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A Comprehensive Asset Evaluation Method for Oil and Gas Projects

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Abstract: The rapid and accurate evaluation of oil and gas assets, specifically for new development projects, poses a significant challenge due to the various project types, limited data availability, brief periods for assessment and decision making, and constraints arising from varying contractual and taxation conditions, political stability, and societal factors. This study leverages the grading standards of the evaluation index system for new oil and gas field development projects, along with relevant mathematical theories and methods for project evaluation and optimization. We developed an asset evaluation approach for new oil and gas projects by analyzing the assets of six new oil and gas field development projects in Brazil. This analysis resulted in the grading and ranking of new projects, and we tested and demonstrated four asset optimization techniques. After a comparative analysis with conventional evaluation results, we established an oil and gas project asset optimization approach centered on the cloud model comprehensive evaluation and linear weighted ranking, exhibiting Kendall's tau coefficient of 0.8667 with conventional methods. The findings suggest that the combination of the cloud model comprehensive evaluation method with the linear weighted ranking method can facilitate asset optimization for oil and gas field development projects, meeting the practical needs for fast selection among various new projects. Furthermore, this research offers a technical and theoretical foundation for rapid evaluation and decision making regarding new assets.

Keywords: asset comprehensive evaluation method; new oil and gas field project; asset grading and ranking; cloud model; linear weighted

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1. Introduction

The evaluation and acquisition of new oil and gas field development assets are crucial for petroleum companies to participate in international competition and seize good investment opportunities. However, the challenge lies in ensuring the scientific nature of decision making and the economic viability of the invested projects, particularly in cases where the new projects are of various types, data availability is limited, and the evaluation time is pressing. Moreover, these decisions are often constrained by different contract terms, financial and tax regulations, as well as political and social stability factors. Therefore, an integrated and efficient evaluation and selection system that combines evaluation indicators and optimization methods is urgently needed to achieve fast decision making in new oil and gas field development projects. This study aims to develop a new asset evaluation and optimization method for new oil and gas field development projects to address the above challenges.

A fundamental aspect of decision making for evaluating new oil and gas field development projects is to determine a set of indicators that can effectively capture various project characteristics. Currently, scholars have adopted methods such as principal component analysis, comparative analysis, fuzzy logic, and grey system theory to evaluate indicators in aspects such as oil and gas reservoir quality [1], economic value [2], and risk [3–5].

However, there is a lack of discussion on overall evaluation indicators for oil and gas field projects. Selecting appropriate indicators plays a crucial role in ensuring the accuracy and reliability of the evaluation and optimization process, which often requires validation based on statistical theory and input from relevant domain experts. Therefore, this article, based on the characteristics of overseas oil and gas field projects, considers factors such as the correlation between project decisions and data availability and adopts methods such as correlation coefficient analysis, system clustering, and factor analysis, with input from experts to establish an evaluation indicator system for overseas oil and gas field projects.

One of the challenges in evaluating new oil and gas field development projects is how to establish a method for asset optimization. The asset optimization process involves utilizing appropriate evaluation methods to optimally select oil and gas assets, with the development of disciplines such as probability theory, mathematical programming, fuzzy mathematics, and multi-attribute evaluation. A plethora of methods have been employed by previous researchers for project evaluation in the oil and gas field, such as gray theory [6,7], grey fuzzy that combines grey theory with fuzzy evaluation [8], cyclical convolution [9], Multi-Attribute Decision Making (MADM) in conjunction with Analytic Hierarchy Process (AHP) [10], Multi-Criteria Decision Analysis (MCDA) [11], as well as the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) and Fuzzy-TOPSIS [12,13].

However, these methods exhibit inherent limitations and challenges in their application. For example, grey theory and the grey fuzzy appraisal method are conducive to handling imprecise and uncertain data but may lack sufficient flexibility to capture the multifaceted characteristics of the complex nature of oil and gas fields. Additionally, they may not fully address the relationship between fuzziness and randomness. Methods such as cyclical convolution may be inefficient in dealing with certain nonlinear and multidimensional problems. Traditional MADM, AHP, and MCDA, although performing well in many scenarios, may encounter difficulties when dealing with large-scale data and complex relationships in oil and gas projects. TOPSIS and Fuzzy-TOPSIS operate by comparing the ideal solution and the negative ideal solution determined by the established development scheme with practical programs but often overlook the fuzziness or randomness of the data.

Therefore, the existing methods are unable to fully meet the needs of asset selection for new oil and gas field development projects, especially in complex and uncertain environments. The introduction of the cloud model has brought new perspectives and possibilities for asset selection in new oil and gas field development projects. The cloud model was proposed by Li et al. in 1995 [14]. The cloud model can simultaneously reflect the qualitative and quantitative aspects, fuzziness and randomness, and uncertainty characteristics of data without having to combine several algorithms capable of handling different data features, and it applies to situations where data are limited or ambiguous. This is extremely beneficial for data analysis and project evaluation. With the gradual perfection of cloud model theory, its application has gradually expanded to many areas such as data mining [15,16], decision analysis [17], and intelligent control [18]. In the field of oil and gas development, the application of the cloud model in reservoir evaluation [19], oil and gas industry control system safety status identification [20], and accident risk assessment [21,22] has proven that it can overcome the limitations of the aforementioned methods.

The integration of the cloud model with traditional methods has significant advantages in multiple domains, enabling more precise and comprehensive evaluation and decision making. Qin et al. [23] comprehensively evaluated the regional energy Internet by combining the cloud model with the Fuzzy Analytic Hierarchy Process (FAHP). This combination allows the model to describe fuzziness and randomness more accurately. Wu et al. [24] combined the cloud model with the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) and Analytic Network Process (ANP) for the optimization of electric vehicle charging station site selection. This integration enhanced the confidence and visibility of decision makers, accurately described the fuzziness and randomness of linguistic terms, simplified the calculation of parameters and required steps, and made the site selection more scientific and reasonable. This combined method has also been applied in the oil industry. Min et al. [25] used the Gray Clustering Analysis based on the cloud model (GCAC) in the comprehensive evaluation of offshore oilfield development planning, successfully integrating the fuzziness, randomness, and uncertainty of the data. This method reduced subjective bias and objective randomness, improving the reliability and accuracy of the evaluation.

Combining the advantages of the cloud model with the characteristics of the grey relational analysis, cloud gravity center deviation, and linear weighted method, this study constructs a comprehensive evaluation method. Grey relational analysis [26–30], evolving based on "black box" and "grey box", can maximally satisfy the data modeling conditions and requires a lower sample size. This enables it to conveniently integrate qualitative and quantitative analysis methods, and the quantitative analysis results can better conform to the qualitative analysis results and actual situations. The cloud gravity center deviation [31–34] is a multi-attribute decision-making method based on the cloud model, evaluating and ranking alternative solutions by calculating the cloud center of gravity of various attributes. This method emphasizes the handling of uncertain information, taking into account both qualitative concepts and quantitative data analysis. By comparing the cloud gravity deviation values of each alternative solution, the optimal solution in the evaluation can be determined. The linear weighted method is popular for its low requirements for data and models, simple and intuitive calculation process, and ease of understanding and implementation. It has been applied in multiple domains within the oil and gas industry, such as reservoir evaluation [35], fiscal term evaluation [36,37], and supplier selection for oilfield development projects [38].

On the foundation of appropriate indicators, the application of robust mathematical methods for evaluating and selecting oil and gas field development assets is crucial. Considering the great potential of the cloud model in handling uncertainty and improving the evaluation process, this research combines the above three methods with the cloud model, not only compensating for the limitations but also inheriting the advantages of each method. This integrated approach demonstrates its strengths in dealing with complex, fuzzy, and uncertain problems. According to the experimental validation results and comparative analysis with conventional evaluation results, this study proposes a new method for oil and gas field development project asset evaluation and optimization by combining the cloud model for comprehensive evaluation and linear weighted ranking methods.

The paper is organized as follows: Section 2 discusses in detail the asset evaluation index set and evaluation methods, including methods and models for selecting and evaluating assets for oil and gas field development projects, such as the cloud model comprehensive evaluation method, grey relational analysis, cloud gravity center deviation method, and linear weighted method. In this section, we mainly use MATLAB for programming to realize these methods. Section 3 discusses the application results of the proposed method in six assets in Brazil to verify the effectiveness of the method proposed in this paper. Finally, Section 4 summarizes the paper.

