Cloud model for new energy vehicle supply chain management based on growth expectation

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Abstract

The goal of supply chain management is to enhance output levels through the integration and collaboration of supply chain members. As such, identifying high-quality cooperative members is critical. However, many decision-making models for supply chain management neglect the consideration of growth expectations for these members, resulting in an unstable decision-making process. Therefore, it is essential to incorporate growth expectations into the decision-making process. To reduce ambiguity, we propose using cloud theory to quantify growth expectations and establish a cloud model of growth expectations. Our study underscores the importance of considering growth expectations when selecting supply chain cooperative members. By utilizing the cloud model of growth expectations, we provide a more comprehensive decision-making approach that enables decision-makers to assess the suitability of potential cooperative members and select the best member based on a multi-attribute decision-making process. We demonstrate the effectiveness of our method through case studies, which ensures its practicality and usability in real-world applications. Ultimately, our method offers a more efficient means of selecting cooperative members, which is expected to enhance output levels and increase supply chain efficiency.

Keywords Growth expectation · Collaborative capabilities · Supply chain management · Cloud models · Multi-attribute decision-making

Mathmatical Subject Classification M11 · L23

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1 Introduction

To improve efficiency and reduce the cost of the supply chain, strategic decisions need to be made throughout the entire production, logistics, and sales stages of the product. However, several obstacles exist in this process, including the involvement of multiple members in the production project, complex and dynamic interactions between members, and the constantly changing production environment. These challenges often lead to conflicting interests among supply chain participants, highlighting the importance of screening for excellent supply chain members. Chen et al. (2018) utilized a complete explanatory structural model (TISM) and fuzzy sets to optimize the selection of supply chain members. Adeinat and Ventura (2018) investigated how suppliers select the ideal provider in a supply chain system by applying mixed-integer nonlinear programming to a coordination model. Mohammed et al. (2019) constructed a model for the preferential selection of supply chain members using fuzzy AHP and TOPSIS. Soosay et al. (2008) proposed a novel approach to selecting supply chain members by examining the cooperative relationship between them, which can lead to high-value collaboration and positively impact members' innovation. Mahsa et al. (2019) introduced a new perspective on the selection of supply chain members using game theory and two methods: numerical calculation and sensitivity analysis. Xu et al. (2016), Liu et al. (2023) explored the agile supply chain's evolution mechanism to maximize the integration of upstream and downstream providers. Schramm et al. (2020) summarized the application of the MCDM/A methodology to supplier selection over the past 30 years. Kheljani et al. (2009) employed mixed-integer nonlinear programming to select the supplier with the lowest total supply chain cost. Amiri et al. (2021) analyzed the degree of uncertainty in the decision-maker's choice of supplier based on the Best–Worst Method (BWM) and the α-cut. Bai et al. (2019) used a grey-based multi-criteria decision support tool to conduct a more objective and comprehensive screening of supply chain members. Chen et al. (2020) applied a hybrid rough-fuzzy method to select sustainable suppliers for intelligent supply chains, addressing both individual linguistic fuzziness and group diversity preferences. Andreas (2021) defined supply chains as social-ecological systems, emphasizing the need for broader environmental considerations and supply chain agility in operations. Yan and Lin (2020) utilized structural modeling to demonstrate the high impact of the relationships between supply chain partners on green innovation performance, as well as the promoting effect of supply chain collaboration on green innovation. Liu et al. (2019) proposed a fuzzy three-stage integrated multi-criteria decision-making (MCDM) method for supplier selection in new energy vehicle procurement. Finally, Rafigh et al. (2022) employed the Economic Order Quantity (EOQ) model to assess the performance of supply chain members.

Academics have developed sophisticated approaches to optimize supply chain participants, as mentioned earlier in the literature. However, there is a need to pay more attention to the growth variability of supply chain members, which we refer to as the expectation of future competitiveness. Numerous studies have been conducted on the topic of expectations. For example, Fang et al. (2018) identified differences in the factors influencing the siting of photovoltaic power plants under varying levels of expectation. Powell et al. (2022) used forecasts of the future business environment

to identify the causes of firms' underperformance and propose solutions. Song et al. (2018) determined optimal solutions by calculating profit and loss intervals using manufacturers' expected values. Yang et al. (2022) investigated the mechanism of influence of alliance goal expectation achievement on stability. Tesch et al. (2005) investigated the relationship between the expectation gap and user satisfaction. Qiu et al. (2021) combined the expectation-confirmation model (ECM) and the Investment Model (IM) to explore consumer performance. Coibion et al. (2018) examined how firms form expectations based on the information and the implications for the development of the enterprise.

In this paper we propose a growth expectation value model based on cloud theory, which combines expectation value and cloud theory. This model aims to address the uncertainty of the supply chain member selection process and ultimately enhance the stability of the supply chain. In addition, this paper establishes a scientific and comprehensive evaluation index system for the cooperative ability of supply chain members with Grounded Theory. By calculating the prospective values of growth expectations for each member under different indices, the optimal choice is determined.

2 Cloud theory

2.1 Cloud modeling principle

The cloud model is a mathematical framework that addresses the challenge of converting qualitative data into quantitative data. This is achieved through the development of a cloud algorithm that performs the conversion. During the evaluation process, the cloud algorithm generates an Expectation, denoted by Ex, Entropy, denoted by En, and Hyper Entropy, denoted by He. These symbols represent the quantitative value of the concept being evaluated, as well as the degree of certainty associated with it.

