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Short communication

Novel method for the rapid evaluation of pressure depletion in tight oil reservoirs

Chao Ding[1,2], Jin Chen[2], Guo Yang[1], Runfei Bao[2], Yan Dou[1], Kaoping Song[2]*

[1]*Fengcheng Oilfield Operation Area, PetroChina Xinjiang Oilfield Company, Karamay 834000, P. R. China*

[2]*Unconventional Petroleum Research Institute, China University of Petroleum, Beijing 102249, P. R. China*

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Abstract:
Tight oil reservoirs hold immense development potential but are characterized by challenging reservoir properties, severe heterogeneity, and extremely low permeability and porosity. Massive hydraulic fracturing of horizontal wells is applied to achieve sustainable production in these reservoirs. The swift assessment of pressure depletion in tight reservoirs is essential for their successful and cost-effective development. Traditional pressure testing methods necessitate well shutdown, impacting subsequent production, while numerical simulation methods demand significant computational resources and expertise from technical personnel. To identify the sensitivity parameters influencing the reservoir pressure drop, this study uses a Plackett-Burman design and variance analysis. Using numerical simulations, variance analysis and multi-linear regression, we formulate evaluation indices and surrogate models for individual well depletion. The method's reliability is validated through multiple experiments along with testing data. Our rapid evaluation method accurately assesses pressure depletion in typical well groups, with a fitting rate exceeding 85%. In regions where the pressure maintenance is below 80%, indicating severe reservoir depletion, enhanced oil recovery treatments, e.g., gas or water injection, are applied based on the evaluation results. The proposed method for evaluating individual well pressure depletions provides crucial guidance for realizing the efficient development of tight oil reservoirs.

1. Introduction

China has an abundance of proven tight oil reservoirs. Achieving the efficient development of tight oil reservoirs holds both practical and strategic significance in alleviating the growing demand for petroleum in the country in the medium to long term (Hu et al., 2018; Kang et al., 2022). In comparison to medium- to high-permeability sandstone reservoirs, tight oil reservoirs exhibit characteristics such as extremely low permeability and porosity, strong heterogeneity, along with complex fluid flow mechanisms (Kang et al., 2022; Ji and Fang, 2023). In recent years, the development of horizontal well hydraulic fracturing has emerged as a crucial approach for the efficient exploitation of low-permeability reservoirs (Ren et al., 2015; Al-Tailji et al., 2016). Through volume fracturing, a complex network of natural and induced fractures is formed in the near-wellbore zone, reducing flow resistance and enhancing development effectiveness (Ranjith et al., 2019; Li et al., 2022a). However, influenced by factors such as poor reservoir properties and low formation energy, the early depletion stage of development faces major challenges such as rapid decline in the formation energy and difficulties in maintaining stable production (Li et al., 2022b). Thus, accurately assessing the pressure depletion in the formation and devising rational energy enhancement strategies are becoming crucial for enhancing production and achieving efficient development in the context of low-permeability depletion development reservoirs.

Currently, the assessment of pressure conditions within the reservoir relies on two main methodologies: pressure testing and numerical simulation. By utilizing pressure testing, dynamic and static pressure conditions within the reservoir

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*Corresponding author.
E-mail address: ptrdc@petrochina.com.cn (C. Ding); chenjin@student.cup.edu.cn (J. Chen); fcytyg@petrochina.com.cn (G. Yang); baorunfei@163.com (F. Bao); fcdouy@petrochina.com.cn (Y. Dou); skpskp01@sina.com (K. Song).

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can be accurately determined. Specifically, static pressure testing involves the deployment of sensors at the well bottom, temporary well shutdown after a routine production period, and the analysis of pressure recovery to evaluate reservoir energy states and fluid supply capacity (Li et al., 2018). Due to the slow recovery of production capacity in tight oil reservoirs, this procedure considerably influences subsequent production rates (Ponomareva et al., 2022).

