A NEW DECISION SUPPORT SYSTEM FOR RANKING A FINITE SET OF MULTICRITERIA ALTERNATIVES

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ABSTRACT
The paper presents a new decision support system (DSS) for solving multicriteria ranking problems: how to rank a set of alternatives - having evaluations in terms of several criteria - in decreasing order of preference. It uses the ELECTRE III methodology to construct a fuzzy outranking relation, and then a genetic algorithm to exploit it and to obtain a recommendation. The genetic algorithm approach rests on the main idea of reducing differences between the global model of preferences and the final ranking. The system operation is showed within an empirical study of a real student selection problem in the Universidad de Occidente in Mexico.

RESUMEN
En este artículo presentamos un nuevo sistema de apoyo a la decisión para resolver el problema del ordenamiento multicriterio. Cómo ordenar un conjunto finito de alternativas, valoradas por un conjunto de criterios, en orden de preferencia decreciente. Utilizamos el enfoque de sobreclasificación del análisis multicriterio de ayuda en la decisión para resolver el problema. Por medio del método ELECTRE III construimos una relación de sobreclasificación borrosa. Para la fase de explotación aplicamos un algoritmo genético y obtenemos una recomendación del sistema. La operación del sistema se ilustra en medio de una aplicación real del problema de selección de estudiantes de posgrado de la Universidad de Occidente de México.

Key words: Multicriteria Decision Analysis, Ranking problem, Genetic algorithms, Decision Support System.

1. INTRODUCTION

Multicriteria Decision Analysis (MCDA) is widely used for selecting, sorting or ranking alternatives in relation to multiple criteria Roy (1996), Vanderpooten (1990). It provides an effective framework for solving this kind of problems and, particularly, the approach of the fuzzy outranking relations has been adequate for dealing with situations in which imprecision and subjective ness is present Roy (1977), Rogers **et al**. (2000).

In outranking methods, we can distinguish two phases: aggregation and exploitation. The aggregation process corresponds to the operation, which transforms the marginal evaluations of separate criteria into a global outranking relation between every pair of alternatives, which is generally neither transitive nor complete. The exploitation process deals with the outranking relation in order to clarify the decision through a partial or total preordering reflecting some of the irreducible indifferences and incomparabilities Fodor and Roubens (1994), Bouyssou and Vincke (1997).

Let A be the set of alternatives or potential actions and let us consider a fuzzy outranking relation S_A^σ defined on A×A; this means that we associate with each ordered pair (a,b) a real number σ(a,b) ($0 \le \sigma(a,b) \le 1$) reflecting the degree of strength of the arguments favoring the crisp outranking aSb. The exploitation phase transforms the global information included in S_A^σ into a global ranking of the elements of A. In this phase, the classic procedures like ELECTRE III Roy (1990) or PROMETHEE II Brans **et al**. (1986), use a ranking method to obtain a score function. But the main difficult consists in finding reasonable ways of dealing with the intransitivities without losing too much of the contents of the original outranking relation. The methods based on score functions do not perform well in presence of irrelevant alternatives or in case of complex graphs with several circuits. Non-rational situations could happen when the prescription is constructed. Most significant is the following: Suppose that a and b are two actions such that $\sigma(a,b) \ge \lambda$ and $\sigma(b,a) \le \lambda-\beta$ ($\beta>0$); if $\lambda \ge c$ and $\beta \ge t$ (c and t representing consensus and threshold levels respectively), we should accept that "a outranks b" ($aS^\lambda b$) and "b does not outrank a" ($bnS^\lambda a$); in this case the global preference model captured in outranking relation is giving a presumed preference favoring a. However, a score function or other similar

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method (based on flow of outranking or "distillation " process) could lead to a final ordering in which b is ranked before a. ELECTRE and PROMETHEE methods do not have a way to minimize this kind of irregularity. In Leyva and Fernandez (1999) and Fernández and Leyva (2004) a method based on genetic algorithms and multiobjective optimization, which allows to exploit a known fuzzy outranking relation is introduced, with the purpose of constructing a recommendation for ranking problems. The problem of obtaining the final ranking is modeled with multiobjective combinatorial optimization; the solution method, based on the genetic algorithm approach, rests on the main idea of reducing differences between the global model of preferences and final ranking.

