Research Article

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Identification and logging evaluation of poor reservoirs in X Oilfield

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Abstract: The reservoirs of X Oilfield have the characteristics of fine lithology particles, strong pore structure heterogeneity, and high argillaceous reservoirs and thin layers are generally developed. Conventional logging interpretation cannot make a fine evaluation, which results in serious discrepancies between the interpretation results of some reservoirs and actual production performance, and reserves are underestimated. Improving poor reservoir identification and logging evaluation accuracy is of great significance to oilfield development. The flow zone indicator (FZI) is used to classify the reservoirs into three types, I, II, and III, and the classification results are combined to establish a reservoir type identification chart based on logging curves; the resolution matching method and the deconvolution method are used to improve the accuracy of thin-layer recognition. Finally, the logging interpretation model is reestablished. Logging evaluations were conducted on 20 wells in X oilfield, and Y core wells were used for verification. The application results show that this method can effectively improve the identification accuracy of thin oilfields and high argillaceous reservoirs; the results of fine logging interpretation of poor reservoirs are consistent with core analysis conclusions and actual production conditions, which are typical of the successful application of poor reservoir technology.

Keywords: reservoir classification, FZI method, reservoir type identification chart, resolution matching method, deconvolution method

1 Introduction

X Oilfield is located in Huizhou Sag in the northern depression zone of the Pearl River Mouth Basin, with an average water depth of about 100 m within the oilfield. Combining geological data, logging data, and core analysis data, X Oilfield has fine lithology particles, strong pore structure heterogeneity, and high argillaceous reservoirs and thin layers are generally developed. According to the analysis of rock thin slices, X-ray diffraction, core description, and logging data, the reservoir lithology of X Oilfield is mainly fine sandstone, followed by siltstone and coarse sandstone. The main mineral components of the reservoir are quartz, feldspar, and a small amount of calcite. In the vertical direction, the reservoir is separated from mudstone; horizontally, the sand layers are distributed stably with good stratification. The reservoir space is dominated by sandstone pores. The physical property analysis data show that the X oilfield reservoir is a medium-high porosity and high-permeability reservoir. The core porosity is concentrated between 18 and 28% and the permeability is concentrated between 100 and 5,000 mD ($1 \text{ mD} = 10^{-3} \mu\text{m}^2$). The porosity and permeability distribution of different lithologies can be seen from the porosity and permeability distribution of different lithologies. Fine sandstone has the best physical properties, followed by siltstone and coarse sandstone; the permeability of siltstone and coarse sandstone is significantly lower than permeability of fine sandstone. Physical properties are mainly controlled by lithology, and reservoirs need to be classified and processed. Based on the core data, the oil-bearing grades of X Oilfield are mainly oil spots, and the oil-bearing grades of fine sandstone, siltstone, and coarse sandstone are higher. Lithology affects the oil and gas content of the block. Comprehensive analysis of core data, the logging data, shows that in fine sandstone reservoirs, the better the rock properties, physical properties, and oil and gas properties, the more obvious the difference between the resistivity of the oil layer and the resistivity of adjacent water layers. Through the above analysis, the lithology, physical

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properties, and oil-bearing properties in the reservoir are both inherently connected and mutually restrictive, lithology playing a leading role; the electrical properties of the reservoir are a comprehensive reflection of lithology, physical properties, and oil-bearing properties. The physical properties and oil-bearing properties of fine sandstone reservoirs are the best; they are mainly represented by medium-high porosity and high-permeability reservoirs; their oil-bearing grades are rich in oil and oil spots. In the same type of reservoir, the purer the lithology, the better the physical properties, the higher the electrical properties, the better the oiliness. Therefore, different reservoirs should be classified and processed. First, on the basis of classification, the logging curve identification template of the reservoir must be established; second, the logging curves of poor reservoirs should be processed; finally, a classified logging evaluation model should be established.

The choice of reservoir classification method is particularly important. At present, the commonly used methods of reservoir classification include flow zone indicator (FZI), mercury intrusion experiment curve analysis method, and nuclear magnetic data analysis method [1–3]. The FZI method has been used to classify reservoirs in the oil fields of the Pearl River Mouth Basin, Lufeng 13-2 oil field, and clastic rock formations; they all achieved good results [4–7]. The FZI method only needs core porosity and permeability data to complete the work of reservoir classification [8]. Moreover, simple reservoir parameter calculation models can be established through classification results, especially the establishment of permeability models; the FZI method is very suitable for wells with less data [9–11]. The study took Pakistan's Sawan gas field as an example, using logging and 3D seismic attributes to classify reservoir facies for reservoir evaluation and to guide further development of the oilfield. The research presents an integrated study of well log facies analysis and 3D seismic attribute analysis for sand-shale facies distribution and their paleoenvironments in the reservoir interval of Sawan gas field [12]. This method makes full use of the advantages of reservoir logging attributes and seismic attributes, which can complete reservoir evaluation efficiently and accurately. The research proposed a novel approach to predict missing shear sonic log responses more precisely and accurately using similarity patterns of various wells with similar geophysical properties [13]. In this study, they only focused on the prediction of missing shear sonic logging, but this method can also be extended to predict reservoir porosity, permeability, and water saturation. The research focused on developing a rock physics model and template to diagnose a consolidated sand reservoir. A rock physics modeling and integrated petrophysical evaluation methods are employed

