Handling Preferences in Evolutionary Multiobjective Optimization: A Survey

Carlos A. Coello Coello
Laboratorio Nacional de Informática Avanzada
Rébsamen 80, A.P. 696, Xalapa, Veracruz 91090, México
ccoello@xalapa.lania.mx

Abstract- Despite the relatively high volume of research conducted on evolutionary multiobjective optimization in the last few years, little attention has been paid to the decision making process that is required to select a final solution to the multiobjective optimization problem at hand. This paper reviews the most important preference handling approaches used with evolutionary algorithms, analyzing their advantages and disadvantages, and then, it proposes some of the potential areas of future research in this discipline.

1 Introduction

Most real-world problems are multiobjective in nature, because they consider several objectives (or alternatives) that are to be optimized simultaneously. Normally, these objectives are non-commensurable (i.e., they are measured in different units), and are in conflict with each other. Multiobjective optimization problems (MOPs) have received considerable attention in Operations Research (see for example [23, 7, 27, 12]), and they have recently become a very popular area of research within evolutionary computation that is normally called Evolutionary Multiobjective Optimization[1] (EMO) [14, 22, 45, 6].

It is important to be aware that the solution of a MOP really involves three stages: measurement, search, and decision making. The central issue in multi-criteria decision making (MCDM) is normally how to measure a certain utility value using a (generally complex) mathematical tool. If a reliable utility function is available, then the decision has been implicitly made and its selection is trivial. Thus, using a mechanical search procedure, the decision making process is unnecessary (i.e., it is implicit in the search itself). That should not be the case, but unfortunately, it normally is. For example, most EMO researchers tend to concentrate on issues related to the search of nondominated solutions. However, these nondominated solutions do not provide any insight into the process of decision making itself, since they are really a useful generalization of a utility function under the conditions of minimum information (i.e., all attributes are considered as having equal importance; in other words, the decision maker (DM) does not express any preferences of the attributes) [8, 13, 19].

Most of the current research on EMO has concentrated on adapting an evolutionary algorithm (EA) to generate nondominated solutions. However, the articulation of preferences has been dealt with by very few researchers (see for example [34, 8, 22, 13, 19]).

The purpose of this paper is to review the most representative research on preferences articulation found in the EMO literature, analyzing their contributions and their weaknesses and sketching some of the potential research areas that remain to be explored.

2 Multicriteria Decision Making

From the Operations Research (OR) perspective, there are two main lines of thought regarding MCDM [44]:

1. The French school, which is mainly based on the outranking concept [46], and
2. The American Multi Attribute Utility Theory (MAUT) [24].

The first is based on an outranking relation which is built up under the form of pairwise comparisons of the objects under study. The main goal is to determine on the basis of all relevant information for each pair of objects if there exists preference, indifference, or incomparability. For this purpose, preference or dominance indicators are defined and compared with certain threshold values. The main drawback of this approach is that it might become very expensive (computationally speaking) when there is a large number of alternatives.

MAUT is, in contrast, based on the formulation of an overall utility function, and its underlying assumption is that such a utility function is available or can be obtained through an interactive process. When this utility function is not available, then the task will be to identify a set of nondominated solutions. In this case, strong preference can only be concluded if there exists enough evidence that one of the vectors is clearly dominating the vector against which it is compared. Weak preference (modelled as weak dominance [26]), on the other hand, expresses a certain lack of conviction. Indifference means that both vectors are equivalent and that it does not matter which of them is selected. It is important to

[1] The author maintains an electronic repository of information on evolutionary multiobjective optimization at: http://www.lania.mx/~ccoello/EMOO/ with a mirror at http://www.jeo.org/emo/

distinguish this "indifference" from the "incomparability" used with outranking methods, since the second indicates vectors with strong opposite merits [44]. MAUT does not work when there are intransitivities in the preferences, which is something that frequently arises when we deal with "incomparable" objects using an outranking approach [52].

These two main lines of thought lead us to define three types of operational attitude of the DM [37]:

1. To wish to exclude incomparability and completely express the preferences by a unique criterion. This would lead to an aggregating approach in which all the criteria would be combined using a single utility function that represents the global preferences of the DM (this would correspond, for example, to MAUT).

