Journal of Petroleum
Science and Technology

A New Screening Evaluation Method for Carbon Dioxide Miscible Flooding Candidate Reservoirs

Li Yanjie*[1], Zhang Yanyu[2], Wang Shichao[3], Chen Huijuan[2], Shi Xiaoying[4], and Bai Xuzheng[5]

[1] Development Research Department, China National Offshore Oil Corporation (CNOOC), Beijing, China
[2] School of Petroleum Engineering, China University of Petroleum (Eastern China), Qingdao, China
[3] Research Institute of Western South China Sea Petroleum Administrative Bureau, CNOOC Zhanjiang Branch, Zhanjiang, China
[4] Exploration and Development Research Institute of Huabei Oilfield Company, Renqiu, China
[5] Gudong Oil Production Plant of Shengli Oil Field Co., Dongying, China

ABSTRACT

Prior to the implementation of CO_2 injection EOR projects, the screening evaluation of candidate reservoirs will promote the economic benefits of CO_2 injection. Currently, a uniform screening method for CO_2 miscible flooding does not exist. Based on more than 112 successfully implemented CO_2 miscible flooding reservoirs, which was referred in 2010 Worldwide EOR Survey, and CO_2 miscible flooding mechanisms, this paper picks out 12 reservoir and fluid parameters affecting CO_2 miscible flooding results as comprehensive evaluation parameters for screening candidate reservoirs. According to investigations on a large number of domestic and international CO_2 miscible flooding projects, the quantitative methods are determined by theoretical analyses, field experience, and probability statistics. By means of calculating the combinational weights by improved analytical hierarchy process (AHP) and entropy method and combining the advantages of technique for order preference by similarity to ideal solution (TOPSIS) with gray relational analysis to construct a new similarity nearness degree, the weighted GC-TOPSIS model is established for screening candidate reservoirs. This screening method was employed for the assessment of five classical candidate reservoirs proposed for CO_2 miscible flooding. The results show that this new method can correctly evaluate and compare the potential of CO_2 miscible flooding.

Keywords: CO_2 Miscible Flooding, Screening Index, Evaluation Criteria, Ideal Solution, Grey Correlation

INTRODUCTION

CO_2 miscible displacement, as a key EOR method, is becoming increasingly important to improve oil recovery efficiency these days. Miscible displacement can recover trapped oil; the main mechanism is associated with higher microscopic displacement efficiency due to the low interfacial tension (IFT) between oil and the injected CO_2. IFT tends towards zero when miscibility is reached, which means that oil recovery can reach the maximum in the swept area. Additional mechanisms such as the assistance of pressure, viscosity reduction, oil

***Corresponding author**
Li Yanjie
Email: liyj65@cnooc.com.cn
Tel: +86 185 1064 0017
Fax: +86 010 6228 9081

Article history
Received: May 6, 2014
Received in revised form: November 1, 2014
Accepted: January 21, 2015
Available online: July 26, 2015

swelling, and improved reservoir contact further contribute to a higher oil recovery. Based on a recently updated report from Department of Energy, within Advanced Resource International's Large Oilfield's Database, 1,719 out of 2,790 reservoirs are favorably for CO_2-EOR. These 1,719 reservoirs contain 305 billion barrels of OOIP (R.C. Ferguson et al., 2010). Therefore, CO_2 miscible flooding to enhance oil recovery has become a major potential in petroleum industry.

According to 2010 Worldwide EOR Survey, gas injection is currently the most common EOR process apart from thermal recovery (Figure 1), and CO_2 miscible displacement is also the most widely applied gas injection EOR method. However, with the gradual improvement to exploitation and development technologies, reservoirs prepared for CO_2 miscible displacement need to be carefully studied in order to optimize economic benefits. Based on the statistics of successful CO_2 miscible displacement examples from 2010 Worldwide EOR Survey, theoretical analysis, probability statistics, screening index systems, and evaluation criteria of key parameters, including reservoir characteristics, rock properties, and crude oil properties, were obtained.

The application of CO_2 injection into oil reservoirs started in the 1970's. From then on, some experts and scholars put forward different screening criteria and evaluation methods for CO_2 injection. In order to single out CO_2-EOR candidates (Geffen, 1973; Lewin et al., 1976; NPC, 1976; McRee, 1977; Lyoho, 1978; OTA, 1978; Carcoana, 1982; Taber & Martin, 1983; Mark A Klins, 1989; O. Rivas et al., 1994; Daniel et al., 1996; Taber et al., 1997; Brent, 1998; J. Shaw, 2002; Ahmad et al., 2010), a variety of parameters have been put forward. These parameters include reservoir characteristics (depth, temperature, pressure, and thickness of the reservoir), rock properties (lithology, permeability, porosity), and crude oil properties (API gravity, oil viscosity, oil saturation). However, most of these criteria just give roughly the appropriate range, while unable to determine the applicability of CO_2 miscible flooding for a specific oil field if one or several parameters fail to fall within the right range. Since Louisiana State University, commissioned by the U.S. DOE, investigated CO_2 flooding comprehensive evaluation method for light oil reservoirs after water flooding in 1992, some experts [18-23] have established comprehensive evaluation methods based on fuzzy analytic hierarchy processes. However, due to the use of objective weighting method to determine the index weight, which apparently has some shortcomings, these methods are relatively restricted and limited. Therefore, twelve screening indexes affecting CO_2 injection miscible flooding results were selected in this paper, and their quantitative methods are determined by theoretical analysis, field experience, and probability statistics. Based on improved AHP and entropy method to determine the comprehensive weight of screening indexes, the weighted GC-TOPSIS model was established to screen candidate reservoirs while the accuracy and stability of this method were also evaluated.

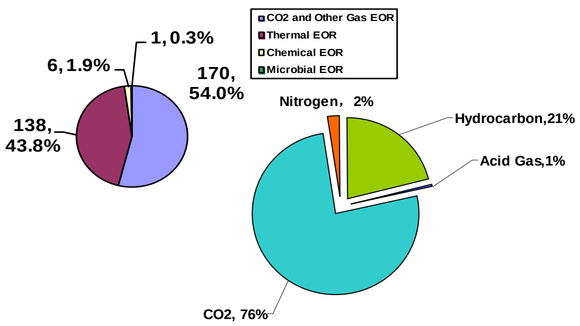

Figure 1: EOR methods distribution based on 2010 Worldwide EOR Survey

The Screening Indexes and Evaluation Criteria

Due to different reservoir conditions, CO_2 injection effect and corresponding flooding mechanism are different. Systematically analyzing the various factors that affect CO_2 injection and selecting the appropriate screening indexes are the basis of the screening model for CO_2 injection miscible flooding.

According to screening indexes mentioned above, and the analysis of factors affecting CO_2 injection, we extract 12 screening indexes, namely reservoir temperature, reservoir depth, reservoir pressure, reservoir thickness, reservoir dip, permeability, porosity, wettability, heterogeneity, API gravity, oil viscosity, and oil saturation. They are divided into three categories, including direct screening indexes, interval screening indexes, and inverse screening indexes.

