A Diagenetic Facies Model for Characterizing Yanan Formation, Ordos Basin, North Central China

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Abstract Low-resistivity pay is a popular phenomenon in many sedimentary formations, and is present in clastic reservoirs of Yanan formation, Ordos Basin of North Central China. The reservoir quality of the studied sandstones is affected positively and negatively by several diagenetic processes, our classification is based on precipitation of pyrite and feldspar and clay minerals authigenesis. The main objective of this study is to integrate lithologic and diagentic information of facies to correctly quantify the reservoir quality. Fifteen sedimentary lithofacies were described based on core description, thin section, and SEM analysis. The quantity and type of clay minerals are examined, using X-ray diffraction technique (XRD) and geochemical analysis using X-ray fluorescence technique (XRF), within the hydrocarbon bearing reservoirs. Facies are lumped together to create a composite database containing eight lithofacies associations. The calibration of log shapes and values by the core is used to establish the suite of logs that would be most suitable for the recognition and discrimination of the various types of facies and facies associations seen in cores before quantitative electro-facies analysis is carried out. Facies association model in the cored intervals is used to predict them in the un-cored intervals. BP-ANN has the most facies prediction power than discriminant function. In particular, with regard to the kaolinite- and pyrite-bearing facies Associations (FA8 and FA6), there is a >90% success rate at predicting the occurrence of them. Facies classification and clustering scheme used in this study are highly successful in prediction of porosity of reservoir rocks. The quality of the reservoirs is generally controlled by the lithologic and diagenetic behavior of rocks forming them.

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1 Introduction

The Ordos basin, with an area of 320,000 km^2, is situated in the western part of the North China block, within the Yellow River drainage basin. The maximum thickness of the stratigraphic section in the Ordos Basin is in excess of 10 km [1].

The study area is near to the western margin of the fold-thrust belt of Ordos Basin. It covers an area of 848.88 km^2 and tectonically it can be divided into structurally stable eastern part; synclinal form central part and western thrust fault-fold zone. Delta front mouth bar and delta plain distributary channel sandstones in the Yanchang and Yanan Formations, of upper Triassic and Lower Jurassic respectively, are economic oil reservoirs in the area. The risk for successful hydrocarbon exploitation is extremely high because of complex stratigraphic relationships within the formations as well as local variability in reservoir-sandstone thickness, distribution, and quality.

Uplift of the Ordos Basin resulting from an isostatic rebound after the cessation of thrusting and rifting during the last stage of the Late Triassic produced a regional unconformity between Triassic and Jurassic formations. The overlying Lower Jurassic Fuxian Formation was deposited in local depressions developed on the pre-Jurassic erosional surface [2]. Deposition of the Yanan Formation over the western Ordos Basin after a period of uplift during the latest Early Jurassic commenced with the deposition of coarse-grained fluvial sediments at the base of the Yanan Formation. At the upper part of the Yanan Formation, the Ordos Lake of the Yanan period gradually dried and infilled with several parasequences consisting of fluvial and large, gentle-sloped lacustrine deltaic coal-bearing deposits sourced from the uplifted western flanks of the basin.

Yanan formation is well exposed in the central and northern parts of the basin. At the type locality, the formation is composed of two members and ten lithostratigraphic units comprising Yan10 through Yan1 from bottom to top. The lower member consists of fine–to coarse-grained sandstone with a basal conglomerate, and interbedded siltstone and shale in the upper part. The upper member consists of interbeded sandstone, mudstone, shale, and locally, coal and oil shale. In the southernmost part of the basin, Yanan is more complex. The reservoirs have good properties, with an average porosity of 18–20% and an average permeability of 50 md and a maximum permeability of 3000 md [3]. The shallow-lacustrine and swamp mudstones of the upper part of the Yanan Formation serve as a regional seal of the Lower Jurassic oil reservoirs, and the flood-plain mudstones that superimposed above the sandstones provide direct seals. Stratigraphic traps are the principal trap types of the Jurassic oil accumulations. These traps include the unconformity onlap and pinch-out traps.

Many oil and gas reservoirs are contained in rocks formed by ancient deltas. Deltaic reservoirs often have complex internal architecture and properties [4]. Shales are the fundamental geologic control of the delta reservoir heterogeneity. Shales have variable effects in controlling reservoir behavior [5]. They may affect vertical permeability [6].

The term electrofacies was originally defined as a set of log responses that characterize a bed and permits it to be distinguished from the others [9].

Some efforts have been made to use statistical methods such as discriminant analysis to identify facies from well logs [7]. The past decade has also seen applications of Artificial Neural Network (ANN) [8] and fuzzy logic in facies classification [2]. All methods use a training data set consisting of observed cases with full information about both predictors (in our application, well-log readings) and groups (in our case, facies). Based on the training data set, one creates a rule (called a classifier) by which future observations of predictors can be used to infer probable group memberships.

