

A SUPPORT TOOL FOR SELECTING AND SCHEDULING PROJECT PORTFOLIOS

TRINIDAD GÓMEZ

trinidad@uma.es

*Universidad de Málaga / Departamento de Economía Aplicada (Matemáticas)
Campus El Ejido s/n, 29071, Málaga*

ANA F. CARAZO

afercar@upo.es

*Universidad Pablo de Olavide / Departamento de Economía, Métodos Cuantitativos e Hª. Económica
Ctra. Utrera Km.1, 41013 Sevilla, Spain*

FÁTIMA PÉREZ

f_perez@uma.es

*Universidad de Málaga / Departamento de Economía Aplicada (Estadística y Econometría)
Campus El Ejido s/n, 29071, Málaga*

JULIÁN MOLINA

julian.molina@uma.es

*Universidad de Málaga / Departamento de Economía Aplicada (Matemáticas)
Campus El Ejido s/n, 29071, Málaga*

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RESUMEN: El problema de la selección de carteras de proyectos es un aspecto crucial en cualquier organización que consiste en cómo planificar y distribuir unos recursos limitados entre un conjunto de proyectos candidatos a lo largo de un periodo temporal. Al mismo tiempo, ha de tenerse en consideración tanto múltiples objetivos como restricciones que pueden variar a lo largo del horizonte temporal.

En este trabajo presentamos un programa informático con un entorno amigable para el usuario denominado Project Portfolio Selection Tool (PPST). Dicho programa ayuda a los decisores a realizar la tarea de la selección y planificación temporal de las carteras de proyectos eficientes. Para ello, incorpora un modelo general multiobjetivo que es resuelto a través de un algoritmo metaheurístico. Posteriormente, a través de un procedimiento interactivo, PPST ayuda a los decisores a explorar el espacio de soluciones a fin de alcanzar la cartera de proyectos que más se ajusta a sus preferencias. Para finalizar, presentamos una aplicación real en una Universidad Pública, como forma de ilustrar el funcionamiento general de la aplicación, así como su utilidad.

Palabras clave: Programación multiobjetivo, selección de carteras de proyectos, metaheurísticos, proceso interactivo.

ABSTRACT: Project portfolio selection is an important issue that arises repeatedly over an organization's lifetime. The problem consists of how to plan and allocate a limited set of resources among a set of candidate projects within a given time horizon, while taking into account multiple objectives and constraints that can be different at each period of the planning horizon.

This article describes a software tool with a user-friendly environment called the Project Portfolio Selection Tool (PPST), which assists decision makers (DMs) to simultaneously select and schedule efficient project portfolios. This software tool incorporates a general multiobjective model and uses a metaheuristic algorithm as a search engine. By using an interactive procedure, PPST also supports DMs in exploring the solution space to find the most suitable portfolio according to their preferences. We present an application of the software in a state university setting to illustrate the rationale underlying this environment and its usefulness.

Keywords: Multiple objective programming, Project Portfolio Selection, Metaheuristics, Interactive process.

1. Introduction

The selection and scheduling of project portfolios is one of the most important decision-making processes in any state or private organization. In this process, the candidate projects compete for funds and other resources (such as manpower, equipment, etc) to fulfil a set of objectives and priorities of the organization. There are usually more projects to choose from than resources to carry them out. There are two negative consequences to any erroneous decision regarding the choice of selected projects. On the one hand, limited resources are spent on inappropriate projects, and on the other, there is a loss of private, social, and state benefits that could have been obtained if the resources had been applied to more useful projects (see Martino, 1995). Thus, these decisions are crucial to the success of any organization. As a consequence of their importance, this process has received significant attention from managers and researchers, as reported in several studies (Archer and Ghasemzadeh, 1999; Teller et al., 2012; Martinsuo, 2013).

Traditionally, decision makers (DMs) in organizations have made decisions based on either their experience alone or by using a mixture of their professional judgment and ranking tools (Moore and Baker, 1969; Cooper et al., 2001), such as financial methods (Silvola, 2006), scoring models (Lawson et al., 2006), analytical hierarchy process (Feng et al., 2011) or multiattribute utility (Duarte and Reis, 2006; Lopes and de Almeida, 2015). Thus, projects were selected from the highest to lowest score until the budget available for the period was spent.

Nowadays, the size and complexity of many organizations makes this process more complicated. The DMs want to adopt a global approach to the problem, and thus, they have to select a group of projects while simultaneously taking into account all the relevant features of the problem (Urli and Terrien, 2010; Li et al., 2016).

The first important issue is that there are often multiple conflicting criteria (such as benefit, cost, risk, etc.) that have to be taken into account in the decision process. Therefore, a multicriteria approach must be followed to analyze the problem (Gutjahr et al., 2010; Cruz et al., 2014; Tofighian and Naderi, 2015).

Secondly, DMs have to deal with several constraints regarding available resources (financing, workforce, equipment, etc) and strategic, technical, political or legal issues (Mavrotas et al., 2006). Consequently, the projects are not independent. There may also be complementarity, incompatibility, or synergies produced by sharing costs and/or extra benefits derived from simultaneously conducting more than one project (Chien, 2002; Dobson, 2002). For these reasons, it is insufficient to simply compare two projects; rather, groups of projects (i.e. a project portfolio) should be compared to identify the one best adapted to the needs of the organization. This issue has been addressed in several studies (see Santhanam and Kyparisis, 1996; Klapka and Piños, 2002; Stummer and Heidenberger, 2003; Li et al., 2016; Arratia et al., 2016), which have suggested that the best individual projects do not necessarily produce the best portfolio. Given this background, optimization models have received much attention as they can address different types of interdependencies, multiple objectives, and constraints. Specifically, it is customary to use multiobjective programming models with binary variables to represent the different candidate projects (Cruz et al., 2014).

A third important aspect refers to integrating the selection process within a planning horizon. Most early studies considering project scheduling have first selected the projects for inclusion in the portfolio and then scheduled the selected projects or assumed that all the projects start during period one (Stummer and Heidenberger, 2003). However, this approach may result in some projects not being implemented due to a lack of resources in a given period. This drawback can be overcome by using models that are more flexible regarding when the projects are launched. The complexity of this situation could explain why literature until the end of the 20th century only presents few models simultaneously addressing both project selection and scheduling. So, in 1996, Coffin and Tailor stated, after a review of project portfolio selection studies, that project scheduling had not been taken into consideration in most of them.

However, in recent years, the joint problem of project portfolio selection and scheduling has received considerable attention, since it allows maximizing of the organizations' stated objectives. In this context, Ghasemzadeh et al. (1999), Medaglia et al. (2008) and Liu and Wang (2011) proposed the use of integer programming models to integrate a project selection mechanism with precedence relationships and technical interdependencies among projects. Jafarzadeh et al. (2011) considered that the time horizon was flexible and the projects were independent and, therefore, the projects could be performed in any order. Naderi (2013) and Emami et al. (2016) presented models for selecting projects and scheduling the activities of the selected projects. In all of these cases, a single function was optimized, the total benefit or the net present value of the selected projects without synergies among them. With the same objective but considering synergistic benefits, Li et al. (2016) formulated an integer model that incorporated the project interruptions as a strategy to improve the scheduling of the projects. Tofighian and Naderi (2015) modelled the joint problem of project selection and scheduling using a mixed integer linear model to optimize both the total benefit of selected projects and resource usage variation, but without synergetic effects. They compared different algorithms to approximate the set of efficient portfolios. In this line, Carazo et al. (2010) and Rabbani et al. (2010) also proposed multiobjective models and analyzed different strategies to determine the solution space of efficient portfolios. At this point, there is no criterion for discriminating among these efficient solutions, so we need to incorporate additional information on preferences of the decision maker(s) into the process in order to select a final solution.

Taking the foregoing into account, we used a multiobjective binary model that incorporates all the key aspects under general conditions and which can be applied in public and private settings. Also, in order to assist DMs in choosing a final efficient portfolio, his/her preferences are included in the process.

The output of a multiobjective problem is a set of efficient solutions (the Pareto Set) rather than a single optimal solution. Generally, this set is very large and it can be difficult to identify or select a final solution from all the efficient solutions. The literature is replete with methods (see Ballester and Romero, 1998) to assist DMs in this task, according to the type of preferences and information the DMs are able to provide: weights, trade-offs, target values, etc. Thus, some studies use goal programming (Santhanam and Kyriasis, 1996), which is suitable when the DMs can provide some thresholds or target values in advance for the conflicting objectives. Other authors (Ghasemzadeh et al., 1999; Medaglia et al., 2008) combine the different objectives into a single function by assigning different weighting scores to each objective according to their importance for the DMs. Some studies use interactive techniques to produce an approximation of the set of efficient solutions and include the DMs' preferences at a later stage (Graves and Ringuest, 2003; Stummer and Heidenberger, 2003; Nowak, 2013). We chose the latter approach, which includes multiple objectives within the model and obtains the efficient portfolios. The DMs can then refine the space of efficient solutions or choose the most suitable solution, according to their own preferences.

The mathematical formulation of the model used is an NP-hard problem (Ehrgott and Gandibleux, 2000; Demeulemeester and Herroelen, 2002) and the use of an exact method makes its solution more difficult as the time horizon and the number of projects and objectives increase. For this reason, we have used a metaheuristic algorithm. This approach offers a good compromise between the quality of the solution obtained and run-time. In a multiobjective context, evolutionary algorithms are particularly suitable as they can obtain a set of efficient solutions in one run instead of separate runs, as occurs when using traditional mathematical programming techniques (Deb, 2001). We use an evolutionary metaheuristic method called Scatter Search for Project Portfolio Selection (SS-PPS), whose problem-solving abilities in this field have proven to be superior to others (Carazo et al., 2010).

