A Multi-attribute Decision-making Optimization Algorithm Based on Conflict Evidence Fusion and Cloud Model

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Abstract: To eliminate fuzziness and uncertainty of linguistic comments in multi-attribute decision-making, this paper introduces D-S evidence theory into cloud model assessment. Golden section method is employed to convert experts’ linguistic comments into cloud decision-making matrix, and then criterion clouds of different levels in comment set are taken as the reference to determine the membership to each level of assessment, so as to construct the basic probability allocation function (mass function) for different experts in respect of different attributes in different schemes. Thereafter, conflict coefficient, Jousselme distance, and Pignistic probability distance are introduced on the basis of D-S evidence theory to define evidence conflict measure. By calculating evidence reliability and relative expert weight, mass functions for experts are modified and fused. In the end, mass functions of different schemes are fused on the basis of attribute weight, and compared with the mass functions of ideal cloud and negative ideal cloud. Therefore, optimal scheme will be determined by comparing average closeness.

1. Introduction
In the stage of design assessment for large complex equipment and key technology in industrial field, there are normally several schemes or methods available, for decision, which often relies on multi-attribute decision-making method [¹]. Nevertheless, while assessing schemes, complex situation often leads to some qualitative indicators or attributes difficult to describe, and these indicators or attributes cannot be effectively combined with quantitative indicators. In most cases, this is reflected in uncertain indicators and fuzzy expert comments. Hence, cloud model assessment method [²] was put forth in the 1990s, and widely applied in multi-attribute decision-making.

Reference [³] proposes a multi-attribute decision-making approach based on cloud model with decision-making information as a linguistic variable, and addresses the fuzziness and randomness of actual decision-making by utilizing Hamming distance and closeness. Reference [⁴] takes into account the fuzziness and randomness of multistage risk decision-making information, and extends prospect theory into the normal environment of cloud model for sequencing and selecting optimal in the principle of maximum value in sequence. All the above studies have solved the problem of indicator quantification, and realized the natural two-way conversion of qualitative and quantitative indicators. Nevertheless, some differences still exist in the knowledge background, personal preference, and focus of experts in the multi-attribute decision-making process based on cloud model. Therefore, the results of their decision-making will be highly subjective. D-S evidence theory [⁵] has some advantages in the decision-making based on experts’ experience and multi-source information, since it regards experts’ comments as evidence to resolve the conflict among bodies of evidence and combine them. For this
reason, it has been quickly applied in the fusion of conflicting evidence in assessment
decision-making.

Reference [6] identifies the relationship between local trajectory and fusion trajectory based on D-S
evidence theory in the trajectory fusion of sensor subject to disorder distribution. Reference [7] applies
D-S evidence theory in the fault diagnosis for the reactor coolant system of nuclear power plant to
effectively deal with the fusion of uncertain information and subjective information in fault diagnosis.

To eliminate the fuzziness and uncertainty of linguistic comments in multi-attribute
decision-making, this paper first applies golden section method to convert the experts’ linguistic
comments into cloud decision-making matrix. After that, criterion clouds are taken as the reference to
determine the membership to each assessment level. On this basis, mass function is constructed for the
experts’ comments on different attributes of schemes. Thereafter, to resolve the conflict and difference
in the knowledge background and logical habit of experts, three values, i.e. conflict coefficient,
Jousselme distance [8], and Pignistic probability distance [9], are introduced on the basis of D-S
evidence theory, to construct ternary array and map it into three-dimensional coordinate system. The
reliability of evidence and relative weight of expert are calculated and mass functions for different
experts are modified and fused. The weights of attributes are used to fuse the mass functions for
indicators in schemes, and the optimal scheme is determined by comparing average closeness [10] with
mass functions of ideal cloud and negative ideal cloud.

2. Conversion of Linguistic Comments Based on Cloud Model

Academician Li Deyi put forth an uncertainty conversion model to convert qualitative words into
numbers for quantitative description. It is called cloud model, and can be used to study fuzziness and
randomness simultaneously as well as their relationship. In the practical study on cloud model, it has
been proved that the expected of membership cloud with multiple uncertainties is approximate to
normal cloud, especially one-dimensional normal cloud. The concepts relating to cloud model are
presented in the following section.

