Journal of the Operational Research Society (2013) 64, 1221–1230

www.palgrave-journals.com/jors/

A DST-based approach for construction project risk analysis

A Taroun[1*] and J-B Yang[2]

[1]*The University of Bedfordshire Business School, Bedford, UK; and* [2]*The University of Manchester, Manchester, UK*

Despite its huge potential in risk analysis, the Dempster–Shafer Theory of Evidence (DST) has not received enough attention in construction management. This paper presents a DST-based approach for structuring personal experience and professional judgment when assessing construction project risk. DST was innovatively used to tackle the problem of lacking sufficient information through enabling analysts to provide incomplete assessments. Risk cost is used as a common scale for measuring risk impact on the various project objectives, and the Evidential Reasoning algorithm is suggested as a novel alternative for aggregating individual assessments. A spreadsheet-based decision support system (DSS) was devised to facilitate the proposed approach. Four case studies were conducted to examine the approach's viability. Senior managers in four British construction companies tried the DSS and gave very promising feedback. The paper concludes that the proposed methodology may contribute to bridging the gap between theory and practice of construction risk assessment.

Journal of the Operational Research Society (2013) **64,** 1221–1230. doi:10.1057/jors.2013.38
Published online 3 April 2013

Keywords: construction; decision support system; Dempster–Shafer Theory of Evidence; Evidential Reasoning; risk assessment

1. Introduction

Risk assessment is an essential part of the project risk management process. Regrettably, the construction industry has a poor record in risk assessment; risk is either ignored or subjectively dealt with by adding approximate contingency (Kangari and Riggs, 1989). Different theories and techniques have been investigated to assess risk, and various decision support systems (DSS) have been devised to aid professionals in assessing construction risk. Unfortunately, the take-up of the various tools is quite limited; individual's judgment and practical experience is still the main tool for analysing construction risk (Akintoye and MacLeod, 1997; Wood and Ellis, 2003; Lyons and Skitmore, 2004). Hence, investigating a novel approach that appeals to practitioners and facilitates closing the gap between theory and practice is crucial. This paper presents a unique assessment methodology that enables assessing risk impact of specific project objectives using risk cost as a common scale. It utilises the professional experience and personal judgment of construction professionals, to handle lacking enough information, through employing the Dempster–Shafer Theory of Evidence (DST) and the Evidential Reasoning (ER) approach innovatively. The paper is structured as follows: A review of the literature of construction risk assessment is presented followed by an introduction to DST and the ER approach; then, the new assessment methodology is discussed and elaborated through an illustrative case study; finally, the paper ends with a critical evaluation of the proposed methodology and a summary of the key findings and conclusions.

2. Literature review

Different approaches have been adopted for assessing project risks. Traditionally the focus has been on quantitative risk analysis (Tah and Carr, 2001); researchers have extensively deployed Probability Theory (PT) for analysing duration risk or cost risk (eg Gates, 1971; Spooner, 1974; Carr, 1977; Chapman and Cooper, 1983; Diekmann, 1983; Beeston, 1986). The PT-based tools require objective probabilities (frequencies) that are not always attainable in construction. The difficulty of obtaining objective probabilities stems from the fact that construction projects are very often one-off enterprises (Flanagan and Norman, 1993). As construction risk analysis, typically, suffers from lacking enough information, researchers concluded that professional experience and personal judgment were crucial for construction risk assessment. This conclusion was

Correspondence: A Taroun, Management and Business Systems Department, The University of Bedfordshire Business School, Room B1.11 in Polhill Avenue campus, Bedford MK41 9EA, UK.

reflected in the risk assessment tools. According to Laryea and Hughes (2008), there has been a paradigm shift from 'classicalism', using PT-based and simulation tools, towards 'conceptualism', using analytical tools. Reviewing the literature reveals that the analytical tools have utilised, mainly, the Fuzzy Sets Theory (FST) and the Analytical Hierarchy Process (AHP) technique. FST was introduced as a viable alternative for handling subjectivity in construction risk assessment, and AHP was perceived as an effective tool for structuring the increasing complexity in construction risk assessment. Yet, both FST and AHP have limitations. Kangari and Riggs (1989) summarised the limitations of the FST by: (1) the problem of assigning the membership values of a fuzzy set to represent a linguistic variable; (2) complexity in performing arithmetic operations; and (3) the problem of associating the final fuzzy set, after aggregating individual assessments, with a linguistic variable. Besides, FST has a major limitation in aggregating risk assessments. Its aggregation rule, the fuzzy union operator, produces an average assessment which may not be suitable in all cases. Indeed, this aggregation rule will weaken the effect of the influencing factors (Cox, 1999). Similarly, AHP has a number of limitations. Mustafa and Al-Bahar (1991) were concerned about the number of judgments required to derive relative priorities. According to Sen and Yang (1998), the large number of judgments required often causes inconsistency problems. This will also make conducting sensitivity analysis very difficult and impractical (Belton and Stewart, 2002). *Rank Reversal* is a major problem in AHP; in certain situations the introduction of a new alternative, which does not change the range of outcomes on any criterion, may lead to a change in the ranking of the other alternatives (Belton and Gear, 1983; Belton and Stewart, 2002). The limitations of FST and AHP do not undermine their usefulness, but they stimulate researching innovative approaches that can overcome such limitations. This research is immensely important as the paradigm shift towards analytical tools did not result in more adoption by professionals as Laryea and Hughes (2008) argued.

