Management and Industrial Engineering

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New Perspectives on Applied Industrial Tools and Techniques

Springer

Chapter 13
Interdependent Projects Selection with Preference Incorporation

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Abstract The Project Portfolio Problem (PPP) has been solved through different approaches. The success of some of them is related to a proper application of the decision-maker's preferences, and a correct identification of organization's resource practices and conditions. However, there are still a small number of classes of PPP that have been solved using these approaches, and there is also a need for increasing them. Due to this situation, the present research develops a strategy, based on ant colony optimization that incorporates the decision-maker's preferences into the solution of a case of PPP under conditions of synergy, cannibalization, redundancy, and with interactions between projects. The algorithm was experimentally tested, and the results show a good performance of it over a random set of instances.

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J.L. García-Alcaraz et al. (eds.), *New Perspectives on Applied Industrial Tools and Techniques*, Management and Industrial Engineering,
DOI 10.1007/978-3-319-56871-3_13

Keywords Ant colony optimization algorithm · Multi-objective project portfolio selection · Outranking model

13.1 Introduction

Any enterprise is interested on the proper investment of its budget and/or resources. This activity includes the selection of the projects that must be financed to ensure an adequate growth of the organization. People involved in this type of decision process are commonly referred as a Decision-Maker (DM), and their preferences play a central role in the evolution of an organization. The actions taken in an organization impact its employees, and when it comes to public organizations the impact is in the society; in any situation the decision must search the improvement of the status-quo of the influenced individuals.

A set of attributes can characterize the *quality of public projects*. These attributes measure the benefits or the level of discomfort produced by the projects on society. For example, one attribute could count the amount of people in the low class society that are favored by the project, and another one could count the number of persons in the medium class society that are affected by it. This situation leads to a multidimensional valuation of the *quality of a portfolio* that integrates the impact of each project. Hence, the best portfolio arises from the evaluation of groups of projects, and not only from the evaluation of single ones. Some other aspects that are relevant to determine the funding of a portfolio also involve factors as the beliefs, experience, or personal ethics of the DM in charge, and the organizational policies.

Commonly, the Project Portfolio Problem (PPP) includes projects that exceed the capacities of private organizations, e.g., they involve larger budgets, they impact over a greater group of individuals, or they consider a greater number of attributes. Also, these projects contemplate synergetic relations, i.e., there are interrelations among projects that cause a variation in their benefits from one group to another. Let us observe that synergy may not be present in PPP if the interrelations are weak, or the impact is uniform among projects, but these cases are rare in real problems.

The PPP has been modeled as a multi-criterion optimization problem (Carazo et al. 2010; Gutjahr et al. 2010; Covantes et al. 2013; Cruz et al. 2014; Mild et al. 2015; Fernandez et al. 2011, 2014, 2015; Khalili-Damghani et al. 2013; Stummer y Heidenberger 2003). Due to the complexity of PPP, it is necessary to solve it through approximate strategies. The traditional algorithms used to solve multi-criteria problems find solutions considered Pareto efficient, i.e., non-dominated solutions that belong to the Pareto front. These approaches are acceptable because they reduce the search space considerably and require small amounts of time; however, they do not provide a unique solution.

The task of choosing one solution can become a challenge for a DM if the provided group does not incorporate its preferences (a common situation in traditional algorithms); this task generally requires a great cognitive effort from the DM

(Fernández González et al. 2011). With the purpose of aiding the DM to choose the best compromise, it is necessary to restrict the final set of solutions provided by an approximated strategy to those that agree with its preferences. Let us note that the best compromise is defined as the solution in the Pareto front provided by a multi-criterion algorithm that is constructed based on the DM's preferences.

According to the revised literature, there are only a few works that incorporate preferences in the formation of public portfolios [e.g., the proposal in (Fernandez et al. 2011)], and just a fraction of them also involve effects of synergy. This chapter presents an Ant Colony Optimization (ACO) algorithm as solution of PPP with synergetic relations, which also considers DM's preferences.

This chapter is organized as follows. Section 13.2 formalizes the theoretical basis of the problem addressed. Section 13.3 shows the proposed solution. Section 13.4 presents the experimental results that demonstrate the performance of our approach. Finally, Sect. 13.5 presents the conclusions, as well as the possible areas of opportunity that would improve our contribution in the future.

