Intelligent Techniques for R&D Project Selection in Large Social Organizations

Técnicas Inteligentes para la Selección de Proyectos de I&D en las Grandes Organizaciones Públicas

Eduardo Fernandez[1], Fernando Lopez[2], Jorge Navarro[3] and Alfonso Duarte[4]
[1] Universidad Autónoma de Sinaloa
[2] Universidad Autónoma de Nuevo León
[3] Centro de Ciencias de Sinaloa
[4] Estudiante de Maestría, Universidad Autónoma de Sinaloa
eddyf@uas.uasnet.mx[1] ferny_65@yahoo.com[2] navarro@computo.ccs.net.mx[3]
alfonsoduarte@gmail.com[4]

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Abstract

Funding R&D projects is perhaps the most important task faced by large public organizations, in charge of promoting science and technology in different countries. However, most popular ways to solve this decision problem are based on too simple decision models and weak heuristics. In this paper a new methodology is presented to assist top level managers of those organizations during the project evaluation phase until the final decision. This methodology covers the following central points: a)a measure of the global impact and probability of success as main attributes to access the quality of a R&D project; b) a way to represent the knowledge, preferences and beliefs from the top level managers, and an approach to take into account that information in the evaluation process ; c) a way to update the beliefs of the top level managers by taking into account the experience of the whole organization; d) a numerical model of the quality of a project portfolio that can be used for improving final portfolios; e) an evolutionary algorithm to explore the set of portfolios searching for the very good solutions. We also discuss the functional structure of a software application which implements the proposed methods. In some examples of real size our proposal clearly outperforms traditional methods.
Keywords: Project management, decision tables, evolutionary algorithms, decision support systems

Resumen

La selección de buenos proyectos es quizás el problema crucial que enfrentan las grandes organizaciones públicas encargadas de promover la ciencia y la tecnología. Sin embargo, a pesar de los avances tecnológicos para el procesamiento de información, la selección de proyectos de I&D en las convocatorias que se llevan a cabo en muchos países se sigue basando en modelos de evaluación y decisión demasiado simples, pobres desde el punto de vista del estado del arte de la ciencia de la administración y de la modelación matemático-computacional. En este trabajo se presenta un nuevo procedimiento cuyo núcleo se compone de a) medición de impacto y probabilidad de éxito como atributos esenciales de calidad de un proyecto de I&D; b) una forma de representar el conocimiento, preferencias y creencias de la alta dirección de la organización, y un método para reflejar esta información en el proceso de evaluación; c) un modo de actualizar las creencias de esa alta dirección utilizando la experiencia de la propia organización; d) un modelo numérico de la calidad de la cartera de proyectos, susceptible de ser optimizado, y e) un algoritmo evolutivo para explorar el conjunto de carteras en busca de las mejores soluciones. Se discute también la estructura funcional de un sistema que implementa el conjunto de métodos propuestos. En ejemplos de tamaño real la propuesta logra soluciones mucho mejores que las tradicionales.
Palabras claves: gestión de proyectos, algoritmos evolutivos, modelos de decisión, sistemas inteligentes de apoyo a la decisión.

1 Introduction

The world public expenditure in R&D approaches 100 billions USD by the year (UNESCO, 2004). Selection of R&D projects is one of the most important problems that top level managers of large public organizations must face (government, universities, foundations, international institutions, etc.) when they should support and fund R&D.

There are two related sub-problems to selection of R&D projects: i) to access the evaluation of individual projects, and ii) to build a portfolio of the most promising projects among all submitted to a certain call for projects. Finally what really matters is the portfolio, which contains only the projects to be funded and respectively the individual amount assigned to each project. However, in order to justify the decision taken when building up the portfolio, some information is required about feasibility, pertinence and potential impact of the candidate projects; this information should be gathered in the framework of the evaluation process.

A R&D public project is characterized by a set of qualitative and quantitative, tangible and intangible attributes, which determine the quality of the project. These attributes are classified in two groups: those directly related to the impact of the project and, on the other hand, those related to the probability of success of projects, understood as a certain integral criteria of feasible achievement of all of its goals.

When facing multiple criteria there is no way of solving a decision problem without taking into account a subjective component representing the solution of the conflict of attributes. It should be accepted the existence of a strategic, organizational "decision-maker", a person or a group which is identified with the interests of the organizations. In the following this entity will be called the Supra-Decision Maker (SDM), whose preferences and beliefs must be modeled to solve i) and ii).

To the best of our knowledge, no integrated methodology based on the most accepted decision-support paradigms has been applied for selecting R&D projects. In a multicriteria decision problem, the decision method must capture the system of preferences, beliefs, and risk attitude of the decision maker. The decision method should help the SDM transform his/her subjectivity in the presence of new information. It should also help exploring and comparing alternatives. None of these tasks is fulfilled by the common heuristics used by public organizations. In this paper we present a methodology and its computational implementation for the selection of R&D projects and build up a portfolio with those selected also indicating the level of funding to each project. This is mainly a tool for decision support as the large R&D management public organizations existing in many countries call for projects. The structure of the paper follows: In next section the problem will be described with some criticisms of the exiting approaches. In Section 3 we describe our proposal for improving the model of preferences and beliefs from the SDM, and how to exploit it in the context of a new approach of the evaluation of projects. In Section 4 a normative model of the R&D portfolio's quality is discussed, and on this background an evolutionary algorithm for exploring efficiently the solutions space is presented. Section 5 shows the functional structure of a DSS which implements the suggested "intelligent" strategies. Then, in Section 6 some examples are shown with results of the application of the different proposed tools, both for project evaluation and for searching the best portfolios, which leads to final project selection. Finally brief conclusions are drawn.

2 The Problem of Selection of Public R&D Projects

The problem is characterized by:

1. There is a set A of N candidate projects, each of them described by a set of attributes Q which define the quality of the project as a research or technological proposal; frequently, fund requirements for projects are not known with precision. There is a natural "fuzziness" at what a sufficiently supported project is.
2. It is admitted the existence of a Decision Agent (a person or a group) that represent very close the preferences, priorities and beliefs of the top level managers of the organization (SDM).
3. The number of projects is too large and their fields are widespread over many disciplines; these conditions make hard for the SDM to participate directly in each project evaluation. Then it is supposed that the SDM delegates his/her authority in groups of experts (peers), who directly evaluate the projects by examining and grade their attributes and judge their funding requirements.
4. Projects can be grouped in M different areas, which are defined by the SDM. In some "calls for projects" the SDM delegates his/her authority on some lower level decision-makers, which are in charge of the selection process on the respective area.
5. Projects compete for funding, not for resources of any other kind.

6. There is a general budget to be distributed among the projects, usually not enough for funding the whole set of acceptable projects under consideration.
7. The general budget is first distributed among the assumed areas, and in general, this distribution is not uniform (it responds to priorities set by the SDM over the areas). But this distribution could also depend of the quality of the projects submitted to each area.
8. To get the final solution is to find a subset A' of A which contain the projects to be supported, and the extend of the funds assigned to each project being in that set. In what follows the set A' together with the description of the funds assigned to each projects belonging to it will be called as "Portfolio of Projects".

Selection of R&D projects is a process composed of two phases: the process of evaluation of each project and the decision of supporting or not each project, and in case of a project being supported the extend of the funds assigned to it. The final decision consists in a description of the portfolio of projects being supported by the organization.

While the results of the first phase are used to carry on the second, the decision about building up the portfolio can not be reduced to a sequence of decisions taken over individual projects, neither to a decision based on a ranking of the projects that follows from their evaluations. A portfolio of projects is an entity by its own, and not only a sum of projects, because there are also synergy, effects and minimization of risk that only make sense when considering the portfolio as an entity. For the organizations what matter is the probable impact of the portfolio as a whole, according to the objectives of the "call for projects".

The real decision problem consists in find the best feasible portfolio with a given budget, taking into account that a trade-off should be made between cost and quality of applicant projects. That is why portfolios should be compared instead of single projects when building the portfolio. But quality of the portfolio depends on the number and the quality of the projects it contains. This information is gathered during the process of evaluation. Then the process of selection of projects is composed of 3 main sub processes: a) evaluation of projects, then classify them in certain categories by quality or by some quantitative measure; b) to use the information gathered in a) to build up the portfolio and to compare them; and finally c) exploit that model of portfolio in the search for the best ones.

The dominant approach for project selection in public organizations follows the proposal of the National Science Foundation, the most important R&D organization in the Unites States of America. This approach is based on the following principles: A) distribution of projects by knowledge areas; B) the SDM delegates his/her authority in several lower level decision-makers by area; C) evaluation by peers; D) the peers evaluate each attribute of each project following a numerical scale, and finally the overall evaluation is obtained by adding the values assigned to each attributes; E) funds are assigned following the ranking generated by the evaluation of each project. The main point of this approach is to obtain a ranking of the projects according to their quality, and then assigning funds to the projects following that ranking (CONACYT, 2001).

In our view, the main drawbacks of this approach are:

In early stages of a research project uncertainty may be very strong. According to the theory of rational decision under risk, a project must be considered as a lottery with prizes (impact of each project), and probabilities to obtain those prizes (probabilities of success), and hence its quality should be measured by its expected utility (French, 1993) As a rule every method of evaluation (quantitative or qualitative) should take this fact into account. Then, any numerical measure of the quality of a project should be an increasing function of the project expected utility, a rule that most of the currently used measures do not respect (Henriksen and Traynor, 1999).

Additive value functions are rough models of SDM preferences, because: 1) their compensatory nature; 2) they require strong conditions of mutual preferential independence (French, 1993); 3) values are assigned to weights in a rather arbitrary way, thus only reflecting some ordinal information 4) the additive model is only valid if the component functions are constructed taking into account cardinal information in their respective dimension (Keeney and Raiffa, 1976); and 5) a constant trade-off rate should be held (French, 1993). There is no evidence that preferences of SDM obey points 2, 4, and 5, which are necessary conditions for the existence of a weighted sum value function (French, 1993)

There is a historical record of funded projects by the organization, including their most relevant characteristics, the evaluation given by peers, and their achievements. This objective information could be valuable for updating SDM beliefs, and hence to make better evaluations of new projects. But this information is not used mainly because of the limitations of the additive model, and because the probability of success is not taken into account as a key factor in the assessment of evaluation.

