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Novel fracture network modeling method for tight reservoirs integrating mechanical and geometric characteristics

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ABSTRACT

Discrete fracture network (DFN) modeling is widely applied to characterize fracture systems in tight reservoirs, yet its accuracy is often limited by the insufficient integration of geological, geometric, and mechanical controls. To address these challenges, a fracture network modeling approach based on mechanical-geometric criteria (FNMmg) is introduced. The method incorporates five analytical strategies: (1) simulation of stratabound fracture dips using gap angles measured relative to bedding normals; (2) scale-weighted orientation statistics to emphasize the contribution of dominant fractures; (3) orientation generation via a cumulative probability curve to avoid errors caused by fracture-group partitioning; (4) fracture element representation to enable hierarchical coalescence; and (5) fusion rules combining geometric similarity with mechanical and diagenetic principles. Application to the Triassic Chang 6 tight sandstone reservoir in the Ordos Basin, China, demonstrates that FNMmg can reproduce multi-scale fracture systems with improved geological consistency. Validation against tracer monitoring data from 34 injector-producer well pairs showed an overall connectivity consistency of about 91%, including 86% accuracy for fracture-related and 93% for pore-related or unconnected cases, demonstrating FNMmg's utility in identifying effective fracture flow paths and supporting reservoir connectivity analysis. These results indicate that FNMmg provides a practical framework that explicitly integrates fracture mechanics, geometry, and data-driven constraints, offering a basis for reservoir characterization, connectivity analysis, and development optimization in tight sandstone settings.

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1. Introduction

Natural fracture networks are extensively developed in tight oil and gas reservoirs, where they act as the primary fluid conduits (Zeng and Li, 2009; Gong et al., 2019; Amer and Olorode, 2022; Xiang et al., 2023). These networks influence the distribution of hydrocarbons in tight reservoirs as well as the efficient extraction of oil and gas (Xu et al., 2007; Alghalandis et al., 2015; Zhang et al., 2021). Fracture network modeling (FNM) has emerged as a robust

methodology for investigating the spatial distribution of fractures in subsurface reservoirs (Dershowitz and Einstein, 1988; Einstein and Locsin, 2012; Ivanova et al., 2014; Fereshtenejad et al., 2016). Consequently, FNM provides a geological foundation and strategic guidance for enhancing the productivity of tight oil and gas reservoirs (Xu et al., 2021; Chen and Yu, 2021).

FNM can be broadly categorized into deterministic and stochastic approaches. Deterministic FNM identifies fractures based on anomalies in physical signals caused by rock discontinuities, and their identification is highly dependent on data resolution. For instance, 3D seismic approaches can characterize large-scale fractures and faults (>300 m), X-ray tomography can detect small- to microscale fractures (<1 m) (Xu et al., 2021), and 3D laser scanning and photogrammetry can provide detailed fracture data from outcrops at various scales (Pan et al., 2019). In contrast,

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stochastic FNM reconstructs subsurface fracture networks using stochastic processes that integrate multiple types of prior information, such as fracture length distributions from outcrops, fracture orientation (strike and dip) from borehole image logs or outcrops, fracture apertures from rock cores or thin sections, and fracture density from well logs or 3D seismic data (Ukar et al., 2019; Huang et al., 2020; Xu et al., 2021). Stochastic FNM methods are commonly classified according to (1) spatial subdivision, (2) discrete fracture network models (Liu et al., 2021), (3) geostatistics, (4) multi-point statistics, and (5) the fractal-characteristic iteration methods (Xu et al., 2021; Zhang et al., 2023). Among these, discrete fracture network (DFN) modeling is the most widely used method because of its ability to effectively integrate diverse data types and existing geological patterns (Dong et al., 2018a; Wang et al., 2024a), and provides a practical statistical framework for representing subsurface fracture systems (Jiang et al., 2025). The DFN method employs a marked point process (MPP) to simulate fracture networks using geometric representations such as scircular disks, elliptical disks, or polygons to model individual fractures (Dowd et al., 2007; Xu et al., 2007; Alghalandis et al., 2015; Wu et al., 2024). The spatial distribution of fracture centers is determined by a point process, while fracture properties (e.g., strike, dip angle, length, and aperture) are defined through a marked process (Dowd et al., 2007; Xu et al., 2007; Zhao et al., 2023a).

In recent years, DFN modeling has been extensively applied to tight sandstone reservoirs and complex geological environments (Dong et al., 2018b; Wu et al., 2025a, 2025b). Table 1 systematically summarizes the underlying principles, applicable scenarios, and inherent limitations of several major fracture network modeling approaches.

Despite the notable advancements achieved by these methods, they still face the following key challenges:

- (1) Bias arises in the simulation of fracture orientation if the bedding or stratal dip angle is not considered (Borghi et al., 2015). Tight sandstone reservoirs often exhibit abundant horizontal bedding planes, with structural fractures typically oriented nearly perpendicular to these planes (Li et al., 2018; Cao et al., 2025). Direct application of prior fracture dip angle data (about 90°) from outcrops to subsurface reservoir simulations has led to significant errors in fracture orientation, particularly in undulating formations (Fig. 1(a)). In such cases, the fractures should be modeled nearly vertical to the local bedding planes. Furthermore, the bedding and layer structures exert a controlling influence on the vertical propagation of fractures in tight sandstone (Fig. 1(a)). Therefore, accurately incorporating this phenomenon into FNM is essential for realistic simulations of tight sandstone reservoirs.
- (2) Inaccuracies may result from the use of prior fracture orientation data without accounting for variations in fracture scale and intensity. The system comprised a dominant NE-NW trending fracture group, a group of nearly N-S-oriented fractures, and a group of nearly W-E-oriented fractures (Fig. 1(b)). The conventional rose diagram of the fracture orientations revealed two predominant fracture strikes (nearly N-S and nearly W-E). Directly utilizing such generalized models can lead to significant errors, as illustrated in cases #2–#4 in Fig. 1(b), where the simulated network deviates from reality even if the point process accurately predicts fracture centers. Consequently, the fracture orientation must be carefully considered to achieve an accurate representation of the fracture network (Koike et al., 2015).

- (3) Simulation inaccuracies arising from the improper classification of fracture groups. Four distinct fracture groups were identified based on the fracture strikes and tectonic influences (Fig. 1(c)). In practice, four probability density functions, such as von Mises distributions (Gómez et al., 2023), are required to model the orientation of these fracture groups. However, based on 984 fractures from the Yanhe section (Fig. 1(c)), strike statistics often appear nearly continuous, making the critical boundaries between fracture systems difficult to define. Ambiguous group boundaries can lead to inaccurate parameter fitting for the orientation functions, resulting in simulated networks that deviate significantly from the actual geological conditions. Therefore, an accurate and systematic division of fracture groups is essential for enhancing the precision of FNM simulations.
- (4) Simulation errors induced by inaccuracies in point processing. The P20 values for the diagonal grids were uniformly set as 1 (Fig. 1(d)). During DFN modeling, even if the marked process (fracture attributes) is accurate, the point process becomes a critical source of error. Since the grids have equal probability, the generated fracture centers are randomly distributed among them. As shown in Fig. 1(d), only one realization (Simulation 3) matches the actual fracture location, while the others (Simulations 1 and 2) exhibit substantial spatial deviation. This indicates that treating fractures as uniform entities based solely on grid-based intensity can lead to models that only partially capture natural fracture characteristics.
- (5) Challenges in coupling multi-scale fracture networks incorporating mechanical mechanisms. Relying solely on geometric constraints is often insufficient to effectively couple multi-scale fractures in tight sandstone reservoirs (Hu and Rutqvist, 2022; Wang et al., 2025). Large-scale fractures typically evolve from the coalescence of numerous smaller fractures, a hierarchical process fundamentally controlled by tectonic stress fields and mechanical origins (Zhang et al., 2024; Wang et al., 2024b)(Fig. 1(e)). While previous studies have addressed mechanical effects in dynamic flow simulations (Hawez et al., 2021; Mariner et al., 2025; Xia et al., 2025), less attention has been paid to explicit mechanical criteria in static geometric modeling. Neglecting these mechanical controls (e.g., topological characteristics and percolation thresholds) can result in inaccurate representations of fracture evolution and connectivity (Sanderson and Nixon, 2018).

To address the challenges inherent in DFN modeling for tight sandstones, FNMmg is introduced, which is a fracture network modeling method that integrates the mechanical and geometric characteristics of tight reservoirs. FNMmg aims to provide a user-friendly approach for accurately and reliably modeling fracture networks. The FNMmg was validated using a dataset from tight sandstone reservoirs in the H oilfield, located in the southwestern Ordos Basin, China.

2. Principle of FNMmg for fracture modeling in tight reservoirs

2.1. Basic principle of FNMmg

To comprehensively address the challenges identified in traditional modeling, this study proposes a systematic workflow for the FNMmg method, comprising five distinct analytical strategies (Fig. 2). The framework is designed to integrate improvements across both the marked process and the point process of DFN modeling, culminating in a mechanically and geometrically constrained network.

Table 1
Comparison of fracture network modeling methods.

