ROMANIAN JOURNAL OF INFORMATION SCIENCE AND TECHNOLOGY
Volume 29, Number 1, 2026, 41–52
doi: 10.59277/ROMJIST.2026.1.04

Cloud Model-Based Improved Evidence Theory and Its Applications to Power Systems

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Abstract. In order to cope with the complex features of ambiguity, randomness and uncertainty in multi-attribute decision-making problems, this paper introduces the Dempster-Shafer evidence theory in the framework of cloud modeling. First, a cloud model is used to calculate the affiliation of each evaluation metric, which was subsequently converted to a basic confidence assignment function. Second, the game theory idea is borrowed to combine the dynamic and static weights of the evidence in the game, to improve the traditional evidence theory and realize the effective integration of information. The idea of average fit is identified again, and a comprehensive evaluation conclusion is drawn by comparing the closeness of the evaluation object to the optimal and worst solutions. The new electric power system investment project is illustrated, and the applicability of the algorithm is verified.

Key-words: Closeness; cloud model; evidence theory; multi-attribute decision-making.

1. Introduction

Multi-Attribute Decision Making (MADM) is widely used as a decision-making framework in complex scenarios such as risk assessment and resource allocation. In recent years, multi-attribute decision models have shown significant value in cross-domain applications [1–4]. However, the intricacies of the real world makes it hard to quantify some attributes with exact numerical values. This intricacy frequently leads to ambiguity in evaluation data and uncertainty in evaluation standards. In order to overcome the shortcomings of traditional models in dealing with ambiguity and uncertainty, and to effectively solve the problem of conflict fusion between expert evaluations, this paper proposes a multi-attribute decision-making model based on cloud modeling and evidence theory. Li [5] presented cloud model theory, a framework based on fuzzy Mathematics and probability theory designed to represent uncertainty information [6]. Cloud models and probability interval-valued hesitant fuzzy sets (PIVHFS) is multi-attribute decision analysis method [7]. Liu et al. design a decision analysis methodology relying on a normal distribution cloud model, which is applied to deal with multi-source [8]. Lu et al. create a multi-attribute decision-making framework that integrates cloud models with Monte Carlo methods [9]. Cloud model can effectively enable a bi-directional transition from qualitative to quantitative metrics. Evidence theory is a approach for addressing uncertainty and incomplete information [10]. Fan et al. introduced a dual-layer framework for multi-attribute group decision-making that combines intuitionistic fuzzy theory with evidence-based reasoning [11]. Subjective and objective empowerment methods are the two primary categories into which the weight-determining way falls. Expert experience and judgment are the primary gauges of the subjective empowerment approach. Typical methods include the Dephi method [12], the analytic hierarchy process (AHP) [13], the Decision-making Trial and Evaluation Laboratory (DEMATEL) method [14], and others. While the subjective weighting method effectively incorporates the insights and experiences of decision-makers, there is also some subjective arbitrariness involved. The entropy approach [15], principal component analysis (PCA) [16], data envelopment analysis (DEA) [17], and so on are based on the statistical properties of the data to determine the weights. One benefit of the objective empowerment approach is that it can determine weights based on the properties of the data, minimizing the influence of subjective considerations. However, it may not entirely consider the decision-maker's personal preference. Consequently, game combination assignments can help address the issue of irrational assignments. Through the coordination mechanism of game theory, weight allocation can be optimized to find consistency and compromise between different sets of weight vectors.

Overall, cloud modeling enables a natural two-way conversion between qualitative and quantitative metrics. However, in the multi-attribute decision-making process based on cloud modeling, the decision conclusions tend to differ significantly due to the differences in the personal preferences, knowledge systems, and focuses of different experts. In the decision-making process based on expert experience and fusion of multi-source information, D-S evidence theory can regard the evaluation of each expert as an independent source of evidence, effectively solve the problem of conflict between the evidence, and integrate different evidence through the fusion mechanism to realize its unique advantages. In addition, the use of the game combination assignment method can break through the limitations of a single assignment method, so that the weight allocation is more suitable for the equilibrium needs in the actual decision-making scenarios.

