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Review

Progress and prospects of numerical methods of fracture propagation and its intelligent transformation during hydraulic fracturing

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Abstract: As the demand for unconventional oil and gas resources grows, hydraulic fracturing has become a critical technology for improving recovery in low-permeability reservoirs. Although traditional numerical simulations accurately capture fracture propagation, their high computational cost limits their use in real-time optimization. In recent years, surrogate models have emerged as efficient alternatives for fracture simulation and diagnostics. This paper reviews recent progress in data-driven surrogate modeling approaches, including machine learning and deep learning, and summarizes their applications in predicting fracture geometry and evaluating fracturing performance. It also examines emerging trends in hydraulic fracturing technology, compares the computational efficiency and accuracy of different methods, and discusses future opportunities and challenges in key areas such as monitoring and diagnostics.

Keywords: Hydraulic fracturing; fracture propagation; numerical simulation; surrogate model; fracture diagnosis

1. Introduction

As global energy demand continues to rise, and the development of unconventional oil and gas resources becomes increasingly important, hydraulic fracturing technology is under growing pressure to adapt to digital innovation while addressing environmental concerns. In response, the National Energy Administration's Shale Gas Development Plan (National Energy Administration of China, 2020) emphasizes the need to accelerate the growth of China's shale gas industry. The plan calls for breakthroughs in shale gas extraction across marine, onshore, and transitional geological phases. It also sets clear goals to discover new large-scale shale gas fields, achieve effective large-scale development, and reach an annual production target of 80 to 100 billion cubic meters by 2030. Hydraulic fracturing is a widely used technique to enhance the flow of hydrocarbons by injecting high-pressure fluids into underground reservoirs (Wang et al., 2020a). This process creates and extends fractures in the rock, connects with existing natural fractures, and increases reservoir permeability (Fig. 1). It has proven effective in extracting hydrocarbons from both conventional sandstone formations and unconventional resources such as shale gas (Gong et al., 2023) and tight gas (Wang et al., 2015). However, hydraulic fracturing involves complex physical processes such as fracture propagation, fluid dynamics (Guo et al., 2023), and thermodynamic interactions (Wang et al., 2020b), which present significant challenges for theoretical analysis and numerical modeling (Wang et al., 2025a). To address these difficulties, researchers have increasingly focused on fracture propagation models (Zheng et al., 2025a). These models provide a vital connection between geological characteristics and fracturing outcomes (Zhang et al., 2025). By simplifying key physical mechanisms (Wang et al., 2023a), they reduce computational demands and play an essential role in improving the efficiency and accuracy of hydraulic fracturing design (Zhang et al., 2024a).

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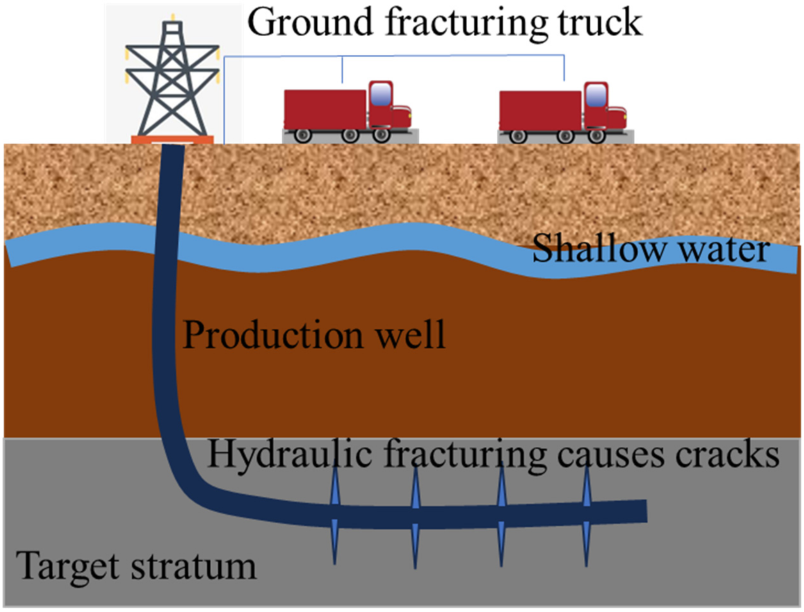


Fig. 1. Schematic diagram of hydraulic fracturing.

The hydraulic fracture propagation model originated from traditional physical models and numerical simulation (Chen et al., 2025) methods. Since the 1950s (Cao et al., 2025), when hydraulic fracturing technology began to be applied in oil and gas extraction, fracture propagation models have undergone multiple developmental stages. Initially, researchers summarized past experience to predict fracture length based on injection flow rate and pressure, as well as the relationship between fracture morphology and pressure distribution. They proposed simplified empirical formulas that primarily addressed single-factor mechanical problems (Hua et al., 2025), laying the groundwork for subsequent theoretical and numerical models. During the 1970s and 1980s (Zhang et al., 2024b), to meet the demands of hydraulic fracturing design under complex conditions (Nguyen, 2024), researchers progressively developed more sophisticated fracture propagation models. The integration of theories such as linear elastic fracture mechanics (Li et al., 2024) and nonlinear fracture mechanics (Yu et al., 2025) further advanced the research and application of hydraulic fracturing technology (Zheng et al., 2025b). However, these traditional models failed to account for multiphysics interactions (Abdelaziem et al., 2023) during hydraulic fracturing, making them inadequate for addressing complex multiphysics coupling problems (Robinson and Kurtz, 1961). With the continuous advancement of hydraulic fracture propagation models and improvements in computational power, researchers began adopting more sophisticated multiphysics coupling models (Gardehansen, 1980). These models integrate factors such as rock mechanics, fluid mechanics, and heat transfer to more accurately describe the fracture propagation process during hydraulic fracturing. Such models (Johnson, 1956) provide theoretical support for optimizing hydraulic fracturing processes by comprehensively considering multiple factors, including fluid flow, rock deformation, and temperature.

Today, driven by significantly enhanced computational capabilities and the rapid advancement of artificial intelligence and big data technologies, data-driven fracture propagation models have emerged as a major research focus in hydraulic fracturing. These models, constructed using machine learning methods, are termed surrogate models. As effective tools, surrogate models have found extensive application across multiple aspects of hydraulic fracturing. By integrating field data with numerical simulation results, they simulate fracture initiation and propagation during fracturing operations. These models deliver more precise predictions of fracture morphology and propagation paths, enable pre-fracturing assessments, and forecast post-fracturing production. This empowers engineers to optimize fracturing design parameters during actual operations, thereby enhancing fracturing efficiency and reducing costs. With ongoing technological advancements, surrogate models will see broader application in hydraulic fracturing, providing increasingly vital support for enhancing oil and gas extraction efficiency while reducing costs. Particularly in unconventional resource development, hydraulic fracturing surrogate models hold immense potential. They enable more precise and rapid predictions for oil and gas extraction while lowering computational costs, making significant contributions to the intelligent and digital transformation of oilfields. As the challenges of developing unconventional oil and gas resources intensify, higher demands are placed on the precision, real-time capability, and accuracy of various models, presenting greater challenges for the construction and application of fracture propagation models. Simultaneously, the insufficient integration between existing models and on-site fracturing operations further constrains their effective application in practical fracturing work.

Therefore, addressing these critical demands and bottlenecks, this paper reviews research progress and development trends concerning three key models in hydraulic fracture propagation simulation: traditional fracture propagation models, numerical simulation methods and multiphysics coupling models, and hydraulic fracturing surrogate models. This review aims to provide guidance for the efficient development of unconventional oil and gas resources in China.

2. Conventional hydraulic fracture propagation methods

Fracture propagation models are central to numerical simulations of hydraulic fracturing, with their accuracy directly impacting the reliability of the results. This section introduces several traditional fracture propagation models, focusing on early empirical models, linear elastic fracture mechanics models, and nonlinear fracture mechanics, including elastic-plastic approaches.

