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Research Article

Multiattribute Group Decision-Making Method Based on Quaternary Connection Number of Cloud Models

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Based on the advantages of cloud theory and the connection number approach in handling uncertain information, this paper established a new quaternary connection number using the domain of interval corresponding to the centroid of a cloud model's expectation curve. Consequently, based on the cloud model theory of transformation between qualitative and quantitative uncertainties, this study suggests a model describing uncertain information more precisely by combining the advantages of quaternary connection numbers with three digital aspects of the cloud model. We defined the weighted nearness degree of the new connection number and gave a solution for finding the weight of the weighted nearness degree given that a three-parameter interval number can more precisely represent the expert's true intention than a classical interval number. The method of multiattribute group decision-making based on a cloud model's quaternary connection number was developed using a novel methodology to find the evaluation-index weight. According to a comparative analysis, the existing membership cloud gravity center (MCGC) method is nothing more than an exception to our proposed decision-making technique. It was also demonstrated that the proposal may present a more complete picture of experts' overall evaluations and communicate their preferences by adjusting the quaternion's uncertain parameters, making the group decision-making approach more widely applicable to a certain extent. The method was used to test a vessel's counterflooding capabilities to ensure its practicality and supremacy.

1. Introduction

Multiattribute decision-making (MADM) is one of the most important and ubiquitous real-life activities for selecting a suitable alternative among those required to achieve a certain goal. The information about accessing the alternatives has always been considered to be in the form of real numbers. However, in everyday life, ambiguity and insufficient knowledge make it difficult for a decision-maker to make an appraisal of an object. Zhao [1] created the set pair analysis (SPA) theory, in which certainty and uncertainty are examined as one system, to better handle uncertainties. The essential notions of SPA theory were addressed by Jiang et al. [2]. The fundamental idea behind SPA is to look at the characteristics of a set pair and create a connection number (CN) for them. To address MADM problems with a specified criteria weight and a criteria value that is an interval random variable, Wang and Gong [3] suggested a decision-making approach based on the SPA. Based on cumulative prospect theory and SPA, Hu and Yang [4] suggested a dynamic stochastic MADM. Using the TOPSIS approach, Xie et al. [5] demonstrated a CN under an interval-valued fuzzy set. Aside from this, some academics [6–9] used the SPA to handle fuzzy decision-making problems. Shen et al. [10] defined binary connection numbers (BCN) in SPA and utilized BCN to multiattribute decision-making issues in an interval-valued intuitionistic fuzzy set environment. Cloud theory, proposed by Li [11], an academician of the Chinese Academy of Engineering, is a method for resolving the fuzziness-randomness problem. The theory reveals the intrinsic relationship between fuzziness and randomness, which presented a unique algorithm architecture that simplifies the conversion between qualitative concepts and their quantitative representations. A cloud model is defined by three digital properties (E_x, E_n, H_e), in which E_x is the primary, or most representative, value of a qualitative idea in the domain. The entropy E_n measures a qualitative concept's fuzziness and reflects the concept-accepted value range in the domain. As the entropyE_n, the hyperentropy H_e indicates the dispersion of cloud drops [11, 12].

A cloud model-based multiattribute decision-making (CM-MADM) with Monte Carlo technique is developed to address several challenges occurring in MADM problems [13]. Based on the probability theory and fuzzy set theory, the cloud model can study the detail of fuzziness of a qualitative concept membership function as well as the stochasticity by three numerical characteristics.

Currently, the cloud model is widely applied in the comprehensive evaluation, systemic decision-making, and data mining [14–16]. Many researchers have had positive outcomes in their research areas using the membership cloud gravity center (MCGC) [17], which is a common approach of evaluating a cloud model. In the study on the distribution of earnings from natural resource development, for example, Li and Zhou employed the MCGC model to show that a novel earning distribution strategy may make such distribution fair and square [18]. Combining the fuzzy extended analytical hierarchy process with the MCGC method, Zheng found a better way to manage enterprise knowledge [19]. To accurately evaluate the performance of portable devices, Peng et al. came up with an MCGC-based method [20]. Likewise, Zheng et al. put forward an MCGC-based approach to cybersecurity evaluation by introducing a cloud model to assess the cybersecurity situation [21]. Large-sample group decision-making is now made possible by the boom in big-data and computer technologies. Cloud theory is effective in presenting the opinions of large groups, whereas the dialectic set pair analysis can competently manage a matter's uncertainties on a macrolevel.

The fact that CNs and interval numbers are isomorphic is one of the key reasons why SPA can be utilized frequently in MADM with interval numbers. The CN is characterized by both certainty and uncertainty. The interval number has upper and lower bounds that have been specified, as well as uncertainty that can be arbitrarily valued within its scope. In the CN, the uncertainty coefficient might range with in the interval [−1, 1].

The particle swarm optimization (PSO) is a relatively new notion of combinatorial metaheuristic algorithm which is based on a metaphor of social interaction, namely, bird flocking or fish schooling. In [22], Chatterjee and Siarry considered nonlinear inertia weight variation for dynamic adaptation in particle swarm optimization, where a new variation of PSO model is considered which introduced nonlinear variation of inertia weight along with a particle's old velocity to improve the speed of convergence and fine-tune the search in the multidimensional space.

In this study, we developed cloud model's connection numbers, by utilizing three parameters' interval number containing upper and lower bounds as well as center of gravity. By integrating CNs in SPA, the production of a cloud model's connection numbers reveals how cloud theory renders data expression understandable within a big-data context and exposes the laws governing the uncertainty of overall information. On the theoretical basis of a cloud model and the connection numbers in set pair analysis, we proposed the following: (1) a cloud model-based method determines quaternary connection numbers, which have three digital features (E_x, E_n, H_e) of the cloud model and fully express the model's fuzzy information; (2) we coined an arithmetic weighted average nearness of quaternary connection numbers and put forth an approach to determination of the nearness's weight; (3) we raised a new method of determining the evaluation-index weight, given that the interval number expressed by three parameters can more accurately express an expert's real intention; (4) we leveraged the results from the above three steps to develop a multiattribute group decision-making method based on the connection numbers of a cloud model and through comparative analysis proved that the MCGC model is merely an exception to our proposed decision-making technique; and (5) we verified our method's practicality and superiority by adopting it in the evaluation of a vessel's counterflooding capabilities.