Furthermore, reservoir numerical simulation plays a crucial role in foreseeing the dynamic properties of reservoirs (Adeosun et al., 2020; Lesan et al., 2023; Scerbacova et al., 2023). Wang et al. (2019) developed a three-dimensional three-phase mathematical model for tight oil reservoirs subjected to microemulsion flooding and conducted comprehensive numerical simulation studies. They analyzed the variation in formation pressure with injection volume, gaining insights into the distinct impacts of water and microemulsion on reservoir energy supplementation and recovery. Compared to liquid media, gaseous media such as CO_2 bring greater advantages to increasing the reservoir energy and enhancing the crude oil recovery rates. Liu et al. (2021) developed a numerical simulation model for a five-spot well pattern to analyze the changes in injection pressure and recovery across various CO_2 injection scenarios, optimizing the development parameters. Similarly, utilizing refined research insights from reservoir description and a detailed three-dimensional geological model, Zhou et al. (2023) established a reservoir numerical simulation model and successfully conducted history matching. Their analysis of changes in oil saturation and pressure fields revealed the remaining development potential and energy characteristics associated with different development stages. Based on the numerical simulation results for reservoirs, the evolution pattern of formation pressure can be analyzed to quantitatively assess the current energy deficit of the formation. However, creating a geological simulation model for reservoirs involves analyzing a large amount of data, which requires a significant workload (Peaceman, 2000; Fanchi, 2005). Moreover, it demands high computational capabilities of the equipment and a proficient level of expertise from the technical personnel, posing challenges to widespread implementation in the oilfield.

In recent years, machine learning and artificial intelligence have found widespread application in reservoir pressure prediction. Based on the analysis of wellbore flow hydraulic models, Liang et al. (2021) established an improved simulated annealing-support vector regression (SA-SVR) system for monitoring the bottom hole pressure in managed pressure drilling by combining the SA algorithm with SVR. Integrating the static mud column pressure, annular pressure loss and surface back pressure data, an enhanced pressure monitoring model was constructed, achieving bottom hole pressure data monitoring without the need for downhole pressure gauge instruments. However, this approach only provides the bottom hole pressure, while the inter-well formation pressure remains unknown. Tang et al. (2022) utilized low-cost interferometric synthetic-aperture radar monitoring data to infer changes in reservoir pressure. They utilized ensemble smoother with ensemble smoother multiple data assimilation to update the three-dimensional geological properties and predict reservoir pressure. The principal component analysis method was applied to reduce dimensionality and facilitate rapid pressure forecasting. However, despite the significant advantages of machine learning in feature extraction and computational efficiency, this approach tends to neglect the inherent physical properties of reservoirs, rendering it ineffective in characterizing the interactions among various parameters.

Extensive research has highlighted the influence of reservoir properties and development methods on the extent of pressure drop, revealing a robust correlation between the associated parameters and the depletion of formation pressure. Shao et al. (2015) conducted depletion development experiments using natural outcrop core samples, and suggested that development methods and liquid production rates significantly influence the development outcomes. Based on physical simulation experiments, Chi and Zhang (2021) utilized reservoir numerical simulations to explore the influence of stress sensitivity on tight oil reservoir productivity, revealing that critical factors like permeability and porosity determine the pressure distribution characteristics in porous media. Similarly, Cheng et al. (2023) delved into the factors influencing air flooding in tight oil reservoirs using reservoir numerical simulation. The results indicated that reservoir permeability and injection rates both influence the development outcomes. On the other hand, Ponomareva et al. (2022) conducted a statistical study to explore the impact of parameters such as initial formation pressure, production time and skin factor on reservoir pressure. They developed a reservoir pressure prediction model using multidimensional regression methods, which was rigorously tested in the Sukharev oil field and the model exhibited strong agreement with the measured data. Nevertheless, this approach may not fully consider the impact of fluid flow capacity on reservoir energy, indicating the need for further refinement. Furthermore, to deepen the evaluation of the correlation between each parameter and reservoir pressure depletion, a sensitivity analysis is necessary. Plackett-Burman designs, as a statistical method, allow for the systematic assessment of the relative importance of various factors in the target output based on a limited number of experiments (Beres and Hawkins, 2001). With this advantage, as well as rapid assessment and high accuracy, it can efficiently identify the impact of each parameter on reservoir pressure depletion.

This study utilizes a Plackett-Burman design and variance analysis to identify the essential sensitivity parameters influencing reservoir pressure drop. Evaluation indices and surrogate models for individual well depletion are developed via numerical simulations, analysis of variance and multilinear regression. Multiple sets of experiments are designed and combined with on-site pressure measurement data to validate the reliability of our methodology, which is then applied to the WX tight oil reservoir in Xinjiang, China, to assess the pressure depletion levels in typical well groups.

