



Research article

Pore pressure estimation in the Asmari formation of the Kupal oil field using 3D seismic inversion

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Keywords

Pore Pressure
Kupal Oil field
Seismic Inversion
Multiple Regression
PNN
MLFN

English Extended Abstract

Summary

This study presents a workflow for pore pressure prediction in the carbonate Asmari Formation of the Kupal oil field, southwestern Iran, by integrating 3D seismic inversion with machine learning. The methodology combines acoustic impedance models derived from post-stack seismic inversion with well-log data (RFT pressure measurements, sonic logs, density logs) to train predictive models. Three approaches—multivariate regression, probabilistic neural networks (PNN), and multilayer feedforward neural networks (MLFN)—were developed and validated using a blind-test well. Results demonstrate that MLFN outperformed other methods, achieving a validation correlation of 87% and a mean relative error of 2.8%. Overpressure zones, attributed to shale layers and structural compartmentalization, were identified through deviations from hydrostatic trends. The study highlights the value of 3D seismic data for spatially continuous pressure modeling in heterogeneous reservoirs, offering practical solutions to reduce drilling risks and optimize reservoir management.

Introduction

Pore pressure prediction is critical for drilling safety and reservoir characterization, yet conventional methods in carbonate reservoirs often lack spatial resolution due to reliance on sparse well data. This study addresses this gap by proposing a hybrid workflow that integrates seismic inversion with machine learning. The Kupal oil field, a structurally complex anticline in the Zagros Basin, serves as a case study. Previous studies emphasize the challenges of pressure prediction in carbonates, particularly where tectonic deformation and lithological heterogeneity dominate. This work advances the field by (1) generating a 3D acoustic impedance model calibrated to well data, (2) developing machine learning models trained on seismic attributes, and (3) mapping overpressure zones to guide drilling operations.

Methodology and Approaches

The workflow began with seismic inversion using Hampson Russell software to generate an acoustic impedance model from 3D seismic data. Well-log data (sonic, density, RFT) from four wells were integrated to calibrate the inversion. Key seismic attributes—acoustic impedance, amplitude-weighted phase, and apparent polarity—were extracted and correlated with RFT-measured pressures. Three predictive models were developed:

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1. Multivariate regression: Linear combinations of seismic attributes.
2. PNN: A probabilistic approach using Gaussian kernel functions.
3. MLFN: A six-layer neural network optimized via backpropagation.

Blind testing was conducted using Well-52 as a validation dataset..

Results and Conclusions

Results:

- MLFN Superiority: MLFN achieved the highest validation accuracy (87% correlation, 2.8% MRE), outperforming regression (85.9%, 3.15%) and PNN (77%, 3.31%) (Table 1).
- Overpressure Zones: Pressure anomalies exceeding hydrostatic gradients by 15–20% were identified at depths >2,020 ms TWT, correlating with shale layers and anticlinal hinge zones (Figure 1).
- Spatial Trends: Pressure deviations aligned with structural compartmentalization, suggesting restricted fluid migration due to tectonic sealing.

Conclusions:

1. Hybrid workflows combining seismic inversion and machine learning enhance pore pressure prediction in data-limited carbonate reservoirs.
2. MLFN's robustness stems from its ability to capture nonlinear relationships between seismic attributes and pore pressure.
3. Overpressure in the Kupal field is structurally controlled, necessitating 3D seismic integration for drilling hazard mitigation.

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