In this paper, is presented a new Decision Support System (DSS) called SADAGE (Sistema de Apoyo a la Decisión con Algoritmos Genéticos y Electre III) for rank a finite set of multicriteria alternatives based on the ELECTRE III – Genetic Algorithm approach. It uses the ELECTRE III methodology to construct a fuzzy outranking relation, and then a genetic algorithm to exploit it and to obtain a recommendation, which is a ranking of the alternatives in decreasing order of preferences. SADAGE is a variant of the ELECTRE III-IV software developed by Vallée and Zielniewicz (1994). Both use the outranking approach to solve the multicriteria ranking problem. The difference is in the phase of exploitation. SADAGE uses a method based on a genetic algorithm and ELECTRE III-IV uses the "distillation" technique (Net Flow Rule). Even when the distillation technique carries out the exploitation process intuitively, quickly, easily and directly, it simplifies excessively the information implicitly contained in the fuzzy outranking relation, leaving out of the analysis important characteristics of the model, constructing sometimes, recommendations inconsistent with respect the aggregation model of preferences Leyva (2000).

The paper is organized as follows: the next section gives a brief methodological presentation of the ELECTRE III – Genetic algorithm method and, the functionalities of the software are presented through an illustrative example in Section 3. Finally, in Section 4 are presented the conclusions.

2. THE (ELECTRE III – Genetic Algorithm) METHODOLOGY

ELECTRE III – Genetic algorithm is a multiple criteria ranking method, i.e. a method that ranks a finite set of alternatives A in decreasing order of preference. Each alternative is supposed perfectly identified but not necessarily exactly and completely known in all its quantitative and qualitative consequences. The consequences can be analyzed by means of a "consistent family" of criteria, g1, g2,..., gn where gj(a) will characterize the evaluation made of an alternative a $\in$ A on the j-th criterion.

2.1. The ELECTRE III method. Construction of the outranking relation

Assuming that there exist defined criteria, $g_j, \quad j = 1,2,...n$ and a set of alternatives A, the ELECTRE methods introduce the concept of an indifference threshold, q, and preference threshold, p. The preference relations are defined as follows:

aPb (a is strongly preferred to b) $\Leftrightarrow$ $g(a) - g(b) > p$

aQb (a is weakly preferred to b) $\Leftrightarrow$ $q < g(a) - g(b) \le p$

aIb (a is indifferent to b; and b to a) $\Leftrightarrow$ $|g(a) - g(b)| \le q$

The ELECTRE method seeks to build an outranking relation S. aSb means that according to the global model of DM' preferences, there are good reasons to consider that "a is at least as good as b" or "a is not worse than b." Each pair of alternatives a and b is then tested in order to check if the assertion aSb is valid or not. The test to accept the assertion aSb is implemented using two principles:

i) A concordance principle which requires that a majority of criteria, after considering their relative importance, is in favor of the assertion – the majority principle, and

ii) A non-discordance principle, which requires that within the minority of criteria, which do not support the assertion, none of them is strongly against the assertion – the respect of minorities' principle.

The operational implementation of these two principles is now discussed, assuming that all criteria are to be maximized. We first consider the outranking relation defined for each of the n criteria; that is, aS_jb means that "a is at least as good as b with respect to the j^{th} criterion," j = 1,2,…,n.

The j^{th} criterion is in concordance with the assertion aSb if and only if aS_jb. That is, if $g_j(a) \geq g_j(b) - q_j$. Thus, even if $g_j(a)$ is less than $g_j(b)$ by an amount up to q_j, it does not contravene the assertion aS_jb and therefore is in concordance. The j^{th} criterion is in discordance with the assertion aSb if and only if bP_ja. That is, if $g_j(b) \geq g_j(a) + p_j$. That is, if b is strictly preferred to a for criterion j, then it is clearly not in concordance with the assertion that aSb. With these concepts it is now possible to measure the strength of the assertion aSb. The first step is to develop a measure of concordance; as contained in the concordance index C(a,b), for every pair of alternatives $(a, b) \in A$. Let k_j be the importance coefficient or weight for criterion j. We define a fuzzy outranking relation as follows:

$$C(a,b) = \frac{1}{k}\sum_{j=1}^{n} k_j c_j(a,b), \quad \text{where} \quad k = \sum_{j=1}^{n} k_j \tag{1}$$

Where

$$c_j(a,b) = \begin{cases} 1, & \text{if} \quad g_j(a) + q_j \geq g_j(b) \\ 0, & \text{if} \quad g_j(a) + p_j \leq g_j(b), \quad j = 1,2,...,n \\ \dfrac{p_j + g_j(a) - g_j(b)}{p_j - q_j} & \text{otherwise} \end{cases}$$

To calculate discordance, a further threshold called the veto threshold is defined. The veto threshold v_j, allows for the possibility of aSb to be refused totally if, for any one criterion j, $g_j(b) > g_j(a) + v_j$. The discordance index for each criterion j, $d_j(a,b)$ is calculated as:

$$d_j(a,b) = \begin{cases} 0, & \text{if} \quad g_j(a) + p_j \geq g_j(b) \\ 1, & \text{if} \quad g_j(a) + v_j \leq g_j(b), \quad j = 1,2,...,n \\ \dfrac{g_j + g_j(a) - p_j}{v_j - p_j} & \text{otherwise} \end{cases} \tag{2}$$

