# Modeling and Project Portfolio Selection Problem Enriched with Dynamic Allocation of Resources

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**Abstract** The problems of the real world, within which the variable *time* is present, have involved continuous changes. These problems usually change over time in their objectives, constraints or parameters. Therefore, it is necessary to carry out a readjustment when calculating their solution. This paper proposes an original way of approaching the project portfolio selection problem enriched with dynamic allocation of resources. A new mathematical model is proposed formulating this multi-objective optimization problem, as well as its exact and approximate solution, the latter based on four of the algorithms that in our opinion stand out in the state of the art: Archive-Based hybrid Scatter Search, MultiObjective Cellular, Nondominated Sorting Genetic Algorithm II and Strength Pareto Evolutionary

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Algorithm 2. We experimentally demonstrate the benefits of our proposal and leave open the possibility that its study will apply to large-scale problems.

**Keywords** Dynamic allocation of resources · Dynamic portfolio Enriched problem · JMetal · ABYSS · MOCell · NSGA-II · SPEA 2

## 1 Introduction

In general, there is a growing need arising from a variety of factors—such as budget adjustments—that demand better output from the resources that are available, which in most cases are increasingly scarce, to generate a greater advantage competitively [1].

Dynamic allocation of resources is key to project portfolio management; this problem consists of monitoring and periodic adjustment of actions, these operations improve the quality of the portfolio due to the greater benefit they produce over time [2]. In Fig. 1 is represented the course of four years, in which the budget is reassigned for different activities, this is an example of what happens in the real world.

An important point within the problem of the dynamic allocation of resources is the need to achieve a correct selection of limited financial, human and technological resources that entail the financing of projects that confer a greater competitive advantage by the strategy adopted by the organization.

In practice, mathematical and heuristic models have limited utility because they do not consider, among others, the intrinsic dynamic nature of portfolio processes [3]. Among the few research efforts, there is a system for project portfolio generation based on a dynamic allocation of resources, which is presented in [2] as a patent. The system allows multi-objective optimization of a project portfolio with resource constraints as a function of time, such as labor and budget constraints. However, the available information is not enough to reproduce the proposed mathematical model and make comparison on it.

The problem in which we focus our study until our knowledge is unprecedented in a similar way. Due to the great thriving that the handling of dynamical problems has recently been having, especially due to the computational power that allows us

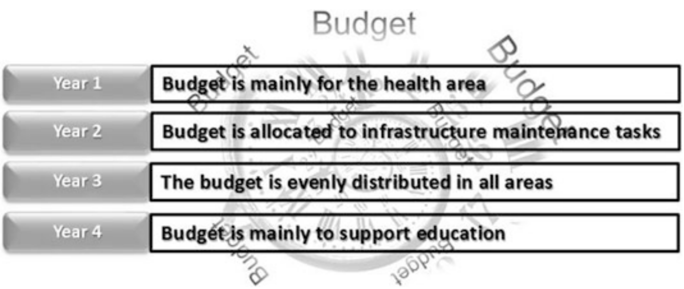


Fig. 1 Budget over time, dynamic allocation of resources

to simulate situations of the world more closely to the real thing, we decided to investigate in state of the art the case study problem. But, on the one hand, we note that to our knowledge there are few researchers who have tackled the subject, and on the other hand none of them see it from the point of view presented here, which we consider relevant due to that its range is very great.

## 2 Background

In this section, a basic definition of project portfolio selection problem is first given. The problem formulated below has been solve with different multi-objective algorithms: Archive-Based Hybrid Scatter Search (ABYSS) [4], MultiObjective Cellular (MOCell) [5], Nondominated Sorting Genetic Algorithm II (NSGA-II) [6], Strength Pareto Evolutionary Algorithm 2 (SPEA2) [7].

### *2.1 Project Portfolio Selection Problem*

One of the main management tasks in public sector organizations, foundations, research centers and companies conducting research and development is to evaluate a set of projects that compete for financial support, to select those that contribute the maximum benefit to the organization. This subset constitutes a project portfolio [8].

The modeling of project portfolio selection problems is based on the following premises:

There is a set of $N$ well-defined projects, each of them perfectly characterized from the point of view of the economic benefits it can provide and its budgetary requirements.