Direct Screening Indexes

Direct screening indexes refer to that larger evaluation value shows better results. In the identified CO_2 injection miscible flooding screening indexes, the oil wettability, reservoir dip, oil saturation, and oil API gravity are direct screening indexes.

Oil Wettability. Rock wettability directly impacts the displacement efficiency of CO_2 miscible flooding process. In the process of drilling, well completion, workover and production operations, the phenomenon that exotic fluid is retained in porous media will appear. The presence of another immiscible phase in the reservoir or when the saturation of original immiscible phase in porous medium increases will harm the reservoir relative permeability; thus the reservoir permeability and oil and gas relative permeability are significantly reduced, and ultimately affect the reservoir recovery. When the immiscible phase is aqueous phase, this phenomenon is called water lock phenomenon. Theoretical research and core test showed that, in a water-wet medium, the contact area of the oil and CO_2 is reduced due to the presence of water, and water lock phenomenon is more serious, which is not conducive to CO_2 displacement efficiency. If CO_2 is injected into these reservoirs without water injection, this adverse effect can be negligible. But if the reservoirs have been developed by water flooding process, the water lock phenomenon in the water-wet reservoir should be considered. Oil-wet index can be used to reflect rock wettability. Therefore, a higher oil-wet index is better.

Reservoir dip. In slanted reservoirs, gravity could be used as the displacement force in CO_2 miscible flooding. Usually we inject CO_2 into the up dip structure of reservoirs at a low injection rate. The gravity can be used to separate CO_2 and crude oil, in order to suppress the fingering phenomenon and enhance displacement efficiency. The dip angle of candidate reservoirs for gravity flooding is usually at least 15°, and a larger the dip angle is better.

Oil saturation. Bigger oil saturation is definitely more suitable. If oil saturation is very low, it will be difficult to form continuous oil in miscible flooding process, and crude oil will not be easily flooded out. As shown in Figure 2, based on 2010 Worldwide EOR Survey, it is found that initial oil saturation for CO_2 miscible displacement reservoirs ranges between 24% and 89%, or more precisely from 40% to 55%, which accounts for 52% of all the candidate reservoirs.

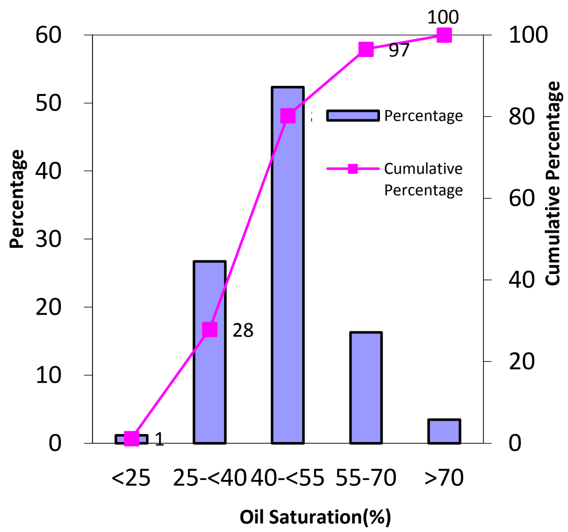

Figure 2: Oil saturation distributions for carbon dioxide miscible displacement reservoirs

Oil API gravity. The lower the API gravity is, the higher the oil viscosity becomes, and CO_2 injection is prone to forming viscous fingering and generating low displacement efficiency. Based on available data, CO_2 miscible displacement reservoirs are characterized by high API gravity, which is usually more than 30°. The proportion of CO_2 miscible flooding reservoirs crude oil API gravity of which is greater than 39° is approximately 37% (Figure 3). Therefore, a smaller API gravity of crude oil is more acceptable.

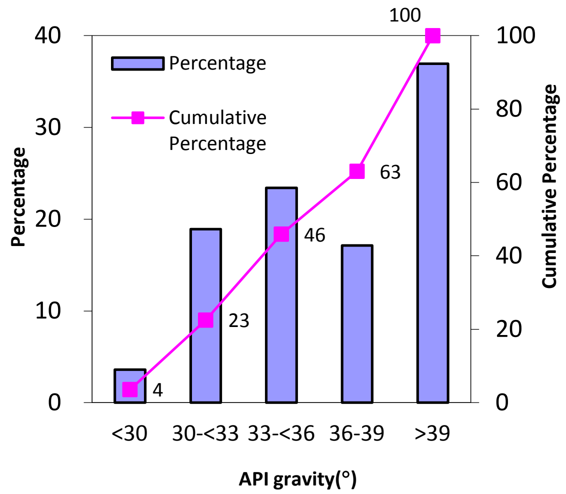

Figure 3: API gravity distributions for carbon dioxide miscible displacement reservoirs

Interval Screening Indexes

Interval screening indexes means that the screening indexes closely approaching a fixed interval (including falling in the interval) are better. Reservoir temperature, reservoir depth, reservoir pressure, and porosity are interval screening indexes.

Reservoir temperature. Reservoir temperature is a key parameter for screening CO_2 miscible displacement process. For CO_2 miscible displacement reservoirs, reservoir temperature ranges from 83 to 257 °F with a typical range between 90 and 130 °F, which accounts for 58% of all the reservoirs (Figure 4). Because distribution parameters are not a continuous function, but discrete screening indexes, the optimal parameters interval for CO_2 miscible flooding can be determined by statistical methods of normal distribution mean. The following equation can be used to calculate the optimal parameters interval:

$$\left[\bar{X} - z_{\alpha/2}\frac{\sigma}{\sqrt{n}}, \bar{X} + z_{\alpha/2}\frac{\sigma}{\sqrt{n}}\right] \quad (1)$$

where, $\bar{X}$ is the mean of the samples; $1-\alpha$ is confidence level, which is calculated at 90% in this paper; $z_{\alpha/2}$ is the quantile; n is the number of the samples and σ stands for standard deviation. The optimal interval of reservoir temperature through calculation using the above formula is [116.35 °F, 130.84 °F].

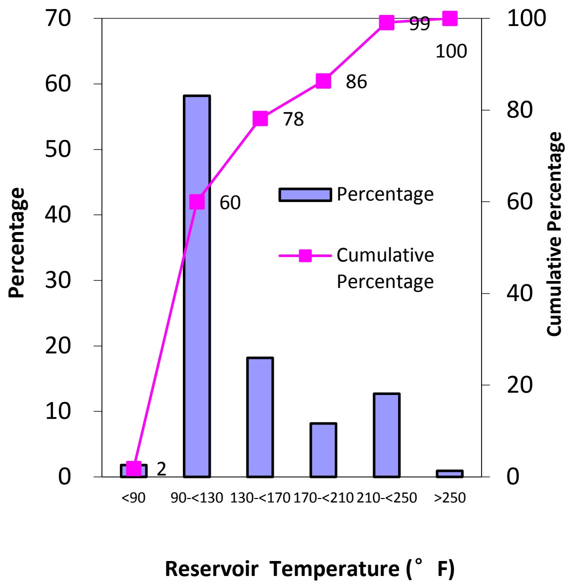

Figure 4: Reservoir temperature distribution for carbon dioxide miscible displacement reservoirs

Reservoir depth. The depth for the CO_2 miscible displacement oil reservoirs in this study ranges from 1150 to 11950 ft below ground level (Figure 5). Approximately 60% of CO_2 miscible displacement reservoirs are at the depth of 4500 to 6500 ft. Very few exceptions of more than 11500 ft are found in Martinville and Soso fields in US, where CO_2 miscible displacement have been successfully applied at depths up to 11550 and 11950 ft respectively. The optimal interval of reservoir depth through calculation using Equation 1 is [5440.06 ft, 6072.08 ft].