The final step in the model building phase is to combine these two measures to produce a measure of the degree of outranking; that is, a credibility index which assesses the strength of the assertion that "a is at least as good as b." The credibility degree for each pair $(a,b) \in A$ is defined as:

$$S(a,b) = \begin{cases} C(a,b), & \text{if} \quad d_j(a,b) \leq C(a,b) \quad \forall j \\ & \dfrac{1 - d_j(a,b)}{1 - C(a,b)} \quad \text{where } J(a,b) \text{ is the set of criteria} \\ C(a,b) \bullet \prod\limits_{j \in J(a,b)} & \text{such that } d_j(a,b) > C(a,b) \end{cases} \tag{3}$$

This concludes the construction of the outranking model. The next step in the outranking approach is to exploit the model and produce a ranking of alternatives from the fuzzy outranking relation.

2.4. The genetic algorithm for deriving final ranking. Exploitation procedure

2.4.1.The exploitation of the fuzzy outranking relation as a multiobjective combinatorial optimization problem

Let A be a finite set of decision alternatives, which is the object of the decision process. This set is not the universe of the potentially feasible alternatives; it is only the set under consideration in a specific decision problem. Let $\sigma(a,b)$ be a valued binary relation defined on $A \times A$ with image in [0,1]. $\sigma(a,b)$ can be interpreted as the credibility degree of the predicate "a is at least as good as b". Let λ be a cut level such that if $\sigma(a,b) \geq \lambda$, we say that a outranks b with credibility λ, denoted by $aS^{\lambda}b$. Otherwise, the outranking is rejected $anS^{\lambda}b$.

We assume the existence of a threshold $\beta > 0$ such that if $aS^{\lambda}b$ and also $\sigma(a,b) \leq (\lambda-\beta)$, then there is an asymmetric preference relation favoring a that will be denoted by $aP^{\lambda,\beta}b$. One can agree that for some values of λ and β, the conditions defining $P^{\lambda,\beta}$ are good arguments for justifying a strict preference relation in the sense proposed by Roy (cf. Roy (1996)).

Let E be a way of exploiting σ and RA the complete ranking derived from applying E to σ. E is a function assigning a ranking R_A to each σ defined on $A\times A$. R_A defines a weak order R on A. $\forall (a,b) \in A\times A$, aRb if and only if b is not ranked before a in R_A. We think that the quality of a final ranking should be judged according to the number of its discrepancies and concordances with σ and the crisp relations S^1, and $P^{\lambda,\beta}$.

Let V be the set of strong discrepancies (violations):

$$V = \{(a,b) \in A\times A \text{ such that } aP^{\lambda,\beta}b,\ bRa\} \text{ and } n_v = \text{card}(V)$$

Note that n_v is a function of R, λ, and β.

We propose to consider the best ordering as the best compromise solution of the following multiple objective optimization problem:

$$\text{Min}(n_v),\ \text{Min}(f),\ \text{Max}(\lambda) \qquad (4)$$

Subject to

$$R \subset A\times A,\ \lambda, \beta \in [0,1],\ \lambda \geq \lambda_0$$

(λ_0 is a minimum level of credibility, usually greater than 0.5) where f is a measure counting the number of incomparable pairs i.e. counting all the pairs $(a,b) \in A\times A$ such that $anS^{\lambda}b$ and $bnS^{\lambda}a$. The structure of (4) strongly suggests the use of genetic algorithms to solve it.

2.4.2. The genetic algorithm

In this section are explained some elements of the genetic algorithm which allows us to exploit a known fuzzy outranking relation with the purpose of constructing a recommendation for the multi criteria ranking problem. A potential solution of a ranking problem is represented as an ordinal representation. In general, a potential solution is a ranking of the set of actions by decreasing order of preference. These actions (known as genes in Genetic Algorithms (GA's)) are joined together forming a string of values (known as chromosome). Any symbol in this string is refereed to as an allele Goldberg (1989), Michalewicz (1996). The chromosome is represented as the string of m-ary alphabet where m is the number of actions into the decision problem. In such representation, each action is coded into m-ary form. Actions are then linked together to produce one long m-ary string or chromosome. An action coded with a_{k_i} value in the i-th entry of the string means that the action coded with a_{k_i} value is ranking in the i-th place of the ordering and a_{k_i} is preferred to a_{k_j} if i < j, where $a_{k_i} \in A = \{a_1, a_2, \ldots, a_m\}$, i = 1, 2,…, m, and $[k_1, k_2, \ldots, k_m]$ is a permutation of [1,2,…,m]. Each individual is associated with a number λ ($0 \leq \lambda \leq 1$), which will be connected with the credibility level of a crisp outranking defined on the set of genes. The fitness of an individual with credibility level λ is calculated according to a given *fitness function*. The approach for defining individual's fitness involves separating the single fitness measure into two, one is called fitness f and the other is called unfitness u. We define the fitness function f of an individual p with credibility level λ as follows:

