Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 26, Issues 2, pp. 719–728, DOI 10.12694/scpe.v26i2.3984

# RESEARCH ON DATA FUSION METHOD OF MATHEMATICAL CREATIVITY EDUCATION BASED ON AHP HIERARCHICAL ANALYSIS

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**Abstract.** Dempster-Shafer (DS) evidence theory is widely employed in the real world as a primary instrument for modeling uncertainty. However, when applying Dempster's combination rule, seemingly conflicting pieces of data could be merged to yield surprising results. There are a number of proposed scales for measuring the level of discrepancy between pieces of evidence. However, the presented methods only use a single metric to analyze the conflicting results. However, it is usually unwise to rely on a single criterion to measure the extent to which the facts conflict with one another. For the reason that flaws, differences, differences, and ambiguity all contribute to a higher level of conflict between the evidence. The objective of this study is to propose a novel data fusion method based on AHP for enhancing mathematical creativity education. This work stands out by effectively integrating multiple criteria to improve decision-making processes in educational settings. Given the efficacy of the approach proposed in this study in bringing together seemingly disparate data, we want to eventually extend its application to other forms of uncertainty theory, such as fuzzy set theory and imprecise probabilities. The concept of direct inquiry into the total ambiguity of evidence within the context of discernment will also be explored. Several criteria factors are used to determine the level of disagreement between the information presented here. A proposed analytic hierarchy technique uses multiple criteria to properly weight each piece of data. The initial stage is to assign a numerical value to each piece of evidence based on how well it satisfies each of the criteria. The criterion layer's covariance matrix can be derived by examining the relationship between the criteria's numerical values. After collecting data on each criterion's quantitative change, a fuzzy preference relation matrix can be built. The scheme layer makes use of a fuzzy preference relation matrix in place of a traditional pairwise comparison matrix. Each piece of evidence is given an overall weight based on its combined scheme weight and criteria weight. Two numerical experiments are offered to illustrate the effectiveness of the proposed method after the final weights have been applied to the primary evidence and the evidence has been combined using Dempster's rule. Results show that the proposed methodology outperforms alternative approaches to dealing with contradictory evidence discussed in the literature.

**Key words:** Analytic hierarchy process; Data Fusion; Mathematical education; Conflict Measurement; Dempster-Shafer Evidence Theory

## 1. Introduction.

Since data from a single sensor may not be adequate to obtain the desired information of target identification, in real applications it is often necessary to supply all of the information of target estimation with several sensors [1]. As a result of this possibility, it is typically necessary to supply all of the information of target estimation with many sensors. Multi-sensor systems frequently provide data that is inconsistent with one another as a result of variations in the precision and resistance to interference of the individual sensors. There have been numerous more hypotheses put forward as potential approaches to modeling uncertainty [2,3]. There is the theory of probability [4], the theory of DS evidence [5], the theory of possibility [6], the theory of fuzzy sets [7], the theory of rough sets [8,9] and so on. The concept of DS evidence was initially proposed by Dempster, and it was then popularized and expanded upon by Shafer. Since its inception in the 1960s, the DS evidence theory [10] has been widely accepted as a powerful instrument for dealing with uncertainty information that cannot be effectively handled using conventional probability theory. The fact that traditional probability theory does not adequately take into account uncertainty and imprecision is yet another issue that can be remedied by DS evidence theory. It has been useful in a variety of fields, including information fusion, decision analysis, the identification of defects, and others [11]. Because it makes it easier to combine data that comes from a number of sources in different locations, It is difficult to meet this condition in many uses of Dempster's rule since it requires ensuring that all of the bodies of evidence share the same dependability, which can be a time-consuming process. Dempster's combination rule has the potential to yield superior fusion outcomes in situations when the level of disagreement between the evidence is relatively low. When we apply Dempster's combination rule to these extremely contradictory pieces of data, however, we obtain two very different sets of findings. The Zadeh