Reservoir pressure. The premise of CO_2 miscible flooding is to achieve the miscible phase between

CO_2 and oil. When the reservoir temperature at a certain depth is more than the critical temperature of CO_2, high reservoir pressure is required to ensure CO_2 and crude oil to reach miscibility. When the reservoir pressure becomes greater than the minimum miscibility pressure, the miscible phase can be reached. The reservoir pressure of CO_2 miscible flooding projects is in the range of 1.2 to 22 MPa. Although CO_2 and oil can be easily reached a miscible phase at high reservoir pressure, the high reservoir pressure will increase the level of risk. Therefore, the reservoir pressure is not too high or too low and it is only in a certain range. According to the range of different minimum CO_2 miscible flooding pressures, the optimal interval of reservoir pressure is [16.8 MPa, 22 MPa].

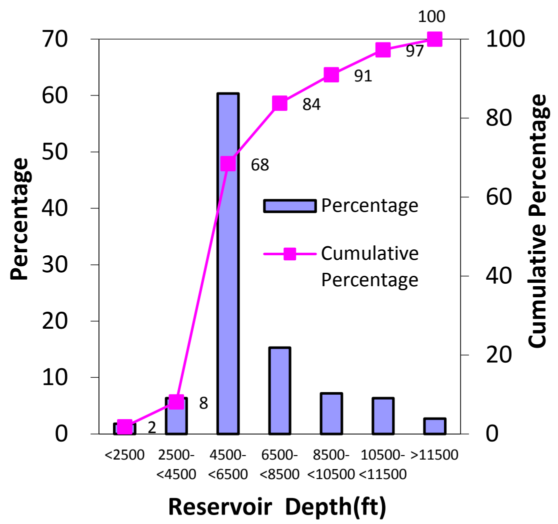

Figure 5: Reservoir depth distribution for carbon dioxide miscible displacement reservoirs

Porosity: CO_2 miscible displacement reservoirs are characterized by low porosity, ranging from 3% to 28% (Figure 6), mainly from 10% to 15%, which accounts for 49% of all the reservoirs. The effective porosity basically obeys normal distribution, and the average effective porosity is 12.33%. The optimal interval of porosity by applying Equation 1 is [11.36%, 13.31%].

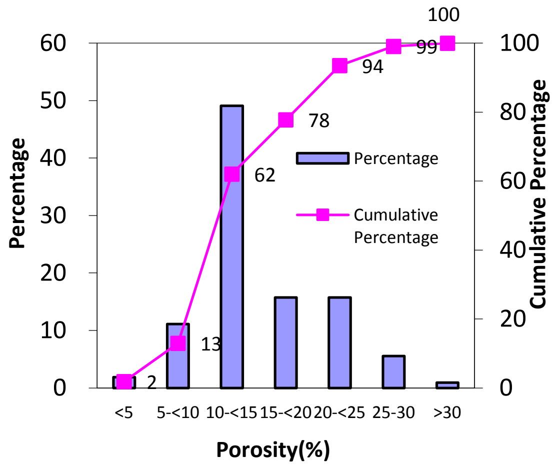

Figure 6: Porosity distribution for carbon dioxide miscible displacement reservoirs

Inverse Screening Indexes

Inverse screening indexes means that the smaller screening indexes are better. Reservoir thickness, heterogeneity, permeability, and oil viscosity are direct screening indexes.

Reservoir thickness. By means of theoretical analysis, it is found that reservoir thickness should not be too large. Because when reservoir thickness becomes larger, the contradiction between layers is more prominent, and thus the overlying effect of the injected gas becomes stronger, which is not beneficial to the expansion of crude oil to reduce viscosity. When reservoir thickness becomes smaller, CO_2 gravity separation becomes weaker; the reservoir is thus less prone to face gas channeling, and CO_2 can spread more evenly to various depths of the reservoir to maximize miscible effect.

Heterogeneity. Vertical heterogeneity has a great effect on CO_2 miscible flooding development, especially for the small plug miscible flooding. Due to the difference in permeability, the volume penetrating into the high permeability layer will be greater than the one into the low-permeability layer. Furthermore, the small plug penetrating into the low-permeability layer becomes diluted due to the transverse and longitudinal dispersion;

hence miscible flooding in low-permeability was reported with little success. The above analysis shows that the smaller the reservoir heterogeneity (represented by permeability variation coefficient) becomes, the better the effects that can be achieved.

Permeability. Low permeability in CO_2 miscible flooding reservoir can fully provide miscible conditions and reduces the gravity separation, while high permeability easily leads to early gas channeling and results in lower sweep efficiency. But for high-dip reservoirs, according to the gravity stable displacement mechanism, the reservoir should have a high vertical permeability. As shown in Figure 7, CO_2 miscible displacement reservoirs are characterized by low permeability, ranging from 1.5 to 3000 mD, mainly less than 10 mD, which accounts for 44% of all the reservoirs. Therefore, the permeability for CO_2 miscible flooding reservoir should be relatively smaller.

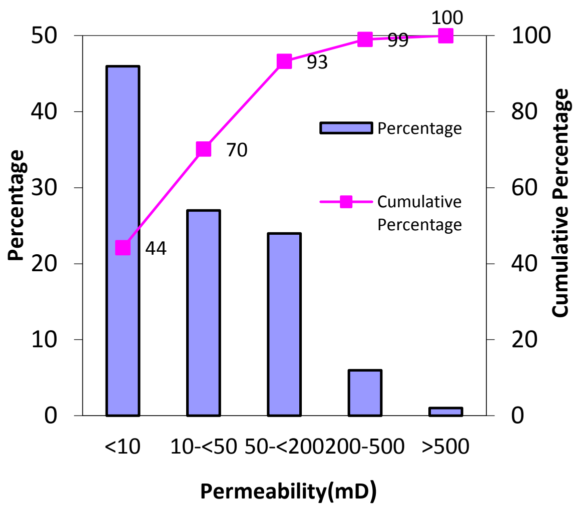

Figure 7: Permeability distribution for carbon dioxide miscible displacement reservoirs

Oil viscosity. The oil for CO_2 miscible displacement reservoirs is characterized by low viscosity. Viscosity is generally less than 4 cp, and typically <1 cp, which accounts for 55% of all the reservoirs (Figure 8). Theoretically, at lower oil viscosity, better effects can be achieved.