Definition 1: Let C be a qualitative concept on a quantitative domain U, and let $x \in U$ be a random realization of concept C. The determination degree $\mu(x) \in [0,1]$ of x with respect to C is a stable distribution of a random number: $\mu(x)$: $U \rightarrow [0,1]$ for $x \in$ U. The distribution of variable x in the domain U is referred to as a cloud, and each x is called a cloud droplet. The numerical characteristics of the cloud are represented by three values (Ex, En, He), known as the cloud model (Ex, En, He). Where Ex represents the certainty of qualitative events, En represents the uncertainty of qualitative events, and He represents the uncertainty of entropy (Yang et al. 2018).

Figure 1 illustrates the specific shapes of the three characteristic values of a cloud model. The advantage of using cloud models is that they can simultaneously reflect the certainty and uncertainty of events, which enables a more objective evaluation of supply chain members.

2.2 The cloud algorithms

The cloud algorithm is a technique that transforms qualitative and quantitative concepts by utilizing the randomness and imprecision of multi-dimensional events, which is
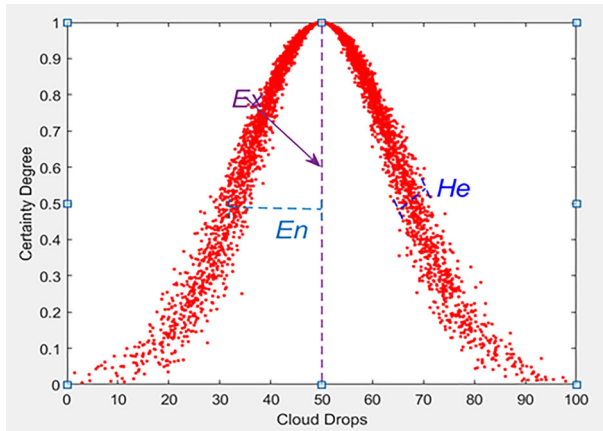
Fig. 1 Cloud model features

crucial for implementing the cloud model. Prior research on cloud algorithms can be broadly classified into deterministic inverse cloud algorithms and probabilistic inverse cloud algorithms. However, the deterministic inverse cloud algorithms lack practicality due to the challenge of obtaining the degree of certainty that represents qualitative concepts in real-world production activities. After comparing various methods, the uncertainty-free inverse cloud algorithm was chosen as the preferred method, which is more suitable for new energy vehicle manufacturing enterprises to collect information in the manufacturing process. The calculation process is shown as follows (Yang et al. 2018).

Input: N cloud droplets x_i ($i = 1, 2, ..., N$).

Output: Cloud characteristic values (Ex, En, He) by Eqs. (1)–(3).

$$Ex = \overline{x} = \frac{1}{N} \sum_{i=1}^{N} x_i. \tag{1}$$

$$En = \sqrt{\frac{\pi}{2}} \times \frac{1}{N} \sum_{i=1}^{N} |x_i - Ex|. \tag{2}$$

$$He = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \overline{x})^2 - En^2}. \tag{3}$$

2.3 Integrated cloud model

Definition 2: Synthesize two or more sub-clouds of the same type to produce a parent cloud representing a higher-level concept. Calculate the numerical features of all sub-clouds to obtain the numerical features of the synthesized cloud as the parent cloud (Xu et al. 2017).

The group decision-making approach based on the cloud model involves combining multiple individual cloud models of the same type into a single integrated model through a computational formula transformation. This process converts discrete base evaluations into a unified evaluation. The merging of the same type of cloud models is achieved through computational equations, such as $C_1(Ex_1, En_1, He_1)$, $C_2(Ex_2, En_2, He_2)$, …, $C_n(Ex_n, En_n, He_n)$, to generate integrated cloud $C(Ex', En', He')$ by Eq. (4).

$$\begin{cases} Ex' = \frac{\sum_{i=1}^{n} Ex_i * En_i}{\sum_{i=1}^{n} En_i}; \\ En' = \sum_{i=1}^{n} En_i; \\ He' = \frac{\sum_{i=1}^{n} He_i * En_i}{\sum_{i=1}^{n} En_i}. \end{cases} \tag{4}$$

2.4 Cloud similarity

When using cloud models for multi-attribute decision-making, it is necessary to conduct quantitative comparisons between the models. We establish the similarity between cloud models by calculating their degree of similarity. There are two primary categories of similarity measures for cloud models. The first uses weighted cloud drop distances to determine similarity, while the second category is based on the numerical eigenvalues of the cloud model. Due to the complexity of the first method and its limited practicality in production activities, we adopt the method of comparing the variance of the cloud model for similarity measurement, as outlined in Wang et al. (2017). Consider two cloud models, $C_i(Ex_i, En_i, He_i)$ and $C_j(Ex_j, En_j, He_j)$, offering the following Eq. (5) for estimating the similarity S, where $D(C) = (En)^2 + (He)^2$.