When projects are evaluated and ordered in a descending ranking the distribution of funds is made almost straightforward, taking into account only that piece of information (Martino, 1995).This approach does not consider measures of portfolio quality and does forget the ranking low confidence. The SDM does not influence in the analysis of alternative portfolios, and his/her preferences over the portfolios are not taken into consideration. In fact, the decision-makers in charge of different areas do not perform any analysis about alternative portfolios. There is no way to model imprecision of the resources needed and also it is not intended to solve the conflict cost-quality. To make things clear let us consider the following situation: the peers assign a score of 82 points to project A, and 80 points to projects B and C; suppose that the cost of A is enough to financing projects B and C. The best solution could be funding B and C, by ignoring the ranking in which project A is prioritized. The main point, which has been generally forgotten, is that selection of portfolio is a decision problem in the set of portfolios, and not in the set of projects. It is mandatory to compare portfolios, not projects. Therefore, the decision problem leading finally to the selection of projects to be funded is ill formulated.

The first three above criticisms are related to evaluation process. It can be inferred from them that models used for preferences, beliefs, and risk attitude of the SDM, all of these essential in a multicriteria decision problem under uncertainty, are not suited to reflect actual SDM subjectivity. There is neither a way to update SDM beliefs taking into account historical data of the organization. On the other hand, the last above criticism is related to the approach of distributing funds to projects only taking into consideration a quality ranking, without solving the conflict cost-quality. In private sector, the problem of portfolio of investment projects is solved by maximizing its measure of net present value, the sum of the expected values of the projects to be funded (Davis y Mc Keoun, 1986). In contrast, there is not such a quality measure in public portfolios, perhaps because of the non tangible nature of many of project attributes.

To overcome the listed drawbacks it is required: A1) A model of the SDM preferences and beliefs that can be used with confidence replacing the SDM in evaluation processes; B1) a model for updating the SDM beliefs about project probability of success based on the historical data kept by the organization; C1) a measure of a R&D portfolio's quality, which should integrate all attributes (objective and subjective ones) and makes it possible to compare portfolios; D1) an effective algorithm to solve the portfolio optimization problem, and E1) integration of all elements in a computational Decision Support System which brings support to solve the problem at the level of a whole large organization.

3 A New Method for R&D Project Evaluation

3.1 Decision Tables as Models of Preferences and Beliefs

A project should be evaluated in terms of its global impact and probability of success. Different dimensions (economic, social, scientific, development of human resources of high level, etc.) are aggregated to measure global impact. Other dimensions (curriculum of research leader, difficulty of the scientific problem to be solved, strength of research group, clarity of the proposal, academic environment of the submitting institution, etc.) are aggregated to measure probability of success. There are arguments, derived from the complexity of the problem, which bring important doubts about the satisfaction of mutual preferential independence and other mathematical conditions necessary for the existence of friendly analytical representation of those functions (Navarro, 2005). Hence, we propose to approximate them using information stored in certain decision tables. In a decision table there is a set C of condition attributes (those that characterize objects), and a set D of decision attributes (those that characterize decision agent preferences) where $C \cap D = \phi$. The rows of decision tables correspond to objects, classified as a stage of D. In our case those objects are projects, does not matter if they are actual or not. We will use three decision tables: In the first table, the condition attributes reflect dimensions of a R&D project impact and the decision attribute is the global impact. Each of the stages of the global impact is a value taken by the function $I_g(\ )$ (global impact). In the second table, condition attributes are those considered by the SDM as important dimensions influencing probability of success, while the decision attribute is just this probability, and each of its stages is a value taken by function $p_{suc}(\ )$, (probability of success). In the third table the condition attributes are p_{suc} and I_g. They together with the SDM risk attitude define the expected utility and hence the evaluation of the project. The decision attribute represents the evaluation of the project, in other words its classification into an evaluation category. We propose to make discrete the domain of every attribute; there is evidence that SDMs and peers are feeling comfortable by employing scales with stages of a clearly defined meaning in natural language (Werner and Souder, 1997), (Henriksen and Traynor, 1999). Trivial examples of decision tables are given in what follows:

Table 1 Decision table for global impact

	Condition attributes of Impact				Decision Attribute
Project	Economical impact	Social impact	Scientific impact	Development of human resources	Global impact
1	Very High	Average	High	High	Very High
2	Very High	Low	Low	Low	High
3	High	Average	Average	Average	High

Table 2 Decision table for probability of success

Project	Leader curriculum	Difficulty of problem	Strength of research group	Design of proposal	Probability of Success
1	Good	High	Average	Good	Average
2	Very Good	High	High	Very Good	High

Table 3 Decision table for project general evaluation

Project	Global Impact	Probability of Success	General Evaluation
1	Very High	Very High	Exceptional
2	Very High	Low	Average
3	High	Average	Above Average
4	Average	Low	Rejected

A decision table is a friendly tool that makes easy for a SDM to express preferences; there is empirical evidence of the fact that many decision makers are more comfortable by aggregating certain information in one decision than by explaining and rationalizing their actions (Slowinski, 1995). Slowinski, Greco and Matarazzo have shown that the logical rules inferred from a decision table have at least the same capacity of preference modeling as other methods of decision support, with one additional advantage: there are not additional axiomatic requirements about decision maker behavior neither about the decision problem being analyzed (Slowinski et. al., 2002).

The SDM must provide the information needed to build the three decision tables. It can happen that the SDM does not want to take a decision between two consecutive categories; this is a consequence of his/her limited power of discrimination and from the “granularity” of employed scale, meaning that both categories are acceptable options to classify the information contained in the condition attribute. That is, same object can be classified in two different ways, but consecutives in the decision attribute scale.

The decision table is a model of the subjectivity of the SDM and has an intrinsic value. Nevertheless that model can be refined. There are many methods to build a preference model from a decision table. "Rough Sets" methodology, proposed by Pawlak (Pawlak, 1991), is a mathematical tool for the discovery of present facts in imperfect data, to manage uncertainty and inconsistency both undesirable characteristics that appear in decision processes for the evaluation and classification of objects. The central philosophy of rough sets states that knowledge is not more than the ability to classify. To make a classification, the decision agent should note some differences between objects and build classes of objects which are very similar. These classes of indiscernible objects are used as building blocks, or elementary concepts to build up knowledge about the real or abstract world.

The preference model (a set of decision rules " If…. Then…") obtained by applying "Rough Sets" has clear advantages over other approaches: in contraposition of the neural model, "Rough Sets" model is transparent, something that is essential to understand the behavior of the decision agent, and may be used to correct some inconsistencies caused by cognitive limitations of the human been. Additionally, this methodology is better than others when help in detecting redundant attributes and establish the dependence over the set Q. The decision rules obtained build a minimal set, what also contributes to the clarity of the model. Firstly, most important attributes are found (those composing reducts), which keep the capacity of classification, the rate of the number of objects correctly classified against the total of objects. One drawback is the low efficiency of the algorithms used in this approach (of exponential complexity), but in our cases we concern only with decision tables with few attributes and stages. In (Zopounidis and Dimitras, 1998) the results of applying the "Rough Sets" methodology perform better than those obtained by other similar methodologies and popular method for multicriteria classification derived from mathematics and statistic. There is still another advantage by applying "Rough Sets" methodology in our problem: Once the decision table is accepted, dispensable attributes are computed. According to "rough sets" approach, dispensable attributes are those that, if eliminated, the classification quality of the decision table is maintained. Suppose that $c \in C$ is dispensable; there are only three possible reasons: 1) c is not really important to classify the project; 2) c is important, but depends of a proper subset of $C - \{c\}$; 3) c has low variability in the table. In fact 1) and 2) define a consistency test, because it is supposed that c should be important to classify project impact or project feasibility (depends of the table being analyzed), and that all attributes are independent. Then, if after being warned about the possible inconsistency, the SDM maintain his/her judgments, he/she should add more rows (objects, projects) to the table, selected in such a way that the variability of c, and hence the richness of the table, would be improved. If there is no dispensable attribute then the set of decision rules has the same cardinality of the whole table.

In case of a project whose decision attribute is in the border between two stages of the scale, it will be considered as a non- deterministic rule. If some dependent attributes are detected, they are eliminated and then the remaining table will be minimal. When the minimal set of decision rules is computed, then it is a model of the decision policy from the SDM. Any real project can be evaluated from the point of view of the SDM if: i) evaluations of all condition attributes of minimal decision tables are available ii) the description of the new project by its condition attributes is "close" enough to some project classified by the SDM and included in the decision tables. i) is guaranteed by the peers designed by the organization as trusted experts; they should evaluate condition attributes for global impact and probability of success (tables 1-2) of each candidate project. ii) requires the definition of a distance measure or the definition of a valued closeness relation reflecting the particular characteristics of our problem.

Each decision table should have enough power to classify new objects. In an informal way, we can state that a decision table is complete if each real project can be associated to some rule of the table by the valued closeness relation defined, with a satisfactory level of credibility. The idea behind the concept of completeness is to express how rich is the information of the table in order to make future classifications. The DSS should ensure that the decision tables being created are complete. In the following the valued closeness relation is described and also the procedure to guarantee the completeness of the decision tables.

3.2 A Preferential Closeness Relation

3.2.1 ¿Why is a New Proposal Necessary?

In general, classification techniques assign a new object to a pre-determined category by comparing the pattern of the new object with the patterns of the existing classes. Most of these techniques employ a distance measure, frequently the Euclidean one to select the nearest class (Han and Kamber, 2001), but also other metrics have been used. Under the Rough Sets philosophy, the assignation of a new object to a certain class is done by comparing the description of the new object with the decision rules derived from the original decision table. If the new object does not mach to any of the rules, then it is classified according to the "nearest rule" defined by certain metric. Slowinski (1993) made a strong criticism to Euclidean norm because of its compensatory character, that is, big differences concerning some condition attributes can be compensated by similarities in other condition attributes thus yielding a reasonable good value for the nearest rule. Slowinski (1993) studied other norms which does not exhibit a compensatory behavior. Slowinski and Stefanowski (1994) proposed a valued closeness relation based on concordance and discordance ideas from the ELECTRE methods which avoids the unnecessary compensations, and hence has prevailed in the applications of "Rough Sets". This closeness relation is based in the result of comparing a new object (A) with each rule (B) in order to evaluate the degree of credibility of the affirmation "A is close to B" denoted by A**R**B. A degree of credibility g(A,B) of the relation A**R**B over the interval [0,1] is defined, where g(A,B)=1 if A**R**B is well founded and g(A,B)=0 if there are no arguments in favor of the relation A**R**B or if there are strong arguments against it.

Some proposed distance measures introduce a weighting factor for each attribute, which intend to reflect discrimination power for the overall classification (Han and Kamber, 2001; Slowinski, 1993). This idea has been applied in a rather arbitrary way, because a consistent approach to obtain that numerical information from the available knowledge has not been proposed.

