation of the square of the heat consumed every 0.1 hour, is used to minimise both the total and instant heat cost of the process. J_7, the maximum difference of heat between two successive intervals, is used to force uniform consume and so to smooth the energy cost.

The last objective is the time of the process (J_8) which if possible, should also be minimised.

The last three columns of table 1 display how the different objectives are considered during the optimisation process. T_1 shows if the objective is considered a constraint (Hard Objective H0) or a function to be optimised (Soft Objective S0); T_2 if the value should be over (o) or under (u) a threshold, or minimised (m); and T_3 if it is related with the quality (Q) of the beer, the spoiling risk (R), the control (C) or the time (T).

3. MULTIOBJECTIVE GENETIC ALGORITHMS

3.1 Genetic Algorithms Description

A great number of GA variants have been developed, during the last years, for different problems (Michalewicz, 1999). For this problem, panmitic, elitist, with tight linkage GAs are implemented. They use selection, crossover and mutation operators, whose probabilities have been chosen following the results obtained in previous research (Andrés-Toro *et al*., 1999). They include a local search operator to improve the solutions cyclically. The population size is variable and they admit immigrants (some new individuals created randomly every generation).

Each individual of the population represents a temperature profile as a sequence of temperature values. The simplest way to represent it is using a piecewise approximation of the temperature profile. In the three first algorithms, the profile is divided into equal intervals of one hour, and the temperature values at the breakpoints are recorded. The sequence of numbers obtained is considered an individual and each gene represents the temperature after an hour. Every gene is a real number between 10ºC and 18ºC. An example can be seen in figure 2 (upper graphic).

The size of the intervals can be used as another variable of the problem. In the last GA presented, each individual stores the information of the temperature at the breakpoints and the interval size. The GA will determine all the values itself. An example can be seen in figure 2 (lower graphic).

3.2 Multiobjective Genetic Algorithms

In multiobjective problems all the components of the vector which stores the different objectives should be optimised simultaneously. These problems usually have no unique solutions, but a set of nondominated solutions, known as the Pareto-optimal set (Miettinen, 1999).

Figure 3 shows an example of a problem with two objective functions and the Pareto-optimal set. In the example, minimizing an objective means to increase the other: a good compromise is near the origin.

Many different MOEAs have been presented in the literature (Coello, 1999; Ban Veldhuizen, 2000). They can be classified in two groups: aggregating functions and non-aggregating functions. The use or not of the Pareto set approach is also another criterion for classifying MOEAs.

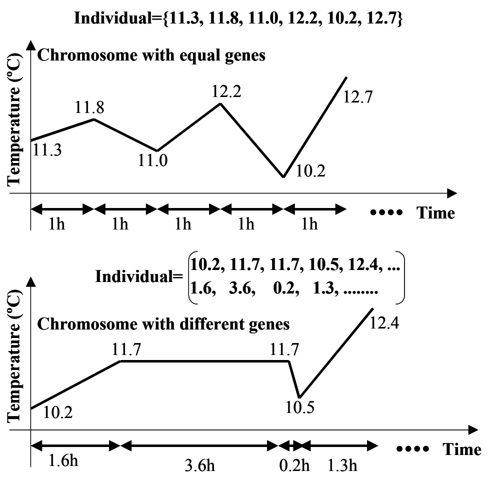

Fig. 2. Individual Representations of the Problem.

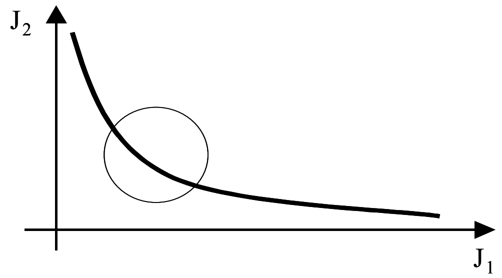

Fig. 3. An Example of Pareto-optimal Set.

The fermentation problem is solved with GAs that implement both techniques, allowing us to compare the results. Let us describe in order the different solutions studied along the research.

