Application of Evidence Theory to Construction Projects

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Abstract: Crucial decisions are necessary throughout the life-cycle of large-scale construction projects. Such decisions are critical in that they have a direct impact upon the outcomes and success of a given project. To improve the decision process, an evidential reasoning framework based on the Dezert-Smarandache theory of plausible and paradoxical reasoning, where heterogeneous evidence sources are fused together, is described and used here. Though they usually contain various levels of uncertainty, imprecision, and conflicts, the sources provide beliefs for decision making; usually the combination of these sources of evidence, with different reliabilities, is done by the classical Shafer's discounting approach. This means that when considering unequal importance of sources, if any, a similar reliability discounting process is generally used, making no difference between the notion of importance and reliability. In multicriteria decision making, however, these notions should be clearly distinguished. This paper is to analyse the impact of source reliability and importance (priority) upon the decision making process. A reliability discounting technique and an importance discounting technique are applied.

Keywords: Evidential Reasoning, Dezert-Smarandache Theory, Dempster-Shafer Theory, Discounting Techniques, Risk Assessment

Introduction

The construction industry, it is held, is exposed to more risk and uncertainty than perhaps any other industry section (Flanagan and Norman 1993) as it involves numerous stakeholders, long production durations and an open production system, entailing significant interaction between internal and external environments (British Standards 2006). Decision-making on construction projects is often undertaken on an ad hoc basis, especially once on-site operations have begun (Gannon and Nigel 2011). Such organizational and technological complexity generates enormous risks (Zou, Zhang and Wang 2007). Making decisions at diverse stages of the project life cycle based on sound evidence must therefore be made to reduce risk and bring the project to a successful outcome.

Evidence items supporting or opposing the various construction options may vary in terms of reliability, completeness, precision and may contain conflicting information. To address these limitations within construction project decision making an evidential reasoning framework to support decision analysis using information fusion techniques to manage uncertainty and conflict in evidence sources should be employed.

Over the past two decades, considerable research has been conducted on integrating techniques from artificial intelligence and operational research for handling uncertain information (Balestra and Tsoukias 1990, White 1990, Keeney and Raiffa 1993). Following on from this line of research, an evidential reasoning approach was developed for multi criteria decision analysis under uncertainty (Yang and Xu 2002) based on an evaluation analysis model (Zhang, Yang and Xu 1990) and the Dempster-Shafer (DS) theory of evidence (Lopez de Mantaras 1990). The kernel of this approach is an evidential reasoning algorithm developed on the basis of a multi-attribute evaluation framework and the evidence combination rule of the DS theory.

However it is claimed that the classical aggregation rules such as the Dempster rule are known to poorly take conflict into account (Dezert and Cemagref 2011). So a method based on the Dezert-Smarandache (DSm) theory will be investigated here. The method replaces the aggregation step by two successive fusion processes (Tacnet, Batton-Hubert and Dezert 2010).

The International Journal of the Constructed Environment
Volume 4, 2014, www.constructedenvironment.com, ISSN 2154-8587

Its main objective is to take into account information imperfection, source reliability and conflict. When doing this, a problem occurs since the importance of criteria is a different concept than the classical reliability concept developed and used in the belief theory context (Dezert and Cemagref 2011). Where DS can represent ignorance caused by lack of information and can aggregate beliefs when new evidence is accumulated, DSm can be considered as a generalization of DS whereby the rule of combination takes into account both uncertain and paradoxical information (Dezert, Tacnet and Batton-Hubert 2010).

Evidence sources involved in the fusion process may not always have equal reliability or importance (priority). Reliability can be viewed as an objective property of an evidence source whereas importance is viewed as a subjective property expressed by an expert (Smarandache, Dezert and Tacnet 2010). Counter-intuitive results could be obtained if unequal sources are fused and these factors are not taken into consideration. Therefore two discounting techniques, the reliability discounting using Shafer's classical discounting approach, and, importance discounting based on the importance discounting technique (Smarandache, Dezert and Tacnet 2010) are applied. A maximal consistent subset is constructed to help in defining where discounting should be applied. To evaluate the proposed framework a scenario from the construction industry is presented concerning external risks of three large-scale projects in different countries. The risk assessment of the three large-scale projects (large shopping malls) concentrated on political, economic, social and weather threats. The large scale objects were of similar design, architecture, construction technology, area, and number of floors.

