Research Article

Comprehensive Evaluation of Offshore Oilfield Development Plans Based on Grey Clustering Analysis with Cloud Model

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Taking the development plans of an offshore oilfield as an example, a new comprehensive evaluation method, the improved Grey Clustering Analysis based on the cloud model (GCAC), is presented in this paper, which takes the ambiguity, randomness, and uncertainty of data into account and overcomes the limits of the general methods, such as subjective prejudice and objective randomness. GCAC converts the data of the oilfield development plans into a cloud, which considers the data of fuzziness, randomness, and the relationship between them. The grey membership degree of each development plan is calculated by this cloud model and an improved grey whitened function is presented in this paper. Then the plans are reordered by their grey membership degrees. In order to make more reasonable consideration of the artificial or unartificial uncertainties, GCAC combines the Grey Entropy Weighting method, Analytical Hierarchy Process (AHP), and Expert Assessment method to determine the weights of each level of indexes, which makes the weights more reasonable and reduces the randomness and the fuzziness of data. GCAC can help obtain a better comparison between the development plans. The reliability of this method is verified by the calculation results.

1. Introduction

As the development of offshore oilfield in our country starts relatively late, the industry standards of offshore oilfield development are not perfect [1–3]. Offshore oilfield development planning is a complicated operation, which requires considering the impact of different types of factors, such as technical factors, economical factors, and uncertainties of the system. Different from the general oilfields, the offshore oilfield development plans are formulated project by project. In the oilfield company of China, there are many different offshore development projects, which are of multiple performance factors and need to be comprehensively evaluated. During an investment cycle, the managers of oilfield enterprises need to determine which of these projects should be implemented to obtain the best benefits. Thus a scientific and reasonable evaluation method plays an important role in the selection of the offshore oilfield development plans.

In recent years, several methods have been applied to meet the problem of the comprehensive evaluation on oilfield development plans. Oilfield data due to man-made records

and by the environment, equipment, and so on have a great deal of uncertainty. Hence, fuzzy set theory [4–6] is a useful tool to deal with imprecise and uncertain data. Liu et al. [7, 8] applied fuzzy comprehensive evaluation method. The method applies prominent impact factors, overcomes the problem, which is the influences of prominent impact factors to the evaluation result, and obtains the optimal order of the programs. Fung et al. [9, 10] present a fuzzy optimal model based on nondeterministic environment, the result of which shows that this model is a powerful tool in designing and ordering the engineering development plans. Grey systems [11–13], proposed by Deng and Ju-Long, is a mathematical method used to solve incomplete information systems, which uses the “small sample” and “poor information” uncertainty systems with “partial information known and part of information not known” as research object to extract valuable information. In 2011 Çelikbilek et al. [14, 15] used the grey decision-making theory in oilfield development program evaluation. Then, Karmakar et al. [16, 17] give a Grey Fuzzy Appraisal method, which is successfully applied to the evaluation of river system and oilfield development programs.

FIGURE 1: Comprehensive evaluation based on cloud model and improved Grey Clustering Analysis.

At the same time, scholars have also proposed a variety of other algorithms; TOPSIS [18] obtains the order of programs by comparing the ideal solution and the negative ideal solution determined by the established development scheme with practical programs. Then there have been many improvements and applications related to the grey system, which are Fuzzy-TOPSIS [19, 20], Principal Component Analysis with grey [21], and Grey-Relational Analysis Method [22]. However, the fuzziness or randomness of data is usually ignored in these methods and the determination of the index weights is not reasonable enough [23–25], which does not consider the relation between fuzziness and randomness or ignore the influence of human in engineering application. Meanwhile, alongside the increase of evaluation indexes, the accuracy of the evaluation scheme is getting lower and lower. Thus it is necessary to put forward a new method to deal with this problem with more reasonable weights.

Cloud model is a novel tool for the study of uncertain knowledges, which can realize the conversion between the qualitative concepts and the quantitative data. It was firstly proposed by the celebrated Academicians Li et al. [26] in 2006. The cloud model integrates the randomness and the fuzziness of the concepts and can be used in Data-Mining and Knowledge Discovery (DMKD), Spatial Data-Mining, and Knowledge Discovery (SDMKD) [27]. In 2014, Lund et al. presented an evaluation model based on the cloud theory for the general engineering development programming [28, 29], which can help sort the development plans reasonably in a certain degree. Cloud model combines randomness and fuzziness to reveal the correlation between them, which reflects the uncertainty of concept. This particular structure has universal applicability and directly completes the process of mutual transformation between qualitative and quantitative information.