Reviewing the literature reveals that risk impact assessment has, typically, focused on project cost risk or duration cost. We lack a comprehensive risk assessment methodology that is capable of capturing risk impact on various project objectives simultaneously. This was attributed to the lack of a common scale (Williams, 1995). Nonetheless, the most convenient common scale is thought to be the risk cost (Franke, 1987; Williams, 1995). Actually, risk cost has been used by many researchers for measuring risk impact (Franke, 1987; Ben-David and Raz, 2001; Fan and Yu, 2004; Cagno *et al*, 2007; Cioffi and Khamooshi, 2009). However, none of them have considered risk impact on different project objectives for obtaining a comprehensive risk assessment. Indeed, comprehensive risk assessments form the basis for reaching a realistic project risk level. Yet, it seems that aggregating individual risk assessments is equally important. The averaging and the weighted sum are the most commonly used aggregation rules. Unfortunately, the averaging rules cannot generate a realistic project risk level in all cases as was discussed earlier. The weighted sum method also has a limitation of being oversimplistic due to the assumption of risk independence (Dikmen *et al*, 2004), assuming risk independence is not a realistic assumption in most of the cases. Subsequently, researching a novel alternative for aggregating individual risk assessments is crucial for improving construction risk assessment.

Simplicity of the analysis is essential for encouraging practitioners to use risk assessment tools. Baker *et al* (1998) surveyed the most successful qualitative and quantitative risk analysis tools in construction and oil and gas industries. They found that personal and corporate experience, and engineering judgement were the most frequently used qualitative risk assessment tool and Expected Monetary Value, break-even analysis, scenario analysis and sensitivity analysis were the most widely used tools for quantitative risk assessment. Almost the same results were obtained in similar studies (Wood and Ellis, 2003; Lyons and Skitmore, 2004; Dikmen *et al*, 2004 and Warszawski and Sacks, 2004). It is notable from these studies that the frequently used quantitative risk assessment tools are not sophisticated. This may suggest that practitioners tend to use them for supporting their experience and judgement when assessing construction risks. Actually, reflecting the real practice of risk analysis and appreciating the practitioners' experience is crucial for enhancing the usability of risk analysis tools, as Laryea and Hughes (2008) concluded. Hence, for any alternative tool to be successful, simplicity and facilitating the professional experience should be key attributes.

3. DST

DST has received considerable attention by different researchers who explored its potential in various domains. It is remarkable, however, that DST has never been used for facilitating construction risk assessment (Taroun *et al*, 2011). The authors believe that DST provides an effective framework for representing ignorance (lack of information) and analysing uncertainty. According to Bloch (1996), DST is able to handle imprecision and uncertainty by means of two functions: 'belief' (*Bel*) and 'plausibility' (*Pla*) which are both derived from the 'mass function' (m). Mass function is a probability function defined on the power set of the frame of discernment Θ. Θ can be defined as a set of all possible answers to a question. The answers should be mutually exclusive and collectively exhaustive. The mass function, represented by m: $2^{\theta} \rightarrow [0, 1]$, satisfies the following conditions:

(1) $m(\varnothing)=0$ and (2) $\sum m(A)=1$, where $\varnothing$ is an empty set and A is any subset of Θ. The probability assigned to a set A according to this mass function, $m(A)$, is called *basic probability assignment* (*bpa*). $m(A)$ measures the belief assigned completely and directly to the set A. In DST, if an amount of belief (x) is assigned to a proposition, the remaining belief ($1-x$) does not need to go to the negation of the proposition. Hence, the beauty of DST is that it allows analysts to assign the remaining belief to the whole frame of discernment $m(\Theta)$ as there is no reason to believe that it must go to the negation. This is a very important feature of DST that enables handling lack of information.

The belief function is a probability function defined as a degree of belief that the true answer lies in the set A. A belief in a set A represents the exact support to the proposition which is represented by the set A (Wang and Elhag, 2007); it is calculated by summing the basic probabilities assigned to all propositions which are fully included in the set A (Khatibi and Montazer, 2010). The belief function is usually given by the following formula:

$$Bel(A)=\sum_{Bi\subseteq A} m(Bi)$$

Basically, the difference between a basic probability assignment $m(A)$ and the belief $Bel(A)$ is that $m(A)$ is the degree of belief exactly in the proposition A as a set excluding any of its subsets while $Bel(A)$ is the degree of belief in A as well as all of its subsets (Liu *et al*, 2002). The Plausibility function, however, represents the extent to which a proposition cannot be rejected; it is the total amount of belief which could be potentially placed in the proposition (Wang and Elhag, 2007), or the extent to which one fails to disbelieve a proposition (Beynon *et al*, 2000). The plausibility of a proposition A is usually given as:

$$Pla(A)=\sum_{A\cap Bi\neq\varnothing} m(Bi)$$

$Pla(A)$, hence, is calculated by adding the basic probabilities assigned to all propositions whose intersection with the proposition A is not an empty set.