The main contributions of this paper include, firstly, using the cloud model to synthesize the ambiguity and randomness of the data, and at the same time, realizing the fusion of multi-source information with the help of evidence theory to construct a complete decision-making model from data characterization, evidence synthesis to decision output. Second, based on the game optimization method to balance the subjective and objective weights, it reduces the sensitivity of the model to data noise and improves the robustness of the model.

The paper is structured as follows: Section 2 focuses on the steps of evidencing the affiliation distribution based on the cloud model and improving the theory of evidence by gaming the combination of weights. Section 3 focuses on the method to determine the average fit between the evaluation objects and obtain the synthesized results by calculating the superior ideal cloud and inferior ideal cloud. Section 4 uses an example to do the validation of the proposed model of the article. Section 5 briefly summarizes the paper.

2. Assessment Model Based on Cloud Model-Improved Evidence Theory

2.1. Quantification of indicators based on cloud models

The cloud model promotes the conversion of qualitative information and quantitative data, and provides a new method for data processing and analysis [18]. Let U be a numerical quantitative domain, and C be a qualitative concept on U. If the quantitative value $x \in U$ is a random implementation of the qualitative concept C, the certainty $x \in U$ of x concerning C is a random variable with a stable trend, that is, $x \in U$ and $x \in U$, then the distribution of x on the domain U is called a cloud, which is $C(x)$, and each x is called a cloud droplet.

The deterministic measure of cloud droplets shows the degree of ambiguity and randomness of the notions, while the cloud droplet generation process reflects the uncertainty of converting qualitative concepts into quantitative values. Cloud droplets are generated by the cloud model using three numerical features: Expectation (Ex), Entropy (En), and Hyperentropy (He), achieving a natural transformation between qualitative information and quantitative data.

Ex , En and He are the numerical parameters that form the basis of the cloud model. A forward cloud generator determines the cloud model's numerical properties by producing a large number of cloud droplets that meet certain distributional criteria. The evaluation benchmarks are then used to produce various tiers of cloud transformation models.

The cloud model parameters corresponding to the j^{th} level of indicator X_i in this scheme are

$$\begin{cases} Ex_{ij} = \dfrac{X_{ij}^{\max} + X_{ij}^{\min}}{2} \\ En_{ij} = \dfrac{X_{ij}^{\max} - X_{ij}^{\min}}{2.3548} \\ He_{ij} = s \end{cases}. \tag{1}$$

where $X_{ij}^{\max}$ and $X_{ij}^{\min}$ are the boundary values of X_i at the jth rank. The indicator's ambiguity, discontinuous and random character, and specific reality can all be taken into account while adjusting the constant parameter s, the text settings that s = 0.05. Indicator membership is computed using (Ex, En, He) and the actual evaluation indicator data X_{ij}:

$$u_{ij} = \exp\left(-\frac{(X_{ij} - Ex_{ij})^2}{2(En'_{ij})^2}\right). \tag{2}$$

In (2), $En' = norm(En, He)$. Calculating the membership of each evaluation indicator one by one, the cloud membership matrix U of the evaluation program can be obtained, where $U = (u_{ij})_{n\times r}$, n, r represents the indicator number and the assessment grade, respectively.

2.2. Evidentialization of membership distributions based on cloud models

When it comes to handle uncertain information, evidence theory is capable of fusing quantitative and qualitative data. Numerous domains. It focuses on the effective blending of evidence and the derivation of rational decisions or inferences from available data and information. In evidence theory, let $\Theta = \{A_1, A_2, \cdots, A_j\}$ be the set of propositions consisting of some mutually exclusive and exhaustive elements, Θ be called the frame of conceptual [19], ϕ denotes the empty set of propositions, and the power set of Θ be 2^Θ, $2^\Theta \to [0,1]$, then the function $m(A)$ satisfies the following conditions. $m(A)$ is the confidence distribution function (mass) for proposition A. $BEL(A)$ represents the overall trust in A:

