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# Public Portfolio Selection Combining Genetic Algorithms and Mathematical Decision Analysis

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## 1. Introduction

A central and frequently contentious issue in public policy analysis is the allocation of funds to competing projects. Public resources for financing social projects are particularly scarce. Very often, the cumulative budget being requested ostensibly overwhelms what can be granted. Moreover, strategic, political and ideological criteria pervade the administrative decisions on such assignments (Peterson, 2005). To satisfy these normative criteria, that underlie either prevalent public policies or governmental ideology, it is obviously convenient both to prioritize projects and to construct project-portfolios according to rational principles (e.g., maximizing social benefits). Fernandez et al. (2009a) assert that public projects may be characterized as follows.

- They may be undoubtedly profitable, but their benefits are indirect, perhaps only long-term visible, and hard to quantify.
- Aside from their potential economic contributions to social welfare, there are intangible benefits that should be considered to achieve an integral view of their social impact.
- Equity, regarding the magnitude of the projects' impact, as well as the social conditions of the benefited individuals, must also be considered.

Admittedly, the main difficulty for characterizing the "best public project portfolio" is finding a mechanism to appropriately define, evaluate, and compare social returns. Regardless of the varying definitions of the concept of social return, we can assert the tautological value of the following proposition.

**Proposition 1:** *Given two social projects, A and B, with similar costs and budgets, A should be preferred to B if A has a better social return.*

Ignoring, for a moment, the difficulties for defining the social return of a project portfolio, given two portfolios, C and D, with equivalent budgets, C should be preferred to D if and only if C has a better social return. Thus, the problem of searching for the best project-portfolio can be reduced to finding a method for assessing social-project returns, or at least a comparative way to analyze alternative portfolio proposals.

The most commonly used method to examine the efficiency impacts of public policies is "cost-benefit" analysis (e.g. Boardman, 1996). Under this approach, the assumed consequences of a project are "translated" into equivalent monetary units where positive

consequences are considered “benefits” and negative consequences are considered “loses” or “costs”. The temporal distribution of costs and benefits, modeled as net-cash-flows and adjusted by applying a “social discount rate”, allows computing the net present-value of individual projects. A positive net present-value indicates that a project should be approved whenever enough resources are available (Fernandez et al., 2009a). Therefore, the net present-value of a particular project can be used to estimate its social return. As a consequence, the social impact of a project portfolio can be computed as the sum of the net-present-value of all the projects in the portfolio. The best portfolio can then be found by maximizing the aggregated social return (portfolio net-present-social benefit) using 0-1 mathematical programming (e.g. Davis and Mc Keoun, 1986).

This cost-benefit approach is inadequate for managing the complex multidimensionality of the combined outcome of many projects, especially when it is necessary to assess intangibles that have no well-defined market values. In extreme cases, this approach favors unacceptable practices (either socially or morally) such as pricing irreversible ecological damages, or even human life. Aside from ethical concerns, setting a price to intangibles for which a market value is highly controversial can hardly be considered a good practice. For a detailed analysis on this issue, the reader is referred to the works by French (1993), Dorfman (1996), and Bouyssou et al. (2000).

Despite this drawback, cost-benefit analysis is the preferred method for evaluating social projects (Abdullah and Chandra, 1999). Besides, not using this approach for modeling the multi-attribute impacts of projects leave us with no other method for solving portfolio problems with single objective 0-1 programming. A contending approach to cost-benefit is multi-criteria analysis. This approach encompasses a variety of techniques for exploring the preferences of the Decision Makers (DM), as well as models for analyzing the complexity inherent to real decisions (Fernandez et al., 2009a). Some of the most broadly known multi-criteria approaches are MAUT (cf. Keeney and Raiffa, 1976), AHP (cf. Saaty, 2000, 2005), and outranking methods (Roy, 1990; Figueira et al., 2005; Brans and Mareschal, 2005).

Multi-criteria analysis represents a good alternative to overcome the limitations of cost-benefit analysis as it can handle intangibles, ambiguous preferences, and veto conditions. Different multi-criteria methods have been proposed for addressing project evaluation and portfolio selection (e.g. Santhanam and Kyparisis, 1995; Badri et al., 2001; Fandel and Gal, 2001; Lee and Kim, 2001; Gabriel et al., 2006; Duarte and Reis, 2006; Bertolini et al., 2006; Mavrotas et al., 2006; Sugrue et al., 2006; Liesio et al., 2007; Mavrotas et al., 2008; Fernandez et al., 2009a,b). The advantages of these methods are well documented in the research literature and the reader is referred to Kaplan y Ranjithan (2007) and to Liesio et al. (2007) for an in-depth study on the topic.

Multi-criteria analysis offers techniques for selecting the best project or a small set of equivalent “best” projects (this is known as the  $P_\alpha$  problem, according to the known classification by Roy (1996)), classifying projects into several predefined categories (e.g. “good”, “bad”, “acceptable”), known as the  $P_\beta$  problem, and ranking projects according to the preferences or priorities given by the decision maker (the  $P_\gamma$  problem).

Given a set of ranked projects, funding resources may be allocated following the priorities implicit in the ranking until no resources are left (e.g. Martino, 1995). This is a simple but

rigid process that has been questioned by several authors (e.g. Gabriel et al., 2006, Fernandez et al., 2009 a,b). According to our perspective, the decision on which projects should receive financing must be made based on the best portfolio, rather than on the best individual projects. Therefore, it is insufficient to compare projects to one another. Instead, it is essential to compare portfolios. Selecting a portfolio based on individual projects' ranking guarantees that the set of the best projects will be supported. However, this set of projects does not necessarily equals the best portfolio. In fact, these two sets might be disjoint. Under this scenario, it is reasonable to reject a relatively good (in terms of its social impact) but expensive project if it requires disproportionate funding (Fernandez et al. 2009 a,b). Therefore, obtaining the best portfolio is, we argue, equivalent to solving the  $P_\alpha$  problem defined over the set of all feasible portfolios.

Mavrotas et al. (2008) argue that, when the portfolio is optimized, good projects can be outranked by combinations of low-cost projects with negligible impact. However, this is not a real shortcoming whenever the following conditions are satisfied.

- Each project is individually acceptable
- The decision maker can define his/her preferences over the set of feasible portfolios (by using some quality measure, or even by intuition)
- The decision maker prefers the portfolio composed of more projects with lower costs.

In order to solve the selection problem over the set of feasible portfolios, the following issues should be addressed.

