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Application of artificial neural network and seismic attributes to predict the distribution of Late Oligocene sandstones in the Cuu Long basin

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ABSTRACT

Artificial neural network (ANN) has been widely applied in oil and gas exploration and production. This study presents the results of predicting the distribution of Late Oligocene sandstones in the Cuu Long basin based on the application of ANN and seismic attributes. These results have great significance, helping to orient the oil and gas prospection and exploration of the Cuu Long basin and other exploration objects on the continental shelf of Vietnam. The authors used unsupervised neural networks (UNN) and UNN methods constantly associated with the principal component analysis (PCA) to divide seismic facies. Seismic attributes such as Root mean square (RMS), Frequency, Envelope, Relative Acoustic Impedance (RAI), Phase, Sweetness, Amplitude, and t-Attenuation were analyzed and selected as input for the ANN training and testing process. These attributes can reflect changes in lithology, and sedimentary facies, from which will have a better view of the distribution of reservoirs in the study area. From 4 to 10 classes of seismic facies have been tested using each method to improve the results. Comparing the results of seismic facies classification by the UNN method and by UNN combined with PCA, it can be seen that the UNN combined with PCA will help reduce noise in seismic data better than UNN only. The research results have identified the distribution of Late Oligocene potential sandstones in the study area in the Cuu Long basin, which are mainly concentrated on the slopes of a large lake, with the direction of sediment transport from the West and Northwest.

1. Introduction

In hydrocarbon exploration, it is important to predict the distribution and characteristics of reservoirs. Recently, artificial intelligence has been applied in different fields. In Vietnam, artificial neural network (ANN) has been widely

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applied in the oil and gas industry. Some recent studies show that the application of ANN greatly improves oil and gas prospecting. For example, Nguyen et al. (2019) showed limited conditions of the number of drilled wells in the Phu Khanh basin, the application of ANN has been effective when integrating the results of analysis of seismic data, well-logs, core analysis to predict the distribution and quality of potential reservoir in the basin. In the Song Hong basin, Le and Ha (2020) used ANN to integrate 2D seismic attributes to identify mud diapirs and hydrocarbon traps. Tran et al. (2020) used ANN to predict the distribution of volcanic materials in Cuu Long basin. Currently, due to the limitation of well data, the research on reservoir distribution still faces many difficulties. Most of the studies focus on the sedimentary environment, and seismic properties analysis without specifying the distribution of the reservoir. Luu et al. (2020) integrated seismic attributes with depositional environmental facies to predict stratigraphic traps. However, the distribution of the reservoir, as well as the characteristics of reservoir rocks, have not been clarified. Therefore, the application of the ANN method in this study to predict the distribution of reservoir rocks for the study area is of great significance, helping to orient the oil and gas prospection and exploration of the Cuu Long basin and other exploration objects on the continental shelf of Vietnam.

The Cuu Long basin is a rift basin in southern Vietnam. Many oil and gas fields have been discovered and produced both in Pre-Cenozoic fractured basement and Paleocene sedimentary rocks for more than 40 years.

The study area is the central part of the Cuu Long basin (Figure 1). In the study area, only 1 well has been drilled into the Miocene sediments. In general, the stratigraphic characteristics and depositional environment of the study area are consistent with the regional stratigraphic framework of the Cuu Long basin. Stratigraphy is described from the oldest to the youngest formations as the followings: i) pre-Cenozoic fractured basement composed of magmatic crystalline rocks. The basement consists of weathered and fractured granitoid and metamorphic rocks of Jura-Cretaceous age; ii) Tertiary sediments overlapping the fractured basement with stratigraphic and angular unconformity, are represented by terrigenous

