ARTICLE IN PRESS

Knowledge-Based Systems xxx (2013) xxx–xxx

Contents lists available at ScienceDirect

Knowledge-Based Systems

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

Integrating textual analysis and evidential reasoning for decision making in Engineering design

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ARTICLE INFO

Article history:
Received 18 February 2013
Received in revised form 24 May 2013
Accepted 23 July 2013
Available online xxxx

Keywords:
Evidential reasoning
Dezert–Smarandache Theory
Information extraction
Textual entailment
Natural language processing
Discounting techniques
Information fusion
Knowledge and data engineering

ABSTRACT

Decision making is an important element throughout the life-cycle of large-scale projects. Decisions are critical as they have a direct impact upon the success/outcome of a project and are affected by many factors including the certainty and precision of information. In this paper we present an evidential reasoning framework which applies Dempster–Shafer Theory and its variant Dezert–Smarandache Theory to aid decision makers in making decisions where the knowledge available may be imprecise, conflicting and uncertain. This conceptual framework is novel as natural language based information extraction techniques are utilized in the extraction and estimation of beliefs from diverse textual information sources, rather than assuming these estimations as already given. Furthermore we describe an algorithm to define a set of maximal consistent subsets before fusion occurs in the reasoning framework. This is important as inconsistencies between subsets may produce results which are incorrect/adverse in the decision making process. The proposed framework can be applied to problems involving material selection and a Use Case based in the Engineering domain is presented to illustrate the approach.

1. Introduction

Decision making in large-scale projects are often sophisticated and complex processes the choices of which have an impact on diverse stages of the project life-cycle. Decision making in such complex projects involves the evaluation of multiple design decision options against criteria such as detailed requirement specifications and Industry Standards. Evidence supporting/opposing decisions can be extracted from diverse heterogeneous information sources including: trade studies, Pugh matrices and expert discussions. However, these evidence sources vary in terms of reliability, completeness, precision and may contain conflicting information. Furthermore, the tracking and modeling of these evidence and rationale is currently lacking in the decision making process making it challenging for decision makers to make critical decisions.

The research proposed in this paper outlines a novel design framework whereby evidence is extracted based on Natural Language Processing (NLP) techniques. The retrieved evidence will form the basis of an evidential reasoning system to aid decision makers in the decision making process. This framework is applicable to any problem which is based on a set of alternatives where the support for any given alternative can be expressed in propositional logic based on the presence of various attributes. To illustrate the application of our proposed conceptual framework we use a Use Case based in the Aerospace domain. This Use Case demonstrates the methodology proposed in the paper. The design decisions or hypotheses in this framework are related to a common one in manufacturing design which is the best choice of a material in the design of a component. We adopt a simple list of choices to aid in the exposition of our process. Other examples of problems which can also be described in terms of a choice of a given alternative based on attributes include the choice of a particular product design [1] or the choice of best performing motorcycle [2].

The application of this novel framework integrates diverse research areas including NLP based information extraction and evidential reasoning. This framework will extract evidence from unstructured information sources which vary in terms of their quality and reliability and are combined using evidential reasoning techniques. This approach diverges considerably from evidential reasoning methods in multi-attribute decision making (MADM) which are described in [3,4,2]. The starting point in such work is that the relevant attributes or properties and their quantitative values are fully specified. We are making no such assumption

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http://dx.doi.org/10.1016/j.knosys.2013.07.014

and rather our starting point for collating evidence is a number of unstructured discursive documents which make qualitative statements which may have varying levels of relevance to a specific design problem.

The focus of information extraction identifies key sentences in documents and makes a determination whether any key sentences in a document is judged to *entail* any proposition in a knowledge base. Textual entailment is a relatively new area of research in NLP and is based on determining whether the truth/validity of one piece of text, is entailed (can be inferred) from another (often larger) snippet of text [5]. This entailment relation is usually based on human judgment and may not always be possible to derive from logical inferencing [6]. There are many approaches to the entailment task and the use of various NLP components have including various similarity based measures, anaphora resolution, paraphrasing, syntactic graph alignment, named entity recognition, semantic parsing and logical inference based on model theoretic approaches. These entailed propositions determine which expert defined rules are applicable.

A number of techniques including Bayesian belief networks, fuzzy logic, rough set theory and evidence theories have been applied to handle imprecise and uncertain information [1,7–9]. Evidence theories provide important reasoning mechanisms in Artificial Intelligence and Information Fusion. These theories have been successfully applied to diverse problem areas to solve a variety of problems with imprecise and incomplete information [10]. For example, theories of evidence including Dempster–Shafer Theory (DS) [11] and Dezert–Smarandache Theory (DSm) [12] have previously been applied in the domain of Aerospace to handle uncertainty when fusing sources of information for decision making purposes. Such areas have involved sensor Information Fusion [13] and target identification [12] where systems are required to deal with imprecise information and conflicts which may arise among sensors. A study in [14] provides an example of how argumentation and reasoning can be applied to handle uncertainty and conflicts in decision making. For both DS and DSm theory, mass functions representing belief are the main concepts that are applied to carry out uncertainty reasoning [10]. In this research we propose to fuse imprecise and potentially conflicting information sources using an evidential reasoning framework based on DS and DSm theory. To ensure consistency exists between these *basic belief assignments* (bbas) before the fusion process we incorporate the process of constructing maximal consistent subsets based on a proposed algorithm. This methodology is required as integration of conflicting sources can result in incorrect decision predictions. The metric distance measure [15] is applied to measure the similarity between the subsets. Subsets which are not considered as part of the maximal consistent subset are subjected to discounting based on the reliability discounting using Shafer's classical discounting approach described in [16]. The evidential reasoning process of maximally consistent subsets was initially proposed in [17], which solely concentrated on evidential reasoning in the presence of available evidence.

The rest of paper is presented as follows. We firstly describe the information extraction techniques applied in the framework to define the bbas. The evidential reasoning processes is then described in Section 3 which applies the knowledge and rules extracted from the Information Fusion phase. An overview of the proposed Methodology is provided in Section 4 which details more the implementation issues concerning information extraction and evidential reasoning. To illustrate the application the proposed framework a Use Case is presented in Section 5. We discuss the findings related to the Use Case in Section 6 and areas for improvement. Finally the key conclusions and contributions of this study are described in Section 7.

