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Multi-Dimensional Cloud Model-Based Assessment and Its Application to the Risk of Supply Chain Financial Companies

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ABSTRACT

The multi-dimensional cloud model is proposed as the expansion of the one-dimensional cloud model. The features of ambiguity and stochasticity in complex information situations are considered; thus, this optimized model can be utilized upon multiple value classifications and ordering via which the objects' attributes of physical and social can be reflected. Therefore, this promoted model is wildly used. This paper provides a knowledge graph by reviewing the theoretical research of the multi-dimensional cloud model and its related bibliographies, and Cite Space is applied here to give a visualization conclusion. In recent years, a multitude of theories and methods have emerged to address the challenges posed by fuzzy and stochastic uncertainty in various domains, such as image segmentation, data mining, prediction techniques, and comprehensive evaluation of multiple metrics and dimensions using uncertain linguistic variables.

KEYWORDS

Cloud Model, Fuzzy Sets, Multi-Dimensional Cloud Model, Natural Language

INTRODUCTION

The cloud model has been applied in various domains, including decision-making, pattern recognition, data mining, and expert systems. It allows for the modeling and reasoning of uncertain and imprecise information, enabling more accurate and robust analysis of complex problems. Many concepts in real-world problems need to be described by multiple metrics, i.e., multi-attribute, multidimensional problems. The traditional cloud model normally suffers from an evaluation process, thus as the size of the data set increases, its operation efficiency decreases; there also exists a dilemma that biased evaluation results may yield when there is a large difference in the scales of each evaluation level interval. To solve such problems, a multidimensional cloud model can be considered (Li & Du, 2017).

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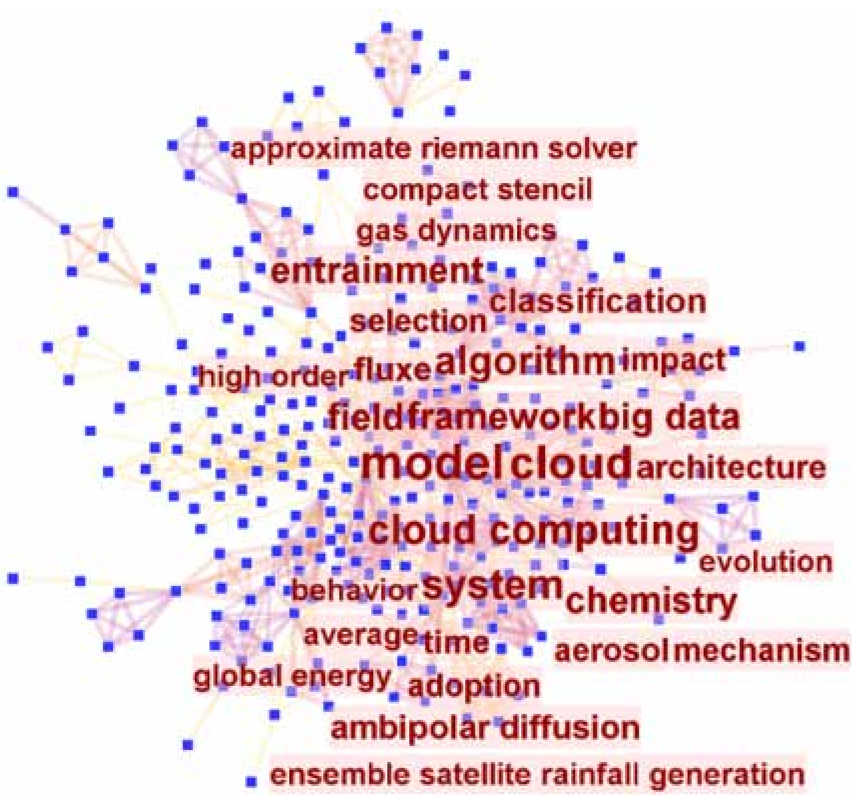
Further, CiteSpace visualization is used here to present the structure, and distributional characteristics for the research of a multidimensional cloud model. CiteSpace information visualization software can present the new dynamics of a certain scientific field in future developments (Chen, 2006) and draw a visual analysis chart of literature author collaboration, research institution collaboration, and literature keyword co-occurrence. By analyzing the size and number of nodes in the graph, as well as the density of connecting lines between nodes, the current research hotspots and future research trends in this field are analyzed.

Keywords are a cluster of natural language words with substantial meaning that express the thematic characteristics of the content of the article. Reading the literature first, locating the keyword section can yield the article's theme, research object, research methodology, etc. Similarly, search keywords can realize the paper's information to find and summarize. Thus, the node information is set as keywords in CiteSpace and visualized as a graph; secondly, a series of intuitive knowledge graphs are used to show the hot keywords of the multidimensional cloud model and their evolution direction in foreign research. Keyword co-occurrence analysis graph in Web of Science (WoS) regarding multidimensional cloud modeling (see Figure 1), where intricate solid lines come together to form dots (nodes) that indicate how many keywords appear in the literature. The larger the dot, the higher the frequency of the keyword, and the thickness of the solid line connecting the dots indicates the strength of the link between the keywords; the thicker the solid line, indicating that the keywords appear in the same article, the greater the intensity (Chen, 2016).

Figure 1 demonstrates the co-occurrence graph of the terms *cloud model*, *cloud computing*, *multidimensional*, *multidimensional cloud*, and *data mining*. Other keywords are centered on the

Figure 1. Multidimensional cloud model (WoS) keyword co-occurrence graph



cloud model, spreading out in all directions to form a mesh, and each of the nodes is connected through the nodes, and then extended to the *multidimensional model*, *multidimensional cloud*, and the *degree of affiliation* composed of the other *groups* by the nodes, and the connection between the nodes to form a *whole* with a certain relationship. Further, on the prospect of nodes, Figure 1 shows that the dots for keywords, including *cloud model*, *field framework*, *big data*, *cloud computing*, and *algorithm* are significantly larger than the dots of other keywords, which indicates that the number of times these keywords appear is relatively frequent. In addition, the network connecting the words is intricate and complex, which means that the closer the connection is, which leads to the conclusion that these words belong to the hot vocabulary in the current research field of cloud modeling. Next, the keyword clustering analysis of the literature obtained from the WoS database can visualize the aggregation of the multidimensional cloud model. Figure 2 shows that the keywords mined from the WoS database are clustered into multiple word clouds, each of which describes the main research directions of the multidimensional cloud model from 2005 to 2022.

According to the above mapping analysis, it can be seen that foreign researchers prefer introducing the cloud model into meteorological prediction, and proposing new methods to construct the planetary modeling of persistent sunny to cloudy to ensure the cloud model can mine part of the meteorological region information. *Fuzziness* (or *vagueness*) results from the imprecise boundaries of FSs. *Non-specificity* (or *imprecision*) relates to sizes (i.e., cardinalities) of relevant sets of alternatives. Zhu and Li (2016) considered not only the difference between the membership degree and non-membership degree but also the hesitation degree. Combining both the cloud model and two-type fuzzy to deal with the problem of image segmentation is also another important optimizing direction. The cloud model is frequently used in web services to create distributed cloud applications based on efficient quality of service awareness techniques. In conclusion, the cloud model is used to advance societal progress through scientific and technology research and development in addition to life safety evaluation. Multidimensional cloud models based on fuzzy mathematics and probability theory have

Table 1. Keyword clustering scenarios

Cluster Number	Cluster Size	Tag Words (Selecting the First Five)
0	45	edge computing, cloud computing, deep reinforcement, resource allocation, wireless communication
1	40	cloud computing, hypervisor-based intrusion detection, change detection, multistage attacks, cloud security monitoring | computational modeling
2	31	machine learning, time convolution network, hidden Markov models, feature extraction, time-series | cloud model
3	31	artificial intelligence, data models, task analysis, smart grids, deep reinforcement | model
4	25	diagnosis, cancer, texture classification, image analysis, algorithm | compact stencil
5	24	cloud, molecule, abundance, temperature, hydrogen chloride
6	23	air mass history, biogenic sources, water-soluble organic matter, multidimensional stoichiometric constraint classification, hill cap cloud experiment | hill cap cloud experiment
7	22	deep neural network, stress prediction, smart health, hypertension attack, connected health | mining excavations
8	22	supernova remnants, shock waves, *n*-body simulations, star formation, data analysis | data analysis
9	17	cumulus cloud, independent pixel, shallow, sensitivity, flux | cloud microphysics
10	14	spatial analysis, dispersal assembly, tropical forest, recruitment strategies, biodiversity maintenance | multidimensional compressible flow
13	10	atmospheric sulfuric acid, galactic cosmic ray, particle formation, nucleation, climate
15	9	crystalline rock, system, connectivity, tracer transport, behavior | multidimensional compressible flow
18	6	photogrammetry, structural geology, neotectonics, 3D surface modelling, structure-from-motion

been widely used in natural language processing, data mining, decision analysis, intelligent control, and image processing.

CONCEPTS AND THEORIES OF THE MULTIDIMENSIONAL CLOUD MODEL

Definition 1

Let U be a universal set described by precise numbers and C be the qualitative concept related to U. If $x\left(x \in U\right)$ is a single random realization of the concept C, it is a random number with stable distribution for the determinant $\mu\left(x\right) \in \left[0,1\right]$ of C, $\mu\left(x\right): U \to \left[0,1\right], \forall x \in U$. Then the distribution of x in the universe U is called the cloud model, and x is defined as a cloud drop (Li et al, 2004). The quantitative value x reflects the randomness of the quantitative value that represents the concept, while $\mu\left(x\right)$ reflects the degree of certainty that the quantitative value x is affiliated with the qualitative concept C.

Definition 2

The concept C is in the quantitative domain U, and C contains three numerical features $\left(Ex, En, He\right)$. If $x \in U$ is a single random realization of concept and the determinacy $\mu\left(x\right) \in \left[0,1\right]$ of x with respect to C is a random number with a tendency to stabilize. Then, $\mu\left(x\right): U \to \left[0,1\right], \forall x \in U$, satisfying $x = R_N\left(Ex, \left|y\right|\right), y = R_N\left(En, He\right)$; the affiliation function satisfies the expression: $\mu\left(x\right) = \exp\left\{-\frac{\left(x - Ex\right)^2}{2y^2}\right\}$. Therefore, the distribution of any variable consisting of cloud drops is called a normal cloud model (Li et al., 2004). The multidimensional normal cloud model is developed from the one-dimensional normal cloud model, which can reflect the multidimensional qualitative concept. The multidimensional normal cloud model is defined as follows.

