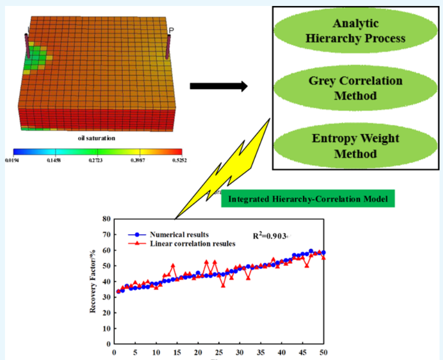
ACS OMEGA

http://pubs.acs.org/journal/acsodf Article

Integrated Hierarchy−Correlation Model for Evaluating Water-Driven Oil Reservoirs

Xiaolong Chai, Leng Tian,* Ge Wang, Kaiqiang Zhang,* Hengli Wang, Long Peng, and Jianguo Wang

Cite This: *ACS Omega* 2021, 6, 34460−34469 Read Online



ABSTRACT: With the increasing demands on energy and environmental domains, not only high oil production but also its accurate quantification has become one of the most important topics in academia and industry. This paper initially proposes a comprehensive workflow in which an integrated hierarchy−correlation model is used to thoroughly evaluate the influences of all relevant reservoir parameters on the ultimate oil recovery for water-flooding oil reservoirs. More specifically, the analytic hierarchy process, grey relation, and entropy weight are combined through the multiplicative weighting method to quantitatively describe the production parameters. Accordingly, novel multivariable linear and nonlinear correlations are developed to predict the production performance and validated through comparisons with numerical reservoir simulations. Seven factors, including five reservoir parameters, namely, permeability and its contrast, porosity, thickness, and saturation, and two production parameters, namely, the injection−production ratio and the operating pressure, have been identified as the most influential factors on recovery performances and thus are employed in the proposed correlations to predict the ultimate oil recovery factor. The results obtained by the proposed method are quite close to the real-time simulation data, while the accuracy is retained. The numerical results show that the recovery factors of water-flooding oil reservoirs are about 33.5−59.5%, and the corresponding linear and nonlinear correlation coefficients are 0.903 and 0.789, respectively. In comparison with the numerical simulation, the approximation error by the linear correlation is about 0.5%, which is lower than that of nonlinear correlation, for example, 12.3%. This study will be beneficial to analyze the reservoir-related parameters and provide a useful tool for rapid production performance evaluation of the water-flooding production scenario.

1. INTRODUCTION

The recovery factor is the ratio of the amount of oil that can be recovered from an oil reservoir to the geological reserves within a certain economic limit under the conditions of modern technology. It is an important indicator to evaluate the production performance and developmental effect. The flow characteristics of oil and water become complicated when the oil field is in the middle and later stages of development. To adjust the developmental project and improve the production and economic benefits, it is important to accurately predict the oil recovery factor. The geological and developmental parameters have some effects on the recovery factor. The geological parameters include the porosity, permeability, heterogeneity, and so forth, while the developmental parameters consist of the injection−production ratio, production rate, water cut, well spacing, recovery rate, and so forth.[1] The recovery factor is affected by multiple parameters,[2−4] which increase the difficulty of accurately predicting the recovery factor of water-driven oil reservoirs.

Over the past several decades, many relevant research works have been carried out to solve the problem of predicting the recovery factor. Mutua et al. (2002) established an empirical prediction model to forecast the recovery factor based on the laboratory data. 100 samples from sandstone and carbonate database were analyzed by using the empirical prediction model. The results showed that the correlation coefficient is more than 0.95. Adrian et al. (2013) also adopted the empirical formula to predict the oil recovery factor and conducted a robustness test to improve the practicability of the formula. The empirical formulas were applied on Niger Delta green oil reservoirs to predict the recovery factor. The results showed that the predicted recovery factor of the empirical formula agreed with those of numerical simulations. Lima et al. (2012) carried out a numerical simulation method to predict the oil reservoir recovery factor and confirmed the influencing parameters of the water-flooding reservoir by using transient three-dimensional numerical simulations. The simulation results revealed that the recovery factor had a positive

Received: August 25, 2021
Accepted: November 26, 2021
Published: December 9, 2021

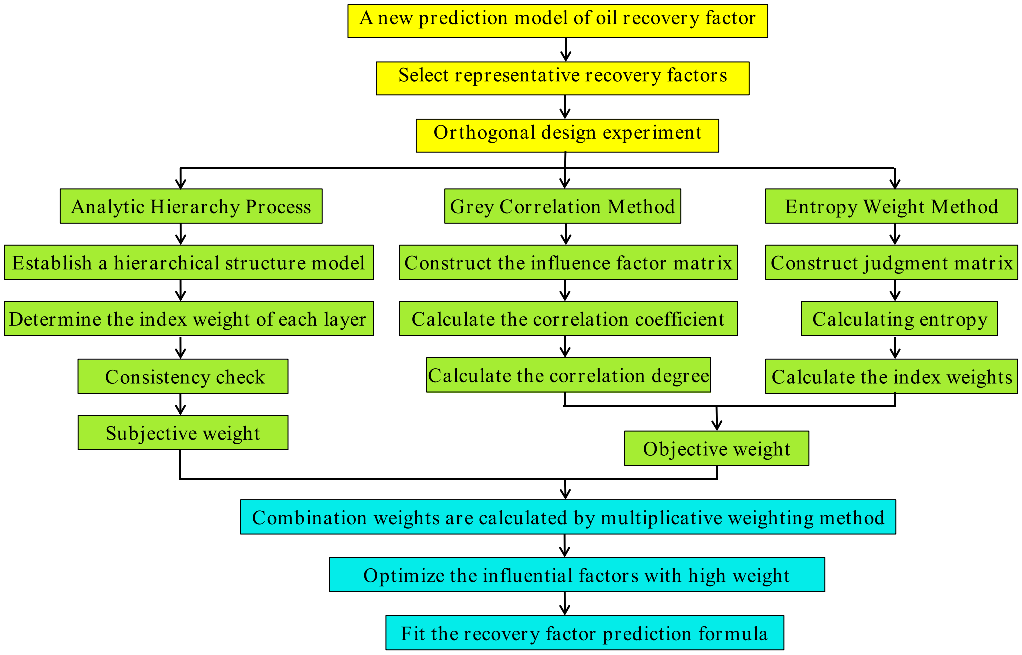


Figure 1. Technology flowchart and research approach to establish the new model predicting the recovery factor for water-driven oil reservoirs.

