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Graph Neural Networks and Multi-Objective Hybrid Optimization: A Review of Intelligent Decision-Making Frameworks for Waterflood Reservoir Injection–Production Regulation

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Abstract: Real-time regulation of water-flooding injection–production systems is a crucial factor in enhancing reservoir development efficiency. However, in practical water-flooding operations, reservoir heterogeneity causes the inter-well fluid connectivity to vary dynamically over time. As a result, conventional regulation methods often require a considerable amount of time to adjust control schemes, leading to significant lag effects. When oilfields enter the medium- to high-water-cut stage, the geological structures and flow patterns become increasingly complex, making it difficult for traditional approaches to maintain real-time management. In recent years, Graph Neural Networks (GNNs) and hybrid multi-objective optimization algorithms such as Genetic Algorithm–Multi-Objective Particle Swarm Optimization (GA-MOPSO) have emerged as promising technologies in the field of reservoir development, demonstrating frontier applications in dynamic optimization and intelligent regulation of water-flooding systems [1-3]. GNNs can effectively model the graph structure of dynamic inter-well connectivity, accurately capturing the spatial–temporal evolution characteristics of the reservoir, while GA-MOPSO achieves a robust trade-off between maximizing the Net Present Value (NPV) and minimizing the Injection–Production Difference (IPD) [4]. In addition, recent studies have shown that surrogate models exhibit strong performance in predicting unseen geological configurations during heterogeneous multiphase flow simulations [5]. This paper provides a comprehensive review of GNN- and GA-MOPSO-based hybrid approaches for water-flooding regulation, with particular emphasis on the advantages of the Heterogeneous Spatiotemporal Fusion Model (HSTMF) in water-cut prediction. Furthermore, it discusses the key challenges and potential directions for future research in terms of model generalization, algorithmic robustness, and engineering deployment [6].

Keywords: Graph neural network (GNN), multi-objective optimization, hybrid algorithm, water-flooding reservoir, intelligent decision-making, closed-loop control.

1. Introduction

Water-flooding development is one of the most common and cost-effective methods for oilfield production. Technological optimization based on this development approach can yield significantly enhanced results, making the optimization of water-flooding injection–production regulation particularly critical. In the middle to late stages of oilfield development, the heterogeneous reservoir formations and the dynamically evolving inter-well fluid connectivity caused by ongoing production activities substantially increase the complexity and difficulty of injection–production control [7, 8].

Traditional reservoir regulation primarily relies on two approaches, both of which exhibit significant limitations [9] First, geological modeling and fluid simulation are typically time-consuming processes, resulting in long decision-making cycles and poor timeliness [10]. Consequently, these methods fail to achieve real-time and fine-grained control. Moreover, due to the complexity and time-varying nature of dynamic changes during reservoir production, such approaches are often inefficient in responding to evolving reservoir conditions [11, 12]. Second, regulation parameters are commonly adjusted manually by production engineers based on empirical knowledge. This experience-driven approach struggles to achieve effective trade-offs in multi-objective optimization tasks, such as maximizing the Net Present Value (NPV) while minimizing the Injection–Production

Data-driven intelligent regulation has gradually become a prominent research focus across various fields. With the advancement and application of machine learning methods in the petroleum industry, intelligent regulation in water-flooding reservoir injection–production control has gained increasing attention. By employing Graph Neural Networks (GNNs) to model inter-well topological relationships and utilizing multi-objective evolutionary algorithms to efficiently address complex decision-making problems, researchers have established effective approaches for constructing real-time, feedback-driven intelligent decision-making frameworks [15-17].

2. Technical Foundations and Methodology

This section focuses on two fundamental technological pillars: surrogate modeling and intelligent optimization. The former is employed to construct predictive models capable of rapidly approximating reservoir behavior, while the latter is utilized to perform optimization and decision-making among multiple conflicting objectives.

2.1. Graph Neural Networks (GNNs) and Spatiotemporal Modeling

The inherent structure of well networks exhibits a graph-based topology, where production and injection wells can be represented as nodes and the inter-well connectivity as edges. This representation naturally positions Graph Neural Networks (GNNs) as powerful tools for characterizing the dependencies among wells. Traditional numerical simulations, when dealing with reservoir heterogeneity, often incur substantial computational costs, and their accuracy is highly sensitive to grid resolution and parameter uncertainty. In contrast, GNNs can capture the complex spatial correlations and temporal dynamics of reservoirs in a data-driven manner, providing an efficient and flexible alternative for spatiotemporal modeling [18].

