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Mutual benefits of two multicriteria analysis methodologies: A case study for batch plant design

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A B S T R A C T

This paper presents a MultiObjective Genetic Algorithm (MOGA) optimization framework for batch plant design. For this purpose, two approaches are implemented and compared with respect to three criteria, i.e., investment cost, equipment number and a flexibility indicator based on work in process (the so-called WIP) computed by use of a discrete-event simulation model. The first approach involves a genetic algorithm in order to generate acceptable solutions, from which the best ones are chosen by using a Pareto Sort algorithm. The second approach combines the previous Genetic Algorithm with a multicriteria analysis methodology, i.e., the Electre method in order to find the best solutions. The performances of the two procedures are studied for a large-size problem and a comparison between the procedures is then made.

1. Introduction and objectives

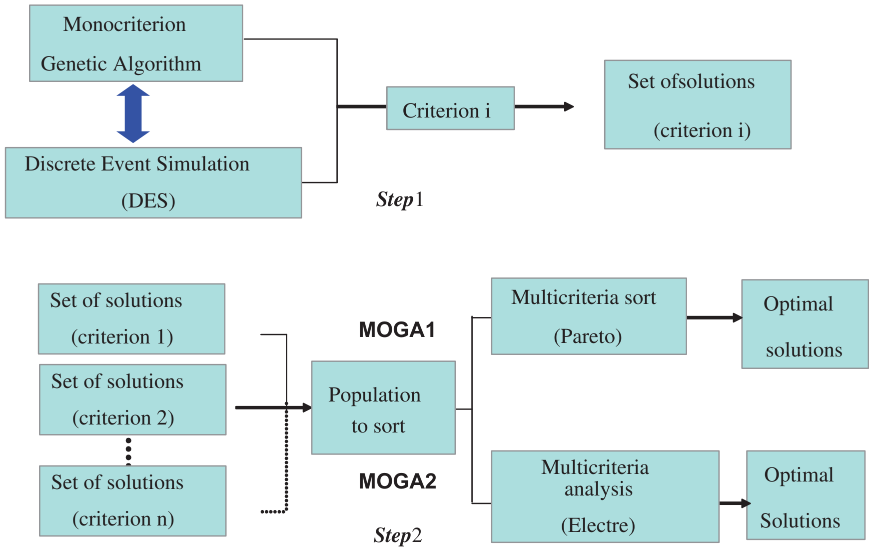
Batch plant design is a traditional and recurrent problem in Process Systems Engineering. It has been tackled by various approaches, involving either deterministic or stochastic methods. A classification is proposed in Bernal-Haro et al. (2002). Due to the combinatorial and multiobjective nature of the problems, Genetic Algorithms (Goldberg, 1989) appear good candidates to solve the problem. On the one hand, the combinatorial aspect may result from the number and size of each equipment item (most often considered as a discrete number) involved in the process, the number of managing rules, etc. On the other hand, the rigorous treatment of batch plant design requires simultaneous optimization of more than one objective function: for instance, a good design attempts simultaneously to minimize a cost criterion (either based on investment or net present value), maximize the inherent flexibility of the plant and minimize the environmental impact. In that context, MultiObjective Genetic Algorithms (MOGAs) are particularly attractive to optimize several conflicting objectives and to explore the trade-offs between conflicts and constraints inherent to this process. They extend the standard evolutionary-based optimization technique (for more detail, see Baudet et al., 1998; Bernal-Haro et al., 2002) to allow individual treatment of several objectives simultaneously. This is consistent with the increasing complexity of decision-making problems which requires the use of more flexible and open approaches, thus providing a more realistic and effective resolution of problems than that offered by the traditional approach in decision making (Bhaskar et al., 2000).

In this work, two approaches are implemented to solve a batch plant design optimization problem with respect to three criteria, i.e., investment cost, equipment number and a flexibility indicator based on Work In Process (the so-called WIP) computed by use of a Discrete-Event simulation model previously developed (see Bernal-Haro et al., 2002). The former is based on a Pareto sorting algorithm whereas the latter uses a multicriteria decision analysis framework, i.e., the Electre methodology.

The two procedures are based on a two-step approach (see Fig. 1), in which the first step is common:

i. At the inner level (slave problem), the AD-HOC[1] discrete-event simulator is used to evaluate different batch plant configurations, thus solving the underlying scheduling phase (see Bernal-Haro et al., 2002).
ii. At the upper level (master problem), the search strategy for finding the most interesting configurations from a given criterion viewpoint is achieved by use of a classical mono-criterion Genetic Algorithm (GA). The size of the chromosome is defined by the maximum number of operations in the recipe list and each gene encodes the number of parallel equipment for each available size into a string of decimal digits. All variables are integer values.

[1] *AD-HOC*: *Ateliers Discontinus-Heuristiques et Ordonnancement à Court-terme.*



The procedures then differ by the multicriteria optimization procedure. On the one hand, multicriteria optimization is implemented using a Pareto algorithm, which is based on the search for good configurations found by the GA, and the solutions are optimum in the sense of Pareto. Let us recall that this definition says that a vector $\mathbf{x}^*$ is Pareto optimal if there exists no feasible vector of decision variables $\mathbf{x}$ which would decrease some criterion without causing a simultaneous increase in at least one other criterion. Unfortunately, this concept almost always gives not a single solution, but rather a set of solutions called the Pareto optimal set. The vectors $\mathbf{x}^*$ corresponding to the solutions included in the Pareto optimal set are called non-dominated. The plot of the objective functions whose non-dominated vectors are in the Pareto optimal set is called the Pareto front.