The key to comprehensive evaluation is the extraction of useful information from the data of the proposed development plans. As the cluster analysis method is a useful tool to achieve this point, we present a novel comprehensive evaluation procedure (Figure 1), Grey Clustering Analysis based on the cloud model (GCAC), in which the advantages of cloud theory [30] and Grey Clustering Analysis [31] are combined.

On the other hand, it is critical to determine the reasonable weights of the index clouds and synthesized clouds in GCAC. However, most of the existing weight calculation methods are solely subjective methods or solely objective methods, which more or less have a certain one-sidedness. So, in order to reduce the subjective randomness and increase the objective prejudice of the data itself, an optimal combination weighting method is presented in this paper, which combines the AHP, Expert Assessment method, and Grey Entropy Weighting method [32, 33]. In this method, not only the objective weights but also the subjective weights are obtained. Meanwhile, in order to get better classification of the plans, the negative/positive plan generated by TOPSIS [18] is added to the offshore oilfield development plans. The feasibility and the effectiveness this method are verified through a practical example. The results of this paper offer some new ideas for the evaluation and selection of the oilfield development plans.

The structure of this paper is organized as follows. In Section 2, the main procedure of our method is presented, which contains data processing, single condition rule cloud generator, combined weighting method, modified synthesized cloud, and improved Grey Clustering Analysis. In Section 3 we make a practical test of the presented method, to evaluate a group of development plans of some offshore field in China, and the comparison results with other methods are listed in this section. Finally, we make a summary about our method.

INPUT: Cloud drops x_i and its certainty degrees $\mu(x_i)$ ($i = 1, 2, \dots, n$)
 OUTPUT: The numerical characteristics (Ex, En, He)
 Step 1. Generate the mean value of the samples x_i , that is the expectation $Ex = \text{MEAN}(x_i)$;
 Step 2. Generate the standard deviation of the samples x_i , that is the entropy $En = \text{STDEV}(x_i)$;
 Step 3. For each pair of (x_i, μ_i) , generate the hyper entropy of the samples x_i ;

$$En'_i = \sqrt{\frac{-(x_i - Ex)^2}{2 \ln \mu_i}}, He = \begin{cases} \text{STDEV}(En'_i), & \mu_i \in (0, 1) \\ 0, & \mu_i = 0, 1. \end{cases}$$

ALGORITHM 1: Backward normal cloud generator.

2. The Main Procedure of GCAC

A cloud is composed of a large amount of cloud drops. The global properties of a cloud can be presented by its digital features, which are Expected value (Ex), En (Entropy), and He (Hyperentropy) [25]. Here, En represents the uncertainty measure of qualitative concept, and He represents the uncertainty measure of the En . The larger the value of He is, the more dispersed the cloud distribution gets.

In Figure 1, it is necessary to ensure the index system for comprehensive evaluation [34]. When the evaluation system has been ensured, we start to handle data processing, that is, normalization. In order to get the standard cloud, which is the first judgment of the advantages and disadvantages for the plans, Golden Selection [35, 36] is used. And the principle of Golden Selection is to generate standard cloud by cloud generator.

To analyze the plans further, its data are normalized and then put into the backward cloud generator to generate index clouds. We can obtain synthesized cloud by synthesized cloud [37] on the basis cloud. In the process of generating synthesized cloud, weight plays a key influence factor. Then AHP, Expert Assessment method, and Entropy Weighting method are combined to obtain the weights. Alongside, we add positive/negative plans generated by TOPSIS [18] into the plans to be evaluated, which help precisely classify plans by the improved Grey Clustering Analysis [38, 39].

2.1. Data Processing. The comprehensive evaluation based on the cloud models always embraces 6 sets:

The set of plans: $O = \{o_1, o_2, \dots, o_n\}$;

The set of indexes: $U = \{u_1, u_2, \dots, u_m\}$;

The attribute value matrix: $X = \{x_{ij} \mid i = 1, 2, \dots, n; j = 1, 2, \dots, m\}$;

The comments set of indexes: $V = \{A_1, A_2, \dots, A_k\}$;

The contribution scores set of indexes: $S = \{B_1, B_2, \dots, B_k\}$;

The set of weights: $W = \{w_1, w_2, \dots, w_n\}$.

And x_{ij} is value of the index u_j in the plan o_i .

For the data sets O, U , and X , they are obtained by the data of development plans themselves. For a complicated evaluation systems, the indexes always contain two types which are technical and economic indexes. For the economic type,

indexes are divided into two types, which are growth indexes and reduced indexes both called second-level indexes. The growth indexes represent the fact that the higher the value are, the better they are. The reduced indexes represent the fact that the lower the values are, the better they are. For the technical indexes, the more moderate the values of indexes are, the better they are.

