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Evaluation of Organic Carbon Logging in the Chang 7 Section of the Yanchang Formation, Huanjiang Area, Ordos Basin

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Abstract: During the early stages of shale oil exploration, challenges such as limited coring of source rocks and the discontinuous distribution of measured samples arise. Logging data can be used to quantitatively evaluate source rocks. Organic-rich source rocks typically exhibit characteristics such as high gamma radiation, low density, high sonic lag, high resistivity, and high neutron porosity on logging curves. This paper systematically introduces two quantitative evaluation methods for source rocks based on logging data: the Δlog R method and the BP neural network model. Corresponding prediction models were developed to forecast the organic carbon content of source rocks in the Chang 7 section of the Yanchang Formation in the Huanjiang area of the Ordos Basin. The predicted TOC (total organic carbon) data were copared with measured TOC data. The results indicate that both the ΔlogR model and the BP neural network model are effective for the study area, with the BP neural network model showing significantly better fitting performance than the ΔlogR model. The study also predicts the plane distribution of TOC content in the source rocks of the study area.

Keywords: Source rock; Organic carbon; Logging evaluation; Ordos Basin; Chang 7 section.

1. Introduction

Source rocks, also known as hydrocarbon-generating rocks, are sedimentary rocks with high organic matter content that produce or have already generated mobile hydrocarbons. They form the foundation of oil and gas reservoir studies[1]. The quality of source rocks determines the degree of shale oil enrichment, making their evaluation a critical task in shale oil exploration. Typically, source rocks are assessed based on three factors: organic matter abundance, organic matter type, and organic matter maturity. Among these, total organic carbon (TOC) is the primary indicator used to evaluate the abundance of organic matter in rocks and serves as an essential basis for further exploration[2].

However, with the recent discovery and research on the heterogeneity of source rocks[3-5], the previous approach—relying on limited samples and averaging TOC values across thick layers of source rocks due to the high cost of coring and experimental analysis—is no longer adequate. Logging data, which can indirectly reflect lithology and fluid characteristics of subsurface formations, have become widely applied in reservoir evaluation. Over recent years, both domestic and international scholars have made significant progress in predicting the distribution of source rocks using logging data. The primary methods currently include natural gamma spectroscopy logging, volume density method, ΔlogR method, multiple linear regression, and neural networks. Sun Zhe et al. (2020) studied the development characteristics of source rocks in the Bohai Sea area and, in light of limited geochemical data and high heterogeneity, used a variable coefficient ΔlogR method to predict organic carbon content in low-exploration areas[6]. Lu Pengyu et al. (2021) applied a neural network model to predict TOC in the Lunpola Basin, located in the harsh natural environment of the Qinghai-Tibet Plateau, where exploration is extremely challenging and expensive. Their study demonstrated that the neural network method was more accurate than the traditional ΔlogR method[7]. Additionally, Liu Zhong et al. (2023) predicted TOC content in coal-bearing shales in the southern block of the Ningwu Basin, finding that the BP neural network model outperformed both multiple linear regression and the ΔlogR method in terms of prediction accuracy[8].

The prediction of TOC content in source rocks is complicated by the diverse lithological combinations, varying types of kerogen, and differences in maturation[9], especially across different regions and geological periods. These factors make it challenging to accurately predict TOC content. Consequently, selecting an appropriate TOC prediction model for different regions is increasingly important. Building on previous research, this study employs the improved ΔlogR method and BP neural network models to predict the TOC content of source rocks in the Chang 7 section of the Yanchang Formation in the Huanjiang area of the Ordos Basin. The prediction results are highly accurate, with good model fit, providing valuable insights for the development and resource potential evaluation of shale oil in the Huanjiang area.

2. Regional Geological Setting

The Ordos Basin is located at central China, occupying the western part of the North China Platform. It stretches from the Yin Mountains in the north to the Qinling Mountains in the south, extending eastward to the Lvliang Mountains and westward to the Liupan Mountains. Spanning across five provinces—Shanxi, Gansu, Ningxia, Inner Mongolia, and Shanxi—the basin covers an area of approximately 370,000 km², making it the second-largest sedimentary basin in China. Based on the characteristics of its basement, current structural features, and distribution patterns, the basin can be divided into six primary structural units: the Yimeng Uplift, Weibei Uplift, Jinxi Fold Belt, Yishan Slope, Tianhuan Depression, and the Western Margin Thrust Belt. The Ordos Basin mainly contains two sets of source rock systems: one from the Paleozoic era, which includes Ordovician source rocks (composed mainly of mudstone, argillaceous limestone, and carbonate rocks) and Carboniferous-Permian source rocks (dominated by dark-colored mudstone and coal); and another from the Mesozoic era, represented by the Jurassic Yan'an Formation coal-bearing rocks and the Upper Triassic Yanchang Formation dark mudstone.