Definition 3

Let U be an m-dimensional theoretical domain $U = \left\{x \middle| x \in \mathbb{R}^m\right\}$, C be a qualitative concept on U. The affiliation μ_i of an element x in U with respect to C is a random number with stable tendency, namely: $\mu_i: U \to \left[0,1\right], \forall x \in U$. The multidimensional normal cloud affiliation function can be expressed as follows.

$$\mu\left(x\left(x_1, x_2, \cdots, x_m\right)\right) = \exp\left\{-\sum_{i=1}^{m} \frac{\left(x_i - Ex_i\right)^2}{2En_i^2}\right\}, \left(i = 1, 2, \cdots, m\right) \tag{1}$$

where Ex_i and En_i are the affiliation degrees of the elements in the thesis domain U corresponding to C, respectively (Liu et al., 2021). The numerical characteristics of the multidimensional cloud model and the types of cloud generators are as follows.

Numerical Feature Model

The numerical feature model characterizes the vagueness and randomness of concepts by three numerical features: expectation $\left(Ex\right)$, entropy $\left(En\right)$, and super entropy $\left(He\right)$.

- *Expectation* is the point in the number field space that best represents the qualitative concept and reflects the center of the corresponding concept cloud.
- *Entropy* can be used to provide a combined measure of the vagueness and probability of a qualitative concept, as well as to illustrate the relationship between vagueness and randomness. The number of points can indicate the probability of the concept, i.e., randomness.
- *Super-entropy* It is an uncertain measure of entropy, i.e., the entropy of entropy, which reflects the agglomeration of cloud droplets, while the magnitude of super-entropy indirectly represents the dispersion and thickness of the cloud.

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

The subjectivity of the prototype multidimensional cloud model in determining the numerical features, leads to bias in the evaluation results, making its application limited. More and more researchers engage in the cloud model-theoretic study, and expansion of this model which merged with other decision-making methods applied to the study of real-world problems, including entropy weighting (Wu et al., 2022), the CRITIC method (Demir et al., 2022), the TOPSIS method (Khodamipour & Shahamabad, 2022), the combined assignment method, the Bayesian network method (Yu et al., 2004), and so on, such that, based on the comparative advantage of describing the transformation of deterministic and uncertain situations, the multidimensional cloud model provides a new way of thinking to solve the deficiencies of the multidimensional normal cloud model. In order to determine the numerical properties of the cloud model more objectively and increase the accuracy and reliability of evaluation outcomes, the multidimensional normal cloud model is investigated based on statistical approaches frequently employed in cloud models.

The significance of this paper is to illustrate the advantages of multidimensional cloud models and show the importance of multidimensional cloud models. Therefore, it is necessary to refer to a multidimensional cloud model to solve multi-attribute decision-making problems. In this paper, the

Figure 3. Cloud model and its three numerical features

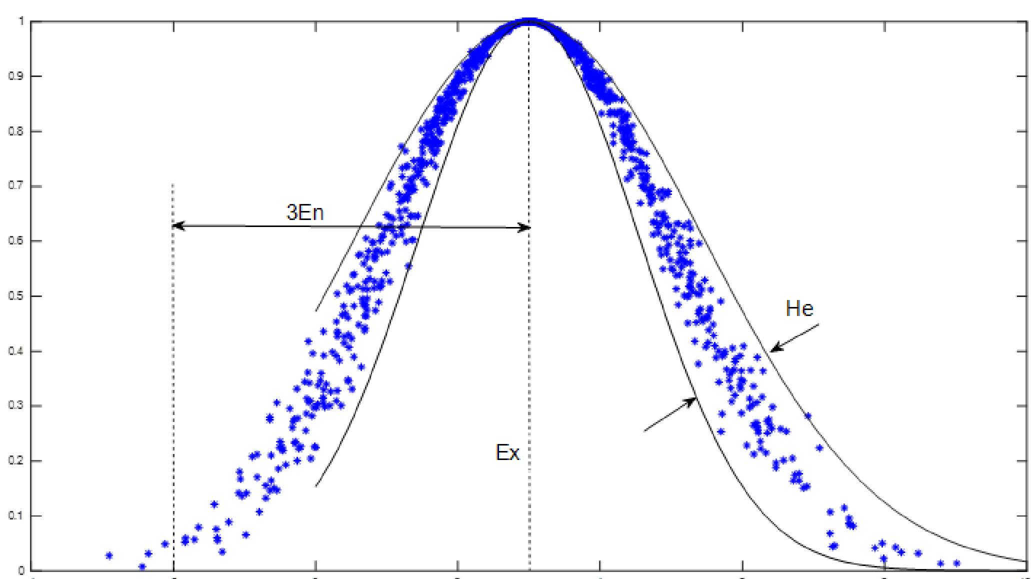
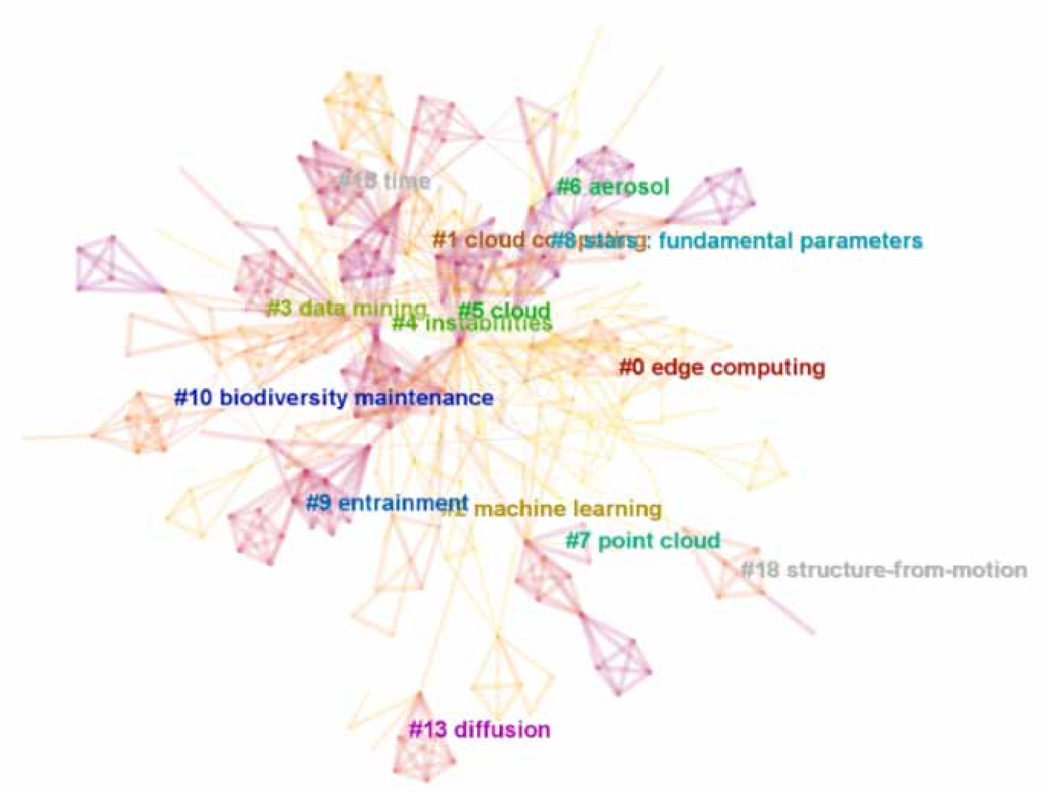


Figure 2. Multidimensional cloud model keyword clustering graph



advantages of multidimensional cloud models over one-dimensional cloud models are integrated, and several decision-making methods combined with multidimensional cloud models are introduced in detail. Then, one of these methods is selected and applied to a specific example to demonstrate that the multidimensional cloud model, which can provide accurate indicator evaluation results when solving multi-attribute decision-making problems.

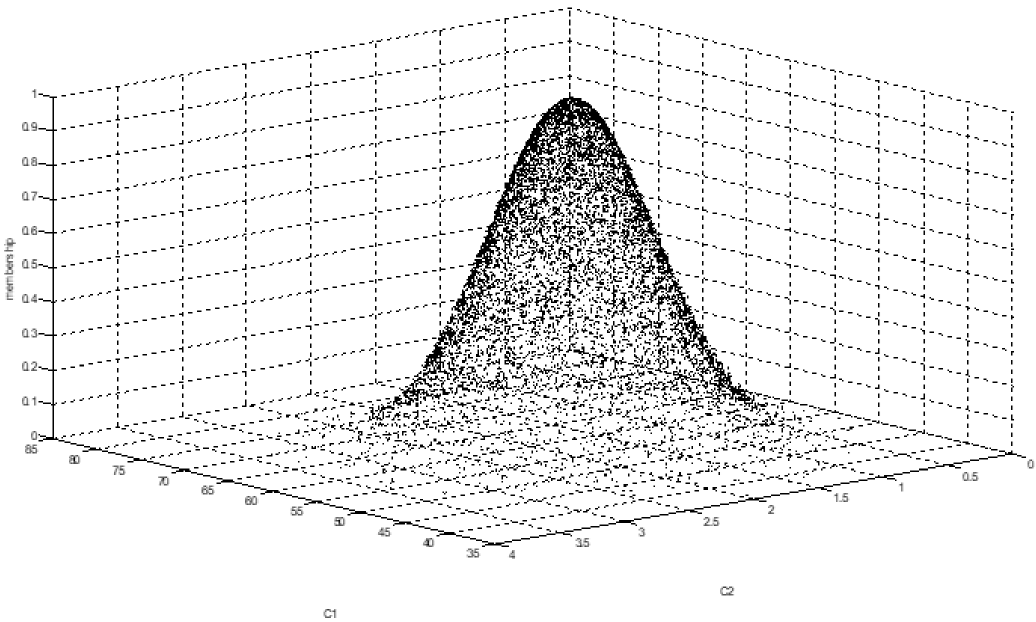
On the basis of summarizing existing research results, this paper summarizes the current research status and development trends of the multidimensional cloud model theory, so that readers can establish a basic framework for the multidimensional cloud model system. Secondly, the procedure of decision-making methods based on multidimensional cloud models is also summarized. Finally, perspectives on the frontiers of multidimensional cloud modeling are presented. This work provides a sense of value for the research with big data and cloud model theory.