It is about deciding which subset of projects make up the ideal portfolio so that a certain measure of quality is optimized. If uncertainty and risk are ignored, and the benefit generated by each project is known, an attempt is made to maximize the net present value of each benefit associated with the portfolio [9]. It is assumed that if a project is accepted in the portfolio, it will receive all the support it requests.

### *2.2 Basic Formulation of the Project Portfolio Selection Problem*

In any decision problem, the person making the final decision is known as the Decision Maker (DM). He is a person (or group), whose system of preferences is determinant in the solution of problems that consider several objectives, which possibly are in conflict with each other [10].

Let $N$ projects of social interest that meet certain minimum requirements of acceptability to be supported. Each project has associated a region $A$, an area $G$ and a cost $C$:

$$A = \langle a_1, a_2, \ldots, a_k \rangle,$$

$$G = \langle g_1, g_2, \ldots, g_r \rangle,$$

$$C = \left\langle c_{1,} c_{2,}, \ldots, c_N \right\rangle,$$

where $c_j$ is an amount of money that fully satisfies the budget requirements of the $j$ project [11].

Let $X = \langle x_1, x_2, \ldots, x_N \rangle$, the set of $N$ projects where:

$$x_i = \begin{cases} 1, & \text{si el i} - \text{ésimo proyecto es soportado} \\ 0, & \text{en otro caso.} \end{cases} \quad (1)$$

One of the most complex tasks is the evaluation of the projects, which considers the contribution that each project has to each of the objectives set by the institution that provides the economic resources. The level of contribution (benefit) of each project $x_i$ to the different objectives can be represented by the vector $f_{x_i} = \left\langle f_{x_i1}, f_{x_i2}, \ldots, f_{x_ip} \right\rangle$; which is called the benefit vector for project $i$, considering $p$ objectives.

Let the matrix $F$ of dimension $N \times p$ be the profit matrix (Table 1), where $p$ is the total number of objectives and $N$ is the total number of projects. Each row represents the benefit vector for the $i$th project.

Let $P$ be the total amount of financial resources available for distribution to different projects. Since each project has a cost $c_i$, any project portfolio must comply with the following budget constraint:

$$\left( \sum_{i=1}^{N} x_i c_i \right) \leq P \quad (2)$$

Assume as possible that there are budgetary restrictions for each investment area. So if $P_l$ is the budget dedicated to area $l$, and there is a minimum budget $P_{l_{min}}$ and a maximum budget $P_{l_{max}}$ established such that:

**Table 1** Profit matrix $F$

| Objectives | Projects | | | |
|---|---|---|---|---|
| | 1 | 2 | … | $N$ |
| 1 | $f_{1,1}$ | $f_{1,2}$ | … | $f_{N,1}$ |
| 2 | $f_{2,1}$ | $f_{2,2}$ | … | $f_{N,2}$ |
| … | … | … | … | … |
| $p$ | $f_{p,1}$ | $f_{p,2}$ | … | $f_{N,p}$ |

$$P_{l_{min}} \leq P_l \leq P_{l_{max}}. \tag{3}$$

The budget constraint by area that each portfolio must fulfill is given by:

$$P_l = \sum_{i=1}^{N} x_i c_i a_{i_l} \tag{4}$$

where

$a_{i_l}$ is a binary variable that indicates whether project $i$ belongs to the socio-economic area $l$

On the other hand, each project benefits a particular region, and as with the areas, there is a minimum budget $P_{r_{min}}$ and a maximum budget $P_{r_{max}}$ per established region such that:

$$P_{r_{min}} \leq P_r \leq P_{r_{max}} \tag{5}$$

where the budget by region for each portfolio is given by:

$$P_r = \sum_{i=1}^{N} x_i c_i g_{i_r} \tag{6}$$

where

$g_{i_r}$ is a binary variable that indicates whether Project $i$ belongs to region $r$ or not.

The quality of a portfolio $X$ depends on the benefits of its projects and is represented by the quality vector $Z(X)$, whose components are at the same time quality values in relation to each of $p$ objectives of the projects:

$$Z(X) = \langle z_1, z_2, z_3, \ldots, z_p \rangle \tag{7}$$

where

$$z_j(X) = \sum_{i=1}^{N} x_i f_{j,i} \tag{8}$$

being $f$ the profit matrix whose rows represent each of the $p$ objectives and their columns each of the $N$ projects.