Method	References	Applicable scenarios	Limitations
Deterministic methods	Xu and Dowd (2010); Karimpouli et al. (2017); Wang et al. (2020); Li et al. (2022); Bandyopadhyay and Mallik (2023); Guo et al. (2025)	Suitable for rock engineering and oil and gas exploration settings where fracture geometries can be explicitly characterized. It supports multi-scale analysis: from large-scale structural interpretation using 3D seismic data to micro-scale fracture networks identified via CT scanning. It can provide the geometric constraints necessary for constructing high-fidelity discrete fracture network (DFN) models.	Highly dependent on data resolution and fidelity. The accuracy of deterministic methods is constrained by the resolution limits of 3D seismic surveys and the scale/representativeness of CT samples.
Geostatistical & multi-point statistical methods	Chugunova and Hu (2008); Chugunova et al. (2017); Jiang et al. (2023); Wang et al. (2023); Zhao et al. (2023b); Cao et al. (2025); Xiong et al. (2025)	These approaches facilitate the construction of statistically representative 3D DFN models by integrating the probability distributions and spatial correlation constraints of key fracture attributes, such as strike, dip, and aperture. It is effective for conducting connectivity analysis, and upscaling equivalent hydraulic and mechanical parameters in complex fractured media.	Their reliance on statistical priors rather than physical genesis mechanisms may lead to non-unique fracture geometries and potentially divergent hydro-mechanical responses.
Fractal iteration methods	Acuna and Yortsos (1995); Dong et al. (2024, 2025a); Wang et al. (2025); Yin et al. (2025); Yan et al. (2026)	These methods are extensively used in hydraulic fracturing simulations to reconstruct complex, self-similar fracture networks. They allow for the characterization of multi-scale heterogeneity and roughness using fractal dimensions and scaling laws.	The fidelity of the model relies heavily on the empirical selection of fractal parameters, and strictly self-similar assumptions may not perfectly capture the complex, localized structural variations found in actual geological environments.
Multi-scale coupling methods	Hu et al. (2014); Loza Espejel et al. (2020); Hu and Rutqvist (2022); Zhao et al. (2023b); Jiang et al. (2025); Maeda et al. (2026); Ren et al. (2026)	Enable hierarchical integration of deterministic macro-fractures and stochastic micro-fractures to characterize cross-scale heterogeneity. They are particularly suitable for analyzing coupled processes and determining equivalent hydro-mechanical properties of complex fractured media.	Objectively defining scale boundaries is challenging, leading to simplified interaction assumptions. Modeling dynamic fracture evolution entails a trade-off between efficiency and fidelity, with upscaled results contingent upon these boundary definitions.
Marked point process (MPP)-based methods	Nakaya and Nakamura (2007); Xu and Dowd (2010); Dong et al. (2018c); Wang et al. (2024a); Dong et al. (2025b)	These methods as the quintessential stochastic DFN modeling approach, widely adopted in hydrocarbon exploration, geothermal energy, and nuclear waste disposal. They excel in statistically reconstructing large-scale 3D fracture networks from sparse data (e.g., boreholes/outcrops), enabling rigorous assessments of reservoir connectivity, permeability tensors, and fluid transport behaviors in complex fractured media.	Model fidelity is inherently contingent upon statistical assumptions and the representativeness of sparse sampling data. The approach typically adopts idealized geometric simplifications to approximate complex, rough fracture surfaces. Consequently, the results are subject to stochastic non-uniqueness.
Machine learning-assisted methods	Tabasi et al. (2022); Chen et al. (2023); Zhou et al. (2025); Teng et al. (2025)	Methods are effective for integrating multi-source data to rapidly predict flow and mechanical responses, particularly in scenarios with poorly observable fracture geometries and complex nonlinear characteristics.	These methods serve primarily as auxiliary “black-box” tools and are significantly constrained by the difficulty in acquiring reliable reliable observational data for subsurface structures.

Specifically, to refine the marked process (simulation of fracture geometry), three strategies are implemented: Strategy (1) introduces a stratabound simulation method to correct dip errors caused by layer folding; Strategy (2) employs a scale-weighted statistical approach to resolve biases where large-scale fractures are underrepresented by simple counting; and Strategy (3) utilizes a cumulative probability curve (CPC) method to simulate orientation continuously, thereby avoiding errors arising from arbitrary fracture group division.

Regarding the point process (simulation of spatial location), Strategy (4) replaces the generation of complete fractures with fracture elements (FEs). This approach allows for a more flexible spatial representation of fracture intensity. Finally, to address the critical issue of multi-scale coupling and the neglect of formation mechanisms (Problem 5), Strategy (5) establishes a hierarchical fusion process. This step iteratively combines the generated FEs into a coherent fracture network using a dual fusion criterion based on both geometrical similarity and mechanical principles, ensuring that the final FNMmg model is geologically consistent.

(1) Stratabound fracture dip analysis and simulation

To address problem (1), a layer-controlled fracture network modeling strategy was adopted. The study area is characterized by gentle stratigraphic geometry and laterally continuous bedding.

Therefore, bedding surfaces were refined based on stratigraphic interfaces and lithologic cycles interpreted from well logs to constrain fracture modeling. Bedding control is mainly reflected in three aspects: layer thickness governs fracture spacing, bedding interfaces restrict vertical fracture propagation, and bedding geometry constrains fracture orientation. Field observations indicate that fractures in tight reservoirs are generally nearly perpendicular to bedding planes. Accordingly, instead of directly modeling fracture dip angles, a gap angle (Δ), corresponding to the angle $\angle P_3C_2P_3$ in Fig. 3(a), was introduced to characterize the deviation between the fracture normal and the bedding normal. When $\Delta = 0^\circ$, the fracture plane is strictly perpendicular to bedding. The specific range and probability distribution of Δ were explicitly quantified based on statistical analysis of actual field measurements (Fig. 4(d)). During fracture network reconstruction, Δ is randomly sampled from this distribution and combined with bedding strike information to recover fracture dip angles, ensuring geological consistency.

(2) Fracture orientation analysis incorporating the fracture scale

To address problem (2), an enhanced fracture strike statistical method was proposed to better represent fracture intensity by incorporating fracture length rather than fracture count. In this

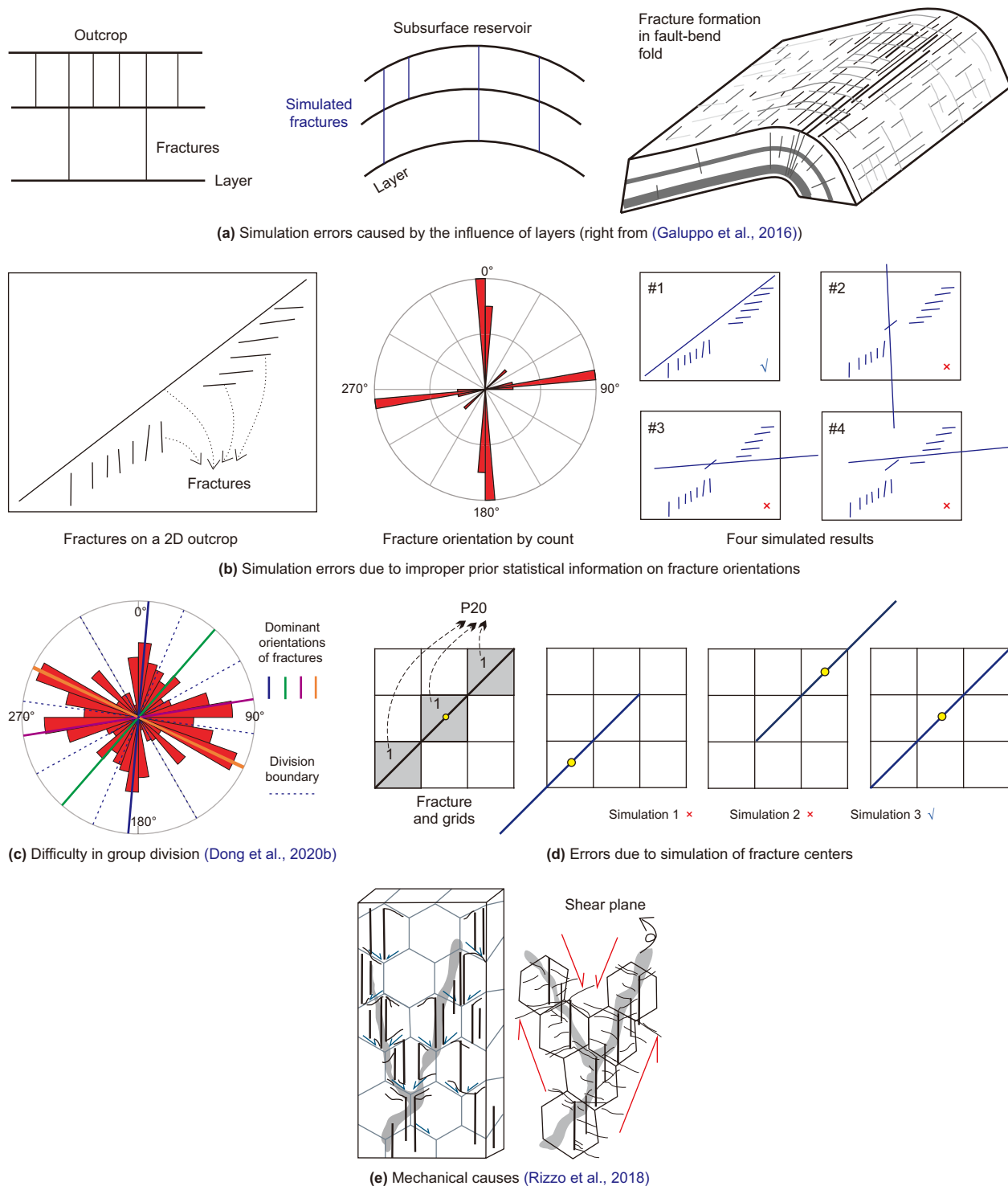


Fig. 1. Critical challenges and limitations in conventional DFN modeling for tight sandstone reservoirs. (a) Simulation errors caused by the influence of layers (right from (Galuppo et al., 2016)). (b) Simulation errors due to improper prior statistical information on fracture orientations. (c) Difficulty in group division (Dong et al., 2020b). (d) Errors due to simulation of fracture centers. (e) Multi-scale fracture coupling (Dong et al., 2020b).

method, the contribution of each fracture orientation to the rose diagram is weighted by fracture length. For example, if a 45° fracture has a length of 10 m and a 90° fracture has a length of 1 m, the revised method counts ten 45° orientations and one 90° orientation, instead of assigning equal weight to both fractures. This approach avoids the bias introduced when fractures of

different scales coexist locally within a fracture network, where traditional count-based statistics may fail to reflect the true structural dominance. In such cases, the original DFN model derived from conventional rose diagrams may not represent the actual fracture system. As shown by the comparison between the conventional rose diagram (Fig. 1(b)) and the revised result

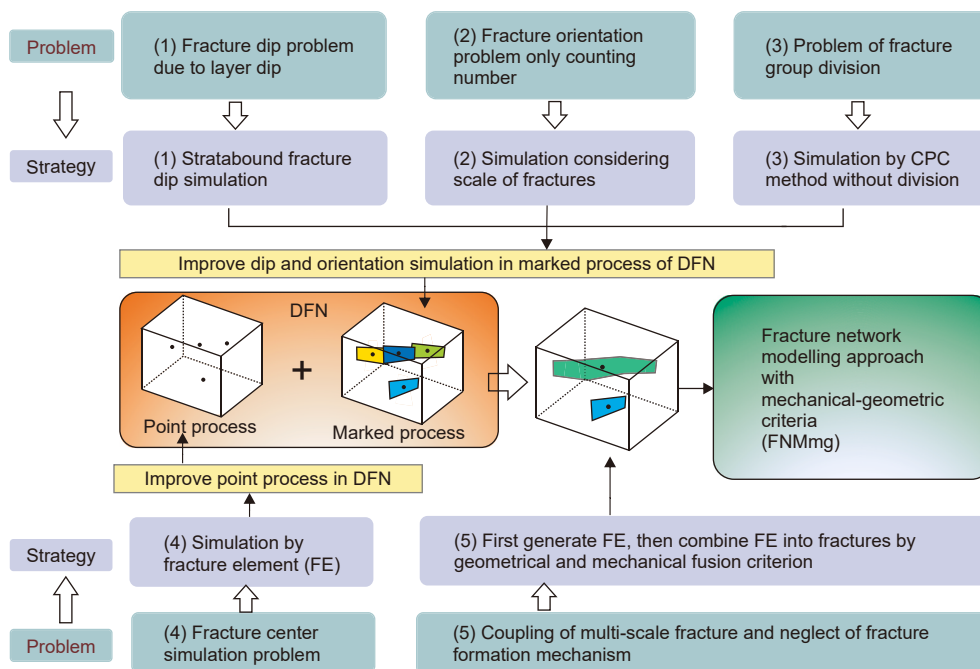


Fig. 2. Workflow of the fracture network modeling approach with mechanical-geometric criteria (FNMmg). CPC, cumulative probability curve; DFN, discrete fracture network; FE, fracture element.