13.2 Theoretical Framework

With the purpose of being able to explain the contribution of our work, this section has been dedicated to describe the main theoretical elements related.

13.2.1 The Project Portfolio Problem

There are differences among project selection in private or public organizations. Within a private enterprise, e.g., profit-making or research and development (R&D) organizations, there are a wide variety of resources that are considered in a Project Portfolio Problem, e.g., personnel, money, equipment, costs, etc. These organizations adjust their financial constraints such that all those resources are contemplated, and they generally rely on indicators of their usability (man-hours available, equipment already acquired, among others). In a public institution, the situation is quite different because all the projects compete for the allocation of one single resource, the budget that they need; in this case each project asks to be granted a fraction from a fixed existing budget for its realization, and it assumes that it requests only the necessary resource for its realization.

The PPP deals with a wide variety of attributes, such as social security, transportation, education, telecommunications, home services, healthiness, recreation, job creation, field support and research, etc. Some of them can even be divided into more attributes, e.g., home services into drinking water, electricity, garbage collection, drainage, and household gas services. While public organizations involve a subset of those criteria in the measurement of the impact of a portfolio, the private institutions take into account the economic benefit, although they might consider other criteria (such as public image, company growth, among others). In all the cases, the main purpose for short or long terms is the financial prosperity of the company.

An instance of the PPP normally involves thousands of projects that compete for funding. For example, in 2012 the Georgia Department of Transportation had a budget of over 538 million dollars, and it received more than 1600 project proposals that were expecting to be funded; those projects were classified in twelve regions used to balance the distribution of the funds (Georgia Department of Transportation 2010, 2012a, b, c).

In general, the PPP pursues the maximization of profits, and the proper distribution of resources among social groups and areas competent to public policy. These conditions of balance allow the healthy development of each group.

The great impact in the economy of an organization that is derived from a proper formation of social portfolios can be seen even from small changes in quality. For example, the United States spent $2.5 trillion in 2011 for health centers only (U.S. Government Printing Office 2012), a change of 0.01% on the way in which that amount was invested would mean a redistribution of 250 million dollars.

The solution of PPP through cost–benefit methods (Boardman et al. 2006) needs the establishment of a monetary equivalence between objectives; this activity can result in serious moral and ethical objections because of the assignment of economic value to aspects such as health, safety, and even life itself. Other approaches that solve PPP are the strategies that produce a linear combination of objectives; these ones have the disadvantages that they require a quantification of the importance of each objective (which is difficult in most practical situations), and they also possess an inability to generate efficient sets of solutions in non-convex search spaces (Coello 1999). A proper alternative for the solution of PPP, according to works in (Carazo et al. 2010; Doerner et al. 2004, 2006; Fernandez et al. 2010, 2011; Rivera et al. 2012a, b), is the construction of sets of portfolios through population algorithms; these strategies approximate in reasonable time what is called the Pareto front, and simultaneously optimize all the objectives.

Nevertheless, the use of population algorithms is not good enough to yield solutions for PPP. The solutions of these algorithms entail serious difficulties in the decision process (Marakas 2002); the main concern is that they let the DM to face the task of deciding which of the provided group of solutions should choose, something that might require a considerable cognitive effort considering that some solutions might involve its preferences, and others not. To overcome this problem, Fernandez et al. (2011) propose an a priori articulation of preferences linked to a genetic algorithm Non-Outranked-Sorting Genetic Algorithm (NOSGA), through which it is possible to identify sets of efficient solutions that incorporate DM's preferences.

This chapter presents an ant colony optimization algorithm called Ant Colony Outranking System (ACOS). The algorithm uses NOSGA principles for incorporation of preferences in the solution of PPP under synergistic conditions.

13.2.1.1 PPP Approach

Let X be a set of N projects that compete for resources, and let x be a portfolio formed by a subset of them. The portfolio is typically modeled as a binary vector $x = \langle x_1, x_2, \ldots, x_N \rangle$, where each variable x_i indicates the presence of a project i in a portfolio that will be financed.