to calculate the reservoir properties of Lower Goru sand reservoir, Pakistan [14]. Their study focuses on finding porosity from the seismically derived impedance. Hence, the study uses the best second-order polynomial regression to relate the porosity with a measured impedance that is generated to distinguish the sand from shale in a single rock physics cross plot. The proposed model and calibrated RPT can be used to enhance seismic reservoir properties. The reliability of the model is helpful for the formation evaluation, reservoir characterization, and prospect evaluation across different fields of the Lower Goru sand reservoir. The predicted model can further be utilized to estimate porosity from the seismically derived impedance worldwide which has the same geological trends and reservoir distribution [15]. The research used the integration of logging data, core data, and 3D seismic attributes to identify a channel in the Hangjinqi area in the northern Ordos Basin of China [16]. The research accurately identified the presence of hydrocarbons in the Missakeswal area by developing a computer program for the Zoeppritz energy distribution equation and its various approximations [17]. These methods provide new ideas for the next step of the study of reservoir classification methods. The research integrated seismic attribute analysis, 2D modeling, and petrophysical experiments, based on this analysis, and finally, successfully predicted the oil and gas potential of Pakistan's Missakeswal area [18]. The research used velocity modeling and interpolation to analyze the Balkasar area to predict the seismic interpretation results of the Indus River Basin and achieved very good results [19,20]. The successful application of these methods in other fields and other regions provides new options for predicting key parameters such as porosity, permeability, and water saturation.

However, because the study area is all old wells with a long history, there are only the most conventional logging curves and core experiment data, and the logging attribute information is not comprehensive. There is a lack of 3D seismic data, nuclear magnetic resonance experimental data, mercury intrusion experimental data, and vertical and horizontal wave acoustic data. So many of the new methods mentioned above cannot be implemented in the study area. Considering that the FZI method only requires core pore permeability data and has achieved good classification results in similar clastic reservoirs, the FZI method was finally selected in this research. The FZI method is widely used in the classification of domestic oilfields due to its simplicity and ease of use. However, after the classification results were obtained, they did not continue to study how to accurately identify the reservoir categories based on the classification results, nor did they combine the classification results with logging curves.

Therefore, the rapid and accurate identification of reservoir categories is still a difficulty. In the past, due to technical limitations and other reasons, the vertical resolution of the logging curves measured was low, but the cost of retesting was too high. Usually, some mathematical methods were used to process the logging curves. The research used the deconvolution method to process the logging curves to effectively identify thin interbeds [21,22]. The research used resolution matching methods to improve the vertical resolution of the logging curves; research has proved that the resolution matching method is more suitable for processing resistivity curves [23,24]. But it is rare to combine two methods to process different logging curves in the processing of the same block curve. Conventional logging interpretation uses multi-mineral models to quickly and efficiently interpret and process, which will make it difficult to interpret some poor reservoirs accurately. The specific performance is that the calculation results of porosity, permeability, and oil saturation are lower than the actual situation; some oil layers are mistakenly interpreted as water layers or even dry layers. Therefore, it is necessary to make separate and fine interpretations for different types of poor reservoirs.

This paper proposes a comprehensive and systematic logging interpretation program for offshore oilfield X oilfield. Through the sensitivity analysis of the logging curve, the logging parameters that are higher for poorer reservoirs are selected [25]. The FZI method is used to classify reservoirs, and based on the classification results combined with natural gamma ray (GR), density (DEN), and neutron (CNL) logging curves, a chart and discriminant formula that can accurately identify the reservoir category based on the logging curves are established. Consider the type of III as poor reservoirs in this study area. Comprehensive analysis of geological data, logging data, and core data shows that the main reasons for the inaccurate logging interpretation of poor reservoirs in this study area are the low vertical resolution of logging curves and high GR characteristics in some thin sections. The resolution matching method and the deconvolution method are used to improve the longitudinal resolution of the logging curve, and separate models are established according to the situation to calculate the shale content, porosity, permeability, and saturation of the reservoir. In this paper, 20 wells in the study area used new data processing methods and interpretation schemes for logging evaluation, and core well Y was used to verify the practicability and accuracy of this scheme. The process of this new logging evaluation plan is shown in Figure 1.

2 Identification of poor reservoirs

In the work of logging evaluation, the most important thing is to identify reservoirs. High-quality reservoirs can be identified simply based on the amplitude change of the logging curve. However, there is currently no qualitative good method for identifying poor reservoirs.