2. Materials and Methods

Based on the objective of selecting projects that can satisfy various requirements, the comprehensive evaluation of new oil and gas field development projects in this study is conducted based on establishing an evaluation indicator system, focusing on research into evaluation methods for both asset grading and asset ranking. The evaluation indicator system includes technical, economic, and risk indicators. The asset grading method utilizes the cloud model, while the asset ranking methods include the grey relational analysis, the cloud gravity center deviation, and the linear weighted method, as shown in Figure 1.

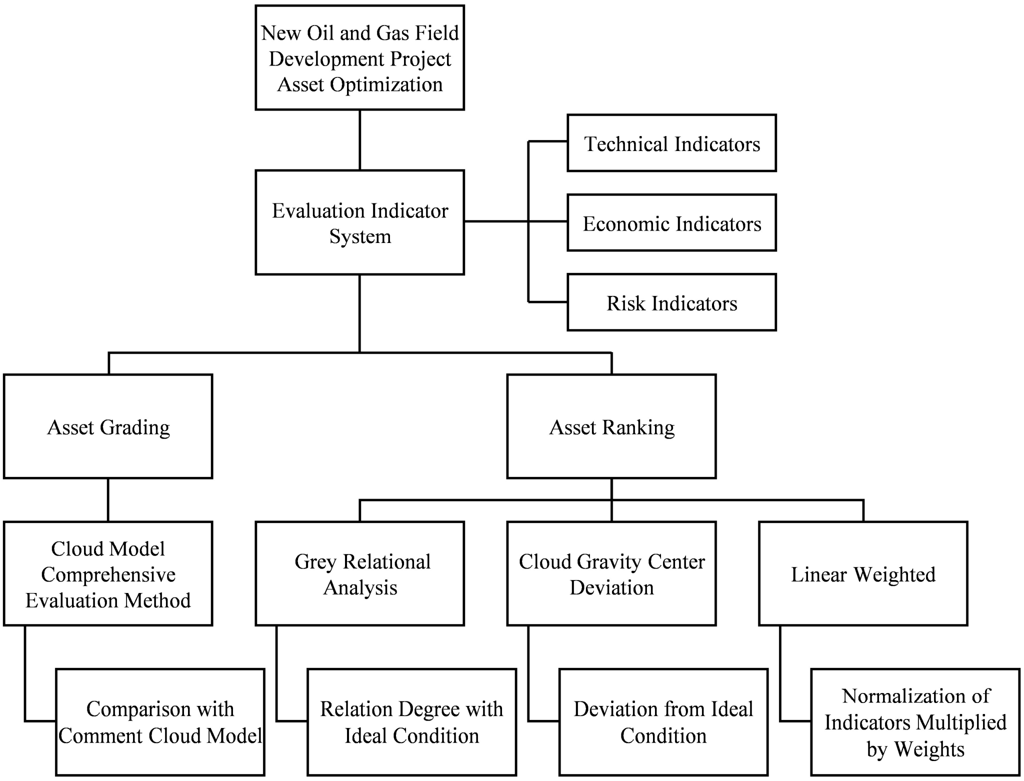

Figure 1. New oil and gas field development project asset evaluation and optimization method.

2.1. *Asset Evaluation Indicator System*

When evaluating oil and gas field assets, multiple attributes need to be considered. In this study, the comprehensive evaluation index of new oil and gas field development projects is divided into three primary indicators: technical, economic, and risk indicators, including 27 secondary indicators such as crude oil gravity and porosity, as shown in Figure A1 (seen in Appendix A). There are 17 quantitative indicators, including crude oil gravity, porosity, permeability, reserve abundance, remaining recoverable reserves, future peak production, reserve recovery, water content, operational cost per barrel, CAPEX per barrel, million-ton capacity investment, net present value, internal rate of return, government revenue, investment payback period, and value per barrel. There are also 10 qualitative indicators, including development potential, commercial operating environment, political and tax risks, competitive advantages and disadvantages, transaction feasibility, company participation level, industry acceptance level, government attitude toward transactions, synergy effects, and natural operating environment.

2.2. *Asset Evaluation Method*

2.2.1. Cloud Model Comprehensive Evaluation Method

The cloud model is composed of a large number of cloud droplets [25]. The cloud droplets generated by the cloud model have no order. A cloud droplet is a random realization of a qualitative concept on a quantitative scale. The more cloud droplets, the more they reflect the overall characteristics of the qualitative concept. The degree of certainty of a cloud droplet $\mu(x)$ can be understood as the degree to which the cloud droplet can represent the qualitative concept. The larger the probability of the cloud droplet, the greater its degree of certainty, which is consistent with people's subjective understanding. Table 1 shows the meaning of cloud numerical features. It illustrates how the cloud model effectively integrates the randomness, fuzziness, and uncertainty of qualitative concepts into a mapping model for qualitative and quantitative representation through *Ex*, *En*, and *He*.

Table 1. Meaning of cloud numerical features.

Numerical Feature	Meaning
Expectation (*Ex*)	The expected value of cloud droplets' distribution in the domain space, which represents the most typical sample quantifying the concept. The closer to the expectation value, the more concentrated the cloud droplets are, reflecting higher cognitive unity among people. Otherwise, it shows unstable cognition.
Entropy (*En*)	The measure of the uncertainty of qualitative concepts is determined by the randomness and fuzziness of concepts. It is the measure of the either-or nature of qualitative concepts and reflects the range of values of cloud droplets that can be accepted by concepts in the domain space.
Hyper-Entropy (*He*)	The measure of the uncertainty of entropy, i.e., the entropy of entropy, is determined by the randomness and fuzziness of entropy. It reflects the randomness of samples that represent qualitative concept values, revealing the correlation between fuzziness and randomness.

In cloud model theory, the forward cloud generator (FCG) and the backward cloud generator (BCG), denoted as FCG and BCG, respectively (as shown in Figure 2), are the two most important and crucial algorithms [39].

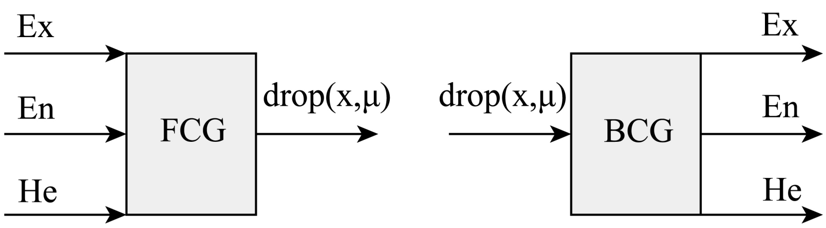

Figure 2. Cloud generator structure.

The FCG produces quantitative values of cloud digital characteristics C (*Ex*, *En*, *He*). The input contains the digital characteristics (*Ex*, *En*, *He*) of the cloud model and the number of cloud droplets n. And the output includes n cloud droplets and their degrees of certainty $\mu(x)$.

The BCG maps a certain quantity of determinate values into appropriate qualitative language values {*Ex*, *En*, *He*}. It is an inverse and indirect process from quantitative to qualitative, and its function is to restore the three digital characteristics of the cloud, *Ex*, *En*, and *He*, from a given quantity of cloud droplets to achieve the conversion from quantitative numerical values to qualitative language values. There are two specific methods: the backward cloud algorithm that utilizes degree of certainty information and the backward cloud algorithm that does not require degree of certainty information.

The cloud model comprehensive evaluation model is mainly composed of a group of experts who score qualitative and quantitative indicators and then generate weighted comprehensive evaluation clouds. By comparing with the standard comment cloud, the evaluation result of the project can be obtained. The flowchart of the cloud model comprehensive evaluation method is shown in Figure 3.

