Summary of Reservoir Model Parameter Inversion Technology based on Artificial Intelligence

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Abstract

Reservoir model parameter inversion (history matching) is a crucial step in oil and gas field development for reducing the uncertainty in reservoir description and improving the accuracy of production prediction. However, traditional methods face issues such as non-uniqueness of solutions and high computational cost. In recent years, advancements in artificial intelligence (AI) technology, particularly deep learning methods, have provided new solutions to these problems. This paper conducts a systematic review of AI-based techniques for reservoir model parameter inversion, including end-to-end inversion methods (Convolutional Neural Networks), Generative Adversarial Networks, Physics-Informed Neural Networks, proxy model-accelerated inversion techniques, and emerging methods like Reinforcement Learning and Meta-learning. It analyzes the principles, advantages, limitations, and applicable scenarios of various methods, investigates key challenges such as data scarcity, uncertainty quantification, physical consistency, and model interpretability, and proposes corresponding solutions. Predictions are made regarding future directions, including the deep integration of physics and AI, efficient uncertainty quantification, and industrial-scale application. This paper aims to serve as a reference for research and application in this field, promoting the use of AI-driven reservoir parameter inversion technology in the digital and intelligent transformation of the oil and gas industry.

Keywords

Artificial Intelligence; Reservoir Model; Parameter Inversion; History Matching; Deep Learning; Proxy Model; Physics-Informed Neural Networks; Uncertainty Quantification.

1. Introduction

Accurate reservoir models are fundamental for oil and gas field development optimization and enhanced oil recovery [1]. Reservoir model parameter inversion, i.e., history matching, is a typical inverse problem-solving process. Its essence involves adjusting the model input parameters so that the numerical simulator's output matches the field-measured data as closely as possible [2]. This process effectively reduces the uncertainty in reservoir description, significantly improves production prediction accuracy, and has an important impact on oil and gas field development decisions [3].

However, the reservoir parameter inversion problem has inherent ill-posed characteristics, such as non-unique solutions, high sensitivity to observation errors, and the massive computational cost of the relied-upon forward models, making it challenging to solve [4].

Traditional inversion methods mainly include deterministic optimization algorithms and stochastic sampling algorithms. Deterministic methods such as gradient descent, conjugate gradient, and Gauss-Newton methods theoretically have fast convergence rates but are prone to falling into local optima in practical applications and are sensitive to initial conditions [5]. Stochastic methods like the Ensemble Smoother with Multiple Data Assimilation (ES-MDA) [6] and Markov Chain Monte Carlo (MCMC) [7] can more comprehensively search the global solution space and provide uncertainty assessment, but they require thousands of forward simulations, resulting in enormous computational costs that limit their application to large, complex reservoir models [8].

In recent years, breakthroughs in artificial intelligence technology, particularly the maturity of deep learning methods, have brought revolutionary changes to reservoir parameter inversion [9]. Due to the strong nonlinear mapping capability, automatic feature extraction, and rapid forward inference characteristics of deep learning, it can directly learn the complex mapping relationship between observation data and model parameters from the data or establish a fast proxy model to replace the numerical simulator, thereby greatly improving inversion efficiency [10]. With the rapid advancement of computational hardware and the continuous maturation of deep learning theory, AI technology has transitioned from initial purely academic exploration to current industrial practice, achieving significant results in various areas of oil and gas production.

The main objective of this paper is to comprehensively organize the system of AI-based reservoir parameter inversion techniques, meticulously analyze the basic principles, strengths and weaknesses of various algorithms, and existing major challenges, forecast future developments, and provide a reference for research and application in this field.

2. End-to-End Inversion Methods Based on Deep Learning

2.1. Convolutional Neural Networks and Encoder-Decoder Architecture

Convolutional Neural Networks (CNNs) are widely used to solve reservoir parameter inversion problems due to their excellent ability to extract spatial features. Among them, the encoder-decoder architecture is the most typical representative of such methods. It compresses high-dimensional input data into a low-dimensional feature representation through an encoder and then reconstructs the required parameter field through a decoder [11]. In reservoir inversion, the encoder typically consists of stacked convolutional and pooling layers to extract multi-level features from the input data; the decoder is mainly composed of upsampling layers and transposed convolutional layers, using a series of upsampling operations to restore the low-dimensional feature representation obtained by the encoder into a form consistent with the size of the target parameter field [12].