2. Collation of evidence

The processes of information extraction for the collation of evidence depends on the use of a knowledge base and a trained entailment model. A key assumption of this paper and illustrated in the Use Case is the ability of a designer to specify a knowledge base without uncertainty which lists propositional qualitative statements describing a material and a desirable or undesirable property. In addition the knowledge base contains simple inferential rules where each rule based on a propositional logic implication linking a design decision as a material choice as head of a rule and a body based on a material and associated desirable or undesirable properties. It is natural to assume that a designer would be able to specify a list of such propositions and simple rules, however it not the case that such information will always be applicable in analyzing a document and its level of support will vary per document. Each document may trigger a varying number of rules or none at all, in support of one or more hypotheses and only by using evidential reasoning can we make an informed decision as to most appropriate material choice. In effect we are assuming the presence of background knowledge and to allow for the fact that support for or against a given proposition may be written in a number of ways and we cannot expect the designer to specify all possible propositions, we apply a textual entailment model [18] to check whether extracted sentences of interest entail any of propositions in our knowledge base, to aid in the process of detecting supported propositions. The process of entailment is based on the principle that a reader can infer from one sentence (referred to as the *text*) that another sentence, (referred to as the *hypothesis*) is true. A closely related mechanism to entailment is paraphrasing however whereas paraphrasing allows for a symmetric entailment relationship, in standard entailment the hypothesis may not be shown to entail the text [19]. Given a textual source of information, we wish to extract key sentences from the source where a key sentence contains a reference to a material and one or more properties. For each key sentence related to a material, a check is made, based on an application of the entailment model whether any proposition in the knowledge base related to the same material is shown to be true. For a list of true propositions, we check whether any of the rules fires. The output from this step is an indexed list of the rules that fire, where each rule supports a possible material selection. Note that the designer would not be able to manually derive an overall design decision as to a material choice and depends upon evidential reasoning mechanisms to provide scientific support for an overall decision.

2.1. Knowledge base

The knowledge base is divided into four sections: materials, properties, propositions and rules. We consider three materials for the purpose of this study: Aluminum, Titanium and Composite. This limited choice of materials aids in the exposition of the process. The constant values for these material as used by propositions and rules are denoted by **Al**, **Ti** and **Comp** respectively. Properties consist of a 3 letter abbreviation denoting the property and a short description of its meaning. Only known materials and properties may be referenced in propositions and rules. Propositions are in the form:

$\langle Material \rangle$ $\langle Property \rangle$ $\langle Statement \rangle$

where $\langle Statement \rangle$ is an example of a textual proposition which relates a property to a material. $\langle Material \rangle$ is set to one of the material constants and $\langle Property \rangle$ is one of the possible properties as denoted by its abbreviation. The use of the property in a proposition may be negated.

Rules are defined in Backus–Naur form [20] :

$$\begin{cases} \langle Material\rangle \& \langle Formula\rangle \Rightarrow \langle Material\rangle \\ \langle Formula\rangle \Rightarrow \sim \langle Formula\rangle \,| \\ (\langle Formula\rangle \& \langle Formula\rangle)\,| \\ (\langle Formula\rangle \| \langle Formula\rangle)\,| \\ Property \end{cases} \quad (1)$$

where $\sim$ denotes negation, $\|$ denotes logical or and & logical and. In effect, a rule body indicates a material and logical formula related to the properties for that material and the head of the rule is the recommendation of a material as the material choice.

Part of the knowledge base is shown in Fig. 1, where only certain properties, propositions and rules are listed Note that the property Dam (indicating the detection of damage), leads to a rule whereby its negation in combination with Comp implies either that Al or Ti should be selected, reflecting the problem of detecting damage in composites.

2.2. Sentence detection

The process of sentence extraction is based on the use of specialized gazetteer lists for materials and properties. We extract only sentences which contain at least one reference to a material and one to a property. In addition we also consider sentences that contain a pronoun that refers to a material in a previous sentence as detected by anaphora resolution and a reference to a property.

2.3. Entailment checking

For each sentence in a list of extracted sentences, we check whether the sentence (S) entails any proposition P from the knowledge base which shares a reference to a particular material. The process of entailment is based on deriving a number of similarity/dissimilarity features from the entailment pair ($\langle S, P\rangle$) similar to those considered in [21] which extracts a number of match and mismatch features in order to build a classification model. We chose this approach as the extracted features do not require computational intensive methods to be derived and as a machine learning method it allows us to consider various classification methods. The features are summarized in Table 1. In general, features are based on discovering overlap counts for matching elements in the text and hypothesis pair. "Lexical" features include the following features: stopwords in common (in absolute and normalized form), content words in common (in absolute and normalized form), all words in common (in absolute and normalized form). "Related words" are based on discovering synonym, causal and entailment relations overlap counts based on WordNet. The latter features are based in absolute and normalized form. "Relations" are based on discovering skip bigrams and grammatical

@materials
Al Aluminium
Ti Titanium
Comp Composite

@properties
Cor Corrosion resistance
Cos Cost
...
Dam Damage easily detected
...
Rat Strength to lightness ratio
Ref Resistant to fatigue
Saf Safety issues
Wei Lighter in Weight
..
@propositions
Al Cor Aluminium has good corrosion resistance
...
Ti Cos Initial high cost in using titanium
Ti Cor Titanium provides excellent corrosion resistance
Ti Rat Titanium has best strength to weight ratio among the metals
Ti Wei Titanium provides weight savings
...
@rules

Al & Dam $\Rightarrow$ Al
...
Comp & $\sim$Dam$\Rightarrow$ Al
Comp & $\sim$Dam$\Rightarrow$ Ti
...
Ti & Cor $\Rightarrow$ Ti
Ti & Cos $\Rightarrow$ Comp
Ti & Rat $\Rightarrow$ Ti
Ti & Wei $\Rightarrow$ Ti
..

Fig. 1. Sample elements from the knowledge base.

Please cite this article in press as: F. Browne et al., Integrating textual analysis and evidential reasoning for decision making in Engineering design, Knowl. Based Syst. (2013), http://dx.doi.org/10.1016/j.knosys.2013.07.014

Table 1
A description of the feature types used for entailment.

Feature type	Number of features	Description
Lexical	10	Lexical overlap
Related words	6	Related words derived though WordNet
Relations	6	Shared relations derived through dependency parsing
MisMatch	3	Features based on negation, antonyms

relations overlaps. The skip bigrams include a normalized count of skip bigrams matches using all words; a similar normalized count of skip bigrams created using only nouns and verbs. Grammatical relation are based on dependency parsing and includes features based on the full relation and a dependency pair of terms excluding the dependency. The previous features are given in absolute and normalized form."Mismatch" features include a normalized count of negated verbs that appear only in the hypothesis and not in the text, the number of antonym pairs in the text hypothesis pair and a normalized value for the latter feature.