- The nature of the decision maker should be defined. It must be clear that this entity can address social interest problems in a legit way. In addition, the following questions should be answered. Is the decision-maker a single person? Or is it a collective with homogeneous preferences such that these can be captured by a decision model? Or is it, instead, a heterogeneous group with conflicting preferences? How is social interest reflected on the decision model?
- A computable model of the DM's preferences on the social impacts of portfolios is required.
- Portfolio selection is an optimization problem with exponential complexity. The set of possible portfolios is the power set of the projects applying for funding. The cardinality of the set of portfolios is  $2^N$ , where  $N$  is the number of projects. The complexity of this problem increases significantly if we consider that each project can be assigned a support level. That is, projects can be partially supported. Under these conditions, the optimization problem is not only about identifying which projects constitute the best portfolio but also about defining the level of support for each of these projects.
- If effects of synergetic projects or temporal dependencies between them are considered, the complexity of the resulting optimization model increases significantly.

The first issue is related to the concepts of social preferences, collective decision, democracy, and equity. The second issue, on the other hand, constitutes mathematical decision analysis' main area of influence. These capabilities for building preference models that incorporate different criteria and perspectives is what makes these techniques useful (albeit with some limitations) for constructing multidimensional models of conflicting preferences.

The DM's preferences on portfolios (or their social impacts) can be modeled from different perspectives, using different methods, and to achieve different goals. Selecting one of these options depends on who the DM is (e.g., a single person or a heterogeneous group), as well as on how much effort this DM is willing to invest in searching for the solution to the problem. Therefore, the information about the impact and quality of the projects that constitute a portfolio can be obtained from the DM using one of several available alternatives. This requires us to consider different modeling strategies and, in consequence, different approaches for finding the solution to this problem. We should note that the DM's preferences can be modelled using different and varying perspectives; ranging from the normative approach that requires consistency, rationality, and cardinal information, to a totally relaxed approach requiring only ordinal information. The chosen model will depend on the amount of time and effort the decision maker is willing to invest during the modelling process, and on the available information on the preferences. Here, we are interested in constructing a functional-normative model of the DM's preferences on the set of portfolios.

Evolutionary algorithms are powerful tools for handling the complexity of the problem (third and fourth issues listed above). Compared with conventional mathematical programming, evolutionary algorithms are less sensitive to the shape of the feasible region, the number of decision variables, and the mathematical properties of the objective function (e.g., continuity, convexity, differentiability, and local extremes). Besides, all these issues are not easily addressed using mathematical programming techniques (Coello, 1999). While evolutionary algorithms are not more time-efficient than mathematical programming, they are often more effective, generally achieving satisfactory solutions to problems that cannot be addressed by conventional methods (Coello et al., 2002).

Evolutionary algorithms provide the necessary instruments for handling both the mathematical complexity of the model and the exponential complexity of the problem. In addition, mathematical decision analysis methods are the main tools for modelling the DM's preferences on projects and portfolios, as well as for constructing the optimization model that will be used to find the best portfolio.

The rest of this chapter is organized as follows. An overview of the functional-normative approach to decision making, as well as its use as support for solving selection, ranking and evaluation problems is considered in Section 2. In Section 3, we study the public portfolio selection problem where a project's impact is characterized by a project evaluation, and the DM uses a normative approach to find the optimal portfolio (i.e., the case where maximal preferential information is provided). In the same section we also describe an evolutionary algorithm for solving the optimization problem. An illustrative example is provided in Section 4. Finally, some conclusions are presented in Section 5.

## **2. An outline of the functional approach for constructing a global preference model**

Mathematical decision analysis provides two main approaches for constructing a global preference model using the information provided by an actor involved in a decision-making process. The first of these approaches is a functional model based on the normative axiom of perfect and transitive comparability. The second approach is a relational model better

known for its representation of preferences as a fuzzy outranking relation. In this work, however, we will focus on the functional approach only.

When using the functional model, also known as the functional-normative approach (e.g. French, 1993), the Decision Maker must establish a weak preference relation, known as the *at least as good as* relation and represented by the symbol  $\succeq$ . This relation is a weak order (a complete and transitive relation) on the decision set  $A$ . The statement “ $a$  is at least as good as  $b$ ” ( $a \succeq b$ ) is considered a logical predicate with truth values in the set  $\{False, True\}$ . If  $a \succeq b$  is false then  $b \succeq a$  must be true, implying a strict preference in favor of  $b$  over  $a$ . Given the transitivity of this relation, if the DM simultaneously considers that predicates  $a \succeq b$  and  $b \succeq c$  are true, then, the predicate  $a \succeq c$  is also set to true. This approach does not consider the situation where both predicates,  $a \succeq b$  and  $b \succeq a$ , are false, a condition known as incomparability. Because of this, the functional model requires the DM to have an unlimited power of discrimination.

The relation  $\succeq$  can be defined over any set whose elements may be compared to each other and, as a result of such comparison, be subject to preferences. Of particular interest is the situation where the decision maker considers risky events and where the consequences of the actions are not deterministic but rather probabilistic. To formally describe this situation, let us introduce the concept of lottery at this point.

**Definition 1.** A lottery is a  $2N$ -tuple of the form  $(p_1, x_1; p_2, x_2; \dots; p_N, x_N)$ , where  $x_i \in \mathfrak{X}$  represents the consequence of a decision,  $p_i$  is the probability of such consequence, and the sum of all probabilities equals 1.

Given that the relation  $\succeq$  is complete and transitive, it can be proven that a real-valued function  $V$  can be defined over the decision set  $A$  ( $V: A \rightarrow \mathfrak{R}$ ), such that for all  $a, b \in A$ ,  $V(a) \geq V(b) \Leftrightarrow a \succeq b$ . This function is known as a value or utility function in risky cases (French, 1993). If the decision is being made over a set of lotteries, the existence of a utility function  $U$  can be proven such that  $\bar{U}(L_1) \geq \bar{U}(L_2) \Leftrightarrow L_1 \succeq L_2$ , where  $L_1$  and  $L_2$  are two lotteries from the decision set and  $\bar{U}$  is the expected value of the utility function (French, 1993).

The value, or utility, function represents a well formed aggregation model of preferences. This model is constructed around the set of axioms that define the rational behavior of the decision maker. In consequence, it constitutes a formal construct of an ideal behavior. The task of the analyst is to conciliate the real versus the ideal behavior of the decision maker when constructing this model. Once the model has been created, we have a formal problem definition. This is a selection problem that is solved by maximizing either  $V$  or  $\bar{U}$  over the set of feasible alternatives. From this, a ranking can be obtained by simply sorting the values of these functions. By dividing the range of these values into  $M$  contiguous intervals, discrete ordered categories can be defined for labeling the objects in the decision set  $A$  (for instance, Excellent, Very Good, Good, Fair, and Poor). These categories are considered as equivalence classes to which the objects are assigned to.