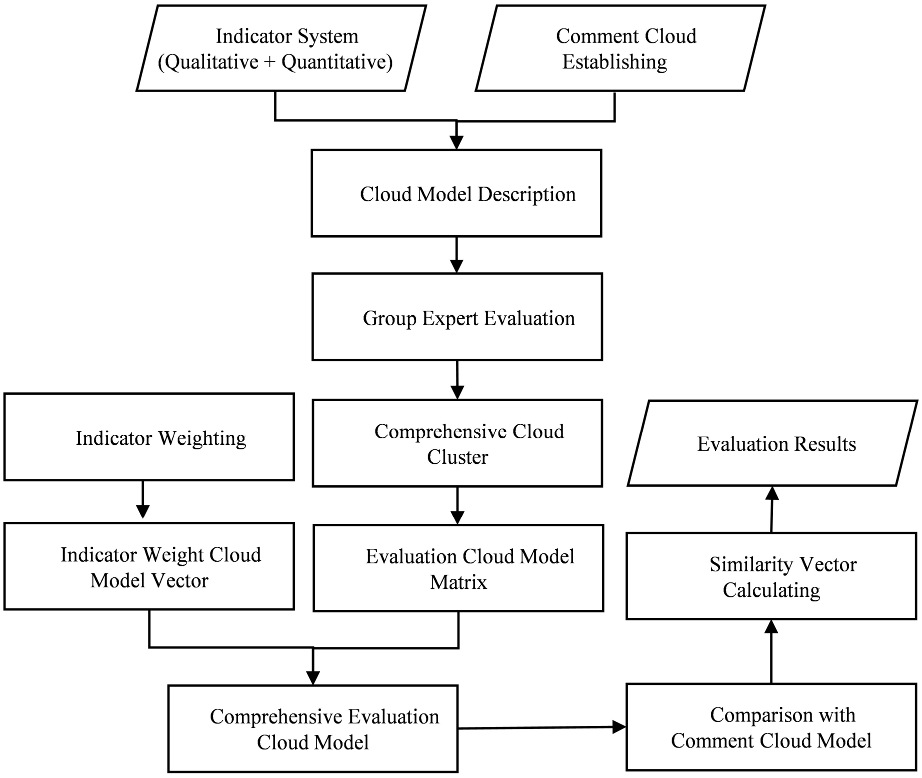

Figure 3. Flowchart of cloud model comprehensive evaluation method.

If the evaluation comment set of the object is V = {V1, V2, ..., Vm}, we use the cloud model to describe these m comments and replace the traditional fixed value membership function with the cloud model membership function. For each comment, we can use an interval [C_{min}, C_{max}] to represent its range, and we can take the midpoint of the interval as the expected value to approximate the cloud model to represent this comment. Finally, we can obtain the standard comment cloud model C (*Ex*, *En*, *He*) for this comment. The parameter calculation formulas are as follows:

Calculation formula of *Ex* based on the upper and lower limits of each interval:

$$Ex = \begin{cases} C_{min}, \ i = 1 \\ \frac{C_{min}+C_{max}}{2} \quad ,1 < i < n \\ C_{max}, \ i = n \end{cases} \tag{1}$$

Calculation formula of *En* based on the calculation results of the previous step:

$$En = \frac{C_{max}-C_{min}}{6} \tag{2}$$

Calculation formula of *He*:

$$He = \eta \tag{3}$$

η reflects the randomness of the entity's trust value, and its value should not be too large, because the larger the He, the larger the error of *Ex*, and the randomness of the evaluation increases, making the evaluation result difficult to determine.

The purpose of establishing the standard comment cloud is to divide the evaluation level. In practical applications, we can divide the trust into a limited number of evaluation levels according to specific practical application situations, and then generate comment clouds corresponding to each evaluation level based on specific evaluation levels.

The index system for new oil and gas field development projects in this study is classified into five levels, and a five-level evaluation system, the evaluation comment cloud, is established based on this classification. The range of the comment cloud is divided into five intervals [C_{min}, C_{max}] on the scale of 1.0 to 5.0: Class I [1.0–1.5], Class II [1.5–2.5], Class III [2.5–3.5], Class IV [3.5–4.5], and Class V [4.5–5.0]. The comment cloud is illustrated in Figure 4.

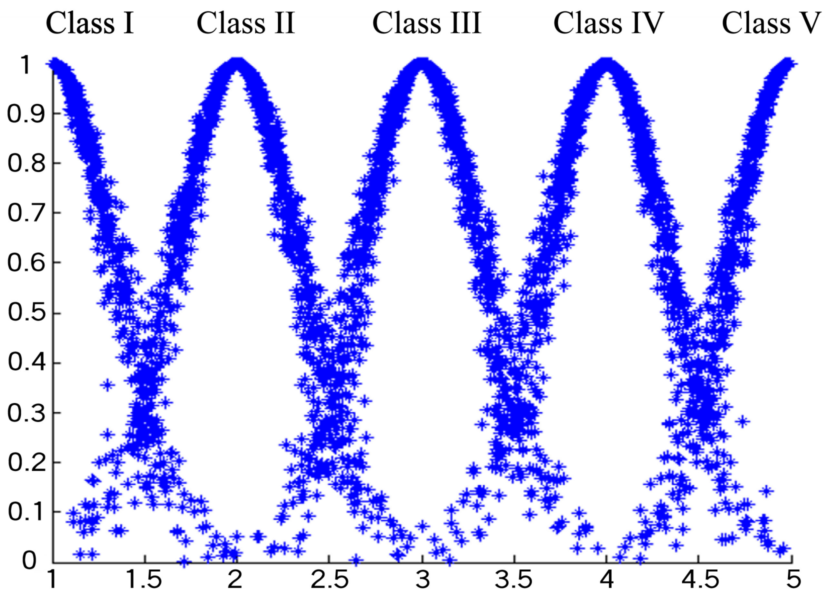

Figure 4. Comment cloud evaluation scale.

In this paper, the experts' grading method and probability statistical analysis are combined to grade each index. The grading standards for each index are shown in Table 2.

Table 2. Grading standards for the index system of new oil and gas field development projects.

Index	Unit	Class I	Class II	Class III	Class IV	Class V
Maximum Porosity	%	<10	10–15	15–20	20–25	>25
API	°	<10	10–20	20–34	34–45	>45
Water Content	%	>80	60–80	40–60	20–40	<20
Maximum Permeability	MD	<10	10–50	50–200	200–500	>500
Remaining Recoverable Reserves	MMboe	<50	50–100	100–500	500–1000	>1000
Reserve Abundance	MMbbl/km^2	<3.5	3.5–7	7–21	21–35	>35
Future Peak Production	kb/d	<5	5–10	10–50	50–100	>100
Reserve Recovery of Recoverable Reserves	%	>80	60–80	40–60	20–40	<20
Development Potential		1	2	3	4	5
Net Present Value	MMSUD	<5	5–50	50–200	200–500	>500
Internal Rate of Return	%	<8	8–12	12–18	18–30	>30
Investment Payback Period	a	>10	8–10	5–8	3–5	<3
Government Revenue	%	>90	70–90	50–70	30–50	<30
Operational Cost per Barrel	USD/boe	>25	15–25	10–15	5–10	<5
Value per Barrel	USD	<5	5–8	8–10	10–15	>15
Maximum Negative Cash Flow	MMUSD	>1000	500–1000	100–500	50–100	<50
CAPEX per Barrel	USD/boe	>20	15–20	10–15	5–10	<5
Investment per Million Tons of Production Capacity	MMUSD	>1500	1000–1500	500–1000	100–500	<100

Based on the actual situation of the project, index descriptions, and grading standards, several experts were invited to grade the quantitative or qualitative indexes for new oil and gas field development projects using the comment cloud. Three experts were invited to grade 18 technical and economic indexes for six assets, and the evaluation values are shown in Table A1 (Seen in Appendix B).

The backward cloud generator was used to form cloud clusters, and the cloud parameter algorithm was applied to calculate the three numbers of the cloud, combining the scores of all experts for each indicator with their respective weights. The comprehensive cloud calculation process and formulas are as follows:

$$Ex = \frac{E_{x1}w_1 + E_{x2}w_2 + \cdots + E_{xn}w_n}{w_1 + w_2 + \cdots + w_n} \quad (4)$$

$$En = \frac{E_{n1}w_1^2 + E_{n2}w_2^2 + \cdots + E_{m}w_n^2}{w_1^2 + w_2^2 + \cdots + w_n^2} \quad (5)$$

$$He = \frac{H_{e1}w_1^2 + H_{e2}w_2^2 + \cdots + H_{en}w_n^2}{w_1^2 + w_2^2 + \cdots + w_n^2} \quad (6)$$

Based on the digital characteristic values of the cloud to which the asset belongs, the forward cloud generator was simulated 1000 times to produce a comprehensive evaluation cloud. The distribution of cloud droplets on the four evaluation levels of the comment cloud can be obtained as shown in Figure 5. If the generated comprehensive cloud is in the form of fog, feedback is given to the expert opinions, and the scores are adjusted and recalculated.