Moreover, our problem exhibits a special feature that invalid the application of any distance measure discussed so far. We are trying to approximate functions, and these are monotonic in one dimension. It means that any improvement in the evaluation of an attribute is compensated, at least partially, with the degradation of other, and that compensation influences the decision attribute. This argument can be seen more clearly in the following example:

Consider projects A and B as is shown in the following table:

Table 4

Project	I_g	P_{suc}	Evaluation
A	Very High	Very High	Exceptional
B	Very High	Average	Good
:	:	:	:

Let us suppose we want to evaluate project C, whose values in condition attributes are: I_g(C)= Above Average; p_{suc}(C) = High. Comparing closeness of C respect to A and B, any reported measure will give the result that C is closer to A, because the evaluations "High" and "Very High" are consecutive in the used scale, while we have more difference between "High" and "Average". However, the SDM can consider C clearly inferior to A (A is better in both important attributes), while in the comparison C-B, the first is outranked in global impact, but is better in probability of success. These differences should be reasonably compensated each other in the SDM's mind, and he/she will support more an evaluation of "Good" than an "Exceptional" one to project C.

3.2.2 Some Auxiliary Definitions

Indifference: Two projects are indifferent with respect to the decision attribute d if there are clear and positive reasons to justify indifference, and there are no strong reasons against it. We shall denote $\boldsymbol{x}I_d\boldsymbol{y}$ the indifference between ***x,y.***

Remarks:

a) If the SDM considers that two projects are indifferent with respect to the decision attribute d, then they should lie in the same indiscernible class of d.
b) One important difference in one or more attributes produces incomparability, in the sense of outranking methods (Roy, 1996). That difference can not be compensated by other attributes to get indifference. Then there is a veto condition to the indifference.
c) Because of the fuzzy nature of the statement about indifference, in practice the decision agent establishes a degree of credibility frequently less than 1. In reality, the statement of indifference is implying that the decision agent has sufficient certainty to establish it. For a model of preferences to be used as a representative of the SDM, it is needed to consider the indifference as a fuzzy relation. Then a level of credibility or value of truth $\sigma(\boldsymbol{x},\boldsymbol{y})$ is associated to the statement $\boldsymbol{x}I_d\boldsymbol{y}$. The SDM considers as true the proposition $\boldsymbol{x}I_d\boldsymbol{y}$ if and only if $\sigma(\boldsymbol{x},\boldsymbol{y}) \geq \lambda$, where λ is a certain cut level. Hence, we prefer to use the notation $\boldsymbol{x}I_d(\lambda)\boldsymbol{y}$. A mathematical expression for the degree of credibility that defines the fuzzy indifference relation will be discussed later.

Projects "close enough": Projects A and B are close enough for approximation purposes if the indifference between them can be established with a high degree of credibility. Note that closeness defined in this way is not a measure of similarity of the projects respect their condition attributes, but how indifferent they are in the SDM preferences.

Project approximated by preferential closeness: Project B can be approximated by preferential closeness to A if both are close enough for approximation purposes. In such a case it is assigned d(B) = d(A) with credibility $\alpha = \sigma(A,B)$, where α is the degree of credibility for the classification of B.

Real function of preferences: Evaluation scales used in decision tables carry certain information about intensity of preferences, that is usually richer than the simple ordinal information. As a reflect of these preferences and without loss of generality, we consider a real function over the set of stages of the scale in which condition attributes are measured, such that: v(Very Low) = 0, v(Low) = 1, v(Below Average) = 2, v(Average) = 3, v(Above Average)= 4, v(High) = 5, v(Very High) = 7. Let denote v_q to this function when referring to an attribute $q \in C$.

Veto threshold: We consider that the value $v_q(B)$ is a strong argument against the statement about indifference between projects A and B if the absolute value of the difference $v_q(B)- v_q(A)$ is above certain threshold which we call veto threshold. In this case we have a veto condition for the statement about indifference.

Neighborhood: The neighborhood of a project A is composed of all projects of the universe that does not hold a veto condition with A.

Dominance: Project A dominates project B if $v_q(A) > v_q(B)$ for some q of C and $v_q(A) \geq v_q(B)$ for any $q \in C$.

Project approximated by dominance in a decision table T: Three cases can be distinguished:

Case 1: There is A in T such that: B dominates A, which has been evaluated as the best stage of the decision attribute d. Then B should be classified also with the best possible evaluation.

Case 2: There is A in T such that: A dominates B, and A has been evaluated as the worst possible stage of the decision attribute. Then B should be evaluated with the worst possible evaluation.

Case 3: There are A and A' in T such that: A and A' share the same evaluation in d; A dominates B and B dominates A'. Then B should be classified to the same level than A and A'.

In all three cases a value of 1 can be assigned to the credibility of the classification.

Table λ-complete: A decision table is λ-complete if any project of the universe can be approximated by some project from T with credibility not less than λ. It is equivalent to state that any project of the universe can be classified with the information stored in T, and that this classification has credibility at least equal toλ...

3.2.3 A Model of Credibility for the Indifference Relation

We want to model indifference in a similar way to ELECTRE philosophy for multicriteria decision making (Roy, 1990). Indifference, in the ELECTRE philosophy, suggests in an implicit way the idea of compensation which we want to reflect here. Indifference between two alternatives does not necessary implies indiscernibility, but suggests that in the characteristics they differ it should exist a partial compensation which generates arguments to support the decision agent in concluding a plausible indifference.

Let us suppose that the projects are characterized by a set C of M condition attributes. Let $w_1, w_2, \ldots, w_M$ be their weights normalized, which reflect the importance given by the SDM to each evaluation criterion.
Let us consider two projects ***x, y,***, and define the following sets:
$J^+(\boldsymbol{x},\boldsymbol{y}) = \{j \in C \text{ such that } x_j P_j\, y_j\}$
$J^=(\boldsymbol{x},\boldsymbol{y}) = \{j \in C \text{ such that } x_j I_j\, y_j\}$
$J^-(\boldsymbol{x},\boldsymbol{y}) = \{j \in C \text{ such that } y_j P_j\, x_j\}$
where
x_j, y_j denote the stage of the j-th attribute in both projects; P_j and I_j denote strict preference and indifference regarding the j-th attribute.

Let us consider the proposition "project ***x*** is at least as good (in the sense of the decision attribute) as project ***y***", and denote it by ***x***S***y***. According to ELECTRE methods that proposition can also be interpreted as "the SDM considers to have enough arguments to believe that ***x*** is at least as good as ***y*** regarding attribute d and there are no strong arguments against this belief" (Ostanello, 1983). Also in the spirit of the ELECTRE method, the degree of credibility of that outranking proposition is defined here as:
$c(\boldsymbol{x},\boldsymbol{y}) = \Sigma_{j\in j+} w_j + \Sigma_{j\in j=} w_j$ .... if $v(y_j) - v(x_j) \le 2\ \forall\ j \in J^-(\boldsymbol{x},\boldsymbol{y})$
$c(\boldsymbol{x},\boldsymbol{y}) = 0$ if exists $j \in J^-(\boldsymbol{x},\boldsymbol{y})$ such that $v(y_j) - v(x_j) \ge 3$ (veto condition)
The veto condition measures the strength of the arguments against the outranking statement. In a more general model the veto threshold could depend of the importance of the attribute in discordance with ***x***S***y.***

The simultaneous veracity of ***x***S***y*** and ***y***S***x*** implies indifference (Roy, 1990) (Ostanello, 1983). Nevertheless, a big difference between $c(\boldsymbol{x},\boldsymbol{y})$ and $c(\boldsymbol{y},\boldsymbol{x})$ could suggest certain preference in favor of one of the projects, and is in fact an argument against the indifference. The strength of that argument can be modeled by a threshold parameterβ. Using the "min" operator (used for conjunction in fuzzy logic), we define the value of truth $\sigma(\boldsymbol{x},\boldsymbol{y})$ of the proposition "the project ***x*** is indifferent (in relation to the decision attribute) with project ***y***" as:

$$\sigma(\boldsymbol{x},\boldsymbol{y}) = \min\,[c(\boldsymbol{x},\boldsymbol{y}),c(\boldsymbol{y},\boldsymbol{x})] \quad \text{if} \quad |\,c(\boldsymbol{x},\boldsymbol{y}) - c(\boldsymbol{y},\boldsymbol{x})\,| \le \beta$$
$$\sigma(\boldsymbol{x},\boldsymbol{y}) = 0 \quad \text{if} \quad |\,c(\boldsymbol{x},\boldsymbol{y}) - c(\boldsymbol{y},\boldsymbol{x})\,| > \beta$$

Observe that:

i) $\sigma(\boldsymbol{x},\boldsymbol{y}) = \sigma(\boldsymbol{y},\boldsymbol{x})$

ii) $\sigma(\boldsymbol{x},\boldsymbol{x}) = 1$

iii) $|\,c(\boldsymbol{x},\boldsymbol{y}) - c(\boldsymbol{y},\boldsymbol{x})\,| > \beta$ can be considered as another veto condition for the indifference. By not imposing this condition there would be situations in which ***x*** is dominated by ***y***, having their indifference a high degree of credibility derived from the value min $[c(\boldsymbol{x},\boldsymbol{y}),c(\boldsymbol{y},\boldsymbol{x})]$. Reasonable values of β lie in the interval 0.15-0.20.

Now we can formally define the binary non-fuzzy relation of indifference Id (λ), as a λ-cut of the corresponding fuzzy binary relation. If ***U*** is the universe of projects, $I_d(\lambda) = \{(\boldsymbol{x},\boldsymbol{y}) \in \boldsymbol{U} \times \boldsymbol{U} \text{ such that } \sigma(\boldsymbol{x},\boldsymbol{y}) \ge \lambda\}$.

If $\boldsymbol{x} I_d(\lambda) \boldsymbol{y}$ for λ large enough it makes sense to assign ***x*** the same level of the decision attribute that the SDM who created the table assigned to the project ***y***. The projects are then reasonably ***indifferent***. In other words, any of the two projects can be approximated to the other by preferential closeness. When a new project ***x*** should be classified with the information stored in the decision table composed of a set T of projects (rows of the table), the algorithm should find such $b \in T$ that maximizes $\sigma(\boldsymbol{x},b)$. Let b^* be the solution project. If $\sigma(\boldsymbol{x},b^*) \ge \lambda$, then project ***x*** can be classified by T with credibility level λ (***x*** can be approximated by b^*). If some project can not be approximated, the table is not complete with that level of credibility. To make it complete only there are two ways: to reduce the level of credibility of the classification, or to increase the cardinality of T in order to improve the capacity of classification of the table.

