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Research on Multi-Wave Pore Pressure Prediction Method Based on Three Field Velocity Fusion

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Abstract

The optimization of velocity field is the core issue in reservoir seismic pressure prediction. For a long time, the seismic processing velocity analysis method has been used in the establishment of pressure prediction velocity field, which has a long research period and low resolution and restricts the accuracy of seismic pressure prediction; This paper proposed for the first time the use of machine learning algorithms, based on the feasibility analysis of wellbore logging pressure prediction, to integrate the CVI velocity inversion field, velocity sensitive post stack attribute field, and AVO P-wave and S-wave velocity reflectivity to obtain high-precision seismic P and S wave velocities. On this basis, high-resolution formation pore pressure and other parameters prediction based on multi waves is carried out. The pressure prediction accuracy is improved by more than 50% compared to the P-wave resolution of pore pressure prediction using only root mean square velocity. Practice has proven that the research method has certain reference significance for reservoir pore pressure prediction.

Keywords

Velocity Field, Resolution, Machine Learning, AVO Inversion, Pore Pressure

1. Introduction

Reservoir seismic pressure prediction is widely used in the fields of basin reservoir dynamics research, reservoir evaluation, unconventional reservoir exploration and development, oil and gas reservoir protection during drilling, and prevention of complex downhole accidents. For a long time, the high-precision velocity field required for pressure prediction is usually infill and interpreted by pre-stack velocity panels, combined with VSP, seismic logging, and synthetic seismic records to establish the velocity field. This classic method of establishing velocity fields has disadvantages such as low efficiency and poor adaptability to complex lithology pressure prediction. In response to many technical bottlenecks in the conventional reservoir pressure prediction process, it is necessary to adopt new technologies and new thinking to innovate the reservoir pressure prediction technology process.

Pore pressure prediction is based on the principle of effective stress in porous media based on the study of mechanical characteristics of water saturated soil (Terzaghi, 1943). Subsequently, a new formation pressure prediction formula was proposed based on the theory of underconsolidation of shale (Eaton, 1972). Through comprehensive research results using logging, drilling, seismic and other data in areas such as Mexico Bay, a trend line independent of normal compaction was proposed. The formula for calculating formation pressure using interval velocity (Fillippone, 1979) was used. Subsequently, a prediction model for formation pressure was established without relying on the theory of undercompaction. The model described the estimation of formation pressure for rocks under loading and unloading conditions based on the relationship between acoustic velocity and effective stress (Bowers, 1995). Since 2010, tomographic inversion has been used to generate depth domain lateral interval velocities that are more accurate than seismic stacking velocities, improve the quality of pore pressure prediction. Numerical modeling studies suggest that S-wave and C-wave velocities are more sensitive to changes in effective stress than P-wave velocities. The application of S-wave and C-wave velocities will be a good tool for detecting abnormal pore pressure (Shaker, 2002). The prediction of overpressure interval mainly relies on the low-speed anomaly characteristics of overpressure layers, and the accuracy of seismic velocities is related to the success or failure of pressure prediction (Guo et al., 2017; Wu et al., 2021; Liu et al., 2021). Integrating multi field and multi-source velocity models, applying machine learning algorithms to improve the accuracy of velocity models, and obtaining high-precision pressure prediction fields are currently the main research directions for reservoir pore pressure prediction.

2. Overview of Research Ideas and Methods

During the research process of the paper, the predicted pressure value of the wellbore was calibrated by the engineering pressure measurement point data, and the consistency between the seismic pressure prediction data and the measured pressure data was checked. At the same time, the accuracy of the forward velocity of the wellbore was verified using the measured velocity of the wellbore. At the wellbore position, the measured or forward velocity curve is used as the target learning curve, and machine learning methods are used to construct a learning model. The CVI constrained velocity inversion velocity field, post-stack velocity sensitive attribute field, and pre-stack AVO P and S wave reflectivity are integrated for multi-field velocity fusion to construct a multi-wave velocity field. Finally, referring to the wellbore pressure conversion parameters, pressure prediction based on multi wave seismic velocity field is carried out. This method fully combines the characteristics of high-resolution vertical logging and dense seismic horizontal data, overcoming the spatial limitations of logging methods and reducing the uncertainty of velocity field prediction using pure seismic methods. It improves the confidence of pressure prediction while improving the accuracy of wellbore prediction (**Figure 1**).

