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Reservoir Quality Evaluation of Miocene Sediments Using Seismic Attributes and Neural Networks in Block 103 & 107, Song Hong Basin

Nguyen Thi Minh Hong*[1]

*[1]Faculty of Petroleum and Energy, Hanoi University of Mining and Geology, Vietnam
Email: mhonghien[at]gmail.com

Abstract: ***This study evaluates the reservoir quality of Miocene sediments in Blocks 103 and 107 of the Song Hong Basin using an integrated approach that combines seismic attribute analysis, machine learning, and geological interpretation. Core data, wireline logs, and seismic inversion were utilized alongside committee-based neural network models to predict porosity and permeability. The results indicate that porosity values in the study area range from a few percent to 20%, with notable variation between stratigraphic zones. The committee modeling approach, using both average and weighted combinations, provided improved predictions over individual models. These findings contribute to a more reliable reservoir characterization and suggest promising zones for future gas exploration and drilling operations.***

Keywords: porosity prediction, permeability modeling, Miocene reservoirs, seismic attributes, neural networks

1. Introduction

The Red River Basin is the largest Cenozoic sedimentary basin in Vietnam. Petroleum exploration activities in this basin began in the 1960s, with the discovery of the Tien Hai C gas field in 1975. To date, a substantial number of geophysical surveys and drilling operations have been conducted, both onshore and offshore. In the northern area of the Red River Basin (Blocks 102, 103, 106, and 107), from 1989 to 1993, Idemitsu and Total Companies have drilled five exploration wells, of which only one was considered successful, yielding a gas discovery from Middle Miocene and Early Miocene sandstone reservoirs. More recently, in Blocks 103 and 107, PVEP POC and its partners drilled four wells, all of which encountered gas discovered. In this block, advanced techniques in 3D seismic acquisition, specialized seismic processing, and interpretation, including seismic attribute analysis, seismic inversion, and AVO analysis—have been employed to optimize well placement.

To further improve the probability of exploration success and reduce risk, it is essential to integrate multidisciplinary data. This includes geological and geophysical information, analyzed through both conventional and advanced techniques such as seismic attribute analysis, integrated data interpretation, and wireline log analysis using neural networks. Such integration is critical for evaluating reservoir quality, predicting hydrocarbon potential, and supporting ongoing petroleum exploration in Blocks 103 and 107. The primary aim of this study is to develop and validate a committee-based modeling approach for predicting porosity and permeability in Miocene sediments using integrated seismic and geological data from Blocks 103 and 107.

2. Methodology

To assess reservoir quality, the evaluation is conventionally based on two key reservoir properties: porosity and permeability. The available data spans multiple disciplines, including petrographic analysis from thin sections (microscopic scale), core plugs (core scale), wireline logs (borehole scale with depth variability), and 3D seismic data (large-scale spatial coverage).

An integrated approach is proposed to combine these diverse data types. High-resolution but spatially limited wireline log data are integrated with lower-resolution, wide-coverage seismic data using mathematical and machine learning methods. Techniques such as multiple linear regression, multilayer feedforward neural networks (MLFN), and probabilistic neural networks (PNN) have been successfully applied to determine the spatial distribution and porosity-permeability (poro-perm) characteristics of the Miocene reservoirs in Block 103 [1, 2].

The study area is in the northern part of the Red River Basin, where four wells—A, B, C, and D—have been drilled. This study focuses on the Middle Miocene section, specifically from horizon U200 (Top Middle Miocene) to U260 (Base Lower Miocene). Interpreted porosity data from the four wells are used as input parameters to develop predictive porosity models based on seismic data.

Various porosity prediction models were implemented as follows: (i) Multiple linear regression and neural network methods were employed, and (ii) the entire Middle Miocene interval was subdivided into two zones for separate training and prediction processes: Zone 1 from U200 to U240, and Zone 2 from U240 to U260. In addition to seismic attributes derived from the 3D raw seismic dataset, two seismic inversion volumes, model-based inversion (MBI) and band-limited inversion (BLI) were also utilized as input variables for porosity prediction.

For each zone, three methods of determining the porosity - seismic attributes relationship are used, namely multiple regression, MLFN and PNN. The number of seismic attributes used to predict porosity is selected at the threshold when the error of validation data started to increase [1, 2]. The results show that for the Zone 1 from U200 to U240, 13 and 14 seismic attributes are used in the model including Apparent

Polarity, Derivative, Integrated Absolute Amplitude, MBI, BLI, Raw Seismic, Filter 23/30 -35/40, Filter 5/10-15/20, 15/20-25/30 Filter, Instantaneous Frequency, Integrate, Weighted Amplitude Phase, Amplitude Envelope, Amplitude Weighted Frequency. For the zone 2 from U240 to U260, using between 8 and 11 attributes, including seismic attributes: Raw Seismic, MBI, BLI, Average Frequency, Dominant Frequency, Filter 35/40-45 / 50, Second Derivative, Integrate, Cosine Instantaneous Phase, Filter 55/60-65/70, Weighted Frequency Amplitude [3, 4].