A common feature of most multiobjective metaheuristics is to approximate the efficient set (Carazo et al., 2010; Rabbani et al., 2010; Yu et al., 2012; Tofighian and Naderi, 2015), regardless of the DMs' preferences. However, in a real-world case, the DMs may not be able to find their preferred solution within this set and thus be unable to make a final decision. In these situations, interactive procedures are a good alternative because they can gradually lead to the areas of the efficient set that may be more

attractive to the DM. Thus, computational effort can be reduced and the drawback of having to choose a solution from a set that is too large is solved. However, few studies have combined interactive procedures with multiobjective metaheuristics (see Branke et al., 2008) compared to the extensive use of these procedures with traditional or multiobjective exact methods. Among interactive schemes, the reference point-based approach has become one of the most widely used because of the intuitive way in which the DM inputs the requested information (Stewart, 2016). Within this framework, Molina et al. (2009) used an interactive scheme based on the g-dominance concept that can be coupled to any multiobjective metaheuristic, whether evolutionary or not.

In this work, we adapted this interactive scheme based on g-dominance to be more generic and included several DMs. Also, we describe a software tool known as the Project Portfolio Selection Tool (PPST) that assists in the process of selecting and scheduling project portfolios taking the preferences of a DM or several DMs into account. This software tool uses the SS-PPS algorithm as the search engine and allows DMs (or users) to easily input and/or modify data step-by-step. PPST consists of two modules: a solution module that approximates the set of efficient portfolios, and a second module that supports DMs in exploring the solution space in order to find the preferred solution, if they so wish. Hence, our paper contributes to the current stand of literature, on the one hand, by adapting the g-dominance interactive scheme to be more generic (including several DMs) and better fit the requirements of a Project Portfolio Selection Problem. On the other hand, we have designed an interactive tool, embedded into a metaheuristic algorithm tested by Carazo et al. (2010), in order to provide the necessary tools to implement interaction with the DMs into a real case. Consequently, the advance from the previous work is to provide a tool to incorporate the decision makers' preferences in the resolution process, helping to explore the efficient portfolios and learning about the situation under consideration.

The article is structured as follows: Section 2 describes the mathematical formulation of the model, the techniques used to obtain a final solution, and the software implemented. Section 3 presents a case study based on a real situation in which DMs from a state university decided which project portfolio would satisfy their needs for a given period, and demonstrates how the software supported the DMs in identifying the best solution. Section 4 presents the main conclusions.

2. Problem Formulation and Resolution Tool

In the following, the mathematical model, the solution technique and the software used are described.

2.1. Mathematical model

This section presents a multiobjective binary model for selecting and scheduling project portfolios from a set of I candidate projects within a fixed planning horizon divided into T periods. It is assumed that a project cannot be partially funded, although different versions of a single project can be addressed on the condition that each version is treated as an indivisible proposal. Thus, the model's decision variable $x_{i,t}$ takes the value 1 if project i ($i = 1, \dots, I$) starts at time t ($t = 1, \dots, T$), and is equal to 0 otherwise. A project portfolio (group of selected projects and their start time) will be denoted by $\mathbf{x} = (x_{1,1}, \dots, x_{1,T}, x_{2,1}, \dots, x_{2,T}, \dots, x_{I,1}, \dots, x_{I,T})$.

The aim is to select the best portfolios according to a set of objectives (value/utility, risk, cash-flows, etc) that the DMs consider important and multiple constraints (e.g. available resources, strategic or political requirements), which can be different at each period of the planning horizon.

The parameters, indices and variables used are as follows:

I : Total number of available projects. (Number of projects)

T : The set of time periods in the planning horizon. (Number of periods)

Q : Overall number of objective functions, in which \hat{Q} of them depend on the time period.

U : Number of resource categories.

S : Overall number of synergy relationships, where the first s synergies affect the objective functions and the rest, $S-s$, affects the resource constraints.

i : Index for projects, $i = 1, 2, \dots, I$.

k : Index for time periods, $k = 1, 2, \dots, T$.

t : Index for time period in which a project could start, $t = 1, 2, \dots, T$.

q : Index for objective functions, $q = 1, 2, \dots, \hat{Q}, \hat{Q} + 1, \dots, Q$.

u : Index for resource categories, $u = 1, 2, \dots, U$.

j : Index for synergy relationships, $j = 1, 2, \dots, s, s+1, \dots, S$.

A_j : The subset of projects corresponding to the synergy j .

M_j, m_j : Maximum and minimum number of projects in A_j to be simultaneously executed to activate synergy j .

d_i : Duration of project i .

$f_{q,k}$: objective function q ($q = 1, 2, \dots, \hat{Q}$) in period k .

$f_{\hat{q}}$: global objective function q ($q = \hat{Q} + 1, \dots, Q$).

$c_{i,q,k+l-t}$: Individual contribution of project i in its execution time $k+l-t$ in period k , for objective function q .

$w_{q,k}$: Weight assigned to the q -th objective function ($q = \hat{Q} + 1, \dots, Q$) in time period k .

$r_{i,u,k+l-t}$: Individual consumption of project i in its execution time $k+l-t$ in period k , for available resource category u .

$R_{u,k}$: Total amount of available resource in category u for period k .

$a_{j,q,k}$ ($a_{j,u,k}$): Additional contribution to the objective function q (resource u) in period k if the synergy j is activated.

$v_{u,k}$: parameter that indicates if the resources not spent in a given period are transferred to the following one ($v_{u,k} = 1$) or not ($v_{u,k} = 0$).

n : index for linear constraints on the portfolio projects in period k , $n = 1, 2, \dots, \eta$.

$b_{n,i}(k)$: Coefficient of project i in linear constraint n , if this project is active in period k .

$b_n^{low}(k), b_n^{upp}(k)$: lower and upper bounds, respectively, for linear constraint n in period k .

z : index for global linear constraints on the portfolio projects, $z = 1, 2, \dots, \mu$. They do not depend on period k .

$b_{z,i}$: Coefficient of project i in linear constraint z .

b_z^{low}, b_z^{upp} : lower and upper bounds, respectively, for linear constraint z ($z = 1, 2, \dots, \mu$).

CL_i : Lower bound, equal to one or zero, depending on whether the i -th project is mandatory or not.

α_i, β_i : Upper and lower bound for the starting time of certain projects belonging to the E subset of the total projects.

L : Subset of projects which are affected by precedence relationships.

l : Index for projects in L .

P_l : set of precursor projects of a project l .

$h_{i,l}, H_{il}$: The minimum and maximum number of time periods which have to elapse before the starting time of the project l .

$x_{i,t}$: Binary variables taking value 1 if project i starts at t , and 0 otherwise.

$y_{j,k}^m$: Binary variables taking value 1 if the number of active projects of A_j , in period k , is at least m_j , and 0 otherwise.

$y_{j,k}^M$: Binary variables taking value 1 if the number of active projects of A_j , in period k , is at most M_j , and 0 otherwise.

$y_{j,k}$: Binary variable taking value 1 if synergy j is active in k and 0 otherwise.

An important issue to be taken into consideration is that we may find interdependencies between the candidate projects. For example, when projects share resources, and the execution of two or more interrelated projects require fewer resources than if implemented separately, or when the benefits of one project are partially increased due to the simultaneous execution of another. These effects mean that the best individual projects do not necessarily make the best portfolio. Consequently, portfolio performance

should be calculated considering the individual project's contribution plus (or minus) the extra contribution due to the interdependence relations (synergistic effects) when they exist.

In our model, to formalize these interdependences, on the one hand, the organization has to specify:

- Subsets of projects $A_j \subset I$, $j = 1, 2, \dots, s, s + 1, \dots, S$.
- The minimum (m_j) and maximum (M_j) number of projects in A_j , which have to be active in period k for activating the synergy j .
- The extra value for the q -th objective function ($a_{j,q,k}$) or the u -th resource constraint ($a_{j,u,k}$). Without loss of generality, we will assume that the first s synergies affect the objective functions and the remaining synergies ($S - s$) the resource constraints. These extra values represent additional benefits or shared costs by the projects in A_j , and we suppose that they do not depend on the execution time in which each project is in k . This may be restrictive in certain situations, and future research may focus on this issue.

Note that the classical types of projects' interdependencies can be modelled as special cases with $m_j = M_j = 2$ and the subset A_j formed by only two projects.

On the other hand, these interactions are linked with the binary variables $y_{j,k}$. These variables must detect if the synergy j takes effect ($y_{j,k} = 1$) or not ($y_{j,k} = 0$) for assessing a portfolio. Moreover, technical constraints will be introduced in the model for assuring this fact.

Thus, portfolio performance should be calculated by taking into account the individual contribution of each project ($c_{i,q,k+1-t}$ for objective function q and $r_{i,u,k+1-t}$ for available resource u) and extra contributions ($a_{j,q,k}$ for objective function q and $a_{j,u,k}$ for available resource u) due to potential interdependencies. It is worth noting that both terms depend on the specific period each project i is in k . If project i starts in period t and lasts d_i periods, then this project would be at execution time $k+1-t$ in period k .