On the other hand, the Electre methodology is adopted (see Roy, 1985), thus offering the decision maker the ability to take into account quantitative and qualitative criteria. As already mentioned, three quantitative criteria are defined but this may be not restrictive (for instance, environmental considerations can also be taken into account).

This paper is organized as follows. Section 2 is devoted to the problem presentation and model formulation. The Multicriteria Genetic Approach combined with an optimization solving is then presented in Section 3 whereas the Multicriteria Genetic Approach combined with the ELECTRE methodology is described in Section 4. The studied case is tackled in Section 5 and the associated results are presented and analyzed. Conclusions and perspectives constitute the core of Section 6.

2. Problem presentation and model formulation

2.1. Literature review

Due to growing interest in batch operating mode, many studies in the chemical engineering community deal with the batch plant design issue. A critical review on the design and retrofit of batch plants is proposed in Barbosa-Póvoa (2007). Basically, batch plants are composed of items operating in a discontinuous way. Each batch then visits a fixed number of equipment items, as required by a given synthesis sequence (the so-called production recipe). The traditional approach used in solving the batch plant design problems has been to formulate it either as a single-objective, mixed integer linear programming (MILP) or as a mixed integer non-linear programming (MINLP) problem and to solve it by employing mathematical programming techniques or optimization techniques, such as branch and bound, heuristics, genetic algorithm, simulated annealing. A typical example concerns minimization of investment cost for all items involved in the plant, which optimizes the number and size of parallel equipment units in each stage. The production requirements of each product and data related to each item (processing times and cost coefficients) are specified, and fixed global production time is also specified. Although many studies deal with the multiproduct batch plant design as reported in Rauch (2003) and Barbosa-Póvoa (2007), the multiobjective plant in which all the products do not necessarily follow the same operating steps has received less attention (Voudouris. and Grossmann, 1996; Petkov Spas and Maranas Costas, 1998; Barbosa-Póvoa et al., 2001; Lin and Floudas, 2001; Cavin et al., 2004; Mosat et al., 2007), due to the difficulty of embedding this kind of constraints in a mathematical formulation. This is why an alternative technique is chosen here to take the multiobjective batch plant structure into account: a classical solution in the operational research community consists in using Discrete-Event Simulation techniques (Fishman, 2001) to model the different paths in which the products flow inside the plant, since the complexity renders mathematical programming approaches quite prohibitive (Bernal-Haro et al., 2002; Dietz et al., 2005). This solution has been adopted in this work. This remark is all the more valid as the multiobjective optimization framework is concerned (Mosat et al., 2008).

2.2. Problem formulation

For each plant structure proposed by the upper-level optimization loop, the technical feasibility of the plant is tested, and for each feasible solution, the various objectives are computed, at the inner level of the procedure. The Discrete-Event Simulator AD-HOC previously developed for solving short-term scheduling problems (Baudet et al., 1998), and extended to design and retrofit purposes on a long-term horizon (Bernal-Haro et al., 2002), is implemented at the inner level, where the problem can be formulated as follows:

Given

- set of N products to be manufactured,
- set of equipment items classified according to their functions in families,
- manufacturing recipes for each product and the associated operating times,
- set of all possible equipments for each product,
- stable or unstable state of intermediate products,
- available levels of utilities,
- transfer times between equipment units,
- storage availability,

the objective is to determine a plant configuration (i.e. number and capacity of both equipment units and storage vessels) in order to minimize investment cost and to maximize the flexibility of the plant. The criteria will be presented in more detail in the dedicated sections. But, it must be pointed out at that level that two criteria were chosen to account for flexibility: the former is relative to the number of campaigns necessary to reach a pseudo-state regime from an empty plant. The lower this number, the best flexible the plant. The latter is relative to different sizes in each unit operation, which has also to be minimized. This criterion was chosen in our previous works since the minimization of the number of different unit sizes of plant equipment leads to minimizing the number of human operation in order to avoid cross contamination. It has been shown that the criteria exhibit pairwise an antagonist behavior (Dedieu et al., 2003).

2.3. Discrete size of equipment

In the literature dedicated to batch plant design (see Ponsich et al., 2007), the item sizes (volumes for batch stages and treatment capacity for semi-continuous stages) are continuous variables. Yet, it seems obvious that in the industrial practice, the design of operation unit equipment does not require such a level of accuracy, which seems not realistic. Besides, equipment manufacturers propose the items following the defined size ranges (volumes or treatment capacity). This means that an item can only adopt a discrete number of predefined values.

2.4. Simulation data

A simulation run requires the following data: (i) plant architecture, (ii) number, amount and supply calendar of raw materials, (iii) number and nature of shared intermediate products, (iv) recycled products, (v) non-recycled products, (vi) final products, (vii) recipes and (viii) production data (simulation horizon, batch treatment priority, and batch release order).

2.5. Discrete-event simulation model

The DES AD-HOC determines the exact chronology of discrete events occurring in the plant, where the time changes by "event jump", i.e., from one event to the following one. In the simulator, raw materials, utilities, final and intermediate products and renewable resources (equipment and storage vessels) are modeled using the formalism of finite state automata. In the design and retrofit version of AD-HOC, operators are not taken into account in the renewable resources. Each finite state automaton is represented by fixed or variable attributes, and by a finite set of states and transitions between them; each transition may be conditional or predetermined.

The list of scheduled events is managed by increasing the occurrence date in the DES, so that when no more events are possible at a time, the next one is considered in the scheduled list. The process is repeated until the final time which fixes the end of the simulation, is reached. The conflict management (for example, competition of two products waiting for the same equipment) is carried out according to a decision rule library, involving classical heuristics like First In–First Out, Shortest Processing Time, etc.