As stated above, the conventional approach for porosity prediction from seismic data involves calculating the porosity volume across the entire 3D seismic dataset using predictive models, including (i) Models based on linear regression relationships between acoustic impedance and porosity; (ii) Models based on multiple regression relationships between seismic attributes and porosity; (iii) Models based on multiple regression relationships incorporating acoustic impedance, seismic attributes, and porosity; (iv) Neural network models (e.g., MLFN, PNN) are capable of capturing complex non-linear relationships between acoustic impedance, seismic attributes, and porosity that are not easily identified through conventional methods.

Thus, for each individual zone of interest, multiple predictive models can be developed to estimate porosity. The selection of the most appropriate model is often subjective, relying on the interpreter's experience or on criteria such as the correlation coefficient of the training data. However, a model that performs well on training data does not necessarily guarantee reliable predictions in undrilled or unknown areas, leading to uncertainty in the results. To address this uncertainty, the authors propose a new committee-based approach as an integrated final model. This approach aims to enhance confidence and reduce the limitations associated with individual models.

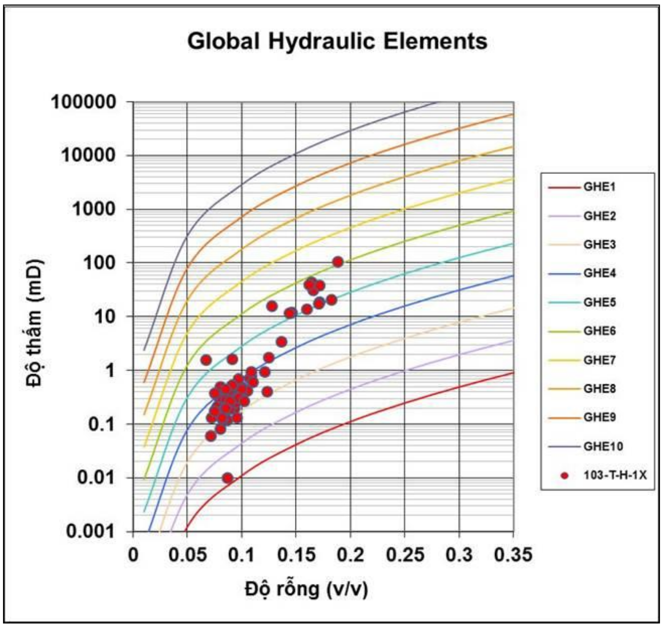

Figure 1: Core data on the GHE template

Assuming that for each zone, n predictive porosity models are developed (denoted as M_1, M_2, ... M_i, ... M_n), the committee model combines the porosity values predicted by each model. Two strategies are employed for this combination:

The averaged combination is expressed as follows:

$$\Phi = \frac{1}{n}\sum_{i=1}^{n} M_i \qquad (1)$$

The weighted combination is expressed as follows:

$$\Phi = a_0 + \rightleftarrows a_1 M_1 + a_2 M_2 + \ldots + \rightleftarrows a_i M_i + \ldots a_n M_n \qquad (2)$$

Similarly, for the permeability prediction, committee approach is also applied. Since there is a good relationship between porosity and permeability, in this study conventional poro-perm equation was used as follows:

$$K = 0{,}002 * e^{56{,}214\Phi} \qquad (3)$$

Although the real correlation between porosity and permeability could be revealed on GHE template (Figure 1). The results showed that GHE ranging from large GHE 1 to 6, reflecting heterogeneity of Miocene sandstone reservoir rock. Thus, to accurately define porosity and permeability relationship of Miocene reservoirs, the prediction should be determined separately for each GHE.

Committee model for permeability prediction is therefore applied. The predicted porosity volumes using average and weighted committee models were used to calculate predicted permeability.

3. Result and Discussion

The predicted porosity results in Block 103 show that porosity values derived from seismic attributes in Miocene sandstones, using integrated models, range from a few percent to approximately 20%. Anomalously high porosity values are primarily concentrated in the 10–15% range. Porosity predicted by the weighted model is generally higher than that predicted by the averaged model. Additionally, porosity in the U200–U240 sequence is higher than in the U240–U260 sequence.

