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Decision Support

Environmental impact assessment using the evidential reasoning approach ☆

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Abstract

Environmental impact assessment (EIA) problems are often characterised by a large number of identified environmental factors that are qualitative in nature and can only be assessed on the basis of human judgments, which inevitably involve various types of uncertainties such as ignorance and fuzziness. So, EIA problems need to be modelled and analysed using methods that can handle uncertainties. The evidential reasoning (ER) approach provides such a modelling framework and analysis method. In this paper the ER approach will be applied to conduct EIA analysis for the first time. The environmental impact consequences are characterized by a set of assessment grades that are assumed to be collectively exhaustive and mutually exclusive. All assessment information, quantitative or qualitative, complete or incomplete, and precise or imprecise, is modelled using a unified framework of a belief structure. The original ER approach with a recursive ER algorithm will be introduced and a new analytical ER algorithm will be investigated which provides a means for using the ER approach in decision situations where an explicit ER aggregation function is needed such as in optimisation problems. The ER approach will be used to aggregate multiple environmental factors, resulting in an aggregated distributed assessment for each alternative policy. A numerical example and its modified version are studied to illustrate the detailed implementation process of the ER approach and demonstrate its potential applications in EIA.

Keywords: Environmental impact assessment; Multiple criteria decision analysis; Uncertainty modelling; The evidential reasoning approach; Utility

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1. Introduction

Environmental impact assessment (EIA) is concerned with the systematic identification and evaluation of the potential impacts (effects), both beneficial and harmful, of proposed projects, plans, programmes or legislative actions related to the physical–chemical, biological, cultural, and socio-economic components of the total environment. The primary purpose of the EIA process is to encourage the consideration of the environment in planning and decision making and to ultimately arrive at actions which are more environmentally compatible (Canter, 1996).

Since its introduction in the United States in the late 1960s, EIA has been adopted and implemented by many developed and developing countries (Sowman et al., 1995; Leu et al., 1996; Bojórquez-Tapia and García, 1998; Barker and Wood, 1999; Chen et al., 1999; Hopkinson et al., 2000; Weston, 2000; Jay and Handley, 2001; Steinemann, 2001; Appiah-Opoku, 2001; Tran et al., 2002; Henne et al., 2002). Numerous EIA methodologies have been developed such as interaction matrices, networks, weighting-scaling (or -ranking or -rating) checklists (Canter, 1996), multicriteria/multiattribute decision analysis (MCDA/MADA) (Parkin, 1992; Marttunen and Hämäläinen, 1995; McDaniels, 1996; Hokkanen and Salminen, 1997a,b,c; Hokkanen et al., 1998, 1999; Kim et al., 1998; Rogers and Bruen, 1998; Salminen et al., 1998; Wang and Yang, 1998; Lahdelma et al., 2000, 2002; Janssen, 2001; Kwak et al., 2002; Pun et al., 2003), input–output analysis (Lenzen et al., 2003), life cycle assessment (LCA) (Tukker, 2000; Brentrup et al., 2004a,b), AHP or fuzzy AHP (Ramanathan, 2001; Goyal and Deshpande, 2001; Tran et al., 2002; Sólnes, 2003), fuzzy sets approaches (Munda et al., 1994; Parashar et al., 1997; Enea and Salemi, 2001; Hui et al., 2002), Rapid Impact Assessment Matrix (RIAM) (Pastakia, 1998; Hagebro, 1998; Pastakia and Jensen, 1998; Pastakia and Bay, 1998), and data envelopment analysis (DEA) (Wei et al., 2004).

Since EIA problems are often characterized by a large number of identified environmental factors, most of which are qualitative in nature and can only be assessed on the basis of human judgments, EIA methods must be able to deal with various uncertainties that are inevitably involved in subjective judgments due to human being's inability to provide accurate judgments, or the lack of information, or the vagueness of meanings about environmental factors and their assessments. There is a clear need to develop methods which can be used to handle various uncertainties such as ignorance and fuzziness simultaneously. This paper is dedicated to exploring an EIA method based on the evidential reasoning (ER) approach which is developed on the basis of decision theory and the Dempster–Shafer (D–S) theory of evidence (Dempster, 1967; Shafer, 1976) and can be used to model various uncertainties in EIA process.

The rest of the paper is organized as follows. Section 2 gives a brief description of the Dempter–Shafer theory of evidence, which is the basis of the ER approach. In Section 3, the ER approach for EIA will be fully investigated, including the identification of environmental factors, the ER distributed modelling framework, the description of the recursive ER algorithm, the development of a new analytical ER algorithm, and the utility interval based ER ranking method. Section 4 presents the examination of an example and its modified version using both complete and incomplete assessment information to show the detailed implementation process of the ER approach and its potential applications in EIA. The paper is concluded in Section 5 with a discussion about the features of the ER approach. The derivation of the analytical ER algorithm is provided in Appendix A.

2. The Dempster–Shafer theory of evidence

The evidence theory was first developed by Dempster (1967) in the 1960s. His work was later extended and refined by Shafer (1976) in the 1970s. Therefore, this theory is also called the Dempster–Shafer theory of evidence, or the D–S theory for short. The theory is related to the Bayesian probability theory in the sense that they both deal with subjective beliefs. However, according to Shafer (1976), the evidence theory includes the Bayesian probability theory as a special case, the biggest difference being in that the former is able to deal with ignorance, while the latter is not and its subjective beliefs are also required to obey the probability rules.

So far, the D–S theory has found wide applications in many areas such as artificial intelligence (AI), expert systems, pattern recognition, information fusion, database and knowledge discovery, multiple attribute decision analysis (MADA), audit risk assessment etc. (Ishizuka et al., 1982; Goicoechea, 1988; Korvin and Shipley, 1993; Yager, 1992, 2002, 2004; Yang and Singh, 1994; Yang and Sen, 1994a,b, 1997; Anand et al., 1996; Bauer, 1997; Chen, 1997; Guan and Bell, 1997; Luo and Caselton, 1997; McClean and Scotney, 1997; Cai et al., 2000; Benferhat et al., 2000; Denoeux, 1995, 1997, 1999, 2000a,b; Denoeux and Zouhal, 2001; Hullermeier, 2001; Bryson and Mobolurin, 1999; Beynon et al., 2000, 2001; Beynon, 2002a,b, 2005a,b; Binaghi et al., 2000; Sönmez et al., 2001, 2002; Jones et al., 2002; Wang et al., 1995, 1996; Wallery, 1996; Wang, 1997; Wang and Yang, 2001; Yang, 2001; Yang et al., 2001a,b, in press-a, in press-b; Yang and Xu, 1998, 2002a,b; Siow et al., 2001; Davis and Hall, 2003; Ji and Marefat, 2003; Xu and Yang, 2003; Xu et al., in press; Sohn and Lee, 2003; Osei-Bryson, 2003; Liu et al., 2004a,b; Soundappan et al., 2004; Srivastava and Shafer, 1992; Srivastava, 1995, 1997; Srivastava and Liu, 2003; Srivastava and Lu, 2002; Srivastava and Mock, 2000, 2002; Cobb and Shenon, 2003).

Let $\Theta = \{H_1, \ldots, H_N\}$ be a collectively exhaustive and mutually exclusive set of hypotheses or propositions, which is called the frame of discernment. A basic probability assignment (bpa) is a function $m: 2^{\Theta} \to [0, 1]$, which is called a mass function, satisfying

$$m(\Phi) = 0 \quad \text{and} \quad \sum_{A \subseteq \Theta} m(A) = 1, \tag{1}$$

where Φ is an empty set, A is any subset of Θ, and 2^{Θ} is the power set of Θ, which consists of all the subsets of Θ, i.e.

$$2^{\Theta} = \{\Phi, \{H_1\}, \ldots, \{H_N\}, \{H_1, H_2\}, \ldots, \{H_1, H_N\}, \ldots, \Theta\}. \tag{2}$$

The assigned probability (also called probability mass) $m(A)$ measures the belief exactly assigned to A and represents how strongly the evidence supports A. All the assigned probabilities sum to unity and there is no belief in the empty set (Φ). The assigned probability to Θ, i.e. $m(\Theta)$, is called the degree of ignorance. Each subset $A \subseteq \Theta$ such that $m(A) > 0$ is called a focal element of m. All the related focal elements are collectively called the body of evidence.

Associated with each bpa is the belief measure, Bel, and the plausibility measure, Pl, which are both functions: $2^{\Theta} \to [0,1]$, defined by the following equations, respectively:

$$\mathrm{Bel}(A) = \sum_{B \subseteq A} m(B), \tag{3}$$

$$\mathrm{Pl}(A) = \sum_{A \cap B \neq \Phi} m(B), \tag{4}$$

where A and B are subsets of Θ. Bel(A) represents the exact support to A, i.e. the belief of the hypothesis A being true; Pl(A) represents the possible support to A, i.e. the total amount of belief that could be potentially placed in A. $[\mathrm{Bel}(A), \mathrm{Pl}(A)]$ constitutes the interval of support to A and can be seen as the lower and upper bounds of the probability to which A is supported. The two functions can be connected by the equation

$$\mathrm{Pl}(A) = 1 - \mathrm{Bel}(\overline{A}), \tag{5}$$

where $\overline{A}$ denotes the complement of A. The difference between the belief and the plausibility of a set A describes the ignorance of the assessment for the set A (Shafer, 1976).

Since $m(A)$, Bel(A) and Pl(A) are in one-to-one correspondence, they can be seen as three facets of the same piece of information. There are several other functions such as commonality function, doubt function, and so on, which can also be used to represent evidence. They all represent the same information and provide flexibility to match a variety of reasoning applications.

The core of the evidence theory is the Dempster's rule of combination by which the evidence from different sources is combined or aggregated. The rule assumes that the information sources are independent and uses the so-called orthogonal sum to combine multiple belief structures:

$$m = m_1 \oplus m_2 \oplus \cdots \oplus m_K, \tag{6}$$

where $\oplus$ represents the operator of combination. With two belief structures m_1 and m_2, the Dempster's rule of combination is defined as follows:

$$[m_1 \oplus m_2](C) = \begin{cases} 0, & C = \Phi, \\ \dfrac{\sum_{A \cap B = C} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \Phi} m_1(A) m_2(B)}, & C \neq \Phi, \end{cases} \tag{7}$$

where A and B are both focal elements and $[m_1 \oplus m_2](C)$ itself is a bpa. The denominator, $1 - \sum_{A \cap B = \Phi} m_1(A) m_2(B)$ denoted by k, is called the normalization factor, $\sum_{A \cap B = \Phi} m_1(A) m_2(B)$ is called the degree of conflict, which measures the conflict between the pieces of evidence (George and Pal, 1996) and the process of dividing by k is called normalization.