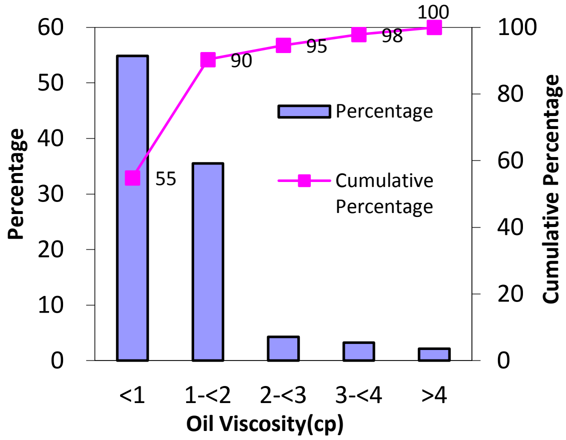

Figure 8: Oil viscosity distribution for carbon dioxide miscible displacement reservoirs

Establishment of the Screening Assessment Model

Conventional screening procedures consist of comparing the properties of reservoirs with certain screening criteria. Those reservoirs matching all the conditions are selected, while those reservoirs failing to match the values are rejected. In studies of selecting the most suitable reservoirs for carbon dioxide flooding in Eastern Venezuela, it was found that the application of the screening method to a large number of reservoirs did not provide adequate results. Different reservoirs were selected depending on the researches and on the weights assigned to each parameter. To overcome those disadvantages, an alternative screen criterion for CO_2 miscible displacement candidates is developed in this paper based on a new GC-TOPSIS model, which combines Euclidean distance and gray relational grade. The combinational weight is calculated by improved AHP and entropy method, giving more accurate results. First, the standardized evaluation matrix should be built. Then, the screening indexes weight is determined. At last, based on the above two steps, the weighted GC-TOPSIS model is established to screen and evaluate reservoirs considering a new "similarity nearness degree" constructed by Euclidean distance and gray relational grade.

Establishing Standardized Evaluation Matrix

The screening method developed in this paper is based on determining each property (*i*) of the reservoir (*j*), X_{ij}, and a corresponding normalized parameter r_{ij}. According to three types of screening indexes, r_{ij} is defined by different equations: for "direct indexes" parameters, it is defined by Equation 2; for "inverse indexes" parameters, it is defined by Equation 3; for "interval indexes" parameters, it is defined by Equation 4.

$$r_{ij} = \frac{\max\limits_i x_{ij} - x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}} \tag{2}$$

$$r_{ij} = \frac{x_{ij} - \min\limits_i x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}} \tag{3}$$

$$r_{ij} = \begin{bmatrix} 1-\dfrac{q_{1j} - x_{ij}}{\max\left(q_{1j} - \min\limits_i x_{ij}, \max\limits_i x_{ij} - q_{2j}\right)} \\ 1 \\ 1-\dfrac{x_{ij} - q_{2j}}{\max\left(q_{1j} - \min\limits_i x_{ij}, \max\limits_i x_{ij} - q_{2j}\right)} \end{bmatrix} \tag{4}$$

$$x_{ij} < q_{1j} \qquad x_{ij} \in [q_{1j}, q_{2j}] \qquad x_{ij} > q_{2j}$$

where, x_{ij} is the magnitude of property (*i*) in the reservoir (*j*). $\max\limits_i x_{ij}$ is the maximum of property (*i*) in a fictitious reservoir, while $\min\limits_i x_{ij}$ is the minimum of property (*i*) in a fictitious reservoir. [q_{1j}, q_{2j}] is the optimal interval for property (*i*). The variable r_{ij}, as given by Equations 2 to 4, changes between 0 and 1. When r_{ij} is closer to 1, reservoir conditions are better. Through the standardization process of screening indexes, the evaluation matrix of the candidates can be transformed into standardized matrix *R*. The columns and rows of the matrix, respectively, reflect the suitability magnitude of all evaluation parameters for one reservoir and that of the same parameter for different reservoirs.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} = (r_{\mathrm{ij}})_{m\times n} \tag{5}$$

Determining Screening Indexes Weight

In the screening index system, the importance of each index to a program is not identical. Furthermore, the weight is used to express relative importance of each index. Some indexes may have considerable effects, while some indexes may have small effects. Thus it is very important and necessary to determine the weight of each index for screening different programs. The scientific and reasonable weights can improve the accuracy and validity of evaluating the results; hence it is one of the most important factors. In the multi-attribute decision problem, if the weights are given, they can directly be used. Otherwise, it is required to determine the weight of each index. Purely subjective weighting methods (Delphi method, the analytical hierarchy process (AHP), efficiency coefficient method, etc.) or objective weighting methods (entropy method, principal component analysis, factor analysis, standard deviation coefficient method, etc.) have certain defects to take into account the relative importance or weight of each reservoir property more reasonably in determining the indexes weight. By comparing the various methods for determining screening indexes weight, the improved analytical hierarchy process and entropy method were used to get screening indexes weight to achieve subjective and objective unity for determining the weights.

The Improved Analytical Hierarchy Process Method

The analytic hierarchy process is a decision making model that aids us in making decisions in our complex world. It is a three-part process which includes identifying and organizing decision objectives, criteria, constraints, and alternatives into a hierarchy; evaluating pair wise comparisons between the relevant elements at each level of the hierarchy; and the synthesis using the solution algorithm of the results of the pair wise comparisons over all the levels. Further, the algorithm result gives the relative importance of the alternative courses of action. The AHP has a special concern with departure from consistency, with the measurement of this departure, and with dependence within and between the groups of the elements of its structure. In comprehensively evaluating programs, the traditional AHP method uses 1-9 scale methods to construct a judgment matrix. When the order of the judgment matrix is large, it is hard to satisfy the consistency requirements of the judgment matrix. It needs to repeatedly adjust the judgment matrix, which is time consuming, and thus the results are not satisfactory. Three-scale AHP method is a simplified algorithm, which is based on the idea of the traditional AHP method. By establishing the judgment matrix, using "optimal transfer matrix" concept, and transforming the matrix, the optimal transforming matrix and consistency matrix are obtained by calculation, which naturally meet the conformance requirements. Therefore, it does not need to be tested for consistency. Comparing with traditional AHP method, this method has better judgment transitivity and a rational scale value, which is conducive for the decision-makers to improve accuracy in pair wise comparison judgment process. The comparison between original AHP consistency check and improved AHP consistency check is shown in Figure 9 and Figure 10.

