

Comparisons of Models for Predicting Permeability from Nuclear Magnetic Resonance (NMR) Logging Data in Heavy Oil-bearing Reservoirs

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Abstract. Permeability prediction always faces great challenge, because it cannot be directly measured from any well logging data. The statistical methods had been widely used. The accuracy was too low to be used. The nuclear magnetic resonance (NMR) logging data was considered to be effective in permeability prediction, and many models had been proposed. However, the NMR logging data was heavily affected by the viscosity in heavy oil-bearing formations. The reliability of the permeability estimation model in heavy oil-bearing reservoirs needed to be checked to make them much valuable in field application. In this study, 24 core samples, which were drilled from the heavy oil-bearing reservoirs of the Zhujiangkou Basin in South China Sea, were applied for NMR and mercury injection capillary pressure (MICP) experimental measurements. The classical permeability prediction models of Timur-Coates model and Schlumberger Doll Research (SDR) model were calibrated. Meanwhile, the permeability prediction model based on the Swanson parameter was also established. These three models were applied in field applications to verify the reliability. Comparisons of the predicted permeabilities by using these three models with the core derived results illustrated that the Swanson based permeability model was widely used. Whereas the permeabilities estimated by using the Timur-Coates and SDR models were underestimated. The Swanson based permeability model was given priority to be recommended.

1. Introduction

Permeability is of great importance in formation evaluation, deliverability prediction and validity analysis in any types of reservoirs [1]. Good quality reservoirs always contain high permeability and deliverability. Petrophysicists and geologists tried to predict precise permeability to improve formation evaluation. However, different from the porosity, the permeability cannot be directly estimated from any well logging data [2-3]. Some statistical models were established based on core experimental data to predict permeability from other parameters, such as the porosity, the shaly content and the conventional well logging data [3-4]. These models were empirically established, and were available in specific regions. They cannot be widely used. This made the permeability prediction faced great challenge.

The NMR logging data was considered to be valuable in permeability prediction [5-7]. From the NMR logging data, many available parameters can be acquired, such as the total porosity, the effective



porosity, the pore size distribution and the permeability [8-9]. To acquire the permeability from NMR logging data, two classical models were established. These two models were named as the Timur-Coates model and SDR model, and were expressed as follows [10-11]:

$$K = \left(\frac{\varphi}{C}\right)^m \left(\frac{1-S_{wi}}{S_{wi}}\right)^n \quad (1)$$

$$K = C_1 T_{2lm}^{m_1} \varphi^{n_1} \quad (2)$$

Where, K is the permeability in mD; φ is the porosity in %; T_{2lm} is the NMR T_2 geometric mean in ms; S_{wi} is the irreducible water saturation in fraction. C , m , n , C_1 , m_1 and n_1 are the involved parameters in the models. Their values need to be first calibrated by using the NMR experimental data. Once no NMR experimental data was available, their values were defined as 10, 4, 2, 10, 4 and 2, separately.

The parameters of φ and T_{2lm} can be directly acquired from the NMR data, the S_{wi} can also be accurately predicted from NMR data once the reasonable $T_{2cutoff}$ is determined [12]. Hence, the permeability can be predicted from NMR data once the values of the involved input parameters were firstly calibrated.

2. Establishment of the Classical Models to Predict Permeability from NMR Data

2.1. Laboratory NMR Experiments

Although the default parameters in equations 1 and 2 can be fixed determined, to make the predicted permeability was much closed to the true value in our target heavy oil-bearing formation in the Zhujiangkou Basin in South China Sea, 24 typical core samples were drilled from the target formations to apply laboratory NMR and MICP experimental measurements. The physical properties of the core samples and the corresponding experimental results were listed in table 1.

Table 1. The Physical Properties of the Core Samples and the Experimental Results