The calculation of the similarity between two cloud models is represented by their uncertainty as a measure. The greater the similarity in shape between the two cloud model representations, the more similar their uncertainties, as a way to compare the similarity.

$$S(C_i, C_j) = \sqrt{\frac{\min(D(C_i), D(C_j))}{\max(D(C_i), D(C_j))}}. \tag{5}$$

3 Cloud similarity-based foreground value measurement

The current evaluation value x_{ij} of each alternative supplier is calculated using the expert scoring method for evaluating indicators, where x_{ij} represents the evaluation value of indicator i at supplier j. Then, an evaluation of the growth expectations for the suppliers is conducted, resulting in an expectation-based evaluation value r_{ij} where r_{ij} represents the growth expectation evaluation value of indicator i at supplier j. The value of each supplier's future development can be projected based on their historical collaboration experience, engineering performance, and the production environment and development trends, as detailed in Zhu et al. (2023). This growth forecast can be assessed at each stage of the supplier's historical development. A set of linguistic evaluations is then created based on their various growth expectations, which are expressed in terms of a number of intervals as illustrated in Table 1.

In the context of multi-attribute decision-making, assigning accurate quantitative values to the linguistic set of candidate solutions can be challenging. As a result, using interval numbers for fuzzy quantitative evaluation is a more practical approach. The value of d is assigned based on different evaluation objects and treated as a real number. The expectation-based evaluation value r_{ij} is transformed into interval number $r'_{ij} = \left[r^l_{ij}, r^u_{ij} \right]$, with r^l_{ij} representing the lower growth limit and r^u_{ij} representing the upper growth limit. The left and right clouds are generated by combining the evaluation value x_{ij} with r^l_{ij} and r^u_{ij} using formulas (1) – (3). Equation (6) from the literature Zhang et al. (2015) is used to derive the following, essentially, it is the synthesis of multiple qualitative concepts into a more generalized concept to generate a comprehensive cloud model.

$$k(Ex, En, He) = (kEx, kEn, kHe). \tag{6}$$

Therefore, the left and right clouds, x^l_{ij} and x^u_{ij}, can be generated based on the number of growth expectation intervals, as shown in Eqs. (7) and (8). These two clouds can be combined using an integrated cloud model to generate the growth expectation integrated cloud x'_{ij} based on Eq. (4), as shown in Eq. (9).

$$x^l_{ij} = \left(\left(1 + r^l_{ij} \right) Ex_{ij}, \left(1 + r^l_{ij} \right) En_{ij}, \left(1 + r^l_{ij} \right) He_{ij} \right). \tag{7}$$

Table 1 Linguistic conversion table

Linguistic evaluation set	Interval number	Sign substitution
Significant increase	$[3d, 5d)$	$++$
Slight increase	$[d, 3d)$	$+$
Stable	$[-d, d)$	$=$
Slight decrease	$[-3d, -d)$	$-$
Significant decrease	$[-5d, -3d]$	$—$

$$x_{ij}^u = \left(\left(1 + r_{ij}^u\right) Ex_{ij}, \left(1 + r_{ij}^u\right) En_{ij}, \left(1 + r_{ij}^u\right) He_{ij} \right). \tag{8}$$

$$x_{ij}' = \left(Ex_{ij}', En_{ij}', He_{ij}' \right). \tag{9}$$

The increasing expectation function is derived from the value function (10) presented in the literature (Kahneman and Tversky 1987; Tversky and Kahneman 1992). The growth expectation value is determined by the extent of deviation from the reference point and reflects the psychological behavior of the decision-maker during the decision-making process.

$$v\left(x_{ij}\right) = \begin{cases} (1-S)^\alpha, \ Ex_{ij}' \geq Ex_{ij}; \\ -\theta[-(S-1)]^\beta, \ Ex_{ij}' < Ex_{ij}, \end{cases} \tag{10}$$

where $(1 - S)$ represents the value of benefit or loss and S represents the similarity between x_{ij} and x_{ij}', while $\alpha \in (0, 1)$ and $\beta \in (0, 1)$ indicate the decision-making disposition in response to risk. A higher value indicates a greater inclination towards riskier options. $\theta > 1$ denotes the degree of sensitivity towards losses resulting from the decision, with a higher value reflecting greater concern for losses. In this study, $\alpha = \beta = 0.88$ and $\theta = 2.25$, based on literature Lin et al. (2017), and the weight w_j of the evaluation index is employed to calculate the comprehensive prospect value, as presented in Eq. (11), where p denotes the number of indicators.

$$V_j = \sum_{i=1}^{p} w_i v\left(x_{ij}\right). \tag{11}$$

4 Establishment of evaluation index system

4.1 Introduction to the method

The grounded theory originates from sociological research, referring to the systematic collection and analysis of data, and the induction and deduction of core concepts from the data itself, gradually constructing or refining corresponding theories, with high reliability and explanatory power (Fang et al. 2022). Based on this foundation, open coding, axial coding, and selective coding are conducted, and theoretical saturation is tested.

