Integrated carbonate reservoir types modeling based on the PRT deep learning and multi-parameters seismic inversion and its application

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Summary

To improve the accuracy of carbonate reservoir modeling, mainly well data such as core, thin section and well logging data had been adopted in conventional methods. Although the reservoir types classification is very detailed, but it is usually difficult to integrate with seismic data to make 3D reservoir types prediction. To address the issue of carbonate reservoir types modeling, a new integrated carbonate reservoir modeling workflow was summarized based on thin section, core, well logging, 3D seismic data and production performance data. The integrated carbonate reservoir modeling workflow integrated thin section, core, well logging, 3D seismic data and production performance data, and improved the accuracy of 3D reservoir types modeling for no well area. It’s useful for new wells optimization and high efficiency development with lower cost. The integrated carbonate reservoir modeling workflow not only suit for carbonate reservoir, but also suit for clastic reservoir.

Introduction

To improve the accuracy of carbonate lithofacies modeling, many experts have done a lot of useful research. Mazzullo, S.J., Harris, P.M., & Boardman, D.R. (1992) presents the hierarchical architecture of carbonate ramps, providing examples of outcrop and subsurface models. It emphasizes the distribution and characteristics of lithofacies at different hierarchical levels within carbonate ramps. Reijmer, J.J.G., & Swart, P.K. (1990) discusses the application of sequence stratigraphy models to carbonate platforms, with a focus on the Middle East. It highlights the importance of sequence stratigraphy in understanding and modeling carbonate lithofacies. Jiang, Z., Luo, P., & Zhang, X. (2018) employs a self-organizing map neural network to model lithofacies in complex carbonate reservoirs. It explores the potential application of this method in simulating lithofacies distribution and provides insights into the modeling of carbonate reservoirs. Romano, M., Caramanna, G., & Coli, M. (2016) summarizes lithofacies and fluid flow modeling approaches for carbonate reservoirs. It discusses different modeling methods, their advantages, and limitations, and the impact of lithofacies on reservoir development. Purser, B.H. (1998) introduces the concept of the carbonate ramp as an alternative to the traditional shelf model. It discusses the characteristics, lithofacies distribution, and controlling factors of carbonate ramps, providing insights into carbonate lithofacies modeling. Mustafa, H.M., & Al-Aasm, I.S. (2011) presents a hierarchical approach to carbonate reservoir modeling, integrating sedimentological, diagenetic, and sequence stratigraphic concepts. It emphasizes the relationship between lithofacies variations and reservoir properties at different scales. These studies provide a integrated overview of carbonate lithofacies modeling, covering topics such as hierarchical architecture, sequence stratigraphy, neural network modeling, and the integration of various geological concepts. They offer valuable insights into the understanding of carbonate lithofacies distribution in different geological settings. However, although the reservoir types classification is very detailed, but it is usually difficult to integrate with seismic data to make 3D lithofacies model. To address the issue of carbonate lithofacies modeling, a new integrated carbonate lithofacies modeling technique was summarized based on thin section, core, well logging, 3D seismic data and production performance data.

Method

In this paper, an integrated carbonate lithofacies modeling workflow mainly contains 5 steps. 1) Integrated lithofacies classification based on the core, thin section, well logging, FMI, CMR and production performance data. 2) Petrophysics lithofacies classification based on the cross-plot analysis between sensitive well log curves. 3) Petrophysics lithofacies prediction based on the sensitive well log curve by deep learning method, and verification by core lithofacies analysis. 4) Seismic inversion volume optimization by well lithofacies calibration. 5) Lithofacies modelling based seismic inversion based on the seismic inversion cut-off analysis. This workflow integrated seismic impedance (continuous variable) with lithofacies (discrete variable), and converts seismic inversion into lithofacies directly.

1) Integrated lithofacies classification

Integrated lithofacies classification refers to the process of combining multiple data sources and analytical techniques to classify and characterize lithofacies within a geological setting. It involves the integration of various types of data, such as well logs, core samples, seismic data, and outcrop studies, as well as the application of different analytical methods, including statistical analysis, deep learning algorithms, and expert interpretation (Fig.1).
The goal of integrated lithofacies classification is to obtain an integrated understanding of lithofacies distribution, variability, and properties within a given area. By integrating multiple data sources and techniques, it can enhance the accuracy and reliability of lithofacies classification and improve the characterization of reservoirs or geological formations.

Integrated lithofacies classification enables a more integrated and robust understanding of lithofacies distribution by leveraging diverse datasets and analytical approaches. It enhances the characterization of subsurface reservoirs, and supports decision-making in the exploration and production of natural resources.

2) Petrophysics lithofacies classification

Petrophysical lithofacies classification is a method that integrates petrophysical data, such as well logs and core measurements, to classify and characterize lithofacies within a reservoir or geological formation. It combines petrophysical properties with lithological information to better understand the spatial distribution, reservoir quality, and flow behavior of different lithofacies (Fig.2-a). AI petrophysical lithofacies classification allows for a more detailed and quantitative understanding of reservoir heterogeneity and flow behavior by integrating petrophysical properties with lithological information.

3) AI petrophysics lithofacies prediction

AI-based petrophysical lithofacies prediction is a technique that utilizes artificial intelligence (AI) algorithms and deep learning models to predict lithofacies based on petrophysical data. It involves training AI models on a dataset that combines petrophysical measurements with corresponding lithofacies labels, and then using the trained models to predict lithofacies for new or unlabeled data (Fig.2). AI petrophysical lithofacies prediction offers the potential to automate and enhance the lithofacies prediction process, allowing for faster and more objective interpretations. By leveraging the power of AI algorithms and deep learning, it can handle large datasets, capture complex relationships, and provide valuable support for reservoir characterization and decision-making.

