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Performance Analysis of Strategies that aid in the Incorporation of Preferences in Public Portfolio Optimization Processes

Laura Cruz-Reyes[1], Mercedes Pérez-Villafuerte[2], Nelson Rangel[3], Claudia G. Gómez.[1], J. Patricia Sanchez-Solis[4], Marcela Quiroz-Castellanos[5], Daniel A. Martínez Vega[2]

[1]National Mexican Institute of Technology/Madero Institute of Technology, México, [2]National Mexican Institute of Technology/Tijuana Institute of Technology, [3]CONACYT Research Fellow, National Mexican Institute of Technology/Madero Institute of Technology, México, Autonomous University of Ciudad Juarez, [5]Artificial Intelligence Research Center, University of Veracruz, México.

lauracruzreyes@itcm.edu.mx, pvmercedes@gmail.com, nrangelva@conacyt.mx, claudia.gomez@itcm.edu.mx, julia.sanchez@uacj.mx, maquiroz@uv.mx, adalbertovega@gmail.com

Abstract. The project portfolio selection is one of the most important strategic problems, both in private and in public sector. This can become an incredibly complex task due to several factors. *Decision maker* (DM) preferences are an essential element for decision-making, vary between decision-makers, and evolve over time. A strategy is required to assist the decision maker in the identification of the best compromise, an optimal or near-optimal solution that satisfies their preferences. This paper addresses the interactive incorporation of preferences to deal with preferences that evolve over time, specifically, involving the participation of the DM during the process of portfolio optimization and analysis. To model DM preferences, the methodology *Preference Disaggregation Analysis* (PDA) is incorporated in a hybrid algorithm that gives a solution to the public portfolio selection problem. This paper presents a study of the efficiency of the PDA incorporation in an interactive search process. The experimental results showed the potential of the proposed method.

Keywords: Public portfolio selection problem, Preference Disaggregation Analysis, preference incorporation.

1 Introduction

Most real-world problems involve multiple objectives [1] [2]. The public portfolio selection is one of the most important strategic problems, both in the private sector and in the public sector.

The conflicting nature of objectives makes it difficult to find an ideal solution for a *Multi-objective Optimization Problem* (MOP), so an ideal solution cannot be achieved. The most commonly used alternative to solve a MOP is the use of multi-objective optimization methods, which provide a set of efficient solutions for the decision maker. This does not completely solve the problem, the decision maker has to choose the best compromise of that set and must incorporate preferences in a multi-objective optimization method so that his/her preferences guide the search and adjust the MOP towards a region of interest for the DM.

When DM preferences are requested, they can be related to objectives, constraints or solutions [3,4,5,6]. Introducing these preferences can become an excessive task for DM, this is why it is necessary to introduce these preferences indirectly so that this effort is lower and this information is obtained in an understandable and natural way for the DM. One of the methods for obtaining preferences indirectly is the *Preferences Disaggregation Analysis* (PDA). In this paper, we present a study of the efficiency of the incorporation of the PDA in an interactive search process.

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2 Preference Disaggregation Analysis

The DM can express preferences indirectly through examples of solutions that meet characteristics of interest to him, and also directly, for example, using weights, thresholds, and parameters.

It is a very difficult task for the DM to be able to express parameter values directly, so a mechanism is needed that allows to transform the preferences given in examples to parameters, this is where the techniques based on *Preference Disaggregation Analysis* (PDA) come into play [7].

The PDA procedures only require that the DM provide a reference set that reflects its decision-making process. With these elements, this technique becomes responsible for inferring the parameter values required by the chosen preference model. Indirectly, the behavior of the DM is captured in an alternatives comparison model with parameters adjusted to him/her; so each set of parameters defines uniquely a decision behavior.

3 Hybrid Multi-Criteria Sorting Genetic Algorithm (H-MCSGA)

The algorithm Hybrid Multi-Criteria Sorting Genetic Algorithm (H-MCSGA), proposed in [8], searches the construction of portfolios based on preferences defined by a reference set. This algorithm uses sorting to establish the reference set, and guides the search for the best compromise. It consists of two phases:

1. Through a multi-objective metaheuristic approach, an approximation to the Pareto front is obtained; and
2. The DM takes this approach and classifies it into a set of ordered categories to build a reference set that is used in the Theseus preference-based classifier. In this second phase, a variant of the popular NSGA-II uses good solution information to guide the search to the *Region of Interest* (ROI).

