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A brief review of multi-objective optimization proposals that interactively incorporate preferences

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Graphical Abstract	**Abstract.**
Insert graphical abstract figure here	The problems in which there is a conflict between objectives, naturally occur in the real world, in which also intervenes the presence of a decision maker. The multi-objective problem solution has been approached through many multi-objective optimization algorithms. There are available many algorithms for solving these types of problems, mostly for two or three objectives problems, but in the real world, the number of conflicting objectives is large-scale. These algorithms provide many solutions to the decision-maker but, even though all of these are good and efficient solutions under the Pareto dominance paradigm (efficient solutions known as non-dominated), this does not solve the problem completely, because, this large number of solutions found, could overwhelm the DM at the time of selecting the one he considers best for him. There is an emerging area in multi-objective optimization, in which decision-makers preferences are incorporated, but these can be done at different times in the optimization process: a priori, a posteriori and interactively. The authors have approached various mechanisms for the preference articulation, for example, statistical methods, reference points, weights, to name a few.

In this paper, a review is presented of some outstanding works that approach the incorporation and obtaining of DM preferences, using reference points in multi-objective optimization, but in an interactively way.

Introduction

In a search for multi-objective problems solutions without taking into account the preferences of the DM, It will be faced two scenarios: In the first, a too much computational effort will be in vain to find solutions that may not be of DM interest. In the second, too many solutions are presented to the DM that hinders his task of choosing those that he considers preferred, which could overwhelm him with too much information.

For this reason, there is an emerging area in multi-objective optimization, in which the decision-maker preferences are incorporated, allowing to narrow the search space. In order to facilitate this task, the preference incorporation must be done intuitively for the DM. This can be done at different times in the optimization process: a priori, a posteriori and interactively.

In the next section, is addressed a description of some recently published papers, which present algorithms that handle preferential information of the DM that is incorporated during the solutions search of multi-objective problems. First, is presented an approach that captures DM preferences using preferential parameters and reference sets. Afterward, three works are addressed that use reference points to articulate the decision maker preferences.

State of the Art

Interactive Multi-Criteria Sorting Genetic Algorithm (I-MCSGA)

Sanchez in [1] proposed I-MCSGA, an algorithm that incorporates DM preferences to define the region of interest, implicitly and interactively in an evolutionary optimization algorithm. The DM preferences are introduced by parameters of an outranking model [2] also expressed in a reference set, that can be update interactively by the DM. Allowing the selection of solutions and creating reference sets with them may be more understandable for the DM in his intervention in the search.

A multi-criteria sorting method is used as an artificial DM to identify new *satisfactory* solutions among those generated by the evolutionary search. This update process is done automatically according to the specified parameters before the optimization process starts. In this way, I-MCSGA let the DM to learn and progressively, adjusts his (initially poorly defined) preferences, and then he drives the search toward the ROI. This algorithm has been tested with Public Portfolio Problems and the DTLZ problems.

Artificial Decision Maker Driven by PSO: An Approach for Testing Reference Point Based Interactive Methods

Barba-Gonzalez in [3] introduce a new artificial decision maker, which reuses the dynamics of particle swarm optimization for guiding the generation of consecutive reference points, replacing the preference articulation of the decision maker. They use this artificial decisión maker (ADM) in order to compare interactive methods. The main idea is to create reference points by moving particles in the swarm that is involved in the search. This artificial DM is tested with the DTLZ benchmark problems with 3, 5 and 7 objectives to compare R-NSGA-II and WASF-GA as interactive methods.

The three main components of the ADM are:
– *Steady part*: This part includes experience and knowledge available at the beginning of the solution process and remains unchanged in the solution process.
– *Current context*: This part includes all the knowledge about the problema which is gained during the solution process by the ADM.
– *Preference information*: The ADM expresses its knowledge during the solution process in order to guide the method towards solutions that are more preferred by the ADM.

Extending the Speed-Constrained Multi-objective PSO (SMPSO) with Reference Point Based Preference Articulation

Nebro in [4] they make an extension of the Speed-constrained Multi-objective PSO (SMPSO) algorithm, but they incorporate a mechanism of articulation of preferences based on the use of reference points. SMPSO/RP is implemented within the jMetal framework.
The incorporation of the reference points provides the ability to deal with one or more preferences of the DM or regions of interest and also allows the change of preferences by interactively changing the desired reference points. This is an algorithm that, given the characteristics of the PSO algorithm, allows the evaluation of particles of the swarm in parallel. This algorithm allows the visualization of the evolution of the front for problems of two and three objectives

As a case study they approach a real-world problem in the field of structural design and also benchmark problems (ZDT, DTLZ and WFG), and have been solved them by indicating both an achievable and an unachievable reference point

InDM2: Interactive Dynamic Multi-Objective Decision Making using evolutionary algorithms

Nebro in [5] proposed a dynamic multi-objective optimization algorithm called InDM2. This algorithm is developed in the JMetal-SP tool [6], which is a framework that combines the characteristics of JMetal (flexible and extensible architecture, many metaheuristics and representative multiobjective problems) and Spark which has become one of the dominant technologies in Big Data.