The paper is organized as follows: in the following section the basics of Evidential Reasoning theory, combination rules and reliability discounting and importance discounting techniques are detailed. This is followed by a section describing the relatively new DSm approach together with a section presenting an applied scenario in the construction area, comparing the DS and DSm approaches and the impact of discounting factors on decision analysis. The paper finishes with the conclusions and some proposals for future work.

Evidential Reasoning Theory

DSmT Basics

This approach uses an aggregation method developed in the framework of discernment when evaluations of criteria and reliability of different sources are uncertain. In this approach, $\Theta = \{\theta_1, \theta_2, \cdots, \theta_n\}$ is a finite set of n elements assumed to be exhaustive and Θ corresponds to the frame of discernment of the problem under consideration. In general, it is assumed that elements of Θ are non-exclusive in order to deal with vague/fuzzy and relative concepts (Smarandache and Dezert 2009). This is the so-called free-DSm model in that there is no need to work on a refined frame consisting in a discrete finite set of exclusive and exhaustive hypotheses (referred to as Dempster-Shafer's model), because DSm rules of combination work for any models of the frame. The hyper-power set D^Θ (Dedekind's lattice) (Smarandache and Dezert 2009) created with $\cup$ and $\cap$ operators is the set of all propositions and a quantitative basic belief assignment expressing the belief committed to the elements of D^Θ by a given source is a mapping $m(\cdot): D^\Theta \rightarrow [0,1]$ such that:

$$m(\emptyset) = 0 \quad \text{and} \quad \sum_{A \in D^\Theta} m(A) = 1 \qquad (1)$$

Elements $A \in D^\Theta$ having $m(A) > 0$ are called focal elements of $m(\cdot)$. When the Dempster-Shafer holds, i.e. all exclusivity constraints are included, the D^Θ reduces to the power set 2^Θ.

In evidence theory, a probability range is used to represent uncertainty with the lower bounds of this probability called Belief(*Bel*) and the upper bounds Plausibility(*Pl*). The generalized *Bel* and *Pl* for any proposition $A \in D^\Theta$ can be obtained by:

$$Bel(A) = \sum_{\substack{B \subseteq A \\ B \in D^{\Theta}}} m(B) \quad \text{and} \quad Pl(A) = \sum_{\substack{B \cap A \neq 0 \\ B \in D^{\Theta}}} m(B) \tag{2}$$

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. PCR5 transfers the conflicting mass only to the elements involved in the conflict and proportionally to their individual masses, so that the specificity of the information is entirely preserved in this fusion process (Smarandache and Dezert 2009).

For two independent basic belief assignments m_1 and m_2 the PCR5 rule is as follows: $m_{PCR5}(\emptyset) = 0$ and $\forall (X \neq \emptyset) \in D^{\Theta}$

$$m_{PCR5}(A) = \sum_{\substack{X_1, X_2 \in D^{\Theta} \\ X_1 \cap X_2 = A}} m_1(X_1) m_2(X_2) + \sum_{\substack{X \in D^{\Theta} \\ X \cap A = \emptyset}} \left[\frac{m_1(A)^2 m_2(X)}{m_1(A) + m_2(X)} + \frac{m_2(A)^2 m_1(X)}{m_2(A) + m_1(X)} \right] \tag{3}$$

All fractions in Equation 3 which have a denominator of zero are discarded. All propositions/sets are in a canonical form and PCR5 is commutative and not associative but quasi-associative.

DS Basics

The Demster-Shafer evidential theory is an extension of traditional probability and provides a method of modelling belief and uncertainty on possible decision options for a given decision making process. For this theory the frame of discernment denoted by $\Theta = \{\theta_1, \theta_2, \cdots, \theta_n\}$ contains a finite set of *n* exclusive and exhaustive hypotheses. The set of subsets of Θ is denoted by the power set 2^{Θ}.