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paradox [12] is an illustration of the type of results that are paradoxical. Another illustration of a situation in which the total is fair but does not help in making a decision [13]. Numerous amendments to Dempster's combination rule have been suggested by industry professionals after they invested a significant amount of time and effort investigating this issue. Some researchers believe that Dempster's combination rule is to fault for the unexpected findings, and as a result, they have offered alternative rules of combination [13]. Smets put up a credible evidence-based belief paradigm that may be shared [14]. In this model, the normalising phase is skipped and the contrasting mass is instead assigned to a null set. In circumstances that call for evidence that can be relied upon, however, it may be challenging to achieve total satisfaction. Lefevre et al. [15] came up with the idea of applying a unified belief function approach to the rules of combination, which proportionally distributes potentially opposing facts across all parts that are concerned. This technique, on the other hand, requires a greater willingness to take risks where there is significant controversy over the facts. Instead of mandating that inconsistent data be normalized, the new method that was developed by Yager assigns the status "unknown" to the data [16]. The method is extremely sensitive to changes in the data, and the degree of uncertainty in its results increases significantly, when contradictions are resolved by allocating them all to the unknown state. Inagaki first introduced the conflict coefficient k by fusing Yager's technique with Dempster's combination rule [17]. This led to the creation of the notion. The conclusion of a combination is not independent of the order in which the evidence was presented; this is true even if the physical importance of this coefficient is unclear. Sun et al. propose a method that addresses both of these issues and measures the credibility of conflicting pieces of evidence [18]. Even when presented with evidence that strongly contradict one other, their approaches are sound; however, they do not satisfy the commutativity and associativity standards. This study aims to address the gap in the literature regarding the integration of AHP with mathematical creativity education, particularly in the context of data fusion methods. The paper addresses the challenge of effectively fusing data in mathematical creativity education using the Dempster-Shafer (DS) evidence theory, particularly in scenarios where evidence presents a high level of conflict.

**1.1. Literature Review.** Some academics have claimed that the flawed data used to support Dempster's counter-intuitive results is the main problem, not the combination rule itself. Dempster's combination rule has been used successfully by certain researchers, while others have discovered its faults [19]. Before Dempster's combination rule was employed, Murphy originally established the procedure that changes the original evidence by calculating the fundamental arithmetic average [20]. The evidence-based similarity metric was suggested by Deng et al, who adapted Murphy's method [21]. This was accomplished by first disclosing the evidence distance, and then modifying the evidence presented in accordance with the strength of the evidence's support. Each piece of evidence gets assigned its own discount rate based on how different it is from the others. However, since they only employed one criterion, we can't know how much evidence disagrees with each other. According to Burger, distance and conflict are two entirely distinct ideas that cannot be interchanged. To account for this problem, An et al. modified the similarity measure to include fuzzy logic [22]. After that, they considered how much room for contradiction and uncertainty the evidence gave them. Despite taking into account two criteria, both methods have limitations and cannot accurately measure various forms of conflict. Previous research has explored various data fusion techniques such as DS evidence theory and fuzzy set theory. However, there is a paucity of studies that integrate AHP with mathematical creativity education, which this study aims to fill.

Numerous researchers have looked into the advantages of the multi-criteria decision-making approach over the more traditional single-criterion evaluation [23]. Using the multi-criteria aggregation method PROMETHEE II, we may quantify the evidence conflict by assigning weights to the various criteria [24]. These two methods were used in tandem. Each piece of evidence is assigned a discounting factor based on a set of criteria developed after considering the features of the evidence conflict. This is done to determine if the evidence may be ignored without consequence. The superior outcomes are a direct result of the multi-criteria idea's design, which takes into account multiple fusion levels. In an effort to lessen the subjectivity and contingency of decision making, a number of performance indicators are used to assign relative importance to the various pieces of information. Silva and de Almeida proposed using a multi-criterion technique to quantify the level of disagreement between the pieces of evidence [25]. The ECTRE TRI multi-criteria decision-making approach was evaluated for this purpose. Through the process of modeling, three separate conflict criteria are combined to provide a quantitative assessment of the evidence discrepancies. Mathematical creativity is crucial for developing innovative problem-solving skills. Existing literature emphasizes the need for advanced methods to accurately assess and enhance these skills, thereby highlighting the relevance of the proposed AHP-based data fusion method.