Scholars have extensively researched supply chain collaboration from various perspectives, including but not limited to supply chain performance, communication, and exchange among personnel, partner trustworthiness, collaborative interaction among suppliers to facilitate information sharing, and enterprise risk management capability (Hartley et al. 2014; Liu et al. 2022; Oh et al. 2010; Jung et al. 2023; Li and Chen 2019). The aim of this paper is to evaluate the collaborative capabilities of supply chain members by constructing measurement indexes (Liu et al. 2022). To obtain the

initial data for evaluating members' collaboration capability, the relevant literature on evaluation indexes and methods is collected. Analysis techniques such as sampling, comparison, summarization, and aggregation are employed to select the most appropriate evaluation indexes, based on the findings of the relevant literature. The literature search involved retrieving 448 articles by selecting core journals with search criteria such as collaboration evaluation, engineering collaboration, collaboration factors, collaboration index, enterprise collaboration impact, or collaboration capability evaluation. After further filtering, 123 journals that were relevant to evaluating collaboration capability were chosen from the search.

4.2 Open coding

Open coding involves simplifying the selected literature by obtaining a summary of its key concepts, which are progressively refined to form a theoretical framework through an in-depth analysis of the material. In this study, a total of 93 literature samples were initially consulted during the open coding phase. After calibration, the remaining 30 samples were used to conduct a saturation test for the coordinating ability index, verifying the comprehensiveness of the obtained evaluation metrics and that no new categories would be generated. By carefully integrating the collected material, organizing its relevant logical concepts, and analyzing it, nine categories were identified and summarized. The method used to generate these categories through open coding is presented in Table 2.

4.3 Axial coding

Axial coding is the next phase in the process of refining the relevant categories derived from the open coding procedure. The results generated are reported in Table 3.

4.4 Selective coding

Selective coding also extracts the core categories by obtaining the axial coding, and it generates an evaluation model and an index assessment system for assessing the collaboration capabilities of supply chain partners. As shown in Table 4 on the next page, the key areas of collaborative capacity include inter-member relationships, internal management, and organizational competitiveness.

Based on the literature review, the evaluation index system for the collaboration capability of supply chain members consists of three evaluation dimensions: inter-member relationship, internal management, and exit cost. There are six primary indicators: manager's perception, enterprise competitiveness, trust degree, economic efficiency, communication ability, and dependence degree. Additionally, there are nine secondary indicators, which include communication ability (Z_1), management philosophy (Z_2), trust level (Z_3), resource sharing ability (Z_4), dependency level (Z_5), economic efficiency (Z_6), local market sophistication (Z_7), risk-taking attitude (Z_8),

Table 2 Open coding

Category	Concept	Statement source
Communication skills	Effectiveness of communication among members	Obstacles in communication methods and a lack of emphasis on active communication philosophy can cause delays in meeting schedule requirements
Management philosophy	Inter-company managerial philosophy to be compatible	Differing values and management concepts among supply chain members can lead to contradictions in production operations and management methods, resulting in a lag in progress and a loss of management in relevant parts of the supply chain
Trustworthiness	A collaborative relationship of mutual trust is a prerequisite to ensure the smooth running of the entire project	The speed and channels of information acquisition vary among members, and trade-offs between interests may lead to temporary breaches of contract, deliberate concealment of information, and deception of partner interests
Resource sharing	Access and sharing of information and technology	Partnerships between engineering firms can facilitate knowledge and information sharing by bringing complementary resources and technical capabilities
Dependency	Have the resources and capabilities with collaborative partners that each other needs	Companies with good resource capabilities are more likely to form partnerships based on their core business requirements for resources
Economic benefits	Cooperation in the interests of all parties to maximize their own	The lack of trust among members can make it difficult to reconcile conflicts based on the distribution of interests, leading to a breakdown in cooperation and decreased economic efficiency of the project
Local market maturity	Capable local companies are more likely to get the job done	Local suppliers may form competitive relationships with each other

Table 2 (continued)

Category	Concept	Statement source
Risk-taking attitude	Companies may make efforts to maximize their interests in the face of risks	Establishing a clear risk-sharing contract can effectively restrain companies from behaving in ways that undermine the stability of the supply chain
Professional Competence	Outstanding technical expertise facilitates overall cooperation	A company's expertise is not only its core competency but also contributes to improving the innovation ability of supply chain members

Table 3 Axial coding

Main category	Category
Manager's perception	Management philosophy, Risk-taking attitude
Enterprise competitiveness	Professional capabilities, Resource sharing capabilities, Local market sophistication
Trustworthiness	Trustworthiness
Economic benefits	Economic benefits
Communication skills	Communication skills
Dependency	Dependency

Table 4 Selective coding

Main category	Category
Inter-member relations	Trustworthiness、Communication skills
Internal management	Manager's perception、Economic benefits
Exit costs	Enterprise competitiveness、Dependency

and professional ability (Z_9). These indicators are essential for assessing the collaborative capacity of supply chain partners.

4.5 AHP-entropy method to determine the weights

4.5.1 Analytic hierarchy process (AHP)

Construct a two-comparison judgment matrix A_{ij} by Eq. (12) based on Table 5, where A_{ij} represents the importance of indicators i over indicators j.

