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A review of AI-driven seismic interpretation, digital twin technology and intelligent reservoir characterization for hydrocarbon exploration

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Abstract

Recent advances in artificial intelligence (AI), seismic interpretation, digital twin systems, and machine learning have significantly transformed hydrocarbon exploration and reservoir management [3, 23, 31, 35, 36]. Traditional seismic interpretation and reservoir characterization techniques often face challenges associated with large-scale data processing, interpretation uncertainty, structural complexity, and real-time reservoir monitoring limitations. This review paper presents a comprehensive overview of modern AI-driven seismic interpretation approaches and digital twin technologies applied to intelligent reservoir characterization and hydrocarbon exploration. The study reviews seismic attribute analysis, deep learning techniques, seismic inversion, digital twins, uncertainty quantification, and predictive reservoir analytics. Various machine learning algorithms including convolutional neural networks (CNNs), recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, and Bayesian learning approaches are analyzed in terms of their applications in fault detection, seismic facies classification, reservoir prediction, and production forecasting. Furthermore, this review examines the integration of digital twin frameworks with real-time seismic monitoring and intelligent reservoir management systems. The review highlights recent developments, key challenges, and future research opportunities in AI-assisted seismic interpretation and intelligent energy systems.

Keywords: Artificial intelligence; Seismic interpretation; Digital twin; Reservoir characterization; Machine learning; Seismic attributes; Hydrocarbon exploration; Predictive analytics

1. Introduction

Hydrocarbon exploration and reservoir characterization are essential components of modern petroleum engineering and geophysical exploration. Accurate interpretation of subsurface geological structures significantly influences hydrocarbon discovery, reservoir management, production forecasting, and field development planning. Seismic reflection methods remain one of the most widely used geophysical techniques for imaging subsurface formations and identifying structural traps associated with hydrocarbon accumulations [1].

Traditional seismic interpretation workflows rely heavily on manual interpretation of seismic sections, horizon picking, and structural mapping [1, 2, 13, 20]. Although these approaches have been widely adopted in the petroleum industry for decades, they are often time-consuming and highly dependent on interpreter experience. Furthermore, increasing seismic data volume and structural complexity introduce additional challenges for accurate interpretation and uncertainty reduction [2].

Recent advances in artificial intelligence (AI), machine learning, and digital technologies have significantly transformed seismic interpretation and reservoir characterization workflows. Deep learning models are increasingly used to automate fault detection, seismic facies classification, lithology prediction, and reservoir property estimation [3, 23, 31–

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37]. Machine learning algorithms can analyze large seismic datasets efficiently and identify complex nonlinear relationships between seismic responses and reservoir properties.

Digital twin technology has further extended these capabilities by enabling continuous synchronization between physical reservoir systems and virtual computational models [4]. Digital twins integrate seismic monitoring, production data, sensor information, and predictive analytics into continuously updated reservoir representations.

This review paper provides a comprehensive overview of:

- AI-driven seismic interpretation,
- Machine learning in reservoir characterization,
- Digital twin technology,
- Seismic attribute analysis,
- Predictive reservoir analytics,
- Uncertainty quantification,
- And intelligent hydrocarbon production systems.

The objective is to summarize recent developments, identify current challenges, and discuss future research directions in intelligent seismic interpretation and reservoir management.

2. Seismic Interpretation and Reservoir Characterization

2.1. Seismic Reflection Principles

Seismic reflection surveying is one of the most important geophysical methods for subsurface imaging and hydrocarbon exploration [1]. The technique relies on the propagation of seismic waves through geological formations and the recording of reflected signals generated by acoustic impedance contrasts between rock layers.

Three-dimensional (3D) seismic surveys provide detailed spatial information regarding:

- Faults,
- Folds,
- Anticlines,
- Stratigraphic traps,
- And reservoir geometry.

Time-lapse or 4D seismic monitoring further extends seismic interpretation by repeatedly acquiring seismic surveys over time to monitor reservoir changes during production [5, 10, 30].

2.2. Seismic Attributes

Seismic attributes are mathematical transformations applied to seismic data to highlight geological features that may not be visible in conventional seismic sections [6].

Commonly used seismic attributes include:

- RMS amplitude,
- Coherence,
- Variance,
- Curvature,
- Instantaneous frequency,
- And envelope amplitude.

Coherence and variance attributes are particularly useful for fault detection because they reveal discontinuities in seismic reflections. RMS amplitude attributes help identify potential hydrocarbon-bearing formations through high-energy reflection anomalies.

Seismic attribute analysis has become an essential component of modern seismic interpretation and reservoir characterization workflows [6, 17, 18, 28].

3. Artificial Intelligence in Seismic Interpretation

3.1. Machine Learning Algorithms

Machine learning techniques are increasingly used for seismic interpretation and reservoir prediction [7, 23, 31, 35, 36]. These approaches automate seismic interpretation tasks and improve interpretation efficiency.