The total budget is denoted as $\mathbb{B}$, and each project i has an associated cost that is identified as c_i. It is clear that any feasible portfolio must satisfy the budget constraint:

$$\left(\sum_{i=1}^{N} x_i \cdot c_i \right) \leq \mathbb{B}. \tag{13.1}$$

To guarantee the balance conditions each project i has associated a group, denoted as a_i. Each group has previously established budgetary limits, either by the DM or some other competent entity. Let L_j and U_j be the lower and upper bounds for a group j. Based on this it is established that, for each group j, a feasible portfolio must be subject to the restriction:

$$L_j \leq \sum_{i=1}^{N} x_i \cdot g_i(j) \cdot c_i \leq U_j, \tag{13.2}$$

where g can be defined as

$$g_i(j) = \begin{cases} 0 & \text{if } a_i = j, \\ 1 & \text{otherwise }. \end{cases} \tag{13.3}$$

Equation 13.2 has two main functions: (1) to prevent the monopolization of the budget by a particular group, and (2) to promote the growth of society in all competent aspects for the organization. Adequate values for budget limits will depend on the characteristics of the problem itself. In addition, the DM may consider more than one criterion for grouping projects, for example, it could make two types of divisions: geographical (grouping them according to the place that benefits from their realization) and by social class (grouping them depending on social class which they intend to favor).

The quality of a project i is modeled as a p-dimensional vector dimensional $f(i) = \langle f_1(i), f_2(i), f_3(i), \ldots, f_p(i) \rangle$, where $f_j(i)$ indicates the benefit of the project i to the objective j in a problem with p objectives. The quality of a portfolio x would be the union of benefits of the projects that compose it, and therefore a vector of dimension p expressed as

$$z(x) = \langle z_1(x), z_2(x), z_3(x), \ldots, z_p(x) \rangle, \tag{13.4}$$

where $z_j(x)$ in its simplest version is defined as

$$z_j(x) = \sum_{i=1}^{N} x_i \cdot f_j(i). \tag{13.5}$$

Let RF be the region of feasible portfolios, and then the PPP objective can be to identify one or more portfolios that solves

$$\max_{x \in RF}\{z(x)\}. \tag{13.6}$$

Subject to the constraints expressed in Eqs. 13.1 and 13.2. In this case the concept of maximization has been commonly associated with Pareto efficiency. The solution space is of exponential order of 2^N, and if additional considerations are taken into account, such as synergy, risk management, partial financing, and project scheduling, the difficulty of the problem and the search space are often increased.

13.2.1.2 Interactions Between Projects

When the DM identifies relevant synergistic effects, it is not easy to find an appropriate way to model and manage synergy, and estimating the impact of such interactions is not a trivial task, especially if the DM considers interactions among more than three projects. The impact produced by the interaction of a group may fall into one of the following categories:

1. *Synergy over objective values*: If two projects i and j have this interaction, the benefits associated by jointly supporting i and j do not fall into the sum of $f(i) + f(j)$. If it is smaller, it receives the name of *cannibalization*, if it is greater, it is simply known as synergy, being the conception more widely associated with this term. The same concept can be scaled for sets of more than two projects.
2. *Redundancy*: If two projects i and j are redundant (or excluding) they cannot be financed simultaneously. This principle also applies to sets with more than two projects.
3. *Synergy over cost*: If projects i and j have this interaction, the associated cost of financing them simultaneously is different from the sum $c_i + c_j$. This type of synergy also applies to sets with higher cardinality.

While redundancy is associated with feasibility conditions, synergy over cost must be considered in budgetary constraints. On the other hand, synergy over objective values should be considered in the quality function of the portfolio. Some approaches to address it have been through the inclusion of artificial projects (Liesiö et al. 2007); however, there is evidence that it is more useful to incorporate it in the evaluation of the objective function (Rivera et al. 2012a, b).

In the case of public projects, redundancy and synergy in objectives are the most characteristic interactions of the problem, unlike the synergy in costs, which is generally not considered in the allocation of public budget. This implies the sharing of resources, such as equipment or personnel, considerations that acquire greater relevance within private organizations or R&D projects.

13.2.2 Identification of Preferences in Multi-criteria Optimization

Because the Pareto front could hardly be determined in real applications, most algorithms are restricted to finding a predetermined number of efficient solutions. In order to find a representative sample of the Pareto frontier, some algorithms include distance measures that favor the dispersion between the solutions (Deb 2001; Knowles and Corne 2000), however, do not ensure that the best compromise is found, and if so, the solution set exceeds the ability of an average DM to perform the decision process satisfactorily.