To do so, the rest of the manuscript is summarized as follows: Section 2 gives some overview on the cloud model and CNs. In Section 3, a cloud model's CN method for MADM has been presented under the SPA in which the assessments related to the attributes are taken in the form of quaternary connection numbers (QCNs). This section also reveals that the following: (i) the definition of weighted nearness degree of a QCN, (ii) determination method of weight of a QCN's nearness degree, (iii) determination method of index weight based on three parameters interval number, and (iv) steps of multiattribute group decision-making based on cloud theory for QCNs; and Section 4 gave the comparison of the proposed model and Section 5 studied a numerical example as a case study.

2. Basic Theories on the Cloud Model and Connection Numbers

2.1. Cloud Model Basics. The cloud model is a type of model investigating the uncertain conversion between the qualitative concepts of natural language and their quantitative representations.

Definition 1. Assume that U is a quantitative domain $U = \{x\}$ expressed by precise numerical values; C is the linguistic value connected to U; the membership $\mu_C(x)$, which shows how the x element in U falls under the qualitative concept expressed by C, represents a random number with steady tendency, and its distribution in the domain U is called a membership cloud, or simply "cloud," which can be expressed as

$$\forall x \in U, \exists \mu_C(x) \in [0,1], f\colon x \longrightarrow \mu_C(x). \tag{1}$$

As a critical cloud model, the normal cloud is most effective in expressing linguistic values.

Definition 2. If the random variable x satisfies $x \sim N(E_x, E_n'^2)$ and $E_n' \sim N(E_n, H_e^2)$ and $\mu(x)$ satisfies $\mu(x) =$

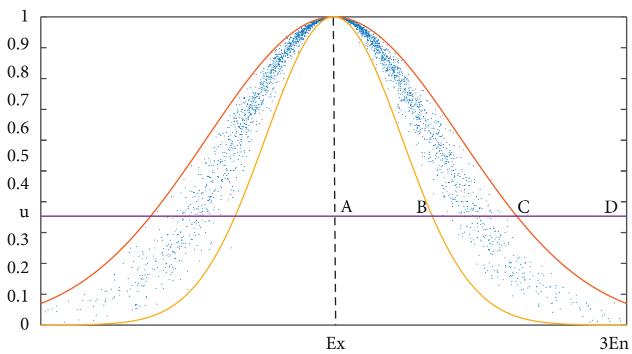

Figure 1: A sketch map of a cloud model.

$e^{-(x-E_x)^2/2E_n'^2}$, then the membership cloud of x in the domain is normal. When $E_n \neq 0$, $y = e^{-(x-E_x)^2/2E_n^2}$ is known as the expectation curve for the normal cloud.

Given that the normal cloud follows the 3σ rule governing the normal distribution, more than 99.73% of cloud drops of the normal random number fall under the $[E_x - 3E_n, E_x + 3E_n]$ range, and the overall features of the cloud model are not affected by the cloud drops outside the range.

As is displayed in Figure 1 (where $u = \sqrt{2}/4$), the digital features of a membership cloud have the following implications [1].

(1) The domain value corresponding to the centroid $A(E_x, \sqrt{2}/4)$ in the membership cloud-covered area reflects the central value of information about fuzzy concepts.

(2) The bandwidth of a membership cloud model's expectation curve indicates the fuzziness of fuzzy concepts.

(3) The randomly distributed variance of a membership corresponding to the point $B(E_x + \sqrt{\ln 8}\, E_n, \sqrt{2}/4)$ on a membership cloud-based expectation curve, or the hyperentropy H_e, suggests the dispersion of the membership cloud.

2.2. Backward Cloud Generator. The backward cloud generator is designed to identify the three digital features (E_x, E_n, H_e) of a cloud model by using the given cloud drops. A variety of ideas about the generator's algorithm have been provided by scholars. Having considered the scale of data for multiattribute group decision-making in practical issues, we offered an optimized Algorithm 1 of the backward cloud generator.

2.3. Connection Number Basics. The connection number is a major instrument in set pair theory. It serves as a connector between a certain number and its range and between macroscopic certainties and microscopic uncertainties. Also, it is a structure function that reflects the relationships of studied subjects under various conditions. Its commonly used form is the ternary connection number.

In [22], Chatterjee and Siarry introduced the concept of an interval number **a** on real number **R** as follows:

$\hat{a} = [a^L, a^U] = \{a\colon a^L \prec a \prec a^U, a \in R\}$, where a^L and a^U are the lower bound and upper bound of the interval, respectively. Sengupta and Pal [23] defined a three-parameter interval as $\hat{a} = [a^L, a*, a^U]$, where a_L is the lower bound, a^* is the center of gravity (the number that has the highest possibility), and a_U is the upper bound of the interval. If $a_L = a^* = a_U$, then the three-parameter interval number is reduced to a real number.

Definition 3. Assuming that A, B, C are real numbers and $i \in [-1, 1]$, $j = -1$, then

$$U = A + Bi + Cj, \tag{2}$$

which is called a ternary connection number and A, B, and C denote the identity, difference, and opposite degrees of any two researched subjects.

Let $A+B+C=N, \mu=U/N, a=A/N, b=B/N, c=C/N\mu$ be regarded as the ternary connection degree:

$$\mu = a + bi + cj, \quad \text{where } a, b, c \in R, a + b + c = 1. \tag{3}$$

Particularly, $U = A + Bi$ is called the binary or identical-different connection number.

In practical decision-making scenarios, the actual identity and difference degrees can be determined on a case-by-case basis, making possible the generation of all forms of the connection number, such as quaternary or quinary connection numbers.

3. Multiattribute Decision-Making Method Based on Cloud Model's Connection Numbers

3.1. Creation of Cloud Model's Connection Numbers. Various uncertain and fuzzy pieces of information must be dealt with in a practical decision-making process. In processing such information, many scholars have created connection numbers according to the expression of information [15]. However, the existing methods of establishing connection numbers find it hard to express the overall features of large-sample data. The creation of a cloud model's connection numbers demonstrates how cloud theory renders data expression reasonable within a big-data context and shows the laws governing the uncertainty of overall information by combining connection numbers in set pair analysis. According to the three implications of a cloud model's digital features mentioned in Section 2.1, the domain value corresponding to the centroid A of the cloud model's expectation curve reflects the central information of fuzzy concepts; that is, the domain value range can be used to develop quaternary connection numbers for the cloud model, which can express the model's uncertain information more accurately. The specific process is as follows.

