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An interval difference based evidential reasoning approach with unknown attribute weights and utilities of assessment grades ☆

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ABSTRACT

In this paper, the concept of interval difference is firstly defined. Then, an interval difference based evidential reasoning approach is proposed to analyze multiple attribute decision making problems in three situations, including (1) unknown attribute weights and utilities of assessment grades, (2) unknown attribute weights, and (3) unknown utilities of assessment grades. Three optimization models are constructed to identify potentially optimal alternatives in the three situations. For each potentially optimal alternative, three pairs of optimization problems are constructed to generate the optimized intervals of attribute weights and utilities of assessment grades or one of them. By using the optimized intervals, the interval difference of potentially optimal alternatives is calculated and used to generate their rank-order. This process is repeated until all alternatives are identified as potentially optimal alternatives. A complete rank-order of all alternatives is then generated. The performance of six executive cars is assessed using the proposed approach to demonstrate its applicability and validity.

1. Introduction

The 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 & Singh, 1994; Yang, Wang, Xu, & Chin, 2006; Yang & Xu, 2002a, 2002b) has been under development since 1994 with a view to modeling and solving multiple attribute decision making (MADM) problems. Assessments of alternatives on each attribute are aggregated after being weighted by attribute weights in the ER approach to make a comparison among alternatives, similar to other MADM methods (e.g., Almomani, Aladeemy, Abdelhadi, & Mumani, 2013; Aouam, Chang, & Lee, 2003; Fan & Feng, 2009; Fan, Hu, & Xiao, 2004; Fan, Zhang, Chen, & Liu, 2013; Kuo, Yang, & Huang, 2008; Wei, 2012; Xu & Yeh, 2012). Thus, attribute weights can significantly influence solutions generated by the ER approach.

In literature, three categories of methods have been proposed to determine attribute weights: subjective, objective, and hybrid methods (Wang & Luo, 2010). Subjective methods use the preferences of a decision maker to determine attribute weights (e.g., Deng, Xu, & Yang, 2004; Figueira & Roy, 2002; Shirland, Jesse, Thompson, & Iacovou, 2003; Wang, 2005; Zhang, Chen, & Chong, 2004). Objective methods use a decision matrix to determine attribute weights (e.g., Chen & Li, 2010, 2011; Deng, Yeh, & Willis, 2000; Wang, 1998; Wang & Luo, 2010; Xu & Xia, 2012). Hybrid methods combine the preferences of a decision maker with a decision matrix to determine attribute weights (e.g., Fan, Ma, & Zhang, 2002; Ma, Fan, & Huang, 1999; Pei, 2013; Rao, Patel, & Parnichkun, 2011; Wang & Parkan, 2006).

Existing objective and hybrid methods rarely handle different risk preferences of experts. However, the ER approach characterizes the risk preferences of experts as the utilities of assessment grades. Although it is feasible to use subjective methods to determine precise attribute weights, different methods may elicit different weights. There is no single method that can generate more accurate weights than others in all situations (Deng et al., 2000). More importantly, a decision maker may feel more comfortable giving interval-valued attribute weights due to lack of knowledge, information, and data about the attributes (Lan, Hu, Ye, & Sun, 2012).

Utilities of assessment grades in the ER approach can be estimated by the indifference-based and choice-based methods (Daniels & Keller, 1992), and the maximum entropy method based

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on an analogy between probability and utility (Abbas, 2006). A decision maker may not have sufficient time or relevant information, knowledge, and data to assign precise utilities to assessment grades (Abbas, 2006). There may also be possible changes of risk attitude of the decision maker as time passes. Intervals of utilities of assessment grades may be a better choice in these situations than single utility values.

In this paper, an interval difference based ER (IDER) approach is proposed to analyze MADM problems in the following three situations: (1) unknown attribute weighs and utilities of assessment grades; (2) unknown attribute weights and precise utilities of assessment grades; and (3) unknown utilities of assessment grades and precise attribute weights. The second and the third situations are two special cases of the first situation. Three optimization models are constructed to identify potentially optimal alternatives in the three situations using the analytical ER algorithm (Wang, Yang, & Xu, 2006) and the minimax regret approach (MRA) (Wang, Yang, Xu, Chin, 2006). Then, for each potentially optimal alternative, three pairs of optimization problems are constructed to generate the optimized intervals of attribute weights and utilities of assessment grades.

The interval difference of each potentially optimal alternative in the three situations is defined by means of the optimized intervals of attribute weights and utilities of assessment grades, or one of them. This produces a rank-order of the potentially optimal alternatives.

Thus, a complete rank-order of all alternatives can be obtained after several iterations of identifying and comparing potentially optimal alternatives. The problems addressed in this paper and the approach applied to analyzing the problems are summarized in Fig. 1.

The rest of this paper is organized as follows. Section 2 presents the preliminaries relevant to the IDER approach, which is described fully in Section 3. Section 4 conducts an investigation into the performance assessment of six executive cars to demonstrate the applicability and validity of the IDER approach. Section 5 discusses the influence of constraints on utilities of assessment grades over solutions in the IDER approach. Section 6 finally concludes this paper.

2. Preliminaries

This section introduces the preliminaries relevant to the IDER approach, including the ER distributed modeling framework for MADM problems and the notations that will be used in Sections 3–5.