(Fig. 3(b)), the length-weighted method more effectively captures the dominance of large-scale NE-SW-trending fractures, leading to a more realistic representation of fracture strike characteristics.

(3) Fracture orientation simulation with CPC method avoiding group division

To address issue (3), a cumulative probability curve (CPC) was constructed to characterize fracture orientation (Fig. 3(c)). The CPC was obtained by sorting all fracture orientations and calculating the normalized cumulative frequency for each orientation value, which represents the cumulative form of the orientation distribution shown in the rose diagram of Fig. 1(c).

As illustrated in Fig. 3(c), a random quantile between 0 and 1 is mapped onto the CPC, and the corresponding fracture orientation is obtained from the intersection with the curve. In this manner, fracture orientations consistent with the observed orientation pattern can be generated while avoiding the influence of subjective fracture-group division.

(4) Using fracture elements for simulations instead of direct fracture representation

To address the limitations identified in issue (4), a fracture-element-based (FE) approach is employed, where each fracture is discretized into smaller constituent segments (Koike et al., 2012, 2015). In this framework, an FE is represented as a short line segment in 2D or a polygon in 3D. The FNMmg workflow adopts a “bottom-up” methodology: numerous FEs are initially generated and subsequently merged into continuous, geologically realistic fractures based on predefined fusion criteria. As exemplified in Fig. 3(d), the coalescence of three minor segments into a single unified fracture enables the model to accurately honor spatial fracture-intensity constraints. This “small-to-large” strategy specifically resolves the common discrepancy between simulated networks and their underlying intensity models. While this element-based approach entails higher memory demands and

longer computational runtimes compared to direct simulation, it offers a more authentic representation of fracture growth and coalescence, thereby significantly improving the geological consistency of the resulting network.

(5) Polygon fusion based on geometric and mechanical fusion criteria

To address issue (5), a dual-fusion criterion incorporating both geometric and mechanical principles was proposed (Fig. 3(e)). The geometric spatial fusion criterion was designed to merge spatially close fractures that exhibit similar orientations (Koike et al., 2012, 2015). The mechanical fusion criterion was employed to combine fractures based on the formation mechanisms of structural shear fractures, which are validated through physical experiments and numerical simulations (Rizzo et al., 2018). The FEs are progressively merged into larger fractures, ultimately forming a comprehensive fracture network. Theoretically, this methodology provides a robust solution for the fusion of multi-scale fracture networks.

2.2. Generation of FEs with different occurrences

The generation of multiple fracture sets follows a systematic two-stage workflow, integrating comprehensive information statistics with cumulative probability simulations (Fig. 4). Taking the fracture architecture illustrated in Fig. 4(a) as a representative case, the host formation is characterized as a monocline with a structural dip of 5°. Within this system, two predominant fracture sets (oriented NNE and NNW) were identified. By applying the intensity-weighted counting method described above, a rose diagram of fracture orientations was derived (Fig. 4(b)). Unlike conventional frequency-based plots, this revised approach facilitates the generation of orientation distributions that are intrinsically coupled with fracture intensity, providing a more statistically robust representation of the fracture network’s directional development. By sorting the orientation values in Fig. 4(b) and computing their cumulative

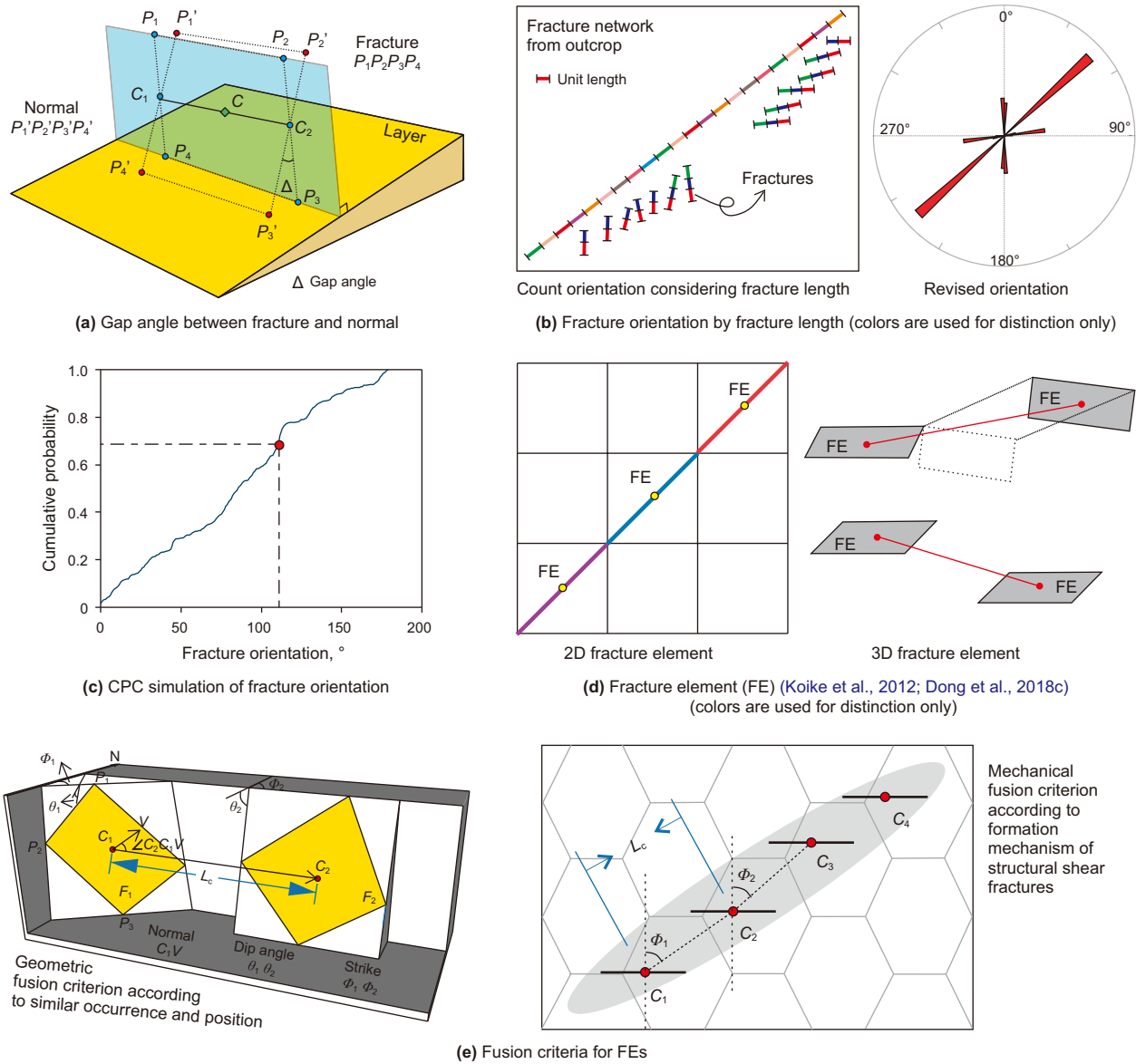


Fig. 3. Schematic illustrations of the five key technical strategies implemented in FNMmg. (a) Gap angle between fracture and normal. (b) Fracture orientation weighted by fracture length (colors are used for distinction). (c) CPC simulation of fracture orientation. (d) Fracture element (FE) (Koike et al., 2012; Dong et al., 2018c) (colors are used for distinction only). (e) Fusion criteria for FEs.

frequencies, a CPC was obtained (Fig. 4(c)). A random number r was generated within the interval $[0, 1]$; the horizontal coordinate corresponding to the vertical coordinate r on the CPC determined the polygon orientation. For instance, in Fig. 4(c), when $r = 0.3$, the corresponding fracture orientation is 31.9° . The orientations of the simulated fractures were systematically determined by generating a series of random numbers within the range of $0-1$. The distribution of the gap angles, defined as the angles between the fracture dips and normals to the layers, is shown in Fig. 4(d). A similar methodological approach can be applied to generate gap angles. Consequently, the fracture dip angles within the simulated fracture network are determined by integrating the layer dips with the corresponding gap angles.