When building a functional model, compatibility with the DM's preferences must be guaranteed. The usual approach is to start with a mathematical formulation that captures the essential characteristics of the problem. Parameters are later added to the model in a way that they reflect the known preferences of the decision maker. Hence, every time the

DM indicates a preference for object  $a$  over object  $b$ , the model (i.e., the value function  $V$ ) must satisfy condition  $V(a) > V(b)$ . Otherwise, the model should satisfy condition  $V(a) = V(b)$ , indicating that the DM has no preference of  $a$  over  $b$ , nor has the DM a preference of  $b$  over  $a$ . This situation is known as indifference on the pair  $(a, b)$ . If  $V$  is an elemental function, these preference/indifference statements on the objects become mathematical expressions that yield the values of  $V$ 's parameters. To achieve this, usually the DM provides the truth values of several statements between pairs of decision alternatives  $(a_i, b_i)$ . Then, the model's parameter values are obtained from the set of conditions  $V(a_i) = V(b_i)$ . Finally, the value and utility functions are generally expressed in either additive or product forms, and, in the most simple cases, as weighted-sum functions.

The expected gain in a lottery is the average of the observed gains in the lottery's history. If the DM plays this lottery a sufficiently large number of times, the resulting gain should be close the lottery's expected gain. However, it is not realistic to assume that a DM will face (play) the same decision problem several times as decision problems are, most of the times, unique and unrepeatable. Therefore it is essential to model the DM's behavior towards risk. Persons react differently when facing risky situations. In real life, a DM could be risk prone, risk averse, or even risk neutral. Personal behavior for confronting risk is obviously a subjective characteristic depending on all of the following.

- The DM's personality
- The specific situation of the DM as this determines the impact of failing or succeeding.
- The amount of the gain or loses that will result from making a decision.
- The relationship of the DM with these gains and loses.

All these aspects are closely related. While the first of them is completely subjective, the remaining three have evident objective features.

The ability for modeling the decision maker's behavior when facing risk is one of the most interesting properties of the functional approach. At this point, it is necessary to introduce the concept of certainty equivalence in a lottery.

**Definition 2.** Certainty equivalence is the "prize" that makes an individual indifferent between choosing to participate in a lottery or to receive the prize with certainty.

A risk averse DM will assign a lottery a certainty equivalence value lower than the expected value of the lottery. A risk prone DM, on the other hand, will assign the lottery a certainty equivalence value larger than the lottery's expected gain. We say a DM is risk neutral when the certainty equivalence value assigned to a lottery matches the lottery's expected gain. This behavior of the DM yields quite interesting properties on the utility function. For instance, it can be proven that a risk averse utility function is concave, a risk prone utility function is convex, and a risk neutral function is linear.

Let us conclude this section by summarizing both the advantages and disadvantages of the functional approach. We start by listing the main advantages of the functional approach.

- It is a formal and elegant model of rational decision making.
- Once the model exists, obtaining its prescription is a straight forward process.
- It can model the DM's behavior towards risk.

Now, we provide a list of drawbacks we have identified on the functional approach.

- It cannot incorporate ordinal or qualitative information.
- In real life, DM's do not exactly follow a rational behavior.
- When decisions are made by a collective, the transitivity of the preference relation cannot be guaranteed.
- It cannot precisely model threshold effects, nor can it use imprecise information.
- In most cases, the DM does not have the time to refine the model until a precise utility function is obtained.

### 3. A functional model for public portfolio optimization using genetic algorithms

Let us consider a set  $P_r$  of public projects whose consequences can be estimated by the DM. These projects have been considered acceptable after some prior evaluation. That is, the DM would support all of them, given that enough funds are available and that no mutually exclusive projects are members of the set. However, projects are not, in general, mutually independent. In fact, they can be redundant or synergetic. Furthermore, they may establish conflicting priorities, or compete for material or human resources, which are indivisible, unique, or scarce.

For the sake of generality, let us consider a planning horizon partitioned in  $T$  adjacent time intervals. When  $T=1$ , this problem is known as the stationary budgeting problem (one budgeting cycle) (Chan et al., 2005). In non-stationary cases, there could be different levels of available funds for each period.

In its more general form, a portfolio is a finite set of pairs of projects and periods  $\{(p_i, t(p_i))\}$ , where  $p_i \in P_r$  and  $t(p_i) \in T$  denotes the period when  $p_i$  starts. A portfolio is feasible whenever it satisfies financial and scheduling restrictions, including precedence, and it does not contain redundant or mutually exclusive projects. These restrictions may also be influenced by equity, efficiency, geographical distribution, and the priorities imposed by the DM. In particular, if only one budgeting cycle is considered, the portfolios are subsets of  $P_r$ .

The set of projects is partitioned in different areas, according to their knowledge domain, their social role, or their geographic zone of action. One project can only be assigned to one area. Such partition is usually due to the DM's interest for obtaining a balanced portfolio. Given a set of areas  $A = \{A_1, A_2, \dots, A_n\}$ , the DM can set the minimum and maximum amounts of funding that will be assigned to projects belonging to area  $A_i \in A$ .

The general problem is to determine which projects should be supported, in what period should the support start, and the amount of funds that each project should receive, provided that the overall social benefit from the portfolio is maximised.

In order to have a formal problem statement, we should answer the following questions.

- How can the return of a public project-portfolio be formally defined?
- How can objective and subjective criteria be incorporated for optimizing project-portfolio returns?
- Under what conditions can the return of a portfolio be effectively maximized?
- What methods can be used to select the best portfolio?



To achieve the goal of maximizing social return we need to formally define a real-valued function,  $V_{social}$ , that does not contravene the relation  $\succeq_{social}$ . The construction of such function is, however, problematical due to the following reasons.

- i. A set of well defined social preferences must exist.
- ii. This set of preferences must be revealed.

The preference-indifference social relation is required to be transitive and complete over social states (premise *i*). However, due to the known limitations for constructing collective rational-preferences (e.g., Condorcet's Paradox, Arrow's Impossibility Theorem, and context-dependent preferences), (Bouyssou et. al., 2000; Tversky and Simonson, 1993; French, 1993), and to the difficulty in obtaining valid information about social preferences from the decision maker, premises *i* and *ii* are rarely fulfilled in real-world cases (Sen, 2000, 2008).