3.1. Evidence aggregation

Different aggregation rules can be used for combining multiple pieces of evidence. Sentz and Ferson (2002) mentioned that aggregation rules range between two extremes: conjunction rules (AND-based) and disjunction rules (OR-based). In critical situations the conjunctive AND-based aggregation rule must be adopted. However, in a situation with loose conditions the disjunctive OR-based rules can be used. Between these two extremes a range of different aggregation rules, trade-off between the two extremes, can be adopted (Dubois and Prade, 1992; Sentz and Ferson, 2002). Dempster proposed a conjunctive AND-operation to aggregate independent sources of evidence. It is an orthogonal sum of evidence sources, pooling together their basic probability assignments and generating a new basic probability assignment (Sentz and Ferson, 2002; Huynh *et al*, 2005). The combination process starts by combining two mass functions and the result is later combined with another mass function and so on until the whole combination process is completed. Dempster's rule for combining two mass functions $m1(A1)$ and $m2(A2)$ is usually given by the following equation:

$$m(A)=\begin{cases}0 & \text{when } A=\varnothing\\ \dfrac{\sum_{A1\cap A2=A} m1(A1)*m2(A2)}{1-K} & \text{when } A\neq\varnothing\end{cases}$$

$$K=\sum_{A1\cap A2=\varnothing} m1(A1)*m2(A2)$$

The above combination rule satisfies the commutative and associative properties (Beynon *et al*, 2000; Liu *et al*, 2002; Wang and Elhag, 2007). It is an important aggregation algorithm as it follows a logical approach; if concordant bodies of evidence are combined, they will reinforce each other and result in stronger support of the proposition, whereas if conflicting pieces of evidence are combined, they will erode each other and generate weaker support of the proposition (Shafer and Logan, 1987; Murphy, 2000). Unfortunately, Dempster's rule of evidence combination has a limitation of being unable to deal with conflicting evidence. It emphasises a total agreement between the different pieces of evidence and ignores any possible conflict among them through dividing the initial combination by ($1-K$) (Sentz and Ferson, 2002), where the normalisation factor K is interpreted as a measure of conflict and contradiction between evidence sources (Murphy, 2000). Owing to this limitation, many researchers have attempted to develop it in different ways (Dubois and Prade, 1986; Yang and Singh, 1994; Zhang, 1994; Murphy, 2000; Smets, 2000; Yong *et al*, 2004; Huynh *et al*, 2005; Liu, 2006; Denœux, 2008). They have come up with different ideas and provided a number of modified versions of Dempster's rule that can deal with conflicting evidence (Sentz and Ferson, 2002). In this paper, the researchers adopt the ER algorithm which is one of the most prominent attempts to improve the original Dempster's rule of evidence combination.

4. The Evidential Reasoning (ER) approach

ER is defined by Lowrance *et al* (2008) as a body of tools and techniques that supports automated reasoning from evidence based on DST. The ER approach, however, is a multi-criteria decision-making (MCDM) approach developed by Yang and Sen (1994), Yang and Singh (1994) on the basis of DST as a reasoning tool capable of aggregating different types of assessments, handling various forms of

uncertainty and representing ignorance and incomplete assessment effectively. The ER approach is different from most conventional MCDM modelling methods in that it uses belief structures to assess alternatives against evaluation attributes in distributed forms. For instance, the quality of a car engine can be assessed in the following form: the engine is 'good' with a confidence level of 40%, 'average' with a confidence level of 30% and 'poor' with a confidence level of 30%. The measures '*good*', '*average*' and '*bad*' are defined as '*assessment grades*'. The assessment grades are required to be mutually exclusive and collectively exhaustive (Yang, 2001). They formulate a frame of discernment denoted as $H = \{H1, H2, \ldots, Hn\}$. Obviously, the number of assessment grades depends upon the problem in question and the required level of detail for assessment. The general formula for assessing the performance of the alternative Ai against the criterion Cj is:

$$S(Cj(Ai)) = (Hn, \beta_{n,i}(Ai)),\ n = 1, \ldots, N,$$
$$i = 1, \ldots, m,\ j = 1, \ldots, l$$
$$\beta_{n,i}(Ai) \geqslant 0,\ \sum_{n=1}^{N} \beta_{n,i}(Ai) \leqslant 1$$

where N: number of assessment grades; m: the number of alternatives; l: the number of evaluation criteria; $\beta_{n,i}$: the degrees of belief.

In the above example, the sum of the degrees of belief is 100%. In this case, the analyst has got enough information to provide a '*complete assessment*'. In other cases, though, the analyst may be forced to provide '*incomplete assessment*'. Incomplete assessment can also result from the novelty and complexity of the problem which prevents the analyst from providing precise assessments (Yang, 2001). The ability to handle incomplete assessments is one of the most powerful features of the ER approach.

The ER algorithm for assessment aggregation is the core of the ER approach. It is a conjunctive aggregation of degrees of belief coming from heterogeneous sources of evidence. The ER algorithm differs from the original Dempster's rule of evidence combination by distributing the ignorance among the criteria according to their importance weight (Yang, 2001; Sonmez *et al*, 2002). The appendix illustrates the formulae of the ER algorithm. As illustrated in the appendix, the ER approach aggregates the ignorance and utilise it for generating upper and lower boundaries of the alternative scores. The degree of ignorance can be allocated in different manners, for instance, Huynh *et al* (2005) adopted the principle of insufficient reason and proposed distributing the degree of ignorance equally among the assessment grades. In theory, the degree of ignorance can be allocated in a form of distribution that best suits the decision-making problem. However, we advocate the ER approach of generating utility intervals that can denote optimistic and pessimistic scenarios of project risk level as it is illustrated in the next section of the paper.

5. A new risk assessment methodology

The DST and the ER algorithm are employed innovatively to provide a new risk assessment methodology. Risk is modelled as the product of likelihood of occurrence and the impact of an event on project success objectives. This model dominates the literature despite a number of improvement proposals. Hence, assessing a risk requires, mainly, assessing its likelihood of occurrence and the impact.