The Huanjiang area, located in the central-western part of the Ordos Basin, lies within the secondary structural unit of the Yishan Slope. The structure is relatively gentle and is primarily controlled by lithologic traps. The area covers 14,615 km², and its stratigraphic development is similar to other regions of the Yanchang Formation in the Ordos Basin[10]. Compared to the Jurassic Yan'an Formation coal-bearing source rocks, the Yanchang Formation source rocks in the Huanjiang area have lower organic carbon content but significantly higher soluble organic matter content and hydrocarbon conversion rates. This suggests that the hydrocarbon generation conditions in the Yanchang Formation source rocks are more favorable, making it the primary Mesozoic source rock in the study area[11].

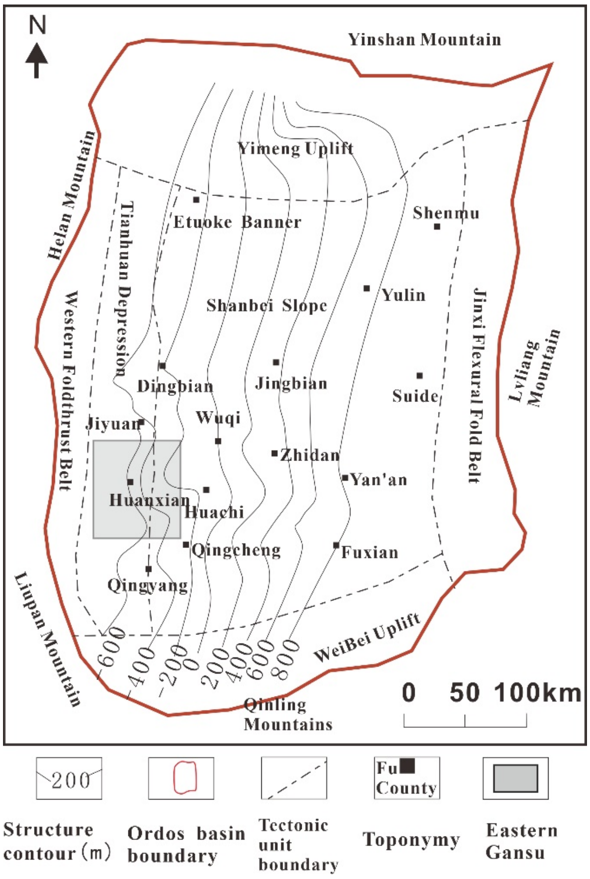

Figure 1. Study area location map

During the deposition of the Chang 7 section of the Upper Triassic Yanchang Formation, the lake basin was in its most developed stage, characterized by a shallow to deep lacustrine sedimentary environment. A widely distributed layer of "Zhangjiatan Shale" was deposited, serving as the primary oil-generating system in the area. According to Wang Yanru and Luo Lirong[12], the dark mudstones of the Chang 7 section are widely distributed within the lake facies, with a thickness of 15 to 40 meters and a high organic carbon content (TOC > 13%). These rocks contain high hydrocarbon-generation rates. The Chang 7 oil-bearing group is divided into three sub-sections: Chang 7_1, Chang 7_2, and Chang 7_3, forming a typical lithological oil reservoir. The upper and middle sections are dominated by gray-black mudstone and thinly bedded fine sandstone, while the lower section consists of thin sandstone, oil shale, and dark mudstone. The lower part of Chang 7_2 to Chang 7_3 is the main development section of the shale, with the source rock in Chang 7_3 accounting for more than 70% of the total source rocks. The oil shale in Chang 7_2 is thinner, accounting for approximately 20%, and the source rock in Chang 7_1 is the thinnest, with an increasing thickness of thinly bedded fine sandstone[13].