Given the foregoing, the general model used in our decision-support tool was based on an improved version of the model presented in Carazo et al. (2010) and features the following mathematical formulation:

$$\text{Optimize}_x \left\{ \begin{array}{l} f_{q,k}(\mathbf{x}) = \sum_{i=1}^I \sum_{t=1}^k c_{i,q,k+1-t} x_{i,t} + \sum_{j=1}^s y_{j,k} a_{j,q,k} \quad q = 1, \dots, \hat{Q}; \quad k = 1, \dots, T \\ f_q(\mathbf{x}) = \sum_{k=1}^T w_{q,k} \left(\sum_{i=1}^I \sum_{t=1}^k c_{i,q,k+1-t} x_{i,t} + \sum_{j=1}^s y_{j,k} a_{j,q,k} \right) \quad q = \hat{Q} + 1, \dots, Q \end{array} \right. \quad (1)$$

Subject to:

$$\sum_{i=1}^I \sum_{t=1}^k r_{i,u,k+1-t} x_{i,t} + \sum_{j=s+1}^S y_{j,k} a_{j,u,k} \leq R_{u,k} + \left(R_{u,k-1} - \left(\sum_{i=1}^I \sum_{t=1}^{k-1} r_{i,u,k-t} x_{i,t} + \sum_{j=s+1}^S y_{j,k-1} a_{j,u,k-1} \right) \right) v_{u,k} \quad u = 1, \dots, U; \quad k = 1, 2, \dots, T \quad (2)$$

$$\left(\sum_{i \in A_j} \sum_{t=\max\{1, k-d_i+1\}}^k x_{i,t} \right) - m_j + 1 \leq I \cdot y_{j,k}^m \leq \left(\sum_{i \in A_j} \sum_{t=\max\{1, k-d_i+1\}}^k x_{i,t} \right) - m_j + I \quad j = 1, 2, \dots, S; \quad k = 1, 2, \dots, T \quad (3)$$

$$M_j - \left(\sum_{i \in A_j} \sum_{t=\max\{1, k-d_i+1\}}^k x_{i,t} \right) + 1 \leq I \cdot y_{j,k}^M \leq M_j - \left(\sum_{i \in A_j} \sum_{t=\max\{1, k-d_i+1\}}^k x_{i,t} \right) + I \quad j = 1, 2, \dots, S; \quad k = 1, 2, \dots, T \quad (4)$$

$$0 \leq y_{j,k}^M + y_{j,k}^m - 2y_{j,k} \leq 1 \quad j = 1, 2, \dots, S; \quad k = 1, 2, \dots, T \quad (5)$$

$$b_n^{low}(k) \leq \sum_{i=1}^I \left(b_{n,i} \cdot \sum_{t=\max\{1, k-d_i+1\}}^k x_{i,t} \right) \leq b_n^{upp}(k) \quad n = 1, 2, \dots, \eta; \quad k = 1, \dots, T \quad (6)$$

$$b_z^{low} \leq \sum_{i=1}^I \left(b_{z,i} \cdot \sum_{t=1}^T x_{i,t} \right) \leq b_z^{upp} \quad z = 1, 2, \dots, \mu \quad (7)$$

$$CL_i \leq \sum_{t=1}^T x_{i,t} \leq 1 \quad i = 1, 2, \dots, I \quad (8)$$

$$\alpha_i \cdot \sum_{t=1}^T x_{i,t} \leq \sum_{t=1}^T t \cdot x_{i,t} \leq \beta_i \quad \forall i \in E \quad (9)$$

$$\sum_{t=1}^T x_{i,t} \geq \sum_{t=1}^T x_{l,t} \quad i \in P_l, l \in L \quad (10)$$

$$\sum_{t=1}^T x_{l,t} \cdot \left(\sum_{t=1}^T t \cdot x_{i,t} + h_{i,l} \right) \leq \sum_{t=1}^T t \cdot x_{l,t} \leq \sum_{t=1}^T t \cdot x_{i,t} + H_{i,l} \quad \forall i \in P_l, l \in L \quad (11)$$

$$x_{i,t}, y_{j,k} \in \{0,1\} \quad (12)$$

The objective functions are defined by (1). There are two blocks of functions.

On the one hand, \hat{Q} objective functions (sales, risk, etc...) in each period k ($k = 1, 2, \dots, T$) of the planning horizon, noted by $f_{q,k}$ ($q = 1, 2, \dots, \hat{Q}$). Thus, in this block, there can be as many objective functions as combinations of attributes and periods in the time horizon ($\hat{Q} \cdot T$).

On the other hand, $(Q - \hat{Q})$ different objective functions that represent the weighted aggregated value of some other attributes at different periods (cash-flow, ...), noted by f_q ($q = \hat{Q} + 1, \hat{Q} + 2, \dots, Q$). In this case, if an attribute has an economic value (it is expressed in monetary units), its weight could, for example, represent a discount factor if one wishes to take the time value of money into account (for example, net present value of cash-flow). In any way, we assume that these weights ($w_{q,k}$) are given by the decision maker according to his/her preferences. Thus, in this block, there can be as many objective functions as temporally aggregate attributes ($Q - \hat{Q}$).

Note that we have used the same sub-index q in both blocks, but the variation range is different and the attributes represented are different too.

The feasible portfolios are defined by equations (2-12). Expressions (2-6) are temporal constraints (for each period k) and expressions (7-11) are global constraints (independent of the period).

Constraints (2) on available resources (workforce, machine hours, funds, etc) have the same structure as the objective functions $f_{qk}(x)$, as mentioned previously, but the interaction sets A_j are different, and now j varies from $s+1$ to S . Furthermore, some unused resources (e.g., funds) in a period can be transferred to the next one, using the corresponding interest rate ($Rate_u(k)$). Thus, the parameter $v_{u,k}$ takes the value $(1 + Rate_u(k))$ for the resources that can be transferred from period $k-1$ and 0 otherwise. Note that $v_{u,l} = 0$.

Inequalities (3-5) are technical constraints related to the variable $y_{j,k}$ linked to the interaction j . According to (5), if the number of active projects of set A_j in period k is at least m_j ($y_{j,k}^m = 1$) and at most equal to M_j ($y_{j,k}^M = 1$), the interaction j becomes activated and $y_{j,k} = 1$.

Constraints (6) and (7) are linear. The first block includes the limitations that the organization wishes to impose on the active projects in each period k but which do not depend on their internal execution time (timing). The second block (7) is independent of the period. For example, let us specify that different versions of the same project or similar projects cannot be part of the same portfolio.

Expression (8) establishes that each project, if selected, can only start once. Furthermore, this restriction allows the DMs to establish project i as a mandatory choice by requiring that the parameter CL_i

be equal to 1. Constraint (9) establishes an upper bound (β_i) and a lower bound (α_i) for the starting time of certain projects pertaining to the E subset of the total project set.

The last two inequalities formalize precedence relationships between projects. Inequality (10) specifies that a project l cannot be selected unless its precursors (P_l) have already been selected, and (11) requires that project l cannot start until a number of fixed periods of time have elapsed, at least (h_i) and at most (H_i), since its precursors began. $L \subset I$ denotes the subset of projects that are affected by precedence relationships. Note that (11) could be transformed into the following linear constraint:

$$\left(\sum_{t=1}^T t \cdot x_{i,t} + h_{i,l} \right) \leq \sum_{t=1}^T t \cdot x_{l,t} + \sum_{t=1}^T (1 - x_{l,t}) T \leq \sum_{t=1}^T t \cdot x_{i,t} + H_{i,l} + \sum_{t=1}^T (1 - x_{l,t}) T \quad \forall i \in P_l$$

It would be interesting in future research to thoroughly explore whether this change could make the entire model easier to solve.

To summarize, the model described by equations (1)-(10) is a nonlinear multi-objective binary programming model that facilitates the selection of efficient portfolios in line with the set of objectives pursued by the organization, as well as their scheduling with regard to the optimum time to launch each project within the portfolio.

2.2. Solution technique

As mentioned in the introduction, the complexity of the formulated model forces the use of a metaheuristic instead of an exact method, as occurs in many real-world problems. In particular, evolutionary methods are among the most widely used methods in metaheuristics multiobjective programming because the set of efficient solutions can be computed in a single run. Nevertheless, the DMs' preferences have to be included to select a solution within the set. Few studies have addressed this issue in a setting in which metaheuristics are used. We apply an evolutionary method called Scatter Search for Project Portfolio Selection (SS-PPS) (Carazo et al., 2010) and, as an innovation, propose to combine it with an interactive scheme which gradually leads to the areas of the efficient set that are more attractive to the DMs. Thus, on the one hand, computational effort can be reduced and, on the other, the DMs are assisted in choosing the best solution according to their preferences.

We use the interactive procedure based on g-dominance proposed by Molina et al. (2009), but extend it to the case in which there are several DMs. The main aim of this method is to reduce the size of the approximation of the efficient frontier, using the information iteratively supplied by one or more DM. Each DM must provide the values they desire for each objective or criteria (i.e., a reference point g). The iterative process continues until the DMs reach the best compromise regarding the best solution according to their preferences.

The main aim in methods that use a reference point to include preferences is to project this point on the efficient frontier to obtain the efficient point closest to this reference point. However, the g-dominance scheme provides an approximation of the efficient frontier (a set of efficient solutions) in the area where this projected solution lies, rather than a single efficient solution. This is illustrated in Figures 1 and 2, in which the areas of interest on the frontier (g-efficient points) are highlighted in red, for a hypothetical bi-objective minimization example.