Relational Graph Attention Module: This module leverages an attention mechanism to assign trainable weights to the connectivity between each pair of wells, dynamically updating these weights in response to temporal variations and changing production conditions. Through this adaptive process, the model can "perceive" which connectivity pathways are more critical at a given time, thereby effectively mitigating the limitations of traditional static connectivity representations in characterizing heterogeneous flow channels.

The Heterogeneous Spatiotemporal Fusion Model (HSTMF) integrates Long Short-Term Memory (LSTM) networks with temporal Transformers, where the LSTM component focuses on sequential evolution and historical dependencies, while the Transformer captures global attention distributions. Spatial topology is constructed through the Relational Graph Attention Network (RGAT), and temporal evolution is modeled using LSTM/Transformer architectures. The fusion of these two components enables high-accuracy predictions of dynamic reservoir indicators such as water cut, pressure, and production rate.

Recent studies have repeatedly employed similar graph–temporal hybrid structures for subsurface tasks such as formation pressure estimation and saturation prediction [19]. For instance, Sasal et al. (ECMOR 2024) proposed a GNN-based model for predicting reservoir pressure and saturation, which demonstrated strong generalization capability to unseen geological realizations while achieving computational speedups by several orders of magnitude [20] [20]. In the context of subsurface flow simulation, Tang and Durlofsky introduced the Graph-based Neural Surrogate Model (GNSM), which utilizes a graph neural surrogate to predict pressure and saturation, subsequently optimizing well placement and control strategies—significantly accelerating computation [21]. Moreover, recent research has explored neural operator frameworks as surrogate models to simulate varying well-control and permeability conditions, exhibiting remarkable generalization performance across heterogeneous reservoir scenarios [22].

Constructing a GNN-based surrogate model that is both efficient and accurate is a nontrivial task. Reservoir systems inherently exhibit high complexity—characterized by substantial geological parameter heterogeneity, strong inter-well interference, and nonlinear coupling in dynamic responses. Consequently, the model must possess sufficient representational capacity to capture such intricate behaviors.

Moreover, because inter-well connectivity and injection–production responses can undergo abrupt or transient changes within short timeframes, the model must also demonstrate adaptability to such sudden dynamics. In other words, a surrogate model capable only of smoothly fitting gradual variations would struggle to handle sharp response transitions arising under newly implemented injection–production schemes. Therefore, when designing architectures such as RGAT and HSTMF, it is essential to ensure that the model maintains adequate complexity to represent real reservoir conditions while preserving sufficient flexibility to respond effectively to transient or unexpected changes.

2.2. Multi-Objective Evolutionary Algorithms (MOEAs)

Water-flooding injection–production regulation is, by nature, a typical multi-objective optimization problem. The objectives involved often conflict with one another—for instance, maximizing the Net Present Value (NPV) requires achieving high oil production and low operational costs, whereas minimizing the Injection–Production Difference (IPD) emphasizes maintaining balanced injection–production performance and improving displacement efficiency. Striking an appropriate trade-off between these competing objectives is challenging, and conventional single-objective optimization methods are generally inadequate for such complex decision-making scenarios.

In the existing literature, a hybrid optimization approach known as GA-MOPSO has been proposed. This method integrates the global exploration capability of the Genetic Algorithm (GA) with the rapid local convergence characteristics of the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, while strategies such as Cauchy perturbation are introduced to further enhance exploration diversity. Such hybrid algorithms have demonstrated superior optimization efficiency and accuracy in high-dimensional objective spaces.

However, applying hybrid optimization algorithms to practical water-flooding regulation problems remains highly challenging. The optimization landscape of reservoir systems is inherently complex, and the objective functions are typically derived from black-box simulators or surrogate model outputs. Under such complex conditions, the algorithm must maintain strong global exploration capabilities without compromising convergence speed. Moreover, reservoir systems may undergo structural response shifts or experience sudden perturbations. If the algorithm converges prematurely during the local search phase, it risks missing newly emergent optimal configurations.

Therefore, when designing the GA-MOPSO framework, perturbation mechanisms and adaptive weight adjustment strategies are typically introduced to maintain global awareness in the presence of abrupt changes. These mechanisms enable the hybrid optimization algorithm to achieve rapid convergence under stable conditions while retaining sufficient "maneuverability" to adapt when system dynamics shift.

In the context of surrogate-assisted optimization, a related line of research involves combining physics constraints with deep learning models to form hybrid surrogates. For instance, Chen et al. proposed a physics-informed convolutional recurrent model for well-control scenarios, in which physical laws are embedded into the loss function to enhance model stability and physical consistency [23].