The indexes of each plan are called first-level indexes. Then we can obtain dimensionless data by normalizing the data, where different index types have different normalization methods. Meanwhile, according to the cloud model [25], the cloud of normalized data can be calculated by backward normal cloud generator, which the Algorithm 1 represented.

Remarks 1. In the Artificial Intelligence With Uncertainty, it does not consider the situation of $\mu_i = 0$ and $\mu_i = 1$ that will lead to the algorithm be meaningless; also it will happen in the actual situation. If $\mu_i = 0$, that is, $x_i \notin U$, all the cloud drops condense into a point. If $\mu_i = 1$, that is, $x_i \in U$, all the drops form a complete one, but it does not diverge anymore. So we set the hyperentropy $He = 0$, when $\mu_i = 0, 1$. Among them, MEAN is used to generate the average of the samples and STDEV is used to generate standard deviation of the samples.

2.2. Single Condition Rule Cloud Generator. For the sets V and S , they involve the cloud generator, and the generator rule is represented as follows:

If A , then B . (1)

A is an antecedent, B is a consequent, and both of them are qualitative concepts. The conditional cloud generator is composed of the antecedent cloud generator and the consequent cloud generator, Figure 2. In this paper, we employ single condition rule cloud generator [25]. The details of the single condition single rule cloud generator are presented in Algorithm 2.

According to the cloud generator and the amount of offshore oilfield development plans, we constructs five rules for antecedent and consequent, which means it needs five basis clouds. For the basis clouds, we apply model-driven method based on Golden Section [33] to construct, which is suitable for a small amount of data. According to the numerical characteristic of the generated clouds of the x_i , the parameters of the basis clouds for antecedent and consequent can be estimated by Golden Section approximately.

INPUT: the qualitative concept of antecedent A , $C_1(Ex_A, En_A, He_A)$ and its initial quantitative value x_0 , the qualitative concept of consequent B , $C_2(Ex_B, En_B, He_B)$;

OUTPUT: Cloud drop y in the consequent universe and its certainty degree μ .

Step 1. Generate a normally distributed random number En'_A with expectation En_A and variance He_A^2 , i.e. $En'_A = R_N(En_A, He_A^2)$;

Step 2. Generate a normally distributed random number En'_B with expectation En_B and variance He_B^2 , i.e. $En'_B = R_N(En_B, He_B^2)$;

Step 3. Calculate certainty degree $\mu(x) = \exp\{-(x_0 - Ex_A'^2)/(2En_A'^2)\}$;

Step 4. Calculate cloud drop's value $\{y = Ex_B - \sqrt{-2 \ln(\mu)} En'_B, x < Ex; y = Ex_B + \sqrt{-2 \ln(\mu)} En'_B, x \geq Ex\}$.

ALGORITHM 2: Single condition rule cloud generator. Among them, Ex_A, En_A, He_A and Ex_B, En_B, He_B respectively, said expectation, entropy, hyper entropy of the antecedent A and the antecedent B .

FIGURE 2: Single condition rule cloud generator. (a) The antecedent cloud generator; (b) the consequent cloud generator.

Suppose that the elements of antecedent in the comments set are $V = \{A_1, A_2, A_3, A_4, A_5\}$, which represent the levels of the quantitative concept of indexes, which are “excellent,” “better,” “common,” “poor,” and “very poor.” The elements of consequent in the contribution scores set are $S = \{B_1, B_2, B_3, B_4, B_5\}$, which stands for “higher,” “high,” “medium,” “low,” and “lower.” What is more, the elements in set V and the elements in set S correspond to each other. So we construct five single condition rules as follows.

If x belongs to excellent (A_1), then the contribution score of x is higher (B_1);

If x belongs to better (A_2), then the contribution score of x is high (B_2);

If x belongs to common (A_3), then the contribution score of x is medium (B_3);

If x belongs to poor (A_4), then the contribution score of x is low (B_4);

If x belongs to very poor (A_5), then the contribution score of x is lower (B_5).

In the single condition rule cloud generator, it involves the backward cloud generator. Given the value of x into the five antecedents of this generator, we choose the rule where the certainty degrees of the x are maximum and then obtain the drops of the contribution score cloud $C_{B(k,x)}$ according to the backward normal cloud generator. Repeat this routine through the single condition rule cloud generator and the clouds of all level indexes can be achieved.