The first algorithm makes use of an aggregating function. The other three GAs implement a non-aggregating function, based on Pareto-optimal sets. All the algorithms are implemented with EVOCOM.

GA based on Aggregating Function. The first GA implemented for solving the problem uses a Weighting Sum Approach. In this way the multiobjective problem is converted in a monoobjective problem. Some knowledge of the objective functions must be used to be successful with the technique of Aggregating Functions. The main advantages of these techniques are the simplicity of the implementation and the computational efficiency. However, they have the disadvantage of missing concave portions of the trade-off curve.

In this first algorithms only the three constraints and the two first objectives were included. The final goal is minimising the next sum:

$$J = \min(10 \cdot J_1 - 5.73 \cdot e^{(95 \cdot J_2 - 18.42)} - 1.16 \cdot e^{(460 \cdot J_3 - 66.77)} - 0.1 \cdot J_4 - 0.01 \cdot J_5)$$

The constants are the weights used to balance the importance of the objectives. The weights were determined experimentally after several tests using information about the model and the importance of each objective. The exponential terms with J_2 and J_3 are used to penalize the violation of the limits of the final by-products concentrations. Note that the process time is not yet subject of optimisation.

GA based on Non-Aggregating Functions. In order to get flexibility for more complex scenarios, a multiobjective approach based on Pareto-optimal sets was used in the next GAs. Three GAs which differ in the way of dealing with the time of process were implemented under this approach.

Goldberg (1989) introduced the idea of Pareto-based fitness assignment. It makes easy to increase the number of objectives, and avoids better the local optima. An interesting advantage of these techniques is that the solution of the problem can be a set with several solutions considered equally good by the GA. Many researchers have developed different MOEAs according to Goldberg's idea. Fonseca and Fleming (1998) proposed a multiobjective method based on goals, priorities and Pareto sets. The objectives are ordered in different priority levels and constraints for each of them can be imposed. The method is advantageous because it can see a concave trade-off surface as convex in some cases. Its main drawback is that it favours some objectives over others, and so it makes the population converge to a particular part of the Pareto set, rather than to cover it totally.

In line with the approach by Fonseca and Fleming several priority levels have been considered by our next three GAs. The method was modified, so all the hard objectives are set to the same value once the constraints have been reached, and the soft objectives are discretised into intervals. These changes, which can make two different individuals have the same objective values, and so be considered equally good, speeds up the GA.

Figure 4 shows the ranking of levels for the beer fermentative process and summarises the differences among the three GAs. All the three look first to the constraints (J_1, J_2 and J_3) because they must be satisfied before optimising the others. Once the constraints satisfaction is guaranteed the procedure works with the second level. This level is dedicated to minimise the spoiling risk (J_4), the total and instant heat (J_6) and the heat smoothness (J_7). Finally the procedure goes to the third level dedicated to the temperature smoothness (J_5).

The way the three GAs handle time is as follows:

The first of them, Multiobjective by Levels (ML), considers that the time interval and total process time are constants in each experiment. The algorithm is run for different process times and the solutions for each of them compared.

The second algorithm, Constant Interval Multiobjective (CIM) optimises also the total process time and so a new objective (J_8) is included. The size of each interval is kept constant in this GA.

For the last one, Variable Interval Multiobjective (VIM), the size of each interval is also a variable of each individual. New crossover, mutation and initialisation operators, which include knowledge about the problem, are implemented (easily with our toolbox EVOCOM) for VIM. The algorithm also optimises the total time of the process.

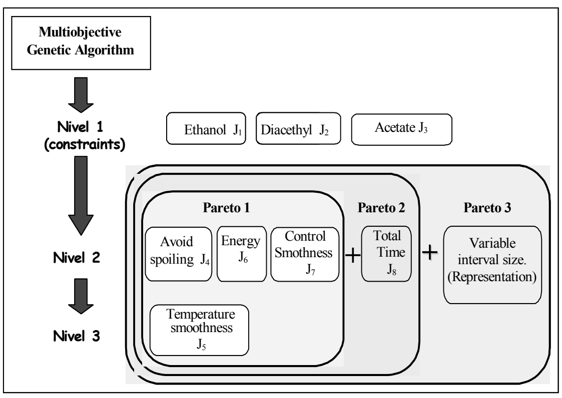

Fig. 4. Non-Aggregating Function GAs.