Let $p = a_{k_1} a_{k_2} \ldots a_{k_m}$ be the schematic representation of an individual's chromosome and suppose that given a_{k_i} and a_{k_j}, two actions such that $\sigma(a_{k_i}, a_{k_j}) \geq \lambda$ and $\sigma(a_{k_j}, a_{k_i}) \leq \lambda - \beta$ ($\beta > 0$, representing a threshold level), we accept that "a_{k_i} outranks a_{k_j}" ($a_{k_i}\ S^{\lambda}\ a_{k_j}$) and "$a_{k_j}$ does not outrank a_{k_i}" ($a_{k_j}\ nS^{\lambda}\ a_{k_i}$). In this case, into the crisp outranking relation generated by λ, S_A^{λ}, a presumed preference favoring a_{k_i}, holds. Then:

$$f(p) = \left| \{(a_{k_i}, a_{k_j}): a_{k_i} \, nS a_{k_j} \text{ and } a_{k_j} nS a_{k_i} \quad i = 1,2,..., m-1,\ j = 2,3,...,m,\ \ i < j\} \right|$$

where $[k_1, k_2,...,k_m]$ is a permutation of $[1,2,...,m]$. f(p) is the number of incomparabilities between pairs of actions (a_{k_i}, a_{k_j}) into the individual $p = a_{k_1} a_{k_2} \dots a_{k_m}$ in the sense of the crisp relation S_A^{λ}. Note that the quality of solution increases with decreasing fitness score.

The unfitness u of an individual p measures the amount of unfeasibility (in relative terms) and we chose to define it as:

$$u(p) = \left| \{(a_{k_i}, a_{k_j}) : a_{k_i} \, S \, a_{k_j} \text{ and } a_{k_j} \, nS \, a_{k_i};\ i = 1,2,...,m\ ,\ \ j = 1,2,...,m,\ \ i > j\} \right| .$$

u(p) is the number of preferences between actions into the individual p which are not "well-ordered" in the sense of S_A^{λ}. We are interested in:

i) Individuals whose unfitness function value is equal to zero. This assures us that the ordering represented by the individual is transitive.

ii) Individuals whose fitness function value is equal (or near) to zero. This objective improves the comparability of S on A.

iii) Individuals whose credibility level λ is near to 1. This indicates us that the ordering represented by the individual with credibility level λ is more trusty whenever the fitness and unfitness function values are zero or near to zero.

Then, we use a genetic search for solving the multiobjective problem:

$$\text{Min } u, \text{ Min } f, \ \text{Max } \lambda \qquad (5)$$

$$R_s,\ \lambda \in [0,1] \quad \lambda \geq \lambda_0$$

where R_s is a strict total order of A.

We can see that the “unfitness function” u coincides with n_v, (see (4) of subsection 2.4.1).

3. IMPLEMENTATION IN THE DECISION AID PROCESS

3.1 Structure of the decision aid process

In a systematic decision aid process; there is a continuous flow of activities between the different phases, but at any phase there may be a return to a previous phase (feedback). However, the general scheme of use of ELECTRE III – Genetic algorithm method can be schematically represented in Figure 1. It needs to be noticed that this procedure is iterative rather than simply sequential. If the Decision Maker is unsatisfied with the result at any stage, it may go back to any step and redo it.