Let $R_F$ be the feasible portfolio space, the solution of the portfolio selection problem is to find one or more portfolios satisfying (9).

$$\max_{x \in R_F} \{z(x)\} \tag{9}$$

That is, the only accepted solutions will be those that meet the constraints established by (2) to (6).

## 3 Mathematical Model Proposed for Project Portfolio Selection Problem Enriched with Dynamic Allocation of Resources

In this section, we describe a new mathematical model which we propose to formulate the project portfolio selection problem enriched with dynamic allocation of financial resources. This model is an extension of the basic model presented in Sect. 2.

The project portfolio selection problem enriched with dynamic allocation of resources is a combination that frequently occurs in organizations because that person (or people) who decides in which the budget allocated for a certain period will be invested must be monitoring the results obtained from their decisions. Based on the results, he will have to make the decisions on future investments; this results in greater profits or greater losses, which can be accumulated over the years, due to the dependence that exists between them.

*Decision variables:*

$x_{i,t}$ = Binary matrix representing if project $i$ is financed (1) at time $t$.
$P_{l,t}$ = Budget required by the area $l$ in the year $t$.
$P_{r,t}$ = Budget required by the region $r$ in the year $t$.

*Constants:*

$N$ = Number of projects.
$O$ = Number of objectives.
$T$ = Number of years to calculate.
$na$ = Number of areas.
$nr$ = Number of regions.
$i$ = Index for projects where $i \in \{1, 2, \ldots, N\}$.
$a$ = Index of areas where $a \in \{1, 2, \ldots, na\}$.
$r$ = Index of regions where $r \in \{1, 2, \ldots, nr\}$.
$o$ = Index for objectives where $o \in \{1, 2, \ldots, O\}$.
$a_{i,l}$ = Binary matrix indicating whether project $i$ belongs to area $l$.
$g_{i,r}$ = Binary matrix indicating whether project $i$ belongs to region $r$.
$P_t$ = Annual budget for year $t$.
$P_{l_{min},t}$ = Minimum budget for area $l$ in year $t$.
$P_{l_{max},t}$ = Maximum budget for area $l$ in year $t$.
$P_{r_{min},t}$ = Minimum budget for region $r$ in year $t$.

$P_{r_{max},t}$ = Maximum budget for region $r$ in year $t$.
$b^i_{o,t}$ = Benefit of project $i$, to objective $o$ at time $t$.
$c_{i,t}$ = Matrix containing the costs of each project $i$ in time $t$.

*Objective function:*

$$\max_{x \in R_F}\{Z(x)\} \tag{10}$$

where:

$$\mathrm{Z(x)} = \langle z_1(\mathrm{x}), z_2(\mathrm{x}), \ldots, z_N(\mathrm{x})\rangle, \tag{11}$$

$$z_i(x) = \sum_{o=1}^{O}\sum_{t=1}^{T} b^i_{o,t} x_{i,t}. \tag{12}$$

*Constraints:*

$$\left(\sum_{i=1}^{N} x_{i,t} c_{i,t}\right) \le P_t \forall_t, \tag{13}$$

$$P_{l_{min},t} \le P_{l,t} \le P_{l_{max},t} \forall_{l,t}, \tag{14}$$

$$P_{r_{min},t} \le P_{r,t} \le P_{r_{max},t} \forall_{r,t}, \tag{15}$$

$$P_{l,t} = \sum_{i=1}^{N} x_{i,t} c_{i,t} a_{i,l} \forall_{l,t}, \tag{16}$$

$$P_{r,t} = \sum_{i=1}^{N} x_{i,t} c_{i,t} g_{i,r} \forall_{r,t}. \tag{17}$$

Equations (10) and (11) indicate that it is a problem that can be approached as a multi-objective problem in which the maximization of all the objectives is sought (where $R_F$ is the feasible portfolio space). Eq. (12) breaks down the way of calculating the value of each of these objectives. Equations (13) to (17) show the constraints of this model:

Equation (13) deals with the total budget constraint per year.