It must be pointed out that discrete-event simulation tools (Arena, ProModel) could be alternatively used for simulation purposes. The main interest of using our "handmade" AD-HOC model is that it has been designed to be easily embedded in an outer optimization loop.

2.6. Simulation results

The simulator provides a wide variety of results on many variables and the most significant ones are:

- beginning/end of treatment times for each operation,
- batch sequence,
- cycle time for every product,
- information about equipment use for detecting bottlenecks,
- number of work-in-process (WIP) products (i.e. number of products which have not completed their production sequence at a given time) at fixed times given by the user and at the end of each production campaign,
- production (number and type of manufactured products).

Let us note that detailed results such as beginning/end times, batch sequence, cycle time and equipment information are often not necessary for design or retrofit problems.

2.7. Campaign mode operation

Since a long-term production level is considered in this study, the planning horizon is partitioned into a number of campaigns, each one devoted to the production of a subset of products. According to Papageorgiou and Pantelides (1996), the management and control of a batch plant is further reduced by operating in a campaign mode, where the same pattern of operations is repeated at a constant frequency, facilitating equipment polyvalence. Campaign length and batch size are assumed to be fixed, and each campaign is associated with a start date corresponding to raw materials availability.

2.8. Steady-state/oscillatory regimes

For a given plant configuration, the goal is not only to satisfy the production requirements in the studied horizon time but also to calculate a production plan minimizing the investment cost while maximizing the flexibility of the plant. The simulation is carried out from an empty workshop (no WIP) and then goes on by updating the corresponding dates at each campaign, until the imposed production level is reached (steady state or oscillatory behavior). The steady-state regime corresponds to identical values for production level (i.e. the WIP), and average and maximal residence times for a given number of consecutive campaigns (five for example). An oscillatory regime, which means that production levels per campaign and/or average and maximal residence times are alternated between two consecutive campaigns, is acceptable under the constraint that the average production level of the two last campaigns reaches the required production level for each product (see Bernal-Haro et al., 2002).

2.9. Checking plant feasibility

A plant configuration is considered to be feasible when simulation leads to a steady state or an oscillatory regime, as defined in the previous section. In that case, the criteria are computed, and control is transferred to the upper optimization level. For an unfeasible plant, the fitness is forced to zero, so that this structure does not compete for optimality in the following generations of the MOGA.

2.10. Returning to the upper level

The DES presented in this section, implemented for long-term scheduling of multiobjective plants, evaluates the plant performances for a given workshop structure. This simulator is now embedded in an optimization loop based on a MOGA for design and retrofit purposes.

3. Presentation of the GA-Pareto approach

Multicriteria optimization involves choices and criteria according to which different choices can be judged, thus an understanding of "better" and "worse". A multicriteria optimization problem consists of choosing among a set of "alternatives" an "optimal one", where optimality refers to certain criteria measuring the quality of the alternatives (Ehrgott, 2000).

As reported in Bhaskar et al. (2000) and Coello (2000), multicriteria optimization has received considerable attention in many domains of chemical engineering. Historically, the first reference to deal with such situations of conflicting objectives is attributed to Pareto in 1896. Of course, multicriteria optimization is not restricted to Pareto optimality approach. This very popular technique, which is well-suited to a GA procedure, where a set of solutions is generated, has been adopted in this study. The main features of the Pareto optimality notion are now briefly recalled. Let us consider the multicriteria optimization problem, defined by

$$\text{Min } \{f(x) = [f_1(x), \ldots, f_k(x)\}, \text{ subject to } x \in X, \quad \text{where } X \text{ is a subset of } R^n.$$

The Pareto optimal solutions can be defined as follows. A solution $x^* \in X$ is called Pareto optimal (minimization case here) if

$$\forall k \in [1, n], \; f_k(x) \leqslant f_k(x^*) \text{ and } \exists j \in [1, n], f_j(x) \leqslant f_j(x^*)$$

In most cases, the Pareto optimal set (also called the Pareto zone) is not constituted of a single solution, but involves a set of solutions, called non-dominated solutions. To characterize the Pareto zone among a population of feasible solutions, a Pareto Sort (PS) has been implemented (Dedieu et al., 2003), based on the following algorithm:

The first individual x' of the population is chosen as reference.

All individuals x of the population are in turn compared with the reference according to the following function h:

$$h_i = 0 \quad \text{if } f_i(x') < f_i(x)$$

$$h_i = 1 \quad \text{if } f_i(x') f_i \leqslant (x)$$

$$H = \prod_{i=1}^{k} h_i$$

where k is the number of criteria.

If $H = 1$, the individual x is dominated by the reference, and so excluded from the current Pareto zone; if $H = 0$, x is not dominated by x'.

When all elements of the population are tested, return to step one, where the new reference is the first individual not yet ousted and not yet chosen as reference.

The Pareto zone is obtained when all individuals of the population are either chosen as reference, or ousted.

The previously described GA and PS are now combined to define the multicriteria genetic algorithm. Several variants of GAs exist and have been widely published (Schaffer, 1985; Fonseca and Fleming, 1993; Srinivas and Deb, 1994; Deb et al., 2002). Following the principles of the Pareto ranking approach, a multiobjective genetic algorithm was developed by Dedieu et al. (2003) with a particular emphasis on structure encoding involved in a batch plant. This algorithm is taken here as a reference in order to compare the obtained results with those of the strategy investigated in this study.

First, a monoobjective genetic algorithm procedure is implemented to optimize separately each one of the k objective functions, then a PS is applied on a population obtained by merging some populations generated when solving the various monoobjective genetic algorithms.