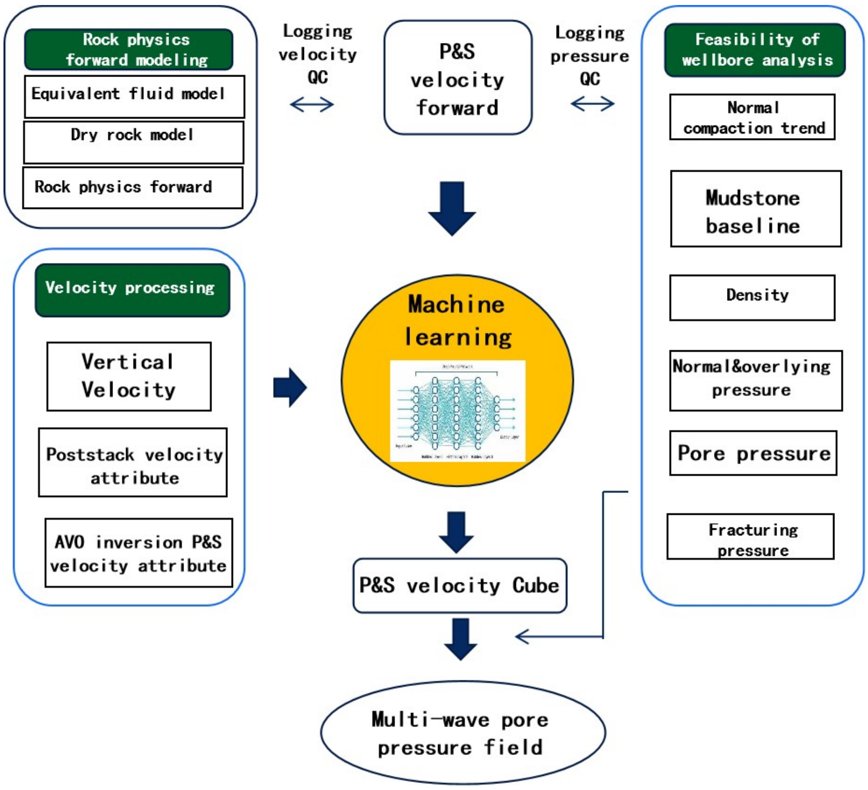

Figure 1. Technical roadmap for paper research.

2.1. Multi-Field Velocity Fusion Method Based on Machine Learning

The establishment of velocity field is one of the key technical challenges faced in the prediction of reservoir pore pressure in oil and gas field exploration and development for Long-term. Reasonable and accurate velocity field construction is the first problem that needs to be solved in the process of pore pressure prediction. At present, domestic and foreign geophysical companies usually use the method of velocity field establishment in reservoir pore pressure prediction to interpret velocity spectral points one by one in the process of pre-stack seismic data processing, and combine VSP, seismic logging, and synthetic seismic records to establish velocity field establishment methods. Based on this velocity field, pressure prediction is carried out; This classic method of establishing a velocity field often has a long working cycle time, coupled with the scarcity of wellbore velocity data such as acoustic logging in the later stage of oil and gas field development, the lack of basic velocity data in the target area, and the long and heavy workload of seismic processing velocity spectrum interpretation research, which seriously restricts the timeliness of establishing a velocity field in the process of predicting reservoir pressure in velocity deficient well areas, The establishment of velocity field has long been the main bottleneck in characterizing reservoir pore pressure. This project proposes a scenario where there is a lack of wellbore velocity data (VSP, seismic logging, and acoustic time difference), and applies rock physics forward modeling methods to forward wellbore velocity data. The rationality of the forward velocity data is jointly verified using measured pressure data and P&S wave data, Innovative joint analysis of feasibility of wellbore pressure prediction using forward velocity validated by measured pressure data and P&S wave velocity data; A new method for constructing fast and high-precision P&S wave velocity fields based on velocity sensitive seismic attributes such as AVO, trace integration, and dessert attributes using machine learning algorithms.

2.2. High Precision Pressure Field Conversion

Seismic pore pressure is an interactive modeling and prediction of pressure based on seismic interval velocity. The quality of pressure estimation depends on the quality of seismic velocity used for prediction. Before starting the pore pressure workflow, high-precision processing of seismic velocity is carried out to obtain the high-resolution velocity that best reflects geological conditions, and then predict the pore pressure and fracture pressure of high-resolution reservoirs.

