Iranian Journal of Mining Engineering (IJME)
Vol 17, No 54, 2022, pp 1-5

DOI: 10.22034/IJME.2021.113997.1751
DOR: 20.1001.1.17357616.1401.17.54.1.7

Iranian Society of Mining Engineering (IRSME)

The Application of Neural Network in Petrophysical Evaluation of Asmari Formation in A Producing Well in Southwestern Iran

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Received: 2019/09/08 - Accepted: 2021/09/22

Abstract

Determination of petrophysical parameters and their distribution in the reservoir can lead to new zonation and change of production thickness zone. Clay minerals exist in most of oil reservoirs and reduce important parameters such as porosity, permeability and production potential. The purpose of this study was to investigate the petrophysical properties of Asmari formation by combination of different traditional petrophysical methods for estimating clay volume and reservoir evaluation studies. The traditional calibration of gamma ray log such as Bhuyan – Passey, Larionov-1, Steiber, Clavier and Jozanikohan relationships were applied which resulted to 45% relative error for estimation of clay minerals compared to the 15 known laboratory values of this parameter. In the next step, neural network modeling was performed to reduce relative error. 259 data were estimated from laboratory values and trained with Tangent Sigmoid Activation Function, Levenberg-Marquardt training algorithm, 6 neurons and 1 hidden layer in an MLP neural network. The clay volume outputs of the neural network were classified and the body of the reservoir determined to be sandstone-clay. By investigating the density-porosity cross-plots, formation lithology and good quality reservoir intervals were introduced for Perforation operation. The gamma-ray data and neutron porosity data were also categorized to give the low to high quality intervals. Finally, by combining all the results in this study, the quality of Asmari formation was estimated to be "good".

Keywords

Clay minerals, clay volume petrophysical estimation, Neural Network modeling, Well logs.

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1- Introduction

A correct understanding of the petrophysical properties is required to predict performance and estimate the production capacity of carbonate reservoirs. The type of minerals available, the petrophysical properties of the clays, the type of fluid, the type of clay minerals, and their distribution pattern in the reservoirs have a significant effect on the petrophysical and mechanical properties of the reservoir. Reservoir classification means the division of reservoir layers based on different parameters such as lithology, porosity, permeability, and water saturation. In general, reservoirs are zoned by the geological team either based on stratigraphic characteristics or using simulation software. This study aims to determine the type, amount, and clay minerals distribution pattern in the formation, and its effect on the formation quality and well-logging parameters as well as petrophysical estimation of clay volume. The petrophysical studies mentioned in this paper have been performed to qualitatively classify the reservoir in terms of physical parameters including porosity, permeability, and formation lithology, considering the depth range of clay minerals, their type, semi-quantitative percentage and formation distribution pattern. Plus, a neural network modelling was applied to decrease the calculated error in the process of clay volume estimation and the best validate performance was derived. The volume of clay was simulated along the investigated reservoir. Finally, the petrology of the formation was determined and classified based on both qualitative and quantitative terms.

2- Methods

In the first phase of the petrophysical studies, the correlation of the clay minerals weight percentage was investigated in terms of gamma-ray log data. In the second phase, the petrophysical estimation of clay volume and conversion of shale volume to clay volume were determined using the clay volume estimation petrophysical relationships of Stieber, Clavier, Buhyan Passey, larionov (based on the age of the formation) Jozanikohan and the experimental relationship of clay volume calibration presented in this research. Then, the best relationships were introduced for estimating and converting clay volume using the least error rate. In the third phase, using well-logging data, density-porosity crossover logs were drawn by Petrol® (2015 version). After that, the qualitative classification of the reservoir was performed, examining the quality of the reservoir and combining the outputs of all stages of the research, and the high-quality reservoir intervals were introduced with a special focus on lithology and clay quantities. The amount of estimated clay volume must be corrected to identify the amount of clay minerals. To correct gamma-ray data according to previous studies, there are five categories of Bhuyan and Passey, Larinov (based on the age of the formation), Steiber, Clavier and the Jozani Kohan experimental correction which are presented in relationships 2 to 6. All estimation relationships were applied to the gamma-ray data graph and the results were presented in Table 1. The mean error percentage of the gamma-ray index is 77.8%, Larinov-1 relationship - 68.45%, Clavier 66%, Bhuyan and Passey relationship 65.35%, Stieber 60% and Jozani Kohan 45.8%. They estimated the volume of clay with a lot of error, and then the decision was made to provide a new relationship for the clay volume petrophysical estimation in this area.