Equation (14) indicates that the budget by area must be within a budget range for each year.

Equation (15) is similar to (11) but refers to the regions instead of the areas.

Equations (16) and (17) explain how the budget is calculated by area and region respectively. It is the accumulation of costs stored in the matrix c, costs will be added only when $x$(which represents those projects which are in the portfolio) and $\frac{a}{g}$

(which indicates which area or region respectively the project belongs) take the value of 1.

# 4 Experimentation and Results

In this section, we present the case of study and the results of the experimentation carried out.

## *4.1 Experimental Design*

This work is the basis of a larger project that seeks to solve multi-objective realistic instances of the dynamic portfolio selection problem on the large scale. For feasibility purpose, the experimentation presented in this work used manually generated mono-objective instances, however, due to the intended final objective, the algorithms that were compared are those commonly used in the literature to solve multi-objective problems. They were adapted to solve the problem modeled mathematically in Sect. 3.

### 4.1.1 Hardware and Software

The hardware and software used in this work are shown in Table 2.

### 4.1.2 Description of the Metaheuristics

A pre-evaluation of the instances was carried out using the mathematical programming tool ILOG CPLEX, to obtain the optimal solutions. It allowed making a comparison based on the error between the results of the metaheuristics ABYSS, MOCell, NSGA-II, SPEA2. These algorithms were adapted to solve the dynamic portfolio problem using the framework JMetal 5.2 [12].

**Table 2** Hardware and software

| Hardware | Software |
|---|---|
| Processor Inside i3 2.1 GHz | S.O. Windows 10 × 64 |
| 6 GB RAM | Java language |
| HDD 7200 rpm HDD 7200 rpm | JDK 1.8.0 |
| | IDE NetBeans 8.0.1 |
| | Framework JMetal 5.2 |

It should be noted that the stop criterion was the number of evaluations of the objective function, it was set in 25,000, the rest of the parameters for each metaheuristic is left with the configuration that JMetal handles by default.

## 4.2 Case Study: The Project Portfolio Problem Enriched with Dynamic Allocation of Resources

In this section, the instances used in our experimentation are discussed, an example of one of the instances used, a summary of the results obtained, and the analysis of algorithms using statistical tests.

### 4.2.1 Description Instances

For the experimentation, manually created mono-objective instances were used, whose names, number of projects and years to calculate are shown in Table 3.

In Table 4 is shown a scalar example of what would be an instance for three projects, two years to calculate, two areas and three regions.

## 4.3 Results

For this experiment, 30 executions were performed on each metaheuristic for each of the instances described in Sect. 4.2.1. In Tables 5 and 6, the results and error averages of the executions are shown.

The worst results are shaded in light gray, while the best results are shaded in dark gray.

Next, a statistical analysis of the error obtained in each instance is presented to determine if there is a significant difference in the performance of the four algorithms compared.

**Table 3** Instances

| Name | Number of projects | No. of years to calculate |
|---|---|---|
| ADR_20p_5y | 20 | 5 |
| ADR_20p_10y | 20 | 10 |
| ADR_20p_20y | 20 | 20 |
| ADR_100p_5y | 100 | 5 |
| ADR_100p_10y | 100 | 10 |
| ADR_100p_20y | 100 | 20 |

**Table 4** Instance example

| Line | Content |
|---|---|
| 1 | 2 //Years to calculate |
| 2 | 3 //Number of projects |
| 3 | 1 //Number of objectives |
| 4 | 2 //Number of areas |
| 5 | 3 //Number of regions |
| 6 | |
| 7 | //For year 1 |
| 8 | 15000 //Total budget |
| 9 | |
| 10 | //Minimum and maximum budgets |
| 11 | 2500 7000 //Area 1 |
| 12 | 3000 5000 //Area 2 |
| 13 | 3000 8000 //Region 1 |
| 14 | 2500 7000 //Region 2 |
| 15 | 0 5000 //Region 3 |
| 16 | |
| 17 | //Cost Area Region Objective 1 |
| 18 | 2500 1 2 400 |
| 19 | 3000 2 3 200 |
| 20 | 4500 1 1 300 |
| 21 | |
| 22 | //For year 2 |
| 23 | 10000 //Total budget |
| 24 | |
| 25 | //Minimum and maximum budgets |
| 26 | 2500 5000 //Area 1 |
| 27 | 1000 3000 //Area 2 |
| 28 | 2000 4000 //Region 1 |
| 29 | 1500 6000 //Region 2 |
| 30 | 1000 5000 //Region 3 |
| 31 | |
| 32 | //Cost Area Region Objective 1 |
| 33 | 2500 2 3 500 |
| 34 | 3000 1 1 100 |
| 35 | 4500 2 2 400 |