Simplifying the decision process involves reducing the set solution to those alternatives that coincide the preferences of the DM, either (1) considering preferences through post-processing, or (2) directing the search to Pareto regions that maximize the preferences of the DM, or (3) through an interactive process that allows redirecting the search if required.

The algorithm proposed in this paper, ACOS, considers DM preferences through the use of an a priori joint suggested by Fernandez et al. (2011), which was originally used in a genetic algorithm called NOSGA, and is now applied within an ant colony. The proposal of Fernandez et al. (2011) uses the relational preference system presented in Roy (1996).

The index of credibility, denoted by $\sigma(x, y)$, measures the degree in which the statement "x is at least as good as y" is true. This index is used to set the correct preference relation between pairs of alternatives x and y. The most common methods used to compute it are the methods ELECTRE (Doumpos et al. 2009) and PROMETHEE (Brans and Mareschal 2005).

For each pair of alternatives x and y, any of the following relations of preference, from the DM point of view, is established:

1. *Indifference* or xIy. This is an equivalence relation among the alternatives in the sense that there is no preference for one of them.
2. *Strict preference* or xPy. This is an asymmetric relation in which there is a clear preference toward the alternative x.
3. *Weak preference* or xQy. This is an asymmetric relation that models doubt among the relations xPy and xIy.
4. *Incomparability* or xRy. This relation indicates that a preference cannot be established due to the heterogeneity existing among the alternatives.
5. *k-Preference* or xKy. This is a representation of uncertainty among xPy and xRy.

The previous set of preference relations forms the base of a preferential system. The situations reflected in such system are of three main types: (a) those in which the DM is unsure of the preference that he/she wants to establish, e.g., the indifference and incomparability relations; (b) those where the DM is confident of the preference, e.g., the strict preference; and (c) those that resembles non-ideal behavior of a DM, e.g., weak preference and *k*-preference.

The model of Fernandez et al. (2011) is based on a set of parameters that must be elicited appropriately according to the DM's preferences. Different strategies can be used to adjust such parameters [cf. (Jacquet-Lagreze and Siskos 2001)]; some of them requiring a direct interaction with the DM, and some others not.

Given a set of alternatives O and a preferential system $A = \{P, Q, I, R, K\}$, the following sets can be defined:

1. $S(O, x) = \{y \in O \mid yPx\}$ is the set composed by alternatives y that are strictly preferred over x.
2. $NS(O) = \{x \in O \mid S(O, x) = \varnothing\}$ is the set of alternatives x which has no relation yPx for any other y in O. This set is commonly referred as the *non-strictly-outranked frontier*.
3. $W(O, x) = \{y \in O \mid yQx \vee yKx\}$ is the set composed by alternatives y that are weakly preferred or k-preferred over x.
4. $NW(O) = \{x \in O \mid W(O, x) = \varnothing\}$ is the set of alternatives x which has no relations yQx or yKx for any other y in O. This set is commonly referred as the *non-weakly-outranked frontier*.

If an alternative x is considered the best compromise between a set O of alternatives, it should be at the intersection of $NS(O)$ and $NW(O)$, but if there is more than one solution with this characteristic, the net flow score can be used to determine the best compromise. Consider the *net flow* score as a preferential measure of an alternative x such as

$$F_n(x) = \sum_{y \in O \setminus \{x\}} [\sigma(x, y) - \sigma(y, x)]. \tag{13.7}$$

Seeing that $F_n(x) > F_n(y)$ denotes some preference of x over y. Based on this idea, Fernandez et al. (2014) establish that

1. $F(O, x) = \{y \in O \mid F_n(y) > F_n(x)\}$ is the set formed by alternatives y that has a greater net flow score than x.
2. $NF(O) = \{x \in O \mid F(O, x) = \varnothing\}$ is the set of alternatives x which has no alternative y in O with a better net flow score. This set is commonly referred as the *net flow non-outranked frontier*.

Thus, the identification of the best compromise can be expressed by Eq. 13.8:

$$x^* = \text{argmin}_{x \in O}\{|S(O,x)|, |W(O,x)|, |F(O,x)|\}. \tag{13.8}$$

Equation 13.8 expresses the search for solutions that lexicographically minimize the sets *S, W,* and *F*.