2.1. Classical Analytial Model

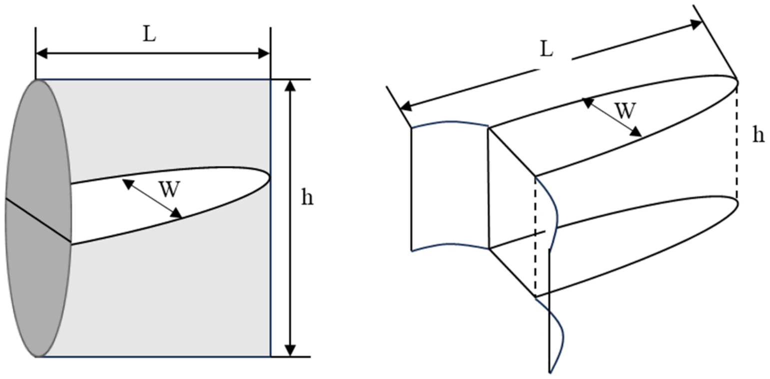
In the early stages of hydraulic fracturing, limited computational tools and an incomplete theoretical framework meant that fracture propagation studies relied primarily on empirical equations and simplified assumptions. These models focused on describing the relationships between fracture geometry, injection pressure, and fluid flow, providing a foundation for the development of more advanced theoretical and numerical approaches.

Dykstra and Parsons (1950) introduced the Dykstra-Parsons equation to predict fracture length based on flow rate and injection pressure, highlighting the importance of injection rate and breakdown pressure in fracture propagation. Despite its simplicity, this equation offered early quantitative support for hydraulic fracturing. Building on this work, Geertsma (1969) examined the relationship between fracture shape and pressure distribution, proposing a vertical fracture propagation model. He also derived empirical relationships based on stratigraphic mechanics, providing a more systematic theoretical framework for predicting fracture geometry.

Khristianovich and Zheltov (1955) introduced the KGD model (Khristianovich-Geertsma-DeKlerk model), which assumes that fractures propagate as horizontal rectangular fractures (Fig. 2(b)). The model derives a mathematical relationship between fracture width, injection rate, and fracturing fluid viscosity. For the first time, it integrated the mechanical aspects of fracture propagation with fluid flow behavior, establishing a crucial theoretical foundation for the quantitative analysis of hydraulic fracturing.

Building on the KGD model, Perkins and Kern (1961) proposed the PKN model (Perkins-Kern-Nordgren model) in 1961. This model assumes a constant fracture height and elliptical propagation in the horizontal plane (Fig. 2(a)), establishing a mathematical relationship between fracture width, injection volume, and fracturing fluid viscosity. The PKN model is particularly suited for thin reservoirs or situations where fracture height growth is constrained. It has provided essential theoretical support for simulating hydraulic fracturing in low-permeability formations such as shale gas and tight sandstones.

Nordgren (1972) further refined the PKN model by incorporating the dynamic characteristics of fracture propagation, enabling a more accurate description of fracture growth over time. Both the KGD and PKN models have been instrumental in advancing hydraulic fracturing technology. Despite relying on simplified assumptions, their straightforward mathematical formu-lations and clear physical interpretations have laid the groundwork for more complex theoretical and numerical models. Today, these models remain widely used in simulating fracture propagation in oil and gas reservoirs as well as geothermal fields, offering reliable tools for rapid estimation of fracture geometry and parameters.



(a) PKN model (b) KGD model

Fig. 2. PKN model and KGD model.

Advances in computational technology and theoretical research have driven the evolution of hydraulic fracturing models from empirical equations to theoretical frameworks grounded in linear and nonlinear fracture mechanics. These models have further progressed into numerical simulations that incorporate multi-physics coupling effects. Despite these developments, the foundational concepts and methodologies of the classical KGD and PKN models remain highly significant, continuing to guide the advancement of modern hydraulic fracturing technology.

2.2. Linear elastic fracture mechanics model

With the development of fracture mechanics theory, linear elastic fracture mechanics (LEFM) has become the foundational framework for modeling fracture propagation in hydraulic fracturing. The early work of Hubbert and Rubey (1961) was the first to systematically establish the quantitative relationships among pressure, in situ stress, rock fracture toughness, and fracture geometry. They demonstrated that fracture initiation occurs when the injection pressure overcomes both the rock's tensile strength and the surrounding stresses. Their findings revealed that fracture geometry such as width and length is directly influenced by injection rate, fluid viscosity, and time. This theory laid the essential groundwork for the engineering design of hydraulic fracturing operations (Papamichos and Vardoulakis, 1989).

In 1920, Griffith proposed the brittle fracture theory, establishing the relationship between material strength and defect size and laying the energy foundation of fracture mechanics, although it did not account for plastic deformation. Irwin (1957) introduced the stress intensity factor, defined fracture toughness, clarified the critical conditions for crack propagation, and established the foundational framework of linear elastic fracture mechanics (LEFM). Building on this framework, later researchers incorporated rock elastic parameters such as the modulus of elasticity and Poisson's ratio, as well as anisotropic characteristics. They explained the tendency of fractures to deflect along the direction of maximum principal stress and established the relationship between dynamic crack propagation and material energy dissipation through the concept of energy release rate.

Within the framework of LEFM, three classical crack propagation criteria have been proposed, each primarily based on the stress field and energy distribution at the crack tip:

- Maximum circumferential stress criterion: cracks propagate in the direction of the maximum circumferential tensile stress.
- Minimum strain energy density criterion: Crack growth follows the path that minimizes local strain energy, emphasizing material energy dissipation.
- Maximum energy release rate criterion: The propagation path is determined by the direction of the greatest decrease in potential energy.

These models are highly applicable to brittle rocks such as shale and quartz sandstone, effectively describing the initiation and propagation of single fractures. However, the assumptions of linear elasticity in LEFM limit its accuracy, as it does not account for plastic deformation at the crack tip, fluid leak-off, or stress shadowing effects among multiple fractures. This leads to less reliable predictions in more ductile rocks, like mudstones and saltstones, or in complex fracture networks. To address these limitations, later studies have incorporated elastic-plastic fracture mechanics and cohesive zone models, providing a more comprehensive representation of nonlinear fracture propagation in real geological settings.

2.3. Nonlinear fracture mechanics modeling

As research has expanded to the mechanical behaviors of deep rock, nonlinear fracture mechanics has emerged as the dominant approach for modeling fracture propagation in hydraulic fracturing. By incorporating rock plastic deformation, energy dissipation, and damage accumulation, this framework significantly enhances the accuracy of fracture propagation predictions under complex geological conditions.

Rice (1968) introduced the J-integral theory to quantify the energy release rate near the crack tip. Building on this, Lemaitre and Bismut (1970) proposed a damage evolution equation, linking damage progression with energy dissipation. Later, researchers integrated plasticity and energy dissipation theories to model the evolution of the plastic zone at the crack tip, material strain softening, damage continuity, and dynamic crack morphology changes. This comprehensive framework revealed the nonlinear interplay between fracturing fluid penetration and rock damage, significantly advancing our understanding of crack propagation beyond the limitations of traditional linear elastic fracture mechanics (LEFM).

At the theoretical level, two primary modeling approaches have been developed for nonlinear fracture mechanics:

- Cohesive zone model (CZM): This model employs a traction-separation law to simulate progressive damage and energy dissipation within the fracture process zone at the crack tip. It provides a quantitative description of the entire fracture process, from microscopic damage initiation to macroscopic rupture.
- Coupled Continuum Damage Mechanics-Flow Model (CDM): This model simulates damage in the near-fracture zone caused by fracturing fluid leak-off during hydraulic fracturing, capturing the interaction between fluid flow and rock damage.