The success of public policies is measured in terms of their contribution to social equity and social "efficiency". A project's social impact should be an integrated assessment of such criteria. In the research literature, it is possible to find several methods that have been proposed for estimating a project contribution to social well-fare. Unfortunately, they all show serious limitations for handling intangible attributes. Furthermore, these methods' objectivity for measuring the contribution of each project or public policy is questionable. In any society, a wide variety of interests and ideologies can coexist. This human condition makes it complicated to reach a consensus on what an effective measure of social benefit should be. In turn, the absence of consensus leads to a lack of objectivity on any defined measure. This lack of objectivity is closely related to a nonexistent function of social preference and to the ambiguity of collective preferences as reported by Condorcet, Arrow, and Sen (Bouyssou et al., 2000; Sen, 2000, 2008).

While the social impact is objective, its assessment is highly subjective as it depends on the ideology, preferences and values of the person measuring the impact. This subjectivity, however, does not necessarily constitute a drawback as it is not arbitrary. In the end, decision making does not lack of subjective elements. The set of criteria upon which the decision making is based should strive to be objective. However, the assessment of the combined effect of such criteria, some of them in conflict with each other, is subjective in nature as it depends on the perception of the decision maker. The objectivity of decision making theory is not based on eliminating all subjective elements. Instead, it is based on creating a model that reflects the system of values of the decision maker.

In every decision problem it is necessary to identify the main actor whose values, priorities, and preferences, are to be satisfied. In this context (the problem of efficiently and effectively allocating public resources), we will call "supra-decision-maker" (SDM) to this single or collective actor. For the rest of the discussion, we drop the idea of modeling public returns from a social perspective in favor of modeling the SDM's preferences.

Focusing exclusively on the SDM's preferences is a pragmatic representation of the problem that raises ethical concerns. This is particularly true when the SDM is elected democratically and, as such, his/her decisions formally represent the preferences of the society. In real life, an SDM may possibly have a very personal interpretation of social welfare and subjective parameters to evaluate project returns that do not necessarily represent the generalized

social values but rather the ambition of a certain group. Thus, even under the premise of ethical behavior, the SDM—who is supposed to distribute resources according to social preferences—can only act in response to his/her own preferences. The reasons for this are that either the SDM hardly knows the actual social preferences, or he/she pursues his/her own satisfaction—according to his/her preferences—in an honest attempt to achieve what he/she thinks is socially better. Unethical behavior or lack of information can cause the SDM's preferences to significantly deviate from the predominant social interests. In turn, this situation might trigger events such as social protests claiming to reduce the distance between the SDM's preferences and social interests. Therefore, solving a public project-portfolio selection problem is about finding the best solution from the SDM's perspective. This solution (under the premise of ethical behavior) should be close to the portfolio with the highest social return.

### 3.1 A Functional model of the subjective return

In order to maximize the portfolio's subjective return (that is, the return from the SDM perspective), we must build a value function that satisfies relation  $\succeq_{\text{portfolios}}$ . For a starting analogy, let us accept that each project's return can be expressed by a monetary value, in a similar way as cost-benefit analysis. If no synergy and no redundancy exist (or they can be neglected) among the projects, the overall portfolio's return can be calculated as follows.

$$R_t = x_1 c_1 + x_2 c_2 + \dots + x_N c_N \quad (1)$$

In Equation 1,  $N$  is the cardinality of  $P_r$ . The value of  $x_i$  is set to 1 whenever the  $i$ -th project is supported, otherwise  $x_i = 0$ . Finally,  $c_i$  is the return value of the  $i$ -th project.

Let  $M_i$  denote the funding requirements for the  $i$ -th project. Let  $\mathbf{d}$  be an  $N$ -dimensional vector of real values. Each value,  $d_i$ , of vector  $\mathbf{d}$  is associated to the funding given to the  $i$ -th project. If a project is not supported, then the corresponding value in  $\mathbf{d}$  associated to such project will be set to zero. With this, we can now formally define the problem of portfolio selection.

**Problem definition 1.** Portfolio selection optimization can be obtained after maximizing  $R_t$ , subject to  $\mathbf{d} \in R_F$ , where  $R_F$  is a feasible region determined by the available budget, constraints for the kind of projects allowed in the portfolio, social roles, and geographic zones.

Problem 1 is a variant of the knapsack problem, which can be efficiently solved using 0-1 programming. Unfortunately, this definition is an unrealistic model for most social portfolio selection problems due to the following issues.

1. For Equation 1 to be valid, the monetary value associated to each project's social impact must be known. Monetary values can be added to produce a meaningful figure. However, due to the existence of indirect as well as intangible effects on such projects, it is unrealistic to assume that such monetary equivalence can be defined for all projects. If we cannot guarantee that every  $c_i$  in Equation 1 is a monetary value, then the expression becomes meaningless.
2. Most of the times, the decision is not about accepting or rejecting a project but rather about the feasibility of assigning sufficient funds to it.

3. The effects of synergy between projects can be significant on the portfolio social return. Therefore, they must be modeled. For instance consider the following two projects, one for building a hospital and the other for building a road that will enhance access to such hospital. Both of such projects have, individually, an undeniable positive impact. However their combined social impact is superior.
4. Time dependences between projects are not considered by Problem definition 1.
5. It is possible that for a pair of projects (i and j)  $c_i \gg c_j$  and  $M_i \gg M_j$ , the solution to this problem indicates that project i should not be supported ( $x_i = 0$ ) whereas project j is supported ( $x_j = 1$ ). The SDM might not agree to this solution, as it fails to support a high-impact project while it provides funds to a much less important project. Furthermore, such situation will be difficult to explain to the public opinion.

The functional normative approach presented in Section 2 is used to address the first issue on this list. Here, we present a new approach based on the work of Fernandez and Navarro (2002), Navarro (2005), Fernandez and Navarro (2005), and Fernandez et al. (2009). Addressing issues 2 to 5 on the list above requires using a heuristic search and optimization methods.

This new approach is constructed upon the following assumptions.

**Assumption 1:** Every project has an associated value subjectively assigned by the SDM. This value increases along with the project's impact.

**Assumption 2:** This subjective value reflects the priority that the SDM assigns to the project. Each project is assigned to a category from a set of classes sorted in increasing order of preference. These categories can be expressed qualitatively (e.g., {poor, fair, good, very good, excellent}) or numerically in a monotonically increasing scale of preferences.

**Assumption 3:** Projects assigned to the same category have about the same subjective value to the SDM. Therefore, the granularity of the discrete scale must be sufficiently fine so that no two projects are assigned to the same class if the SMD can establish a strict preference between them.

**Assumption 4 (Additivity):** The sum of the subjective values of the projects belonging to a portfolio is an ordinal-valued function that satisfies relation  $\succeq_{\text{portfolios}}$ .