In an effort to address conflicts and problems that come from a lack of data, we apply multiple criteria to conduct a comprehensive examination of the degree of difference between the evidence. The final outcome is a state-of-the-art, comprehensive framework for assessing legal disputes. To account for the wide variety of conflicts that can occur between the pieces of evidence, it is necessary to take into consideration their uncertainty, imprecision, imperfection, dissimilarity, and disparity. To solve these criterion problems thoroughly, we present a revised analytical hierarchy process. To begin, we determine how well each piece of evidence meets each of the evaluation criteria and assign a score. The quantitative values of each criterion are used to calculate the covariance between them, and this information is stored in a covariance matrix that constitutes the criteria layer. In order to get the criterion layer weights, we invert the covariance matrix into the pairwise comparison matrix. Absolute value dissimilarity between criteria is used to build a fuzzy preference relation matrix. The scheme layer uses fuzzy preference relation matrices in place of pairwise comparison matrices to calculate weights. The sum of everyone's opinion on how important each piece of evidence is. Several numerical examples are provided to show how the suggested method works and how effective it is.

## 2. Methodology.

**2.1. Evidence Theory Dempster and Shafer.** The DS evidence theory and its associated theories are briefly introduced. 2 = F1, F2, FN, a set of exhaustive and mutually exclusive hypotheses, is the framework for judgments. The two groups' merger is 22.

$$2^{\emptyset} = \{\emptyset, F_1, F_2 \dots F_N, \{F_1, F_2\}, \{F_1, F_2, F_3\} \dots \emptyset\} \tag{1}$$

Let's pretend 2 is a framework for analysis, and that the set 22 of propositions is the power set in 2, where A 2 is any subset in 2. The mass function is a good fit for these parameters because it maps 22 to [0, 1].

$$\begin{cases} m\{\emptyset\} = 0 \\ \sum_{A \in \emptyset} m(A) = 1 \end{cases} \tag{2}$$

Basic probability assigns m.

The fundamental probability assignment function on 2 is m.

$$Bel\ (A) = \sum_{B \in C} m(A), A \in \emptyset \tag{3}$$

Bel(A) values indicate entire belief. A single set proposition A has a belief function that meets the following conditions:

$$\begin{cases} Bel(A) = 0 \\ Bel(A) = 1 \end{cases} \tag{4}$$

The belief function constraint rule is equation (4).

**2.2. Conflict Metrics.** Sensor data is unreliable, therefore information sources conflict. Dempster's data fusion rule prioritises consistency above conflict. Dempster's combination rule won't apply in circumstances of strong evidence disagreement, therefore the fusion will be startling. Solving this problem requires quantifying evidence disagreement. Conflict measurement methodologies vary. The research design and data collection method involves the following: First it is required to provide each piece of evidence with a numerical value that will represent how effectively each specific item satisfies the proposed criteria. The covariance matrix for the next layer may be acquired by evaluating the relationship between the numerical values of each criterion. Once the acquired data is carefully analyzed, a fuzzy preference relation matrix can be constructed. The fuzzy preference relation matrix is constructed by comparing each pair of elements based on their relative importance, allowing for degrees of preference rather than binary judgments. It helps in capturing the uncertainty and imprecision in decision-making.