5.1. Assessing risk impact

Assessing risk impact on different project objectives can be handled in the same way as approaching an MCDM problem. Risk impact assessment can be represented by a risk impact matrix with rows standing for key risk factors and columns for project objectives like project cost, duration, quality, etc. Let Oi stand for objective i, Rj for risk j, and $S(RIj(Oi))$ for the assessment of the impact of the risk Rj on the objective Oi. In order to reflect the uncertainty of risk impact, the impact is assessed in a distributed form according to the following formula:

$$S(RIj(Oi)) = (Gn, \beta_{n,i,j}),\ n = 1, \ldots, N,$$
$$i = 1, \ldots, m,\ j = 1, \ldots, l$$
$$\beta_{n,i,j} \geqslant 0,\ \sum_{n=1}^{N} \beta_{n,i,j} \leqslant 1$$

where N: the number of assessment grades; m: the number of project objectives; l: the number of key risk; $\beta_{n,i,j}$: the degree of belief that the impact of risk Rj on project objective Oi equals the grade Gn.

The impact of every risk on all project objectives is assessed in the same way. In the proposed methodology, the evaluation grades are considered to be percentages of the project initial cost. For instance Gn can be 1, 2, 3%, or any percentage. It is a common language that everyone in construction industry can understand. The grades reflect the uncertainty of measuring risk impact due to lack of information or different impact scenarios. A risk analyst expresses his or her confidence in the size of risk impact by assigning a degree of belief to every assessment grade. Nonetheless, the total belief can be assigned to one proposition, for instance risk impact equals 1% of the initial project cost, if there is enough evidence to support that. Clearly, the analyst can provide incomplete assessment of risk impact due to lack of information or previous experience. The proposed approach is capable of accommodating the ignorance and utilising it for generating realistic assessment as will be illustrated later.

5.2. Assessing likelihood of occurrence

Likelihood of occurrence can be assessed in a distributed form as well. For instance, it can be 10, 40, 70 or 100% with degrees of belief of 0.3, 0.5, 0.2 and 0, respectively. Although this is a detailed assessment, likelihood of occurrence is proposed to be assessed, as it is usually done, by a single figure. This is suggested merely for simplicity and practicality of risk assessment. Using a single figure for measuring the likelihood of occurrence reduces the number of required inputs and, subsequently, reduces the required time and effort for conducting a project risk assessment. Simplicity is crucial for enhancing the usability of the methodology bearing in mind the large number of risks and the different project objectives to be considered.

5.3. Risk assessment

Risk assessment is obtained through multiplying the likelihood of occurrence by the degrees of belief in the distributed assessment of risk impact. As a result, a new set of degrees of belief is generated and associated with the same assessment grades of risk impact. Hence, a distributed assessment of risk size (cost) is obtained in the following form:

$$S(Rj(Oi)) = (Gn, \beta'_{n,i,j}),\ n = 1, \ldots N,$$
$$i = 1, \ldots m,\ j = 1, \ldots l$$
$$\beta'_{n,i,j} = L_j * \beta_{n,i,j}$$

where N: the number of assessment grades; m: the number of project objectives; l: the number of key risk; Lj: the likelihood of occurrence of risk Rj; $\beta'_{n,i,j}$: the degree of belief that the cost of risk Rj on project objective Oi equals the grade Gn.

The new set of belief degrees may not sum to unity due to the discounting effect of the likelihood of occurrence, besides the effect of an incomplete assessment of risk impact. Hence, in order to differentiate the discounting effect of Lj from the ignorance, we added an additional assessment grade (0%) which represents the case of no cost, or no impact at all. This assessment grade will be associated with a degree of belief equal to $(1-Lj)$, which represents the degree of belief in the risk not occurring. Actually, the inclusion of the (0%) assessment grade is very important to satisfy the exhaustiveness condition of the assessment grades. Moreover, it enriches risk assessment through allowing measuring the belief in risk effects not materialising as will be explained later.

5.4. Assessments aggregation

Usually, project risks are organised in a hierarchical structure and risk assessment is conducted at the lowest level of the hierarchy. In order to generate a project risk level, individual risk assessments need to be aggregated. Obviously, risks are different in terms of importance. The importance issue is usually reflected by associating every risk with an importance weight ωi. The importance weights of every group of risks, classified under one category in the upper level, must be levelled so their values sum up to unity. The analyst has the total freedom to use any methodology for generating the weights.

For aggregating the individual risk assessments, we are using the ER algorithm which is illustrated in the appendix. The aggregation process can be followed in order to generate an overall risk assessment at any level in the risk hierarchy. Obviously, it may continue to the top of the hierarchy to produce the overall assessments of project risk on every objective, and ultimately the project risk level. The aggregation results are presented in distributed formats. However, they can be easily consolidated into percentages of the project initial cost by summing up the multiplications of the assessment grades and the associated degrees of belief. The aggregated degree of ignorance, however, can be used to generate upper and lower boundaries of the consolidated figures. The upper limit is generated after allocating the ignorance to the highest assessment grade. For instance, in the case of having the following assessment grades 1, 1.5 and 2%, the degree of ignorance would be added to the aggregated degree of belief associated with the 2% grade. On the other hand, the lower limit is obtained after assigning the ignorance to the lowest assessment grade; in this example the 1%. Obviously, the upper limit, lower limit and their average value can be used for comparing different projects as explained in the appendix.