Two procedures were initially developed (Dedieu et al., 2003): in MOGA-Version 1 (Fig. 2), the PS is applied on a population resulting on the union of the k final populations obtained when solving each one of the k MOGAs; in MOGA-Version 2, the PS is applied on a larger population, consisting of the merging of all populations generated during the solutions of the k MOGAs.

For small-sized populations in the MOGAs, Version 1 may lead to restricted Pareto zones. Version 2, requiring longer computation times, insofar as the PS may be performed on a very large population, does not exhibit this drawback. In Version 1, the PS is performed on a population of size $k \times popsize$, whereas, in Version 2, the population size concerned by the PS, is $maxgen \times k \times popsize$. In these expressions, *popsize* represents the size of populations, *maxgen* the maximum number of generations and k the number of objective functions in the multiobjective optimization problem.

In Dedieu et al. (2003), the two versions were thoroughly compared on the basis of bench mathematical functions (Viennet, 1997) with known solutions. On the one hand, this study shows that Version 1 gives too restricted Pareto zones. On the other hand, good Pareto zones are obtained with Version 2, which shows a good repeatability in the definition of the Pareto zones. Indeed, the repeatability is an important feature, because like every stochastic procedure, the MOGA has to be run several times (10 times for example), with different initial populations to solve efficiently a given problem. The final Pareto zone is defined as the superposition of the Pareto zones obtained for each MOGA run. For the sake of illustration, two numerical examples are reported below.

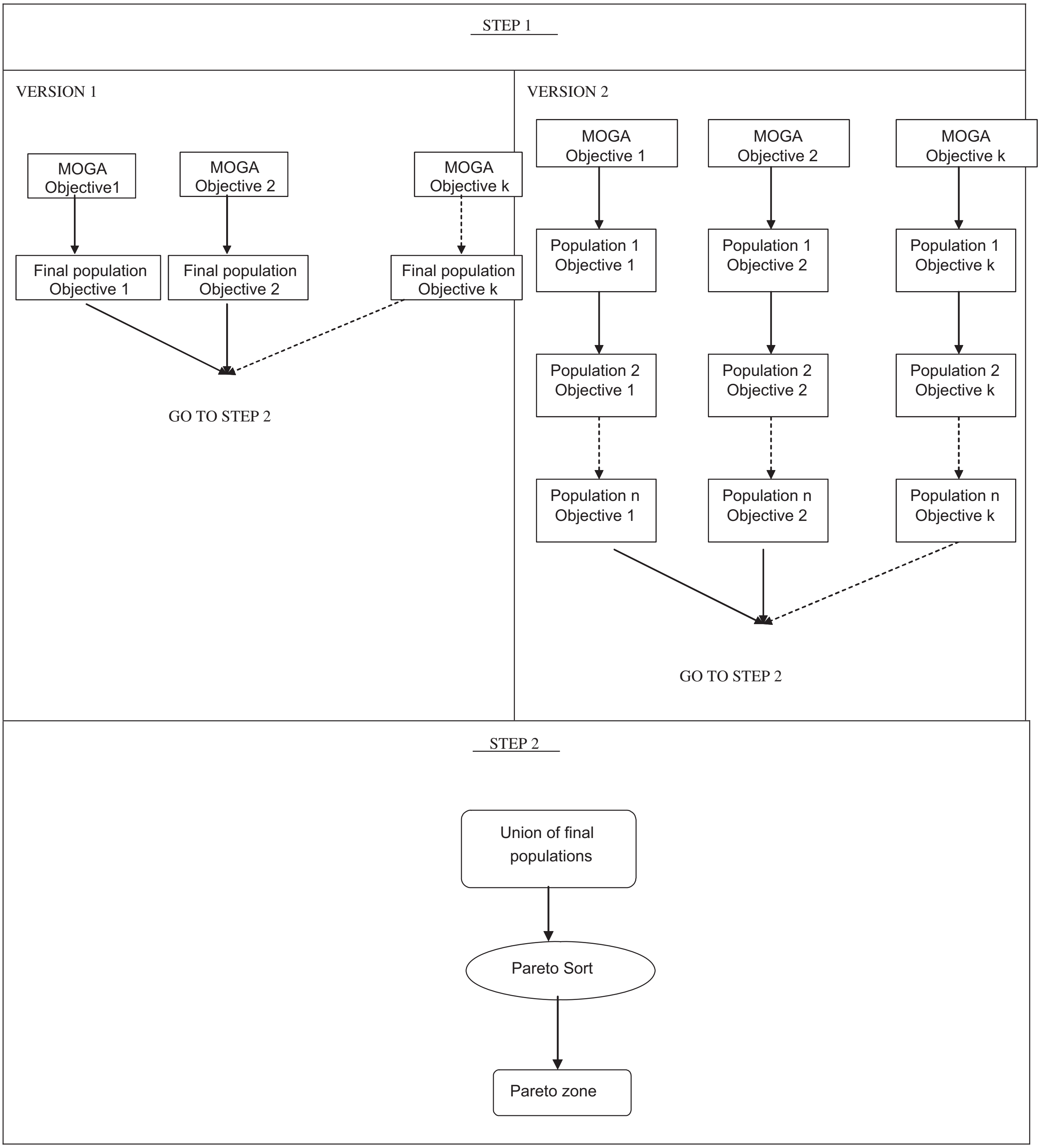
The presentation of the various steps of the Genetic Algorithm will not be recalled here in detail (Dedieu et al., 2003). Let us only mention the encoding procedure used for the design problems, since the results will be presented with this formalism.

The size of the chromosome is defined by the maximum number of operations in the whole recipe list, and each gene encodes the number of parallel equipment for each available size into a string of decimal digits. Let us consider for example a plant involving three types of operations, and three sizes for each operation. Fig. 3 shows an example of chromosome and the corresponding plant structure.