13.2.3 Formation of Portfolios Using the Ranking Method

In portfolio formation, a wide range of approaches have been proposed, the benefits of which depend on the particular conditions of the application problem, for example, the available information about the projects, the organization's practices for allocating resources, and the characteristics of DM.

The proposed approach in this work supposes conditions in which the impact to realize the projects can be characterized by a set of attributes, and this information is available for the DM. In addition, if the DM is a group of people, must be homogeneous enough to achieve a consistent representation of their preferences, and also be willing to invest the time needed to achieve it.

An unbiased DM will select projects based on (1) the benefits provided by the project, (2) the amount of budget required, and (3) the risk that the project cannot be completed when it has already received financial support. Risk can be modeled as an objective to be minimized (Rădulescu and Rădulescu 2001), while the expected benefits are the criteria to be maximized.

If $v(i)$ is a value function for project i, which integrates into a scalar the benefits associated with project i, and c_i is the requested amount, a rational DM will form its portfolio by selecting projects whose relation $v(i)/c_i$ is the maximum among the candidate projects; the selection will end when there is no project that can be incorporated into the portfolio. In the case of synergistic sets, the same ratio can be calculated for such sets.

Hereafter we will name this procedure as the method of *ranking*. It can be automated by calculating $v(i)$ by a weighted sum, whose weights reflect the importance of each benefit according to DM preferences. This may present serious objections; however, it is the most practiced way for DMs in portfolio selection. It also has the advantage of being a fast method which, if the weights are well adjusted, finds a solution with which the DM will have an acceptable degree of satisfaction.

The work here presented makes use of an ant colony optimization algorithm to form project portfolios, which incorporates DM preferences using the model proposed in Fernandez et al. (2011) and includes the ability to handle interactions between projects.

13.3 Proposed Solution

Our algorithm, ACOS, is based on the optimization idea proposed by Dorigo and Gambardella (1997) which has been adapted in more than one occasion to search for a set of Pareto solutions (Chaharsooghi and Kermani 2008; Duan and Yong 2016; del Sagrado et al. 2015; Mousa and El_Desoky 2013; Zhang et al. 2014), but incorporates a preferential model (Fernandez et al. 2011) that offers a better compromise for DM.

The algorithm performs its optimization process through a set of agents called *ants*. Each ant in the colony builds a portfolio by selecting one project at a time. It is known as the *selection rule* for the way in which each project is chosen.

Once all the ants have finished building their portfolio, these are evaluated and each ant drops pheromone according to this evaluation. The *pheromone* is a form of learning that will promote, in ants of the next generation, to find better solutions. To avoid premature convergence, the colony includes a strategic oblivion mechanism, known as *evaporation*, which consists in reducing the traces of pheromone every given period of time. The search terminates when a predetermined termination criterion is reached, such as a maximum number of iterations, or the subsequent repetition of the best solution. In the following sections the ACOS elements are described in more detail.

13.3.1 Representation of the Pheromone

The pheromone is usually represented with the Greek letter τ and is modeled as a two-dimensional matrix of size $N \times N$, where N is the total of project proposals. The pheromone between two projects i and j is represented as $\tau_{i,j}$, and indicates how helpful it is for both projects to receive economic support. The pheromone values are in the range (0, 1], initializing at the upper limit to avoid premature convergence. The pheromone matrix functions as a reinforced learning structure, reflecting the knowledge acquired by the ants that formed wallets of high quality, and is transmitted to ants of future generations in order to build better solutions.

13.3.2 Selection Rule

Each ant builds its portfolio by selecting the projects one by one, taking into account two factors:

1. *Local knowledge*: This considers the benefits provided by the project to the portfolio and how many resources the project consumes. Local knowledge for the *i*-th project is denoted by η_i and is calculated by the following expression:

$$\eta_i = \frac{\frac{1}{c_i}\sum_{j=0}^{p} f_j(i)}{\max_{k \in X}\left\{\frac{1}{c_k}\sum_{j=0}^{p} f_j(k)\right\}}, \tag{13.9}$$

where c_i is the cost of the project i, p is the number of objectives, and $f_j(i)$ are the benefits of the project i to the j-th objective. Equation 13.9 favors the inclusion of projects that have a good relation between objectives and requested amount.