2. Selection of pressure depletion indexes

Drawing upon dynamic and static production data from the oilfield, a preliminary assessment has pinpointed 10 key factors significantly affecting reservoir energy: permeability,

Table 1. Sensitive parameters and their value ranges.

Parameter	Low level	Intermediate value	High level
Permeability (mD)	4	12	20
Temperature (°C)	40	60	80
Viscosity (cp)	0.28	2.24	4.2
Oil density (kg/m^3)	680	780	880
Porosity (%)	8	11.5	15
Liquid production rate (m^3/d)	10	20	30
Production duration (years)	1	3	5
Reservoir depth (m)	2,550	2,600	2,650
Formation dip angle (°)	4	14	24
Reservoir thickness (m)	3	6	9

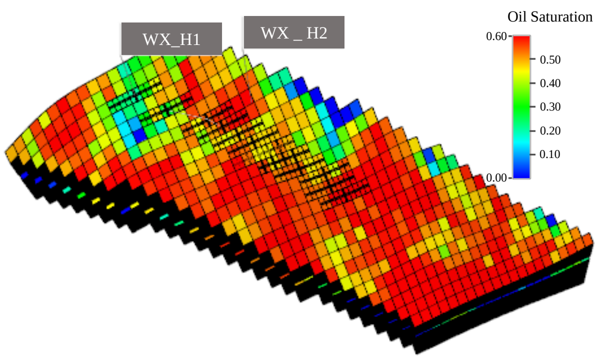

Fig. 1. Numerical simulation model of the WX_H well group reservoir.

temperature, viscosity, oil density, porosity, liquid production rate, production duration, reservoir depth, formation dip angle, and reservoir thickness. For a deeper comprehension of the impact of these ten parameters on the formation pressure drop in the target reservoir, we selected the Plackett-Burman experimental design method, referred to as "P-B design" (Plackett and Burman, 1946) for the sensitivity analysis of parameters. The P-B design is a two-level experimental design method suitable for rapidly and effectively screening out the most important factors from a multitude of factors. The main steps are as follows: firstly, analyzing the impact of each parameter on evaluation indicators such as formation pressure drop, clarifying the value range, and determining their low-level (minimum) and high-level (maximum) values. We then establish the experimental design based on the number of parameters, creating a P-B matrix to determine parameter values and formulating the experimental plan. The number of experiments is generally a multiple of 4, with commonly used values including 8, 12, 16, 20, etc. Subsequently, based on the experimental plan, physical or numerical simulation experiments are conducted to obtain simulation results for each scenario. Finally, to determine the sensitivity of each parameter to the evaluation target, variance analysis is performed on the results by comparing the differences between the two levels of each parameter and determining the overall differences.

By utilizing the research framework described earlier and integrating geological and developmental insights, we could accomplish the initial establishment of adjustable ranges for the 10 parameters (Table 1).

We established a P-B matrix (Table 2) for a 15-run experiment, encompassing 3 control groups corresponding to the two levels of the 10 parameters. In the matrix, -1, 0 and +1 respectively represent the low-level value, intermediate value and high-level value for the corresponding parameter. Each column represents the different values of the corresponding parameter in each scenario, while each row represents an experimental plan. The control groups consist of scenarios where all values are set to 0.

In order to examine the pressure depletion conditions in depleted reservoirs under diverse reservoir and development conditions, we focused on a typical well group in the WX tight oil reservoir. We established reservoir numerical simulation models for different well groups based on the geological model (Fig. 1). We adjusted the oil-water phase permeability curves, permeability, porosity, and other parameters to achieve dynamic history matching. Based on Table 1 and Table 2, we made corresponding modifications to the parameters to establish different numerical simulation scenarios. Then, we conducted reservoir numerical simulations and analyzed the evolution patterns of pressure and saturation fields. By analyzing the average formation pressures at the end and the beginning of development, we could assess the formation pressure depletion. We used the pressure drop value (ΔP) to characterize the extent of reservoir pressure depletion under each scenario, reflecting the conditions at the end of the development period compared to the initial development stages.

