A group evidential reasoning approach for enterprise architecture framework selection

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Abstract: Enterprise architecture (EA) frameworks are used to ensure interoperability of information systems and improve the effectiveness and efficiency of business organisations. Several methods have been proposed for selecting suitable frameworks. Although these methods are useful, none of them captures the uncertainties inherent in multi-attribute framework selection problems that embrace both qualitative and quantitative attributes. We propose an evidential reasoning (ER) approach to aggregate subjective and objective judgements associated with qualitative and quantitative attributes rationally and systematically. The ER approach proposed here has the following advantages over other multi-attribute decision-making (MADM) approaches used for EA framework selection:

1 the relative importance of different attributes is incorporated into the model
2 attribute ratings are treated as assessment grades rather than precise numerical values
3 attributes can be assessed with belief functions to capture uncertainties.

A case study is provided to illustrate the implementation process of the ER approach proposed in this study.

Keywords: multiple-attribute decision making; MADM; evidential reasoning approach; distributed assessment; belief degrees; evaluation grades; enterprise architecture framework; uncertainty modelling.

Reference to this paper should be made as follows: Zandi, F. and Tavana, M. (2010) 'A group evidential reasoning approach for enterprise architecture framework selection', *Int. J. Information Technology and Management*, Vol. 9, No. 4, pp.468–483.

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1 Introduction

Enterprise architecture (EA) framework selection problems are multi-attribute decision-making (MADM) problems that embrace both qualitative and quantitative attributes. When facing such multi-attribute problems, the literature and research show that the following difficulties may be encountered:

1. Decision makers (DMs) often use verbal expressions and linguistic variables for subjective judgements which lead to ambiguity in human decision-making (Poyhonen et al., 1997).
2. DMs often provide imprecise or vague information due to lack of expertise, unavailability of data, or time constraint (Kim and Ahn, 1999).
3. Meaningful and robust aggregation of subjective and objective judgements causes problems during the evaluation process (Valls and Torra, 2000).

A decision may not be properly made without fully taking into consideration all the attributes in MADM (Belton and Stewart, 2002; Yang and Xu, 2002a). Yang and Singh (1994) have proposed and developed an evidential reasoning (ER) approach to deal with MADM problems under uncertainties and improve the insightfulness and rationality of a DM. The ER approach uses the Dempster-Shafer (D-S) theory of evidence to aggregate subjective and objective judgements associated with qualitative and quantitative attributes rationally and systematically (Yang and Sen, 1994; Yang, 2001). The D-S theory of evidence was first developed by Dempster (1967) and then extended and refined by Shafer (1976). The D-S theory has found wide applications in many areas such as expert systems (Goicoechea, 1988; Beynon et al., 2001; Jones et al., 2002), database and knowledge discovery (Anand et al., 1996; McClean and Scotney, 1997; Cai et al., 2000), risk assessment (Liu et al., 2004a, 2004b; Soundappan et al., 2004), and MADA (Korvin and Shipley, 1993; Yager, 2002; Yang and Singh, 1994; Yang and Sen, 1997; Beynon et al., 2000; Beynon, 2005a, 2005b; Yang, 2001; Yang and Xu, 2002a, 2002b; Xu and Yang, 2003; Osei-Bryson, 2003).

ER uses the concept of degree of belief to elicit DM's preferences (Bryson and Mobolurin, 1999). The degree of belief depends on the knowledge of the subject and the experience and can be described as the degree of expectation that an alternative will yield a certain outcome on a particular attribute (Cobb and Shenon, 2003). The use of belief functions can be justified by the fact that DMs tend to make judgements intuitively and it may not always be possible to expect precise judgements when evaluating decision attributes (Srivastava and Mock, 2000). However, it is important to obtain the DM's true preferences in a decision-making problem in order to ensure that a robust and rational decision can be made based on the real preferences of the DM (Srivastava and Liu, 2003).

ER has increasingly been applied to different multi-attribute problems. Interested readers may refer to the following references for a complete explanation of the method: Yang and Singh (1994); Yang and Sen (1994, 1996, 1997); Wang et al. (1995, 1996); and Yang (2001). In recent years, a growing volume of research has been performed in the use of MADM and EA framework selection (Petkov et al., 2007; Salling and Leleur, 2007; Sun et al., 2006). The central issue in EA framework selection is how to incorporate different types of uncertainties and risks, as well as quantitative and qualitative information in the selection process.

Over the past several years, the selection of EA frameworks has garnered considerable attention from both practitioners and academics in the fields of information. Fayad and Hamu (2000) have presented a detailed list of guidelines and attributes for selection of EA frameworks. Tang et al. (2004) have studied and compared the EA frameworks analytically and provided a model of understanding through analysing the goals, inputs and outcomes of six architecture frameworks. However, their model did not consider any uncertainties such as uncertainty in subjective judgements or uncertainties due to lack of data and incomplete information. In this study, we consider the following five multi-attribute EA frameworks: Zachman framework for enterprise architecture (ZF), Federal enterprise architecture framework (FEAF), The open group architecture framework (TOGAF), Department of Defence architecture framework (DoDAF), and Treasury enterprise architecture framework (TEAF). We propose the following 13 attributes of good EA to evaluate the five EA frameworks as suggested by Fayad and Hamu (2000) and Fayad et al. (2000):

1 management expectation

2 compatibility needed with national EA framework

3 availability of existing architecture products

4 priorities, desired level of detail

5 resource and schedule constraints

6 mature run-time functionality

7 support for extensibility, and customisability, flexibility and scalability

8 support for role object pattern and ease of use

9 EA framework supportive tools

10 make use of standard terms

11 employ processes and mechanisms that support systems evolution

12 provide consistent standards to document architecture specifications for planning

13 ensure development and architecture standards are maintained.

