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An evolutionary approach to preference disaggregation in a MURAME-based creditworthiness problem

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ABSTRACT

In this paper, we propose to use an evolutionary methodology in order to determine the values of the parameters for implementing the MUlticriteria RAnking MEthod (MURAME). The proposed approach has been designed for dealing with a creditworthiness evaluation problem faced by an important north-eastern Italian bank needing to score and/or to rank firms (which act as alternatives) applying for a loan. The point of the matter, known as preference disaggregation, consists in finding the MURAME parameters which minimize the inconsistency between the MURAME evaluations of given alternatives and those properly revealed by the decision maker (DM). To find a numerical solution of the involved mathematical programming problem, we adopt an evolutionary algorithm based on the particle swarm optimization (PSO), which is an iterative metaheuristics grounded on swarm intelligence. The obtained results show a high consistency between the MURAME outputs produced by the PSO-based solution algorithm and the actual scoring/ranking of the applicants provided by the bank (which acts as the DM).

1. Introduction

The classical concept of preference disaggregation in multicriteria analysis regards the problem of specifying the preference model of the decision maker (DM) from a given reference set of her/his decisions, so that the evaluations of given alternatives obtained by the adopted multicriteria model is as consistent as possible with the actual evaluations of the DM.

In [1] the general philosophy of preference disaggregation is presented, together with a description of the most important results obtained in the development of disaggregation methods over the last two decades. Moreover, recently the connections between the preference disaggregation methods and the machine learning tools have been investigated in [2].

According to the various multicriteria methods, the preference disaggregation analysis can be implemented in different ways.

For instance, the UTA method,[1] one of the most representative example of the preference disaggregation approaches, aims at inferring additive value functions from a given ranking on a reference set by adopting linear programming techniques [3].

With regard to the outranking methods,[2] such as those belonging to ELECTRE and PROMETHEE families [4,5], the considered preference model is characterized by several parameters, which consist of various thresholds (preference, indifference, veto) and weights associated to each criteria. The explicit direct determination of these preferential parameters by the DM cannot be considered realistic for several real-world applications, like for example the financial ones. Indeed, the involved institutions do not generally possess the knowledge to handle such quantitative approaches and thus to explicitly provide the values of the criteria thresholds and weights.

On this subject, there is a general consensus in the literature to recognize the difficulty for the DM to determine precise values for the preferential parameters (see for instance [3,6–8]. Some possible reasons have been suggested: the DM's weak understanding of what these preferential parameters stand for; the possibility that the DM's preferences change; and the difficulties to achieve consensus in group decisions. Therefore, in all cases where the preferential parameters are not explicitly provided by the DM, the use of preference disaggregation methods may be appropriate to infer the values of the parameters themselves. In particular, much effort has been done in literature to deal with problems related to preference disaggregation in multicriteria outranking models [1]. Recently, some evolutionary algorithms have been used in special contexts. For example, [9] focuses on the multiple criteria classification method PROAFTN and uses an approach based on

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[1] In short, its purpose consists in valuating given alternatives by assessing various additive utility functions, each of them consistent with the DM's a priori preferences, which aggregate given criteria in a final single evaluation for each considered alternative.

[2] In short, in these methods a given alternative outranks another alternative if with respect to a meaningful part of given criteria the former performs at least as good the latter, and with respect to the remaining criteria its performances are still acceptable. After the determination of the outranking assessments for each pair of alternatives, these assessments are aggregate in a final single evaluation for each considered alternative.

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variable neighborhood search metaheuristic in order to disaggregate preferences. Also [10] handles classification problems, but the authors undertake their analysis in the ELECTRE TRI context. For determining the parameters, they propose to use a procedure based on an evolutionary methodology, namely the differential evolution (DE) algorithm, that allows to obtain a simultaneous estimation of all the parameters of the considered multicriteria model.