This paper presents an analysis of the performance of a prototype that adjusts, using the PDA methodology, the values of the parameters of a preference model that characterizes a DM. The set of identified parameter values is used by a multi-objective optimization algorithm with preferences, such as H-MCSGA, to guide the search toward the best compromise in the approximated Pareto front. In the end, it pursues the analysis of the robustness of PDA strategies to identify appropriate parameters values for a preferences model incorporated in optimization processes. The analysis of the proposed prototype is presented in the following section.

4 Basic prototype for preference incorporation in optimizers

The construction of a basic interactive optimization prototype is proposed in this work. This prototype involves the integration of three previous works conducted in the research group in which they were developed. These works try to solve problems derived from the general public portfolio selection problem.

The decision maker can express his or her preferences in many ways. Whenever an expression is made indirectly, the DM is provided with a set of solution alternatives and with them the DM can either categorize them or make paired comparisons, producing examples.

Since we do not currently have a real DM, in the proposed architecture a DM emulation is done in the process of expressing the preferences. To emulate this process, a routine is used within the NO-ACO optimizer [9], an algorithm based on ant colony optimization strategy that incorporates preferences in the solution of portfolio problems (See Figure 1).

In the prototype presented, it is incorporated a preference definer [10] that makes use of the PDA techniques. A DM emulator is used to specify preferences, and to provide the pair-wise set required by the PDA; it is based on the NO-ACO algorithm. The H-MCSGA was selected as the optimizer to solve the instances of the portfolio problem and uses as input the reference set provided by the NO-ACO algorithm. Figure 2 shows the integration of the mentioned works and the moment in which the DM preferences are incorporated; this figure also represents the experimental process described in section 5.