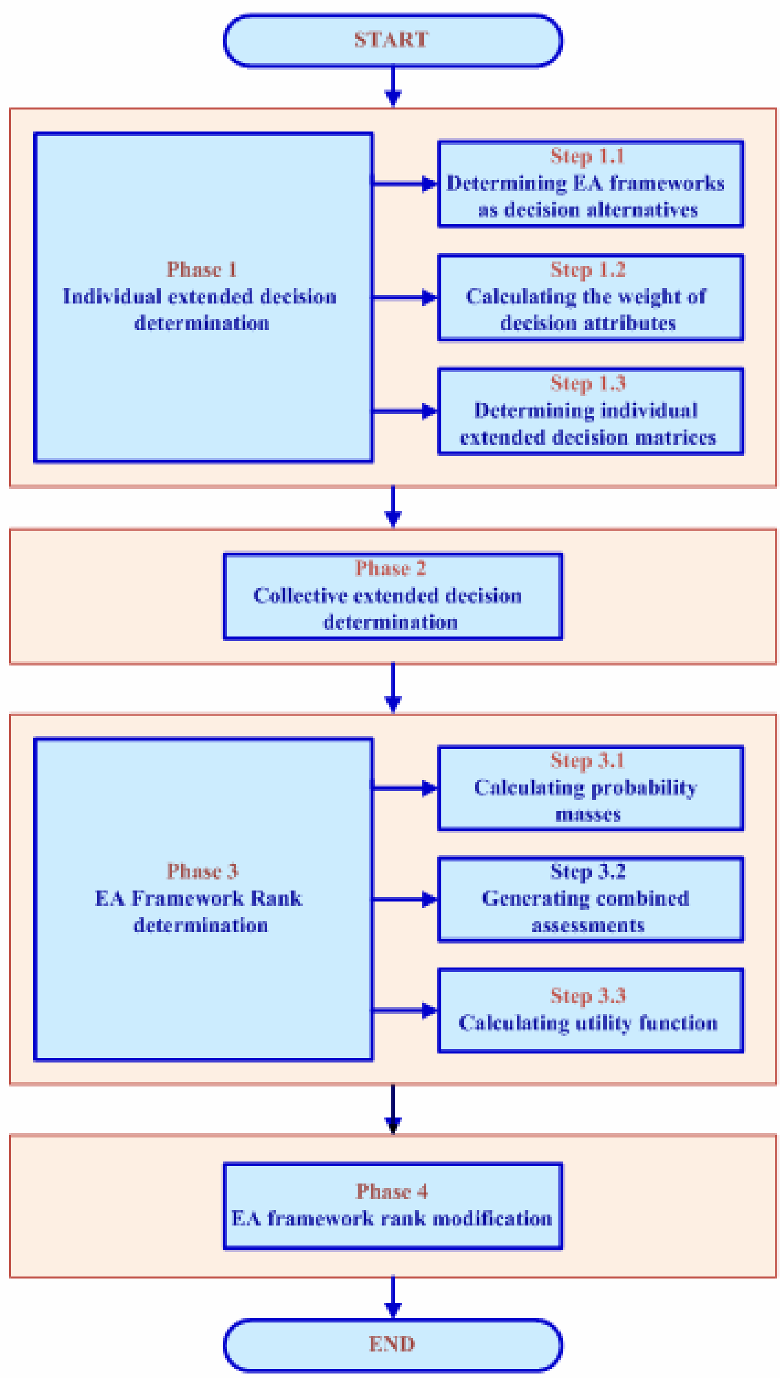
We propose an ER approach to aggregate subjective and objective judgements associated with qualitative and quantitative attributes rationally and systematically. Using the ER approach proposed here, we identify suitable alternatives, evaluate them in terms of both quantitative and qualitative attributes, and aggregate all the attributes using the ER approach. This procedure is illustrated by means of an EA framework selection example. The results of this study show that the ER approach can support multi-attribute EA framework selection processes when both objective and subjective judgements with or without uncertainties have to be taken into consideration. The outcomes generated by the method include the ranking of the candidate EA frameworks and indications of their strengths and weaknesses in the form of performance distributions over different assessment intervals. Such information is crucial in helping DMs to make an informed decision and be aware of any potential risk implication associated with their selection.

The proposed method can be implemented using intrusion detection system (IDS) software that can be used to investigate how sensitive the ranking of EA frameworks is to changes in weights and belief degrees for certain attributes. Because this method calculates the absolute ranking score for each EA framework independently, when new EA frameworks are added, it does not need to re-evaluate the previously assessed EA frameworks. In additional to the ranking score of EA frameworks, this method produces a distributed assessment, which provides the DM with a panoramic view about the diversity of the performance of an EA framework, thereby helping the DM to identify areas for improvement and to design and test action plans to make improvement. This paper is organised into four sections. The next section presents the details of the ER approach proposed in this study. In Section 3, we present a case study to illustrate the implementation process of the ER, and in Section 4, we present our concluding remarks and future research directions.