For a given source [22] the classification model discovers the following entailments (where ⊨ denotes an entailment relation) between sentences in the source and propositions in the knowledge base:

The chemical industry is the largest user of titanium due to its excellent corrosion resistance ⊨ Titanium provides excellent corrosion resistance

The primary attributes that make titanium an attractive material include an excellent strength-to-weight ratio, providing weight savings ⊨ Titanium has best strength to weight ratio among the metals

The high strength and low density of titanium (40% lower than that of steel) provide many opportunities for weight savings ⊨ Titanium provides weight savings

This led to 3 rules being fired for the given source as shown in Table 3.

3. Evidential reasoning

An evidential reasoning framework based on DS and DSm theory is proposed to fuse information sources to aid in the decision making process. For a given information source, the applicability of propositional rules and information associated with information sources allows us to derive and estimate bbas outlined in the textual analytics steps above. Before fusion of these bbas occur we apply a pre-processing step to ensure consistency exists between bbas thereby obtaining the maximal consistent subset. This is important as imprecise and highly conflicting information can have a detrimental impact upon the fusion process. This section provides an overview of the Theory of belief functions, distance measures, evidential operators and discounting techniques some of which are applied in the proposed framework.

3.1. Theory of belief functions

The DS (evidential theory) is a generalization of traditional probability. This theory provides a mathematical formalism to model our belief and uncertainty on possible decision options for a given decision making process. The application of the Dempster–Shafer rule of combination of belief functions has been advantageous in the fusing of uncertain evidence supporting different hypotheses [5]. However, when conflict between sources becomes high the DS can generate errors in decision making. To address this problem we use the DSm which can be considered a generalization of DS. DSm overcomes limitations of DS by proposing new models for the frame of discernment and new rules of combination that take into account both paradoxical and uncertain information. A review of DS and DSm theory is presented below.

3.1.1. DS theory

In DS the frame of discernment (FOD) denoted by $\Theta = \{\theta_1, \ldots, \theta_n\}$ contains a finite set of n exclusive and exhaustive hypotheses. The set of subsets of Θ is denoted by the power set 2^Θ. For instance, $\{Al, Comp, Ti\}$ is the frame for materials (Aluminum, Composite, Titanium) from which an engineer selects one to construct a component.

3.1.2. DSm

DSm proposes new models for the frame of discernment and new rules of combination that take into account both paradoxical and uncertain information. In DSm, the free DSm model, $\Theta = \{\theta_1, \ldots, \theta_n\}$ is assumed to be exhaustive but not necessarily exclusive due to the intrinsic nature of its elements, the set of subsets are denoted by the hyper power-set D^Θ (Dedekind's lattice) described in detail in [23] which is created with ∪ and ∩ operators. Using the hybrid DSm (hDSm) model integrity constraints can be set on elements of Θ reducing cardinality and computation time compared to the free model. When Shafer's model holds i.e. all exclusivity constraints on elements are included the D^Θ reduces to the power set 2^Θ. We denote G^Θ the general set on which will be defined the basic belief assignments, i.e. $G^\Theta = 2^\Theta$ when DS is adopted or $G^\Theta = D^\Theta$ when DSm is preferred depending on the nature of the problem. A normalized basic belief assignment (bba) or mass function expressing belief assigned to the elements of G^Θ provided by an evidential source is a mapping function $m: G^\Theta \to [0,1]$ representing the distribution of belief satisfying the conditions:

$$m(\emptyset) = 0 \wedge \sum_{A \in G^\Theta} m(A) = 1 \tag{2}$$

In general the condition $m(\emptyset) = 0$ need not hold for a basic belief assignment [24]. As basic belief assignments in the paper are always normalized we do not make any further distinction in the paper and our reference to bbas are always normalized. In evidence theory, a probability range is used to represent uncertainty. The lower bounds of this probability is called ***Belief(Bel)*** and the upper bounds ***Plausibility(Pl)***. The generalized Bel and the Pl for any proposition $A \in G^\Theta$ can be obtained by:

$$Bel(A) = \sum_{\substack{B \subseteq A \\ B \in G^\Theta}} m(B) \tag{3}$$

$$Pl(A) = \sum_{\substack{B \cap A \neq \emptyset \\ B \in G^\Theta}} m(B) \tag{4}$$

3.1.3. Rules of combination

In DS, Dempster's rule of combination is symbolized by the operator ⊕ and used to fuse two distinct sources of evidence B_1 and B_2 over the same frame Θ. Let Bel_1 and Bel_2 represent two belief functions over the same frame 2^Θ and m_1 and m_2 their respective bbas. The combined belief function $Bel = Bel_1 \oplus Bel_2$ is obtained by the combination of m_1 and m_2 as: $m(\emptyset) = 0$ and $\forall C \neq \emptyset \subseteq \Theta$

$$m(C) \equiv [m_1 \oplus m_2](C) = \frac{\sum_{A \cap B = C} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \emptyset} m_1(A) m_2(B)} \tag{5}$$

Dempster's rule of combination is associative ($[m_1 \oplus m_2] \oplus m_3 = m_1 \oplus [m_2 \oplus m_3]$) and commutative ($m_1 \oplus m_2 = m_2 \oplus m_1$).

In DSm the Proportional Conflict Redistribution Rule no. 5 (PCR5) has been proposed as an alternative to Dempster's rule for combining highly conflicting sources of evidence. Below Dempster's combination rule and PCR5 are briefly detailed, a complete presentation of DSm can be found in [23].

$$m_{PCR5}(A) = \sum_{\substack{X_1, X_2 \in G^{\Theta} \\ X_1 \cap X_2 = A}} m_1(X_1)m_2(X_2) + \sum_{\substack{X \in G^{\Theta} \\ X \cap A = \emptyset}} \left[\frac{m_1(A)^2 m_2(X)}{m_1(A) + m_2(X)} + \frac{m_2(A)^2 m_1(X)}{m_2(A) + m_1(X)} \right] \tag{6}$$

All fractions in (6) which have a denominator of zero are discarded. All propositions/sets in the formula are in canonical form. PCR5 is commutative and not associative but quasi-associative.