3. Log Response Characteristic

The fundamental principle behind the logging-based evaluation of organic-rich shales is to utilize the characteristic responses of various logging tools to the organic matter content in rocks[14]. Previous studies indicate that the Chang 7 oil-bearing group is predominantly self-generating and self-storing, with oil-saturated sandstone typically exhibiting high resistivity. Oil shales, characterized by extremely high organic matter content, are reflected on logging curves by the "three highs and one low" pattern—high natural gamma, high resistivity, high sonic lag, and low density. Carbonaceous mudstones and dark-colored mudstones exhibit a "five highs and one low" pattern—high neutron porosity, high sonic transit time, high resistivity, high natural gamma, high uranium content, and low density.

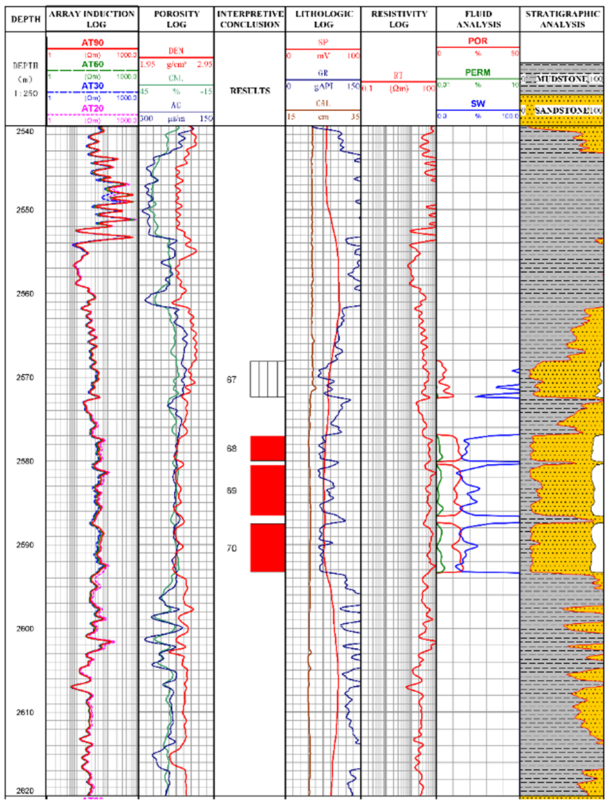

Figure 2. Logging response characteristics of Chang 7 in Huanjiang area

The magnitude of the spontaneous potential anomaly is related to the permeability of the formation. Generally, the higher the content of plastic material in the formation, the lower the permeability and the smaller the amplitude of the spontaneous potential anomaly. Therefore, organic-rich mud shales usually have lower spontaneous potential values.

Natural gamma logging primarily reflects the amount of clay in the formation. The natural gamma value increases with clay content. In mudstones with high organic content, the organic matter content is positively correlated with radioactive and trace elements. As radioactive elements increase, a higher natural gamma value can be used to identify source rocks. Thus, TOC is positively correlated with natural gamma values.

The propagation speed of sonic waves is slower in mature organic matter, and high-quality source rocks show clear increases in sonic transit time. Mudstones typically display high values in sonic transit time logs, which vary with compaction. When mudstones contain organic matter, the slower wave propagation further increases the transit time, meaning that higher TOC results in longer sonic transit times.

Organic matter has a low bulk density, so the density of mudstone without organic matter is generally higher than that of source rocks. Bulk density logging can thus be used to distinguish source rocks. Variations in TOC content is reflected by changes in formation density—an increase in TOC content decreases the density of the mudstone. Therefore, TOC content is negatively correlated with density[15].

4. Organic Carbon Logging Evaluation of Source Rock

4.1. Establishment of model

4.1.1. Improved ΔlogR model

The ΔlogR method was first introduced by Exxon and Esso, and later refined and popularized by Passey et al[16]. It is a technique used to calculate and predict the total organic carbon (TOC) of source rocks using sonic transit time and resistivity log data. Compared to the rock matrix, kerogen has distinct logging response characteristics, exhibiting lower velocity and higher resistivity. These differences cause the two logging curves to show varying patterns in intervals with different levels of organic matter enrichment. The higher the organic carbon content, the more pronounced the difference between the two curves.