Although these models effectively capture the nonlinear rock behavior, multi-field coupling, and fracture network interactions, they rely heavily on detailed intrinsic parameters and large-scale numerical computations. This leads to an exponential increase in computational costs, posing ongoing challenges in algorithm optimization and computational power requirements for practical engineering applications.

3. Numerical simulation methods and coupled multi-physics field modeling

With advances in computing technology and increased computational power, numerical simulation methods have become essential tools for studying fracture propagation in hydraulic fracturing. To address the complexity of multi-physics coupling in hydraulic fracturing, various numerical methods, most notably the finite element method (FEM), are widely applied to simulate fracture growth, fluid flow, and rock behavior. To enhance the accuracy and versatility of fracture propagation models, researchers increasingly develop multi-physics coupled models that integrate interactions among solid mechanics, fluid mechanics, and heat transfer. This section reviews the current state of the finite element method, boundary element method, discrete element method, and multi-physics coupled modeling in hydraulic fracturing, while also discussing their prospects and challenges in practical applications.

3.1. Finite element method

The finite element method is a crucial tool for simulating fracture propagation in hydraulic fracturing. By discretizing complex geological formations and solving governing equations, FEM accurately characterizes stress distribution, fluid flow, and the coupling of thermal, hydraulic, and mechanical fields during fracture propagation. It is particularly effective in handling irregular fracture geometries and complex boundary conditions, enabling precise representation of three-dimensional crack evolution and quantification of the relationship between fracture width, length, and local stress conditions.

In fracture propagation modeling, the incremental finite element method simulates crack growth by breaking down the nonlinear fracture process into small steps. It iteratively solves mechanical equilibrium equations and determines crack propagation direction at each step using failure criteria such as maximum principal stress or energy release rate. The extended finite element method (XFEM) (Zhou et al., 2024) builds on traditional FEM by introducing discontinuous enrichment functions, like jump functions and fracture-tip fields, to model fracture propagation and shear slip without remeshing fracture paths. This allows efficient simulation of complex scenarios, including multiple fracture intersections and interactions, while significantly reducing computational costs.

Tariq et al. (2021) developed a three-dimensional thermochemical fracturing model within the FEM framework, combining the cohesive zone model (CZM) and the concrete damage plasticity model (CDP) to represent crack tip propagation and tensile compressive damage evolution in the cement matrix, respectively. Their model demonstrated that localized exothermic heat release coupled with chemical etching lowers fracture initiation pressure and promotes multiscale fracture network formation. This study demonstrated that temperature gradients and reaction rates nonlinearly affect fracture propagation paths. Using the improved fracturing method, the rock breakdown pressure was reduced from 7.55 MPa to 4.86 MPa.

For fluid behavior in hydraulic fracturing, FEM quantifies fracture fluid seepage and fracture propagation by coupling Darcy's law with the porous media deformation equations. This approach dynamically captures the spatial and temporal evolution of fracture inflow capacity. Additionally, FEM models that incorporate thermal-mechanical coupling account for temperature changes in the reservoir caused by fracturing fluid injection. They reveal how temperature variations affect rock fracture toughness, fluid viscosity, and pore pressure, providing theoretical support for optimizing fracturing fluid parameters. However, FEM still faces a trade-off between computational efficiency and accuracy when simulating ultra-large-scale fracture networks, requiring substantial computational resources.

3.2. Boundary Element Method

The Boundary Element Method (BEM) has become a key numerical tool for efficiently addressing boundary-dominated problems in fracture propagation simulations for hydraulic fracturing. Unlike the finite element method, which requires discretization of the entire domain, BEM only discretizes fracture surfaces and geometric boundaries. It solves boundary stress-displacement relationships through integral equations, significantly reducing the computational scale of complex multidimensional fracture networks. BEM is especially effective in capturing dynamic stress singularities at crack tips and modeling interactions among multiple fractures.

In single-fracture propagation scenarios, Harris et al. (2017) used BEM to accurately reconstruct the stress concentration distribution at the crack tip, demonstrating that the fracture deflection path is controlled by the local tension-shear combined stress state. In multi-fracture systems, Zhu et al. (2023) addressed the stress shadowing effect between fractures using Green's functions, showing that the competitive propagation of adjacent fractures is limited by the efficiency of stress transfer at their distal ends. This finding explains the synchronous propagation or suppression behavior observed in multiple fracture clusters. By analyzing interference between fractures at cluster spacings of 10 m, 15 m, and 20 m, they identified 15 m as the optimal spacing for fracture clusters.

BEM's flexibility is also evident in its ability to handle complex boundary conditions. By incorporating factors such as fluid pressure loads, non-uniform stress fields, and heterogeneous rock mechanical properties (including rupture strength and elastic modulus gradients), the method can efficiently predict changes in fracture morphology under varying injection parameters.

3.3. Discrete element method

The Discrete Element Method (DEM), known for its ability to model discontinuous media, has become a valuable tool for uncovering the microscopic mechanisms of rock fracture and simulating complex fracture networks in hydraulic fracturing. By explicitly tracking contact forces and energy transfer between rock particles, DEM can accurately reconstruct the processes of fracture initiation and propagation. This makes it particularly well-suited for simulating fracture behavior in anisotropic reservoirs, such as shale and coalbed methane, which feature developed laminae and dense joint networks.

In fracture mechanism studies, Zhou et al. (2023) advanced the DEM by incorporating coupled thermal-force analysis to address challenges in deep shale reservoir stimulation. They developed a shale damage evolution model that accounts for lamination anisotropy, revealing the mechanical basis for the preferential extension of cleavage cracks along laminae during damage. The model distinguishes mechanical properties, including tensile and shear strength and friction coefficients, between lamina surfaces and the surrounding matrix, providing a theoretical framework for predicting fracture network morphology in deep reservoirs. Their results show that under high pressure (50 MPa), shale experiences thermal damage when heated from 20 °C to 400 °C, accompanied by enhanced ductility and increased susceptibility to induced cracking.

The core advantage of the DEM in fracture propagation simulation lies in its ability to overcome the limitations of traditional continuum mechanics. It effectively models the initiation and propagation of fractures in heterogeneous rocks. By establishing a coupled multi-field model that integrates fluid flow, rock deformation, and temperature evolution, this method accurately captures the interactions among these processes. Compared to the finite element method, the DEM can dynamically update contact networks, making it well-suited to handle complex fracture behaviors such as bifurcation and diversion.

3.4. Coupled multi-physics field modeling of hydraulic fractures

With the advancement of unconventional oil and gas development into deep and complex reservoirs, coupled multi-physics numerical simulation has become central to hydraulic fracturing research. This approach simulates fracture initiation and propagation by capturing the multi-scale interactions of mechanics, fluid flow, thermochemistry, and other processes. Commercial software such as COMSOL and ABAQUS, equipped with modular solvers, can couple physical phenomena like poroelastic deformation, non-Newtonian fluid flow, and thermally induced damage to provide accurate simulation results for fracture propagation in anisotropic reservoirs.

The phase-field method is a key technique for multi-physics coupling, allowing the integration of mechanical and fluid fields to simulate hydraulic fracturing processes. Zhang et al. (2017) reviewed the computational implementation of the phase-field method, providing a comprehensive overview of its development and modeling approaches. Zhuang et al. (2022) addressed mixed-mode fracture propagation in rock-like materials, introducing an energy-driven description of diffuse fractures to simulate complex fracture evolution under combined tensile-shear stress conditions. Wang et al. (2024c) extended the method to heterogeneous reservoirs, simulating crack initiation and propagation with a focus on multi-crack interactions, material inhomogeneity, and hydraulic behavior, including shear bulging effects. These studies collectively demonstrate the phase-field method's capability to capture the complex evolution of fracture networks under realistic geological and mechanical conditions (Wang et al., 2024d).