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}. \tag{12}$$

Calculating the weights u_i by Eqs. (13) and (14), where u represents the weight vector

$$u_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij}}}{\sum_{i=1}^{n} \sqrt[n]{\prod_{j=1}^{n} a_{ij}}}. \tag{13}$$

$$u = (u_1, u_2, ..., u_n)^T. \tag{14}$$

Consistency tests by Eqs. (15) and (16),

$$CI = \frac{\lambda_{max-n}}{n-1}. \tag{15}$$

$$CR = \frac{CI}{RI}, \tag{16}$$

Table 5 Judgment matrix scale and meaning

No	The importance of i over j denoted by symbol	The meaning of symbol	Assignment
1	=	Equally important	1
2	↑	Slightly important	3
3	↑↑	Significantly important	5
4	↑↑↑	Strongly important	7
5	↑↑↑↑	Extremely important	9
6	↓	Slightly unimportant	1/3
7	↓↓	Obviously unimportant	1/5
8	↓↓↓	Strongly unimportant	1/7
9	↓↓↓↓	Extremely unimportant	1/9

Table 6 Indicator judgment matrix

Indicators	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Weights
Z_1	1	1/5	1	3	1/5	1/3	1	1/3	1	0.05
Z_2	5	1	3	7	3	3	7	1	3	0.26
Z_3	1	1/3	1	3	1/3	1/5	1	1/7	1/3	0.05
Z_4	1/3	1/7	1/3	1	1/3	1/3	1	1/5	3	0.04
Z_5	5	1/3	3	3	1	1	3	1/3	1	0.12
Z_6	3	1/3	5	3	1	1	5	1	1	0.14
Z_7	1	1/7	1	1	1/3	1/5	1	1/3	1	0.05
Z_8	3	1	7	5	3	1	3	1	5	0.22
Z_9	1	1/3	3	1/3	1	1	1	1/5	1	0.07

$CI = 0.1428$, $RI = 1.451$, $CR = 0.0984 < 0.1$.

where $\lambda_{max} = \sum_{i=1}^{n} \frac{(Au)_i}{nu_i}$ represents the maximum eigenvalue of the matrix, and RI represents the mean random consistency index of the matrix. If $CR \leq 0.1$, indicates that the judgment matrix passes the consistency test. The results of the weight calculation are shown in Table 6.

4.5.2 Entropy weight method

A decision matrix can be constructed by having m experts score n indicators, generating a decision matrix D_{ij} by Eq. (17), where D_{ij} represents the evaluation value of experts i at indicators j.

$$D_{ij} = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \dots & \dots & \ddots & \dots \\ d_{m1} & d_{m2} & \dots & d_{mn} \end{bmatrix}. \tag{17}$$

The data is standardized using Eqs. (18) and (19).

$$e_{ij} = \frac{d_{ij} - \min(d_{ij})}{\max(d_{ij}) - \min(d_{ij})}. \tag{18}$$

$$s_{ij} = \frac{e_{ij}}{\sum_{i=1}^{m} e_{ij}}. \tag{19}$$

The entropy weight method is used to calculate weights by Eqs. (20) and (21), where the information entropy E_j and weight o_j are obtained.

$$E_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} s_{ij} \ln(s_{ij}). \tag{20}$$

Table 7 Expert ratings

Experts	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9
A	70	85	55	75	75	80	65	30	70
B	50	50	35	60	65	75	50	70	35
C	55	50	75	65	65	70	60	35	40
D	60	40	50	80	60	75	50	50	30
E	75	20	20	70	60	70	40	50	60

Table 8 Weight calculation

Indicators	Information entropy value e	Information utility value d	Weights
Z_1	0.77	0.23	0.10
Z_2	0.80	0.20	0.09
Z_3	0.80	0.20	0.08
Z_4	0.80	0.21	0.09
Z_5	0.60	0.41	0.18
Z_6	0.65	0.35	0.15
Z_7	0.81	0.19	0.08
Z_8	0.75	0.25	0.11
Z_9	0.71	0.30	0.12

$$o_j = \frac{1 - E_j}{\sum_{i=1}^{n}\left(1 - E_j\right)}. \tag{21}$$

Weight results are calculated based on the experts ratings in Table 7 and presented in Table 8.

The composite weight w_j is calculated using Formula (22), where u_j and o_j are the weights obtained from analytic hierarchy process and the entropy weight method, respectively (Li et al. 2020). The weight summary table is presented in Table 9.

$$w_j = \frac{u_j o_j}{\sum_{j=1}^{n}\left(u_j o_j\right)}. \tag{22}$$

Table 9 Summary of weights

Methods	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9
AHP weights	0.05	0.26	0.05	0.04	0.12	0.14	0.05	0.22	0.07
Entropy method weights	0.10	0.09	0.08	0.09	0.18	0.15	0.08	0.11	0.12
Composite weights	0.04	0.20	0.04	0.03	0.19	0.18	0.04	0.21	0.07

5 Analysis of calculation cases

5.1 Decision-making process

In the decision-making process for a corresponding set of indicator attributes $Z = (Z_1, Z_2, \ldots, Z_p)$, and the set of alternative suppliers $A = (A_1, A_2, \ldots, A_k)$, an evaluation matrix $X = [x_{ij}]_{p \times k}$ is obtained, where x_{ij} represents the evaluation value of indicator i at supplier j. The values of p and k represent the number of indicators and suppliers, respectively. The decision-making process can be summarized as follows,

1. The indicators are scored using the expert scoring method. Based on the obtained scores, the evaluation value x_{ij} is generated using Eqs. (1)–(3).
2. To convert this value into the growth expectation composite cloud x'_{ij}, Eqs. (4), (6) and (7)–(9) are utilized in conjunction with the evaluation value x_{ij}.
3. Apply Eq. (5) to calculate the cloud similarity between the evaluation value x_{ij} of the candidate supplier and the expected evaluation value x'_{ij}.
4. The comprehensive prospect value of supplier j, denoted as V_j, is calculated by first using formulas (12)–(22) to determine the comprehensive weight, and then applying formulas (10) and (11) to calculate V_j. A higher V_j value indicates a better solution.