2. To accept incomparability and to use an outranking relation to model the preferences of the DM. In this case, the DM only has to model those preferences that he/she is capable of establishing objectively and realiably, and then use outranking when such preferences cannot be established. In this case, the DM is asked to compare the criteria two by two and each objective is assigned a weight derived from the eigenvector of the pairwise comparison matrix [44]. It is important to be aware that these pairwise comparisons can lead to intransitive or incomplete relations. One example of this approach would be ELECTRE in its different versions [35, 38, 40].

3. To determine, through an interactive process, the different compromises based on local preferences. In this case, the DM experiments with his/her local preferences at each stage of the search process, which allows to explore only a certain region of the search space. When no further improvement is no longer necessary or is impossible, then we say that we have reached a compromise, which can be seen as a local optimum relative to an implicit criterion. An example of this approach is the STEP Method (STEM) [3].

Both MAUT and outranking procedures can be applied in an interactive manner, and that is normally the approach taken when there is not enough a priori information of the objectives as to allow the DM to define his/her preferences in an accurate way.

Although *a priori* and *a posteriori* decision making procedures are common in the OR literature [7], interactive approaches (i.e., the progressive articulation of preferences) have been normally favored by researchers [15] for several reasons [29]:

1. Perception is influenced by the total set of elements in a situation and the environment in which the situation is embedded.

2. Individual preference functions or value structures cannot be expressed analytically, although it is assumed that the DM subscribes to a set of beliefs.

3. Value structures change over time, and preferences of the DM can change over time as well.

4. Aspirations or desires change as a result of learning and experience.

5. The DM normally looks at trade-offs that satisfy a certain set of criteria, rather than at optimizing all the objectives at a time.

3 Preferences in Evolutionary Algorithms

As indicated by Horn [22], preferences can also be expressed *a priori*, *a posteriori*, or in an *interactive* way when using EAs. If preferences are expressed *a priori*, the DM has to define his/her preferences in advance (before actually performing the search). The classical example of this are the aggregating approaches in which weights are defined beforehand to combine all the objectives into a single objective function. In the second case, we search first, and decide later. This is the category where most EMO approaches fall into (i.e., EMO techniques based on Pareto ranking such as MOGA [13] and NSGA [41]). In this case, we use an evolutionary algorithm (EA) to search the "best possible" alternatives, where "best possible" normally means nondominated or Pareto optimal solutions. The third case is the less common in the EA literature: approaches that allow to guide the search of the EA using preferences from the DM, but assuming that such preferences could change over time. There is very little work in which the handling of preferences is explicitly dealt with in the EMO literature. The most representative research within this area is the following:

1. **Goal attainment**: Fonseca and Fleming [13] is probably the earliest attempt to incorporate preferences from the DM into an EA. The proposal was to extend MOGA to accomodate goal information as an additional criterion to non-dominance to assign ranks to the population. The goal attainment method [16] was used for this sake, so that the DM could supply goals at each generation of the EA, reducing in consequence the size of the set under inspection and learning, at the same time, about the trade-offs between the objectives. This is an *interactive* approach. They also proposed the use of an expert system to automate the task of the DM. Such an expert system would use built-in knowledge obtained from the preferences expressed by the (human) DM. Shaw and Fleming [39] used a

similar approach to incorporate preferences into a scheduling problem, but in their case, preferences were defined *a priori*. The main disadvantage of this approach is that it requires the user to know beforehand the ranges of variation of each objective in order to establish coherent goals. This could be an expensive process (in terms of CPU time) in many real-world applications. Nevertheless, the approach is simple and easy to implement.

2. **Utility functions**: Greenwood et al. [19] used elements of *imprecisely specified multi-attribute value theory* (ISMAUT) to perform imprecise ranking of attributes [49]. The idea is to rank a set of solutions of the MOP instead of explicitly rank the attributes of the problem (this is implicitly done by the approach). Preference information is also incorporated into the survival criteria used by the EA. This is an *a priori* approach. Its main disadvantage is that this method assumes that all attributes are mutually, preferentially independent (i.e., the value function associated with attribute a_i is not affected by the values of some other attribute a_j, where $j \neq i$). That is not always the case, and despite the fact that the approach would still work when this asumption does not hold, it would certainly become more complicated. Also, since this approach uses a utility function, the problems associated with this sort of approach that were previously mentioned are applicable here (e.g., unable to handle intransitivities).