2.3. Combined Weighting Method. In the determination of weights, it not only needs the experience of experts, but also should consider the relations of data itself, so we should take both object weights and subject weights into consideration.

To calculate weights more reasonable and valuable, the method combining the Expert Assessment method, AHP, with Grey Entropy Weight method [31, 32] is employed. Among them, AHP is used to analyze different level indexes, Expert Assessment method is used to calculate the subjective weight caused by human, and Grey Entropy Weight method is used to obtain the objective weight caused by the relations of data itself. Meanwhile, AHP is adopted to analyze the structure of the problem. Then the plan layer is the clouds of all x_i , the rule layer is the clouds of different type indexes of each plan, and the goal layer is the comprehensive clouds of the plans. The algorithm is as follows.

$$\gamma_i = \frac{\alpha_i + \beta_i}{\sum_{i=1}^n (\alpha_i + \beta_i)}, \quad i = 1, 2, \dots, n. \quad (2)$$

Here α_i is the subjective weight given by Expert Assessment method, β_i is the objective weight computed by Grey Entropy Weight method, γ_i is the combining weight, and i represents the number of layers.

2.4. Modified Synthesized Cloud. The synthesized clouds of second-level indexes and plans are keys to meet the problem. Synthesized Cloud is a kind of Virtual Cloud, which refers to the cloud with new digital features generating by the basis cloud. The core idea is converting the uncertain linguistic values into interval synthesized cloud. On this basis, we give an explanation for the handling of abnormal point. The algorithm of synthesized is as follows.

Given n basis clouds with $C_1(Ex_1, En_1, He_1)$, $C_2(Ex_2, En_2, He_2), \dots, C_n(Ex_n, En_n, He_n)$ of indexes, suppose the synthesized cloud with $C(Ex, En, He)$, and then its numerical characteristics satisfy

$$\begin{aligned}
Ex &= \omega_1 Ex_1 + \omega_2 Ex_2 + \cdots + \omega_n Ex_n, \\
He &= \sqrt{\frac{He_1^2 + He_2^2 + \cdots + He_n^2}{n}}, \\
En &= \begin{cases} \frac{\omega_1 Ex_1 En_1 + \omega_2 Ex_2 En_2 + \cdots + \omega_n Ex_n En_n}{\omega_1 Ex_1 + \omega_2 Ex_2 + \cdots + \omega_n Ex_n}, & Ex_i \neq 0, (i = 1, 2, \dots, n), \\ \frac{\omega_1 En_1 + \omega_2 En_2 + \cdots + \omega_n En_n}{\omega_1 + \omega_2 + \cdots + \omega_n}, & Ex_i = 0, (i = 1, 2, \dots, n). \end{cases}
\end{aligned} \tag{3}$$

When $Ex_i = 0$, then we obtain $En = (\omega_1 En_1 + \omega_2 En_2 + \cdots + \omega_n En_n)/(\omega_1 + \omega_2 + \cdots + \omega_n)$ by using L'Hopital rule. Here, $\omega_1, \omega_2, \dots, \omega_n$ represent the attribute weight values, and $\omega_i > 0$. The improved formula is as follows.

2.5. Improved Grey Clustering Analysis. The purpose of this paragraph is to obtain the results of cluster analysis and sort the plans. In this process, in fact, the results of sorting the plans usually can be visually resolved by comparing the relative position of each plan's cloud distribution and the standard contribution score cloud. An exact comparison cannot be carried out when two clouds are relatively close with each other, so the Grey Clustering Analysis is taken into consideration. According to the different clustering attributes, we can do comprehensive evaluation for plans more clear.

In the traditional grey whitened model, the grey whiten function is linear and represents whitening function value maintaining steady growth. Actually, it shows a growth trend in the actual situation. Then we improve the algorithm by replacing linear function with Logistic curve which is more in line with the growth trend.

If $k = 1$, then

$$\begin{aligned}
f_k(x_{ij}) &= \begin{cases} \frac{1.005}{1 + e^{-(5.2933/(\lambda_{j1}/2)(x_{ij}-\lambda_{j1}/2))}}, & x_{ij} \in [0, \lambda_{j1}) \\ 1, & x_{ij} \in [\lambda_{j1}, \infty). \end{cases}
\end{aligned} \tag{4}$$