3. Case Study

This paper proposes a velocity field establishment method based on heterogeneous velocity sensitive attribute fusion. Machine learning techniques are applied to fuse the velocity fields of ordinary seismic processing, post stack velocity sensitive attribute fields, and seismic inversion velocity attribute data fields, namely the "three fields" velocity, to obtain a high-resolution longitudinal and transverse wave velocity field. Based on this, multi wave reservoir pressure prediction can be carried out, which can solve the problem of low resolution and complex lithology in typical reservoir seismic pressure prediction. To provide high confidence pressure prediction data for exploration and development, drilling and completion engineering due to the difficulty of predicting mid to deep pressure.

3.1. Basic Geological Characteristics of the Research Area

The drilling in Zone X of Penglai 19-3 Oilfield mainly revealed the strata of the Cenozoic and Mesozoic. Based on lithology, electrical characteristics, paleontological analysis, and regional stratigraphic correlation, it can be divided from top to bottom into the Neogene Pingyuan Formation, Minghuazhen Formation, Guantao Formation, and Paleogene Dongying Formation. The main oil bearing series developed in the lower section of the Minghuazhen Formation and the Guantao Formation of the Neogene. Starting from the Neogene, the local area has entered a quasi plain period, forming a sedimentary system mainly composed of fluvial facies. The Guantao Formation is a braided river sediment, while the lower section of the Minghuazhen Formation belongs to meandering river sediment. The reservoir lithology is terrestrial clastic rocks deposited in river facies. The pressure value of the Guantao Formation, the main target layer of this paper's pressure prediction research, is mainly between 0.8 and 1.3.

3.2. Quality Control Method for Rock Physics Modeling Using the Two-Step Method

On the basis of logging formation evaluation (**Figure 2**), initial reservoir temperature and pressure data, mineral components, elastic parameters, etc. are set, and the Xu White forward model was applied for velocity forward modeling. The "two-step" quality control method is used for the forward velocity curve and pore pressure prediction curve. First, the measured P&S wave velocity data was used to compare and control the forward P&S wave velocity curve, and then the measured pressure measurement point data was used (**Figure 3**), calibrate the quality control of static pressure data and pore pressure data calculated using forward velocity curves, and optimize the quality control of rock physics modeling from the two dimensions of forward velocity and forward pressure curves.

3.3. Establishment of High-Precision P&S Velocity Fields Using "Three Field" Velocity Fusion

The optimal selection of input velocity sensitive attribute data was crucial in the process of applying machine learning methods for "three field" velocity fusion. Firstly, the root mean square velocity field of seismic data pre-stack processing was a reliable low-frequency velocity information that can provide a reliable description of the basic spatial distribution characteristics of velocity; Secondly, based on velocity sensitive attributes such as post-stack seismic trace integration,

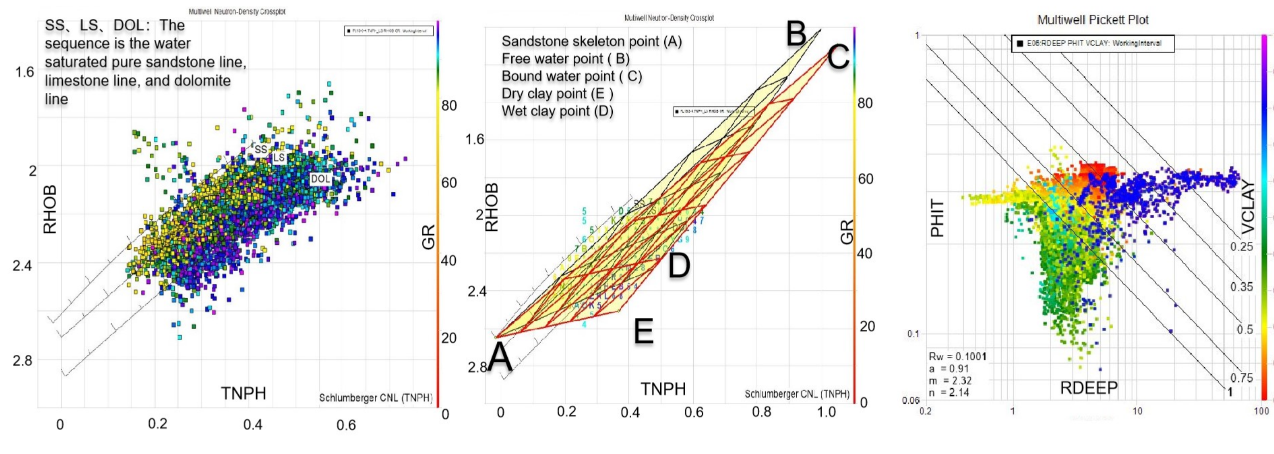

Figure 2. Study area 4 well rock physical modeling P-wave forward curve.