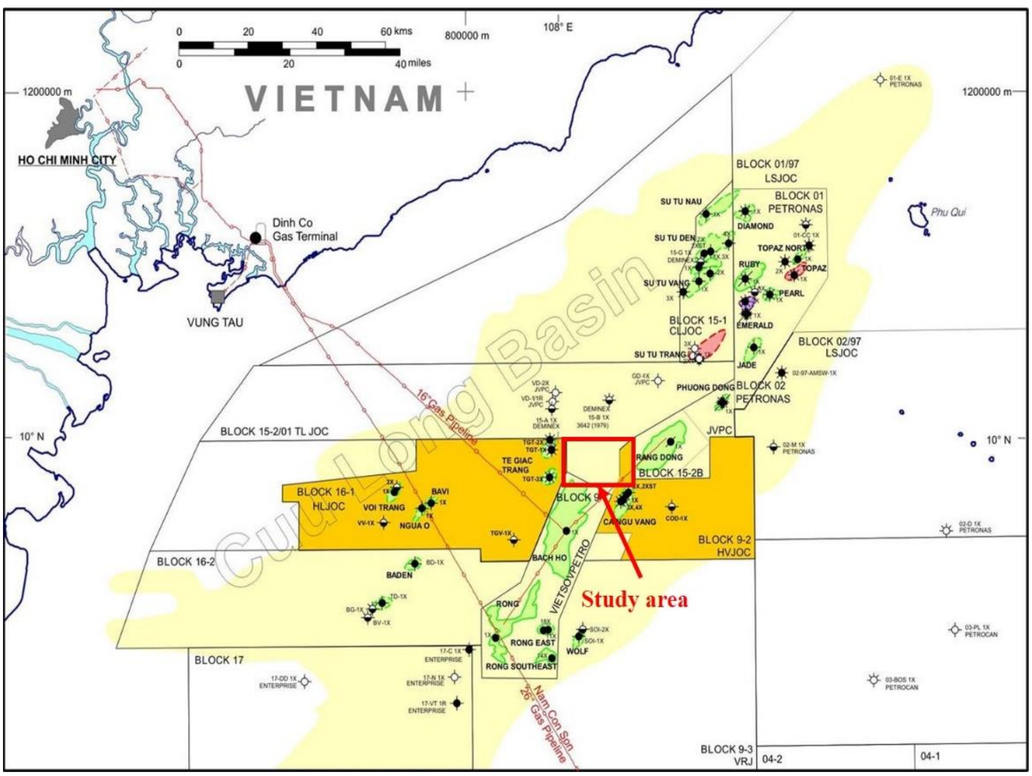

Figure 1. Red rectangle showing study area.

sediments of Early Oligocene, Late Oligocene and Early Miocene. Late Oligocene formation mainly composes sandstones, siltstones, shale, and claystone interbedded. Depositional environments are fluvial and lacustrine.

Structural-tectonic characteristics of the study area are controlled by the general tectonic setting of the Cuu Long basin. The study area is dominated by the main fault system in the direction of Northeast - Southwest, North - South and East - West.

2. Database and methodology

2.1. Database

The seismic data used for this study is a 300 km^2 PSTM 3D seismic cube. High-resolution 3D seismic data enabled to image of structural and stratigraphic features and ensured the seismic interpretation and seismic attribute analysis. Two horizons top C and top D were extracted these data to define the top and base of the reservoir. The data collected and used to predict the distribution of Late Oligocene sandstones include petrographic analysis reports, core samples, well geological reports and paleontological analysis of wells drilled around the study area. The study used Unsupervised Neural Network (UNN) and UNN constantly associated with PCA to predict the distribution of reservoirs (Figure 2).

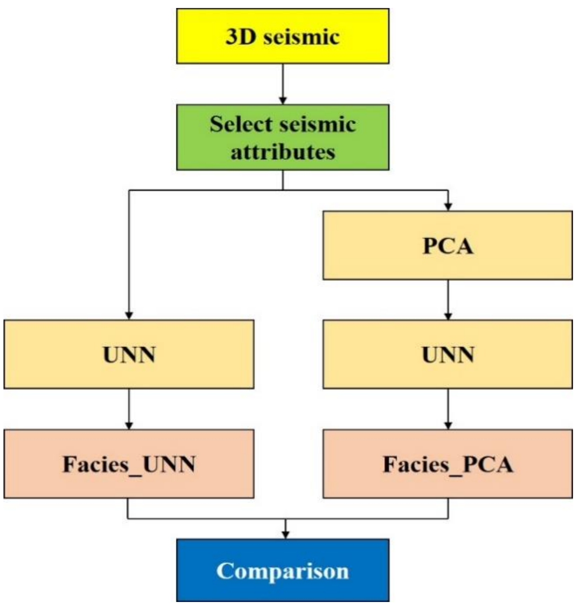

Figure 2. The workflow for seismic facies classification using ANN.