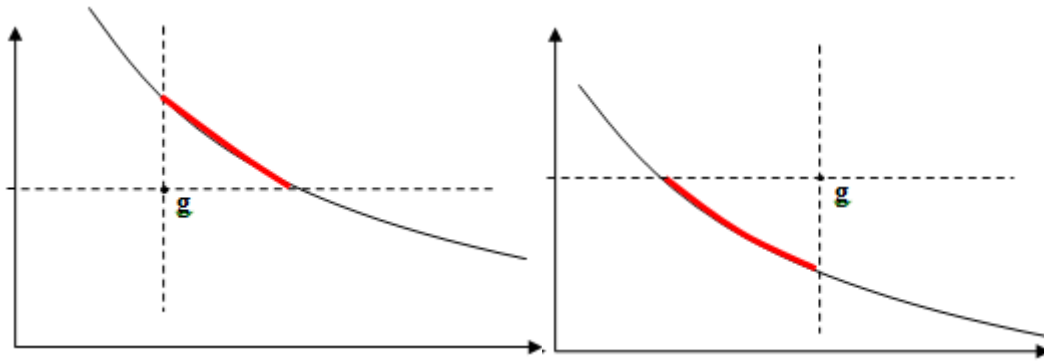


Figure 1. Unfeasible reference point

Figure 2. Feasible reference point

We use this g -dominance scheme in an interactive framework for one or more DMs, who will be iteratively guided to their best solution.

When there is a single DM, the DM is shown a representative subset of efficient portfolios at each iteration h , according to the offered reference point g^h . This set is denoted by RS^h . If the DM is not satisfied with any of these solutions, he/she can either modify the reference point in order to refine the preferences or select a solution $p(x^{ph})$ in RS^h to focus the search in this area. In the latter case, a new reference point g^{h+1} is calculated as a convex linear combination of the selected solution and the current reference point g^h :

$$g^{h+1} = (1 - \theta) \cdot g^h + \theta \cdot x^{ph} \quad \theta \in (0, 1) \quad (13)$$

When there are several DMs, all of their preferences have to be combined to obtain a solution acceptable to all of them.

In this case, we follow the classic scheme of using the reference point based on scalarized achievement functions (Miettinen, 1999). According to this scheme, given a reference point and a distance L , the efficient portfolio that best matches the DMs' preferences is computed. This portfolio is the efficient point (i.e. the most preferred solution [PS]) that minimizes the distance L to the reference point. However, we have several reference points and therefore several preferred portfolios. Thus, we have to modify the g -dominance scheme to find a reference point g that represents a compromise for each of the DMs. We attempt to find the ideal reference point g of all the most preferred solutions calculated. That is, if we have N DMs for a problem with Q objectives, and we have obtained N preferred solutions $PS1^h, \dots, PSN^h$ at iteration h , then g^h is the reference point whose set of g -efficient points is the smallest set that includes the N preferred solutions, i.e.,

$$g^h = (g_1^h, g_2^h, \dots, g_Q^h) \quad \text{with} \quad g_q^h = \max_{e=1, \dots, N} \{PSe_q^h\} \quad (14)$$

where $PSe^h = (PSe_1^h, PSe_2^h, \dots, PSe_Q^h)$ denotes the most preferred solution for DMe ($e = 1, 2, \dots, N$), obtained from the reference point specified by this DM, $ge^h = (ge_1^h, ge_2^h, \dots, ge_Q^h)$. Once this point is calculated (see Figure 3), we solve the problem again as if there was a single DM, but using this ideal reference point g^h to generate a new representative set of g -efficient solutions (RS) that will be shown to each DM. Thus, each DM can evaluate how far from the consensus area his/her preferences are and assess how to modify his/her reference point at the next iteration to achieve consensus with the other DMs or influence them.

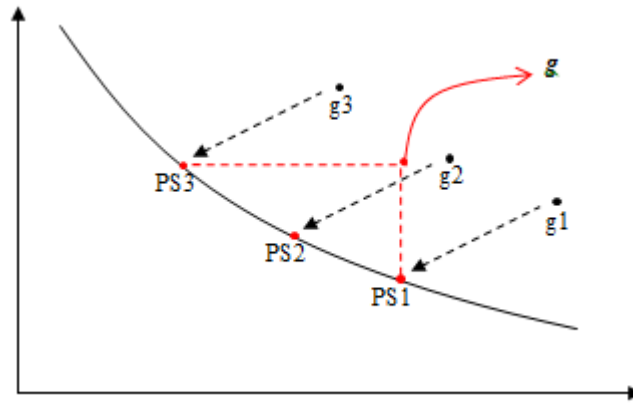


Figure 3. Calculation of the reference point (g) integrating the preferred solutions (PSe)

If the DMs are not satisfied with any of the solutions in set RS^h , then they must specify a new set of reference points (to obtain a new set of preferred solutions, PSe^{h+1}), or select a solution in RS^h and repeat the process until all the DMs reach a consensus on a single common solution. If a DM e ($e = 1, 2, \dots, N$) selects a solution in RS^h , then a new reference point g_e is calculated as a convex linear combination of the selected solution and the current common reference point g^h . Furthermore, in each iteration, the DMs are shown a value for the distance between their reference points as a guide to how far apart their preferences are. This distance is in the range $[0, 1]$ such that the closer to zero the value, the shorter the distance between points, and therefore the least difference between the reference points provided by DMs. The following pseudo-code shows how the scheme of g -dominance is extended to the case of several DMs:

Interaction with g -dominance (more than one DM):

- 1: $h = 0$. Request from each DM one reference point, g^e .
- 2: DO WHILE no common solution is reached.
 - 3: Calculate the distance and the set of preferred solutions $PS1^h, \dots, PSN^h$.
 - 4: Calculate the reference point g^h associated with these solutions.
 - 5: Calculate the set of g^h -efficient solutions.
 - 6: Select a set of representative g^h -efficient solutions: RS^h .
 - 7: Show this set of representative solutions to the DMs.
 - 8: IF the DM e wishes to change his/her reference point, THEN
 - 9: Let the DM e add the new values of $g^{e^{h+1}}$.
 - 10: Ask the DM e to choose a solution in RS^h and use this information to compute the new reference point $g^{e^{h+1}}$.
 - 10: END IF
 - 11: $h = h + 1$.
- 12: END DO

2.3. Project Portfolio Selection Tool (PPST)

The multiobjective binary nonlinear model presented in Section 2.1 and the interactive procedure shown in Section 2.2 have been embedded in a new software tool implemented by the authors called PPST. This tool has been designed to be used into a Windows environment and, as mentioned in the introduction, uses the SS-PPS heuristic procedure as a search engine, given its demonstrated competitive problem-solving abilities (Carazo et al., 2010). Then, regarding codification of the solutions, we followed the scheme in the original code, in which they were explicitly defined. Therefore, each solution is represented by two arrays:

- $\bar{x} = [x_1, x_2, \dots, x_I]$ in which each $x_i (i = 1, 2, \dots, I)$ takes the value 1 if project i is selected and equal to 0 otherwise.
- $\bar{t} = [t_1, t_2, \dots, t_I]$ in which each $t_i (i = 1, 2, \dots, I)$ indicates the starting time for project i .

The PPST starts with a Splash screen in which the user can *Create* a new data file *or Open* an existing data file, by clicking on the *File* menu. In the first case, the user has to input the general parameters (number of projects, the number of periods in the time horizon, the number of objectives and constraints, etc). Figure 4* shows the general data of the empirical real case described in Section 3, and which we use to demonstrate how PPST works in practice.

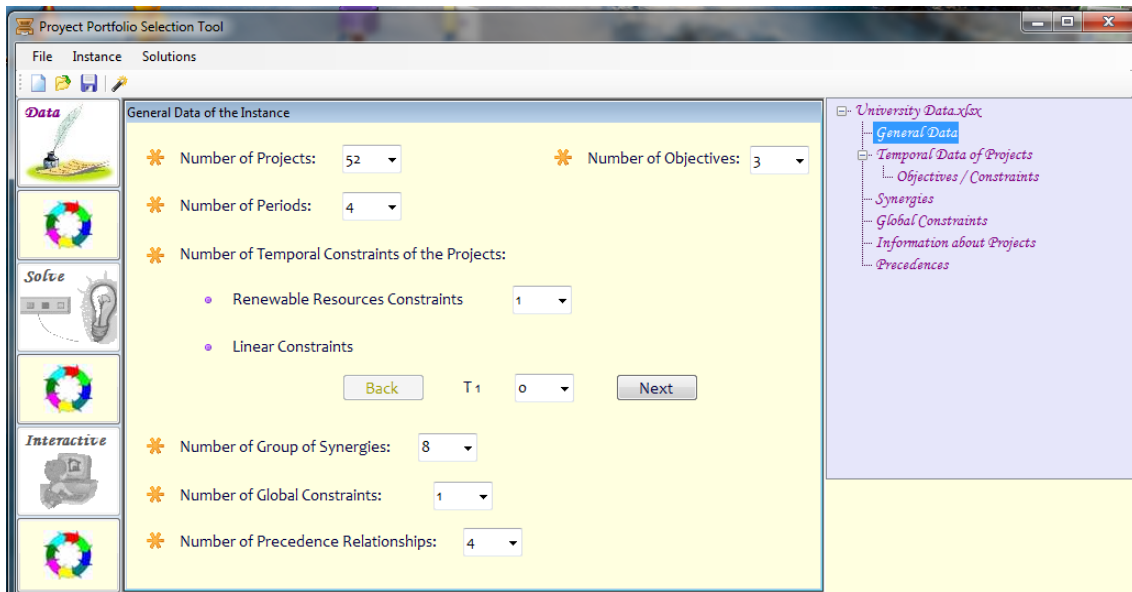


Figure 4. General Data of the empirical application

Then, in a sequence of screens, the user provides further parameter values, such as the duration of each project, its contribution to each objective, synergies between certain projects, and so on. For example, Figure 5 shows the duration of project 6 and the temporal contribution of this project to the objectives under consideration (coefficients $c_{i,q,k+1-t}$) or constraints (coefficients $r_{i,u,k+1-t}$), as shown in Section 2, which have been input by the user.