Sun et al. (2021) proposed an end-to-end inversion method based on CNN that can directly obtain heterogeneous permeability distributions from time-series production data [13]. Research has shown that a well-trained CNN model can complete the inversion operation in seconds, which is many orders of magnitude faster than traditional algorithms. U-Net, as a special type of encoder-decoder, incorporates skip connections to fuse shallow information from the encoder with deep information from the decoder, thereby preserving spatial details well [14]. Laloy et al. (2018) applied the U-Net structure to geophysical data inversion, achieving high-precision conversion from resistivity data to hydrogeological parameters [15].

In recent years, introducing attention mechanisms into CNNs has improved network performance. Adding channel attention and spatial attention modules allows the network to adaptively select important feature channels and key spatial locations, thereby better learning discriminative features. The improvement is more pronounced in processing multi-source heterogeneous data, effectively integrating feature information from various data sources to enhance inversion accuracy. Research results show that CNN models with attention mechanisms can improve inversion accuracy by about 15-20% under complex geological conditions [17].

2.2. Generative Adversarial Networks and Their Variants

Generative Adversarial Networks (GANs) utilize a competitive learning process between a generator and a discriminator to discover the complex distribution structure of data and excel at generating high-quality, diverse samples [18]. In reservoir inversion, the generator takes observation data or random noise as input to create geological models, while the discriminator's task is to determine whether the models generated by the generator resemble real geological models. This adversarial training prompts the generator to continuously produce geological models that are more realistic [19].

Mosser et al. (2020) proposed an inversion method that utilizes the latent space of GANs for optimization, transforming the inversion problem into a search problem within the GAN's latent space [20]. A GAN is trained on a large number of geological models to learn the prior distribution of geological structures. Gradient descent is then used in the latent space to find models that match the observation data. This method effectively narrows the search space and greatly improves inversion efficiency. CycleGAN, as an unsupervised image-to-image translation model, can perform well even without paired training samples [21]. Dupont et al. (2021) used CycleGAN to convert seismic data into acoustic impedance without needing paired data for training [22].

Conditional Generative Adversarial Networks (cGANs) input observation data as conditions to control the generation process [23]. In reservoir inversion, production history or seismic attributes can be input as constraints to the generator, guiding it to generate geological models consistent with the observation data. This method shows great advantages in integrating multi-source data. In recent years, diffusion models, as a new type of generative model, have surpassed GANs in image generation quality. Although not widely used in reservoir inversion yet, their advantages in modeling complex distributions suggest broad application prospects [24].

2.3. Physics-Informed Neural Networks and Differentiable Modeling

Physics-Informed Neural Networks (PINNs) incorporate governing equations into the loss function as soft constraints during training, ensuring that predictions fit the data while also adhering to physical laws, thus making the results more reasonable [25]. The PINN framework proposed by Raissi et al. embeds partial differential equations into neural networks, achieving the integration of physical laws and data-driven approaches [26]. The main idea of PINNs is to add a physical residual term to the loss function, forcing the network's predictions to comply with the physical rules defined by the governing equations.

In reservoir inversion, Almajid and Abu-Al-Saud (2022) integrated Darcy's equation into a PINN, directly inverting the permeability field using only pressure and production data [27]. Their method does not require large amounts of training data; physical constraints alone can yield results consistent with physical laws. Kadeethum et al. (2021) applied PINNs to multiphase flow problems, demonstrating their applicability to complex physical field inversions [28].

Differentiable modeling involves building fully differentiable numerical simulators, allowing gradients to be backpropagated through the entire simulation process for gradient-based inversion [29]. Holl et al. (2020) proposed a differentiable physics engine capable of end-to-end differentiation, significantly improving gradient computation efficiency and accuracy [30]. Ren et al. (2022) implemented differentiable computation in reservoir simulation, establishing a differentiable finite volume discretization form, making the entire reservoir simulation process differentiable [31].

The design of physics-constrained neural network architectures is another important direction. Using special network structures ensures that the output automatically satisfies physical constraints such as mass conservation and boundary conditions [32]. This hard constraint method is more stringent than the soft constraints in PINNs, guaranteeing that the output strictly adheres to physical laws. For example, when predicting flow velocity fields, designing a convolution kernel that satisfies mass conservation can ensure the results satisfy the continuity equation everywhere.