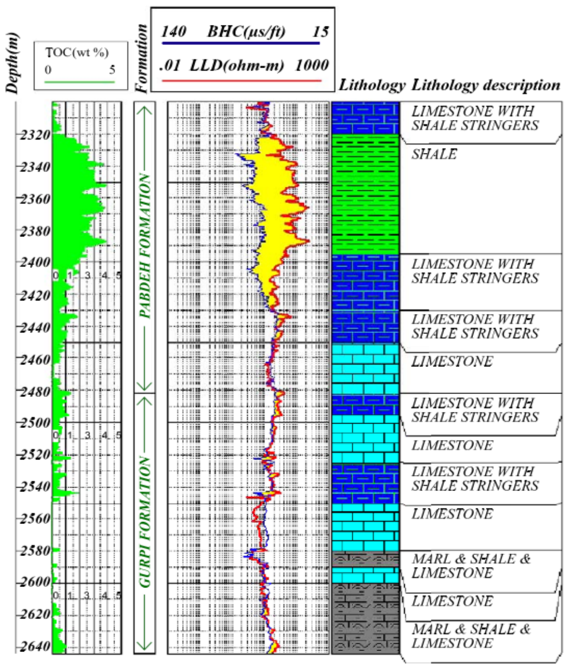

Figure 3. Sonic/resistivity overlay and calculated TOC (wt.%)M R Kamali and A Allah Mirshady [17]

When applying the ΔlogR method to calculate TOC, the resistivity and sonic transit time curves are overlaid inversely on the same coordinate system. In low organic matter intervals, the two curves overlap, forming the baseline. In intervals with high organic matter content, the values of both curves increase and separate from each other, creating an amplitude difference, which is defined as the ΔlogR value[17]. The formula used to calculate TOC via the ΔlogR method is

$$\Delta \log R = \lg(R_t / R_{t,base}) + K(\Delta t - \Delta t_{base}). \quad (1)$$

$$TOC = \Delta \log R \times 10^{2.297-0.1688 L_{om}} + \Delta TOC. \quad (2)$$

In the formula, R represents shallow lateral resistivity (Ω·m); Rt and Δt are the formation resistivity(Ω·m) and sonic lag logging values (μs/m); $R_{t,\ base}$ and Δt_{base} are the resistivity (Ω·m) and sonic lag values (μs/m) in the baseline interval. K is the overlay coefficient, L_{om} is the formation maturity parameter, and ΔTOC is the background TOC value.

Liu Chao proposed an improved ΔlogR model based on the traditional ΔlogR method. In this model, the coefficient K is set to an optimal value, which maximizes the coefficient of determination between the calculated TOC and the measured TOC. The simplified formula for calculating TOC is as follows:

$$TOC_{fitting} = a \log R + b\Delta t + c. \quad (3)$$

In the formula, a, b, and c are fitting coefficients. The simplified model follows the same principles as the traditional ΔlogR model but eliminates the need to determine the thermal maturity index and baseline values. This reduction in manual selection minimizes errors and makes the calculation more objective and convenient[18]. By applying the above formula to the depth logging data corresponding to the measured TOC in the study area, the improved ΔlogR model was derived as follows:

$$TOC_{fitting} = 1.938 \log R + 0.051\Delta t - 13.646. \quad (4)$$

The traditional ΔlogR method predicts TOC based on the abnormal responses of resistivity and sonic transit time curves in source rocks. Its advantage lies in its ability to reduce the interference of porosity on the TOC logging response. However, its limitation is that it was developed for normally compacted marine formations, where conductivity components are relatively low and surrounding rock resistivity is smaller. In contrast, in continental formations, higher conductivity components and greater surrounding rock resistivity, combined with deep, well-compacted and denser formations, cause the sonic transit time curves to flatten, reducing the amplitude difference between the two curves. As a result, the accuracy of TOC calculations in deep continental source rocks is significantly reduced[19].

4.1.2. BP neural network

The BP neural network, an artificial neural network based on the error backpropagation algorithm, is adept at identifying patterns and constructing mapping models from given samples. It is widely applied across various problems and has demonstrated significant effectiveness[20]. The BP neural network model consists of an input layer, hidden layers, and an output layer. The input layer receives external data, while the output layer provides the network's predictions. The hidden layers, situated between the input and output layers, process and refine the input data. Neurons within each layer are independent of one another, but neurons between layers are interconnected. The learning process involves both forward computation and backward propagation, mapping the nonlinear function from input data to output data. During forward propagation, the hidden layers assign weights to the data from the previous layer and propagate it to the output layer. If the output error does not meet the desired threshold, the error signal is propagated backward from the output layer to the input layer, adjusting weights accordingly before being propagated forward again. This process repeats until the error falls within an acceptable range, at which point training concludes[21].