6. Illustrative case study

A spreadsheet-based DSS was devised to utilise the proposed methodology. Four case studies were conducted in four British construction companies to evaluate the proposed risk assessment methodology against their own. A real project, described in Table 1, was used as an illustrative example. The project was provided by a giant construction company with an annual turnover of £4.3 billion. A senior manager in the company participated actively in this research and applied the tool for analysing the financial risks of the project.

The senior manager decided that the major risks were financial and identified the top four as: inflation, payment security, programme overrun and subcontractors' pricing. He estimated their likelihood of occurrence as 1, 0.1, 0.1 and 0.8 respectively. Risk impact was assessed on project cost, duration and quality using three assessment grades; 1, 2 and 4% of the project initial cost. He assigned his degrees of belief based on his experience in the industry and the

project. He was unsure of the actual impact of all the risks on the three objectives so he provided incomplete assessments as displayed in Table 2.

The tool multiplied the likelihood of occurrence of every risk with the associated degrees of belief and generated the individual risk assessments in distributed formats as illustrated in Table 3.

The individual risk assessments were aggregated after assigning importance weights to each of them. The importance weights to the above four risks were decided as 0.2, 0.05, 0.25 and 0.5 correspondingly. Using the ER algorithm, the tool generated the following results.

Table 1 Details of the case study's project

Project type	Health sector, Care home facility
Location	UK, North London
Client	Private client
Duration	Initially 110 weeks started May 2006, eventually it took 150 weeks.
Estimated cost	£22.5 million. The contract was won with a profit margin of 8%.
Final cost	£27 million
Major problems	• The client was always late in providing the design information. • The contract was signed based on wrong quantities; the client produced bills and quantities without complete design information.

Table 4 shows the aggregated degrees of belief and the aggregated degrees of ignorance. The ignorance is used to generate upper and lower risk assessment boundaries. For instance, the minimum and maximum risk assessments on project quality are calculated as follows:

$$\text{Min} - R - ProjectQuality = (0.18 + 0.29) \times 1 + 0.1 \times 2 + 0.05 \times 4 = 0.85\%$$

$$\text{Max} - R - ProjectQuality = 0.29 \times 1 + 0.1 \times 2 + (0.18 + 0.05) \times 4 = 1.14\%$$

The other boundaries can be calculated in the same way. These boundaries and their averages are summarised in Table 5.

As mentioned earlier in the paper, the aggregated degree of belief assigned to the assessment grade (0%) is used to measure the belief in risk effects not materialising. It can also be used to predict the degree of belief in risk effects materialising. The materialisation of risk effect is the complement event and the degree of belief in it is the

Table 2 Risk impact assessments in distributed forms

	Risk impact on project cost			*Risk impact on project duration*			*Risk impact on project quality*		
Top risks	1%	2%	4%	1%	2%	4%	1%	2%	4%
Inflation	0.7	0.2	0.05	0	0	0	0	0	0
Payment security	0	0	0	0.5	0.3	0.1	0	0	0
Programme overrun	0.6	0.1	0	0.1	0.2	0.6	0	0	0
Subcontractor pricing	0.6	0.3	0.1	0	0	0	0.6	0.2	0.1

Table 3 Distributed forms of risk assessments on the three project objectives

	Risk on project cost				*Risk on project duration*				*Risk on project quality*			
Top risks	0%	1%	2%	4%	0%	1%	2%	4%	0%	1%	2%	4%
Inflation	0	0.7	0.2	0.05	0	0	0	0	0	0	0	0
Payment security	0.9	0	0	0	0.9	0.05	0.03	0.01	0.9	0	0	0
Programme overrun	0.9	0.06	0.01	0	0.9	0.01	0.02	0.06	0.9	0	0	0
Subcontractor pricing	0.2	0.48	0.24	0.08	0.2	0	0	0	0.2	0.48	0.16	0.08

Table 4 Aggregated risk assessments on the three objectives in distributed forms

	Risk on project cost				*Risk on project duration*				*Risk on project quality*			
All risks	0%	1%	2%	4%	0%	1%	2%	4%	0%	1%	2%	4%
Degrees-of-belief	0.345	0.42	0.17	0.05	0.464	0.01	0.01	0.02	0.387	0.29	0.1	0.05
Ignorance		0.01				0.5				0.18		

Table 5 Upper and lower boundaries and average values of risk assessments on every objective

	Risk on project cost (%)	*Risk on project duration (%)*	*Risk on project quality (%)*
Minimum risk assessment	0.98	0.6	0.85
Maximum risk assessment	1.02	2.11	1.41
Average risk assessment	1.00	1.36	1.13

Table 6 Aggregated degrees of belief in risk effect materialisation on every objective

	Project cost (%)	*Project duration (%)*	*Project quality (%)*
Degree of belief in risk effects not materialising	34.5	46.4	38.7
Degree of belief in risk effects materialising	65.5	54.6	61.3

Table 7 Project risk assessment in a distributed form

	Project financial risk			
All risks	0%	1%	2%	4%
Degrees-of-belief	0.412	0.302	0.114	0.041
Ignorance		0.132		

remaining proportion of belief, the complement to unity, as illustrated in Table 6.

These results, together with the upper, lower and average risk boundaries, are rich and useful for an informative decision making.

Another aggregation can be conducted in order to generate the project risk level. The senior manager assigned the following importance weights: 0.5, 0.3 and 0.2 to project cost, duration and quality, respectively. Again, using the ER algorithm, the distributed assessments in Table 4 were aggregated and the project risk level was generated in its distributed format as presented in Table 7.

Again, the aggregated degree of ignorance was utilised to provide the upper and lower boundaries of the project risk level and to measure the probability of risk effect materialisation as illustrated in Tables 8 and 9.