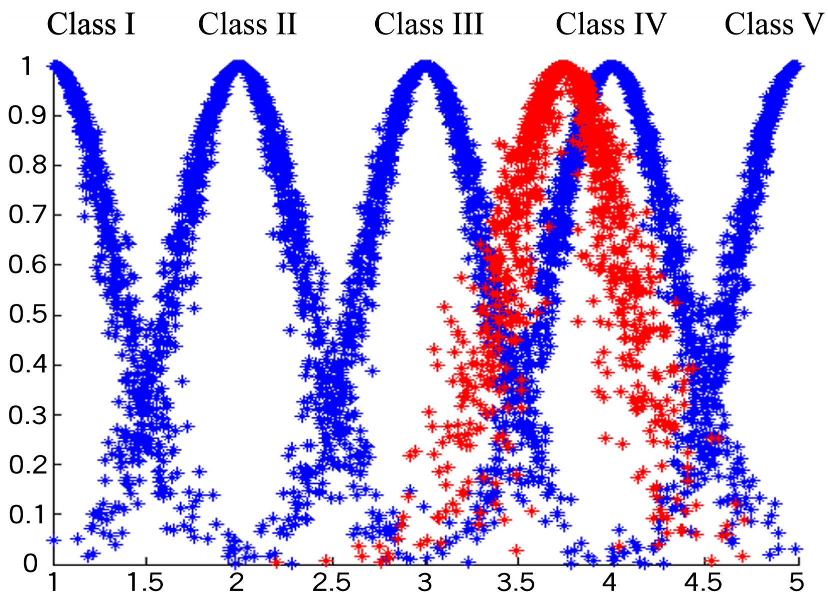

Figure 5. Comprehensive evaluation cloud (red) in comment cloud evaluation scale (blue).

The comprehensive evaluation cloud is compared with the comment cloud. By using the cloud scale (blue cloud figure), the final evaluation cloud figure (red cloud figure) is output, and the level of the asset is qualitatively observed. At the same time, to more accurately describe the distribution of the comprehensive evaluation cloud and the comment cloud, we calculate the membership degree of each cloud droplet in the evaluation cloud with each comment cloud, in order to obtain the similarity between the evaluation cloud and each comment cloud.

We provide an algorithmic procedure of the cloud model comprehensive evaluation method, which is shown in Algorithm A1 (Seen in Appendix C). These steps strictly follow the procedure of the algorithm in this subsection. Readers can refer to these algorithms.

2.2.2. Grey Relational Ranking Method

The grey relational evaluation model determines an ideal optimal sample from the sample set as a reference sequence and compares and ranks the evaluated objects by calculating the degree of association between each sample sequence and the reference sequence. The project ranking steps based on the grey relational comprehensive evaluation method are shown in Figure 6. The basic idea is to first perform dimensionless processing on the original data, obtain the optimal (ideal) asset sequence of the indicators (the optimal value of the evaluation asset indicators), calculate the grey relational coefficient matrix between each evaluated asset sequence and the ideal sequence, and then weight to obtain the degree of correlation between each asset and the optimal (ideal) asset.

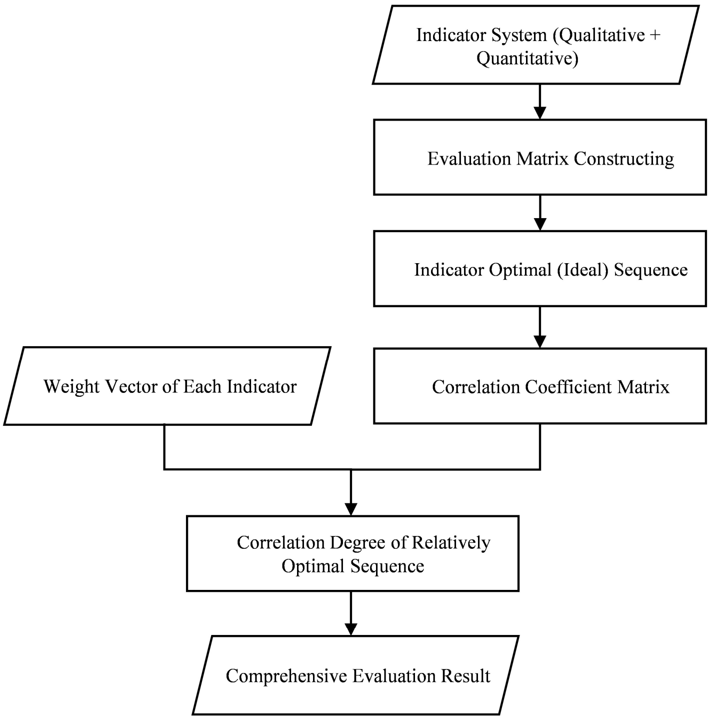

Figure 6. Flowchart of grey relational comprehensive evaluation method.

The m-evaluated assets are taken as row vectors of the matrix, and the n-selected indicators are taken as column vectors of the matrix to form an evaluation matrix. Qualitative indicators are scored by experts, and the optimal asset sequence of each indicator is selected from the evaluated objects based on the meaning of each evaluation indicator to form a reference sequence $x_i = \{x_{i1}, x_{i2}, \ldots, x_{in}\}$, $i = 1, 2, \ldots, m$.

Because the evaluation indicators are affected by different dimensions and magnitudes, comparability between them is not available. Therefore, dimensionless processing must be performed on the actual values of each indicator. The linear dimensionless formula is used as follows:

$$x_{ij} = \frac{x_{ij}}{x_{0j}}, i = 1, 2, \cdots, m; j = 1, 2, \cdots, n \quad (7)$$

The absolute difference sequence between each evaluated object sequence and the optimal reference sequence is calculated by the formula as follows:

$$\Delta_{ij} = \left|x_{ij} - 1\right|, i = 1, 2, \cdots, m; j = 1, 2, \cdots, n \quad (8)$$

On this basis, the maximum difference $\Delta(\max)$ and the minimum difference $\Delta(\min)$ between two levels can be obtained according to the formula as follows:

$$\Delta(\min) = \min\min\Delta_{ij}(k) \quad (9)$$

$$\Delta(\max) = \max\max\Delta_{ij}(k) \quad (10)$$

Then, the correlation coefficient ξ_{ij} between the i-th evaluated object and the optimal reference sequence can be calculated by the formula as follows:

$$\xi_{jj} = \frac{\Delta(\min)+\rho\Delta(\max)}{\Delta_{ij}+\rho\Delta(\max)} \tag{11}$$

In the formula, ρ is the resolution coefficient, with a value in the interval [0, 1], usually taking $\rho = 0.5$. In specific calculations, the value of ρ can be adjusted according to the correlation degree between each data sequence to increase the resolution of comparative analysis.

We calculate the weighted correlation coefficient of each indicator according to the following formula to obtain the correlation degree of the relatively optimal sequence E_i:

$$E_i = \sum_{k=1}^{m} w(k)\xi_{ij}(k), k = 1,\ 2, \cdots, m \tag{12}$$

Subsequently, the assets are ranked according to the degree of correlation with the ideal asset, and the greater the correlation, the better the asset.

2.2.3. Cloud Gravity Center Deviation Ranking Method

The cloud gravity center deviation ranking method calculates the deviation of each asset from the ideal asset by weighting the cloud gravity of each indicator with respect to the ideal indicator. The process based on cloud gravity deviation is illustrated in Figure 7.

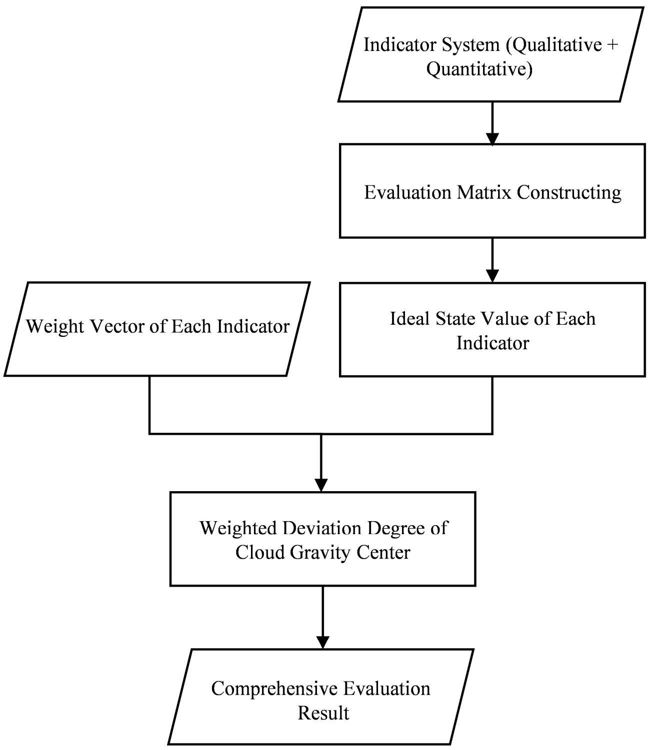

Figure 7. Flowchart of cloud gravity center deviation ranking method.

The m assets to be evaluated are taken as row vectors of a matrix, and the n-selected indicators are taken as column vectors of the matrix to form an evaluation matrix. The qualitative indicators are scored by experts.