$$\begin{cases} m(\phi) = 0 \\ \sum_{A \subseteq \Theta} m(A) = 1, \end{cases} \tag{3}$$

$$BEL(A) = \sum_{B \subseteq A} m(B), (\forall A \subseteq \Theta). \tag{4}$$

According to that each evaluation index should meet conditions $\sum\limits_{A \subseteq \Theta} m(A) = 1$ as defined by evidence theory, the cloud model's calculation of the sum of membership degrees does not always equal 1. To transform the evaluation indicator membership in the cloud model into a fundamental trust assignment that meets the requirements of evidence theory, the indicator rank assignment uncertainty probability rank θ is introduced:

$$\begin{cases} m_i(A_j) = \frac{(1-\theta_i)u_{ij}}{\sum_{j=1}^{r} u_{ij}}, \\ m_i(\theta_i) = \theta_i, \\ \theta_i = 1 - \max(u_{i1}, u_{i2}, \cdots, u_{ij}), \end{cases} \tag{5}$$

where $i = 1 \cdots n$ keeps track of indicators, $j = 1 \cdots r+1$ keeps track of levels and $m_i(\theta_i)$ denotes the present confidence assignment for the uncertainty level. Transform all evaluation indicators to meet the definition of evidence theory, and construct a basic trust allocation matrix $\mathbf{M}_{n\times(r+1)}$, where $\mathbf{M} = (\mathcal{P}, \mathcal{T}), \mathcal{P} = (m_i(A_j))_{n\times n}, \mathcal{T} = (\theta_j)_{n\times 1}$.

2.3. Improving evidence theory based on game combinatorial empowerment

Information fusion is a prominent strength of traditional Dempster-Shafer (DS) evidence models, yet the outcomes may fall short of expectations when highly contradictory evidence is involved. A game-theoretic approach is employed to resolve the paradoxical issue brought on by high-conflict evidence.

2.3.1. Dynamic weights

Dynamic weights can flexibly adjust the weight allocation according to the changes in the body of evidence, thus adapting to the dynamic changes in the conflict and importance of different indicators in the evaluation process.The identification framework of the theory of evidence has n assessment indicators and $r + 1$ evaluation levels, as per the basic confidence assignment matrix $\mathbf{M}_{n\times(r+1)}$. Each evaluation level involves the fusion processing of i pieces of evidence. Dynamic Weight Coefficient approach employs these steps to derive assessment indicator weights:

Step 1. Calculate the average membership degree of the indicator, denoted as $\overline{m}(A_j)$:

Step 2. Distance between quantitative indicators and the average membership degree:

$$d_i = \sum_{j=1}^{r+1} |m_i(A_j) - \overline{m}(A_j)|. \tag{6}$$

Step 3. Figure out the indicators' dynamic weights:

$$\xi_i = 1/d_i, \tag{7}$$

$$\omega_{1i} = \frac{\xi_i}{\sum_{i=1}^{n} \xi_i}. \tag{8}$$

When figuring out how much weight to give each indicator, we look at how far its membership degree strays from the average. The further it deviates, the more significant the conflict caused by the indicator in the evaluation system. As a result, the relationship between an indicator's weight and its distance from the average membership is inverse.

2.3.2. Static weights

Indicators' static weights were established using an entropy-reduction weighting method. By improving the weight calculation logic of the traditional entropy weighting method, the anti-entropy method can effectively avoid the problem of extreme weight allocation due to the excessive differences in indicator data. The following steps are carried out:

Step 1. Consider an evaluation system with e experts and n evaluation indicators, with evaluation data x_{gi}, and standardize the indicator data to ensure consistency and comparability of the data:

$$\vartheta_{gi} = \frac{x_{gi} - \min(x_{gi})}{\max(x_{gi}) - \min(x_{gi})}. \tag{9}$$

Step 2. Normalize processing ϑ_{gi} to obtain δ_{gj}:

$$\delta_{gi} = \frac{\vartheta_{gi}}{\sum_{i=1}^{n} \vartheta_{gi}}. \tag{10}$$

Step 3. Do the anti-entropy calculation for each indicator:

$$\varsigma_i = -\sum_{g=1}^{e} \delta_{gi} \cdot \ln(1 - \delta_{gi}). \tag{11}$$