These are the results of analysing the project financial risks. Obviously, in more complicated projects other risk categories could be considered. In these cases, a similar approach would be followed for analysing the other risk categories and further aggregation can be conducted to generate an overarching risk level on every success objective and, ultimately, a project risk level.

Table 8 The upper and lower boundaries and the average value of project risk assessment

Minimum risk level	0.82%
Maximum risk level	1.22%
Average risk level	1.02%

Table 9 The aggregated degrees of belief in project risk effect materialisation

	The project
Degree of belief in project risk effect not materialising	41.2%
Degree of belief in risk effect materialisation	58.8%

6.1. Critical evaluation of the proposed methodology

The proposed assessment methodology was also presented to senior managers in three different construction companies in the UK. The companies varied in size; their annual turnovers were £15 million, £65 million and £250 million. The above project was used, anonymously, as an illustrative example. In the four cases, participants were asked to evaluate the proposed methodology and to compare it with the ones they already use. Four evaluation criteria were considered: analysis complexity, methodological clarity, time and resource consumption, and quality and usefulness of the results. The feedback from the participants was positive. They found the proposed approach simple, practical and easy to understand. The simplicity and practicality of the approach was attributed to the deployment of Microsoft Excel package and the use of a monetary equivalent as a measurement scale. The concept of ignorance and the flexibility of providing incomplete assessments were very much appreciated by the managers. They found this feature very effective for expressing their experience and providing realistic assessments. Two of the senior managers were particularly enthusiastic. They found the tool better than those used in their companies, which mainly depended on risk registers, where people used risk registers routinely without thinking enough of the risks. According to them, the proposed approach forces risk analysts to think of the risks before assigning any value. The clarity of the methodology and the convenience of tuning the parameters for conducting sensitivity analysis were valued. The detailed analysis and the panoramic nature of the analysis results, which can be easily transformed into consolidated figures, were praised. The participants realised the usefulness of the proposed methodology especially when analysing complex and unique projects. Moreover,

they appreciated that the simplicity of the methodology does not consume a lot of time or demand highly skilled people or experts to conduct the analysis. Hence, cost effectiveness of the DSS was considered a positive attribute.

The participants were also encouraged to express their concerns about the proposed approach. The large number of inputs was considered as the main concern. However, the importance of balancing the analysis accuracy and practicality is emphasised. It was clarified that in strategic projects more objectives and more assessment grades are required to be considered, whereas in other cases fewer assessment grades and objectives would be sufficient. It was concluded that it takes some time for potential users to master the tool and input the right values when analysing different situations.

7. Summary and conclusions

This paper presents a novel methodology for assessing construction risk in an attempt to fill a gap in the literature. Risk cost is used as a common scale for assessing risk impact on various project success objectives, DST is employed for utilising the cumulative experience and personal judgment of risk analysts, and belief structures are used to assess risk impact using the available evidence. This approach is flexible and allows risk analysts to provide complete or incomplete risk assessments. It permits expressing ignorance transparently and utilising it for generating upper and lower boundaries of the analysis results. The ER algorithm is deployed to aggregate individual risk assessments without averaging them or compromising their panoramic nature. The analysis results are detailed and informative. Besides measuring the belief degrees in the various assessment grades, the results measure the degree of belief in risk effect materialisation which is crucial for justifying any decision or action. A spreadsheet-based DSS was devised to facilitate the assessment methodology and four case studies were conducted to evaluate its viability. Promising and constructive feedback was expressed by the participants in these cases. The proposed methodology was found to be simple, practical and easy to understand. The level of detail of the analysis was welcomed, and the possibility of providing incomplete assessments was very much appreciated as it allows risk analysts to express their experience and to provide realistic assessments without making inappropriate assumptions. It is concluded that the DST and the ER approach can provide a viable alternative for aiding risk analysis and decision making in construction management. Moreover, it is believed that the simplicity and practicality of the proposed approach may help in bridging the gap between the theory and practice of construction risk assessment. This research is part of a wider research project aiming at rethinking construction risk modelling and assessment.

References

Akintoye AS and MacLeod MJ (1997). Risk analysis and management in construction. *International Journal of Project Management* **15**(1): 31–38.

Baker S, Ponniah D and Smith S (1998). Techniques for the analysis of risks in major projects. *Journal of the Operational Research Society* **49**(6): 567–572.

Beeston D (1986). Combining risks in estimating. *Construction Management and Economics* **4**(1): 75–79.

Belton V and Gear T (1983). On a short-coming of Saaty's method of analytic hierarchies. *Omega* **11**(3): 228–230.

Belton V and Stewart TJ (2002). *Multiple Criteria Decision Analysis: An Integrated Approach*. Springer: New York.

Ben-David I and Raz T (2001). An integrated approach for risk response development in project planning. *Journal of the Operational Research Society* **52**(1): 14–25.

Beynon M, Curry B and Morgan P (2000). The Dempster–Shafer theory of evidence: An alternative approach to multicriteria decision modelling. *Omega* **28**(1): 37–50.

Bloch I (1996). Some aspects of Dempster–Shafer evidence theory for classification of multi-modality medical images taking partial volume effect into account. *Pattern Recognition Letters* **17**(8): 905–919.

Cagno E, Caron F and Mancini M (2007). A multi-dimensional analysis of major risks in complex projects. *Risk Management* **9**(1): 1–18.

Carr RI (1977). Paying the price for construction risk. *Journal of the Construction Division* **103**(1): 153–161.