2.1 Reservoir classification based on flow units

The flow unit is proposed by Hearn, which refers to a reservoir zone that is continuous in the horizontal and vertical directions and has similar permeability, porosity, and bedding characteristics [26]. The flow unit is a relative concept, from the macro to the micro level; the rock characteristics that affect the fluid flow and the fluid flow characteristics similar to the reservoir rock mass can be called the flow unit. The definition of flow unit provides a more quantitative definition for the division and mapping of sandstone reservoirs, and at the same time, provides an ideal basis for the numerical simulation of reservoir dynamics. With the deepening of knowledge and understanding of the flow unit, many different definitions of

Figure 1: Flow chart of logging evaluation.

this concept have gradually emerged. Research on reservoir flow units is of great significance to quantitatively characterize reservoir heterogeneity, improve logging interpretation accuracy, and understand remaining oil distribution. The research proposed a new method of quantitatively dividing flow units – the FZI method [27]. FZI is a parameter that comprehensively reflects the pore structure and mineral characteristics; this method is to study the complex changes of pore geometry in different lithofacies by processing core data, so it can better classify the reservoir.

2.1.1 Principles of flow stratification index (FZI) method

The same porosity often corresponds to multiple permeability in the reservoir, which indicates that there are multiple flow units. Combining Poiseuille's law and Darcy's law, assuming that the porous medium is composed of many straight capillaries, Kozeny proposed the relationship between permeability, effective porosity, and capillary radius:

$$K = \frac{r^2}{8} \varphi. \quad (1)$$

Carmen introduced the parameters of curvature, shape factor, and particle-specific surface area, improved the Kozeny formula, and proposed a generalized Kozeny-Carmen formula, namely:

$$K = \frac{1}{F_s \tau^2 S_{gv}^2} \frac{\varphi^3}{(1 - \varphi)^2}, \quad (2)$$

where K is permeability, μm^2 ; φ is effective porosity, %; r is capillary radius, μm ; F_s is shape factor; τ is tortuosity; S_{gv} is particle-specific surface area, μm^{-1} .

In practical applications, the Kozeny-Carmen formula is suitable for man-made homogeneous porous media, because the value of $F_s \tau^2 S_{gv}^2$ is almost unchanged in this medium, while in rock media with strong heterogeneity and complex pore structure, the value of $F_s \tau^2 S_{gv}^2$ changes greatly, and the Kozeny-Carmen formula is no longer applicable. Therefore, Amaefule introduced the concept of FZI and discussed the definition and classification of flow units. Based on the Kozeny-Carmen formula, they proposed the FZI method. The purpose is to use core data to establish different correspondences between permeability and porosity in the flow unit. Dividing both sides of the equation (2) by the porosity and extract the square, and converts the permeability unit from D ($1\text{D} = 1\mu\text{m}^2$) to mD to obtain formula (3). According to formula (3), FZI, RQI, and φ_z are defined.

$$0.0314 \sqrt{\frac{K}{\varphi}} = \frac{1}{F_s \tau S_{gv}} \frac{\varphi}{(1 - \varphi)}, \quad (3)$$

$$\text{FZI} = \frac{1}{F_s \tau S_{gv}}, \quad (4)$$

$$\text{RQI} = 0.0314 \sqrt{\frac{K}{\varphi}}, \quad (5)$$

$$\varphi_z = \frac{\varphi}{(1 - \varphi)}, \quad (6)$$

where 0.0314 is the permeability unit conversion factor; K is the permeability, $10^{-3}\mu\text{m}^2$; FZI is the flow zone indicator; RQI is the reservoir quality factor; φ_z is the standardized porosity index. Substituting formula (4)–(6) into formula (3), FZI can be expressed as:

$$\text{FZI} = \frac{\text{RQI}}{\varphi_z}. \quad (7)$$

Take the logarithm of both sides at the same time to get:

$$\lg(\text{RQI}) = \lg(\text{FZI}) + \lg(\varphi_z). \quad (8)$$

Equation (8) shows that in the double logarithmic intersection of RQI and φ_z , the sample points with the same FZI value are all distributed on the same straight line with a slope of 1 and they have similar pore-throat structure characteristics and belong to the same type of flow unit; the points with different FZI values are distributed on parallel lines and belong to different flow units [27].

Due to the existence of random errors, the FZI of the same flow unit is normally distributed around its true mean, which is a line segment on the FZI cumulative probability graph. When there are multiple heterogeneous flow units, the overall FZI distribution is the superposition of several normal distributions, so it appears as multiple line segments on the probability map.

2.2 Practical application and result verification of FZI method

The FZI method is used to process the core porosity and permeability data of the X oilfield, complete the classification of the reservoir, and verify the reliability of the results, and finally, determine the classification standard.

2.2.1 Practical application

The intersection of porosity and permeability of the core data of several core wells in the offshore oilfield X oilfield

(Figure 2) shows that the porosity and permeability are poorly correlated, and it is difficult to directly classify the reservoir type. Use FZI method for reservoir classification and calculate the RQI, FZI, and ϕ_z of the samples in Figure 2 through equations (4)–(6). As shown in Figure 3, according to the FZI cumulative probability curve, three types of flow units can be divided (The classification criteria are shown in Table 1). Make a double logarithmic intersection graph of RQI and ϕ_z (Figure 4); according to different FZI, three types of flow units are divided, and correspondingly, the reservoirs are divided into three types.

Generally speaking, reservoirs with finer particles and that are poorly sorted have higher particle surface area and tortuosity; their FZI values are lower. The reservoirs with relatively pure particles, coarse particles, and being well-sorted have lower particle surface area, shape factor, and tortuosity; their FZI values are relatively high; so this paper considers the types of reservoirs with low FZI values to be poor reservoirs.