4) Seismic inversion volume optimization

Seismic inversion volume optimization is a process that aims to enhance the quality and reliability of seismic inversion results by optimizing various aspects of the inversion results. Seismic inversion is a technique used to estimate subsurface properties, such as acoustic impedance or rock elastic properties, from seismic data. The optimization process involves adjusting parameters, methodologies, or algorithms to improve the accuracy and interpretability of the seismic inversion volumes. By optimizing various aspects of the
seismic inversion workflow, such as data quality, parameter selection, and integration with well data, the quality and reliability of the inverted volumes can be enhanced. This, in turn, improves the interpretation, reservoir characterization, and decision-making processes related to the subsurface.

5) Lithofacies modelling based seismic inversion

Lithofacies modeling based on seismic inversion refers to the integration of seismic inversion results with lithofacies information to create detailed models of lithofacies distribution within a subsurface reservoir or geological formation. Seismic inversion is a technique that estimates subsurface properties from seismic data, such as acoustic impedance or rock elastic properties. By combining these inverted properties with lithofacies data, a more accurate and high-resolution representation of lithofacies distribution can be achieved (Fig.3). Key steps involved in lithofacies modeling based on seismic inversion: Lithofacies modeling based on seismic inversion provides a detailed and realistic representation of lithofacies distribution, allowing for improved reservoir characterization, reservoir modeling, and decision-making in the exploration and production of hydrocarbons. By integrating seismic inversion results with lithofacies information, a more accurate understanding of subsurface reservoir properties and heterogeneity can be achieved.

Application

M oil field located in the southeast of the Mesopotamian basin with an anticline structure from northwest to southeast. The structure of the M field is an elongated structure that is SE-NW oriented to nearly S-N oriented. The structure exhibits a closure of 350 m to 400 m. The sedimentary facies of Yamama reservoirs are shoal and back shoal. The thickness of the reservoir is 100 ~250m with pores and fractures. The porosity of the reservoir is 12%~ 28%, and the permeability is 100-2200mD. All the information indicates that the Yamama reservoir is the type with bottom water. According to the certification of new wells, this technique had been applied successfully in carbonate reservoir of M oil field in Middle East, it not only improves the accuracy of 1D lithofacies prediction for wells by deep learning method, but also improves the accuracy of 3D lithofacies modeling for the whole oilfield by well and seismic inversion integrated. The lithofacies modeling not only matched with lithofacies from core analysis and petrophysics lithofacies prediction from well log analysis (Fig.3), but also matched with seismic inversion data in no well area.

The integrated carbonate lithofacies modeling workflow integrated thin section, core, well logging, 3D seismic data and production performance data, and improved the improves the accuracy of 3D lithofacies modeling for no well area. It’s useful for new wells optimization and high efficiency development with lower cost. The integrated carbonate lithofacies modeling workflow not only suit for carbonate reservoir, but also suit for clastic reservoir.

Conclusions

An integrated carbonate lithofacies modeling based on the deep learning and seismic inversion was proposed. By integrated lithofacies classification, it can enhance the accuracy and reliability of lithofacies classification and improve the characterization of reservoirs or geological formations. Petrophysics lithofacies classification combines petrophysical properties with lithological information to better understand the spatial distribution, reservoir quality, and flow behavior of different lithofacies. AI petrophysical lithofacies prediction offers the potential to automate and enhance the lithofacies prediction process, allowing for faster and more objective interpretations. By leveraging the power of AI algorithms and deep learning, it can handle large datasets, capture complex relationships, and provide valuable support for reservoir characterization and decision-making. By seismic inversion volume optimization, such as data quality, parameter selection, and integration with well data, the quality and reliability of the inverted volumes can be enhanced. Lithofacies modeling based on seismic inversion provides a detailed and realistic representation of lithofacies distribution, allowing for improved reservoir characterization, reservoir modeling, and decision-making in the exploration and production of hydrocarbons. By integrating seismic inversion results with lithofacies information, a more accurate understanding of subsurface reservoir properties and heterogeneity can be achieved. The integrated carbonate lithofacies modeling workflow integrated thin section, core, well logging, 3D seismic data and production performance data, and improved the improves the accuracy of 3D lithofacies modeling for no well area. It’s useful for new wells optimization and high efficiency development with lower cost. The integrated carbonate lithofacies modeling workflow not only suit for carbonate reservoir, but also suit for clastic reservoir.

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Fig. 2. Lithofacies prediction by deep learning method of Y layer in M oil-field in Mid-East: (a) Sensitive well log curve analysis, lithofacies classification based on the cross-plot analysis between density and acoustic, (b) Petrophysics lithofacies classification based on the sensitive well log curve by deep learning method, (c) Well 02 petrophysics reservoir lithofacies prediction by deep learning method, and matched with lithofacies analysis by core.

Fig. 3. Lithofacies modelling based seismic inversion of Y layer in M oil-field in Mid-East: (a) Seismic impedance inversion data cut-off analysis based on the cross-plot between impedance and acoustic from well log and core data, (b) Cut-offs statistics for reservoir types, (c) Seismic impedance inversion section from south to north, (d) Carbonate lithofacies modelling profile based on seismic impedance inversion and well lithofacies prediction by deep learning.