Chapman C and Cooper DF (1983). Risk engineering: Basic controlled interval and memory models. *Journal of the Operational Research Society* **34**(1): 51–60.

Cioffi DF and Khamooshi H (2009). A practical method of determining project risk contingency budgets. *Journal of the Operational Research Society* **60**(4): 565–571.

Cox E (1999). *The Fuzzy Systems Handbook*. AP Professional: New York.

Denœux T (2008). Conjunctive and disjunctive combination of belief functions induced by nondistinct bodies of evidence. *Artificial Intelligence* **172**(2-3): 234–264.

Diekmann JE (1983). Probabilistic estimating: Mathematics and applications. *Journal of Construction Engineering and Management* **109**(3): 297–308.

Dikmen I, Birgonul MT and Arikan AE (2004). A critical review of risk management support tools. *20th Annual ARCOM Conference*, Heriot-Watt University, Edinburgh, UK.

Dubois D and Prade H (1986). A set-theoretic view of belief functions: Logical operations and approximations by fuzzy sets. *International journal of general systems* **12**(3): 193–226.

Dubois D and Prade H (1992). On the combination of evidence in various mathematical frameworks. In: Flamm J and Luisi T (eds). *Reliability Data Collection and Analysis*. Deventer: The Netherland, Kluwer, pp 213–241.

Fan CF and Yu YC (2004). BBN-based software project risk management. *Journal of Systems and Software* **73**(2): 193–203.

Flanagan R and Norman G (1993). *Risk Management and Construction*. Wiley-Blackwell: Oxford.

Franke A (1987). Risk analysis in project management. *International Journal of Project Management* **5**(1): 29–34.

Gates M (1971). Bidding contingencies and probabilities. *Journal of the Construction Division, ASCE* **97**(2): 277–303.

Huynh VN, Nakamori Y and Ho TB (2005). Assessment aggregation in the evidential reasoning approach to MADM under uncertainty: Orthogonal versus weighted sum. In: Maher MJ (ed). *Advances in Computer Science-ASIAN 2004. Higher-Level Decision Making*. Vol. 3321/2005, Springer: New York, pp 3144–3144.

Kangari R and Riggs LS (1989). Construction risk assessment by linguistics. *Engineering Management, IEEE Transactions on* **36**(2): 126–131.

Khatibi V and Montazer GA (2010). A fuzzy-evidential hybrid inference engine for coronary heart disease risk assessment. *Expert Systems with Applications* **37**(12): 8536–8542.

Laryea S and Hughes W (2008). How contractors price risk in bids: Theory and practice. *Construction Management and Economics* **26**(9): 911–924.

Liu J, Yang J, Wang J and Sii H (2002). Review of uncertainty reasoning approaches as guidance for maritime and offshore safety-based assessment. *Journal of UK Safety and Reliability Society* **23**(1): 63–80.

Liu W (2006). Analyzing the degree of conflict among belief functions. *Artificial Intelligence* **170**(11): 909–924.

Lowrance J, Garvey T and Strat T (2008). A framework for evidential-reasoning systems. In: Yager RR and Liu L (eds). *Classic Works of the Dempster–Shafer Theory of Belief Functions*. Springer: New York, pp 419–434.

Lyons T and Skitmore M (2004). Project risk management in the Queensland engineering construction industry: A survey. *International Journal of Project Management* **22**(1): 51–61.

Murphy CK (2000). Combining belief functions when evidence conflicts. *Decision Support Systems* **29**(1): 1–9.

Mustafa MA and Al-Bahar JF (1991). Project risk assessment using the analytic hierarchy process. *Engineering Management, IEEE Transactions on* **38**(1): 46–52.

Sen P and Yang JB (1998). *Multiple Criteria Decision Support in Engineering Design*. Springer: New York.

Sentz K and Ferson S (2002). *Combination of Evidence in Dempster–Shafer Theory*. Citeseer: New Mexico, California.

Shafer G and Logan R (1987). Implementing Dempster's rule for hierarchical evidence. *Artificial Intelligence* **33**(3): 271–298.

Smets P (2000). Data fusion in the transferable belief model. *Proceedings of the Third International Conference on Information Fusion*. Bruxelles, Belgium.

Sonmez M, Yang JB, Graham G and Holt G (2002). An evidential reasoning based decision making process for pre-qualifying construction contractors. *Journal of Decision Systems, Special issue on Decision Making on Urban & Civil Engineering* **11**(3–4): 355–381.

Spooner JE (1974). Probabilistic estimating. *Journal of the Construction Division* **100**(1): 65–77.

Tah J and Carr V (2001). Knowledge-based approach to construction project risk management. *Journal of computing in civil engineering* **15**(3): 170–177.

Taroun A, Yang J and Lowe D (2011). Construction risk modelling and assessment: Insights from a literature review. *The Built & Human Environment Review* **4**(1): 87–97.

Wang YM and Elhag T (2007). A comparison of neural network, evidential reasoning and multiple regression analysis in modelling bridge risks. *Expert Systems with Applications* **32**(2): 336–348.

Warszawski A and Sacks R (2004). Practical multifactor approach to evaluating risk of investment in engineering projects. *Journal of construction engineering and management* **130**(3): 357–367.

Williams T (1995). A classified bibliography of recent research relating to project risk management. *European Journal of Operational Research* **85**(1): 18–38.

Wood GD and Ellis RCT (2003). Risk management practices of leading UK cost consultants. *Engineering, Construction and Architectural Management* **10**(4): 254–262.