2. *Global knowledge (learning)*: This takes into account the experience of previous generations of ants, expressed in the pheromone matrix. The global knowledge for project i to be included in a portfolio x is denoted by $\overline{\tau(x,i)}$ and is defined by the following expression:

$$\overline{\tau(x,i)} = \frac{\sum_{j=1}^{N}(x_j)\tau_{i,j}}{\sum_{j=1}^{N} x_j}, \tag{13.10}$$

where N is the total number of applicant projects, x_j is the binary value indicating whether the j-th project is included in the portfolio x, and $\tau_{i,j}$ is the pheromone for projects i and j. The numerator in Eq. 13.10 is the total sum of pheromone between i and each project in portfolio x; the denominator is the cardinality of x. The global knowledge favors the selection of projects that were part of the best portfolios in previous generations. At the first iteration this knowledge has no effect on portfolio formation process.

Both types of knowledge are linearly combined into a single evaluation function, which corresponds to the following equation:

$$\Omega(x,i) = w \cdot \eta + (1-w) \cdot \overline{\tau(x,i)}, \tag{13.11}$$

where w is a weight parameter between both knowledge with values between zero and one, and each ant of the colony has a different value for w. The Ω function forms the basis of the selection rule.

If x is a partially constructed portfolio, at least one more project can be included. Of all project proposals, only those that are not part of it and whose inclusion maintains budgetary constraints should be considered; this set is known as a *list of candidates* and is denoted as $X^{\ominus}$. Note that $X^{\ominus}$ is a subset of X. The choice of which $j \in X^{\ominus}$ will be added can be made using the selection rule:

$$j = \begin{cases} \text{argmax}_{i \in X^{\ominus}}\{\Omega(x,i)\} & \text{if } \wp \le \alpha_1, \\ \mathcal{L}_{i \in X^{\ominus}}\{\Omega(x,i)\} & \text{if } \alpha_1 < \wp \le \alpha_2, \\ \ell_{i \in X^{\ominus}} & \text{otherwise,} \end{cases} \tag{13.12}$$

where j is the next project to be included, $\wp$ is a pseudorandom number between zero and one, and α_1 is a parameter that indicates the probability of intensification in the algorithm, choosing the project with highest value of Ω; While $\alpha_2 - \alpha_1$ is the probability of activating a mean state between intensification and diversification, where a project i is randomly selected with a probability proportional to its evaluation Ω, this selection mechanism is represented as $\mathcal{L}$, in the case that $\wp > \alpha_2$ is randomly selected equiprobable some project through the function ℓ, promoting diversification.

13.3.3 Pheromone Laying and Evaporation

In a colony with n ants we will have a total of n new solutions at the end of each iteration, and also a set of size m with the best portfolios found in previous generations. If all the alternatives are integrated into a single set O of cardinality $n + m$, it is possible to create a partial order in O applying the preferential model of Fernandez et al. (2011) (see Sect. 13.2.2).

The c solutions that were not strictly exceeded neither weakly nor in net flow (*NS, NW* and *NF*) lay the greatest amount of pheromone; While solutions that belong only to one or two of the exceedance frontiers receive a less intense reinforcement. Each solution $c \in O$ will intensify the pheromone trace for each pair of projects i and j that conform it, according to the following expression:

$$\tau_{i,j} = \begin{cases} \tau_{i,j} + \Delta\tau_{i,j} & \text{if } c \in NS, \\ \tau_{i,j} & \text{otherwise}, \end{cases} \tag{13.13}$$

where

$$\Delta\tau_{i,j} = \begin{cases} 1 - \tau_{i,j} & \text{if } c \in NW(O) \cap NF(O), \\ 0.50(1 - \tau_{i,j}) & \text{if } c \in NW(O) \wedge c \notin NF(O), \\ 0.25(1 - \tau_{i,j}) & \text{otherwise}. \end{cases} \tag{13.14}$$

If there are cycles in the strict preference relationship, it will not be possible to identify solutions that belong to *NS*(*O*), which may result from an inappropriate adjustment of the model parameters, in this case a closer interaction with the DM to achieve a consistent representation of their preferences. Another reason may be a high heterogeneity in DM preferences when it is made up of more than one person. If there is no solution not strictly exceeded, the algorithm stores all non-dominated solutions and increases the pheromone to its upper limit for each of them.

At the end of each iteration the entire pheromone matrix evaporates by multiplying by a constant factor between zero and one, denoted as ρ.