correlation with the mass of injected water. The water injection and oil production increased when the rate of water injection was 0.10 ~ 0.25 kg/s, and the oil recovery factor increased by 16.7% at the same time. Dutta et al. (2014) pointed out the disadvantages of the traditional decline curve for forecasting the oil recovery factor in complex reservoirs and proposed a new method combining the power law, stretched exponential index decline model, and the Duong model to predict the production and recovery factors. The results confirmed that the new model was better than a single method at predicting the recovery factor. Suparit (2018) used the desirability model to assess the impact of related factors on the recovery factor. To relate to the index of recovery factor, the factors were divided and combined into a single parameter. The relevant results became an empirical method to predict recovery with a good consistency between the single parameters and the recovery factor. Ma et al. (2018) proposed a nonlinear extension of Arps decline model (NEA) prediction method. The NEA method used one-step linear recursion to cope with the nonlinear relationship between the input parameters and production data. Case studies evaluating the efficiency of the NEA model with the production data in China and India were conducted, and their results showed that the uncertainty of the nonlinear NEA model is 4.22% compared with the results of numerical simulations, indicating that it was suitable to accurately forecast the oil production. Lim et al. (2014) proposed an overall production data analysis workflow for the ultimate recovery factor forecast and obtained a probabilistic type curve which is generated from the uncertain oil and gas production data. The falling envelope forecast was applied in a probabilistic production decline area. The results showed that the application of the probability concept in DCA could effectively enhance the reliability of prediction. Dong et al. (2015) comprehensively evaluated the effects of reservoir parameters, fluid parameters, and operation parameters on the dynamics of SAGD recovery and determined the degree of effect factors by using the grey correlation method based on typical thick offshore oil reservoirs. A static multiparameter nonlinear prediction formula of recovery factor, rate, and cumulative gas−oil ratio was put forward, and the prediction results of this formula showed less than 10% deviation in comparison with numerical simulations. The research results showed that this correlation prediction formula could be used to quickly obtain the oil field recovery factor. To decrease the disadvantages of uncertain accuracy, cumbersome operations, and expensive manpower and time, Dzurman et al. (2013) adopted the artificial neural network (ANN) to predict the recovery factor based on the production performance and evaluation. Based on the application of this method to Canadian oil sand reservoirs, the predicted results demonstrated that the error of the predicted model compared with the real recovery factor was less than 10%. Chen et al. (2019) applied ANN to predict the recovery factor and determine the main factors affecting the recovery factor based on the reservoir properties, development parameters, and historical recovery data collected from 1381 actual oil fields. 90% of these oil fields was randomly selected as the training set, and the remaining 10% oil fields was used to test the performance of ANN. The results indicated that the error between the predicted value of ANN and the actual recovery factor was about 10%. Recently, El-Amin et al. (2021) established a stochastic regression model of gradient boosting (SGB) to predict the recovery factor based on the gradient boosting (GB) regression, which is one of the practical machine learning (ML) methods. The different timescale data were selected to train the machine learning models. The numerical results confirmed the superiority of the SGB model in predicting the oil recovery factor.[5,7−10,12−15]

To sum up, the commonly used methods to predict the oil recovery factor can be summarized as follows:

1 Core experiment method. It is mainly used to simulate the development process of an oil reservoir by laboratory physical simulation experiments, and the experimental results are highly reliable. However, the experimental results cannot reflect the vertical and horizontal reservoir heterogeneity due to the limitations of real cores.

https://doi.org/10.1021/acsomega.1c04631
ACS Omega 2021, 6, 34460−34469

2 Analogy method. The recovery factor can be acquired by this method through comparing the geological and operational parameters of newly discovered reservoirs with those of old reservoirs.[16,17] However, its application capacity is limited, and the accuracy is also not high.
3 Decline curve method. It can be used to predict the production performance and recovery factor in the statistical stage of decline for production.[6,11] The disadvantages are that the operational measures have some effects on the recovery factor, and the predicted accuracy of the recovery factor is relatively low.
4 Numerical simulation method. This method is generally used to simulate the flow of underground oil and water and predict the production performance and recovery factor. Although the heterogeneity of the reservoir can be described, it is difficult to confirm the main influencing parameters of the recovery factor.
5 Empirical formula method. It was proposed by the American Petroleum Institute (API) Recovery Efficiency Subcommittee in 1967.[18] Based on the principle of mathematical statistics, the recovery factor is obtained by using the multiple regression equation according to the main factors affecting recovery.[19] However, the accuracy of predicted results has strong uncertainty, such as the errors between the calculated recovery factors by the empirical formula, considering the porosity, water saturation, initial pressure, viscosity, and permeability, and those of numerical results is about 10−60%.
6 Artificial neural network method. It can be used to analyze the relationship between the recovery factor and various influencing parameters and to predict the production performance and recovery factor.[20,21] However, as a huge amount of data is strictly required, the application of this method is limited.

To accurately predict the recovery factor of a water-flooding oil reservoir, in this paper, the main parameters affecting the recovery factor were comprehensively evaluated through three types of methods, including the analytic hierarchy process (AHP), grey correlation method, and entropy method, as shown in Figure 1. Then, a new integrated hierarchy−correlation model was proposed to predict the recovery factor by using multivariate regression based on the main influencing parameters. Meanwhile, the new model was compared with the actual real-time numerical simulations.

2. DESCRIPTION OF THE RESERVOIR AND THE NUMERICAL MODEL

The sedimentary characteristics of an oil reservoir are in accordance with the braided river delta of A block in China. The reservoir is a typical layered lithological structure, and the sedimentary types consist of an underwater channel. The majority of the rock components is clastic sandstone and the remaining is detrital feldspar sandstone. The oil reservoir has strong water sensitivity, acid sensitivity, alkali sensitivity, salt sensitivity, and weak velocity sensitivity based on the indoor sensitivity analysis experiments. The depth of the oil reservoir ranges from −2500 to −3140 m, and the average thickness is 5.7 m. The ranges of permeability are 10−50 mD and 50−500 mD, and the average permeability is 139.6 mD. The porosity of the oil reservoir is from 15 to 35%, and the average porosity is 26%. The initial pressure of formation is 26.38 MPa. The viscosity of surface crude oil is 7.5 mPa·s, which is typical for light oil. The total area of A block is 0.35 km^2 and that of the geological reserve is 214.8×10^4 t.

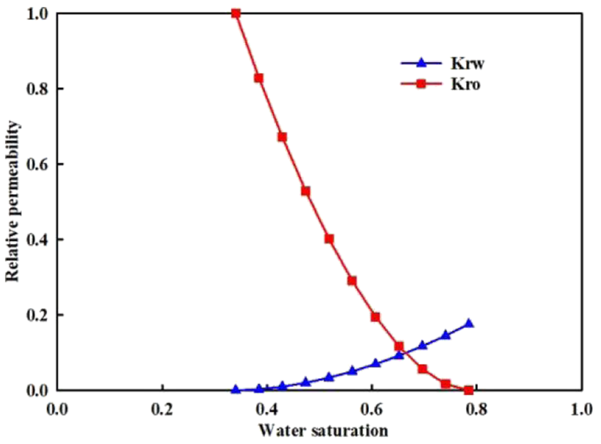


Figure 2. Relative permeability curves for the oil−water system.