2 The proposed ER approach

We propose a four-phase group ER approach depicted in Figure 1 for selecting EA frameworks. In Phase 1, we determine the individual extended decisions followed by collective extended decision determination in Phase 2. In Phase 3, we rank order the EA frameworks and in Phase 4, we use a mathematical programming model to modify the rankings derived in Phase 3.

Figure 1 The proposed enterprise architecture framework selection method (see online version for colours)



Let us define the following parameters:

$\underline{W}$	the weight vector of the decision attributes
$w_i^{(k)}$	the normalised weight of attribute A_i assigned by committee member k
w_i	the normalised collective weight of attribute A_i assigned by the committee
$u(H_i)$	the utility of the evaluation grade H_i
$U(O_j)$	the utility of the EA framework O_j
$S(O_j)$	the combined assessment for the EA framework O_j
$S_k(A_i(O_j))$	the attribute A_i assessed to grade H_n to degree $\beta_{n,i}$ for the EA framework O_j by committee member k
$S(A_i(O_j))$	the attribute A_i assessed to grade H_n to degree $\beta_{n,i}$ for the EA framework O_j by the committee
$\beta_n(O_j)$	the combined degrees of belief
$\beta_{n,i}{}^{(k)}(O_j)$	the degree of belief that attribute A_i is assessed to the evaluation grade H_n by committee member k
$\beta_{n,i}(O_j)$	the degree of belief that attribute A_i is assessed to the evaluation grade H_n by the committee
$m_n(O_j)$	the combined probability masses of the EA framework O_j
$m_{n,i}(O_j)$	the basic probability mass representing the belief degree to which attribute i is assessed by the evaluation grade H_n
$m_{H,j}(O_j)$	the remaining belief for attribute i unassigned to individual grade H_n
$v(w)_j^k$	the voting power assigned to committee member k for weighting attribute A_i.

The process of ranking EA frameworks involves certain committee members. Let us further assume l committee members are selected to evaluate EA frameworks. Also, all members have equal power, and their evaluations have equal importance. Steps of the proposed method are follows:

2.1 Phase 1: Individual extended decision determination

In this phase, *grades* are used to assess the qualitative attributes associated with the EA frameworks. Furthermore, *belief degrees* represent the subjective probabilities associated with the assessment grades and *distributed assessment* is the result of assigning grades and the associated degrees of belief to an attribute based on the decision guidelines and evidence. The advantage of using distributed assessments is their capability in modelling uncertainty in subjective judgements.

Step 1.1 Determining EA frameworks as decision alternatives

A list of EA frameworks is provided by the committee members. There is no limit on the number of frameworks to be assessed.

Step 1.2 Calculating the weight of decision attributes

The committee uses multiple attributes in ranking the EA frameworks. There is no limit on the number of attributes. These attributes can either be classified as quantitative which is measurable or qualitative. Since all attributes may or may not be of equal importance, the weight vectors of decision making attributes can be indicated as follows:

$$\underline{W}^{(k)} = [w_1^{(k)}, w_2^{(k)}, \ldots, w_m^{(k)}] \text{ for } k = 1, 2, \ldots, l \tag{1}$$

Step 1.3 Determining individual extended decision matrices

The assessment of attribute A_i on EA framework O_j by committee member k can be written by the following *individual* decision matrix:

$$C^k = \begin{array}{cc} & \begin{array}{ccc} O_1 & \cdots & O_m \end{array} \\ \begin{array}{c} A_1 \\ . \\ . \\ . \\ A_r \end{array} & \left[\begin{array}{ccc} S_k(A_1(O_1) & \cdots & S_k(A_1(O_m) \\ . & \cdots & . \\ . & & . \\ . & \cdots & . \\ S_k(A_r(O_1) & \cdots & S_k(A_r(O_m) \end{array}\right] \end{array} \tag{2}$$

Or equivalently:

$$C^k = \begin{array}{cc} & \begin{array}{ccc} O_1 & \cdots & O_m \end{array} \\ \begin{array}{c} A_1 \\ . \\ . \\ . \\ A_r \end{array} & \left[\begin{array}{ccc} \begin{array}{l} \{(H_1, \beta_{1,1}^{(k)}(O_1)), .., \\ (H_n, \beta_{n,1}^{(k)}(O_1))\} \end{array} & \cdots & \begin{array}{l} \{(H_1, \beta_{1,1}^{(k)}(O_m)), \ldots, \\ (H_n, \beta_{n,1}^{(k)}(O_m))\} \end{array} \\ . & \cdots & . \\ . & & . \\ . & \cdots & . \\ \begin{array}{l} \{(H_1, \beta_{1,r}^{(k)}(O_1)), \ldots, \\ (H_n, \beta_{n,r}^{(k)}(O_1))\} \end{array} & \cdots & \begin{array}{l} \{(H_1, \beta_{1,r}^{(k)}(O_m)), \ldots, \\ (H_n, \beta_{n,r}^{(k)}(O_m))\} \end{array} \end{array}\right] \end{array} \tag{3}$$