In DS, Dempster's rule of combination is symbolized by the operator $\oplus$ and used to fuse two distinct sources of evidence over the same frame. If β_1 and β_2 represent two belief functions over the same frame Θ and $m_1(\cdot)$ and $m_2(\cdot)$ their respective basic belief assignments. The combined belief function $\beta = \beta_1 \oplus \beta_2$ is obtained by the combination of $m_1(\cdot)$ and $m_2(\cdot)$ as: $m(\emptyset) = 0$ and $\forall C \neq \emptyset \subseteq \Theta$

$$m(C) \equiv [m_1 \oplus m_2](C) = \frac{\sum_{A \cap B = C} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \emptyset} m_1(A) m_2(B)} \tag{4}$$

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

Probabilistic Transformation

Pignistic probabilities are needed for decision making purposes during this study. Fused beliefs are mapped to a probability measure using the generalized pignistic transformation approach *DSmP* (Dezert and Smarandache 2008), an alternative to the more familiar approach *BETP* proposed by Smets et al (Smets and Kennes 1994). *DSmP* has the advantage that it can be applied to all models (DS, DSm, hDSm)and can work on both refined and non-refined frames. *DSmP* is defined by $DSmP_{\epsilon}(\emptyset) = 0$ and $\forall X \in D^{\Theta}$ by

$$DSmP_{\epsilon}(X) = \sum_{Y \in D^{\Theta}} \frac{\sum_{\substack{Z \subseteq X \cap Y \\ C(Z)=1}} m(Z) + \epsilon \cdot C(X \cap Y)}{\sum_{\substack{Z \subseteq Y \\ C(Z)=1}} m(Z) + \epsilon \cdot C(X \cap Y)} m(Y) \qquad (5)$$

$C(X \cap Y)$ and $C(Y)$ denote the cardinals of the sets $X \cap Y$ and Y respectively, $\epsilon \geq 0$ 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 (Dezert and Smarandache 2008). The PIC value is applied to measure distribution quality for decision making. The PIC of a probability measure denoted P associated with a probabilistic source over a discrete finite set $\Theta = \{\theta_1, \theta_2, \ldots, \theta_n\}$ is defined by:

$$PIC(P) = 1 + \frac{1}{H_{max}} \cdot \sum_{i=1}^{n} P\{\theta_i\} \frac{\ln(P\{\theta_i\}}{\ln 2}) \qquad (6)$$

where H_{max} 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 (Dezert and Smarandache 2008).

DSmT-AHPApproach

The DSmT-AHP approach consists of three stages:

Stage 1

Selection of heterogeneous information from disparate sources and construction of a maximal consistency subset to provide basic belief assignments.

Stage 2

Here the DSmT fusion rules are used to combine the basic belief assignments obtained from Stage 1 to get a final multi-criteria decision making ranking. This stage must take into account the different importance of criteria.

Stage 3

Decision making can be done based either on the maximum of belief (credibility) or on the maximum of the plausibility of decision alternatives, as well as on the maximum of the approximate subjective probability of decision alternatives obtained by different probabilistic transformations like the pignistic.

To manage the reliability and importance of evidence sources in the fusion process prior knowledge is applied to estimate both reliability and importance discounting values with the construction of a maximal consistent subset (Browne et al. 2012). Here a subset of sources consistent with each other is constructed and discounting could be applied to sources deemed dissimiliar or non-coherent. The Euclidean similarity measure based on distance is applied to measure the coherence. If $\Theta = \{\theta_1, \theta_2, \cdots, \theta_n\}$ where n > 1 and $m_1(\cdot)$ and $m_2(\cdot)$ are defined over D^{Θ} , X_i is the ith element of D^{Θ} and $|D^{\Theta}|$ the cardinality of D^{Θ}, the function can be defined as:

$$S(m_1, m_2) = 1 - \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^{|D^{\Theta}|} \left(m_1(X_i) - m_2(X_i)\right)^2} \qquad (7)$$

In reliability discounting, a factor λ on $[0,1]$ can be applied to characterize the quality of an evidence source with the reliability factor transform the belief of each source to reflect credibility. Shafer's discounting technique (Shafer 1976) has been proposed (Browne et al. 2012) for the combination of unreliable evidence sources. Incorporation of the reliability factor $1-\lambda \in [0,1]$ in the decision making process is defined as:

$$\begin{cases} m_\lambda(X) = \lambda \cdot m(X), \text{for } X \neq \Theta \\ m_\lambda(\Theta) = \lambda \cdot m(\Theta) + (1-\lambda) \end{cases} \quad (8)$$

where $\lambda = 1$ represents a fully reliable source and $\lambda = 0$ an unreliable source.