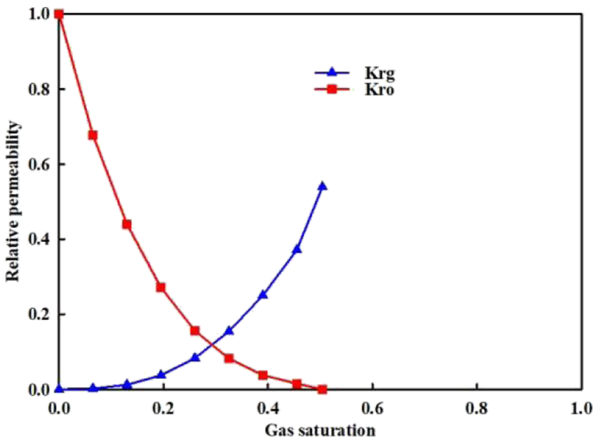


Figure 3. Relative permeability curves for the oil−gas system.

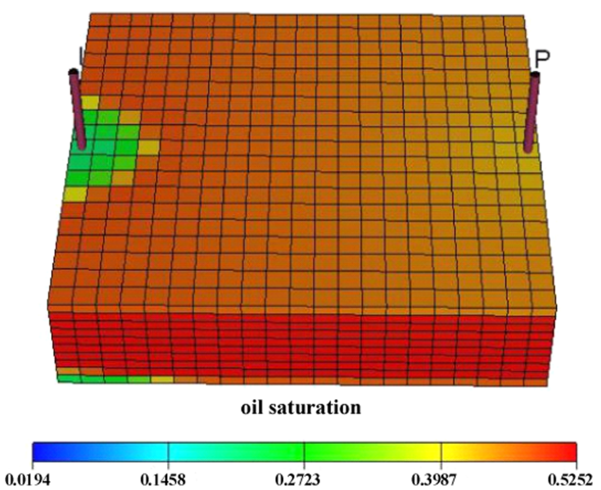


Figure 4. Reservoir numerical simulation model of a water-flooding reservoir.

For the oil−water relative permeability, the initial water saturation is 34%, and the residual oil saturation is 21.5%. The two-phase co-permeability zone is relatively wide, as shown in Figure 2. For the oil−gas relative permeability, the maximum gas saturation is 50.4%.

https://doi.org/10.1021/acsomega.1c04631
ACS Omega 2021, 6, 34460−34469

Table 1. Basic Parameters of the Reservoir Numerical Simulation Model

parameter	value
reservoir depth (m)	2700
NTG	0.2
porosity (%)	26
permeability (*x* direction) (mD)	139.6
permeability contrast	1

To investigate the influences of various parameters on oil production and recovery factor for water-flooding reservoirs, the reservoir numerical model is established according to the range of parameters (Figure 3). The size of the reservoir numerical model in *X, Yi,* and *Z* dimensions is 210, 190, and 50 m, respectively. As shown in Figure 4, an oil well and a water well are located at the two sides of the model domain. Some other parameters are shown in Table 1.

3. NUMERICAL SIMULATION OF RECOVERY FACTOR PREDICTION

The orthogonal design experiment is generally used in studies with multiparameters and multilevels, and it can reflect the essential discipline and contradictions in a large number of schemes with a limited number of representative schemes.[22−24] In the orthogonal design experiment, the geological and developmental parameters are selected as influencing factors, and the values of parameters are called levels.[25] The orthogonal design can be carried out after the number of factors and levels are determined (Figures 5 and 6).

The parameters affecting the oil recovery factor include geological factors (permeability, viscosity, porosity, fluidity, etc.) and developmental factors (well spacing, injection−production ratio, well pattern, etc.).[4,26,27] In this study, 50 sets of an orthogonal experiment table L_{50} (5^{11}) with 11 factors (including 1 blank column) and 5 levels are intentionally designed according to the principle of orthogonal design. These influencing factors contain six geological factors, such as the reservoir thickness (H), porosity (ϕ), permeability (K), oil saturation (S_o), viscosity (μ_o), and permeability contrast (k_{max}/k_{min}), and four developmental factors, for example, the injection−production ratio (IPR), production rate (q_o), pressure coefficient (αp), and water cut (f_w). The details about the various factors and level data of the orthogonal design experiment are displayed in Table 2.

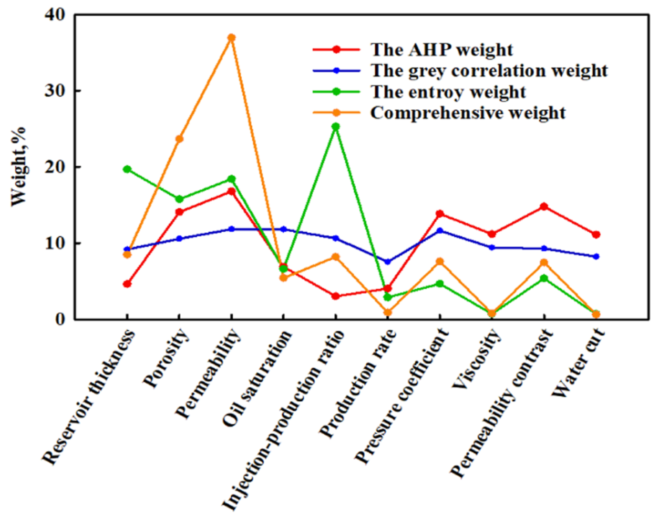


Figure 6. Weight of each of the influencing parameters calculated by different methods.

Based on the 50 experimental sets, 85% of water cut is selected as a stopping criterion in these reservoir numerical experiments. Subsequently, the recovery factors can be correspondingly obtained as shown in Table 9. Afterward, the AHP, grey correlation method, and entropy weight method are combined to comprehensively determine the weight of each parameter. On the basis of these results, the prediction models of the recovery factor can be established.

4. RESULTS AND DISCUSSION

4.1. Analytic Hierarchy Process. The AHP is a decision analysis approach to qualitatively and quantitatively solve complex multiobjective problems. Through this method, decision makers can judge whether each measurement target can achieve the relative importance of the standards based on experience. The weight of each parameter can be reasonably acquired, and the rank of each parameter can be calculated based on the weight. It is effective to solve the problem of

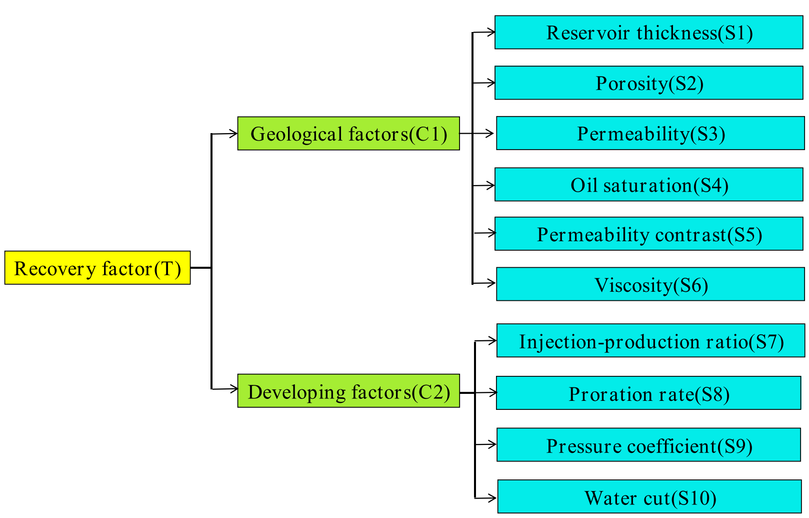


Figure 5. Analytic hierarchy diagram of influencing parameters of the recovery factor.