Step 1: develop the equations for the internal and external envelopes by involving the standardized cloud model (E_x, E_n, H_e):

Input: the quantitative location of N cloud drops in the number field and the certainty of the quantitative concept represented by each cloud drop.
Output: the expectation value E_x, entropy E_n and hyperentropy He of a quantitative concept.
The detailed algorithm is as follows.
Step 1: solve $\hat{E}_x$ and $\hat{E}_n$ through the given cloud drop and the fitting using the least-squares method and the equation of the cloud model's expectation curve $\mu(x) = e^{-(x-E_x)^2/2E_n^2}$;
Step 2: remove the points satisfying $\mu(x) > 0.999$ and mark the remaining number of cloud drops as m;
Step 3: solve $_{En'_i}$ using the equation $_{En'_i} = \sqrt{-(x_i - \hat{E}_x)/2\ln(\mu_i)}$;
Step 4: solve $\hat{H}_e$ with the standard deviation function $\hat{H}_e^2 = 1/m - 1\sqrt{\sum_{i=1}^{m}(_{En'_i} - \hat{E}_n)^2}$;
Step 5: output $\hat{E}_x$, $\hat{E}_n$, and $\hat{H}_e$, which are the expectation value E_x, entropy E_n , and hyperentropy H_e of a certain qualitative concept.

Algorithm 1: The process of reverse cloud generator

$$\begin{cases} y = e^{-\left(\left(x-E_x\right)^2/2\left(E_n-H_e\right)^2\right)}, \\ y = e^{-\left(\left(x-E_x\right)^2/2\left(E_n+H_e\right)^2\right)}. \end{cases} \tag{4}$$

Step 2: given the cloud model's asymmetry, the right half of the internal and external envelopes was extracted for calculation of the corresponding abscissa value when $u = \sqrt{2}/4$:

$$\begin{cases} x_B = E_x + \sqrt{\ln 8}\,(E_n - 3H_e), \\ x_C = E_x + \sqrt{\ln 8}\,(E_n + 3H_e). \end{cases} \tag{5}$$

In light of the 3σ rule, the abscissa of the D point was $x_D = E_x + 3E_n$.

Step 3: ensure that the quaternary connection number satisfies $U = A_1 + B_1 i_1 + C_1 i_2 + D_1 i_3$ and make $i_1, i_2, i_3 \in [-1, 1]$, where

$$\begin{cases} A_1 = E_x, \\ B_1 = \sqrt{\ln 8}\,(E_n - 3H_e), \\ C_1 = 6\sqrt{\ln 8}\,H_e, \\ D_1 = (3 - \sqrt{\ln 8})E_n - 3\sqrt{\ln 8}\,H_e. \end{cases} \tag{6}$$

Upon normalization, it was found that the quaternary identical-different connection number for the cloud model was $\mu = a + bi_1 + ci_2 + di_3$ and $i_1, i_2, i_3 \in [-1, 1]$:

$$\begin{cases} a = \dfrac{A_1}{N}, \\ b = \dfrac{B_1}{N}, \\ c = \dfrac{C_1}{N}, \\ d = \dfrac{D_1}{N}, \\ N = A_1 + B_1 + C_1 + D_1. \end{cases} \tag{7}$$

Built on the research on the abscissa interval of an expectation curve's centroid, the method of creating the quaternary connection number fully takes into account the implications of the cloud model's three digital features, thus expressing the model's uncertain data in a more comprehensive way.

3.2. Definition of the Weighted Nearness Degree of a Quaternary Connection Number. As a concept in fuzzy mathematics, nearness degree measures the extent to which two fuzzy subsets are similar to each other.

Definition 4. Assume $A, B, C \in F(U)$, if the mapping $T: F(U) \times F(U) \longrightarrow [0, 1]$ satisfies the following conditions:

(1) $T(A, B) = T(B, A)$.
(2) $T(A, A) = 1, T(U, \varphi) = 0$.
(3) If $A \subseteq B \subseteq C$, then $T(A, C) \le T(A, B)$ and $T(A, C) \le T(B, C)$.

Then, $T(A, B)$ is known as the nearness degree of A and B fuzzy sets, and T is the nearness function in $F(U)$.

Based on the aforementioned definition of the fuzzy set nearness and the importance of fuzzy information contained in all parts of a quaternary connection number, the nearness of the quaternary connection number is defined.

Definition 5. Assuming that (μ_1, μ_2) are quaternary connection numbers, $\mu_1 = a_1 + b_1 i_1 + c_1 i_2 + d_1 i_3$ and $\mu_2 = a_2 + b_2 i_1 + c_2 i_2 + d_2 i_3$, where $a_1 + b_1 + c_1 + d_1 = 1$, $a_2 + b_2 + c_2 + d_2 = 1$, and $a_1, b_1, c_1, d_1, a_2, b_2, c_2, d_2 \in [0, 1]$; then the nearness of the two connection numbers is

$$\begin{aligned} T(\mu_1, \mu_2) = 1 - \{ & w_a\|a_1 - a_2\| + w_b\|b_1 - b_2\| + w_c\|c_1 - c_2\| \\ & + w_d\|d_1 - d_2\|\}, \end{aligned} \tag{8}$$

where $0 \le w_a, w_b, w_c, w_d \le 1$ and $w_a + w_b + w_c + w_d = 1$. The definition can be straightforwardly proved to meet the three conditions in Definition 3.

3.3. Weight Determination in Definition of a Quaternary Connection Number's Nearness Degree. This section provides a new method of determining the weight in the definition of a quaternary connection number's nearness.

Assuming that, after standardizing the evaluation information of the evaluation index $j(j=1,2,\ldots,m)$ for all plans $\{A_1, A_2, \ldots, A_n\}$, the cloud model's connection number is $\mu_{ij} = a_{ij} + b_{ij}i_1 + c_{ij}i_2 + d_{ij}i_3$ and $i_1, i_2, i_3 \in [-1,1]$, where $i = 1,2,\ldots,n$, $j = 1,2,\ldots,m$. Let the ideal cloud model's connection number of the indexes $j(j=1,2,\ldots,m)$ in the model be $\mu_j^0 = a_j^0 + b_j^0 i_1 + c_j^0 i_2 + d_j^0 i_3$ and its average cloud model's connection number be $\overset{j}{\mu} = \overset{j}{a} + \overset{j}{b} i_1 + \overset{j}{c} i_2 + \overset{j}{d} i_3$, where

$$\begin{cases} \overline{a}_j = \dfrac{1}{n}\displaystyle\sum_{i=1}^{n} a_{ij}, \\ \overline{b}_j = \dfrac{1}{n}\displaystyle\sum_{i=1}^{n} b_{ij}, \\ \overline{c}_j = \dfrac{1}{n}\displaystyle\sum_{i=1}^{n} c_{ij}, \\ \overline{d}_j = \dfrac{1}{n}\displaystyle\sum_{i=1}^{n} d_{ij}. \end{cases} \tag{9}$$

