Chapter 4
Incorporation of Preferences in an Evolutionary Algorithm Using an Outranking Relation:
The EvABOR Approach

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ABSTRACT

The incorporation of preferences into Evolutionary Algorithms (EA) presents some relevant advantages, namely to deal with complex real-world problems. It enables focus on the search thus avoiding the computation of irrelevant solutions from the point of view of the practical exploitation of results (thus minimizing the computational effort), and it facilitates the integration of the DM's expertise into the solution search process (thus minimizing the cognitive effort). These issues are particularly important whenever the number of conflicting objective functions and/or the number of non-dominated solutions in the population is large. In EvABOR (Evolutionary Algorithm Based on an Outranking Relation) approaches preferences are elicited from a decision maker (DM) with the aim of guiding the evolutionary process to the regions of the space more in accordance with the DM's preferences. The preferences are captured and made operational by using the technical parameters of the ELECTRE TRI method. This approach is presented and analyzed using some illustrative results of a case study of electrical networks.

DOI: 10.4018/978-1-4666-4253-9.ch004

1. INTRODUCTION

In real-world multi-objective optimization (MOO) problems, the dimension of the search space is usually very large and irregular due to the number of objective functions to be evaluated and the non-linear and/or combinatorial characteristics of the mathematical model. This leads to a prohibitive computational effort for the characterization of the non-dominated front or, at least, obtaining a well spread non-dominated solution set. Besides this, when the number of conflicting objectives to be dealt with increases, the number of non-dominated solutions also increases significantly. Despite the success of EAs in dealing with these issues (Coello et al., 2002; Deb, 2001), whenever a high number of non-dominated solutions exists the selection operator is usually less effective and the selection of solutions to the next generations becomes practically random thus making the evolutionary process slow (di Pierro et al., 2007; Garza-Fabre et al., 2009; Deb et al., 2010). This further complicates the practical exploitation of results in real-world problems when a solution (or a small set of solutions for further screening) must be chosen, due to the large number of solutions in the non-dominated front that generally occurs.

The difficult characteristics of most real-world MOO problems and the associated issues mentioned above require methodological tools to improve the efficiency and the efficacy of the solution search methods. The incorporation of preferences in EAs aimed at providing decision support in real-world problems presents two main advantages: it contributes to reducing the computational effort by focusing the search on regions of the search space that appear more interesting according to the preferences elicited from a DM, and it reduces the cognitive effort imposed on the DM by offering him/her solutions more in accordance with those expressed preferences and therefore displaying, in principle, more satisfactory trade-offs between the competing objectives (Branke & Deb, 2004; Coello, 2004). As a result, the overall efficiency of the algorithm is increased, as well as the effectiveness of the decision support process since the search process has been guided towards a final non-dominated solution (or a reduced set of the most preferred solutions) according to meaningful preference expression mechanisms having in mind a practical implementation.

An EA has been developed which incorporates and makes the preferences elicited from a DM by means of the technical parameters of the ELECTRE TRI method operational during the search process. The version of the algorithm presented in this work (EvABOR-III) is based on an outranking relation combining it with the non-dominance relation.

The motivation to this work has been presented is this section. In Section 2 some issues about the incorporation of preferences in EAs are presented and discussed. The ELECTRE TRI method is briefly described in Section 3 and the EvABOR-III approach is presented in Section 4. The main features of the algorithm are exploited in Section 5 using a case study of electrical networks. Finally, some conclusions are drawn in Section 6.

2. INCORPORATION OF PREFERENCE INFORMATION IN EAs

As in MOO mathematical programming algorithms, the incorporation of preferences into an EA can be done using one of the three main approaches classified in Horn (1997) as *a priori*, *a posteriori* and progressively (interactive).

In the *a priori* approach (Fonseca & Fleming, 1993; Deb, 1999) the preferences are elicited from the DM before the EA starts. A value (or utility) function is usually considered to transform the MOO problem into a scalar optimization problem, in which the single objective function embodies the preference expression parameters. A disadvantage usually pointed out to this approach lies in the fact that it is necessary to elicit all the preference information from the DM without knowledge of