Through analysis of variance, we further determined the sensitivity of each parameter to the single-well pressure depletion. The overall variance is divided into two components: within-group variance and between-group variance, with the former reflecting the random variation among individuals within a group, and the latter reflecting the differences among groups. By calculating the ratio of between-group mean square to within-group mean square, the assessment of whether the

Table 2. P-B design matrix for 10 parameters (15 runs).

Experiment	Permeability	Temperature	Viscosity	Oil density	Porosity	Liquid production rate	Production duration	Reservoir depth	Formation dip angle	Reservoir thickness
1	0	0	0	0	0	0	0	0	0	0
2	+1	-1	+1	-1	-1	-1	+1	+1	+1	-1
3	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
4	+1	-1	+1	+1	-1	+1	-1	-1	-1	+1
5	+1	+1	+1	-1	+1	+1	-1	+1	-1	-1
6	+1	-1	-1	-1	+1	+1	+1	-1	+1	+1
7	-1	+1	-1	-1	-1	+1	+1	+1	-1	+1
8	-1	-1	-1	+1	+1	+1	-1	+1	+1	-1
9	+1	+1	-1	+1	+1	-1	+1	-1	-1	-1
10	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0
12	+1	+1	-1	+1	-1	-1	-1	+1	+1	+1
13	-1	+1	+1	+1	-1	+1	+1	-1	+1	-1
14	-1	+1	+1	-1	+1	-1	-1	-1	+1	+1
15	-1	-1	+1	+1	+1	-1	+1	+1	-1	+1

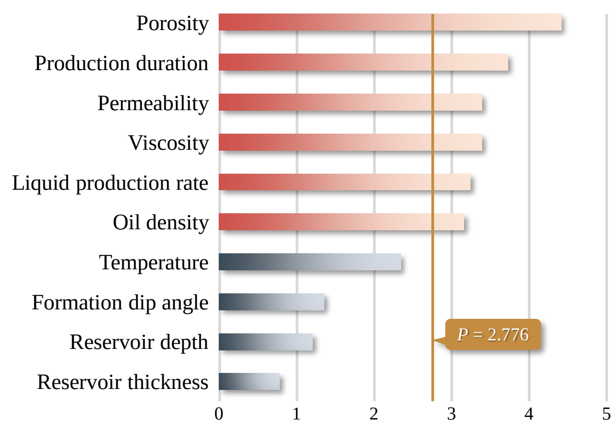

Fig. 2. Results of variance analysis.

between-group differences are significant, indicating sensitivity, can be made. The critical value can be determined based on the significance level and the degrees of freedom. Fig. 2 presents the results of variance analysis. It can be observed that permeability, oil density, crude oil viscosity, porosity, liquid production rate, and production duration are the most sensitive parameters to the formation pressure deficit. Consequently, we selected these parameters as the indicators for the single-well pressure depletion evaluation method.

3. Pressure depletion surrogate model

Considering the reservoir characteristics of the target well group, we divided the six selected indexes into multiple levels within a reasonable range to simulate different reservoir and development conditions. Following the principles of orthogonal experimentation, we designed different experimental schemes and conducted reservoir numerical simulations to obtain the formation pressure depletion. Finally, through the utilization of multiple linear regression, we constructed a surrogate model to characterize the corresponding relationships between each parameter and the drop in formation pressure. Orthogonal experimentation allows the simultaneous consideration of multiple factors based on fewer experimental runs. By adopting a stratified approach in the design process, different levels of multiple factors can be combined, avoiding the adverse effects of interactions between factors on the experimental results. Based on the principles of orthogonal experimentation, we designed 25 experimental schemes for six parameters at five levels each. Using the established reservoir numerical simulation model, we performed corresponding parameter modifications and conducted reservoir numerical simulations. We subsequently employed linear regression to establish the correlation between parameter values and simulation results, leading to the derivation of the surrogate model. The rapid evaluation expression for the model is as follows:

$$\begin{aligned}\Delta P = 1.1659 + 0.2062K - 0.0046\rho + 0.3022\mu \\ - 22.9355\phi - 0.0094v + 1.0104t\end{aligned} \tag{1}$$

where ΔP represents pressure drop, K represents permeability, ρ represents crude oil density, μ represents crude oil viscosity, ϕ represents reservoir porosity, v represents liquid production rate, and t represents production duration.