Fernandez et al. (2009) rationalize this last assumption by considering that each project is a lottery. A portfolio is, in consequence, a "giant" lottery being played by a risk-neutral SDM. Under this scenario, the subjective value of projects and portfolios corresponds to their certainty equivalent value.

Under Assumption 4, the interaction between projects cannot be modeled. Synergy and redundancy in the set of projects are characteristics that require special consideration that will be introduced later.

Under Assumptions 1 and 4, the SDM assess a subjective value to portfolio given by the following equation.

$$V = x_1 c_1 + x_2 c_2 + \dots + x_N c_N \quad (2)$$

In Equation 2,  $c_i$  represents the subjective value of the  $i$ -th project. Equations 1 and 2 are formally equivalent. However, the resulting value of  $V$  only makes sense if there is a process to assign meaningful values to  $c_i$ .

Before we proceed to the description of the rest of the assumptions, we need to introduce the concept of elementary portfolio.

**Definition 3:** An elementary portfolio is a portfolio that contains only projects of the same category. It will be expressed in the form of a  $C$ -dimensional vector, where  $C$  is the number of discrete categories. Each dimension is associated to one particular category. The value in each dimension corresponds to the number of projects in the associated category. Consequently, the  $C$ -dimensional vector of an elementary portfolio with  $n$  projects will have the form  $(0, 0, \dots, n, 0, \dots, 0)$ .

**Assumption 5:** The SDM can define a complete relation  $\succeq$  on the set of elementary portfolios. That is, for any pair of elementary portfolios,  $P$  and  $Q$ , one and only one of the following propositions is true.

- Portfolio  $P$  is preferred to portfolio  $Q$
- Portfolio  $Q$  is preferred to portfolio  $P$
- Portfolios  $P$  and  $Q$  are indifferent.

**Assumption 6 (Essentiality):** Given two elementary portfolios,  $P$  and  $Q$ , defined over the same category. Let  $P = (0, 0, \dots, n, 0, \dots, 0)$  and  $Q = (0, 0, \dots, m, 0, \dots, 0)$ .  $P$  is preferred to  $Q$  if and only if  $n > m$ .

From the set of discrete categories, let  $C_1$  be the lowest category,  $C_L$  be the highest, and  $C_j$  a category preferred to  $C_1$ .

**Assumption 7 (Archimedean):** For any category  $C_j$ , there is always an integer value  $n$  such that the SDM would prefer a portfolio composed of  $n$  projects in the  $C_1$  category to any portfolio composed of a single project in the  $C_j$  category.

**Assumption 8 (Continuity):** If an elementary portfolio  $P = (x, 0, \dots, 0, \dots, 0)$  is preferred to an elementary portfolio  $Q = (0, \dots, 1, 0, \dots, 0)$ , defined over category  $j$  for  $1 < j \leq L$ , there is always a pair of integers values  $n$  and  $m$  ( $n > m$ ) such that an elementary portfolio with  $n$  projects of the lowest category is indifferent to another elementary portfolio with  $m$  projects of the  $j$ -th category.

Assumption 5 characterizes the normative claim of the functional approach for decision-making. Assumption 6 is a consequence of Assumption 4 (additivity) combined with the premise that all projects satisfy minimal acceptability requirements. Assumption 7 is a consequence of both essentiality and the non-bounded character of the set of natural numbers. Assumption 8 simulates the way in which a person balances a scale using a set of two types of weights whose values are relative primes.

Let us say that  $c_1$  is a number representing the subjective value of the projects belonging to the lower category  $C_1$ . Similarly, let us use  $c_j$  to represent the value of projects in category  $C_j$ . Now, suppose that the elementary portfolios  $P$  (containing  $n$  projects in  $C_1$ ) and  $Q$  (integrated by  $m$  projects in  $C_j$ ) are indifferent. That is,  $P$  and  $Q$  have the same  $V$  value. If we combine Assumption 8 with Equation 2, we obtain the following expression.

$$n c_1 = m c_j \Leftrightarrow c_j = (n/m)c_1$$

If  $V$  is a value function, then every proportional function is also a value function satisfying the same preferences. Therefore, we can arbitrarily set  $c_1=1$  to obtain Equation 3 below.

$$c_j = n/m \quad (3)$$

In consequence, Equation 2 can now be re-stated as follows.

$$U = \sum_{i,k} w_{ik} x_{ik} \quad (4)$$

In Equation 4, the variable  $j$  is used to index categories, whereas variable  $k$  indexes projects. The value of  $w_{1k}$  is set to 1, and  $w_{jk} = n/m_j$ , where  $m_j$  denotes the cardinality of an elementary portfolio defined over category  $C_j$ . Additionally, factors  $w_{ik}$  might be interpreted as importance factors. These weights express the importance given by the SDM to projects within certain category. Therefore, they should be calculated from the SDM's preferences, expressed while solving the indifference equations between elementary portfolios, as stated by Assumption 8 and according to Equation 3. A weight must be calculated for every category. If the cardinality of the set of categories is too large, the resolution of such categories can be reduced to simplify the model. A temporary set of weights is obtained using these coarse categories. By interpolation on such set, the values of the original (finer resolution) set can be obtained.

### 3.2 Fuzziness of requirements

Another important issue is the imprecise estimation of the monetary resources required by each project. If  $d_k$  are the funds assigned to the  $k$ -th project, then there is an interval  $[m_k, M_k]$  for  $d_k$  where the SDM is uncertain about whether or not the project is being adequately supported. Therefore, the proposition "the  $k$ -th project is adequately supported" may be seen as a fuzzy statement. If we consider that the set of projects with adequate funds is fuzzy, then the SDM can define a membership function  $\mu_k(d_k)$  representing the degree of truth of the previous proposition. This is a monotonically increasing function on the interval  $[m_k, M_k]$ , such that  $\mu_k(M_k) = 1$ ,  $\mu_k(m_k) > 0$ , and  $\mu_k(d_k) = 0$  when  $d_k < m_k$ .