2.3. Generation of FE centers

A point process constrained by a trend model was employed to generate the center locations of the FEs. It is assumed that the

central position of the i -th grid within the 3D density constraint (Fig. 5(a)) is (x_i, y_i, z_i) , with the corresponding fracture intensity denoted as P_i . The FE centers were determined as follows:

- (1) To establish the statistical foundation for stochastic simulation, each grid cell within the model was first assigned a unique identifier to facilitate sequential indexing. The attribute values (e.g., fracture intensity or density) were then cumulatively aggregated, and the global sum across the entire grid domain was calculated. By normalizing these accumulated grid values against the total sum, a cumulative probability distribution was derived. This workflow effectively generates the step-wise CPC illustrated in Fig. 5(b), which serves as the quantitative basis for mapping random variables to specific spatial locations during the fracture modeling process.
- (2) A random number is generated within the interval $[0, 1]$. The corresponding grid numbers are determined using the CPC. Based on the probability density function $f(x, y, z) = 1/Vol$,

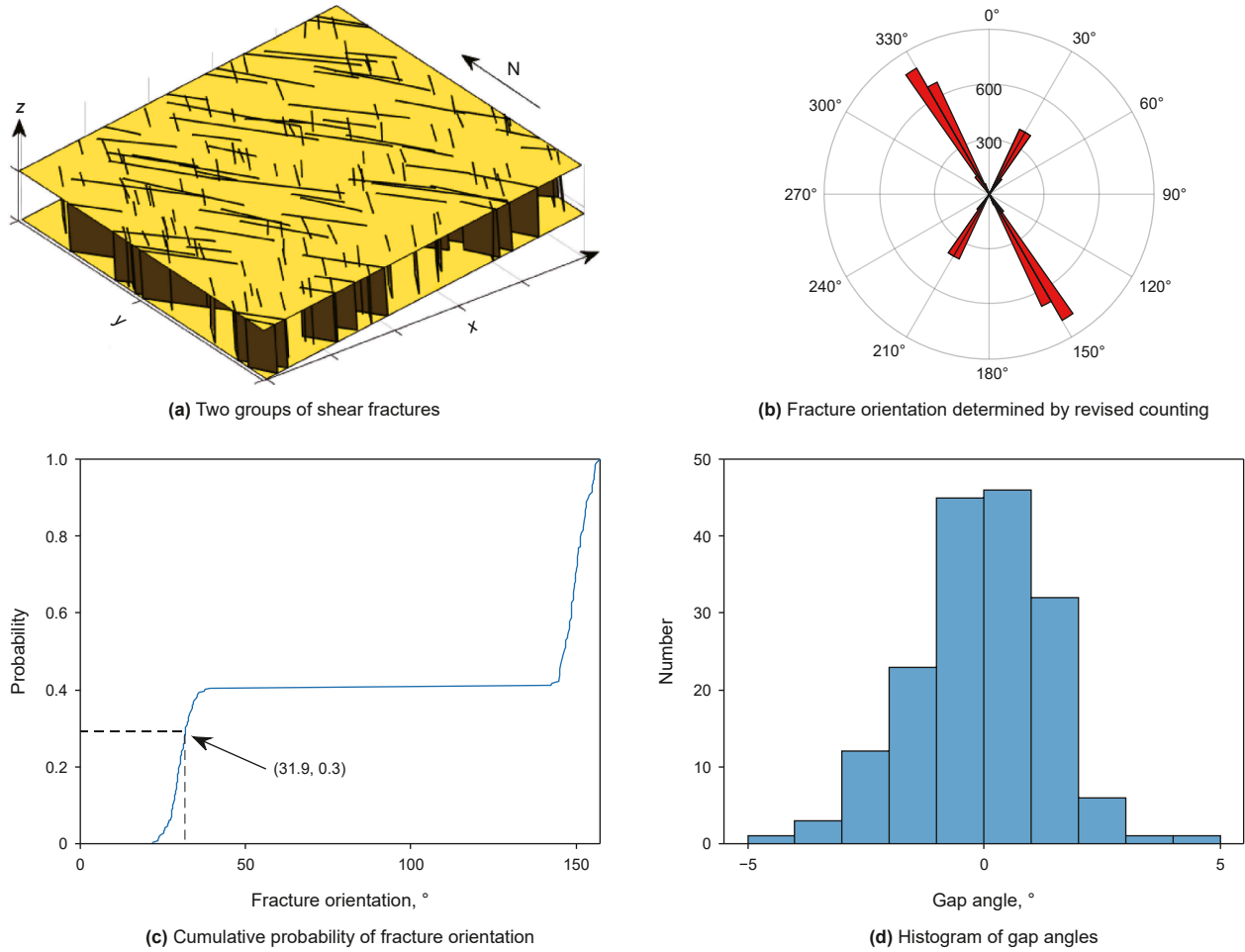


Fig. 4. Derivation of statistical input parameters for FNMmg based on fracture length-weighted analysis. (a) Two groups of shear fractures. (b) Fracture orientation determined by revised counting. (c) Cumulative probability of fracture orientation. (d) Histogram of gap angles.

random coordinates (x , y , z) within the selected grid are generated to represent the centers of the FEs. Here, x , y , and z are independent continuous random variables following a uniform distribution, and Vol represents the grid volume.

2.4. Fusion criteria of FEs

A fracture surface can be conceptualized as a composite of numerous small FEs represented as small polygons. FEs belonging to the same fracture type typically exhibit similar orientations and spatial characteristics. If two small polygons are in close proximity and have comparable orientations, they are likely to be part of the same fracture (Koike et al., 2012, 2015). This principle is foundational to the geometric-similarity fusion criterion, which is used to merge FEs into coherent fracture surfaces.

The spatial positions of two FEs are presented in Fig. 3(e), where the similarity criterion is defined by their proximity and comparable orientations. The fusion criteria for these characteristics are defined in Eqs. (1)–(3) (Koike et al., 2012, 2015). The distance between the FEs must not exceed a predefined threshold value, and the differences in their dip angles and orientations must remain within their respective threshold limits.

$$L_c \leq L_t \quad (1)$$

$$\Delta\phi = |\phi_1 - \phi_2| \leq \phi_t \quad (2)$$

$$\Delta\theta = |\theta_1 - \theta_2| \leq \theta_t \quad (3)$$

$$|90^\circ - \angle C_2 C_1 V| \leq \theta_T \quad (4)$$

Here, L_c represents the distance between the centers of two FEs, ϕ_1 and ϕ_2 denote the strikes of the two FEs, $\Delta\phi$ is the strike difference between them, θ_1 and θ_2 are the dip angles of the two FEs, and $\Delta\theta$ is the dip angle difference. $C_1 V$ is the unit normal vector of the first FE, that is, F_1 , which can be derived from the cross-product of the two adjacent sides of the polygon. Taking Fig. 3(e) as an example, $C_1 V = P_2 P_1 \times P_2 P_3$, where $|P_2 P_1|$ is the length of the line segment $P_2 P_1$. $\angle C_2 C_1 V$ is the angle between the normal vector and line connecting the centers of the two FEs, which can be calculated using the dot product of the two vectors: $\angle C_2 C_1 V = \arccos(C_1 C_2 \cdot C_1 V / |C_1 C_2| / |C_1 V|)$, where “ $\cdot$ ” represents the dot product of the vectors $C_1 C_2$ and $C_1 V$. The threshold values for distance, strike difference, dip angle difference, and normal vector angle are denoted as L_t , ϕ_t , θ_t , and θ_T , respectively. However, relying solely on geometric similarity is insufficient to capture the physical formation of fractures. Therefore, a mechanical fusion criterion is introduced to complement the geometric rules. Rizzo et al. (2018) investigated the formation mechanisms of mechanical fractures using physical simulations and numerical analyses. When an ideal rock sample is subjected to biaxial loading (e.g.,

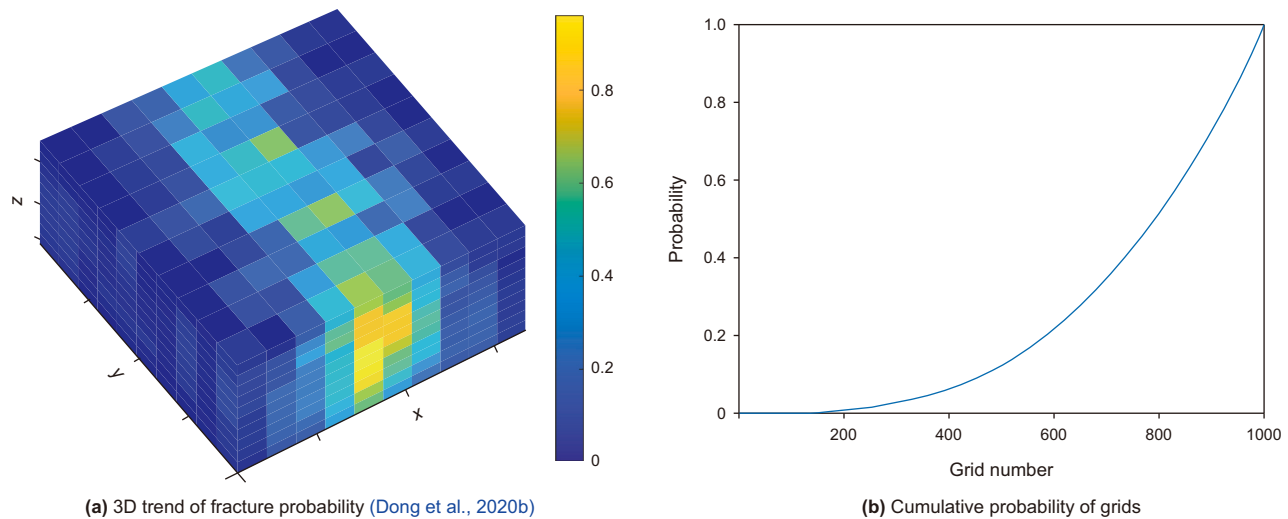


Fig. 5. Process of generating fracture element (FE) centers constrained by 3D fracture intensity. (a) 3D trend of fracture probability (Dong et al., 2020b). (b) Cumulative probability of grids.

$\sigma_1 = 5$ MPa; $\sigma_3 = 5$ MPa), a series of tensile fractures parallel to the maximum principal stress initially form (Fig. 3(e)). As internal deformation progresses, new fractures gradually develop. Once these fractures reach a critical length and density, they begin to cluster, interact, and coalesce, ultimately forming shear fractures. Fig. 3(e) demonstrates the formation of conjugate shear fractures. Under higher initial stress conditions, such as an effective stress of $P_{\text{eff}} = 30$ MPa, rapid local strain causes the initially formed echelon tensile fractures to quickly merge into the shear surfaces. Outcrop observations often indicate the development of a single set of conjugate fractures.