https://doi.org/10.1021/acsomega.1c04631
ACS Omega 2021, 6, 34460−34469

Table 2. Influencing Parameters of the Recovery Factor and Levels

parameter	H (m)	Φ (%)	K (mD)	S_o (%)	IPR	q_o (m^3/d)	αp	μ_o (mPa·s)	k_{max}/k_{min}	f_w (%)
1	6	20	79.6	43.5	0.8	10	0.9	4	1	75
2	8	23	109.6	46.5	0.9	15	0.95	8	2	80
3	10	26	139.6	49.5	1	20	1	12	3	85
4	12	29	169.6	52.5	1.1	25	1.05	16	4	90
5	14	32	199.6	55.5	1.2	30	1.1	20	5	95

Table 3. Meaning of the Judgment Matrix Scale

meaning	scale number (a_{ij})
factors i and j are equally important	1
factor i is slightly more important than factor j	3
factor i is stronger than factor j	5
factor i is very stronger than factor j	7
factor i is more extremely important than factor j	9
the intermediate value to reflect the importance	2,4,6,8

Table 4. T−C Judgment Matrix of Influencing Parameters of the Recovery Factor

T−C	C1	C2
C1	1	2
C2	1/2	1

Table 5. C1−S Judgment Matrix of Geological Parameters of the Recovery Factor

C1−S	S1	S2	S3	S4	S5	S6
S1	1	0.25	0.33	0.5	0.5	0.5
S2	4	1	2	3	0.5	3
S3	3	0.5	1	2	0.5	0.5
S4	2	0.3	0.5	1	1	0.33
S5	2	2	2	1	1	2
S6	2	0.33	2	3	0.5	1

Table 6. C2−S Judgment Matrix of Developing Parameters of the Recovery Factor

C2−S	S7	S8	S9	S10
S7	1	0.5	0.25	0.33
S8	2	1	0.33	0.2
S9	4	3	1	2
S10	3	5	0.5	1

Table 7. Weight of the Influencing Parameters of the Recovery Factor with Various Methods

influencing factors	AHP weight	grey correlation weight	entropy weight	comprehensive weight
H	0.0463	0.0917	0.1967	0.0846
Φ	0.1406	0.1055	0.1575	0.2365
K	0.1677	0.1183	0.1841	0.3698
S_o	0.0688	0.1180	0.0659	0.0541
IPR	0.0302	0.1061	0.2529	0.0820
q_o	0.0403	0.0752	0.0288	0.0088
Ap	0.1385	0.1162	0.0465	0.0759
Mo	0.1117	0.0942	0.0072	0.0077
k_{max}/k_{min}	0.1477	0.0928	0.0536	0.0744
f_w	0.1110	0.0820	0.0068	0.0062

quantitative description.[28,29] The entire implementing procedure includes four steps:

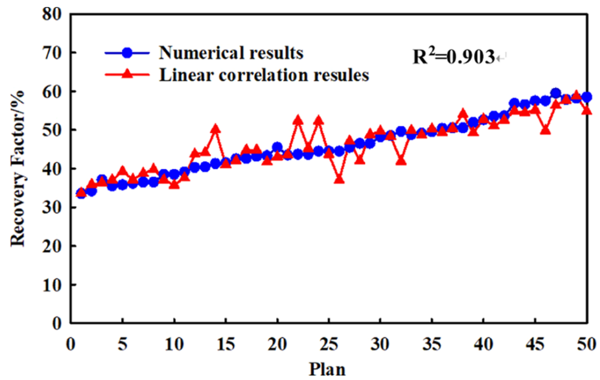


Figure 7. Oil recovery factor results of linear correlation.

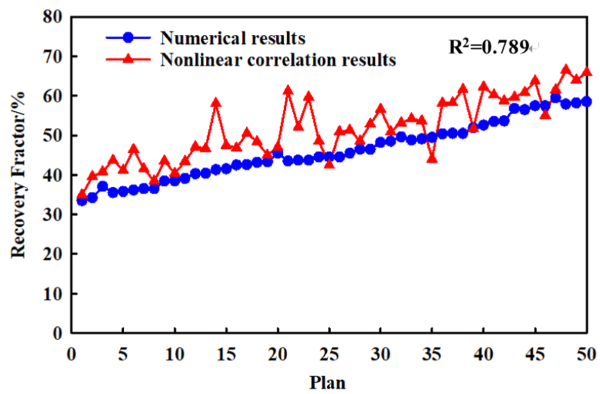


Figure 8. Oil recovery factor results of nonlinear correlation.

1 The hierarchical structure model for each parameter is established based on the objective of decision-making and the considered parameters.
2 The two factors are compared with each other from the second layer based on the consensus matrix method proposed by Saaty and the relationship among the parameters at different levels. Then, a judgment matrix will be formed. The importance of each parameter is confirmed by the judgment standard of nine levels, as shown in Table 3. The term a_{ij} represents the importance and quantized value of factors i and j. $a_{ij}$and a_{ji} also have a relationship in the judgment matrix, as shown in eq 1.
3 The weight vector of the matrix is calculated to check the consistency.
4 The combined weight vector of the lowest layer to the target layer is calculated to check the consistency.

$$a_{ij} = \frac{1}{a_{ji}} \tag{1}$$

The influencing parameters, influencing parameter types, and various influencing factors are selected as the target layer, criterion layer, and scheme layer, respectively. The diagram of

https://doi.org/10.1021/acsomega.1c04631
ACS Omega 2021, 6, 34460−34469

three-level hierarchy on the basis of the principle of analytic hierarchy is shown in Figure 5.

The target layer, criterion layer, and scheme layer are denoted as T, C, and S, respectively. As underground reserves play a pivotal role in the recovery factor, the geological factors should be slightly more important than the developmental factors. However, although the developmental program has been extremely consistent with production requirements, it cannot contribute to a significant impact on recovery due to less well in the basic physical parameters. The criterion-layer judgment matrix is displayed in Table 4.

The judgment matrix of the scheme layer for geological and developmental parameters is C1−S and C2−S, respectively, as shown in Tables 5 and 6. The geological parameters influencing the recovery factor include S1 to S6 and the developmental parameters are S7 to S10. Based on the judgment matrix of the scheme layer, the weight of each factor can be calculated by using the AHP.