Our approach looks to ensure the "completeness" of the decision tables, with a level of credibility large enough to ensure good approximations to the SDM subjectivity. Given a kernel of initial information, the first step is to ensure that any project of the universe that can not be classified by dominance belongs to the neighborhood of some project in the table. In the second step the goal is to assure that for any project $\boldsymbol{x}$ of the universe exists b in the table such that $\sigma(\boldsymbol{x},b)\neq 0$. Then the table will be enhanced with new projects to increase its classification power. The whole process for ensuring “completeness” is described by Navarro (2005). When the table reaches a sufficient level of credibility, the accuracy of the classification is tested; new projects are randomly generated, which are evaluated by the model and then submitted to be judged by the SDM, who has in that way the opportunity to control the quality of the approximation of his/her subjectivity. New evaluations approved by the SDM are added to the table, increasing the credibility of the classification. The SDM has also the opportunity to reformulate his/her decision policy and modify the information given previously.

3.2.4 Estimation of Weights for the Condition Attributes

Weight estimation should be performed before the closeness relation is applied. Weights should reflect the importance that the SDM assigns to each evaluation criterion, but they carry certain cardinal information which should be characterized with precision. If we want to model SDM preferences, it is necessary to use the preferential information contained in the decisions given by the SDM when the decision table was populated, because this is the more accurate expression of his/her preferences. We then choose the approach to obtain the parameters of the expression of the SDM preferences, and in turn not take into account his/her doubtful intuition. Similar approaches have been proposed by (Mousseau and Dias, 2004) and (Mousseau and Slowinski, 1998), criticizing the “heuristic” and rather arbitrary assignation of weights performed by ELECTRE III and ELECTRE TRI. The idea proposed in the present paper has the advantage of its simplicity.

The decision attribute characterizes the SDM preferences about the projects contained in a decision table. For each pair of different projects (A and B) in the decision table, if no veto condition holds between them, one of the following conditions arises:

- A is indifferent to B (A I B)
- A is preferred to B (A P B)
- B is preferred to A (B P A)

Case A I B

This case is presented when the SDM assigns the same decision value to both projects. Suppose that A S B and B S A are both true.

Suppose also that 0.67 is a reasonable level of credibility to establish the proposition “project A is at least as good (in the sense of the decision attribute) as project B”. Considering normalized weights, the following inequalities are generated:

$$\mathbf{\Sigma_{J+(A,B)}Wj + \Sigma_{J=(A,B)}Wj \geq 0.67 + \gamma}$$
$$\mathbf{\Sigma_{J+(B,A)}Wj + \Sigma_{J=(B,A)}Wj \geq 0.67 + \gamma}$$

Case A P B

This case arises when the SDM assigns one decision of a greater level to project A. Suppose that ASB and BnSA. The following inequalities are generated:

$$\mathbf{\Sigma_{J+(A,B)}Wj + \Sigma_{J=(A,B)}Wj \geq 0.67 + \gamma}$$
$$\mathbf{\Sigma_{J+(A,B)}Wj - \Sigma_{J+(B,A)}Wj > 0}$$

(under the consideration of normalized weights)

Case B P A

This case arises when the SDM assigns a decision of a greater level to project B. Suppose that BSA and AnSB. Consequently:

$$\mathbf{\Sigma_{J+(B,A)}Wj + \Sigma_{J=(B,A)}Wj \geq 0.67 + \gamma}$$
$$\mathbf{\Sigma_{J+(B,A)}Wj - \Sigma_{J+(A,B)}Wj > 0}$$

Using the set of inequalities generated by the SDM decisions, the problem of estimating weights is transformed into:

Max $\boldsymbol{\gamma}$

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s.a.
(Set of inequalities generated)
M
ΣWj = 1 (normalization)
1
with Wj ≥ 0 ∀j

The set of decision variables is composed of the weights and γ. The problem is lineal and can be solved easily using SIMPLEX method.

3.3 Updating the Decision Tables

Decision tables reflect three different aspects of the SDM subjectivity:

Tables related to global impact store preferences, priorities about different results of the project. This information changes in correspondence to the objective of the "call for projects"; it should be different for basic research, applied research and technological development. Even, inside the same category the table could change from one call to another. The table can also change when government policy is radically modified.

The evaluation table reflects mainly trade-off solutions between project impact and probability of success. It is an expression of the SDM risk attitude, which should be stable in time, but it can be different judging basic research or technological development projects. In fact, that information should be only modified when a very important change takes place in the top management of the organization or in government policy.

Tables related to probability of success model the SDM's opinion about the importance of the attributes that influence the success feasibility. It is a compromise between the quality of the proposal and the researcher team in one side, and the difficulty of the scientific problem to solve in other. Basically it does not depend of the objectives of the organizations neither of the government policy to support research. The information associated to probability of success can be modified with the knowledge of new data about results of real projects, which are evaluated and developed by the institution. Some results will confirm the previous beliefs of the SDM and another will refute them. The SDM's beliefs reflected in the table should be updated every time new information is acquired. During their history, large management R&D organizations store information about thousands of projects, such that should be employed to obtain better estimations of the probability of success. In fact, the original information given by the SDM and stored in a table of "type 2" before any updating process, contains "a priori" probability. Hence, the revision of the SDM's beliefs should be performed using Bayes' theorem.

3.3.1 Using the Historical Experience to Update the SDM's Beliefs

Suppose that our system has access to a database where the description of thousands of projects is stored. This description includes the condition attributes influencing the probability of success, all evaluated in the scale *E*. In addition, for each description there is a field maintaining information about the success or failure of each particular project in achieving their main objectives. The following approach is proposed.

Let $\{a_1, \dots a_m\}$ be the set of projects represented by the rows of a decision table for probability of success given by the SDM. Let Y be the set of projects stored in the database.

Step 1: For each $\boldsymbol{y} \in Y$, obtain the closest a_i that as defined by the closeness relation σ proposed in (Fernandez and Navarro, 2005). If the degree of closeness is higher than a given threshold we consider that $\boldsymbol{y}$ belongs to the cluster of a_i . Otherwise, y does not belong to this cluster. a_i will be denoted as the center of the cluster.

Step 2: Once $k \le m$ clusters have been defined in Y, we check for the representativeness of each cluster. If the cluster of a_i contains less than a certain quantity n_{min} of projects from Y, it will be considered a weak cluster and it will be eliminated. The projects that used to belong to the cluster of a_i will be distributed among the rest of the clusters according to the same criterion based on the degree of closeness. Note that it could happen that a particular project is not associated to any cluster. At the end of that process a subset $Y' \subset Y$ is partitioned in k' clusters ($k' \le k \le m$).

Let us suppose now that the probability of success of a new project $\boldsymbol{z}$ should be estimated. Then, execute the following steps:

Step 3: Taking into account the description of **z** in terms of its feasibility attributes (i.e. the condition attributes of a decision table of type ii), and using the decision table for calculating the probability of success, we get the probability of success that the SDM estimates without the knowledge stored in the database. In the Bayesian language this is known as the prior probability. We will denote this probability by *P(success).*

Step 4: Associate **z** to the center of the cluster a_j that holds the highest degree of closeness with the new project. If the degree of closeness is less than certain threshold, it means that the information stored in the database cannot be used for updating the SDM's belief about that particular project. In such case *P(success)* is retained as the best result. If the degree of closeness is greater than the stated threshold, then we should consider that z is a member of the cluster with center aj and continue with Steps 5 and 6.

Step 5: Calculate the frequency of success in the cluster to which **z** belongs. Since the cluster is statistically representative, this frequency is a good estimation of the probability. Then translate such frequency into a value of the qualitative scale *E*.

Step 6: Use Bayes' Theorem to calculate the so-called posteriori probability, denoted by *P(success/x).* This is the probability that this particular project (**z**) will be successful if we know that the probability of success of similar projects is *x,* and considering that the initial SDM estimation was *P(success).*

3.4 Groupware for Project Evaluation: The Role of Peers

A group of experts (peers) will be in charge for evaluating the attributes of each project; the same expert can integrate different groups. The most popular approaches used by R&D public organizations do not implement any kind of communication among peers. Peers work alone, without exchanging opinions with anybody else. In order to express their evaluation, they use a numerical scale on each attribute. The evaluation of attributes is then aggregated in a global measure representing their opinion (CONACYT, 2001). After each peer evaluates numerically the project, the mean value of all their evaluations is calculated, and this is taken as the group project evaluation. Often this value does not represent the group majority opinion. This mean value only reflects a rough numerical balance between extreme opinions. We propose to eliminate the numerical evaluation. Instead, we propose to evaluate projects in terms of the stage of condition attributes and to facilitate the opinion exchange among peers through the use of Internet technologies (while preserving anonymity). Because discussions tend to avoid extreme opinions, peer interaction should improve the group consensus and consistency in the evaluation. . Every group member identifies the positive and negative aspects of the project with respect to the attribute under evaluation. However, its evaluation can be different from peer to peer. We keep anonymity because in this way we can avoid the imposition of personalities and facilitate the freedom of expression. After discussion, the peers vote expressing their preferences on the particular scale for condition attributes. If the consensus level was not reached, the algorithm for group decision proposed by Fernandez and Olmedo (2005, 2006) (see Appendix 1) would be used. This process will be repeated for every condition attribute in decision tables for global impact and probability of success.

3.5 Summary of the Methodology for Project Evaluation

Step 1: The SDM defines the sets of condition attributes for tables of global impact and the table probability of success.

Step 2: The SDM creates tables λ-complete for global impact, probability of success and general evaluation of projects.

Step 3: Exploitation of the tables. The peers evaluate condition attributes for impact and success probability of each submitted project. Then, using the decision tables and the preferential closeness relation described in 3.2, the SDM's opinion about the level of global impact, probability of success and general evaluation can be associated to each particular project. Historical data of the organization about project feasibility, if exist, can be used to update the SDM´s beliefs as was explained in Section 3.3.1.

Remarks: In large organizations, it is a common practice to organize different calls for each kind of project, at least separating basic research, applied research and technological development. Clearly, each call for projects may have different condition attributes; even being the same attributes, their relative importance may change. Then, decision tables (and their condition attributes) can change within the same organization from a call for projects to another. Nevertheless, the suggested decision tables have a relative stability, unless organizational policy changes.

But as the policy of the organization remains unchanged, in each new call for projects the SDM may accept the tables created in a preceding call of the same kind of project, making the two first steps unnecessary.

4 Searching for the Best Project Portfolio

A second moment in the process of projects selection is related to decide about the amount of money that will be assigned to each project. This is done by using information about project evaluations. Returning to the discussion in Section 2, we want to remark that the real decision problem it is not between projects but between portfolios. The process of finding the best portfolio needs a) to compare portfolios using a certain measure of their quality; and b) to have an effective procedure to explore the set of feasible portfolios. Point a) will be discussed in the following, and in section 4.2 we will return to point b).