The aforementioned fracture formation mechanism illustrates the transition from tensile fractures to shear fractures. These tensile fractures are typically in close proximity and exhibit similar orientations. Eqs. (1)–(3) define the similarity criteria in terms of distance and orientation. When the azimuths of the segments connecting the centers of the fracture elements are comparable, it is necessary to evaluate whether the elements should be fused according to Eqs. (5) and (6), where θ_T represents the critical threshold value. Therefore, it is essential to assess whether the fracture elements share similar orientations. For instance, if the first to third fracture elements belong to the same shear fracture surface, the orientations of the segments C_2C_1 and C_3C_2 must satisfy the condition $|\phi_1 - \phi_2| \leq \phi_T$ (Fig. 3(e)).

$$45^\circ < |90^\circ - \angle C_2C_1V| \leq \theta_T \quad (5)$$

$$\begin{cases} \angle C_2C_1V > \theta_T, & \angle C_2C_1V \leq 90^\circ \\ 180^\circ - \angle C_2C_1V > \theta_T, & \angle C_2C_1V > 90^\circ \end{cases} \quad (6)$$

3. Fracture network modeling in tight sandstone reservoirs

3.1. Geological settings

The study area, which covers approximately 250 km², is situated in the H oilfield, southwestern Ordos Basin (Fig. 6) (Lyu et al., 2016; Wang et al., 2016; Li et al., 2018; Dong et al., 2020a). The area is characterized by the Triassic Chang 6 Formation, which is composed of tight sandstones with thicknesses of 105–130 m. The reservoir is subdivided into three intervals, Chang 6₁, Chang 6₂, and

Chang 6₃, with thicknesses of 35–45 m, 35–45 m, and 35–40 m, respectively (Dong et al., 2020a). Its lithology is predominantly composed of lithic feldspathic sandstone and feldspathic lithic sandstone. In terms of grain size, fine sandstone and siltstone dominate. The primary pore types include intergranular, feldspar dissolution, and lithic fragment dissolution pores. The porosity of the reservoirs ranges from 5.6% to 19.0% with an average of 11.9%, whereas the permeability varies between 0.003 and 67.1 mD, with an average of 0.51 mD. The study area contains a typical tight sandstone reservoir with low porosity and permeability (Zeng and Li, 2009; Lyu et al., 2016; Dong et al., 2020a). The terrain is relatively gentle, with an average dip of approximately 1°. A series of nose-like structures have developed in this area (Fig. 6) (Dong et al., 2020a), which play an important role in the fracture simulation.

Fractures are extensively developed in the study area and can be categorized into structural and diagenetic fractures based on their geological origin. Structural fractures are further subdivided into shear and tensile fractures, whereas diagenetic fractures primarily include bedding and contraction fractures (Dong et al., 2020a). In the study area, the fractures are predominantly high-angle tectonic fractures, which serve as critical conduits for fluid migration in tight reservoirs (Zeng and Li, 2009; Lyu et al., 2016). Consequently, the 3D FNM focused on networks composed of high-angle structural fractures.

3.2. Fracture network modeling

3.2.1. Fracture properties

To investigate fracture network characteristics in tight reservoirs, field geological investigations were conducted at representative outcrops of the Chang 6 along the Yanhe River in Yan'an, China. The outcrop geometry is shown in Fig. 7(a) (Dong 2019), where the red curves indicate bedding interfaces, black dashed lines represent fracture traces on the bedding plane, and yellow dashed lines denote fracture traces on vertical sections. The outcrops are characterized by the widespread development of high-angle regional tectonic fractures, which are mainly distributed within individual layers, are nearly perpendicular to bedding, and commonly terminate at lithologic interfaces, indicating strong bedding control. The bedding surfaces are relatively flat and laterally continuous, providing favorable conditions for fracture development. Fracture properties, including fracture orientations

and the angles between fracture planes and the normal direction of bedding, were obtained from field measurements where possible. For outcrops that were difficult to measure directly, 3D point-cloud data were acquired using a terrestrial laser scanner (Fig. 7(b)), from which fracture orientations and dip angles were interpreted (Fig. 7(c)). Fracture extraction from the point-cloud data was performed using a semi-automatic workflow. Fracture planes were first automatically detected using the Random Sample Consensus (RANSAC) method, after which manual removal and fine adjustment were applied to correct local deviations. These operations were carried out in CloudCompare software, and the interpreted fracture sections are shown in Fig. 7(d). Fracture attributes were characterized across six well-exposed outcrops (Fig. 7(e)), yielding a comprehensive dataset of 183 individual fractures with recorded strike and length measurements. The observed fracture lengths exhibit significant variability, ranging from 0.35 m to 33.5 m, with a calculated average length of 5.0 m. To evaluate the directional trends within the study area, orientation data were quantified and visualized via rose diagrams using a revised counting method (Fig. 8(a)), ensuring a statistically robust representation of the fracture network's geometric properties. Two dominant fracture groups (NNE and EW) are relatively well developed. The cumulative probability distribution curve corresponding to the rose diagram (Fig. 8(b)) exhibits four distinct steps corresponding to the near N-S, NNE-SSW, near W-E, and NWW-SEE directions.

Through a comprehensive analysis of 213 fractures combining automatic and manual interpretation techniques, the angular deviations between the normal and horizontal fracture planes were systematically quantified. The mean value was 0° and the standard deviation was 4° (Fig. 8(c)). Furthermore, the CPC (Fig. 8(d)) served

as a critical input for determining the dip angles of the individual fracture elements in the subsequent numerical simulations.

3.2.2. FE simulation in FNMmg

The 3D constraint of fracture development intensity is illustrated in Fig. 9(a). By accumulating the fracture intensity grids according to the grids, the cumulative probability curve can be obtained, as shown by the black line in Fig. 9(b). To evaluate the efficacy of the point process within the FNMmg framework, a comparative analysis was performed using 1000 simulated fracture elements (FEs). This validation focuses on two primary dimensions: the degree of alignment with the target probability model and the resulting spatial distribution of the fracture network. The grid locations for the FEs were determined by sampling 1000 random quantiles from a uniform distribution. As illustrated by the red histogram in Fig. 9(b), these quantiles exhibit a near-uniform distribution, as expected. These values were then mapped onto the cumulative probability curve (CPC, black) of the fracture intensity constraint model to identify specific grid indices (indicated by green crosses). By aggregating these simulated locations, a cumulative frequency curve was generated (shown as the red curve in Fig. 9(b)). A comparative analysis reveals that the simulated red curve aligns closely with the black CPC model, demonstrating that the stochastic point process effectively honors the a priori probability constraints and accurately reflects the intended fracture intensity.

In Fig. 9(c), the scatter points represent the centers of each grid within the 3D model depicted in Fig. 9(a), with the color and size of the points corresponding to the fracture development intensity within each grid. The density of fracture elements originating in regions with high fracture development intensity (indicated by

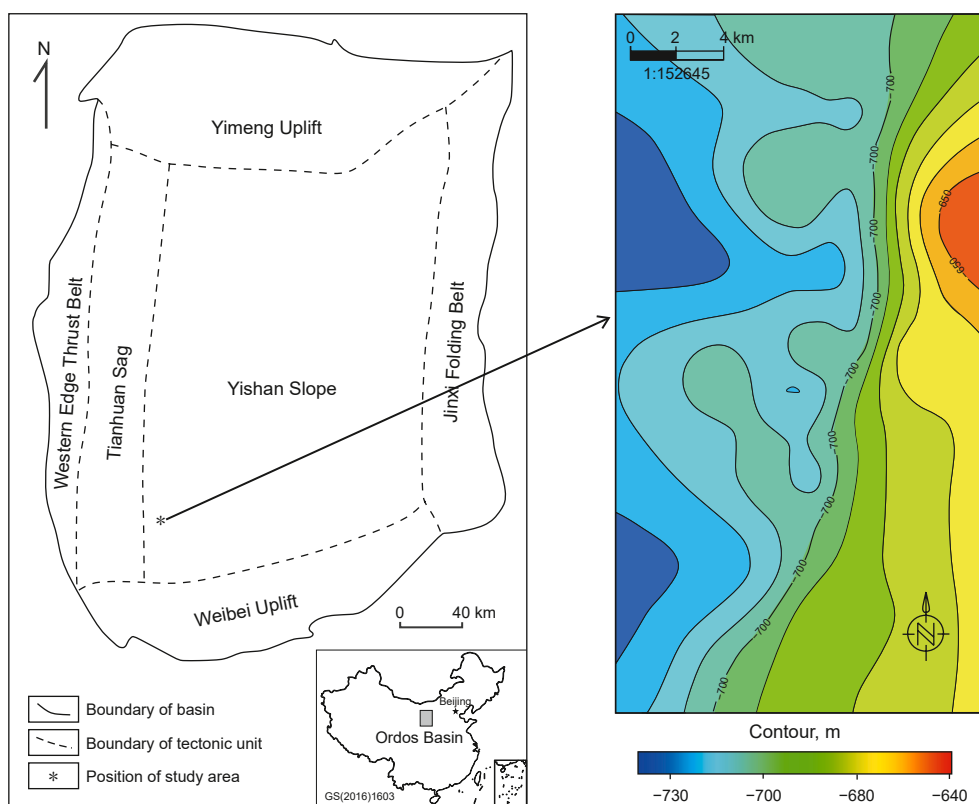


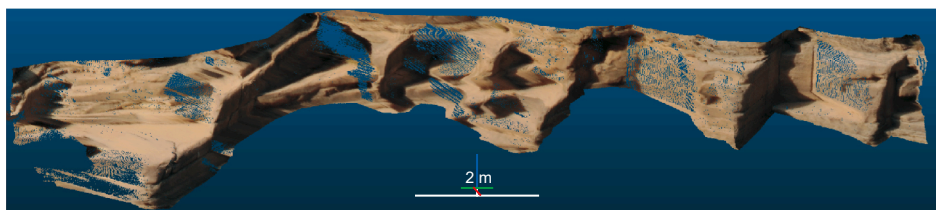
Fig. 6. Map of study area (Dong et al., 2020a).



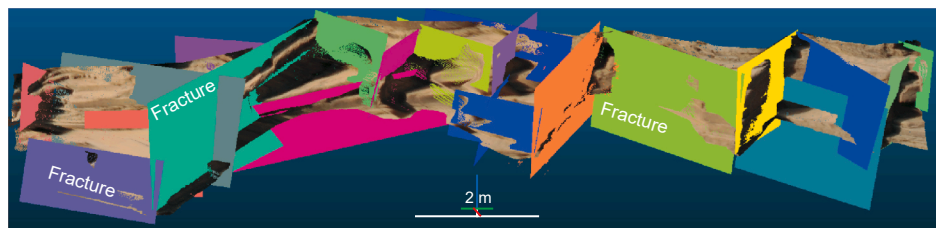
(a) Outcrop for measuring fracture strike and dip angle



(b) Terrestrial 3D laser scanner



(c) 3D laser point-cloud data for outcrop



(d) Fractures extracted from 3D laser point cloud data



(e) Outcrop for measuring fracture length and strike

Fig. 7. Outcrop near Tanjiahe village along Yanhe section used for manually measuring fracture properties. (a) Outcrop for measuring fracture strike and dip angle (Dong, 2019). (b) Terrestrial 3D laser scanner. (c) 3D laser point-cloud data for outcrop. (d) Fractures extracted from 3D laser point cloud data. (e) Outcrop for measuring fracture length and strike.

warm colors) is substantially greater than that in regions with low fracture development intensity (represented by cool colors).