2.2. Methodology

2.2.1. Seismic facies and seismic attribute analysis

The recent development of seismic methods enables geologists to increase efficiency when studying geological structures and defining reservoir parameters. New seismic methods have been developed and have been increasingly used in petroleum exploration and production. One of the most widely used seismic methods for improving the efficiency of seismic interpretation is seismic attribute analysis. Seismic attributes can be conveniently defined as the quantities that are measured, computed or implied from seismic data (Chopra and Kurt, 2005). Seismic attribute analysis can extract information from seismic data and increase the ability to interpret geological structure, and identify prospects, stratigraphy and fluid properties.

Seismic facies analysis is a useful tool for reservoir characterization. A seismic facies unit can be defined as a sedimentary unit in which the seismic signatures differ from adjacent units in their seismic characteristics (Mitchum et al., 1977). When analyzing seismic facies, the following parameters should be considered, namely, position, external form, configuration, amplitude, frequency, interval velocity, reflection continuity, reflection polarity, reflection configuration, the abundance of reflections, the geometry of seismic facies unit, bright spots, thickness, and relationship with other units (Mitchum et al., 1977; Roksandić, 2006; Chopra and Marfurt, 2007; Xu and Haq, 2022). The interpretation of seismic facies data aims to find out the geological causes responsible for the seismic signature of a seismic facies unit. So, the interpretation may be aimed at predicting depositional properties, fluid content, bed thickness, lithofacies, relative age, overpressure shales, type of strata, etc. Generally, frequency attributes relate to bed thickness, wave scattering, and absorption. Time attributes relate to structure and amplitude attributes relate to stratigraphy (Le and Ha, 2020).

2.2.2. Seismic facies classification

ANN is becoming more popular as a tool utilized in the field of reservoir characterization. There are two methods of classifying seismic facies according to ANN: Supervised and unsupervised neural network (UNN). The supervised neural network (SNN) is applied mainly for classifying facies and for predicting reservoir properties from the combination of various samples based on seismic attributes including acoustic impedance and well log data. Meanwhile, UNN is most commonly used. Unsupervised facies classification algorithms are a data-driven way to determine clusters present in data, independent of the interpreter. The unsupervised seismic facies classification methods consist of K-means clustering, Principal Component Analysis (PCA), and the Self-Organizing Map (SOM) (Puzyrev and Elders, 2022).

In this paper, the authors used the UNN method, in order to minimize duplicate data and data noise due to the use of many seismic attribute groups at the same time to run the UNN Principal component analysis (PCA) method was used. After testing and analyzing many different groups of seismic attributes, the authors decided to use basic seismic properties such as Instantaneous Phase, Frequency, RMS, RAI, Sweetness, and Amplitude to analyze. These attributes can reflect changes in lithology, and sedimentary facies, from which there will be a better view of the distribution of reservoirs in the study area.

Principal component analysis was introduced decades ago to detect subtle features in seismic data (Scheevel and Payrazyan, 1999). PCA is a linear mathematical technique that reduces a set of variables, such as seismic attributes, to a smaller set that consists of most of the variation in the large set (Roden et al., 2015). PCA will aid in combining the most meaningful seismic attributes generated from an initial set of groups. The first principal component accounts for the maximum possible variation in the data with each successive orthogonal component accounting for the remaining variation (Guo et al., 2009; Haykin, 2009). PCA can improve the identification of geological characteristics by using a group of data seismic attributes in a certain seismic volume. The first principal component (PC1) represents the largest linear attribute combinations that best represent the variability of the majority of the data, it can not define the specific characteristics of interest (Roden et al., 2015). When interpreting seismic data, succeeding principal components should be evaluated because they can be associated with other important sides of the data and geological characteristics not defined by the first principal component. Thus, PCA is a tool used in the interpretation of seismic data, which can provide direction for more meaningful seismic attributes and improve interpretation results.