**Definition 1:** It is assumed that $U$ is a quantitative universe of discourse represented by a number,
and $C$ is a qualitative concept in the universe of discourse $U$. If there is a quantitative value $x \in U$
where $x$ is a stochastic realization of $C$, and its membership to $C$ is $\mu(x) \in [0, 1]$, which is a
random number with stability tendency. In this case, the distribution of $\mu(x)$ in the universe of
discourse $U$ is called cloud, and each $(x, \mu(x))$ is called a cloud droplet.

Cloud model has three digital characteristics, i.e. expectancy $Ex$, entropy $En$, and hyper entropy $He$. Expectancy $Ex$ refers to the expected value for spatial distribution of cloud droplet in universe
of discourse; entropy $En$ represents a measure for uncertainty of qualitative concept, and it reflects
the discreteness of cloud droplets. Hyper entropy $He$ is a measure for uncertainty of entropy $En$, and
indicates the discreteness of entropy.

**Definition 2:** It is assumed that there are $n$ clouds $\{C_1(Ex_1, En_1, He_1), C_2(Ex_2, En_2, He_2),$
$\ldots, C_n(Ex_n, En_n, He_n)\}$ in universe of discourse, and these clouds may be combined into a
comprehensive cloud $C(Ex, En, He)$.

\[
\begin{align*}
Ex &= \lambda_1 Ex_1 + \cdots + \lambda_n Ex_n \\
En &= \lambda_1 En_1 + \cdots + \lambda_n En_n \\
He &= \sqrt{\lambda_1 He_1^2 + \cdots + \lambda_n He_n^2}
\end{align*}
\]

where $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n)$ is the weight value of $n$ clouds.

According to the above definitions and based on the actual condition of multi-attribute
decision-making, the linguistic comments of decision-making experts are converted in the following
steps:

Step 1 Experts’ linguistic comments on each scheme are obtained in the expert evaluation method.

Step 2: Natural linguistic comment set $H$ consists of $n$ linguistic comment levels. Normally, $n$ is an odd. The effective universe of discourse for experts’ comments is $[X_{\min},X_{\max}]$. There is $H = \{h| = -t, \cdots, 0, \cdots, t, t \in N\}$ . Golden section method[11] is employed to convert linguistic comment set into criterion cloud for comments $C_{ij}(Ex_{ij},En_{ij},He_{ij})$, where $r = 1, \cdots , n$ is the $r$ th comment level.

Criterion cloud is utilized again to convert the $s$ th expert’s linguistic comment on the $j$ th attribute in a scheme $X_j$ into comment cloud decision-making matrix $C_{ij}(Ex_{ij},En_{ij},He_{ij})$. 

3. Conflict Evidence Fusion Based on Evidence Theory

Multi-attribute decision-making is uncertain to some extent since decision-making is fuzzy, e.g. indicators “Great, Good, Medium, Poor”, and experts’ personal preference. To obtain a more straightforward result of decision-making, evidence theory can be introduced to describe it. Comments given by experts can be regarded as evidence, and then conflict evidence is modified and fused to obtain a more scientific and reasonable result of decision-making. First of all, the terms relating to evidence theory[12] are as follows:

Let $\Theta$ be a finite set formed by $N$ certain objects. It is called frame of discernment, $\Theta$, $\Theta = \{1,2,3,\cdots,N\}$, where $\{1,2,3,\cdots,N\}$ stands for elements only and does not have any actual meaning. Event $A$ is included in $\Theta$. Meanwhile, let $P(\Theta)$ be power set of $\Theta$, which contains $2^N$ elements, each of which represents an event of event $A$. In other words, $P(\Theta)$ is represents all possible subsets of event $A$. $P(\Theta) = (\emptyset,1,\cdots,N,(1,2),(1,3),\cdots,(N-1,N),(1,2,3),\cdots,\Theta)$