The gamma-ray index (IGR) has long been the criterion for estimating the clay volume (Norouzi, 2009). The experimental corrections of the gamma-ray index presented by previous researchers (Clavier, Larinov-1, etc.) in the study formation had many errors, even the best indices (Jozani Kohan and Stieber) estimated the volume of clay with an error of about 50%, therefore the team made an effort to reduce the mean error by applying a Neural Network model in order to simulate the volume of clay all along the reservoir, comparing the XRD results and the calculated volume derived from the Neural Network . First a sensitivity analysis was applied on the given data in order to find the most proper logs for this stage and DT, NPHI, CGR and SGR were chosen as the input and experimental Clay volumes as the output of the network. Then, the data were examined by Levenberg algorithm, 6 neurons and 1 hidden layer. After 52 epochs, at the epoch 46, the best validation performance was achieved with the most appropriate properties (R=0.93, MSE=1.27).

According to the given Fig. (Figure 7 in the text), there is a good coordination between the calculated clay volume and derived volume from Neural Network modeling, which indicated that the method was considered the best to calculate and simulate the clay through the reservoir.

Determining petrophysical parameters and evaluating their distribution in reservoir spaces can lead to new zoning and change in production width of fields. Two of the most important physical properties related to fluid storage and transport in the reservoir are the porosity and permeability of reservoir rocks. Reservoir quality was interpreted using well-logging data from 3270 to 3700 meters above the sea level. After that, petrophysical logs of density (RHOB), porosity (NPHI), photoelectric (PEF), and sonic (DT) were used to identify the reservoir interval in order to identify the amount of porosity and the reservoir rock type in the study range,. A density log was drawn versus the porosity (Fig 1 to 3) in order to identify the porosity range of the samples,. The sandstone porosity range is between 20 to 25% and the carbonate porosity range is between 25 to 30%. Fig. 1 shows the log of density versus neutron porosity in the reservoir interval. The maximum porosity of sandstone and dolomite is 25% but the maximum porosity of carbonate is about 15% according to this log. According to the log in Fig. 2, anhydrite up to 5% porosity is also observed in the reservoir interval, which plays an important role in determining the quality of the reservoir as it reduces the reservoir quality. According to Fig. 3, three types of rock including sandstone and carbonate are distinguished in the log of sonic log versus porosity. The estimated porosity range for sandstone is between 20% and 25%, which is consistent with the results of Figs. 1 and 2. Therefore, the results of this log are not reliable. Finally, as can be seen in Table 1, according to Figs. 1, 2 and 3, the reservoir intervals are identified, having the appropriate quality. These intervals were determined by comparing the parameters of lithology, porosity, water saturation percentage, and permeability, calculated based on the petrophysical relationships, mainly carbonate and sandstone with a low volume of clay. To recognize an interval as an interval candidate with good reservoir quality, all the issues mentioned must be compared together, while the insufficiency of each parameter weakens that interval. The intervals listed in Table 1 are identified as suitable options for perforation operations and production from wells.