3. Application of GNNs in Dynamic Predictive Surrogate Modeling

The core role of Graph Neural Networks (GNNs) in water-flooding regulation lies in constructing a high-precision spatiotemporal predictive surrogate model [24], which serves as an efficient alternative to computationally intensive numerical simulations. This enables regulation and decision-making to be performed at a near real-time pace.

3.1. Dynamic Connectivity Characterization and the HSTMF Model

The Heterogeneous Spatiotemporal Fusion Model (HSTMF) conceptualizes the reservoir state as a sequence of spatiotemporal graphs. In the spatial dimension, the model employs a Relational Graph Attention (RGAT) module, in which the connectivity weights between each pair of wells are defined as trainable variables. These weights are dynamically updated in response to variations in operational parameters and reservoir feedback, thereby encoding implicit patterns such as inter-well fluid interference and the strength of connectivity into the model representation.

In the temporal dimension, the model integrates Long Short-Term Memory (LSTM) or Transformer architectures to capture the temporal evolution of injection–production history, connectivity weight dynamics, and key indicators such as water cut and pressure differentials. The spatial encoder provides structural awareness of the reservoir topology, while the temporal module predicts future system states. Through the fusion of these two components, the HSTMF model enables multi-step forecasting of critical dynamic indicators—including water cut, pressure, and production rate—over future time horizons.

The design of the HSTMF architecture explicitly accounts for the inherent complexity of reservoir systems—characterized by heterogeneous geological parameters, irregular well-network topologies, and nonlinear fluid responses—all of which demand a model with strong representational capacity. At the same time, the model must be capable of responding to abrupt dynamic changes, such as water coning breakthroughs or the formation of new connectivity pathways. Achieving robust performance under stable conditions while maintaining stability during sudden transitions requires careful trade-offs in module design, regularization strategies, input feature selection, and the flexibility of the attention mechanism.

In existing research, several hybrid graph–temporal architectures have been employed to approximate subsurface dynamics and support optimization tasks. Tang and Durlofsky, in their study Graph Network Surrogate Model for Subsurface Flow Optimization, proposed a GNN-based surrogate model for predicting pressure and saturation. Their model achieved prediction errors of only 1–2% across multiple test sets and was applied to joint well placement and control optimization, yielding approximately a 36-fold improvement in computational speed [25].

Liu et al., in Automated Reservoir History Matching Framework, adopted a GNN + Transformer architecture for interwell connectivity inversion and history matching. During training, the model achieved a correlation coefficient of $R^2 \approx 0.95$, and in complex scenarios, it reached 87.8% accuracy in water-cut fitting [26]. Another study applied a GNN–LSTM model to dynamic control prediction, where under datasets with extensive injection–production control variations, the model achieved an average prediction error of 4–5% and an online execution speed approximately 1000 times faster than conventional simulators [27].

More recently, Ju et al. (2023) employed a GConvLSTM + MeshGraphNet framework for predicting CO_2 saturation and pore pressure in faulted reservoirs, demonstrating significant generalization capability across unseen grids and heterogeneous permeability fields [28]. Additionally, the work Cell-level Deep Learning as Proxy Model for Reservoir Simulation and Production Forecasting explored the use of deep neural surrogate models at the grid-cell scale for production and water-cut prediction, achieving notable improvements in both accuracy and computational efficiency [29].

3.2. Model Performance and Validation

In existing studies, data-driven HSTMF surrogate models have achieved R^2 values exceeding 0.96 in water-cut prediction tasks, with prediction times reduced to the order of minutes. This level of efficiency enables their integration into injection–production optimization loops, facilitating high-frequency control adjustments. Such an approach significantly shortens the traditional simulation–optimization–regulation cycle, endowing the regulation strategy with near real-time adaptive capability.

In reservoir simulation case studies, the HSTMF model can effectively replace portions of the numerical simulation process without substantial loss of accuracy, thereby greatly reducing computational costs. Its high efficiency and predictive precision provide reliable input data for subsequent optimization algorithms, supporting more responsive and data-informed decision-making in reservoir management.

4. Application of Hybrid Optimization Algorithms in Injection–Production Parameter Optimization

Based on the future forecasts of water cut, production rate, and other key indicators generated by the surrogate model, optimization of the injection–production parameters are required. At this stage, hybrid optimization algorithms have become a widely adopted approach for achieving effective and balanced parameter optimization.