3. Results and discussion

In this study, the authors UNN and UNN methods are constantly associated with PCA to divide seismic facies. After experimenting with several seismic attributes, the authors decided to use 8 seismic attributes as Amplitude (RAW), RMS, Frequency, Envelope, RAI, Phase, Sweetness, and t-Attenuation as input data for seismic facies classification.

Based on the retained variability criteria (Stanford, 2018), the algorithm automatically outputs eight principal components (PC1 – PC8), from which the independent components are computed because they represent the variability of the data (Figure 3). Principal components are sorted and represented by their eigenvalues. Thus, the first principal component (PC1) is the strongest in these data and represents 39.23% of the variability (Figure 3). We have decided to choose 4 principal components (PC1-PC4) that represent 86.49%.

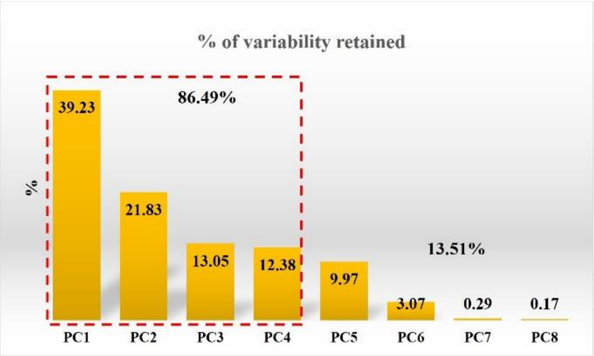

Figure 3. Variability retained.

Both UNN and UNN combined with PCA are used to divide 8 attributes of 3D seismic data into a number of different facies (Seismic facies) to predict the distribution of reservoirs in the study area. From 4 to 10 classes of seismic facies have been tested using each method to improve the results. The results are shown in Figure 4 for UNN method and Figure 5 for UNN combined with PCA.

Comparing the results from Figure 4 and Figure 5, it can be seen that the UNN method combined with PCA will help reduce noise in seismic data better than UNN only.

Based on the histogram of 10 seismic facies (Figure 6), the authors have decided to reduce the number of seismic facies to 2 classes and combined with other geological data, it is possible to show 2 classes of attributes, respectively shale (class I – non-reservoir) and sand (class II – reservoir). The facies model has been smoothed to reduce noise's influence in the 3D seismic data.

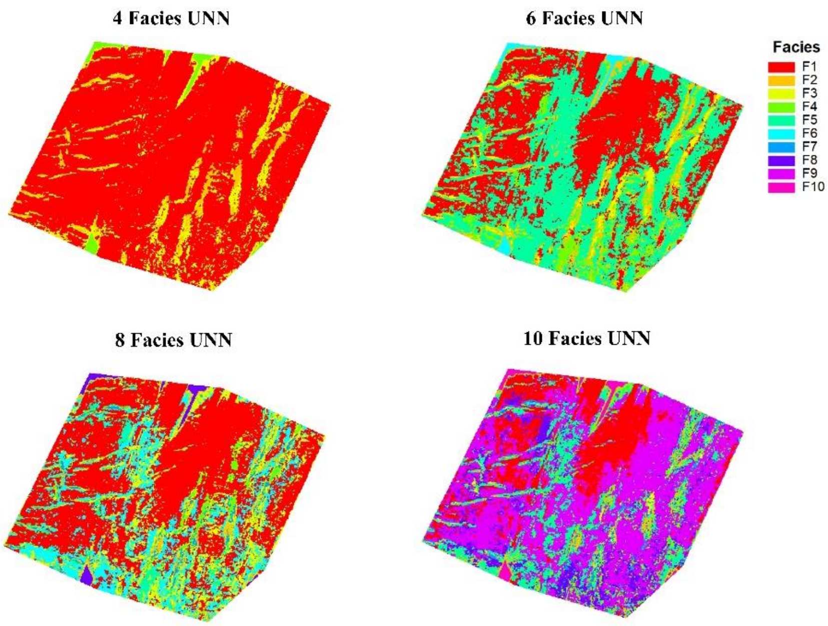

Figure 4. Result of seismic facies classification by UNN method.