5.2 Calculation example analysis

According to step 1, we will use the supply chain system of a new energy vehicle company as an example. We will randomly select five supply chain members in its system and form a three-member expert group to score and evaluate the nine secondary indicators. The evaluation values and growth expectation values of suppliers across different indicators can be found in Tables 10 and 11, respectively.

The expectations for growth can be based on the subject's historical performance data, taking into account its production environment and development conditions, and a prognosis of its expected future growth trends by specialists. The meanings of the different symbols used in Table 11 have been explained in detail in Table 1.

The expected evaluation value x'_{ij} is calculated by assigning a value of 0.01 to d based on step 2, and the calculation results are obtained as shown in Table 12.

Based on step 3 and step 4, the expected value of each supplier under the corresponding index is calculated as shown in Table 13.

Table 10 Evaluation value of each supplier

	A_1	A_2	A_3	A_4	A_5
Z_1	(80.33,4.89,4.10)	(71.67,3.49,2.12)	(76.33,6.98,5.99)	(75.67,6.63,5.35)	(80.67,5.93,4.18)
Z_2	(73.33,3.49,2.12)	(72.00,7.33,4.50)	(75.60,4.54,3.47)	(79.30,3.49,2.55)	(78.00,8.38,7.60)
Z_3	(75.67,9.78,6.09)	(79.33,9.08,6.95)	(73.67,3.84,2.43)	(65.33,16.06,10.62)	(80.00,5.24,4.75)
Z_4	(67.00,12.57,8.72)	(78.33,3.84,3.15)	(78.33,6.98,4.46)	(76.33,10.12,6.49)	(82.67,4.89,2.96)
Z_5	(59.00,9.43,6.10)	(73.30,3.49,2.12)	(68.3,13.96,8.58)	(71.33,6.63,4.55)	(80.00,5.24,4.75)
Z_6	(56.67,8.73,6.36)	(70.00,5.24,4.75)	(75.33,0.70,0.42)	(76.30,11.87,7.20)	(76.67,8.73,6.36)
Z_7	(61.67,8.73,6.36)	(71.67,3.49,2.12)	(81.00,6.28,4.06)	(79.30,9.78,6.57)	(73.30,19.2,12.16)
Z_8	(73.33,3.49,2.12)	(72.00,4.19,2.54)	(80.00,5.24,4.75)	(80.30,1.75,1.27)	(78.67,19.55,12.18)
Z_9	(81.67,3.49,2.12)	(67.30,12.92,8.11)	(78.67,6.63,4.08)	(81.33,5.59,4.41)	(81.67,3.49,2.12)

Table 11 Growth expectations by supplier

	A_1	A_2	A_3	A_4	A_5
Z_1	+	=	−	+ +	=
Z_2	=	+	+	=	−
Z_3	−	=	+	=	=
Z_4	−	+ +	+	=	=
Z_5	+	+	=	−	=
Z_6	=	+ +	+	=	−
Z_7	=	+	+	+ +	−
Z_8	+	+	−	=	=
Z_9	+	+	−	−	=

After incorporating the indicator weights, each supplier is assigned a comprehensive prospect value as follows, $V_{A1} = 0.3764$, $V_{A2} = 0.4861$, $V_{A3} = -0.0182$, $V_{A4} = 0.0775$, and $V_{A5} = -0.0857$. The suppliers ranking are expressed as $A_2 > A_1 > A_4 > A_3 > A_5$.

5.3 Contrast analysis

To further illustrate the impact of introducing a cloud model and growth expectations on supplier prioritization, a comparison approach was employed with other selected methods. Different methods are as follows,

1. Method 1, expert evaluation method.
   The established evaluation index system is utilized to score the nine secondary indicators by experts. Based on the weighting of each indicator, a comprehensive score is then calculated, with higher scores indicating higher ranking priority.
2. Method 2, expert evaluation method based on growth expectations.
   Based on Method 1, growth expectations were introduced and evaluated separately for the nine secondary indicators. The interval value for growth expectations was then obtained by assigning a value to d in Table 1, according to the actual situation.
3. Method 3, evaluation method based on cloud similarity (Wang et al. 2022).