13.3.4 Algorithmic Description

Algorithm 13.1 presents the algorithmic outline for ACOS. Line 1 shows the initialization of the control variables, and in the Lines 2–23 the search process is represented. Lines 4–12 of Algorithm 1 illustrate the process of portfolio formation. Each ant is part of an empty portfolio, and they are adding the projects, one at a time, through the selection rule. The set of solutions formed are stored in the set *O*. Later the pheromone traces are evaporated (Line 13). The reinforcement of the pheromone is performed in Lines 15–16. The level of pheromone enhancement is a function of the membership of each solution to the sets *NS*(*O*), *NW*(*O*), and *NF*(*O*). In Line 17, the best commitments are identified and compared to the best known ones. The algorithm ends when the same group of solutions has been maintained as the best compromise during rep_{max} iterations, or if the maximum number of $iter_{max}$ iterations was reached.

Algorithm 13.1
Algorithm ACOS

```
     Input: X (list of projects), (total budget)
1    Initialization: iter←1, best←∅, rep←0
2    Repeat
3      O←∅
4      for each ant in the colony do
5        x ← CreateEmptyPortfolio()
6        X⊖← GetCandidateProjects(X, x)                  // Section 13.3.2
7        Repeat
8          j←SelectionRule(X⊖, x)                         // Equation 13.12
9          xj←1
10         X⊖← GetCandidateProjects(X, x)                // Section 13.3.2
11       until X⊖ = ∅
12       O←O ∪ x
13     Evaporate pheromone trail                          // Section 13.3.3
13     O ← O ∪ best
15     for each x∈O do
16       LayPheromone(x,O)                                // Section 13.3.3
17     best* ← arg min_{x∈O} {|S(O,x)|, |W(O,x)|, |F(O,x)|}   // Equation 13.8
18     if best = best* then
19       rep←rep+1
20     Else
21       rep←0
22     update: iter←iter+1, best←best*
23   until rep=rep_max ∨ iter=iter_max
24   return best
```

13.4 Case of Study: Project Portfolio Optimization

Let us consider a DM that faces a portfolio problem which involves 100 projects that try to benefit the most precarious social classes. The quality of the projects is measured through the number of persons beneficiated on each of the nine objectives established previously. Each objective is associated to one of three social classes (extreme poverty, low class, and medium low class) and a level of impact (low, medium, and high). The budget is of 250 billion of pesos.

The projects can be classified into three different types according to their nature, and into two different geographic regions according to their zone where they impact. In addition, with the purpose of keeping equality condition, the DM poses the following constraints: (1) the budget assigned to favor each type of project can vary between 20% and the 60% of it; and (2) the budget assigned to each region must be of at least 30% of the total, and of 70% as maximum. In the same way, the DM has identified 20 interactions that are relevant among projects; four correspond to cannibalism phenomena, six to situations of projects that are exclusive among them, and the last ten are synergy interactions. The minimum number of projects per interaction is of two, while the maximum is of five.

The strategy required the search of the parameter values to the preference model that reflects a plausible situation of decision. The chosen values were the ones suggested by Fernandez et al. (2011) with the purpose of achieving a consistent preferential system.

The algorithm was programmed in Java language using the JDK 1.6 compiler and the Netbeans development framework; and it was run in a Mac Pro computer with a 2.8 GHz Intel Quad-Core processor, with 3 GB of RAM memory, and a SATA hard disk of 1 TB and of 7200 rpm.

Two stop criteria were used by the algorithm: (1) due to convergence, when the same group of solution remains as the best compromise during five consecutive generations; and (2) due to divergence, which occurs when the maximum number of iteration (which is 1000) is achieved.

Table 13.1 presents a set of ten portfolios, the first nine of them are identified by ACOS as the non-strictly outranked front, and one is obtained through the *ranking* method. To identify the best compromise, each solution was evaluated using Eq. 13.8. According to this, the Solution 1, i.e., the first portfolio, satisfies all the necessary conditions to be the best compromise. The remaining portfolios obtained through ACOS are identified by numbers, from two to nine, numbered in decreasing ordered of their level of preference.

Based on the previous results, it can be concluded that the proposed algorithm, ACOS, does not only identify solutions with a better concordance with the DM preferences, but also achieve a better approximation of the Pareto frontier than the widely used method in the solution of the problem, the *ranking*.