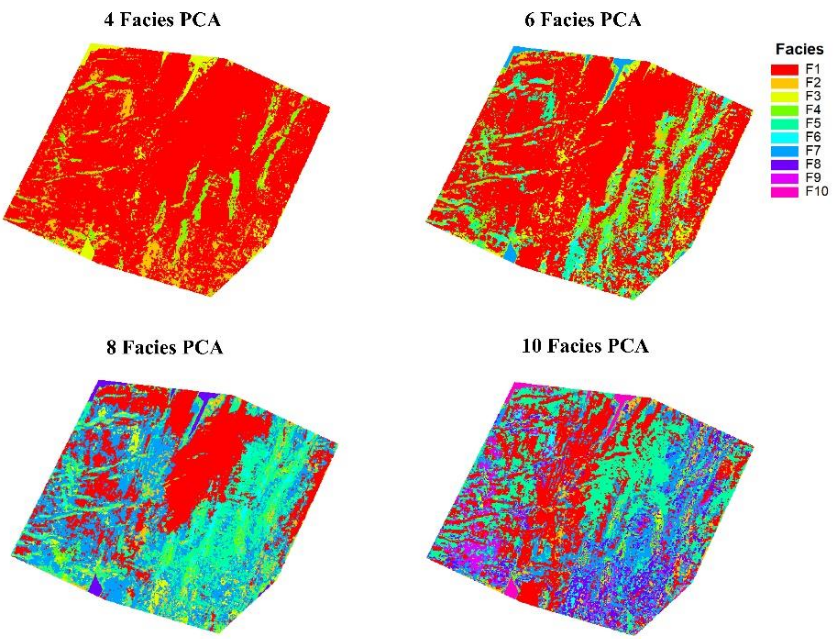

Figure 5. Result of seismic facies classification by UNN method combined with PCA.

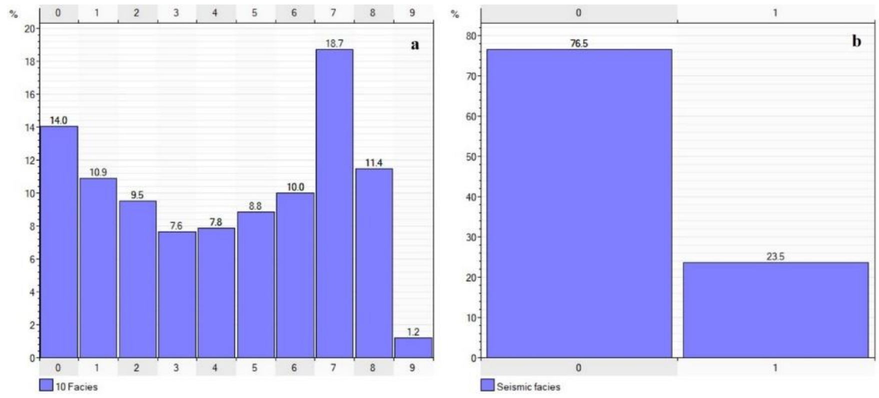

Figure 6. Distribution histogram of 10 seismic facies by UNN method combind with PCA: a) 10 seismic facies classes; b) 2 seismic facies classes (reduced from 10 classes).