If $k = 2, 3, \dots, n-1$, then

$$f_k(x_{ij}) = \begin{cases} \frac{1.005}{1 + e^{-(5.2933/(\lambda_{jk}/2)(x_{ij}-\lambda_{jk}/2))}}, & x_{ij} \in [0, \lambda_{jk}) \\ 1 - \frac{1.005}{1 + e^{-(5.2933/((\lambda_{jk-1}-\lambda_{jk})/2)(x_{ij}-(\lambda_{jk-1}+\lambda_{jk})/2-\lambda_{jk}))}}, & x_{ij} \in [\lambda_{jk}, \lambda_{jk-1}) \\ 0, & x_{ij} \in [\lambda_{jk-1}, \infty). \end{cases} \tag{5}$$

If $k = n$, then

$$f_k(x_{ij}) = \begin{cases} 1, & x_{ij} \in [0, \lambda_{jn}) \\ 1 - \frac{1.005}{1 + e^{-(5.2933/((\lambda_{jn-1}-\lambda_{jn})/2)(x_{ij}-(\lambda_{jn-1}+\lambda_{jn})/2-\lambda_{jn}))}}, & x_{ij} \in [\lambda_{jn}, \lambda_{jn-1}) \\ 0, & x_{ij} \in [\lambda_{jn-1}, \infty). \end{cases} \tag{6}$$

Subsequently, it uses the cloud's attributes (Ex, En, He) to establish clustering weight matrix. This paper improved the formula which calculates the clustering weights, as follows:

$$cw_{jk} = \frac{\lambda_{jk}}{\sum_{j=1}^n f_k(x_{ij}) \lambda_{jk}} \quad (k = 1, 2, \dots, n, \dots). \tag{7}$$

Equation (7) makes the clustering weights more effective and reasonable, because it considers not only thresholds λ_{jk} , but also the value of grey whiten function $f_k(x_{ij})$.

Then we can get clustering coefficient matrix, as follows:

$$\sigma_{ik} = \sum_{j=1}^n f_k(x_{ij}) cw_{jk} \quad (k = 1, 2, 3, 4, 5; i = 1, 2, 3). \tag{8}$$

Step 1. Establish plan set, index set, the basis comment set and the matrix of plan's indexes;
 Step 2. Establish the 5 types grey whitening function based on the Logistic function
 Step 3. Establish clustering weight vector and clustering weight matrix
 Step 4. Clustering coefficient vector and clustering coefficient matrix
 Step 5. Determine the pros and cons of the plan $\sigma_i = \max(\sigma_{ik})$ ($k = 1, 2, 3, 4, 5$).

ALGORITHM 3: Improved Grey Clustering Analysis.

For the first class, in which the indexes of higher values are better ($j = 1, 5, 6, 8$), the data cloud be normalized by
 $x'_{ij} = |x_{ij} - \max_{1 \leq i \leq 8} \{x_{ij}\}| / (\max_{1 \leq i \leq 8} \{x_{ij}\} - \min_{1 \leq i \leq 8} \{x_{ij}\})$;
 For the second class, in which the indexes of lower values are better ($j = 2, 4, 7, 9$), the data cloud be normalized by
 $x'_{ij} = |x_{ij} - \min_{1 \leq i \leq 8} \{x_{ij}\}| / (\max_{1 \leq i \leq 8} \{x_{ij}\} - \min_{1 \leq i \leq 8} \{x_{ij}\})$;
 For the second class, in which the indexes of moderate values are better ($j = 3$), the data cloud be normalized by
 $x'_{ij} = |x_{ij} - \text{mor}\{x_{ij}\}| / \text{mor}_{1 \leq i \leq 8} |x_{ij} - \text{mor}\{x_{ij}\}|$.

ALGORITHM 4: The normalization method.

In (4)–(8), x_{ij} represents the synthesized information for Ex , En , and He .

The formulation of Improved Grey Clustering Analysis is summarized in Algorithm 3.

2.6. Grey Membership Degree for Clouds. According to the above content, the characteristics of plans are transformed into the synthesized clouds in Section 2.4, which contains three characteristics: Ex , En , and He . According to the cloud model [25], the bigger Ex is, the better it is, and the smaller En and He are, the better they are. The tendency of numerical characteristic is different, so the reciprocal of En and He is used to replace their value. Later the characteristics of clouds are also divided into 5 parts which are lower, low, moderate, high, and higher groups; then whitened function will have 5 types for every characteristic. Then we can determined the grey membership degree for each plans by the three characteristics. The detail is represented as follows:

(1) Calculating the synthesized information for Ex , En and He ,

$$EEH = \gamma_1 * Ex + \gamma_2 * \left(\frac{1}{En}\right) + \gamma_3 * \left(\frac{1}{He}\right), \quad (9)$$

where $\gamma_1, \gamma_2, \gamma_3$ are the weights for Ex , En , and He .