We used Statistical Tests for Algorithms Comparison (STAC) [13], a web platform for the analysis of algorithms using statistical tests, in this case, the Friedman non-parametric test was applied. In cases where significant differences were found in the Friedman test, we proceeded to apply the Post hoc Holm test, which is widely used in the scientific community.

**Table 5** Average results of 30 executions by metaheuristic

| Instance | Optimum value | Average results | | | |
|---|---|---|---|---|---|
| | | ABYSS | MOCell | NSGA-II | SPEA2 |
| 20p-5a | 307,425 | 271,684 | 287,236 | 288,733 | 290,552 |
| 20p-10a | 1,051,550 | 865,615 | 989,490 | 992,341 | 992,142 |
| 20p-20a | 2,103,100 | 1,483,233 | 1,868,003 | 1,896,677 | 1,896,007 |
| 100p-5a | 2,347,300 | 1,599,723 | 2,048,696 | 2,090,016 | 2,074,784 |
| 100p-10a | 4,694,600 | 2,673,296 | 3,827,630 | 3,935,976 | 3,896,230 |
| 100p-20a | 9,389,200 | 5,333,722 | 6,788,788 | 7,117,285 | 7,070,974 |

**Table 6** Error rate of 30 executions by metaheuristic

| Instance | Optimum value | Error rate | | | |
|---|---|---|---|---|---|
| | | ABYSS | MOCell | NSGA-II | SPEA2 |
| 20p-5a | 307,425 | 0.116261 | 0.065673 | 0.060802 | 0.054885 |
| 20p-10a | 1,051,550 | 0.176820 | 0.059017 | 0.056306 | 0.056496 |
| 20p-20a | 2,103,100 | 0.294740 | 0.111786 | 0.098152 | 0.098471 |
| 100p-5a | 2,347,300 | 0.318484 | 0.127212 | 0.109608 | 0.116098 |
| 100p-10a | 4,694,600 | 0.430559 | 0.184674 | 0.161595 | 0.170061 |
| 100p-20a | 9,389,200 | 0.431930 | 0.276958 | 0.241971 | 0.246903 |

To perform the Friedman test, we establish the null hypothesis ($H_0$): "the mean of the results of two or more algorithms is the same and a significance level of 0.05".

For the post hoc Holm test, we establish the null hypothesis ($H_0$): "the mean of the results of each pair of algorithms compared is equal and with a significance level of 0.05".

*Instance 20p5a*

As shown in Table 7, the result of the Friedman test rejects $H_0$, that is, it indicates that there is a significant difference between the performances of the algorithms for this instance.

To determine the cause of this significant difference, we proceeded to apply the Post hoc test; the results are presented below Table 8.

The pairs marked according to $H_0$ of the test indicate that the average of these pairs of algorithms compared is not the same, and the pairs MOCell-NSGA_II and SPEA2-NSGA_II have a similar performance.

*Instance 20p5a, 20p10a, 20p20a, 100p5a, 100p10a and 100p20a*

The two previous tests were carried out with the rest of the instances, and the results are in the Tables 9 and 10.