4. Presentation of GA-Electre approach

The second approach involves the following two steps:

1. The first step consists in the generation of good solutions for each criterion using the same genetic algorithm.



2. The set of solutions is ranked using the Electre methodology (for more detail about the Electre procedures, see Roy, 1985).

The alternatives to rank are those given by the different monocriterion Genetic Algorithms. The solutions are then scored on each criterion in order to give the so-called performance matrix. This matrix is usable only if the decision maker gives some weight to each criterion. All these performances and weights are aggregated by the Electre procedure through indifference and preference thresholds. The main advantage of this approach is taking into account user's expertise throughout the solving process. The Electre methodology was designed to solve decision-making problems with a qualitative approach based on decision maker's know-how.

This methodology allows decision makers to order solutions of a decision-making problem according to several criteria. Several versions of Electre (I, II, III, IV and Tri) are based on the same

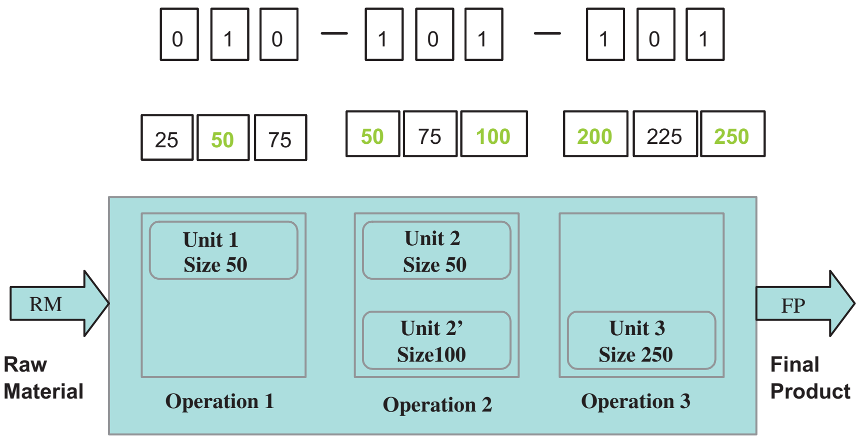


Fig. 3. Example of the encoding procedure (chromosome) and the corresponding plant structure (the equipment sizes are expressed in liters).

fundamental concepts but are different from the viewpoints of both involved mechanisms and the decision-making process. The main feature of this methodology is that the decision maker gives preferences (preference and indifference thresholds) to the system. Based on these thresholds, the system compares two actions on one criterion. An outranking by criterion is then obtained. The system then compares two actions on all criteria by calculating the concordance and discordance matrices. Finally, an outranking is obtained on all criteria.

Electre I is developed for choice problems, Electre Tri for sorting problems, Electre II, III and IV for ranking problems. In this study, the Electre III methodology was selected because it is well adapted for ranking problems and, more particularly, for outranking problems.

The objective of the next section is to describe briefly the principles of Electre methodology.

4.1. *Electre methodology*

For a set of actions A and a set of criteria, $g_j(a)$ measures the efficiency of the action a on the criterion j. A performance matrix is then defined for each action a on each criterion j. Independently, several relations (P and I) are defined *in order to* compare the actions between them.

Nevertheless, in order to avoid the pairwise comparison on each criteria, the ELECTRE methodologies include an indifference threshold q and the preference relations are defined as follows:

aPb (a is strongly preferred to b) $\Leftrightarrow g(a)-g(b)>p$	($g(b)-g(a)>p$ minimization)
aQb (a is weakly preferred to b) $\Leftrightarrow q<g(a)-g(b)\leqslant p$	($q<g(b)-g(a)\leqslant p$ minimization)
aIb (a is indifferent to b, and b to a $\Leftrightarrow \lvert g(a)-g(b)\rvert \leqslant q$	

Using thresholds, the methodology Electre tries to establish an outclassing relation S, in order to obtain a matrix called *Final Preorder Matrix*.

The aggregation procedure for which the Outclassing relation is accepted aSb uses two principles:

- Concordance principle which requires that a majority of criteria, considering their relative importance, is in favor of the S relation (majority principle);
- Discordance principle which requires that a minority of criteria are not in favor of the relation, none of them being strongly against this S relation.

The operational implementation of these two principles is then discussed, having for assumptions that all criteria must be maximized. We consider the outclassing relation S defined for each criteria r, that is aS_jb means that "a is at least as good as b for the criterion j" $j=1,\ldots,r$. The criterion j is in concordance with the relation (aSb) if and only if (aS_jb) that is if $g_j(a)\geqslant g_j(b)-q_j$. Even if the value $g_j(a)$ is less than $g_j(b)$ except a quantity until q_j that allows to verify the affirmation (aS_jb) and then the criterion is in concordance. The criterion j is in discordance with the relation (aSb) if and only if (bS_ja) that is if $g_j(b)\geqslant g_j(a)+p_j$ or if b is strongly preferred to a for the criterion j, then it is not in concordance with the affirmation aSb.

These concepts of concordance and discordance could be considered as respectively harmony and disharmony. For each criterion j, the methodology examines for each pair of actions $(a,b)\in A$, if there is harmony or disharmony with the affirmation (aSb); that is a is at least as good as b. Including these concepts, the strength of the affirmation S can be measured.

The final step consists in combining the two previously defined matrixes to obtain one unique measure, i.e. a Credibility Degrees Matrix which evaluates the strength of the affirmation "a is at least as good as b".

Two preorders are then designed, using an ascendant distillation and a descendant distillation, and these preorders are then combined to build the final preorder matrix and the final preorder graph.

The Electre methodology is used here with our expertise on the studied production plan. Weights of criteria, performance matrix and all preferences are obtained through several simulations.