(2) Calculating the grey membership degree for each plan by the Section 2.5,

$$\sigma = \max(EEH). \quad (10)$$

The method not only takes into account the effect of expectation, entropy and hyperentropy on the ordering, but also emphasizes the importance of the expectation of the clouds. It means the clustering analysis for plans can be achieved just through 3 digital features of the generated synthesized cloud.

3. Case Study

3.1. Application on the Evaluation of Offshore Oilfield Plans

3.1.1. Data Processing. Taking 8 different development plans of an offshore oilfield as example, both technical and economic indexes are taken into consideration in our method. We divided all the indexes into 3 types described in Section 2.1. The indexes contain the final recovery, the net present value, the total profit, and the internal rate of return as the first class; the composite decline rate, the dynamic investment payoff, the total investment, and the average unit cost as the second class; the oil recovery rate as the third class. The detail of normalization method is in Algorithm 4. In this case study, we just consider the 6 indexes from the actual situation. The numbers of indexes are 2, 5, 6, 7, 8, and 9. The normalized result is represented in Table 1.

3.1.2. Determination of Weights. For weights, when there is no such index, suppose the weight is 0. For the first-level and second-level indexes, the combining weights are generated by combined weighting method described in Section 2.3. The results are shown in Table 2.

3.1.3. Score Cloud and Synthesized Cloud. With these data and methods, the contribution score clouds of all the plans' indexes can be generated, showing in Table 3. By using the cloud generator and weights, we can compute synthesized cloud for each plans. In this application, the amount of the cloud drops is to be 1000. The result is represented in Table 4.

From Table 4, the attributes of indexes for each plan have been transformed into the cloud characteristics (Ex , En , He). Figure 3 is the graph of the standard evaluation clouds which generated by Golden Selection, where the digital result is represented in Table 5. Figure 4 is the graph of the synthesized score clouds of the plans.

From Figure 4, the sorting results of the plans can be visually resolved by comparing the relative position of each

TABLE 1: The normalized data of the development plans.

Plan	Technical indexes		Economic indexes		Economic indexes	
	u_1	u_2		u_3		
	u_{12}	u_{22}	u_{23}	u_{31}	u_{32}	u_{33}
1	0.900	0.334	0.063	0.395	0.544	0.187
2	0.178	0.225	0.242	0.843	0.030	0.352
3	0.044	0.231	0.163	1.000	0.083	1.000
4	0.344	0.668	1.000	0.144	0.308	0.514
5	0.000	0.229	0.311	0.889	0.000	0.413
6	1.000	1.000	0.000	0.000	0.745	0.087
7	0.278	0.034	0.022	0.840	0.284	0.000
8	0.344	0.000	0.132	0.226	1.000	0.243

TABLE 2: The combining weights of indexes.

First-level	u_1				u_2			u_3	
Weight	0.42				0.41			0.17	
Second-level	u_{11}	u_{12}	u_{13}	u_{21}	u_{22}	u_{23}	u_{31}	u_{32}	u_{33}
Weight	0	1	0	0	0.28	0.72	0.65	0.19	0.16

TABLE 3: The contribution score clouds of the indexes.

Plan	u_{12}	u_{22}	u_{23}	u_{31}	u_{32}	u_{33}
1	(89.85, 1.38, 0.85)	(33.38, 0.3, 0.46)	(6.4, 0.82, 0.77)	(39.58, 1.17, 0.49)	(53.79, 0.51, 0.26)	(18.5, 1.74, 0.64)
2	(17.75, 1.92, 0.7)	(22.3, 1.14, 0.5)	(24.09, 0.9, 0.49)	(84.09, 2.06, 0.82)	(3.07, 0.41, 0.8)	(35.21, 0.57, 0.49)
3	(4.49, 0.58, 0.79)	(22.99, 1.01, 0.49)	(16.45, 1.99, 0.73)	(100, 0, 0)	(8.36, 1.11, 0.79)	(100, 0, 0)
4	(34.49, 0.49, 0.5)	(66.64, 0.32, 0.5)	(100, 0, 0)	(83.81, 2.01, 0.77)	(30.83, 0.01, 0.49)	(51.26, 0.17, 0.26)
5	(0, 0, 0)	(22.86, 1.07, 0.49)	(31.12, 0.03, 0.48)	(14.67, 1.99, 0.8)	(0, 0, 0)	(41.33, 1.3, 0.48)
6	(100, 0, 0)	(100, 0, 0)	(0, 0, 0)	(0, 0, 0)	(74.75, 0.73, 0.52)	(8.75, 1.12, 0.77)
7	(27.76, 0.41, 0.49)	(3.46, 0.47, 0.84)	(2.26, 0.29, 0.81)	(88.76, 1.45, 0.79)	(28.4, 0.33, 0.5)	(0, 0, 0)
8	(34.47, 0.44, 0.46)	(0, 0, 0)	(13.36, 1.8, 0.84)	(22.42, 1.1, 0.49)	(100, 0, 0)	(24.27, 0.84, 0.48)

FIGURE 3: The standard evaluation clouds.