The Dempster's rule of combination proved to be both commutative and associative (Shafer, 1976), i.e. $m_1 \oplus m_2 = m_2 \oplus m_1$ (commutativity) and $(m_1 \oplus m_2) \oplus m_3 = m_1 \oplus (m_2 \oplus m_3)$ (associativity). These two properties show that evidence can be combined in any order. Therefore, in the case of multiple belief structures, the combination of evidence can be carried out in a pairwise way.

Note that the crude application of the D–S theory and the combination rule can lead to irrational conclusions in the aggregation of multiple pieces of evidence in conflict (Murphy, 2000). This issue is overcome in the ER approach introduced in the next section by generating basic probability assignment through the combination of belief degrees and normalised weights and by normalising the combined probability masses.

3. The ER approach for EIA

The ER approach for EIA consists mainly of four key parts, which are the identification of environmental factors, the ER distributed modelling framework for the identified environmental factors, the recursive and analytical ER algorithms for aggregating multiple identified environmental factors, and the utility interval based ER ranking method which is designed to compare and rank alternatives/options systematically. Each part will be described in detail in this section.

3.1. The identification of environmental factors

This is the first step to conduct EIA analysis. In this part all environmental factors that will possibly be affected need to be investigated and carefully identified. Generally speaking, environments can be described in two broad categories: the natural environment, consisting of physical–chemical and biological factors, and the man-made environment, consisting of cultural resources and socio-economic concerns. Typical environmental factors in each category may include the following (Canter, 1996):

- *Natural environment*. Air quality and odor, water quantity and quality, groundwater quantity and quality, saltwater intrusion, water usage and water rights, meteorology climatology, catastrophic meteorological events, benthal deposits, noise, soils, geology, seismicity, topography, aquatic and terrestrial biology, threatened or endangered plant or animal species, visual characteristics, and aesthetic features of recreational areas, open spaces, and natural areas.
- *Man-made environment*. Historical, archaeological, and paleontological sites; land use; population (permanent versus temporary or recreational); skiing and other recreational uses of area; infrastructure; resource consumption in terms of energy and minerals; and regulatory and planning frameworks for the area, including water laws and regulations and planning groups and agencies.

The key issue in this step is to ensure that all environmental factors that need to be considered are included, while excluding those items that require extensive identification and interpretation effort but have little relevance to the environmental impact of the proposed action or any of its alternatives.

Simple and descriptive checklist approaches, including questionnaire checklists, provide a structured approach for identifying pertinent environmental factors for consideration (Canter, 1996). Usually, an initial list of environmental factors of potential relevance to a proposed project may be first determined through extensive literature review, review of other recent EIAs on similar projects or projects in the same geographical area as the proposed project, and the use of professional knowledge regarding the anticipated impacts of similar projects. And then, a selected list of pertinent environmental factors for a given project can be screened through site visits, interdisciplinary team discussions, professional judgments, criteria questions, and so on.

Site visits can provide familiarization with an area in question and enable more effective review of extant environmental data. Interdisciplinary team discussions can lead to greater familiarity with project impacts and, possibly, to the identification of pertinent environmental factors not included in any initial list. Professional judgments can be a part of interdisciplinary team discussions, or it can be solicited during conversations with recognized experts in relevant disciplines for a project. The following three criteria questions are helpful in identifying and screening environmental factors; if any of these criteria apply to a given factor, then that factor should be included (Canter, 1996):

- Will the environmental factor be affected, either beneficially or adversely, by any of the alternatives (including the no-action or no-project alternative) under study?
- Will the environmental factor exert an influence on project scheduling or a subsequent operational phase of any of the alternatives?
- Is the factor of particular public interest or controversy within the local community?

3.2. The ER distributed modelling framework for EIA—the belief structure

To carry out EIA analysis, the impacts of the identified environmental factors need to be further identified, predicted and assessed. The identified environmental impacts can be assessed on the grades of Table 1, which are also the grades used for evaluating the total environmental impact (Pastakia, 1998; Hagebro, 1998; Pastakia and Jensen, 1998; Pastakia and Bay, 1998). Note that the choice of assessment grades depends on the need of real applications. They may be defined more precisely or more roughly. The ER approach even allows a different set of assessment grades to be defined for each environmental factor. But different sets of assessment grades need to be unified before the implementation of the ER algorithm. Interested readers may refer to Yang (2001) and Yang et al. (in press-b) for details.

All the assessment grades are mutually exclusive and collectively exhaustive and thus form a frame of discernment in D–S terminology, which is denoted by

Table 1
Assessment grades used for the description of environmental impacts

Assessment grades	Description of assessment grades
+E	Major positive impact
+D	Significant positive impact
+C	Moderately positive impact
+B	Positive impact
+A	Slightly positive impact
N	No impact (status quo)
−A	Slightly negative impact
−B	Negative impact
−C	Moderately negative impact
−D	Significant negative impact
−E	Major negative impact

$$H = \{+\mathrm{E}, +\mathrm{D}, +\mathrm{C}, +\mathrm{B}, +\mathrm{A}, \mathrm{N}, -\mathrm{A}, -\mathrm{B}, -\mathrm{C}, -\mathrm{D}, -\mathrm{E}\}. \tag{8}$$

Cross impact matrix and descriptive checklist approaches as well as Pastakia's RIAM can all be used to identify environmental impacts and assess the identified environmental factors. Suppose an EIA problem has M alternatives or options a_l ($l = 1, \ldots, M$), one general environmental factor (i.e. evaluation goal) and L lower level environmental factors e_i ($i = 1, \ldots, L$), which are called *basic* environmental factors. For illustration purpose, only a two-level hierarchy is assumed in the analysis. However, the ER approach introduced in the paper is applicable to multiple-level hierarchies. This will be illustrated using an example in the next section. Suppose the relative weights of the L basic environmental factors are given by $W = (w_1, \ldots, w_L)$, which are normalised to satisfy the following condition:

$$\sum_{i=1}^{L} w_i = 1 \quad \text{and} \quad w_i \geqslant 0, \;\; i = 1, \ldots, L. \tag{9}$$

Note that the determination of the relative weights is an important issue. They may be determined by using approaches based on pairwise comparisons of factors such as AHP (Saaty, 1980), or estimated by using mathematical programming techniques (see Yang et al., 2001b). If alternative a_l is assessed on an environmental factor e_i to a grade H_n with a degree of belief of $\beta_{n,i}(a_l)$, we denote this by $S(e_i(a_l)) = \{(H_n, \beta_{n,i}(a_l)), n = 1, \ldots, N\}$, which is a distributed assessment and is referred to as a belief structure, where H_n represents the nth element (assessment grade) of the set H and $N = 11$ corresponding to (8). For example, suppose 100 experts coming from different fields and subjects are invited to assess the impact of one project on air quality. If 40 experts assess the impact to be major negative (−E), 25 experts to be significant negative (−D) and the other 35 experts to be −A (slightly negative impacts), then such an assessment can be expressed in the form of a belief structure as $S(e_i(a_l)) = \{(-\mathrm{A}, 35\%), (-\mathrm{D}, 25\%), (-\mathrm{E}, 40\%)\}$.

One of the features of the ER approach is its distributed modelling framework, which can capture the diversity of original assessment information and is well suited to modelling EIA problems. In a distributed assessment, it is required that $\beta_{n,i}(a_l) \geqslant 0$ and $\sum_{n=1}^{N} \beta_{n,i}(a_l) \leqslant 1$. If $\sum_{n=1}^{N} \beta_{n,i}(a_l) = 1$, the assessment is said to be complete; otherwise, it is incomplete. If $\sum_{n=1}^{N} \beta_{n,i}(a_l) = 0$, then the assessment stands for complete ignorance. Take the above assessment about air quality for example. The above assessment is complete. If the assessments are that 40 experts assess the impact to be major negative (−E), 25 experts to be significant negative (−D), 30 experts to be −A (slightly negative impacts), and the other five experts are not sure about the impact, then such a distributed assessment $S(e_i(a_l)) = \{(-\mathrm{A}, 30\%), (-\mathrm{D}, 25\%), (-\mathrm{E}, 40\%)\}$ is incomplete as the total belief degree is 95% with a degree of ignorance of 5%. If the 100 experts are all not sure about the impact of the project on air quality, then the assessment will be totally ignorant. The ER approach can hand such ignorance if environmental factors are assessed with certain degrees of ignorance. This is another distinct feature of the ER approach.

The assessment results of every alternative on each basic environmental factor are represented by the following belief decision matrix:

$$D_g = (S(e_i(a_l)))_{L\times M}. \tag{10}$$

Based on the belief decision matrix, all the distributed assessment information can be aggregated in a rational and effective way using the ER algorithms discussed in the next section.

3.3. The recursive and analytical ER algorithms

Different from the existing EIA methodologies such as the most-used weighting-scaling (or -ranking or -rating) checklists and RIAM, the ER approach provides an effective process of synthesising the assessment information on identified environmental factors. The process is based on the belief decision matrix and the combination rule of the D–S theory of evidence. A recursive ER algorithm for aggregating L basic attributes for alternative a_l ($l = 1, \ldots, M$) was developed in the past decade (Yang and Singh, 1994; Yang and Sen, 1994; Yang, 2001; Yang and Xu, 2002a; Yang et al., in press-b), which can be used to aggregate L basic environmental factors.

The recursive ER algorithm is briefly introduced as follows. First of all, the degrees of belief are transformed into basic probability masses by combining the relative weights and the degrees of belief using the following equations:

$$m_{n,i} = m_i(H_n) = w_i\beta_{n,i}(a_l), \quad n = 1, \ldots, N; \quad i = 1, \ldots, L, \tag{11}$$

$$m_{H,i} = m_i(H) = 1 - \sum_{n=1}^{N} m_{n,i} = 1 - w_i \sum_{n=1}^{N} \beta_{n,i}(a_l), \quad i = 1, \ldots, L, \tag{12}$$

$$\bar{m}_{H,i} = \bar{m}_i(H) = 1 - w_i, \quad i = 1, \ldots, L, \tag{13}$$

$$\widetilde{m}_{H,i} = \widetilde{m}_i(H) = w_i\left(1 - \sum_{n=1}^{N} \beta_{n,i}(a_l)\right), \quad i = 1, \ldots, L \tag{14}$$

with

$$m_{H,i} = \bar{m}_{H,i} + \widetilde{m}_{H,i}$$

and

$$\sum_{i=1}^{L} w_i = 1,$$

where $m_{n,i}$ represents the basic probability mass of a_l being assessed to the assessment grade H_n on the basic environmental factor e_i. Note that the probability mass assigned to the whole set H, $m_{H,i}$ which is currently unassigned to any individual grades, is split into two parts: $\bar{m}_{H,i}$ and $\widetilde{m}_{H,i}$, where $\bar{m}_{H,i}$ is caused by the relative importance of environmental factors and $\widetilde{m}_{H,i}$ by the incompleteness of the assessment on the basic environmental factor e_i for a_l. $\bar{m}_{H,i}$ represents how much the other factors can play in assessing the general factor (goal) and it is the proportion of beliefs that remains to be assigned depending upon how other factors are assessed. In essence, $\bar{m}_{H,i}$ provides scope for conflict resolution in the presence of conflicting evidence. $\widetilde{m}_{H,i}$ will be zero if there is no ignorance in the assessment.

