Improved TOC prediction method for shale reservoir of Wufeng Formation and the Lower part of Longmaxi Formation in Jiaoshiba Area, Sichuan Basin

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Abstract: The total organic carbon (TOC) content is the core index of shale gas reservoir evaluation. It is of great significance to quickly and accurately obtain a large number of TOC values for shale gas reservoir evaluation and sweet spots identification. The Lower Paleozoic shale gas reservoirs in southern China were once buried to a depth of more than 6000m, and the diagenesis was relatively complete. The application of various TOC estimation methods was not satisfactory so far. This paper takes the shale of Wufeng Formation and the Lower part of Longmaxi Formation in Jiaoshiba area of Sichuan Basin as the key research object. Based on the analysis and summary of well logging results, a method to improve the accuracy of TOC prediction is proposed. The improved △LogR technology with the participation of natural gamma-ray and bulk density logs has strong applicability, leading to accurate calculated TOC content, which has important guiding significance for exploration and development.

1. Introduction

Shale gas is a kind of important unconventional resource. The production of shale gas has constituted a major part of the energy structure in the United States (Zou et al., 2020). China has also made major breakthroughs in the shale gas in recent years. The discovery and development of the Jiaoshiba shale gas field in the southeastern Sichuan Basin is an important symbol (Guo, 2014).

Shale gas production layers are usually rich in organic matter, which is not only the source material, but also provides space for the natural gas storage (Jarvie et al., 2007). Therefore, the total organic carbon (TOC) content is the core indicator in the evaluation of shale gas formations. However, the TOC data that can be obtained through the rock sample measurement is limited, with poor representation, high cost and weak continuity. Therefore, it is generally used to predict TOC content by geophysical logs with the relatively high vertical resolution (Beers, 1945; Schmoker et al., 1981, 1983; Meyer and Nederlof, 1984).
The shale of the Upper Ordovician Wufeng Formation and Lower Silurian Longmaxi Formation in the southeastern Sichuan Basin is the deep-water shelf deposit, maintaining a long-term deep-water anoxic environment (Li et al., 2017). Black shale and silty shale characterized by the constant thickness and wide distribution are deposited, with high organic matter content and thermal evolution, which is the most important shale gas production layer in China at present (Zhang et al., 2012; Guo, 2014). The first shale gas field in China was developed in Jiaoshiba area. The main gas production layer in this area is the black shale section at the Wufeng Formation and the Lower part of the Longmaxi Formation. Its geothermal field tends to be relatively stable; the roof and floor plates constitute good sealing units, and the damage of faults is limited. Overall, it has good preservation conditions, which is conducive to the enrichment and storage of shale gas (Liu, 2015; Liu et al., 2011; Guo, 2014). However, this shale section was once buried more than 6000 m, and diagenesis of the shale is relatively complete. So the application effects of various TOC estimation methods are not ideal (Tyson, 2001).

The commonly used methods for predicting TOC using multiple logs conclude the logging curve superimposition evaluation method (that is, the $\Delta \log R$ method and its variants) (Passey et al., 1990), multiple linear regression evaluation methods (Mendelson and Toksoz, 1985), neural network and other mathematical evaluation methods (Huang and Williamson, 1996). Among them, the $\Delta \log R$ method uses the amplitude difference between the porosity curve and the resistivity curve in the organic-rich layer to calculate TOC content. It uses two kinds of logs and considers the changes in porosity, fluid composition, and organic maturity. Therefore, it is widely used (Wang et al., 2002; Li et al., 2013).

Taking the shale of Wufeng Formation and the Lower part of Longmaxi Formation in the Jiaoshiba area of the Sichuan Basin as the main research object, this paper discusses how to improve the prediction accuracy of TOC content based on traditional $\Delta \log R$ method by using a large number of TOC data measured from drilling cuttings and cores.

2. Methods

The traditional $\Delta \log R$ method was proposed by Passey in 1990. The porosity curve (generally the acoustic logging curve) and the resistivity curve overlap in the fine-grained organic-poor formations. In the organic-rich formations, there is a gap (defined as $\Delta \log R$) between the two curves. This amplitude difference is linear with the TOC content and is a function of maturity, so it can be used to calculate TOC content. The formula for calculating this amplitude difference is as follows:

$$\Delta \log R = \lg \left(\frac{R}{R_b}\right) + 0.02 \times (\Delta t - \Delta t_b)$$  \hspace{1cm} (1)

In the formula (1), $\Delta \log R$ is the curve amplitude difference measured in logarithmic resistivity units; $R$ is resistivity, $\Omega \cdot m$; $\Delta t$ is acoustic transit time, $\mu s/ft$; $R_b$ and $\Delta t_b$ are the base values corresponding to the overlapping sections of the two curves in the fine-grained organic-poor formation; 0.02 is the calibration coefficient.