InDm2 allows the intervention of a real DM when defining a region of interest through reference points, which can be modified interactively from the keyboard at runtime, also offering a visualization of the ROI solutions that are being generated during the process of solution.
Two reference point-based evolutionary multi-objective optimization algorithms (R-NSGA-II and WASF-GA) are incorporated in InDM2 to solve and handle the preference information. InDM2 was tested with the bi-objective standard problems FDA 2, 3 and 5, and the bi-objective TSP.

In Figure 1, InDM2 is shown in execution solving the dynamic problem FDA2 and an intervention of the DM is shown when making a change of the desired reference point (0.4,0.6).

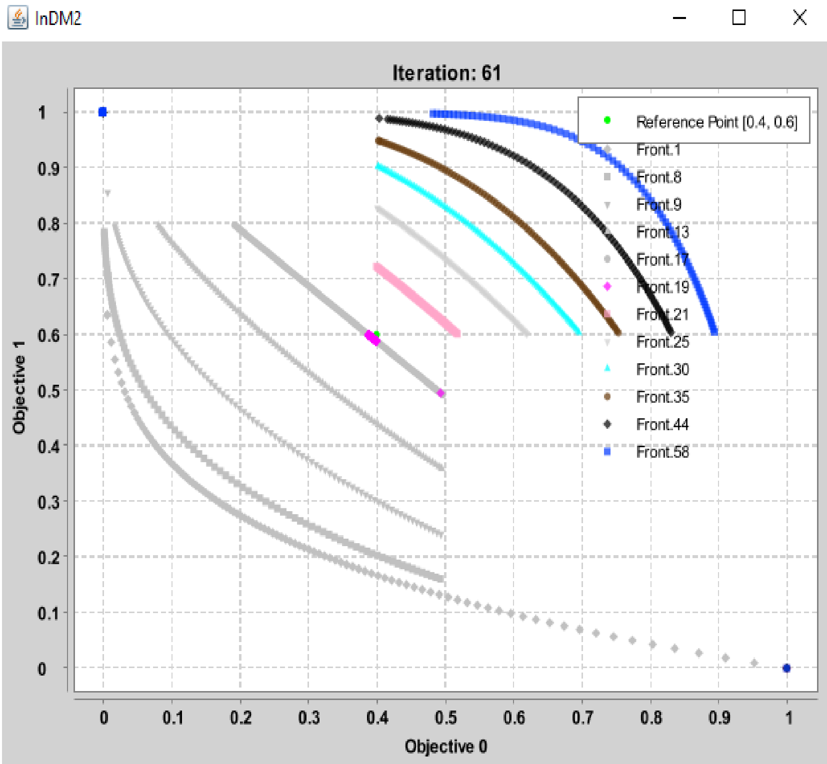

Figure 1. InDM2 in execution

At the end of this section, Table 1 is shown, concentrating the most relevant details of the interactive algorithms reviewed in this work. Algorithms were reviewed in which reference points are used to delimit the region of interest of the DM, but this strategy may not be easily understood by the DM if the results are not visually shown.

Table 1. Comparison of revised algorithms that incorporate DM preferences interactively.

	Problem		**Preference Infomation**	**Metaheuristic**	**Preference incorporation-based approaches**	**DM**
Author	**Real**	**Standard**				
Barba-González et al. 2018 [3]		DTLZ with 3, 5 and 7 objectives	Reference point	ADM-PSO	Interactive	Artificial
Nebro et al. 2018*a* [4]	Structural design problem	ZDT, DTLZ, WFG	Reference point	SMPSO/RP	A priori	Real
Nebro et al. 2018*b* [5]	Bi-objective TSP	Bi-objective FDA 2, 3 and 5	Reference point	InDM2	Interactive	Real
Sánchez 2017 [1]	Project Portfolio Problem	DTLZ 2 y 3	Preferential model parameters, Reference set	I-MCSGA	Interactive	Artificial

It is necessary to consider the availability of participation that the DM may have. InDM2 manages to cover this aspect but is limited to bi-objective problems due to the visualization of them. On the other hand, the proposal in I-MCSGA using reference sets can facilitate the understanding and learning of the DM about their preferences. It would be favorable to implement this strategy with a real DM.

It is necessary to remember that in the real world, multi-objective problems involve more than three conflicting objectives, the revised algorithms are limited in this aspect and it is still necessary to develop strategies that allow the DM to participate in the search process.

Conclusions

One of the of the revised algorithms and that has generated the most interest in the group of collaborators is InDM2, which combines Multi-Objective Dynamic Optimization, Multicriteria Decision Making and interactivity using the visualization of the approximate regions of interest in optimization time; the preferences are expressed through reference points that can be changed at the disposal of the DM during the execution time. Given the limitation of the visualization of conflicting objectives, the problems solved by this metaheuristic are limited to bi-objective problems. The source code is available so it is possible to reproduce their tests and it is also possible to work on the JMetalSP framework.

To our knowledge, since there is no general definition that associates the mechanisms of incorporation of preferences with the region of interest, it is desired to develop a procedure that can compare the degree of satisfaction of a preferential profile using some approach of incorporation of preferences of some algorithm that is used in the literature.

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