Then, the basic probability masses are combined using the following recursive ER algorithm:

$$\{H_n\}:\ m_{n,I(i+1)} = K_{I(i+1)}[m_{n,I(i)}m_{n,i+1} + m_{n,I(i)}m_{H,i+1} + m_{H,I(i)}m_{n,i+1}]$$
$$m_{H,I(i)} = \bar{m}_{H,I(i)} + \widetilde{m}_{H,I(i)}, \quad n = 1,\ldots,N, \tag{15}$$
$$\{H\}:\ \widetilde{m}_{H,I(i+1)} = K_{I(i+1)}[\widetilde{m}_{H,I(i)}\widetilde{m}_{H,i+1} + \widetilde{m}_{H,I(i)}\bar{m}_{H,i+1} + \bar{m}_{H,I(i)}\widetilde{m}_{H,i+1}], \tag{16}$$
$$\{H\}:\ \bar{m}_{H,I(i+1)} = K_{I(i+1)}[\bar{m}_{H,I(i)}\bar{m}_{H,i+1}], \tag{17}$$
$$K_{I(i+1)} = \left[1 - \sum_{n=1}^{N}\sum_{\substack{t=1\\t\neq n}}^{N} m_{n,I(i)}m_{t,i+1}\right]^{-1}, \quad i = 1,\ldots,L-1 \tag{18}$$
$$\{H_n\}:\ \beta_n = \frac{m_{n,I(L)}}{1-\bar{m}_{H,I(L)}}, \quad n = 1,\ldots,N, \tag{19}$$
$$\{H\}:\ \beta_H = \frac{\widetilde{m}_{H,I(L)}}{1-\bar{m}_{H,I(L)}}, \tag{20}$$

where $m_{n,I(1)} = m_{n,1} (n = 1,\ldots,N)$ and $m_{H,I(1)} = m_{H,1}$ with $\bar{m}_{H,I(1)} = \bar{m}_{H,1}$ and $\widetilde{m}_{H,I(1)} = \widetilde{m}_{H,1}$; β_n and β_H represent the belief degrees of the aggregated assessment, to which the general environmental factor is assessed to the grade H_n and H, respectively. The combined assessment can be denoted by $S(y(a_l)) = \{(H_n, \beta_n(a_l)), n = 1,\ldots,N\}$. It has been proved that $\sum_{n=1}^{N}\beta_n + \beta_H = 1$ (Yang and Xu, 2002a). Yang and Xu also put forward four axioms and have proved the rationality and validity of the above recursive ER algorithm. The nonlinear features of the above aggregation process have been investigated in detail (Yang and Xu, 2002b). Note that Eqs. (19) and (20) provide a normalisation process to assign the remaining belief $\bar{m}_{H,I(L)}$ back to the focal elements proportionally after the combination of all basic factors. This step is necessary as $\bar{m}_{H,I(L)}$ is not a degree of ignorance but the unassigned belief caused due to the relative importance of the factors.

The recursive ER algorithm combines various piece of evidence on a one-by-one basis. The advantage of doing so is its clarity in concept. In situations where an explicit ER aggregation function is required such as in optimization, an analytical ER algorithm will be desirable. In view of this, the following analytical ER algorithm is developed:

$$\{H_n\}:\ m_n = k\left[\prod_{i=1}^{L}(m_{n,i} + \bar{m}_{H,i} + \widetilde{m}_{H,i}) - \prod_{i=1}^{L}(\bar{m}_{H,i} + \widetilde{m}_{H,i})\right], \quad n = 1,\ldots,N, \tag{21}$$
$$\{H\}:\ \widetilde{m}_H = k\left[\prod_{i=1}^{L}(\bar{m}_{H,i} + \widetilde{m}_{H,i}) - \prod_{i=1}^{L}\bar{m}_{H,i}\right], \tag{22}$$
$$\{H\}:\ \bar{m}_H = k\left[\prod_{i=1}^{L}\bar{m}_{H,i}\right], \tag{23}$$
$$k = \left[\sum_{n=1}^{N}\prod_{i=1}^{L}(m_{n,i} + \bar{m}_{H,i} + \widetilde{m}_{H,i}) - (N-1)\prod_{i=1}^{L}(\bar{m}_{H,i} + \widetilde{m}_{H,i})\right]^{-1}, \tag{24}$$
$$\{H_n\}:\ \beta_n = \frac{m_n}{1-\bar{m}_H}, \quad n = 1,\ldots,N, \tag{25}$$
$$\{H\}:\ \beta_H = \frac{\widetilde{m}_H}{1-\bar{m}_H}. \tag{26}$$

The equivalence between the recursive and analytical ER algorithms are provided in Appendix A. The analytical ER algorithm offers the ER approach more flexibility in aggregating a large number of environmental factors (or basic attributes). It clearly shows its nonlinear features (Yang and Xu, 2002b) and provides a straightforward way to conduct sensitivity analysis for the parameters of the ER approach such as weights and belief degrees. It also facilitates the estimation and optimization of these parameters. Note that due to the fact that only a finite number of environmental factors (criteria or attributes) is considered in any EIA or MADA problem, both the recursive and analytical ER algorithms have no convergence issues.

3.4. The utility interval based ER ranking method

The aggregated distributed assessment $S(y(a_l)) = \{(H_n, \beta_n(a_l)), n = 1, \ldots, N\}$ stands for the total environmental impact assessment for the alternative a_l. It provides a panoramic view about the assessment of the alternative, from which one can tell which grades the alternative a_l is assessed to, what belief degrees are assigned to all the defined grades, and what major impacts on the total environment the alternative has. However, it may not be straightforward to use the distributed assessments for ranking alternatives.

In order to rank M alternatives in the presence of incomplete assessments, maximum, minimum and average utilities are introduced. Suppose the utility of an evaluation grade H_n is $u(H_n)$, then the expected utility of the aggregated assessment $S(y(a_l))$ is defined as follows:

$$u(S(y(a_l))) = \sum_{n=1}^{N} \beta_n(a_l) u(H_n). \tag{27}$$

The belief degree $\beta_n(a_l)$ represents the lower bound of the likelihood that a_l is assessed to H_n, whilst the corresponding upper bound of the likelihood is given by $(\beta_n(a_l) + \beta_H(a_l))$ (Yang, 2001; Yang and Xu, 2002b), which leads to the establishment of a utility interval if an assessment is incomplete. According to the assessment grades defined in Table 1, the least preferred assessment grade is H_N, namely −E, which has the lowest utility and the most preferred assessment grade is H_1, namely +E, which has the highest utility. The maximum, minimum and average utilities of a_l can be calculated by

$$u_{\max}(a_l) = (\beta_1(a_l) + \beta_H(a_l))u(H_1) + \sum_{n=2}^{N} \beta_n(a_l) u(H_n), \tag{28}$$

$$u_{\min}(a_l) = \sum_{n=1}^{N-1} \beta_n(a_l) u(H_n) + (\beta_N(a_l) + \beta_H(a_l))u(H_N), \tag{29}$$

$$u_{\text{avg}}(a_l) = \frac{u_{\max}(a_l) + u_{\min}(a_l)}{2}. \tag{30}$$

It is obvious that if $u(H_N) = 0$, then $u(S(y(a_l))) = u_{\min}(a_l)$; if all the original assessments $S(e_i(a_l))$ in the belief matrix are complete, then $\beta_H(a_l) = 0$ and $u(S(y(a_l))) = u_{\min}(a_l) = u_{\max}(a_l) = u_{\text{avg}}(a_l)$. It has to be made clear that the above utilities are only used for characterizing a distributed assessment but not for the aggregation of environmental factors. According to the maximum, minimum utilities and the corresponding utility interval, the ranking of two alternatives can be made as follows. If $u_{\min}(a_l) \geqslant u_{\max}(a_k)$, a_l is said to be preferred to a_k; if $u_{\min}(a_l) = u_{\min}(a_k)$ and $u_{\max}(a_l) = u_{\max}(a_k)$, a_l is said to be indifferent to a_k. In other cases, the degree of preference of a_l over a_k can be computed by

$$P(a_l > a_k) = \frac{\max[0, u_{\max}(a_l) - u_{\min}(a_k)] - \max[0, u_{\min}(a_l) - u_{\max}(a_k)]}{[u_{\max}(a_l) - u_{\min}(a_l)] + [u_{\max}(a_k) - u_{\min}(a_k)]}. \tag{31}$$

If $P(a_l > a_k) > 0.5$, then a_l is said to be superior to a_k to the degree of $P(a_l > a_k)$, denoted by $a_l \overset{P(a_l>a_k)}{\succ} a_k$; if $P(a_l > a_k) = 0.5$, then a_l is said to be indifferent to a_k, denoted by $a_l \sim a_k$; if $P(a_l > a_k) < 0.5$, then a_l is said to be inferior to a_k to the degree of $1 - P(a_l > a_k)$, denoted by $a_l \overset{1-P(a_l>a_k)}{\prec} a_k$. If $P(a_l > a_k) > 0.5$ and $P(a_k > a_q) > 0.5$, then $P(a_l > a_q) > 0.5$, which means the above preference relations are transitive. More details about the above ranking approach can be found in Wang et al. (2005).

In order to produce a more reliable ranking between a_l and a_k, it is suggested that the quality of original assessments should be improved by reducing imprecision or incompleteness presented in the original information.

4. Numerical example

An initial environmental evaluation (IEE) of alternative methods to conserve Rupa Tal Lake, Nepal was conducted using the Rapid Impact Assessment Matrix (RIAM) method (Pastakia and Bay, 1998). In this section, this example will be re-investigated and modified to demonstrate the implementation process of the ER approach and its validity and applicability in EIA. Some comments will also be made. The description of the assessment problems is entirely based on the published work by Pastakia and Bay (1998).

4.1. The description of problem

Rupa Tal ('The Lake of Beauty') lies in the Begnash and Rupa Lakes watershed area in the northeast of Kaski District in the mid-western region of Nepal. It is a major tourism area and also provides a small amount of fishery income, including rudimentary cage aquaculture. Its surrounding hills are all terraced along the lower slopes for rice production. But the lake was undergoing sedimentation at a rapid rate, with the lake area being reduced from 194 to 115 ha between 1978 and 1995 (a loss of 40% in 17 years). At the time of conducting the IEE, the lake basin was continuing to receive sediments from the up streams to the northeast. The lake was fed from an upland system (Dobhan Khola) to the Seti River. The southern margin of the lake became a small marginal marsh, which drained the southern agriculture lands into the lake before entering the Tal Khola. In addition to these geophysical changes, the lake was highly eutrophic, with a considerable biomass of subsurface and emergent macrophytes. It was possible that the deposition of weed peat would accelerate the sedimentation of the lake area.

