Decision Support Systems 72 (2015) 33–43

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Parametric evaluation of research units with respect to reference profiles

Miłosz Kadziński [a,*], Roman Słowiński [a,b]

[a] Institute of Computing Science, Poznań University of Technology, Poznań, Poland
[b] Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland

ARTICLE INFO

Article history:
Received 21 January 2014
Received in revised form 30 January 2015
Accepted 3 February 2015
Available online 8 February 2015

Keywords:
Multiple criteria decision aiding
Reference profiles
Outranking
Inference procedure
Class cardinalities
Parametric evaluation

ABSTRACT

We introduce a method that jointly considers multiple criteria sorting and ranking. The method derives from a real-world problem of parametric evaluation of research units carried out by the Polish Ministry of Science and Higher Education. It assigns the units to three classes representing different qualities of both acquired effects and activities undertook in the evaluation period. Although units placed in the same class are guaranteed the same level of funding, they are not considered indifferent in the subsequent analysis and, thus, need to be ordered from the best to the worst in each class. A proposed outranking relation compares the units pairwise and the result is exploited so as to get a ranking of the units. The ranking is transformed to class assignments based on the attained comprehensive scores and ranks. To enhance interpretability of the results, we infer two reference profiles (artificial reference research units) separating the classes so that each class accumulates units ranked not worse than the corresponding lower profile and worse than the respective upper profile. The procedure takes into account desired cardinalities of classes, i.e., shares of units that are judged as leading, average, or weak. We discuss several procedures with different ways of inferring the reference profiles and scoring the units. We also analyze robustness of the results.

© 2015 Elsevier B.V. All rights reserved.

1. Introduction

Each multiple criteria decision aiding (MCDA) method is distinguished by the type of admitted preference information, the procedures used to construct a preference model, and the techniques used to work out a final recommendation [36]. Usually, these methods are designed for dealing with either ranking and choice (e.g., [8,20,37,46]) or sorting problems (e.g., [9,19,32]). In this paper, we introduce a novel MCDA method able to deal with multiple criteria sorting and ranking considered jointly. Its development has been motivated by the specific requirements of the Polish Ministry of Science and Higher Education facing a real-world problem of the parametric evaluation of research units.

Every 3 years, the ministry is carrying out an evaluation of research units applying for the statutory activity funds. This evaluation, called categorization, is performed within groups of few tens of units having similar activity profiles, called groups of joint evaluation (GJE). The categorization consists in assigning each unit of a GJE to one of three classes corresponding to different qualities of both acquired effects and activities undertook in the evaluation period. These effects and activities are represented by four independent criteria. The assignment procedure needs to respect desired cardinalities of classes, i.e., shares of alternatives that can be judged as leading, average, or weak units (see [33,40,50]). Let us emphasize that multiple criteria evaluation of education and/or research quality of different units, universities, cities, and countries is an appealing issue that has recently motivated a wide variety of studies (see, e.g., [10,23,38]).

In our application, the research units from a GJE assigned to the same class are getting the same funding level. However, they are not considered indifferent in the subsequent analysis. It is the case since the Ministry would like to differentiate over- and underperforming units within each class, to potentially distinguish a small subset of the leading research units that merit additional funds in case they prove clearly better than the remaining units, and to provide all of them with a feedback on their effectiveness against all other units. This indicates the need for ordering the units within a given GJE from the best to the worst one.