Based on the judgment matrix of the scheme layer, the feature vector (u) can be acquired, and the feature vectors for geological and developmental parameters are (0.0685, 0.2645, 0.1398 0.1121, 0.2448, 0.1701) and (0.0917, 0.1304, 0.4404, 0.3373), respectively.

4.2. Grey Correlation Method. The grey correlation analysis is a comparative analysis method of multifactors, and its theory is the same as the similarity of the geometric shapes of the curves. The correlation has a positive relationship with the consistent trend of two parameters.[30,31] The grey correlation method can be used to evaluate the correlation degree between one parameter and the other parameter. Both independent variables and dependent variables are chosen to form the following matrix

$$(X_1',\ X_2'...,\ X_n') = \begin{pmatrix} x_1'(1) & x_2'(1) & \cdots & x_n'(1) \\ x_1'(2) & x_2'(2) & \cdots & x_n'(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_1'(m) & x_2'(m) & \cdots & x_n'(m) \end{pmatrix}$$
$$X_i' = (x_i'(1),\ x_i'(2),\ \cdots,\ x_i'(m))^{\mathrm{T}}, \qquad i = 1,\ 2,\ \cdots n \tag{2}$$

where m is the number of indicators, and n is the number of evaluated objectives.

To avoid the impact of data units, the original matrix is dimensionless after the referenced sequences and the comparative sequences are selected.

$$x_i(k) = \frac{x_i'(k)}{\frac{1}{m}\sum_{k=1}^{m} x_i'(k)} \qquad i = 0,\ 1, \text{|||}, n;\ k = 1,\ 2, \text{|||}\, m \tag{3}$$

The absolute difference between the comparative sequence and the referenced sequence of each parameter is calculated.

$$|x_0(k) - x_i(k)| \qquad (k = 1, \text{|||},\ m)\ i = 1, \text{|||}\, n \tag{4}$$

The two-level maximum difference and the two-level minimum difference are calculated according to eqs 5 and 6 in the absolute difference matrix.

$$\Delta_{\max} = \max_i \max_k |x_0(k) - x_i(k)| \tag{5}$$

$$\Delta_{\min} = \min_i \min_k |x_0(k) - x_i(k)| \tag{6}$$

Then, the correlation coefficient between each comparative sequence and the corresponding element of the referenced sequence can be calculated according to eq 7.

$$\varsigma_i(k) = \frac{\Delta_{\min} + \rho\cdot\Delta_{\max}}{|x_0(k) - x_i(k)| + \rho\cdot\Delta_{\max}} \qquad (k = 1, \text{|||}\, m) \tag{7}$$

where ρ is the resolution coefficient (and generally 0.5).

The correlation degree can be obtained through calculating the mean value of the correlation coefficient of each index in the comparative sequence, which can reflect the influencing degree of each parameter.

$$r_{0i} = \frac{1}{m}\sum_{k=1}^{m} \varsigma_i(k) \tag{8}$$

Based on the above principle, 10 kinds of influencing parameters and the recovery factors are formed into a matrix. The recovery factor is selected as the referenced sequence to normalize the matrix. Meanwhile, the permeability contrast and the water cut are the contrarian indicators. According to eqs 2−8, the weight of each parameter can be calculated. The weight of each influencing factor is shown in Table 7.

4.3. Entropy Weight Method. The entropy weight method is an objective weighting method, which is related to the dispersion degree of the data itself. The entropy weight of each indicator can be calculated by using information entropy. To obtain an objective indicator weight, the weight of each indicator is adapted through the entropy weight. In general, the smaller the entropy index, the greater the degree of variation of the index value is. The more the amount of information, the greater the weight is.[32,33] This method merely requires to establish a correlation among independent variables.

For n samples and m evaluation indicators, the following matrix can be established

$$X = \begin{pmatrix} x_{11} & x_{12} & \text{|||} & x_{1m} \\ x_{21} & x_{22} & \text{|||} & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \text{|||} & x_{nm} \end{pmatrix} \tag{9}$$

where x_{ij} is the j index of sample i.

The samples are divided into two categories of maximum and minimum values, and normalized processing is performed before the comprehensive index is calculated. The processing method of the index is shown in eqs 10 and 11.

Positive indicator

$$x_{ij}' = \frac{x_{ij} - \min\{x_{ij}, \text{|||}, x_{nj}\}}{\max\{x_{1j}, \text{|||}\, x_{nj}\} - \min\{x_{1j}, \text{|||}, x_{nj}\}} \tag{10}$$

Negative indicator

$$x_{ij}' = \frac{\max\{x_{ij}, \text{|||}, x_{nj}\} - x_{ij}}{\max\{x_{1j}, \text{|||}\, x_{nj}\} - \min\{x_{1j}, \text{|||}, x_{nj}\}} \tag{11}$$

Subsequently, the proportion of the i sample to the index under the j index is evaluated as shown in eq 12

$$p_{ij} = \frac{x_{ij}'}{\sum_{i=1}^{n} x_{ij}'} \tag{12}$$

The entropy value of sample j is given by

https://doi.org/10.1021/acsomega.1c04631
ACS Omega 2021, 6, 34460−34469

Table 8. Value of Geological and Developmental Parameters of All Production Wells

well name	H (m)	φ (%)	K (mD)	S_o (%)	Ap	IPR	k_{max}/k_{min}	RF (%)
A	3.20	22	100.00	68.13	0.83	0.86	56.00	36
B	3.95	21	26.97	55.20	0.80	0.96	120.60	26
C	2.05	21	78.41	56.56	1.05	0.55	233.20	29
D	1.40	19	16.90	55.91	0.95	0.13	33.50	20
E	3.73	19	22.90	56.57	0.89	1.51	178.50	26
F	16.40	21	57.70	54.40	0.95	3.77	50.10	45
G	5.40	19	7.80	60.10	1.08	1.02	41.60	22
H	7.40	27	167.70	53.50	0.89	0.91	9.70	51
I	4.26	24	159.30	61.60	0.91	0.89	13.10	47
J	4.87	27	170.00	51.43	0.84	0.60	30.60	50
K	1.56	17	6.98	53.44	0.85	0.66	2.30	21
L	5.06	19	52.85	60.99	1.05	0.21	16.80	26
M	7.00	23	157.49	63.72	1.03	0.39	11.40	44
N	5.80	21	196.84	41.67	1.02	0.80	17.50	52

$$e_j = -k\sum_{i=1}^{n} p_{ij}\ln(p_{ij}) \tag{13}$$

As the entropy value has a negative relationship with the comprehensively estimated consequence, the issue is solved by using the information entropy redundancy as follows

$$d_j = 1 - e_j \tag{14}$$

The weight of each indicator can be obtained from eq 15.

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{15}$$

The influencing parameters are formed into a matrix according to the results of 50 experimental sets and the calculation principle of the entropy weight method. The weight of each parameter is calculated by eqs 12−15 after the positive and negative indicators are normalized. The weight of each parameter is shown in Table 7.