Yang JB (2001). Rule and utility based evidential reasoning approach for multiattribute decision analysis under uncertainties. *European Journal of Operational Research* **131**(1): 31–61.

Yang JB and Sen P (1994). A general multi-level evaluation process for hybrid MADM with uncertainty. *Systems, Man and Cybernetics, IEEE Transactions on* **24**(10): 1458–1473.

Yang JB and Singh MG (1994). An evidential reasoning approach for multiple-attribute decision making with uncertainty. *Systems, Man and Cybernetics, IEEE Transactions on* **24**(1): 1–18.

Yong D, WenKang S, ZhenFu Z and Qi L (2004). Combining belief functions based on distance of evidence. *Decision Support Systems* **38**(3): 489–493.

Zhang L (1994). Representation, independence, and combination of evidence in the Dempster–Shafer theory. In: Yager RR, Kacprzyk J and Fedrizzi M (eds). *Advances in the Dempster–Shafer Theory of Evidence*. John Wiley & Sons: New York, pp 51–69.

Appendix

In a hierarchy of two levels, the aggregation of the distributed assessments of l criteria is conducted according to the following steps:

(1) Assign importance weights ωi $(i=1, \ldots, l)$ to decision criteria. The weights must be normalised, so that $0 \leqslant \omega i \leqslant 1$ and $\sum_{i=0}^{l} \omega i = 1$.

(2) Transform the degrees of belief into basic probability assignments by multiplying them with the importance weights:

$$m_{n,i} = m_i(H_n) = w_i * \beta_{n,i}(A_m),$$
$$n = 1, \ldots, N,\ i = 1, \ldots, l.$$

$m_{n,i}$ represents the probability mass assigned to the evaluation grade H_n when considering the criterion C_i, N is the number of assessment grades.

(3) Calculate the probability mass assigned to the whole frame of discernment, a set of N evaluation grades, on every criterion by the following formula:

$$m_{H,i} = m_i(H) = 1 - \sum_{n=1}^{N} m_{n,i}\ i = 1, \ldots, l.$$

This probability mass can be split into two parts:

- $\bar{m}H, i = 1 - \omega i$ caused by the weight of the criterion Ci and
- $\tilde{m}H, i = \omega i * (1 - \sum_{n=1}^{N} \beta_{n,i}(Ai))$ $i = 1, \ldots, l$ caused by the incompleteness of the assessment

(4) Aggregate the probability assignments by means of the following equations:

$$m_n = k * \left[\prod_{i=1}^{l} (m_{n,i} + \bar{m}H, i + \tilde{m}H, i) - \prod_{i=1}^{l} (\bar{m}H, i + \tilde{m}H, i) \right],$$
$$n = 1, \ldots, N$$

$$k = \frac{1}{\left[\sum_{n=1}^{N} \prod_{i=1}^{l} (m_{n,i} + \bar{m}H, i + \tilde{m}H, i) - (N-1) * \prod_{i=1}^{l} (\bar{m}H, i + \tilde{m}H, i) \right]}$$

(5) Aggregate the probability masses assigned to the whole frame of discernment:

$$\tilde{m}H = k * \left[\prod_{i=1}^{l} (\bar{m}H, i + \tilde{m}H, i) - \prod_{i=1}^{l} (\bar{m}H, i) \right]$$

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

(6) Transform the aggregated probability masses into an aggregated belief structure in the shape of $S(Cj(Ai)) = (Hn, \beta_{n,i}(Ai))$. Such a transformation requires calculating the belief degrees $\beta_n (n = 1, \ldots, N)$ using the following equation:

$$\beta_n = \frac{m_n}{1 - \bar{m}H}, \quad n = 1, \ldots, N$$

(7) Calculate the aggregated degree of ignorance β_H:

$$\beta_H = \frac{\tilde{m}H}{1 - \bar{m}H} = 1 - \sum_{i=1}^{N} \beta_n, \quad n = 1, \ldots, N$$

The aggregation result is an overall belief structure. In this belief structure, the overall degrees of belief β_n together with the degree of ignorance β_H always sum to unity which is perfectly logical.

In order to compare different alternatives, the overall assessment should be transformed from its distributed form into a representative score. Yang (2001) proposed calculating an expected utility for every alternative $u(S(Aj))$as follows:

$$u(S(Aj)) = \sum_{n=1}^{N} u(H_n) * \beta_n, \quad n = 1, \ldots N$$

Hence, by agreeing upon the utility value of every evaluation grade, the expected utility values of the competing alternatives can be estimated. In the case of incomplete assessment, the degree of ignorance can be utilised in order to generate a utility interval with upper and lower levels (Yang, 2001) as follows:

$$u_{\max}(A_j) = \sum_{n=1}^{N-1} \beta_n * u(H_n) + (\beta_N + \beta_H) * u(H_n)$$

$$u_{\min}(A_j) = (\beta_1 + \beta_H) * u(H_1) + \sum_{n=2}^{N} \beta_n * u(H_n)$$

where H_1 is the assessment grade with the lowest utility value; H_N the assessment grade with the maximum utility value.

These two utility levels can be easily averaged in order to rank the alternatives accordingly. However, using the average utility for comparison is not always reliable. According to Yang (2001), alternative $A1$ is preferred to alternative $A2$ if: $u_{\min}(A1) > u_{\max}(A2)$ and they are indifferent if $u_{\min}(A1) = u_{\min}(A2)$.

Received March 2012;
accepted February 2013 after one revision