2.2 Phase 2: Collective extended decision determination

Under a given attribute and an EA framework O_j, a collective value can be obtained as follows:

$$C_1 = \begin{array}{c} \\ A_1 \\ . \\ . \\ . \\ A_r \end{array} \begin{array}{c} \begin{array}{ccc} O_1 & \cdots & O_m \end{array} \\ \begin{bmatrix} S\ (A_1(O_1) & \cdots & S\ (A_1(O_m) \\ . & \cdots & . \\ . & & . \\ . & \cdots & . \\ S\ (A_r(O_1) & \cdots & S\ (A_r(O_m) \end{bmatrix} \end{array} \tag{4}$$

or equivalently:

$$C_1 = \begin{array}{c} \\ A_1 \\ . \\ . \\ . \\ A_r \end{array} \begin{array}{c} \begin{array}{ccc} O_1 & \cdots & O_m \end{array} \\ \begin{bmatrix} \{(H_1,\beta_{1,1}(O_1)),..,(H_n,\beta_{n,1}(O_1))\} & \cdots & \{(H_1,\beta_{1,1}(O_m)),...,(H_n,\beta_{n,1}(O_m))\} \\ . & \cdots & . \\ . & & . \\ . & \cdots & . \\ \{(H_1,\beta_{1,r}(O_1)),...,(H_n,\beta_{n,r}(O_1))\} & \cdots & \{(H_1,\beta_{1,r}(O_m)),...,(H_n,\beta_{n,r}(O_m))\} \end{bmatrix} \end{array} \tag{5}$$

where:

$$\beta_{n,i}(O_j) = \frac{\sum_{k=1}^{l} w_i^{(k)} \beta_{\mathrm{n,i}}{}^{(k)}(O_j)}{\sum_{k=1}^{l} w_i^{(k)}} \tag{6}$$

2.3 Phase 3: EA framework rank determination

Step 3.1 Calculating probability masses

Basic probability mass for the EA frameworks can be obtained as follows:

$$C_2 = \begin{array}{c} \\ A_1 \\ . \\ . \\ . \\ A_r \end{array} \begin{array}{c} \begin{array}{ccc} O_1 & \cdots & O_m \end{array} \\ \begin{bmatrix} \begin{array}{l}\{(H_1,w_1\beta_{1,1}(O_1)),..,\\(H_n,w_1\beta_{n,1}(O_1))\}\end{array} & \cdots & \begin{array}{l}\{(H_1,w_1\beta_{1,1}(O_m)),...,\\(H_n,w_1\beta_{n,1}(O_m))\}\end{array} \\ . & \cdots & . \\ . & & . \\ . & \cdots & . \\ \begin{array}{l}\{(H_1,w_r\beta_{1,r}(O_1)),...,\\(H_n,w_r\beta_{n,r}(O_1))\}\end{array} & \cdots & \begin{array}{l}\{(H_1,w_r\beta_{1,r}(O_m)),...,\\(H_n,w_r\beta_{n,r}(O_m))\}\end{array} \end{bmatrix} \end{array} \tag{7}$$

Because of the different knowledge and priority of the group members, we define voting powers for weighting the attributes as:

$$w_j = \frac{\sum_{k=1}^{l} v(w)_j^k . w_j^k}{\sum_{k=1}^{l} v(w)_j^k} \tag{8}$$

Noting that $m_{n,i} = w_i \beta_{n,i}(O_j)$, we can write (7) as:

$$C_2 = \begin{array}{c} \\ A_1 \\ . \\ . \\ . \\ A_r \end{array} \begin{array}{c} \begin{array}{ccc} O_1 & \cdots & O_m \end{array} \\ \begin{bmatrix} \{(H_1, m_{1,1}(O_1)),.., (H_n, m_{n,1}(O_1))\} & \cdots & \{(H_1, m_{1,1}(O_m)),..., (H_n, m_{n,1}(O_m))\} \\ . & & . \\ . & \cdots & . \\ . & \cdots & . \\ \{(H_1, m_{1,r}(O_1)),..., (H_n, m_{n,r}(O_1))\} & \cdots & \{(H_1, m_{1,r}(O_m)),..., (H_n, m_{n,r}(O_m))\} \end{bmatrix} \end{array} \tag{9}$$

The remaining belief denoted by $m_{H,j}$ can be calculated as:

$$C_3 = \begin{array}{c} \\ A_1 \\ . \\ . \\ . \\ A_r \end{array} \begin{array}{c} \begin{array}{ccc} O_1 & \cdots & O_m \end{array} \\ \begin{bmatrix} m_{H,1}(O_1) & \cdots & m_{H,1}(O_m) \\ . & \cdots & . \\ . & & . \\ . & \cdots & . \\ m_{H,r}(O_1) & \cdots & m_{H,r}(O_m) \end{bmatrix} \end{array} \tag{10}$$

or equivalently:

$$C_3 = \begin{array}{c} \\ A_1 \\ . \\ . \\ . \\ A_r \end{array} \begin{array}{c} \begin{array}{ccc} O_1 & \cdots & O_m \end{array} \\ \begin{bmatrix} 1-[m_{1,1}(O_1)+.+m_{n,1}(O_1)] & \cdots & 1-[m_{1,1}(O_m)+...+m_{n,1}(O_m)] \\ . & \cdots & . \\ . & & . \\ . & \cdots & . \\ 1-[m_{1,r}(O_1)+...+m_{n,r}(O_1)] & \cdots & 1-[m_{1,r}(O_m)+...+m_{n,r}(O_m)] \end{bmatrix} \end{array} \tag{11}$$