Step 4. Calculation of objective weights for indicators:

$$w_{2i} = \frac{\varsigma_i}{\sum_{i=1}^{n} \varsigma_i}. \tag{12}$$

2.3.3. Game-theoretic combinatorial empowerment

The central tenet of game theory involves balancing the conflicts between various weight factors, achieve the unity and coordination of indicator weights calculated by different methods, and aim to find a balance point, that is, to seek the maximum intersection of interests between various indicators, while considering the advantages and disadvantages of various weighting methods. Nash equilibrium is achieved through game assignment to optimize weight allocation.

Step 1. Given a total of L weighing techniques, the set of fundamental weight vectors for evaluation indexes is represented by $W_k = (w_{k1} \cdots w_{kn})\,,\,, (k = 1 \cdots L)$, and the linear combination of weight coefficients is represented by $\alpha = (\alpha_1 \cdots \alpha_k)$. The n evaluation metrics' weight vector may be expressed as a linear composite:

$$W = \sum\nolimits_{k=1}^{L} \alpha_k {w_k}^T. \tag{13}$$

Step 2. The game's countermeasure model is built as follows in to find the Nash equilibrium point, which is the minimum difference between the combined weight vector w and the basic weight vector w_k:

$$\min \| \sum\nolimits_{k=1}^{n} (\alpha_k {w_k}^T - w_k) \|_2. \tag{14}$$

Step 3. Determine the optimization problem's first-order derivative condition using the matrix differentiation approach:

$$\sum\nolimits_{k=1}^{n} \alpha_k w_k {w_k}^T = w_k {w_k}^T. \tag{15}$$

Step 4. Normalization of the coefficients α_k solved for the system of equations yields the best linear combination of coefficients α_k^*. Calculate the weight vector for the game-theoretic portfolio:

$$w^* = \sum\nolimits_{k=1}^{L} \alpha_k^* {w_k}^T. \tag{16}$$

2.3.4. Improving the integration of evidence theory

Additionally, synthetic rules are essential to the convergence of evidence models. Several common synthesis rules include Dempster synthesis, Yager's rule, and synthesis based on distance between evidence. Due to the limitations of the evidence theory, potential paradoxes may affect the accuracy of the synthesized results, leading to deviations from actual situations and ultimately reducing the precision of the theory in inferring evidence. The causes of evidence conflicts can be divided into two categories, one is due to the defects of the evidence itself, and the other is due to the synthesis rules used in the evidence fusion process. Consequently, it is possible to categorize the primary research paths in the study of developing the theory of evidence into two groups, adjusting the synthetic rules and making amendments based on the original evidence [20]. Each assessment metric's state membership function is ascertained with the cloud model as the first piece of evidence, which is trustworthy, so the improvement of this paper will focus on optimizing the synthetic rules of the theory of evidence in terms of the following steps:

Step 1. Calculate the similarity coefficient between any two pieces of evidence $m_x(A_i)$ and $m_y(A_i)$. $x, y = 1 \cdots l$, $x \neq y$ and l is the number of pieces of evidence:

$$s\left(m_x\left(A_i\right), m_y\left(A_i\right)\right) = \frac{\sum_{i=1}^{n} m_x\left(A_i\right) \cdot m_y\left(A_i\right)}{\sqrt{\sum m_x^2(A_i) \sum m_y^2(A_i)}}. \tag{17}$$

To quantify evidentiary resemblance, the evidence similarity coefficient s_{ij} is introduced to quantify the degree of similarity between evidence i and evidence j, where r is the level number and $0 \leq s_{ij} \leq 1$.