These findings suggest that the fracture center positions generated by the point process in FNMmg are strongly aligned with the 3D fracture intensity constraints.

The bedding architecture and associated fracture elements (FEs) for a representative stratigraphic layer were extracted as shown in Fig. 9(c). In this framework, the bedding plane is defined by the top or bottom surfaces of the grid cells (Fig. 9(d)). For any generated FE, the normal vector of the local bedding surface is calculated based on the fracture's centroid location within the grid. The final dip angle of the FE is then derived by combining this localized normal vector with a stochastic deviation. Although the study area is characterized by a predominantly west-dipping monocline, significant local structural fluctuations persist. Relying solely on a global dip-angle distribution function (without considering these local variations) results in unrealistic intersection angles between the fractures and the strata, a phenomenon that contradicts observations from field outcrops. By contrast, the proposed methodology accounts for local formation geometry, thereby ensuring a more geologically consistent representation of the spatial relationship between the fracture network and the host formation.

3.2.3. FE fusion in FNMmg

During the initial stages of tectonic activity in the simulated models, only a limited number of fractures are generated within the subsurface formation, and these have not undergone significant growth or coalescence. With the progressive intensification of the applied tectonic forces in the simulations, an increasing number of fractures are produced, which subsequently propagate and merge to form extensive large-scale fractures or fracture zones. To illustrate this process, fracture coalescence was simulated using FNMmg by generating a set of 6000 fracture elements, as highlighted in red in Fig. 10(a). The results indicated that fracture development remained limited in some regions. Fig. 10(b) clearly illustrates the spatial heterogeneity of fracture intensity across the study area, highlighting localized regions where fracture development was notably sparse or absent. It should be noted that this description refers specifically to the simulation process, rather than to the actual geologic history of the Ordos Basin.

Based on the geometric fusion criterion, the fused fracture elements are illustrated in Fig. 10(c) (marked in blue). The expansion and fusion of the fracture elements mainly developed in two parts with dense fractures. The orientations of fracture coalescence and propagation are primarily aligned with the near-east-west (EW) and north-northwest (NNW) directions, respectively (Fig. 10(d)).

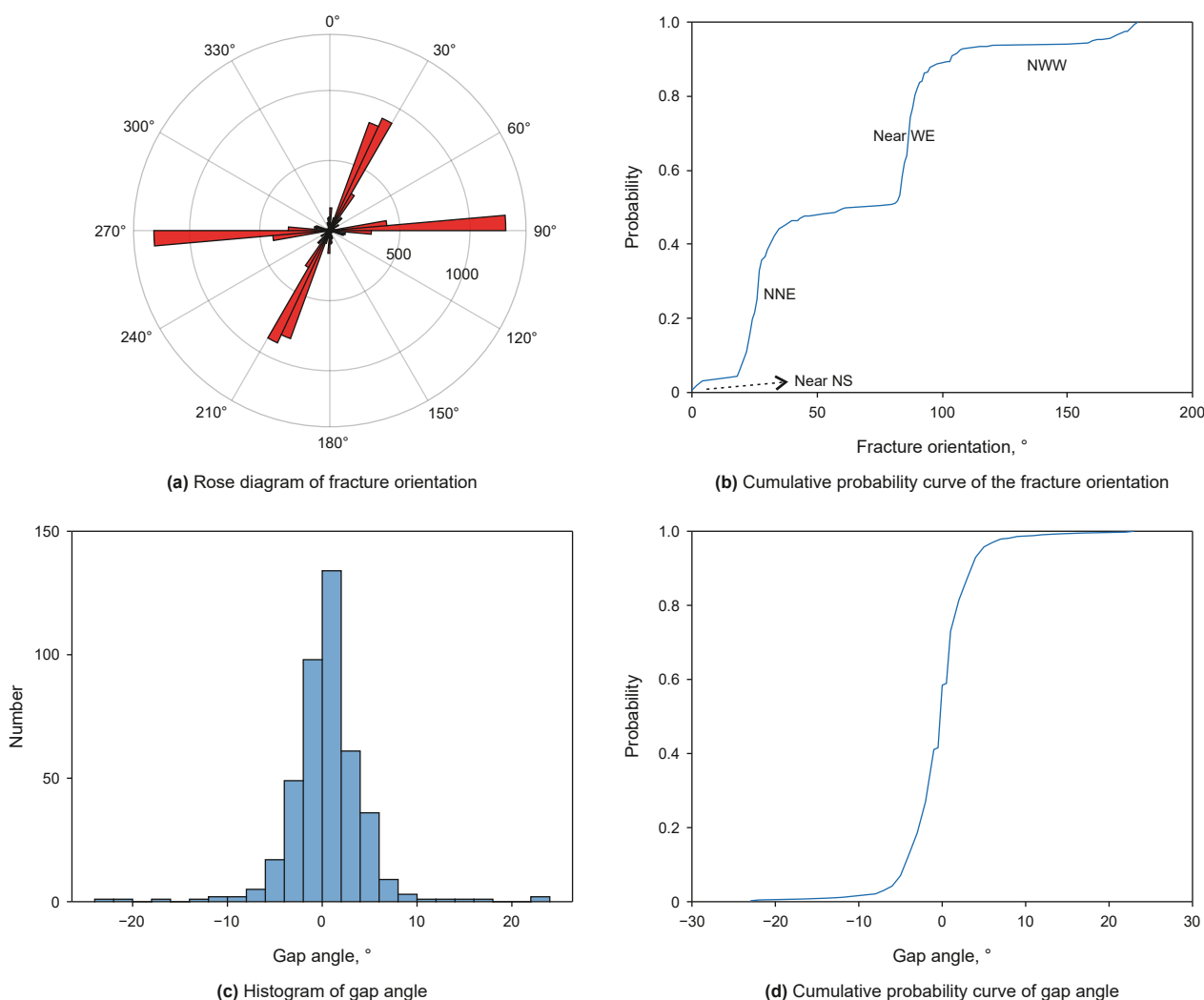


Fig. 8. Fracture strike and dip characteristics. (a) Rose diagram of fracture orientation. (b) Cumulative probability curve of the fracture orientation. (c) Histogram of gap angle. (d) Cumulative probability curve of gap angle.

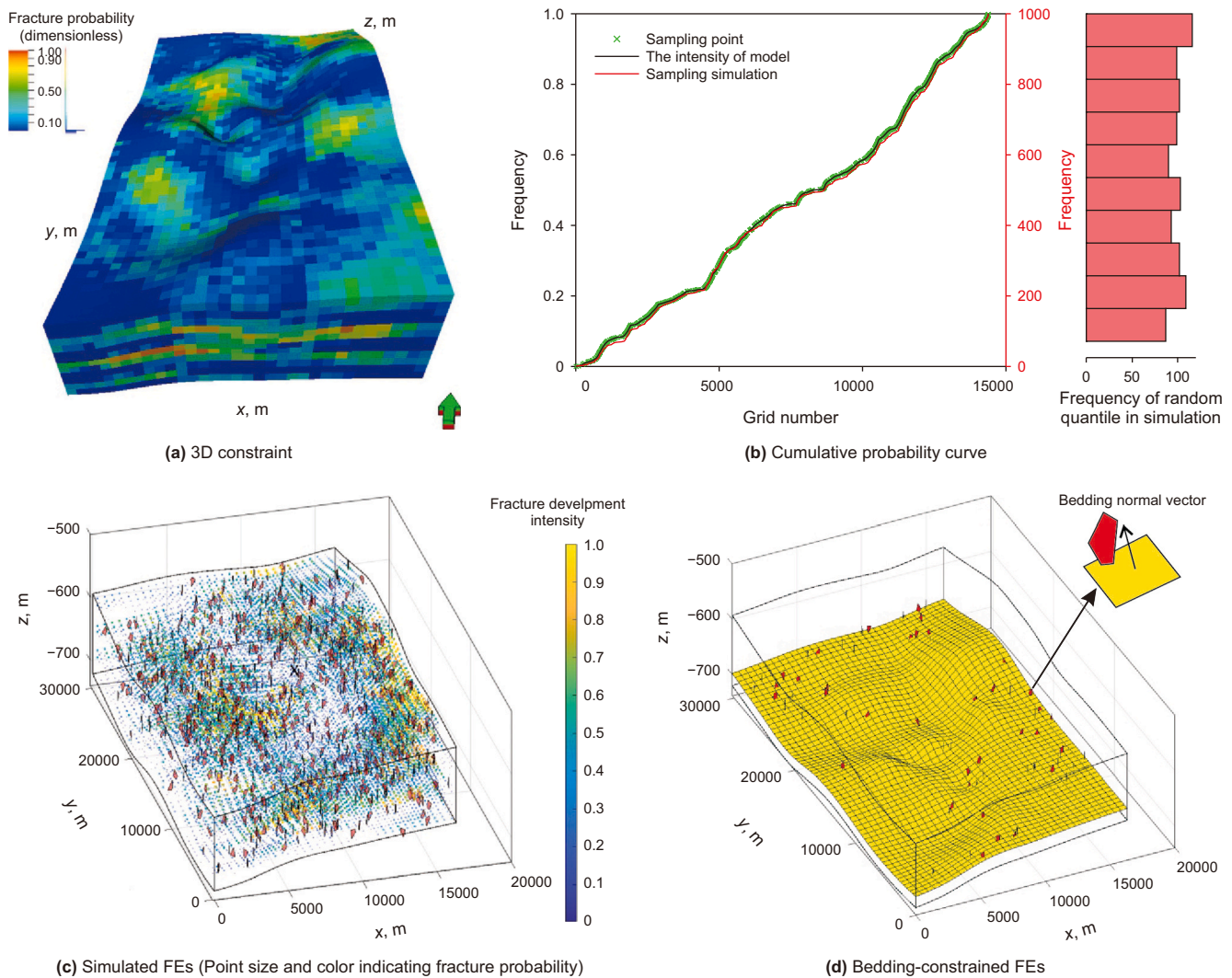


Fig. 9. Point process and fracture dip angle simulations. (a) 3D constraint. (b) Cumulative probability curve. (c) Simulated FEs (Point size and color indicating fracture probability). (d) Bedding-controlled FEs.