The research pointed out that FZI is closely related to the pore structure characteristics of rocks. If the FZI value is close, the pore structure characteristics of the rock are similar, so that the porosity and permeability show a good correlation [27]. Therefore, after dividing the flow unit according to the value of the FZI, the porosity can be used to accurately classify and evaluate the permeability [28].

2.3 Log recognition of reservoir classification results

Read the GR, DEN, and CNL (%) values corresponding to the core data points and construct the intersection graph

Figure 2: Intersection diagram of porosity and permeability in the study area.

Figure 3: Cumulative probability distribution chart of flow unit index.

of ΔGR (normalized GR) and ΔD (normalized difference of density-neutrons) based on the results of the above reservoir classification, so as to make a chart (Figure 5) and discriminant formula (Table 2) for classification of reservoir types according to logging curves. The results prove that this method can quickly, efficiently, and simply identify reservoir types quantitatively based on logging curves.

$$\Delta GR = (GR - GR_{\min}) / GR_{\max} - GR_{\min}, \quad (9)$$

$$D1 = (DEN - 1.95) / (2.95 - 1.95), \quad (10)$$

$$D2 = (CNL - 45) / (-15 - 45), \quad (11)$$

$$\Delta D = D1 - D2. \quad (12)$$

To sum up, first, the X oilfield is divided into three types of reservoirs by the FZI method. The type III reservoir is defined as poor reservoir, using the cumulative probability distribution map of the flow unit index to verify the accuracy of the classification results. Second, construct the intersection chart of ΔGR and ΔD based on the classification results and accurately and easily identify the reservoir category through logging curves. Finally, formulate the discriminant formula and the reservoir characteristics' description of the reservoir category based on the logging curve identification chart (Table 2). Through

Table 1: Reservoir classification standard

Flow unit type	Classification standard
I	$7 \leq FZI$
II	$1 \leq FZI < 7$
III	$FZI < 1$

Figure 4: RQI and ϕ_z double logarithmic intersection graph.

Figure 5: Gamma-neutron density normalized difference in intersection plot.

the analysis of geological data and logging interpretation data, the results show that poor reservoirs are reflected in the logging curve as higher gamma, lower resistivity, and thin layers in some well sections. The above methods can effectively identify poor reservoirs.

3 Cause analysis and data processing of poor reservoirs

First, analyze the intervals with inaccurate log evaluation results by conventional methods to find out the reasons why it is difficult to accurately evaluate them, and second, carry out targeted treatment according to the existing problems.

3.1 Analysis of difficulties in log interpretation of poor reservoir

After completing the identification of poor reservoirs, the most important task is to study the difficulties of logging evaluation of poor reservoirs in X oilfield; it is necessary to find the reasons why it is difficult to accurately explain porosity, water saturation, and permeability using conventional multi-mineral models. Selecting well Y in X Oilfield, compare the interpretation results of conventional multi-mineral models with core data and combine logging data and core data for research.

3.1.1 Thin interbeds with low logging curve resolution

For thin interbedded reservoirs, as shown in Figure 6, taking the H6A layer as an example, the description of logging data shows that the lithology of H6A section is mainly quartz sandstone, with uneven shale distribution and thin interbeds. From the logging curve, the core GR fluctuates greatly, while the logging GR is relatively smooth. The analysis believes that the natural gamma measurement value of thick layer is low, and the influence of surrounding rock and layer thickness is small, so the measured value is close to the true value of the formation. The high natural gamma measurement value of thin layers is mainly limited by the longitudinal resolution

Table 2: Logging curve identification and description of reservoir types

Flow unit type	Feature description	Recognition methods
I	GR: 60-85API, The neutron-density has a large intersection, the curve is box-shaped and smooth, and the reservoir lithology is mainly fine sandstone	$\Delta GR \leq 0.2$ $\Delta D \geq 0.1$
II	GR: 78-104API, The neutron-density has small intersections and the curve fluctuates	$0.14 < \Delta GR < 0.55$ $0.05 < \Delta D < 0.15$
III	GR > 100API, The neutron-density has a tendency to intersect, but does not. The reservoir lithology is dominated by siltstone	$\Delta GR \geq 0.5$ $\Delta D \leq 0.05$

Figure 6: Interpretation results of conventional method for layer H6A in well Y.

of the logging tool, and the surrounding rock-layer thickness has a large influence. The measured density of the thin layer is significantly higher than that of the thick layer. On the one hand, it shows that the physical properties of the thin layer may be slightly worse than that of the thick layer. On the other hand, because the thin layer is limited by the longitudinal resolution of the instrument, the surrounding rock is too much affected. The measured value of sheet resistivity is much lower than that of thick layer. There are two main reasons: First of all, the longitudinal resolution of the instrument is not high, and the measured value is greatly affected by surrounding rock and layer thickness. Second, the measured value is affected by mud invasion [29,30]. The above-mentioned dual factors have caused the measured value of sheet resistivity to be low. The characteristics of high gamma, high density, and low resistance in most thin layers compared to thick layers are mainly caused by the lower longitudinal resolution of logging tools and do not represent true formation information [31]. As shown in Figure 6, the green curve in the sixth track represents the permeability calculated by the conventional method, and the black scattered points represent the permeability obtained from the experimental analysis of the core sample. In the eighth track, the black curve represents the porosity calculated by conventional methods, and the red scattered points represent the porosity obtained from the experimental analysis of the core sample. At present, the porosity, permeability, and saturation data obtained by sampling the rock and then performing experimental analysis are considered to be the closest method to the true value of the formation. It is also the only standard to measure the accuracy of all calculation methods. From the figure, we can also see that the porosity and permeability curves calculated by the traditional method do not overlap with the core scatter data, which shows that the traditional

