Logging Identification for Diagenetic Facies—An Example in Lower Jurassic Ahe Formation, Tarim Basin, China

Introduction

As a typical tight sandstone reservoir, the lower Jurassic Ahe Formation in Kuqa Depression of Tarim Basin, China, is a vital oil and gas productive interval (Zhao et al., 2018). However, this tight sandstone reservoir has experienced a complicated diagenesis modification in geological history, now generally characterized by high compactness, complicated pore structure and strong heterogeneity, which increased the difficulty of the reservoir classification and recognition. Therefore, in order to reasonably and effectively classify the types of tight sandstone reservoirs, the influence of diagenesis should be considered (Lin et al., 2017). Diagenetic facies are defined as the results of sediments interacting with diagenetic processes in certain tectonic settings, and it is the integration of diagenesis, diagenetic minerals and pore systems (Liu et al., 2015; Zou et al., 2008). Thus, the distribution of diagenetic facies is critical to predict the spatial variability of diagenesis-controlled reservoir properties (Lai et al., 2016).

Core is the most accurate data to classify and identify different diagenetic facies, but only limited intervals of Ahe Formation are cored due to its deep buried depth and high costs. The logging data is characterized by better longitudinal continuity, easy access and low price, so it is of great practical significance to quantitatively identify different diagenetic facies in Ahe Formation by using well logs. However, there are relatively few literatures on the prediction of diagenetic facies by using well logs. One of few cases is that of Lai et al. (2019) who summarized the log characteristics of diagenetic facies in cored wells, and predicted the diagenetic facies of the uncored wells according to these qualitative log characteristics. The other is to build biplots of well logs, or to build models based on multiple statistic method such as principal component analysis (Cui et al., 2017). However, the above methods can be a tedious, time-consuming and subjective task for even the most experienced of well log geologists.

The goal of this study is to partition the tight sandstone of Ahe Formation into several diagenetic facies based on cores, and correlate them with well logs to build a model in order to predict diagenetic facies in uncored intervals. Specifically, four diagenetic facies are determined based on lithologic characteristics, diagenesis, as well as diagenetic minerals, and they are: (1) tightly compacted facies; (2) dissolution of unstable components facies; (3) carbonate cement facies; (4) microfracture facies. Then these four facies are correlated with well logs, and BP neural network model is built for prediction of diagenetic facies using well logs. This model is validated by blind testing log-predicted diagenetic facies against petrographic features from core samples of the Lower Jurassic Ahe Formation in Tarim Basin, which indicates it is a helpful predictive model.

Method and Theory

Four diagenetic facies have been identified by thin section observation and core experiments from 4 Wells. Four representative photographs for each diagenetic facies are provided in Fig.1. Porosity, permeability and pore throat structures characteristics are provided in Fig.2, Fig.3 and Fig.4 respectively. Compared with the other two diagenetic facies, dissolution of unstable components facies and microfracture facies show the best reservoir quality due to their higher porosity or permeability value and larger pore throat radius.

Data used in the training and testing of BP neural network model come from 575 samples (53 cores) which are known diagenetic facies from well YN4. Each sample is associated with as many as six available well log properties which consist of gamma-ray (GR), bulk density (DEN), borehole-compensated sonic (AC), compensated neutron correction porosity (CNC), deep laterolog (RD) and shallow laterolog (RS). These well log properties are selected based on their mutual presence for all of the wells in study area. Then these samples are divided into two subsets: a training set (41 cores, 455 samples, including 111 tightly compacted facies, 107 dissolution of unstable components facies, 107 carbonate cement facies 130 microfracture facies) and a testing set (12 cores, 120 samples, 30 for each diagenetic facies). Prior to the creation and training of the BP neural network model, several
preprocessing subtasks is needed to perform on well log data (Bhattacharya et al., 2001) to help reduce errors: (1) core-to-log depth shift corrections are made to all well log curves; (2) well log curves are visually inspected to remove obvious data errors or spikes; (3) a new parameter $\Delta R = \text{Abs}(R_D - R_S)$ which is sensitive to microfracture is introduced; (4) and GR, DEN, AC, CNC, RD and $\Delta R$ are normalized using Z-Score method.

The three-layer BP neural network is created in this study. The input layer contains five neurons, corresponding to the selected six sensitive log parameters (GR, DEN, AC, CNC, RD and $\Delta R$), and the output layer includes four neurons corresponding to probabilities of the four diagenetic facies, and the number of neurons in second layer is set 15. The transfer function of second layer is set to be 'logsig', while that of output layer is set to be 'purelin', and the training function of BP neural network is 'trainscg'. During the training process, the training set is used to train BP neural network, while testing set is used for testing the accuracy of the trained BP neural network. The training process is set to stop once the accuracy calculated on testing set reaches maximum, and this final accuracy is regarded as the accuracy for the trained BP neural network model. In this study, the trained BP neural network model accuracy is 80%, which indicates this model can be used in other uncored wells to predict diagenetic facies.

![Photomicrographs of four diagenetic facies](image1.png)

**Figure 1** Photomicrographs of four diagenetic facies. A) Tightly compacted facies, in which no evident pores can be detected, and micas or soft rock fragments are abundant; well YN2, 4839.20m; B) Dissolution of unstable components facies, in which unstable components have commonly dissolved and have enhanced reservoir quality; well DB102, 5094.70m; C) Carbonate cement facies, in which carbonate cements occupy most intergranular volume or calcite metasomatic feldspar; well YN4, 4458.27m; D) Microfracture facies, in which micro-fracture cuts through grains and appear to be oriented; well YN5, 4534.76m.

![Porosity characteristics of four diagenetic facies](image2.png)

**Figure 2** Porosity characteristics of four diagenetic facies. A) Tightly compacted facies; B) Dissolution of unstable components facies; C) Carbonate cement facies; D) Microfracture facies. The porosity of B) and D) is generally greater than that of A) and C).
**Figure 3** Permeability characteristics of four diagenetic facies. A) Tightly compacted facies; B) Dissolution of unstable components facies; C) Carbonate cement facies; D) Microfracture facies. The permeability of B) and D) is generally greater than that of A) and C).

**Figure 4** Characterization of pore throat structures of each diagenetic facies using mercury intrusion method. A) Tightly compacted facies; B) Dissolution of unstable components facies; C) Carbonate cement facies; D) Microfracture facies. The size of throats in B) and D) is larger than that in A) and C).

**Examples**

A blind test has been performed to evaluate the validation of the trained BP neural network model in well DB102 in study area, which is not used to train the model. Fig. 5 shows that the predicted diagenetic facies are corresponding with the thin sections, which suggests this model can be used to predict diagenetic facies in other wells of the study area.

**Figure 5** Prediction of diagenetic facies in well DB102 to validate the model.
Conclusions

1. According to the thin section petrography and core experiments, four diagenetic facies are identified, and they are: (1) tightly compacted facies; (2) dissolution of unstable components facies; (3) carbonate cement facies; (4) microfracture facies. The dissolution of unstable components facies and microfracture facies show the best reservoir quality.

2. BP neural network can be used to build a model for diagenetic facies prediction using well log, and the application of this model in well DB102 suggest it could be applied for uncored wells in the study area.

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References