Geological evidence confirms that fracture development in the Chang 6 reservoir is dominated by shear fractures. Therefore, despite the discrepancy in absolute stress magnitudes compared with those reported by Rizzo et al. (2018), the shared mechanical mode of shear propagation justifies using their work as a theoretical basis for extracting qualitative topology rules, namely the mechanical fusion criterion.

Based on the mechanical fusion criterion outlined in Section 2.4, the predominant direction of fracture fusion aligns closely with the near-east-west (EW) direction, as illustrated in Fig. 10(e), fused FEs are highlighted in green and are synthesized from smaller constituent fracture elements characterized by red fills and black outlines. A top view is presented in Fig. 10(f). Additionally, fusion was observed along the near-north-south (NS), north-northwest (NNW), and northwest-west (NWW) directions.

Based on the aforementioned fusion criteria, a fracture network comprising fractures of multiple scales was generated (Fig. 10(g) and (h)).

3.2.4. Fracture network built by FNMmg

Utilizing the FNMmg workflow, fracture elements were sequentially generated under rigorous density constraints to

construct a representative discrete fracture network (DFN) model (Fig. 11). Following initial generation, the network underwent a series of topological refinements (merging, clipping, and element-wise corrections) to ensure structural consistency. The accuracy of the resulting model was evaluated through comprehensive error statistics, which served as a feedback mechanism to iteratively calibrate the total number of fracture elements. This optimization ensures that the finalized fracture distribution effectively captures multi-scale characteristics while maintaining good consistency with 3D spatial development constraints.

3.3. Validation of built fracture network

Tracer monitoring is a commonly used dynamic method for diagnosing reservoir production issues such as waterflooding behavior in tight reservoirs. In such formations, water channeling is generally associated with connected fracture networks rather than the low-permeability matrix, so tracer monitoring is often applied to determine whether effective fracture-flow pathways exist. A stable, detectable tracer was injected into an injection well, and the surrounding wells were periodically sampled to determine the tracer concentration and infer the connectivity types. For example, the tracer injected into well B1 was monitored in wells

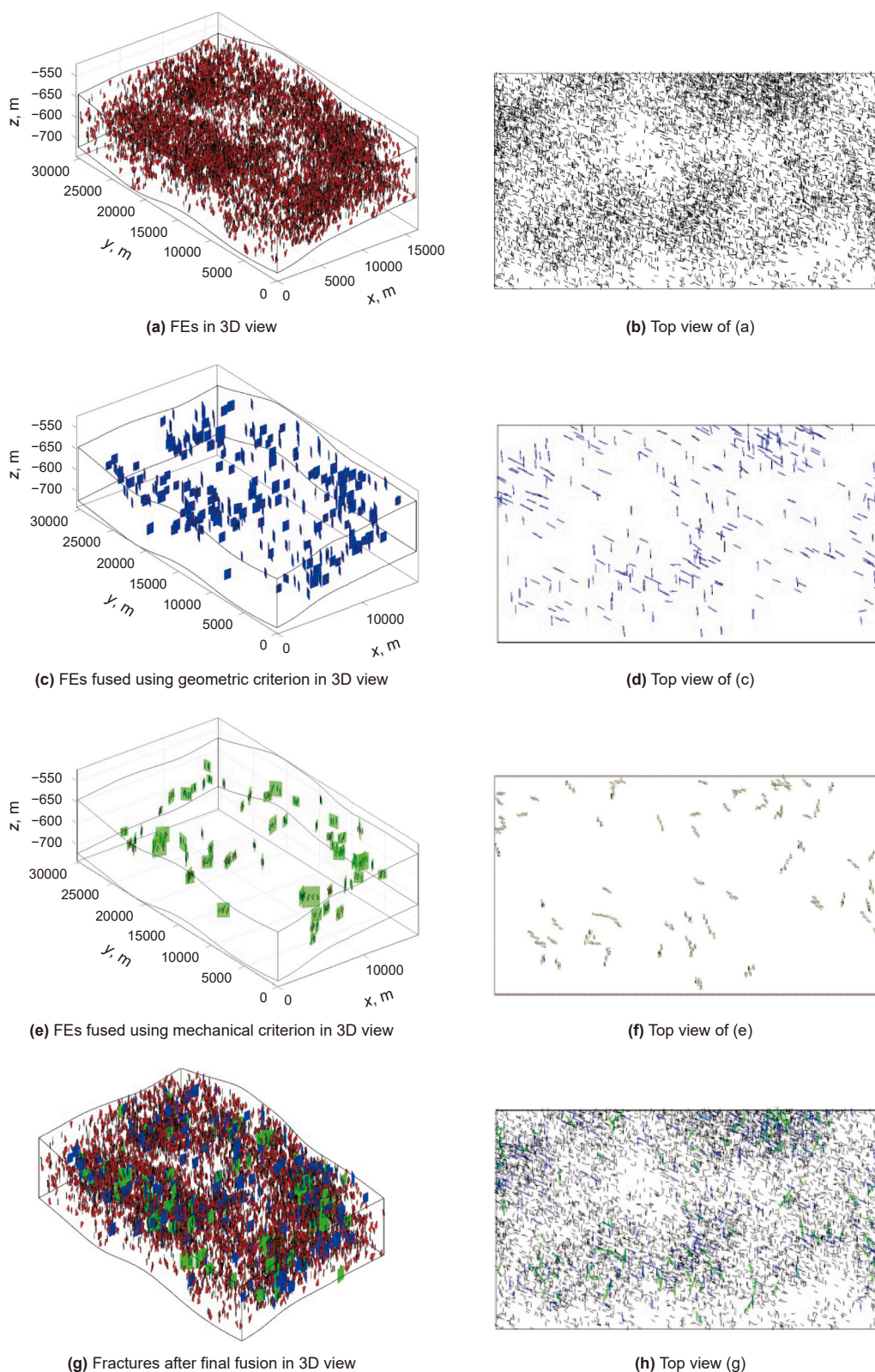


Fig. 10. Fused fracture elements. Red shows fracture elements; blue, fusion by geometric criterion; green, fusion by mechanical criterion. **(a)** FEs in 3D view. **(b)** Top view of (a). **(c)** FEs fused using geometric criterion in 3D view. **(d)** Top view of (c). **(e)** FEs fused using mechanical criterion in 3D view. **(f)** Top view of (e). **(g)** Fractures after final fusion in 3D view. **(h)** Top view of (g).

A1–A8 (Fig. 12(a) and (b)). The observations suggest that sharp peaks and relatively fast waterfront velocities from B1 to A4 and from B1 to A8 most likely indicate fracture connectivity, whereas smoother curves and slower velocities from B1 to A1 and to A3 are more consistent with pore-related connectivity. The absence of detectable tracers in A5–A7 probably indicates no detectable effective connection. Owing to reservoir heterogeneity in tight formations, multi-peak profiles may occur, so a combined analysis of waterfront velocity and tracer curves is generally required for a more reliable connectivity assessment.

In the processing of tracer monitoring data, data points with concentrations below the detection limit (e.g., <0.01 mg/L) or those exhibiting isolated outliers were first excluded to eliminate background noise. The classification criteria for reservoir connectivity are defined as follows: “fracture-related” connectivity is characterized by a high-concentration peak with a sharp curve profile appearing shortly after injection (typically <15 days); “pore-related” connectivity is identified by a delayed response time, lower peak concentration, and a relatively flat, dispersive curve; and well pairs with no detectable tracer response are classified as unconnected.

Tracer monitoring was employed to analyze the connectivity types among the four well groups (Y298-49, Y302-49, Y308-55, and Y304-71), as shown in Fig. 12(c)–(f). Connectivity was classified based on tracer response speed, waterfront velocity, and concentration profiles; gradual changes indicated pore type, whereas sharp rise/fall patterns indicated fracture type. Groups Y298-49 and Y302-49 exhibited pore-related connectivity, whereas groups Y308-55 and Y304-71 exhibited predominantly fracture-type responses in specific wells. A total of 34 well pairs were identified, including 7 fracture-related and 27 pore-related or unconnected pairs (Table 2).

The connected fracture clusters in the fracture network model were identified using the bounding box and sweep line detection (BBSL) method (Dong et al., 2018a). By comparing the connected fracture clusters with the tracer-monitored connected (or unconnected) well pairs, the overall consistency rate was found to be $31/34 \approx 91\%$. A confusion matrix was derived based on the computational results (Table 3). The coincidence rate for the fractured connected well pairs was $6/7 \approx 86\%$, whereas that for the non-fracture-related well pairs reached $25/27 \approx 93\%$. In conclusion, the established 3D multi-scale fracture network model demonstrates

good agreement with tracer-derived connectivity patterns in terms of spatial connectivity.

4. Limitations and future work

(1) Fracture element configuration

The proposed framework constructs complex fracture systems utilizing fracture elements, where the configuration of key parameters, specifically polygon geometry and scale, plays a significant role in balancing geometric fidelity with computational efficiency. In this study, a simplified configuration using uniform quadrilateral FEs with a 10 m side length was adopted to align with the grid resolution. As the primary objective of this work was to establish and validate the core FNMmg methodology, a comprehensive optimization of FE parameters was not the central focus of the current investigation. However, we recognize that FE geometry and scale play a significant role in balancing geometric fidelity with computational efficiency. Therefore, a systematic sensitivity analysis covering varying FE scales and vertex configurations remains a critical direction for future research. Such studies will further quantify the influence of discretization parameters on network topology and connectivity accuracy.

(2) Determination of geometric similarity fusion thresholds

The implementation of the FNMmg framework involves the determination of specific threshold parameters for geometric similarity fusion. Currently, these parameters are calibrated semi-empirically based on local geological characteristics to ensure model accuracy. While effective for the study area, applying the method to complex geological settings may require adaptive adjustments to these thresholds. Future research will focus on developing more systematic and automatic strategies for parameter optimization to enhance the method's generalizability and robustness.