FIGURE 4: The synthesized score clouds of the development plans.

plan's cloud distribution and the standard contribution score cloud. However, the clouds of 6 plan and 8 plan are relatively close to each other; we cannot make an exact comparison. Then the improved grey cluster analysis is employed to sort the plans clearly.

3.1.4. Grey Membership Degree for Each Plan. We divide grey membership degree of plans' clouds into lower, low, moderate, high, and higher-benefit groups. Meanwhile, the thresholds for each groups are 20, 15, 10, 5, and 1. And the thresholds for *Ex*, *En*, and *He* of grey membership

TABLE 4: The synthesized score clouds of the plans.

Plan	1	2	3	4	5	6	7	8
Synthesized score cloud	(50.073, 1.229, 1.498)	(27.474, 1.578, 1.594)	(23.423, 0.587, 1.422)	(63.307, 0.448, 1.186)	(22.743, 0.823, 1.153)	(44.652, 0.046, 0.935)	(15.262, 0.571, 1.574)	(36.268, 0.460, 1.180)

TABLE 5: The cloud parameters of the comment set and the contribution score set.

Comment set	Antecedent cloud parameters	Contribution score set	Consequent cloud parameters
Excellent	(1, 0.103, 0.013)	Highest	(100, 10.31, 0.26)
Better	(0.691, 0.064, 0.008)	Higher	(69, 6.37, 0.16)
Common	(0.50, 0.039, 0.005)	Medium	(50, 3.39, 0.10)
Poor	(0.309, 0.064, 0.008)	Low	(30.9, 6.37, 0.16)
Very poor	(0, 0.103, 0.013)	Very low	(0, 10.31, 0.26)

Note. They are also suitable for other complicated systems.

FIGURE 5: The Indicators of plans.

TABLE 6: Grey threshold matrix.

λ_{jk}	Ex ($j = 1$)	En ($j = 2$)	He ($j = 3$)
$k = 1$	60	2.5	1
$k = 2$	50	2	0.9
$k = 3$	40	1.5	0.8
$k = 4$	30	1	0.7
$k = 5$	20	0.5	0.6

Note. They are also suitable for other complicated systems.

degree are shown in Table 6. Then the clustering weight matrix can be got; see Table 7. With Table 7 and grey whitening function, we can generate a cluster coefficient matrix for the 5 groups of each plan; the results is presented in Table 8.

Comparing the thresholds of groups with the maximal value of σ_{ik} for each plan, it shows that the plans 4, 6, and 1 belong to the higher-benefit groups, the plan 8 is in the high-benefit groups, the plans 2, 3, and 5 are in the moderate-benefit groups, plan 7 belongs to the low-benefit groups, and no plan is in the lower-benefit group. Then we can preliminarily make a further sequencing of the plans, that is, (4, 6, 1)/8/(2, 3, 5)/7. From the perspective of cluster analysis of the plan, the good or bad classification is carried

TABLE 7: Clustering weight matrix.

cw_{jk}	Ex ($j = 1$)	En ($j = 2$)	He ($j = 3$)
$k = 1$	0.327	0.383	0.265
$k = 2$	0.359	0.299	0.238
$k = 3$	0.349	0.25	0.243
$k = 4$	0.333	0.19	0.255
$k = 5$	0.275	0.179	0.268

Note. Ex, En, and He of five groups in Table 6 are obtained by the experts' advice.

out. However, the results we need is the rank from priority to inferiority of the plans. So if we want it, one method is taking more grey whitening functions to get more clear classification, but it will need more computing resources. Then we can sort plans according the value of $\max(\sigma_{ik})$ with plans, because the bigger $\max(\sigma_{ik})$ is, the better it is. According to the value of $\max(\sigma_{ik})$ of programs, the sequence can be obtained as follows: 4, 6, 1, 8, 2, 3, 5, 7.