Where $\emptyset$ stands for null set, and $1,\cdots,N$ with single element only is called singleton. Therefore, mapping from $P(\Theta)$ to $[0,1]$ could be defined, e.g. basic probability allocation function (BPA, mass function): $m : P(\Theta) \rightarrow [0,1], A \mapsto m(A)$. Where $\sum_{A \in P(\emptyset)} m(A) = 1$, $m(\emptyset) = 0$. When $m(A) > 0$, $A$ is known as focal element, and $m(A)$ represents the mass function corresponding to event $A$. The set of all focal elements is called the kernel of mass function. The set of bodies of evidence is represented by $(\emptyset, m) = \{[A,m(A)]; A \in P(\Theta), m(A) > 0\}$. This paper takes into account the condition of closed space for comment set. Let $m(\emptyset) = 0$.

Golden section method is employed to calculate the $s$ th expert’s cloud decision-making matrix for the $j$ th attribute of the scheme $X_j$, that is, $C_{ij}(Ex_{ij},En_{ij},He_{ij})$. The membership of comments to comment level $\mu_s(x_{ij})$, can be calculated on the basis of comment criterion cloud.

$$\mu_s(x_{ij}) = e^{\frac{(Ex_{ij}-(En_{ij}))}{2(En_{ij})}}$$ (1)

Thereafter, the membership matrix $U_j$ for the $j$ th attribute of the $i$ th scheme can be further constructed as follows:

$$U_j = \begin{bmatrix} \mu_i(x_{ij}) & \mu_1(x_{ij}) & \cdots & \mu_s(x_{ij}) \\ \mu_2(x_{ij}) & \mu_2(x_{ij}) & \cdots & \mu_s(x_{ij}) \\ \vdots & \vdots & \ddots & \vdots \\ \mu_n(x_{ij}) & \mu_n(x_{ij}) & \cdots & \mu_s(x_{ij}) \end{bmatrix}$$ (2)

After normalizing each line of membership matrix $U_j$, the mass function for the $s$ th expert with regard to the $j$ th attribute of the scheme $X_j$ can be calculated as follows:

$$m_F(x_{ij}) = \frac{\mu_s(x_{ij})}{\sum_{i=1}^{n} \mu_s(x_{ij})}$$ (3)
3.1. Evidence Conflict Measure

Generally speaking, evidence conflict is originated from two types of factors. One type is caused by bodies of evidence, while the other results from the rules of evidence fusion. This paper first focuses on the optimization of the first type, i.e. bodies of evidence, on the basis of D-S evidence theory, three values, that is, conflict coefficient, Jousselme, and Pignistic probability distance, are introduced to form ternary array, which is mapped into three-dimensional coordinate system, so as to define evidence conflict measure. In this way, a new algorithm for evidence conflict modification is designed in the following steps:

(1) Calculate conflict coefficient $K$

Under the same frame of discernment $\Theta$, mass function for event $A$ may be formed by mass functions of two bodies of evidence according to the following rule:

$$m(A) = m_1(A) \oplus m_2(A) = \sum_{B \subseteq A} m_1(B)m_2(C) \frac{1}{1-K}$$

$$K = \sum_{B \subseteq A} m_1(B)m_2(C)$$

Where $B$ and $C$ are sub-events of event $A$, and $K$ is conflict coefficient. In multi-attribute decision-making, the evidence conflict coefficient of experts $g_1$ and $g_2$ with regard to the $j$th attribute of the $i$th scheme $X_i$ is

$$K_{ij} = \sum_{g_1 \in g_1, g_2 \in g_2} m_{g_1}(x_1) \times m_{g_2}(x_2).$$

(2) Calculate Jousselme distance

Jousselme et al. put forth Jousselme distance $d_\text{Jousselme}$ in 2001 to measure the similarity between two bodies of evidence. The larger distance, the lower similarity between bodies of evidence. The distance $d_\text{Jousselme}$ is defined as follows:

$$d_\text{Jousselme}: \mathcal{G} \times \mathcal{G} \rightarrow \mathbb{R}$$

$$(A,B) \mapsto d(A,B)$$

Where $A$ and $B$ are events in $\mathcal{G}$, and have the following characteristics: non-negativity $d(A,B) \geq 0$; non-degeneracy $d(A,B) = 0 \iff A = B$; symmetry $d(A,B) = d(B,A)$; triangular inequality $d(A,B) \leq d(A,C) + d(C,B)$.