4.4. Multiplicative Weighting Method. Although the above three methods can determine the weight of each influencing parameter, each method has its own advantages and disadvantages. The weight of the AHP is determined by expert scores, and the weights of the grey correlation method are calculated by the trend between the independent variables and the dependent variables. The entropy weight method just relies on the information entropy of the independent variables. To comprehensively take advantage of the advantages of each method, the combined weight of each parameter can be acquired by using the multiplicative weighting method. The calculation formula of the multiplicative weighting method is as follows

$$w_i = \frac{w_{AHP}w_{GR}w_{EW}}{\sum_{i=1}^{m} w_{AHP}w_{GR}w_{EW}} \qquad i = 1,\ 2,\ \ldots,\ m \tag{16}$$

where w_{AHP} is the weight calculated by the AHP method; w_{GR} is the weight calculated by the grey correlation method; and w_{EW} is the weight calculated by the entropy weight method.

4.5. Establishment of a Prediction Model for Oil Recovery. Accounting for the advantage of considering the influence of multiple parameters on the dependent variable, multiple linear regression is used to predict oil recovery for better fitting the actual situation of oil fields. Based on the weights of the AHP, grey correlation method, and the entropy method, the permeability, porosity, reservoir thickness, injection−production ratio, pressure coefficient, permeability contrast, and oil saturation can be regarded as independent variables, while the recovery factor is selected as the dependent variable. The prediction model of the recovery factor, as shown as in eq 17, is obtained after the prediction formula of the recovery factor is fitted by using the multiple linear regression method in SPSS software. The results of linear correlation for the recovery factor are shown in Figure 7. The linear correlation coefficient is 0.903, and the average difference between the linear correlation and numerical simulation is about 0.5%.

$$\mathrm{RF} = 0.1599 + 0.002h + 0.4375\phi + 0.0015k + 0.041\mathrm{IPR} - 0.0362\alpha p - 0.0001\frac{k_{max}}{k_{min}} - 0.0007s_o \tag{17}$$

The results of nonlinear correlation for the recovery factor are shown in Figure 8. It can be clearly seen that the method of linear correlation achieves better results than that of nonlinear correlation, for example, R^2 = 0.789 in this case study. The average difference between nonlinear correlation and numerical simulation is about 12.3%. The nonlinear correlation used to predict recovery is acquired as follows.

$$\mathrm{RF}' = 0.0884 + 0.0044h + 0.4958\phi + 0.0016k + 0.0647\mathrm{IPR} - 0.0171\alpha p - 0.0001\frac{k_{max}}{k_{min}} - 0.0007s_o - 0.00002h{*}k \tag{18}$$

5. APPLICATION OF THE PREDICTION MODEL

In this section, the predicted model of recovery factor is applied on 14 wells to further verify the performance. The physical properties and developmental parameters of each well are shown in Table 8. Based on the previous results, the linear correlation model is adopted to calculate the recovery factor. The recovery factor ranges from 20 to 52%, and the average recovery factor is about 35%.

6. CONCLUSIONS

In this paper, we propose a novel integrated hierarchy−correlation model, which includes the AHP, grey relation, entropy weight, and empirical correlations, to investigate water-flooding oil reservoir performances. Key remarks from this study are summarized as follows in items 1−4.

https://doi.org/10.1021/acsomega.1c04631
ACS Omega 2021, 6, 34460−34469

Table 9. Orthogonal Design Scheme of the Reservoir Numerical Simulation

parameter	H (m)	φ (%)	K (mD)	S_o (%)	IPR	q_o (m^3/d)	αp	μ_o (mPa·s)	k_{max}/k_{min}	f_w (%)	RF (%)
1	6	0.2	79.6	52.5	0.8	10	0.9	8	60	90	33.5
2	6	0.23	109.6	49.5	1.2	25	1.1	4	240	95	36.5
3	6	0.26	139.6	46.5	1.1	15	1	20	1	80	45.5
4	6	0.29	199.6	55.5	1	20	0.95	16	180	85	58.5
5	6	0.32	169.6	43.5	0.9	30	1.05	12	120	75	44.5
6	8	0.2	109.6	55.5	1.1	30	1.1	20	180	75	39.1
7	8	0.23	139.6	43.5	1	10	1	16	120	90	42.6
8	8	0.26	199.6	52.5	0.9	25	0.95	12	60	95	56.8
9	8	0.29	169.6	49.5	0.8	15	1.05	8	240	80	50.4
10	8	0.32	79.6	46.5	1.2	20	0.9	4	1	85	49.6
11	10	0.2	139.6	49.5	0.9	20	1.05	4	1	90	40.4
12	10	0.23	199.6	46.5	0.8	30	0.9	20	240	95	43.7
13	10	0.26	169.6	55.5	1.2	10	1.1	16	180	80	41.3
14	10	0.29	79.6	43.5	1.1	25	1	12	120	85	35.8
15	10	0.32	109.6	52.5	1	15	0.95	8	60	75	43.2
16	12	0.2	199.6	43.5	1.2	15	1.05	20	240	85	52.6
17	12	0.23	169.6	52.5	1.1	20	0.9	16	180	75	48.2
18	12	0.26	79.6	49.5	1	30	1.1	12	120	90	36.2
19	12	0.29	109.6	46.5	0.9	10	1	8	60	95	40.3
20	12	0.32	139.6	55.5	0.8	25	0.95	4	1	80	51.9
21	14	0.2	169.6	46.5	1	25	1.1	8	120	85	49.1
22	14	0.23	79.6	55.5	0.9	15	1	4	60	75	37.1
23	14	0.26	109.6	43.5	0.8	20	0.95	20	240	90	41.5
24	14	0.29	139.6	52.5	1.2	30	1.05	16	1	95	48.8
25	14	0.32	199.6	49.5	1.1	10	0.9	12	180	80	58.2
26	6	0.2	109.6	43.5	0.9	25	0.9	16	1	80	36.5
27	6	0.23	139.6	52.5	0.8	15	1.1	12	180	85	46.5
28	6	0.26	199.6	49.5	1.2	20	1	8	120	75	57.5
29	6	0.29	169.6	46.5	1.1	30	0.95	4	60	90	53.6
30	6	0.32	79.6	55.5	1	10	1.05	20	240	95	38.5
31	8	0.2	139.6	46.5	1.2	10	0.95	12	240	75	45.5
32	8	0.23	199.6	55.5	1.1	25	1.05	8	1	90	56.5
33	8	0.26	169.6	43.5	1	15	0.9	4	180	95	50.5
34	8	0.29	79.6	52.5	0.9	20	1.1	20	120	80	35.5
35	8	0.32	109.6	49.5	0.8	30	1	16	60	85	43.5
36	10	0.2	199.6	52.5	1	30	1	4	240	80	53.5
37	10	0.23	169.6	49.5	0.9	10	0.95	20	1	85	49.5
38	10	0.26	79.6	46.5	0.8	25	1.05	16	180	75	38.5
39	10	0.29	109.6	55.5	1.2	20	0.9	12	120	90	44.5
40	10	0.32	139.6	43.5	1.1	15	1.1	8	60	95	57.5
41	12	0.2	169.6	55.5	0.8	15	1	12	1	95	48.5
42	12	0.23	79.6	43.5	1.2	30	0.95	8	180	80	44.5
43	12	0.26	109.6	52.5	1.1	10	1.05	4	120	85	42.5
44	12	0.29	139.6	49.5	1	25	0.9	20	60	75	46.5
45	12	0.32	199.6	46.5	0.9	20	1.1	16	240	90	59.5
46	14	0.2	79.6	49.5	1.1	15	0.95	16	120	95	34.2
47	14	0.23	109.6	46.5	1	20	1.05	12	60	80	43.3
48	14	0.26	139.6	55.5	0.9	30	0.9	8	240	85	43.7
49	14	0.29	199.6	43.5	0.8	10	1.1	4	1	75	57.9
50	14	0.32	169.6	52.5	1.2	25	1	20	180	90	50.5