The importance of a source can be thought of as a subjective attribute where an expert can assign a importance value to an individual source (Dezert, Tacnet, Batton-Hubert and Smarandache 2010). Importance is characterized using a factor κ in $[0,1]$ with the maximum importance assigned to a source as $\kappa = 1$ and the minimum as $\kappa = 0$. In this work the importance discounting (Browne et al. 2012) is defined with respect to the empty set rather than total ignorance Θ as done with Shafer's discounting (Shafer 1976). The discounting of a source having a importance factor κ can be defined as:

$$\begin{cases} m_\kappa(X) = \kappa \cdot m(X), \text{for } X \neq \emptyset \\ m_\kappa(\emptyset) = \kappa \cdot m(\emptyset) + (1-\kappa) \end{cases} \quad (9)$$

which allows $m(\emptyset) \geq 0$, thereby preserving specificity of the primary information as all focal elements are discounted with the same importance factor (Smarandache, Dezert and Tacnet 2010).

Case Study

A team of three construction project experts were given the task of selection of a project from three potential projects ($v_1 - v_3$), situated in different countries, which has the least risk from the point of view of external risks, namely political, economic, social and weather. The experts followed the steps on Figure 1, and they jointly assigned importance and reliability values to the risk categories. In order to determine if the assessments of the potential construction sites were consistent with these values, evidence was found from 20 heterogeneous sources including, 4 government statistical documents, 8 academic journals, 5 books, and 3 blogs from the internet (Figure 2). These sources were retrieved by using the following key words: country name, "construction risk", "political risk", "economic risk", "social risk" and "weather risk". The sources varied in terms of certainty and consistency and probably contained some national bias, for example, when a country's government commented on the country's political risk. The resulting database probably contained conflicting evidence. For the evidence theory approach tested here, risks themselves were not measured, rather the belief regarding the importance of perceived risks and their source reliability.

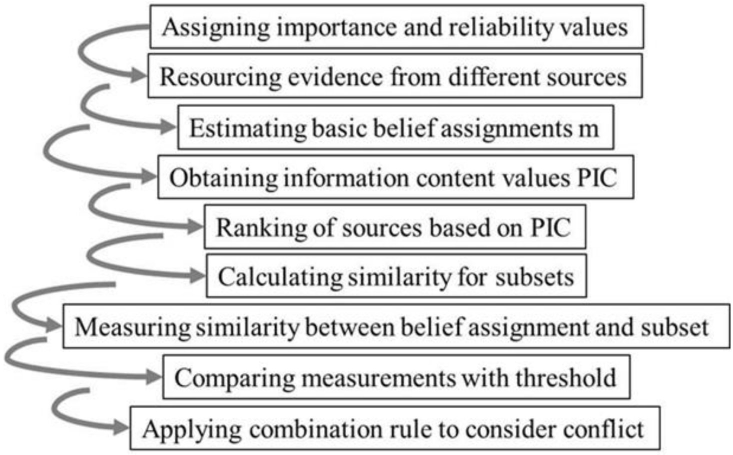

Figure 1: Steps of Risk Assessment using Evidence Theory

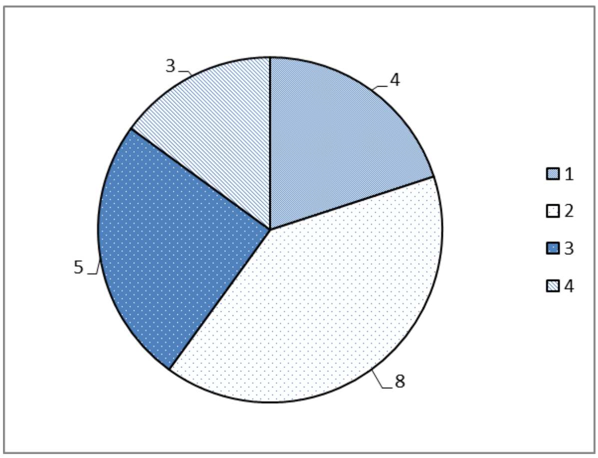

Figure 2: Resources (1-statistical documents, 2-academic journals, 3-books, 4-internet blogs)

Four different evidence sources are used to assign belief to the hypotheses with the estimated respective basic belief assignments (m_1, m_2, m_3, m_4) given in Table 1. For example, the experts believed that the government statistical documents they found (m1) were more reliable for project 1 (0.5) than for projects 2 and 3 (each 0.2).