In order to validate the accuracy of the pressure depletion function, the parameters of the 25 numerical simulation models were input into the surrogate models to calculate the reservoir pressure drop values. Fig. 3 illustrates the comparison between

Table 3. Comparison of numerical simulation and surrogate model calculations.

Case	Permeability (mD)	Oil density (kg/m^3)	Viscosity (cp)	Porosity (%)	Liquid production rate (m^3/d)	Production duration (years)	Simulated pressure drop (MPa)	Calculated pressure drop (MPa)	Error (MPa)	Fitting Rate (%)
26	20	830	4.2	13	30	3	9.575	9.126	0.449	95.31
27	8	780	3.4	15	20	5	9.590	8.454	1.136	88.15
28	20	880	1.7	15	25	4	9.754	9.176	0.578	94.07
29	16	730	4.2	15	15	5	9.823	9.764	0.059	99.40

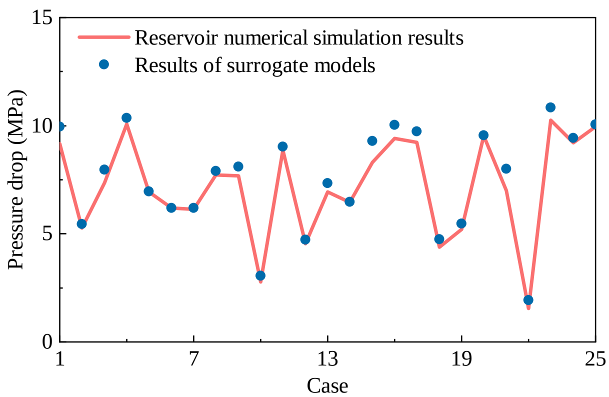

Fig. 3. Comparison of reservoir numerical simulation results and surrogate model calculations.

the numerical simulation results and the calculated results from the pressure drop function. The multiple linear regression results show a good fit, indicating that the surrogate models effectively characterize the corresponding relationships between various sensitive parameters and the pressure drop under different value conditions. Furthermore, we designed four sets of experimental schemes to conduct numerical simulations and obtain pressure drop values. By comparing the calculated pressure drop values with the numerical simulation results (Table 3), it can be seen that the pressure drop values calculated using the surrogate models are close to those obtained from numerical simulations, with a fitting rate above 85% and within an acceptable range of error. Therefore, using the surrogate models to calculate the reservoir pressure drop values provides a reliable means to assess the extent of reservoir pressure depletion.

4. Applications

The established method was applied to typical well groups in the WX tight oil reservoir in the Xinjiang oilfield, China. The WX reservoir is mainly composed of sandy gravel reservoirs, with a predominant porosity ranging from 10% to 15%, averaging 13.5%. Here, the reservoir permeability varies from tight to low-permeability and is mostly less than 5 mD, with an average of 4.3 mD. High-pressure reservoirs are rare, with pressure coefficients usually ranging from 0.8 to 1.06 and averaging 1.00. In the early stages of development, hydraulic fracturing was performed on horizontal wells in the reservoir, and a depletion development strategy was adopted. Due to the poor reservoir properties and low reservoir energy, the contradiction between rapid decline and the difficulty in achieving stable production during development became increasingly prominent. To address the challenge of rapid and accurate evaluation of the current reservoir energy of each horizontal well and the formulation of reasonable energy supplementation plans, we reviewed the basic data of typical single wells in the WX reservoir. We then used the established method to evaluate the reservoir pressure depletion for each well (Table 4). We conducted pressure measurements on-site for wells W1 to W4. From the data, it can be observed that the calculated results have a small margin of error compared to the pressure measurement data, confirming the accuracy of the method. According to these results, it is evident that the pressure in the target well area generally remains below 80%, indicating an urgent need for an enhanced energy design to replenish the reservoir energy.