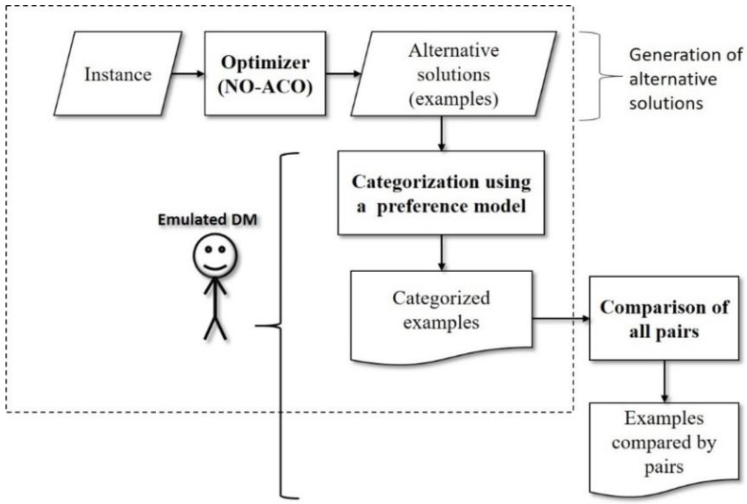

Fig. 1. Emulation of a DM in the expression of preferences

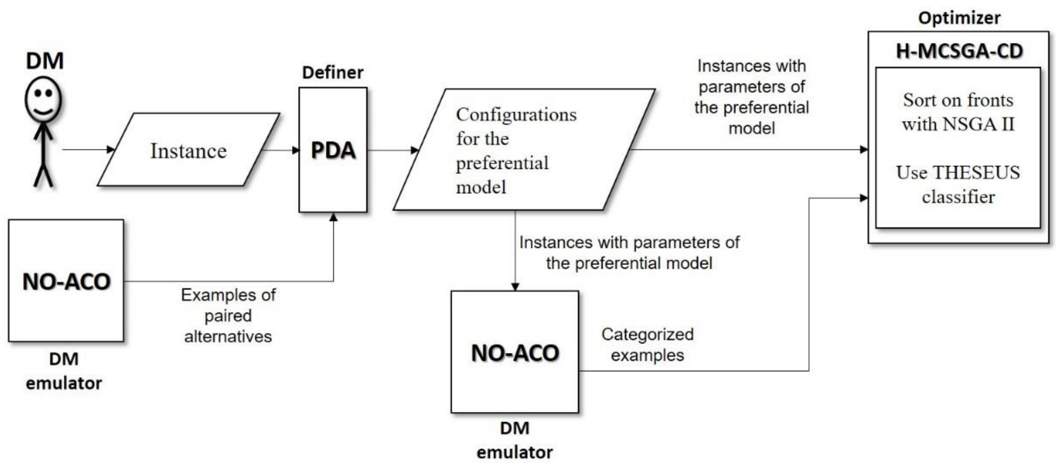

Fig. 2. Scheme for a basic prototype for preference incorporation in optimizers.

5 Experimental process

The experiment was designed to evaluate the entire optimization process, from the definition of the parameter values of the preference model to the solution of the instances through the optimization algorithm. The experiment is summarized in the steps described below. They were performed over a set of 10 random instances of the public portfolio selection problem taken from [11], with 4 objectives and 25 projects.

1. Repeat the next steps for each instance of the public portfolio selection problem.
2. Create the pair-wise set through the emulated DM (NO-ACO). This set contains pairs of portfolio alternatives; the first alternative of each pair is the most preferred by the DM.
3. Generate *n* parameter configurations of preferential model using the PDA strategy; the input is the pair-wise set and the output is a variable number of configurations because PDA is a multi-objective algorithm.
4. Create an extended instance of the portfolio problem per configuration, by incorporating the corresponding parameter values of the preference model. There will be as many extended instances as configurations were generated by the PDA.
5. Create the reference set through the emulated DM (NO-ACO). The reference set contains portfolio alternatives organized by categories.
6. Introduce the extended instance and the reference set into the H-MCSGA optimizer, and solve the instance 30 times, each of these represents an experiment.
7. Identify the approximated Pareto front derived from the runs of the previous step.

8. After this, proceed to calculate the contribution of each configuration to the approximated non-dominated front. All configurations are collected for each experiment. Here, for each experiment and each configuration, it is determined how many of the solutions obtained in the given instance belong to the set of non-dominated solutions. After that, it is calculated the average contribution per experiment.

The results of this experimental process for the ten random instances and the 30 experiments are concentrated in Table 1. In this table, the column header contains the identifier of the ten random instances and the row header represents the experiment number performed for each instance, each experiment assembles all the parameters configurations of that experiment number. The cells contain the average percentage of contribution to the approximated non-dominated front for each experiment in the same instance (by column); in summary, they contain the results obtained in step 8 of the experimental process previously described. This information was subject to statistical analysis, described in the following section, to determine the stability and the quality of solutions that PDA can offer, i.e. its robustness.

Table 1. Averages of contributions for 10 random instances (4 objectives and 25 projects) and 30 experiments