5. Case study presentation

5.1. *Problem formulation*

The example, adapted from a problem presented in Dedieu et al. (2003), is related to the manufacturing of 7 products by using 10 types of equipment. The chosen example exhibits the classical features of an industrial-size batch plant (even from problem size). Unlimited utility and storage are assumed. All data are given in arbitrary units. The problem data are reported in Tables 1–3.

Table 3 involves the values of coefficients used for computing the investment cost (IC) for each type of equipment, according to the following relation:

$$IC=\alpha+\beta\times(Volume)^{\gamma}$$

Table 1
Data set for simulation.

Time horizon	30 000 (arbitrary unit)
Campaign duration	2880 (idem)
Number of campaigns	100
Equipment type	10
Number of final products	7 (A, B, C, D, E, F, G)
Number of raw materials	10

Table 2
Requirement of final product volumes per campaign.

A	2 batches of 1000/campaign
B	1 batch of 1000/campaign
C	1 batch of 1000/campaign
D	2 batches of 1000/campaign
E	1 batch of 1000/campaign
F	2 batches of 1000/campaign
G	1 batch of 1000/campaign

Table 3
Equipment cost factors.

Equipment type	α	β	γ
1	250 000	600	0.6
2	100 000	550	0.6
3	120 000	450	0.6
4	300 000	650	0.6
5	260 000	500	0.6
6	150 000	500	0.6
7	180 000	500	0.6
8	350 000	700	0.6
9	90 000	500	0.6
10	300 000	600	0.8

Table 4
Considered criteria.

Criterion 1	Investment cost
Criterion 2	(Number of equipment) × (Sum of equipment volumes)
Criterion 3	(Number of campaigns to reach the steady state or oscillatory regime) × (Number of equipment)

The available size range for each type of equipment is {2000, 1000, 500} (in l). By lack of space (10 unit operations are involved), the manufacturing recipes for the 10 products are not presented (please refer to Dedieu et al. (2003) for more precision).

Three criteria are considered (see Table 4), i.e., investment cost and two criteria related to workshop flexibility, number of equipment items and number of campaigns to reach steady state are considered. In this example inspired by the study treated in Bernal-Haro et al. (2002), the number of possible configurations is about 3.5×10^{24}. The main parameter set presented in Table 5 results from a sensibility study, which will not be reported here.

5.2. Bicriteria results

In order to analyze the problem step by step, a bicriteria study is first performed.

Table 5
Parameters for GA.

Population size	30
Generation number	20
Mutation probability	0.4
Crossover probability	0.8
Maximal number of individual copies	5

5.2.1. Results of MOGA1

The first series of results concerns the bicriteria analysis {cost; equipment number}. The optimal solutions for 10 simulations are given in Table 6.

They clearly exhibit three optimal solutions, with a major interest in C#1, since the two other solutions present greater values with order of magnitudes of 29% and 69%, respectively, which seem unacceptable even at early design stage.

The second series of results is devoted to the bicriteria analysis {cost; campaign number}. Similarly, the optimal solutions for 10 simulations are given in Table 7.

As previously observed, three optimal solutions are found. If we consider the criterion cost, the following outranking can be deduced:

C#1 < C#2 < C#3

If we consider the criterion campaign number, the inverse outranking is exhibited:

C#3 < C#2 < C#1

5.2.2. Results of MOGA2

The same analysis is performed for the two pairs of criteria. For both cases, the following parameters were used for the Electre methodology (see Table 8).

For the analysis based on the criteria cost and equipment number, the optimal solutions for 10 simulations are given in Table 9.

Four optimal solutions are obtained, including the solutions already found with MOGA1 and an additional one that seems unacceptable from the cost criterion viewpoint for the above-mentioned reasons.

For the bicriteria {cost; campaign number} approach, the optimal solutions for 10 simulations are given in Table 10.

The three optimal solutions are found again in that case, with the same trends already observed with MOGA1.

As a conclusion of this bicriteria approach, it can clearly be said that results of the two methodologies, i.e., Pareto and Electre outranking, lead to the same results, thus validating their reliability for the decision maker.

5.3. Tricriteria results

The same case study is then studied and analyzed following the three criteria previously described.

5.3.1. Results of MOGA1

With the tricriteria approach, three different batch plant structures are obtained (see Table 11), and these three structures however present a similar scheme (this is not shown in the table since the generated results may be prohibitive to analyze), as they exhibit that step 2 is the most limiting one, since it requires more equipment. This can be predicted from the observation of the recipes (not presented here). Without going into their detailed presentation, let us say that equipment items of

Table 6
Results of the bicriteria analysis by MOGA1 {cost; equipment number}.

Run #	Chromosome	Chromosome identification	Cost	Equipment number
1	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
2	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
3	200-700-110-200-110-120-010-210-200-300	C#2	7 281 451	27
4	200-700-110-200-110-120-010-210-200-300	C#2	7 281 451	27
5	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
6	312-313-202-010-110-800-131-300-100-200	C#3	9 545 884	40
7	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
8	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
9	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
10	200-700-110-200-110-120-010-210-200-300	C#2	7 281 451	27

Table 7
Results of the bicriteria analysis by MOGA1 {cost; campaign number}.