When applying neural networks to this domain, the aim is to enhance the three-dimensional accuracy of the model and reduce uncertainty due to errors. To achieve this, logging curve data is first input into the network's input layer and subjected to standard normalization.

The formula for normalizing logging data is:

$$\Delta\varphi = \frac{\varphi - \varphi_{\min}}{\varphi_{\max} - \varphi_{\min}} . \tag{5}$$

In the formula, $\Delta\varphi$ is the normalized curve value without dimension; φ is the value of any curve, without dimension; $\varphi_{\max}$ is the maximum curve value, without dimension; $\varphi_{\min}$ is the minimum curve value and has no dimension.

Let $W_{ij}^{(L)}$ be the connection weight between the input layer of layer L and the hidden neuron, and $b_i^{(L)}$ be the threshold value of the i neuron of layer L, then the output formula of the hidden layer in the forward propagation process is as follows:

$$Y_{(i)}^{(L)} = f_{(ai)}^{(L)} . \tag{6}$$

$$a_{(i)}^{(L)} = \sum_{j=1}^{n} W_{ij}^{L} h_j^{(L-1)} + b_i^{(L)} . \tag{7}$$

In the formula, f represents the activation function. In this study, the tansig function is selected as the activation function for the hidden layers. $a_i^{(L)}$ denotes the input to the i neuron in the L layer, where i ranges from 1 to m and j ranges from 1 to n. During backpropagation, the connection strengths and thresholds are iteratively adjusted until the desired output is achieved. The overall error of the function is defined as:

$$E = \frac{1}{2m} \sum_{i=1}^{m} (X_{(i)} - x_{(i)})^2 . \tag{8}$$

In the formula, $X_{(i)}$ represents the expected output for $x_{(i)}$.

The formulas for adjusting the connection strengths and thresholds during each iteration are given by:

$$W_{ij}^{(L)} = W_{ij}^{(L)} - \alpha \delta_j^{(L)} Y_{(i)}^{(L-1)} . \tag{9}$$

$$b_i^{(L)} = b_i^{(L)} - \alpha \delta_j^{(L)} . \tag{10}$$

$$\delta_i^{(L)} = W_i^{(L+1)} \delta_i^{(L+1)} f'_{(x)} \,|x = a_i^L . \tag{11}$$

In the formula, α represents the learning rate, which ranges from 0 to 1.

The BP neural network uses various sensitive curve values from core drilling sections as input variables and the corresponding rock facies types as output variables. Through adjustments and iterations, the mapping relationship between each curve value and the corresponding TOC (total organic carbon) content of source rocks is determined.

In this study, a BP neural network model was constructed using the multifunctional toolbox in MATLAB R2023a. Input sample data points were provided to the neural network model in the format of [GR, DEN, SP, AC, TOC]. The number of input layer nodes was set based on the number of curve types, using 4 logging curves (GR, DEN, SP, AC), resulting in 4 input layer nodes. One hidden layer was designed with 9 nodes, where the number of hidden layer nodes is typically set to 2n+1 when the number of input nodes is n. Since the output is only the TOC content of source rocks, the output layer was designed with a single node, creating a 4 × 9 × 1 neural network model as shown in the Fig 4The network's initialization parameters were set as follows: learning rate α=0.1; target error δ=0.000001; minimum gradient grad=0.000001, and 1000 iterations.

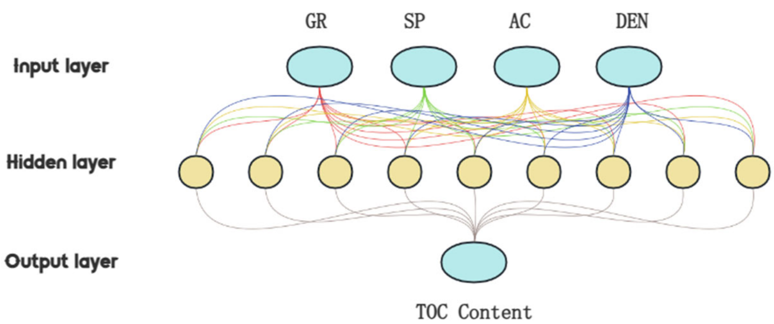

Figure 4. Schematic diagram of neural network model

Logging curve values are used as training samples, with the corresponding TOC (total organic carbon) content of source rocks serving as supervised data for input into the BP neural network training process. The learning process involves forward propagation of neuron signals, where each layer's learning results only affect the subsequent layer. If the error in the output layer exceeds the predefined tolerance, a feedback mechanism is activated, returning the error signal to the input and hidden layers. Subsequently, the training algorithm adjusts the weights and thresholds of the neurons in each layer to minimize the error, iteratively calculating and propagating the error backward until it is reduced to the minimum.