Core No.	Depth	Porosity	Permeability	Swi	T_{2lm}
	m	v/v	mD	%	ms
1	1333.35	0.23	19.15	66.23	12.19
2	1336.80	0.25	65.49	66.98	12.99
3	1339.35	0.20	17.06	85.95	9.90
4	1354.60	0.25	344.52	97.41	14.87
5	1357.60	0.36	932.71	22.57	24.00
6	1359.10	0.27	68.97	52.57	17.63
7	1363.10	0.27	86.76	52.36	20.79
8	1374.10	0.23	37.44	88.39	13.13
9	1378.35	0.33	457.13	15.90	26.51
10	1385.60	0.30	298.08	29.84	24.57
11	1387.10	0.28	100.99	29.84	27.71
12	1388.85	0.25	87.09	30.93	32.05
13	1393.60	0.21	15.73	61.61	17.18
14	1396.60	0.23	19.63	59.97	22.82
15	1429.90	0.28	2588.71	13.86	21.88
16	1434.35	0.27	154.12	55.13	15.09
17	1436.35	0.33	581.27	35.85	32.89
18	1439.25	0.25	90.88	99.89	11.20
19	1462.10	0.23	24.20	63.93	12.57
20	1467.10	0.22	48.63	67.78	15.89
21	1474.66	0.24	76.77	72.07	44.12
22	1476.60	0.31	573.63	53.99	29.76
23	1479.15	0.26	262.57	95.32	30.95
24	1484.35	0.27	291.69	39.33	42.32

2.2. Calibration of the Involved Model Parameters

By using the NMR experimental results, equations 1 and 2 were calibrated, the involved parameters of C , m , n , C_1 , m_1 and n_1 were determined, and these two models were expressed as follows:

$$K = \left(\frac{\phi}{14.823}\right)^{8.395} \times \left(\frac{1-S_{wi}}{S_{wi}}\right)^{-0.064} \quad (3)$$

$$K = 1389952 \times \left(\frac{\phi}{100}\right)^{7.577} \times T_{2lm}^{0.271} \quad (4)$$

Equations 3 and 4 illustrated that the involved input parameters in the classical permeability prediction models in our target formations deviated the empirical values, especially the value of C_1 , it was heavily different from the classical values. In addition, the NMR experimental results illustrated that the permeability was negative associated to the ratio of the free fluid volume and bound water content (the value of n lower than 0.0). This might cause by the experimental errors. In the NMR experiment, high centrifugal rotational speed of 9000 round/min was used. The pore structure might be broken, and some free water was through away, this made the determined irreducible water lower than the true value.

2.3. Determination of the Involved Input Parameters

To use equations 3 and 4 to predict permeability from NMR logging data in field applications. The values of ϕ , T_{2lm} and S_{wi} should be first determined. Although the NMR data can directly offer porosity and T_{2lm} , the results were heavily affected by the viscosity of occupied heavy oil in the pore space, this made the directly extracted porosity lower than true values (figure 1). In this figure, it can be identified that the porosities directly estimated from the NMR logging (TCMR) were lower than the core derived results (PORC) and predicted porosities from conventional well logging (PHIT) in formations with resistivity higher than 1.2 Ω .m. In the other water saturated intervals, these three types of porosities were coincided well with each other. Meanwhile, the S_{wi} prediction is also a difficulty at present. The fixed $T_{2cutoff}$ value was commonly used, and the inaccurate results were acquired [12].

To remove the effect of saturated heavy oil to the parameters acquired from NMR logging data, a proposed technique was used [13]. Based on the proposed technique, the NMR T_2 spectra with oil saturated were corrected as fully water saturated condition. From the corrected NMR T_2 distributions, NMR porosity and T_{2lm} were acquired. Meanwhile, technique of predicting various $T_{2cutoff}$ from NMR T_2 distribution based on the morphological difference was also used in this research to calculate reasonable S_{wi} for permeability prediction [14].

3. Permeability Prediction Based on Formation Pore Structure Characterization

3.1. The Mercury Injection Capillary Pressure (MICP) Curve

Generally, the MICP curve is always displayed in semi-log coordinates, mercury injection saturation (S_{Hg}) is displayed in linear coordinate in X-axis, and mercury injection pressure (P_c) is displayed in logarithmic coordinate in Y-axis [11]. If the MICP curve is displayed in log-log coordinates, it displays as a hyperbolic curve [14]. This hyperbolic curve can be expressed by equation 5:

$$\log_{10}\left(\frac{P_c}{P_d}\right) \times \log_{10}\left(\frac{S_{Hg}}{S_{Hg\infty}}\right) = C \quad (5)$$

Where, P_d is the threshold pressure in MPa; $S_{Hg\infty}$ is the non-wetting phase saturation under infinite mercury injection pressure in % and C is the geometric factor.