The rest of the paper proceeds as follows: Section 2 furnishes concepts and theories related to a multidimensional cloud model, Section 3 introduces the theoretical study of the cloud model, the applied research of the cloud model is proposed in Section 4. An application of the multidimension cloud model is illustrated by examining the risk of supply chain financial companies in Section 5. Section 6 conducts frontier issues in multidimensional cloud modeling research, followed by remarks in Section 7.

Cloud Generator

In many practice circumstances, the cloud generation algorithm is also called a cloud generator (Ma et al., 2022), which is divided into a forward cloud generator and an inverse cloud generator (CG).

Figure 4. Multidimensional cloud model (2D)

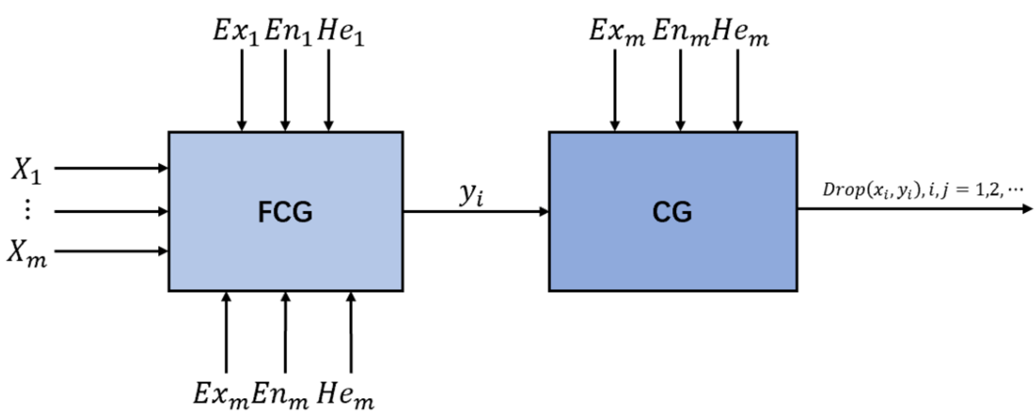


The forward cloud generator generates cloud drops by computing the three numerical characteristics of the concept, which realizes the transformation of the qualitative concept into a quantitative process. The inverse cloud generator $\left(CG^{-1}\right)$ is the inverse of the forward cloud generator and enables the conversion from quantitative to qualitative concepts.

In response to the inability of traditional cloud generation methods to effectively process high-dimensional data, some experts suggest using multidimensional Gaussian cloud generators (MCG). The numerical features of the most basic 1D cloud model are extended to the multidimensional case, as shown in Figure 5.

However, its inverse cloud generator first calculates three data features of the cloud model, based on the transformation of quantitative data into digital features of the cloud. The mean value $\overline{x}$ of the

Figure 5. Multidimensional Gaussian cloud generator



data set is used as the expectation $Ex = \overline{x}$, entropy $En = \sqrt{\frac{\pi}{2}} \times \frac{1}{n}\sum_{i=1}^{n}\left|x_{i} - Ex\right|$, super-entropy $He = \sqrt{\left|S^{2} - Ex^{2}\right|}$, (S^{2} is the sample variance of the data set, $S^{2} = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_{i} - Ex\right)^{2}$) of the cloud model.

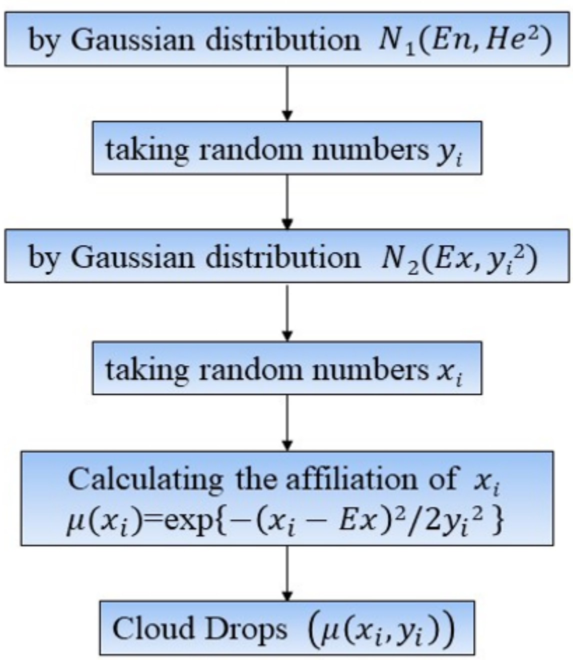
THEORETICAL STUDY OF THE CLOUD MODEL

The multidimensional cloud model concept is widely utilized in numerous fields, such as intelligent control, data mining, system evaluation, signal processing, image processing, and knowledge modeling (Yang et al., 2018). In this section, the theoretical study of cloud modeling will be elaborated in terms of how decision-making methods and cloud modeling are combined, the value generated by applying them to practice, and the prospects.

The TOPSIS–Cloud Model

TOPSIS (technique for order preference by similarity to an ideal solution) is a multi-objective decision-making problems (Zeng et al., 2020) based on the concept of the relative-closeness coefficient in the TOPSIS, auxiliary nonlinear programming models are constructed to solve MADM problems (Li, 2010). The basic idea is to normalize the original data matrix, find the positive and negative ideal solutions using the TOPSIS method, and then seek the distance between the positive and negative ideal solutions, according to the distance of the relative proximity of each program, and as a basis for evaluating the advantages and disadvantages of the program to rank the program, to select the optimal program. Chen (2000) studied TOPSIS in a fuzzy environment and proposed a linguistic decision process for solving multi-criteria problems. The TOPSIS–cloud model is a new

Figure 6. Multidimensional forward cloud generator algorithm



computational method for solving interval decision information based on the cloud model, which combines the distance measurement algorithm of the cloud with TOPSIS to solve the problem of uncertainty and stochasticity of the information contained in evaluation schemes (Lu et al., 2022), and gives the method of determining positive and negative ideal clouds and the distance measurement formula of the cloud model, based on which the cloud TOPSIS method is proposed, and this method is applied to the problem of uncertainty and randomness in evaluation schemes. Uncertainty and stochasticity problems (Lu et al., 2022), the method of determining the positive and negative ideal clouds, and the distance measure formula of the cloud model are given, based on which the cloud TOPSIS method is proposed, and this method is applied to many fields such as engineering design, economic management, and military, and the main steps are specified as follows.

Step 1: Transforming the Traditional Evaluation Decision Matrix Into a Cloud Model Evaluation Decision Matrix

The matrix given by the decision maker is transformed into a cloud evaluation decision matrix $\left[A_{ij}\right]_{m\times n}$, of which $\left[A_{ij}\right]=\left[a^{L}{}_{ij},a^{U}{}_{ij}\right]$, $a^{L}{}_{ij}$ and $a^{U}{}_{ij}$ are the minimum and maximum boundary values of the interval, respectively, and the three numerical parameters in the cloud model evaluation decision matrix are defined as:

$$Ex_{ij}=\left(a^{L}{}_{ij}+a^{U}{}_{ij}\right)/\,2, En_{ij}=\left(a^{U}{}_{ij}-a^{L}{}_{ij}\right)/\,6 \tag{2}$$

$$He_{ij}=\left|\max_{1<i<m} En_{ij}-\min_{1<i<m} En_{ij}-2En_{ij}\right|/\,3 \tag{3}$$

Step 2: Cloud Distance

Following Chen (2000) and Zhou et al. (2018), arbitrarily give two clouds, $C_i\left(Ex_i,En_i,He_i\right)$ and $C_j\left(Ex_j,En_j,He_j\right)$. Then the Hamming distance between C_i and C_j is:

$$d_H\left(C_i,C_j\right)=\left|\left(1-\frac{En_i^2+He_i^2}{En_i^2+He_i^2+En_j^2+He_j^2}\right)Ex_i-\left(1-\frac{En_j^2+He_j^2}{En_i^2+He_i^2+En_j^2+He_j^2}\right)Ex_j\right| \tag{4}$$

The Euclidean distance between C_i and C_j is:

$$d_E\left(C_i,C_j\right)=\sqrt{\left(Ex_j-Ex_i\right)^2+\left(En_j-En_i\right)^2+\left(He_j-He_i\right)^2} \tag{5}$$

The Manhattan distance between C_i and C_j is:

$$d_M\left(C_i,C_j\right)=\left|Ex_j-Ex_i\right|+\left|En_j-En_i\right|+\left|\rho_j\sqrt{En_j^2+He_j^2}-\rho_i\sqrt{En_i^2+He_i^2}\right| \tag{6}$$

The variable ρ is the uncertainty of the cloud, such that $\rho=1-\frac{En}{\sqrt{En^2+He^2}}$, $0\le\rho\le\min\left\{\frac{He}{\sqrt{En^2+He^2}},1\right\}$.

Step 3: Determining the Positive and Negative Ideal Solutions

According to the cloud model matrix $\left[A_{ij}\right]_{m\times n}$, the positive and negative ideal solutions of the scheme with different attribute indicators are determined as:

$$A^{+}=\left(\max_{1\le i\le m} Ex_{i},\min_{1\le i\le m} En_{i},\min_{1\le i\le m} He_{i}\right),A^{-}=\left(\min_{1\le i\le m} Ex_{i},\max_{1\le i\le m} En_{i},\max_{1\le i\le m} He_{i}\right) \tag{7}$$

Step 4: Calculating Objective Weight Values

If the weight information ω_i is known, then the integrated cloud model algorithm integrated by the positive and negative ideal scheme weighting is:

$$C_{i}\left(Ex,En,He\right)=\sum_{j=1}^{n}\omega_{i}A_{ij}\left(Ex_{ij},En_{ij},He_{ij}\right) \tag{8}$$

$$C_{i}\left(Ex,En,He\right)=\sum_{j=1}^{n}\omega_{i}A_{ij}\left(\max Ex_{ij},\min En_{ij},\min He_{ij}\right) \tag{9}$$

$$C_{i}^{-}\left(Ex,En,He\right)=\sum_{j=1}^{n}\omega_{i}A_{ij}\left(\min Ex_{ij},\max En_{ij},\max He_{ij}\right) \tag{10}$$

If the weight information ω_i is unknown, the objective weights are determined using the idea of minimizing the cloud uncertainty ρ. The objective planning function is thus constructed.

$$\min f=\sum_{i=1}^{m}\sum_{j=1}^{n}\rho_{ij}\omega_{i} \tag{11}$$

$$s.t.\begin{cases}\omega_{i}\ge 0\\ \sum_{i=1}^{m}\omega_{i}=1\end{cases}$$

By constructing the Lagrangian function method, the objective weight values are obtained as:

$$\omega_{i}=\frac{\sum_{j=1}^{n}\rho_{ij}}{\sum_{j=1}^{n}\left(\sum_{i=1}^{m}\rho_{ij}\right)^{2}} \tag{12}$$

Step 5. Calculating the Relative Cloud Distance

Applicable to different cases, use the above distance formula to solve the weighted integrated cloud model distance values $d\left(C_{i},C^{-}\right)$ between each scheme and the positive and negative ideal scheme, and calculate the relative cloud distance (Yu et al., 2019).

$$P_{i}=\frac{d\left(C_{i},C_{i}^{-}\right)}{d\left(C_{i},C_{i}^{+}\right)+d\left(C_{i},C_{i}^{-}\right)} \tag{13}$$

The larger P_i means the better solution, and the ranking result of each solution is calculated to select the best solution.

