Expert Systems with Applications 41 (2014) 6718–6727

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Integrated evidential reasoning approach in the presence of cardinal and ordinal preferences and its applications in software selection

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ARTICLE INFO

Article history:
Available online 15 May 2014

Keywords:
Decision analysis
Multiple-attribute decision making
Evidential reasoning approach
Integrated decision
Cardinal and ordinal preferences

ABSTRACT

A combination of cardinal and ordinal preferences in multiple-attribute decision making (MADM) demonstrates more reliability and flexibility compared with sole cardinal or ordinal preferences derived from a decision maker. This situation occurs particularly when the knowledge and experience of the decision maker, as well as the data regarding specific alternatives on certain attributes, are insufficient or incomplete. This paper proposes an integrated evidential reasoning (IER) approach to analyze uncertain MADM problems in the presence of cardinal and ordinal preferences. The decision maker provides complete or incomplete cardinal and ordinal preferences of each alternative on each attribute. Ordinal preferences are expressed as unknown distributed assessment vectors and integrated with cardinal preferences to form aggregated preferences of alternatives. Three optimization models considering cardinal and ordinal preferences are constructed to determine the minimum and maximum minimal satisfaction of alternatives, simultaneous maximum minimal satisfaction of alternatives, and simultaneous minimum minimal satisfaction of alternatives. The minimax regret rule, the maximax rule, and the maximin rule are employed respectively in the three models to generate three kinds of value functions of alternatives, which are aggregated to find solutions. The attribute weights in the three models can be precise or imprecise (i.e., characterized by six types of constraints). The IER approach is used to select the optimum software for product lifecycle management of a famous Chinese automobile manufacturing enterprise.

1. Introduction

Considering multiple criteria (attributes) in decision making resolves nearly all decision problems (Malakooti, 2000). Multiple attribute decision making (MADM) is a mainstream approach to evaluating and comparing alternatives. MADM problems are divided into three categories according to the preferences (assessments) of a decision maker, namely, problems with cardinal assessments, problems with ordinal assessments, and problems with cardinal and ordinal assessments. Numerous attempts at analyzing the three categories of MADM problems have been reported.

A number of methods have been developed to solve both certain and uncertain MADM problems with cardinal assessments. Multi-attribute utility theory, a popular method often substituted by multi-attribute value theory, is usually employed to solve specific MADM problems (Duarte & Reis, 2006). Other methods have been proposed to solve uncertain MADM problems based on different types of uncertain expressions such as interval numbers (Tsaur, 2011), fuzzy numbers (Chen & Li, 2010; He et al., 2014; Li & Wan, 2014; Nguyen, Zawiah Md Dawal, Nukman, & Aoyama, 2014; Senthil, Srirangacharyulu, & Ramesh, 2014), interval-valued fuzzy numbers (Chen & Tsao, 2008), fuzzy preference relations (Dash Wu, 2009), hesitant fuzzy information (Rodríguez, Martínez, & Herrera, 2012; Zhao, Lin, & Wei, 2014), linguistic preference relations (Chang, Hsu, Wang, & Wu, 2012), probability distributions (Lourenzutti & Krohling, 2014), and grey numbers (Li, Yamaguchi, & Nagai, 2007). These uncertain expressions on each attribute are combined to form collective assessments of alternatives, which are used to compare the alternatives.

Ordinal assessments are less complex and easier to derive from a decision maker than cardinal assessments. Ordinal assessments may be used to generate a partial rather than complete rank-order of alternatives (Moshkovich, Mechitov, & Olson, 2002). A number of methods have been proposed to aid in decision making using

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http://dx.doi.org/10.1016/j.eswa.2014.04.046
0957-4174/

ordinal assessments. In these methods, the ordinal assessments on each attribute are generally aggregated as joint ordinal assessments of alternatives to implement comparison of alternatives (e.g., Greco, Mousseau, & Słowiński, 2008; Moshkovich et al., 2002), which is similar to the case of cardinal assessments. Specially, robust ordinal regression was combined with stochastic multicriteria acceptability analysis to form an outranking method for multiple criteria sorting problems (Kadziński & Tervonen, 2013), and a preference programming model was developed to deal with incomplete ordinal information about both alternatives and attribute weights (Punkka & Salo, 2013) in MADM.

Solving MADM problems in the presence of cardinal and ordinal assessments has been attempted. On one hand, a decision maker provides reliable cardinal assessments based on his or her knowledge and experience, as well as data regarding alternatives, and avoids arbitrary cardinal assessments. On the other hand, the decision maker provides ordinal assessments, if possible and reasonable, when providing cardinal assessments on a number of attributes. A combination of cardinal and ordinal assessments yields more reliable and flexible results compared with the sole application of either assessment. Data envelopment analysis (DEA) is an approach to evaluating efficiencies of decision making units based on a set of cardinal output and input factors (Charnes, Cooper, & Rhodes, 1978). The approach was extended as imprecise DEA models to consider cardinal and ordinal data, that is, inputs and outputs. Bounded and ratio bounded data were also considered in the models (Cook, Kress, & Seiford, 1996; Cooper, Park, & Yu, 1999; Kim, Park, & Park, 1999; Saen, 2007). In addition, weight restrictions and nondiscretionary factors were considered in other extended DEA models (Saen, 2009; Sarkis & Talluri, 1999), in which the model of Saen was questioned by Azizi (2013). However, outputs and inputs rather than decision alternatives are ranked as complete ordinal constraints, and the imprecision of outputs and inputs is only expressed by interval numbers in these models. Cardinal and ordinal data in some models (Cook et al., 1996; Sarkis & Talluri, 1999) are not expressed by a uniform style. Ordinal relations between imprecise data are not considered in these models.