2.1. ER distributed modeling framework for MADM problems

Suppose there are M alternatives denoted by $a_l(l=1,\ldots,M)$ and L attributes denoted by $e_i(i=1,\ldots,L)$ in a MADM problem. The relative weights of the L attributes are denoted by $w=(w_1,w_2,\ldots,w_L)$ such that $0\leqslant w_i\leqslant 1$ and $\sum_{i=1}^{L}w_i=1$.

Assume that $\Omega=\{H_1,H_2,\ldots,H_N\}$ denotes a set of assessment grades. The M alternatives are assessed on the L attributes using $H_n(n=1,\ldots,N)$. Let $B(e_i(a_l))=\{(H_n,\beta_{n,i}(a_l)),\ n=1,\ldots,N\}$ denote a distributed assessment vector of an alternative a_l for an attribute e_i to a grade H_n with a belief degree of $\beta_{n,i}(a_l)$ such that $\beta_{n,i}(a_l)\geqslant 0$, $\sum_{n=1}^{N}\beta_{n,i}(a_l)\leqslant 1$, and $\sum_{n=1}^{N}\beta_{n,i}(a_l)+\beta_{\Omega,i}(a_l)=1$. Here, $\beta_{\Omega,i}(a_l)$ denotes the uncertainty of $B(e_i(a_l))$, also called the degree of global ignorance. If $\beta_{\Omega,i}(a_l)=0$, the assessment is complete; otherwise, it is incomplete.

Suppose $u(H_n)$ $(n=1,\ldots,N)$ denotes utilities of assessment grades. The assessments $B(e_i(a_l))$ $(i=1,\ldots,L,\ l=1,\ldots,M)$ weighted by w are combined using the analytical ER algorithm (Wang, Yang, Xu, 2006) to generate the aggregated assessment $B(y(a_l))=\{(H_n,\ \beta_n(a_l)),\ n=1,\ldots,N\}$ $(l=1,\ldots,M)$ such that $\sum_{n=1}^{N}\beta_n(a_l)+\beta_{\Omega}(a_l)=1$. Here, a belief degree of $\beta_n(a_l)$ is assigned to a grade H_n and the uncertainty of $B(y(a_l))$ is denoted by $\beta_{\Omega}(a_l)$. The $B(y(a_l))$ is then combined with $u(H_n)$ $(n=1,\ldots,N)$ to form expected utilities of each alternative. They can be used to select an optimal alternative or obtain a rank-order of the M alternatives as a solution to the MADM problem by means of the MRA.

Suppose the quietness of an engine is assessed using $\Omega=\{H_n,n=1,\ldots,6\}=\{Worst,\ Poor,\ Average,\ Good,\ Excellent,\ Top\}$. When an expert states that he is 50% sure the engine is good and 30% sure it is excellent, his assessment can be expressed as $\{(H_4,0.5),(H_5,0.3)\}$. The assessment is incomplete and the remaining belief 0.2 means the expert is 20% uncertain about the engine; that is, the expert is not sure to which grade (or grades) the belief 0.2 should be assigned in the assessment.

More examples about complete and incomplete assessments can be seen in Yang (2001).

2.2. Notations

The notations that will be used in Sections 3–5 are presented as follows:

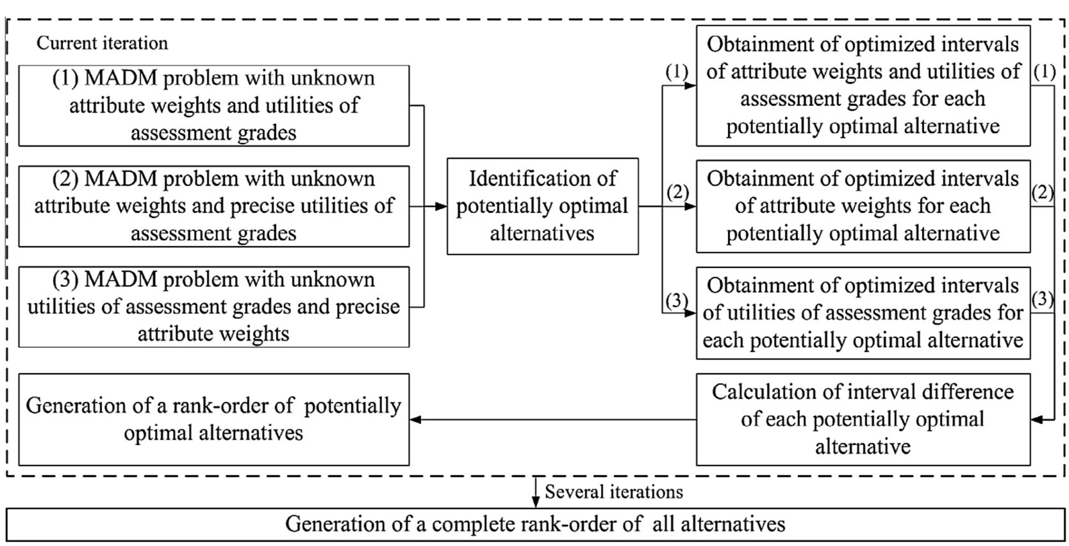

Fig. 1. Problems and the approach applied to analyzing the problems.