The subjective value assigned by the SDM to the  $k$ -th project is based on the belief that the project receives the necessary funding for its operation. When  $d_k < m_k$  the SDM is certain that the project is not sufficiently funded. When  $m_k \leq d_k < M_k$ , the SDM hesitates about the truth of that statement. This uncertainty affects the subjective value of the project, because it reduces the feasible impact of the project, which had been subjectively estimated under the premise that funding was sufficient. The reduction of the project's subjective value can be modeled by the product of the original value and a feasibility factor  $f$ . This factor is a monotonically increasing function with  $\mu_k$  as an argument such that  $f(0) = 0$  and  $f(1) = 1$ . Equation 5 below, is generated by introducing this factor into Equation 4, and assuming that  $f(\mu_{ik}) > 0 \Leftrightarrow x_{ik} = 1$ .

$$U = \sum_{i,k} f(\mu_{ik}) w_{ik} \quad (5)$$

The simplest definition of the feasibility factor is to make  $f(\mu_{ik}) = \mu_{ik}$ . This is equivalent to a fuzzy generalization of Equation 4. In such case,  $x_{ik}$  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 substituting this function with a membership function expressing “the degree of membership” to the more general fuzzy set. In this way, Equation 5 becomes Equation 6 shown below.

$$U = \sum_{ik} w_{ik} \mu_{ik} \quad (6)$$

Equation 6 was proposed by Fernandez and Navarro (2002) as a measure of a portfolio’s subjective value.

### 3.3 Synergy and redundancy

Redundancy between projects can be addressed using constraints. For every pair of redundant projects,  $(p_i, p_j)$ ,  $i < j$ , condition  $\mu_i(d_i) \times \mu_j(d_j) = 0$  should be enforced.

Let  $S = \{S_1, S_2, \dots, S_k\}$  be the set of coalitions of synergetic projects. In a model like the one represented by Equation 5, each of these coalitions should be treated as an (additional) individual project. As a result, each coalition has an associated cost (i.e., the sum of the costs of the individual projects in the coalition), and an evaluation. This evaluation should be better than the evaluation of any of the projects in the coalition. Let us assume that coalitions  $S_i$  and  $S_j$  become projects  $P_{N+i}$  and  $P_{N+j}$ , respectively. If  $S_i$  is a subset of  $S_j$ , then it does not make sense to include them both in a portfolio. Therefore,  $P_{N+i}$  and  $P_{N+j}$  must be considered redundant projects. Furthermore, if project  $p_n$  is a member of  $S_i$ , then the pair  $(p_n, p_{N+i})$  is also redundant (since the value of  $p_n$  is included in the value of  $p_{N+i}$ ).

### 3.4 A Genetic algorithm for optimizing public portfolio subjective value

Suppose that a feasible region of portfolios,  $R_F$ , is defined by constraints on the total budget and on the distribution of projects by area. In addition, the SDM could include further constraints on the portfolios due to following reasons.

- The particular budget distribution of the portfolio could be very difficult to justify. Let us suppose that the SDM asserts that “project  $p_j$  is much better than project  $p_i$ ”. In consequence, any portfolio in which  $\mu_i$  is greater than  $\mu_j$  could be unacceptable. This implies the existence of some veto situations that can be modeled with the following constraint. For every project  $p_i$  and  $p_j$ , being  $s_i$  and  $s_j$  their corresponding evaluations, if  $(s_i - s_j) \geq v_s$ , then  $(\mu_i(d_i) - \mu_j(d_j))$  must be greater than (or equal to) 0, where  $v_s$  is a veto threshold. In the following they will be called veto constraints.
- A possible redundancy exists between projects.

Let us use  $R'_F$ ,  $R'_F \subset R_F$ , to denote the set of values for the decision variables that make every portfolio acceptable. All the veto constraints are satisfied in  $R'_F$  and there are no redundant projects in the portfolios belonging to this region. The optimization problem can now be defined as follows.

**Problem definition 2.** An optimal portfolio can be selected by maximizing  $U = \sum_{ik} f(\mu_{ik}(d_{ik})) w_{ik}$ , subject to  $d \in R'_F$ , where  $d_{ik}$  indicates the financial support assigned to the  $k$ -th project belonging to the  $i$ -th category.

Solving this problem requires a complex non linear programming algorithm. The number of decision variables involved can be in the order of thousands. Due to the discontinuity of  $\mu_i$ , the objective function is discontinuous on the hyper planes defined by  $d_{ik} = m_{ik}$ . Therefore, its continuity domain is not connected. The shape of the feasible region  $R'_F$  is too convoluted, even more if synergy and redundancy need to be addressed.  $R'_F$  hardly has the mathematical properties generally required by non linear programming methods. Note that veto constraints on the pairs of projects  $(p_i, p_k)$  and  $(p_j, p_k)$  are discontinuous on the hyper planes defined by  $d_{ik} = m_{ik}$  and  $d_{jk} = m_{jk}$ . In a real world scenario, where hundreds or even thousands of projects are considered, non-linear programming solutions cannot handle these situations. Using Equation 6, a simplified form of Problem definition 2, was efficiently solved by Fernandez et al. (2009) and later by Litvinchev et al. (2010) using an integer-mixed programming model. Unfortunately, this approach cannot handle synergy, redundancy, veto constraints, nor can it handle the non-linear forms of function  $f$  in Problem definition 2.

Evolutionary algorithms are less sensitive to the shape of the feasible region, the number of decision variables, and the mathematical properties of the objective function (e.g., continuity, convexity, differentiability, and local extremes). In contrast, all of these issues are a real concern for mathematical non linear programming techniques (Coello, 1999). While evolutionary algorithms are not time-efficient, they often find solutions that closely approximate the optimal. Problem definition 2 represents a relatively rough model. However, the main interest is not on fine tuning the optimization process but rather on the generality of the model and on the ability to reach the optimal solution or a close approximation.

In Figure 1, we illustrate the genetic algorithm used for solving the optimization problem stated in Problem definition 2. This algorithm is based on the work of Fernandez and Navarro (2005). As in any genetic algorithm, a fundamental issue is defining a codification for the set of feasible solutions to the optimization problem. In this case, each individual represents a portfolio and each chromosome contains  $N$  genes, where  $N$  is the number of projects. For the chromosome, we use a floating point encoding representing the distribution of funding among the set of projects in the portfolio. The financial support for each project is represented by its membership function,  $\mu_j(d_j)$ , which is real-valued with range in  $[0, 1]$ . That is, a floating point number represents each project's membership value. This membership value is a gene in our definition of chromosomes. As discussed earlier, the number of genes can be increased in order to address the effects of synergetic projects.