3.1.4. Probabilistic transformation

We need to obtain pignistic probabilities for decision making purposes for this study. Fused beliefs are mapped to a probability measure using the generalized pignistic transformation approach *DSmP* [25], an alternative to the approach *BetP* proposed by Smets and Kennes [26]. *DSmP* is advantageous as it can be applied to all models (DS, DSm, hDSm). *BetP* is defined as $BetP(\emptyset) = 0$, $\forall (X) \in 2^{\Theta} \setminus \emptyset$ by:

$$BetP(X) = \sum_{Y \in 2^{\Theta}, Y \neq \emptyset} \frac{|X \cap Y)| \cdot m(Y)}{|Y| \cdot (1 - m(\emptyset))} \tag{7}$$

DSmP is defined by $DSmP_{\epsilon}(\emptyset) = 0$ and $\forall X \in G^{\Theta}$ by

$$DSmP_{\epsilon}(X) = \sum_{Y \in G^{\Theta}} \frac{\sum_{\substack{Z \subseteq X \cap Y \\ C(Z) = 1}} m(Z) + \epsilon \cdot C(X \cap Y)}{\sum_{\substack{Z \subseteq Y \\ C(Z) = 1}} m(Z) + \epsilon \cdot C(X \cap Y)} m(Y) \tag{8}$$

where G^{Θ} corresponds to the hyper power set; $C(X \cap Y)$ and $C(Y)$ denote the DSm cardinal of the sets $X \cap Y$ and Y respectively; $\epsilon \geqslant 0$ is a tuning parameter which allows the value to reach the maximum Probabilistic Information Content (PIC) of the approximation of m into a subjective probability measure [25]. The PIC value is applied to measure distribution quality for decision-making. The PIC of a probability measure denoted P over a discrete finite set $\Theta = \{\theta_1, \ldots, \theta_n\}$ is defined by:

$$PIC(P) = 1 + \frac{1}{H_{max}} \cdot \sum_{i=1}^{n} P\{\theta_i\} \log_2(P\{\theta_i\}) \tag{9}$$

where $H_{max} = \log_2(n)$ is the maximum entropy value. A PIC value of 1 indicates the total knowledge to make a correct decision is available whereas zero indicates the knowledge to make a correct decision does not exist [25].

3.2. Estimation of basic belief assignments

From the output of the information extraction and textual entailment processes, the bbas for evidence sources can be estimated. In this research, to estimate the bba values, different factors are discounted which are described below.

3.2.1. Rules fired

For each evidence source, a number of rules can be fired which support a hypothesis. More than one hypothesis may be supported by a source. In our Use Case, the hypothesis relates to a material choice. The greater the number of rules fired to support a particular hypothesis, the more confidence we have in this hypothesis. Different weights will be assigned based on the number of rules fired.

3.2.2. Priority sources

Different sources are discounted differently depending on the reliability of the source. In other words, different category of sources have different reliability weightings.

3.2.3. Priority of the rules

Experts have ranked the different rules with respect to their priority. This factor is utilized as a further discounting step when we consider the formation of maximal consistent subsets.

Before these bbas are fused using the evidential reasoning framework, a maximal consistent subset is constructed with the aim of reducing the errors in the fusion process caused by conflicts in the evidence. This novel approach is detailed in the following section.

3.3. Maximal consistent subsets

Evidence acquired from diverse heterogeneous sources are often inconsistent and conflicting. Furthermore, these evidence differ in terms of reliability and priority. To reduce errors in the fusion process caused by conflicts in the evidence, the construction of a maximal consistent subset is proposed which can aid with determining which sources should be discounted before fusion. This involves constructing a subset of sources that are consistent with each other. Discounting could be applied to sources deemed dissimilar or non-coherent. To measure the coherence between evidence sources, a evidence distance measure can be applied.

3.4. Evidence distance measures

Within a given problem domain, evidences obtained from various sources may give rise to different bbas. The distances between these bbas have an important effect upon the fusion of evidence in evidence theory. The distance between bbas can be defined to represent dissimilarity between sources of evidence. To measure the distances between bbas a number of measures can be applied including the *Metric Distance* [15], *Euclidean Distance* [27] and the *MaxDiff Distance* proposed in [28,29]. A comprehensive review of distance measures can be found in [30]. In this research we apply the commonly used metric distance defined in [15].

3.4.1. Metric distance

Let E_1 and E_2 represent evidences within a frame of discernment Θ. The corresponding mass functions are m_1 and m_2 with focal elements A_i and B_i. The distance between m_1 and m_2 can be defined as:

$$d(m_1, m_2) = \sqrt{\frac{1}{2} (\vec{m}_1 - \vec{m}_2)^T D (\vec{m}_1 - \vec{m}_2)} \tag{10}$$

where $\vec{m}_1$ and $\vec{m}_2$ are the bba vectors and D is a matrix with size of $2^{|\Theta|} \times 2^{|\Theta|}$ whose elements are defined by Jaccard's indexes

$$D(A, B) = \frac{|A \cap B|}{|A \cup B|} A, B \in 2^{\Theta} \tag{11}$$

The similarity between m_1 and m_2 can be obtained using the distance measure $d(m_1,\ m_2) \in [0,1]$ which takes into consideration both the values and specificity of the focal elements of each bba.

3.5. Evidential operations

Evidence to support or refute design options in a decision making process can be extracted from numerous information sources including reports, journals and magazine articles. Some sources may be regarded as being reliable or having a higher priority than others. It is important to manage these factors in the fusion process to reduce errors in reporting beliefs for decision options. Prior knowledge is applied to estimate both the discounting values.

3.5.1. Discounting technique

In discounting, a discounting factor α in $[0,1]$ can be applied to weight a given factor according to a certain criteria [23]. For instance, evidence extracted from an aviation journal is considered higher quality than a blog post. In the latter case, the factor transforms the belief of each source to reflect credibility. Shafer's discounting technique [31] has been proposed for the combination of unreliable evidence sources and is used for discounting for the various factors such as rules fired, the priority of the source and the priority of rules. Incorporation of the factor $\alpha \in [0,1]$ in the decision making process is defined as:

$$\begin{cases} m_\alpha(X) = \alpha \cdot m(X), & \forall X \subset \Theta \\ m_\alpha(\Theta) = \alpha \cdot m(\Theta) + (1-\alpha) \end{cases} \tag{12}$$

whereby $\alpha = 0$ represents a fully unreliable source and $\alpha = 1$ a fully reliable source. The discounted mass is committed to $m(\Theta)$.

4. Methodology

An overview of the proposed methodology illustrating how the information extraction mechanisms in support of Evidence Collation provide input to the evidential reasoning processes is presented in Fig. 2. In this figure for each evidence source a number of information extraction comprising textual entailment steps 1–5 are carried out leading to an evidence file. This file is processed by a number of evidential reasoning steps. Depending on the application area, evidential sources can be extracted from a diverse number of resources including: journals, white papers, standards, online presentations and blog articles. In order to analyze the textual information contained in these sources, each source is required to be converted into a plain text format based on a manual process based of converting the file to plain text before the information extraction phase.

4.1. Collation of evidence

The process of Evidence Collation is based on the use of embedded GATE [32]. GATE Embedded is an open source object-orientated framework developed in Java to provide embedded language processing functionality in diverse applications. It supports a number of processing resources such as sentence detection, tokenization, tagging and through a plugin Stanford dependency parsing [33]. To analyze textual content GATE processing pipelines can be constructed. In this research each source is processed in a GATE pipeline whereby for a given source the text is tokenized and split into sentences. Gazetteer lists are used to detect whether a sentence contains at least one reference to a material and to a property (step 1). Further processing is applied to the key sentences to identify entailment features (step 2). The given sentences are used to detect if any proposition in the knowledge base is entailed and considered true, based on their extracted entailment features and a trained entailment model as described in the following sub-section (step 3). Based on a given hypothesis and a list of associated true propositions, the set of rules are checked to see if any rule fires (step 4). For a given source, the source name and zero or more material selections are written to an evidence file (step 5). Associated with each selection is an indexed list of rules which fired and supported the selection.