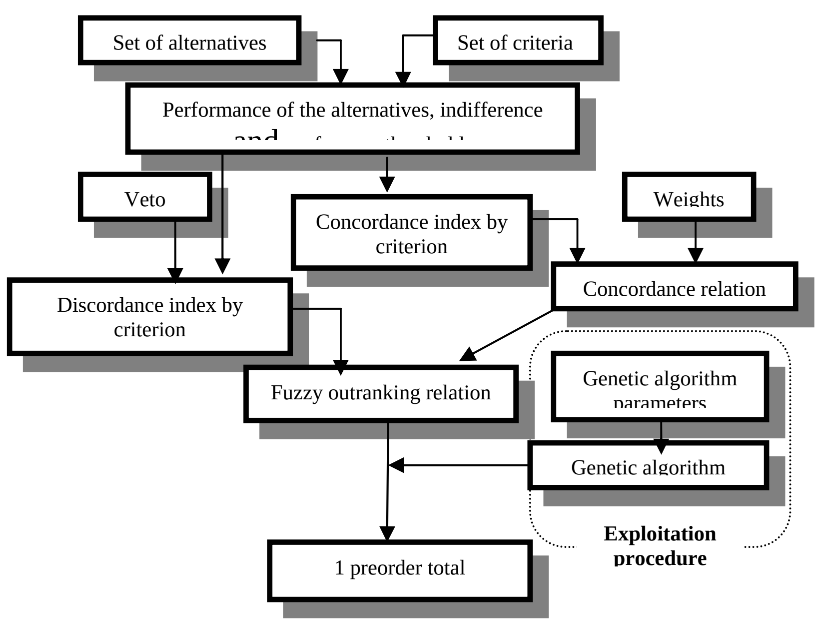

Figure 1.
General scheme of the use of ELECTRE III – Genetic algorithm method.

3.2. Main functionalities of the software

The SADAGE software has been written in the Visual Basic programming language. The minimal hardware and software requirements are the following:

- IBM-PC compatible computer (Pentium II processor with 64 MB RAM),
- Microsoft Windows (98 or higher).

The structure of the options available in the software is described hereafter in Figure 2.

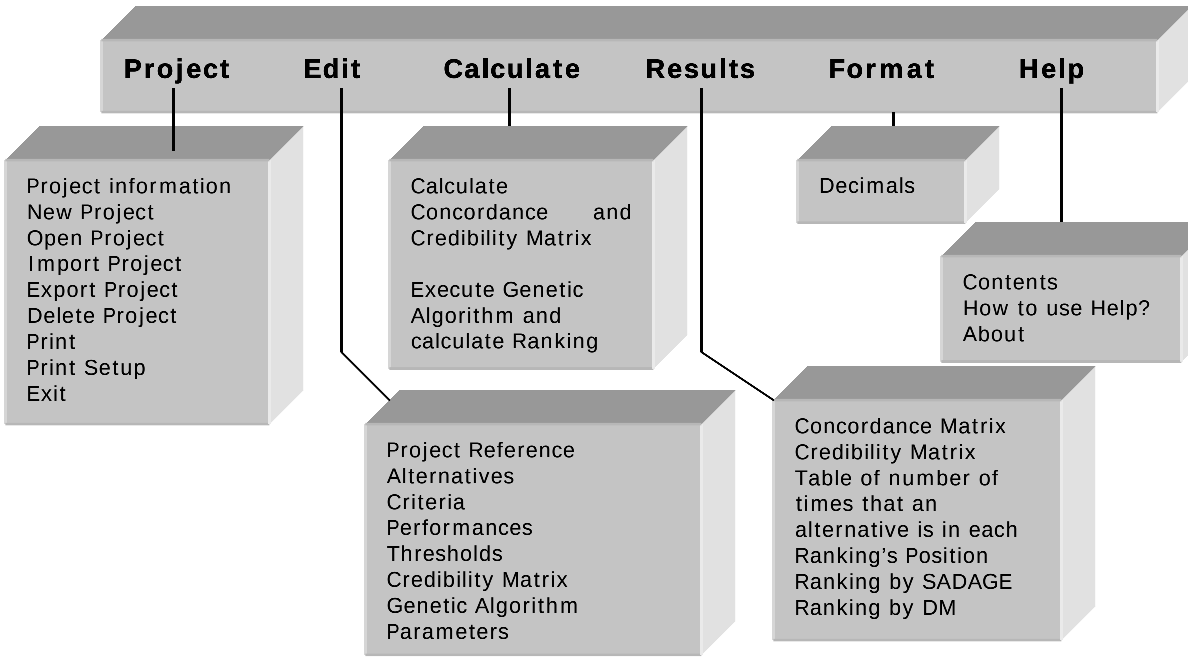

Figure 2. Description of the main options of the software.

To illustrate the main functionalities of the new software, we provide a short description of a real world application in the Mexican educational system where this software was used (the reader may found a detailed description in Leyva (2004)).

3.3. Postgraduate student selection: A Mexican case

The next instance of the ranking problem discusses an empirical study of the following real selection problem.

The Universidad de Occidente will offer another generation of the Master of Science in Management Information Systems and a selection process of candidates will be held. The problem is to identify the best possible candidates. After that the DM saw many interested persons to enroll in the program, they finally accepted to competing by a place to 21 applicants labeled in this application as A1, A2,…,A21. The DM is a committee of posgrade's academics, where one of them played the role of the decision analyst. The study was supported with a new decision aid system for rank a finite set of multicriteria alternatives, developed by our working group and whose main window is presented in Figure 3.