* Please note that we only show a few example screenshots as our aim is simply to illustrate the user-friendly nature of the software.

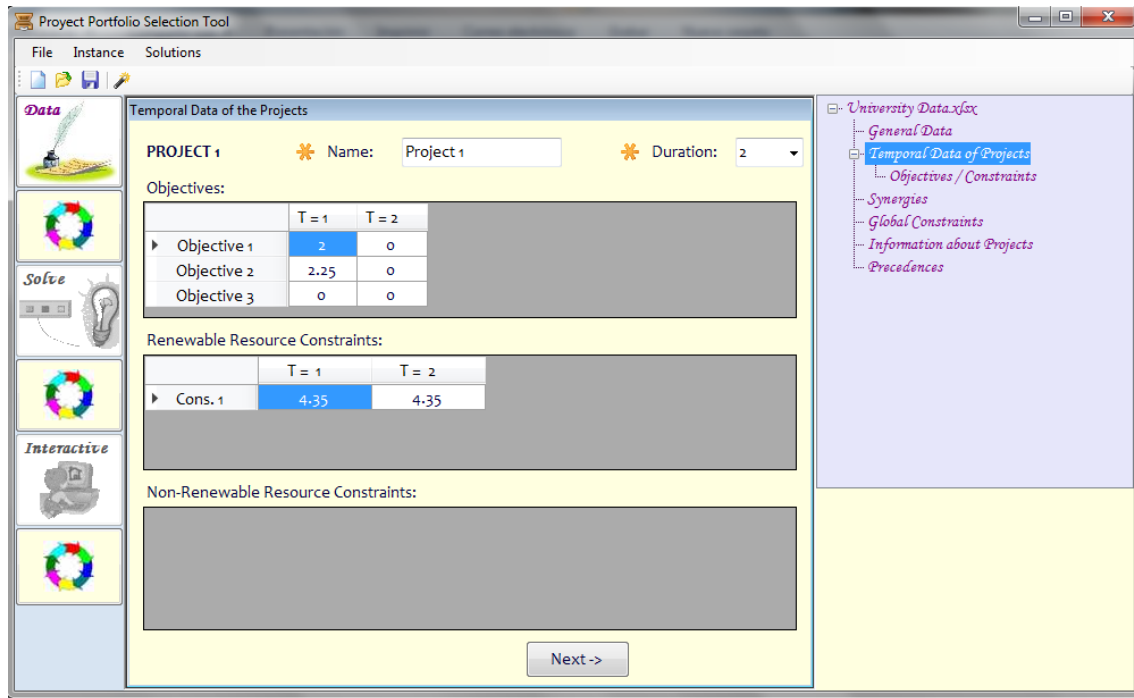


Figura 5. Screen to input temporal data of a project

Once the final file includes all the data pertinent to the problem, the user can save it as an Office Excel format file, indicating its name and location. The editing process is similar to the previous one.

Once data have been introduced, the user begins the solution process by clicking on the *Instance* > *Solve* command and a new screen appears in which the user chooses the search intensity for the solution. There are four options: *Very High*, *High*, *Medium*, and *Low*. The lower the search intensity, the shorter the computational time; however, the solutions obtained may be further from the real efficient frontier. At this point it is important to emphasize that this option is used just for a first approximation to the whole efficient frontier, so as to be able to start the interactive procedure. Later, when interactive procedure is applied, new and better solutions are found but only in areas of interest for DMs. The key issue is to deal with the computational burden of solving a complex problem whose computational time may vary from seconds to hours.

If the interactions cannot be efficiently performed because the time needed to compute the initial solutions to show to the DMs is excessive, then the problem could be solved off-line using the option *Very High* in the menu. With this option, a first and in-depth resolution will be implemented without the presence of the DM. After this possibly long resolution process, the solutions obtained are loaded into the module *Solutions* and the interaction process is restarted, but using these good solutions obtained as a starting point, as well as in a more reduced area of the Pareto set. This drastically reduces the computational time of each new interaction with the DMs, even in large problems, and allows them to interact without having to wait hours for a solution. This is, within this option the algorithm could consume time as needed to compute a set of initial solutions of high quality, which will be used as seeds for the interactive procedure, so that, once good solutions have been obtained, the subsequent iterations, focused on a precise area and already endowed with high quality solutions, will consume quite less computational time.

The user clicks on *Solutions* > *Interactive* > *One decisor* (or *Several decisors*) to include the information for the interactive process, either by changing the reference point or by selecting a representative solution from those shown to him/her. The process repeats until the DM (or DMs) is satisfied with one of the solutions.

When several DMs are involved, the software asks for the initial reference points (ge), which are used to compute the most preferred solution for each DM (PSe) and the ideal point g that contains the best value for the solutions generated for each objective (see Section 2.2). This ideal point will be used as a common reference point to conduct the interactive procedure. In addition, the DMs are provided with a sample of efficient portfolios at each iteration. This set, called RS^h in Section 2.2, includes the best portfolio for each objective and the compromise portfolios, which show the range of diversity at the efficient frontier. Thus, as mentioned in Section 2.2, each DM can refine his/her preferences by modifying his/her current reference point or by choosing a solution from the offered sample. It is worth noting that after each iteration during the interactive procedure, the output can be saved in an Excel file containing the efficient portfolios and the values for each objective function. The software also provides the user with a graph of the temporal distribution of each efficient portfolio, additional information on the money spent in each period, and the active synergies.

Thus, PPST software is a user-friendly tool for project portfolio selection and scheduling problems (with multiple objectives, constraints, synergies...) that incorporates the DMs' preferences to obtain a compromise solution. It can be used as a practical tool in which the managers can make decisions rationally.

3. A practical approach to the problem: an empirical application

The decision-making process for selecting and scheduling a suitable project portfolio occurs in public organizations (Mavrotas et al., 2006; Medaglia et al., 2008, Arratia et al., 2016; Cruz et al., 2014) and private ones (Stummer and Heidenberger, 2003; Ding and Cao, 2008). There are some differences between them, such as the methods used for pricing and evaluating performance, and the goals and priorities to be achieved, but this does not affect the formal model. Therefore, a general framework can be used for the decision-making process, regardless of the type of organization.

In this section, we illustrate the potential of the proposed approach by applying it to a real case in a Spanish state university. The university's Department for the Strategic Planning of Infrastructure (DSPI) needs to plan — at the beginning of the period and for a given time horizon — the budget available to fund a project portfolio by choosing among all the candidate projects. The aim is to choose the best project portfolio to implement, given the resources available and to simultaneously decide when to start each project in the portfolio while taking into account the organization's needs, objectives and priorities, and several strategic and political constraints.

The university's current selection system starts with the proposals made by the different university departments according to their needs in the areas they represent. These proposals are analyzed by the DSPI management team, which decides which project portfolio to fund and implement. This selection is based on the DMs' experience and does not use any mathematical model. We refer to this scheme as the *Traditional* selection system. The disadvantage of this system is that DMs have to manage a large amount of information: multiple objectives, restrictions, interdependencies between the projects, and a planning horizon. These issues make it very difficult to obtain efficient solutions without using a structured and formal tool, and can lead to suboptimal solutions.

The alternative approach involves selecting projects by using software based on a mathematical model. We refer to this method as the *Technical* selection system. In this case, the DMs have to specify the following data in advance: the assessment and availability of resources, the resource requirements for each candidate project, and the evaluation of each candidate project according to the objectives set. The problem with this selection system is that the DMs do not directly participate in it. They only offer technical information to solve the corresponding multiobjective problem. The DMs then have to select a final solution from the set of efficient portfolios obtained, which is not easy because this set is normally very large.

The advantages and disadvantages of these two selection systems have led us to propose a *Mixed* selection system that adds an interactive process to the *Technical* selection system. This has all the advantages of the *Technical* system — the selection is supported by a mathematical model solved with a software application— while preserving the main feature of a *Traditional* system — it generates a final solution taking all the DMs' preferences into consideration. As mentioned, PPST software is a tool for generating an approximation of the set of efficient portfolios and assisting DMs in finding the solution yielding the best compromise among the objectives through an interactive process to reach the ideal solution for all decision-makers.

We tested this system with the cooperation of three members of the DSPI management team. They were asked to indicate their preferences regarding the efficient solutions previously obtained. In order to use PPST, the DMs had to provide desirable levels for each of the objectives of the problem.

3.1. Preliminary data

The main information provided by the university can be summarized as follows:

There are fifty-two alternative projects ($i = 1, 2, \dots, 52$) and the time planning horizon consists of 4 consecutive semesters ($k = 1, 2, 3, 4$). Projects 3, 12, 20, 21, 22, 28, 29, 30, 32, 33, 35, 36, 37, 41, 42, 43, 46 and 47 last one period (semester), projects 2, 7, 11, 14, 16, 18 and 19 last three periods, and projects 6, 7 last four periods. The other projects last two periods.

The objectives considered by the organization are as follows:

- *Maximize the positive impact* (f_1). The DSPI management team assigned a score to each project based on the percentage of individuals who would benefit from it. The scores range from 1 to 10, where 1 is the least positive impact and 10 the most positive. These scores only affect the first execution period of each project selected (see Figure 5; Section 2.3).