3. Proxy Model-Accelerated Inversion Techniques

3.1. Types and Construction of Proxy Models

Proxy models refer to using statistical or machine learning models with lower computational cost to replace numerical simulators, greatly improving efficiency while maintaining a certain level of accuracy [33]. Gaussian Process Regression (GPR) was an early common parametric proxy model method, using Bayesian statistics to provide prediction uncertainty [34]. Sarma et al. (2008) combined GPR with gradient optimization algorithms to achieve good history matching [35]. However, GPR's computational complexity increases cubically with problem dimensionality, limiting its applicability to high-dimensional problems.

Deep Neural Networks, due to their powerful nonlinear fitting capability, are the primary means of building proxy models [36]. Tang et al. (2020) compared different types of neural networks as reservoir simulation proxies and found that deep neural networks are more accurate and have better generalization than traditional methods [37]. Wang et al. (2022) proposed a multi-fidelity proxy modeling framework, using simulation data of different accuracies to reduce data generation costs while maintaining precision [38].

Recurrent Neural Networks (RNNs) and their variants have advantages in processing time-series data [39]. The production dynamic data in reservoir inversion has strong temporal sequential characteristics, making RNNs well-suited for extracting these features. Jiang and Durlofsky (2021) used Long Short-Term Memory (LSTM) networks to predict reservoir production dynamics, obtaining accurate dynamic response models [40]. In recent years, Graph Neural Networks (GNNs) have shown unique advantages in handling unstructured data and are suitable for representing complex inter-well relationships [41]. Sanchez et al. (2021) used GNNs for reservoir history matching, improving the geological plausibility of inversion results based on spatial correlations between wells [42].

3.2. Integration of Proxy Models and Inversion Algorithms

After building an accurate proxy model, it can be integrated with various inversion algorithms to achieve rapid history matching and conduct uncertainty assessment. The Ensemble Smoother with Multiple Data Assimilation (ES-MDA) is a commonly used ensemble-based method; combining it with proxy models can significantly improve computational efficiency [43]. Canchumuni et al. (2021) combined a deep proxy model with ES-MDA to perform rapid history matching for complex reservoir models [44].

Markov Chain Monte Carlo (MCMC) methods can provide relatively accurate posterior distribution estimates, but traditional MCMC has high computational complexity and is difficult to apply to practical reservoir problems [45]. Laloy et al. (2018) combined a deep proxy model with MCMC, greatly improving sampling efficiency [46]. Their method can handle multi-modal posterior distributions, providing a reliable tool for inversion under complex geological conditions.

Differentiable proxy models have gained attention recently [47]. Compared to traditional proxy models, besides the advantage of fast forward simulation, they can also compute accurate gradients through automatic differentiation technology. Liu et al. (2021) proposed a differentiable proxy model suitable for optimization problems with complex constraints, showing good performance under various engineering constraints [48].

Using ensemble learning methods can enhance the robustness of proxy models [49]. Multiple different prediction models are trained, and their predictions are aggregated to reduce the uncertainty of any single model and improve overall prediction reliability. Deep ensembles create diverse model clusters through random initialization and data sampling, possessing strong uncertainty quantification capabilities. Research shows that deep ensemble proxy models can reduce prediction errors by 10-30% and have good uncertainty characterization capabilities [50].

4. Reinforcement Learning and Other Emerging Methods

4.1. Application of Reinforcement Learning in Inversion

Reinforcement Learning (RL) enables agents to learn optimal decision-making strategies through interaction with the environment, demonstrating strong capabilities in solving sequential decision-making problems [51]. In inversion problems, the environment is the numerical simulator or proxy model, the state is the match between current model parameters and observation data, the action is adjusting model parameters, and the reward is the improvement in the match degree.

Ma et al. (2022) formulated the inversion problem as a Markov Decision Process, using Deep Q-Networks to learn inversion strategies. The method can automatically adjust parameter update methods based on past experience and shows good robustness in complex geological environments [52]. Actor-critic methods like the Deep Deterministic Policy Gradient (DDPG) perform well in continuous action spaces, suitable for the continuous adjustment of reservoir parameters [53].

Miftakhov et al. (2022) applied RL to reservoir management, demonstrating its potential in solving sequential decision problems [54]. Integrating inversion with production optimization enables a complete workflow from data assimilation to development decision-making. Hierarchical Reinforcement Learning decomposes complex problems into smaller sub-problems, solving them individually, which improves learning speed and makes the strategies more interpretable [55]. In reservoir inversion, the parameter inversion process can be divided into global trend adjustment and local fine-tuning to learn different levels of strategies separately.