The Bayesian Network – Cloud Model

Bayesian networks are a network topology of directed acyclic graphs, an uncertainty processing model that simulates the causal relationship in human reasoning, with nodes representing random variables $\left\{X_1, X_2, \cdots X_n\right\}$. If there is only a single arrow between two nodes, it means that one of the nodes is the *cause* and the other is the *effect*. The strength of the association of nodes and connecting lines, i.e., the weights, is represented by the conditional probabilities.

Bayesian network is widely used in real life, constructed a Bayesian network based transport aircraft runway risk assessment model, accurately evaluates the level of various types of indicators, effectively evaluates the risk of over-wheel speed, can help airlines to take reasonable measures to achieve over-wheel speed risk control, which is of great significance to ensure safe operation; based on the cloud model and the Bayesian network of the missile status assessment method, assesses the state of the missile, and according to the monitoring results of the missile for regular repair and testing and maintenance. The Bayesian network model improved by using the theory of the cloud model is applied to the practical problems with the main steps as follows.

Step 1: Constructing the Bayesian Network

$G = \left(I, E\right)$ denotes a directed acyclic graph, I denotes the set of all nodes, E denotes the set of directed connected line segments, and the joint probability of the random variables $X = \left\{X_i \middle| i \in I\right\}$ is denoted as:

$$P\left(x\right) = \prod_{i \in I} p\left(x_i \middle| x_{pa(i)}\right) \tag{14}$$

Then we call X a Bayesian network relative to a directed acyclic graph G, where $pa\left(i\right)$ denotes the parent of the i^{th} node (Wu et al., 2016).

Step 2: Generating the Integrated Cloud

According to the Bayesian network in cloud computing and the actual situation in establishing the indicator system, the indicators will be discretized and processed to determine the cloud digital features to generate a comprehensive cloud.

$$\begin{aligned} Ex &= \sum_{j=1}^{n} \left(Ex_j P\left(x\right)\right) \\ En &= \sqrt{\sum_{j=1}^{n} \left(En_j^2 P\left(x\right)\right)} \\ He &= \sqrt{\sum_{j=1}^{n} \left(He_j^2 P\left(x\right)\right)} \end{aligned} \tag{15}$$

Step 3: Network Parameter Learning

Computing conceptual certainty from the numerical characterization of cloud model, and after the mutual transformation of certainty and probability, the Bayesian network structure is constructed, and then network parameter learning, network inference to obtain the node a posteriori probability, and finally the forward assessment and reverse inference are implemented, which finally leads to the indicator assessment results.

The Combination Weighting Method Cloud Model

The combination weighting method is the combination of subjective and objective weight to obtain the optimal weight. Subjective assignment is based on the decision maker's subjective information, according to the importance of the indicators to give relatively appropriate weights. This method has strong effectiveness, but its subjectivity is relatively strong. Common subjective weight calculation methods include the Delphi method, hierarchical analysis method, etc. Objective weighting cannot reflect the degree of importance attached to different indicators by the participating decision makers, but its weight can be determined by the connection between the original data, which has a strong theoretical basis, and the entropy weighting method is usually used to calculate the objective weights.

Combination weighting method is an important element in the research of rational allocation program evaluation, which can balance the subjective judgment and objective evaluation of decision-makers and make the ranking results of multi-indicator evaluation more scientific. Generally, the combination assignment-cloud model first calculates the subjective weights by hierarchical analysis method, and then calculates the comprehensive weights by combining subjective and objective combination assignments. Finally, using the cloud model theory, the numerical values are transformed into qualitative language, and the evaluation cloud diagram is used to visualize the degree of deviation of the indicators. This combined assignment evaluation can make the assessment results more scientific.

Step 1: Calculating the Subjective Weights

Taking the AHP method as an example (Saaty, 2004), the evaluation system is set up with a matrix of n indicators and m expert ratings $A = \left(x_{ij}\right)_{m \times n}$, the subjective weights of each indicator were calculated through the following formula.

The weight of each indicator is calculated as:

$$w_i = \frac{\sqrt[n]{\prod_{j=1}^{n} x_{ij}}}{\sum_{i=1}^{m} \sqrt[n]{\prod_{j=1}^{n} x_{ij}}}, \left(i = 1, 2, \cdots, n\right) \tag{16}$$

Each weight is then normalized to obtain the subjective weights of the index values W_i^s:

$$W_i^s = \frac{w_i}{\sum_{i=1}^{n} w_i}, \left(i = 1, 2, \cdots, n\right) \tag{17}$$

where n is the number of evaluation indicators, m is the number of experts, and $W^s = \left(W_1^s, W_2^s, \cdots, W_n^s\right)$.

Step 2: Calculating the Objective Weights

The entropy weight method is used to calculate the objective assignment (Wei et al., 2016), which determines the entropy weight of the indicator through information entropy according to the dispersion of the indicator data and obtains a more objective weight by correcting the entropy weight. There are n evaluation samples for each evaluation indicator, x_{ij} denotes the evaluation value of the evaluation sample R_i on evaluation indicator I_j, and the original data matrix is noted as $\left(x_{ij}\right)_{m \times n}$. The steps for determining the weights of each indicator are as follows.

First, standardize the data:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \left(i = 1,2,\cdots,m; j = 1,2,\cdots,n\right) \tag{18}$$

Then calculate the information entropy of each index:

$$e_j = \frac{1}{\ln\left(m\right)} \sum_{i=1}^{m} p_{ij} \ln\left(p_{ij}\right), j = 1,2,\cdots,n \tag{19}$$

Then calculate the indicator weights:

$$W_j^o = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_j}, \left(j = 1,2,\cdots,n\right) \tag{20}$$

where e_j is the entropy value of the evaluation metric; I_j and W_j represent the weight of the evaluation metric I_j, $W^o = \left(W_1^o, W_2^o, \cdots, W_n^o\right)$.

Step 3: Determining the Portfolio Weights

Let the portfolio weights be $\omega_j = \alpha W_j^s + \left(1 - \alpha\right) W_j^o, \left(j = 1,2,\cdots,n\right)$, where $\alpha, 1 - \alpha$ are the proportions of subjective and objective weights in the portfolio weights, respectively. Variables W^s, W^o are the subjective and objective weights of the indicators, respectively.

Step 4: Cloud Digital Features Under Empowerment Combination

Based on the three numerical characteristics of the cloud and the calculation method of the combined weight ω_j, it is applied to the calculation of the integrated cloud

$$\left\{C_1\left(Ex_1, En_1, He_1\right), C_2\left(Ex_2, En_2, He_2\right), \cdots, C_j\left(Ex_j, En_j, He_j\right)\right\}.$$

The numerical characteristics algorithm of the integrated cloud is obtained as follows.

$$\begin{cases} Ex = \dfrac{Ex_1\omega_1 + Ex_2\omega_2 + \cdots + Ex_j\omega_j}{\omega_1 + \omega_2 + \cdots + \omega_j} \\ En = \dfrac{\omega_1^2 En_1 + \omega_2^2 En_2 + \cdots + \omega_j^2 En_j}{\omega_1^2 + \omega_2^2 + \cdots + \omega_j^2} \\ He = \dfrac{\omega_1^2 He_1 + \omega_2^2 He_2 + \cdots + \omega_j^2 He_j}{\omega_1^2 + \omega_2^2 + \cdots + \omega_j^2} \end{cases} \tag{21}$$

The cloud model digital features are obtained from the above equation and then the visualization of the integrated cloud is given.

Discussion of Methods

The above methods can all consider the weights and correlations between different indicators. However, TOPSIS is ranked based on the proximity of the evaluation object to the idealized goal (Li, 2010), and there is a certain degree of subjectivity when calculating indicator weights. The main purpose of the Bayesian network is to solve problems of uncertainty and incompleteness. The combination weighting method combines subjective and objective weights, which has stronger applicability.

APPLIED RESEARCH OF THE CLOUD MODEL

The TOPSIS–Cloud Model

The TOPSIS–cloud modeling approach is characterized by simplicity and ease of use in solving interval-based decision information problems. Gong (2022) used the cloud similarity TOPSIS method for water resource management and allocation scheme problems to effectively solve the fuzzy uncertainty of indicator weights (Wei, 2016; Gong et al., 2018), and optimized the assessment of relay protection status under the combination of the cloud modeling method, grayscale correlation, and TOPSIS; In addition, the TOPSIS–cloud model validates the applicability of the metrics and models on construction safety, disaster risk assessment, and building engineering.

Bayesian Network and Cloud Model

Bayesian network – cloud model is well known for its powerful reasoning ability, commonly used in security risk, threat assessment, reliability analysis, etc. Especially in the fields of railroad transportation, automation technology, weapons industry and military technology, and Internet technology, this expansion is preferred. Yu (2023) established a novel multi-objective decision model for the grade assessment of network security situations under multi-source information. Wu et al. (2016) utilized the rough set and Bayesian network for building subway shield construction adjacent bridge safety problem for risk assessment. Shen et al. (2019) applied this model to the construction safety of assembled housing components lifting; this model can effectively reduce the housing safety hazards easier to attract people's attention.