4.1 A Model of R&D Portfolio's Quality

In this section, we discuss some characteristics of the R&D portfolio problems in public organizations that are relevant to build a model of portfolio's quality.

A). A portfolio is an aggregation of lotteries, in fact a giant lottery. Let us suppose that I_1, I_2, … I_N denote the "prizes" of the individual lotteries (the impacts of the projects). So, the portfolio is a lottery with a very great number of possible outputs; some of them with very low prizes; others with very high prizes. The portfolio is not reduced to the individual lotteries; it is a new entity with its specific properties. For instance, the variance of portfolio measure of quality and diversification are important concerns (cf. Markowitz, 1991).

B). Unlike investment portfolio problem, it is very reasonable here the supposition of statistical independence among projects, because the probability distributions are basically independent (the projects are independent). As a consequence, very low prizes (a relatively small part of the projects is successful) or especially high prizes (an important majority succeeded) have an almost insignificant probability. The mass of probability is concentrated on the average prizes.

C). As a result of statistical independence, there is no correlation between projects. Diversification, an important issue in an investment portfolio problem (cf. Markowitz, 1991), is given here in a natural way. Although the beneficial effects of the diversification with negative correlation cannot be obtained, statistical independence makes almost impossible to get very bad global results.

D). The group of stakeholders that constitutes or represents the SDM does not feel they own the money, (after all public money), that is distributed among the projects.

E). That group of stakeholders has a budget P for the support that is never going to be considered as a loss, but an investment. Whenever projects of acceptable quality exist that require support, the SDM will consider advisable to exhaust P (CONACYT, 2001). The possible failure of a project rather tends to be valued not like a loss but like a lost opportunity (CONACYT, 2001).

Note that the impact I_k of a particular project is very low in comparison to the total impact that a portfolio could achieve. According to Taylor's Theorem, a linear form kI is a suitable approximation to the SDM's utility function in the interval $[0, I_k]$. Let c_j be the certainty equivalent of the j-th project. In the relevant range of this project the utility function is linear; so, $c_j = E(I_j)$, where $E()$ is the expected value.

Consider the sum

$$C' = x_1 c_1 + x_2 c_2 + \ldots + x_N c_N = x_1 E(I_1) + x_2 E(I_2) + \ldots + x_N E(I_N) \quad (1)$$

where $x_i = 1$ if the i-th project is supported. Otherwise $x_i = 0$. C' is the sum of the certainty equivalents of the projects in the portfolio.

Let $I = x_1 I_1 + x_2 I_2 + \ldots + x_N I_N$ be the impact of the entire portfolio. From Equation (1), it follows that

$$C' = E(I) \quad (2)$$

Let C'' denote the portfolio's certainty equivalent. C'' should be a strictly increasing function on each c_j . In linear cases, $C'' = E(I)$ and $C'' = C'$.

Only in this case the certainty equivalent of the portfolio equals the sum of the certainty equivalents of the projects that compose the portfolio. In our problem items B), C), D) and E) play an important role for understanding why the risk attitude of the SDM moves away from aversion. In the zone of average prizes, where the mass of probability is concentrated, it is natural to suppose that the SDM behaves neutrally towards risk. A utility linear model seems suitable for representing the SDM's risk attitude in that zone (cf.(French, 1993)). Some deviations from the linear form may occur in the zones of very high prizes. By all the arguments exposed above we propose that C'' be approached by expression (1).

Another important issue is the imprecise estimation of the monetary resources handled by each project. Let d_j be the funding assigned to the j-th project. There is an interval $[m_j, M_j]$ such that if $m_j \leq d_j < M_j$, the SDM hesitates whether the project is adequately supported. The proposition "*the j-th project is adequately supported*" may be seen as a fuzzy statement with a degree of truth. If we consider as fuzzy the set of projects adequately funded, then the SDM can define a membership function $\mu_j(d_j)$ representing the degree of truth. $\mu_j(d_j)$ is a monotonically increasing function on $[m_j,M_j]$, such that $\mu_j(M_j) = 1$, $\mu_j(m_j) > 0$, and $\mu_j(d_j<m_j) = 0$. Without arguments in favor of a more complicated functional form, it seems reasonable to admit that μ is piece-wise linear. The expected utility assessed by the SDM for the j-th project is based on the premise that it receives the necessary funding for its operation. When $d_j<m_j$ the SDM is convinced that the project is not sufficiently funded; in case $m_j \leq d_j < M_j$ the SDM hesitates about the truth of that statement. This uncertainty must affect the expected utility of the project, because it reduces the subjective probability of success, which had been estimated under the premise of sufficient funding. The easiest way to introduce this issue in the model is by replacing x_j in Equation (2) with $\mu_j(d_j)$. This is equivalent to a fuzzy generalization of Equation (2); x_j can be considered as the indicator function of the set of supported projects. When a non-fuzzy model includes the binary indicator function of a crisp set, the fuzzy generalization provided by classical "fuzzy technology" is made by substituting this function with a membership function expressing "the grade of membership" to the more general fuzzy set. In this way Equation (2) becomes

$$\sum_{j=1}^{N} c_j \, \mu_j(d_j) \tag{3}$$

Since the certainty equivalents are given in a ratio scale, c_j can be replaced by $w_j = k'c_j$ (k'>0) and the function

$$V = \sum_{j=1}^{N} w_j \, \mu_j(d_j) \tag{4}$$

is still an ordinal function on the set of portfolios. That is, a measure of the portfolio's quality. But in Equation (4) the factors w_j might be interpreted as importance factors, which depend both on the project evaluation and on the the kind of project, (i.e. the project's scientific field or area of knowledge A_k). These parameters express the importance assessed by the SDM to a project with certain evaluation, belonging to a particular scientific field. Hence, the w_j's should be calculated from the SDM's preferences, expressed when he/she solves certain "*indifference equations"* between portfolios. The ratios w_i/w_j correspond to a comparison of the respective certainty equivalents contained in the project evaluations given in the decision scale *E'* of Table 3 . This is the last step needed to model the SDM's subjectivity.

Once the w_j's have been estimated, the "best" portfolio can be found solving the problem:

$$\begin{array}{ll} \text{Maximize} & V = \sum_{j=1}^{N} w_j \, \mu_j(d_j) \\ \text{s.t.} & D \in R_F, \end{array} \tag{5}$$

where $D = (d_1,\ldots,d_N)$. The feasible region R_F is determined by the constraints imposed to the available funds and to their distribution by area, which is not uniform in general. There are other constraints which should be considered since there are many possible portfolios that could be unacceptable for the DM due to some particular budget distributions very difficult to justify. Suppose that the DM agrees with the assertion "project j is much better than project i". Then, portfolios in which μ_i greater than μ_j could be unacceptable. It means the existence of some veto situations which can be modeled with the following constraints: for every project i and j belonging to the same area A_k, if $(s_i - s_j) \geq v_{S'}$ (s_i, s_j are stages of the decision attribute of tables type 3), then $(\mu_i(d_i) - \mu_j(d_j))$ must be greater than (or equal) 0, where $v_{S'}$ is a veto threshold. These veto constraints were analyzed by Fernandez and Navarro (2002).

4.2 An Evolutionary Algorithm for Optimizing the Portfolio´s Quality

Expression (5) denotes a non linear optimization problem, with objective and constraint functions being discontinuous on hyperplanes $d_i = m_i$ with i = 1..N (see below the shape of membership functions). In this problem the number of variables can be considerably large (reaching thousands) and the feasible regions are also very complex. So, in this case the traditional methods of non linear optimization can not be applied in an effective manner. Considering those facts, we propose an evolutionary algorithm to solve the decision problem, because these algorithms are less sensitive to the shape of the feasible region, the number of decision variables and the mathematical properties of the objective and constraints (Coello, 2002). The proposed algorithm is an extension of a version firstly appeared in (Fernandez and Navarro, 2002), and is presented below:

(1) Create a feasible initial solution. Assign RESTART_NUMBER=0.
(2) Repeat until the maximum restart number (cycles) is reached:
  a. Generate the initial population (with N' members) by N'-1 mutations starting from initial solution, which is kept in population.
  b. Assign to Best Solution the fittest individual in population.
  c. Repeat until the maximum number of generations is reached. Assign GENE=1:
    i. Apply the crossover operator.
    ii. Apply the mutation operator.
    iii. Evaluate each individual in population.
    i. Add Best Solution to the population.
    ii. Select the best individual of its generation and compare it with Best Solution; update Best Solution if the best individual is more adapted.
    iii. Assign GENE = GENE + 1. If GENE is already the maximal number of generations, assign RESTART_NUMBER = RESTART_NUMBER + 1, take Best Solution (the best individual found so far) as an initial solution in order to repeat the cycle beginning in step 2.

4.2.1 Individual Structure

Each individual is represented as a float coding of a particular distribution of funding among the *N* projects (Figure 1). In this structure, the funding that each project receives is represented by its membership function $\mu_j(d_j)$, with values between zero and one. Each floating point is stored in a gene.

μ_1	μ_2	μ_3	…	μ_N

Fig. 1. Individual structure

4.2.2 Evaluation of the Objective Function

Fitness of each individual is given by Equation (4); a model of $\mu_j(d_j)$ is needed to carry out the evaluation of that equation. Let us suppose that the shape of the membership function is the same for all projects. As discussed in section 4.1, $\mu_j(d_j)$ is a non decreasing function in $[m_j, M_j]$, such that $\mu_j(M_j) = 1$, $\mu_j(m_j) > 0$, and $\mu_j(d_j<m_j) = 0$. Without further arguments in favor of a more complicated shape, we propose to represent the objective function as a piece-wise linear function, with a discontinuity in m_j (Figure 2). We propose to choose parameters $0<\alpha<1$, $m/M<\beta\leq 1$ such that:

$$
\mu(d) = \begin{cases} 0 & \text{if } d < m, \\ \alpha & \text{if } d = m, \\ \dfrac{(1-\alpha)d+\alpha\beta M-m}{\beta M-m} & \text{if } m \le d \le \beta M, \\ 1 & \text{if } \beta M < d \end{cases}
$$

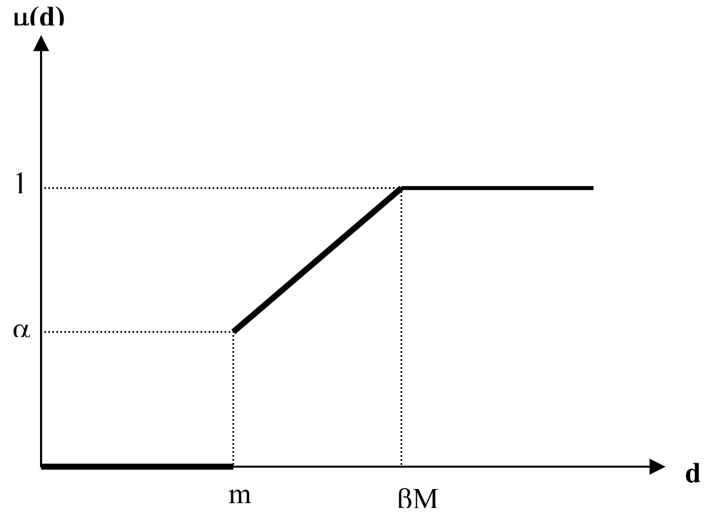


Fig. 2. Membership function

β and α model the meaning of what is a "sufficiently supported project " for the SDM. We have performed our test experiments with $\alpha = 0.5$ and $\beta = 1$; their natural values lies in intervals [0.5,0.7] and [0.9,1], respectively.