**2.3. Analysis.** Shafer initially used the conflict coefficient k to quantify the evidence's disagreement [26]. Here are two examples:

*Example 1.* Two independent bodies of evidence m1 and m2 in the whole frame of discernment 2 = 'A, B, C, D' have the following basic probability assignment:

$$\text{m1: } 0.25(\text{A})\ 0.25(\text{B})$$
$$\text{m1(C)} = 0.25\ \text{m1(D)} = 0.25$$
$$\text{m2: A}=0.25\ \text{B}=0.25$$
$$\text{m2(C)} = 0.25\ \text{m2(D)} = 0.2$$

Calculating the conflict coefficient yields 0.75. The conflict analysis shows that the evidence disagrees proportionally to k. Thus, m1 and m2 evidence disagree greatly. These two evidence sets are identical, hence there is no conflict. Intuition cannot support this conclusion.

*Example 2.* Consider two fundamental probability assignments m1 and m2 in the frame of perceiving 2 = -1, -2, -3, which is complete:

$$\text{m1: m1}(\theta1,\ \theta2) = 0.6\ \text{m1}(\theta1,\ \theta3) = 0.4$$
$$\text{m2: m2}(\theta2,\ \theta3) = 0.5\ \text{m2}(\theta1,\ \theta2,\ \theta3) = 0.$$

Calculation yields the conflict coefficient k = 0. Conflict analysis shows that m1 and m2 evidence are consistent, hence there is no conflict. The following example shows why the conflict coefficient k cannot appropriately assess how much the two sets of evidence disagree. Jousselme measured evidence distance in vector space [27].

If there are two bodies of evidence m1 and m2 in the second frame of discernment, their evidence distance is defined as

$$d(m_1, m_2) = \sqrt{\frac{1}{2}(\bar{m}1 - m2)^T \underline{D}(m1 - m2)} \tag{5}$$

where the two primary probability assignment functions, mE 1 and mE 2, are represented by vectors. A and B are the m1 and m2 proofs for power set 22. The focus element cardinality is represented by the || symbol. When two sets of evidence are diametrically opposed to one another, their distance is defined as one, and when they are similar to one another, it is close to zero. Conflict coefficient's oversimplification can be corrected by increasing evidence distance. It is possible that unreal situations will be exposed by the evidence distance test.

**2.4. Conflict Assessment Criteria.** We can show that the level of disagreement between pieces of evidence cannot be reliably established using a single criteria evaluation methodology to quantify conflict by studying the aforementioned conflict measurement techniques. One measure of evaluation cannot possibly capture the full picture. Some measuring procedures reveal just slight disagreement at the same level of evidence, whereas others show substantial discrepancy. The disagreement in the evidence needs to be measured using multiple criteria. We include flaws like similarity, dissimilarity, disparity, imprecision, and ambiguity to form a more grounded assessment of the evidence's reliability. The reasons for these occurrences are then discussed.

*Number one, Overview.* The evidence isn't very convincing because it lacks detail. Doubt is viewed as a complex set in the DS evidence theory. As the size of the subset grows, so does the quality of the evidence and the trustworthiness of the beliefs.

*Second, Inequality.* The discrepancy in the evidence provides insight into the different base probabilities attached to the various claims. Mutually adjusting their perspectives may be facilitated by concentrating on shared interests. They also calculated the concordance between the primary points of evidence. This is the strongest evidence of disagreement that can be found between the two camps. Here, we may utilize the evidence distance to quantify the discrepancies between pieces of evidence.

*Third, Distinction.* Burger made a geometric analogy between the importance of proof in the law. Incorporating the Pignistic probability transform into vector space is a key part of Zhao et al. The function of the Pignistic vector angle evidence dispute measured the degree of similarity between two pieces of evidence by using the sine of the angle between them. Medium-range distance and angle measurement technique.