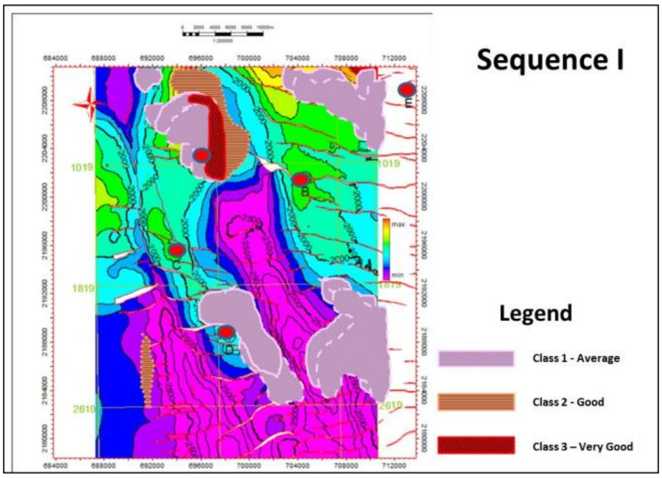

Figure 2: Reservoir quality zonation in sequence I

Moreover, the predicted porosity generally reflects the environment in accordance with Miocene sedimentation, high porosity and average quality reservoir in sequence III of the deltaic environment to delta front with influence of the marine environment. High porosity and the average to good quality reservoir in sequence II of the swamp lagoons environment to pro-delta. Lower porosity and worse quality reservoir in sequence I of sedimentary environments delta to delta front. Spatially, porosity varies from north to south and west to east, with zones with high porosity are generally concentrated near the crests of anticlines in Prospects A, B, C, D, and their vicinity. Porosity gradually decreases with increasing distance from these prospective structures.

The predicted permeability results from the committee models indicate that permeability in block 103 ranges from 0,01mD to several thousand millidarcies, with low permeability values being predominant. High permeability anomalies have been observed in the vicinity of well D.

Reservoir quality assessment based on predicted porosity and permeability

The modern methods and technologies in the geology-geophysics data integration have been applied. The high-resolution and narrowly distributed wireline log data were integrated using mathematical approaches, including multiple linear regression, MLFN, and PNN, to accurately characterize the porosity–permeability properties of Miocene reservoirs in Blocks 103 and 107.

Both weighted and average committee models have shown better results in predicting of porosity and permeability as well as their distribution of Middle Miocene reservoir than that of one model.

The derived outcomes show that in block 103, the Miocene sandstone is main reservoir with porosity ranging from approximately 5% to 20% based on wireline log and predicted porosity from seismic data and distributed widely within the block. Porosity anomalies are located mainly in A, B, C and D prospects and its vicinity. Permeability varied from 0,01 mD to several thousand mD but low permeability is dominant. High permeability zone is coincided with high porosity zone. In general, the Miocene reservoir quality varied from moderate to good and gas-bearing is dominant.

The reservoir quality zonation was done based on predicted porosity, permeability and seismic attributes anomalies. Zones with moderate reservoir quality (class-1), good (class – 2) and very good (class-3) have been delineated (Fig. 2 to Fig. 4)

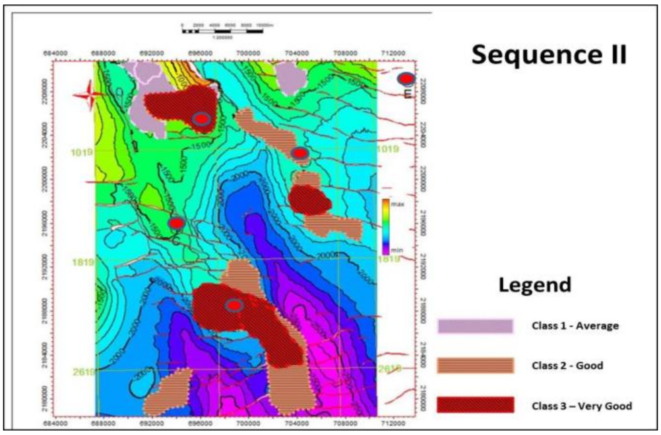

Figure 3: Reservoir quality zonation in sequence II

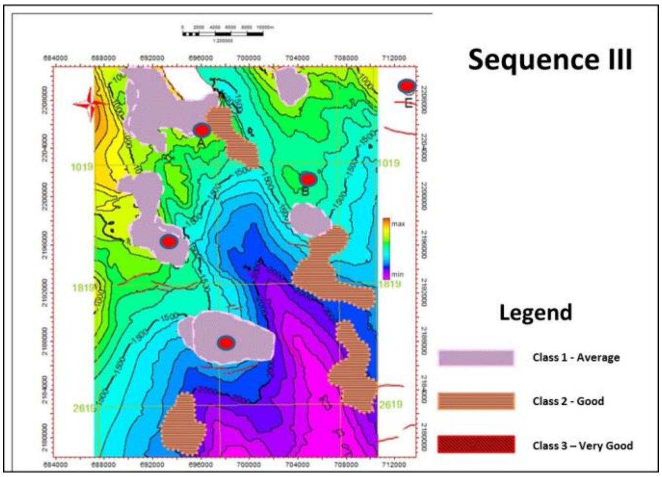

Figure 4: Reservoir quality zonation in sequence III

4. Conclusions

This study successfully applied a committee-based modeling framework to predict porosity and permeability in Miocene reservoirs of Blocks 103 and 107, integrating seismic data and well logs. The dual-model strategy (averaged and weighted) enhanced prediction robustness and highlighted reservoir heterogeneity across stratigraphic zones. The findings suggest that Middle Miocene intervals, particularly in the Phu Cu 2 and 3 sequences, present moderate to good quality gas-bearing reservoirs. Future work should prioritize facies-based classification to refine reservoir assessments further.

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