Based on Table 10, the TOPSIS theory was employed to determine the optimal and worst comprehensive cloud models, denoted as C^+ and C^- respectively. For each indicator, a higher value of Ex indicates better performance, whereas higher values of En and He suggest poorer performance. Subsequently, a comprehensive weighted cloud model was computed separately for each supplier. Finally, the comprehensive similarity S_t was found using formulas (5) and (23), where S_{C+} and S_{C-} represent the cloud similarity of the comprehensive weighted cloud model with C^+ and C^-, respectively. The specific results are presented in Table 14, where a higher value

Table 12 Growth expectation rating by supplier

	A_1	A_2	A_3	A_4	A_5
Z_1	(81.95,9.97,4.18)	(71.67,6.98,2.12)	(74.8,13.69,5.87)	(78.70,13.00,5.57)	(80.67,11.87,4.18)
Z_2	(73.33,6.98,2.12)	(73.45,14.96,4.59)	(77.19,9.26,3.54)	(79.30,6.98,2.55)	(76.45,16.42,7.45)
Z_3	(74.16,19.16,5.97)	(79.33,18.15,6.95)	(75.15,7.83,2.48)	(65.33,32.12,10.62)	(80.00,10.47,4.75)
Z_4	(67.24,63.00,8.55)	(81.47,7.99,3.28)	(79.91,14.24,4.55)	(76.33,20.25,6.49)	(82.67,9.78,2.96)
Z_5	(60.19,19.23,6.22)	(74.81,7.12,2.20)	(68.30,27.93,8.75)	(69.91,13.27,4.55)	(80.00,10.47,4.66)
Z_6	(56.67,17.46,6.36)	(72.81,10.89,4.94)	(76.85,1.42,0.43)	(76.30,23.74,7.20)	(75.14,17.11,6.24)
Z_7	(61.67,17.46,6.36)	(73.11,7.12,2.16)	(82.63,12.82,4.14)	(82.51,20.33,6.83)	(71.87,37.63,11.92)
Z_8	(76.27,7.12,2.16)	(73.45,8.55,2.59)	(78.41,10.26,4.66)	(80.30,3.49,1.27)	(78.67,39.10,12.18)
Z_9	(84.94,7.12,2.16)	(68.69,26.35,8.27)	(77.10,13.00,4.00)	(79.70,10.95,4.32)	(81.67,6.68,2.12)

Table 13 Expected value of each supplier

	A_1	A_2	A_3	A_4	A_5
Z_1	0.4564	0.4860	− 0.9650	0.4438	0.4693
Z_2	0.4860	0.4954	0.4695	0.4648	− 0.9438
Z_3	− 1.0619	0.4582	0.4922	0.4767	0.4319
Z_4	− 1.0340	0.4707	0.4912	0.4801	0.4860
Z_5	0.4900	0.4975	0.4855	− 1.0631	0.4298
Z_6	0.4648	0.4551	0.4966	0.4860	− 1.0196
Z_7	0.4648	0.4966	0.4900	0.4962	0.4702
Z_8	0.4966	0.4966	− 0.9438	0.4648	0.4831
Z_9	0.4966	0.4931	− 1.0649	− 0.9942	0.4860

Table 14 Integrated weighted cloud model

Suppliers	Integrated weighted cloud model	C^+	C^-
A_1	(67.91,6.35,4.24)	(79.60, 2.65,1.67)	(65.60, 13.54,8.84)
A_2	(72.02,5.61,3.80)		
A_3	(75.57,6.14,4.31)		
A_4	(76.83,6.46,4.34)		
A_5	(78.68,9.95,7.21)		

indicates a better solution.

$$S_t = \frac{S_{C+}}{S_{C+} + S_{C-}}. \tag{23}$$

The comprehensive similarity values for each supplier are as follows: $S_{A1} = 0.4729$, $S_{A2} = 0.5324$, $S_{A3} = 0.4812$, $S_{A4} = 0.4637$, and $S_{A5} = 0.2573$. A higher S value indicates a better solution. Thus, the suppliers are ranked as $A_2 > A_3 > A_1 > A_4 > A_5$.

4. Method 4, evaluation method of cloud models based on growth expectations.

The rankings of suppliers obtained from each of these methods are presented in Table 15.

The evaluation results for Method 1 and Method 2 are consistent, as shown in Fig. 2. The comparison of evaluation scores reveals significant fluctuations among suppliers A_1, A_2, and A_5. This is because suppliers A_1 and A_2 have better growth expectations in each indicator, whereas supplier A_5 has a slightly lower growth expectation in management concept, economic efficiency, and local market indicators, which have relatively higher weights.

The comparison between Method 1 and Method 3 reveals that the introduction of cloud theory to incorporate uncertainty into the evaluation system has a greater impact

Table 15 Comparison of different evaluation methods

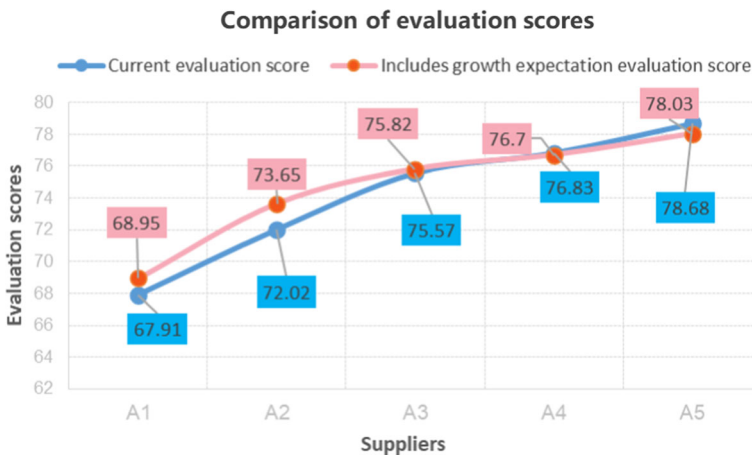| Suppliers	Method 1	Method 2	Method 3	Method 4
A_1	5	5	3	2
A_2	4	4	1	1
A_3	3	3	2	4
A_4	2	2	4	3
A_5	1	1	5	5

Fig. 2 Comparison of evaluation scores

on the overall ranking. Suppliers A_5 and A_4 have higher levels of uncertainty, leading to a lower ranking, which is consistent with the risk-averse psychology of decision-makers in actual production activities. This verifies the rationale for introducing cloud theory into supply chain evaluation. The uncertainty can be expressed as $D = (En)^2 + (He)^2$, as shown in Table 16.