Portfolio Empowerment and Cloud Model

The empowerment cloud model fully considers the subjective and objective information of the indicator weights and realizes the mutual transformation of the qualitative and quantitative, subjective and objective. Numerous scholars have transformed real-life linguistic uncertainty variables into precise quantitative data based on the combinatorial assignment cloud model to propose reasonable evaluations and find suitable solutions. The method was common in the field of mathematics in the early days, and later, experts and scholars extended it to the field of road and waterway transportation for solving the problems of high-speed railroad system experiments, subway construction risk evaluation, and so on. In water conservancy and hydropower engineering, the operation and management of long-distance water transfer projects, as well as the integrated problems related to distribution network planning, are more accurately and effectively assessed after combining the combined-empowerment cloud model.

EMPIRICAL ANALYSIS

Fuzzy multi-attribute decision-making (MADM) problems are widely spread in real-life situations. However, it may not be easy to identify the exact value for the membership degree of an element to a given set. A range of values may be a more appropriate measurement to accommodate the uncertainty, imprecision, or vagueness (Li, 2011). In the traditional financing environment, small and medium-sized enterprises (SMEs) normally find it hard to earn sufficient loans from the banks, which may be necessary for their daily operation, because of their credit rating or other reasons. However, this dilemma is partly mitigated by the neo-founded supply chain finance plants. A Chinese enterprise QR is chosen as an example to assess the risk level of supply chain finance (because of China's privacy policy regulation, the enterprise's name is presented only by the initials QR).

Supply Chain Finance Risk Indicator System

Supply chain finance risks are usually influenced by environmental and human factors, leading to the damage of some industries' interests. Starting from the actual situation of QR's supply chain finance operation, five first-level indicators consisting of the qualification of financing applicant enterprises, the qualification of core enterprises, the status of enterprise assets, macro and industry risks and supply chain risks are selected following the principles of science, feasibility, and representativeness, as shown in Table 2.

Data Sources-Expert Scoring Method

In this case, the expert scoring method was adopted, and 10 experts with knowledge and experience in the automotive and financial industries were invited to evaluate the importance of the above 20 indicators. The scoring scale is based on a five-point scale, $\left[0,1\right)$ means *very low*, $\left[1,2\right)$ means *low*, $\left[2,3\right)$ means *medium*, $\left[3,4\right)$ means *high*, and $\left[4,5\right]$ means *very high*. The scoring results of each expert are shown in Table 3 below. Based on 10 experts' scores on QR supply chain finance's metrics, $\left[a_{ij}^{-},a_{ij}^{+}\right]$ is the results of the scores given to the j^{th} indicator by the i^{th} expert and normalized (Hwang et al., 1981).

The benefit type is defined as:

$$b_{ij}^{-}=a_{ij}^{-}\,/\,\sqrt{\sum_{i=1}^{m}a_{ij}^{+}},\, j=1,2,\cdots,n \tag{22}$$

$$b_{ij}^{+}=a_{ij}^{+}\,/\,\sqrt{\sum_{i=1}^{m}a_{ij}^{+}},\, j=1,2,\cdots,n \tag{23}$$

The cost type is defined as:

$$b_{ij}^{-}=\left(1\,/\,a_{ij}^{+}\right)/\left(\sqrt{\sum_{i=1}^{m}\left(1\,/\,a_{ij}^{-}\right)^{2}}\right),\, j=1,2,\cdots,n \tag{24}$$

$$b_{ij}^{+}=\left(1\,/\,a_{ij}^{-}\right)/\left(\sqrt{\sum_{i=1}^{m}\left(1\,/\,a_{ij}^{+}\right)^{2}}\right),\, j=1,2,\cdots,n \tag{25}$$

Vector transformation methods are defined as:

$$\left[b_{ij}^{-},b_{ij}^{+}\right]=\frac{\left[a_{ij}^{-},a_{ij}^{+}\right]}{\left\|A\right\|},\, i=1,2,\cdots,m;\, j=1,2,\cdots,n \tag{26}$$

The expression $\left\|A\right\|=\max_{1\le i\le m}\left(\max_{1\le j\le n}\left(\left|a_{ij}^{-}\right|,\left|a_{ij}^{+}\right|\right)\right)$, $\left\|A\right\|$ defines the interval series vector parametrization. The initial matrix in Table 3 is normalized according to the above equation, and the norms of the column vectors of the decision matrix are denoted as A_i respectively, and the resulting normalized matrix is shown in Table 4.

Table 2. Supply chain finance risk indicator system

First level Indicator	Second-Level Indicator	Indicator Description
Financing application for corporate qualification U_1	Enterprise quality U_{11}	Scores managers based on their personal credit history and the quality of their financial information
	Business capability U_{12}	Scoring based on total return on assets = profit before interest and tax / ((total assets at beginning of period + total assets at end of period) / 2)
	Solvency U_{13}	Scoring based on current ratio = current assets / current liabilities
	Profitability U_{14}	Scoring based on sales margin = sales profit / sales revenue
	Capacity of goods organization U_{15}	Scoring according to the ability of transport enterprises to organize the flow of goods, the flow of goods
	Financial disclosure status U_{16}	Scoring based on the company's financial status, business performance and growth prospects as released to the public
Core corporate qualifications U_2	Credit rating of core companies U_{21}	Credit rating at the bank
	Industry position of core companies U_{22}	Concentration, monopoly, and cycle characteristics of the industry in which it is located
	Gearing ratio U_{23}	Scoring based on gearing ratio = total liabilities / total assets
	Accounts payable to net assets U_{24}	Scoring based on the efficiency of the use of corporate funds
Corporate assets U_3	Material characteristics U_{31}	Scoring based on pledge liquidity, ability to convert into cash
	Accounts receivable characteristics U_{32}	Scoring based on the quality of sales and how quickly the company recovers capital
Macro and Industry Risks U_4	Interest rate risk U_{41}	Divided equally according to the level of interest rates
	Exchange rate risk U_{42}	Rating based on the appreciation and depreciation of the RMB
	Policy system risk U_{43}	Scoring according to the degree of perfection of the policy system
Supply Chain Risk U_5	Supply chain management level U_{51}	Number of defaults / total number of transactions
	Supply chain collaboration level U_{52}	Combined with industry average times
	Supply chain finance competitive intensity U_{53}	Scoring based on ability to conduct online business

Based on the normalization matrix, the entropy weight of each indicator is calculated $W_j^o, j = 1,2,\cdots,n$, as shown in Table 5.

Table 3. Expert scoring data for supply chain finance risk indicators

Experts	U_1						U_2			
	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{21}	U_{22}	U_{23}	U_{24}
x_1	[1,1]	[1,2]	[1,2]	[4,4]	[3,3]	[3,4]	[3,3]	[3,3]	[2,3]	[2,2]
x_2	[1,2]	[2,3]	[1,2]	[4,5]	[2,3]	[3,3]	[2,3]	[4,4]	[3,3]	[2,3]
x_3	[1,2]	[2,2]	[2,3]	[3,4]	[3,4]	[4,4]	[3,4]	[3,4]	[3,4]	[2,2]
x_4	[1,1]	[2,3]	[2,3]	[3,3]	[4,4]	[2,3]	[3,3]	[3,4]	[2,3]	[1,2]
x_5	[2,2]	[2,2]	[3,3]	[3,4]	[3,4]	[2,2]	[3,4]	[4,4]	[2,2]	[3,3]
x_6	[1,2]	[1,1]	[2,3]	[4,4]	[2,3]	[2,3]	[2,3]	[3,3]	[3,4]	[2,3]
x_7	[2,2]	[3,3]	[2,3]	[4,5]	[3,3]	[3,3]	[3,4]	[2,3]	[2,3]	[3,4]
x_8	[2,3]	[1,2]	[1,2]	[3,4]	[3,4]	[3,4]	[2,3]	[3,4]	[3,3]	[3,3]
x_9	[2,3]	[2,3]	[3,3]	[3,4]	[3,4]	[3,3]	[3,3]	[2,3]	[4,4]	[3,4]
x_{10}	[1,1]	[2,2]	[2,2]	[3,3]	[4,4]	[3,4]	[2,3]	[3,4]	[3,4]	[2,2]

Continued Table 3. Supply chain finance risk indicator expert score data

Experts	U_3		U_4			U_5		
	U_{31}	U_{32}	U_{41}	U_{42}	U_{43}	U_{51}	U_{52}	U_{53}
x_1	[1,1]	[2,2]	[1,1]	[0,1]	[2,2]	[1,3]	[2,3]	[4,4]
x_2	[1,2]	[2,3]	[1,2]	[1,2]	[2,3]	[2,3]	[2,2]	[4,5]
x_3	[2,2]	[1,2]	[1,1]	[1,2]	[1,2]	[3,3]	[1,2]	[3,4]
x_4	[1,2]	[2,2]	[0,1]	[1,1]	[1,2]	[2,3]	[3,3]	[3,3]
x_5	[1,1]	[2,3]	[1,2]	[0,1]	[2,3]	[1,2]	[2,3]	[3,4]
x_6	[1,2]	[2,2]	[1,1]	[0,1]	[1,1]	[3,4]	[2,2]	[4,4]
x_7	[2,3]	[1,2]	[0,1]	[1,1]	[2,3]	[2,3]	[2,3]	[4,5]
x_8	[2,2]	[1,2]	[1,1]	[1,2]	[1,1]	[2,2]	[3,4]	[3,4]
x_9	[1,2]	[2,2]	[1,2]	[1,1]	[1,1]	[2,3]	[2,3]	[3,4]
x_{10}	[2,2]	[2,3]	[1,1]	[0,1]	[1,2]	[2,3]	[2,2]	[3,3]