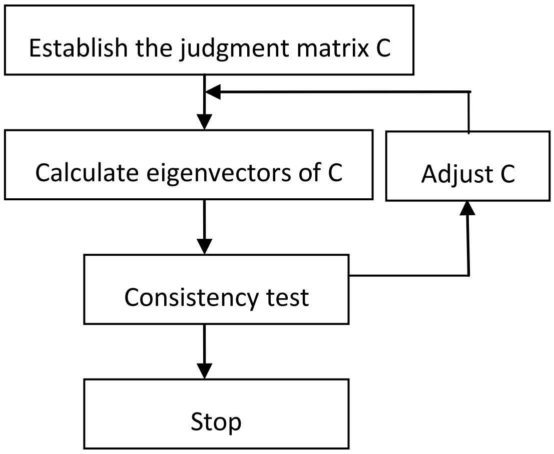

Figure 9: Original AHP consistency check

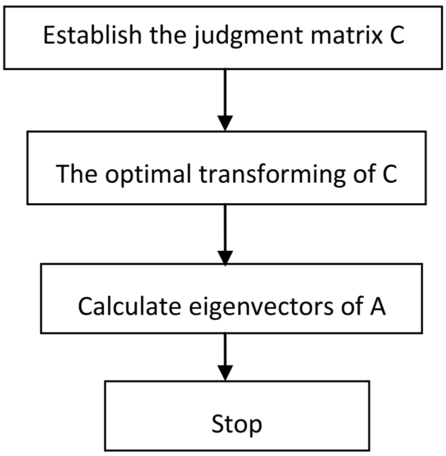

Figure 10: Improved AHP consistency check

The calculation steps of three-scale AHP method are as follows:

(1) Through the pair wise comparisons of screening indexes, the judgment matrix C is established.

$$C=\begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ c_{m1} & c_{m2} & \cdots & c_{mn} \end{bmatrix}=(c_{\text{ij}})_{m\times n} \tag{6}$$

where, c_{ij} is the ratio of the relative importance of property (i) to property (j), and

$$c_{ij} = \begin{cases} 1 & property(i) \text{ is more important than } property(j) \\ 0 & property(i) \text{ is as important as } property(j) \\ -1 & property(i) \text{ is less important than } property(j) \end{cases}$$

$i = 1,2,3,\cdots n$

$j = 1,2,3,\cdots m$

(2) Calculate the optimal transfer matrix of the judgment matrix C.

$$D = \left(d_{ij}\right)_{nm} = \left(\frac{1}{m}\sum_{k=1}^{m}\left(c_{ik} + c_{kj}\right)\right)_{nm} \qquad \forall i, j \tag{7}$$

(3) Transform the matrix D to the consistency judgment matrix A.

$$A = \left(a_{ij}\right)_{nm} = \left(\exp\left(d_{ij}\right)\right)_{nm} \qquad \forall i, j \tag{8}$$

(4) Calculate the eigenvectors of the matrix A with square root method.

$$\omega = \left(\omega_i\right)_n = \left(\sqrt[n]{\prod_{j=1}^{n} a_{ij}}\right)_n \qquad \left(i = 1,2,\cdots,n\right) \tag{9}$$

Conduct normalization processing to the eigenvectors.

$$W_1 = \left(\overline{\omega_i}\right)_n = \left(\omega_i \Big/ \sum_{i=1}^{n}\omega_i\right)_n \tag{10}$$

Then $W_1 = \left(\overline{\omega_1}, \overline{\omega_2}, \cdots, \overline{\omega_n}\right)$ is the weight vector.

The Entropy Method

The entropy method is to determine the index weight based on the judgment matrix constituted by the evaluation indexes, which eliminates anthropogenic interference to the index weight. To some extent, this method avoids the subjective arbitrariness, which makes the evaluation results more in a linear distribution with actual data. The calculation steps of the entropy method are as follows:

(1) Establish standardized evaluation matrix $R=(r_{ij})_{m\times n}$.

(2) Determine the entropy value of property (*i*).

$$H_i = -\frac{1}{\ln n}\sum_{j=1}^{n} f_{ij}\ln f_{ij}, \quad i = 1,2,\cdots m;\ j = 1,2,\cdots,n \tag{11}$$

$$f_{ij} = \frac{1 + r_{ij}}{\sum_{j=1}^{n}\left(1 + r_{ij}\right)} \tag{12}$$

(3)Determine difference coefficient of screening indexes.

$$d_i = 1 - H_i \tag{13}$$

(4) Calculate the entropy weight of screening indexes.

$$\omega_i' = \frac{d_i}{\sum_{i=1}^{m} d_i} \tag{14}$$

where, $0 \le \omega_i' \le 1$, and $\sum_{i=1}^{m}\omega_i' = 1$.

Then $W_2 = \left(\omega_1', \omega_2', ..., \omega_n'\right)$ is the entropy weight vector.

Comprehensive Weight Calculation

A large number of screening indexes are presented in this paper, and in order to avoid the weight of screening indexes without a big difference, the multiplication synthesis method is used to empower comprehensive weight to the screening indexes. First, the weight coefficients determined by the subjective and objective weighting methods are multiplied respectively, and then the normalization processing of the product is made.

$$\omega_i = \frac{\left(\overline{\omega_i}\right)^{\alpha} \times \left(\omega_i^{'}\right)^{\beta}}{\sum_{j=1}^{m}\left(\overline{\omega_i}\right)^{\alpha} \times \left(\omega_i^{'}\right)^{\beta}} \qquad (15)$$

where, $\overline{\omega_i}$ and $\omega_i^{'}$ are the weight of property (*i*) determined by improved analytical hierarchy process and entropy method respectively. ω_i is the comprehensive weight of property (*i*). α and β are the relative importance of the subjective and objective weight respectively; $0 \le \alpha, \beta \le 1, \alpha + \beta = 1$.

Then, $W = (\omega_1, \omega_2, ..., \omega_n)$ is the comprehensive weight vector.

Establishing the Weighted GC-TOPSIS Mathematical Model

TOPSIS (technique for order preference by similarity to ideal solution) method and the improved gray correlation analysis method both can be applied to the screening evaluation of CO_2 miscible flooding candidate reservoirs. Euclidean distances in TOPSIS method can better reflect the curve position of program data, but there are some defects in shape similarity or reflecting the trend changes between program data curves; however, gray correlation analysis method can precisely reflect the similarity of curve geometry and the trend change between the program data curve. Therefore, they can be organically combined to build "similar approach degree" indexes to reflect the curve position of program data, as well as the trend changes between program data curve and geometry similarity. On this basis, the weighted GC-TOPSIS model was built to improve the accuracy and reliability of the screening evaluation methods.

The calculation steps are as follows:

(1) Establish the evaluation matrix X of the screening indexes to CO_2 miscible flooding candidate reservoirs. Build the corresponding standardized evaluation matrix $R=(r_{ij})_{m\times n}$ by Equations 2-4.

(2) Determine the screening indexes weight. In this paper, we use the above comprehensive weight method to determine the weight of the screening indexes, $W = (\omega_1, \omega_2, ..., \omega_n)$.

(3) Calculate the grey correlation of property(*i*) of the reservoir(*j*) with the positive ideal program and negative ideal program.