4.1. Definition of the Multi-Objective Optimization Problem

The objectives of injection–production optimization typically involve at least two key aspects: maximizing the Net Present Value (NPV) and minimizing the Injection–Production Difference (IPD). This can be formally expressed as:

$$\max f_1(x)=NPV(x), \min f_2(x)=IPD(x), x \in \mathbb{R}^n$$

Under this formulation, no single solution can simultaneously optimize both objectives to their global optima. Therefore, it is more meaningful to obtain a Pareto-optimal solution set, in which any improvement in one objective cannot be achieved without a corresponding compromise in the other [30].

4.2. GA-MOPSO Optimization Strategy

The GA-MOPSO algorithm represents a hybrid optimization framework that integrates the advantages of Genetic Algorithms (GA) and Multi-Objective Particle

Swarm Optimization (MOPSO) [31, 32]. In the global exploration phase, GA employs crossover and mutation operations to enhance population diversity and facilitate escape from local optima. During the local convergence phase, PSO leverages swarm intelligence and cooperative search behaviors to accelerate convergence.

To effectively address the challenges posed by complex, multimodal objective spaces and potential abrupt changes in system states, GA-MOPSO commonly incorporates mechanisms such as Cauchy mutation perturbation, dynamic weighting strategies, and diversity preservation schemes. These mechanisms collectively improve the efficiency and robustness of the search process in high-dimensional optimization landscapes [33-35].

The design of hybrid algorithms must accommodate such complex scenarios: they should ensure a broad search space while preventing premature convergence, and maintain the ability to restart the search or adjust the step size when control strategies undergo abrupt changes. Existing studies have demonstrated that hybrid algorithms often outperform single Multi-Objective Evolutionary Algorithms (MOEAs) in water-flooding regulation tasks [36][36]. For instance, the Active Learning Surrogate-Ensemble Assisted Multi-Objective Optimization framework has been shown to reduce the number of simulations required while improving the quality of the Pareto front in water-flooding applications [37] Similarly, Fast Well Control Optimization approaches that combine surrogate models with GA/PSO hybrids have achieved both high accuracy and approximately sixfold computational acceleration in the UNISIM-I-D benchmark model [38].

5. “Monitoring–Prediction–Optimization–Control” Closed-Loop Decision Framework

5.1. Framework Design Concept and Workflow

In conventional water-flooding reservoir management, the standard workflow typically follows the sequence of geological modeling → numerical simulation → scheme optimization → field implementation. Although these stages are closely interlinked, the primary limitation lies in their sluggishness—by the time an optimized scheme is implemented in the field, the reservoir conditions may have already changed significantly.

The concept of closed-loop control aims to overcome this inherent latency by integrating these discrete stages into a self-adaptive intelligent system, in which control strategies are continuously updated and optimized in response to real-time reservoir dynamics [39]. In designing such a system, several critical factors must be carefully considered: the frequency of data updates, system stability, computational cost, and the framework’s adaptability to complex and rapidly changing reservoir conditions.

How, then, does this closed-loop system operate in practice? The entire process begins with various field-deployed sensors that continuously collect real-time data on parameters such as pressure, flow rate, injection volume, and water cut. After preprocessing—namely data cleaning, normalization, and integration—these raw measurements are fed into the HSTMF model, which forecasts key indicators such as future water cut, production rate, and pressure differential over a given time horizon.

Subsequently, the GA-MOPSO optimization algorithm utilizes these predictive outputs to search for the optimal set of injection–production control parameters under multiple competing objectives (e.g., maximizing production while minimizing water cut). The optimized control scheme is then transmitted to field actuators for execution.

Following implementation, the reservoir’s dynamic response generates new monitoring data, which are captured by the sensing system and fed back into the model, thereby initiating a new “prediction–optimization” iteration. This process establishes a fully closed-loop system. Moreover, the framework incorporates a self-correction mechanism: when the deviation between observed and predicted data exceeds a predefined threshold, the system automatically triggers re-prediction and, if necessary, withdraws or updates previously issued control commands to maintain operational stability and reliability.

5.2. Engineering Significance and Comparative Analysis

The core value of the closed-loop system lies in its ability to drastically shorten the decision-making cycle, transforming reservoir management from a process traditionally measured in days or even months into one capable of minute-level real-time responsiveness. This advancement enables more timely and precise control over injection–production operations.

Empirical studies have demonstrated that by integrating surrogate modeling with optimization algorithms, such closed-loop systems can maintain high predictive accuracy while significantly reducing computational demand [40]. This synergy not only enhances operational efficiency but also allows for more frequent adjustment of control strategies, thereby improving recovery performance and ensuring the system’s adaptability to rapidly changing reservoir dynamics.