4.1.1. Textual entailment

An entailment model was developed to determine if an extracted sentence obtained from a source entails a propositional sentence defined in the constructed knowledge base. The model was trained using a combination of the Recognizing Textual Entailment challenge, RTE2 [34] and RTE3 [35] training and test data sets (RTE2+3). A total of 25 entailment features were selected as described in Section 2.3. The entailment model was trained using the Learning plug-in in GATE which provides a range of different classifier methods including SVM (support vector machines), C4.5 (decision tree learner), PAULM (on line perception) and KNN (K-nearest neighbor). We trained an entailment model using a combination of the Recognizing Textual Entailment challenge, RTE2 [34] and RTE3 [35] training and test data sets (RTE2+3). An initial assessment was carried out based on a 10-fold cross-validation of the RTE2+3 for a number of available classification methods to assess the level of accuracy in terms of its F1 measure which is the harmonic mean of the precision and recall. The results of this assessment are shown in Table 2. The "Options" column contains the setting of particular classifier option values in the case that non-default settings were tried and a higher accuracy was obtained than for the default settings.

The values reflect the level of accuracy shown by Inkpen et al. [21]. As C4.5 returned the highest F1 measure, we chose this classification mechanism as the approach to create a model for all the training data and act as the entailment model in the pipeline. Given that the level of accuracy was not high we raised the threshold for the confidence of a positive classification from 0.5 to 0.8 to minimize the number of false positives shown by entailment.

4.2. Evidential reasoning

4.2.1. Estimation of basic belief assignments

Output knowledge from the Evidence Collation process in the form of an evidence file is used to estimate the bbas of the diverse sources of information (step 6). An excerpt of these outputs obtained for three different sources from the pipeline are presented in Table 3. It can be viewed from Table 3 that the output for each source contains knowledge concerning the hypothesis, the number of rules fired for a particular hypothesis and the origin of the source. Estimation of bbas is based on the information in the evidence file and the application of discounting using the *classical Shafer discounting approach*. A source is discounted based on the combination of the number of rules that were fired and the origin of the source. Tables 4 and 5 highlight the different discounting factors applied to estimate the bbas. These discounting factors values have been estimated using expert knowledge. For example, as the number of rules fired for hypotheses increases, confidence in this hypotheses increases. Furthermore, evidence extracted from a journal article is considered more reliable than a blog source.

To combine the two discounting factors the product of the discounting factors is calculated. For example, using Source 1 in Table 3 along with the discounting factors described in Table 4 the combined discounting factor applied in the estimation of bbas can be determined as follows: evidence from Source 1 was extracted from the journal paper "Attributes, characteristics, and applications of titanium and its alloys [22]". Based on the source origin the first discount factor is 1 as the source is a journal paper. From Table 3 it can be seen using Source 1 that 3 rules were fired for the hypothesis Titanium. Therefore the second discounting factor is 0.75 obtained from the Table 4. The combined discounting factor for Source 1 is therefore $1 * 0.75 = 0.75$. Using this discounting factor one can estimate the bba for Source 1. The process applied in this research to estimate bbas is described in Algorithm 1.

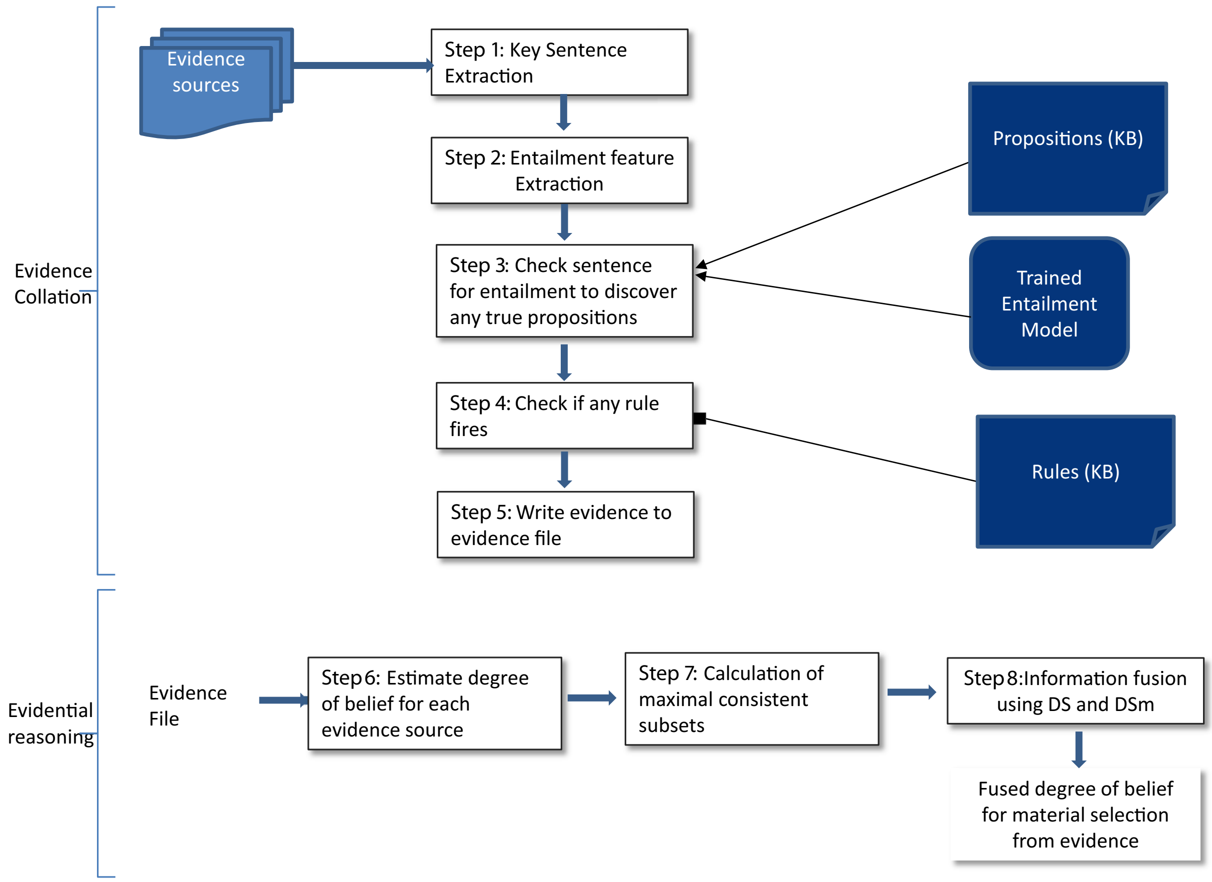

Fig. 2. Overview of the framework.