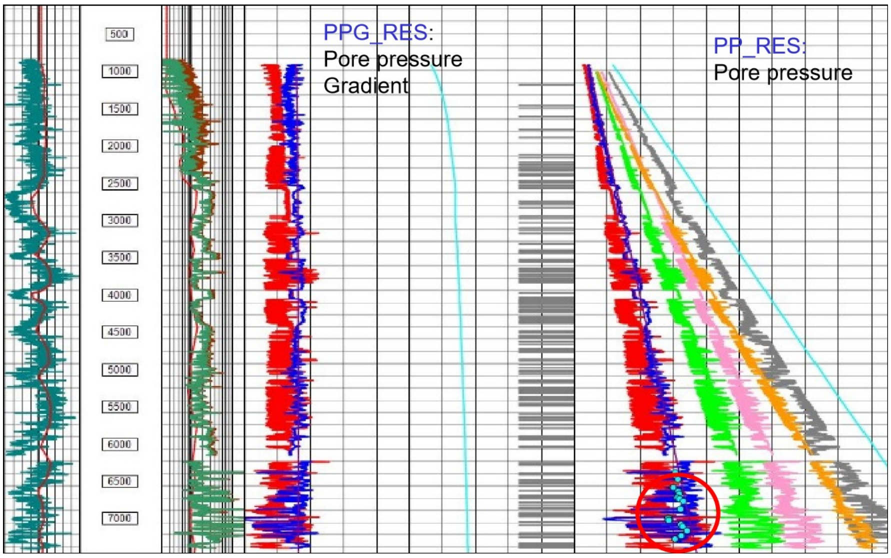

Figure 3. Overlap plot of measured pore pressure (sky blue scatter) and logging pore pressure curve (blue curve).

root mean square amplitude, and sweet spot attributes, the velocity field contains more abundant thin layer velocity information compared to pre-stack processing; Once again, EEI inversion and AVO inversion are used to analyze velocity sensitive angle information and further optimize seismic data to obtain more effective P&S wave information for the reservoir; On the basis of determining the "three field" attributes sensitive to seismic velocity, a machine learning model is constructed with measured or forward P&S wave velocities as training objectives and the "three field" attributes as input data. In the process of constructing a neural network model, each learning sample is set to perform nonlinear correlation from ten attribute samples. At the same time, to address the problem of massive seismic data and high computational complexity, principal component analysis is used for data compression. At the same time, the basic architecture of the learning model, such as the number of iterations and hidden layers, is experimentally customized, Finally, based on the prediction effectiveness evaluation algorithm (i.e. assuming that this well does not participate in the calculation during the calculation process, the velocity curve of this well is predicted using other well velocity curves and seismic attributes in the work area, and correlated with the velocity curve of this well's forward or actual measurement), quality control of the neural network model is carried out to obtain a high fidelity and resolution P&S wave velocity field profile (**Figure 4**).

3.4. Multi Wave Reservoir Seismic Pressure Prediction Based on Machine Learning

Generally speaking, pressure anomalies can be divided into four types: under compaction, under compaction supplemented by hydrocarbon generation, hydrocarbon generation supplemented by under compaction, and fluid conduction. Geophysical velocity anomalies can be used to predict pressure for under compaction and its dominant pressure anomalies. By comparing the wellbore velocity curve and pressure prediction curve, it can be seen that the negative phase correspondence between high-pressure measuring points and low-speed sections and earthquakes is good, indicating the theoretical feasibility of characterizing the pressure field based on velocity anomalies, seismic pre stack and post stack attributes; This article is based on rock physics forward modeling, high-precision velocity field construction, and nested machine learning factors to improve the traditional reservoir pressure prediction process. The resolution of multi wave reservoir pressure coefficient profiles based on P&S wave velocities is increased by more than 50% compared to conventional pressure prediction coefficient profiles. At the same time, reservoir pressure prediction based on P&S waves is carried out, which is more adaptable to reservoir pressure prediction dominated by fracture types (**Figure 5**, **Figure 6**).