The local authorities were very anxious to know if the beauty of the lake and its valley could be preserved. They considered the rate of lake sedimentation to be an adverse phenomenon in respect of the preservation of the lake and the valley; and accordingly wished to consider possible interventions that might conserve a lake area and preserve the valley for tourism, agriculture and fishery, as had been done elsewhere in this region of Nepal.

Four possible causes of action were considered in respect of the conservation of the lake area:

1. No action, allowing the present sedimentation to continue, resulting in the total loss of the lake and the creation of a small gorge to take the inflow/outflow streams.
2. Building a high retaining dam along the southern margin to raise the overall water level. This would be a major structure, and would inundate in-lake areas that had been created by sedimentation over the last few decades.
3. Building a smaller, high dam set between two bluffs, about one third of the way up from the southern shore. This partial dam would be a smaller structure than (2) but would have similar upstream effects.
4. Either a single large sedimentation reservoir in the upstream area, or a series of smaller retaining walls, forming a sedimentation cascade. This option allowed solids to settle out well upstream of the lake, and the water area would be able to remain intact.

4.2. Rapid Impact Assessment Matrix (RIAM)

To assist in the evaluation of the above four alternative options, Pastakia and Bay made a short three-day visit to Rupa Tal and conducted an initial environmental evaluation (IEE) using the Rapid Impact

Assessment Matrix (RIAM). Due to the rapidity of the exercise and the need to make comparative evaluations in the absence of quantitative data, the final impact assessment was considered to be an initial environmental evaluation (IEE) rather than a full environmental impact assessment (EIA). Although the example presented here is not a full EIA, it does not affect the examination of the validity, rationality and applicability of the ER approach for EIA. A detailed in-depth EIA analysis/study can be conducted in the same way. The purpose of this study is to demonstrate the process of implementing the ER approach for EIA.

A reconnaissance of the lake environments and observations of possible environmental problems related to changes in sedimentation were conducted and the local people, members of the Village Department Council, and the members and ex-members of the local authority and planning bodies were involved in discussion. The following environmental factors were identified for assessment:

• *Physical/Chemical (P/C)*. Covering all physical and chemical aspects of the environment, including finite (nonbiological) natural resources, and degradation of the physical environment by pollution. In the initial environmental evaluation of alternative methods to conserve Rupa Tal Lake, these factors were restricted to those that related to the changes in lake water volume and the process of sedimentation, with the concomitant changes in agricultural land that each option might cause. They are listed as follows:

P/C 1. Changes in lake water volume.
P/C 2. Changes in the lake sedimentation (measure of reduction of water surface).
P/C 3. Changes in crop and grazing areas.

• *Biological/Ecological (B/E)*. Covering all biological aspects of the environment, including renewable natural resources, conservation of biodiversity, species interactions, and pollution of the biosphere. In the initial environmental evaluation of alternative methods to conserve Rupa Tal Lake, these factors reflected changes that might occur with each option in respect of the biota in the lake, specially primary production, the change in aquatic macrophytes (secondary production) and finally changes in lake fisheries (including its ability to support aquaculture). The biodiversity of the southern margin marsh and the changes in insect disease vector populations also needed considering. The concrete factors considered are presented below:

B/E 1. Changes in lake fisheries.
B/E 2. Changes in biodiversity.
B/E 3. Changes in primary production.
B/E 4. Changes in aquatic macrophytes.
B/E 5. Changes in disease vector populations.

• *Sociological/Cultural (S/C)*. Covering all human aspects of the environment, including social issues affecting individuals and communities together with cultural aspects, including conservation of heritage, and human development. In the initial environmental evaluation of alternative methods to conserve Rupa Tal Lake, it was evident that each option would provide different results to the human settlement pattern of the area. Sedimentation had provided new land both for agriculture as well as houses and public buildings. Shops, temples and a school had been developed within the sedimented areas of the lake, and housing was found both in these areas as well as along the margins and higher reaches of the shores. This dwelling and development pattern had set access routes to the area and would be affected by some options. The biological changes would have an impact on both diet and disease. The aesthetic value of any option would relate to tourism attractiveness. All these together with an evaluation in the change in quality of life of the local communities were considered. They are recorded in the following:

S/C 1. Loss of housing.
S/C 2. Loss of shops/public buildings.
S/C 3. Changes to access routes.
S/C 4. Changes induced by changes in tourism patterns.
S/C 5. Changes to water supplies.
S/C 6. Changes to diet/nutrition.
S/C 7. Changes to aesthetic landscapes.
S/C 8. Changes in water/vector borne disease.
S/C 9. Changes to upstream quality of life.
S/C 10. Changes to downstream quality of life.

• *Economic/Operational (E/O)*. Covering all economic consequences of the environmental change, both temporary and permanent, as well as the complexities of project management. In the initial environmental evaluation of alternative methods to conserve Rupa Tal Lake, economic/operational factors reflected the changes in agriculture, fishery and tourism incomes that might be expected from each option. The cost of mitigation in the form of rehabilitation of building and access routes and both the cost and complexity of the operations and maintenance of each option were considered. The following environmental factors were selected for assessment:

E/O 1. Changes in crop-generated incomes.
E/O 2. Changes in fishery generated incomes.
E/O 3. Ease of Operation and Maintenance of option.
E/O 4. Cost of Operation and Maintenance of option.
E/O 5. Cost of resettlement/compensation for land loss.
E/O 6. Cost of rehabilitation/restoration of shops/public buildings.
E/O 7. Cost of restoration of access routes.
E/O 8. Changes in tourism-generated incomes.

To complete the IEE, the above identified environmental factors were all evaluated using the RIAM, which was developed by Pastakia in 1998. The results are summarized in Table 2. The corresponding overall assessment results for the four alternative options are shown in Fig. 1. The RIAM analysis showed that a 'do nothing' situation (option 1) would result in a complete loss of the lake. To maintain the lake, the authors thought that both options 4 and 2 were effectively technical solutions. If capital and running costs were not a major impediment to development, there was much to recommend option 2. But in terms of both cost and disruption, they suggested that option 4 should be the solution most likely to be affordable and able to meet the objectives of preserving the character of Rupa Tal.

4.3. Comments on RIAM

As a newly developed EIA tool, the major advantage of RIAM is its rapidity and simplicity. There is no need for complicated computations before arriving at assessment results. However, the disadvantages of RIAM are also quite obvious. There are at least the following drawbacks when using RIAM to conduct EIA. First, RIAM takes no account of the relative importance of each environmental factor. All the identified environmental factors are treated equally. In practical EIA analyses or studies, this is usually unrealistic. It is argued that key or critical environmental factors should have more importance (greater weights) than other factors. Second, RIAM must and can only assess each environmental factor to one of the assessment grades with 100% degree of belief. RIAM cannot deal with the problem of distribution assessments or it does not allow any environmental factor to be evaluated to several different assessment

Table 2
The assessment results on the identified environmental factors by RIAM

Environmental factors	Option 1	Option 2	Option 3	Option 4
Physical/Chemical (P/C)				
P/C 1	−C	B	B	N
P/C 2	−B	B	−A	B
P/C 3	C	−B	N	N
Biological/Ecological (B/E)				
B/E 1	−B	D	A	N
B/E 2	−B	−A	−B	N
B/E 3	−B	−B	−A	N
B/E 4	−B	−B	−A	N
B/E 5	A	A	A	−A
Sociological/Cultural (S/C)				
S/C 1	N	−A	−A	N
S/C 2	N	−A	−A	N
S/C 3	A	−A	−A	N
S/C 4	−A	B	A	N
S/C 5	−A	C	A	A
S/C 6	N	A	A	N
S/C 7	−B	B	A	N
S/C 8	A	−A	A	−A
S/C 9	N	A	A	−A
S/C 10	−A	B	B	N
Economic/Operational (E/O)				
E/O 1	B	−A	B	N
E/O 2	−B	B	N	N
E/O 3	N	−A	−A	−B
E/O 4	N	−A	−A	−B
E/O 5	N	−A	−A	N
E/O 6	N	−A	−A	N
E/O 7	N	−A	−A	N
E/O 8	−A	C	A	N

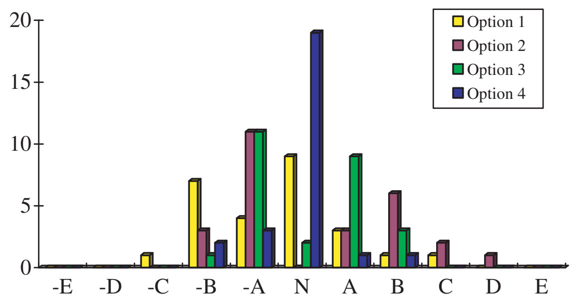

Fig. 1. The overall assessment results for the four alternative options by RIAM.

grades simultaneously. However, distribution assessments could be commonplace in public surveys or group decision making because different people or experts may have different opinions. Thirdly, RIAM can only handle evaluations with certainty and cannot handle incomplete assessment information with ignorance. Although robustness/sensitivity analysis is a simple way to take into account parameter uncertainty, it is usually conducted for the assumed changes of individual parameters on a point to point basis, thereby only generating a partial view about the possible impact of uncertainty on final outcomes. Fourthly, RIAM adopts a simple additive method to synthesis and aggregate assessment information on different environmental factors, which requires that all the environmental factors be additively independent. In reality, linear additive independence assumption may not always be acceptable. Fifthly, RIAM fails to provide a systematic and effective method to rank or compare different alternatives (options). Finally, RIAM is not suited to dealing with EIA problems if vague or fuzzy information is available. The above comments on RIAM do not necessarily mean that RIAM is not regarded to be a good method for EIA. However, they do lead to a conclusion that new methods are needed for more complicated EIA under uncertainty.

4.4. The ER approach

The ER approach provides a novel systematic way to aggregate assessment information on the identified environmental factors. It can overcome the shortcomings mentioned above. For comparison, the original assessment information shown in Table 2, together with the relative weights of all the environmental factors being assumed to be equal, is firstly utilized to carry out the ER synthesis, and then a detailed in-depth IEE analysis is conducted using the ER approach based on the modified assessment information and relative weights.

To carry out ER synthesis, the assessment information presented in Table 2 is equivalently represented in the form of distributed assessments, which are shown in Table 3, where the figures in parentheses for the environmental factors represent their respective relative weights. It is obvious that this is a hierarchical EIA problem. Fig. 2 shows the assessment hierarchy.

When the ER algorithm is used to aggregate assessment information for the environmental factors, P/C 1–P/C 3, B/E 1–B/E 5, S/C 1–S/C 10, and E/O 1–E/O 8 are first aggregated to generate assessments for P/C, B/E, S/C and E/O, respectively, and then P/C, B/E, S/C and E/O are aggregated to generate an overall assessment for each option. These results are presented in Table 4 and shown in Fig. 3.