3. **Preference Relations**: Cvetković and Parmee [8, 9] proposed the use of binary preference relations that can be expressed qualitatively (i.e., using words) and are then translated to quantitative terms (i.e., weights) to narrow the search of an EA. The weights generated can be used with a simple aggregating approach or with Pareto ranking. In the second case, the weights are used to modify the definition of nondominance used by the ranking scheme of the EA. This approach has some resemblance with the Surrogate Worth Trade-Off method [21]. This is also an *a priori* approach, since the weights are assumed constant throughout the optimization process, but nothing in the approach really precludes its use in an interactive way. Since this approach relies on the use of transitive relationships, it is also incapable of handling intransitivities. The direct use of weights to estimate the importance of solutions that have been already identified as Pareto optimal has been suggested by other researchers as well (see for example [4]).

4. **Outranking**: Rekiek et al. [34] proposed the use of PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations [5]) combined with an EA. PROMETHEE methods belong to the family of outranking approaches (such as ELECTRE) introduced by Bernard Roy. These methods include two phases [5]:

   - The construction of an outranking relation on the different criteria or objectives of the problem.
   - The exploitation of this relation in order to give an answer to the multiobjective optimization problem.

   In the first phase, a valued outranking relation based on a generalization of the notion of criterion is considered: a preference index is defined and a valued outranking graph, representing the preferences of the DM, is obtained.

   The exploitation of the outranking relation is realized by considering for each action a leaving and an entering flow in the valued outranking graph: a partial preorder (PROMETHEE I) or a complete preorder (PROMETHEE II) on the set of possible actions can be proposed to the DM in order to achieve the decision problem. Rekiek et al. [34] used PROMETHEE II to order each population processed by the EA (i.e., the algorithm was used to select individuals from the population). Preferences of certain objectives over the others were expressed in the form of weights. This is an *a priori* approach. Massebeuf et al [28] used PROMETHEE II in an *a posteriori* form: an EA would generate Pareto optimal solutions from which PROMETHEE II would select a certain subset based on the preferences of the DM (expressed through preference relationships).

   Brans et al. [5] criticize outranking methods because they require too many parameters, the values of which are to be fixed by the DM and the analyst. They argue that even though some of these parameters have a real practical meaning and can, therefore, be fixed clearly, some others (such as concordance discrepancies and discrimination thresholds) playing an essential role in the procedures, only have a technical character, and their influence on the results is not always well understood. Moreover, in some outranking approaches, the notion of "degree of credibility" is rather difficult for practitioners [5].

5. **Fuzzy Logic**: Voget and Kolonko [47] used a fuzzy controller that automatically regulates the selection pressure of an EA by using a set of predefined goals that define the "desirable" behavior of the population. Although the approach was used only to keep diversity in the population, it could easily

be extended to incorporate preferences of the DM. The idea is similar to goal attainment, except that in this case membership functions are used to express goals in vague terms (i.e., it allows to handle uncertainties). A similar fuzzy controller was proposed by Lee and Esbensen [25], but in their case, on-line and off-line performance of the EA were used to guide the search. The main issue that deserves attention when extending this approach to incorporate user's preferences is the definition of the goals (the definition of membership functions is the main issue when using fuzzy logic). An *a priori* approach within these lines was proposed by Pirjanian [33]. However, in this case, fuzzy rules were used to compute weights that would narrow the search of the EMO approach.

4 Issues that deserve attention

Regardless of the approach used to handle preferences in an EA, there are several issues that should be kept in mind:

1. **Preserving dominance**: It is important to make sure that the preference relationships introduced in the EA preserve existing dominance relationships. Otherwise, the search would be biased towards undesired regions of the search space. Despite the fact that this property can be easily preserved in most cases (see for example [19]), it should be nevertheless kept in mind when proposing approaches to incorporate preferences into an EA.