4.2.3 Generating an Initial Feasible Solution

In order to generate an initial feasible solution, we intend to perform a simulation of a natural heuristic used by a DM that conforms the portfolio, without support of a decision analysis tool. First, the feasible percentages to be distributed in the several areas are determined, initially based on the maximum percentages permitted to each area, to subsequently reduce them in equal percentage until having in each area a percentage that fulfils the maximum and minimum established requirements. Once the total budget percentages to be assigned by area are established, we proceed to distribute it among projects. Let R(j) be a ranking of the projects belonging to the jth- area. Heuristic consists of assigning quantity of resource d_{j1} holding $\mu(d_{j1})=1$ to the most important project (j1), and to continue checking the ranking in the same way, until ending the projects in this area or until the established resource for the area is consumed. If at the end of the process there is still budget available, it is distributed according to the general ranking, being careful not to overcome the maximum bounds in the corresponding areas.

4.2.4 Generation of the Initial Population

Each individual incorporated to population results from a mutation process applied to the present population. Initially the population is composed of only one individual (initial solution). The generation process finishes when the dimension established for population is completed.
premise the probability to be chosen is proportional to each particular fitness.

The crossover operator takes genes from each parent string and combines them in order to create a "child" string. The main reason is that by creating new strings from fit parent strings, new and promising zones of the search space will be explored. Many crossover techniques have been reported. Particularly, we use the classic crossover technique based on a random cut point, and a crossover probability of 20 % is used here.

The replacing process refers to how to update current population with the individuals obtained by crossover. In a previous work (Fernandez and Navarro, 2002), replacement was based on an opposite criteria used for crossover, that is, the less fitted individuals have a higher probability to be selected for being replaced. This caused an increase of the selective pressure and therefore the diversity of the population was degraded. Beside, the temporal complexity of the algorithm was increased due to the number of processes involved in that replacement form. In the present work, a random replacement criterion (every individual has the same probability to be replaced) is used avoiding the problems described above.

A similar approach is used for implementing an elitist policy: an individual is randomly chosen from the current population and is replaced by Best Solution. In such a way, the presence of Best Solution in the updated population is guaranteed.
In our work we use a constant mutation index previously defined, that is, a probability to mute any individual. Each individual of the population is considered in order to decide if it will be mutated, according to a generated random number between zero and one. Once it has been decided to apply the mutation operator to a given individual, it is randomly decided which one of its genes will change; that change is realized randomly choosing a value in the interval [-0.2 , 0.2], without considering the value of zero as a possible result, adding this number to the gene to mute, considering the maximum amount not to be bigger than 1 neither lesser than zero. Let us mention that all individuals have the same probability to be mutated.

4.2.5 Fitness Function and Handling Constraints

There are many ways of handling constraints into an EA (e.g. Bäck et. al., 2000). We use here an approach proposed by (Fernandez and Navarro, 2002) which combines some good features of penalty function and "death penalty" methods. It is based on the following ideas:

It is rather obvious that most constraints of our problem are soft ones. Suppose that they suffer a small weakness which defines a new region R' ($R_F \subseteq$ R'). An individual with a high value of the objective function belonging to R' - R_F could be accepted as a satisfactory solution of the original problem (because of the softness of constraints). Suppose also that R'' is defined by an additional weakness of the set of constraints (R' $\subseteq$ R''). An individual $\underline{x}$ belonging to R''-R' is not accepted as a satisfactory solution; it should suffer some kind of "penalty". But, when a high score of the objective function is associated to $\underline{x}$, this individual could enhance the genetic information contained into population. Otherwise, if the objective function score associated to $\underline{x}$ is not sufficient high, it should be rejected.

In this sense, the penalty effect is defined in such a way that a value of the fitness function F is associated to each individual $\underline{D}$ according to the following procedure:

Step 1: Find the best individual D_b into the current population. $V(D_b) = \max \{V(D_i)\}$ $D_i \in$ current_population, V is given by Equation (4).

Step 2: Find the worst individual Dw into the current population. $V(Dw) = \min \{V(Di)\}$ $Di \in$ current_population.

Step 3: Calculate the fitness F of each individual $\underline{D}$, so that

$F = V(\underline{D})$ if $\underline{D} \in R'$
$F = V(D_w)$ if $\underline{D} \in R''-R'$ and $V(\underline{D}) \geq V(D_b)$
$F = 0$ otherwise

Note that this approach is almost as simple as "death penalty", but it permits to perform an exploration of the infeasible zone containing individuals with high objective function scores. To some extent, the penalty effect depends on the distance to the feasible region. Additionally, any feasible individual is more fitted than any infeasible one (excepting D_w whose fitness can be equal to infeasible individuals). Other more complicated ways are possible following the same idea.

5 Brief Description of the Functional Structure of the Proposed System

The two central steps of the projects selection process can be integrated in a hybrid organizational decision support system performing the following main functions:

1. To establish interaction with the SDM in order to determine the set of attributes and their relative importance
2. To create and validate decision tables λ-complete for global impact, probability of success, and general evaluation...
3. To manage the organization of the peer groups and their virtual meeting. As a result, the system obtains peer evaluations about the condition attributes of each candidate project.
4. To exploit the created decision tables in order to achieve the general evaluation of each project. If it exists in a proper format, the historical experience of the organization should be used for bayesian updating of the SDM's beliefs about probability of success .
5. To establish interaction with the SDM in order to obtain the parameters of the model of portfolio's quality discussed in Section 4.1.
6. To carry out an experiment running the evolutionary algorithm with different sequences of random numbers. To interact with the SDM until the final decision.

The system core, performing the critical task of selecting the best portfolio, is composed of the decision tables manager and the evolutionary algorithm. One important subsystem is the *groupware*, (see Figure 3), in charge of negotiating the inter-component communication. This subsystem works in close relationship with the system core and with the *data administration* subsystem. The latter is in charge of the administration of the system's distributed databases. Finally, we have the *user interface* subsystem, implemented as a web-based application on dynamic pages. This subsystem was developed using ASP.NET technology. The functional scheme of the complete system is shown in Figure 4. The groupware subsystem contains a module to manage the virtual meetings in an asynchronous way between the peers of each group evaluating particular projects, and between the members of the SDM as it is a collective entity. By the first function this subsystem supports the exploitation of the decision tables at the moment of projects evaluation, while the second function is important to build the decision tables.

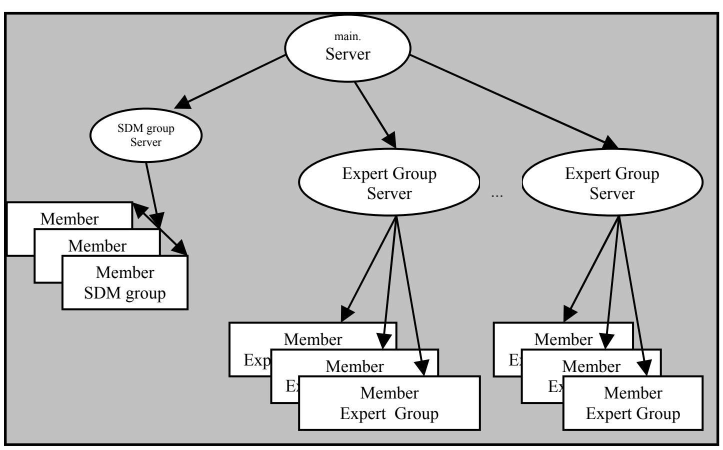


Fig. 3. Groupware architecture.

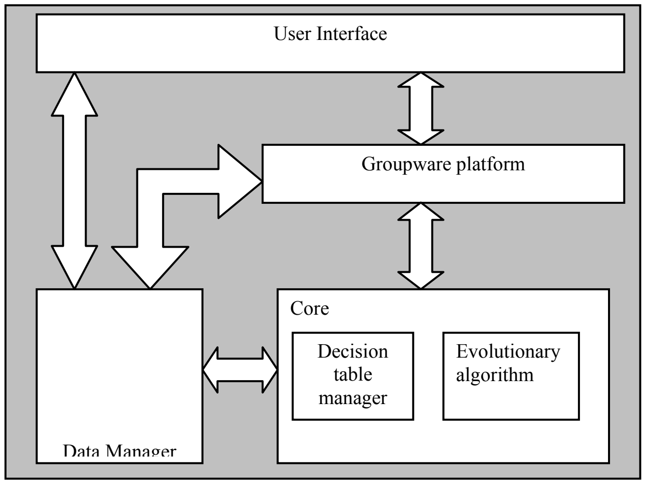


Fig. 4. Basic functional structure of the DSS

6 Some Test Examples

6.1 Evaluation Model

To illustrate the application of our proposal and prove its effectiveness we show an example based on a decision table integrating the global impact of projects. Judgments of a real decision maker were obtained, who considered that all condition attributes are equally important for the final decision. His evaluations are consistent with this hypothesis.

Considering that premise, if the model for calculating weights is correct (Section 3.2.4), we should get similar values of these parameters for all attributes. In order to validate the model we chose 5 pairs of projects, each satisfying an indifference relation with respect to the global impact. Table 5 presents this sample.

Table 5

Project	Economical impact	Social impact	Scientific impact	Human resources	Global impact
A	Above average	Above average	High	Below Average	Very High
B	Average	Above average	High	Average	Very High
C	Below Average	Very low	Average	Very low	Average
D	Very low	Very low	Above average	Very low	Average
F	Very low	Below Average	Average	Very low	Average
G	Below Average	Very low	Average	Very low	Average
H	Very low	Below Average	Average	Very low	Average
I	Very low	Very low	Above average	Very low	Average
J	Very low	Below Average	Very low	Average	Average
K	Very low	Very low	Very low	Above average	Average

Solving the linear optimization problem of 3.2.4 we obtained w_{ig}= 0.25, I=1, 2, 3, 4. This result perfectly agrees with the premise of equal importance of the condition attributes.