It is clear from Table 4 and Fig. 3 that option 4 has the least negative impacts on the total environment. Its impacts on the environment are basically neutral. Option 1 is the no-action plan. It produces the greatest negative impacts on the total environment among the four options. Both options 2 and 3 produce lots of positive impacts on the total environment, but option 2 produces greater negative impacts. So, it is not straightforward to compare these options directly. In order to compare or rank them, the decision maker (DM)'s preference information is required. For illustration purpose, utility functions are assumed to represent the DM's preferences. Fig. 4 shows three different types of utility functions for different DMs. They represent risk-neutral, risk-averse and risk-taking DMs, respectively.

Suppose the DM is risk-neutral (curve I) and his/her utilities for each assessment grade are given below:

$$u(-\mathrm{E}) = 0, \quad u(-\mathrm{D}) = 0.1, \quad u(-\mathrm{C}) = 0.2, \quad u(-\mathrm{B}) = 0.3, \quad u(-\mathrm{A}) = 0.4, \quad u(\mathrm{N}) = 0.5,$$
$$(\mathrm{A}) = 0.6, \quad u(\mathrm{B}) = 0.7, \quad u(\mathrm{C}) = 0.8, \quad u(\mathrm{D}) = 0.9, \quad u(\mathrm{E}) = 1.0$$

Then the expected utility of each option can be calculated using formula (27) as follows:

$$u(\text{option 1}) = 0.4307, \quad u(\text{option 2}) = 0.5231, \quad u(\text{option 3}) = 0.4984, \quad u(\text{option 4}) = 0.4987.$$

So, the DM prefers option 2 to the other three options.

Suppose the DM is risk-taking (curve II) and provides the following utilities for every assessment grade:

$$u(-\mathrm{E}) = 0, \quad u(-\mathrm{D}) = 0.08, \quad u(-\mathrm{C}) = 0.16, \quad u(-\mathrm{B}) = 0.24, \quad u(-\mathrm{A}) = 0.32, \quad u(\mathrm{N}) = 0.40,$$
$$u(\mathrm{A}) = 0.52, \quad u(\mathrm{B}) = 0.64, \quad u(\mathrm{C}) = 0.76, \quad u(\mathrm{D}) = 0.88, \quad u(\mathrm{E}) = 1.0$$

Table 3
The distributed assessments of the environmental factors equivalent to Table 2

Environmental factors (relative weights)	Option 1	Option 2	Option 3	Option 4
Physical/Chemical (P/C) (0.25)				
P/C 1 (0.333)	{(−C, 1.0)}	{(B, 1.0)}	{(B, 1.0)}	{(N, 1.0)}
P/C 2 (0.333)	{(−B, 1.0)}	{(B, 1.0)}	{(−A, 1.0)}	{(B, 1.0)}
P/C 3 (0.333)	{(C, 1.0)}	{(−B, 1.0)}	{(N, 1.0)}	{(N, 1.0)}
Biological/Ecological (B/E) (0.25)				
B/E 1 (0.2)	{(−B, 1.0)}	{(D, 1.0)}	{(A, 1.0)}	{(N, 1.0)}
B/E 2 (0.2)	{(−B, 1.0)}	{(−A, 1.0)}	{(−B, 1.0)}	{(N, 1.0)}
B/E 3 (0.2)	{(−B, 1.0)}	{(−B, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
B/E 4 (0.2)	{(−B, 1.0)}	{(−B, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
B/E 5 (0.2)	{(A, 1.0)}	{(A, 1.0)}	{(A, 1.0)}	{(−A, 1.0)}
Sociological/Cultural (S/C) (0.25)				
S/C 1 (0.1)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
S/C 2 (0.1)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
S/C 3 (0.1)	{(A, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
S/C 4 (0.1)	{(−A, 1.0)}	{(B, 1.0)}	{(A, 1.0)}	{(N, 1.0)}
S/C 5 (0.1)	{(−A, 1.0)}	{(C, 1.0)}	{(A, 1.0)}	{(A, 1.0)}
S/C 6 (0.1)	{(N, 1.0)}	{(A, 1.0)}	{(A, 1.0)}	{(N, 1.0)}
S/C 7 (0.1)	{(−B, 1.0)}	{(B, 1.0)}	{(A, 1.0)}	{(N, 1.0)}
S/C 8 (0.1)	{(A, 1.0)}	{(−A, 1.0)}	{(A, 1.0)}	{(−A, 1.0)}
S/C 9 (0.1)	{(N, 1.0)}	{(A, 1.0)}	{(A, 1.0)}	{(−A, 1.0)}
S/C 10 (0.1)	{(−A, 1.0)}	{(B, 1.0)}	{(B, 1.0)}	{(N, 1.0)}
Economic/Operational (E/O) (0.25)				
E/O 1 (0.125)	{(B, 1.0)}	{(−A, 1.0)}	{(B, 1.0)}	{(N, 1.0)}
E/O 2 (0.125)	{(−B, 1.0)}	{(B, 1.0)}	{(N, 1.0)}	{(N, 1.0)}
E/O 3 (0.125)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(−B, 1.0)}
E/O 4 (0.125)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(−B, 1.0)}
E/O 5 (0.125)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
E/O 6 (0.125)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
E/O 7 (0.125)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
E/O 8 (0.125)	{(−A, 1.0)}	{(C, 1.0)}	{(A, 1.0)}	{(N, 1.0)}

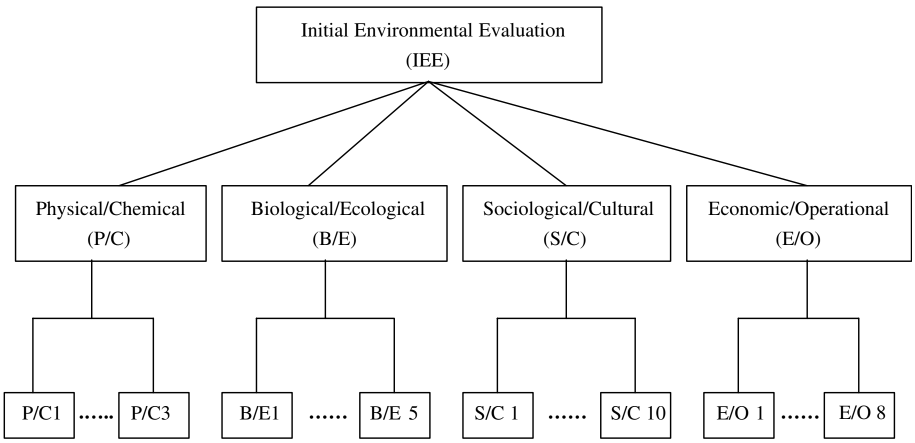

Fig. 2. The hierarchy for initial environmental evaluation of Rupa Tal Lake.

Table 4
The aggregated distributed assessments for the four options

Options	Environmental factors	Degrees of belief assessed to each assessment grade										
		−E	−D	−C	−B	−A	N	A	B	C	D	E
Option 1	P/C	0	0	0.3333	0.3333	0	0	0	0	0.3333	0	0
	B/E	0	0	0	0.8522	0	0	0.1478	0	0	0	0
	S/C	0	0	0	0.0895	0.2994	0.4222	0.1889	0	0	0	0
	E/O	0	0	0	0.1037	0.1037	0.6890	0	0.1037	0	0	0
	IEE	0	0	0.0776	0.3630	0.0962	0.2811	0.0805	0.0241	0.0776	0	0
Option 2	P/C	0	0	0	0.2857	0	0	0	0.7143	0	0	0
	B/E	0	0	0	0.4286	0.1905	0	0.1905	0	0	0.1905	0
	S/C	0	0	0	0	0.4222	0	0.1889	0.2994	0.0895	0	0
	E/O	0	0	0	0	0.8113	0	0	0.0944	0.0944	0	0
	IEE	0	0	0	0.1732	0.3723	0	0.0898	0.2783	0.0428	0.0437	0
Option 3	P/C	0	0	0	0	0.3333	0.3333	0	0.3333	0	0	0
	B/E	0	0	0	0.1818	0.4091	0	0.4091	0	0	0	0
	S/C	0	0	0	0	0.2724	0	0.6461	0.0814	0	0	0
	E/O	0	0	0	0	0.6890	0.1037	0.1037	0.1037	0	0	0
	IEE	0	0	0	0.04	0.4584	0.0988	0.2834	0.1194	0	0	0
Option 4	P/C	0	0	0	0	0	0.7143	0	0.2857	0	0	0
	B/E	0	0	0	0	0.1478	0.8522	0	0	0	0	0
	S/C	0	0	0	0	0.1633	0.7593	0.0774	0	0	0	0
	E/O	0	0	0	0.1995	0	0.8005	0	0	0	0	0
	IEE	0	0	0	0.0366	0.0585	0.8383	0.0142	0.0524	0	0	0

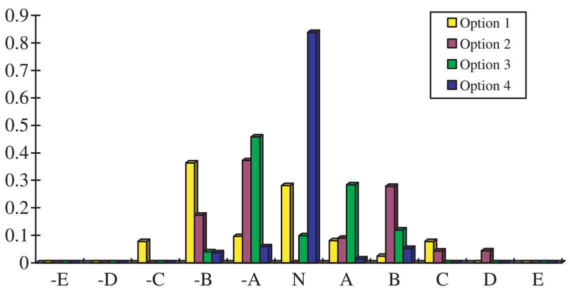

Fig. 3. The overall assessment results for the four alternative options by the ER approach.

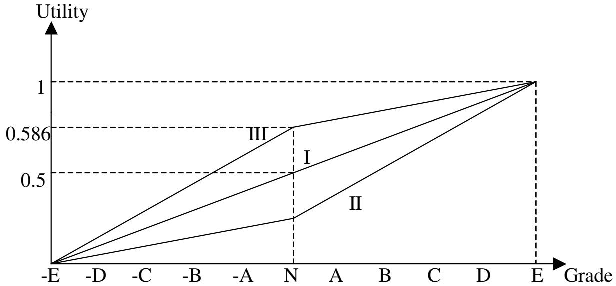

Fig. 4. Decision maker's utility function.

Then the expected utility of each option can be calculated as follows:

$$u(\text{option 1}) = 0.3590, \quad u(\text{option 2}) = 0.4565, \quad u(\text{option 3}) = 0.4196, \quad u(\text{option 4}) = 0.4037.$$

Option 2 is still the best choice.