Table 2
Cross validation accuracy of entailment classifiers based on GATE Learning.

Classifier	F1 measure	Options
SVM	0.578	(-c 0.7 -tau 0.4)
C4.5	0.595	
PAULM	0.574	(-p 50 -n 5 -optB 0.3)
KNN	0.565	-k 3

Table 3
Rules fired for a selection of sources.

ID	Source type	Source	Hypothesis	Rule
1	Journal	[22]	Titanium	Ti & Cor ⇒ Ti Ti & Rat ⇒ Ti Ti & Wei ⇒ Ti
2	Blog	[36]	Aluminum	Al & Cor ⇒ Al
3	Web Source	[37]	Titanium Composite Aluminum	Ti & Wei ⇒ Ti Ti & Cos ⇒ Comp Ti & Wei ⇒ Al

Table 4
Discounting factors applied to estimate basic belief assignments.

Rules Fired	Discount	Origin Importance	Discount
<= 1	0.25	Journal	1
= 2	0.5	White paper	0.6
= 3	0.75	Standards	0.8
>= 4	1	Magazine	0.4
		Web source	0.2

Table 5
Additional discounting factors applied to basic belief assignments not members of the maximal consistent subset.

	Rule importance	Discount
1	Highly important	1
2	Important	0.66
3	Less important	0.33

Algorithm 1. Estimation of Basic Belief Assignments

STEP 1 Calculate discounting factor for each hypothesis on Frame of Discernment
FOREACH hypothesis
COUNT the number of rules fired in the textual entailment phase for a particular hypothesis and obtain discounting factor
DETERMINE the source origin and obtain discounting factor
COMBINE both discounting factors based on rules fired and source origin.
END FOREACH
STEP 2 Calculate discounting factor for each hypothesis on Frame of Discernment
DETERMINE the hypotheses where rules have fired
ALLOCATE mass to hypotheses on the Frame of Discernment where rules have fired.
DISCOUNT these masses according to their combined discount factor obtained in Step 1 and discounting based on (12)
ALLOCATE remaining mass to Θ

To estimate the bba based on evidence extracted from Source 1 we apply the discounting factor 0.75 to the one hypothesis Titanium on the frame of discernment. Mass is only allocated to the Titanium hypothesis as no rules fired for either the Aluminum or Composite hypotheses in this instance. The remaining mass is then distributed over Θ therefore the bba based on Source 1 is estimated as $\{m(Ti) = 0.75,\ m(\Theta) = 0.25)$. This same approach is applied to all the Sources used in this research.

4.2.1.1. Maximal consistent subset algorithm. After all bbas are estimated the next step in the process is to construct the Maximal Consistent Subset (step 7). This subset consists of a set of bbas which have been deemed to be consistent with one another. This is an essential step in the evidential reasoning process as fusing inconsistent subsets can result in erroneous and inaccurate results. Algorithm 2 summarizes the steps involved in constructing the set of consistent subsets. Subsets which do not reach the required consistency to be members within the Maximal Consistent Subset are further discounted based upon rule importance. This is the second phase of discounting. Each rule within the knowledge base has been graded in terms of importance by an expert. Table 5 presents the discounting factors based on the importance allocated to different rules in the knowledge base. For example the rule: Aluminum & (Corrosion & (Fatigue & Strength)) $\Rightarrow$ Aluminum has been rated as highly important by an expert as it addresses key requirements of a material namely resistance to corrosion, fatigue and high strength. Only bbas which do not reach the criteria to become members of the Maximal Consistent Subset are further discounted using these rules.

To determine which bbas are considered consistent and therefore members of the Maximal Consistent Subset we present an algorithm to construct a maximal consistent subset. To start, information content for each bba is calculated using the PIC approach. The PIC is used to depict the strength of a critical decision by a specific probability distribution [38]. The bba which obtains the highest PIC value will become the first member of the maximal consistent subset. If more than one bba obtains the highest PIC value, we chose one arbitrarily. Next, using the *Metric Distance* we measure the similarity of remaining bbas to those in the maximal consistent subset. It is important to state that other similarity measures can also be applied such as those mentioned in Section 3.4. A bba obtaining a similarity greater than the threshold 0.6 is permitted to join the maximal consistent subset. Furthermore, different thresholds can be selected, the threshold selected in this research was chosen by an expert. This process is repeated until there are either no remaining bbas or no bbas left which obtain a similarity value greater than or equal to the set threshold.

Algorithm 2. Calculation of Maximal Consistent Subset

FORALL bbas calculate information content using PIC approach based on (9)
SELECT bba with highest information content, add to maximal consistent subset. If more than one bba have the same PIC value, choose one arbitrarily
REPEAT
  FIND most similar bbas using distance measure (based on (10)) to those bbas in maximal consistent subset
  IF similarity value > threshold then join bba to maximal consistent subset
UNTIL similarity values for all remaining bbas not in maximal consistent subset obtain value < threshold or no bbas remain

4.2.1.2. Information Fusion. After discounting has been applied and the maximal consistent subsets defined, all bbas are fused together using techniques from DS and DSm theory (step 8). To fuse any quantity of estimated bbas a Java application has been developed by the authors. Using this application the DS and DSm theory and the Dempster's rule of combination along with the PCR5 combination rule can be applied to fuse the bbas both in the maximal consistent subset and those further discounted bbas not in the maximal consistent subset.

5. Use Case

The selection of material(s) to construct a component a key design decision in the Engineering. It is important to state that the framework proposed is applicable to other fields where important decisions have a critical affect on projects. Materials selection is a task normally carried out by design and materials engineers. The aim of materials selection is the identification of materials, which after appropriate manufacturing operations, will have the dimensions, shape and properties necessary for the product or component to demonstrate it meets its requirements. Properties may include physical properties, electrical properties, magnetic properties, mechanical properties, chemical properties and manufacturing properties [39].

The final choice of material can be viewed as a design decision which is subject to uncertainty as it often not clear early in the lifecycle which properties or attributes are relevant to the design decision or their level of importance. Uncertainty may also rise through the level of imprecision in attribute values where an attribute may take a value within a range of values [40].