Step 2. Compile the n pieces of evidence into the similarity matrix S, where $S = (s_{ij})_{n \times n}$, $s_{ii} = 1$, $i = 1 \cdots n$:

Step 3. Quantify how well the evidence supports the hypothesis or conclusion:

$$Sup(m_x(A_i)) = \sum_{y=1}^{l} s(m_x(A_i), m_y(A_i)). \tag{18}$$

Step 4. Quantify the credibility of the evidence to the hypothesis or conclusion:

$$Crd(m_x(A_i)) = \frac{Sup(m_x(A_i))}{\sum_{x=1}^{l} Sup(m_x(A_i))}. \tag{19}$$

Step 5. When calculating the fusion coefficient, consider the weight and credibility of the evidence as equally important factors. After improving the evidence fusion rules, calculate the synthetic credibility of the target under multi-source fusion decision-making:

$$\wp(m_x(A_i)) = 0.5w(m_x(A_i)) + 0.5Crd(m_x(A_i)), \tag{20}$$

$$M(A_i) = \sum_{x=1}^{l} \wp(m_x(A_i)) \cdot m_x(A_i), \tag{21}$$

where $M(C_j)$ denotes fused evidence's basic probability, j is the recognition framework order, and n is the quantity of convergence indicators.

3. Multi-Attribute Decision-making Based on Average Closeness Degree

TOPSIS [21] is considered a ranking approach based on ideal solutions in MADM. Whereas the negative ideal solution denotes the worst answer, the ideal solution represents the best one. The Mass function of the alternative plan reflects the probability distribution characteristics of the plan on evaluation indicators. The average proximity of the Mass function to the ideal solution and the negative ideal solution Mass function was calculated for each scenario to inform the decision. The calculation steps is shown as follows.

Step 1. Select the optimal and worst values from various indicators of the evaluation object, and utilize cloud models to calculate the membership matrices of positive and negative ideal solutions, then convert these matrices into basic reliability functions that comply with evidence theory, and use improved evidence fusion rules to fuse the basic reliability functions into ideal cloud m_r^+ and negative ideal cloud m_r^-.

Step 2. Calculate the closeness of each alternative to m_r^+ and m_r^-. Let D^+ denote the fit matrix of each project to the ideal cloud mass function. $D^+ = (d_{ij})^+_{m\times n}$.

Among them, $d_{ij}^+ = |m_i(A) - m_r^+|$ represents the fit of the mass function between the i solution and the ideal solution at the r evaluation level, $i = 1\cdots m$, $j = 1\cdots n$. Compute each alternative's proximity in relation to the negative ideal solution in a similar manner, $d_{ij}^- = |m_i(A) - m_r^-|$.

Step 3. Take the average of the fit between each option, where $\overline{D}$ represents the average fit matrix between each alternative option and m_r^+ and m_r^-:

$$\overline{D} = \begin{pmatrix} \overline{d_1^+} & \overline{d_2^+} & \cdots & \overline{d_m^+} \\ \overline{d_1^-} & \overline{d_2^-} & \cdots & \overline{d_m^-} \end{pmatrix}^T, \tag{22}$$

where $\overline{d_i^+} = \frac{1}{n}\sum_{j=1}^{n} d_{ir}^+, \overline{d_i^-} = \frac{1}{n}\sum_{j=1}^{n} d_{ir}^-$.

Step 4. Determine the difference between the assessment object's average proximity to the ideal solutions, both positive and negative:

$$\begin{cases} \Delta\overline{d_i^+} = \max(\overline{d_1^+}\cdots\overline{d_m^+}) - \overline{d_i^+}, \\ \Delta\overline{d_i^-} = \overline{d_i^-} - \min(\overline{d_1^+}\cdots\overline{d_m^+}), \\ \Delta d_i = \frac{\Delta\overline{d_i^+}+\Delta\overline{d_i^-}}{2}. \end{cases} \tag{23}$$

The magnitude of the difference reflects the degree to which the evaluated object approaches the ideal solution. The larger the difference, the more significant the performance of the evaluated object in approaching the optimal solution. Assessing the similarity of the evaluation objectives to the optimal solution by measuring the value of variance can efficiently identify the evaluation objectives which are closest to the positive ideal solution.