- *Minimize the risk* (f_2)[†]. The management team assigned risk scores to each project on a scale of 0-10, where 0 represents the absence of risk, and 10 maximum risk. This estimation was based on possible factors that could affect the correct execution of each project (delays in project execution, etc). These scores only affect the first execution period of each project selected, as above (see Figure 5; Section 2.3).

- *Maximize the number of active projects in at least three periods within the time horizon* (f_3). The aim is to avoid choosing small projects on the basis of them being shorter and less expensive. The score allotted to each project is equal to 1 if the project is active for at least three periods within the time horizon, and 0 otherwise.

On the other hand, DMs established the following requirements:

Projects 1, 2 and 3 are very similar, so only one could be selected in one portfolio. This implies that in (7), $b^{low} = 0$, $B = (1,1,1,0,\dots,0)$, and $b^{upp} = 1$.

Some projects are mandatory, so $CL_i = 1$, for $i = 6, 7, 11, 14, 15, 26, 27, 28, 29, 30, 31, 32, 49$, and $CL_i = 0$ otherwise, in constraint (8).

Four precedence relationships ($L = \{45, 36, 41, 34\}$ in (10) and (11)):

- Project 45, if selected, must start during the last execution period of project 27 ($P_{45} = \{27\}$ in (10), and $h_{27,45} = H_{27,45} = 1$ in (11)).
- Projects 36 and 41, if selected, cannot start before projects 18 and 19 have finished, respectively ($P_{36} = \{18, 19\}$ and $P_{41} = \{18, 19\}$ in (10); $h_{18,l} = 3$, $H_{18,l} = 4$ ($l = 36, 41$) and $h_{19,l} = 3$, $H_{19,l} = 4$ ($l = 36, 41$) in (11)).

[†]We decided to assess risk according to estimates made by the DMs, since several studies (Badri et al., 2001; Dickinson et al., 2001; Klapka and Piños 2002; Glickman, 2008) have found a strong correlation between the estimates provided by professional managers and the final result.

- Finally, Project 34, if selected, cannot start until project 49 has finished ($P_{34} = \{49\}$ in (10); $h_{49,34} = 2$, $H_{49,34} = 4$ in (11)).

In addition, the total monetary resources available for each period (semester) were $478.69 \times 10^4 \text{€}$ ($R_{1,1}$), $189.53 \times 10^4 \text{€}$ ($R_{1,2}$), $900.57 \times 10^4 \text{€}$ ($R_{1,3}$) and $325.81 \times 10^4 \text{€}$ ($R_{1,4}$), respectively.[‡] There are also three sets of interdependencies between projects that define potential synergies that have an effect on the funds needed to conduct each group of projects:

- The simultaneous execution of project 46 and project 47 yields a cost reduction of $2.19 \times 10^4 \text{€}$ when they coincide in the 3rd or 4th period.
- The simultaneous implementation of project 45 and project 33 yields a cost reduction of $3.125 \times 10^4 \text{€}$ when they are executed in the 3rd or 4th period.
- The simultaneous implementation of at least two of the projects $\{8, 22, 25\}$ yields a cost reduction of $2.766 \times 10^4 \text{€}$ for the respective period, when they are executed in the 1st, 2nd, 3rd or 4th period.

3.2. Analysis, numerical results, and comparison of the solution reached by both selection systems

Using the *Traditional* selection system, the real solution adopted by the university department included 38 of the 52 candidate projects. As follows: $x_{12,1}, x_{13,1}, x_{14,4}, x_{15,4}, x_{16,3}, x_{18,3}, x_{19,4}, x_{20,3}, x_{21,2}, x_{22,2},$

$x_{23,1}, x_{24,1}, x_{25,1}, x_{26,1}, x_{27,2}, x_{28,2}, x_{29,2}, x_{30,2}, x_{31,2}, x_{32,4}, x_{33,3}, x_{42,4}, x_{43,4}, x_{44,3}, x_{45,3},$

Figure 6 shows the temporal distribution of the project portfolio chosen, the assessment of the objectives, the number of synergies, and the money spent in each period.

This chart depicts time along the X-axis: the vertical dashed black line represents the time horizon in this problem (four semesters). The boxes containing the selected projects are on the Y-axis. Each box shows the projects to be carried out, and when they have to start and finish. For example, project 6 begins in the first period and finishes at the end of the fourth semester because it lasts four semesters. Similarly, projects $\{16, 18\}$ begin in the third period and finish at the end of the fifth period, i.e., these projects would not finish within the planning horizon and would thus leave a committed budget for the next planning horizon.

By means of this selection system, the university's DSPI committed a total of $649.94 \times 10^4 \text{€}$. to future projects. This amount was calculated as the difference between the budget required to complete the execution of the projects that had started ($689.34 \times 10^4 \text{€}$) and the resources that had not been spent in the last period of the planning horizon ($39.40 \times 10^4 \text{€}$).

To use the *Mixed* selection system, we introduced the data of the 52 candidate projects into the PPST software. We solved the problem using the *Instance>Solve* command and a set of 378 efficient Pareto portfolios were identified in 7932 seconds (s.). As regards the parameters used in the algorithm, all of them were set as suggested by the authors. The size of the reference set was set to 8 points, the size of the tabu reference set was set to 50 points, the number of iterations of the tabu searches was 3900 and the maximum number of searches without improvement was set to 4. Subsequently, we had a meeting with three DMs from the DSPI management team to conduct the interactive process. As the problem was already solved, the solutions obtained were loaded in order to start the interaction with the DMs. At this stage, the procedure required information from the DMs about their desired level (i.e., reference points), for each of the objectives of the problem.

[‡] For comfort all economic data are in ten thousand euros (10^4).

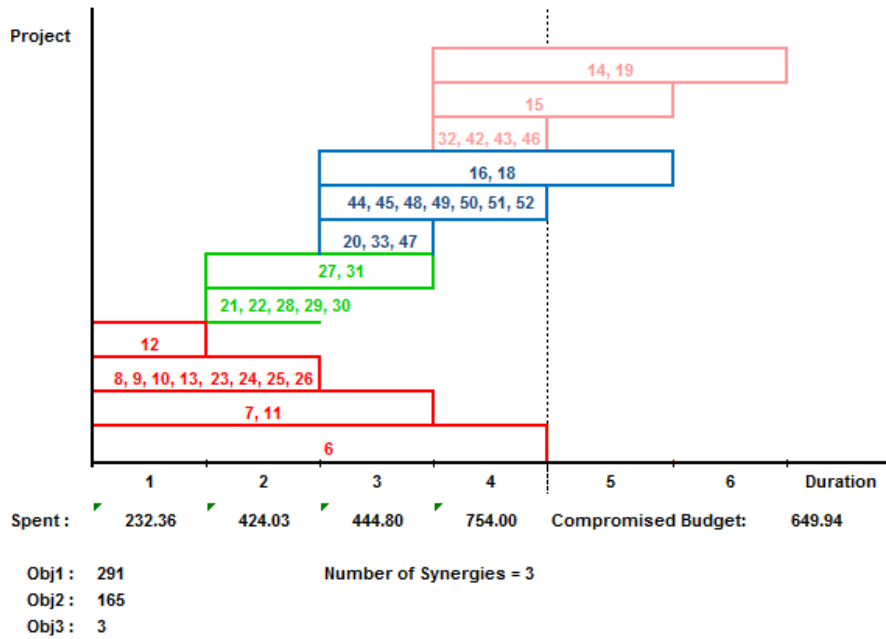


Figure 6. Selection adopted by the university using the traditional system

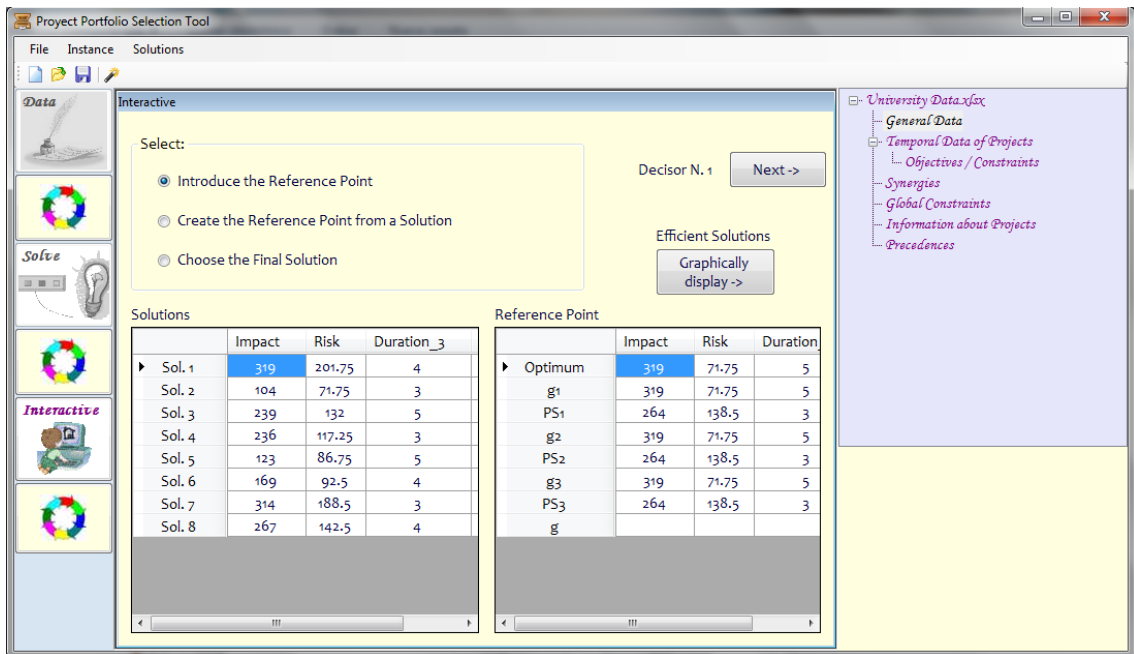


Figure 7. Screenshot after loading solutions to apply interactive (several dec.)