4. EXPERIMENTAL RESULTS

In this section some experimental results obtained with the different GAs explained in this paper are shown. Figure 5 displays the temperature and energy profiles that actually breweries are applying. The objective of this research is to improve these profiles. When analysing the figures, note that the energy and temperature axis are not the same in all the cases.

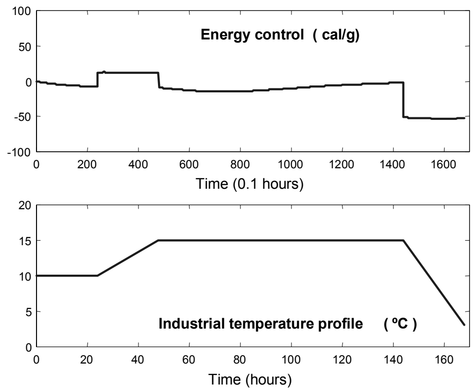

Fig. 5. Industrial Fermentation Profile.

4.1 Results of Aggregating GA

This Aggregating GA was our first approach to solve the problem. It was run for different process times, from 120 hours to 160 hours.

Good results were obtained considering only the five objectives used in this GA. Figure 6 shows the results obtained with the 150 hour optimisation. Although the temperature profile reached is quite smooth, this algorithm obtains an energy control really difficult to apply due to the peak of energy that must be applied at the beginning. After analysing these results, it was clear that new optimisation objectives should be included for obtaining more feasible energy managements (no steep peaks).

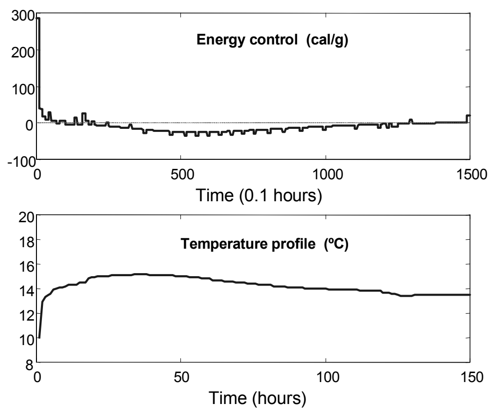

Fig. 6. Profiles for the Aggregating GA.

4.2 Results of ML Algorithm

New objectives (J_6 and J_7) were added to improve the energy profile and a Pareto set approach used to deal better with the complexity of the new scenario.

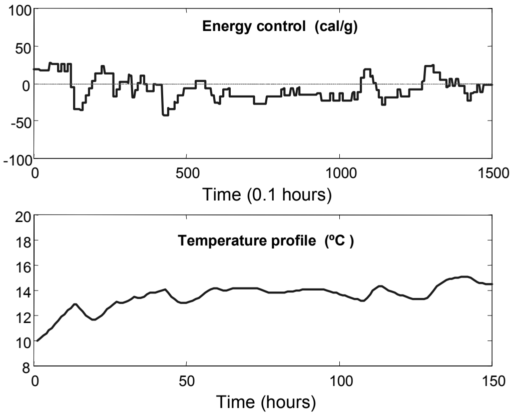

Fig. 7. Profiles with ML.

The first Pareto set based GA (ML) was run for constant process times, from 120 hours to 160 hours. Figure 7 shows the results for 150 hours. The new objectives used for optimising the control and the new GA specification (Pareto set fitness) show improvements compared to the results of the Aggregating GA. The initial great peak has disappeared and the control is smoother with less energy consume.

4.3 Results of CIM Algorithm

After the promising results of the previous GA, an additional objective, minimising the time of process (J_8) was included. A new algorithm, denoted CIM, was developed. The range for the total process time was defined between 120 and 160 hours. This algorithm searches for optimal profiles with optimal time inside this range. The result found by CIM was of 125 hours. Figure 8 shows the solution of this GA.