4. Numerical Example

Taking the optimization of investment in new power system projects as an example for research. Since the "3060" dual-carbon target is proposed, the primary role of new energy in the power system's future development has been evident. The State is actively promoting a renewable energy substitution program and is committed to establishing a "clean, low-carbon, safe and efficient" energy system, aiming to build a new power system dominated by new energy sources.

4.1. Evaluation indicators system

The research on new power system investment projects covers five alternative options $\{P_i\}_{i=1}^{5}$. Based on the existing literature, a multi-dimensional assessment system covering four perspectives, namely greenness, security, intelligence and economic efficiency, is developed to provide a comprehensive evaluation of investment. The hierarchical structural of the assessment system involves 4 primary indicators, subdivided into 8 secondary indicators, which are further split into 16 third-level indicators. Referring to relevant literature, a set of evaluation criteria {I, II, III, IV} is established, corresponding to four levels, such as poor, moderate, good and excellent. According to the data provided in reference [22].

4.2. Computing basic reliability allocation based on the cloud model

Based on evaluation criteria, the cloud numerical characteristic parameters (Ex, En, He) are calculated for different levels of indicators. By inputting the numerical parameters of the cloud model for the evaluation criteria into the forward cloud generator and setting the number of cloud droplets to 3000.

Combining the quantitative data of the indicators and (Ex, En, He), the hierarchical membership of the evaluation indicators is calculated and the membership matrix of the project is generated.

To determine the cloud model's indicator affiliation matrix meets the theory of evidence's fundamental probability distribution requirements, an uncertainty level parameter θ is introduced, and (5) is utilized for the calculation to obtain the basic reliability allocation function matrix that meets the definition of evidence theory. Taking project 1 as an example, calculate its basic reliability allocation function matrix.

4.3. Evidence fusion based on game empowerment

The membership degrees that are derived by (6) to (8), to determine the dynamic weights of each indicators. According to (9) to (12), the anti-entropy weight method is used to calculate the static weights of evaluation indicators. Equations (13) to (16) are used to give the normalized coefficients $\alpha_1^* = 0.1876$ and $\alpha_2^* = 0.8124$, and the game combination weights of each indicator can be obtained. The dynamic, static, and game combination weights of each indicator in Project 1 are shown in Table 1.

Calculate the support, credibility, and fusion coefficient of each indicator using (17)–(20), and relevant outcomes appear in Table 2. Based on the fusion coefficient to improve the evidence synthesis rule, through the fusion of (21) to get the basic confidence distribution function, to realize the fusion of the third-level indicators to the second-level indicators, the fusion of the second-level indicators to the first-level indicators and the fusion of the first-level indicators to the final program, and ultimately to get the basic confidence distribution m_1(P) of the program. Similarly, the basic reliability assignments m_2(P), m_3(P), m_4(P), and m_5(P) for Project 2, 3, 4, and 5 are obtained via the above steps, as illustrated in Table 3.

4.4. Results based on the idea of average closeness

Here, the optimal and worst values of each indicator are selected from all projects to form positive and negative ideal solution projects, respectively. Table 4 details the positive ideal solution cloud m_i^+ and the negative ideal solution cloud m_i^-.

Table 1. Weights of level 3 indicators in Project 1

Criterion	Weight	Secondary criterion	Weight	Tertiary criterion	Static weight	Dynamic weight	Cmbined weight
C_1	0.1685	S_1	0.0801	T_1	0.0728	0.0253	0.0342
				T_2	0.0753	0.0391	0.0459
		S_2	0.0884	T_3	0.0752	0.0391	0.0459
				T_4	0.077	0.0345	0.0425
C_2	0.4316	S_3	0.2683	T_5	0.075	0.1478	0.1341
				T_6	0.0461	0.1546	0.1342
		S_4	0.1633	T_7	0.0485	0.0493	0.0491
				T_8	0.052	0.1286	0.1142
C_3	0.1808	S_5	0.096	T_9	0.0465	0.0392	0.0406
				T_{10}	0.0615	0.054	0.0554
		S_6	0.0848	T_{11}	0.0532	0.0383	0.0411
				T_{12}	0.0465	0.043	0.0437
C_4	0.2191	S_7	0.128	T_{13}	0.0504	0.0747	0.0701
				T_{14}	0.0776	0.0533	0.0579
		S_8	0.0911	T_{15}	0.0881	0.0497	0.0569
				T_{16}	0.0543	0.0295	0.0342