4.2. Comparison of fitting effect

The L57 well, which has a substantial amount of measured TOC data, was selected as the reference well for the study area. The hydrocarbon source rock evaluation model for the study area was established using the improved ΔlogR method, resulting in a correlation coefficient R^2 of only 0.5467. In contrast, the BP neural network prediction model, which uses GR, DEN, SP, and AC as input layers, achieved a higher correlation coefficient of R^2=0.8495 between the predicted and measured organic carbon content. This indicates that the BP neural network prediction model provides a better fit for predicting TOC content in this study area and demonstrates superior performance in handling nonlinear models.

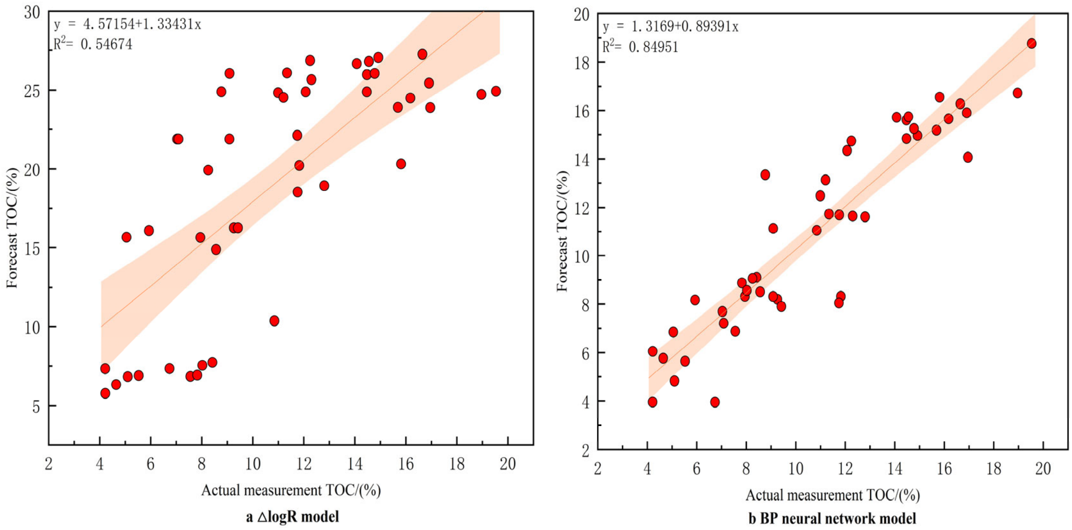

Figure 5. The relationship between TOC content predicted by two models and measured TOC content

Predicting TOC content from logging data primarily involves correlating the logging response characteristics of organic matter in hydrocarbon source rocks with TOC to obtain vertical distribution predictions. This approach allows for the quantification of TOC content distribution. Utilizing the BP neural network prediction model, which provides better fitting results, the vertical distribution of TOC for the Ba 22 well in the study area was forecasted. Although the model's predictions deviate from the actual TOC values at some points, the overall fit is relatively close, indicating a good prediction performance.

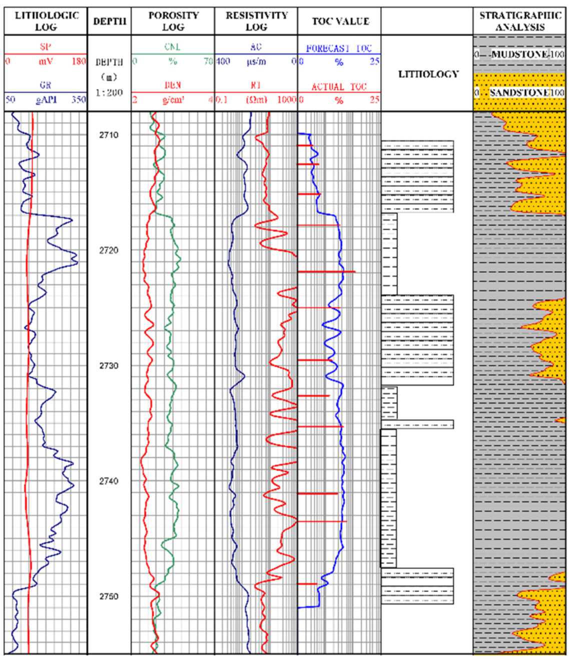

Figure 6. Logging interpretation results of Chang 7 member Yanchang, Huanjiang area, Ordos Basin