method is not suitable for the study area, and a new method is needed to calculate the parameter. According to the original thin-layer measurement calculated from the well data, the mud content is higher, the porosity is lower, and the oil saturation is lower. This not only underestimates the reserves and production capacity of the thin layer, but may miss the thin oil layer. Therefore, only by improving the vertical resolution of thin-bed logging data can we obtain more realistic formation porosity, permeability, and oil saturation parameter values.

3.1.2 Poor reservoir with high GR

For high GR reservoirs, as shown in Figure 7, the comprehensive interpretation results show that the porosity and permeability curves calculated by the traditional method do not overlap with the core scattered data, and the calculated porosity and permeability data are both low, which shows that the traditional method is not suitable for the study area. A new method is needed to calculate this parameter. It is very important to study the mineral composition of mud in the reservoir. The research used the SIS method under cell-based facies modeling of 50 vertical layers which was utilized successfully to model the facies distribution spatially [32]. Facies simulation showed that the study area has five lithofacies. During the research process, we analyzed the data of X-ray diffraction scanning rock samples, and the results showed that the main mineral groups of the reservoirs in the study area are quartz, calcite, feldspar, and argillaceous clay minerals. As shown in Figure 8, the argillaceous clay minerals in the H6B layer are mainly composed of oil montmorillonite, illite, kaolinite, and chlorite, of which montmorillonite and illite account for 90%.

curves, and the other is an absolute thin layer, that is, the logging curves have slight changes, but they are not sufficient for quantitative interpretation. For absolute thin layers, the longitudinal resolution of the logging curve must be improved before the next logging interpretation can be performed. In the study of improving the longitudinal resolution of its logging curves, it is necessary to develop a new type of thin-layer logging instrument on the hardware, and the software mainly uses some mathematical methods to improve the resolution of the logging curves [36,37]. Most of the wells in this study area are old wells. Due to the cost and difficulty of retesting, the software is usually selected for research. Commonly used methods to improve the longitudinal resolution of logging curves include resolution matching and deconvolution.

3.2.1 Resolution matching method

The logging curve can be regarded as a finite discrete signal in the depth domain, and the logging signal can be expressed in the frequency domain after fast Fourier transform. Analyze its frequency and amplitude spectrum: usually no matter what kind of logging signal, the low-frequency part has a large amplitude and the high-frequency part has a small amplitude [38,39]. The high-frequency signal reflects the resolution information of the logging curve to the thin layer, and of course, it may also be interference. But in general, interference has its fixed frequency and amplitude. Therefore, spectrum analysis can distinguish whether high-frequency signals are interference or reflect high-resolution information. The frequency domain filtering method has the advantages of wide application range and not needing to know the logging response function. Longitudinal resolution matching refers to matching a low-resolution curve to a high-resolution curve, and the longitudinal resolution of the high-resolution curve is consistent with that of the original high-resolution curve [40,41]. For each point on the logging curve, first determine an optimal correlation interval including the processing point. In this interval, the correlation between the high and low-resolution curve data is very good. Then, regression analysis is performed on the data of the curve in the interval, and the slope, intercept, correlation coefficient of the best fit line and the standard deviation of each point relative to the best fit line are obtained. The frequency domain matching method has a wide range of applications, and there is no need to know the response coefficient of the logging method. Frequency matching can not only match the low-resolution curve to the high-resolution, but also vice versa. Frequency domain

matching can effectively analyze and remove the interference components of logging signals. The resistivity curve processed by the frequency matching method has increased the lateral amplitude in many layers, and in some depth sections, the deep resistivity curve highlights the bimodal characteristic similar to the high-resolution shallow resistivity curve. All these are conducive to the study of thin layers.

3.2.2 Deconvolution method

From the perspective of signal processing, the logging curve can be abstractly regarded as the superposition of formation signals within the detection range of the logging tool. Taking the GR curve as an example, the GR value measured by the logging tool at a certain depth is not the true logging response value at this depth point. Affected by its upper and lower surrounding rocks, the measured value of this depth point is actually the weighted average of the measured values of its upper and lower surrounding rocks [42]. According to the relevant theory of signal analysis, the actual logging signal can be regarded as the output of an ideal formation signal after filtering through a filter system that is similar to a low-pass filter. There is a certain correspondence between frequency and formation thickness. In the frequency domain, the logging response of formations with different thicknesses corresponds to the frequency response of different frequency bands. In other words, the frequency response of different frequency bands corresponds to the logging response of different thickness formations. The frequency response of the high-frequency band corresponds to the logging response of a thin formation, and the frequency response of the low-frequency band corresponds to the logging response of a thick formation. The study of the frequency response of a certain frequency band in the logging curve spectrum is actually a depth domain research on the logging response of a certain thickness of the formation. In the thin layer and the thin interlayer, because the thin-layer information in the curve is greatly affected by the surrounding stratum, the high-frequency component reflecting the thin layer is weakened, and the ability to divide the thin layer is reduced. Therefore, the resolution information in the depth domain can be studied in the frequency domain. From the perspective of signal principle, the logging curve can be regarded as the superposition of the comprehensive response signal of the formation in the detection range of the instrument. The natural gamma logging signal can be regarded as the convolution filtering input of the formation truth value and the natural