Let $d_\text{Jousselme}[g_1g_2(x_j)]$ be the conflict distance between the comments $m_1$ and $m_2$ of experts $g_1$ and $g_2$ on the $j$th attribute of the $i$th scheme $X_i$. The comments $m_1$ and $m_2$ as bodies of evidence can be represented by their corresponding vectors in space, i.e. $\overline{m}_1$ and $\overline{m}_2$. Therefore, $d_\text{Jousselme}[g_1g_2(x_j)]$ can be defined as follows:

$$d_\text{Jousselme}[g_1g_2(x_j)] = \frac{1}{2} \left( \overline{m}_1 - \overline{m}_2 \right)^T D(\overline{m}_1 - \overline{m}_2)$$

Where $D$ is a non-negative matrix, and $D(A,B) = \frac{|A \cap B|}{|A \cup B|} \in D$, $A, B \in P(\Theta)$.

$d_\text{Jousselme}[g_1g_2(x_j)]$ is simplified and calculated as follows:

$$d_\text{Jousselme}[g_1g_2(x_j)] = \frac{1}{\sqrt{2}} \left( \|m_1\|^2 + \|m_2\|^2 - 2 <\overline{m}_1, \overline{m}_2> \right)$$

(3) Calculate Pignistic probability distance

Pignistic probability function is defined as follows:

Let $m$ be mass function in frame of discernment $\Theta$, and then the correlation function for mapping from $\Theta$ to $[0,1]$ can be defined. In other words, Pignistic probability function $Bet_{\omega}(\omega)$
When $g_{Am}$, evidence conflict is extremely high.

The attribute of the $m$th expert with regard to the $i$th attribute of the $A$th scheme $A$, the support for $x_{ij}$, is the measure for the conflict between the $i$th expert and the $j$th attribute of the $i$th scheme $X_i$, and then maps it into $x_{ij}$ as a coordinate point, and then maps it into three-dimensional coordinate system. In this way, evidence conflict measure can be defined as the distance from this coordinate point to the origin $d_{aa}$:

$$d_{aa} = \sqrt{(K_{x_{ij}(x_j)})^2 + (d_{maxine}(g_{1}g_{2}(x_j)))^2 + (d_{pignistic}(x_{ij})_{g_{2}})^2}$$

(7)

When $K_{x_{ij}(x_j)}$, $d_{maxine}(g_{1}g_{2}(x_j))$, and $d_{pignistic}(x_{ij})_{g_{2}}$ are all equal to 1, $d_{aa}$ is $\sqrt{3}$. Let $d_{aa} = d_{aa}/\sqrt{3}$ to normalize $d_{stereoscopic}$. When $d_{aa} = 0$, there is no conflict between bodies of evidence; when $d_{aa} = 1$, evidence conflict is extremely high.

3.2. Evidence Modification Coefficient

First of all, $d_{aa}$ is used to construct the following conflict matrix $D_{iS}(x_{ij})$, which represents the conflict between experts with regard to the $j$th attribute of the $i$th scheme $X_i$ in decision-making:

$$D_{iS}(x_{ij}) = \begin{pmatrix}
0 & d_{iS(12)} & \cdots & d_{iS(1n)} \\
d_{iS(21)} & 0 & \cdots & d_{iS(2n)} \\
\vdots & \vdots & \ddots & \vdots \\
d_{iS(n1)} & d_{iS(n2)} & \cdots & 0
\end{pmatrix}$$

(8)

Where $d_{iS(ik)}$ is the measure for the conflict between the $i$th expert and the $k$th expert with regard to the $j$th attribute of the $i$th scheme $X_i$.