3.5. Application Effect

The innovative method for predicting seismic pressure in offshore oilfield

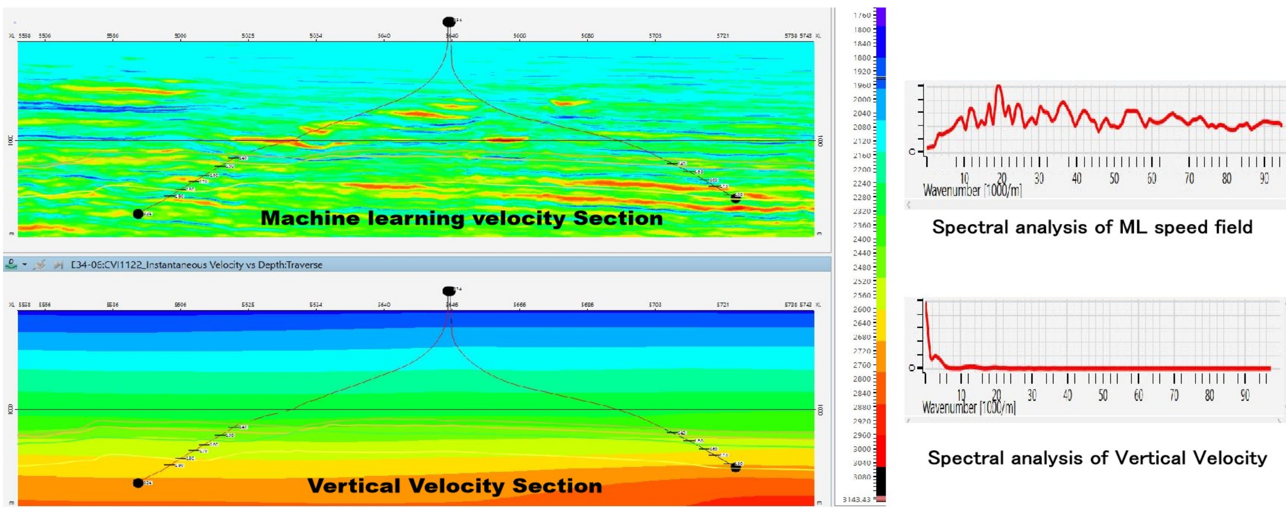

Figure 4. Comparison profile between machine learning velocity field and seismic processing velocity field accuracy.

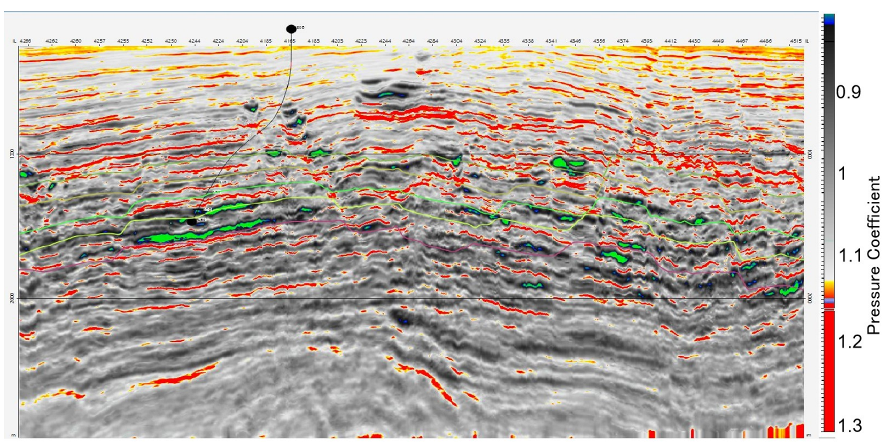

Figure 5. Pore pressure coefficient profile in the study area.

reservoirs formed through research has effectively supported the characterization of reservoir pore pressure in Penglai 19-3 oilfield, Zhonglian LX-11 well area, and Caijiahui target area, improving the reliability of predicting pore pressure in mid to deep layers. The formed technical process can be extended to the fields of mid to deep layers, buried hills, and unconventional reservoir pressure prediction in China's offshore areas, and has good promotion and application value. For under compacted overpressure, the predicted pressure coefficient error is between −0.11 and +0.11; For other types of overpressure, the predicted pressure coefficient error is between −0.15 and +0.15, which meets the accuracy requirements for predicting seismic reservoir pressure at the work site (**Figure 7**).