Run #	Chromosome	Chromosome identification	Cost	Campaign number
1	312-313-202-010-110-800-131-300-100-200	C#3	9 545 884	5
2	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	7
3	312-313-202-010-110-800-131-300-100-200	C#3	9 545 884	5
4	200-700-110-200-110-120-010-210-200-300	C#2	7 281 451	6
5	312-313-202-010-110-800-131-300-100-200	C#3	9 545 884	5
6	312-313-202-010-110-800-131-300-100-200	C#3	9 545 884	5
7	120-311-020-010-100-210-200-210-200-100	C#1	5643 025	7
8	120-311-020-010-100-210-200-210-200-100	C#2	5 643 025	7
9	312-313-202-010-110-800-131-300-100-200	C#3	9 545 884	5
10	200-700-110-200-110-120-010-210-200-300	C#2	7 281 451	6

Table 8
Parameters used with the Electre methodology for the bicriteria analysis {cost; equipment number}.

Criteria	Criteria weights (Pc)	Indifference thresholds		Preference thresholds	
		α	β	α	β
Cost	0.6	0.2	1	0.2	1
Equipment number	0.4	0.2	1	0.2	1

Table 9
Results of the bicriteria analysis by MOGA2 {cost; equipment number}.

Run #	Chromosome	Chromosome identification	Cost	Unit number
1	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
2	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
3	200-700-110-200-110-120-010-210-200-300	C#2	7 281 451	27
4	200-700-110-200-110-120-010-210-200-300	C#2	7 281 451	27
	002-800-103-104-004-003-102-403-101-103	C#4	10 827 407	42
5	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
6	312-313-202-010-110-800-131-300-110-200	C#3	9 545 884	40
7	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
1	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
2	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	23
3	200-700-110-200-110-120-010-210-200-300	C#2	7 281 451	27

Table 10
Results of the bicriteria analysis by MOGA2 {cost; campaign number}.

Run #	Chromosome	Chromosome identification	Cost	Campaign number
1	312-313-202-010-110-800-131-300-110-200	C#3	9 545 884	5
2	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	7
3	312-313-202-010-110-800-131-300-110-200	C#3	9 545 884	5
4	200-700-110-200-110-120-010-210-200-300	C#2	7 281 451	6
5	200-700-110-200-110-120-010-210-200-300	C#3	7 281 451	6
6	312-313-202-010-110-800-131-300-110-200	C#3	9 545 884	5
7	120-311-020-010-100-210-200-210-200-100	C#1	5 643 025	7
8	120-311-020-010-100-210-200-210-200-100	C#2	5 643 025	7
9	312-313-202-010-110-800-131-300-110-200	C#3	9 545 884	5
10	200-700-110-200-110-120-010-210-200-300	C#2	7 281 451	6

Table 11
Results of GA (before Pareto sort).

#C	Cost	# Unit	# Camp
RUN # 1			
1-1	9 545 884	40	5
1-2	10 390 540	40	9
1-3	10 827 407	42	10
1-4	10 956 312	44	11
1-5	11 522 842	42	9
1-6	12 351 483	45	5
1-7	12 732 121	44	5
RUN # 2			
2-1	72 814 514	27	6
2-2	9 545 884	40	11
2-3	9 636 421	41	10
2-4	10 732 413	42	9
2-5	11 142 309	40	12
2-6	11 522 842	42	7
2-7	11 843 192	44	5
RUN # 3			
3-1	5 643 025	23	7
3-2	7 281 451	27	6
3-3	9 545 884	40	5
3-4	9 973 141	41	7
3-5	10 956 312	44	11
3-6	11 432 713	40	10
3-7	11 740 273	44	5
3-8	12 411 371	45	5
RUN # 4			
4-1	5 643 025	23	7
4-2	7 281 451	27	6
4-3	9 545 884	40	5
4-4	10 470 337	40	9
4-5	11 251 226	41	9
4-5	11 633 935	43	9
4-6	11 952 074	44	5
4-7	13 232 126	45	5
4-8	13 321 235	45	5
RUN # 5			
5-1	5 643 025	23	7
5-2	10 480 631	41	10
5-3	10 964 221	43	10
5-4	12 351 483	45	5
5-5	12 732 121	44	5
5-6	13 232 126	45	5
RUN # 6			
6-1	5 643 025	23	7
6-2	7 281 451	27	6
6-3	9 545 884	40	5
6-4	9 973 141	41	7
6-5	10 827 407	42	10
6-6	11 843 192	44	5
6-7	12 351 483	45	5
RUN # 7			
7-1	9 636 421	41	10
7-2	10 732 413	42	9
7-3	11 142 309	40	9
7-4	11 633 935	43	9
7-5	12 732 121	44	5
7-6	13 321 235	45	5
RUN # 8			
8-1	5 643 025	23	7
8-2	7 281 451	27	6
8-3	9 545 884	40	5
8-4	10 390 540	40	9
8-5	10 827 407	42	10
8-6	11 522 842	42	9
8-7	12 351 483	45	5
RUN # 9			
9-1	10 390 540	40	9
9-2	10 964 221	43	10
9-3	11 142 309	40	9
9-4	11 432 713	40	10
9-5	11 952 074	44	5
9-6	13 232 126	45	5
RUN # 10			
10-1	5 643 025	23	7
10-2	7 281 451	27	6
10-3	9 545 884	40	5
10-4	9 973 141	41	7
10-5	10 732 413	42	9
10-6	11 142 309	40	9
10-7	11 432 713	40	10
10-8	11 952 074	44	5

Table 12
Best solutions obtained for MOGA1 (after Pareto sort).

Solutions C	Cost	# Unit	# Camp
3-1; 4-1; 5-1; 6-1; 8-1; 10-1	5 643 025	23	7
2-1; 3-2; 4-2; 6-2; 8-2; 10-2	7 281 451	27	6
1-1; 3-3; 4-3; 6-3; 10-3	9 545 884	40	5

Table 13
Parameter set used for Electre methodology.