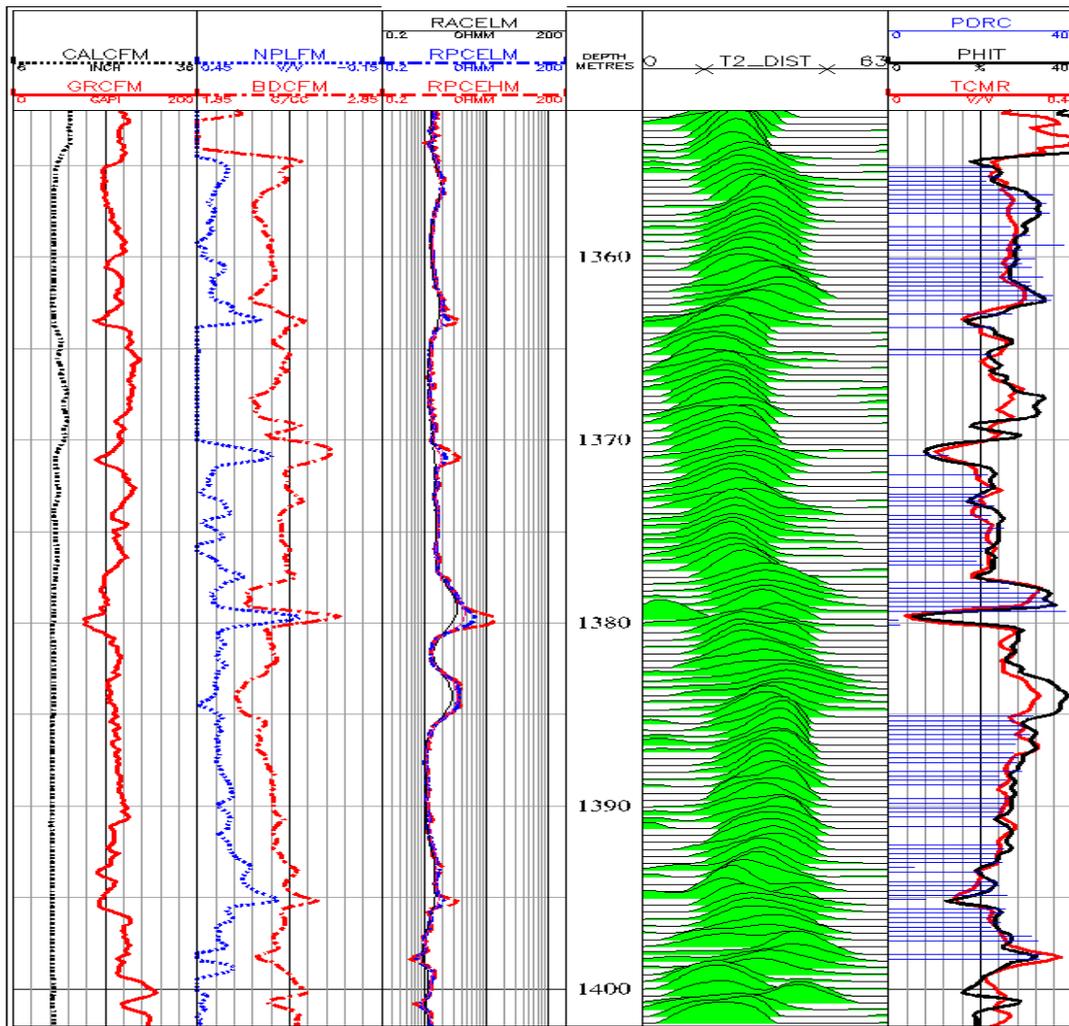


Figure 1. Effect of Saturated Heavy Oil to the NMR T_2 Spectra and NMR Porosity

Based on the analysis of the MICP curves acquired from different types of core samples drilled from common formations, low permeability and tight sandstones, separately, many researchers found that the inflection points of capillary pressure curves were well associated with air permeabilities [14-15]. The physical significance of the inflection point is the mercury injection saturation threshold in the main pore system which primarily controls the fluid flow. If S_{Hg} is displayed in X-axis and the ratio of S_{Hg} and P_c is in Y-axis, the inflection point is located at the apex (figure 2), it was called as the

Swanson parameter, and expressed as $(\frac{S_{Hg}}{P_c})_{max}$. the relationship between the Swanson parameter and permeability can be expressed as follows:

$$K = A \times (\frac{S_{Hg}}{P_c})_{max}^B \tag{6}$$

Where, $(\frac{S_{Hg}}{P_c})_{max}$ is the Swanson parameter; A and B are the statistical model parameters. For different types of reservoirs, the values of A and B are various, and their values can be calibrated by using the data sets of mercury injection experiment of core samples.