First, calculate the weighted standardization matrix U

$$U = \omega^T \times R = \left(\omega_i r_{ij}\right)_{m\times n} = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ u_{m1} & u_{m2} & \cdots & u_{mn} \end{bmatrix} \qquad (16)$$

Then, determine the positive ideal program and negative ideal program U_0^-, which is composed of the maximum value of the screening indexes as the best program and the minimum value of the screening indexes as the worst program respectively.

$$U_0^+ = \left\{ \max_{1\le i\le m} r_{ij} \middle| 1 \le j \le n \right\} = \left(u_0^+(1), u_0^+(2), ..., u_0^+(m)\right) \qquad (17\text{-a})$$

$$U_0^- = \left\{ \min_{1\le i\le m} r_{ij} \middle| 1 \le j \le n \right\} = \left(u_0^-(1), u_0^-(2), ..., u_0^-(m)\right) \qquad (17\text{-b})$$

Calculate the grey correlation of R_j^+ and R_j^- property (*i*) of the reservoir (*j*) with the positive ideal program U_0^+ and negative ideal program U_0^- by the following equations.

Calculate the grey correlation coefficient of property (*i*) between the reservoir (*j*) and the positive ideal program U_0^+.

$$r_{ij}^+ = \frac{m + \zeta M}{\Delta_i(k) + \zeta M}, \quad \zeta \in (0,1) \qquad (18\text{-a})$$

where, $\Delta_i(k) = \left|u_0^+(k) - u_{ij}\right|, \quad 1 \le j \le n$, $m = \min_i \min_k \Delta_i(k)$, $M = \max_i \max_k \Delta_i(k)$. ζ is a distinguishing coefficient and $\zeta = 0.5$ in this paper. Due to $0 \le m \le \Delta_i(k)$, then $\frac{1}{3} \le r_{ij}^{-} \le 1$

Calculate the grey correlation coefficient matrix between the reservoir (*j*) and the positive ideal program U_0^+.

$$r_{ij}^{-} = \frac{m + \zeta M}{\Delta_i(k) + \zeta M}, \quad \zeta \in (0,1) \tag{18-b}$$

where, $\Delta_i(k) = \left|u_0^{-}(k) - u_{ij}\right|$, $1 \le j \le n$, $m = \min_i \min_k \Delta_i(k)$, $M = \max_i \max_k \Delta_i(k)$. ζ is a distinguishing coefficient and $\zeta = 0.5$ in this paper.

Calculate the grey correlation coefficient matrix between the reservoir (*j*) and the negative ideal program U_0^-.

$$R^{+} = \left(r_{ij}^{+}\right)_{m \times n} = \begin{bmatrix} r_{11}^{+} & r_{12}^{+} & \cdots & r_{1n}^{+} \\ r_{21}^{+} & r_{22}^{+} & \cdots & r_{2n}^{+} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1}^{+} & r_{m2}^{+} & \cdots & r_{mn}^{+} \end{bmatrix} \tag{19-a}$$

Then calculate the grey correlation between the reservoir (*j*) and the positive ideal program U_0^+.

$$R^{-} = \left(r_{ij}^{-}\right)_{m \times n} = \begin{bmatrix} r_{11}^{-} & r_{12}^{-} & \cdots & r_{1n}^{-} \\ r_{21}^{-} & r_{22}^{-} & \cdots & r_{2n}^{-} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1}^{-} & r_{m2}^{-} & \cdots & r_{mn}^{-} \end{bmatrix} \tag{19-b}$$

Then, calculate the grey correlation between the reservoir (*j*) and the negative ideal program U_0^-.

$$R_j^{+} = \frac{1}{m}\sum_{i=1}^{m} r_{ij}^{+}, \quad (j = 1,2,...,n) \tag{20-a}$$

Similarly, calculate the grey correlation coefficient of property (*i*) between the reservoir (*j*) and the negative ideal program U_0^-.

$$R_j^{-} = \frac{1}{m}\sum_{i=1}^{m} r_{ij}^{-}, \quad (j = 1,2,...,n) \tag{20-b}$$

(4) Calculate the Euclidean distance D_j^+ and D_j^- of the reservoir (*j*) with the positive ideal program U_0^+ and negative ideal program U_0^-.

$$D_j^{+} = \sqrt{\sum_{i=1}^{m}\left(V_j^{+} - u_{ij}\right)^2} \quad j = 1,2,...,n \tag{21-a}$$

$$D_j^{-} = \sqrt{\sum_{i=1}^{m}\left(V_j^{-} - u_{ij}\right)^2} \quad j = 1,2,...,n \tag{21-b}$$

where, V^+ is the positive ideal solution, and $V^{+} = \left\{\max_{1 \le i \le n}\left(u_{ij}\right) \middle| j = 1,2,...,m\right\} = \left(v_1^{+}, v_2^{+}, ..., v_m^{+}\right)$,

While V^- is the negative ideal solution, and $V^{-} = \left\{\max_{1 \le i \le n}\left(u_{ij}\right) \middle| j = 1,2,...,m\right\} = \left(v_1^{-}, v_2^{-}, ..., v_m^{-}\right)$

(5) Make indexes (R_j^+, R_j^-, D_j^+, and D_j^-) being dimensionless by the following equation.

$$M_{new} = \frac{M_j}{\max_{1 \le i \le n}\left(M_j\right)} \tag{22}$$

where, M_j is R_j^+, R_j^-, D_j^+, and D_j^- respectively.

(6) Combine R_j^+, R_j^-, D_j^+, and D_j^-

According to the definition, greater values of R_j^+ and D_j^- make the program closer to the negative ideal program, while greater values of R_j^- and D_j^+ make the program closer to the positive ideal solution program. Thus, the combined formula can be determined as:

$$S_j^{+} = \alpha_1 D_j^{-} + \alpha_2 R_j^{+}, \quad (j = 1,2,...,n) \tag{23}$$

$$S_j^- = \alpha_1 D_j^+ + \alpha_2 R_j^-, \quad (j = 1, 2, ..., n) \tag{24}$$

where α_1 and α_2 reflects the preference of the decision-makers on the position and shape, and $\alpha_1 + \alpha_2 = 1$. The decision-makers can decide these two values according to their preference. In this paper, $\alpha_1 = \alpha_2 = 0.5$. S_j^+ reflects the closeness of the candidate program to the positive ideal program; the greater the S_j^+ value is, the closer the program to the positive ideal program becomes; on the other hand, S_j^- reflects the closeness of the candidate program to the negative ideal program; greater S_j^- values make the program closer to the negative ideal program.

(7) Calculate the "similarity nearness degree" C_j of the candidate program decided by the S_j^+ and S_j^-.

$$C_j = \frac{S_j^+}{S_j^- + S_j^+}, \quad (j = 1, 2, ..., n) \tag{25}$$

where, C_j is based on the Euclidean distance and the grey correlation, reflecting the position relation and the similar differences of the data curves between the candidate program with the positive/negative program, and the physical meaning is more explicit .

