

A Multiobjective Evolutionary Algorithm for Deriving Final Ranking from a Fuzzy Outranking Relation

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Abstract. The multiple criteria aggregation methods allow us to construct a recommendation from a set of alternatives based on the preferences of a decision maker. In some approaches, the recommendation is immediately deduced from the preferences aggregation process. When the aggregation model of preferences is based on the outranking approach, a special treatment is required, but some non-rational violations of the explicit global model of preferences could happen. In this case, the exploitation phase could then be treated as a multiobjective optimization problem. In this paper a new multiobjective evolutionary algorithm, which allows exploiting a known fuzzy outranking relation, is introduced with the purpose of constructing a recommendation for ranking problems. The performance of our algorithm is evaluated on a set of test problems. Computational results show that the multiobjective genetic algorithm-based heuristic is capable of producing high-quality recommendations.

1 Introduction

Multiple Criteria Decision Analysis provides two major approaches of constructing a global preference model from an actor involved in the decision process. The first one is the functional model, which has been widely used within the framework of multi-attribute utility theory (e.g. [10, 17, 30]). The second one is the relational model, which has its most known representation in the form of a fuzzy or crisp outranking relation (e.g. [26]). This paper is concerned with the outranking approach to Multiple Criteria Decision Aid. Methods related to this approach, including the well-known family of ELECTRE methods, are often presented as the combination of two phases: aggregation (or construction) and exploitation. The aggregation process corresponds to the operation, which transforms the marginal evaluations of separate criteria into a global outranking relation between every pair of alternatives, which is generally neither transitive nor complete. Outranking relations, in most methods, are built using a concordance-discordance principle.

It is well known that this principle does not, in general, lead to binary relations possessing “remarkable properties” such as transitivity and completeness [2]. The exploitation process deals with the outranking relation in order to clarify the decision through a partial or total preordering reflecting some of the irreducible indifferences and incomparabilities [8]. ELECTRE-III, PROMETHEE and other methods for decision aid (e.g. [25, 1, 8]) build and exploit a fuzzy outranking relation.

Let A be the set of decision alternatives or potential actions and let us consider a fuzzy outranking relation S_A^σ defined on AXA ; this means that we associate with each ordered pair $(a, b) \in AXA$ a real number $\sigma(a, b)$ ($0 \leq \sigma(a, b) \leq 1$) reflecting the degree of strength of the arguments favoring the crisp outranking aSb . The exploitation phase transforms the global information included in S_A^σ into a global ranking of the elements of A . Usually; three different ways are used [8]:

- 1: transform S_A^σ into another valued relation R that presents some interesting property needed for ranking purposes, i.e. transitivity,
- 2: determine a crisp binary relation, close to S_A^σ which presents crisp properties needed for ordering,
- 3: use a ranking method to obtain a score function.

Way 1 includes the process of finding the transitive closure or the intersection of traces. Way 3 is most commonly used in classical procedures like ELECTRE-III and PROMETHEE. But the main difficulty consists in finding reasonable ways of dealing with the intransitivities without losing too much of the contents of the outranking relation. In this sense, the methods included in ways 1 and 2 lose information coming from S_A^σ when exploiting a not so close transitive valued relation R , or a crisp binary relation with desirable properties for ranking purposes. On the other hand, the methods based in score functions do not perform well in presence of irrelevant alternatives or in case of complex graphs with many circuits. Nonrational situations could happen when the prescription is constructed. Most significant is the following: Suppose that a_i and a_j are two actions such that $\sigma(a_i, a_j) \geq \lambda$ and $\sigma(a_j, a_i) \leq \lambda - \beta$, ($\beta > 0$); if $\lambda \geq c$ and $\beta \geq t$ (c and t representing consensus and threshold levels respectively), we should accept that “ a_i outranks a_j ” ($a_i S^\lambda a_j$) and “ a_j does not outrank a_i ” ($a_j n S^\lambda a_i$); in this case the global preference model captured in outranking relation is giving a presumed preference favoring a_i . However, a score function or any other similar method could lead to a final ordering in which a_j is ranked better. ELECTRE and PROMETHEE methods do not have a way to minimize this kind of irregularity. In any case, the exploitation phase could then be treated as a multiobjective optimization problem [19]. In this way, a number of solutions can be found which provide the decision maker with insight into the characteristics of the problem before a final solution is chosen.

Evolutionary Multiobjective Optimization (EMOO) seeks to optimize the components of a vector-valued cost function. Unlike single objective optimization, the solu-