**Table 7** Result of Friedman test for Instance 20p5a

| Statistic | p-value | Result |
|---|---|---|
| 72.79407 | 0 | $H_0$ is rejected |

**Table 8** Result of Post hoc test for instance 20p5a

| Comparison | Statistic | Adjusted p-value | Result |
|---|---|---|---|
| SPEA-2 vs. ABYSS | 7.5 | 0 | $H_0$ is rejected |
| ABYSS vs. NSGA-II | 6.2 | 0 | $H_0$ is rejected |
| ABYSS vs. MOCell | 4.3 | 0.00007 | $H_0$ is rejected |
| SPEA-2 vs. MOCell | 3.2 | 0.00412 | $H_0$ is rejected |
| MOCell vs. NSGA-II | 1.9 | 0.11487 | $H_0$ is accepted |
| SPEA-2 vs. NSGA-II | 1.3 | 0.1936 | $H_0$ is accepted |

**Table 9** Results of Friedman tests

| Instance | Statistic | p-value | Result |
|---|---|---|---|
| 20p10a | 46.60834 | 0 | $H_0$ is rejected |
| 20p20a | 81.40609 | 0 | $H_0$ is rejected |
| 100p5a | 122.39211 | 0 | $H_0$ is rejected |
| 100p10a | 189.22742 | 0 | $H_0$ is rejected |
| 100p20a | 244.01255 | 0 | $H_0$ is rejected |

Table 9 shows that according to the results of the Friedman tests all the $H_0$ were rejected, then there is a significant difference between the performances of the algorithms for all instances.

In Table 10, shaded lines show that the average of these pairs of algorithms compared is not the same, and the unshaded lines indicate that the pair of algorithms compared each has a similar performance.

We conclude that there is a significant difference in performance between the algorithms, and in 5 of the 6 instances analyzed, the SPEA2 and NSGA-II algorithms presented similar performance, obtaining the best results.

## 5 Conclusions and Future Work

In this paper, a new mathematical model was proposed to formulate the project portfolio selection problem with dynamic allocation of resources, its operation was verified through the experimentation described in Sect. 4.

This work is a precedent and a basis for the conformation of a benchmark for the solution (optimization) of the dynamic project portfolio selection problem. Mono-objective instances were generated manually and given solutions with state-of-the-art algorithms for the small scale; a multi-objective instance generator is currently in the process of being developed to maximize the proposed mathematical model.

The final results show that there is no better algorithm for all test cases analyzed. For these cases, the algorithm NSGA-II obtained the best results in 5 of the 6 test instances, on the other hand, ABYSS presented the poorest performance.

**Table 10** Results of Post hoc tests

| Instance | Comparison | Statistic | Adjusted p-value | Result |
|---|---|---|---|---|
| 20p10a | SPEA2 vs. ABYSS | 6.4 | 0 | $H_0$ is rejected |
| | ABYSS vs. NSGA-II | 6.3 | 0 | $H_0$ is rejected |
| | ABYSS vs. MOCell | 5.3 | 0 | $H_0$ is rejected |
| | SPEA2 vs. MOCell | 1.1 | 0.814 | $H_0$ is accepted |
| | MOCellvs. NSGA-II | 1 | 0.814 | $H_0$ is accepted |
| | SPEA2 vs. NSGA-II | 0.1 | 0.92034 | $H_0$ is accepted |
| 20p20a | SPEA2 vs. ABYSS | 7.3 | 0 | $H_0$ is rejected |
| | ABYSS vs. NSGA-II | 6.7 | 0 | $H_0$ is rejected |
| | ABYSS vs. MOCell | 4 | 0.00025 | $H_0$ is rejected |
| | SPEA2 vs. MOCell | 3.3 | 0.0029 | $H_0$ is rejected |
| | MOCellvs. NSGA-II | 2.7 | 0.01387 | $H_0$ is rejected |
| | SPEA2 vs. NSGA-II | 0.6 | 0.54851 | $H_0$ is accepted |
| 100p5a | ABYSS vs. NSGA-II | 8 | 0 | $H_0$ is rejected |
| | SPEA2 vs. ABYSS | 6.3 | 0 | $H_0$ is rejected |
| | MOCellvs. NSGA-II | 4.3 | 0.00007 | $H_0$ is rejected |
| | ABYSS vs. MOCell | 3.7 | 0.00065 | $H_0$ is rejected |
| | SPEA2 vs. MOCell | 2.6 | 0.01864 | $H_0$ is rejected |
| | SPEA2 vs. NSGA-II | 1.7 | 0.08913 | $H_0$ is accepted |
| 100p10a | ABYSS vs. NSGA-II | 8.4 | 0 | $H_0$ is rejected |
| | SPEA2 vs. ABYSS | 6.1 | 0 | $H_0$ is rejected |
| | MOCellvs. NSGA-II | 4.9 | 0 | $H_0$ is rejected |
| | ABYSS vs. MOCell | 3.5 | 0.0014 | $H_0$ is rejected |
| | SPEA2 vs. MOCell | 2.6 | 0.01864 | $H_0$ is rejected |
| | SPEA2 vs. NSGA-II | 2.3 | 0.02145 | $H_0$ is rejected |
| 100p20a | ABYSS vs. NSGA-II | 8 | 0 | $H_0$ is rejected |
| | SPEA2 vs. ABYSS | 6.9 | 0 | $H_0$ is rejected |
| | MOCell vs. NSGA-II | 4.9 | 0 | $H_0$ is rejected |
| | SPEA2 vs. MOCell | 3.8 | 0.00043 | $H_0$ is rejected |
| | ABYSS vs. MOCell | 3.1 | 0.00387 | $H_0$ is rejected |
| | SPEA2 vs. NSGA-II | 1.1 | 0.27133 | $H_0$ is accepted |