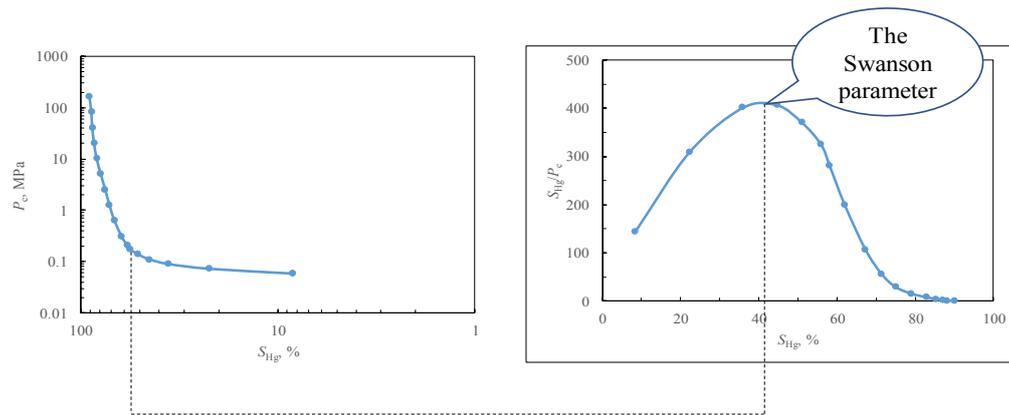


Figure 2. Diagram of Obtaining the Swanson Parameter from MICP Data

3.2. Establishment of Permeability Prediction Based on the Swanson Parameter

Based on above analysis, the MICP curves of 24 core samples in our target formations were reused, the Swanson parameter of every core sample was extracted. We tried to establish the relationship between the Swanson parameter and rock physical properties. Finally, we found that the Swanson parameter was heavily associated with the rock physical parameter of $\sqrt{\frac{K}{\phi}}$. Hence, we changed the expression of equation 6, and established a permeability prediction model displayed in figure 3 and expressed as equation 7.

$$\sqrt{\frac{K}{\phi}} = 0.0089 \times \left(\frac{S_{Hg}}{P_c}\right)_{\max} + 0.1029, \quad R^2 = 0.928 \quad (7)$$

Figure 3 illustrated that the Swanson parameter was heavily associated with the rock physical parameter. Based on this equation, once the Swanson parameter and the porosity were first predicted, the permeability can be accurately determined.

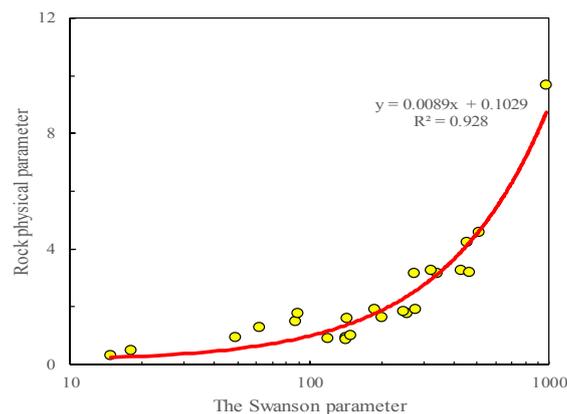


Figure 3. The Relationship between the Swanson Parameter Versus Rock Physical Parameter

4. Comparison of Permeability Prediction Models in Heavy Oil-bearing Reservoirs

To verify the reliability of these three permeability prediction models, we applied them in field applications to process the acquired NMR logging data. The proposed techniques were first used to correct the effect of heavy oil to NMR T_2 spectra [13-14]. Meanwhile, to use equation 7 to consecutively predict permeability, the method of constructing pseudo capillary pressure curves from