(1) Primary controlling factors of oil recovery are analyzed based on the AHP, grey correlation method, and entropy weight method. Among them, permeability shows the most obvious influence on the recovery factor for the AHP and grey correlation method. By contrast, for the entropy weight method, the influences of injection and production are the most significant. Based on the analysis of the multiplicative weighting method, seven factors, for example, permeability, porosity, reservoir thickness, injection−production ratio, pressure coefficient, permeability contrast, and oil saturation, are found to have significant influences on the recovery factor prediction.

(2) Based on the multiplicative weighting method and sensitivity analysis, the seven influencing factors have been determined to be the combined static−dynamic indicator for predicting the recovery factor of the waterflooding reservoir. The oil recovery prediction model is

https://doi.org/10.1021/acsomega.1c04631
ACS Omega 2021, 6, 34460−34469

obtained through multiple regression fitting methods with high fitting accuracy, especially for the linear fitting method.

(3) The recovery factor of the water-flooding oil reservoir calculated by numerical simulation ranges from 33.5 to 59.5%, and the linear and nonlinear correlation coefficients are 0.903 and 0.789, respectively. The uncertainty of the calculated result between linear correlation and numerical simulation is about 0.5%, which is smaller than that of nonlinear correlation, for example, 12.3%.

(4) The proposed model has been validated by means of actual data for a fault block in the well A area. In comparison with the actual recovery factor of each well, the calculated results from the model are demonstrated to be quite accurate, with deviations less than 10%. This finding verifies the model and indicates its great potential for applications in the actual oil field recovery factor with satisfactory speed and acceptable accuracy.

AUTHOR INFORMATION

Corresponding Authors

Leng Tian − *State Key Laboratory of Petroleum Resources and Prospecting, China University of Petroleum (Beijing), Beijing 102249, China; Department of Petroleum Engineering, China University of Petroleum (Beijing), Beijing 102249, China;* orcid.org/0000-0002-5796-7154; Phone: 86-10-8973-3740; Email: tianleng2008@126.com

Kaiqiang Zhang − *Institute of Energy, Peking University, Beijing 100871, PR China; Department of Chemical Engineering, Imperial College London, London SW7 2AZ, United Kingdom;* orcid.org/0000-0002-3011-0505; Phone: +44-(0)7742200006; Email: kaiqiang.zhang@imperial.ac.uk

Authors

Xiaolong Chai − *State Key Laboratory of Petroleum Resources and Prospecting, China University of Petroleum (Beijing), Beijing 102249, China; Department of Petroleum Engineering, China University of Petroleum (Beijing), Beijing 102249, China*

Ge Wang − *State Key Laboratory of Petroleum Resources and Prospecting, China University of Petroleum (Beijing), Beijing 102249, China; Department of Petroleum Engineering, China University of Petroleum (Beijing), Beijing 102249, China*

Hengli Wang − *State Key Laboratory of Petroleum Resources and Prospecting, China University of Petroleum (Beijing), Beijing 102249, China; Department of Petroleum Engineering, China University of Petroleum (Beijing), Beijing 102249, China;* orcid.org/0000-0001-5997-8474

Long Peng − *State Key Laboratory of Petroleum Resources and Prospecting, China University of Petroleum (Beijing), Beijing 102249, China; Department of Petroleum Engineering, China University of Petroleum (Beijing), Beijing 102249, China;* orcid.org/0000-0001-9654-953X

Jianguo Wang − *State Key Laboratory of Petroleum Resources and Prospecting, China University of Petroleum (Beijing), Beijing 102249, China; Department of Petroleum Engineering, China University of Petroleum (Beijing), Beijing 102249, China*

Complete contact information is available at: https://pubs.acs.org/10.1021/acsomega.1c04631

Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

The authors would like to acknowledge the funding by the project (51974329) sponsored by the National Natural Science Foundation of China and the project (2019D-5007-0202) sponsored by Science and Technology Innovation Fund of CNPC. In addition, X.C. wants to thank Yanan Xue for her support, kindness, and great motivation.

REFERENCES

(1) Talluru, G.; Wu, X. R. *Using Data Analytics on Dimensionless Numbers to Predict the Ultimate Recovery Factors for Different Drive Mechanisms of Gulf of Mexico Oil Fields*; SPE Annual Technical Conference and Exhibition: Texas, USA, 2017.

(2) Arjmand, O.; Roostaei, A. Experimental Investigation of Viscous Surfactant Based Enhanced Oil Recovery. *Pet. Sci. Technol.* **2014**, *32*, 1607−1616.

(3) Pajouhandeh, A.; Schaffie, M.; Ranjbar, M. Evaluation of Nanoparticle-stabilized Emulsion Flooding: Glass-micromodel Experimental Study. *J. Jpn. Pet. Inst.* **2019**, *62*, 126−135.

(4) Zhou, X.; Wang, Y.; Zhang, L.; Zhang, K.; Jiang, Q.; Pu, H.; Yuan, Q. Evaluation of enhanced oil recovery potential using gas/water flooding in a tight oil reservoir. *Fuel* **2020**, *272*, 117706.

(5) Mutua, D.; Htay, A.; Barasi, M. Research and Development of an Empirical Method for Predicting Oil Recovery During EOR Studies Publisher. *J. Can. Pet. Technol.* **2002**, *41*, 11−14.

(6) Adrian, O.; Charles, N. *Application of Empirically Derived Oil Recovery Factor Regression Equations to Water Drive Reservoirs in Niger Delta*. Nigeria Annual International Conference and Exhibition, Lagos, Nigeria, 2013.

(7) de Lima Cunha, A.; de Farias Neto, S. R.; de Lima, A. G. B.; Santos Barbosa, E. Secondary oil recovery by water injection: a numerical study. *Defect Diffus. Forum* **2013**, *334*−*335*, 83−88.

(8) Dutta, R.; Meyet, M.; Burns, C.; Cauter, F. *Comparison of Empirical and Analytical Methods for Production Forecasting in Unconventional Reservoirs: Lessons from North America*; PSPE/EAGE European Unconventional Resources Conference and Exhibition: Vienna, Australia, 2014.