Suppose the DM is risk-averse (curve III) and provides the following utilities for the 11 assessment grades:

$$u(-\mathrm{E}) = 0, \quad u(-\mathrm{D}) = 0.13, \quad u(-\mathrm{C}) = 0.26, \quad u(-\mathrm{B}) = 0.39, \quad u(-\mathrm{A}) = 0.52,$$
$$u(\mathrm{N}) = 0.65, \quad u(\mathrm{A}) = 0.72, \quad u(\mathrm{B}) = 0.79, \quad u(\mathrm{C}) = 0.86, \quad u(\mathrm{D}) = 0.93, \quad u(\mathrm{E}) = 1.0$$

Then his/her expected utility for each option will be:

$$u(\text{option 1}) = 0.5382, \quad u(\text{option 2}) = 0.6231, \quad u(\text{option 3}) = 0.6166, \quad u(\text{option 4}) = 0.6412.$$

In this case, option 2 is no longer the best choice and option 4 becomes the most preferred choice.

In this example, as long as $u(N) \geqslant 0.5862$ under the assumption of piecewise linear utility function, a risk-averse DM would always prefer option 4 to option 2. If the DM is a highly risk-averse person, curve III will become more convex. Suppose a highly risk-averse DM provides the following utilities about each assessment grade:

$$u(-\mathrm{E}) = 0, \quad u(-\mathrm{D}) = 0.17, \quad u(-\mathrm{C}) = 0.34, \quad u(-\mathrm{B}) = 0.51, \quad u(-\mathrm{A}) = 0.68,$$
$$u(\mathrm{N}) = 0.85, \quad u(\mathrm{A}) = 0.88, \quad u(\mathrm{B}) = 0.91, \quad u(\mathrm{C}) = 0.94, \quad u(\mathrm{D}) = 0.97, \quad u(\mathrm{E}) = 1.0$$

His/Her expected utility about each option can be computed as follows:

$$u(\text{option 1}) = 0.6816, \quad u(\text{option 2}) = 0.7564, \quad u(\text{option 3}) = 0.7741, \quad u(\text{option 4}) = 0.8312.$$

In this case, the DM prefers not only option 4 to option 2, but also option 3 to option 2. So, once the assessment framework and factor weights are decided, the DM's attitude towards risk will to a large extent decide which option is the most preferred. For a risk-neutral or risk-taking DM, option 2 is the best choice; but for a highly risk-averse DM, option 4 is the first choice.

The above ER evaluation is conducted using exactly the same assessment information as used in RIAM. In general, EIA is a multi-person evaluation problem. It requires the participation of multiple experts having different backgrounds and expertise. Due to differences in background, knowledge, experience, and cross influence among experts, it is highly likely that different experts may provide nonconsensus assessment information even for the same identified environmental factor. The original assessment information provided by RIAM did not reflect such differences. To illustrate the modeling and processing of different types of assessment information that may be provided by different experts, we modify the above example in the following ways.

4.5. The modified belief matrix and ER reevaluation

Table 5 is an illustrative belief decision matrix based on Table 3, where incomplete information is highlighted in grey and the completely ignorance in dark. The meaning of each distributed assessment in Table 5 would be explained in the way as discussed in Section 3.2. In Table 5, more weights are put on the P/C factor and less on E/O. Using the ER algorithm to aggregate the above information, the results are presented in Table 6 and shown in Fig. 5, where H stands for ignorance about assessments due to the incomplete information.

It can be seen from Table 6 and Fig. 5 that a no-action plan (option 1) has significant negative impacts and only marginal positive impacts on the total environment and is obviously the worst option. The impacts of option 4 on the environment are mainly neutral, so the option does not cause significant positive or negative impacts. Option 2 has significant positive impacts on the environment, mainly on

Table 5
The modified distributed assessments matrix for the four options

Environmental factors (relative weights)	Option 1	Option 2	Option 3	Option 4
Physical/Chemical (P/C) (0.35)				
P/C 1 (0.35)	{(−D, 0.3), (−C, 0.7)}	{(A, 0.1), (B, 0.9)}	{(B, 0.8), (C, 0.2)}	{(N, 1.0)}
P/C 2 (0.50)	{(−B, 0.8), (−A, 0.2)}	{(A, 0.1), (B, 0.85)}	{(−A, 0.85), (N, 0.15)}	{(A, 0.3), (B, 0.7)}
P/C 3 (0.15)	{(B, 0.45), (C, 0.35)}	{(−C, 0.2), (−B, 0.8)}	{(N, 0.5), (A, 0.5)}	{(N, 1.0)}
Biological/Ecological (B/E) (0.25)				
B/E 1 (0.2)	{(−C, 0.5), (−B, 0.4)}		{(N, 0.2), (A, 0.8)}	{(N, 1.0)}
B/E 2 (0.2)	{(−B, 0.5), (−A, 0.5)}	{(−A, 1.0)}	{(−B, 0 8), (−A, 0.1)}	{(N, 1.0)}
B/E 3 (0.2)	{(−B, 1.0)}	{(−B, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
B/E 4 (0.2)	{(−B, 1.0)}	{(−B, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
B/E 5 (0.2)		{(A, 1.0)}	{(A, 1.0)}	{(−A, 0.4), (N, 0.5)}
Sociological/Cultural (S/C) (0.25)				
S/C 1 (0.1)	{(N, 1.0)}	{(−A,1.0)}	{(−A, 1.0)}	{(N, 1.0)}
S/C 2 (0.1)	{(N, 1.0)}	{(−A, 0.65), (N, 0.3)}	{(−A, 1.0)}	{(N, 1.0)}
S/C 3 (0.1)	{(N, 0.5), (A, 0.5)}	{(−A, 1.0)}		{(N, 1.0)}
S/C 4 (0.1)	{(−B, 0.2), (−A, 0.8)}	{(B, 0.8), (C, 0.2)}	{(A, 1.0)}	{(N, 1.0)}
S/C 5 (0.1)	{(−B, 0.3), (−A, 0.7)}	{(C, 1.0)}	{(A, 1.0)}	{(A, 0.8)}
S/C 6 (0.1)	{(N, 1.0)}	{(A, 0.8), (B, 0.2)}	{(A, 0.5), (B, 0.5)}	{(N, 1.0)}
S/C 7 (0.1)	{(−B, 1.0)}	{(B, 1.0)}	{(A, 0.4), (B, 0.6)}	{(N, 1.0)}
S/C 8 (0.1)	{(A, 0.5), (B, 0.3)}	{(−A, 1.0)}	{(A, 1.0)}	{(−A, 1.0)}
S/C 9 (0.1)	{(N, 1.0)}	{(A, 1.0)}	{(N, 0.2), (A, 0.7)}	{(−A, 1.0)}
S/C 10 (0.1)	{(−A, 1.0)}	{(B, 1.0)}	{(B, 1.0)}	{(N, 1.0)}
Economic/Operational (E/O) (0.15)				
E/O 1 (0.125)	{(B, 0.8)}	{(−A,1.0)}	{(B, 0.9)}	{(N, 1.0)}
E/O 2 (0.125)	{(−B, 1.0)}	{(B, 1.0)}	{(N, 1.0)}	{(N, 1.0)}
E/O 3 (0.125)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(−B, 1.0)}
E/O 4 (0.125)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(−B, 1.0)}
E/O 5 (0.125)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
E/O 6 (0.125)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
E/O 7 (0.125)	{(N, 1.0)}	{(−A, 1.0)}	{(−A, 1.0)}	{(N, 1.0)}
E/O 8 (0.125)	{(−A, 1.0)}	{(C, 0.7)}	{(A, 1.0)}	{(N, 1.0)}

the improvements of physical-chemical, sociological and cultural environments. However, it also leads to some negative impacts, including the degeneration of biological/ecological and economical/operational environments. Compared with option 2, option 3 has more negative impacts on the environment. So, option 3 is obviously inferior to option 2. As for options 2 and 4, which one is better depends primarily on the DM's preferences, which can be represented using utility functions.

For a risk-neutral DM, the minimum, maximum and average expected utilities for each option can be calculated using formula (28)–(30). The results are shown in Table 7. It is obvious that option 2 is the best choice in this case.

For a risk-taking DM, who provides the following utilities about each assessment grade:

$$u(-\mathrm{E}) = 0, \quad u(-\mathrm{D}) = 0.06, \quad u(-\mathrm{C}) = 0.12, \quad u(-\mathrm{B}) = 0.18, \quad u(-\mathrm{A}) = 0.24,$$
$$u(\mathrm{N}) = 0.30, \quad u(\mathrm{A}) = 0.44, \quad u(\mathrm{B}) = 0.58, \quad u(\mathrm{C}) = 0.72, \quad u(\mathrm{D}) = 0.86, \quad u(\mathrm{E}) = 1.0$$

Table 6
The aggregated distributed assessments with uncertainty for the four options

Options	Factors	Degrees of belief assessed to each assessment grade											
		−E	−D	−C	−B	−A	N	A	B	C	D	E	H
Option 1	P/C	0	0.09453	0.22056	0.46813	0.11703	0	0	0.04488	0.03491	0	0	0.01995
	B/E	0	0	0.08737	0.6658	0.08956	0	0	0	0	0	0	0.15727
	S/C	0	0	0	0.13852	0.24246	0.48561	0.09007	0.02601	0	0	0	0.01734
	E/O	0	0	0	0.10395	0.10395	0.69103	0	0.08085	0	0	0	0.02021
	IEE	0	0.03406	0.1004	0.41345	0.13653	0.20429	0.02019	0.03208	0.01258	0	0	0.04643
Option 2	P/C	0	0	0.01709	0.06837	0	0	0.07469	0.81678	0	0	0	0.02306
	B/E	0	0	0	0.44554	0.19802	0	0.19802	0	0	0	0	0.15842
	S/C	0	0	0	0	0.3827	0.02698	0.1708	0.30451	0.11052	0	0	0.0045
	E/O	0	0	0	0	0.81443	0	0	0.09473	0.06359	0	0	0.02725
	IEE	0	0	0.00623	0.12505	0.25305	0.00615	0.11488	0.41515	0.03313	0	0	0.04637
Option 3	P/C	0	0	0	0	0.49185	0.14551	0.05106	0.24926	0.06232	0	0	0
	B/E	0	0	0	0.14241	0.43836	0.03649	0.36493	0	0	0	0	0.0178
	S/C	0	0	0	0	0.18824	0.01764	0.50448	0.20145	0	0	0	0.08819
	E/O	0	0	0	0	0.69005	0.1038	0.1038	0.09211	0	0	0	0.01023
	IEE	0	0	0	0.03044	0.46679	0.07592	0.23504	0.14694	0.02164	0	0	0.02324
Option 4	P/C	0	0	0	0	0	0.4475	0.16575	0.38675	0	0	0	0
	B/E	0	0	0	0	0.05242	0.93447	0	0	0	0	0	0.01311
	S/C	0	0	0	0	0.16357	0.76063	0.06064	0	0	0	0	0.01516
	E/O	0	0	0	0.19952	0	0.80048	0	0	0	0	0	0
	IEE	0	0	0	0.02	0.04124	0.75197	0.06315	0.11831	0	0	0	0.00532

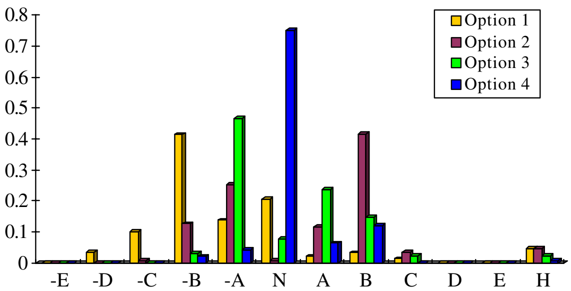

Fig. 5. The overall reassessment results for the four alternative options by the ER approach.

the minimum, maximum and average expected utilities for each option are shown in Table 8, from which it is clear that option 2 is still the best choice.