In the field of deep geothermal reservoir stimulation, Fu et al. (2011) developed an explicit coupled hydraulic-geomechanical model based on the Livermore Distinct Element Code (LDEC), integrating finite-element solid mechanics, finite-volume fluid flow, and an adaptive re-segmentation algorithm to simulate dynamic interactions between discrete fracture networks and continuous media. Bazargan et al. extended thermal-hydraulic-mechanical coupling using COMSOL to quantify the combined effects of thermal stress and fluid phase changes during fracturing of hot dry rock (HDR), providing guidance for optimizing fracturing fluid temperatures in high-temperature reservoirs. Their research indicates that within the range of 27 ℃ to 327 ℃, thermal stress alone is insufficient to drive further crack propagation. Chen et al. (2017) developed a two-dimensional model coupling the displacement discontinuity method (DDM) with the finite-volume method (FVM) to investigate competitive fracture propagation mechanisms. Their study systematically examined the effects of tectonic stress deflection, fluid viscous dissipation, and fracture spacing, showing that when the angle between hydraulic and natural fractures is small, fractures tend to propagate along natural fractures, whereas larger angles favor propagation along the original hydraulic path.

The hydraulic fracturing multi-field coupling model simulates the interactions among mechanical deformation, fluid seepage, temperature evolution and chemical reactions during underground reservoir stimulation (Mohammed et al., 2017). By constructing cross-scale multi physical equations of the reservoir's intrinsic structure, the model quantitatively reveals mechanisms such as fluid viscous resistance, thermally induced phase change stresses and natural shear slip along weak planes during fracture propagation. Numerical simulations based on multi field coupling can not only evaluate the influence of engineering parameters such as fracturing fluid viscosity, injection volume and temperature on fracture complexity but also predict the non uniform placement efficiency of proppant in scenarios involving competitive propagation of multiple fractures. These insights provide critical theoretical support for optimizing fracturing segment clusters and assessing the hydraulic conductivity of fracture networks.

In the complex context of multi-physics coupling, the computational complexity of hydraulic fracturing numerical simulations increases exponentially, placing extremely high demands on computational resources. Current simulations typically involve key physical processes such as solid mechanics, fluid flow, temperature, and chemical fields. Although cutting-edge research is focused on establishing fully coupled "thermal-hydraulic-mechanical-chemical" frameworks, practical engineering applications remain constrained by existing computational capabilities and theoretical understanding. Consequently, simplified coupled simulations are commonly performed by selecting two to three physical fields based on specific geological conditions and fracturing objectives.

During complex three-dimensional geological modeling, the computational resources and time costs required for fully coupled simulations are enormous, severely limiting the application of this method in rapid decision-making at oilfield sites and large-scale parameter optimization. Furthermore, the predictive accuracy of this model heavily relies on the precision of input parameters, including in-situ stress fields, rock mechanical properties, fracture toughness, permeability, and thermal-physical parameters. These parameters exhibit strong heterogeneity and anisotropy underground, making it challenging to characterize them accurately using limited logging and core data alone. This leads to significant discrepancies between simulation results and actual formation conditions.

The hydraulic fracturing process encompasses the propagation of fractures from millimeter-scale microfractures to hundred-meter-scale primary fractures, alongside flow processes spanning from nanoscale pores to macroscopic fractures. Existing numerical methods struggle to efficiently and accurately describe such vast scale differences within a unified model, presenting a significant methodological challenge. Furthermore, many critical mechanisms, such as rock fatigue under cyclic loading and chemical corrosion, proppant migration and placement within complex fracture networks, and the failure criterion that govern the interaction between tensile and shear failure in unconventional reservoirs, remain oversimplified in current models, limiting their ability to capture the underlying physical processes accurately.

In summary, while multiphysics coupling models hold significant value in hydraulic fracturing simulations, limitations in computational efficiency, parameter determination, multiscale modeling, mechanism description, and geological characterization prevent them from fully and realistically reproducing the entire fracturing process under formation conditions.

4. Surrogate model of hydraulic fracturing

In recent years, driven by the urgent need for efficient development of unconventional oil and gas resources, hydraulic fracturing surrogate models have become a prominent research focus. These models play a crucial role in enhancing reservoir stimulation efficiency, reducing development costs, and supporting engineering decision-making. As simplified alternatives to traditional physical models or numerical simulations, surrogate models are built by fitting large datasets from experiments and simulations. They offer high precision at significantly lower computational cost, thereby reducing reliance on intensive numerical simulations. This approach provides a new framework for dynamically predicting fracture propagation and conducting sensitivity analyses of key parameters.

4.1. Prediction of hydraulic fracture propagation

Hydraulic fracturing surrogate models have attracted significant attention for their role in optimizing fracturing design, enhancing engineering efficiency, and reducing computational costs. Initially developed alongside traditional physical and numerical simulation methods, the research on surrogate models has evolved rapidly with advances in computational capabilities and the accumulation of large-scale data. In response to the growing demand for intelligent and digital oilfield development, data driven approaches, particularly those based on machine learning and deep learning, have been increasingly applied to model and predict hydraulic fracture propagation processes with high efficiency and accuracy.

Qu et al. (2023) proposed a new surrogate model for rapid shale stress prediction that considers the geomechanical heterogeneity of shale gas and the multiscale seepage mechanism, and analyzed the interaction of key influencing factors on shale stress. Wang et al. (2024b) introduced a framework of physically informed neural networks (PINNs), which guide the geometric evolution of fracture surfaces by embedding bi-adjusted summation equations. This approach reduced the prediction error by 62% compared to purely data-driven models. Hamid et al. (2023) developed a coupled geomechanical-permeability surrogate model using artificial neural networks (ANN) to replace traditional finite element solvers and predict permeability based on pore pressure. The model efficiently predicted permeability, achieving a mean squared error of only 0.0438 using 80% of the 5,400 data points for training and the remaining 20% for testing. Wang et al. (2024a) employed LSTM to forecast wellbore pressure over the following 400 days, training on production data from days 359 to 732 (Fig. 3), which enabled optimized development strategies for deep coalbed methane. The model predicted permeability efficiently, achieving a mean squared error of 0.0438 using 80% of the 5,400 data points for training and 20% for testing.

The fracture propagation surrogate model facilitates a deeper understanding of the dynamic stress field, permeability variations, and fracture evolution in shale reservoirs, offering valuable guidance for hydraulic fracturing design and real-time optimization.

The fracture propagation surrogate model facilitates a deeper understanding of dynamic stress fields, permeability changes, and fracture propagation in shale reservoirs, providing guidance for hydraulic fracturing design and dynamic optimization. Unlike multi-physics coupled models, the surrogate model extracts features from historical data, trains itself using data generated by high-fidelity models, and then performs engineering tasks requiring massive simulations, thereby significantly accelerating computational speed.

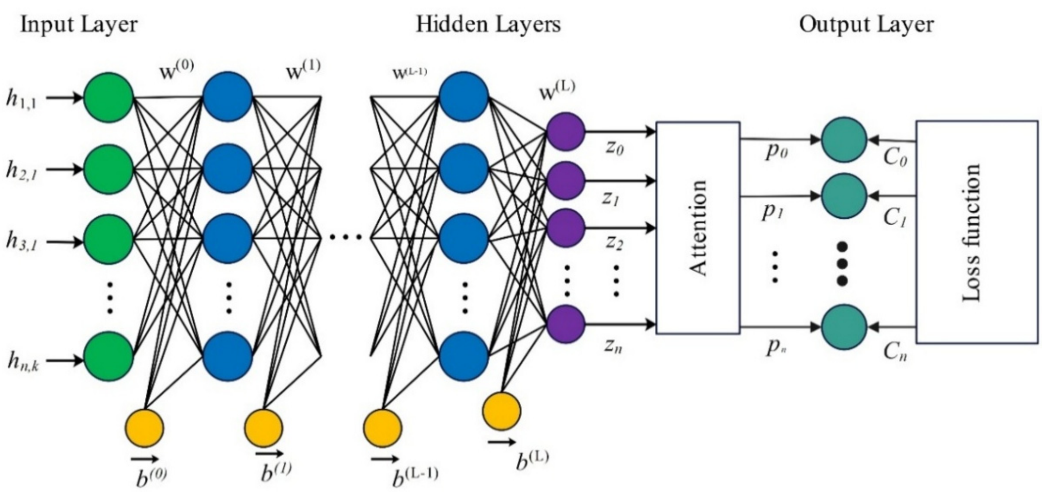


Fig. 3. LSTM predictive modeling.