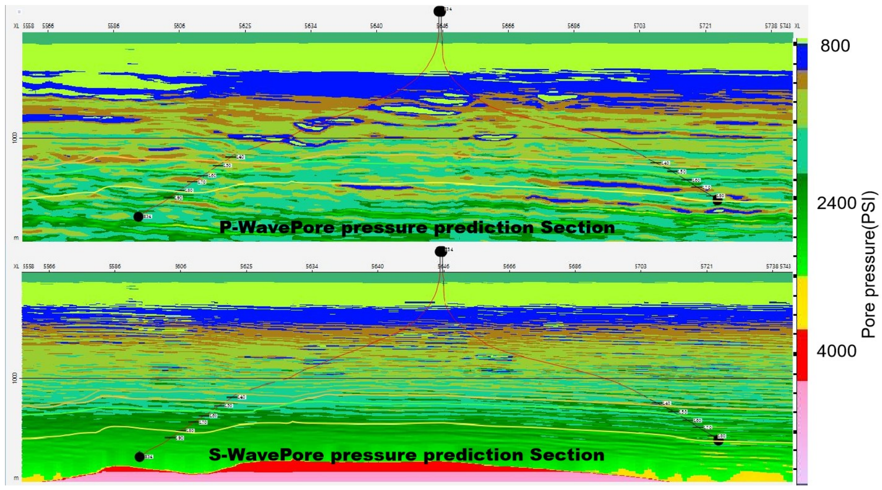

Figure 6. Comparison of multi wave pore pressure prediction profiles.

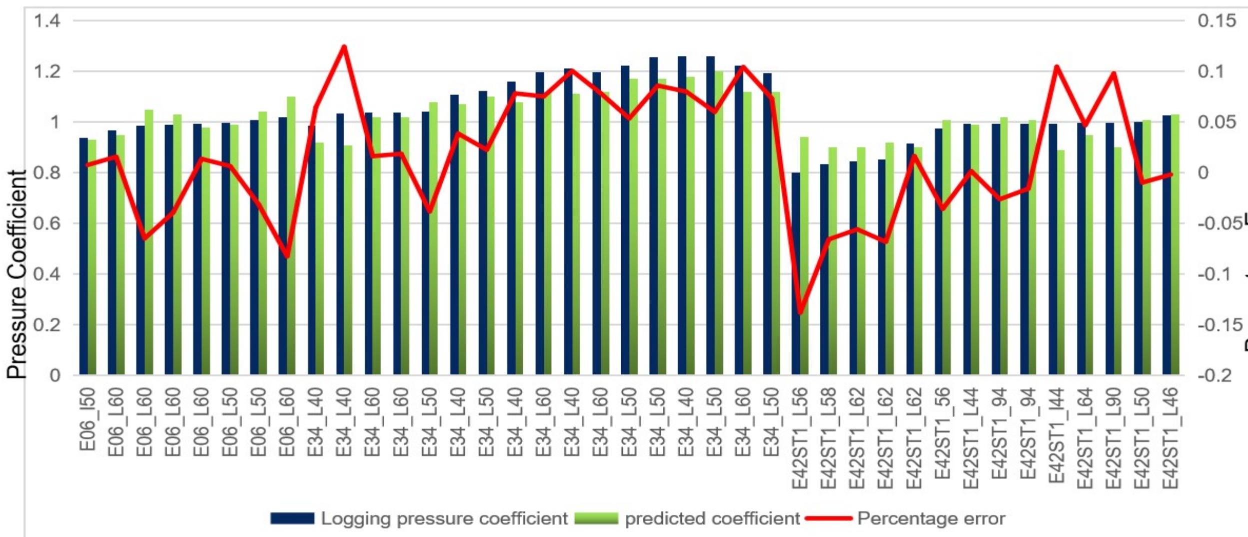

Figure 7. Statistical chart of pore pressure coefficient error in the study area.

4. Conclusions and Recommendations

1) Using the selected velocity sensitive integral, sweet spot attribute, and the

P&S wave velocity reflectivity as the input attribute data volume, and using the P&S wave velocities curve obtained from seismic forward modeling as the learning target curve, a machine learning model based on fast simulated annealing is constructed and could obtain high-precision pressure velocity field data.

2) Based on high-precision velocity field, the traditional pressure prediction technology process has been optimized to improve the efficiency of pressure prediction. The application of reservoir pressure characterization not only obtains pore pressure and fracture pressure data volumes, but also applies its results to calculate horizontal and vertical effective stresses, providing high-precision pressure prediction technology support for reservoir stress field modeling, unconventional oil and gas exploration, and deep oil and gas field exploration and development.

3) Supported by classical geophysical theories, obtaining velocity sensitive attribute datasets through seismic attribute optimization, wellbore rock physics forward modeling, and AVO inversion, and establishing a multi-attribute velocity field fusion in a digital environment, is an effective way to improve the resolution of and the accuracy of pore prediction.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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