For a highly risk-averse DM, who gives the following utilities about the eleven assessment grades:

$$u(-\mathrm{E}) = 0,\quad u(-\mathrm{D}) = 0.17,\quad u(-\mathrm{C}) = 0.34,\quad u(-\mathrm{B}) = 0.51,\quad u(-\mathrm{A}) = 0.68,$$
$$u(\mathrm{N}) = 0.85,\quad u(\mathrm{A}) = 0.88,\quad u(\mathrm{B}) = 0.91,\quad u(\mathrm{C}) = 0.94,\quad u(\mathrm{D}) = 0.97,\quad u(\mathrm{E}) = 1.0$$

the minimum, maximum and average expected utilities about each option are presented in Table 9. It is clear that option 2 is no longer the best choice and option 4 becomes the best. In fact, as the degree of risk-aversion increases, the superiority of option 4 becomes more apparent. When $u(N) \geqslant 0.7024$, option 4 becomes absolutely superior to option 2.

Table 7
A risk-neutral DM's expected utilities and rankings about the four options

Options	Expected utilities			Rank
	Minimum	Maximum	Average	
Option 1	0.3489	0.3953	0.3721	4
Option 2	0.5291	0.5755	0.5523	1
Option 3	0.4950	0.5182	0.5066	3
Option 4	0.5192	0.5245	0.5219	2

Table 8
A risk-taking DM's expected utilities and rankings about the four options

Options	Expected utilities			Rank
	Minimum	Maximum	Average	
Option 1	0.2191	0.2655	0.2423	4
Option 2	0.4010	0.4474	0.4242	1
Option 3	0.3445	0.3678	0.3561	2
Option 4	0.3355	0.3408	0.3382	3

Table 9
A highly risk-averse DM's expected utilities and rankings about the four options

Options	Expected utilities			Rank
	Minimum	Maximum	Average	
Option 1	0.5761	0.6225	0.5993	4
Option 2	0.7532	0.7996	0.7764	2
Option 3	0.7584	0.7816	0.7700	3
Option 4	0.8407	0.8460	0.8433	1

In summary, risk-neutral and risk-taking DMs tend to choose option 2 as the best choice, whilst a highly risk-averse DM will select option 4 as the best choice. Of course, the final recommended option still needs the further consideration of real financial capability. This is beyond the scope of the paper and will not be discussed in the paper. Also, estimating the utility of the DM or DMs is itself a very important and time-consuming process because changing the points of discontinuity in the piecewise linear utility function may affect the choice of the best option. How to elicit the DM's preferences and his utilities will not be discussed here either. The interested reader may refer to Keeney and Raiffa (1976), Zeleny (1982) or Winston (1994) for details.

From the comparison of the RIAM and ER approach, it can be found that the ER approach provides a flexible and pragmatic way for EIA. It can deal with various kinds of uncertainties involved in EIA. Even the assessment grades may also be expressed in the form of fuzzy linguistic variables. The interested reader may refer to Yang et al. (in press-b).

5. Concluding remarks

Most real world EIA problems involve large amount of human judgments and various types of uncertainties, which significantly increase the complexity and difficulty in the EIA process. The support to the solution of such EIA problems requires powerful methodologies that are capable of dealing with uncertainties in a way that is rational, systematic, reliable, flexible and transparent. The evidential reasoning (ER) approach provides a novel, flexible and systematic way to support EIA analysis. The new analytical ER algorithm developed in this paper provides an explicit aggregation function, which can be used in many decision situations such as optimisation.

In particular, the ER distributed modelling framework makes it possible to deal with various human judgments, either complete or incomplete, crisp or vague (fuzzy), using the belief structure, which allows assessors to describe assessment information in a flexible, natural and reliable manner. The ER algorithms provide two systematic yet rigorous procedures for aggregating assessment information in a recursive or an analytical fashion. The utility interval based ranking method opens a systematic and effective way to compare and rank alternatives. A numerical example and its modified version demonstrate the implementation process of the ER approach for EIA. It is expected that the ER approach can be used to deal with a range of EIA problems with various types of uncertainties.

The ER approach is a kind of MADA method. Different from most existing MADA approaches such as the simple additive weighting (SAW) method (Hwang and Yoon, 1981), AHP (Saaty, 1980), TOPSIS (Hwang and Yoon, 1981; Chen, 2000), PROMETHEE (Brans and Vincke, 1985; Brans et al., 1986; Keyser and Peeters, 1996; Le Téno and Mareschal, 1998; Goumas and Lygerou, 2000; Macharis et al., 2004), ELECTRE (Roy, 1991; Huylenbroeck, 1995; Hokkanen and Salminen, 1997c; Rogers and Bruen, 1998) and MAUT (Keeney and Raiffa, 1976; Zeleny, 1982; Winston, 1994), the ER approach models both quantitative and qualitative attributes/criteria using a belief structure, leading to a belief decision matrix, where each element of the matrix is a vector rather than a single value. The ER approach makes no assumptions about the aggregated functional form that is nonlinear in general and it only requires utility independence among individual attributes (Keeney and Raiffa, 1976). The ER approach does not result in rank reversal, a phenomenon which might occur in AHP. This is because the ER approach models each decision alternative independently.

Both the DS/AHP (Beynon et al., 2000, 2001; Beynon, 2002a,b, 2005a,b) and the ER approaches are developed on the basis of the D-S theory of evidence, but they are quite different in nature. The former is an extension of the traditional AHP, while the latter has little to do with AHP. So, they are different in many ways such as modeling mechanisms, algorithms and so on.

However, the attribute aggregation process of the ER approach is more complicated than several other MADA methods such as MAUT, though this shortcoming is to a large extent overcome by generating a Windows-based intelligent decision system (IDS) software package to support the implementation of the ER approach. The interested reader may refer to Xu and Yang (2003).

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Appendix A. The derivation of the analytical ER algorithm

Since the normalization in the evidence combination rule of the Dempster–Shafer (D–S) theory of evidence can be applied at the end of the evidence combination process without changing the combination result (Yen, 1990), we first take no account of the normalization when combining all factors and then apply the normalization at the end. Such an evidence combination process, as Yen (1990) claimed for combining fuzzy evidence, can preserve the unique feature of the D–S theory that the belief and plausibility measures provide the lower and the upper bounds of the degrees of belief.

First of all, let us combine two factors. Table 10 shows the combination process of two factors without normalization. The combined probability masses generated by aggregating the two factors are given as follows. Note that $m_{1-l}(H_n)$ and $m_{1-l}(H)$ denote the belief degree assigned to H_n and H generated by combining the first l factors:

$$\begin{aligned} m_{1-2}(H_n) &= m_{n,1}m_{n,2} + (\widetilde{m}_{H,1} + \bar{m}_{H,1})m_{n,2} + m_{n,1}(\widetilde{m}_{H,2} + \bar{m}_{H,2}) = m_{n,1}m_{n,2} + m_{H,1}m_{n,2} + m_{n,1}m_{H,2} \\ &= m_{n,1}(m_{n,2} + m_{H,2}) + m_{H,1}m_{n,2} = m_{n,1}(m_{n,2} + m_{H,2}) + m_{H,1}(m_{n,2} + m_{H,2}) - m_{H,1}m_{H,2} \\ &= (m_{n,1} + m_{H,1})(m_{n,2} + m_{H,2}) - m_{H,1}m_{H,2} = \prod_{i=1}^{2}(m_{n,i} + m_{H,i}) - \prod_{i=1}^{2} m_{H,i} \\ &= \prod_{i=1}^{2}(m_{n,i} + \widetilde{m}_{H,i} + \bar{m}_{H,i}) - \prod_{i=1}^{2}(\widetilde{m}_{H,i} + \bar{m}_{H,i}), \quad n = 1, \ldots, N, \end{aligned}$$

$$\begin{aligned} \widetilde{m}_{1-2}(H) &= \widetilde{m}_{H,1}\widetilde{m}_{H,2} + \widetilde{m}_{H,1}\bar{m}_{H,2} + \bar{m}_{H,1}\widetilde{m}_{H,2} = (\widetilde{m}_{H,1} + \bar{m}_{H,1})\widetilde{m}_{H,2} + \widetilde{m}_{H,1}\bar{m}_{H,2} \\ &= (\widetilde{m}_{H,1} + \bar{m}_{H,1})\widetilde{m}_{H,2} + (\widetilde{m}_{H,1} + \bar{m}_{H,1})\bar{m}_{H,2} - \bar{m}_{H,1}\bar{m}_{H,2} \\ &= (\widetilde{m}_{H,1} + \bar{m}_{H,1})(\widetilde{m}_{H,2} + \bar{m}_{H,2}) - \bar{m}_{H,1}\bar{m}_{H,2} = \prod_{i=1}^{2}(\widetilde{m}_{H,i} + \bar{m}_{H,i}) - \prod_{i=1}^{2} \bar{m}_{H,i}, \end{aligned}$$

$$\bar{m}_{1-2}(H) = \bar{m}_{H,1}\bar{m}_{H,2} = \prod_{i=1}^{2} \bar{m}_{H,i}.$$