For instance, in a closed-loop workflow employing a CNN–RNN surrogate, Kim and Durlofsky integrated the CNN–RNN predictive model within a Closed-Loop Reservoir Management (CLRM) framework to conduct multiple rounds of iterative optimization. Their results demonstrated notable improvements in net present value (NPV) and enhanced constraint satisfaction, while achieving several orders of magnitude acceleration compared with full-physics simulation–based optimization [41].

Other studies have introduced deep reinforcement learning (DRL) strategies into closed-loop control [42], directly mapping production data to control decisions, thereby eliminating intermediate optimization steps and further reducing computational overhead [43].

Similarly, Nasir and Durlofsky proposed a multi-asset closed-loop reservoir management framework that employs DRL-based global control to enable knowledge sharing across multiple reservoir assets, achieving approximately threefold speed improvement [44].

In the Fast Well Control Optimization framework coupling a proxy model with particle swarm optimization (PSO), the integration of surrogate modeling and optimization has also been shown to substantially enhance both efficiency and stability in complex reservoir scenarios [45].

Of course, practical implementation also presents several challenges. The “heartbeat” of the system—that is, the data update frequency—must be carefully designed: if the update rate is too high, the system may become overly sensitive and oscillatory; if too low, it may miss optimal control opportunities. Furthermore, prediction errors, optimization bias, and control delays can accumulate and amplify within the closed-loop process, potentially degrading overall system stability. Therefore, a robust “safety tether” mechanism is indispensable—when abnormal behavior is detected, the system must be capable of promptly retracting or overriding control commands to ensure operational safety and reliable production performance.

6. Challenges and Future Perspectives

6.1. Current Key Challenges

In implementing closed-loop systems in real oilfield operations, several key challenges persist.

First, the issue of model interpretability remains prominent. The internal hidden layers, attention weights, and connection-updating logic of models such as GNNs and HSTMF are often opaque, making it difficult for engineers to intuitively understand or trust the resulting control decisions. Within the GNN research domain, methods such as GNNExplainer have been developed to generate interpretability through subgraph and feature selection mechanisms [46], while approaches like GOAt provide edge- and node-level attribution explanations [47]. However, these techniques are primarily designed for generic GNN architectures; interpretable frameworks tailored to reservoir control applications remain scarce. As noted by Kakkad et al. in their survey on GNN explainability, many existing interpreters rely on structural assumptions that are not easily transferable to complex physical-field models [48, 49].

Second, limited generalization capability represents another major obstacle. Many existing studies train models on a single block or under specific geological conditions, leading to significant performance degradation when deployed in new reservoirs or under varying formation properties. Even within the broader field of surrogate modeling, research has demonstrated that embedding physical constraints can enhance model generalization [50]. For instance, Physics-informed GNNs have shown promising potential in spatiotemporal prediction tasks; the HGNS architecture, which integrates a U-Net with graph networks, has achieved large-scale surrogate simulation on grids exceeding one million cells, demonstrating strong scalability and providing a feasible pathway toward improved generalization in complex systems [51].

Finally, there exists a pronounced computational bottleneck associated with high-frequency data processing. [52] Real-time monitoring, data transmission, online prediction, and optimization impose stringent demands on computational power, networking, and storage infrastructure—challenges that are particularly acute in remote oilfields or offshore platforms. While surrogate models can alleviate part of the computational burden, excessively high closed-loop frequencies or overly complex model architectures may still lead to systemic latency and undermine the real-time responsiveness of the control process.

6.2. Future Research Directions

In light of the aforementioned challenges, several research avenues can be pursued to advance the development and practical deployment of closed-loop intelligent control systems for water-flooding reservoirs.

First, it is essential to integrate physical knowledge with data-driven models by embedding constraints derived from flow equations, boundary conditions, and rock–fluid interactions into GNN or surrogate architectures. This fusion enhances physical consistency and interpretability [53]. Such an approach has been demonstrated in studies on Physics-Informed Graph Neural Networks (PI-GNN) and other physics-informed architectures, which effectively bridge data-driven learning with domain theory.

Second, the incorporation of reinforcement learning (RL) or meta-learning within the closed-loop framework represents a promising direction. These methods can enable adaptive policy adjustment during ongoing interactions with the reservoir system. Early applications of deep reinforcement learning (DRL) in reservoir control have shown that direct mappings from monitoring data to control actions can reduce intermediate optimization delays, thereby enhancing real-time decision-making efficiency.