The fitness value of each individual is calculated based on function  $U$  given by Equation 5. Remember that this is a subjective value that captures the SDM's certainty that the project receives the necessary funding for its operation. The SDM's idea that a project has been assigned sufficient funds is modeled using two parameters,  $\alpha$  and  $\beta$ . The domain for both parameters is the continuous interval  $[0, 1]$ . The first parameter,  $\alpha$ , can be interpreted as the degree of truth of the assertion "the project has sufficient financial support if it receives  $m$  monetary units of funding". When this financial support reaches the value  $\beta M$ , the predicate "the project has sufficient funding" is considered true. The value of these two parameters is needed to establish models for function  $\mu_j$  in order to calculate the value of  $U$ . To generate

these models, we propose to choose parameters  $\alpha$  and  $\beta$  ( $0 < \alpha < 1$ ,  $m/M < \beta \leq 1$ ) for modelling  $\mu$  as shown in Figure 2. For the experiments presented here, the values of  $\alpha = 0.5$  and  $\beta = 1$  have been used. The most promising values for these parameters are reasonably found in the intervals  $[0.5, 0.7]$  and  $[0.9, 1]$ , respectively.

<b>Algorithm 1.</b> A Genetic Algorithm for Project Portfolio Selection.	
<b>Input:</b>	cycles, the number of iterations before the algorithm converges generations c_r, the Crossover rate m_r, the Mutation rate
<b>Output:</b>	best solution, the best solution found
1	Set best_solution $\leftarrow$ any feasible portfolio. // this is the best so far
2	Set N $\leftarrow$ the number of projects (chromosomes)
3	Set Population $\leftarrow$ {best_solution}
4	<b>for</b> (i = 1 to cycles) <b>do</b>
5	<b>for</b> (j = 1 to N - 1) <b>do</b>
6	set new_solution $\leftarrow$ best_solution
7	randomly select a gene in new_solution and mutate it
8	set Population $\leftarrow$ Population $\cup$ {new_solution}
9	<b>end</b>
10	evaluate every individual $\in$ Population
11	set best_solution $\leftarrow$ the fittest individual $\in$ Population
12	<b>for</b> (k = 1 to generations) <b>do</b>
13	perform crossover on ( $N \times c_r$ ) individuals $\in$ Population
14	perform mutation on ( $N \times m_r$ ) individuals $\in$ Population
15	set Population $\leftarrow$ Population $\cup$ {best_solution}
16	evaluate every individual $\in$ Population
17	set best_solution $\leftarrow$ the fittest individual $\in$ Population
18	<b>end</b>
19	<b>end</b>
20	<b>return</b> best_solution

Fig. 1. A Genetic Algorithm for Project Portfolio Selection

For the selection stage, the roulette wheel technique was used. That is, the probability that a particular individual is selected for reproduction is proportional to its fitness value. For the experiments, the crossover rate was set to 0.2. Therefore twenty percent of the population is selected for crossover in any given reproductive trial. The crossover operator takes genes from each parent string and combines them to produce the offspring of the next generation. The main reason for doing this is that by creating new strings from fit parent strings, new and promising zones of the search space will be explored. While many crossover techniques



have been reported, in this algorithm the classic crossover technique based on a random cut point was used. The number of offspring resulting from this process is one fifth the size of the population.

The replacing process dictates how to update the current population with the individuals obtained by crossover. A random replacement approach (every individual has the same probability to be replaced) is used for reducing selective pressure. A similar approach is used for implementing an elitist policy. That is, an individual is randomly chosen from the current population and is replaced by the individual with the highest evaluation. Consequently, the presence of the best individual (`best_solution` in Algorithm 1) in the updated population is guaranteed.

Algorithm 1 uses a constant mutation rate that is set a priori. Each individual in the population is considered for mutation, and all the individuals have the same probability of mutating, which is defined by the mutation rate. Once an individual has been selected for mutation, one of its genes is randomly chosen. This gene will change by adding to it a random value in the  $[-0.2, 0.2]$  interval, excluding zero. The resulting gene value, however is limited to the  $[0, 1]$  interval.

Redundancy is addressed in a very simple way. If, as the result of some genetic operator an individual (i.e., a portfolio) containing redundant projects is generated, this individual is immediately “killed”. That is, its incorporation to the current population is denied.

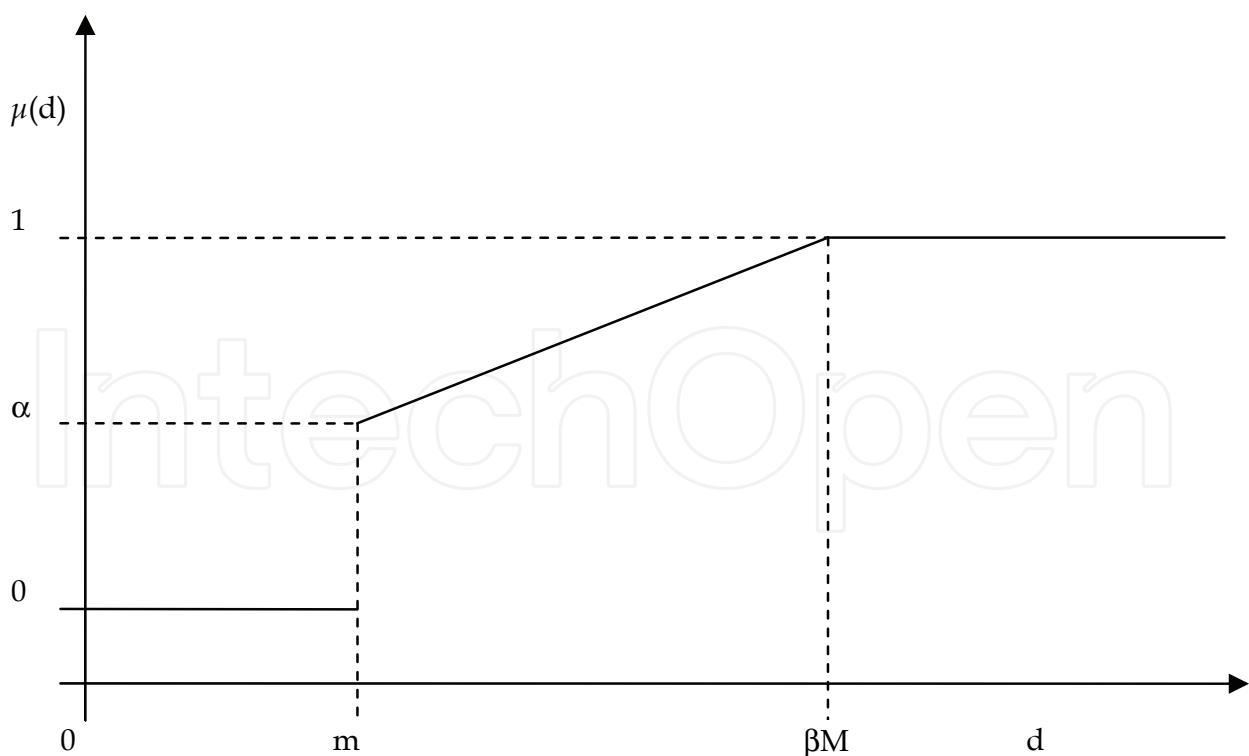


Fig. 2. The Membership Function

### 3.5 An illustrative example

Let us now consider the following example taken from (Fernandez and Navarro, 2005). The goal is to distribute a budget of 50 million dollars among of 400 R&D projects. These projects are distributed in four areas, namely engineering, life sciences, formal sciences, and social sciences. There are 140 projects in the first area (engineering), 80 projects in the second one (life sciences), 100 projects in the third area (formal sciences), and 80 project in the last area (social sciences). No synergetic effects are considered.