5. TOC Distribution Characteristics of Chang 7 Section Source Rock

In the southwestern part of the Yishan Slope in the Ordos Basin, during the Chang 7 period, the area was predominantly part of the lake-shelf sedimentary zone [22]. During the Chang 7_3 period, the lake reached its maximum depth, leading to the deposition of a well-distributed "Zhangjiatan Shale" [23], characterized by high organic carbon content and high-quality hydrocarbon source rocks. Due to significant tectonic and sedimentary effects, the heterogeneity of the region was pronounced during the Chang 7_3 period. By the Chang 7_2 and Chang 7_1 periods, the water body gradually shallowed, sediment accumulation increased, and the hydrocarbon generation capacity deteriorated. Based on the analysis of vertical variations in TOC values of hydrocarbon source rocks from individual wells, a total of 100 wells within the study area were selected. Using the model, TOC values of Chang 7 hydrocarbon source rocks were calculated for each well, averaged, and used to create a spatial distribution map of TOC values.

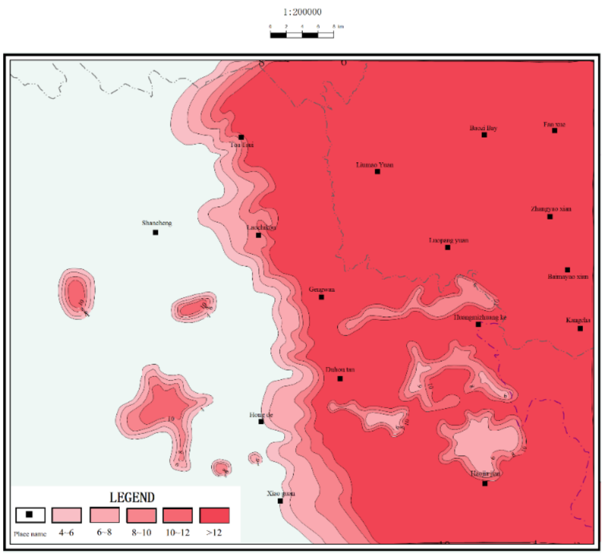

Figure 7. TOC plane distribution was calculated for source rocks in Chang 7 member of the study area

The Fig 6 shows that the hydrocarbon source rocks in the study area are distributed in a northwest-southeast direction. The Chang 7 hydrocarbon source rocks generally have high TOC values, with an average exceeding 5%, indicating good source rock quality. High-value areas are concentrated in the eastern part of the study area, where the average TOC exceeds 12%. Moving westward, TOC values decrease gradually, with lower values observed in the western region. In the western part of the Hongde area, some regions have average TOC values above 8%, marking them as favorable oil-generation zones. The highest TOC content is concentrated in the eastern part of the Dabazhi-Gengwan-Duhou Tan area.

6. Conclusion

(1) Based on a comparison of the correlation coefficients between TOC content and well log parameters, four highly sensitive well log curves—natural potential logging, natural gamma logging, sonic transit time logging, and bulk density logging—were selected as input parameters to predict TOC content in the study area. The test samples indicate that the neural network method provides more accurate predictions compared to the improved ΔlogR model, demonstrating higher accuracy. This model is suitable for predicting TOC values of Chang 7 hydrocarbon source rocks in the Upper Triassic of the Huajiang area.

(2) From the computed planar distribution map of Chang 7 TOC values, it is evident that the TOC content in the Chang 7 hydrocarbon source rocks in the study area is generally high (with 90% of the region having an average TOC greater than 4%), indicating good source rock quality. The TOC content predominantly ranges from 4% to 15%, with a maximum reaching up to 20%. There is a significant variation in organic carbon content across the area, showing a trend of decreasing from east to west. The highest TOC values are concentrated in the eastern region, specifically in the Dabazhi-Gengwan-Duhou Tan area, indicating strong hydrocarbon generation potential and guiding further exploration and development in the region.

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