The ideal values of each indicator are calculated, and the cloud gravity center of each asset is calculated concerning the ideal state. The weighted deviation of each asset is then determined.

In the evaluation indicator system, n sets of related data indicators are extracted to form a decision matrix, and a cloud model can represent these precise numerical indicators. The parameter calculation formulas are as follows:

$$Ex = (Ex_1 + Ex_2 + \cdots + Ex_n) \tag{13}$$

$$En = \frac{[\max(Ex_1, Ex_2, \cdots, Ex_n) - \min(Ex_1, Ex_2, \cdots, Ex_n)]}{6} \tag{14}$$

Additionally, a cloud model can also represent linguistic value indicators. An indicator represented by n linguistic values (cloud models) can be characterized by a one-dimensional comprehensive cloud. The parameter calculation formulas are as follows:

$$Ex = \frac{(Ex_1En_1 + Ex_2En_2 + \cdots Ex_nEn_n)}{(En_1 + En_2 + \cdots En_n)} \tag{15}$$

$$En = En_1 + En_2 + \cdots En_n \tag{16}$$

The cloud gravity center can be expressed as follows:

$$T = a \times b \tag{17}$$

where a represents the position of the cloud gravity center, b represents the height of the cloud gravity center, and the expected value Ex reflects the information center value of the corresponding fuzzy concept, i.e., the position of the cloud gravity center. If p cloud models can characterize p performance indicators, then the system state reflected by p indicators can be represented by a p-dimensional comprehensive cloud. When the system state changes, the shape of this p-dimensional comprehensive cloud also changes, and its gravity center changes accordingly. The gravity center of the p-dimensional comprehensive cloud, T, can be represented by a p-dimensional vector, i.e., $T = (T_1, T_2, ..., T_p)$, where:

$$T_i = a_i \times b_i, i = 1, 2, \cdots, p \tag{18}$$

When the system state changes, the gravity center of the p-dimensional comprehensive cloud changes to T', i.e., $T' = (T'_1, T'_2, ..., T'_p)$.

In the ideal state, the position vector a of the p-dimensional comprehensive cloud gravity center can be expressed as follows:

$$a = \left(Ex_1^0 + Ex_2^0 + \cdots + Ex_p^0\right) \tag{19}$$

The corresponding height vector of the cloud gravity center can be expressed as follows:

$$b = \left(b_1, b_2, \cdots, b_p\right) \tag{20}$$

where $b_i = w_i \times 0.371$, and the gravity center vector of the cloud in the ideal state can be expressed as follows:

$$T^0 = a \times b^T \tag{21}$$

Similarly, for a certain system state, the p-dimensional comprehensive cloud gravity center vector is $T = (T_1, T_2, ..., T_p)$. After normalization, it can be expressed as $T^G = (T_1^G, T_2^G, ..., T_p^G)$, where:

$$T_i^G = \begin{cases} \frac{(T_i - T_i^0)}{T_i} & T_i \geq T_i^0 \\ \frac{(T_i - T_i^0)}{T_i^0} & T_i \leq T_i^0 \end{cases}, i = 1, 2, \cdots, p \tag{22}$$

The weighted deviation degree θ ($0 \leq \theta \leq 1$) is obtained by multiplying the normalized vector values of each indicator by their weight values and adding them up, as shown in the following formula:

$$\theta = \sum_{j=1}^{p} w_j \cdot T_i^G \tag{23}$$

where w_j represents the weight value of the j-th indicator in a certain system state.

The assets are then ranked according to their weighted deviation degrees. The larger the value of θ, the better the asset.

2.2.4. Linear Weighted Ranking Method

The linear weighted ranking method used in this study is based on calculating relative scores, and the process is shown in Figure 8. The main evaluation step is to normalize each indicator and calculate the weighted score concerning each asset.

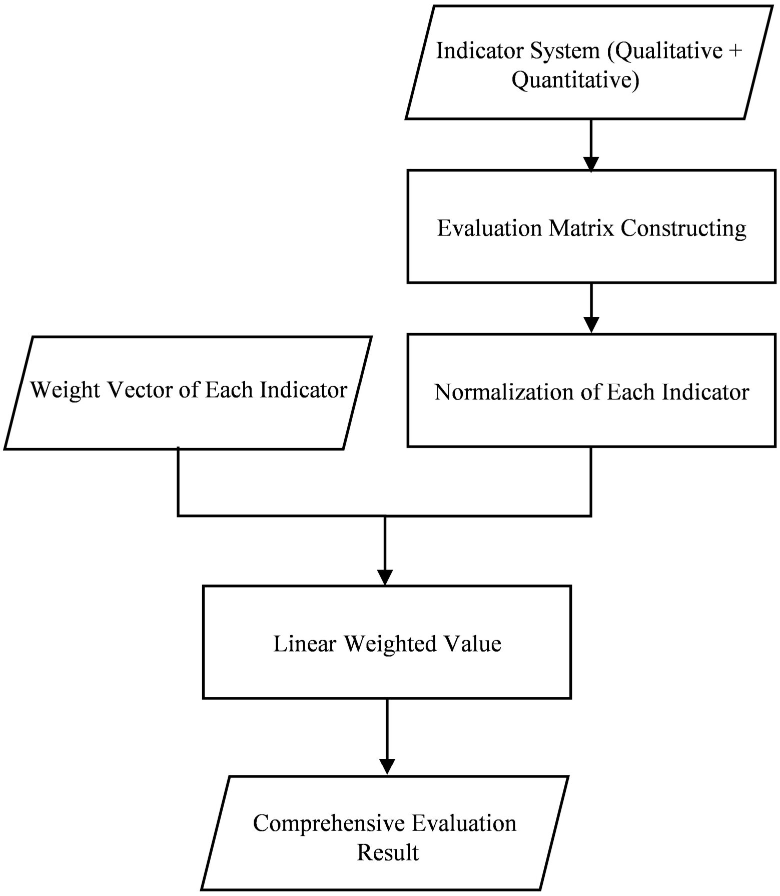

Figure 8. Flowchart of linear weighted comprehensive evaluation method.

The m assets to be evaluated are treated as row vectors of a matrix, and the n-selected indicators are treated as column vectors of the matrix, forming an evaluation matrix. The qualitative indicators are scored by experts.

The assets' indicators are normalized using the range method, which is a dimensionless normalization method.

The positive indicators can be expressed as follows:

$$x'_{ij} = \frac{x_{ij} - \min\{x_{ij}\}}{\max\{x_{ij}\} - \min\{x_{ij}\}} \tag{24}$$

The negative indicators can be expressed as follows:

$$x'_{ij} = \frac{\max\{x_{ij}\} - x_{ij}}{\max\{x_{ij}\} - \min\{x_{ij}\}} \quad (25)$$

Then, the linear weighted value is calculated for each asset, and the linear weighted comprehensive value is obtained by summing the linear weighted values.

The assets are then ranked based on their linear weighted comprehensive values, where higher values indicate better assets.

3. Results Analysis

3.1. Cloud Model Comprehensive Evaluation Method

Based on the actual data of six Brazilian assets (M, MS, B, C, J, and R), Table 3 shows the similarity between each evaluation cloud and each comment cloud of these assets. All six oil and gas assets are in the range of [2.5–2.5] and belong to "Class III" assets. The evaluation results of each asset are similar, basically overlapping on the comprehensive evaluation cloud, and it is difficult to distinguish them. The comparison between the comprehensive evaluation cloud and the comment cloud of six assets is shown in Figure 9. By ranking the comprehensive expectations, it can be seen that R is the best and C is the worst. From Table 3, it can be seen that the similarity between the C asset and "Class III" is the highest, and R deviates the most from "Class III" and is closest to Class IV.

Table 3. The similarity between the evaluation cloud and each comment cloud.