The classification of the projects, according to their evaluations and areas, is described in Table 1. The projects subjective values corresponding to each category and area are shown in Table 2. These values were obtained taking a social sciences project evaluated as Below Average as baseline ( $w = 1$ ). These values define a ranking on the set of projects that can be used to allocate funds according to the conventional heuristic described in Section 1 (with all its known limitations).

	Area 1	Area 2	Area 3	Area 4
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
<b>Total</b>	<b>140</b>	<b>80</b>	<b>100</b>	<b>80</b>

Table 1. Distribution of Projects by Area.

	Area 1	Area 2	Area 3	Area 4
Very Good	5.838	4.3785	3.892	2.9190
Good	4.540	3.4055	3.027	2.2700
Above Average	3.027	2.2700	2.018	1.5135
Average	2.108	1.5810	1.405	1.0540
Below Average	2.000	1.5000	1.333	1.0000

Table 2. Projects Subjective Values.

Four different instances of the problem were generated by assigning random budget ranges to each area. For each project, random values of  $m_{ik}$  and  $M_{ik}$  were defined, representing its minimum and maximum funding requirements. The proposed evolutionary algorithm was run 30 times to optimize the expression given by Problem definition 2. For simplicity  $f(\mu_{ik})$  was taken to be identical to  $\mu_{ik}$ .

The algorithm was coded using Visual C++. Its execution time was about 25 minutes for one million generations running on a Pentium-4 processor with a, 2.1 GHz clock cycle. This architecture was complemented with 256 MB of physical memory and a 74.5-GB hard disk drive. The experimental results shown in Table 3 indicate a significant improvement in the value of the optimized portfolio with respect to conventional approaches.

These results represent an average saving of 6.514 million dollars, equivalent to 13.02% of the total budget. This improvement has a positive impact on the number of supported projects, as Table 4 reveals. The average number of supported projects is 12.5 % higher than when conventional methods were used.

Instance	Value of the portfolio funding following the ranking given by project evaluations	Value of the optimized portfolio	Improvement
1	1406.80	1533.95	9%
2	1282.36	1496.16	16.67%
3	1279.58	1458.48	14%
4	1393.58	1566.97	12.44%

Table 3. Traditional Funding versus our Approach.

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%

Table 4. Traditional Funding versus our Approach (portfolio's cardinality).

### 3.6 Modeling temporal dependencies

The model described in Problem definition 2 can be generalized to incorporate temporal restrictions.

**Problem definition 3.** An optimal portfolio of projects with temporal dependencies can be selected by maximizing  $U = \sum_{ik} f(\mu_{ik}(d_{ik})) w_{ik}$ , subject to  $(\mathbf{d}, \mathbf{t}) \in R''_F$ , where vector  $\mathbf{t} = (t(p_1), t(p_2), \dots)$  denotes the decision variables valid during the period of time when each project starts.  $R''_F$  contemplates time-precedence restrictions, restrictions on the time projects can start, and the available funds for each time interval.

This problem can be solved using a genetic algorithm similar to the one previously presented. However, a different encoding for individuals must be devised. Our proposal is to encode individuals as a  $2N$ -dimensional vector of the form  $(\mu_1, t_1, \mu_2, t_2, \dots, \mu_N, t_N)$ . As before, genes corresponding to  $\mu_i$  have domain defined by the continuous interval  $[0, 1]$ . Genes corresponding to  $t_i$  have a domain defined by the set  $\{1, 2, 3, \dots, T\}$ , where  $T$  is the maximum number of time periods. Crossover can only occur between genes of the same kind. However, mutations may occur at any gene. Restrictions such as time precedence and the earliest time a project can start are controlled by constraints as described by Carazo et al. (2010).

#### 4. Concluding remarks

Given a set of premises, it is possible to create a value model for selecting optimal portfolios from an SDM perspective. While this problem is Turing-decidable, finding its exact solution requires exponential time. However, the use of genetic algorithms for solving this problem can closely approximate the optimal portfolio selection.

Inspired by a normative approach, the set of premises presented here is based on the following assumptions.

- To the SMD, every project and every portfolio has a subjective value that depends on its social impact. This value exists even if it cannot be initially quantified.
- The SDM either has already defined a consistent system of preferences, or has the aspiration of doing so.
- The SDM is willing to invest a considerable amount of mental effort in order to define this consistent set of preferences and produce the aforementioned value model.

As for the algorithmic solution to the portfolio problem, its computational complexity can increase considerably when synergic effects and temporal dependencies are considered. However strategic planning requires a high quality model. The problems defined in this scenario are so important that they justify the use of computational intensive solutions.

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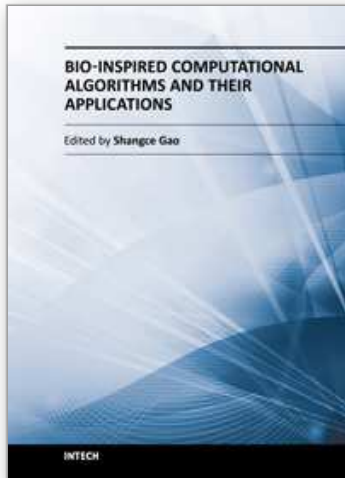
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Bio-inspired computational algorithms are always hot research topics in artificial intelligence communities. Biology is a bewildering source of inspiration for the design of intelligent artifacts that are capable of efficient and autonomous operation in unknown and changing environments. It is difficult to resist the fascination of creating artifacts that display elements of lifelike intelligence, thus needing techniques for control, optimization, prediction, security, design, and so on. Bio-Inspired Computational Algorithms and Their Applications is a compendium that addresses this need. It integrates contrasting techniques of genetic algorithms, artificial immune systems, particle swarm optimization, and hybrid models to solve many real-world problems. The works presented in this book give insights into the creation of innovative improvements over algorithm performance, potential applications on various practical tasks, and combination of different techniques. The book provides a reference to researchers, practitioners, and students in both artificial intelligence and engineering communities, forming a foundation for the development of the field.

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