Table 2. Integration factor for the three-level indicator

Indicator	Support	Credibility	Intra-level credibility	Integration factor
T_1	2.6816	0.0267	0.2977	0.3623
T_2	6.3256	0.063	0.7023	0.6377
T_3	6.3203	0.0629	0.5173	0.5182
T_4	5.8994	0.0587	0.4827	0.4818
T_5	8.6405	0.086	0.4991	0.4995
T_6	8.6699	0.0863	0.5009	0.5005
T_7	5.6561	0.0563	0.3973	0.349
T_8	8.5728	0.0854	0.6027	0.651
T_9	6.3143	0.0629	0.511	0.4669
T_{10}	6.0482	0.0602	0.489	0.5331
T_{11}	5.6325	0.0561	0.4758	0.4803
T_{12}	6.211	0.0618	0.5242	0.5197
T_{13}	7.1885	0.0716	0.5424	0.5451
T_{14}	6.0618	0.0604	0.4576	0.4549
T_{15}	5.645	0.0562	0.5526	0.5886
T_{16}	4.5711	0.0455	0.4474	0.4114

Table 3. Distribution of basic confidence for each project

Project	I	II	III	IV	θ
m_1(P)	0.14	0.1921	0.2844	0.2145	0.169
m_2(P)	0.417	0.084	0.1473	0.1232	0.2285
m_3(P)	0.3189	0.0868	0.136	0.2387	0.2196
m_4(P)	0.0992	0.0815	0.1098	0.3976	0.3119
m_5(P)	0.2702	0.2459	0.1091	0.1308	0.244

Table 4. Basic confidence assignments for positive and negative ideal solutions

Project	I	II	III	IV	θ
m_i^+	0.0269	0.0263	0.0306	0.4865	0.4297
m_i^-	0.4453	0.0296	0.0298	0.0519	0.4434

Based on the results of evidence fusion presented in Table 5, for each alternative, the average proximity between it and the basic confidence assignments of the positive ideal solution and the negative ideal solution is calculated.

Using the criterion that the greater the difference in the average closeness, the closer the solution is to the ideal outcome, the final prioritization of the alternatives can be established based on the difference between the average closeness of the alternatives to the mean and the positive and negative ideal solutions. The larger the difference in values, the closer the program is to the ideal state.

Table 5. Ranking results

Project	Difference		Average	Rank
	from PI	from NI		
m_1(P)	0.0127	0.1346	0.0737	2
m_2(P)	0.0000	0.0000	0.0000	5
m_3(P)	0.0426	0.0428	0.0427	3
m_4(P)	0.1431	0.0938	0.1184	1
m_5(P)	0.0092	0.0525	0.0309	4

5. Conclusions

Addressing randomness, ambiguity, and imprecision inherent in multi-criteria decision analysis, this paper proposes an evaluation model based on cloud model improved evidence theory. To overcome the limitations of standard membership functions in managing ambiguity and unpredictability, the membership function values between target data and reference clouds are computed using cloud models, transforming qualitative description into quantitative data. The use of the game combination assignment method improves and complements the evidence synthesis rules, thus overcoming to a certain extent the one-sidedness inherent in the traditional method of relying only on a single weight calculation, which in turn enhances the accuracy and reliability of the evidence fusion results. Leveraging TOPSIS, the field of multi-attribute decision-making, identify the ideal solution via closeness measurement. In the end, thorough mathematical examples are used to confirm the accuracy and applicability of the suggested assessment model, creating a new avenue for resolving the multi-attribute decision-making problems.

Acknowledgements. This work was supported by the Outstanding Young Talents of Anhui Polytechnic University (Nos. S022021054, S022022012) and the National Social Science Fund General Project (No. 20BTJ048).

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