The optimized model is developed as follows:

$$\begin{aligned} \min H &= w_{aj}^2\left(a_j^0 - \overline{a}_j\right)^2 + w_{bj}^2\left(b_j^0 - \overline{b}_j\right)^2 + w_{cj}^2\left(c_j^0 - \overline{c}_j\right)^2 \\ &\quad + w_{dj}^2\left(d_j^0 - \overline{d}_j\right)^2 \\ \text{s.t.} &\, w_{aj} + w_{bj} + w_{cj} + w_{dj} = 1, 0 \le w_{aj}, w_{bj}, w_{cj}, w_{dj} \le 1. \end{aligned} \tag{10}$$

The Lagrange function $L = H - \lambda(w_{aj} + w_{bj} + w_{cj} + w_{dj} - 1)$ is created and solved:

$$\frac{\partial L}{\partial \lambda} = 0, \frac{\partial L}{\partial w_{aj}} = 0, \frac{\partial L}{\partial w_{bj}} = 0, \frac{\partial L}{\partial w_{cj}} = 0, \frac{\partial L}{\partial w_{dj}} = 0. \tag{11}$$

Then, we obtain

$$\begin{cases} w_{aj} = \dfrac{1}{\left[G\cdot\left(\overline{a}_j - a_j^0\right)^2\right]}, \\ w_{bj} = \dfrac{1}{\left[G\cdot\left(\overline{b}_j - b_j^0\right)^2\right]}, \\ w_{cj} = \dfrac{1}{\left[G\cdot\left(\overline{c}_j - c_j^0\right)^2\right]}, \\ w_{dj} = \dfrac{1}{\left[G\cdot\left(\overline{d}_j - d_j^0\right)^2\right]}, \end{cases} \tag{12}$$

where

$$G = \frac{1}{\left(\overline{a}_j - a_j^0\right)^2} + \frac{1}{\left(\overline{b}_j - b_j^0\right)^2} + \frac{1}{\left(\overline{c}_j - c_j^0\right)^2} + \frac{1}{\left(\overline{d}_j - d_j^0\right)^2}. \tag{13}$$

The weight determination method is designed to develop a nonlinear planning model using the objective function or the quadratic sum of the difference between the expected and ideal values. The smaller the objective function, the more reasonable the corresponding plan for assigning the weight. In this method, the difference between the expected and ideal values of group decision-making information is fully considered, which can objectively show how each part of the connection number is prioritized in group opinions by specific evaluation indices.

3.4. Method of Determining the Index Weight Based on the Interval Number Expressed by Three Parameters. In the practical decision-making process, decision-makers tend to evaluate information in the form of interval numbers, given that experts find it complicated and uncertain to describe the importance of indices. When a parameter is expressed by an interval number expressed by two parameters, the opportunity to obtain a value within the whole interval is believed to be equal, which would produce a result far from the real intention of experts. Hence, the section offers a novel method of determining the index weight based on the interval number expressed by three parameters.

Assume that, in the hundred-mark system, the score of the index $j(j=1,2,\ldots,m)$ given by the expert $S_i(i=1,2,\ldots,n)$ is $[\underline{V}_{ij}, \widetilde{V}_{ij}, \overline{V}_{ij}]$; then the estimated weighted value of the interval number expressed by three parameters $[\underline{w}_{ij}, \widetilde{w}_{ij}, \overline{w}_{ij}]$ can be obtained upon normalization through the following equation:

$$\underline{w}_{ij} = \frac{\underline{V}_{ij}}{\sum_{j=1}^{m} \underline{V}_{ij}}, \widetilde{w}_{ij} = \frac{\widetilde{V}_{ij}}{\sum_{j=1}^{m} \underline{V}_{ij}}, \overline{w}_{ij} = \frac{\overline{V}_{ij}}{\sum_{j=1}^{m} \underline{V}_{ij}}, \tag{14}$$

where $\widetilde{w}_{ij}$ is the gravity center of the interval number. Let $d_j^{\pm} = \overline{w}_j^+ - \underline{w}_j^-$ be the maximal measure of the upper and lower bounds of the index j's estimated weights, where $\underline{w}_j^- = \min\left\{\underline{w}_{1j}, \underline{w}_{2j}, \ldots, \underline{w}_{nj}\right\}$ represents the minimal value of the lower bound of the index's $j(j=1,2,\cdots m)$ estimated values, while $\overline{w}_j^+ = \max\left\{\overline{w}_{1j}, \overline{w}_{2j}, \ldots, \overline{w}_{nj}\right\}$ is the maximal value of the upper bound of the index's $j(j=1,2,\ldots,m)$ estimated values.

Let the weighted preference deviation of the expert s_i be h_{si}:

$$\begin{aligned} h_{si} &= \frac{w_{ij}^* - \widetilde{w}_{ij}}{d_j^{\pm}} = \frac{w_{ij}^* - \widetilde{w}_{ij}}{\overline{w}_j^+ - \underline{w}_j^-} = \frac{\sum_{j=1}^{m}\left(w_{ij}^* - \widetilde{w}_{ij}\right)}{\sum_{j=1}^{m}\left(\overline{w}_j^+ - \underline{w}_j^-\right)} \\ &= \frac{\sum_{j=1}^{m} w_{ij}^* - \sum_{j=1}^{m} \widetilde{w}_{ij}}{\sum_{j=1}^{m}\left(\overline{w}_j^+ - \underline{w}_j^-\right)} = \frac{1 - \sum_{j=1}^{m} \widetilde{w}_{ij}}{\sum m\left(\overline{w}_j^+ - \underline{w}_j^-\right) j = 1}, \end{aligned} \tag{15}$$

where w_{ij}^* is what the expert S_i believes the real weight of the index $j(j=1,2,\ldots,m)$ is and h_{si} is the ratio of the index j's weight error to $d_j^{\pm}$ given by the expert s_i. (Note: the expert's weight error is measured by the difference between the gravity center of the interval number expressed by three parameters and the real weight.) Each evaluating expert may regard h_{si} consistently with each evaluation index, expressed as $j\,(j = 1, 2, \ldots, m)$. Therefore, the estimated value of j's weight, expressed as $w_j^*\,(j = 1, 2, \ldots, m)$, is

$$\hat{\omega}_j^* = h_s\left(\overline{w}_j^+ - \underline{w}_j^-\right) + \widetilde{\omega}_j, \tag{16}$$

where $\widetilde{\omega}_j$ is an aggregation of $\widetilde{\omega}_{ij}\,(i = 1, 2, \ldots, n)$ and h_s is an aggregation of $\hat{h}_{si}$ involving all participating experts. The equation $\sum_{j=1}^{m} \hat{\omega}_j = 1$ can be easily proved.