4.2. Equilibrium growth of hydraulic fractures

In hydraulic fracturing operations, achieving balanced propagation of multiple fractures is a critical indicator of treatment effectiveness. When multiple fractures propagate simultaneously, their mutual interactions, particularly the stress shadow effect, can significantly increase the risk of non-uniform propagation. This effect may suppress the growth of adjacent fractures, resulting in disparities in fracture length and width. Such uneven development can lead to engineering challenges such as irregular fluid distribution and premature proppant bridging or sand plug. Therefore, an in-depth investigation into the synergistic propagation mechanisms of multiple fractures, including stress interference patterns and their influence on the final fracture geometry, is essential. This research provides the theoretical foundation for optimizing fracture spacing, perforation design, and operational parameters. Ultimately, it supports the mitigation of engineering risks, maximization of reservoir stimulation volume, and enhancement of well productivity.

Cheng et al. (2023) used a polynomial chaos expansion (PCE) surrogate model combined with the self-developed hydraulic fracturing simulator DeepFrac to analyze the geological factors that influence the average fracture growth extent during the fracturing process. Goswami et al. (2022) proposed a physics-informed variational deep operator network for predicting fracture propagation paths. By integrating physical laws and data through a hybrid loss function, their approach significantly reduces computational costs while maintaining high prediction accuracy. Liu et al. (2022) developed a fracturing simulator based on the displacement discontinuity method that incorporates geological, mechanical, and completion parameters as input and generates detailed fracture geometry, reducing simulation time from one week to three hours.

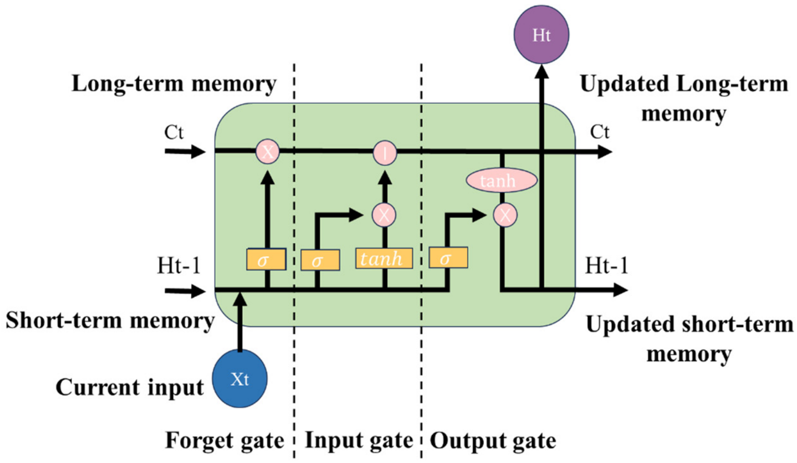


Fig. 4. LSTM workflow diagram.

Currently, efficiently training surrogate models (Fig. 4) to rapidly predict the equilibrium growth of hydraulic fractures under varying conditions has become a powerful technical approach for achieving uniform fracture propagation and improving fracturing effectiveness. This provides important decision-making support for practical engineering applications.

4.3. Fracturing effectiveness evaluation

With the rapid development of artificial intelligence technologies, machine learning-driven hydraulic fracturing simulation methods are driving the intelligent transformation of the oil and gas engineering field. Research in this area is evolving from purely data-driven approaches to physically-informed intelligent models. By incorporating prior knowledge such as rock mechanics principles and mass conservation laws into deep learning architectures, these models significantly enhance generalization ability and interpretability, even under limited data conditions.

The post-fracturing evaluation model generally consists of three components: fracture diagnosis during fracturing, post-fracturing effect assessment, and comprehensive evaluation of fracturing modification (Fig. 5). This model predicts the reservoir modification effect through real-time monitoring of pressure and injection rate. It integrates microseismic monitoring, fiber-optic data feedback, fracturing parameter optimization, and an intelligent decision-making system to provide precise guidance for fracturing operations.

Chen et al. (2022) employed artificial neural networks (ANN) to map fracturing curves to fracture parameters for predicting fracture permeability. This approach significantly reduces computational time during execution, from 374 minutes to 102 minutes, and lowers the error rate from 10.33% to 0.29% compared with traditional methods. Song et al. (2022) designed a dual-channel deep network combining convolutional neural networks (CNN) and U-Net to evaluate fracturing effects in coalbed methane reservoirs. Their approach improved fracture half-length prediction accuracy by 37% compared with traditional methods and enabled visualization and diagnosis of two-phase seepage flow of gas and water. Qu et al. (2023) employed deep neural networks (DNN) to build an evaluation model that, combined with the fracture volume conservation law and k-fold cross-validation, enabled prediction of fracture inflow capacity in small-sample tight reservoir scenarios. To address the computational bottleneck of coupled multi-physics fields, Wang et al. (2023b) developed a semi-physical information multi-input operator network (SPI-MIONet), which reduced the computation time of the phase field model by two orders of magnitude while maintaining accuracy in predicting fracture paths by mapping weak constraints of some control equations into an infinite-dimensional function space. Mu et al. (2024) proposed a surrogate model for rapid prediction of stress field in shale, quantifying pore pressure changes in natural gas reservoirs induced by hydraulic fracturing. The surrogate model achieved a prediction accuracy of 99.26%.

Currently, new deep learning algorithms, such as physics-informed neural networks (PINNs), are driving hydraulic fracturing simulations toward greater mechanism interpretability and computational efficiency. These advancements aim to establish an intelligent fracturing decision-making system with a closed loop of “monitoring, simulation, and optimization.” However, balancing the depth of physical law embedding with the network’s characterization capability remains a challenge that limits the large-scale application of this technology.

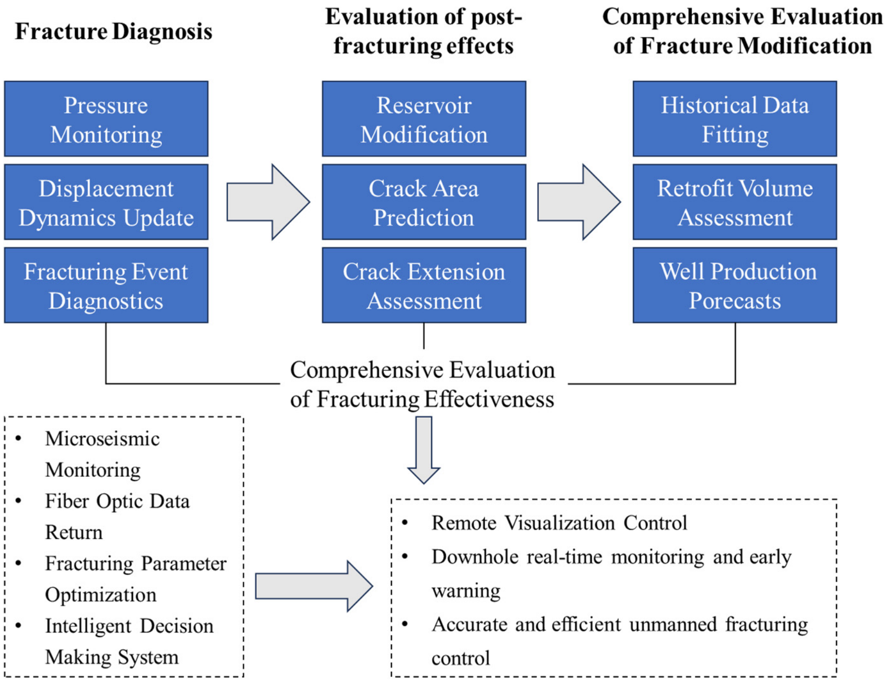


Fig. 5. Comprehensive evaluation method for fracturing effectiveness.