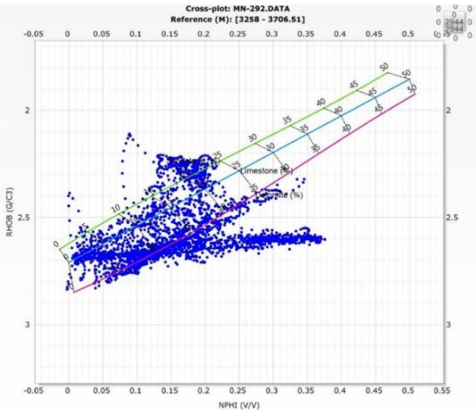

Fig. 1: Log of density versus porosity

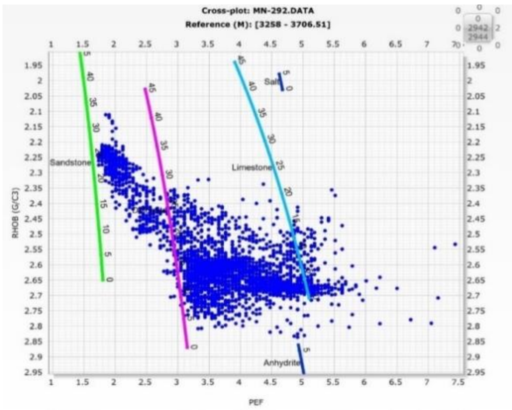

Fig. 2. Log of density versus photoelectric

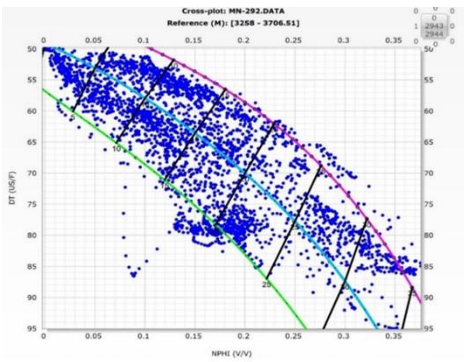

Fig. 3. Log of sonic porosity versus neutron porosity

Table 1. Reservoir depth intervals (meters) with appropriate quality

Lithology	Thickness (meter)	Start of interval (meter)	End of interval (m)
Calcite, dolomite and low volume of clay	40	3258	3298
Calcite, dolomite and low volume of clay	13	3343	3356
Dolomite and the composition of clay and calcite	26	3401	3427
Calcite and the composition of clay and dolomite	15	3501	3516
Sandstone and low volume of clay	29	3520	3549
Calcite	8	3698	3706

According to the neutron log (NPHI), the minimum and maximum values were determined. According to the minimum and maximum values and other intermediate data, the neutron porosity log was divided into four intervals. Table 2 shows the neutron porosity-based classification, which divides the formation quality into four categories. Based on this classification, 448.5 meters of the reservoir could be divided to bad, medium, good and excellent parts. To interpret pore specifically, about 104 meters of the total reservoir was determined as excellent, 94 meters as good, 92 meters as medium, and 96 meters as poor. According to gamma-ray log data, the minimum value was 10.31 and the maximum value was 199. The average of these two numbers was taken and two new intervals were introduced as the medium reservoir with average amounts of clay. According to these two numbers and other intermediate data, reservoir intervals were divided into three intervals, with 258 meters of the total reservoir having low clay content thus being high quality, 90.68 meters of the total reservoir having medium clay content, thus being medium, and 258 meters containing high clay content, and being known to be poor.

3- Conclusion

During this investigation, in every single part of the studies, different results were obtained, the results were often in accordance with each other, and finally, the reservoir was classified in terms of quality considering all the results. According to the current research, the studied well in Asmari formation of Marun oil field proved to be made of sandstones, sandstone-clay, carbonate and clay. Porosity and density logs were used to determine the formation nature. According to the initial studies on porosity and density logs, the formation was made of carbonate-sandstone, but the carbonate material was more dominant in this formation. According to the high percentage of error in petrophysical relationships of clay volume estimation (Stieber, Clavier, etc.), a neural network modelling was derived to reduce the error of calculation clay minerals volume, simulating this parameter all across the investigated reservoir. Examining the clay minerals in the formation with special attention to the gamma-ray log, it was concluded that clay minerals were present in large quantities in the formation with three patterns of scattering, filling and pore-bridging, which has reduced the quality of the reservoir in some formation depths.

In Table 2 the reservoir quality was classified by combining all the results to introduce low, medium, and good reservoir conditions. At some limited depths, the quality of the reservoir was low. For example, at a depth of 3620 to 3630 meters the neutron porosity and the gamma-ray logs determined the quality of the formation as "low", at depths of 3400 to 3600 meters, the quality changes from "medium" to "good". In conclusion, the production wells studied in Asmari Formation, Marun field were introduced as medium to good, defining the formation combined with sandstone – carbonate - clay.

Table 2. the overall structure of the quality of the reservoir

Depth	Formation type based on well logs	Formation quality based on Gamma ray	Formation quality based on φN	SEM/EDAX (Clay pattern)	XRD
3400 - 3500	Carbonate with clay layers	"medium"	"medium"	No data	carbonate clay silicate
3550 - 3570	Dolomite - clay	"medium"	"good"	dispersed pore - filling	silicate clay carbonate
3590 - 3600	Limestone – clay	"good"	"good"	dispersed pore - filling	silicate clay carbonate
3620 - 3630	Carbonate with high volume of clay	"low"	"low"	dispersed pore – filling pore - bridging	carbonate clay silicate