4.2. Meta-Learning and Few-Shot Learning

Meta-learning aims to find methods that can quickly adapt to new tasks; its core idea is "learning to learn" [56]. In reservoir inversion, meta-learning models can learn the inversion mapping for a specific field from small amounts of data, which is particularly important for new fields with scarce data. Gonzalez and Tran (2021) proposed a meta-learning framework using the Model-Agnostic Meta-Learning (MAML) algorithm to pre-train the model on many related tasks, enabling rapid adaptation to new geological conditions [57].

Few-shot learning uses special network structures and training methods to ensure good generalization ability even with few training samples [58]. When actual field data is scarce, few-shot learning methods like Prototypical Networks and Relation Networks can achieve good performance through metric learning. When a field has only a few wells, few-shot learning can leverage knowledge from other similar fields to quickly build an inversion model. Self-supervised learning designs pre-training tasks to learn feature representations from unlabeled data, reducing dependence on labeled data [59]. In reservoir inversion, contrastive learning can be used to learn useful feature representations from unlabeled geological models or seismic data, followed by fine-tuning on downstream tasks [60]. Research indicates that self-supervised pre-trained models can achieve performance comparable to fully supervised models even when fine-tuned on small amounts of labeled data [61].

4.3. Multi-Modal Data Fusion

Practical reservoir characterization involves various types of data, such as production data, seismic data, well log data, and geological models. Effectively fusing these multi-modal data is crucial for improving inversion accuracy. Liu and Grana (2020) proposed a method using attention mechanisms for cross-modal fusion, adaptively adjusting the importance weights of different modalities [62]. Using cross-attention mechanisms establishes connections between modalities, enabling deep fusion at the feature level.

Graph Neural Networks (GNNs), with their advantages in processing unstructured data, are particularly significant for integrating geological spatial information like well locations and faults [63]. Sanchez et al. used GNNs for reservoir history matching, achieving geologically more reasonable inversion results through spatial correlations between wells [42]. Multi-task learning uses shared representations to complete multiple related tasks, improving model generalization and training data utilization [64]. In reservoir inversion, multiple parameter fields such as permeability, porosity, and saturation can be predicted simultaneously. The correlation between these tasks often leads to higher overall performance.

5. Key Challenges and Countermeasures

5.1. Data Scarcity and Quality Issues

Deep learning models often require large amounts of high-quality training data, but reservoir engineering often faces data scarcity. Synthetic data generation is a common solution, using geostatistical methods and numerical simulation to create training samples that conform to geological rules [65]. However, synthetic data and real data suffer from domain shift, causing model performance to degrade on real data.

Transfer learning involves pre-training on large amounts of synthetic data and then fine-tuning with a small amount of real data from the target field. This effectively addresses the lack of real data [66]. Domain adaptation techniques reduce the impact of domain shift, helping models generalize better to real fields. For example, adversarial training can be used to force the feature extractor to learn domain-invariant features, improving model performance in real fields. Self-supervised learning uses the inherent structure of the data itself as pre-training tasks, reducing dependence on external labeled data [60]. For reservoir inversion, pre-training tasks can be designed by predicting augmented data or reconstructing masked parts of the data. In practical applications, a combination of synthetic data and limited real data is often used to train models: pre-training with large-scale synthetic data first, then fine-tuning with limited real data from the target area. Research shows that this approach allows models to maintain good performance even with scarce data, achieving similar accuracy with only 10-20% of the real data required by traditional methods [67].

5.2. Uncertainty Quantification

Reliable uncertainty assessment is crucial for reservoir management decisions. Bayesian Deep Learning treats network weights as probability distributions, providing uncertainty estimates for predictions [68]. Monte Carlo Dropout is an effective Bayesian approximation method, where Dropout is kept active during testing, and multiple forward passes are performed to obtain the prediction distribution.

Zhu and Zabaras (2018) proposed a Bayesian convolutional encoder-decoder network that can provide both parameter estimates and uncertainty [69]. This method uses variational inference to approximate the posterior distribution and the reparameterization trick for end-to-end training. Deep ensembles train multiple independent models and aggregate their prediction distributions to estimate uncertainty, achieving a good balance between accuracy and computational efficiency [70].