Suppose the following equations are true for combining the first $(l-1)$ factors and let $l_1 = l{-}1$

$$m_{1-l_1}(H_n) = \prod_{i=1}^{l-1}(m_{n,i} + \widetilde{m}_{H,i} + \bar{m}_{H,i}) - \prod_{i=1}^{l-1}(\widetilde{m}_{H,i} + \bar{m}_{H,i}), \quad n = 1, \ldots, N,$$

$$\widetilde{m}_{1-l_1}(H) = \prod_{i=1}^{l-1}(\widetilde{m}_{H,i} + \bar{m}_{H,i}) - \prod_{i=1}^{l-1} \bar{m}_{H,i},$$

$$\bar{m}_{1-l_1}(H) = \prod_{i=1}^{l-1} \bar{m}_{H,i}.$$

Table 10
The combination of two pieces of evidence

$m_1 \oplus m_2$			m_1				
			$\{H_1\}$	$\{H_2\}$	… $\{H_N\}$	$\{H\}$	$\{H\}$
			$m_{1,1}$	$m_{2,1}$	… $m_{N,1}$	$\widetilde{m}_{H,1}$	$\bar{m}_{H,1}$
m_2	$\{H_1\}$	$m_{1,2}$	$m\{H_1\} = m_{1,1}m_{1,2}$	$m\{\Phi\} = m_{2,1}m_{1,2}$	… $m\{\Phi\} = m_{N,1}m_{1,2}$	$m\{H_1\} = \widetilde{m}_{H,1}m_{1,2}$	$m\{H_1\} = \bar{m}_{H,1}m_{1,2}$
	$\{H_2\}$	$m_{2,2}$	$m\{\Phi\} = m_{1,1}m_{2,2}$	$m\{H_2\} = m_{2,1}\, m_{2,2}$	… $m\{\Phi\} = m_{N,1}m_{2,2}$	$m\{H_2\} = \widetilde{m}_{H,1}m_{2,2}$	$m\{H_2\} = \bar{m}_{H,1}m_{2,2}$
	…	…	…	…	… …	…	…
	$\{H_N\}$	$m_{N,2}$	$m\{\Phi\} = m_{1,1}m_{N,2}$	$m\{\Phi\} = m_{2,1}m_{N,2}$	… $m\{H_N\} = m_{N,1}m_{N,2}$	$m\{H_N\} = \widetilde{m}_{H,1}m_{N,2}$	$m\{H_N\} = \bar{m}_{H,1}m_{N,2}$
	$\{H\}$	$\widetilde{m}_{H,2}$	$m\{H_1\} = m_{1,1}\widetilde{m}_{H,2}$	$m\{H_2\} = m_{2,1}\widetilde{m}_{H,2}$	… $m\{H_N\} = m_{N,1}\widetilde{m}_{H,2}$	$m\{H\} = \widetilde{m}_{H,1}\widetilde{m}_{H,2}$	$m\{H\} = \bar{m}_{H,1}\widetilde{m}_{H,2}$
	$\{H\}$	$\bar{m}_{H,2}$	$m\{H_1\} = m_{1,1}\bar{m}_{H,2}$	$m\{H_2\} = m_{2,1}\bar{m}_{H,2}$	… $m\{H_N\} = m_{N,1}\bar{m}_{H,2}$	$m\{H\} = \widetilde{m}_{H,1}\bar{m}_{H,2}$	$m\{H\} = \bar{m}_{H,1}\bar{m}_{H,2}$

The above combined probability masses are further aggregated with the lth factor. The results are generated using Table 11. The combined probability masses are then given below

$$\begin{aligned}
m_{1-l}(H_n) &= m_{n,1-l_1}m_{n,l} + (\widetilde{m}_{H,1-l_1} + \bar{m}_{H,1-l_1})m_{n,l} + m_{n,1-l_1}(\widetilde{m}_{H,l} + \bar{m}_{H,l}) \\
&= m_{n,1-l_1}m_{n,l} + m_{H,1-l_1}m_{n,l} + m_{n,1-l_1}m_{H,l} = m_{n,1-l_1}(m_{n,l} + m_{H,l}) + m_{H,1-l_1}m_{n,l} \\
&= m_{n,1-l_1}(m_{n,l} + m_{H,l}) + m_{H,1-l_1}(m_{n,l} + m_{H,l}) - m_{H,1-l_1}m_{H,l} \\
&= (m_{n,1-l_1} + m_{H,1-l_1})(m_{n,l} + m_{H,l}) - m_{H,1-l_1}m_{H,l} \\
&= (m_{n,l} + m_{H,l})\left(\prod_{i=1}^{l-1}(m_{n,i} + m_{H,i}) - \prod_{i=1}^{l-1}m_{H,i} + \prod_{i=1}^{l-1}m_{H,i}\right) - m_{H,l}\prod_{i=1}^{l-1}m_{H,i} \\
&= \prod_{i=1}^{l}(m_{n,i} + m_{H,i}) - \prod_{i=1}^{l}m_{H,i} = \prod_{i=1}^{l}(m_{n,i} + \widetilde{m}_{H,i} + \bar{m}_{H,i}) - \prod_{i=1}^{l}(\widetilde{m}_{H,i} + \bar{m}_{H,i}), \quad n = 1, \ldots, N,
\end{aligned}$$

$$\begin{aligned}
\widetilde{m}_{1-l}(H) &= \widetilde{m}_{H,1-l_1}\widetilde{m}_{H,l} + \widetilde{m}_{H,1-l_1}\bar{m}_{H,l} + \bar{m}_{H,1-l_1}\widetilde{m}_{H,l} = (\widetilde{m}_{H,1-l_1} + \bar{m}_{H,1-l_1})\widetilde{m}_{H,l} + \widetilde{m}_{H,1-l_1}\bar{m}_{H,l} \\
&= (\widetilde{m}_{H,1-l_1} + \bar{m}_{H,1-l_1})\widetilde{m}_{H,l} + (\widetilde{m}_{H,1-l_1} + \bar{m}_{H,1-l_1})\bar{m}_{H,l} - \bar{m}_{H,1-l_1}\bar{m}_{H,l} \\
&= (\widetilde{m}_{H,1-l_1} + \bar{m}_{H,1-l_1})(\widetilde{m}_{H,l} + \bar{m}_{H,l}) - \bar{m}_{H,1-l_1}\bar{m}_{H,l} = \prod_{i=1}^{l}(\widetilde{m}_{H,i} + \bar{m}_{H,i}) - \prod_{i=1}^{l}\bar{m}_{H,i},
\end{aligned}$$

$$\bar{m}_{1-l}(H) = \bar{m}_{H,1-l_1}\bar{m}_{H,l} = \prod_{i=1}^{l}\bar{m}_{H,i}.$$

Therefore, the above equations are true for any $l \in \{1, \ldots, L\}$. For $l = L$, we get the following non-normalized combined probability assignments generated by aggregating the L factors:

$$m_{1-L}(H_n) = \prod_{i=1}^{L}(m_{n,i} + \widetilde{m}_{H,i} + \bar{m}_{H,i}) - \prod_{i=1}^{L}(\widetilde{m}_{H,i} + \bar{m}_{H,i}), \quad n = 1, \ldots, N,$$

$$\widetilde{m}_{1-L}(H) = \prod_{i=1}^{L}(\widetilde{m}_{H,i} + \bar{m}_{H,i}) - \prod_{i=1}^{L}\bar{m}_{H,i},$$

$$\bar{m}_{1-L}(H) = \prod_{i=1}^{L}\bar{m}_{H,i}.$$

Define by k the normalization constant for the evidence combination. Then, we have the normalized combined probability masses as follows:

$$m(H_n) = km_{1-L}(H_n) = k\left\{\prod_{i=1}^{L}(m_{n,i} + \widetilde{m}_{H,i} + \bar{m}_{H,i}) - \prod_{i=1}^{L}(\widetilde{m}_{H,i} + \bar{m}_{H,i})\right\}, \quad n = 1, \ldots, N,$$

$$\widetilde{m}(H) = k\widetilde{m}_{1-L}(H) = k\left\{\prod_{i=1}^{L}(\widetilde{m}_{H,i} + \bar{m}_{H,i}) - \prod_{i=1}^{L}\bar{m}_{H,i}\right\},$$

$$\bar{m}(H) = k\bar{m}_{1-L}(H) = k\left[\prod_{i=1}^{L}\bar{m}_{H,i}\right],$$

Table 11
The combination of l pieces of evidence

$m_{1-l_1} \oplus m_l$			m_{1-l_1}					
			$\{H_1\}$	$\{H_2\}$	...	$\{H_N\}$	$\{H\}$	$\{H\}$
			$m_{1,1-l_1}$	$m_{2,1-l_1}$	...	$m_{N,1-l_1}$	$\widetilde{m}_{H,1-l_1}$	$\bar{m}_{H,1-l_1}$
m_l	$\{H_1\}$	$m_{1,l}$	$m\{H_1\} = m_{1,1-l_1} m_{1,l}$	$m\{\Phi\} = m_{2,1-l_1} m_{1,l}$	...	$m\{\Phi\} = m_{N,1-l_1} m_{1,l}$	$m\{H_1\} = \widetilde{m}_{H,1-l_1} m_{1,l}$	$m\{H_1\} = \bar{m}_{H,1-l_1} m_{1,l}$
	$\{H_2\}$	$m_{2,l}$	$m\{\Phi\} = m_{1,1-l_1} m_{2,l}$	$m\{H_2\} = m_{2,1-l_1} m_{2,l}$	...	$m\{\Phi\} = m_{N,1-l_1} m_{2,l}$	$m\{H_2\} = \widetilde{m}_{H,1-l_1} m_{2,l}$	$m\{H_2\} = \bar{m}_{H,1-l_1} m_{2,l}$
	...	...	...	...	...	...	...	...
	$\{H_N\}$	$m_{N,l}$	$m\{\Phi\} = m_{1,1-l_1} m_{N,l}$	$m\{\Phi\} = m_{2,1-l_1} m_{N,l}$	...	$m\{H_N\} = m_{N,1-l_1} m_{N,l}$	$m\{H_N\} = \widetilde{m}_{H,1-l_1} m_{N,l}$	$m\{H_N\} = \bar{m}_{H,1-l_1} m_{N,l}$
	$\{H\}$	$\widetilde{m}_{H,l}$	$m\{H_1\} = m_{1,1-l_1} \widetilde{m}_{H,l}$	$m\{H_2\} = m_{2,1-l_1} \widetilde{m}_{H,l}$	...	$m\{H_N\} = m_{N,1-l_1} \widetilde{m}_{H,l}$	$m\{H\} = \widetilde{m}_{H,1-l_1} \widetilde{m}_{H,l}$	$m\{H\} = \bar{m}_{H,1-l_1} \widetilde{m}_{H,l}$
	$\{H\}$	$\bar{m}_{H,l}$	$m\{H_1\} = m_{1,1-l_1} \bar{m}_{H,l}$	$m\{H_2\} = m_{2,1-l_1} \bar{m}_{H,l}$	...	$m\{H_N\} = m_{N,1-l_1} \bar{m}_{H,l}$	$m\{H\} = \widetilde{m}_{H,1-l_1} \bar{m}_{H,l}$	$m\{H\} = \bar{m}_{H,1-l_1} \bar{m}_{H,l}$

where k can be determined using the following normalization constraint condition

$$\sum_{n=1}^{N} m(H_n) + \widetilde{m}(H) + \bar{m}(H) = 1$$

from which we get

$$k = \left[\sum_{n=1}^{N}\prod_{i=1}^{L}(m_{n,i} + \bar{m}_{H,i} + \widetilde{m}_{H,i}) - (N-1)\prod_{i=1}^{L}(\bar{m}_{H,i} + \widetilde{m}_{H,i})\right]^{-1}.$$

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