In this paper, we also use an evolutionary methodology in order to determine the values of the parameters in an outranking method. This approach has been designed in order to deal with a credit scoring problem and a credit ranking one using a large real data set provided by an important north-eastern Italian bank, the Banca Popolare di Vicenza. The main elements of novelty of our paper are: first, we deal with a preference disaggregation problem in the context of MUlticriteria RAnking MEthod (MURAME), a multicriteria methodology developed in [11] and, to our knowledge, a topic not yet explored; then, in order to solve the preference disaggregation problem formulated in the MURAME framework, we employ an evolutionary algorithm for constrained optimization, recently introduced in [12,13], based on the swarm intelligence approach particle swarm optimization (PSO) [14].[3]

It is to point out that when considering multicriteria outranking models, the search for an optimum solution of the preference disaggregation problem is generally not an easy task because of the complexity of the involved optimization problem. Even more so, focusing on MURAME, the complexity of the optimization problem increases due to the fact that this method manages both the ranking (as done in literature up to now) and also the scoring of the considered alternatives.

Before to continue, in order to avoid any possible misunderstanding, it is quite important to note what follows. In the standard financial terminology, by "credit scoring problem" one means the creditworthiness evaluation of applicants for loans.[4] This evaluation is articulated in two phases: first, scoring the applicants according to their credit risk characteristics; then, sorting them into a prefixed number of homogeneous creditworthiness groups. On the other hand, the expression "credit ranking problem" has not a so precise financial definition, although it concerns issues of the same kind, and it is less used than "credit scoring problem".

In this regard, note that we are not interested in problems of classifying debtors into different homogeneous risk groups (second phase of the credit scoring problem), as it would be usual in the application of classification techniques. Rather, recalling that we are in a multicriteria framework in which the ultimate purpose consists in producing the scoring and the ranking of a set of given alternatives, we focus our attention on the determination of cardinal scores for the applicants (what we call in this paper "credit scoring problem") and on the determination of ordinal ranks for them (what we call in this paper "credit ranking problem"). These light terminological differences with respect to the standard ones are due to the fact that we act in a strongly multidisciplinary context. Of course, the scoring and the ranking of a set of generic alternatives are strictly connected problems. In fact, once the former is solved, the solution of the latter trivially follows. But, as we explain in Section 3, in evaluating the creditworthiness of loan applicants, the scoring and the ranking of the same set of firms can provide different financial information to the DM.

Coming back to our experimental analysis, it is articulated as follows. First, we take into account the problem of scoring and ranking the firms applying for bank loans from the best to the worst according to a score computed through MURAME. As criteria we use a set of indicators supplied by the bank itself. Then, we consider a preference disaggregation problem to determine the bank's preference model. Such an approach consists in determining the MURAME parameters which minimize the inconsistency between the MURAME evaluations of the firms and the evaluations provided by the bank through a hidden internal model. In order to solve the preference disaggregation problem, we employ a recently proposed evolutionary algorithm based on PSO.

The remainder of the paper is organized as follows. In Section 2 we briefly describe MURAME. In Section 3 we present the optimization problem that has to be solved to disaggregate the preference structure in a MURAME framework with respect to a credit scoring and ranking problem. In Section 4 we describe PSO and its implementation in a preference disaggregation context again with respect to a credit scoring and ranking problem. We present the application in Section 5. This application is articulated in two steps: first we investigate both the training and predictive performance of the considered approach in relation to the real world application; then, in the second part of the application, we deal with the problem of eliciting the bank's preferences. In Section 6 we conclude with some final remarks.

[3] As we illustrate in Section 3, the preference disaggregation optimization problem is constrained. But, as known, the PSO was conceived for solving unconstrained optimization problem. So, the PSO is not directly applicable to such a constrained optimization problem. For overcoming this difficulty, we decided to use the above mentioned solution algorithm based on PSO as, under mild assumptions, it is possible to prove that the solutions it provides coincide with those of the original constrained optimization problem.