The TOC content is obtained by empirical relationship:

$$\text{TOC} = \Delta \log R \times 10^{(2.397 - 0.1698 \times \text{LOM})}$$  \hspace{1cm} (2)

In the formula (2), TOC is the total organic carbon content, $\%$; LOM is the maturity parameter, which can be replaced with the $R_o$.

In Jiaoshiba area of Sichuan Basin, drilling core samples from the shales of Wufeng Formation and the Lower part of Longmaxi Formation were systematically collected. The traditional $\Delta \log R$ method is used to calculate the TOC. The correlation between the results obtained and the measured TOC is rather weak (Fig. 1).
Fig. 1 Correlation between the measured TOC and the calculated TOC by the traditional \( \Delta \text{LogR} \) method

To improve the method, the relationship between various logging curves and the measured TOC is counted. It is found that the correlation between density log and TOC content is obviously better than that of acoustic log and compensated neutron log, and there is also an obvious correlation between natural gamma-ray log and TOC content (Fig. 2).

Fig. 2 Correlation between various logging values and the measured TOC

We add the natural gamma-ray log into the calculation of \( \Delta \text{LogR} \) on the basis of the traditional \( \Delta \text{LogR} \) method. Furthermore, density log is used instead of acoustic log. An improved \( \Delta \text{LogR} \) method for TOC prediction using gamma-ray log, porosity log and resistivity log is established as follows:

\[
\Delta \text{LogR} = \frac{1}{L} \times \log \left( \frac{R}{R_b} \right) + \frac{1}{K} \times \left( \rho - \rho_b \right) + \frac{1}{J} \times \log \left( \frac{\text{GR}}{\text{GR}_b} \right)
\]

(3)

In the formula (3), L, K, and J are dimensionless parameters; R is resistivity log value, \( \Omega \cdot \text{m} \); GR is natural gamma-ray log value, API; \( \rho \) is density log value, \( \text{g/cm}^3 \); \( R_b \), \( \rho_b \) and \( \text{GR}_b \) are base values corresponding to the mud-rich layer of non-source rock where TOC is 0.
The measured TOC data in the study area is used for modeling. By fitting the values of the calculated TOC with the measured TOC, the optimal parameters $L = 1.1$, $K = 0.03$, $J = 0.13$ are obtained. The final template is as follows:

$$\text{TOC} = \left[ \frac{1}{1.1} \times \log \left( \frac{R}{R_b} \right) + \frac{1}{0.03} \times (\rho - \rho_b) + \frac{1}{0.13} \times \log \left( \frac{GR}{GR_b} \right) \right] \times 10^{-(2.297 \times 10^{-10} / \rho)}$$

(4)

3. Application

The above template is applied to estimate TOC of some wells in the study area, and the measured TOC in these wells is used to verify the estimated results. The results show that the accuracy of TOC calculated by the template is high, and the relative error is less than 6.49% (Tab. 1, Fig. 3).

**Table 1.** Error analysis of the calculated TOC in different wells

| Well | Mean value of the calculated TOC | Mean value of the measured TOC | Difference | Relative Error |
|------|---------------------------------|--------------------------------|------------|----------------|
| JY1  | 2.55                            | 2.48                           | 0.07       | 2.95%          |
| JY3  | 2.26                            | 2.21                           | 0.05       | 2.21%          |
| JY4  | 2.58                            | 2.62                           | -0.04      | -1.50%         |
| JY5  | 1.63                            | 1.55                           | 0.08       | 5.18%          |
| JY8  | 1.62                            | 1.73                           | -0.11      | -6.49%         |

**Fig. 3** Correlation between the measured TOC and the calculated TOC by the improved $\Delta \log R$ method

Compared with the traditional $\Delta \log R$ method and bulk density method, the improved $\Delta \log R$ method obtains the best TOC prediction effect (Tab. 2). The correlation coefficient $R^2$, slope and intercept in the Tab. 2 come from the correlation between the measured TOC and the calculated TOC of different methods.