Criteria	Weight criteria Pc	Indifference thresholds α, β	Preference thresholds α, β
Cost	0.25	0.1-1638	0.1-1639
Number of equipment items	0.25	0.1-7	0.1-8
Number of campaigns	0.5	0.1-8	0.1-2

type 2 are common to all recipes (except that of product D) and require long operating times as compared with other steps.

Besides, the decrease in the number of campaigns necessary to reach the steady-state regime leads to a slight equipment oversizing of step 2, which in turn traduces more flexibility for achieving production.

The results seem thus encouraging since the combined use of simulation and optimization can predict the behavior of the plant and detect bottleneck.

The results show that the approach allows obtaining satisfactory solutions (with relatively short computational time), that are very important in a multicriteria environment. Table 11 (respectively 12) presents the obtained results before (respectively after) the application of the Pareto sort procedure (Table 12).

5.3.2. *Results of MOGA2*

Several parameters are to be defined before using the Electre methodology. As proposed with MOGA1, the used criteria are the cost of the obtained solution, number of equipment items and number of campaigns. The relative weight for each criterion and value scale must be defined. Two preference thresholds are also introduced, giving an interval of values, meaning that the decision maker prefers one action rather than the other one. Two indifference thresholds give an interval of values, between which the decision maker is indifferent between two actions. The Electre methodology is used with the results obtained before the Pareto sort procedure application. The parameter set is summarized in Table 13.

The performance matrix required for Electre III is presented in Table 14. The best compromises obtained with Electre III with

Table 14
Performance matrix for Electre III.

Solution name	Solutions	Cost criterion ($\times 10^3$)	Unit number	Campaign number
A1	3-1; 4-1; 5-1; 6-1; 8-1; 10-1	5643	23	7
A2	2-1; 3-2; 4-2; 6-2; 8-2; 10-2	7281	27	6
A3	1-1; 3-3; 4-3; 6-3; 10-3	9545	40	5
A4	2-3; 7-1	9636	41	10
A5	3-4; 6-4;10-4	9973	41	7
A6	1-2; 8-4; 9-1	10 390	40	9
A7	4-4	10 470	40	9
A8	5-2	10 480	41	10
A9	2-4; 7-2; 10-5	10 732	42	9
A10	1-3; 6-5; 8-5	10 827	42	10
A11	1-4; 3-5	10 956	44	11
A12	5-3	10 964	43	10
A13	7-3; 9-3; 10-6	11 142	40	9
A14	4-5	11 251	41	9
A15	3-6; 10-7	11 432	40	10
A16	1-5; 8-6	11 522	42	9
A17	4-5; 7-4	11 633	43	9
A18	3-7	11 740	44	5
A19	2-7; 6-6	11 843	44	5
A20	4-6; 9-5; 10-8	11 952	44	5
A21	1-6; 5-4; 6-7; 8-7	12 351	45	5
A22	3-8	12 411	45	5
A23	1-7; 5-5; 7-5	12 732	44	5
A24	4-7; 5-6; 9-6	13 232	45	5
A25	4-8; 7-6	13 321	45	5

respect to the three criteria considered simultaneously are given below:

A1, A2 are preferred to A3 and A13
A3 and A13 are preferred to A18, A19, A20, A21, A22
A18, A19, A20, A21, A22 are preferred to A23, A24, A25
A23, A24, A25 are preferred to A5
A5 is preferred to A4
A4 is preferred to A6, A7, A9, A14, A16, A17
A6, A7, A9, A14, A16, A17 are preferred to A8, A10, A11, A12, A15.

It can be concluded that the three best solutions obtained are the same using MOGA1 and MOGA2, but the hierarchical order presents some differences for the other ones. Based on these differences, it is interesting to point out that the three first actions are the same in both approaches. Some differences yet exist in the last outranked actions, mainly due to the introduced preference thresholds. This similarity could be explained by the fact that the Electre results are obtained by our expertise on the given production plan. Weights of criteria and performance matrix could differ between decision makers. In order to study the robustness of each methodology, the influence of the criterion weight could be studied.

The main advantage of MOGA1 is that the results are computed automatically from steps 1 to 2. One perspective of this work could be to generate automatically data transfer between steps 1 and 2 in MOGA2.

Another one could consist in analyzing these preference thresholds by giving minimum and maximum thresholds for which the outrankings are comparable for the two approaches. Globally speaking, the good agreement between the results validates both methodologies. This is all the more interesting as the hybrid strategy could be used in application to examples that lead to a Pareto set involving a greater number of solutions, from which a fraction could be evaluated by an Electre methodology.

6. Conclusions and perspectives

This work presents a comparative analysis of two decision-making analysis methodologies, i.e., a Pareto rank and an Electre approach, used separately after a genetic algorithm procedure, involved in a batch plant design strategy. These approaches are compared firstly on two criteria and, then, on three criteria. Both give similar results. A limitation stems from the data parameters used in the Electre methodology. These parameters (thresholds and criteria weights) depend on engineers' expertise on workshop design. These parameters are yet in agreement with those used in the Pareto approach and during the step of solution generation. The Pareto ranking approach, which can be qualified as an *a posteriori* method, is interesting since the results are automatically generated. The Electre strategy is interactive and needs the definition of threshold parameters.

The didactic example, which presents the typical features of an industrial batch plant, serves as a test bench of methodologies. Due to the discrete nature of the problems, only a small number of solutions were generated by the genetic algorithms. Since other applications are now under investigation, involving mixed variables with environmental criteria to minimize, the number of solutions to be evaluated is likely to increase so that other strategies need to be evaluated and combined and for that the present study the first step. A further study is to use a genetic algorithm procedure with an embedded Pareto sort after which an Electre method could be applied to some attractive ranges of solutions in order to give some guidelines to the decision maker.

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