Table 4. Decision information normalization matrix

Experts	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{21}	U_{22}	U_{23}
x_1	[0.1258, 0.158]	[0.0775, 0.2033]	[0.0398, 0.1402]	[0.0625, 0.0737]	[0.0731, 0.0916]	[0.12, 0.081]	[0.0646, 0.0849]	[0.0731, 0.0916]	[0.0470, 0.0855]
x_2	[0.0629, 0.158]	[0.0517, 0.1016]	[0.0398, 0.1042]	[0.0625, 0.0921]	[0.0731, 0.1374]	[0.0683, 0.081]	[0.0646, 0.1273]	[0.0548, 0.0687]	[0.0706, 0.0855]
x_3	[0.0629, 0.1580]	[0.0775, 0.1016]	[0.0796, 0.1563]	[0.0468, 0.0737]	[0.0548, 0.0916]	[0.0512, 0.061]	[0.0484, 0.0849]	[0.0548, 0.0916]	[0.0706, 0.114]
x_4	[0.1258, 0.158]	[0.0517, 0.1016]	[0.0796, 0.1563]	[0.0468, 0.0552]	[0.0548, 0.0687]	[0.0683, 0.1213]	[0.0646, 0.0849]	[0.0548, 0.0916]	[0.0470, 0.0855]
x_5	[0.0629, 0.079]	[0.0775, 0.1016]	[0.1195, 0.1563]	[0.0468, 0.0737]	[0.0548, 0.0916]	[0.1025, 0.1213]	[0.0484, 0.0849]	[0.0548, 0.0687]	[0.0470, 0.057]
x_6	[0.0629, 0.158]	[0.1550, 0.2033]	[0.0796, 0.1563]	[0.0625, 0.0737]	[0.0731, 0.1374]	[0.0683, 0.1213]	[0.0646, 0.1273]	[0.0731, 0.0916]	[0.0706, 0.114]
x_7	[0.0629, 0.079]	[0.0517, 0.0678]	[0.0796, 0.1563]	[0.0625, 0.0921]	[0.0731, 0.0916]	[0.0683, 0.081]	[0.0484, 0.0849]	[0.0731, 0.1373]	[0.0470, 0.0855]
x_8	[0.0629, 0.079]	[0.0775, 0.2033]	[0.0398, 0.1042]	[0.0468, 0.0737]	[0.0548, 0.0916]	[0.0512, 0.081]	[0.0646, 0.1273]	[0.0548, 0.0916]	[0.0706, 0.0855]
x_9	[0.0419, 0.079]	[0.0517, 0.1016]	[0.1195, 0.1563]	[0.0468, 0.0737]	[0.0548, 0.0916]	[0.0683, 0.081]	[0.0646, 0.0849]	[0.0731, 0.1373]	[0.0941, 0.114]
x_{10}	[0.1258, 0.158]	[0.0775, 0.1016]	[0.0796, 0.1042]	[0.0468, 0.0552]	[0.0548, 0.0687]	[0.0512, 0.081]	[0.0646, 0.1273]	[0.0548, 0.0916]	[0.0706, 0.114]

Continued Table 4. Decision information normalization matrix

Experts	U_{24}	U_{31}	U_{32}	U_{41}	U_{42}	U_{43}	U_{51}	U_{52}	U_{53}
x_1	[0.0545, 0.0662]	[0.1258, 0.1701]	[0.0898, 0.1197]	[0.1147, 0.1767]	[0, 0.2041]	[0.0629, 0.0801]	[0.0357, 0.1508]	[0.057, 0.1093]	[0.0625, 0.0737]
x_2	[0.0545, 0.0993]	[0.0629, 0.1701]	[0.0898, 0.1795]	[0.1147, 0.3534]	[0.1147, 0.4082]	[0.0419, 0.0801]	[0.0715, 0.1508]	[0.057, 0.0729]	[0.0625, 0.0921]
x_3	[0.0545, 0.0662]	[0.0629, 0.085]	[0.0449, 0.1197]	[0.1147, 0.1767]	[0.1147, 0.4082]	[0.0629, 0.1603]	[0.1072, 0.1508]	[0.0285, 0.0729]	[0.0469, 0.0737]
x_4	[0.0273, 0.0662]	[0.0629, 0.1701]	[0.0898, 0.1197]	[0, 0.1767]	[0.1147, 0.2041]	[0.0629, 0.1603]	[0.0715, 0.1508]	[0.0855, 0.1093]	[0.0469, 0.0552]
x_5	[0.0818, 0.0993]	[0.1258, 0.1701]	[0.0898, 0.1795]	[0.1147, 0.3534]	[0, 0.2041]	[0.0419, 0.0801]	[0.0357, 0.1006]	[0.057, 0.1093]	[0.0469, 0.0737]
x_6	[0.0545, 0.0993]	[0.0629, 0.1701]	[0.0898, 0.1197]	[0.1147, 0.1767]	[0, 0.2041]	[0.1258, 0.1603]	[0.1072, 0.2011]	[0.057, 0.0729]	[0.0625, 0.0737]
x_7	[0.0818, 0.1325]	[0.0419, 0.085]	[0.0449, 0.1197]	[0, 0.1767]	[0.1146, 0.2041]	[0.0419, 0.0801]	[0.0715, 0.1508]	[0.057, 0.1093]	[0.0625, 0.0921]
x_8	[0.0818, 0.0993]	[0.0629, 0.085]	[0.0449, 0.1197]	[0.1147, 0.1767]	[0.1146, 0.4082]	[0.1258, 0.1603]	[0.0715, 0.1006]	[0.0855, 0.1458]	[0.0469, 0.0737]
x_9	[0.0818, 0.1325]	[0.0629, 0.1701]	[0.0898, 0.1197]	[0.1147, 0.3534]	[0.1146, 0.2041]	[0.1258, 0.1603]	[0.0715, 0.1508]	[0.057, 0.1093]	[0.0469, 0.0737
x_{10}	[0.0545, 0.0662]	[0.0629, 0.085]	[0.0898, 0.1795]	[0.1147, 0.1767]	[0, 0.2041]	[0.0629, 0.1603]	[0.0715, 0.1508]	[0.057, 0.0729]	[0.0469, 0.0552]

According to the information entropy in Table 5, the weights of the primary and secondary indicators can be calculated as shown in Table 6.

Table 5. Entropy weighting table

Information entropy									
e_j	0.928	0.917	0.959	0.986	0.974	0.97	0.98	0.975	0.973
Information entropy									
e_j	0.955	0.936	0.97	0.871	0.767	0.923	0.966	0.964	0.986

Although the two first-level indicators of core enterprise qualification and enterprise asset status account for a relatively small proportion, the characteristics of the pledge in the second-level indicators under the enterprise qualification status occupy a larger weight, and the pledge usually refers to the real estate, movable property or rights owned by the debtor provided to the creditor. Here, according to the company's pledge liquidity and ability to convert into cash as the second-level evaluation indicators to judge the key factors of the company's supply chain financial credit risk, the higher the pledge liquidity and the stronger the ability to convert into cash, the lower the supply chain risk faced by the company.

Macro and industry risks are the most important factors affecting the development of supply chain finance, with exchange rate risk accounting for the highest proportion, followed by interest rate risk. The reason mainly lies in the fact that when QR company trades with foreign countries, the changes in the economic strength of each country and the choice of macroeconomic policies determine the trend of exchange rate changes. In recent years, the impact of the new crown epidemic hit the global economy hard, so that the exchange rate has great volatility, foreign banks in order to maintain economic stability, to avoid the adverse impact of exchange rate changes to the domestic economy, often intervene in the market, so the exchange rate change is facing the key risk of supply chain finance.

Determining Risk Indicator Characteristics

Standard Risk Cloud Graph

According to the principle of the five-point scoring system, the corresponding range of theoretical domain values are: $\left[0,1\right),\left[1,2\right),\left[2,3\right),\left[3,4\right),\left[4,5\right]$. Based on the range of values for each evaluation level, the cloud number characteristic values are calculated by the specific formula: $Ex = \left(b_{\min} + b_{\max}\right) / 2, En = \left(b_{\max} - b_{\min}\right) / 3, He = k$ where k is a constant, generally taken as 0.1. The results of the calculations are shown in Table 7.

The cloud digital eigenvalues from the above table are entered into the cloud generator and a risk level cloud map is generated as shown in Figure 7.

Calculating Eigenvalues

Using the expressions

$$Ex = \frac{Ex_1\omega_1 + Ex_2\omega_2 + \cdots + Ex_j\omega_j}{\omega_1 + \omega_2 + \cdots + \omega_j}$$

and

$$En = \frac{\omega_1^2 En_1 + \omega_2^2 En_2 + \cdots + \omega_j^2 En_j}{\omega_1^2 + \omega_2^2 + \cdots + \omega_j^2},$$

Table 6. QR supply chain finance risk weights

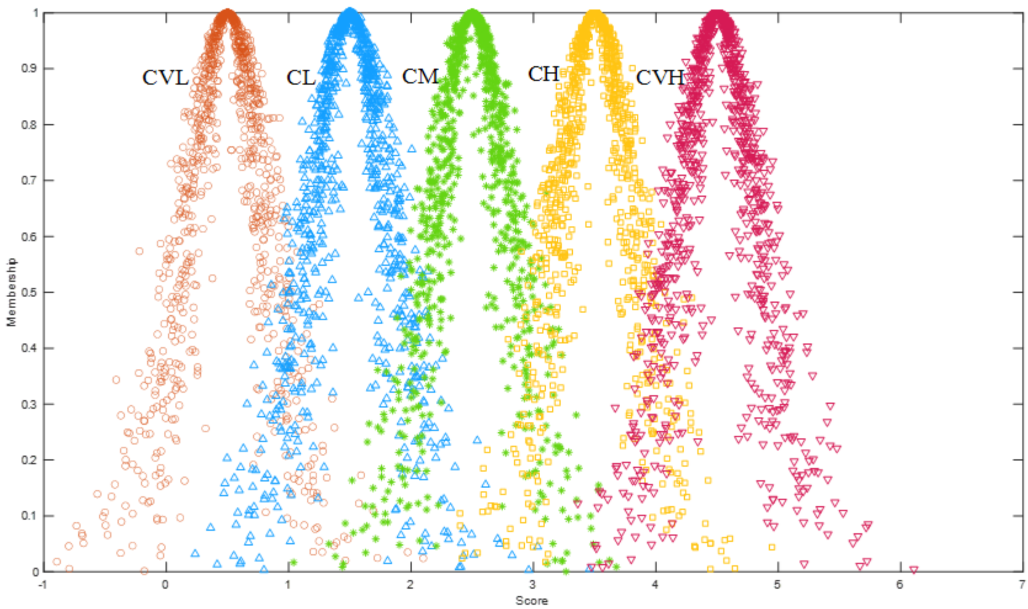
First-Level Indicator	Weight	Second-Level Indicator	Weight
U_1	0.266	U_{11}	0.2707
		U_{12}	0.3120
		U_{13}	0.1541
		U_{14}	0.0526
		U_{15}	0.0977
		U_{16}	0.1128
U_2	0.117	U_{21}	0.1709
		U_{22}	0.2137
		U_{23}	0.2308
		U_{24}	0.3846
U_3	0.094	U_{31}	0.6809
		U_{32}	0.3191
U_4	0.439	U_{41}	0.2939
		U_{42}	0.5308
		U_{43}	0.1754
U_5	0.084	U_{51}	0.4048
		U_{52}	0.4286
		U_{53}	0.1667

Table 7. Cloud digital characteristic values for each evaluation level

Evaluation Level	Expectation	Entropy	Hyper-Entropy
Very Low	0.5	0.3333	0.1
Low	1.5	0.3333	0.1
Medium	2.5	0.3333	0.1
High	3.5	0.3333	0.1
Very High	4.5	0.3333	0.1

Figure 7. Standard risk level graph

Note. The horizontal coordinate is the score, and the vertical coordinate is the affiliation degree. The orange-red circles indicate cloud very lower (CVL); the sky blue triangles indicate cloud lower (CL); the grass-green stars indicate cloud medium (CM); the ginger squares indicate cloud high (CH); the plum-red inverted triangles indicate cloud very high (CVH).



these numerical characteristics of the secondary indicators were calculated as shown in Table 8. The characteristic values of the primary indicators were calculated according to Tables 6 and 8, as shown in Table 9.