Under the same premise about similar importance of the condition attributes, the following information was obtained from the decision maker, until a 0.75-complete table was populated (Table 6):

Table 6

Project	Economical impact	Social Impact	Scientific impact	Human resources	Global impact
1	Very High	Average	Very High	Very High	Outstanding
2	High	High	High	High	Outstanding
3	Average	Average	Average	Average	Very High
4	Low	Average	Average	Average	High
5	Low	Low	Average	Average	Above average or High
6	Low	Low	Low	Average	Above average
7	Low	Low	Low	Low	Average
8	Very low	Low	Low	Low	Low or Below Average
9	Very low	Very low	Very low	Very low	Very low
10	Below Average	Below Average	Below Average	High	High
11	Below Average	Below Average	High	Below Average	High
12	Below Average	Below Average	High	High	Very High
13	Below Average	High	Below Average	Below Average	High
14	Below Average	High	Below Average	High	Very High
15	Below Average	High	High	Below Average	Very High
16	Below Average	High	High	High	Very High
17	High	Below Average	Below Average	Below Average	High
18	High	High	Below Average	High	Very High
19	High	Below Average	High	Below Average	Very High
20	High	Below Average	High	High	Very High
21	High	High	Below Average	Below Average	Very High
22	High	High	Below Average	High	Very High
23	High	High	High	Below Average	Very High
24	Low	Low	Above average	Very low	Average
25	Above average	Very low	Low	Low	Average
26	Above average	Above average	Very low	Low	High
27	Low	Above average	Very low	Low	Average
28	Very low	Above average	Very low	Below Average	Average
29	Below Average	Very High	Very High	Very High	Outstanding
30	Very High	Very High	Below Average	Very High	Outstanding
31	Very High	Very High	Very High	Below Average	Outstanding
32	Above average	Above average	Below Average	Very low	High
33	Very High	Low	Above average	Below Average	Very High
34	Very low	Very low	Average	Average	Average
35	Very low	Very low	Above average	Very low	Average
36	Very low	Below Average	High	Very low	High
37	Very low	Very low	Very low	High	Above average
38	Very low	Very low	Very low	Low	Very low
39	Very low	Very low	Very low	Very High	High
40	Very low	Very low	Very low	Below Average	Low
41	Very low	Very low	Very low	Average	Below Average

Remarks:

1. The credibility level $\lambda= 0.75$ is usually considered reasonably high to establish an acceptable level of outranking in applications of ELECTRE methods. It is worth noting the low number of necessary samples to obtain an acceptable level of completeness; the core of the training examples required by a typical Artificial Intelligence technique to get good accuracy in further classifications is considerable higher (e.g.Doumpos and Zopounidis, 2002).

2. Note that in few rows of Table 6 (projects 5^{th} and 8^{th}) the decision maker did not want to make a choice between two neighboring categories. It is a consequence of the discrete nature of the evaluation scale and the decision maker limited discrimination capacity.

In order to evaluate the classification accuracy of our proposal, the decision agent was questioned about the evaluation of 43 new projects. The same questions were made to our model and to an artificial neural network trained with the examples of Table 6. The software Neurosolutions, version 5.0 (NeuroDimension Inc., 2005) was used. As neural architecture, a Perceptron Multilayer was chosen, with 28 neurons in the input layer, two hidden layers with 8 neurons each, and 8 neurons in the output layer. Other characteristics of the neural network follow:

Kind of learning employed: supervised learning**.**

Activation function: Hyperbolic tangent**.**

Propagation rule: M**omentum**.

The results of the three classifications are presented in Table 7.

Table 7

Proj.	Economical impact	Social impact	Scientific Impact	Human resources	Evaluation of model	Evaluation of real decision maker	Evaluation of neural network
1	Low	Very High	High	Below Average	Very High	Very High	High
2	Below Average	High	Low	Below Average	High	High	High
3	High	Below Average	Very low	Very High	Very High	Very High	Very High
4	Very low	Very low	Low	Below Average	Below Average	Below Average	Average
5	Below Average	Low	Very low	Low	Average	Average	Low
6	Above average	Above average	High	Below Average	Very High	Very High	High
8	Average	Above average	High	Average	Very High	Very High	High
9	Average	Average	Low	Above average	High	High	High
10	Below Average	Low	Low	Low	Above average	Above average	Average
11	High	Above average	High	Very low	Very High	Very High	Outstanding
12	Average	High	Low	Very low	High	High	Average
13	Very low	High	Low	Average	High	High	Above average
14	Very low	High	Below Average	Average	High	High	High
15	Below Average	Very low	Average	Very low	Average	Average	Average
16	Above average	Low	Below Average	High	High	High	Very High
17	High	Below Average	Very High	Low	Very High	Very High	Very High
18	Below Average	Average	Low	High	High	High	Very High
19	High	High	Very High	Very low	Very High	Very High	Outstanding
20	Average	Low	Average	Below Average	Above average o High	High	Low
21	Low	Very low	Average	Above average	Above average	Above average	Average
22	Above average	Average	Very low	Below Average	High	High	High
23	High	High	Very High	Very High	Outstanding	Outstanding	Outstanding
24	Below Average	Average	High	Average	High	High	Very High
25	Average	Below Average	Low	Very High	Very High	Very High	High
26	Above average	Low	High	High	Very High	Very High	Outstanding
27	Low	Very High	Below Average	Below Average	Very High	Very High	High
28	High	Above average	Very low	High	Very High	Very High	Very High
29	Very low	Very low	Above average	Very low	Average	Average	Average
30	Very low	Below Average	High	Very low	High	High	Average
31	Low	Above average	Very High	Below Average	Very High	Very High	Average
32	Average	Very low	Average	Low	Average	Average	Average
33	Average	Very High	Below Average	Very low	Very High	Very High	High
34	Very low	High	Above average	High	Very High	Very High	Average
35	Average	Below Average	High	Low	High	High	High
36	High	Very low	High	Average	Very High	Very High	Below Average
37	Below Average	Above average	Above average	Very low	High	High	Average
38	Low	Average	Below Average	Above average	High	High	High
39	Above average	Below Average	Low	Low	High	High	High
40	Very low	Average	Average	High	High	High	Average
41	High	Above average	Low	Below Average	High	High	High
42	Low	Low	Above average	Low	High o Above average	Above average o High	Average
43	Very low	Very High	Above average	High	Very High	Very High	Outstanding

A comparison between the proposed model and the decision maker evaluations reveals a high level of coincidence. Note that there is a single and very light discrepancy (row 20th). The real decision maker prefers

"High" and the model can not distinguish between "Above Average" and "High". This classification is supported by row 5^{th} from Table 6; the decision maker stated that he would not be against to consider the project (Low, Low, Average, Average) (row 5^{th} from Table 6) on a fuzzy border between "high" and "above average". On the other hand, we can observe a considerable discordance degree between real decisions and classifications from the neural network. One can only see 15 exact coincidences. Nine important discrepancies are underlined in Table 7.

Table 6 is a model of the SDM preferences regarding the integration of attributes of impact in a global evaluation. By the results of Table 7, this model shows a very high precision, and thus can replace the SDM when the global impact of new projects is evaluated. The system only needs to obtain the evaluation given by the peers to the condition attributes.

Navarro (2005) presents an example, omitted here by space, in which a table of probability of success, (similar to Table 2) is populated, with five condition attributes of very unequal relevance. 254 rows were needed to get a reasonable λ-complete table. A validation of the model against a sample of 50 evaluations performed by a real decision maker also gave a very high coincidence. This result clearly outperforms those given by an artificial neural system, but also the exhaustive experiments reported by Doumpos and Zopounidis (2002), in which the main classification multicriteria methods obtain an average error greater than 20% in problems with five condition attributes and only three categories of evaluation.

6.2 Searching for the Best Portfolio

Consider the following example for testing our model for portfolio optimization: To allocate a budget of 50 million dollars on a set of 400 projects, distributed in four areas: 140 in the first area (engineering projects), 80 in the second one (health and biological sciences), 100 in the third area (basic sciences), and 80 in the last area (social sciences). A classification of the projects based on their evaluations and areas is described in Table 8.

Table 8 Distribution of projects by area

	Engineering	Natural and exact sciences	Biological and medical sciences	Social sciences
Very Good	54	28	13	12
Good	23	9	18	24
Above average	62	32	36	28
Average	1	9	17	11
Below Average	0	2	16	5
Total	140	80	100	80

A measure proportional to the certainty equivalent for each class of projects was calculated considering its evaluation and particular area. Their values were obtained taking as reference (w =1) a social science project evaluated as Below Average (see Table 9). These values define a ranking on the set of projects which can be used to allocate funds according to the classical heuristic criticized in Section 2.

Table 9 Certainty equivalent by class of projects

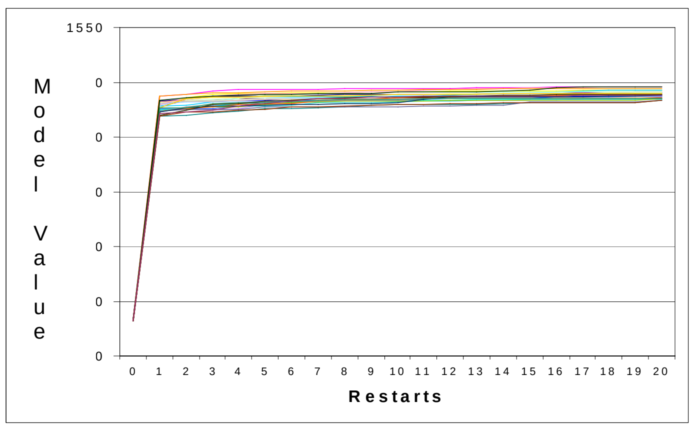
	Engineering	Natural and exact sciences	Biological and medical sciences	Social sciences
Very Good	6	4.5	4	3
Good	4.5	3.5	3	2.25
Above average	3	2.33	2	1.5
Average	2.2	1.65	1.466	1.1
Below Average	2	1.5	1.333	1

Four different instances (Problems 1-4) were generated assigning randomly budget ranges to each area, and random numbers m_j, M_j to each project, representing its minimum and maximum funding requirements evolved in its membership function. Those maximum and minimum budget ranges by area for each particular random problem are pointed out in Table 10.