Latent space sampling methods perform MCMC sampling in the latent space of VAEs or GANs to obtain an ensemble of model realizations consistent with the observation data [71]. This method allows thorough exploration of the posterior distribution, providing comprehensive uncertainty analysis. Evidential Deep Learning uses evidence theory to directly learn higher-order statistics of the predictive distribution, offering a new research direction for uncertainty modeling [72].

5.3. Ensuring Physical Consistency

Purely data-driven models may produce results that violate physical laws, making them unsuitable for engineering applications. Hard constraint methods use specific network structures to ensure outputs comply with physical constraints [73]. For example, using a mass conservation layer ensures flow predictions satisfy conservation laws. The advantage is guaranteed physical consistency of the output, but the design is more complex.

PINNs incorporate physical equations as regularization terms into the loss function [26], which is a more flexible approach but requires balancing the weights between the data fitting term and the physical constraint term. Adaptive weight adjustment strategies dynamically adjust the constraint strength during training to improve stability. Multi-fidelity modeling utilizes low-fidelity physical models and fast numerical simulations, balancing physical consistency with computational efficiency [74].

In practical applications, suitable physical constraint strategies should be selected based on the specific problem. For strong physical constraints like mass and energy conservation, hard constraints can be used to ensure strict compliance. For weak physical constraints, soft constraint methods like PINNs can be adopted to balance physical consistency and data fit.

5.4. Model Interpretability

The black-box nature of deep learning models hinders their industrial application, especially in reservoir engineering which supports critical decisions [75]. Attention mechanisms can visualize the regions the model focuses on, aiding the understanding of decision bases [76]. In reservoir inversion, one can see which areas of the data (e.g., production data from certain wells or specific seismic attributes) most influence the inversion results.

Feature importance analysis evaluates the importance of each feature to the prediction by perturbing input features and observing changes in the output [77]. Shapley values, based on cooperative game theory, can fairly distribute feature contributions, providing more credible feature importance assessments. Concept validation compares model predictions with known geological rules to check their reasonableness. For example, checking if the inverted permeability field aligns with the sedimentary facies distribution, or if high-permeability channels develop along the main river channels.

Visualization analysis is another method to enhance interpretability, using multi-dimensional data visualization techniques to show the relationship between model inputs, intermediate features, and outputs. Dimensionality reduction methods like t-SNE can project high-dimensional features into a 2D plane, allowing investigation of the relationship between feature clusters and geological patterns. These techniques help build engineers' confidence in AI models and promote their application and development in the industry.

6. Future Outlook

6.1. Deep Integration of Physical Mechanisms and AI

Future research will place greater emphasis on the integration of physical mechanisms and AI, developing truly physics-aware intelligence. Differentiable modeling technology continues to advance, enabling differentiation of more complex physical processes [78]. This requires considering the differentiability of equations and representing complex physical phenomena (e.g., constitutive relations, phase behavior) in differentiable forms.

Physics-constrained neural network architectures can incorporate more expert knowledge to improve model generalization and extrapolation capabilities [25]. Embedding physical constraints into the network structure itself, rather than applying them via loss functions, can better ensure the physical plausibility of outputs. Neural networks for differential equations view the network from a dynamical systems perspective, providing a new paradigm for physical modeling through discretization.

Operator learning frameworks like Fourier Neural Operators (FNO) can learn mappings between function spaces, showing great promise in reservoir inversion [79]. This approach can accept input data with different grid resolutions, broadening the application scope, and can learn directly in function space without the need for discretization. Neural operators can solve PDEs tens of times faster than traditional PINNs with better performance.

6.2. Efficient Uncertainty Quantification Methods

With the development of Bayesian deep learning, better uncertainty quantification methods will emerge. The combination of variational inference and deep learning has produced scalable uncertainty estimation methods [80]. Stochastic Gradient Langevin Dynamics adds noise during the optimization process to approximately sample from the posterior distribution.

Distributed computing enables large-scale Bayesian inference [81]. Model parallelism or data parallelism can be used to solve extremely large inversion problems. Federated learning allows for multi-field joint uncertainty analysis while protecting data privacy, which is crucial for conducting multi-field joint studies.

Uncertainty propagation analysis studies the propagation of uncertainty from data noise to parameter estimation throughout the entire process [82]. This helps better understand the impact of each link on the final result, thereby guiding data collection strategy improvements. Sensitivity analysis quantitatively analyzes how input uncertainties affect outputs and identifies the most significant uncertain factors. For example, global sensitivity analysis can identify which geological parameters most influence production predictions to guide data acquisition and model refinement.