4.4. Production prediction

Deep learning-based production dynamics prediction technology is gradually transforming the traditional numerical simulation methods used for history matching and production capacity forecasting by uncovering the nonlinear mapping relationship between reservoir parameters and production performance (Fig. 6). By integrating geological parameters, fracturing engineering parameters, and production dynamics data, research in this field has developed an intelligent prediction system with strong generalization capabilities, providing real-time decision support for optimizing development plans.

In the field of history fitting and production dynamics prediction, alternative modeling techniques based on deep learning demonstrate significant advantages. Alqahtani et al. (2022) established an XGBoost model that verified the strong nonlinear correlation between twelve key parameters, such as porosity and permeability, and hydrocarbon production, reducing the mean absolute error (MAE) to 5.6% in gas well production prediction. Ma et al. (2022) developed an efficient spatiotemporal convolutional recurrent neural network based on CNN-LSTM (Convolutional Neural Network–Long Short-Term Memory) to predict production. Using 1,500 training samples and 500 test samples, the model achieved a prediction accuracy of 0.98. Zhang et al. (2023) developed an improved visual transformer neural network (IViT-NN) for accurate and efficient acquisition of production data. Testing on 200 fracturing time series datasets, the model achieved an accuracy of 92.7% to 99.6% in identifying six distinct fracturing events.

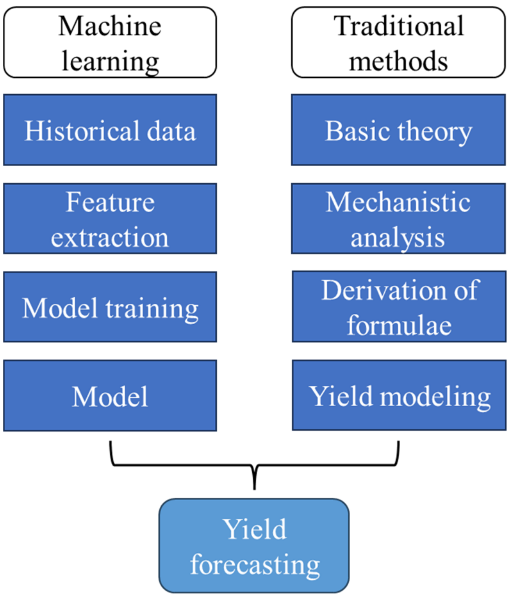


Fig. 6. Yield prediction process based on machine learning vs. yield prediction process of traditional methods.

The current research trend is shifting from static parameter modeling to dynamic data-driven prediction, focusing on the multiple effects of time-varying reservoir physical properties during production and changes in the reservoir after fracturing. By integrating high-frequency monitoring data such as wellhead pressure and fluid production components, developing adaptive surrogate models with dynamic adjustment capabilities has become a primary direction to improve the accuracy of whole-life production prediction. However, effectively characterizing the nonlinear correlation between the dynamic evolution of reservoir heterogeneity and the decline of artificial fracture inflow capacity remains a key scientific challenge that limits the reliability of long-term production capacity forecasts.

Compared with the various surrogate models discussed in this chapter, these approaches exhibit distinct technical characteristics and complement each other. For fracture propagation prediction, especially under complex geological conditions requiring high accuracy, Physics-Informed Neural Networks (PINNs) provide notable advantages by embedding fracture mechanics governing equations as constraints within deep learning frameworks. This ensures predictions comply with physical laws and addresses the high computational costs and dependence on precise constitutive relationships typical of traditional numerical simulations. PINNs are increasingly applied in pre-construction virtual experiments and preliminary plan evaluations.

In contrast, assessing fracturing effectiveness focuses on rapidly extracting reusable empirical patterns from historical data. Classical machine learning algorithms, including random forests and support vector machines, are widely used in this context to efficiently map fracturing parameters to operational outcomes, enhancing both the speed and automation of plan design.

For long-term production forecasting, a typical time-series problem, Long Short-Term Memory (LSTM) networks have emerged as the preferred approach. Their internal gating mechanisms effectively capture medium- to long-term dependencies in oil and gas production. This variation in model selection reflects differing priorities across applications, including physical consistency, computational efficiency, and temporal forecasting capability. Collectively, these approaches form a comprehensive technological chain for intelligent fracturing, covering design, evaluation, and prediction.

Table 1. Comparison of Computational Methods and Applicable Scenarios for Different Surrogate Model.

Proxy Model Type	Method	Speed	Physical realism	Applicable Scenarios
Crack Propagation Prediction	DNN, PINN	Slow	Introducing physical formulas	Fracturing Operation Prediction
Cracks propagate uniformly	ANN, PINN	Slow	Introducing physical formulas	Fracturing Site Assessment
Fracturing Effect Evaluation	XGBoost, CNN-LSTM	Fast	Comprehensive Evaluation	Fracturing Plan Design
Production Forecast	LSTM	Fast	Time Series Data	Oilfield Production

5. Trends in the development of hydraulic fracturing surrogate models

The advancement of intelligent hydraulic fracturing models is transforming traditional hydraulic fracturing practices and driving the digital evolution of the oil and gas industry. By integrating diverse data sources, including fracturing operation records, geological characteristics, and microseismic monitoring, and applying advanced algorithms such as random forests and deep neural networks, these models accurately predict fracture geometry and production responses. Additionally, they enable real-time assessment of fracturing performance and provide early warnings of potential risks. Compared to conventional approaches, data-driven evaluation models excel at uncovering complex nonlinear relationships and quantifying uncertainties, offering a more robust foundation for engineering decisions.

5.1. Fracture monitoring and real-time diagnostics

In recent years, advancements in artificial intelligence driven by big data, machine learning, and increased computational power have progressed rapidly. Leveraging extensive historical fracturing data, AI algorithms now learn patterns from large datasets to develop intelligent diagnostic methods for real-time monitoring and evaluation of fracturing conditions. For instance, integrated platforms like Halliburton's Octiv Intelligent Fracturing Platform and Drill2Frac Inc. support these efforts by combining multiple data sources, including distributed fiber-optic sensing, microseismic monitoring, and high-precision wellhead pressure measurements. These platforms utilize deep learning based decision algorithms to manage the entire process from data collection and analysis to real-time monitoring and automated equipment control. This has enabled the initial realization of automated workflows (Fig. 7).

Ramirez et al. (2019) employed injection pressure, pumping rate, and proppant concentration data from the hydraulic fracturing process to automatically identify events at each stage using supervised learning methods. LeBlanc et al. (2023) utilized optical fibers as strain sensors to monitor hydraulic fracturing operations and provided a detailed discussion of practical challenges encountered in their application. Mohammed et al. (2017) analyzed fluid injection rate and pressure signals to determine fracture initiation and propagation, thereby enabling an automated workflow. Chen et al. (2023) applied low-frequency distributed acoustic sensing of strain rate combined with deep learning to classify and locate competing fracture propagation events. Sui et al. (2023) reviewed current fracture monitoring techniques in hydraulic fracturing, highlighting their roles in interpreting proppant distribution, fracture temporary plugging and diverting, inter-segmental cluster interference, fracture hit, and fracture morphology. They also proposed future technical strategies for distributed fiber optic joint monitoring of hydraulic fracturing.

Distributed fiber-optic sensing technology has become a key tool in hydraulic fracturing for developing unconventional oil and gas reservoirs such as shale and tight sandstone. It provides real-time data to analyze proppant distribution, temporary plugging, and fracture initiation and propagation, helping to address practical challenges encountered during hydraulic fracturing.