Definition 6. Assuming that f_k: $R^n \longrightarrow R$ is an n-element function, $k = (k_1, k_2, \ldots, k_n)^T$ is a weighted vector associated with f_k and satisfies $\sum_{i=1}^{n} k_i = 1, k_i \geq 0$ and $i = 1, 2, \ldots, n$. If $f_k(a_1, a_2, \ldots, a_n) = \sum_{i=1}^{n} k_i b_i$, where b_i is the number of i in $a_1, a_2, \ldots, a_n$, a progression that goes from largest to smallest, then the function f_k denotes the orderly weighted average (OWA) operator in the n dimension.

The definition suggests that the weighted coefficient k_i of the OWA operator is associated with the i spot in $a_1, a_2, \ldots, a_n$, rather than the number a_i. When $k = (1/n, 1/n, \ldots, 1/n)^T$, the OWA operator can be reduced to a simple arithmetic average operator. Thus, the aggregation can be conducted by using the following simplified equation.

$$h_s = \frac{1}{n}\sum_{i=1}^{n} h_{si}, \widetilde{\omega}_j = \frac{1}{n}\sum_{i=1}^{n} \widetilde{\omega}_{ij}. \tag{17}$$

And, after they are substituted into (14), the estimated aggregated value of the index weight, expressed as $\hat{\omega}_j^*$, can be calculated.

3.5. Steps of Multiattribute Group Decision-Making Based on Cloud Model's Quaternary Connection Number. Plan sorting has always been of critical importance in multiattribute decision-making methods. The section provides a method of this kind by ranking plans based on the calculation of the weighted arithmetic average nearness of the quaternary connection number and ideal connection number in different cloud models. The specific steps are as follows.

Step 1: have experts score of all plans in light of the evaluation-index system and standards, generate standardized cloud drops by indices oriented to benefits and costs, translate these cloud drops into a cloud model by using the backward cloud generator constructed according to Section 2.2, and subsequently create digital features.

Step 2: use the method of creating a cloud model's connection numbers, as indicated in Section 3.1, to construct the quaternary connection number for a cloud model founded on scoring by experts, and obtain a connection number-based decision-making matrix.

Step 3: develop the ideal cloud model by each index for the creation of the quaternary connection number, and, as instructed in Section 3.3, calculate the weight of each part of the cloud model's quaternary connection number.

Step 4: calculate the weight of all indices in the given index system as suggested in Section 3.4.

Step 5: measure the nearness of all proposed plans and the ideal plan by using (8) and (12), respectively, and calculate T_{ip}, the overall nearness of all these plans, through the following equation, where $i = 1, 2, \ldots, M$ (M is the total of plans):

$$T_{ip} = \sum_{j=1}^{t} w_j T_j\left(\mu_{ij}, \mu_{pj}\right). \tag{18}$$

In this equation, T is the total number of evaluation indices, w_j indicates the weight of each index, and μ_{pj} denotes the quaternary connection number of each index for the ideal plan.

Step 6: rank plans based on their overall nearness T_{ip}.

4. Comparative Analysis between the MCGC Model and the Decision-Making Method Based on Cloud Model's Quaternary Connection Number

The MCGC method is typical for evaluating a system using a cloud model. Specifically, if the system status of m evaluation indices is described by the m-dimensional comprehensive cloud, then a changing system status would make the comprehensive cloud and its gravity center altered. Therefore, a possible evaluation way is through the weighted deviation of the comprehensive cloud gravity center and ideal cloud gravity center under a certain status. Also, proposed plans can be sorted based on the weighted deviation between their comprehensive cloud gravity center and that of the ideal plan. The detailed process is as follows [5].

(1) For a system to be evaluated, calculate the gravity center vector G^0 of the m-dimensional comprehensive cloud for the ideal plan A_0 through

$$G^0 = \left(G_1^0, G_2^0, \ldots, G_m^0\right) = \mathbf{a}^0 \times \mathbf{b}^0, \tag{19}$$

where $\mathbf{a}^0 = (E_{x1}^0, E_{x2}^0, \ldots, E_{xm}^0)$ is the position vector of the m-dimensional comprehensive cloud gravity center and its component is the expectation value of each index; $\mathbf{b}^0 = (b_1^0, b_2^0, \ldots, b_m^0)$ represents the altitude vector of the comprehensive gravity center, which is a determined value in a to-be-evaluated system and is commonly known as the weight value of each index [8].

(2) For a given proposed plan A_i, provide its corresponding m-dimensional cloud gravity center vector, expressed as G^i, through the equation $G^i = (G_1^i, G_2^i, \ldots, G_m^i) = \mathbf{a}^i \times \mathbf{b}^i$, where $i = 1, 2, \ldots, n$.

(3) Give the definition of deviation of G^i and G^0 in the proposed plan A_i, calculate the deviation using equation (17), and evaluate A_i based on the weighted deviation.

$$\theta_i = \sum_{j=1}^{m} w_j \theta_j^i, \quad i = 1, 2, \ldots, n, \tag{20}$$

where

$$\theta_j^i = \begin{cases} \left(G_j^0 - G_j^i\right)/G_j^0 G_j^i < G_j^0 \\ \left(G_j^i - G_j^0\right)/G_j^i G_j^i \geq G_j^0 \end{cases} \quad j = 1, 2, \ldots, m. \tag{21}$$

Building on the aforementioned MCGC logic and steps, we found the following.

Theorem 1. *For a cloud model's quaternary connection number $\mu = a + bi_1 + ci_2 + di_3$ and $i_1, i_2, i_3 \in [-1, 1]$, when $i_1 = i_2 = i_3 = 0$, the evaluation method based on a cloud model's quaternary connection number is equivalent to the MCGC model.*

Proof. As is known in the method of creating a cloud model's quaternary connection number (see (7)), $a = A_1/N, N = A_1 + B_1 + C_1 + D_1, A_1 = E_x$. When $i_1 = i_2 = i_3 = 0$, the quaternion needs not to be normalized, meaning that it is reduced to $\mu = E_x$. And, for the proposed plan A_i, all its indices are reduced to the cloud model's expectation values, expressed as $E_{x1}^i, E_{x2}^i, \ldots, E_{xm}^i$.