#E/ID	*o4p25_1*	*o4p25_2*	*o4p25_3*	*o4p25_4*	*o4p25_5*	*o4p25_6*	*o4p25_7*	*o4p25_8*	*o4p25_9*	*o4p25_10*
E1	0.9920	0.9518	0.9980	0.9864	0.9023	0.9776	0.9934	0.9858	1.0000	0.9142
E2	0.9974	0.9553	0.9945	0.9725	0.8620	0.9804	0.9950	0.9864	1.0000	0.8829
E3	0.9909	0.9624	0.9934	0.9866	0.8999	0.9840	0.9946	0.9788	1.0000	0.8982
E4	0.9898	0.9858	0.9979	0.9874	0.8893	0.9566	0.9905	0.9800	0.9988	0.8902
E5	0.9886	0.9778	1.0000	0.9837	0.8723	0.9759	0.9921	0.9806	1.0000	0.8850
E6	0.9937	0.9628	1.0000	0.9777	0.8535	0.9867	0.9952	0.9836	1.0000	0.8921
E7	0.9915	0.9762	0.9889	0.9871	0.9151	0.9888	0.9938	0.9797	1.0000	0.8855
E8	0.9870	0.9557	0.9966	0.9887	0.8732	0.9715	0.9931	0.9799	1.0000	0.8843
E9	0.9816	0.9589	0.9966	0.9872	0.8951	0.9848	0.9968	0.9819	0.9983	0.8965
E10	0.9865	0.9707	1.0000	0.9953	0.8707	0.9790	0.9943	0.9859	1.0000	0.8881
E11	0.9832	0.9738	1.0000	0.9799	0.9007	0.9779	0.9943	0.9804	1.0000	0.8963
E12	0.9831	0.9766	0.9945	0.9865	0.8715	0.9849	0.9896	0.9879	1.0000	0.8695
E13	0.9942	0.9722	0.9980	0.9804	0.8954	0.9857	0.9954	0.9816	1.0000	0.8871
E14	0.9879	0.9631	1.0000	0.9809	0.8940	0.9778	0.9945	0.9814	1.0000	0.8945
E15	0.9922	0.9685	1.0000	0.9912	0.8882	0.9788	0.9977	0.9812	1.0000	0.9115
E16	0.9935	0.9706	1.0000	0.9755	0.8708	0.9874	0.9954	0.9816	1.0000	0.8788
E17	0.9878	0.9678	0.9968	0.9867	0.9180	0.9868	0.9902	0.9852	1.0000	0.9018
E18	0.9868	0.9680	0.9952	0.9868	0.8995	0.9822	0.9923	0.9836	1.0000	0.8952
E19	0.9919	0.9785	0.9983	0.9864	0.9237	0.9823	0.9970	0.9796	1.0000	0.8868
E20	0.9915	0.9742	1.0000	0.9796	0.8549	0.9779	0.9976	0.9790	1.0000	0.8883
E21	0.9863	0.9599	0.9982	0.9855	0.8894	0.9773	0.9861	0.9824	1.0000	0.8850
E22	0.9893	0.9857	1.0000	0.9894	0.8590	0.9803	0.9962	0.9807	1.0000	0.8726
E23	0.9895	0.9791	0.9965	0.9814	0.8774	0.9780	0.9965	0.9771	1.0000	0.8932
E24	0.9901	0.9806	1.0000	0.9859	0.8800	0.9749	0.9942	0.9849	1.0000	0.9129
E25	0.9895	0.9716	0.9985	0.9835	0.9304	0.9816	0.9912	0.9797	0.9960	0.9093
E26	0.9874	0.9792	0.9942	0.9911	0.8986	0.9797	0.9936	0.9815	1.0000	0.9057
E27	0.9886	0.9709	1.0000	0.9851	0.8645	0.9695	0.9942	0.9830	1.0000	0.8855
E28	0.9906	0.9604	1.0000	0.9918	0.8685	0.9722	0.9975	0.9806	1.0000	0.8936
E29	0.9916	0.9587	0.9982	0.9909	0.9002	0.9795	0.9967	0.9801	1.0000	0.8999
E30	0.9885	0.9758	0.9982	0.9865	0.8792	0.9757	0.9949	0.9867	1.0000	0.8997

6 Statistical Analysis of the Performance of the PDA

The purpose of this section is to evaluate the performance of the PDA as provider of a set of parameter values for model preferences incorporated in optimizers. In particular, it evaluates the results obtained in the previous section. The analysis consists in the verification of the significant difference in the behavior between the solutions that are obtained from the configurations given by the PDA, and used by the optimizer. The tool used to perform the evaluation was STAC [12], a web platform for algorithms analysis using statistical tests; in this work, the non-parametric Quade test was applied.

The significant difference in the performance of the configurations obtained by the PDA was firstly evaluated under the null hypothesis (H_0) that *the mean of the results of two or more configurations is the same*; the significance level used was 0.05. The result obtained in this test is concentrated in Table 2.

Table 2. Quade test (significance level of 0.05)

Statistic	***p-value***	***Result***
70.75644	0	H_0 is rejected

According to previous results, the Quade test showed that there is significant difference in the behavior of the solutions (i.e., the H_0 was rejected). We proceeded to conduct a Post-hoc test to find the cause of that significant difference. For this purpose, we applied the Holm test, under the null hypothesis (H_0) that *the mean of the results of each pair of configurations is equal*, with a level of significance of 0.05.