NMR logging data was also used [17]. The consecutive pseudo capillary pressure curves and the Swanson parameters were acquired in the intervals with which the NMR logging data was acquired. The permeability estimation models expressed as equations 3, 4 and 7 were used to predict permeabilities. We compared these predicted permeabilities with those of the core derived results, and displayed in figure 4. In the fourth track of figure 4, we compared the corrected porosity (PHIT) from NMR logging data with the core derived porosities (CPOR), good consistency of these two porosities meant well correction of the NMR data. T2_DIST displayed in the fifth track was the corrected NMR T₂ distribution. In the sixth track, the extracted irreducible water saturations (SWICAL) were compared with the core derived results (CSWI). Good consistency of calculated porosity and Swi with the core derived results meant that not any errors would be introduced in permeability prediction. In the last three tracks, we compared the predicted permeabilities from the established models with the core derived results. The results illustrated that the predicted permeability by using the Swanson parameter based model (PERMSWAN) were coincided with the core derived results (CPERM) very well. The estimated permeabilities by using the SDR model (KSDR) and Timur-Coates model (KTIM) were also coincided with the core derived results very well in the majority of intervals. However, in heavy oil-bearing formations (resistivity higher than 1.2 Ω.m), the estimated permeabilities were underestimated; whereas the Swanson parameter based on model was well used.

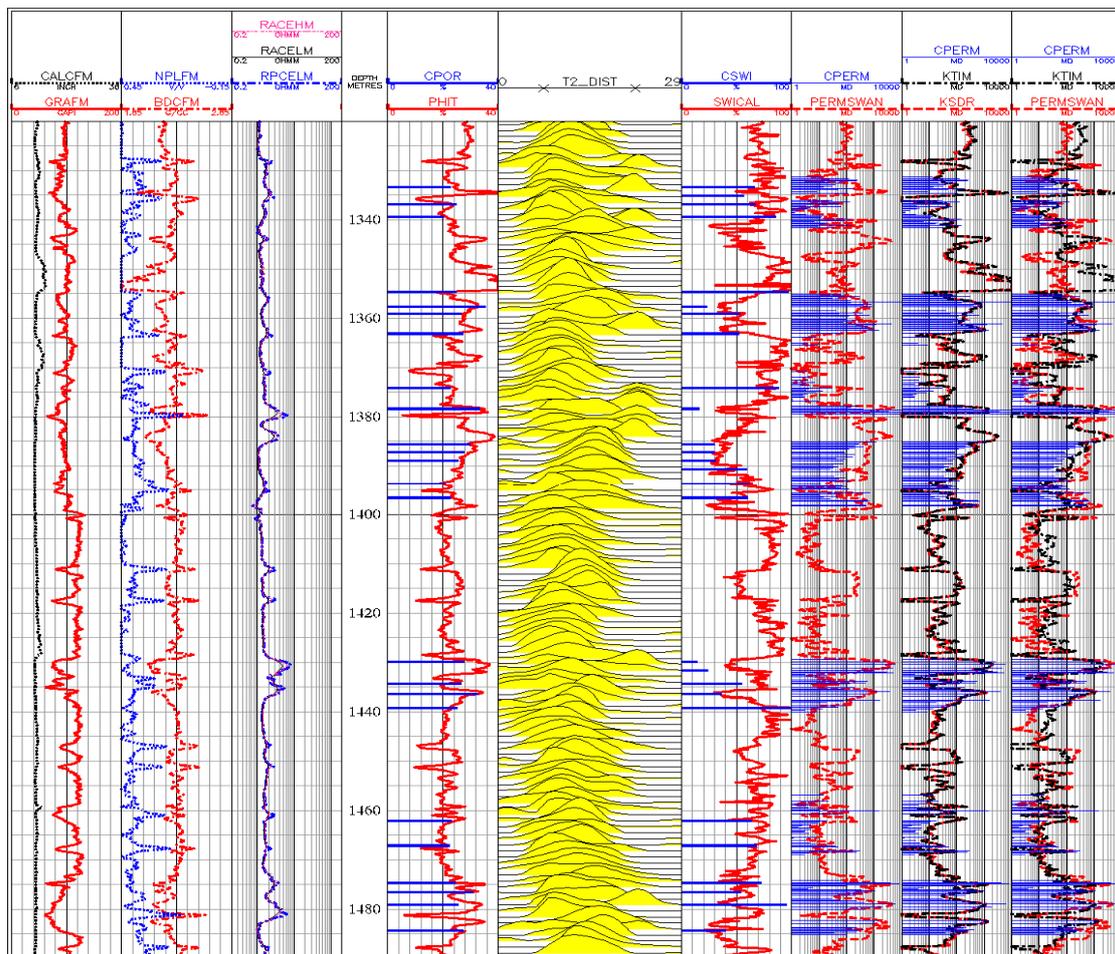


Figure 4. Comparisons of Predicted Permeabilities from Three Models by Using the NMR Logging Data with the Core Derived Results

To verify the wide application of the permeability prediction models, we extended them into the adjacent regions to predict permeability. Figure 5 displayed the comparisons of the predicted permeabilities with the core derived results. This comparison illustrated that the permeability predicted by using the Swanson based model was much reasonable. The Swanson based permeability model was

much valuable than those of the SDR and Timur-Coates models. Hence, in our target heavy oil-bearing formation, the Swanson based permeability model was given priority to recommend, it can be well used.