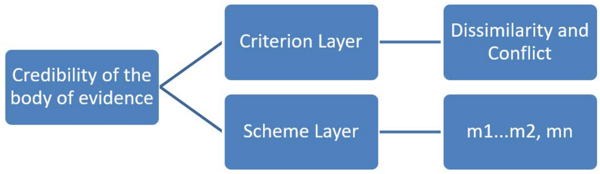


Fig. 2.1: Evidence Credibility Evaluation's Hierarchical Structure Model

*Fourth.* It is usual practice to utilize the Shannon entropy derived from probability theory when assessing the reliability of evidence. If one wants to make accurate calculations, this method should be used instead of the DS evidence theory method. Probability theory is another approach. Please see Fig. The uncertainty interval is a statistical tool used to quantify degrees of knowledge. Information entropy measures of uncertainty only consider m(A), Bel(A), and Pl(A) information. Uncertainty data from measurements have been greatly reduced, making precise descriptions impossible. The degree of doubt is quantified by averaging the gap between the most definite case and each singleton's confidence interval [58]. This procedure takes into consideration the inherent uncertainty in each piece of evidence. According to the theory of belief intervals, the interval between zero and one is the most suspect.

*Criteria-based decision making.* The previous section covered the first five of the evidence conflict factors. A combination of these factors provides a reliable evaluation of the evidence's degree of disagreement. In practice, there is a disagreement between the various evidence standards because they all offer something different and have different preferences. This means that the same data set can give contrasting images of conflict according to different criteria. By calculating the weight given to each criterion, we may analyze the degree of discrepancy in the data. The multi-criteria decision-making process determines how heavily various criteria should be weighted. Using AHP and the notion of fuzzy preference relations, we rank each criterion in this analysis. Using AHP and the theory of fuzzy preference relations facilitates the making of multi-criteria judgments. Below you can find the instructions.

The AHP method of hierarchical weighted decision making was created to making decisions based on a number of different factors. By taking this tack, officials can simplify difficult situations. A scheme's weights can be calculated by comparing and weighing its constituent pieces. It provides an organizational structure for identifying the optimal strategy [28]. This method incorporates quantitative computation with qualitative analysis, assigns appropriate weights to each criterion for each choice scheme based on the experience of the decision-makers, and establishes whether or not the goal is attainable.

*Use of the AHP Technique Steps.* We make a hierarchical order. Modeling decision-making problems effectively requires layering them as part of an analytic hierarchy. We sort problems by importance and take a closer look. On the basis of their interplay, the decision objective, the criterion, and the object are placed on the top, middle, and bottom layers, respectively. The lowest level is the scheme, the middle level is the criteria, and the highest level is the objective. In Figure 2.1 we see the study's hierarchical structure model. The 'Hierarchical Structure Model' consists of three levels: the goal at the top, criteria in the middle, and alternatives at the bottom. Each component represents a step in the decision-making process, from setting objectives to evaluating options based on weighted criteria. A comparison matrix with each pair consisting of two cells. Over and over, you can refer to aij to indicate the relative impact of xi and xj on C. A = (aij) $(n \times n)$ represents the comparison matrix. Pair comparison Matrix A. The ratio of the effects of xi on component C's aji to those of xj is 1/aij. Pairwise comparison matrix A has the scores on Santy's 1-9 scale as its entries (aij and aj).

We verify that the weights are consistent and perform a simple computation. In order to assign relative importance to each criterion, the pairwise comparison matrix A was used. Matrix If aijajk = aik and i, j, and k are 1, 2, and n, then the elements of A must be accurate. If and only if the value of the biggest eigenvalue of the consistency matrix A is equal to n, then A is a positive reciprocal matrix of order N. Here is how we characterize the CI:

$$CI = \frac{\gamma_{max} - n}{n - 1} \tag{6}$$

Find the data's mean random consistency index RI. CR formula:

$$CI = \frac{CI}{RI} \tag{7}$$

When the CR is less than 0.1, pairwise comparison matrix discrepancies are acceptable. If not, modify the pair comparison matrix.

To make sure everything is in order, we need to add up the weights. Using the findings from the previous stage, we can now determine how much weight to give to each criterion and the contribution of each scheme layer. The results are verified at last.

Although subject matter experts typically produce pairwise comparison matrices for use in AHP, these matrices are not immune to the influence of bias.

**2.5. The Connection Between Unclear Preferences.** Multi-attribute decisions benefit from the use of the fuzzy preference relation. The decision-making process necessitates the comparison of the schemes in pairs and the expression of preferences. The preference relation is a useful tool for conveying and understanding the preferences of decision-makers.