6.3. Technological Breakthroughs for Industrial-Grade Applications

Most existing research uses simplified models. Future work needs to address the complexities of real reservoirs [83], developing corresponding inversion methods for specific geological conditions like fractured reservoirs and complex fault blocks. This requires models capable of handling complex geological heterogeneity and anisotropy.

Multiphase and multicomponent flow inversion needs to consider complex fluid behaviors [84]. Incorporating compositional models and thermodynamic equilibrium complicates the inversion but enhances the model's practical value. Integrating data assimilation with process optimization enables seamless connection from inversion to decision-making.

Real-time inversion and closed-loop management technologies enable automatic updates of reservoir models in response to real-time data like logging-while-drilling and production data [85]. Reservoir management will develop towards intelligence and automation, improving field development efficiency. Edge computing combined with cloud computing provides computational power for real-time inversion. For instance, lightweight models deployed at the wellsite perform real-time inversion, while the cloud executes large-scale, high-precision simulations, periodically updating the edge models.

6.4. Few-Shot and Self-Supervised Learning

Future directions aim to reduce reliance on synthetic data. Self-supervised pre-training methods that leverage large amounts of unlabeled data can improve model performance in data-scarce scenarios. Contrastive learning, using positive and negative sample pairs to learn meaningful feature representations, has shown outstanding performance in unsupervised pre-training.

Domain generalization techniques can improve model performance when facing new fields [87], by simulating domain shifts during the learning process to give the model stronger universality. With the development of meta-learning, AI models can truly learn how to learn, allowing rapid adaptation to new geological conditions and new types of data.

Causal representation learning uses causal inference to improve model generalization and interpretability [88]. In reservoir inversion, understanding the causal relationships between geological processes and observation data can lead to more reasonable modeling. Distinguishing correlation from causation, and avoiding basing predictions on spurious correlations, can improve performance on out-of-distribution data.

6.5. Explainable AI and Decision Support

Explainable AI will incorporate more domain knowledge [89]. Visualization analysis software allows engineers to interpret results more intuitively, aiding in understanding the model's decisions. Attention flow can visualize the propagation of information through the network, revealing the model's reasoning process.

Considering both prediction results and their reliability provides better scientific decision support for decision-makers [90]. It is necessary to provide not only point estimates but also the entire probability distribution and risk analysis. Bayesian decision theory provides the foundation for optimal decision-making under uncertainty.

Human-in-the-loop inversion frameworks combine human experience with machine intelligence. Interactive inversion integrates engineering expertise with computational power, leading to better inversion results. Explainable interactive interfaces enable effective collaboration between engineers and AI systems. For example, allowing engineers to interactively provide feedback to correct the search direction of the inversion process and incorporate domain knowledge into the inversion.

7. Conclusion

Artificial intelligence technology is reshaping the research and application landscape of reservoir parameter inversion. From end-to-end deep learning models to various AI techniques relying on proxy models for acceleration, AI shows great potential in addressing challenges faced by traditional inversion methods, such as computational speed, nonlinearity, and non-uniqueness.

End-to-end inversion methods use deep learning to directly establish the relationship between observations and model parameters, significantly accelerating the inversion speed. Encoder-decoder structures and generative adversarial networks perform well in spatial inversion. The emergence of physics-informed neural networks makes results more consistent with physical laws, transitioning from purely data-driven to physically constrained approaches.

Proxy models accelerate the inversion process. Fast computational proxies enable traditional stochastic inversion methods to be applied to practical problems. Deep proxies not only provide fast forward simulations but are also differentiable, facilitating integration with gradient-based optimization. Combined with algorithms like ES-MDA and MCMC, they enable uncertainty quantification within feasible timeframes.

However, inversion techniques still face many challenges in practical application. Data scarcity can be mitigated through methods like synthetic data generation and transfer learning. Developing more efficient Bayesian inference algorithms can enhance uncertainty quantification capabilities. Integrating more domain knowledge helps ensure physical consistency. Combining explainable AI techniques with domain expertise improves interpretability.

Looking ahead, the deep integration of physics and AI, efficient uncertainty quantification, industrial-scale application technology, few-shot and self-supervised learning, and explainable AI and decision support will be key development directions. These advancements will drive AI-driven reservoir parameter inversion technology to play a greater role in the digital and intelligent transformation of the oil and gas industry.

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