gamma logging system response function. That is, the value of the logging curve at a certain depth point is not a reflection of the real physical quantity at that point, but the weighted average of the physical quantity at the point and the surrounding formations. Without considering noise, the logging response signal can be expressed for:

$$Y = X \times \alpha. \quad (13)$$

In the formula, X is the measured value at a certain depth point, α is the deconvolution factor, and Y is the true value of the formation; it can be seen from the formula that the deconvolution point method can eliminate the influence of factors such as upper and lower surrounding rocks and circuits, thereby improving the longitudinal resolution of logging curves and the ability of logging curves to identify thin layers.

The basic idea of the deconvolution method is to design a filter operator through which the known input signal is converted into the actual output and the given expected output signal in the sense of least square error. It is transformed into the problem of the extreme value of the error between the expected output and the actual output, and then a linear equation system is constructed to solve the deconvolution factor of the equation system. Therefore, the key of the deconvolution method is to obtain the deconvolution factor. The past researches have verified the rationality of this method for improving the ability of thin-layer recognition.

Suppose the input signal is

$$b(t) = (b(0), b(1), \dots, b(n)),$$

the deconvolution factor is

$$\alpha(t) = (\alpha(0), \alpha(1), \dots, \alpha(m)),$$

the actual output is

$$y(t) = \alpha(t) * b(t) = \sum_{\tau} \alpha(\tau) * b(t - \tau) = (y(0), y(1), \dots, y(M)),$$

expected output is

$$d(t) = (d(0), d(1), \dots, d(M));$$

output error is

$$e(t) = d(t) - y(t),$$

error energy is

$$Q = \sum_{i=0}^M e(t)^2 = \sum_{i=0}^M (d(t) - y(t))^2,$$

where $M = m + n$.

The above problem is reduced to the problem of finding the minimum value of the minimum error Q :

$$\begin{aligned} \min(Q) &= \min \left\{ \sum_{i=0}^M (d(t) - y(t))^2 \right\} \\ &= \min \left\{ \sum_{i=0}^M \left[\sum_{\tau=0}^M \alpha(\tau) * b(t - \tau) - d(t) \right]^2 \right\}. \end{aligned} \quad (14)$$

Take the partial derivative of Q with respect to the deconvolution factor $\alpha(t)$ and set it to 0 to obtain:

$$\begin{aligned} \sum_{\tau=0}^m \alpha(\tau) \sum_{t=0}^M b(t - \tau) b(t - s) &= \sum_{t=0}^M d(t) b(t - s), \\ (s = 0, 1, \dots, m). \end{aligned} \quad (15)$$

Make:

$$r_{bb}(\tau - s) = \sum_{t=0}^M b(t - \tau) b(t - s), \quad (16)$$

$$r_{db}(s) = \sum_{t=0}^M d(t) b(t - s). \quad (17)$$

Substituting equations (16) and (17) into equation (15), we get:

$$\sum_{\tau=0}^m \alpha(\tau) r_{bb}(\tau - s) = r_{db}(s), \quad (s = 0, 1, \dots, m). \quad (18)$$

Write formula (18) in matrix form as:

$$\begin{pmatrix} r_{bb}(0) & r_{bb}(1) & \cdots & r_{bb}(m) \\ r_{bb}(1) & r_{bb}(0) & \cdots & r_{bb}(m-1) \\ \vdots & \vdots & \ddots & \vdots \\ r_{bb}(m) & r_{bb}(m-1) & \cdots & r_{bb}(0) \end{pmatrix} * \begin{pmatrix} \alpha(0) \\ \alpha(1) \\ \vdots \\ \alpha(m) \end{pmatrix} = \begin{pmatrix} r_{db}(0) \\ r_{db}(1) \\ \vdots \\ r_{db}(m) \end{pmatrix}. \quad (19)$$

Solve the above equation and use the deconvolution factor $\alpha(t)$ to perform convolution processing on the logging curve. It is an effective, simple, and feasible method to apply the signal deconvolution correction method to logging curve processing. The method not only eliminates the influence of surrounding rock, logging speed, and sampling interval, but also eliminates the circuit and other factors. The impact on the logging curve produces a characteristic “magnification” effect on the low-amplitude subtle changes, thereby improving the logging curve’s ability to identify thin deposit interfaces.