As to the cloud gravity center's structure, A_i's position vector $\mathbf{a}^i = (E_{x1}^i, E_{x2}^i, \ldots, E_{xm}^i)$ is, in essence, the expected value of each index, and the altitude vector $\mathbf{b}^i = (b_1^i, b_2^i, \ldots, b_m^i)$ is the determined weighted value of each index. For a particular evaluation system, the index weight, once generated, is a determined value. Hence, each component of A_i's cloud gravity vector $G^i = (G_1^i, G_2^i, \ldots, G_m^i) = \mathbf{a}^i \times \mathbf{b}^i$ is the constant multiple of an expected value or $G^i = (w_1 E_{x1}^i, w_2 E_{x2}^i, \ldots, w_m E_{xm}^i)$, where $w_1, w_2, \ldots, w_m$ are weights of indices.

As shown in (18) and (21), θ_j^i is determined by investigating the extent to which the two weighted vectors, namely, $(w_1 E_{x1}^i, w_2 E_{x2}^i, \ldots, w_m E_{xm}^i)$ and $(w_1 E_{x1}^0, w_2 E_{x2}^0, \ldots, w_m E_{xm}^0)$, deviate from each other. In the evaluation method based on a cloud model's connection number, the overall nearness T_{ip} is determined by observing the deviation between $(E_{x1}^i, E_{x2}^i, \ldots, E_{xm}^i)$ and $(E_{x1}^0, E_{x2}^0, \ldots, E_{xm}^0)$. Therefore, when $i_1 = i_2 = i_3 = 0$, the two evaluation approaches are in practice equivalent.

The abovementioned theorem and proof indicate that the following.

(1) The MCGC method is an exception to the evaluation method based on a cloud model's connection number, where $i_1 = i_2 = i_3 = 0$. For the latter, the quaternary identical-different connection number demonstrates how the expectation value plays its role in index evaluation information and takes into account the full impact of the model's entropy and hyperentropy on evaluation.

(2) The steps of evaluation based on a cloud model's quaternary connection number showed that, in a practical decision-making process, expressing expert preferences through appropriate adjustments to (i_1, i_2, i_3) can offset the evaluation error arising from how the quaternary connection number's weight relies merely on objective numerical values rather than expert preferences.

(3) Compared with the MCGC approach, the evaluation method based on a cloud model's quaternary connection number collects more information from experts, thus producing more science-based results. Beyond that, (i_1, i_2, i_3) in the connection number can be tailored to the needs of the application context, which makes results better aligned with the operating condition of the evaluation system. That is how the proposed method can be further applied across different scenarios. □

5. Case Study

Among the damage control capabilities of a vessel, counterflooding is vital. There are four indices to evaluate a ship's overall counterflooding performance, namely, the cabin's capabilities of leak stoppage, bearing, drainage, and balancing. All these indices are oriented to benefits. Eight experts were invited to score the importance of these four evaluation indices in the hundred-mark system using the interval number expressed by three parameters, as is displayed in Table 1.

Table 1 is then normalized using (14), as shown in Table 2.

Using (13), we calculated the determined weight deviation degrees of experts, which were [−0.2186 −0.1976 −0.3100 −0.1524 −0.1993 −0.2141 −0.1706 −0.1857]. And upon the aggregation of the OWA operator, we input these values into (15) and obtained

$$\begin{aligned} h_s &= -0.2060, \widetilde{w}_1 = 0.1808.\widetilde{w}_2 = 0.2286.\widetilde{w}_3 \\ &= 0.3121, \widetilde{w}_4 = 0.3184. \end{aligned} \tag{22}$$

Lastly, with (16), we measured the estimated weight value of these four counterflooding indices, which were

$$\hat{w}_1^* = 0.1727, \hat{w}_2^* = 0.2193, \hat{w}_3^* = 0.2996, \hat{w}_4^* = 0.3084. \tag{23}$$

In addition, we had these experts' score of the counterflooding performance of three vessels, and each of them was required to provide the score and corresponding membership degree of the four indices in ideal and actual scenarios. Then, the backward cloud generator, as instructed in Section 2.2, was employed to translate the cloud drops offered by experts into a cloud model, whose digital features

Table 1: Scoring of the importance of a vessel's counterflooding indices.

Expert no	Cabin leak stoppage capability	Cabin bearing capability	Cabin drainage capability	Cabin balancing capability
s_1	[40, 42, 46]	[51 53 54]	[71 74 80]	[74 77 82]
s_2	[39, 41, 44]	[54 55 60]	[71 75 79]	[71 73 80]
s_3	[43, 44, 46]	[50 56 57]	[69 72 77]	[71 75 79]
s_4	[40, 42, 45]	[51 52 55]	[70 73 75]	[76 77 78]
s_5	[38, 40, 43]	[49 51 56]	[74 76 83]	[72 75 81]
s_6	[40, 43, 47]	[53 55 58]	[73 74 82]	[75 79 84]
s_7	[44, 45, 49]	[53 56 57]	[72 74 81]	[73 75 82]
s_8	[45, 48, 50]	[55 58 59]	[75 77 84]	[75 76 83]

Table 2: Normalized scoring of the importance of a vessel's counterflooding indices.

Expert no.	Cabin leak stoppage capability	Cabin bearing capability	Cabin drainage capability	Cabin balancing capability
s_1	[0.1695 0.1780 0.1949]	[0.2161 0.2246 0.2288]	[0.3008 0.3136 0.3390]	[0.3136 0.3263 0.3475]
s_2	[0.1660 0.1745 0.1872]	[0.2298 0.2340 0.2553]	[0.3021 0.3191 0.3362]	[0.3021 0.3106 0.3404]
s_3	[0.1845 0.1888 0.1974]	[0.2146 0.2403 0.244]	[0.2961 0.3090 0.3305]	[0.3047 0.3219 0.3391]
s_4	[0.1688 0.1772 0.1899]	[0.2152 0.2194 0.2321]	[0.2954 0.3080 0.3165]	[0.3207 0.3249 0.3291]
s_5	[0.1631 0.1717 0.1845]	[0.2103 0.2189 0.2403]	[0.3176 0.3262 0.3562]	[0.3090 0.3219 0.3476]
s_6	[0.1660 0.1784 0.1950]	[0.2199 0.2282 0.2407]	[0.3029 0.3071 0.3402]	[0.3112 0.3278 0.3485]
s_7	[0.1818 0.1860 0.2025]	[0.2190 0.2314 0.2355]	[0.2975 0.3058 0.3347]	[0.3017 0.3099 0.3388]
s_8	[0.1800 0.1920 0.2000]	[0.2200 0.2320 0.2360]	[0.3000 0.3080 0.3360]	[0.3000 0.3040 0.3320]

Table 3: Digital features of a cloud model for evaluating a vessel's counterflooding performance.