Although the total process time is optimised by CIM, the control profile obtained is too irregular for practical application. Furthermore, after repeated running of the three previous GAs, different optima where obtained which showed that all the algorithms were falling in local optima.

This situation can be improved incorporating specific problem knowledge to the algorithm. That leads to the last GA presented in this paper.

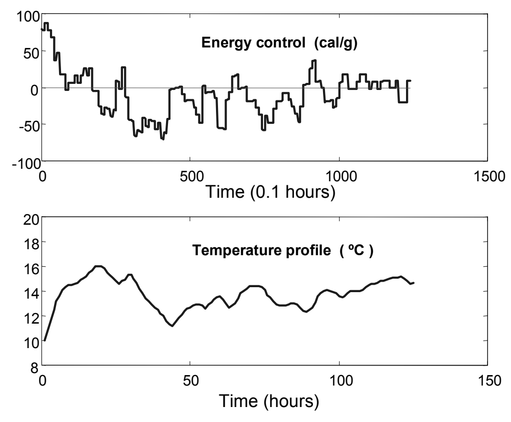

Fig. 8. Profiles with CIM.

4.4 Results of VIM Algorithm

VIM algorithm considers the length of the intervals as variables included in the individuals. Variable time intervals mean two important advantages. First, the initial population, created at random, corresponds to smoother initial solutions. Second the size of the Pareto set increases, and so local optima are more easily avoided.

The results presented in this paper are selected from the final Pareto-optimal set (of ninety different optima solutions) returned by VIM. Its large size give us an interesting freedom for selecting a practical solution. Users can compare the different solutions and choose the one they prefer according with any of the optimisation criteria or a compromise among several of them. Different examples are shown below.

This individual representation is also advantageous because the individuals are smaller (they need less storing space). The total process time is represented with a moderate number of time intervals, and a temperature for each of them.

Let us show some of the solutions selected from the final VIM Pareto set according with different beer industrial requirements.

Figure 9 shows the solution with minimal instant heat (J_6), especially interesting if minimising the total and instant energy consumption is an important requirement. The total fermentation time is 145 hours a both the energy and temperature profiles are very smooth, and so they can be easily applied by the industry. Not only has the energy cost been reduced (half of the industrial one) in this solution, but also the time has been decremented (in 20 hours) and the smoothness of the energy and temperature profiles improved. So, this temperature profile is better than the industrial one and could be a good selection.

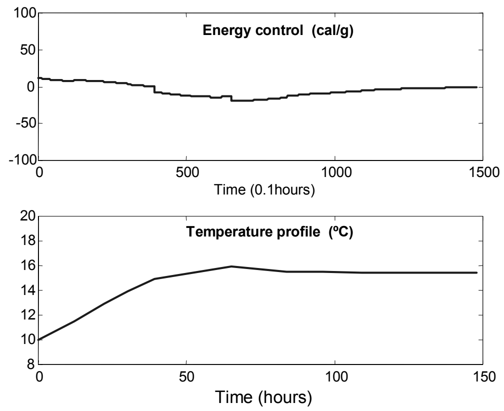

Fig. 9. Profiles with VIM and Minimum J_6.

However, if minimising the total process time (J_8) is an important requirement and the improvement of 20 hours is not enough, the individual of the Pareto-Optimal set with minimum process time (120 hours) can be selected. Figure 10 shows the corresponding profiles.

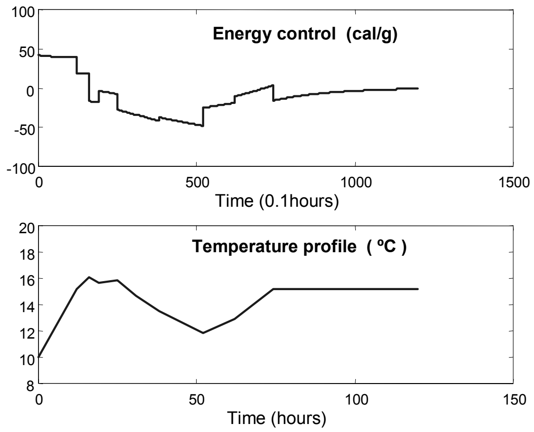

Fig. 10. Profiles with VIM and Minimum J_8.