(9) Tangparitkul, S. Evaluation of effecting factors on oil recovery using the desirability function. *J. Pet. Explor. Prod. Technol.* **2018**, *8*, 1199−1208.

(10) Ma, X.; Liu, Z. Predicting the oil production using the novel multivariate nonlinear model based on Arps decline model and kernel method. *Neural. Comput. Appl.* **2018**, *29*, 579−591.

(11) Lim, J.-S.; Shin, H.-J.; Shin, S.-H. Estimated ultimate recovery prediction using oil and gas production decline curve analysis and cash flow analysis for resource play. *Geosystem Eng.* **2014**, *17*, 78−87.

(12) Dong, X.; Liu, H.; Hou, J.; Chen, Z.; Zhang, T. *An Empirical Correlation to Predict the SAGD Recovery Performance*; SPE/IATMI Asia Pacific Oil & Gas Conference and Exhibition: Bali, Indonesia, 2015.

(13) Dzurman, P. J.; Leung, J. W.; Zanon, S. J.; Amirian, E. *Data-Driven Modeling Approach for Recovery Performance Prediction in SAGD Operations*; SPE Heavy Oil Conference-Canada: Alberta, Canada, 2013.

(14) Chen, Y. J.; Zhu, Z. Y.; Lu, Y. X.; Hu, C. H.; Gao, F.; Li, W.; Sun, N.; Feng, T. *Reservoir Recovery Estimation Using Data Analytics and Neural Network Based Analogue Study*; SPE/IATMI Asia Pacific Oil & Gas Conference and Exhibition: Bali, Indonesia, 2019.

(15) El-Amin, M. F.; Subasi, A.; Selim, M. M.; Mousa, A. Predicted Oil Recovery Scaling-Law Using Stochastic Gradient Boosting Regression Model. *Cmc-Comput. Mater. Contin.* **2021**, *68*, 2349−2362.

(16) Wang, Z.; Wang, Q.; Ma, D.; Zhao, W.; Feng, X.; Liu, Z. The Fast Potential Evaluation Method of Enhanced Oil Recovery Based on Statistical Analysis. *Processes* **2019**, *7*, 795.
(17) Ahmed, A.; Elkatatny, S.; Abdulraheem, A.; Mahmoud, M. *Application of Artificial intelligence techniques in estimating oil recovery factor for water derive sandy reservoirs*; SPE kuwait Oil & Gas Show and Conference: Kuwait, 2017.
(18) Arps, J. *Reasons for Differences in Recovery Efficiency*; Symposium on Petroleum Economics and Evaluation: Texas, USA, 1968.
(19) Onolemhemhen, R. U.; Isehunwa, S. O. *Salufu. Development of Recovery Factor Model For Water Drive and Depletion Drive Reservoirs in The Niger Delta*; SPE Nigeria Annual International Conference and Exhibition: Lagos, Nigeria, 2016.
(20) Okpere, A.; Njoku, C. *Application of Neural Networks in Developing an Empirical Oil Recovery Factor Equation for Water Drive Niger Delta Reservoirs*; SPE Nigeria Annual International Conference and Exhibition: Lagos, Nigeria, 2014.
(21) Tewari, S.; Dwivedi, U. D.; Shiblee, M. *Assessment of Big Data Analytics Based Ensemble Estimator Module for the Real-Time Prediction of Reservoir Recovery Factor*; SPE Middle East Oil and Gas Show and Conference: Manama, Bahrain, 2019.
(22) Wang, H.; Tian, L.; Gu, D.; Li, M.; Chai, X.; Yang, Y. Method for Calculating Non-Darcy Flow Permeability in Tight Oil Reservoir. *Transp. Porous Media* **2020**, *133*, 357−372.
(23) Liang, T.; Chang, Y.; Guo, X.; Liu, B.; Wu, J. Sort of the impact of individual well productivity parameters in the Bakken tight reservoir. *Petrol. Explor. develop.* **2013**, *40*, 383−388.
(24) Tian, L.; Xiao, C.; Wang, G.; Deng, Y.; Wang, Y. Establishment of Productivity Model and Orthogonal Test Design for Analysis of Dominating Factors in Fractured Shale Gas Reservoirs. *J. Porous Media* **2019**, *22*, 693−711.
(25) Sun, J. F.; Wang, H. The influence of horizontal well pattern parameters on development effect is analyzed by orthogonal experimental design method. *Petrol. Geol. Eng.* **2009**, *23*, 66−68.
(26) Yuan, Z.; Wang, J.; Li, S.; Ren, J.; Zhou, M. A new approach to estimating recovery factor for extra-low permeability water-flooding sandstone reservoirs. *Petrol. Explor. Dev.* **2014**, *41*, 377−386.
(27) Peng, C.; Gao, W.; Li, Z.; Yuan, S. Effect of injection-production well pattern on water drive recovery factor. *Xinjiang Pet. Geol.* **2000**, *21*, 315−317.
(28) Zhou, H. F. Classification and optimization method of complex fault-block reservoir. *Pet. Geol. Dev. Daqing* **2016**, *35*, 68−73.
(29) Wang, X.; Hou, J.; Liu, Y.; Ji, L.; Sun, J. Studying reservoir heterogeneity by Analytic Hierarchy Process and Fuzzy Logic, case study of Es1x formation of the Wang guan tun oilfield, China. *J. Petrol. Gas Eng.* **2017**, *156*, 858−867.
(30) Yin, D.; Guo, Z.; Zhang, C. Apply the Combination of Grey Correlation Method and Fuzzy Evaluation Method to Evaluate Water Flooding Development Effect in Extra High Water-cut Stage. *Mathe. Pract. Theory* **2015**, *45*, 215−222.
(31) Tao, L.; Guo, J. C.; Zeng, J.; Huang, C. X.; Zhao, Z. H. *Refracturing Candidate Selection for Multi-Fractured Horizontal Wells Using a New Hybrid Method in Tight Oil Reservoirs*; SPE/AAPG/SEG Asia Pacific Unconventional Resources Technology Conference: Brisbane, Australia, 2019.
(32) Yang, Z.; He, R.; Chen, J.; Li, X.; Xie, B.; Meng, J.; Li, W. *A Hybrid Model for Selecting Horizontal Candidate Wells for Re-Fracturing of Tight Oil Reservoirs-A Case Study in the Baikouquan Formation, North Mahu Oil Field, Western China*; SPE Russian Petroleum Technology Conference: Moscow, Russia, 2019.
(33) Ju, Y.; Wu, G.; Wang, Y.; Liu, P.; Yang, Y. 3D Numerical Model for Hydraulic Fracture Propagation in Tight Ductile Reservoirs, Considering Multiple Influencing Factors via the Entropy Weight Method. *SPE J.* **2021**, *26*, 2685.

https://doi.org/10.1021/acsomega.1c04631
ACS Omega 2021, 6, 34460−34469