Step 3.2 Generating combined assessments

The combined assessment for the EA frameworks is denoted by:

$$\underline{V_3} = \left[S(O_1) \ \ ... \ \ S(O_m) \right] \tag{12}$$

or equivalently:

$$\underline{V_3} = \left[\{(H_1, \beta_1(O_1)), ..., (H_n, \beta_n(O_1))\} \ \ ... \ \ \{(H_1, \beta_1(O_m)), ..., (H_n, \beta_n(O_m))\} \right] \quad (13)$$

Note that belief degrees are aggregated by:

$$\beta_n(O_j) = \frac{\mathrm{m_n}(O_j)}{1 - m_H(O_j)} \quad (14)$$

where:

Combined probability masses, denoted m_n and m_H, can be generated using the following vectors:

$$\underline{V_1} = \left[m_n(O_1) \ \ ... \ \ m_n(O_m) \right] \quad (15)$$

$$\underline{V_2} = \left[m_H(O_1) \ \ ... \ \ m_H(O_m) \right] \quad (16)$$

where

$$m_H(O_j) = k[m_{H,i}(O_j).m_{H,i+1}(O_j)] \quad (17)$$

$$\begin{aligned} m_n(O_j) = k[&m_{n,i}(O_j).m_{n,i+1}(O_j) + m_{H,i}(O_j).m_{n,i+1}(O_j) \\ &+ m_{n,i}(O_j).m_{H,i+1}(O_j)] \end{aligned} \quad (18)$$

for $n = 1, 2, ..., N$

$$k = [1 - \sum_{t=1}^{N} \sum_{\substack{i=1 \\ j \neq t}}^{N} m_{t,i}(O_j) m_{j,i+1}(O_j)]^{-1} \quad (19)$$

Step 3.3 Calculating utility function

Finally, EA frameworks can be ranked based on a utility function to map all grades or values of an attribute to the predefined range of utilities. This utility is an assessment grade if the attribute is qualitative or a value if the attribute is quantitative. The highest number is assigned to the most preferred grade or value while the lowest number is assigned to the least preferred grade or value. Thus, the EA frameworks can be ranked based on the following vector:

$$\underline{U} = \left[u(H_1) \quad u(H_2) \quad ... \quad u(H_n) \right] \begin{bmatrix} \beta_1(O_1) & ... & \beta_1(O_m) \\ . & & . \\ . & & . \\ . & & . \\ \beta_n(O_1) & ... & \beta_n(O_m) \end{bmatrix} \quad (20)$$

2.4 *Phase 4: EA framework rank modification*

To select the optimal EA framework, we construct the following mathematical programming model:

Max. $Z = \underline{U} . \underline{X}$ (Model P)

subject to:

$$G(\underline{X}) \leq 0$$

$$\underline{X} = [x_1, x_2, ..., x_m]$$

$$\sum_{j=1}^{m} x_j = 1$$

$$\mathrm{x_j} = 0,1 \quad j = 1, 2, ..., m$$

The optimal solution of model (*P*) is the selected EA framework. In the following section, the proposed method is illustrated for EA framework selection in the Institute of Energy and Hydro Technology (IEHT) in Iran.

3 Case study

The Institute for Energy and Hydro Technology (IEHT) is the largest energy institute in Iran. IEHT is located in a 65-acre campus and has a 50,000 person training capacity per month. The institute employs over 80 full-time and 100 part-time faculties. We used the group EA approach proposed in this study to select an EA for IEHT. A committee of nine DMs from marketing, finance, and information technology was formed to participate to evaluate the following four frameworks: ZACHMAN, TEAF, TOGAF and DODAF.

Phase 1 The committee identified the following two constraints:

a the length of the EA evaluation process should not exceed six months

b the cost of the assessment process should not exceed 180,000 dollars.

In addition, the committee agreed to consider the following attributes in evaluating the EA frameworks:

1 EA framework maturity

2 support for role object pattern and ease of use

3 availability of existing architecture framework

4 EA framework openness

5 EA framework supportive tools.

Phase 2 The committee also decided to use four evaluation grades to measure each attribute:

$$\begin{aligned} H &= \{H_1, H_2, H_3, H_4\} \\ &= \{\text{slightly preferred, moderately preferred, preferred, greatly preferred}\} \\ &= \{0, 1/3, 2/3, 1\} \end{aligned}$$

Next, we used equations (5) and (6) to identify the committee's collective extended decision:

$$C_1 = \begin{array}{cc} & \begin{array}{cc} O_1 & O_2 \end{array} \\ \begin{array}{c} Zachman \\ \\ TEAF \\ \\ TOGAF \\ \\ DODAF \end{array} & \left[\begin{array}{cc} \{(H_1,0.356),(H_2,0.22), & \{(H_1,0.32),(H_2,0.26), \\ (H_3,0.08),(H_4,0.02)\} & (H_3,0.38),(H_4,0.02)\} \\ \{(H_1,0.32),(H_2,0.32), & \{(H_1,0.26),(H_2,0.22), \\ (H_3,0.18),(H_4,0.12)\} & (H_3,0.28),(H_4,0.24)\} \\ \{(H_1,0.46),(H_2,0.30), & \{(H_1,0.34),(H_2,0.28), \\ (H_3,0.20),(H_4,0.04)\} & (H_3,0.28),(H_4,0.10)\} \\ \{(H_1,0.24),(H_2,0.24), & \{(H_1,0.26),(H_2,0.14), \\ (H_3,0.30),(H_4,0.12)\} & (H_3,0..30),(H_4,0.30)\} \end{array} \right. \end{array}$$