In this study, a key issue for a design engineer is the choice of a particular material for example, aluminum, titanium or composite for the construction of a rib post component between the wing rib and spar. The rib post is an important element within an aircraft wing providing the structural join between the wing spar and internal rib. The aim of this Use Case is to demonstrate the application of our proposed framework to utilize information extraction and textual entailment techniques for the estimation of bbas along with evidence theory to fuse disparate sources to aid decision making in an Engineering domain. A colleague from QUB's Aeronautical Engineering Department acted as a design engineer in our study. He formed a knowledge base and checked it manually for consistency. The knowledge base consisted of 64 propositions and 54 rules. His construction of the knowledge base centered on considering propositions and consequently rules that are particularly relevant to the problem. The information extraction and entailment steps were applied as described in the Methodology section to allow for discovery of supported rules. DSmT has been selected to fuse together pieces of evidence using the PCR5 rule of combination. This rule has been selected as it has been designed to cope with highly conflicting and uncertain information. However, other combination rules such as Dempsters Rule of Combination can also be applied within the framework. The Metric distance measure is applied to determine similarity/highlight potential conflict between sources. This measure has been selected and applied in the Maximal Consistent Subset algorithm as it has been proved an effective principled approach when measuring distance between bbas. Similarity is calculated to weight agreement between sources as it is known that conflicting and inconsistent data can be detrimental to the decision making process. Determining the Maximum Consistent Subsets will aid in determining which sources should be further discounted. By determining both the maximal consistent subsets and applying discounting factors to dis-similar sources we aim to improve the correctness of fusion results. Decision making is based on pignistic probabilities where results are

Please cite this article in press as: F. Browne et al., Integrating textual analysis and evidential reasoning for decision making in Engineering design, Knowl. Based Syst. (2013), http://dx.doi.org/10.1016/j.knosys.2013.07.014

presented using both DSmP and BetP transformation methods for comparative purposes.

5.1. Sources

Forty-nine evidence sources were drawn from a number of evidence sources related to the general issues of materials and aeronautical design. These varied in terms of their origin and were extracted from web searches of: journals, white papers, magazines, web pages/blogs and International Aviation Standards, which we considered relevant to the design problem. The source materials are summarized in Table 6.

5.2. Estimation of basic belief assignments

Output knowledge from the information extraction/textual entailment steps is used to estimate the bbas of the diverse sources of information. The classifier selected for the textual entailment process is the C4.5 classifier as it obtained the highest accuracy among the four different classification methods. An excerpt of these outputs are presented in Table 3. It can be viewed from Table 3 that the output for each source contains knowledge concerning the hypothesis as a material selection, the number of rules fired and the origin of the source. Using this information we estimate bbas for each source. Highlighted in Table 4 are the different discounting factors applied to estimate the bbas based upon the number of rules fired and the source origin. The bbas are discounted using the classical Dempster discounting approach described in Section 4.2. This approach was applied to all the output sources from the entailment step to produce a total of 20 bbas defined in Table 7 where $\{E1,\ldots,E20\}$ refer to the different evidence sources and Ti, Al, $Comp$, Θ show how belief is distributed for each bba. Only 20 of the 49 sources produced supporting evidence. This would be likely to have been higher in a real world scenario where an expert had constructed the knowledge base allowing for a more detailed coverage of appropriate propositions and rules, and all sources were evaluated in detail in terms of relevancy.

5.3. Construction of maximal consistent subset

It is known that conflict between evidence sources can have a detrimental impact upon the evidential reasoning process. To address this, an algorithm to construct the maximal consistent subsets amongst a group of subsets was outlined in Section 4.2. This algorithm was applied to the 20 bbas defined as $\{E1,\ldots,E20\}$. PIC values were calculated for each bba in the first step. The bba $E3$ obtained the highest PIC value and became the first member of the maximal consistent subset. To determine the next member(s) of the Maximal Consistent Subset the Metric distance is applied to measure the similarity between the subsets in the Maximal Consistent Subset to non-members of the subset. A cut off threshold of 0.6 was selected by the expert system designer and judged as an acceptable threshold similarity value. If a distance value obtained by measuring a subset to the Maximal Consistent Subsets was greater than or equal to this threshold then this subset became a member of the Maximal Consistent Subset. This was repeated until the remaining subsets did not reach the threshold for membership of the Maximal Consistent Subset. The resulting Maximal Consistent Subset consisted of 6 members $\{E1, E3, E5, E7, E8, E20\}$. A second phase of discounting based on the rule importance described in Section 4 was applied to the remaining 14 subsets which did not reach the specified similarity threshold. The application of this rigorous approach provides the bbas which are used as input into the evidential reasoning application to aid in the decision making process.

Table 6
Document sources.

Source type	Number of sources
Journals	11
Magazines	2
Standards	1
Web sources (blogs, etc.)	30
Whitepapers	5

Table 7
Estimated basic belief assignments.

Evidence	Ti	Al	Comp	Θ
E1	0.75	0	0	0.25
E2	0	0	0.5	0.5
E3	0	0	1	0
E4	0.25	0	0.25	0.5
E5	0	0.05	0	0.95
E6	0.017	0.0417	0.0167	0.925
E7	0	0	0.05	0.95
E8	0	0.05	0	0.95
E9	0	0	0.05	0.95
E10	0	0	0.05	0.95
E11	0	0	0.1	0.9
E12	0	0	0.05	0.95
E13	0	0	0.05	0.95
E14	0.1	0	0	0.9
E15	0.15	0	0	0.85
E16	0	0	0.15	0.85
E17	0	0.075	0.15	0.775
E18	0	0.225	0.15	0.625
E19	0.15	0	0.15	0.7
E20	0.3	0	0.4	0.3

5.4. Evidential reasoning

In this Use Case, an engineer is tasked with selecting a material to construct a rib post from the set: Aluminum (Al), Titanium (Ti) or Composite (Comp). The following Frame of Discernment $\Theta = \{Al, Ti, Comp\}$, in accordance with Shafer's model is used to model the fusion problem. A Java application has been developed by the authors implementing the DSm Theory to fuse the diverse bbas estimated in the steps above. In total, the PCR5 Rule of Combination is applied to fuse all 20 bbas. To highlight the impact the construction of Maximal Consistent Subsets and therefore the reduction of conflict and uncertainty between information sources has upon the evidential reasoning process we present results where (1) all subsets are viewed as equal and are fused, (2) only the Maximal Consistent Subsets are fused and (3) the Maximal Consistent Subsets are fused with the discounted subsets.

5.4.1. Fusion of all sources when no maximal consistent subset constructed

In this experiment, no pre-processing has been performed to determine the Maximal Consistent Subset (i.e. set of consistent sources). Instead, all 20 bbas are assumed to be equal with no additional discounting applied to conflicting bbas. The results for this scenario is presented in Table 8 where pignistic probabilities for each hypothesis are presented using both the generalized BetP and DSmP approaches. Interestingly, high pignistic probabilities are obtained for the *Comp* hypothesis by both generalized pignistic transformation approaches. These are followed by *Ti* and finally *Al*.