Chemical processes in shales begin at an intermediate diagenetic level (80–140 °C), including the transformation of smectite to illite and liberation of organic acids from organic matter [9].

2 Methodology

The full core was taken from each of four cored wells for sedimentologic and petrophysical analysis. Core plugs (about 10 cm long) were taken at 0.4 + 0.24 m intervals from each cored section for porosity, and permeability measurements.

The detailed petrographical analysis is conducted on 24 thin sections using transmitted light optical microscopy, cathodoluminescence (CL), scanning electron microscopy (SEM) with energy dispersive X-ray spectroscopy (EDS).

Clay mineral analysis using X-ray diffraction technique (XRD) and geochemical analysis using X-ray fluorescence technique (XRF) are also conducted on selected samples from the reservoir intervals.

Well logs used for this study include calipers, induction logs (ILD, ILM) and LL8, dual laterolog (LLD, LLS) and MSFL, Gamma ray (GR), Spontaneous Potential (SP), Acoustic (AC) and borehole-corrected neutron log (CNL), and bulk density (DEN).

The depth shift, standardization, and normalization of logs from different wells is carried out using multi-well histogram and cross-plot displays of various logs as a routine data quality work.

Log readings calibrated by core observations is used for the recognition and discrimination of the various types of facies (F) and facies associations (FA) (training and validation) before quantitative electro-facies analysis is carried out within the whole study area.

Electrofacies analysis in this study is based on the discriminant function analysis and ANN approaches which involve two steps for facies classification and prediction: (1) creation of an electrofacies database with reference to the core-defined facies; and (2) assigning electrofacies to the unknown depth levels with reference to the electrofacies database and a linear discriminant function and pattern-processing of ANN functions.

3 Results

Fifteen electrofacies (F1, F2, F3, F4, F5, F6, F7, F9, F12, F13, F14, F15, F16, clay and coal) could be created corresponding to fifteen core-defined facies using the same set of cross-plots (Fig. 1).

Pyritization is more effective than kaolinitization on DEN and AC (Fig. 2). This made the former affect petrophysical properties more than the latter i.e. kaolinitic sandstone is more porous than pyretic one.

Facies are lumped into facies associations including gravelly sub-litharenite (FA16), medium- to coarse-grained sedimentary sub-litharenite (FA15), fine-grained

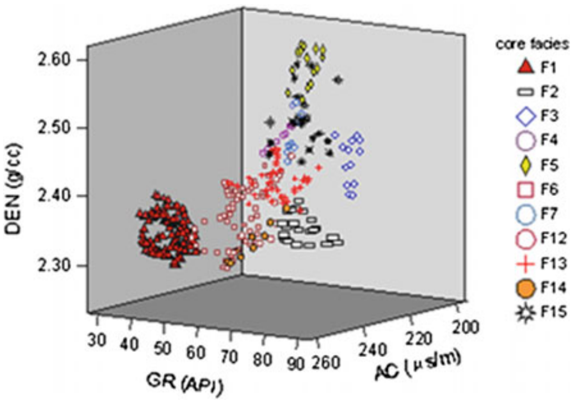

Fig. 1 3D scatter plot of the study area facies

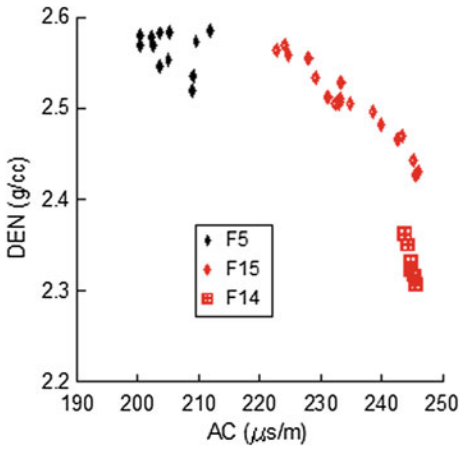

Fig. 2 The effect of pyritization and kaolinization on AC-DEN logs

sedimentary sub-litharenite (FA14), arkose sandstone (FA12), kaolinitic sandstone (FA8), pyritic greywacke (FA6), mudstone (FA4) and coal (FA0).

3.1 Facies Association Prediction from ANN Approach

All facies associations, except FA14, are classified with 100% accuracy Fig. 3. 18.5% of FA14 is misclassified as FA12 because the igneous fragments can be changed to detritus feldspar of the arkose sandstone. The overall accuracy of this method was 98.9%.