Vessel no.	Cabin leak stoppage capability	Cabin bearing capability	Cabin drainage capability	Cabin balancing capability
V_0	[85.20, 18.70, 1.20]	[83.40 17.90 1.30]	[86.50 19.20 2.10]	[82.40 11.30 1.70]
V_1	[83.70 19.10 1.50]	[84.10 18.90 1.41]	[83.20 14.50 3.11]	[81.70 10.10 1.54]
V_2	[85.70 18.20 2.10]	[81.50 16.50 1.00]	[85.70 17.10 2.30]	[82.60 12.10 1.60]
V_3	[84.50 17.80 1.80]	[82.90 18.20 1.20]	[87.30 21.10 1.40]	[80.70 12.30 1.43]

Table 4: Connection numbers of the cloud model for evaluating the ideal counterflooding capabilities of vessel V_0.

Evaluation indices	Cloud model's connection number values by indices
Cabin leak stoppage capability	$0.6030 + 0.1541i_1 + 0.0735i_2 + 0.1694i_3$
Cabin bearing capability	$0.6083 + 0.1473i_1 + 0.0820i_2 + 0.1624i_3$
Cabin drainage capability	$0.6003 + 0.1291i_1 + 0.1261i_2 + 0.1445i_3$
Cabin balancing capability	$0.7085 + 0.0769i_1 + 0.1265i_2 + 0.0881i_3$

Table 5: Connection numbers of the cloud model for evaluating the ideal counterflooding capabilities of vessel V_1.

Evaluation indices	Cloud model's connection number values by indices
Cabin leak stoppage capability	$0.5936 + 0.1493i_1 + 0.0920i_2 + 0.1650i_3$
Cabin bearing capability	$0.5973 + 0.1502i_1 + 0.0866i_2 + 0.1658i_3$
Cabin drainage capability	$0.6567 + 0.0588i_1 + 0.2124i_2 + 0.0721i_3$
Cabin balancing capability	$0.7295 + 0.0706i_1 + 0.1190i_2 + 0.0810i_3$

Table 6: Connection numbers of the cloud model for evaluating the counterflooding capabilities of vessel V_3.

Evaluation indices	Cloud model's connection number values by indices
Cabin leak stoppage capability	$0.6108 + 0.1223i_1 + 0.1295i_2 + 0.1374i_3$
Cabin bearing capability	$0.6221 + 0.1486i_1 + 0.0660i_2 + 0.1632i_3$
Cabin drainage capability	$0.6174 + 0.1122i_1 + 0.1434i_2 + 0.1270i_3$
Cabin balancing capability	$0.6947 + 0.0885i_1 + 0.1164i_2 + 0.1003i_3$

Table 7: Connection numbers of the cloud model for evaluating the ideal counterflooding capabilities of vessel V_4.

Evaluation indices	Cloud model's connection number values by indices
Cabin leak stoppage capability	$0.6128 + 0.1297i_1 + 0.1129i_2 + 0.1446i_3$
Cabin bearing capability	$0.6029 + 0.1531i_1 + 0.0755i_2 + 0.1685i_3$
Cabin drainage capability	$0.5797 + 0.1618i_1 + 0.0804i_2 + 0.1781i_3$
Cabin balancing capability	$0.6862 + 0.0982i_1 + 0.1052i_2 + 0.1103i_3$

are shown in Table 3. Among others, V_0 represents the ship equipped with ideal counterflooding capabilities.

Adopting the method of establishing a cloud model's connection number, as displayed in Section 3.1, we obtained

Table 8: Weights of the connection number's identical and three difference degrees in each evaluation index.

Evaluation indices	w_a	w_b	w_c	w_d
Cabin leak stoppage capability	0.9604	0.0174	0.0050	0.0172
Cabin bearing capability	0.8677	0.0587	0.0183	0.0553
Cabin drainage capability	0.2732	0.2574	0.2281	0.2412
Cabin balancing capability	0.5622	0.1811	0.0847	0.1720

the following decision-making tables, as shown in Tables 4–8.

The weights of the connection number's identical and three difference degrees in each evaluation index were calculated, as instructed in Section 3.3, and are shown as follows.

According to (18), the nearness degrees between the three vessels' counterflooding capabilities and their ideal performance were $T_1 = 0.9902, T_2 = 0.9682, T_3 = 0.9780$, respectively. That suggested that vessel V_1 boasted the strongest counterflooding capabilities, followed by vessel V_3 and vessel V_2, consistently with the practical scenario.

6. Conclusions

The quantitative analysis of uncertain and fuzzy information has always been important in information processing. Quantifying such information in group decision-making would lead to reasonable and science-based results. Cloud theory and set pair analysis have made great contributions to the research area. In this paper, based on the strengths of a cloud model and the connection number method in processing uncertain data, we (1) proposed a new cloud model-based method of establishing a quaternary connection number, which has the model's three digital features (E_x, E_n, H_e) that render the expression of the model's uncertain information more accurately and comprehensively; (2) we defined a new weighted arithmetic average nearness degree of the quaternary connection number and provided specific steps to determine the weight of such a nearness degree; (3) we offered a novel method of determining the weight of an index based on interval numbers expressed by three parameters, given the fact that the deviation degree remains unchanged when each expert determines the index weight; (4) we proposed an innovative multiattribute group decision-making method built on a cloud model's connection number and through comparative analysis proved that the MCGC method is an exception to our proposed decision-making method. The proposed approach can provide a fuller picture of the overall evaluation made by experts and express their preferences through adjustments to the quaternary connection number's uncertain parameters, which makes the group decision-making method more broadly applicable. Also, the technique can be applied to decision-making involving large-sample data and to the decision-making context where evaluation values are measured through modal particles. Nonetheless, when it comes to an application context, it awaits more research efforts to find out how to translate these particles into a cloud model reasonably and make sensible adjustments to the values (i_1, i_2, i_3) in the model's connection number, so that the resulting decisions better suit the context [24–29].

Abbreviations

MCGC:	Membership cloud gravity center
MADM:	Multiattribute decision-making
SPA:	Set pair analysis
CN:	Connection number
BCN:	Binary connection number
E_n:	Entropy
H_e:	Hyperentropy
CM-MADM:	Cloud model-based multiattribute decision-making
PSO:	Particle swarm optimization
QCNs:	Quaternary connection numbers
U:	Quantitative domain
$\mu_C(x)$:	Membership
$F(U)$:	Set of fuzzy sets
$T\backslash(A, B)$:	Nearness degree of A and B
M:	Total number of planes
V_0:	Ideal counterflooding capabilities.