In the lower right box in Figure 7, the row labelled “Optimum” shows the optimal values of each objective (ideal point) that closely match the values on the rows “ge” (reference point of DM_e , $e = 1, 2, 3$) during this first stage and, consequently, the solution preferred by each DM (PS_e , $e = 1, 2, 3$) is the same. In the lower left box, under the heading “Solutions”, there is a sample of eight efficient solutions with their respective attribute values. This is a representative sample of the efficient frontier (set RS), where extreme and intermediate solutions are shown, as mentioned in Section 2.3. For example, the solution with the greatest value for function f_1 (Impact), Sol.1, is the one with greater risk (f_2). However, the

solution with the least risk, Sol.2, is the one with the least impact (f_1). In the third solution, the number of projects that last longer than 3 periods (objective function f_3) is 5, which is the highest value for this objective because its value ranges between 0 and 5 along the efficient frontier. It is evident that there is an important trade-off between the first two objectives. Choosing, for example, Sol.2 instead of Sol.1 leads to a 67.4% deterioration in f_1 and a 64.4% improvement in f_2 .

Based on this analysis, the DMs set their desired value ($g_e, e = 1, 2, 3$) for each objective. DM₁ is more interested in the portfolios with the greatest impact on the organization, i.e. solutions that affect the greatest percentage of people (f_1), $g_1 = (300, 222, 2)$. DM₂ favours portfolios with less risk (f_2), $g_2 = (247, 100, 2)$, and DM₃ prefers portfolios with projects that last longer than 3 periods (f_3), $g_3 = (283, 200, 5)$. The distance between these reference points was 0.6.

Using this data, the PPST software obtained a new group of 83 efficient project portfolios (81 s.). A new sample of eight solutions was shown to the DMs and they decided to continue the interaction process by determining new reference points. Table 1 contains the solutions shown on-screen after this first iteration.

Table 1. Sample of solutions after the first iteration

	Impact	Risk	Duration
Sol.1	319	201.75	4
Sol.2	226	117.25	4
Sol.3	229	118.25	4
Sol.4	297	168.25	3
Sol.5	236	117.25	3
Sol.6	282	154.00	4
Sol.7	317	197.00	3
Sol.8	269	141.00	3

Once again, the solution (Sol.1) with the greatest impact (f_1) involves the highest risk (f_2) and the solution (Sol.2) with the least risk (f_2) has the least impact (f_1). However, the trade-off between these two objectives is lower. Choosing Sol.2 instead of Sol.1 leads to a 29.2% deterioration in impact and a 41.9% improvement in risk. Given that the number of solutions remained very high and a suitable solution from the sample presented was not found, the DMs decided to continue the interactions and set new values. DM₁ reduced the desired value of the impact level of the projects on the organization (f_1) to 295 and the risk level (f_2) to 192; DM₂ was more permissive with the risk level (f_2) and increased its value to 135 and also increased the value of f_1 to 260; and DM₃ reduced f_2 and f_3 to 185 and 4, respectively. The distance between these points was 0.5.

After this iteration, 65 efficient portfolios (79 s.) were obtained. The DMs were still not satisfied with the solutions found, and performed two more interactions. Table 2 shows the desired values for each objective in the third and fourth iteration. The distance between reference points was 0.5 and 0.25 respectively.

Table 2. Reference points for each decision-maker at the third and fourth iteration

Iteration	$g1^h$	$g2^h$	$g3^h$	Distance	N. Efficient Points (seconds)
$h = 3$	(290, 180, 3)	(275, 145, 2)	(285, 175, 4)	0.5	44 (50 s.)
$h = 4$	(290, 170, 4)	(280, 155, 3)	(270, 175, 4)	0.25	20 (87 s.)

After the fourth iteration, the DMs analyzed the Excel file that contained the last set of efficient portfolios (Figure 8) and noticed that there were five portfolios dominating the solution shown in Figure

6. These portfolios were Sol.1, Sol.4, Sol.6, Sol.11, and Sol.16. At the end, they selected Sol.1 even though Sol.4 has higher values for all the objectives considered.

	A	B	C	D	E
1		Impact	Risk	Duration_3	Active Synergies
2	Sol. 1	291	161.75	4	3
3	Sol. 2	288	159	4	4
4	Sol. 3	284	155.25	4	3
5	Sol. 4	294	164.75	4	3
6	Sol. 5	283	154.25	4	3
7	Sol. 6	292	163	4	3
8	Sol. 7	288	158.5	3	4
9	Sol. 8	282	153.5	4	4
10	Sol. 9	289	159.75	3	4
11	Sol. 10	286	156.75	3	4
12	Sol. 11	293	163.75	3	3
13	Sol. 12	287	158	3	4
14	Sol. 13	285	156	3	3
15	Sol. 14	290	160.75	3	4
16	Sol. 15	289	160	4	3
17	Sol. 16	291	161.5	3	3
18	Sol. 17	285	156.5	4	3
19	Sol. 18	283	153.75	3	3
20	Sol. 19	286	157	4	3
21	Sol. 20	287	158.25	4	3
22					

Figure 8. Output after the fourth iteration (several DMs)

Sol.1, which has the same impact ($f_1 = 291$) as the portfolio adopted by the university using the *Traditional system* (Figure 6), has a lower risk and a greater number of projects that last more than 3 periods. Figure 9 shows the graph obtained by PPST for Sol.1. This graph is similar to the one shown in Figure 6, but the projects and values are different.

Unlike the *Traditional selection system*, no money was committed to the future planning periods using the *Mixed selection system* because Sol.1 leaves a surplus of $590.19 \times 10^4 \text{€}$ in the fourth period. This is enough to cover the completion of the projects that had not been completed in period 4, i.e., projects 15, 40, 44, 49, 50, 51, and 52 for the fifth period, and projects 14 and 18 for the fifth and sixth periods. Thus, if the university decides to continue with these projects, the expenditures would be $314.55 \times 10^4 \text{€}$ for the fifth period and $193.64 \times 10^4 \text{€}$ for the sixth. Given that the remainder in the fourth period was $590.19 \times 10^4 \text{€}$, there is surplus of $82 \times 10^4 \text{€}$.

To test our approach, the result obtained (Figure 9) was compared to the solution initially adopted by DSPI (Figure 6). The following differences were found:

1. Our solution not only dominates the solution initially adopted by the university, but also presents *better values in two of the three objectives under consideration*:

University: $f_1 = 291; f_2 = 165; f_3 = 3$; Our solution: $f_1 = 291; f_2 = 161.75; f_3 = 4$

2. The project portfolio presented by Sol. 1 is similar to that obtained using the *Traditional selection system*, but it differs regarding the number of projects and the schedule. It includes additional projects (projects 2, 4, 5, 38, and 40), but excludes projects 16 and 19. Thus, with the same budget, our solution allows us to execute more projects (41 compared to 38).
3. An additional advantage: the solution reached with the *Mixed selection system* was more conservative than that obtained with the *Traditional selection system*. The *Mixed selection system* does not commit resources to future periods ($80 \times 10^4 \text{€}$ surplus), whereas the *Traditional solution* commits a budget of $558.86 \times 10^4 \text{€}$ to future planning periods.

Thus, the PPST can help DMs to iteratively refine their preferences, explore the efficient frontier, and gain insight into the situation they are addressing. The PPST does not involve the DMs in excessive cognitive burden, because it only asks them to give the desired value for each objective, once they know the range of objective functions.

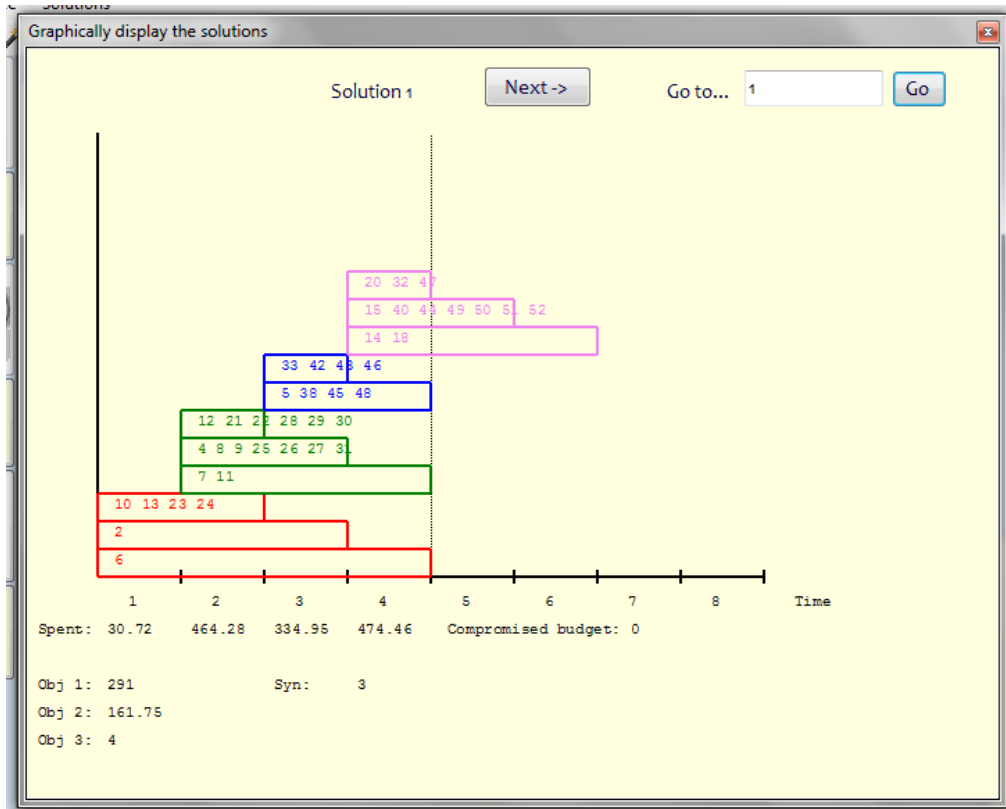


Figura 9. Schedule of project portfolio Sol.1, using a mixed selection system

Under the *g*-dominance approach, these individual preferences are used to establish a frontier area, rather than being aggregated to obtain a unique consensual solution. This area represents the smallest set of efficient solutions that not only includes the solution preferred by each DM, but also the intermediate solutions that represent a compromise between all the individual solutions chosen by each DM. Once the most satisfactory area of the efficient frontier is located, the DMs can focus on it and more deeply analyze the alternatives to reach a joint decision. Thus, although the final set of efficient portfolios depends on the reference points established by the DMs in successive stages, minor modifications to these points will lead to very similar regions of the efficient frontier.