Other attempts have been made to consider cardinal and ordinal assessments, except for imprecise DEA models. Ordinal information was interpreted as random variables following an unknown probability distribution function to implement stochastic dominance in the method suggested by Hinloopen, Nijkamp, and Rietveld (2004). Inspired by the idea of stochastic dominance, Yang and Wang (2013) developed a linguistic decision aiding technique called multiple criteria semantic dominance (MCSD), which can analyze risky decision making problems by using ordinal information from linguistic assessments and preferences on value functions of linguistic terms. Cardinal and ordinal evaluations were unified as interval-valued fuzzy (IVF) data in an IVF permutation method developed by Chen and Wang (2009). Under Simon's framework of bounded rationality, a satisfying modeling approach was proposed to reach a consensus between inconsistent cardinal and ordinal assessments of alternatives, both of which are provided by a decision maker (González-Pachón, Diaz-Balteiro, & Romero, 2014). However, the coexistence of cardinal and ordinal assessments on an attribute is not allowed in the methods of Hinloopen, Nijkamp, & Rietveld, and Chen & Wang. Value styles on cardinal and ordinal attributes in the method of Hinloopen, Nijkamp, & Rietveld are not unified. Preferences on value functions of linguistic terms rather than cardinal assessments coexist with ordinal information of alternatives on each attribute in the method of Yang & Wang. The method of González-Pachón, Diaz-Balteiro, & Romero is not designed for MADM.

To avoid the deficiencies in the above methods of analyzing MADM problems with cardinal and ordinal assessments and find flexible and reliable solutions to the problems, this paper develops an integrated evidential reasoning (IER) approach in the presence of cardinal and ordinal assessments based on an evidential reasoning (ER) approach (Chin, Wang, Poon, & Yang, 2009; Fu, Huhns, & Yang, 2014; Fu & Yang, 2010, 2011, 2012; Guo, Yang, Chin, & Wang, 2007; Wang, Yang, Xu, & Chin, 2006; Yang, 2001; Yang, Wang, Xu, & Chin, 2006). Although the ER approach recently has combined with other methods, such as intuitionistic fuzzy MADM method (Dymova & Sevastjanov, 2014; Wang, Nie, Zhang, & Chen, 2013) and DEA model (Yang, Yang, Liu, & Li, 2013), the generated methods still cannot handle cardinal and ordinal assessments simultaneously. In the IER approach, distributed assessment vectors (see Section 2) and pairwise comparison relations of alternatives on an attribute express cardinal and ordinal assessments, respectively. This relation reflects no uncertain cardinal information, unlike the ordinal relations of outputs and inputs based on a five-point scale in the model by Sarkis and Talluri (1999). Attributes are not simply divided into cardinal and ordinal attributes. The decision maker can provide cardinal assessments for a number of alternatives and pairwise comparison relations of other alternatives on an attribute. Cardinal assessments of all alternatives and pairwise comparison relations of all or a number of alternatives on the attribute are also allowed. In general, both cardinal and ordinal assessments can be complete or incomplete.

Whereas the decision maker provides cardinal assessments as distributed assessment vectors, completely unknown distributed assessment vectors denote unprovided cardinal assessments, which may be missing or considered ordinal assessments. Provided and unprovided assessments are combined using the ER analytical algorithm (Wang, Yang, & Xu, 2006) to form aggregated assessments of alternatives and then construct the minimal satisfaction of alternatives (see Section 4) using the minimax regret approach (MRA) (Wang et al., 2006). Three optimization models are constructed based on the minimal satisfaction of alternatives according to the minimax regret rule, the maximax rule, and the maximin rule (see Section 3.2). Complete and incomplete ordinal assessments of alternatives on some attributes are quantified using the minimal satisfaction of alternatives and incorporated into the three models as constraints. The first model generates the minimum and maximum minimal satisfaction of each alternative. The second and third models generate the simultaneous maximum and minimum minimal satisfaction of each alternative, respectively. Three kinds of value functions of alternatives resulting from the three models are integrated to generate solutions. Attribute weights can be precise or imprecise. Imprecise attribute weights are characterized by six types of constraints (see Section 3.4).

Product lifecycle management (PLM) is generally regarded as a strategic business approach to support collaborative creation, management, dissemination, and use of enterprise data in the entire product lifecycle (Vezzetti, Moos, & Kretli, 2011). PLM systems manage information throughout all stages of the product lifecycle, from early stages of development process to disposal (Sudarsan, Fenves, Sriram, & Wang, 2005). Key functions of PLM systems usually comprise the followings: (i) document and content management, (ii) engineering change process management, (iii) collaborative product design, (iv) bill of materials management, (v) supply chain integration, (vi) part classification management, (vii) product service management, (viii) program and project management, (ix) product portfolio management and analysis, (x) data authoring and analysis, and (xi) digital manufacturing (Chiang & Trappey, 2007). PLM is also considered to construct a decision model for the refinement and reconstruction of the supply chain (Aitken, Childerhouse, & Towill, 2003). In general, PLM provides a framework to adopt and integrate new business and technique models to manage information in the entire product lifecycle efficiently and coherently and thus, improve product and service quality, efficiency, sustainability, and competence. Global