The ranking is transformed to class assignments based on the attained comprehensive scores and ranks. To enhance the interpretability of the results, some reference profiles (artificial reference research units) separating the classes need to be constructed so that each class accumulates the units not worse than the corresponding lower profile and worse than the respective upper profile. The need for inclusion of the reference profiles in the method was indicated by the representatives of the Ministry. Moreover, within the method, the existing research units need to be considered jointly with the reference profiles. This requirement implies that one cannot first rank the existing units and only then discover the profiles dividing the ranking into pre-defined proportions so that to separate the classes. Instead, the ranking and

* Corresponding author at: Institute of Computing Science, Poznań University of Technology, Piotrowo 2, Poznań 60-965, Poland. Tel.: +48 61 665 3022.
E-mail addresses: milosz.kadzinski@cs.put.poznan.pl (M. Kadziński), roman.slowinski@cs.put.poznan.pl (R. Słowiński).

http://dx.doi.org/10.1016/j.dss.2015.02.004
0167-9236/© 2015 Elsevier B.V. All rights reserved.

class assignments need to be constructed simultaneously. Respecting desired class cardinalities imposes constraints on the ranks attained by the reference profiles.

Let us note that decision aiding in the context of traditional sorting problems with unsized classes is based on the absolute evaluation of each alternative to be assigned. Considering the alternatives' intrinsic values, e.g., all of them can be assigned to the same class while some other classes may remain empty [2]. When taking into account desired class cardinalities, this formulation of the sorting problem does not hold. Considering such requirements creates a partial dependence between the alternatives and implies the need for introducing a relative comparison approach. This can be achieved by integrating the constraints on the class cardinality into the assignment process. Even if the relative comparisons need to be performed, this does not contradict, however, the interpretability of the pre-defined and ordered decision classes. First, it is the particular decision aiding context that provides constraints on the size of the classes. Second, the definition of decision classes in sorting problems is first and foremost related to the way in which alternatives assigned to each class would be further processed. This treatment needs to be the same for all alternatives assigned to the same class, which holds for our problem in the phase related to granting the funds.

When comparing the alternatives in a pairwise fashion with respect to their performances on all criteria, we wish to avoid compensatory aggregation of scientific achievements measured on different scales. Thus, each criterion is characterized by the following parameters: its weight, expressing its relative importance with respect to other criteria, as well as by its indifference and preference thresholds corresponding to the differences between performances of units compared pairwise on this criterion that are negligible or significant, respectively. In other words, the indifference and preference thresholds permit to discriminate between indifference, weak preference, and strict preference in a pairwise comparison of units on this criterion. The comparison of a pair of units on all criteria is then summarized by a valued outranking relation defined in a specific way.

The rank of each unit (including existing research units and reference profiles) and, thus, the corresponding assignment is determined by its comprehensive score resulting from exploiting the outranking relation on the set of all units using the net flow score (NFS) procedure (see, e.g., [4,45]). Generally speaking, this procedure assigns to each alternative $a \in A$ a "measure of its desirability" by aggregating arguments which are in favor of its strength and weakness. We discuss different scoring procedures, which may be divided into two groups. On the one hand, a unit may get a score of one when it outranks another unit in the pairwise comparison, or no score, otherwise. Alternatively, it may be assigned a score between zero and one, corresponding to the degree of credibility of the outranking. In any case, a comprehensive score of each unit is obtained as the sum of scores corresponding to the outranking of this unit over all the others. The comprehensive score thus represents the relative power of a unit derived from its pairwise comparisons with all remaining units. Since the existing research units and reference profiles are considered jointly in the ranking procedure, let us emphasize that each existing research unit (reference profile) is compared against all reference profiles (existing units) and the remaining existing units (reference profiles).

Let us remind that reference profiles have been already used in different contexts in MCDA. For example, in the ELECTRE Tri sorting method (see, e.g., [48,14]), the class profiles are interpreted as bounds between the classes. Traditionally, these profiles had to be provided directly by the decision maker (DM), but various elicitation techniques for admitting indirect preference information have been proposed. In particular, Mousseau and Słowiński [41] suggest to infer the ELECTRE Tri preference model parameters from the assignment examples given by the DM, using non-linear optimization. Further, Ngo The and Mousseau [42] use mixed-integer linear programming (MILP) to infer these class profiles, considering other parameters as fixed. Moreover, Cailloux et al. [7] propose elicitation procedure to infer class profiles from assignment examples provided by multiple DMs. On the other hand, in ELECTRE Tri-C [3] and ELECTRE Tri-rC [35], the alternatives are not compared against the class boundaries but rather with characteristic profiles that contain the representative description of each class. Finally, Rolland [43] introduce decision rules using reference profiles (levels) for multiple criteria ranking. The results show that employing reference levels overcomes the usual weakness of the ranking methods based on pairwise comparisons, which is the sensitivity of the ranking to the change of the considered set of alternatives. The disaggregation approach for inferring these profiles in an indirect way is discussed by Zheng [49].