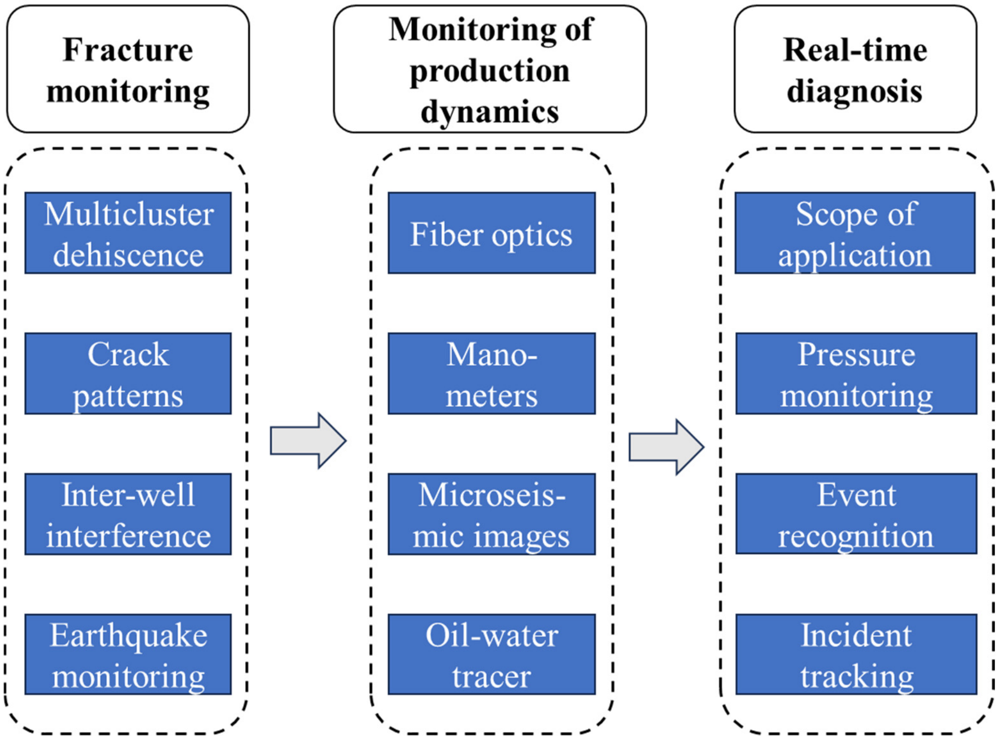


Fig. 7. Fracture monitoring and real-time diagnostics.

5.2. Optimization of fracturing parameters

Hydraulic fracturing intelligent optimization technology creates a closed-loop system of modeling, assessment, and optimization by integrating surrogate models with post-fracturing evaluation models. Utilizing intelligent algorithms such as ant colony optimization and particle swarm optimization, it overcomes the limitations of traditional manual experience by automatically identifying optimal fracturing parameters, including injection rate, proppant concentration, and cluster or fracture spacing, within complex constraints. The system adjusts construction plans in real time to respond to dynamic geological conditions. This collaborative optimization approach not only enhances the scientific rigor and adaptability of hydraulic fracturing design but also advances oilfield development toward greater digitalization and intelligence.

Chen et al. (2023) proposed a differential evolutionary algorithm (GLSADE) to assist both global and local optimization in surrogate modeling for water-driven reservoir development. Their approach effectively balances global and local strategies to enhance recovery. Zhang et al. (2020) developed a surrogate model that combines high-precision finite element simulations with low-order analytical solutions. They constructed a three-dimensional optimization framework based on fracture inflow capacity, fracture network complexity, and economic cost. Applied to the Sichuan shale gas field, this model achieved a 23% increase in single-well production while reducing proppant usage by 18%.

These advancements signify a shift in fracturing parameter optimization from static, experience-based design to dynamic, intelligent decision-making, providing essential algorithmic support for the efficient development of complex reservoirs. By deeply integrating geomechanical modeling, real-time monitoring feedback, multi-scale surrogate models, and multi-objective optimization algorithms, a comprehensive optimization framework has emerged that combines mechanistic understanding with data-driven strategies. This approach has demonstrated strong engineering adaptability in challenging reservoirs such as those in the Sichuan and Ordos Basins. It effectively addresses key industry challenges including limited control over fracture networks, low proppant utilization efficiency, and poor economic returns in the stimulation of heterogeneous reservoirs.

5.3. Fracturing pumping intelligent decision system

In the early stages of computer technology adoption, the emergence of expert systems played a key role in advancing decision-making processes in hydraulic fracturing. As a major branch of artificial intelligence, expert systems addressed complex problems by storing domain knowledge in a structured knowledge base and using rule- or logic-based reasoning to simulate expert thinking. These systems provided decision support by replicating the problem-solving approaches of human experts in the field.

Holditch et al. (1987) developed a fracturing expert system based on logical reasoning, which was used to optimize fracturing fluid type and volume. Fan (1998) and colleagues introduced the first neural network-based expert system for fracturing and acidizing decision making in China. This system was initially applied to the selection of wells and target formations for fracturing and acidizing treatments. Research in this area progressed further after 2000. Jiang et al. (2004) developed an expert system specifically designed for low permeability oilfields, targeting reservoirs that are difficult to stimulate. This marked a significant step in applying expert systems (Wang et al., 2023b) to challenging reservoir types. Popa et al. (2011) explored the use of case-based reasoning (CBR) in the planning and execution of fracturing operations. By leveraging historical field data, they proposed a method to enhance design, planning, and execution with the goal of increasing operational success rates and avoiding previously encountered issues.

However, expert systems have faced significant challenges related to knowledge acquisition, representation, and the limitations of their reasoning mechanisms. These constraints have made it difficult to generate reliable decisions in complex scenarios, hindering further development and widespread adoption over the past decade. The emergence of a new generation of artificial intelligence technologies (Wang et al., 2025b) has now opened up new opportunities for advancing intelligent decision-making in hydraulic fracturing operations.

Mondal et al. (2022) proposed an enhanced integrated system for real-time decision-making in hydraulic fracturing operations, which significantly reduced the cost of fracture optimization design. Surtman et al. (2024) introduced a screen tubing-free sand control strategy for intelligent fracturing systems in cemented single-tube completions. This approach eliminates the need for expensive wellbore cleanup operations and simplifies the process by removing steps such as perforation injection, packer setting fluid, and the installation of screen tubing and packer assemblies. Halliburton has developed a real-time interpretation and visualization platform by integrating surface fracturing equipment with downhole monitoring data, including fiber-optic sensing, microseismic signals, and pressure measurements. This platform supports expert decision-making by combining automation and machine learning, leading to optimized fracturing designs and improved economic outcomes.

Investigation on intelligent decision-making systems for fracturing pump injection remains in its early stages. With the advancement of technologies such as distributed fiber-optic sensing and edge computing, the focus is gradually shifting from static parameter optimization toward the development of intelligent control systems. This transition involves building real-time decision-making frameworks (Wang et al., 2024c) that couple multiple physical fields, addressing challenges such as the heterogeneous integration of geomechanical models with machine learning algorithms, and resolving millisecond-level synchronization between high-frequency downhole data streams and surface equipment control. The theories and methods underpinning autonomous decision-making for fracturing injection scenarios still require ongoing exploration (Fig. 8).