The comparison between Method 3 and Method 4 reveals that the addition of growth expectations resulted in a change in the ranking, with supplier A_3 dropping from second to fourth place. Figure 3 shows the results of further analysis of the effects of the growth expectation value d extracted from Table 1 on the prospective values, using $d = 0.2$ as a comparison. As the value of d increases, the outlook for suppliers A_1 and A_2 tend to decrease, while suppliers A_3, A_4, and A_5 tend to rise, resulting in

Table 16 Uncertainty comparison

Suppliers	A_1	A_2	A_3	A_4	A_5
Uncertainty	58.3297	45.9562	56.4048	60.5082	151.0226
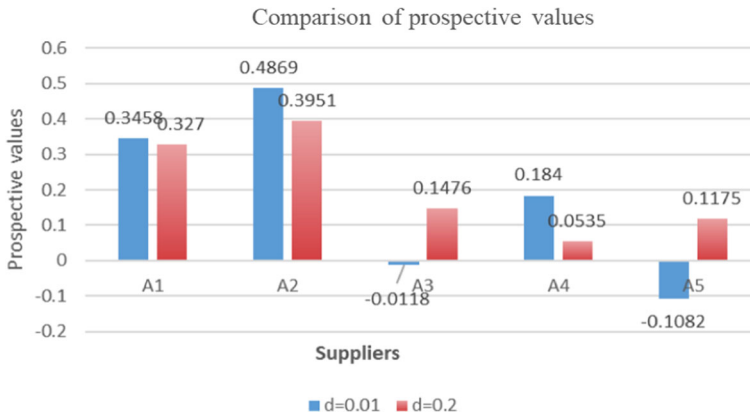
Fig. 3 Comparison of prospective value

a change in the ranking of suppliers A_3, A_4 and A_5. The decision-maker can choose a preferred solution based on the actual situation with respect to the value assigned to d.

6 Conclusions

6.1 Effectiveness of the method

Through analysis of the integrated prospect values and evaluation scores obtained from our case study, we determined the impact of growth expectations on various supplier members, thus confirming the effectiveness of our proposed method. Previous research on supply chain member optimization has primarily focused on improving the evaluation method, while neglecting the variability of the supply chain in different environments. This limitation has resulted in an evaluation method that is inadequate for production enterprises with rapid technological updates and long production cycles, such as those involved in the production of new energy vehicles. To address this issue, we combined the cloud model with the concept of growth expectations to provide an objective and comprehensive evaluation of supply chain members when selecting suppliers for new energy vehicles. We offered a more comprehensive evaluation method than decisions made solely based on existing data. In particular, we considered the potential growth prospects of supplier members in addition to their current evaluation scores. By incorporating growth expectations, we provided a more accurate and complete evaluation of the suitability of suppliers for the dynamic and rapidly-evolving production of new energy vehicles. In conclusion, by incorporating growth expectations, we provided a more comprehensive evaluation method that considers the dynamic and complex nature of the supply chain in this industry which is crucial to ensure the efficiency of production enterprises.

6.2 Stability of the method

By incorporating the cloud model into the evaluation process, we transformed qualitative events into quantitative values, which improves the stability of decision-making and effectively addresses the problem of fuzziness and randomness in linguistic multi-attribute decision-making. The resulting quantitative values enable the new energy vehicle manufacturing industry to adjust its production activities more effectively.

6.3 Accuracy of the method

Utilizing the cloud similarity-based value function allows for the computation of the prospect value and current evaluation value of each index. We provided a comprehensive evaluation of the strengths and weaknesses of each supply chain member and enables the identification of weak links in the supply chain. By addressing deficiencies, the productivity of the supply chain is enhanced. We developed a model that offers a clear roadmap for optimizing the supply chain, allowing decision-makers to make more comprehensive and objective decisions when selecting supply chain members.

6.4 Simplicity of the method

We developed a model that is user-friendly and has a simple data organization, making it more accessible compared to prior research. It is highly applicable to the production operations of new energy vehicle firms, offering stability to the decision-making process and mitigating risks caused by uncertainty in the production environment and supply chain members.

In summary, in this article we proposed an innovative cloud model-based approach for supply chain member selection in the new energy vehicle manufacturing industry. The incorporation of the cloud model and the cloud similarity-based value function enables a comprehensive evaluation of supply chain members and facilitate the optimization of the supply chain. Moreover, the model we proposed is user-friendly and highly applicable to the production operations of new energy vehicle firms.

Declarations

Conflict of interest Authors declare that they have no conflicts of interest.

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