Table 3. Holm Post-hoc test (significance level of 0.05)

Comparison	Statistic	Adjusted p-value	Result
o4p25_5 vs o4p25_9	4.46729	0.00036	H0 is rejected
o4p25_10 vs o4p25_9	4.19668	0.00119	H0 is rejected
o4p25_5 vs o4p25_3	4.09591	0.00181	H0 is rejected
o4p25_10 vs o4p25_3	3.82531	0.00549	H0 is rejected
o4p25_7 vs o4p25_5	3.56659	0.01483	H0 is rejected
o4p25_2 vs o4p25_9	3.31806	0.03626	H0 is rejected
o4p25_10 vs o4p25_7	3.29598	0.03825	H0 is rejected

The summary of the result of the second test can be described as follows. The Holm test was used to make the comparison of the 45 pairs that result from the combination of the ten instances that were an object of study; from them, only seven pairs resulted in a rejection of this null hypothesis, these pairs are shown in Table 3. However, it can be observed that the pairs in which the rejection is made are those that have the greatest differences among them according to the average obtained by each instance. With this results, evidence is provided of the robustness of PDA applied to optimization, because the maximum common performance of the parameters provided by the strategy that was tested in the optimizer is 84%; this means that any configurations taken at random from the ones provided by the PDA will work with a similar performance in the H-MCSGA. This results in stability in the PDA, with which it can be assured that any configuration given by the PDA can be taken because these configurations will provide similar quality solutions. The contribution averages of the configurations on the approximated non-dominated front can be considered constant for all instances. This results can be extended in a future work to include different metaheuristics.

After the statistical stability test, an analysis of the quality (contribution of non-dominated solutions) offered by the configurations provided by the PDA was made. For this analysis, the Bernoulli parametric statistical test was applied. Bellow, it is described the test procedure and the obtained results; to exemplify the procedure the results of the instance o4p25_1 were used (See Table 1). If we establish a quality level of 98.3%, we can consider that the 30 experiments of each instance are a Bernoulli experiment. To demonstrate that the PDA satisfies the specified quality is formulated the H_0 = having the quality established and H_1 = not having the quality established.

Given the probability of success (having the quality) is 0.983, we proceed to count the experiments that satisfy the quality level, and in this case, 29 experiments satisfied the established level.

With the *binomial distribution*, we determine the probability of obtaining 29 successes in 30 experiments and with a level of significance of 0.05. The calculations to determine the p-value were performed in the R language and the obtained p-value is 0.4021317; therefore, the H_0 is accepted. For the instance o4p25_1, the minimum quality level offered by PDA is 98.3%.

This procedure was used to determine the minimum quality obtained for each instance, the result of these tests is concentrated in Table 3. The Quality column contains the percentage of quality set for each instance; the column Successes shows the total of experiments that met the established quality level and the p-value obtained for each instance is also shown to satisfy the H_0 with a significance level of 0.05.

Table 4. Bernoulli test results

Instance	Quality	Successes	P-value
o4p25_1	0.983	29	0.40213169
o4p25_2	0.958	27	0.13011834
o4p25_3	0.993	29	0.19001411
o4p25_4	0.977	28	0.15105814
o4p25_5	0.87	24	0.18714933
o4p25_6	0.972	27	0.05081485
o4p25_7	0.989	29	0.28238956
o4p25_8	0.978	29	0.48694297
o4p25_9	0.998	29	0.05829205
o4p25_10	0.885	25	0.25839269

As can be observed in the results of Table 4, the minimum expected quality that the PDA could provide 87% and in this experiment, corresponds to the instance o4p25_5. Then it can be concluded that the PDA provides quality solutions since the minimum percentage of success reported is very high.

7 Final Comments

This article reports the results of an analysis of the efficiency of obtaining and incorporating preferences in the optimization process using the techniques of analysis of disaggregation of preferences (PDA). The prototype described and built will be the basis for developing interactive optimization methods.

Good preliminary results were obtained with the random instances of the portfolio problem with 4 objectives and 25 projects. It was determined statistically that the quality of the optimization process with the incorporation of preferences is greater than 87%, and that this quality can be obtained by almost any configurations provided by the PDA strategy, showing its robustness.

It is important to notice that the obtained quality is relative to an approximated Pareto front, so an extensive experimentation, including standard instances with known Pareto front, is needed to make a conclusive statement about the proposal.

As future work, the proposed methodology will be tested with larger scale instances, and we will develop interactive optimization methods based on the proposed architecture.

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