Asset	Class I	Class II	Class III	Class IV	Class IV	Evaluation Result
M	0.000	0.052	0.530	0.397	0.021	III
MS	0.001	0.054	0.508	0.413	0.024	III
B	0.001	0.082	0.610	0.297	0.010	III
C	0.003	0.095	0.623	0.268	0.011	III
J	0.002	0.063	0.556	0.359	0.020	III
R	0.001	0.052	0.504	0.415	0.028	III

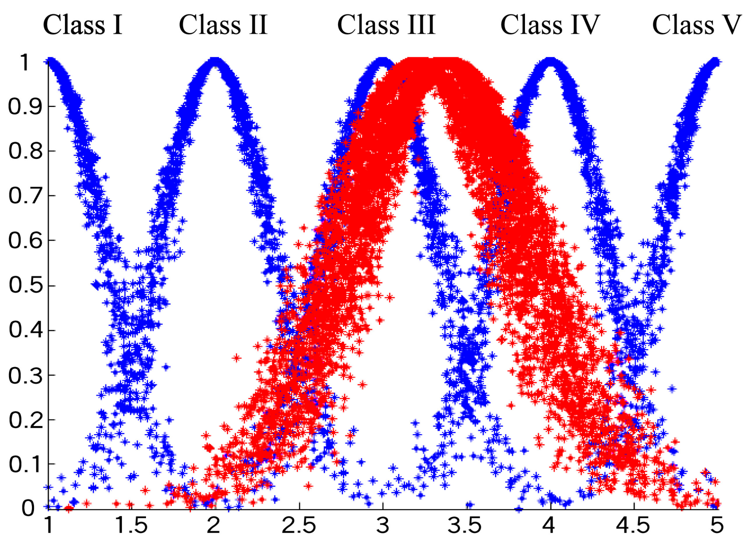

Figure 9. Comprehensive evaluation clouds (red) in comment cloud evaluation scale (blue) for six assets.

For the six assets, the comprehensive expectation of each asset's evaluation cloud and the ranking were calculated and are shown in Table 4. The ranking of the evaluation cloud has a significant difference compared to the conventional evaluation method. The judgment based solely on the cloud model for asset ranking still has limitations. Therefore, this study introduced three asset ranking methods, namely, grey relational analysis, the cloud gravity center deviation method, and the linear weighted method, and combined them with the cloud model asset grading method to conduct comprehensive and effective research methods.

Table 4. Comprehensive expectation and ranking of evaluation cloud.

Asset	Comprehensive Evaluation Score of Evaluation Cloud	Evaluation Cloud Asset Ranking	Conventional Evaluation Method Asset Ranking
M	3.375	3	4
MS	3.389	2	3
B	3.234	5	5
C	3.188	6	6
J	3.342	4	2
R	3.412	1	1

3.2. Grey Relational Ranking Method

Based on the degree of correlation between each asset and the ideal asset, the assets are ranked. The calculation results for the six assets are shown in Table 5 and Figure 10.

Table 5. Evaluation results of the grey relational method.

Asset	Technology		Economy		Risk		Comprehensive	
	Correlation Degree	Ranking	Correlation Degree	Ranking	Correlation Degree	Ranking	Correlation Degree	Ranking
M	0.7721	1	0.4814	6	0.9350	1	0.7393	2
MS	0.6396	3	0.5712	5	0.9107	3	0.7170	4
B	0.439	6	0.6785	4	0.9140	2	0.6857	6
C	0.5375	4	0.6812	3	0.8829	5	0.7120	5
J	0.5024	5	0.7759	1	0.8490	6	0.7218	3
R	0.6683	2	0.6928	2	0.9027	4	0.7644	1

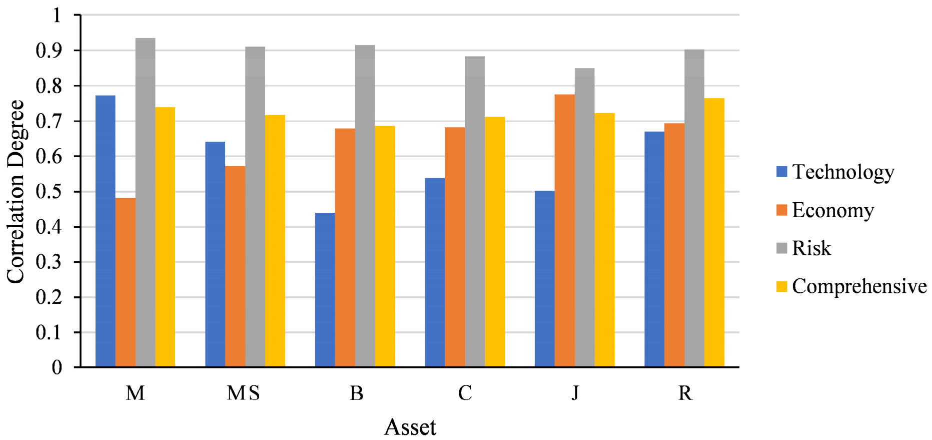

Figure 10. Evaluation results of the grey relational method.

3.3. Cloud Gravity Center Deviation Ranking Method

The assets are ranked according to their weighted deviation degrees. The evaluation results for six assets are shown in Table 6 and Figure 11.

Table 6. Evaluation results of cloud gravity deviation method.

Asset	Technology		Economy		Risk		Comprehensive	
	Deviation Degree	Ranking	Deviation Degree	Ranking	Deviation Degree	Ranking	Deviation Degree	Ranking
M	0.7672	1	0.4467	6	0.9637	1	0.7261	4
MS	0.6235	3	0.6301	5	0.9272	3	0.7269	3
B	0.3154	6	0.6969	3	0.9364	2	0.6496	6
C	0.4343	5	0.6764	4	0.9272	4	0.6794	5
J	0.4743	4	0.8135	1	0.9001	6	0.7294	2
R	0.693	2	0.7507	2	0.9270	5	0.7903	1

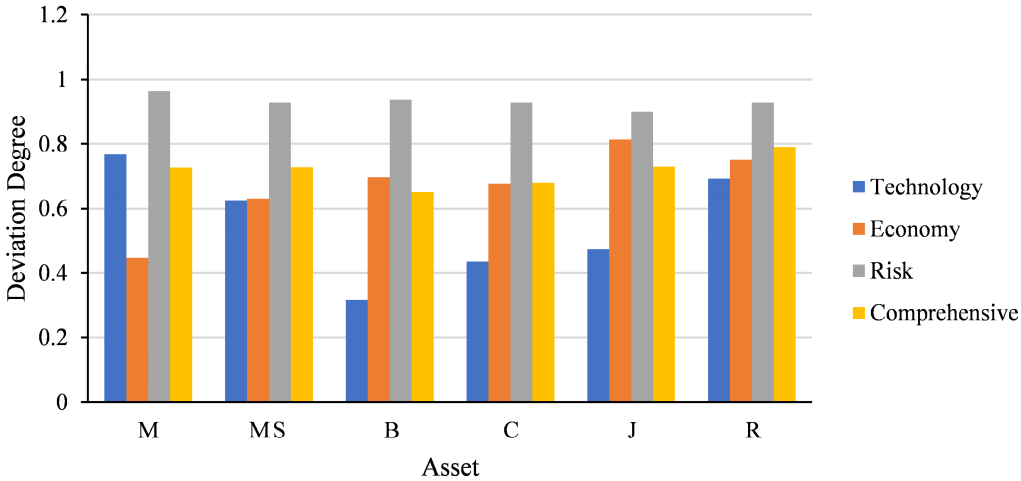

Figure 11. Evaluation results of cloud gravity center deviation method.

3.4. Linear Weighted Ranking Method

The assets are ranked based on their linear weighted comprehensive values. The results are shown in Table 7 and Figure 12.

Table 7. Evaluation results of the linear weighted method.

Asset	Technology		Economy		Risk		Comprehensive	
	Linear Weighted Value	Ranking	Linear Weighted Value	Ranking	Linear Weighted Value	Ranking	Linear Weighted Value	Ranking
M	0.675	1	0.0826	6	0.9183	1	0.5587	4
MS	0.5271	3	0.4223	5	0.8727	2	0.6072	3
B	0.1186	6	0.6091	2	0.8546	4	0.5271	6
C	0.2706	5	0.5617	3	0.8423	5	0.5580	5
J	0.3023	4	0.7413	1	0.8033	6	0.6154	2
R	0.6222	2	0.5047	4	0.8632	3	0.6631	1

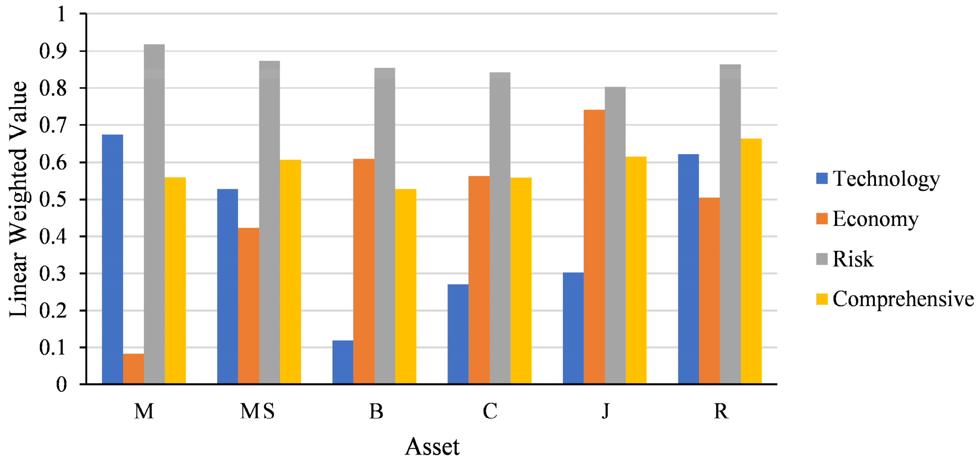

Figure 12. Evaluation results of the linear weighted method.