2. **Transitivity**: As Cvetković and Parmee indicate [9], the use or not of intransitivities has been subject of a lot of debate in OR. It is not difficult to come up with an example in which intransitivies of preferences occur (see for example [44]). The main argument against intransitivities is that their absence considerably simplifies the modelling of the preferences (intransitivies can lead to contradictions that are much more difficult to handle). However, the issue remains open, and the French school of MCDM prefers to use outranking procedures that allow intransitivities to occur. These approaches have been combined with EAs only by a few researchers, as seen in the previous section.

3. **Scalability**: Some early researchers indicated that MUAT was sound only when few attributes were considered [52]. EMO approaches in general are victim of the "dimensionality curse" [2], because they tend to become cumbersome or even useless as we increase the number of objectives. Approaches such as preference relations, are sensitive to the number of objectives and to changes in the order of the questions asked to the DM. Cvetković and Parmee [9] empirically show that the number of questions that the DM needs to answer in their approach are, on average, much less than the theoretical upper bound, but the numbers still get very high as the amount of objectives increases (for example, for 21 objectives, 62 questions must be answered). This issue certainly deserves attention.

4. **Several decision makers**: If expressing the preferences of a single DM is difficult, the participation of several (which is not rare in the real world) raises additional questions. The main approach is to use group preferences to aggregate the preferences of each individual DM. However, the economist Kenneth J. Arrow [1] showed that apart from some very special cases, utility functions cannot be used in general to aggregate individual preferences into a group utility function. The so-called *Arrow's Impossibility Theorem* has very important consequences in MCDM. To explain how it works, let's consider the following assumptions [24]:

   - **Complete Domain**: The utility function should be able to define an ordering for the group, regardless of the individual members' ordering.
   - **Positive Association of Social and Individual Values**: If the group ordering indicates that alternative x is preferred to alternative y for a certain set of individual rankings, and (1) if there are no changes on the ordering of each individual, and (2) each individual's paired comparison against x remains unchanged or is modified in x's favor, then the group ordering must imply that x is still preferred to y.
   - **The Independence of Irrelevant Alternatives**: If an alternative is eliminated and the preference relations for the remaining alternatives remain unchanged for all the individuals, then the new group ordering should remain the same as before.
   - **Individual's Sovereignity**: For each pair of alternatives x and y, there is some set of individual orderings which causes x to be preferred to y.
   - **Nondictatorship**: It is impossible that the preferences of the group be always in agreement with the preferences of a single individual.

   So, what Arrow's Impossibility Theorem says is that any joint decision process which is reasonably democratic and respecting of individuality (following the assumptions described before) is also irrational or unreliable. It is likely to have at least one of the following problems: a) the order of the decisions affects the final outcome, b) the independence of its elements might not be respected, and c) the unanimous will of its elements might be ignored.

Some authors have shown that Arrow's conditions can be ignored in practical problems, but its mere existence has triggered a considerable amount of research in economics [36], and cannot be disregarded by EMO researchers.

5 Some potential research paths

There is a considerable amount of MCDM approaches reported in the OR literature that have not been used with EAs. Some examples are the following:

- **PROTRADE**: The motivation of this method was to be able to handle risk in the development of the objective trade-offs, and at the same time being able to accomodate the preferences of the DM in a progressive manner. In this technique, we assume that our MOP has a probabilistic objective function and probabilistic constraints [17]. According to a 12-step algorithm, an initial solution is found using a surrogate objective function, then a multiattribute utility function is formed leading to a new surrogate objective function and a new solution. The solution is checked to see if it is satisfactory to the DM. The process is repeated until a satisfactory solution is reached, as described in Goicoechea et al. [18]. The results of the multiobjective optimization provide not only levels of attainment of the objective function elements (as in the goal attainment method), but also the probabilities of reaching those levels. The technique is *interactive* and is called *probabilistic trade-off development method*, or PROTRADE, for short. One interesting aspect of this approach is that the DM actually ranks objectives in order of importance (a multi-attribute utility function is used to assist the DM in articulating his/her preferences) at the beginning of the process, and later uses pairwise comparisons to reconcile these preferences with the "real" (observed) behavior of the attributes. This allows not only an *interactive* participation of the DM, but it also allows him/her to gain knowledge about the trade-offs of the problem. The computational requirements of the technique are low and it can be easily coupled with an EA.