$$\begin{array}{c} \begin{array}{ccc} O_3 & O_4 & O_5 \end{array} \\ \left. \begin{array}{ccc} \{(H_1,0.48),(H_2,0.36), & \{(H_1,0.46),(H_2,0.36), & \{(H_1,0.62),(H_2,0.30), \\ (H_3,0.14),(H_4,0.02)\} & (H_3,0.18),(H_4,0.02)\} & (H_3,0.06),(H_4,0.00)\} \\ \{(H_1,0.24),(H_2,0.30), & \{(H_1,0.22),(H_2,0.26), & \{(H_1,0.24),(H_2,0.03), \\ (H_3,0.32),(H_4,0.14)\} & (H_3,0.32),(H_4,0.20)\} & (H_3,0.42),(H_4,0.04)\} \\ \{(H_1,0.32),(H_2,0.30), & \{(H_1,0.36),(H_2,0.30), & \{(H_1,0.36),(H_2,0.26), \\ (H_3,0.26),(H_4,0.10)\} & (H_3,0.26),(H_4,0.08)\} & (H_3,0.20),(H_4,0.18)\} \\ \{(H_1 0.26),(H_2,0.30), & \{(H_1,0.26),(H_2,0.28), & \{(H_1,0.36),(H_2,0.28), \\ (H_3,0.34),(H_4,0.06)\} & (H_3,0.32),(H_4,0.14)\} & (H_3,0.20),(H_4,0.14)\} \end{array} \right] \end{array}$$

Phase 3 We then used the IDS software to find the utilities of the four EA frameworks presented in Table 1.

As it is shown in Table 1, the ZACHMAN framework had the highest utility. However, after obtaining the utilities presented in Table 1, the committee decided to also include FEAF in their evaluation process. The ER method proposed in this study does not require a re-evaluation of the previously assessed frameworks. Therefore, the collective extended decision for FEAF was calculated as:

$$C_1 = \begin{bmatrix} \{(H_1,0.64),(H_2,0.24),(H_3,0.12),(H_4,0.00)\} \\ \{(H_1,0.58),(H_2,0.28),(H_3,0.12),(H_4,0.02)\} \\ \{(H_1,0.58),(H_2,0.26),(H_3,0.14),(H_4,0.02)\} \\ \{(H_1,0.50),(H_2,0.32),(H_3,0.16),(H_4,0.02)\} \\ \{(H_1,0.58),(H_2,0.28),(H_3,0.12),(H_4,0.02)\} \end{bmatrix}$$

The IDS software was used again to re-calculate the utility of FEAF. The FEAF framework had the highest utility of 0.7667 among the five frameworks under consideration.

Table 1a The EA framework utilities and rankings

The initial rankings		
Ranking	*EA framework*	*Utility*
1	ZACHMAN	0.7467
2	TOGAF	0.6467
3	TEAF	0.5000
4	DODAF	0.4933
The revised rankings		
Ranking	*EA framework*	*Utility*
1	FEAF	0.7667
2	ZACHMAN	0.7467
3	TOGAF	0.6467
4	TEAF	0.5000
5	DODAF	0.4933

Phase 4 Next, we formulated model (P) using the utilities, time estimates and cost estimates associated with each framework:

$$\text{Max. } Z = 0.7667x_{FEAF} + 0.7467x_{ZACHMAN} + 0.6467x_{TOGAF} + 0.5000x_{TEAF} + 0.4933x_{DODAF}$$

Subject to:

$$x_{DODAF} + 4x_{TEAF} + 3x_{TOGAF} + 5x_{ZACHMAN} + 6x_{FEAF} \leq 6$$

$$160,000x_{FEAF} + 150,000x_{ZACHMAN} + 140,000x_{TOGAF} + 145,000x_{TEAF} + 175,000x_{DODAF} \leq 180,000$$

$$x_{FEAF} + x_{ZACHMAN} + x_{TOGAF} + x_{TEAF} + x_{DODAF} = 1$$

$$x_{FEAF}, x_{ZACHMAN}, x_{TOGAF}, x_{TEAF}, x_{DODAF} = 0,1$$

Finally, using LINDO software, TEAF framework was selected as the optimal EA framework for IEHT.

4 Conclusions and future research directions

In this paper, we have presented a MADM model for evaluation and selection of EA frameworks in conditions of uncertainty. This model draws on D-S belief functions to evaluate decision-making attributes that cannot be easily quantified. We applied the model to select the best EA framework in a complex system with multiple and competing attributes and values. Organisations often fail in practice to follow a systematic and well-structured decision-making process for assessing potential EA frameworks. We have shown that our model considers the multi-dimensional nature of such problems and generates vital information for selecting the most appropriate framework. While previous studies have valued multi-attribute frameworks, they have failed to consider both subjective and objective judgements in a systematic and consistent model. Combining the D-S theory with EA framework assessment supports both qualitative and quantitative decision attributes, as well as different types of risk for both quantitative and qualitative attributes. The case study shows that a combined analysis can generate valuable insight that can help DMs to select the most suitable framework from a range of competing alternatives.