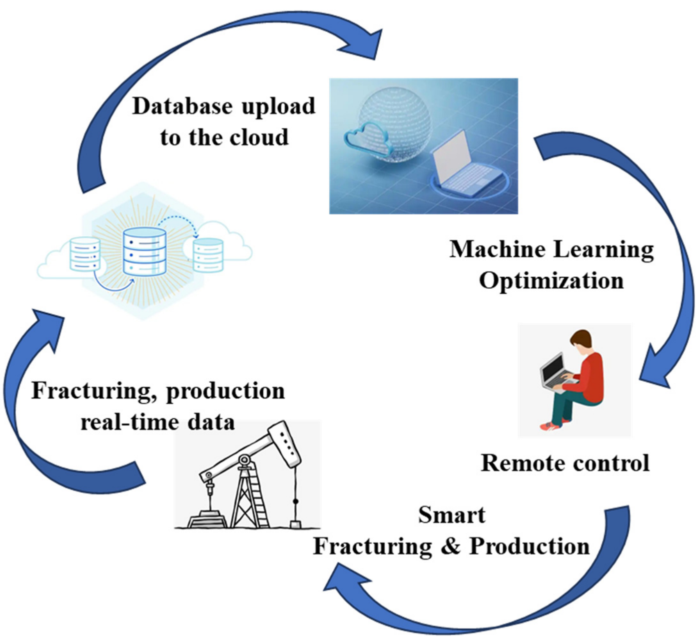


Fig. 8. Fracturing Pump Injection Intelligent Decision System Schematic Diagram.

6. Outlook

6.1. Summarize

Research on the numerical simulation of hydraulic fracturing and fracture propagation has evolved over several decades, resulting in a mature technical system that integrates theoretical innovation with engineering practice. Classical models such as the KGD and PKN remain valuable for quickly estimating fracture geometry under simplified mechanical assumptions and continue to be widely used in simulations involving multi-physics coupling and complex geological conditions. With advances in computing power, multi-physics coupling models developed using commercial finite element software like COMSOL and ABAQUS can now account for both linear and nonlinear fracture mechanics, rock failure mechanisms, non-Newtonian fluid dynamics, and thermo-chemical interactions. These models enable detailed simulations of fracture behavior in deep, high-temperature, high-pressure reservoirs. Furthermore, innovative applications of numerical methods such as theFEM, BEM, and DEM have enhanced understanding of fracture evolution in complex conditions, including bedding anisotropy of shale and natural fracture network reactivation. These insights provide a critical foundation for optimizing fracturing design parameters.

Currently, data driven intelligent technological innovation is reshaping the hydraulic fracturing engineering paradigm. Surrogate models based on machine learning and deep learning such as PINN and LSTM have demonstrated high computational efficiency and prediction accuracy in fracture morphology prediction, fracturing parameter optimization, and production forecasting by integrating physical laws and data features. The deep integration of intelligent technology systems, including distributed fiber optic monitoring, digital twins, and reinforcement learning has initially constructed a closed loop decision making system covering real time sensing, dynamic simulation, and autonomous optimization. This advancement is driving a paradigm shift in fracturing engineering from empirical trial and error to mechanism driven approaches, and from local optimization to global synergy.

Traditional physical models provide a top-down, universal framework whose accuracy depends largely on a few key initial parameters, such as porosity and permeability. These models are inherently static and computationally intensive. While grounded in universal physical equations and highly versatile, solving them requires complex partial differential equations, often taking hours or even days for a complete simulation.

In contrast, surrogate-based modeling represents a bottom-up paradigm shift. Rather than serving as a universal tool, it functions as a highly customized digital twin, learned and iterated from extensive historical and real-time data specific to a given oilfield or block. Its strength lies in the deep integration of operational details, such as fracturing plans, and the ability to rapidly update with new data. This approach overcomes the slow responsiveness of traditional models and maintains long-term accuracy in rapidly changing production environments through continuous learning. Similarly, surrogate models, though requiring substantial time for training and iteration, can perform single predictions or scenario analyses in seconds or minutes. This near-instantaneous responsiveness enables real-time optimization and rapid decision-making.

The transition from energy-intensive, slow-response physical models to lightweight, fast-response surrogate models is therefore more than a technological upgrade; it is a methodological revolution. It transforms the extraction of insights from massive datasets into actionable, field-deployable intelligence, ushering in a new era of highly personalized, dynamically optimized oilfield development.

Table 2. Model Comparison.

Model Category	Simulation Method	Calculation Accuracy	Software
Traditional Crack Propagation Model	Classical Analytical Model	Low	Artificial
	Linear Elastic Fracture Mechanics Model	Low	Artificial
	Nonlinear Fracture Mechanics Model	Low	Artificial
Numerical Simulation Methods and Multiphysics Coupling Model	Finite Element Method	Relatively high	Abaqus, Ansys, Comsol
	Boundary Element Method	Relatively high	Ansys
	Discrete Element Method	Relatively high	Itasca
	Hydraulic Fracturing Multiphysics Coupling Model	Relatively high	Abaqus, Ansys, Comsol
Hydraulic Fracturing Surrogate Model	Crack Propagation Prediction	Extremely high	Python
	Uniform Crack Propagation	Extremely high	Python
	Fracturing Effect Evaluation	Extremely high	Python, Matlab
	Production Forecast	Extremely high	Python, Matlab

6.2. Prospect

The main limitation of current data-driven approaches in hydraulic fracturing simulation is their weak connection to the underlying physical mechanisms. Purely data-driven surrogate models depend heavily on the amount and quality of training data, yet in practice, available data are often limited. Downhole measurements are costly, geological parameters carry significant uncertainty, and data collected across different scales are difficult to reconcile. As a result, these models may interpolate well within familiar conditions but lose reliability when extrapolating to new geological settings or operational scenarios. Their black-box nature further reduces confidence in their predictions, as the lack of physical interpretability makes it challenging for engineers to trust and apply the results in decision-making.

Improving the reliability of surrogate models under complex geomechanical conditions requires a shift from purely data-driven fitting to approaches that integrate physical mechanisms with data. A key direction is the incorporation of physical knowledge, such as through physics-informed machine learning, which embeds governing equations as constraints during training. This integration strengthens extrapolation performance and enhances model generalization.

At the same time, moving from deterministic to probabilistic prediction is critical. Techniques such as

Bayesian inference can quantify uncertainty and provide risk-informed intervals that support more robust decision-making. Additionally, transfer learning offers a practical pathway for enabling models to adapt quickly to new work areas by leveraging prior knowledge and limited new data, helping overcome the current challenge of requiring "one model per well."

Despite significant progress in the intelligent evolution of hydraulic fracturing, limitations remain in both theoretical maturity and large-scale application. Further research is required in the following areas:

(1) Multi-scale and multi-field coupling: Multi-physical field coupling models for complex reservoirs still face computational efficiency challenges. To address this, techniques such as adaptive grids and reduced-order models should be employed to streamline algorithms. At the same time, cross-scale coupling frameworks need to be developed to better understand the interaction mechanisms between macro and micro scale fractures.

(2) Synergy between model mechanism and data driven: Although current surrogate models demonstrate high efficiency, their integration of physical laws remains limited. Future research should focus on hybrid modeling approaches such as Physics-Informed Machine Learning (PINN) to achieve a balance between mechanistic interpretability and data generalization capabilities.

(3) Breakthrough of autonomous decision-making systems: Existing intelligent decision-making systems remain largely at an auxiliary stage. It is therefore necessary to develop a fracturing control platform that integrates reinforcement learning with real-time data monitoring to enable dynamic feedback and autonomous optimization.

Leveraging surrogate models to extract insights from large datasets is not merely a means of improving computational efficiency; it represents a fundamental methodological shift. This approach moves oilfield development beyond reliance on generalized experience and slow, conventional simulations, opening the door to a new era of intelligent decision-making characterized by enhanced personalization, adaptive strategies, and real-time optimization.

In summary, the intelligent transformation of hydraulic fracturing technology will involve the deep integration of numerical simulation, artificial intelligence, and Internet of Things technologies. This integration will drive a transition from empirical trial-and-error approaches to accurate prediction, and from localized optimization to global synergy. Ultimately, it will serve as a core driving force for the efficient development of unconventional oil and gas resources and support the sustainable growth of the energy industry.

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Conflicts of Interest

The authors declare that they have no conflict of interest.

Use of AI and AI-assisted Technologies

During the preparation of this work, the authors used DeepSeek to polish the language and improve the expression of parts of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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