3.5. Results Compared

Using the actual data of six Brazilian assets (M, MS, B, C, J, and R) as an example, we compared the asset ranking results of four mathematical methods with the conventional evaluation method, as shown in Table 8. The asset ranking results of the cloud gravity center deviation method and the linear weighted method were the same and were not significantly different from the conventional evaluation results. For instance, the correlation between the conventional method and each of these two methods could be expressed through Kendall's tau coefficient, with a value of approximately 0.8667 in both cases. This value indicates a strong agreement between the conventional method and each of the proposed methods, providing additional evidence of their effectiveness. For the M and MS oil and gas field assets, the difference in their linear weighted values was greater than the difference in their cloud gravity center weighted deviation degrees, indicating that the linear weighted method has better discrimination. Therefore, this study concludes that the linear weighted method is most suitable for asset ranking tasks. According to the research results, the cloud model comprehensive evaluation method and the linear weighted ranking method can be used for asset grading and ranking in new oil and gas development projects.

Table 8. Comparison of asset rankings from various methods.

Asset	Cloud Model	Grey Relational	Cloud Gravity Center Deviation	Cloud Gravity Center Weighted Deviation Degree	Linear Weighted	Linear Weighted Value	Conventional Evaluation Method
M	3	2	4	0.7261	4	0.5587	4
MS	2	4	3	0.7269	3	0.6072	3
B	5	6	6	0.6496	6	0.5271	5
C	6	5	5	0.6794	5	0.5580	6
J	4	3	2	0.7294	2	0.6154	2
R	1	1	1	0.7903	1	0.6631	1

The following analyzes the reasons for these results. The cloud model, which combines fuzzy logic with stochastic distribution, offers an effective means to quantify qualitative concepts and analyze uncertainty information, due to its excellent ability to handle uncertainty and ambiguity. However, in the application of complex and variable oil and gas field development project assets, the cloud model might exhibit certain limitations when tasked with more intricate and deterministic assignments. Hence, the results show that the cloud model is proficient in performing asset grading tasks but showed insufficiency in further detailed asset ranking assignments.

The grey relational method involving the measurement of similarities between factors aims to capture the mutual relationships between data points. This method might be particularly sensitive to specific data points or outliers, thereby identifying associations that differ from those detected by conventional methods, which consider more global integrative characteristics. This could lead to significant disparities in the ranking results.

Both the cloud gravity center deviation method and the linear weighted method resulted in rankings that were relatively consistent with conventional methods. These methods typically base their assessments on the global characteristics and distributions of the entire data set, balancing the relative importance of each attribute. For asset evaluation, where a holistic consideration of multiple indicator factors is required, these methods might be more suitable for capturing the characteristics of the data set from an overall perspective. The ranking by the linear weighted method showed a smaller numerical gap between the M and MS assets compared to the cloud gravity center deviation method. This may be due to the linear weighted method's emphasis on balance and overall coordination between factors, allowing it to better reflect the comprehensive characteristics of the assets.

To sum up, by combining the grading and ranking classification system for new project evaluation indicators and in-depth research on relevant mathematical theories and methods for project prioritization, this method was applied to six oil and gas field development projects in Brazil, which can achieve asset grading and ranking for these new projects and provide valuable insights for decision makers.

To verify the effectiveness of the proposed method, we conducted experimental demonstrations on four different asset selection methods and compared their results with the conventional evaluation method. First, the cloud model comprehensive evaluation method was used to grade and rank assets, and the asset ranking results were significantly different from those of the conventional evaluation method. Therefore, this study introduced three asset ranking methods, including the grey relational method, the cloud gravity center deviation method, and the linear weighted method, to study their comprehensive effectiveness in combination with the cloud model asset grading method. The results showed that the method proposed in this paper, based on the cloud model comprehensive evaluation method and the linear weighted ranking method, can effectively select and prioritize oil and gas field development projects. This method meets the practical needs of rapid decision making for various types of projects and provides technical and theoretical support for all parties involved in the evaluation and selection process.

4. Conclusions

This paper proposes a comprehensive asset evaluation method, combining the cloud model with the linear weighted ranking method. This combination embraces the advantages of handling ambiguity and uncertainty while maintaining a balance between simplicity and practicality. The proposed method was empirically tested using real data from Brazil's six overseas oil and gas development assets. The results demonstrate that compared to other methods, it is better suited to accommodate different evaluation needs and provides ranking results that are closer to conventional evaluations in practice. This also validates the effectiveness and reliability of this combined method in real applications.

The cloud model, which combines fuzzy logic with stochastic distribution, offers an effective means to quantify qualitative concepts and analyze uncertainty information, due to its excellent ability to handle uncertainty and ambiguity. However, in the application of complex and variable oil and gas field development project assets, the cloud model might exhibit certain limitations when tasked with more intricate and deterministic assignments. The results show that the cloud model is proficient in performing as-set grading tasks but showed insufficiency in further detailed asset ranking assignments.

In the asset ranking section, three asset ranking methods—namely, the grey relational method, the cloud centroid deviation method, and the linear weighting method—are introduced for study and combined with the cloud model asset grading method to conduct a comprehensive and effective methodological investigation. The ranking results of the cloud centroid deviation method and the linear weighting method are identical, and they are relatively consistent with the conventional method. Furthermore, the linear weighting method has better differentiation, so this study considers it to be the most suitable for asset ranking tasks.

The results indicate that the integrated evaluation method based on the cloud model and linear weighted ranking method can achieve asset evaluation and optimization for oil and gas field development projects, meeting the practical needs for rapid selection of various new projects, and providing both technical and theoretical support for quick decision making in new project evaluation. It is important to note that the cloud model comprehensive evaluation method relies on experts' scoring of each asset's indicators according to a set of comments, based on their understanding of both qualitative and quantitative metrics. This requires that the group of experts have a comprehensive understanding of the various asset indicators. Otherwise, it may result in evaluations with significant errors.

In this study, the indicators are divided into three categories, namely, technical, economic, and risk, comprising a total of 27 indicators. The purpose of this classification is to maximize the consideration of factors that influence the assessment of assets. However, in the practical evaluation of projects, restrictions on the availability of information often lead to situations where not all indicator data can be obtained. In future work, the impact of missing different indicators on the evaluation results when using the method proposed in this article to assess assets can be studied to evaluate the robustness of this approach.

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Data Availability Statement: The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