(8) Rank the candidate programs.

Rank the alternatives in accordance with the magnitude of the "similarity nearness degree" C_j, the greater the "similarity nearness degree" is, the more superior the program is; on the contrary, the smaller the "similarity nearness degree" is, the more inferior the program becomes.

Model Validation

On the basis of GC-TOPSIS mathematical model, an example is carried out to verify whether this model is accurate in screening candidate reservoirs for CO_2 miscible displacement. Basic reservoir characteristics and fluid properties for five cases (California CO_2 injection programs) have been put forward in (Table 1). The simplified calculation steps are shown in appendix. Based on the magnitude of the similarity nearness degree, the sequence of the five reservoirs from superior to inferior is: 3 (Gatchell)>1 (Emery)>5 (Potroro)>2 (Stevens)>4 (Westerm21-1), which is entirely consistent with the ultimate recovery. The contrast between the reservoir evaluation results and total ultimate recovery is shown in Table 2. Hence the example analysis verifies that this model is accurate in screening candidate reservoirs for CO_2 miscible displacement.

Table 1: Parameter values of candidate reservoirs

Parameters	1	2	3	4	5
Permeability [mD]	83	200	421	108	75
Reservoir thickness [ft]	302.8	109.9	385.8	309.1	191.9
Oil viscosity [mPa˙s]	1.05	0.37	0.65	0.45	0.72
Oil API gravity [°]	33.0	37.0	31.9	34.0	35.0
Heterogeneity [fraction]	0.52	0.63	0.46	0.64	0.6
Oil saturation [fraction]	63	62	72.3	53	70
Wettability [fraction]	0.58	0.43	0.78	0.38	0.52
Reservoir dip [°]	32	13	35	7	9
Porosity [fraction]	26.5	22	15	19.5	18
Reservoir temperature [°C]	185.0	209.8	212.0	234.9	169.9
Reservoir pressure [MPa]	17.7	24.2	23.7	27	21.1
Reservoir depth [ft]	5299	8199	7500	8799	7001

Table 2: The comparison of reservoir evaluation results and total ultimate recovery

Reservoirs	1	2	3	4	5
Reservoirs evaluation results [fraction]	0.541	0.482	0.574	0.388	0.519
Total ultimate recovery [fraction]	0.447	0.331	0.585	0.213	0.367

During the process of calculating the comprehensive weights and similarity nearness degree, we assume weighting coefficients α and β and similarity nearness degree coefficients α_1 and α_2 for the given values. Usually, considering the different preferences of the decision-makers on the position and shape similarity between the subjective/objective weights and program data curves, the changes of α and β and α_1 and α_2 may have an impact on the final results of the evaluation. Therefore, we make a stability test on the values of α_1 and α, which varies within the range of 0 to 1, and the evaluation results are shown in Figures 11 and 12.

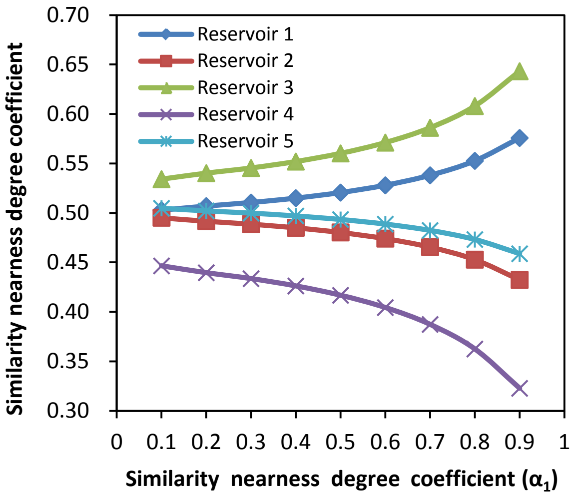

Figure 11: α=0.5 Pictorial diagram of comprehensive evaluation

The results demonstrate that the change of comprehensive weights α and α_1 has a little effect on the relative similarity nearness degree of each reservoir; thus the impact on the final results of the evaluation can be ignored. In addition, the effect of similarity nearness degree because of the changes of weighting coefficients α and β are less obvious than the changes of similarity nearness degree coefficients α_1 and α_2. Through these analyses, it is found that this model is also stable in screening candidate reservoirs for CO_2 miscible displacement to enhanced oil recovery.

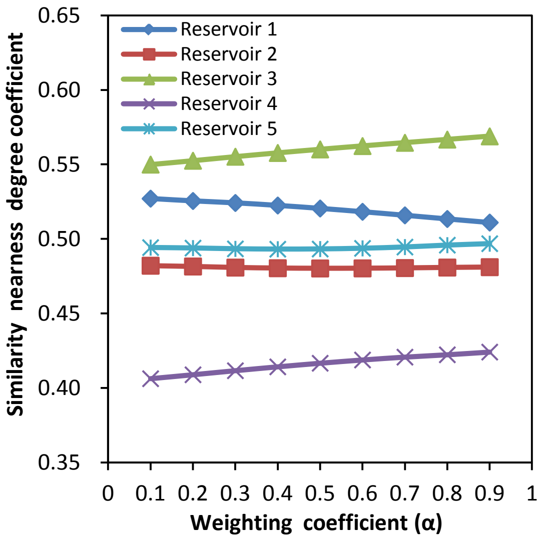

Figure 12: α_1=0.5 Pictorial diagram of comprehensive evaluation

CONCLUSIONS

According to the theoretical analysis, field experience, and probability statistics, 12 parameters affecting CO_2 injection miscible flooding are analyzed and the correct screening indexes system is established. In addition, by respectively applying the improved AHP and entropy method to determine the subjective weight and objective weight, then the comprehensive weight is determined by the multiplication synthesis method. So the comprehensive weight can better reflect expertise, and the inherent law between data to avoid simple use of objective weighting method for determining the index weights. This model is validated in the last part, the accuracy and stability of the screening evaluation model is proved. Therefore, the model can be applied to CO_2 miscible flooding screening studies of other reservoirs.

ACKNOWLEDGEMENTS

This research was supported by the China National Key Development Planning Project for Basic Research “973” Project (Grant No.2006CB705804): Greenhouse Gas EOR Resource Utilization and Underground Sequestration and the Fundamental Research Funds for the Central Universities (Grant No. 11CX06022A). The authors would like to thank the assistance of the petroleum engineering institute staff.