Table 10 Funding restrictions by knowledge area

Area	Problem 1		Problem 2		Problem 3		Problem 4	
	Min (%)	Max (%)	Min (%)	Max (%)	Min (%)	Max (%)	Min (%)	Max (%)
1	30	50	20	40	15	28	24	50
2	20	40	10	24	25	35	8	25
3	16	30	30	50	20	45	8	25
4	10	24	16	30	10	20	15	30

The proposed Evolutionary Algorithm was coded in Visual C++. The elapsed time was about 25 minutes for one million generations running on Pentium-4, 2.1 GHz microprocessor, 256 Mb RAM and 74.5 GB hard disk. Thirty different running of the algorithm were performed using 20 restarts by running and 50000 generations by restart for each problem. We did this in an effort to control the random behavior of the algorithm. The performance of the function by restart and by running for Problem 1 is presented in Figure 5 (in the other problems we obtained similar results). We could identify a significant improvement in the four instances; in the following, we discuss some results.



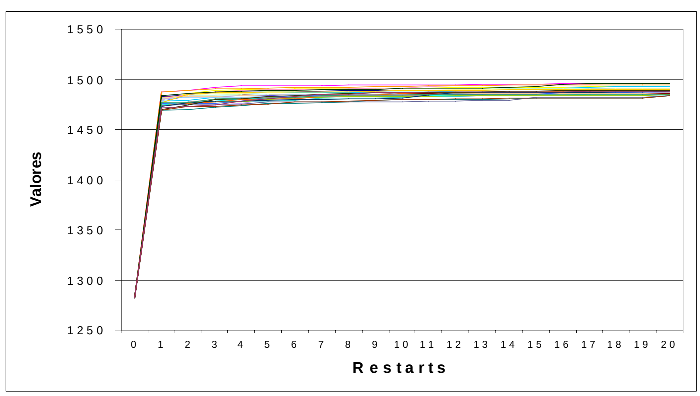


Fig. 5. Evolution of results
Note: Colors identify different runs

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Table 11 shows the values of the portfolio's quality (Equation 4) obtained using both our proposal and the traditional way of funding.

Table 11 Traditional way of funding versus our proposal

Instance	Portfolio's quality funding following the ranking given by project evaluations	Optimized portfolio's quality	Improvement
1	1406.8	1533.95	9%
2	1282.36	1496.16	16.67%
3	1279.58	1458.48	14%
4	1393.58	1566.97	12.44%

These results are equivalent to an average saving of 6.514 million dollars, 13.02% of the total budget... This improvement is reflected on the number of supported projects, as pointed-out in Table 12. The average number of supported projects is increased 12.5 %.

Table 12 Traditional way of funding versus our proposal (portfolio's cardinal)

Instance	Number of supported projects funding following the ranking given by project evaluations	Number of supported projects in the optimized portfolio	Increment
1	237	267	12.76%
2	257	285	10.89%
3	265	299	12.83%
4	246	279	13.41%

For Problem 2, Table 13 describes the portfolio composition comparing the traditional solution (following the ranking information (R)) with the solution achieved by the new proposal (NP).

Table 13 Traditional solution(R) vs. our proposal (NP)

	Engineering		Natural and exact sciences		Biological and medical sciences		Social sciences	
	R	NP	R	NP	R	NP	R	NP
Very Good	54	54	27	28	13	13	12	12
Good	6	15	0	4	18	1	24	24
Above average	0	32	0	13	36	34	28	17
Average	0	0	0	0	17	5	7	2
Below Average	0	0	0	0	15	12	0	2
Total	60	101	27	45	99	82	71	57

Note that the improvements are obtained redistributing funds, solving trade-offs cost-quality. Comparing R and NP, Table 14 shows the distribution of projects which are taken off the final portfolio. 37 projects are eliminated from the traditional portfolio, mainly small relevance proposals. Finally, Table 15 points-out the project belonging to both portfolios (R and NP) but suffering an important reduction on their support. This set is composed of 13 small relevance projects and 11 evaluated as *Very Good* but with elevated costs. Hence, the improvement of the portfolio's quality is given mainly by a more rational resource allocation, and not by the decreasing support to relevant projects.

Table 14 Projects laying in R and not in NS

	Area 1	Area 2	Area 3	Area 4
Very Good	0	0	0	0
Good	3	0	0	0
Above average	0	0	2	11
Average	0	0	12	5
Below Average	0	0	4	0
Total	**3**	**0**	**18**	**16**

Table 15 Supported projects suffering important reduction of their funds

	Area 1	Area 2	Area 3	Area 4
Very Good	0	11	0	0
Good	0	0	0	0
Above average	0	0	1	3
Average	0	0	2	1
Below Average	0	0	6	0
Total	0	11	9	4

A "simulated annealing" process was applied to find out the local or global character of the obtained solution. Taking the best solution as starting point, five "annealing" runs were performed with negligible changes of the portfolio's quality.

7 Concluding Remarks

The proposed approach satisfies the need of a scientific methodology for R&D project selection in public organizations. To the best of our knowledge, this is the first time an integrated methodology is proposed to address five fundamental problems: a) how to model the preferences, beliefs and priorities of the top management, and how to use the resulting model (combined with the opinions from peers) for project evaluation; b) how to measure the "quality" of a R&D portfolio; c) how to efficiently explore the space of portfolios looking for the best ones; d) how to discover "knowledge" embedded in historical data that describes the desirable characteristics of projects; and e) how to handle the imprecision related to the project funding requirements.

To create complete decision tables provides a good framework to model preferences and beliefs of the higher management of public organization evaluating and funding R&D projects. Using the set of sorting rules included in these tables as intelligent tool, it is possible to assure that those preferences and beliefs are taken into account during the evaluation process of the projects, what is not fulfilled at the moment in most of the cases.

The imprecision concerning real fund requirements is modeled in simple and natural way by fuzzy predicates. Our proposal of building a linear function using project's specific evaluations (translated to certainty equivalents) seems to be a reasonable model for the decision maker's preferences on R&D portfolios. This model gives us a measure of portfolio quality which is used as objective function. A powerful evolutionary heuristic was developed to explore the set of feasible portfolios, arriving to clearly improved solutions. In examples of real size the method performed very well in the sense of quality of solutions; the computational effort on PC is acceptable.

Our approach is considerably superior to traditional and popular heuristics used to allocate funds for R&D, because:

1. Using the model of the portfolio's quality and an evolutionary algorithm, the set of portfolios can be explored and a solution close to the optimum can be obtained. The redistribution of funds suggested by the exploration allows an increase of nearly 13% on the number of supported projects and on the measure of the portfolio's quality in comparison to typical heuristics.

2. The results of the evaluation process are more reliable, because: a) it reflects top management's preferences and beliefs; b) the decision model based on decision tables is better than the rough additive models; c) our proposal takes into consideration the historical data of the organization, which allows us to obtain knowledge valid to update preferences of the top management; d) the virtual discussion among peers makes it easy to achieve a group consensus, providing a more consistent evaluation; e) the proposed system is a platform for project management at the top level of the organization, independently of its size.

The proposed methodology gracefully combines several techniques based on different paradigms (Bayesian theory, multicriteria decision making, Artificial Intelligence, Fuzzy Logic and Evolutionary computation). They are used eclectically in a proposal that addresses essential drawbacks of previous approaches, and whose implementation can give benefits of remarkable meaning.

Finally, it is important to make clear that the scope of this work exceeds the frame of the R&D management; most approaches discussed here can be applied to more general situations of project management in non profitable or governmental organizations. The optimization problem is similar to that studied by authors in a previous work devoted to portfolio selection of social projects; the evolutionary algorithm described here can be directly applied to that wider problem. The model of decision policy captured in λ-complete decision tables can be applied to more general classification problems.

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Appendix 1. A Method for Group Sorting

We have developed a new method for group evaluation different from traditional approaches based on voting or average values. The main reason for choosing a more complicated way comes from the fact that a compensatory scheme or a majority rule are not always well suited for group decision-making. In these decision processes, veto effects are often very important to be ignored. The proposed method works with the natural heuristic used by collaborative groups for making reasonable or consensus agreements, based on universally accepted majority rules combined with the necessary observance of significative minorities, principles of fairness and equity. The ELECTRE's ideas of concordance and discordance are in the basis of this approach, which can be summarized as follows:

Let E be a scale used for group evaluation. Each group member expresses his/her opinion using stages of E.

$\forall$ (s,s') $\in$ E

1.a To measure the strength of the arguments in favor to the proposition PG ≡ " s is collectively preferred to s'". The power of the concordance coalition is modeled by a concordance index, which depends on the number of group members supporting PG .

1.b To measure the strength of the arguments against PG. The power of discordance coalition is modeled by a veto function, which depends on the number of group members in strong disagreement with PG.

1.c To combine the previous measures for defining a degree of truth σG(s,s') associated to PG.

To use σG for deriving a preference ranking of the levels $s \in E$. The first ranked level s* is identified as the group choice.

A deep discussion and a favorable comparison of this proposal to Borda's and Condorcet's methods can be found in (Fernandez and Olmedo, 2005, 2006).

***Eduardo Rene Fernandez** was born in Cuba, 1951. He received the B.Sc degree in Physics from the University of Havana in 1973; the Ph.D degree in Computer Aided Design of Electronic Circuits, from Poznan University of Technology, 1987. He is currently Senior Professor in the Faculty of Engineering, Autonomous University of Sinaloa, Mexico. His main areas of interest are mathematical decision models and intelligent decision support systems. Dr. Fernandez has been a member of the Research National System since 2002.*

***Jorge Adalberto Navarro** was born in Sinaloa, México, 1963. He received his B.Sc degree in Mathematics, M.Sc and Ph.D degree in Computer Science from the Autonomous University of Sinaloa in 1989, 2000 and 2005 respectively. He is currently Senior Researcher in the Sciences Center of Sinaloa and Associated Professor in the School of Computer Science, Autonomous University of Sinaloa. His main areas of interest are mathematical decision models and intelligent decision support systems.*

***Fernando Lopez** was born in Cuba, 1965. He received the BSc degree in Computer Science from the University of Jena (1989), and the MSc and PhD degree in Computer Science from the Higher Polytechnic Institute "Jose Antonio Echeverria" in 1994 and 1998 respectively. Dr. Lopez is currently Senior Professor in the System Engineering doctoral program, Autonomous University of Nuevo Leon. His main areas of scientific interest are decision support systems and heuristic methods for optimization.*

***Alfonso Duarte** was born in Sinaloa, Mexico. He received the BSc degree in Computer Science (2000) from the Autonomous University of Sinaloa. He is currently preparing his dissertation in the Computer Science master program, Autonomous University of Sinaloa.*