The analysis was presented to the real decision makers and the feedback was that they have now become more conscious of the importance of using a quantitative tool for selecting and scheduling project portfolio. They found the tool intuitive and readily applicable and highlighted that they had learned more about the problem, the possibility of knowing how their preferences affect the final set reached, and the fact that it was possible to find an efficient portfolio that was better than the one previously chosen.

In order to analyse the influence of the reference points in the final set of efficient portfolios, we considered different scenarios in the interactive process shown in this section.

Firstly, we assume that during the iterative process, the DMs adhere to their preferred value for each of the functions they are interested in. Thus, DM1 does not change the value of 300 for the impact of the portfolio (f_1), DM2 does not change the value of 100 for risk (f_2), and DM3 does not change the value of 5 for the number of projects in the portfolio lasting more than three periods (f_3). In this hypothetical case, named "All", a total of 66 solutions are obtained and 13 of them match those obtained in the initial

process (Figure 8). Furthermore, if all the other solutions obtained are carefully analysed, it can be seen that there is a great range of variations in f_1 and f_2 , which is only to be expected since the DMs do not intend to give up their initial choices. This process leads to a final set with a greater diversity of solutions and a greater range of variations in the first two objective functions. Figure 10 shows the distribution of the values obtained in each of the two objective functions in the initial scenario and the alternative scenario. In the “All” scenario the distance between the preference points obtained in the last iteration is 0.43.

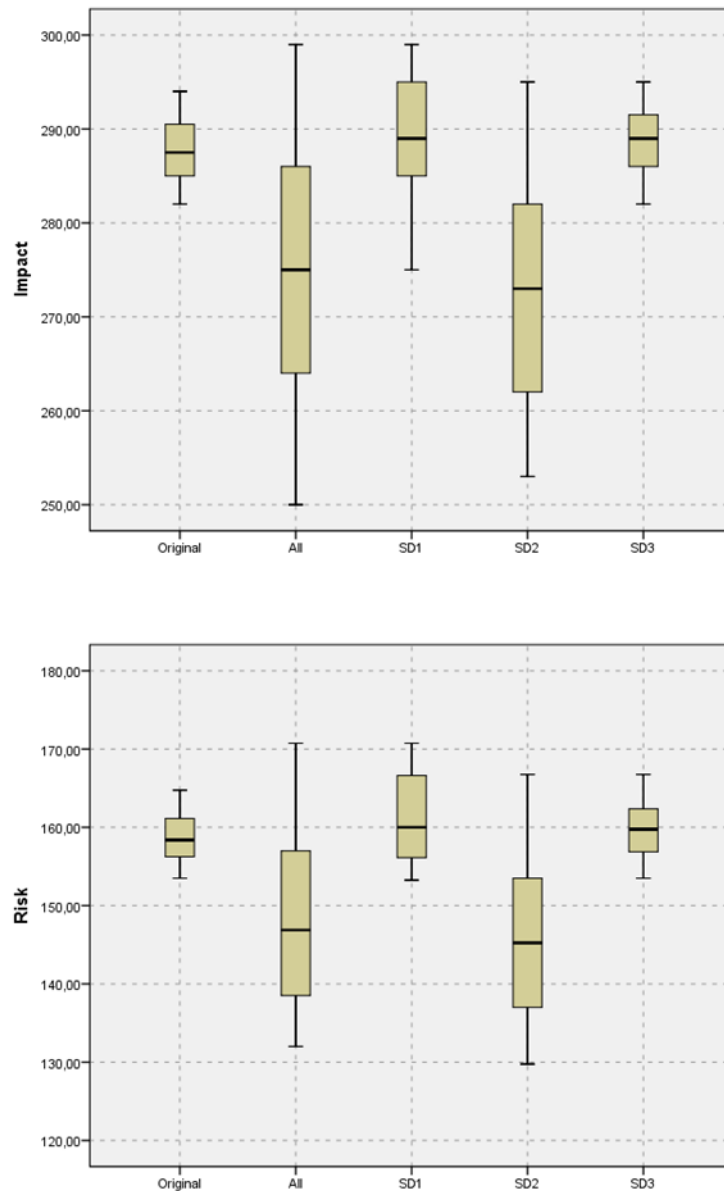


Figure 10. Box-and-whisker plot of the final efficient points under different scenarios

Figure 10 also shows the other three possible scenarios, in which it is assumed that only one of the DMs (DM1, DM2, or DM3) does not make changes to his/her initial value for f_1 or f_2 or f_3 , respectively, during the entire process. The 3 potential scenarios are denominated SD1, SD2, and SD3, respectively. In SD1, a final set of 31 solutions is obtained with the first two objective functions distributed as shown in Figure 10. In this case, the new set of solutions includes 18 matches with those obtained at the end of the original process, and the rest generally have higher values in the first objective function due to the high

value set by DM1 for f_i . In the case of SD2, the final set obtained contains 62 solutions, of which 10 match the original final set, whereas the remainder mainly consist of solutions with a lower value for the second objective function, due to the fact that DM2 preferred to set a low value for this objective. Finally, if DM3 does not change his/her initial preference for the third objective function (SD3), then a final set consisting of 19 solutions is obtained, 17 of which are the same as those obtained in the original set. Thus, the distribution of these solutions has very similar core and dispersion values to those found in the original set (see Figure 10).

The distances obtained between the reference points in the last iteration for each of the last three scenarios are 0.25, 0.43, and 0.4, respectively. These results, when added to information previously described, show that DM2 is the DM who makes more concessions during the original process. If DM2 had been less willing to reach a consensus, he/she would have caused a major change in the set of solutions finally obtained. However, even in this case, the solution set includes solutions obtained in the original set, while providing a wider view of the approximate efficient frontier. In particular, Sol.4 (original final set), which improved all the objectives of the solution finally adopted by the university, appeared in all the final sets obtained in the different scenarios.

Given the foregoing, it follows that the zone of the efficient frontier finally obtained will vary according to the positions of the DMs in such a way that the further the DMs' preferences are from each other the greater the zone of the efficient frontier will be, without entailing a dramatic change in the results.

Thus, the PPST tool helps DMs to identify the efficient frontier area on which they should focus their attention, since it contains the solutions preferred by each DM and the other intermediate solutions. Political and legal issues or other aspects (resources committed to subsequent periods, the number of projects that compose them, etc) can be addressed to reach a final decision. If this procedure is insufficient to reach consensus, the DMs could use any voting rule or more elaborated procedures, such as those proposed by González-Pachón and Romero (2011).

4. Conclusions

This article analyzed the theory and practice of selecting and scheduling a project portfolio from a group of candidate projects with a fixed planning horizon.

From the theoretical point of view, we described the three components involved in the process: the mathematical model, the solution technique, and the software. The mathematical model is a nonlinear multiobjective binary programming model that facilitates the selection of efficient portfolios according to the set of objectives pursued by the organization, as well as their scheduling regarding the optimum time to launch each project within the portfolio. The solution technique makes use of a metaheuristic approach rather than an exact method because of the complexity of the model formulated. We also described an interactive procedure based on g -dominance that is used to assist one or several DMs in the task of selecting a project portfolio from the efficient frontier. To make it easy for the DMs to find the solution, the multiobjective binary model and the interactive procedure were embedded into new software, called PPST, which uses the SS-PPS heuristic procedure as a search engine.

In practical terms, we tested an empirical application of the process of project portfolio selection and scheduling in a Spanish university. The software described in the first part of the paper provided a better solution in less time than the solution originally reached by the DSPI. In addition, it allows the DMs to add their preferences during the decision-making process.

The main contribution of this study is that it presents a decision-making model that is integrated with computer-based support. The model provides DMs with quantitative support when they have to make satisfactory decisions on project portfolio selection within a short period. The tool is based on a multi-

objective binary model and has the flexibility to cover a wide range of practical situations in both public and private settings.

Finally, we point out some aspects worth exploring in the future. Firstly, it would be interesting to use the tool in other real problems, in order to obtain more feedback from the DMs. Secondly, we would like to generalize the model used. At this point, the model could be enriched: modelling of synergies between projects so as to take into account the execution time in which each project is, or exploring whether the transformation of expression (11) in a linear constraint could make the whole model easier to solve.

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