The profile which requires minimum total time means an improvement of 48 hours with respect to the industrial process. However, the energy and temperature profiles are more jagged, which will make more difficult their application. The industry should decide if the time improvement justifies the control difficulties.

Of course many other solutions could be considered, selecting other optimisation objectives and compromises between them.

5. CONCLUSIONS

This paper has presented several Evolutionary methods to deal with multiobjective optimisation of dynamic processes. One of the methods is based on an aggregating function, while the others adopt a Pareto set approach.

As an example of the type of processes where the multiobjective optimisation methods can be applied, the paper takes the case of beer fermentation. The problem is to find an optimal trajectory of the process *and* an optimal control effort profile, fulfilling some constraints. Many other different cases, such as batch chemical processes, spacecraft motions, mobile robotics path planning and following, etc., could be also considered by our methods (perhaps with minor adaptations).

The main advantage of the multiobjective GAs is their versatility for including a variety of objectives and constraints. The VIM optimal set lets users select amongst different solutions, all equally good for VIM, according with some final requirements.

In particular, the VIM beer fermentation profile with minimum total and instant energy cost improves the heat waste, reduces the total process time, and smoothes the control.

Acknowledgments

The authors want to thank the support of the CICYT Spanish Committee (Project TAP97-0607-C03-01).

REFERENCES

Andrés-Toro, B., J.M Girón-Sierra, J.A. López-Orozco, C. Fernández-Conde, P. Fernández-Blanco, (1998), A Fast Genetic Optimization for Batch Fermentation Processes. *7th International Conference on Computer Application in Biotechnology*. Osaka (Japan). 61-66.

Andrés-Toro, B., J.M. Girón-Sierra, J.A. López-Orozco, J.M. Peinado (1998). A Kinetic Model For Beer Production Under Industrial Operational Condition: *Mathematics and Computers in Simulation,* Vol.48 nº 1**,** nov.98, 65-74.

Andrés-Toro, B., J.M. Girón-Sierra, J.A. López-Orozco, J. Álvarez-Ruiz, P. Fernández-Blanco (1999). A Genetic Optimization Method for Dynamic Processes. *Proceedings of the 14th World Congress. IFAC* Beijing, P.R. China, 5-9 jul. 99, Vol.C, 373-377. Pergamon Editorial.

Besada-Portas, E., J.A. López-Orozco, B. Andrés-Toro (2001a). EVOCOM ver 2.0: A Multipurpose Evolutionary Algorithm Toolbox. Technical Report Dacya 01/01. Dpto de Arquitectura de Computadores y Automática. UCM. January 2001

Besada-Portas, E., J.A. López-Orozco, B. Andrés-Toro (2001b). A Versatile Toolbox for Solving Industrial Problems With Several Evolutionary Techniques. Admitted to be presented in *EUROGEN2001*.

Coello Coello, C.A. (1999). An Updated Survey of GA-Based Multiobjective Optimization Techniques. *ACM Computing Surveys*. Vol. 32. nº 2. June 2000, 109-143.

D.A. Ban Veldhuizen, G.B Lamont. Multiobjective Evolutionary Algorithms: Analysing the State-of-the-Art. (2000) *Evolutionary Computation* 8(2):149-172.

Fonseca, C.M. and P.J. Fleming (1998). Multiobjective Optimization and Multiple Constraint Handling with Evolutionary Algorithm-Part I: Unified Formulation. *IEEE Transactions on Systems, Man, and Cybernetics. Part A: Systems and Humans*. Vol. 28, nº 1. January 1998, 26-37.

Goldberg, D.E. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley Publishing Co., Inc., Redwood City, Ca.

Michalewicz, Z. (1999). *Genetic Algoritm + Data Structures = Evolution Programs*. 3rd Edition. Springer-Verlag.

Miettinen, K.M. (1999). *Nonlinear Multiobjective Optimization*. Kluwer Academic Publishers.

Ramirez, W.F. (1994). *Process Control and Identification.* Academic Press.