[PS]Evaluation Method of Low Permeability Reservoirs Based on Logging Petrophysical Facies Identification: A Case Study of the Upper Member of Mengyin Formation in Gaoqing Area, Dongying Depression*

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Abstract

The mechanism of the low-permeability reservoirs is complex in the upper member of Mengyin Formation of Jurassic age in the Gaoqing area of the Dongying Depression. The strong heterogeneity of rock physical properties within the same micro-facies makes it difficult to evaluate and predict effectively using conventional methods. From the perspective of the mechanism of low-permeability reservoirs, comprehensive analysis of sedimentary rock facies and diagenetic reservoir facies was conducted using drilling, well logging, and thin section analysis. Taking the physical properties and pore structure parameters in the coring segment as constraints, the reservoirs were divided into five types of petrophysical facies. On this basis, the method of using the self-organizing neural network for neuron competition learning and mutual supervision in a supervised mode to fully tap the log response information and identify petrophysical facies was proposed.

The results show that from using petrophysical facies division in the coring segment as learning samples, and using the LDA algorithm to optimize the logging curve input samples, the average accuracy of logging petrophysical facies identification is 84%. Based on single-well identification results, a comprehensive evaluation of the upper member of the Mengyin Formation was carried out. The petrophysical facies of PF1, PF2 and PF3 are favorable types of pore-penetration development with well-developed secondary pores, good pore connectivity and percolation ability. The displacement pressure ranges from 0.02 to 0.20 MPa and the permeability is 1-200 mD. PF4 and PF5 are poor in pore connectivity and percolation ability, with a relative high displacement pressure greater than 0.20 MPa and low permeability less than 1 mD, which are non-favorable pore-penetration development types. The prediction of favorable pore-penetration development zones can be achieved by favorable planar distribution of petrophysical facies, which would provide a basis for future exploration and development.

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INTRODUCTION

- The mechanism of the low-permeability reservoirs is complex in the upper member of Jurassic Mengyin formation of Gaoqing area, Dongying depression. The strong heterogeneity of rock physical properties within the same micro-facies makes it difficult to evaluate and predict effectively using conventional methods.(Fig. 1) .
- The self-organizing map neural network algorithm has unique theoretical advantages in solving the pattern recognition problems with complex nonlinear relationships. Therefore, the method of using the self-organizing neural network for neuron competition learning and mutual supervision in a supervised mode to fully tap the log response information and identify petrophysical facies was proposed.