Analysis of Results and Suggestions for Countermeasures

According to the calculated eigenvalues of the first-level indicators, the five first-level indicators of financing application enterprise qualification risk U_1, core enterprise qualification risk U_2, enterprise asset status risk U_3, macro and industry risk U_4, and supply chain risk U_5 are randomly grouped in two groups, respectively.

From the two-dimensional diagram drawn from the core enterprise qualification risk U_2 and the supply chain risk U_5, the respective one-dimensional floor plan is obtained by observing from the two perspectives of U_2 and U_5, respectively, and from the comparative analysis of the floor plan and the standard risk cloud diagram, it can be seen that: the risk of U_5 is lower than that of U_2, and then we obtain $U_5 \succ U_2$.

From the two-dimensional diagram drawn from the supply chain risk U_5 and the financing applicant enterprise qualification risk U_1, the respective one-dimensional floor plan is obtained by observing from the two perspectives of U_1 and U_5, respectively, and from the comparative analysis of the floor plan and the standard risk cloud diagram, it can be seen that: the risk of U_1 is lower than that of U_5, then $U_1 \succ U_5$.

Table 8. QR supply chain finance secondary risk indicator characteristic values

Second-Level Indicator	Cloud Model
Enterprise quality	(1.6500,0.6014,0.1000)
Business capability	(2.0500,0.5764,0.1000)
Solvency	(2.2500,0.6265,0.1000)
Profitability	(3.8000,0.5012,0.1000)
Capacity of goods organization	(3.3000,0.5513,0.1000)
Financial Disclosure Status	(3.0500,0.5764,0.1000)
Credit rating of core companies	(2.9500,0.4511,0.1000)
Industry position of core companies	(3.3000,0.5513,0.1000)
Gearing ratio	(3.0000,0.6265,0.1000)
Accounts payable to net assets	(2.5500,0.7017,0.1000)
Material characteristics	(1.6500,0.4761,0.1000)
Accounts receivable characteristics	(2.0000,0.3759,0.1000)
Interest rate risk	(1.0500,0.3383,0.1000)
Exchange rate risk	(0.9500,0.4511,0.1000)
Policy system risk	(1.7000,0.6766,0.1000)
Supply chain management	(2.1000,0.8771,0.1000)
Supply chain collaboration	(2.4000,0.5263,0.1000)
Supply chain finance competitive intensity	(3.7000,0.5513,0.1000)

Table 9. Primary indicators and characteristic values

First-Level Indicator	Eigenvalue
Financing application for corporate qualification	(2.2996,0.5881,0.1000)
Core corporate qualifications	(2.8825,0.6358,0.1000)
Corporate assets	(1.7617,0.4581,0.1000)
Macro-risks and industry risks	(1.1109,0.4441,0.1000)
Supply chain risk	(2.4952,0.6813,0.1000)

From the two-dimensional diagram drawn from the financing application enterprise qualification risk U_1 and enterprise asset condition risk U_3, the respective one-dimensional floor plan is obtained by observing from the two perspectives of U_1 and U_3, respectively, and from the comparative analysis of the floor plan and the standard risk cloud diagram, it can be seen that: the risk of U_3 is lower than that of U_1, then $U_3 \succ U_1$.

From the two-dimensional diagram drawn from the enterprise asset condition risk U_3 and macro and industry risk U_4, the respective one-dimensional floor plan is obtained by observing from two perspectives, U_4 and U_3, respectively, and from the comparative analysis of the floor plan and the standard risk cloud diagram, it can be seen that: the risk of U_4 is lower than that of U_3, then we obtain $U_4 \succ U_3$.

Figure 8. U_2, U_5 **2D risk cloud graph**

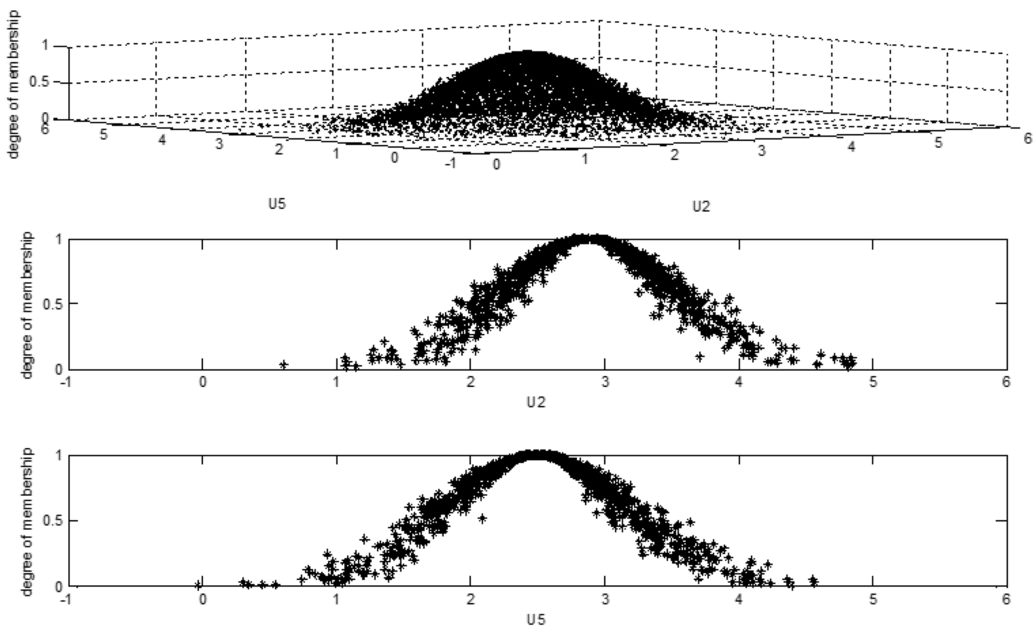
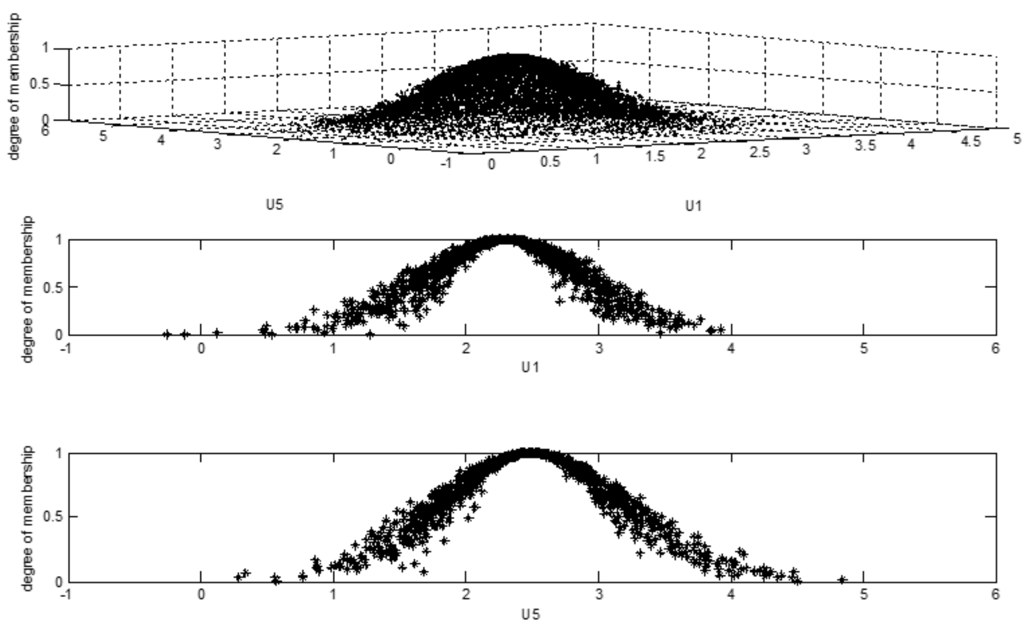


Figure 9. U_1, U_5 **2D risk cloud graph**



In summary, the evaluation results of each level of risk indicators are as follows: macro and industry risk $U_4 \succ$ enterprise asset condition risk $U_3 \succ$ financing application enterprise qualification risk $U_1 \succ$ supply chain risk $U_5 \succ$ core enterprise qualification risk U_2.