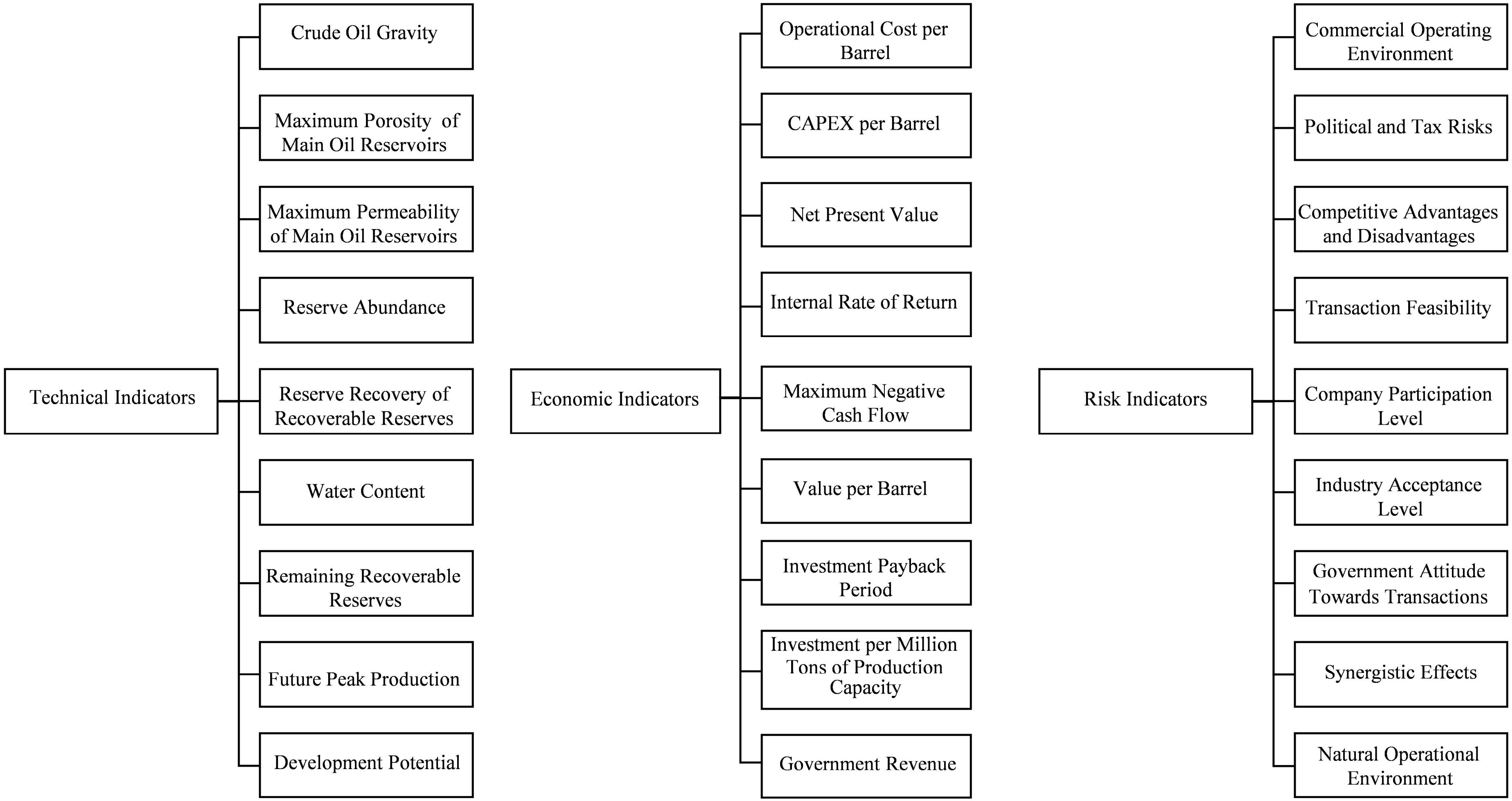

Figure A1. Decision indicator system for new oil and gas field development projects.

Appendix B

Table A1. Scoring table of expert groups.

Assets	Marlim			Marlim Sul			Barracuda			Caratinga			Jubarte			Roncador		
Crude Oil Gravity	2.056	2.57	3.084	2	2.5	3	2.288	2.86	3.432	2.512	3.14	3.768	2.2	2.75	3.3	2.232	2.79	3.348
Porosity	3.696	4.62	5	3.704	4.63	5	3.672	4.59	5	3.704	4.63	5	3.664	4.58	5	3.688	4.61	5
Permeability	4	5	5	3.992	4.99	5	3.696	4.62	5	4	5	5	4	5	5	4	5	5
Reserve Abundance	2.696	3.37	4.044	1	1.05	1.26	1	1.25	1.5	1	1.03	1.236	1.672	2.09	2.508	1.408	1.76	2.112
Remaining Recoverable Reserves	3.592	4.49	5	3.504	4.38	5	2.072	2.59	3.108	1.632	2.04	2.448	2.528	3.16	3.792	3.168	3.96	4.752
Future Peak Production	3.784	4.73	5	3.84	4.8	5	2.784	3.48	4.176	2.424	3.03	3.636	3.608	4.51	5	3.976	4.97	5
Reserve Recovery of Recoverable Reserves	3.072	3.84	4.608	2.2	2.75	3.3	1.752	2.19	2.628	1.696	2.12	2.544	2.312	2.89	3.468	2.32	2.9	3.48
Water Content	2.2	2.75	3.3	1.944	2.43	2.916	2.68	3.35	4.02	3.976	4.97	5	1.92	2.4	2.88	3.32	4.15	4.98
Development Potential	3.2	4	4.8	4	5	5	2.4	3	3.6	2.4	3	3.6	3.2	4	4.8	3.2	4	4.8
Operational Cost per Barrel	1.632	2.04	2.448	1.752	2.19	2.628	2.528	3.16	3.792	2.368	2.96	3.552	1.688	2.11	2.532	1.664	2.08	2.496
CAPEX per Barrel	3.624	4.53	5	3.048	3.81	4.572	3.336	4.17	5	3.064	3.83	4.596	2.776	3.47	4.164	2.864	3.58	4.296
Investment per Million Tons of Production Capacity	1	1	1.2	1	1	1.2	1	1.02	1.224	1	1.09	1.308	1	1	1.2	1	1	1.2
Net Present Value	3.912	4.89	5	4	5	5	3.984	4.98	5	3.864	4.83	5	4	5	5	4	5	5
Internal Rate of Return	2.4	3	3.6	3.264	4.08	4.896	3.224	4.03	4.836	3.184	3.98	4.776	3.688	4.61	5	3.224	4.03	4.836
Government Revenue	1.768	2.21	2.652	2.088	2.61	3.132	2.464	3.08	3.696	2.568	3.21	3.852	2.232	2.79	3.348	1.968	2.46	2.952
Investment Payback Period	3.976	4.97	5	3.96	4.95	5	3.928	4.91	5	3.928	4.91	5	3.912	4.89	5	3.96	4.95	5
Value per Barrel	1	1.16	1.392	2.536	3.17	3.804	3.032	3.79	4.548	2.912	3.64	4.368	3	3.75	4.5	2.36	2.95	3.54
Operational Environment	4	5	5	1.6	2	2.4	4	5	5	3.2	4	4.8	2.4	3	3.6	1.6	2	2.4
Commercial Operating Environment	1.6	2	2.4	1.6	2	2.4	1.6	2	2.4	1.6	2	2.4	1.6	2	2.4	1.6	2	2.4
Political and Tax Risk	3.2	4	4.8	3.2	4	4.8	3.2	4	4.8	3.2	4	4.8	3.2	4	4.8	3.2	4	4.8
Competitive Advantages and Disadvantages	2.4	3	3.6	2.4	3	3.6	2.4	3	3.6	2.4	3	3.6	2.4	3	3.6	2.4	3	3.6
Transaction Feasibility	1.6	2	2.4	1.6	2	2.4	1.2	1.5	1.8	1.6	2	2.4	1.6	2	2.4	2.4	3	3.6
Company Participation Level	1.6	2	2.4	1.6	2	2.4	1.6	2	2.4	1.6	2	2.4	1	1	1.2	1.6	2	2.4
Industry Acceptance Level	1.6	2	2.4	1.6	2	2.4	1.6	2	2.4	1.6	2	2.4	1.6	2	2.4	1.6	2	2.4
Government Attitude Towards Transactions	2.4	3	3.6	2.4	3	3.6	2.4	3	3.6	2.4	3	3.6	2.4	3	3.6	2.4	3	3.6
Synergistic Effects	3.2	4	4.8	4	5	5	2.4	3	3.6	2.4	3	3.6	3.2	4	4.8	3.2	4	4.8

Appendix C

Algorithm A1 Cloud model comprehensive evaluation method

INPUT: Evaluation comment set V, Five comment cloud intervals: Class I–V, Experts' grading, Number of cloud droplets n
OUTPUT: Final evaluation cloud figure, Asset level, Similarity
// Process each comment to obtain the standard comment cloud model
FOR each comment in V:
    Determine interval [C_{min}, C_{max}]
    Calculate *Ex*, *En*, *He* as described
    Store standard comment cloud model C (*Ex*, *En*, *He*)
// Establish a five-level evaluation comment cloud based on the classification
// Collect experts' grading for new oil and gas field development projects using comment cloud
// Backward Cloud Generator (BCG) to form cloud clusters
FOR each indicator:
    Input samples x_1, x_2, ..., x_n
    Calculate $Ex = \Sigma(x_i)/n$
    Calculate sample variance S^2
    Calculate *En* and *He* as described
// Comprehensive cloud calculation process and formulas using FCG
Calculate *Ex*, *En*, *He* using the provided comprehensive cloud calculation formulas
// Forward Cloud Generator (FCG) to simulate a comprehensive evaluation cloud
FOR *i* from 1 to 1000:
    Generate normal random number y_i with *En* and *He*
    Generate normal random number x_i with *Ex* and y_i
    Calculate $\mu(x_i)$
    Store cloud droplet x
// If the comprehensive cloud is foggy, adjust and recalculate
// Compare the comprehensive evaluation cloud with the comment cloud
// Use the cloud scale to output the final evaluation cloud figure
// Observe the asset level qualitatively
// Calculate the similarity between the evaluation cloud and each comment cloud

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