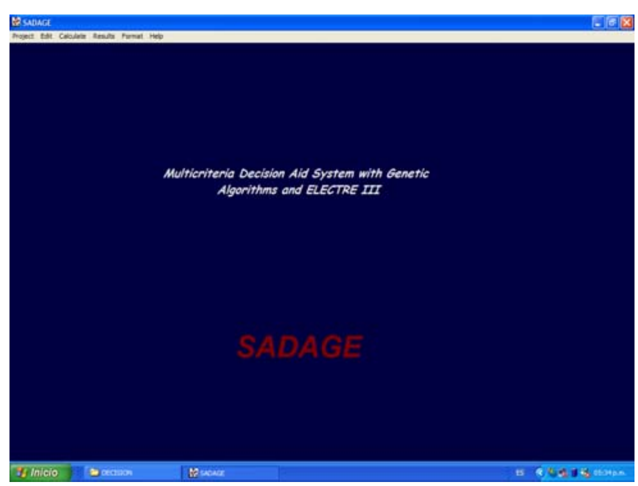

Figure 3. Main window of the software SADAGE.

The DM has made an adequately comprehensive description of each applicant available. For this application, the 5 following criteria and its scale are formulated in the Table 1.

Table 1. Criteria and its scale.

Label 1	Label 2	Criterion	Scale
C1	INT	Intelligence	0-10
C2	AP	Academic Performance	0-10
C3	TSS	Time spent in studying	0-50
C4	EP	English Proficiency	0-10
C5	RP	Responsibility Performance	0-10

As mentioned in Subsection 2.1, three are the main inputs of the ELECTRE method.

3.3.1.The performance matrix

All applicants were evaluated using the criteria and scale showed in the Table 1. All criteria were treated as quantitative ones. A 21x5 matrix was produced. Table 2 provides the performance matrix, for twenty-one applicants and five criteria. Figure 4 illustrates part of the performance matrix.

Table 2. Performances of the alternatives.

	C1 INT	C2 AP	C3 TSS	C4 EP	C4 RP
A1	9.76	8.00	40	7	8.5
A2	6.52	8.20	20	4	8.5
A3	9.86	9.64	40	8	10
A4	3.07	8.0	30	5	6
A5	8.53	9.02	25	6	8
A6	9.87	9.82	25	10	10
A7	9.73	9.20	40	8	9.5
A8	9.03	9.50	25	6	9.5
A9	8.23	9.12	30	5	8
A10	9.33	8.40	25	5	10
A11	9.83	9.36	30	8	10
A12	9.03	8.90	40	8	10
A13	5.78	8.33	30	4	7
A14	9.20	9.05	40	8	8
A15	9.20	9.10	30	5	8.5
A16	9.00	8.20	30	6.5	9
A17	9.90	9.5	30	8	10
A18	9.53	8.96	25	4	9
A19	9.63	8.4	25	6	9
A20	0	9.34	50	4	5
A21	9.33	8.55	30	6	8.5

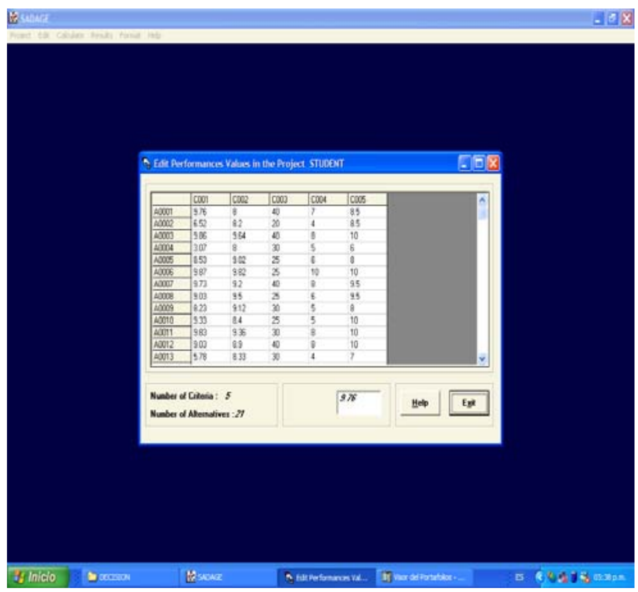

Figure 4. Edit Performance matrix window.

3.3.2. The thresholds

The DM was supported in the definition of its preferences and uncertainties through the indifference threshold (q), the preference threshold (p), and veto threshold (v) for all criteria. Agreeing with Rogers and Bruen (1998) we did not propose a specific relation between q and p values. As far as the veto threshold v is concerned, we suggested that veto should be the most important factor for the most important criteria. The threshold values are summarized in Table 3. Figure 5 shown the threshold values of a criterion.