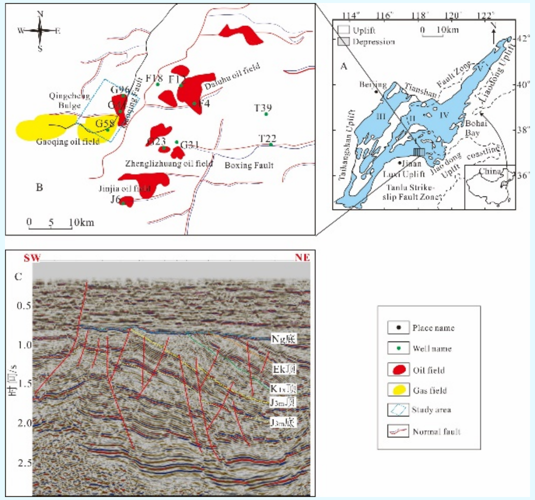

Fig. 1 Structural location of study area

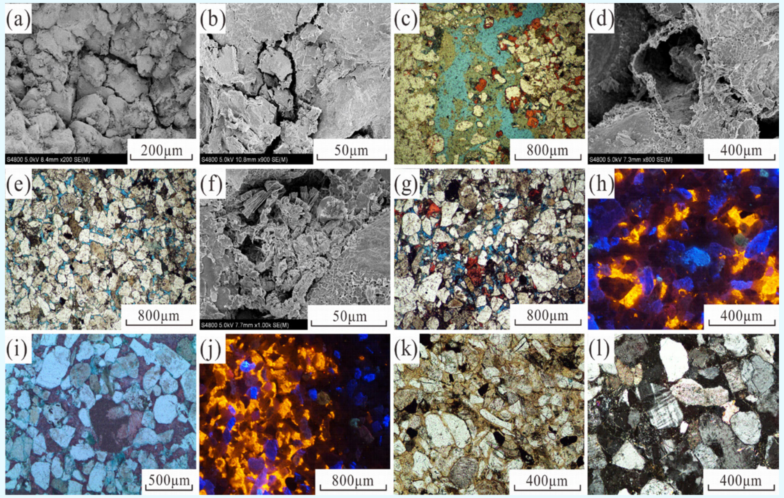

Fig. 2 Characteristics of diagenetic facies in the Upper Member of Mengyin Formation

THEORY AND METHOD

- The self-organizing map (SOM) algorithm is an unsupervised artificial neural networks invented in 1982 by Kohonen. The network structure consists of input layer and competition layer (Fig. 3). The SOM in unsupervised mode is often clustered according to the most significant data features of the input samples, which has achieved good application effects in lithology identification, fluid prediction and remote sensing image classification.
- However, SOM algorithm in unsupervised mode has the disadvantages of poor recognition effect, low classification accuracy and being difficult in mining non-significant information when solving the pattern classification problem with strong nonlinear relationship. Therefore, a self-organizing map algorithm in the supervised mode (SSOM) (Fig. 4) is carried out to identify petrophysical facies in Gaoqing Area.

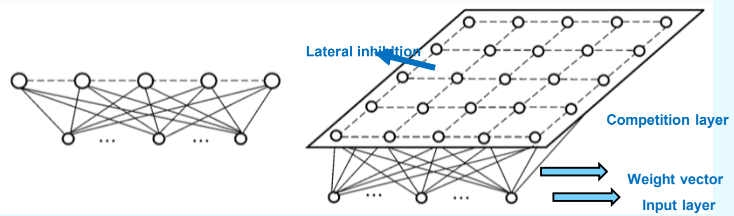

Fig. 3 The topology of SOM neural network

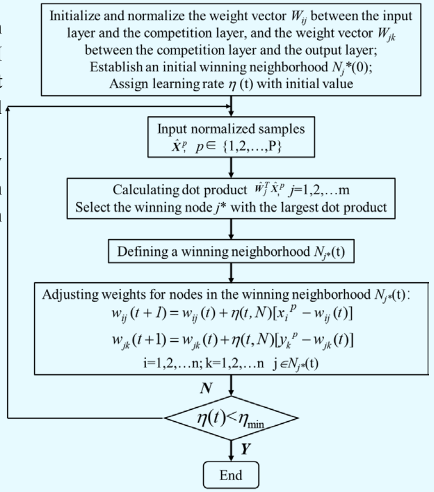

Fig. 4 The flowchart of SOM network algorithm

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RESULTS

Identification of petrophysical facies based on thin section analysis

➢ Considering the genesis of petrophysical facies in the upper member of mengyin formation, the diagenetic facies obtained by thin section analysis were taken as the main basis for superposition with sedimentary rock facies (Fig. 1, Fig. 5). The reservoir in the coring section was divided into five types of petrophysical facies: PF1, PF2, PF3, PF4 and PF5.

➢Statistical core physical properties data and pore structure parameters of all kinds of petrophysical phases were collected (Fig. 6). Using the physical properties data and pore structure parameters as constraints, the division criteria of petrophysical phases of coring layers were determined comprehensively.