**2.6. Approach.** Weights can only be allocated with some subjectivity due to the random nature with which comparison matrices for pairs are formed. Based on the notion of fuzzy preference relations, the authors of this study propose a refined version of the AHP approach. This allows us to avoid the issues that have plagued more conventional approaches. The fuzzyness of the preference relation matrix reflects the changes in the quantitative criteria. Next, we give each piece of evidence a weight that takes into account how persuasive it is at both the criterion and scheme levels. Combining these methods reduces the impact of subjectivity and variability.

The generation of the pairwise comparison matrix is difficult because of the complexity of the objective items, and it does not always pass the consistency test. Because of the intricate nature of the objects. The covariance is used in this paper to determine the importance of each criterion. This was quantified by statisticians. More covariance between random variables indicates that they are not truly independent. The covariance matrix was constructed from the numerical values of the criteria characteristics. The parwise comparison matrix is built in the following way:

1. Determine the numerical index value for all n qualifying characteristics.
2. Use numerical data to compute covariance. Let X = x1, x2, xn and Y = y1, y2, yn be two random variables, and let x and y stand for their respective expectations.

The fuzzy preference relation matrix measures attribute index value dissimilarity across evidence sources and evaluation criteria. Judgements are less biassed. Computing Methods:

1. Calculate variance Quantifying the attribute index of each body of evidence for each criteria attribute. The ith and n-1 body of evidence have Vi attribute index value differences. Vi's weight reduces system-i gap.
2. Determine the dissimilarity between the evidence body attribute and the pijth element of the fuzzy preference relation matrix.

$$P_{ij} = \frac{V_i}{V_i + V_j} \tag{7}$$

Due to differences in information collection and accuracy amongst sensors, the evidence in multi-sensor data fusion is inconsistent. To determine the weight and credibility of each piece of evidence, we must first determine the extent to which they diverge. This article suggests adopting a modified AHP approach for in-depth conflict analysis to evaluate the reliability of each piece of evidence. The weighted average can be calculated after giving weights to the various pieces of evidence. Combine the evidence using Dempster's weighted average method.

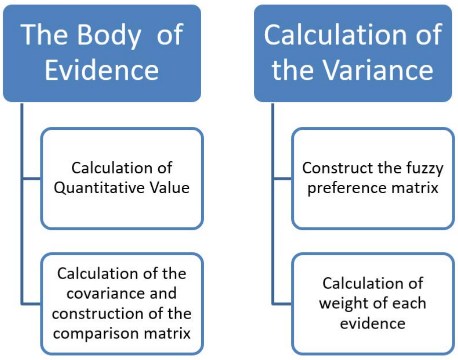


Fig. 2.2: Weight Determination

Table 2.1: Quantitative numerical

| | N(m) | DifS(m1) | Diss(m1) | Conf(m1) | TU(m1) |
|---|---|---|---|---|---|
| M1 | 0.065 | 0.664 | 0.965 | 0.563 | 0.045 |
| M2 | 0.40 | 0.465 | 0.413 | 0.655 | 0.055 |
| M3 | 0.030 | 0.600 | 0.310 | 0.420 | 0.66 |

Table 2.2: The Covariance Matrix

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| C1 | 0.0242 | 0.532 | 0.463 | 0.0643 | 0.04343 |
| C2 | 0.0423 | 0.643 | 0.0432 | 0.03245 | 0.06145 |
| C3 | 0.0543 | 0.302 | 0.0463 | 0.0435 | 0.0735 |
| C4 | 0.0513 | 0.342 | 0.0543 | 0.0654 | 0.0554 |
| C5 | 0.0234 | 0.534 | 0.0364 | 0.0643 | 0.04413 |

*A. Establishing Ranking Systems.* In this analysis stage, you will build a three-tiered hierarchy, the top level of which will be evidence weight (A measure of the credibility and importance assigned to each piece of evidence in the analysis, used to calculate the weighted average in decision-making). Finally, we'll use weight to indicate how credible each piece of evidence is. Using this dual-pronged method, targets can be located. The organizational chart is depicted in Figure 2.2.