Third, hybrid surrogate modeling should be further developed by combining graph networks, convolutional architectures (CNNs), transformers, and physics-based components into unified modeling strategies. Such composite architectures offer superior adaptability for complex system modeling. For instance, the Graph-based Network Surrogate Model (GNSM) exemplifies the integration of GNN and surrogate paradigms for improved predictive robustness and scalability.

Fourth, advancements in computational infrastructure are necessary to support low-latency, high-throughput closed-loop operations. This includes leveraging edge computing, heterogeneous hardware architectures (e.g., CPU–GPU–FPGA hybrids), and distributed system designs to efficiently handle high-frequency data and model inference demands in field environments.

Fifth, the introduction of explainability mechanisms is crucial for building trust in intelligent control decisions. Techniques such as attention visualization, subgraph extraction, and SHAP/LIME analysis can be employed to make model reasoning more transparent and interpretable for engineers. Integrating these explainable AI tools with domain knowledge will further enhance the system’s credibility and operational reliability.

Sixth, cross-field model transferability can be improved through transfer learning, few-shot fine-tuning, and domain adaptation. By jointly training base models on multi-reservoir datasets and applying adaptive fine-tuning, the system’s generalization capability under varying geological conditions can be significantly strengthened.

Finally, robust optimization and uncertainty modeling should be incorporated into the optimization process to ensure resilience against prediction errors, model bias, and abrupt disturbances. Recent studies have explored robust multi-objective optimization frameworks that explicitly account for geological uncertainty in water-flooding optimization.

Ultimately, future research should emphasize engineering-scale validation through deployment in real oilfield scenarios. This includes stability testing, risk control strategies, human–machine interface design, anomaly recovery protocols, and system fault tolerance evaluation, ensuring that theoretical advancements can be reliably and safely translated into practical, field-deployable intelligent reservoir management systems.

7. Conclusion

This review has examined recent advances in the application of Graph Neural Networks (GNNs) and multi-objective hybrid optimization algorithms for water-flooding reservoir injection–production control. GNN architectures demonstrate a strong capability to represent dynamic interwell connectivity within reservoir well networks, effectively capturing both spatial topological dependencies and temporal evolution patterns. Meanwhile, multi-objective evolutionary algorithms (MOEAs) exhibit excellent trade-off performance when dealing with conflicting objectives, such as maximizing economic returns while maintaining injection–production balance.

The integration of these two methodologies gives rise to a closed-loop intelligent control framework encompassing real-time monitoring, dynamic prediction, multi-objective optimization, field-level execution, and feedback adjustment. This closed-loop design effectively eliminates the lag between reservoir response and control actions, enabling near real-time optimization of injection–production parameters. As a result, the responsiveness and adaptability of reservoir management are greatly enhanced.

Such a framework not only improves the scientific rigor and systematicity of decision-making, but also demonstrates substantial economic potential in practical applications—manifested through reduced water cut, enhanced net present value (NPV), and improved oil recovery efficiency. Similar findings have been reported in related studies, such as "Intelligent Optimization of Gas Flooding Based on Multi-Objective Approach", where a MOPSO + Transformer model achieved significant performance gains in gas-flooding and injection–production strategy optimization [54].

Despite the remarkable progress achieved, several constraints continue to hinder the broader deployment of such approaches. Model generalization has yet to be fully validated across varying geological conditions and distinct reservoir environments. The robustness of the models to abrupt dynamic responses—such as water breakthrough, connectivity reconfiguration, or sudden changes in interwell flow paths—remains limited. Furthermore, challenges persist regarding the real-time performance and operational stability of the system under resource-constrained conditions. As noted in existing studies, even within MOPSO-based hybrid optimization frameworks, factors such as hardware resource limitations, data acquisition frequency, and control latency have been identified as significant bottlenecks to practical implementation [55].

Future research directions should include enhancing model interpretability, enabling engineers to understand why a model proposes a particular scheme. Introducing physical constraints or hybrid physics–data-driven approaches can improve the physical consistency of the model. Reinforcement learning or meta-learning methods may be employed for adaptive adjustment of control strategies. Optimizing computational architectures will support high-frequency data processing and low-latency control. Emphasis should be placed on validation at industrial scale and field deployment, including the design of fault-tolerance and anomaly-response mechanisms. Furthermore, optimization algorithms should incorporate geological uncertainty and resource constraints to enhance the robustness and practical reliability of closed-loop systems.

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