Table 3. q, p, v threshold values.

Criterion	q	P	v
C1. Intelligence	0.2	0.5	1.0
C2. Academic Performance	0.2	0.5	1.0
C3. Time spent in studying	4	9	40
C4. English Proficiency	1	1.5	6
C5. Responsibility Performance	0.5	1.0	7.0

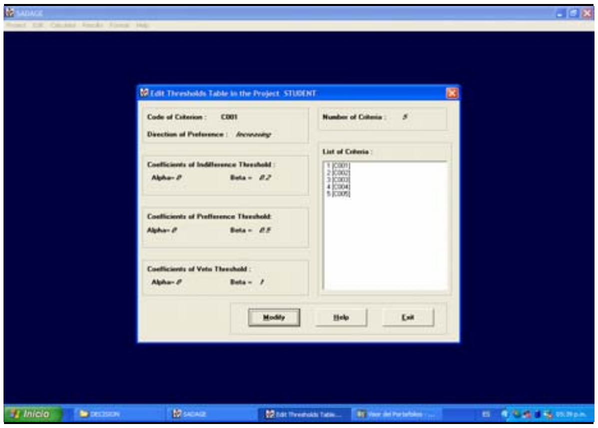

Figure 5. Edit threshold values window.

3.3.3.The weights (Relative importance of the criteria)

The DM was supported in the definition of the 5 criteria weights, as shown in Table 4. Personal Construct Theory – PCT as suggested by Rogers et al. (2000) was used for the weight definition.

Table 4. Criteria weights.

	C1	C2	C3	C4	C5	RtC	RtC+ 1	Weight	Final weight
C1	----	X	X	X	X	4	5	38.4	4
C2		----	X	X	X	3	4	30.7	2.5
C3			----	E	X	1	2	15.3	1.5
C4				----	E	0	1	7.7	1.0
C5					----	0	1	7.7	1.0
					Total	13			

Note: Final RtC = RtC + 1 so as C4 and C5 to be taken into account.

3.3.4. Calculations and the final ranking

According to the additional information pointed out before, we applied ELECTRE III to construct a fuzzy outranking relation. Tables 5 show the credibility matrix obtained.

Table 5. Credibility matrix.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	A21
A1	1	1	0	1	0	0	0	0	0	0.73	0	0.37	0.89	0	0	1	0	0.24	0.83	0	0.75
A2	0	1	0	0.85	0	0	0	0	0	0	0	0	0.85	0	0	0	0	0	0	0	0
A3	1	1	1	1	1	0.9	1	1	1	1	1	1	1	1	1	1	1	1	1	0.85	1
A4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A5	0	1	0	0.97	1	0	0	0.27	0.97	0.40	0	0.25	0.97	0.35	0.57	0.51	0	0	0	0.75	0.53
A6	0.85	1	0.85	0.97	1	1	0.85	1	0.97	1	0.97	0.85	0.97	0.85	0.97	0.97	0.97	1	1	0.85	0.97
A7	1	1	0.80	1	1	0.65	1	0.92	1	1	1	1	1	1	1	1	0.92	1	1	0.85	1
A8	0.45	1	0.18	0.97	1	0.16	0.32	1	0.97	0.87	0.35	0.75	0.97	0.75	0.97	0.97	0.23	0.60	0.60	0.85	0.84
A9	0	1	0	1	0.87	0	0	0.22	1	0	0	0.12	1	0.03	0.09	0.31	0	0	0	0.83	0
A10	0.44	1	0	0.97	0.75	0	0.10	0	0.72	1	0.02	0.50	0.97	0.50	0.72	0.87	0	0.75	0.87	0.18	0.97
A11	0.85	1	0.78	1	1	0.68	0.85	1	1	1	1	0.85	1	0.85	1	1	1	1	1	0.85	1
A12	0.60	1	0.15	1	1	0.02	0.52	0.75	0.98	0.87	0.25	1	1	1	1	1	0.14	0.60	0.60	0.65	0.87
A13	0	0.5	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
A14	0.60	1	0.23	1	1	0.06	0.50	0.69	1	0.90	0.41	0.90	1	1	1	0.90	0.25	0.73	0.59	0.78	1
A15	0.35	1	0	1	1	0.02	0.22	0.73	1	0.90	0.35	0.65	1	0.75	1	0.90	0.16	0.83	0.69	0.82	1
A16	0.39	1	0	1	0.75	0	0	0	0.48	0.73	0	0.40	1	0.30	0.60	1	0	0.26	0.60	0	0.70
A17	0.85	1	0.85	1	1	0.80	0.85	1	1	1	1	0.85	1	0.85	1	1	1	1	1	0.85	1
A18	0.71	1	0.11	0.97	0.9	0	0.72	0.65	0.97	0.90	0.39	0.65	0.97	0.75	0.97	0.87	0.18	1	0.90	0.70	0.87
A19	0.85	1	0	0.97	0.75	0	0.40	0	0.72	0.90	0.09	0.40	0.97	0.50	0.72	0.97	0	0.75	1	0.18	0.97
A20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
A21	0.54	1	0	1	0.78	0	0.10	0.19	0.75	0.90	0.07	0.53	1	0.50	0.75	1	0.02	0.83	0.87	0.60	1