*B: Weighing in.* The pairwise comparison matrix evaluates each criterion. Pairwise comparison matrices are created by correlating numerical values for each criterion for each piece of evidence. Five things:
C1: Non-specific measurement N(mi);
C2: difS(mi) discrepancy;
C3: Dissimilarity (diss(mi));
C4: Conf (mi).
C5: Uncertainty measurement, TU(mi);

We divide each column component by the column's major diagonal to update the covariance matrix C (in cij/cii). Matrix B, the relative covariance, is then available. Table 2.3 shows the findings.

A criteria covariance pairwise comparison matrix eliminates expert knowledge-related judgement differences.

**3. Result and Discussions.** Let's imagine many sensors are unable to identify targets, despite the fact that each sensor is providing valuable context for the type of target being identified. This table depicts the

Table 2.3: The relative Covariance Matrix

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| C1 | 1 | 0.4522 | 0.463 | 0.5443 | 0.4743 |
| C2 | 0.4123 | 0.56423 | 0.4173 | 0.6143 | 0.6845 |
| C3 | 0.5443 | 0.2352 | 0.2443 | 0.2143 | 0.7385 |
| C4 | 0.5137 | 0.3742 | 0.8237 | 0.727 | 0.5554 |
| C5 | 0.2134 | 0.1831 | 0.5184 | 0.5584 | 0.4413 |

Table 3.1: Basic Probability Distribution

| | O1 | O2 | (O1, O2) | (O2, O3) | O |
|---|---|---|---|---|---|
| m1 | 0.8 | 0.4 | 0.4 | 0.5 | 0.4 |
| m2 | 0.4 | 0.5 | 0.4 | 0.6 | 0.6 |
| m3 | 0 | 0.2 | 0.2 | 0.2 | 0.7 |
| m4 | 0.5 | 0.3 | 0.8 | 0.7 | 0.5 |
| m5 | 0.2 | 0.1 | 0.5 | 0.5 | 0.3 |

basic probability distribution for each sensor reading within the context of the system's acquired data from five different types of sensors, where 2 = 1, 2, 3. According to Table 3.1, the majority of the sensors (m1, m2, m4, and m5) believe in H1, while sensor m3 believes in H2. It appears that sensor m3's data does not correspond to the others. The standard deviation of your answers will be extremely high if you utilise Dempster's combination rule as written. The evaluation index value associated with each criterion is used to calculate the covariance between the criteria.

The difference in evaluation indices across all accessible bodies of evidence for each criterion must be computed before building the fuzzy preference relation matrix or the consistency fuzzy preference relation matrix. Consistency matrix for the evidence's P1 fuzzy preference relations is as follows:

$$P_1 = \begin{pmatrix} 0.4533 & 0.254 & 0.654 \\ 0.3645 & 0.342 & 0.543 \\ 0.534 & 0.522 & 0.555 \end{pmatrix}$$

$$\overline{P}_1 = \begin{pmatrix} 0.4533 & 0.254 & 0.654 \\ 0.3645 & 0.342 & 0.543 \\ 0.534 & 0.522 & 0.555 \end{pmatrix}$$

Table 3.2 shows the results of applying criterion C2 to the consistency fuzzy preference relation matrix, which is subsequently used to weight the evidence presented in the scheme layer (A hierarchical level in the AHP method where different schemes or plans are evaluated and weighted based on their consistency and preference relations.).

$$P_1 = \begin{pmatrix} 0.4731 & 0.5534 & 0.3524 \\ 0.3725 & 0.4462 & 0.1143 \\ 0.5132 & 0.3212 & 0.1255 \end{pmatrix}$$

$$\overline{P}_1 \begin{pmatrix} 0.5132 & 0.3051 & 0.3752 \\ 0.6511 & 0.5012 & 0.3513 \\ 0.3656 & 0.4372 & 0.3154 \end{pmatrix}$$

Applying the following formula to the weights assigned to each piece of evidence yields the weighted average: The values for the first dimension are: m(1) = 0.5949, m(2) = 0.1617, m(3) = 0.0515, m(1, 2) = 0.0772, m(2, 3) = 0.0153, and m(2) = 0.0994.