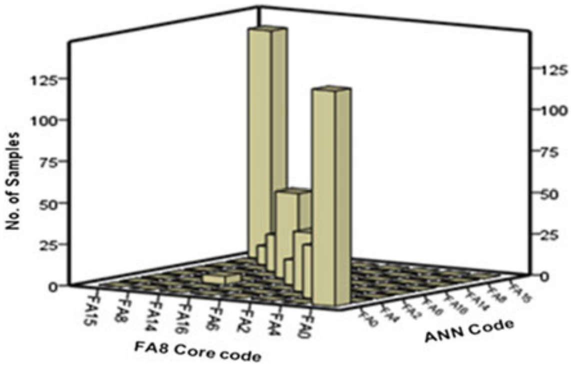

Fig. 3 3D barplot of 8 FA using ANN method for training data sets

3.2 Discrimination Analysis of the Reservoir Zone Testing Data Set

The best measure of a predictive discrimination power is a classification of observations in the testing dataset. In the discussed example, the result of such a classification is given in Table 1. All facies associations are correctly classified with 100% accuracy percentage.

3.3 Porosity Estimation

Estimation of porosity in this work based on facies association (FA) concept. A multiple regression analysis of core porosity with a suit of well logs, GR, DEN, AC, and CNL, was applied based on acceptable correlation coefficient so as to predict porosities in uncored intervals of cored wells and other uncored wells.

Porosity estimation in different depth intervals for different wells, including both training and test data sets, was good (Fig. 4). The accuracy was increasing from fractured lithologies of porous facies, FA15, in A3 and A5 areas, the upper part of the figure, to FA16, FA4, FA8, FA6, and FA14 in A2 and A3 areas lower part of the figure.

Table 1 Five facies associations' classification results of the testing dataset

Facies association (FA)			Predicted facies association membership					No. of samples
			FA15	FA8	FA14	FA16	FA6	
Core facies	Count	FA15	38	0	0	0	0	38
		FA8	0	31	0	0	0	31
		FA14	0	0	21	0	0	21
		FA16	0	0	0	55	0	55
		FA6	0	0	0	0	25	25
	%	FA15	100	0	0	0	0	100
		FA8	0	100	0	0	0	100
		FA14	0	0	100	0	0	100
		A16	0	0	0	100	0	100
		FA6	0	0	0	0	100	100

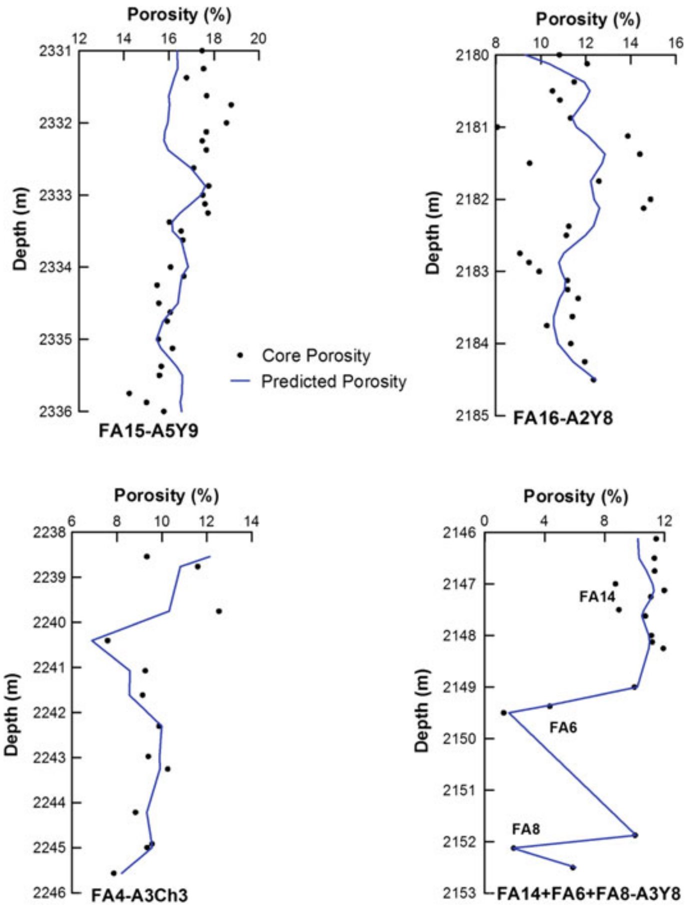

Fig. 4 Core and calculated Porosities for different facies associations

4 Conclusion

Well logs and core data; including detailed lithologic and diagentic information; are integrated to classify facies of reservoir rocks in the study area.

Discrimination of those facies and their associations using back-propagation artificial neural networks (BP-ANN) and discriminant function analysis and a comparison between those techniques has been done.

The prediction accuracy of the eight facies association (FA), for the whole study area, in training dataset by ANN is 98.9%, and the prediction accuracy of the five reservoir sands facies association (FA) by discriminant function analysis using only four well logs, for both training and testing datasets, is 100.0%.

Facies association prediction helped in determining valid porosities for different units of the studied formation.

The above mentioned diagenetic transformations can be considered as some of the causes of low resistivity pays, increasing conductivity by pyrite and forming micro-resistivity by kaolinite.

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