The conflict measure is converted into similarity by letting $s_{ij} = 1 - d_{aa}$, so as to obtain reliability matrix $S_{ij}(x_{ij})$.  

Based on $S^i_j(x_i^j)$, experts’ recognition of evidence can be calculated. In other words, experts’ support for evidence $g_k$ is as follows:

$$\text{Rec}(g_k) = \sum_{j=1}^{n} s^{i(j)}_{ij}$$

Recognition by expert $g_k$ is compared with the highest recognition among experts to obtain the evidence reliability $\text{Rel}(g_k)$.

$$\text{Rel}(g_k) = \frac{\text{Rec}(g_k)}{\max_{k'} \{ \text{Rec}(g_{k'}) \}}$$

Thereafter, the weight of each expert is determined to be $\lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_n\}$, $\sum_{j=1}^{n} \lambda_j = 1$, considering their professional focus, knowledge background, and work experience. As revealed in the definition of weight, the larger weight of expert, the higher reliability of his comments. Hence, this relative weight $\lambda(g_k)$ is calculated as follows:

$$\lambda(g_k) = \frac{\lambda_i}{\max_{j=1,2,\ldots,n} \{\lambda_j\}}$$

At last, reliability of evidence is combined with relative weight of expert to modify evidence and obtain evidence modification coefficient $\eta_k$ as follows:

$$\eta_k = \beta_1 \text{Rel}(g_k) + \beta_2 \lambda(g_k)$$

Where $\beta_1$ and $\beta_2$ are allocation coefficients, $0 \leq \beta_1 \leq 1$, $0 \leq \beta_2 \leq 1$, and $\beta_1 + \beta_2 = 1$.

### 3.3. Evidence Conflict Fusion Rules

The second type of factor causing evidence conflict, i.e. evidence fusion rules, will be analyzed for improvement in this section. Evidence modification coefficient $\eta_k$ is utilized to modify the mass function for all bodies of evidence in $\Theta$. $m_{g_k}(x_i^j)$, represents the modified mass function for the comment level of the $k$th expert $g_k$ with regard to the $j$th attribute of the $i$th scheme $X_i$. It is presented as follows:

$$m_{g_k}(x_i^j) = \eta_k \times m_{g_k}(x_i^j)$$

After modification, $\sum m_{g_k}(x_i^j) \neq 1$. Therefore, $m(\Theta)^*$ is added to jointly form a new modified mass function as follows:

$$m(\Theta)^* = 1 - \sum m_{g_k}(x_i^j)$$

Since there are certainly some differences in experts’ preference to schemes, and experts’ comments in grading are fuzzy and uncertain to some degree. For this reason, there is global conflict between bodies of evidence $[13]$. Evidence modification coefficient can be only used to determine the allocation percentage of mass function, but fail to resolve the global conflict allocation to focal elements. The larger value of focal element, the more conflicts allocated to it. For this reason, this paper breaks down global conflict into local conflicts, and allocates based on the value of focal element in pairwise comparison. The specific algorithm is as follows:
Where $C(x_j)$ is the local conflict of focal elements after breakdown, and $\gamma$ is allocation coefficient. After obtaining the mass function for the $j$th attribute of the $i$th scheme after fusion, the mass functions of all attributes are weighted based on the weight of each attribute to obtain the mass function for the $i$th scheme $m(X_i)$.

$$m(X_i) = \sum_{j=1}^{n} \omega_j m(x_j)$$

(12)

4. Multi-attribute Decision-making Based on Average Closeness

The idea of TOPSIS in multi-attribute decision-making is employed in this paper. TOPSIS is a method to approach ideal solution and sequence based on the similarity to ideal value. Thus, a judgment is made mainly by virtue of the closeness of the assessed to ideal solution and negative ideal solution. Negative ideal solution represents the worst scheme. When the assessed is closest to ideal solution, and farthest from negative ideal solution, it is the optimal scheme. In this paper, the mass function for each scheme is actually the probability allocation of the scheme to each comment level. Its average closeness to the mass functions for the most ideal scheme and the least ideal scheme may reveal whether the scheme is close to ideal solution. The specific steps are as follows:

Step 1: Solve the mass function for ideal cloud. According to their characteristics, attributes are classified into cost-related attributes and benefit-related attributes. Comment criterion cloud $(C^+_y, E^+_y, H^+_y)$ is utilized to obtain positive ideal cloud $(C^+_y, E^+_y, H^+_y)$. Under normal circumstances, the higher cost, the better benefit. Ideal cloud is suitable only if it leads to lower cost and better benefit, so that some conflicts also exist between its bodies of evidence. For this reason, Equations (1)-(3) can be used to calculate the mass function for the $j$th attribute of ideal cloud $m^+_y(x_j)$. After that, evidence conflict fusion is conducted to obtain the mass function for ideal cloud $m^+_y$. Similarly, negative ideal cloud can be calculated, i.e. the mass function for cloud of the least ideal scheme $m^-_y$.

Step 2: Calculate the closeness of each scheme to the mass functions for ideal cloud and negative ideal cloud. Let $y^+$ be the matrix for closeness of each scheme to the mass function for ideal cloud:

$$y^+ = \begin{pmatrix} y^+_{11} & y^+_{12} & \cdots & y^+_{1m} \\ y^+_{21} & y^+_{22} & \cdots & y^+_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ y^+_{n1} & y^+_{n2} & \cdots & y^+_{nm} \end{pmatrix}$$

Where $y^+_i = |m(X_i) - m^+_i|$ represents the closeness of the $i$th scheme to the mass function for the ideal scheme at the $r$th comment level, $i = 1, 2, \cdots, m$, $r = 1, 2, \cdots, n$. Similarly, the matrix $y^- = (y^-_i)$ for the closeness of each scheme to the mass function for negative ideal cloud is calculated, where

$$y^-_i = |m(X_i) - m^-_i|$$
\[ y_i = m(X_i) - m_r, \quad i = 1, 2, \ldots, m, \quad r = 1, 2, \ldots, n. \]

Step 3: The average closeness of schemes is obtained. Let \( \bar{y} \) be the matrix for the average closeness of schemes to the mass functions for ideal cloud and negative ideal cloud as follows:

\[
\bar{y} = \begin{pmatrix}
  y_1^- & y_1^+
  \\
  \vdots & \vdots
  \\
  y_m^- & y_m^+
\end{pmatrix}
\]

Where \( y_i^+ = \frac{1}{n} \sum_{r=1}^{n} y_{ir}^+, \quad y_i^- = \frac{1}{n} \sum_{r=1}^{n} y_{ir}^-, \quad i = 1, 2, \ldots, m. \)

Convert \( \bar{y} \), and let \( \Delta(y_i) = \max_{i=1,2,\ldots,m} (y_i^+) - y_i^- \), \( \Delta(y_i) = y_i^- - \min_{i=1,2,\ldots,m} (y_i^-) \), \( i = 1, 2, \ldots, m. \) At this time, the larger value of \( \Delta(y_i^+) \) and \( \Delta(y_i^-) \), the closer of scheme \( X_i \) to the ideal scheme. Generally speaking, \( \Delta(y_i^+) \) and \( \Delta(y_i^-) \) have the identical weight, so that there is:

\[
\Delta(y_i) = \frac{\Delta(y_i^+) + \Delta(y_i^-)}{2}
\]  

Therefore, the scheme \( X_i \) corresponding to \( \max_{i=1,2,\ldots,m} (\Delta(y_i)) \) is the optimal scheme for comprehensive decision-making.

5. Conclusion
Considering the conflicts between comments given by multiple experts in the assessment of complicated equipment design schemes, this paper designs a new algorithm for conflict evidence modification. Moreover, the idea of TOPSIS method in multi-attribute decision-making is borrowed to obtain the optimal scheme based on the comparison of average closeness with the mass functions for ideal cloud and negative ideal cloud. This paper proposes a new solution for multi-attribute decision-making, which is highly valuable in practical applications.

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