The proposed model in this study could be easily modified to perform a wide range of sensitivity analysis of the stated preferences and parameters. There are no limits on the number of attributes and the number of EA frameworks to be assessed. Therefore, this method can be easily modified to handle large-scale problems. In the proposed method, each EA framework was ranked based on its utility function independently. Hence, when new EA frameworks are added, the proposed method does not need to re-evaluate the previously assessed frameworks.

In this paper, the ER approach was used to solve an EA framework selection problem allowing rational and consistent aggregation of subjective and objective judgements. DMs may be able to provide only imprecise or vague information because of time constraint or lack of data. In addition, the DM may feel more comfortable evaluating qualitative attributes by using linguistic variables resulting in two potential problems:

1 how to reconcile quantitative and qualitative attributes

2 how to deal with imprecise and vague information rationally and consistently.

We showed that the ER approach is able to address these problems and can assist DMs reach a robust decision.

More recently, the MADM research community has extended their interest in fuzzy set theory (Zadeh, 1998). The integration of MADM with fuzzy sets for handling uncertainty is of major interest, both from a research and practical perspective (Kaliszewski, 2006, Zopounidis and Doumpos, 2001). Fuzzy sets could be used in our framework to develop various membership functions and for evaluating uncertainties in subjective judgements and assessments.

References

Anand, S., Bell, D.A. and Hughes, J.G. (1996) 'EDM: a general framework for data mining based on evidence theory', *Data & Knowledge Engineering*, Vol. 18, No. 3, pp.189–223.

Belton, V. and Stewart, T.J. (2002) *Multiple Criteria Decision Analysis: An Integrated Approach*, Kluwer, Norwell, MA.

Beynon, M. (2005a) 'Understanding local ignorance and non-specificity within the DS/AHP method of multi-criteria decision making', *European Journal of Operational Research*, Vol. 163, No. 2, pp.403–417.

Beynon, M. (2005b) 'A method of aggregation in DS/AHP for group decision-making with the non-equivalent importance of individuals in the group', *Computers & Operations Research*, Vol. 32, No. 7, pp.1881–1896.

Beynon, M., Cosker, D. and Marshall, D. (2001) 'An expert system for multi-criteria decision making using Dempster-Shafer theory', *Expert Systems with Applications*, Vol. 20, No. 4, pp.357–367.

Beynon, M., Curry, B. and Morgan, P. (2000) 'The Dempster-Shafer theory of evidence: an alternative approach to multicriteria decision modeling', *Omega*, Vol. 28, No. 1, pp.37–50.

Bryson, N. and Mobolurin, A. (1999) 'A process for generating quantitative belief functions', *European Journal of Operational Research*, Vol. 115, No. 3, pp.624–633.

Cai, D., McTear, M.F. and McClean, S.I. (2000) 'Knowledge discovery in distributed databases using evidence theory', *International Journal of Intelligent Systems*, Vol. 15, No. 8, pp.745–761.

Cobb, B. and Shenon, P.P. (2003) 'A comparison of Bayesian and belief function reasoning', *Information Systems Frontiers*, Vol. 5, No. 4, pp.345–358.

Dempster, A.P. (1967) 'Upper and lower probabilities induced by a multi-valued mapping', *Annals of Mathematical Statistics*, Vol. 38, No. 2, pp.325–339.

Fayad, M. and Hamu, D. (2000) 'Enterprise frameworks: guidelines for selection', *ACM Computing Survey*, Vol. 32, No. 1, pp.1–23.

Fayad, M.E., Hamu, D. and Brugali, D. (2000) 'Enterprise frameworks: characteristics, criteria, and challenges', *Communication of the ACM*, Vol. 43, No. 10, pp.39–46.

Goicoechea, A. (1988) 'Expert system models for inference with imperfect knowledge: a comparative study', *Journal of Statistical Planning and Inference*, Vol. 20, No. 3, pp.245–277.

Jones, R.W., Lowe, A. and Harrison, M.J. (2002) 'A framework for intelligent medical diagnosis using the theory of evidence', *Knowledge-Based Systems*, Vol. 15, Nos. 1–2, pp.77–84.

Kaliszewski, I. (2006) *Soft Computing for Complex Multiple Criteria Decision Making*, Springer, Berlin.

Kim, S.H. and Ahn, B.S. (1999) 'Interactive group decision making procedure under incomplete information', *European Journal of Operational Research*, Vol. 116, No. 3, pp.498–507.

Korvin, A.D. and Shipley, M.F. (1993) 'A Dempster-Shafer-based approach to compromise decision making with multiattributes applied to product selection', *IEEE Transactions on Engineering Management*, Vol. 40, No. 1, pp.60–67.

Liu, J., Yang, J.B., Wang, J. and Sii, H.S. (2004a) 'Engineering system safety analysis and synthesis using fuzzy rule-based evidential reasoning approach', *Quality and Reliability Engineering International*, Vol. 21, No. 4, pp.377–401.

Liu, J., Yang, J.B., Wang, J., Sii, H.S. and Wang, Y.M. (2004b) 'Fuzzy rule-based evidential reasoning approach for safety analysis', *International Journal of General Systems*, Vol. 33, Nos. 2–3, pp.183–204.