After that, we used the GA, (see the Subsection 2.4) for exploiting the outranking relation and deriving a final ranking of the alternatives in decreasing order of preferences. The computation in the GA was realized with the following parameters: 100 trials of the GA heuristic (each one with a different random seed) were generated. We worked with groups of 25 trials, which finished when {400, 350, 300, 300} populations had been generated. The population size was set to {55, 50, 40, 60}. The crossover probability was chosen {0.85, 0.75, 0.75, 0.70} and the mutation probability was {0.50, 0.60, 0.65. 0.50} respectively in each case. Figure 6 illustrates the parameters values of the genetic algorithm.

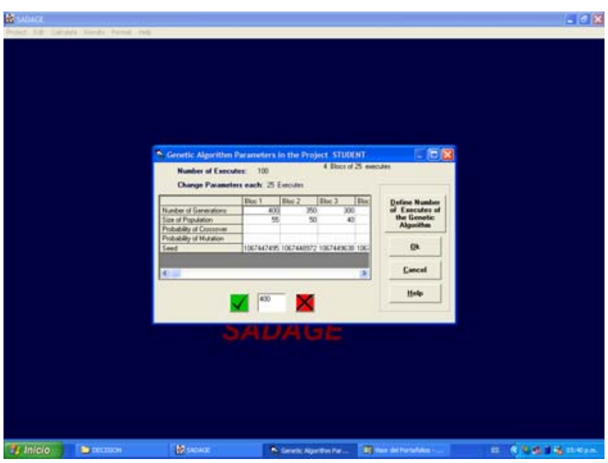

Figure 6. Edit parameters values screen of the genetic algorithm.

The final ranking obtained using the genetic algorithm is shown in Figure 7. Figure 8 illustrates part of the final ranking window.

A6 ≻ A17 ≻ A7 ≻ A3 ≻ A11 ≻ A1 ≻ A8 ≻ A18 ≻ A14 ≻ A19 ≻ A21 ≻ A12 ≻ A15 ≻ A16 ≻ A10 ≻ A9≻ A5 ≻ A2 ≻ A13 ≻ A20 ≻ A4

The credibility level was $\lambda = 0.7039$.

Figure 7. Final ranking.

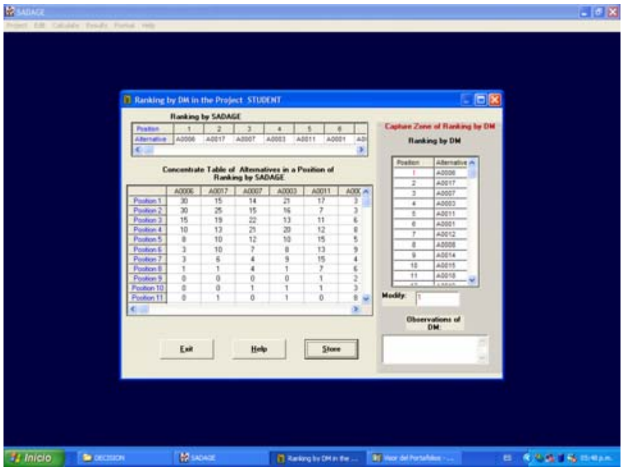

Figure 8. Final ranking window.

4. CONCLUSIONS

An implementation of the ELECTRE III – Genetic algorithm method is presented. Our attention has been focused on the exploitation phase. Here, the problem of exploit a fuzzy outranking relation and obtain a final ranking is modeled with multiobjective combinatorial optimization. To solve this problem we used a genetic algorithm approach, which rests on the main idea of reducing differences between the global model of preferences and the final ranking. The final ranking proposed is obtained counting the number of times that an alternative is found at a certain place in the ranking when the genetic algorithm is run n times. This inference procedure to obtain the final ranking is integrated in a trial-and-error interactive process in which the DM can check what is the impact of modifications of the input on the result of the inference procedure. The software has been presented through an illustrative example.

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