In order to address the issue of insufficient energy, we conducted field enhancement experiments, which showed preliminary success. For well W5, after a thorough analysis of the oil-water movement patterns, we performed a nanoparticle emulsion squeeze test. A total of 3,028 cubic meters of fluid was injected, and oil production was observed as early as 3 days after soaking. Initially, a 2 mm oil nozzle self-sprayed, reaching a peak daily oil increase of 7.6 tons per day. Over 55 days, the cumulative incremental oil production reached 287 tons. For well W7, following an in-depth study of the reservoir energy changes, we conducted a nitrogen-assisted enhancement test, wherein a total of 450,000 cubic meters of nitrogen and 1,440 cubic meters of water were injected. The oil production increased from 2.8 tons per day to 18.4 tons per day. Over 152 days, the cumulative oil production reached 2,339 tons (Fig. 4).

5. Conclusions

In this work, P-B design, analysis of variance and multi-linear regression were combined to formulate a rapid pressure depletion evaluation method. The following conclusions can be drawn:

1) The sensitive parameters that significantly impact reservoir pressure depletion include permeability, oil density, oil viscosity, porosity, liquid production rate, and production duration.
2) Surrogate models were established through linear regres-

Table 4. Evaluation of reservoir pressure depletion for typical single wells.

Well	Permeability (mD)	Oil density (kg/m^3)	Viscosity (cp)	Porosity (%)	Liquid production rate (m^3/d)	Production duration (years)	Calculated pressure drop (MPa)	Actual pressure drop (MPa)	Pressure maintenance level (%)	Error (MPa)
W1	40	880	2.8	8	1.1	2	4.093	4.041	74.33	-0.052
W2	24	880	2.8	8	0.1	7	7.456	7.115	55.49	-0.341
W3	8	780	0.28	13	15	5	8.004	7.96	47.96	0.044
W4	22	780	0.28	15	15	5	9.698	9.38	39.01	0.318
W5	20	880	2.8	3	1.3	1	3.588	/	66.93	/
W6	3.9	880	2.8	17	1.8	3	5.180	/	73.21	/
W7	4.3	880	2.8	14	0.2	3	5.965	/	59.61	/
W8	4	880	2.8	16	17	3	5.444	/	68.59	/
W9	1.5	840.5	0.39	10	30	5	7.858	/	71.28	/
W10	2	840.5	0.34	10	15	3	6.041	/	48.93	/

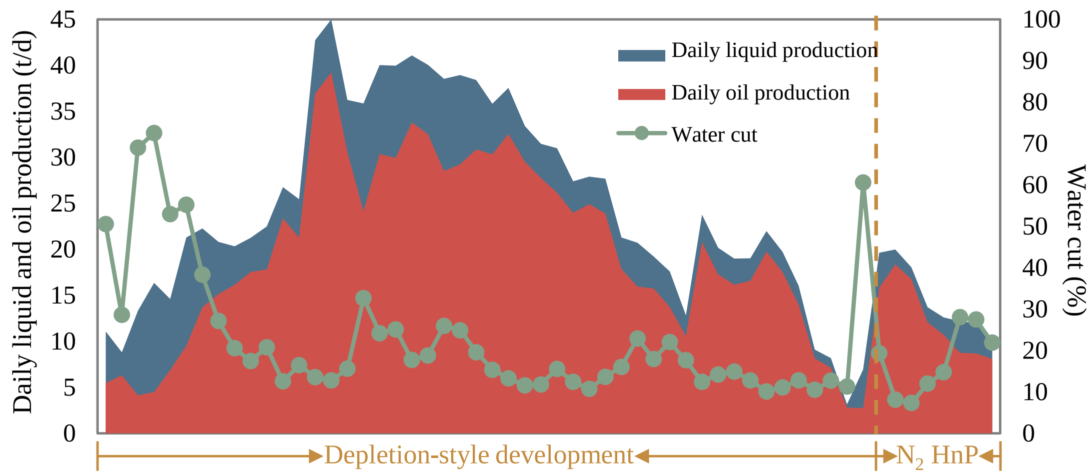

Fig. 4. Production dynamic curve before and after nitrogen-assisted enhancement for well W7.

sion, forming a single-well pressure depletion evaluation method. The reliability of this method was validated through numerical simulation results and on-site well pressure test data.

3) In typical well groups of WX tight oil reservoirs where the degree of pressure drop maintenance is generally below 90%, various methods such as nanoscale emulsion flooding and nitrogen injection can be employed to supplement reservoir energy and the improve production efficiency.

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Conflict of interest

The authors declare no competing interest.

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