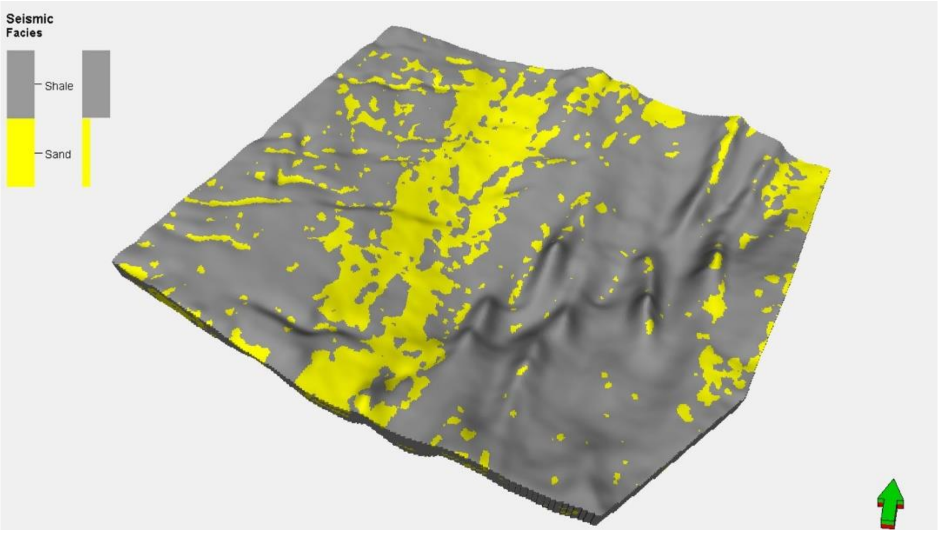

Figure 7. Two seismic facies classes are illustrated in the 3D model.

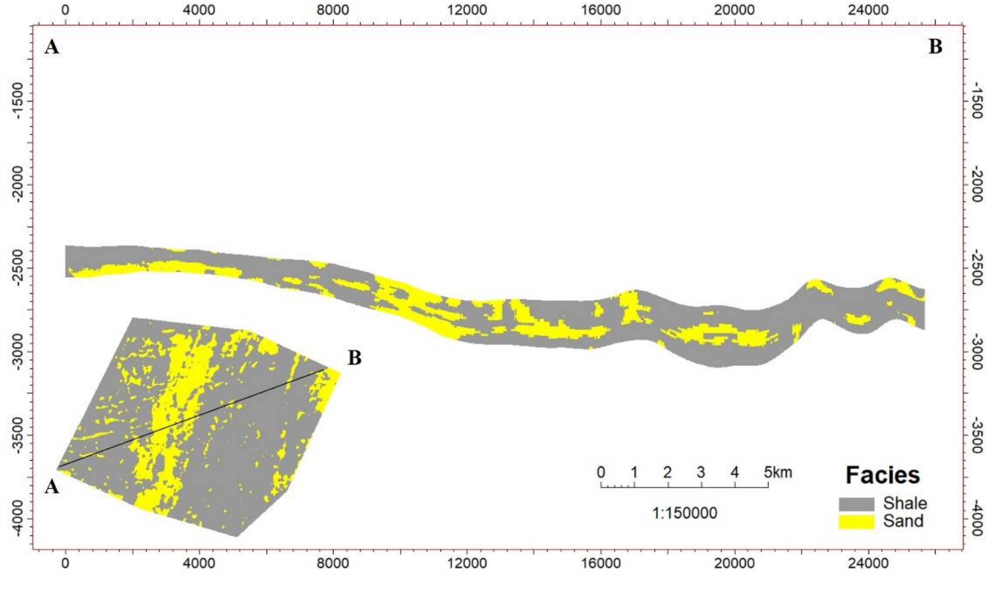

Figure 8. Section AB through the study area.

After synthesizing and analyzing ANN, the facies model shows the potential sand bodies (yellow) in Figure 7. The distribution area is mainly concentrated on the slopes of a large lake, with the direction of sediment transport from the West and Northwest. Figure 8 illustrates the A-B section through the study area showing the distribution of the reservoir.

According to the research results of the Late Oligocene depositional environment in the study area (Luu et al., 2020), the study area was completely located in the lacustrine environment, with the main sediment transport and supply direction from West to East. The results of seismic attribute analysis, facies model, and depositional environment show quite consistency and reliability.

4. Conclusion

Integrated seismic attribute analysis and statistical method (PCA) and Artificial Neural Network (ANN, UNN) help to clarify the distribution of Late Oligocene sandstone reservoirs in the study area of the Cuu Long basin.

UNN method is a useful tool to divide seismic facies classes when the study area does not have many or no well data. When using the UNN method in combination with PCA, helps to reduce input data noise better than using UNN only.

The results of the UNN method need to be verified after the study area has new wells. 3D models from UNN can be used as input conditions for facies models or petrophysical models when building 3D geological models.

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Contribution of authors

Muoi Duy Nguyen: writing manuscript, designing the study, analyzing the geological setting. Hoa Minh Nguyen: analyzed seismic attributes, and UNN, PCA. Ngan Thi Bui prepared the methodology and database, editing the article.

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