The organization of the paper is as follows. In the next section, we introduce notation that will be used along the paper. The decision aiding process with the proposed method is described in Section 3. The details of mathematical preference modeling underlying the introduced approach are outlined in Sections 4 and 5. They concern the definition of the employed model, procedures for deriving recommendation with the use of reference profiles selected according to some pre-defined rules, as well as algorithms for analyzing robustness of the suggested recommendation. The use of the presented method is illustrated on a problem of parametric evaluation of research units in Poland (see Section 6). Although the study consists in assigning the units to three classes, when introducing the method, we discuss a more general case with any number of classes greater than one. The last section concludes the paper.

2. Notation and basic concepts

We shall use the following notation:

- $A = \{a_1, a_2, \ldots, a_i, \ldots, a_n\}$—a finite set of n alternatives (research units);
- $G = \{g_1, g_2, \ldots, g_j, \ldots, g_m\}$—a finite set of m evaluation criteria, $g_j : A \to \mathbb{R}$ for all $j \in J = \{1, 2, \ldots, m\}$;
- $X_j = \{x_j \in \mathbb{R} : g_j(a_i) = x_j, a_i \in A\}$—the set of all different evaluations on g_j, $j \in J$; we assume, without loss of generality, that the greater $g_j(a_i)$, the better alternative a_i on criterion g_j, for all $j \in J$;
- $x_j^1, x_j^2, \ldots, x_j^{n_j(A)}$—the ordered values of X_j, $x_j^k < x_j^{k+1}$, $k = 1, \ldots, n_j(A) - 1$, where $n_j(A) = |X_j|$ and $n_j(A) \le n$;
- C_h, $h = 1, \ldots, p$—pre-defined preference ordered classes such that C_{h+1} is preferred to C_h, $h = 1, \ldots, p - 1$; $H = \{1, 2, \ldots, p\}$;
- $R = \{r_1, \ldots, r_{p-1}\}$—reference profiles separating the classes; they are unknown a priori and need to be constructed according to some rules;
- $B = A \cup R$—a set of existing alternatives and reference profiles which are all treated equally in the ranking procedure.

Outranking relation is a preference model intended to represent preferences of a DM on a set of alternatives by a pairwise comparison function:

$$s(g_1(a), g_1(b), \ldots, g_m(a), g_m(b)) : \mathbb{R}^{2m} \to \mathbb{R}, \quad \text{for } a, b \in A.$$

In this study, we adopt the procedure for construction of the outranking relation used in the PROMETHEE method (see, e.g., [5,6,17,18]). PROMETHEE and its further extensions have proven to be well suited for real-world multiple criteria problems in various areas such as, e.g., stock trading [1], equipment selection [47], bank rating [15], infrastructure assessment [21], energy market [24], outsourcing in information systems [11], or climate protection [39]. In this method, for each criterion g_j, $j = 1, \ldots, m$, one considers a preference function $\pi_j(a, b)$, such that for all $a, b \in B$:

$$\pi_j(a, b) = F_j\left(d_j(a, b)\right) \in [0, 1],$$

where $d_j(a, b) = g_j(a) - g_j(b)$.

Download English Version:

https://daneshyari.com/en/article/554711

Download Persian Version:

https://daneshyari.com/article/554711

Daneshyari.com