Table 1: Basic Belief Assignments for Evidence Sources

	m_1	m_2	m_3	m_4
v_1	0.5	0.3	0.2	0.2
v_2	0.2	0.6	0.1	0.3
v_3	0.2	0.0	0.7	0.5
Θ	0.1	0.1	0.0	0.0

Maximal Consistent Subset

Here the evidential sources represented by basic belief assignments, in this case (m_1, m_2, m_3, m_4) are ranked according to their information content. The information content values were obtained using Equation 6, with m_3 and m_4 identified as having equally the highest PIC value. The basic belief assignment m_4 was then chosen arbitrarily from these two as the first member of a potential maximal consistent subset. Next, the similarity for the subsets $\{m_{4,}m_1\}$, $\{m_{4,}m_2\}$ and $\{m_4, m_3\}$ was calculated with a threshold parameter set at 0.7 which was subjectively judged as an acceptable threshold similarity value, and the basic belief assignment most similar was found to be m_3 now giving a maximal consistent subset consisting of m_4 and m_3. The similarity between the basic belief assignments in the current maximal consistent subset and m_1 and m_2 are now measured with the resulting $S(m_1, m_{3,4})$ and $S(m_2, m_{3,4})$ found to be 0.38 and 0.32 respectively, which is much lower than the required threshold and therefore m_1 and m_2 could not be thought of as members of the maximal consistent subset.

To show that conflict must be considered in decision making a number of examples are now presented using both the PCR5 and Dempster's rule of combination. In the three examples below, no discounting, reliability discounting and importance discounting will be demonstrated respectively.

No Discounting Example

In this example the evidence is fused using both PCR5 and Dempster's rule of combination with no discounting used, i.e. all sources are presumed to be equal in terms of reliability and importance. Here dissimilar sources nor the maximal consistent subset were not considered. The results are given in Table 2 together with pignistic values for both of the combination rules. In the table $m_{12}, \dots, m_{1234}$ refer to the sequential fusion of the sources (m_1, m_2, m_3, m_4).

Table 2a: PCR5 (No Discounting)

	BetP approach				$DSmP_{\epsilon=0}$ approach			
	v_1	v_2	v_3	Θ	v_1	v_2	v_3	Θ
m_{12}	0.4465	0.4924	0.0133	0.0478	0.4465	0.4924	0.0133	0.0478
m_{123}	0.4771	0.4767	0.0406	0.0055	0.4771	0.4767	0.0406	0.0055
m_{1234}	0.4592	**0.5176**	0.0230	0.0002	0.4592	**0.5176**	0.0230	0.0002

Table 2b: Dempster's Rule of Combination (No Discounting)

	BetP approach				$DSmP_{\epsilon=0}$ approach			
	v_1	v_2	v_3	Θ	v_1	v_2	v_3	Θ
m_{12}	0.5359	0.4285	0.0000	0.0358	0.5359	0.4285	0.0000	0.0358
m_{123}	0.7140	0.2860	0.0000	0.0000	0.7140	0.2860	0.0000	0.0000
m_{1234}	**0.6246**	0.3754	0.0000	0.0000	**0.6246**	0.3754	0.0000	0.0000

From Table 2 it can be observed that different probability values to the hypotheses were found using PCR5 and Dempster's rule of combination. Dempster's rule of combination uniformly distributes over all focal elements of 2^{Θ} the total conflicting mass, which results potentially in misleading and even incorrect results. PCR5 on the other hand seems to obtain much more realistic values in that conflicting masses were transferred to non-empty sets in proportion.