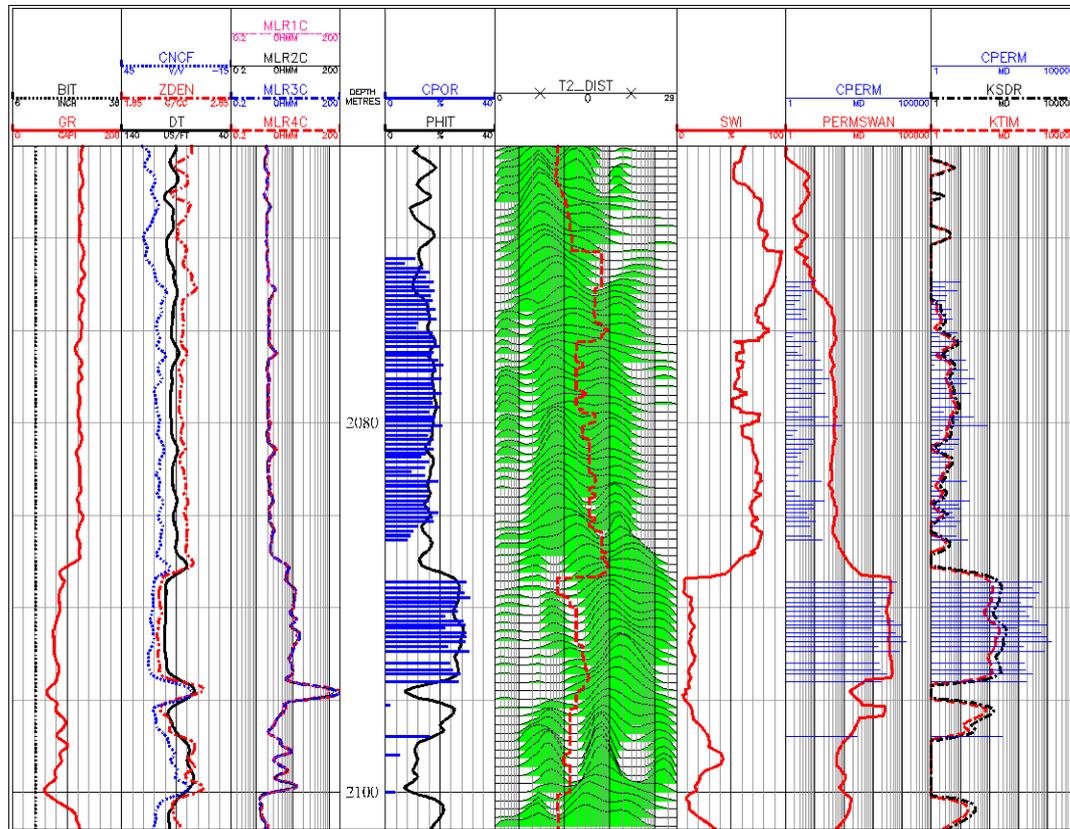


Figure 5. The Reliability Analysis and Comparisons of the Permeability Estimated Models

5. Conclusions

Permeability is an important input parameter in formation estimation and deliverability prediction, not any conventional well logging data can be directly used to calculate permeability. The NMR logging data was advantage in permeability prediction. The SDR and Timur-Coates models were two classical NMR based permeability models. The Swanson based model can be well used to predict permeability after formation pore structure was first characterized.

Based on the laboratory NMR and MICP experiments of 24 core samples, the classical SDR and Timur-Coates models were calibrated, and an improved Swanson parameter based model was also established. These models were applied in field applications in the target and adjacent regions to predict permeabilities. Comparisons of predicted permeabilities with core derived results illustrated that the Swanson parameter based model was optimal. It can be well used to predict permeability in our target heavy oil-bearing formation.

6. Reference

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