3.2. Discussion about the Results

3.2.1. The Analysis of Result for Our Method. For the index value, the bigger u_{22} , u_{23} and u_{32} are, the better they are; the smaller u_{12} , u_{31} and u_{33} are, the better they are. Then according to the thought of TOPSIS, the negative/positive plan's indexes are (1, 0, 0, 1, 0, 1)/(0, 1, 1, 0, 1, 0) by ignoring the influence of weights. In order to illustrate the effectiveness of the method more clearly, we enumerate the index values of the sorting plans by adding the negative plan and positive plan, which is represented in Figure 5.

Figure 5 shows that the bigger u_{23} (the internal rate of return) is, the better it is. Then according to its value, we can get the rank of plans, which is as follows: 4, 5, 2, 3, 8, 1, 7, 6. And the smaller u_{31} (the total investment) is, the better it is. It can generate the rank is as follows: 6, 4, 8, 1, 7, 2, 5, 3. As the Figure 5 shows, for the six indicators, when the point of the indicator value representing the different plan is closer to the center of the green circle, the corresponding index value of the plan is better, so considering the influence of the weight of each indicator from expert's advice, it is possible to judge the good and bad by the six indexes. Then it can initially judge if a plan is good or bad by all indexes of each plan. Using this principle, we can confirm that the method used in this paper and the sorting result (4, 6, 1, 8, 2, 3, 5, 7) represented in Table 8 are reasonable and effective and demonstrate our method is valuable.

TABLE 8: The grey membership degree matrix of plans.

σ_{ik}/plan	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$\max(\sigma_{ik})/\text{EHH}$
$i = 1$	21.353	0.337	0.534	0.507	−0.002	21.353
$i = 2$	8.722	11.596	13.017	11.062	0.446	13.017
$i = 3$	6.007	8.307	10.279	10.300	−0.027	10.300
$i = 4$	22.625	−0.002	0.000	0.000	0.000	22.625
$i = 5$	5.189	7.363	10.146	10.165	−0.026	10.165
$i = 6$	21.274	17.770	−0.055	0.000	0.000	21.274
$i = 7$	2.435	2.817	3.379	5.828	7.337	7.337
$i = 8$	17.335	16.524	14.246	−0.041	0.000	17.335

TABLE 9: Comparison of different methods.

Plan	TOPSIS	Fuzzy comprehensive method	Experts' Assessment	The method of this article
1	1	4	4	4
2	4	1	6	6
3	8	6	1	1
4	6	8	8	8
5	2	2	2	2
6	5	3	5	3
7	3	5	3	5
8	7	7	7	7

3.2.2. Comparison with Other Methods. In order to investigate the effectiveness of the method, we compare our result with the results of the ideal solution, the fuzzy comprehensive evaluation method, and experts' advice. Meanwhile the initial weight of fuzzy comprehensive evaluation method and the TOPSIS are the weights of Table 1, so it can calculate the ranking of the plans. The result is repented in Table 9.

According to the results of Table 9, the optimal plan should be generated in plans 4, 1, and 6. In addition, the order of plans 4, 1, and 6 of our method is different from the other three methods. Then comparing the six indicators of plans 4, 1, and 6, the plans 4 and 6 are the first class for the three indicators among them, so it is supposed that the optimal plan should be plans 4 or 6. For the order of plan 1, the TOPSIS and the Fuzzy comprehensive method result are different from the experts' advice and the result of our method, but the order of plan 1 is reasonable for our method by the six indicators. What is more, the order of plan 2 and plan 7 can be determined; that is, the order of plan 2 is fifth and the order of plan 7 is eighth, which is the worst plan. For plan 3 and plan 5, the order should be sixth or seventh. For plan 8, according to the three methods' results, the fourth order is reasonable. Then we can get a rough sorting plan, which is (4, 6, 1)/8/2/(3,5)/7. For the result of expert's assessment and our method, there are just plans 3 and 5 that are different; the cause of this phenomenon is because the weight allocation for some indicators is not the same. As a result, from the perspective of multiple methods, the result of this paper is effective and reasonable for the plans.

4. Conclusion

A comprehensive evaluation method is proposed in this paper based on the cloud model and the improved grey cluster analysis, which takes the randomness, fuzziness, and relation of randomness with fuzziness for data into consideration. Meanwhile, a combined weight method is employed to reduce subjective prejudice and objective randomness in the determination of weights. In this paper, 8 development plans of an offshore oilfield in China are taken as a practical example to verify the validness and effectiveness of our method. Through the method, we can get a better classification for the plans and reasonably sort the plans. What is more, our method is only an analysis of the data, so it also can be applicably used in the comprehensive evaluation of other complicated systems.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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