Table 3.2: The Weight of each body

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| m1 | 0.38 | 0.54 | 0.2 | 0.8 | 0.2 |
| m2 | 0.44 | 0.55 | 0.2 | 0.5 | 0.4 |
| m3 | 0.6 | 0.25 | 0.8 | 0.1 | 0.3 |
| m4 | 0.55 | 0.76 | 0.4 | 0.2 | 0.5 |
| m5 | 0.20 | 0.14 | 0.2 | 0.5 | 0.2 |

The evidence will be combined four times with a weighted average in accordance with the Dempster rule before a decision is reached. Dempster's combination rule states that although most evidence points to target 1, target 2 is more likely and target 1 is impossible. Since the majority of evidence is in favour of H1 and only one piece of evidence is in favour of H2, the result is unreasonable. This Evidence m1 provides the most convincing backing for the m1 hypothesis. Conflicting evidence receives less weight in the final combination outcomes when more criteria are utilised to set weights for the body of evidence. Our method works best when there are conflicting pieces of evidence. A probability estimate of the underlying distribution of sensor data for a task involving fault diagnostics. To establish the validity of the findings, we thoroughly analysed five distinct measures of conflict. The suggested procedure has the potential to generate more accurate and reasonable fusion findings than alternative methods, even in highly contested circumstances.

This demonstrates that Dempster's method, which can even yield counterintuitive results, cannot be used to the strongly contradictory data. It is challenging to make firm inferences from the available evidence due to the intricacy of the scenario. These results validate the usefulness of the suggested methodology for determining the evidence weighting factor. A more believable fusion outcome can be achieved by precisely characterising the degree of disagreement between the pieces of evidence, as discussed in the analysis offered in the third part. The proposed approach not only successfully modifies the conflict evidence, but also has improved convergence and precision. Its treatment of the multiple conflicting facts is both remarkable and successful when compared to other methods. The proposed method in this paper demonstrates remarkable efficacy in reconciling data that initially appear incongruous, opening avenues for its application in other realms of uncertainty theory, including fuzzy set theory and imprecise probabilities.

**4. Conclusion.** The research introduces an advanced method, bolstered by a refined Analytic Hierarchy Process (AHP), adept at harmonizing discordant datasets. This approach surpasses traditional measures by integrating a nuanced fuzzy preference relation matrix, significantly reducing subjective bias and aligning more closely with intuitive assessments of evidence conflict. Our method has been validated through a numerical example that underscores its robustness, even amidst scenarios rife with conflict. However, the method's efficacy is not without its vulnerabilities; it may falter in the face of starkly contradictory data, and the initial subjectivity in pairwise comparison matrices could influence the accuracy of evidence weighting. Looking ahead, the scope of this method will be expanded to encompass other domains within uncertainty theory, including fuzzy set theory and imprecise probabilities. Additionally, we aim to delve deeper into the overall uncertainty of evidence, refining our technique to better accommodate the complexities of discernment processes. Despite these challenges, the experimental validation through a fault diagnosis application confirms the method's substantial potential, offering a reliable and informed decision-support framework.

**Acknowledgments.** Project Source: higher education reform research subject in Jiangsu Province, Project Title: Practical Research on the Construction of Advanced Mathematics Gold Course Based on Self-learning Network Platform (2019JSJG335)

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*Edited by:* Bradha Madhavan
*Special issue on:* High-performance Computing Algorithms for Material Sciences
*Received:* May 19, 2024
*Accepted:* Jul 15, 2024