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Appendix

(1) Build the standardized evaluation matrix $R=(r_{ij})_{m\times n}$ using Equations 1-3.

$$R=\begin{array}{c|l} \begin{pmatrix} 0.976879 & 0.638728 & 0.000000 & 0.904624 & 1.000000 \\ 0.666667 & 0.055556 & 1.000000 & 0.000000 & 0.222222 \\ 0.300832 & 1.000000 & 0.000000 & 0.278240 & 0.702735 \\ 0.000000 & 1.000000 & 0.588235 & 0.882353 & 0.485294 \\ 0.221374 & 1.000000 & 0.000000 & 0.419847 & 0.618321 \\ 0.000000 & 0.341219 & 0.872005 & 0.530786 & 0.644525 \\ 0.479322 & 0.240526 & 0.219761 & 0.000000 & 0.624676 \\ 1.000000 & 0.560000 & 0.660000 & 0.000000 & 1.000000 \\ 0.948113 & 0.220156 & 0.476403 & 0.000000 & 0.659264 \\ 0.500000 & 0.125000 & 1.000000 & 0.000000 & 0.350000 \\ 0.892857 & 0.214286 & 1.000000 & 0.000000 & 0.071429 \\ 0.518135 & 0.466321 & 1.000000 & 0.000000 & 0.880829 \end{pmatrix} & \begin{array}{l} \text{Permeability} \\ \text{Heterogeneity} \\ \text{Reservoir thickness} \\ \text{Oil viscosity} \\ \text{Oil API gravity} \\ \text{Porosity} \\ \text{Reservoir temperature} \\ \text{Reservoir pressure} \\ \text{Reservoir depth} \\ \text{Wettability} \\ \text{Reservoir dip} \\ \text{Oil saturation} \end{array} \end{array}$$

(2) Determine the screening indexes weight.

The judgment matrix C

$$C=\begin{bmatrix} 0 & -1 & 1 & -1 & 1 & 1 & -1 & -1 & -1 & -1 & -1 & -1 \\ 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & -1 & 1 \\ -1 & -1 & 0 & -1 & -1 & 1 & -1 & -1 & -1 & -1 & -1 & -1 \\ 1 & -1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & -1 & 1 \\ -1 & -1 & 1 & -1 & 0 & 1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & 0 & -1 & -1 & -1 & -1 & -1 & -1 \\ 1 & -1 & 1 & -1 & 1 & 1 & 0 & -1 & -1 & -1 & -1 & -1 \\ 1 & -1 & 1 & -1 & 1 & 1 & 1 & 0 & 1 & -1 & -1 & -1 \\ 1 & -1 & 1 & -1 & 1 & 1 & 1 & -1 & 0 & -1 & -1 & -1 \\ 1 & -1 & 1 & -1 & 1 & 1 & 1 & 1 & 1 & 0 & -1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 \\ 1 & -1 & 1 & -1 & 1 & 1 & 1 & 1 & 1 & -1 & -1 & 0 \end{bmatrix}$$

The AHP weight vector

$$\omega_1=(0.046801,0.15029,0.033534,0.127218,0.039616,0.028386,\\ 0.055289,0.077161,0.065316,0.107688,0.177547,0.091155)$$

The entropy weight vector

$$\omega_2=(0.080687,0.111962,0.087050,0.077050,0.082948,0.061909,\\ 0.041477,0.080864,0.077895,0.090564,0.128755,0.078837)$$

The comprehensive weight vector

$$\begin{cases} \text{Permeability} & 0.062938 \\ \text{Heterogeneity} & 0.132856 \\ \text{Reservoir thickness} & 0.055336 \\ \text{Oil viscosity} & 0.101401 \\ \text{Oil API gravity} & 0.058711 \\ \text{Porosity} & 0.042935 \\ \text{Reservoir temperature} & 0.049046 \\ \text{Reservoir pressure} & 0.080902 \\ \text{Reservoir depth} & 0.073054 \\ \text{Wettability} & 0.101145 \\ \text{Reservoir dip} & 0.154853 \\ \text{Oil saturation} & 0.086823 \end{cases}$$

(3) Calculate the grey correlation of property (*i*) of the reservoir (*j*) with the positive ideal program and negative ideal program.

The weighted standardization matrix *U*

$$U = R \times W = \begin{pmatrix} 0.061483 & 0.040200 & 0.000000 & 0.056935 & 0.062938 \\ 0.088571 & 0.007381 & 0.132856 & 0.000000 & 0.029524 \\ 0.016647 & 0.055336 & 0.000000 & 0.015397 & 0.038887 \\ 0.000000 & 0.101401 & 0.059648 & 0.089471 & 0.049209 \\ 0.012997 & 0.058711 & 0.000000 & 0.024650 & 0.036302 \\ 0.000000 & 0.014650 & 0.037439 & 0.022789 & 0.027673 \\ 0.023509 & 0.011797 & 0.010778 & 0.000000 & 0.030638 \\ 0.080902 & 0.045305 & 0.053395 & 0.000000 & 0.080902 \\ 0.069264 & 0.016083 & 0.034803 & 0.000000 & 0.048162 \\ 0.050572 & 0.012643 & 0.101145 & 0.000000 & 0.035401 \\ 0.138262 & 0.033183 & 0.154853 & 0.000000 & 0.011061 \\ 0.044986 & 0.040488 & 0.086823 & 0.000000 & 0.076477 \end{pmatrix}$$

The positive ideal program U_0^+ and negative ideal program U_0^- are given by:

$$U_0^+ = (0.062938 \quad 0.132856 \quad 0.055336 \quad 0.101401 \quad 0.058711 \quad 0.037439 \quad 0.030638 \quad 0.080902 \quad 0.069264 \quad 0.101145 \quad 0.154853 \quad 0.086823)$$

$$U_0^- = (0 \; 0 \; 0 \; 0 \; 0 \; 0 \; 0 \; 0 \; 0 \; 0 \; 0 \; 0)$$

The grey correlation of R_j^+ and R_j^- property (*i*) of the reservoir (*j*) with U_0^+ and U_0^-

$$R^+ = (0.751135, 0.707539, 0.798245, 0.610789, 0.756061)$$

$$R^- = (0.673621, 0.711659, 0.667081, 0.867118, 0.654708)$$

(4) Calculate the Euclidean distance D_j^+ and D_j^- of the reservoir (*j*) with U_0^+ and U_0^-:

$$D^+ = (0.218320, 0.155006, 0.261795, 0.112298, 0.166966)$$

$$D^- = (0.147878, 0.214508, 0.120632, 0.273548, 0.199551)$$

(5) Make indexes (R_j^+, R_j^-, D_j^+, and D_j^-) dimensionless.

$$R^+ = (0.866243, 0.815966, 0.920573, 0.704390, 0.871925)$$
$$R^- = (0.776850, 0.820718, 0.769309, 1.000000, 0.755039)$$
$$D^+ = (0.170539, 0.247381, 0.139119, 0.315468, 0.230131)$$
$$D^- = (0.251777, 0.178760, 0.301914, 0.129507, 0.192553)$$

(6) Combine R_j^+, R_j^-, D_j^+, and D_j^- ($\alpha_1 = \alpha_2 = 0.5$).

$$S^+ = (0.559010, 0.497363, 0.611243, 0.416949, 0.532239)$$

$$S^- = (0.473695, 0.534050, 0.454214, 0.657734, 0.492585)$$

(7) Calculate the "similarity nearness degree" C_j of the candidate program.

$$C = (0.541307, 0.482216, 0.573691, 0.387974, 0.519347)$$