[4] As known, creditworthiness assessment of debtors and loan applicants is one of the main activities of financial institutions like banks and regulatory authorities. In short, it provides quantities for measuring credit features like the scoring or the rating of obligor quality, the probability that a debtor does not fulfill her/his obligations in accordance with agreed terms, and so on.

2. A brief description of MURAME

MURAME is a multicriteria methodology that allows to obtain a scoring and consequently a complete ranking of a set of alternatives $A = \{a_1, \ldots, a_i, \ldots, a_m\}$, on the basis of a set of given criteria $\{crit_1, \ldots, crit_j, \ldots, crit_n\}$. In credit scoring and ranking problems, as the one considered in Section 5, the alternatives are the firms applicants for a loan and the criteria are the various indicators according to which the credit risk may be evaluated.

MURAME has been proposed in [11] and combines two well known multicriteria methods, namely ELECTRE III [15] and PROMETHEE II [5] ones. Similarly to ELECTRE III, some key features of MURAME are the specification of the thresholds and the weights in the DM's preference model, the adoption of the concordance–discordance principle based on pairwise comparison of the alternatives for each criterion, and the notion of outranking. Moreover, like PROMETHEE II, MURAME aims to compute an overall score according to which a complete ranking of the alternatives is obtained.

In this section we briefly introduce the concept of indifference, preference and veto thresholds explicitly considered by the method. Then we summarize the two phases in which MURAME is structured.

How to model preferences is a crucial question in decision-making problems. We refer the reader to [16] for an overview of different types of preference structures and for a discussion of the main issues related to preference modeling. We remind that in classical preference systems there are no thresholds and weights, and that the DM, when comparing two alternatives a_i, $a_k \in A$, with i, $k = 1, \ldots, m$ and $i \neq k$, either states that one alternative is preferred to the other or shows its indifference between them.[5] There is no uncertainty in judgments.

Unlike the approaches based on classical preference structure, ELECTRE III and MURAME make both use of the concepts of indifference, preference and veto thresholds, allowing therefore to consider also the case of hesitation in which the DM is not completely sure to prefer a given alternative to another one. This leads to the concept of "weak preference" which ≪shows the uncertainty on the decision-making between indifference and strict preference≫, as stated in [17].

In the following we describe such a non-classical preference structure in which the case of hesitation is taken into account.

Denoting by p_j the preference threshold and by q_j the indifference threshold associated to the criterion $crit_j$, with $0 \le q_j \le p_j$, the following preference relations with respect to $crit_j$ are considered:

$$\begin{array}{lll} a_i\,\mathbf{P}\,a_k & (a_i \text{ is strictly preferred to } a_k) & \text{iff} \quad g_{ij} > g_{kj} + p_j \\ a_i\,\mathbf{Q}\,a_k & (a_i \text{ is weakly preferred to } a_k) & \text{iff} \quad g_{kj} + q_j \le g_{ij} \le g_{kj} + p_j\,, \\ a_i\,\mathbf{I}\,a_k & (a_i \text{ is indifferent to } a_k) & \text{iff} \quad |g_{ij} - g_{kj}| \le q_j \end{array}$$

where a_i, $a_k \in A$, g_{ij} represents the mark of the alternative a_i in relation to criterion $crit_j$ (assumed to be maximized), and $\mathbf{P}$, $\mathbf{Q}$ and $\mathbf{I}$ indicate the preference, the weak preference and the indifference relation with respect to $crit_j$, respectively. Preference models characterized by two preference thresholds can be appropriate to deal with many real-life situations where the human behavior is often imprecise and contradictory [17].

MURAME implements such a non-classical preference structure in the two following phases.

In the first phase, MURAME aims at defining an outranking relation by building for each a_i, $a_k \in A$, with $i \neq k$, an outranking (or credibility) index.

[5] For simplicity's sake, in the following of the paper we omit or ease notations of the type ≪with i, $k = 1, \ldots, m$ and $i \neq k$≫, unless it creates interpretative problems.