3.3 Practical application

The above method is used to process the well sections with low longitudinal resolution of the Y well logging

curve in X Oilfield. The longitudinal resolution matching method is used for the resistivity curve (RT before processing and RT2 after processing); for the gamma curve (GR before treatment, GR2 after treatment), density curves (DEN before treatment, DEN2 after treatment) are processed by deconvolution method, and the processing results (Figure 9) show that the original low-amplitude fluctuations on the logging curve have produced an “amplification” effect; this effect is most obvious in a thin interbedded formation with a single layer thickness of about 0.5 meters. The longitudinal resolution of the processed logging curve has been significantly improved.

Figure 9: Comparison chart of Y well logging curve before and after processing.

4 Evaluation scheme of fine logging for poor reservoir

After completing the early identification of poor reservoirs and data processing of logging curves, a separate interpretation method model should be used for poor reservoirs with inaccurate interpretations of conventional multi-mineral models. The reservoirs in the study area generally have the characteristics of high gamma and low-amplitude resistance on the logging curve. Therefore, in the subsequent interpretation of poor reservoirs, the GR curve should be avoided as much as possible. Separate calculation models for mud content, porosity, water saturation, and permeability should be established.

4.1 Calculation model of shale content

Some siltstone reservoirs in the study area have too high GR values. Since neutron, density, and sonic time difference logging are not affected by the shale distribution, and these three logging curves are sensitive to fine-grained components, they are suitable for the calculation of shale content in silty reservoirs in the study area. When calculating the shale content, according to the quality of these three curves, two curves with better quality are selected to calculate the shale content. The calculation formula is as follows:

$$V_{sh} = A/B. \quad (20)$$

- (1) Calculated mud content by neutron-sonic time difference intersection:

$$A = \Delta(t)(\Phi_{Nma} - 1) - \Phi_N(T_{ma} - T_f) - \Phi_{Nma} \times T_f + T_{ma}, \quad (21)$$

$$B = (\Phi_{Nma} - 1)(T_{sh} - T_f) - (T_{ma} - T_f)(\Phi_{Nsh} - 1). \quad (22)$$

- (2) Neutron-density intersection calculation of mud content:

$$A = \rho_b(\Phi_{Nma} - 1) - \Phi_N(\rho_{ma} - \rho_f) - \Phi_{Nma} \times \rho_f + \rho_{ma}, \quad (23)$$

$$B = (\rho_{sh} - \rho_f)(\Phi_{Nma} - 1) - (\Phi_{Nsh} - 1)(\rho_{ma} - \rho_f). \quad (24)$$

- (3) Calculate the mud content by density-sonic time difference intersection:

$$A = \Delta(t)(\rho_{ma} - \rho_f) - \rho_b(T_{ma} - T_f) + \rho_f \times T_{ma} - \rho_{ma} \times T_f, \quad (25)$$

$$B = (T_{sh} - T_f)(\rho_{ma} - \rho_f) - (\rho_{sh} - \rho_f)(T_{ma} - T_f). \quad (26)$$

In these formulas, V_{sh} is the shale content; T_{ma} , T_f , T_{sh} , respectively, are the rock skeleton sonic time difference, the formation fluid sonic time difference, and the muddy sonic time difference. Φ_{Nma} and Φ_{Nsh} , respectively, are the rock skeleton neutron value and mudstone neutron value, decimal. Δt is target layer sonic time difference logging value. Φ_N is target layer neutron logging value, decimal. ρ_{ma} and ρ_f , respectively, the rock skeleton density value and the formation fluid density value, g/cm³, ρ_{sh} is the mudstone density value, g/cm³, ρ_b is the target layer density logging value, g/cm³.

4.2 Porosity calculation model

For the calculation of poor reservoir porosity, especially poor physical property reservoirs, the porosity is

calculated separately by modeling [43]. In this paper, we use the neutron-density geometric average method to calculate:

$$\varphi_D = \frac{\rho_{ma} - \rho_b}{\rho_{ma} - \rho_f} - V_{sh} \left(\frac{\rho_{ma} - \rho_{sh}}{\rho_{ma} - \rho_f} \right). \quad (27)$$

In the formula (27), φ_D is density porosity, decimal, ρ_{ma} and ρ_f , respectively, rock skeleton density value, formation fluid density value, g/cm³, ρ_b is target layer density logging value, g/cm³, ρ_{sh} is mudstone density value, g/cm³, V_{sh} is reservoir shale content, decimal.

$$\varphi_N = (CNL - N_{ma} - 0.5 \times V_{sh} \times N_{sh}) \times 0.01. \quad (28)$$

In the formula (28), φ_N is neutron porosity, decimal, CNL target layer compensation neutron logging value, %, N_{ma} is rock skeleton neutron value, %, V_{sh} is target layer shale content, decimal, N_{sh} is mudstone neutron value, %.

$$\varphi = \sqrt{\frac{\varphi_D^2 + \varphi_N^2}{2}} \quad (29)$$

4.3 Water saturation calculation model

For reservoirs with high shale content in poor reservoirs, when calculating water saturation, separate modeling is used to calculate the saturation of argillaceous sandstone with dispersed shale:

$$S_w = \sqrt{\left(\frac{aR_w(1-q)^{m-2}}{R_t\varphi^m} \right)^2 + \left(\frac{(R_w - R_{sh})V_{sh}}{2R_{sh}\varphi} \right)^2} - \left(\frac{(R_w + R_{sh})V_{sh}}{2R_{sh}\varphi} \right) \quad (30)$$

In the formula (30), R_t is target layer resistivity, R_{sh} is target layer mudstone layer resistivity, R_w is formation water resistivity, V_{sh} is target layer shale content, decimal, φ is target layer effective porosity, decimal, m is target layer porosity index (cement index), a is lithology additional conductivity correction coefficient.