Popular machine learning algorithms include:

- Artificial Neural Networks (anns),
- Convolutional Neural Networks (cnns),
- Support Vector Machines (svms),
- Random Forests,
- Recurrent Neural Networks (rnns),
- And Long Short-Term Memory (LSTM) networks.

CNNs are particularly effective for image-based seismic interpretation because they can automatically extract spatial features from seismic sections [23, 32, 33, 34].

LSTM models are widely used for time-series production forecasting and reservoir monitoring because they capture temporal dependencies in production data [8, 11, 24].

3.2. Fault Detection Using Deep Learning

Fault detection is one of the most important applications of AI in seismic interpretation. Traditional fault interpretation relies on manual identification of seismic discontinuities, which can be time-consuming and subjective.

Deep learning models significantly improve fault detection accuracy by automatically identifying fault planes and structural discontinuities in seismic datasets [9, 32, 33, 36]. CNN-based models are commonly trained using labeled seismic images to identify:

- Fault traces,
- Fractures,
- And structural deformation patterns.

These approaches improve structural mapping and reduce interpretation uncertainty.

3.3. Seismic Facies Classification

Seismic facies analysis classifies seismic reflection patterns into geological units representing distinct depositional environments.

Machine learning algorithms can automatically classify seismic facies using:

- Seismic amplitude,
- Frequency,
- Texture,
- And attribute information.

Automated facies classification improves reservoir characterization and sedimentary interpretation [10, 33, 34, 37].

4. Digital Twin Technology in Reservoir Engineering

4.1. Concept of Digital Twins

Digital twins are virtual replicas of physical systems that continuously synchronize with operational data [4, 29, 30]. The digital twin framework consists of:

- Physical assets,
- Virtual models,
- Communication infrastructure,
- And predictive analytics.
- In reservoir engineering, digital twins integrate:
- Seismic monitoring,
- Production history,
- Reservoir simulation,
- Sensor data,
- And ai-driven prediction models.

4.2. Digital Twin Applications in Reservoir Monitoring

Digital twin systems are increasingly used for:

- Real-time reservoir monitoring,
- Predictive maintenance,
- Production optimization,
- And anomaly detection.

Time-lapse seismic monitoring integrated with digital twins enables continuous evaluation of:

- Pressure depletion,
- Fluid movement,
- Reservoir compaction,
- And water breakthrough.

Machine learning models continuously update reservoir conditions within the digital twin environment using predictive analytics and real-time monitoring systems [29, 30, 35].

5. Predictive Analytics and Uncertainty Quantification

5.1. Production Forecasting

Production forecasting is critical for reservoir management and economic planning.

LSTM-based deep learning models have demonstrated strong capabilities for predicting hydrocarbon production trends using:

- Historical production data,
- Reservoir pressure,
- Seismic attributes,
- And operational parameters.

These models improve forecasting accuracy compared with traditional decline curve analysis techniques [11, 24, 31].

5.2. Bayesian Uncertainty Modeling

Uncertainty quantification is essential for reliable reservoir prediction and decision-making.

Bayesian machine learning approaches estimate predictive uncertainty by generating probabilistic outputs rather than deterministic predictions [12].

Monte Carlo dropout and Bayesian neural networks are commonly used for:

- Uncertainty estimation,
- Confidence-aware prediction,
- And probabilistic reservoir forecasting.

These methods improve decision reliability in complex reservoir systems by generating probabilistic prediction intervals and uncertainty-aware analytics [12, 25, 31].

6. Challenges and Limitations

Despite significant advances, several challenges remain in AI-assisted seismic interpretation and digital twin applications.

Key challenges include:

- Limited labeled seismic datasets,
- High computational requirements,
- Interpretation uncertainty,
- Data quality limitations,
- And integration complexity.

Additionally, deep learning models often require large training datasets and substantial computational resources.

Interpretability of AI models also remains an important concern because many deep learning approaches function as black-box systems [23, 31, 35]

7. Future Research Directions

Future research should focus on:

- Explainable AI for seismic interpretation,
- Autonomous reservoir management,
- Reinforcement learning for production optimization,
- Cloud-based digital twin systems,
- Edge AI for real-time monitoring,
- And integration with carbon capture and storage systems.

Federated learning and distributed AI frameworks may further improve collaborative reservoir analytics while preserving data privacy and enabling distributed reservoir intelligence [30, 35, 36].

8. Conclusion

This review paper presented a comprehensive overview of AI-driven seismic interpretation, digital twin technology, and intelligent reservoir characterization for hydrocarbon exploration.

Recent developments in:

- Machine learning,
- Deep learning,
- Seismic attribute analysis,
- Predictive analytics,
- And digital twin systems

- Have significantly improved seismic interpretation efficiency, reservoir prediction accuracy, and production optimization.

The integration of AI and digital twins represents an important advancement toward intelligent hydrocarbon exploration and next-generation digital energy systems [29, 30, 35, 36].

Future developments in explainable AI, autonomous reservoir management, and cloud-based digital twins are expected to further transform reservoir engineering and seismic interpretation workflows.

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