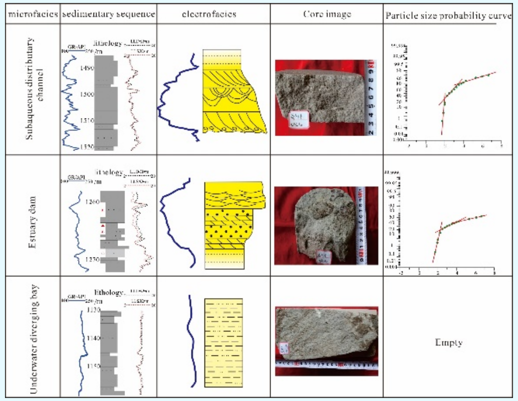


Fig.5 Characteristics of sedimentary rock facies in the upper member of Mengyin Formation

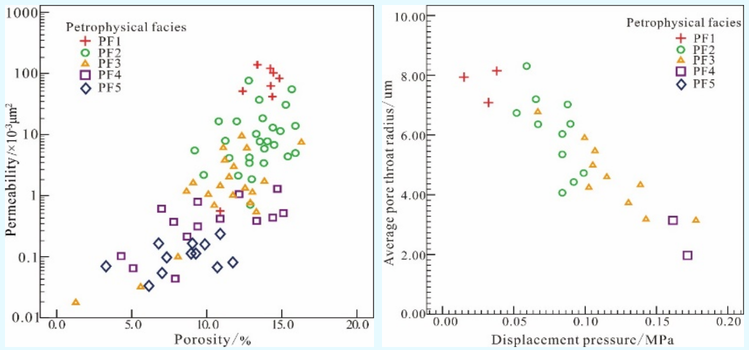
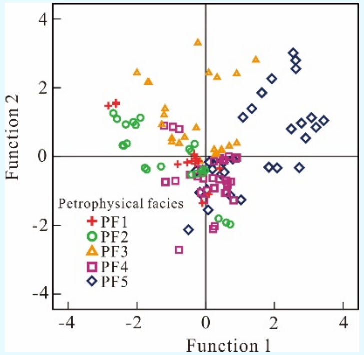


Fig.6 Physical properties and pore structure characteristics of different types of coring petrophysical facies in the Upper Member of Mengyin Formation

Optimization of Input data via LDA



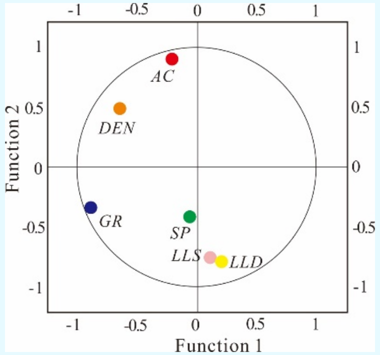


Fig.7 Projection distribution of petrophysical facies on eigenvector   Fig.8 Correlation of various logging curves and eigenvectors

➢LDA (linear discriminant analysis) was used for dimensionality reduction in order to select log data that can be used to characterize and distinguish the physical characteristics of rocks to the greatest extent without making noise due to too many variables. LDA is a dimensionality reduction method with supervised learning. It projects high-dimensional samples composed of logging data of different types of rock physical phases onto low-dimensional eigenvectors, so that the projected values of samples of different types of rock physical phases in the direction of eigenvectors have the best separability, that is, the maximum distance between classes and the minimum distance within classes can be realized (Fig. 7 and Fig. 8).

Quantitative evaluation of petrophysical facies based on SSOM

➢The neural network of the competition layer is the 10×10 symmetric network. The neuron nodes of the output layer represent the flow unit types of core samples. Selecting random initialization, respectively assigning the weight Wij and Wjk as distinct random numbers between 0 and 1. Defining the learning radius r to be 2; the initial learning rate η(0) is 0.5; the learning rate threshold is 0.001, and the maximum number of iterations is 120,000.

➢The SSOM prediction model was finally established, based on the training process of 132 groups of training samples. Figure 9 shows the self-organizing map topology diagram and 3DSammon mapping projection diagram, which reflect the classification results of the petrophysical facie.