Reliability Discounting

Reliability weightings are found using basic belief assignments and depend on the sources from which the basic information was found. In this case, books (λ_1), blogs from the internet (λ_2), academic journals (λ_2), and government statistical documents (λ_4), were used with the discounting factors assigned being ($\lambda_1 = 0.1,\ \lambda_2 = 0.5,\ \lambda_3 = 0.1$ and $\lambda_4 = 0.0$). From the maximal consistent subset analysis above it was appropriate to apply reliability discounting to the dissimilar sources m_2 and m_4 only. The results when reliability discounting was used and evidence sources combined using PCR5 and Dempster's rule of combination are shown in Table 3.

Table 3a: PCR5 (Reliability Discounting)

	BetP approach				$DSmP_{\epsilon=0}$ approach			
	ν_1	ν_2	ν_3	Θ	υ_1	ν_2	υ_3	Θ
m_{12}	0.4078	0.5643	0.0091	0.0188	0.4123	0.5698	0.0053	0.0126
m_{123}	0.3934	0.5865	0.0041	0.0159	0.3945	0.5988	0.0010	0.0057
m_{1234}	0.3876	**0.5999**	0.0056	0.0069	0.3795	**0.6002**	0.0008	0.0000

Table 3b: Dempster's Rule of Combination (Reliability Discounting)

	BetP approach				$DSmP_{\epsilon=0}$ approach			
	ν_1	ν_2	ν_3	Θ	υ_1	ν_2	υ_3	Θ
m_{12}	0.4320	0.5284	0.0078	0.0318	0.4365	0.5166	0.0065	0.0405
m_{123}	0.4227	0.5481	0.0126	0.0165	0.3645	0.5766	0.0027	0.0562
m_{1234}	0.4198	**0.5809**	0.0001	0.0000	0.3754	**0.5982**	0.0005	0.0258

It can be seen that both Dempster's rule of combination and PCR5 assign the highest belief to project ν_2 followed by ν_1 when consistent subsets and reliability factors are taken into consideration. This would indicate that by considering reliability discount factors the conflict between m_2 and m_4 has been reduced. It can be noticed that the results of Table 3 are in contrast to those of Table 2 where discounting was not imposed for the Dempster rule of combination, in that the discounted mass was placed to Θ.

Importance Discounting Example

Evidence was ranked in order of importance using expert opinion for the four external threats posed to each project, i.e. political (κ_1), economic (κ_2), social (κ_3) and weather (κ_4), with the four basic belief assignments set at $\kappa_1 = 0.9$, $\kappa_2 = 0.4$, $\kappa_3 = 0.7$ and $\kappa_4 = 0.2$. For example, the experts believed that political risks were more import (0.9) than economic risks (0.4). PCR5 is used in this example with m_1 and m_3 found with the highest importance. Both of these are also members of the maximal consistent subset and by applying importance basic belief assignments to m_2 and m_4 the changes in the results can be viewed in Table 4 where ν_2 remains the highest followed again by ν_1.

Table 4: Dempster's Rule of Combination (Importance Discounting)

	BetP approach				$DSmP_{\epsilon=0}$ approach			
	v_1	v_2	v_3	Θ	v_1	v_2	v_3	Θ
m_{12}	0.3963	0.5478	0.0404	0.0155	0.4027	0.5538	0.0190	0.0245
m_{123}	0.3651	0.5743	0.0016	0.0590	0.3777	0.5923	0.0080	0.0220
m_{1234}	0.3722	**0.5998**	0.0019	0.0261	0.3765	**0.6017**	0.0070	0.0148

The results above show how the use of consistency and discounting contribute to decision support systems.

Conclusions

This paper provides an overview of an evidential reasoning framework with application to the construction project domain. It was found important when dealing with conflicting and uncertain information to take consistency and discounting into account before to obtain good data for decisions. Dempster's rule of combination, using importance discounting, is capable of incorporating conflicting and uncertain information and allows practitioners to analyse construction risks with higher confidence, yet without dealing with detailed quantification of risk impacts or likelihoods and, therefore, it presents a less time-intensive approach. Further work needs to be completed to investigate the effect of using different, possibly more sophisticated measures of similarity and the ensuing impact on results. The Dezert-Smarandache (DSm) theory of fusion will be incorporated into a multi-criteria decision making algorithm as the main method of aggregation.

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