Table 13.1 Comparison among the solution set produced by ACOS and the ranking method

	Portfolio	Objectives' values									# of solutions that outrank it		
		1	2	3	4	5	6	7	8	9	Strict	Weak	Net flow
Obtained by ACOS	1	146	110	168	109	183	136	223	171	178	0	0	0
	2	148	113	168	106	184	137	217	162	176	0	0	2
	3	143	108	161	113	191	125	224	164	186	0	1	3
	4	147	112	167	108	184	130	221	155	184	0	1	4
	5	143	106	160	114	189	129	225	165	184	0	2	1
	6	141	111	165	113	183	131	227	164	179	0	2	5
	7	141	110	168	114	177	134	215	154	179	0	3	3
	8	143	109	163	111	189	128	228	163	182	0	5	6
	9	142	112	165	111	181	136	223	154	182	0	5	7
Ranking		146	107	163	108	182	131	220	165	177	9	0	9

Table 13.2 Results from ACOS over instances with 100 projects and nine objectives

Instance	# of runs in which the Solution of ranking was:		# of runs where it achieved the best compromise[a]
	Dominated	Strictly outranked	
1	28	30	28
2	22	30	27
3	20	30	26
4	27	30	27
5	24	30	24
6	19	30	25
7	28	30	28
8	27	30	27
9	18	30	29
10	30	30	28

[a]With respect to the best compromise obtained in the 30 runs

In order to prove the robustness of the proposed metaheuristic, ten synthetic instances were generated with the mentioned characteristics in this section: 100 projects evaluated in nine objectives, the presence of 20 synergetic groups, and a total budget to spare of 250 billion of pesos. In addition, they were imposed balancing constraints for the three types of projects and the two geographic zones.

Table 13.2 concentrates the results obtained after the 30 runs of the algorithm over each test instance. For every analyzed case, the solutions obtained by ACOS were strictly preferred over the solutions formed by the *ranking* of the projects. Also, it was observed a good algorithmic behavior in terms of robustness.

13.4.1 Efficiency Analysis of the Algorithm

With the purpose of estimating the efficiency of our algorithm, instances with 25 projects and four objectives were generated, also having a total budget of 80 billion of pesos, and the participation of five interactions that are relevant to the projects. For this set of instances, the Pareto frontier was generated through an exhaustive search, and it was identified that there is only one solution that satisfies all the conditions to be the best compromise.

According to Table 13.3, the non-strictly outranked frontier obtained through our algorithm was a subset of the Pareto frontier in 93% of the runs, but the most notable fact is that the best compromise solution found by ACOS was always Pareto efficient.

Table 13.3 Results from ACOS over instances with 25 projects and four objectives

Instance	# of runs in which:	
	All the solutions from the non-strictly-outranked front was Pareto optimal	The best compromise was Pareto efficient
1	30	30
2	30	30
3	30	30
4	23	30
5	23	30
6	25	30
7	30	30
8	30	30
9	28	30
10	30	30

13.5 Conclusions and Future Work

This chapter was elaborated with the purpose of presenting an original algorithm to give solution to the formation of portfolio of public projects. This algorithm is an adaptation of the well-known ant colony optimization metaheuristics, and was named ACOS. Unlike other approaches to portfolio creation, ACOS is characterized by specifically targeting project selection in the context of allocating a public budget. Our algorithm seeks the creation of optimal portfolios under synergistic conditions and can handle synergistic, cannibalistic, and redundant interactions. ACOS can work with interactions between more than two projects; in the test cases, we used up to five projects per interaction.

In comparison with the most popular method of selecting projects (*ranking*), ACOS has the advantage of presenting to the DM not only a solution, but also a set of non-dominated portfolios ordered according to a previously identified preferential pattern. In addition, in all test cases used, ACOS finds solutions that exceed either the Pareto dominance or preference terms, to the *ranking* solution.

As future work we plan to incorporate ACOS the possibility of partially supporting the projects. This consideration is relevant in the allocation of the public budget, because it is a frequent phenomenon in this type of problems. In addition, it is contemplated to add to the algorithm the ability to schedule projects within a given planning horizon.

Acknowledgements This work has been partially supported by PRODEP and the following projects: (a) CONACYT Project 236154; (b) Project 3058 from the program Catedras CONACYT; and, (c) Project 269890 from CONACYT networks.

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