- **SEMOPS**: This method was proposed by Monarchi, Kisiel and Duckstein [29], and it basically involves the DM in an *interactive* fashion in the search for a satisfactory course of action. It is intended for cases in which the DM does not know how to trade off one objective versus another except in a subjective way. A surrogate objective function is used based on the goal and aspiration levels of the DM. The goal levels are conditions imposed on the DM by external forces, and the aspiration levels are attainment levels of the objectives which the DM personally desires to achieve [29]. One would say, then, that goals do not change once they are stated, but that the aspiration levels may change during the iteration process. Operationally, the *Sequential Multiobjective Problem Solving* method (SEMOPS) is a three-step procedure involving setup, iteration, and termination. Setup involves structuring a principal problem and a set of auxiliary problems with surrogate objective function. The iteration step involves cycling between an optimization phase (by the analyst), and an evaluation phase (by the DM) until a satisfactory solution is reached, if it exists. The procedure terminates when either a satisfactory solution is found, or the DM concludes that none of the nondominated solutions obtained are satisfactory and gives up in the search (he/she might re-start the search process in that case). The resulting solutions from each iteration are used in the evaluation process to assist the DM to determine the "direction of change" for the next iteration. This technique allows the DM to change his/her mind as he/she receives additional information about the trade-offs of the problem. At each cycle, the DM is only asked to provide the most important unsatisfied goal (this is similar to the lexicographic method [23]). Over time, the method generates a complete ordering (equivalent to the direct use of a utility function) using information from the achievement of the DM's goals. A ranking scheme is also possible at the beginning of the algorithm, but the preferences can be changed over time. This approach can also be easily coupled with an EA.

- **Compromise Programming**: In this method, we try to minimize a function which defines a global criterion which is a measure of how close the DM can get to an *ideal* point $\vec{f}^0$. The most common distance measure is the family of L_p-metrics [11]:

$$L_p(\bar{x}) = \left[\sum_{i=1}^{k} w_i^p \left| \frac{f_i(\vec{x}) - f_i^0}{f_{i\ max} - f_i^0} \right|^p \right]^{1/p} \tag{1}$$

where w_i are the weights, $f_{i\ max}$ is the worst value obtainable for criterion i; $f_i(\vec{x})$ is the result of implementing decision $\vec{x}$ with respect to the ith criterion. The value of p indicates the type of distance: for $p = 1$, all deviations from f_i^* are taken into account in direct proportion to their magnitudes, which corresponds to 'group utility' [51]. For $2 \le p < \infty$, the larger deviations carry greater weight in L_p; for $p = \infty$, the largest deviation is the only one taken into consideration, which leads to a purely 'individual utility' (min-max criterion [31]), in which all weighted deviations are equal.

The 'displaced ideal' technique [52] which proceeds to define an ideal point, and then proceeds to approach this ideal in an interactive manner (during the process, the *ideal* point, which will displaced closer or farther away from the feasible region), is an extension of compromise programming.

Another variation of this technique is the method suggested by Wierzbicki [50] in which the global function has a form such that it penalizes the deviations from the so-called reference objective. Any reasonable or desirable point (i.e., any preference) in the space of objectives chosen by the DM can be considered as the reference objective.

Deb [10] and Bentley [4] have suggested variations of compromise programming to bias the search of an EMO approach, but there is plenty of room for more research in this area. For example, more sophisticated articulations of preferences are possible with this approach and, if used in an *interactive* way (it is normally used as an *a priori* technique), it can allow the DM to change his/her mind over time and to adjust his/her goals (i.e., the *ideal* solutions) according to the behavior of the trade-offs initially selected. Dynamic compromise programming has been suggested in OR long ago [42], but such an approach has not been coupled with an EA so far, to the author's best knowledge.

Several other approaches can also be coupled with EAs. For example, the concept of **stochastic dominance** [12], the **conflict analysis model** [44], the **expected utility maximization** [43], **EVAMIX** [48], **NAIADE** [30], **QUALIFLEX** [32], and the **multiobjective statistical method** [20].

6 Conclusions

In this paper we have reviewed the most representative approaches to incorporate preferences into an EMO algorithm and we have discussed some of their advantages and disadvantages. We have also provided a general view of MCDM from an OR perspective, indicating some possible paths of future research.

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