McClean, S. and Scotney, B. (1997) 'Using evidence theory for knowledge discovery and extraction in distributed databases', *International Journal of Intelligent Systems*, Vol. 12, No. 10, pp.763–776.

Osei-Bryson, K.M. (2003) 'Supporting knowledge elicitation and consensus building for Dempster–Shafer decision models', *International Journal of Intelligent Systems*, Vol. 18, No. 1, pp.129–148.

Petkov, D., Petkova, O., Andrew, T.N. and Nepal, T. (2007) 'Mixing multiple criteria decision making with soft systems thinking techniques for decision support in complex situations', *Decision Support Systems*, Vol. 43, No. 4, pp.1615–1629.

Poyhonen, M.A., Hamalainen, R.P. and Salo, A.A. (1997) 'An experiment on the numerical modelling of verbal ratio statements', *Journal of Multi-Criteria Decision Analysis*, Vol. 6, No. 1, pp.1–10.

Salling, K.B., Leleur, S. and Jensen, A.V. (2007) 'Modelling decision support and uncertainty for large transport infrastructure projects: the CLG-DSS model of the Øresund fixed link', *Decision Support Systems*, Vol. 43, No. 4, pp.1539–1547.

Shafer, G. (1976) *A Mathematical Theory of Evidence*, Princeton University Press, Princeton.

Soundappan, P., Nikolaidis, E., Haftka, R.T., Grandhi, R. and Canfield, R. (2004) 'Comparison of evidence theory and Bayesian theory for uncertainty modelling', *Reliability Engineering & System Safety*, Vol. 85, Nos. 1–3, pp.295–311.

Srivastava, R.P. and Liu, L. (2003) 'Applications of belief functions in business decisions: a review', *Information Systems Frontiers*, Vol. 5, No. 4, pp.359–378.

Srivastava, R.P. and Mock, T.J. (2000) 'Belief functions in accounting behavioral research', *Accounting Behavioral Research*, Vol. 3, pp.225–242.

Sun, L., Srivastava, R. and Mock, T. (2006) 'An information systems security risk assessment model under the Dempster-Shafer theory of belief functions', *Journal of Management Information Systems*, Vol. 22, No. 4, pp.109–142.

Tang, A., Han, J. and Chen, P. (2004) 'A comparative analysis of architecture frameworks', Technical report, Swinburne University of Technology.

Valls, A. and Torra, V. (2000) 'Using classification as an aggregation tool in MCDM', *Fuzzy Sets and Systems*, Vol. 15, No. 1, pp.159–168.

Wang, J., Yang, J.B. and Sen, P. (1995) 'Safety analysis and synthesis using fuzzy sets and evidential reasoning', *Reliability Engineering System Safety*, Vol. 47, No. 2, pp.103–118.

Wang, J., Yang, J.B. and Sen, P. (1996) 'Multi-person and multiattribute design evaluations using evidential reasoning based on subjective safety and cost analysis', *Reliability Engineering System Safety*, Vol. 52, No. 2, pp.113–128.

Xu, D.L. and Yang, J.B. (2003) 'Intelligent decision system for self-assessment', *Journal of Multi-Criteria Decision Analysis*, Vol. 12, No. 1, pp.43–60.

Yager, R.R. (2002) 'On the valuation of alternatives for decision-making under uncertainty', *International Journal of Intelligent Systems*, Vol. 17, No. 9, pp.687–707.

Yang, J.B. (2001) 'Rule and utility based evidential reasoning approach for multiattribute decision analysis under uncertainties', *European Journal of Operational Research*, Vol. 131, No. 1, pp.31–61.

Yang, J.B. and Sen, P. (1994) 'A general multi-level evaluation process for hybrid MADM with uncertainty', *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 24, No. 10, pp.1458–1473.

Yang, J.B. and Sen, P. (1996) 'Preference modelling by estimating local utility functions for multiobjective optimization', *European Journal of Operational Research*, Vol. 95, No. 1, pp.115–138.

Yang, J.B. and Sen, P. (1997) 'Multiple attribute design evaluation of large engineering products using the evidential reasoning approach', *Journal of Engineering Design*, Vol. 8, No. 3, pp.211–230.

Yang, J.B. and Singh, M. (1994) 'An evidential reasoning approach for multiple attribute decision making with uncertainty', *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 24, No. 1, pp.1–18.

Yang, J.B. and Xu, D.L. (2002a) 'On the evidential reasoning algorithm for multiattribute decision analysis under uncertainty', *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, Vol. 32, No. 3, pp.289–304.

Yang, J.B. and Xu, D.L. (2002b) 'Nonlinear information aggregation via evidential reasoning in multiattribute decision analysis uncertainty', *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, Vol. 32, No. 3, pp.376–393.

Zadeh, LA. (1998) 'Roles of soft computing and fuzzy logic in the conception, design and deployment of information/intelligent systems', *Computational Intelligence: Soft computing and Fuzzy-Neuro Integration with Applications*, pp.1-9.

Zopounidis, C. and Doumpos, M. (2001) 'Multicriteria decision aid in uncertainty and financial risk management', in Gil-Aluja, J. (Ed.): *Handbook of Management under Uncertainty*, Kluwer Academic Publishers, Dordrecht.