**Table 2.** Comparison of TOC prediction effect of different methods

| Method               | Correlation coefficient $R^2$ | The slope | The intercept | Accuracy |
|----------------------|--------------------------------|-----------|---------------|----------|
| Bulk Density method  | 0.8195                         | 0.7060    | 0.4244        | Medium   |
| The traditional $\Delta \log R$ | 0.3302                             | 0.5090    | 0.6382        | Low      |
| The improved $\Delta \log R$ | 0.9082                             | 1.0024    | -0.0104       | High     |

In order to verify the applicability of this method, it is further applied to part of the wells in Dingshan area of Sichuan Basin, and the calculated results match well with the measured TOC (Fig. 4). Among them, the shale in DYS1 well belongs to deep source rock, indicating that this improved method has good application effects in deep formations.
4. Discussion

Acoustic and resistivity logs are sensitive to porosity changes. The increase of porosity leads to the increase of acoustic transit time and the decrease of resistivity. The change amplitude of the two logs is proportional. If lithology is known, and the acoustic transit time and resistivity are correctly scaled, the porosity changes will cause the two curves to have the same magnitude offset once the baseline is determined. So the influence of porosity on the organic carbon logging response can be eliminated. This is the most important advantage of the $\triangle \text{LogR}$ method. However, the prerequisite for this method is that the lithology and diagenesis degree of the stratum at the baseline are consistent with the stratum to be measured, and it is believed that the acoustic transit time is the best test information reflecting the porosity of shale (Wang et al., 2002). But for the shale once buried deeply, the diagenesis has been relatively complete, and mechanical and chemical compaction make the rock compact. These make the change of acoustic transit time and resistivity values so small that the ability to distinguish rock properties deteriorates (Fig. 2 and Fig. 4). Moreover, the shale is rich in over-mature organic matter; the formation contains a large amount of natural gas, and fractures are developed in some sections (Guo and Zhang, 2014). These factors have a strong impact on the two kinds of logging information.

Therefore, only using the amplitude difference of acoustic and resistivity logging curves to calculate TOC will cause problems of poor resolution and weak anti-interference ability (Fig. 1). The improved $\triangle \text{LogR}$ method has a good application effect, indicating that a variety of geophysical information can reflect the changes in the composition of the material in the formation from different physical quantities, and the method composed of multiple information has relatively strong anti-interference ability.

The correlation between shale density logging value and TOC in Jiaoshhiba area is better than that between acoustic logging value and TOC. The reason may be that acoustic logging value is greatly affected by under-compaction, while density logging value is relatively less affected (Li et al., 2017; Goulty and Sargent, 2016; Andras, 2018). In the study area, the strata is uplifted and eroded on a large scale, and the shale is in an unloaded strain state. The abnormal fluid pressure in different depths varies greatly, which may also affect the acoustic transit time, but has a relatively small impact on the density (Bowers, 2002).

Natural gamma-ray information not only reflects the amount of the radioactive material in shale, but also indicates the content of fine-grained clay minerals in rocks (Ozkan et al., 2011). The existence of radioactive materials is conducive to biological reproduction, while biological remains are easy to be
adsorbed on fine-grained clay minerals, and then precipitated and preserved (Ayres and Theilen et al., 2001). Therefore, the relationship between natural gamma-ray information and organic matter content is very close. In addition, natural gamma-ray information is less affected by compaction and is more sensitive to changes in organic matter content. Therefore, the accuracy of TOC prediction can be improved by adding natural gamma-ray logging information.

5. Conclusions

The diagenesis is relatively complete in deep buried shale gas reservoirs. The sensitivity of geophysical logs has reduced, and the density of rocks has increased. Besides, high organic maturity and high natural gas saturation will bring strong interference. A variety of geophysical information can reflect changes in the composition of materials in the stratum from different physical quantities, and the TOC calculation method that integrates multiple information has stronger anti-interference ability.

The improved △LogR method uses density log to replace acoustic log and adds natural gamma-ray log in it, which is more applicable in shale gas reservoirs that have undergone the deep geological transformation. The application effect is excellent in the shale of Wufeng Formation and the Lower part of Longmaxi Formation both in Jiaoshiba area and Dingshan area of Sichuan Basin.

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