4.4 Permeability calculation model

For the calculation of permeability in the study area, the porosity-permeability model of the core is established

Table 3: Permeability calculation model

Flow unit type	Permeability calculation model
I	$y = 0.8801 \times 10^{0.3479x}$
II	$y = 0.0156 \times 10^{0.4374x}$
III	$y = 0.0009 \times 10^{0.5181x}$

using the results of reservoir classification to perform classification calculations (Table 3) (Figure 10).

4.5 Actual application effect analysis

The above new method is used to perform fine logging interpretation processing on the Y core well of X oil field. As shown in Figure 11, in the sixth track, the black curve is the porosity calculated by the new method, and the red scattered points are the porosity obtained by the core experiment analysis. In the seventh track, the black curve is the permeability calculated by the new method, and the red scattered points are the permeability obtained from the core experiment analysis. The curves calculated by the new method overlap with the core data, which shows that the new method has high accuracy and applicability in the study area, compared with the previous interpretation results; it is obvious that the porosity, permeability, and oil saturation of the new scheme have different degrees of increase in the thin layer, which is consistent with the changes in logging curves before and after high-resolution processing, and the logging evaluation results are consistent with the core knot calibration results, which are consistent with the actual formation conditions.

Figure 10: Permeability calculation model.

5 Results and discussion

This research puts forward a new method to solve the problems often encountered in the secondary fine logging evaluation of the old oil fields. In the case of only logging data and lack of 3D seismic attribute data, geological and sedimentary data. The core data should be analyzed first, and the FZI method should be used to classify the reservoir, and then, on the basis of this classification combined with logging parameters, to complete the classification of the entire well section. After completing the classification and identification of the reservoir, fully analyze the reasons why it is difficult to accurately calculate reservoir porosity and permeability using conventional methods. Through a detailed analysis of the mineral composition content of the formation, the study found that the reason for this imagination is the high GR phenomenon caused by the low resolution of the logging curves of some well sections and the high shale content of the reservoir. The resolution matching method and deconvolution method are used to improve the resolution of logging curves. Establish calculation models for porosity, permeability, and water saturation separately according to the situation. Finally, the calculation results are compared with the core data. The comprehensive interpretation result diagram shows that the calculation results under the new method are basically consistent with the core data calibration results, and the calculation

accuracy is high, which is suitable for the study area. The accurate calculation of the three key reservoir parameters of porosity, permeability, and water saturation can help the oilfield to carry out the next step of development and deployment. The optimal interval can be determined for perforation and oil production, which is of great significance for increasing the output of the oil field. It provides new ideas for the study of logging interpretation and evaluation methods in other areas.

6 Conclusion

In the identification and logging evaluation of poor reservoirs, first, the reservoir types of X oilfield are divided into I, II, and III using the FZI method. Second, automatic logging recognition of reservoir classification is realized by using the ΔD and ΔGR intersection map method. Finally, the new scheme was used to perform fine logging evaluation on 20 wells, and the following conclusions were obtained:

- (1) Based on the FZI method, the classification of non-tight sandstone reservoirs can be achieved. The accuracy and rationality of the classification results can be verified through the cumulative probability distribution map of the flow unit index. The proposed intersecting chart method of the difference between the

Figure 11: Log interpretation results of H6A and H6B layers in well Y.

normalization of the gamma curve and the normalization difference of the density-neutron can simply and efficiently realize the accurate identification of the reservoir type according to the logging curve; this is also the biggest advantage of this method.

- (2) The resolution matching method and the deconvolution method are used in combination to improve the longitudinal resolution of the logging curve, the resolution matching method is used to correct the resistivity curve, and the deconvolution method is used to correct the resolution of GR, neutron, sonic time difference, and density curve. The advantages of the two methods are fully utilized, and good practical application effects have been achieved. However, these two methods are common classical methods, so the study of methods to improve the resolution of logging curves is still the focus of the next step.
- (3) For poor reservoirs that are difficult to accurately interpret by conventional interpretation methods, the actual stratigraphic conditions, geological data, and core data of the study area should be fully combined to analyze the reasons for their inaccurate interpretations. A separate calculation model is established for the mud content, porosity, water saturation, and permeability of poor reservoirs to complete its logging evaluation. After the new plan is processed, the porosity of the middle-poor reservoir in well Y has increased from 15.6 to 18.7%, and the water saturation has dropped from 66.1 to 48.1%, which is more in line with the results of core data. The method and calculation model proposed in this paper are mainly for logging evaluation of conventional sandstone reservoirs. They may not be completely applicable to logging evaluation of unconventional reservoirs, but they still have great significance for reference.

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