5.4.2. Fusion of maximal consistent subsets only

In this scenario the results presented have been obtained from fusing only those 6 bbas which are members of the Maximal Consistent Subset. Using the algorithmic approach described in the Methodology section only 6 bbas from a total of 20 subsets were determined to be similar and therefore consistent. By fusing consistent subsets the aim is to improve the quality of the pignistic probabilities obtained in the fusion process for decision making purposes. Table 9 highlights the results obtained using this approach. In comparison to the results obtained when no Maximal Consistent Subsets were obtained one can see that *Comp* obtained the highest probability, however, with less weight allocated to this hypothesis and more to the *Ti* hypothesis.

5.4.3. Fusion of maximal consistent subsets and discounted subsets

In this scenario we present results obtained when the Maximal Consistent Subsets were fused with the remaining 14 bbas. In this case however, the 14 bbas which did not reach the consistency criteria of the Maximal Consistent Subset are further discounted. This discounting is important as these diverse sources could be possibly conflicting and inconsistent with the preprocessed Maximal Consistent Subset. The discounting reduces the potential for conflict allowing additional knowledge to be applied in the decision making process. The aim of this is to obtain realistic pignistic probabilities for the different hypotheses which are not detrimentally affected by potential conflict in the process. It can be viewed from the results in Table 10 that similar to the results in Table 9 and Table 8 the *Comp* hypothesis obtains the highest pignistic probabilities. However, these probabilities are less than the values obtained when no discounting or Maximal Consistent Subsets were calculated and slightly more than only using the 6 bbas in the Maximal Consistent Subset.

It can be viewed for all scenarios that the material *Al* obtained low pignistic probabilities. This is because out of the 20 bbas only 5 bbas contained mass allocated to the *Al* hypothesis. Furthermore the mass allocated was minimal. This is due to the information extracted from the original evidence sources provided little support for this material. There is the possibility that if other evidence sources were utilized this may not be the case. In comparison 15 estimated bbas contained mass assignment for the *Comp* hypothesis.

6. Discussion

This Use Case aimed to illustrate a exploratory application of the proposed novel conceptual framework integrating the areas of information extraction and evidential reasoning. This is a first attempt at being able to collate and combine evidence from a number of natural language based qualitative sources related to a material selection problem. It has shown encouraging prelimary results, admitttedly based on a number of ad hoc settings. Certain improvements are needed in the different steps of this framework to increase its applicability and allow for a proper evaluation. A property is based on a binary choice between its presence or absence, however for real world problems a property often takes a categorical value to allow for varying degrees (e.g. the property *elasticity* could have the categories {low, medium, high}), so we would need to consider how best a knowledge based should be constructed to allow for this. Also our knowledge base was constructed manually and its consistency checked manually. This served the purpose of the Use Case, however it would be better to automate its construction and further refinement of the process is required to make it practically applicable. For example a method for automated proposition discovery would utilize NLP based processes relying on specialized lexicons and template matching based on an analysis of the sources. Rules would still need to be specified by an expert but model checking is needed to check for a consistent set of rules as in [41]. In the estimation of the bbas, discounting is performed using knowledge obtained from the information extraction process. The discounting was based on rules fired and source origin with an additional discounting based on rule importance. The discounting was not an automated process and was guided by the design engineer. Other more complex criteria for discounting could be applied by incorporating other discounting criteria, and appropriate methods developed to guide this discounting process. Also a more refined process for judging the relevancy of sources is needed. For instance, all web sources had the same discount applied, however some sources may be more reliable than others. In addition, the set of retrived documents may omit sources of information which is particularly apposite to an given problem. But in the absence of existing available data specific to the given problem, we were constrained to providing our own. The construction of Maximal Consistent Subsets is beneficial to the evidential reasoning stage as inconsistencies and conflict are identified and addressed before fusion. This is important as these inconsistencies and uncertainty can have an adverse effect on the decision making process. Further work could be performed on the given algorithm to construct different Maximal Consistent Subsets, for instance, different distance measures could be applied to measure the similarity between bbas. Finally in the evidential reasoning process the DSm Theory was employed to handle uncertainty between evidence sources when fusing information using the PCR5 rule of combination. This stage is not limited to this one approach and it would be interesting to apply other combination rules. In summary, it would be more appropriate especially for the purposes of evaluation that the sources were available as part of an actual industry based design, where each source is more tightly coupled to the identified material selection problem. The sources could be based on a number of different company engineers' reports concerning the material selection issue. Other sources could be supporting documents that the engineers consider valuable. In the latter case, each engineer writes using the same language style and it would be possible to confer with the engineers the outcomes of the evaluation. The engineers could also assist in the process by which an automatically generated knowledge base is generated. Discounting mechanisms may still be applicable as each report/document may not receive the same weighting.

Table 8
Fusion of all subsets where all subsets are assumed equal.

Hypothesis	*Generalized BetP*	$DSmP_{\epsilon=0}$
Comp	0.783	0.783
Ti	0.204	0.204
Al	0.014	0.014

Table 9
Fusion maximal consistent subsets only.

Hypothesis	BetP	DSmP
Comp	0.684	0.684
Ti	0.315	0.315
Al	0.000	0.000

Table 10
Fusion of maximal consistent subsets and discounted subsets.

Hypothesis	BetP	DSmP
Ti	0.259	0.259
Comp	0.733	0.733
Al	0.008	0.008

7. Conclusion

In this paper, a novel conceptual framework integrating the diverse areas of information extraction, textual entailment and evidential reasoning is proposed to solve decision making issues under the constraints of uncertain and inconsistent information. An algorithm to determine a set of maximal consistent subsets is presented based on the Metric distance of evidences. To estimate basic belief assignments textual analysis was performed with the assistance of a manually constructed knowledge base. A Use Case based in the Aerospace domain is provided to illustrate the effectiveness of the proposed approach. This Use Case highlighted the importance of applying discounting factors based on knowledge extracted using textual analysis approaches and measuring consistency between evidential sources before making decisions. Furthermore, this framework could be applied to other problem areas involving the selection of materials based on qualiitative descriptions linking properties to recommendations of materials, with appropriate enhancements to make it an automated process. Our framework is only the first step in realizing a more seamless realization of extracting knowledge from textual documents and interpreting this potentially conflicting knowledge using evidential reasoning. We have demonstrated an initial capability but we recognize that the knowledge base as specified is key, and further NLP/ AI techniques are needed to automate its construction for any working system, as the range and diversity of sources becomes greater, the construction of an extensive and comprehensive knowledge base is laborious if done manually.

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