DISCUSSION

➢The results showed that there are only 21 groups of samples were misjudged and the accuracy rate of the model reaches 84.09% (Table 1). The reason of the error may be that the learning samples are insufficient. Therefore, more core samples should be collected as much as possible in the actual work, but the error rate of 15.91% is able to meet the geological requirements.

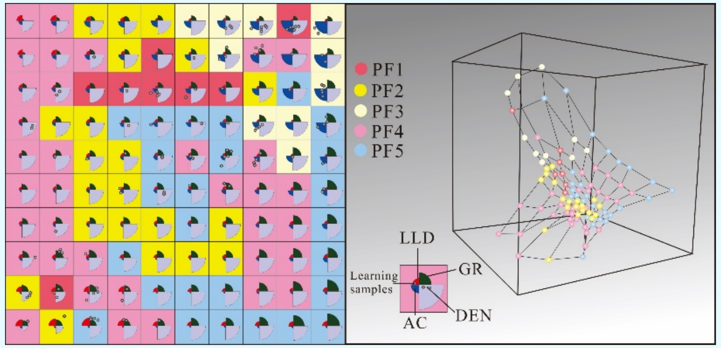


Fig.9 Self-organizing map topology and 3D Sammon mapping projection of competing neuron nodes

Table 1 Identification results of petrophysical facies in the Upper Member of Mengyin Formation

petrophysical facies type	PF1		PF2		PF3		PF4		PF5	
colour										
number of training samples	16		24		24		34		34	
number of predicting sample	13		21		20		29		28	
prediction accuracy/%	81. 25		87.50		82. 30		85. 29		82.35	
statistics	average	deviation	average	deviation	average	deviation	average	deviation	average	deviation
GR/API	145.75	89.76	150.35	76.77	152.16	334.76	152.63	491.93	174.61	538.00
AC/μs/m	250.54	125.11	233.51	377.60	222.56	444.23	221.98	294.38	217.70	45.51
DEN/g/cm³	2.4045	0.0101	2.3693	0.0180	2.4344	0.0238	2.4319	0.0007	2.4381	0.0008
LLD/Ω·m	7.17	9.43	4.99	41.73	11.49	30.42	12.42	20.34	13.70	22.70

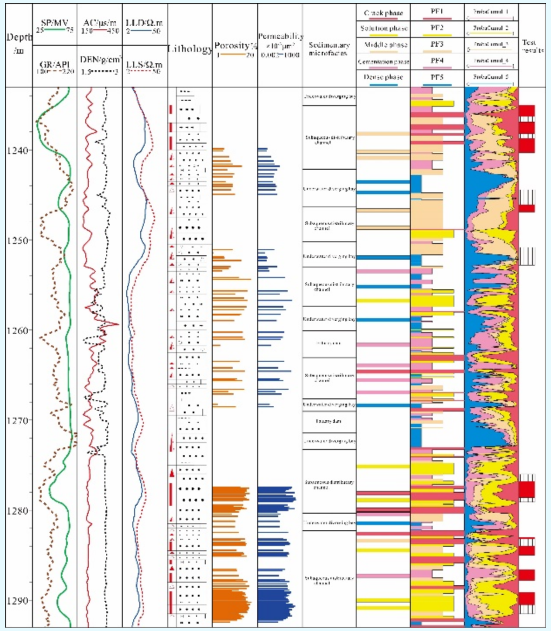


Fig. 10 The results of single well identification of petrophysical

➢Using the supervision mode of self-organizing neural network model for logging petrophysical facies identification (Fig. 10), sedimentary microfacies can be subdivided into different types of petrophysical facies with an average accuracy of 84%. And the coring interval - diagenetic facies in composite coincided basically with the results and test results, identify the results with higher reliability. Based on single-well identification results, a comprehensive evaluation of the upper member of the Mengyin formation was carried out. The petrophysical facies of PF1, PF2 and PF3 are favorable types of pore-penetration development with well-developed secondary pores, good pore connectivity and percolation ability (Fig. 10).