Data Availability

All data, models, and codes generated or used during the study are included within the submitted article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] K. Zhao, "Set pair and set pair analysis-a new concept and systematic analysis method," in *Proceedings of the National Conference on System Theory and Regional Planning*, pp. 87–91, Zhengzhou, China, May 1989.

[2] Y. L. Jiang, C. F. Xu, Y. Yao, and K. Q. Zhao, "Systems information in set pair analysis and its applications," *Proceedings of 2004 international conference on machine learning and cybernetics*, vol. 3, pp. 1717–1722, 2004.

[3] J. Q. Wang and L. Gong, "Interval probability stochastic multi-criteria decision-making approach based on set pair analysis," vol. 24, pp. 1877–1880, 2009.

[4] J. Hu and L. Yang, "Dynamic stochastic multi-criteria decision-making method based on cumulative prospect theory and set pair analysis," *Systems Engineering Procedia*, vol. 1, pp. 432–439, 2011.

[5] Z. Xie, F. Zhang, J. Cheng, and L. Li, "Fuzzy multi-attribute decision making methods based on improved set pair analysis," *Sixth international symposium on computational intelligence and design*, vol. 2, pp. 386–389, 2013.

[6] W. ChangJian, "Application of the set pair analysis theory in multiple attribute decision-making," *Journal of Mechanical Strength*, vol. 6, p. 029, 2007.

[7] S. Fu and H. Zhou, "Triangular fuzzy number multi-attribute decision-making method based on set pair analysis," *Journal of Software Engineering*, vol. 11, no. 1, pp. 116–122, 2016.

[8] R. Yue, Z. Wang, and A. Peng, "Multi-attribute group decision making based on set pair analysis," *International Journal of Advancements in Computing Technology*, vol. 4, no. 10, pp. 205–213, 2012.

[9] J. Yang, J. Zhou, L. Liu, Y. Li, and Z. Wu, *Similarity Measures between Connection Numbers of Set Pair Analysis*, Springer, Berlin, pp. 63–68, 2008.

[10] Q. Shen, X. Huang, Y. Liu, Y. Jiang, and K. Zhao, "Multi-attribute decision making based on the binary connection number in set pair analysis under an interval-valued intuitionistic fuzzy set environment," *Soft Computing*, vol. 24, no. 10, pp. 7801–7809, 2020.

[11] D. Y. Li, H. J. Meng, and X. M. Shi, "Membership clouds and membership cloud generators[J]," *Journal of Computer Research and Development*, vol. 32, no. 6, pp. 16–21, 1995.

[12] D. Y. Li, "Uncertainty in knowledge representation[J]," *Engineering and Science*, vol. 2, no. 10, pp. 73–79, 2000.

[13] L. Ren, L. He, Y. Chen, P. Tian, and J. Liu, "A cloud model based multi-attribute decision making approach for selection and evaluation of groundwater management schemes," *J Hydrology*, vol. 555, 2017.

[14] G. R. Su, B. S. Jia, P. Wang et al., "Risk identification of coal spontaneous combustion based on COWA modified G1 combination weighting cloud model[J]," *Scientific Reports*, vol. 2, no. 1, pp. 1–7, 2022.

[15] M. Guo, J. W. Zhao, D. Pan, M. Sun, Y. Zhou, and B Yan, "Normal cloud model theory-based comprehensive fuzzy assessment of wooden pagoda safety," *Journal of Cultural Heritage*, vol. 55, no. 3, pp. 1–10, 2022.

[16] S. L. Wang, D. R. Li, W. Z. Shi, and W. Xinzhou, "Cloud model-based spatial data mining," *Geographical Information Science*, vol. 9, no. 2, pp. 67–78, 2003.

[17] W. J. Wu, H. J. Cheng, and N. Cao, "The application of cloud barycenter theory to air defense forces operational capability evaluation model," *Fire Control and Command Control*, vol. 30, no. 4, pp. 82–84, 2005.

[18] T. Li and J. S. Zhou, "Study on the distribution of mineral resources development revenue based on Shapley value of cloud center of gravity," *China Mining Magazine*, vol. 29, no. 12, pp. 55–60, 2020.

[19] J. L. Zheng, "Enterprise knowledge management application evaluation based on cloud gravity center model and fuzzy extended AHP," *Journal of Computers*, vol. 6, no. 6, pp. 1110–1116, 2011.

[20] W. S. Peng, W. Wu, C. Li, and Q. Li, "Performance evaluation of man-portable devices based on the cloud center of gravity," *Journal of Physics: Conference Series*, vol. 1955, Article ID 012124, 2021.

[21] R. J. Zheng, W. Y. Wei, M. C. Zhang, and W. Qingtao, "Network security situation evaluation strategy based on cloud gravity center judgment," *Journal of Networks*, vol. 9, no. 2, pp. 283–290, 2014.

[22] A. Chatterjee and P. Siarry, "Nonlinear inertia weight variation for dynamic adaptation in particle swarm optimization," *Computers & Operations Research*, no. 3, pp. 859–871, 2006.

[23] A. Sengupta and T. K. Pal, "On comparing interval numbers," *European Journal of Operational Research*, vol. 127, no. 1, pp. 28–43, 2000.

[24] L. Kuai, X. Y. Fei, J. s Jiang et al., "A novel evaluation system of psoriasis curative effect based on bayesian maximum entropy weight self-learning and extended set pair analysis," *Evidence-based Complementary and Alternative Medicine*, pp. 1–13, 2021.

[25] X. Li, W. Q. Zhang, X. Wang, Z. Wang, and C Pang, "Evaluation on the risk of water inrush due to roof bed separation based on improved set pair analysis–variable fuzzy sets," *ACS Omega*, vol. 7, no. 11, pp. 9430–9442, 2022.

[26] X. M. Liu and K. Q. Zhao, "Quadratic-connection-number-based method and its applications for multiple attributes decision-making with interval numbers," *Fuzzy Systems and Mathematics*, no. 5, pp. 115–120, 2011.

[27] W. J. Wang, "Connection numbers method for ranking interval number," *Computer Engineering and Design*, no. 8, pp. 2055–2057, 2009.

[28] K. Kumar and H. Garg, "Connection number of set pair analysis based TOPSIS method on intuitionistic fuzzy sets and their application to decision making," *Applied Intelligence*, no. 8, pp. 2112–2119, 2018.

[29] D. Luo and X. Wang, "The multi-attribute grey target decision method for attribute value within three-parameter interval grey number," *Applied Mathematical Modelling*, vol. 36, no. 5, pp. 1957–1963, 2012.