The conclusion about the performance of the algorithms is not absolute, but it shows the feasibility of our proposal is not absolute; it should be noted that these results are for the set of test instances used in this work. To obtain more meaningful conclusions in future work, it must be done a more exhaustive experimentation with a greater number of larger instances regarding the number of objectives, the number of projects and periods.

## References


1. K. Weicker, *Evolutionary algorithms and dynamic optimization problems* (Der Andere Verlag, Berlin, 2003)
2. C.P.A. Santos, I.A. Lopez-Sanchez. Portfolio Generation Based on a Dynamic Allocation of Resources. U.S. Patent Application No. 14/485,339 (2014)
3. J. Pajares, A. López, A. Araúzo, C. Hernández, Project Portfolio Management, selection and scheduling. Bridging the gap between strategy and operations, in XIII *Congreso de Ingeniería de Organización* (pp. 1421–1429) (2009, April)

4 A.J. Nebro, F. Luna, E. Alba, B. Dorronsoro, J.J. Durillo, A. Beham, AbYSS: adapting scatter search to multiobjective optimization. IEEE Trans. Evol. Comput. 12(4), 439–457 (2008)

5 A.J. Nebro, J.J. Durillo, F. Luna, B. Dorronsoro, E. Alba, Design issues in a multiobjective cellular genetic algorithm, *in International Conference on Evolutionary Multi-Criterion Optimization*. (Springer Berlin Heidelberg, 2007, March) (pp. 126–140)

6 K. Deb, A. Pratap, S. Agarwal, T.A.M.T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 6(2), 182–197 (2002)

7 E. Zitzler, M. Laumanns, L. Thiele, SPEA2: improving the strength Pareto evolutionary algorithm (2001)

8 A. Nebro, F. Luna, B. Dorronsoro, J. Durillo, Un algoritmomultiobjetivobasadoen búsqueda dispersa. Quinto Congreso Español de Metaheurísticas, Algoritmos Evolutivos y Bioinspirados (MAEB 2007), pp. 175–182 (2007)

9 K.R. Davis, R. Davis, P.G. Mckeown, Modelos cuantitativos para administración. Grupo Editorial Iberoamérica (1986)

10 P. Sánchez, Propuesta de anteproyecto de tesis: Nuevos métodos de incorporación de preferencias en metaheurísticas multiobjetivo para la solución de problemas de cartera de proyectos (2012)

11 H. Jain, K. Deb, An improved adaptive approach for elitist nondominated sorting genetic algorithm for many-objective optimization, *in International Conference on Evolutionary Multi-Criterion Optimization* (Springer Berlin Heidelberg, 2013, March) (pp. 307–321)

12 J.J. Durillo, A.J. Nebro, jMetal: a Java framework for multi-objective optimization. Adv. Eng. Softw, **42**(10), 760–771 (2011)

13 I. Rodríguez-Fdez, A. Canosa, M. Mucientes, A. Bugarín, STAC: a web platform for the comparison of algorithms using statistical tests. *in Fuzzy Systems (FUZZ-IEEE), 2015 IEEE International Conference* on (2015, August) (pp. 1–8). IEEE