Figure 10. U_1, U_3 **2D risk cloud graph**

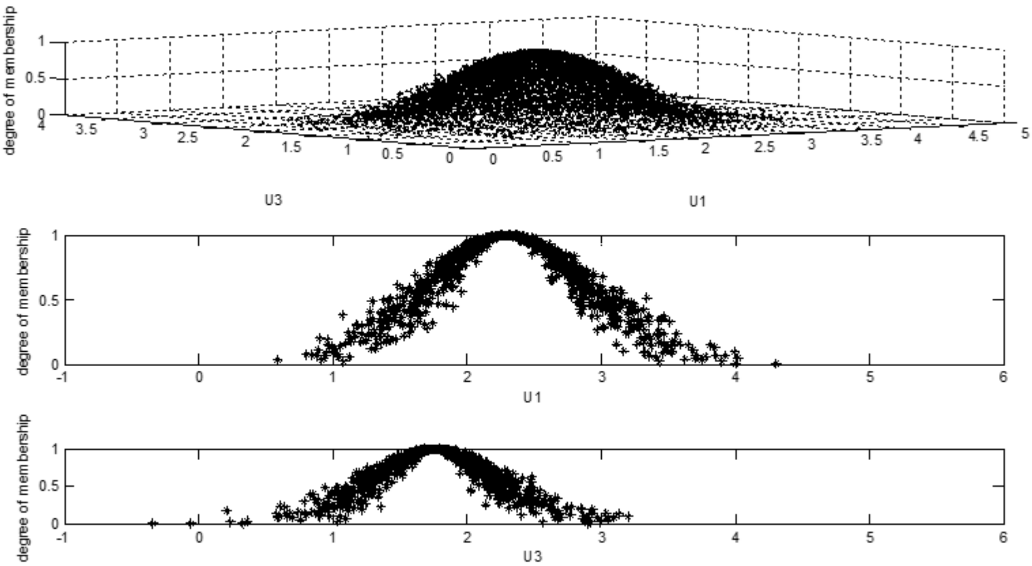
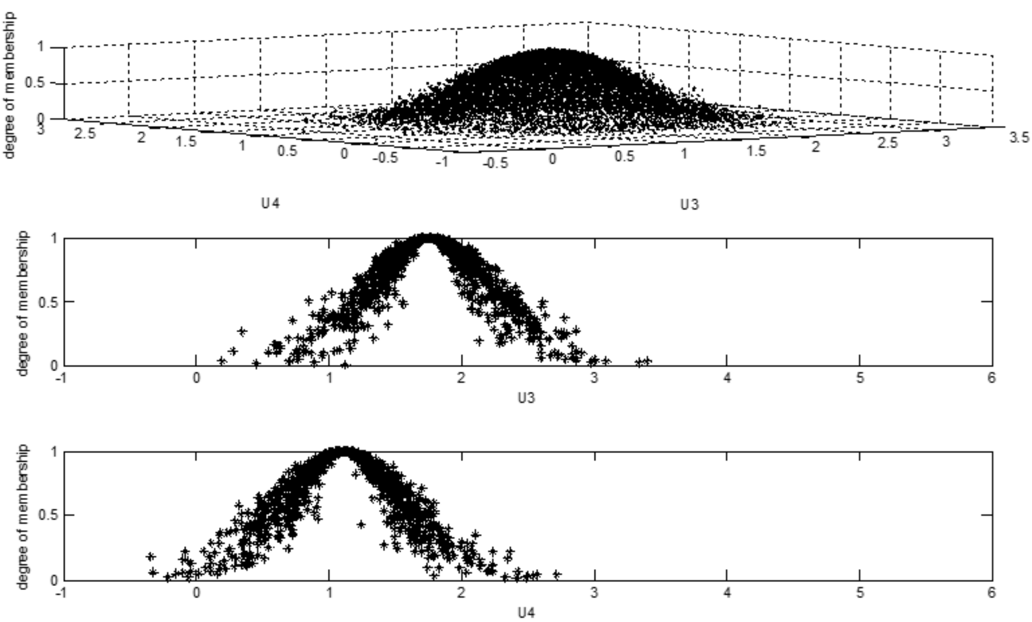


Figure 11. U_3, U_4 **2D risk cloud graph**

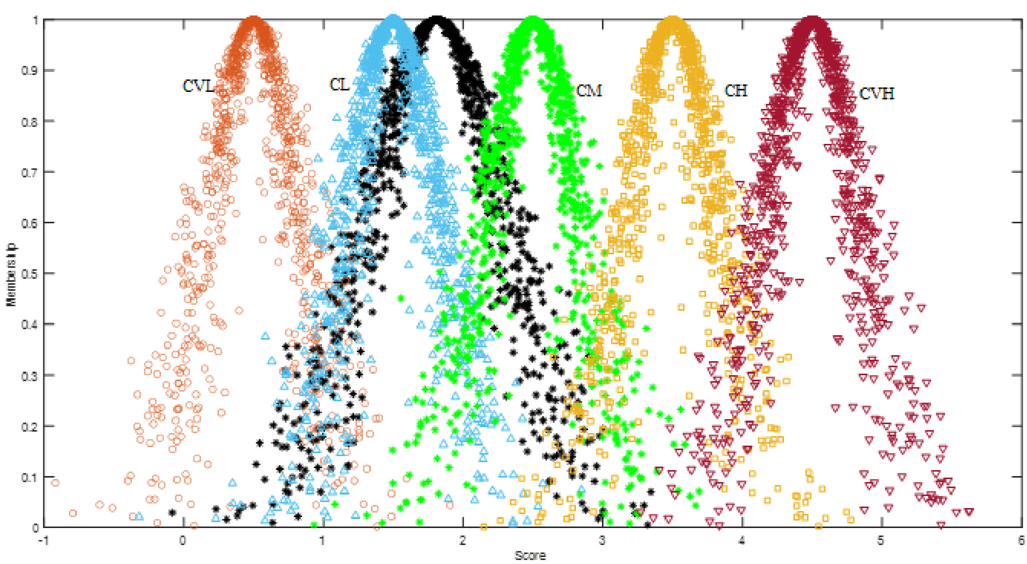


Then the comprehensive cloud characteristic value of QR company's supply chain finance is calculated as (1.8119, 0.4939, 0.1) based on the first-level indicators, and the comparison of the comprehensive cloud characteristic value of QR company's supply chain finance with the standard cloud risk cloud diagram shows that the overall risk level of QR company's supply chain finance is moderate-low risk, as shown in Figure 12.

The case introduces a multidimensional cloud model on the basis of supply chain finance to explore some risks that exist in the process of a company's supply chain finance operation mode, and finds that the risks faced by the company are controllable in general through the comprehensive cloud characteristic value of supply chain finance of QR Company, and puts forward relevant suggestions and improvement measures as follows.

1. QR faces significant core enterprise qualification risks. It is suggested that the company constructs a more complete credit evaluation system, pays attention to the credit rating of core enterprises in banks and the industry status of core enterprises, and can implement a strict reward and punishment system to give certain preferential policies, such as preferential interest rates, to enterprises with higher credit ratings. The credit risk of the enterprise can be improved by including the defaulting enterprise in the blacklist and refusing to provide relevant financial-type services to the defaulting enterprise, etc.
2. Improve the transparency of information and the internal management system of the company. The supply chain can leverage the leading technology of financial technology to provide sufficient power for supply chain development, enhance information flow and business cooperation among online companies, and reduce supply chain collaboration and management risks.
3. To strengthen the regulatory system for all aspects of supply chain finance operations, the government needs to actively improve the relevant policies and regulations, improve the supply chain finance mechanism, do a good job of risk prevention and control measures, protect the rights and interests of stakeholders, improve the enthusiasm of investors, purify the market environment, ensure the stable operation of the market, achieve the purpose of reducing macro and industry risks, and achieve the ideal state of healthy development of supply chain finance.

Figure 12. QR corporation supply chain finance risk integration cloud



FRONTIER ISSUES IN THE MULTIDIMENSIONAL CLOUD MODEL

Throughout the existing literature, there are fruitful research results on cloud modeling. Thanks for the effort of the research, the cloud model is promoted from one-dimensional to two-dimensional, three-dimensional, or more multidimensional cloud model, the research field is getting wider and wider, and the research method tends to be improved, but the research difficulty is also getting higher and higher. The following will focus on the research of multidimensional cloud model in dealing with the cutting-edge issues in image segmentation technology, evidence theory, linkage number theory and time series analysis, and the prospect of the application of the multidimensional cloud model.

Image Segmentation Processing Techniques

The images generated by introducing the cloud model into the field of image segmentation processing are better than the simulated image generation technique of the analytical model in terms of realism, universality, and rapidity. Due to the existence of many uncertainties in the image processing process, as well as the color, shape, and size of the image to be presented need to be consistent with the actual image, the complete and accurate transmission of image information is the cloud transformation process using the region growth method to achieve the key difficulties of automatic image segmentation technology, and similarly for the segmentation of images with more concepts, the perfection of the image simulation, whether it is possible to be from the most basic cloud model image segmentation Processing technology naturally transitions to the multidimensional cloud model image segmentation processing technology, and whether the effect presented after the transition is the same, is the model applied to the field is highly valued issues.

Cloud Model Fusion Evidence Theory Approach

With the development of information technology, there are more and more methods improved by experts on uncertainty inference rules, and different people have different ideas. Complex management systems suffer from a variety of elements, the coexistence of subjective and objective information, and difficulties in quantitative evaluation. Dempster proposed a comprehensive performance evaluation model with improved evidence theory (Beynon et al., 2000), and the combination of the cloud model and evidence theory became a new research hotspot. In the updating of D–S evidence, the results of the evidence update obtained will vary due to the differences in the combination weights obtained by the various methods, but there is still room for further exploration of the methods used and the variables relied upon.

Cloud Model and Connection Number Coupling Techniques

In engineering applications, the form of distribution of many indicators is restricted to the normal cloud model. However, the actual situation cannot fully achieve the ideal state, and the cloud model combined with the linkage number of the model can be applied to the form of distribution does not satisfy the normal distribution of the actual indicators to solve the problem of stochasticity and ambiguity in practical applications. The coupling of the one-dimensional cloud model with the number of links can intuitively evaluate the decision-making of intervals through the trend of the number of links, and when the dimensionality rises to multidimensional, it must consider the intrinsic connection between the indicators and whether a single indicator will cause excessive influence or not to be eliminated (Wang et al., 2020). Therefore, finding the optimal method of coupling between indicators still needs to be deeply investigated, and the validity and practicality of the model must be verified.

Time Series Forecasting Techniques

Time series represent an important class of complex data whose distributional properties change with time. Time series based on cloud model has become a research hotspot in China, which is mainly used for data mining of time series knowledge, and there are many expandable fields, the division and representation of information granulation in time granularity problem is a difficult point in time series problem. In real life, the development of the law of things by a variety of factors, how to decompose the multivariate time series into a one-dimensional time series for information granularity, so that this method is more and more simple and easy to operate to be further studied.

CONCLUSION

As the application areas of cloud modeling become more and more extensive, there are more and more methods combined with it. Early research was to deal with uncertainty and two-way cognitive problems through cloud modeling, with a single computational method that could not better handle the transformation between data and models. This paper makes a description of the theoretical study of multidimensional cloud models. The example applies the approach among those approaches to calculate supply chain risk. This paper reflects that the data source adopts the expert scoring method subjectively. A novel method proposed will be both objective and subjective. We will highlight the advantages of multidimensional cloud models compared with other methods in the future. Cloud modeling moves from theoretical research to the technical problems that need to be solved for practical applications. The complexity of multidimensionality, the feasibility and operability of the constructed model, and the uncertainty of the parameters of the multidimensional cloud model are the research directions that need to be solved.

COMPETING INTERESTS

The authors declare there is no conflict of interest.

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