(3) Model validation and performance evaluation

Model validation in this study is primarily restricted to fracture connectivity via consistency checks against limited tracer monitoring data. Quantitative verification of geometric attributes, such as fracture aperture and length, was not explicitly conducted because the current framework treats them as parameterized inputs rather than optimization targets. Furthermore, detailed validation across varying structural positions remains incomplete. Future efforts will focus on establishing a multidimensional evaluation framework, incorporating specific validation protocols for geometric parameters and refining assessment strategies to capture model performance across multiple spatial scales.

(4) Applicability and implementation

As the current research focuses on establishing the core framework of FNMmg, its transferability to diverse geological settings, such as non-sandstone tight reservoirs or data-scarce scenarios, has not been systematically evaluated. Additionally, comprehensive assessments regarding software integration are pending. Future investigations will focus on delineating the application boundaries under varying lithologies and data environments. Emphasis will also be placed on algorithmic optimization and developing dedicated software support to facilitate efficient implementation in practical oilfield operations.

(5) Computational cost and optimization

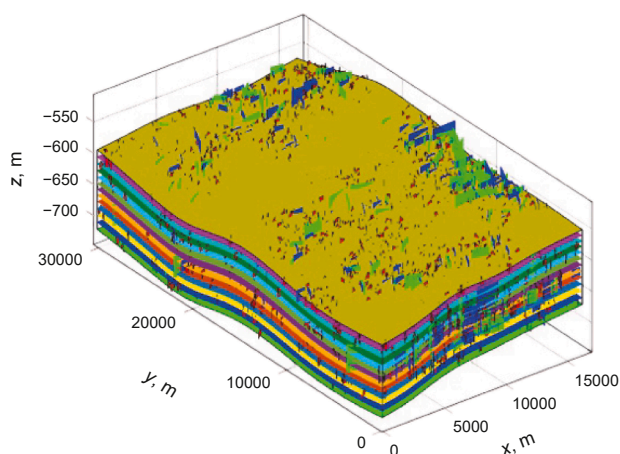


Fig. 11. Discrete fracture network in the target formation of the study area. Red shows fracture elements; blue, fusion by geometric criterion; green, fusion by mechanical criterion. Layer colors represent different stratigraphic intervals. The x- and y-coordinates are expressed in meters.

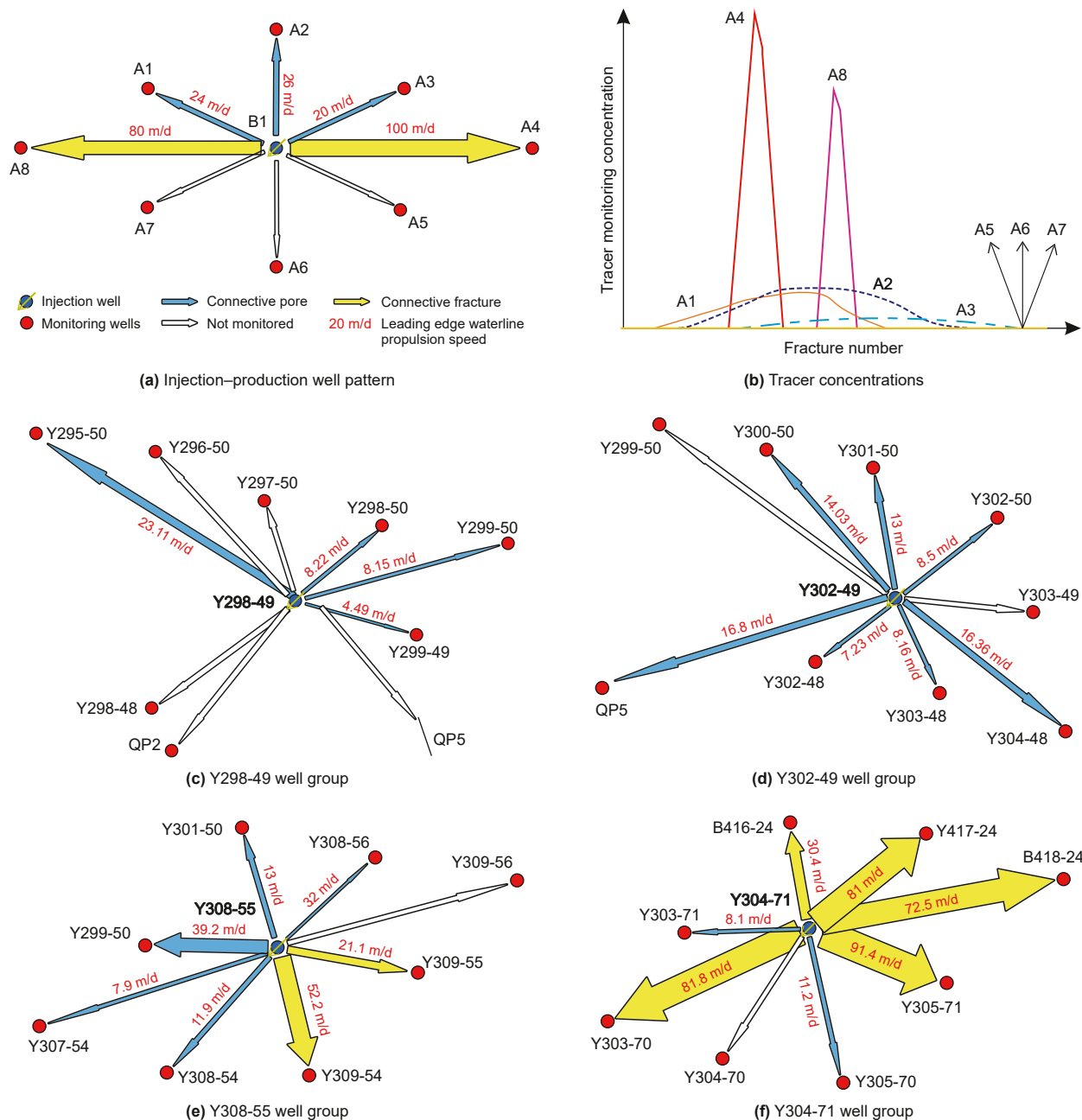


Fig. 12. (a)–(b) Schematic diagram of tracer test for assessing connectivity types between well pairs, (c)–(f) tracer test results. (a) Injection–production well pattern. (b) Tracer concentrations. (c) Y298-49 well group. (d) Y302-49 well group. (e) Y308-55 well group. (f) Y304-71 well group.

While the proposed FNMmg method demonstrates some advantages over conventional approaches in characterizing the complex geological features of tight reservoirs, this improved geological realism entails a necessary trade-off in computational cost. Fig. 13 presents a comparative analysis of algorithmic efficiency, plotting the runtime against the number of fractures ranging from 5000 to 100000. Due to the intensive iterative calculations required to ensure geometric and mechanical compatibility during the hierarchical fusion process, the FNMmg algorithm exhibits a higher computational overhead than traditional

stochastic algorithms. As illustrated, the runtime for FNMmg is approximately 5–8 times higher than that of the standard DFN and density-controlled DFN (dcDFN) methods; for instance, at a scale of 100,000 fractures, FNMmg requires roughly 200 s compared to approximately 40 s for the baseline methods. However, a critical observation from Fig. 13 is that FNMmg maintains a nearly linear growth trend, with narrow error bars indicating high algorithmic stability across independent runs. This linear scalability confirms that despite the higher computational cost, the method remains feasible for larger-scale fracture network simulations.

Table 2
Tracer test of fracture network connectivity.

Tracer-injected well	Monitoring well	Fracture-related connectivity		Tracer-injected well	Monitoring well	Fracture-related connectivity	
		Monitoring	Fracture model			Monitoring	Fracture model
Y298-49	Y295-50	No	No	Y302-49	Y299-50	No	No
	Y296-50	No	No		Y300-50	No	No
	Y297-50	No	No		Y301-50	No	No
	Y298-50	No	No		Y302-50	No	No
	Y299-50	No	No		Y303-49	No	No
	Y299-49	No	Yes		Y304-48	No	No
	QP5	No	No		Y303-48	No	No
	QP2	No	No		Y302-48	No	No
	Y298-48	No	No		QP5	No	No
	Y301-50	No	No	Y304-71	B416-24	Yes	Yes
Y308-55	Y308-56	No	No		B417-24	Yes	Yes
	Y309-56	No	No		B418-24	Yes	Yes
	Y309-55	Yes	Yes		Y305-71	Yes	Yes
	Y309-54	Yes	No		Y305-70	No	No
	Y308-54	No	No		Y304-70	No	No
	Y307-54	No	No		Y303-70	Yes	Yes
	Y299-50	No	Yes		Y303-71	No	No

Table 3
Confusion matrix of fracture-related connectivity.

Dynamic monitoring results		Fracture-related connectivity in the fracture network	
		Connected	Not connected/pore-related
Tracer monitoring	Fracture-related connectivity	6 (86%)	1 (14%)
	Other	2 (7%)	25 (93%)

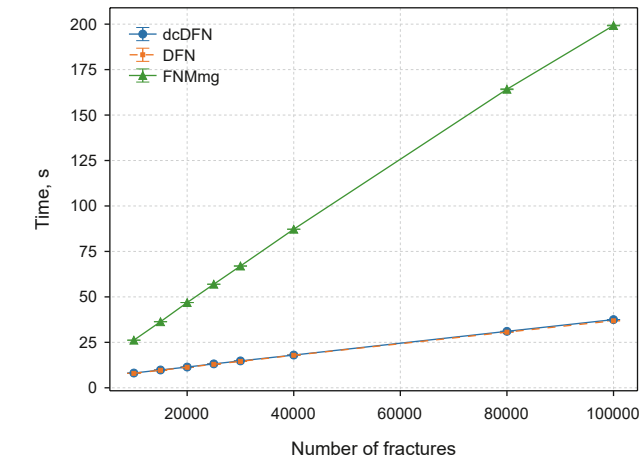


Fig. 13. Comparison of computational efficiency. The central markers represent the mean runtime over five independent runs, with error bars indicating two times the standard error. DFN and dcDFN refer to the standard DFN and the density-controlled DFN, respectively.

Consequently, improving algorithmic efficiency is a pivotal direction for our future work. We specifically aim to implement spatial indexing structures and parallel computing techniques to accelerate the neighbor-search and fusion processes, thereby reducing the time costs while preserving model accuracy.

5. Conclusions

Conventional DFN modeling approaches encounter significant challenges in tight reservoirs, particularly in capturing the coupled influences of fracture geometry, mechanical conditions, and stratigraphic controls. This study proposed a fracture network

modeling method that integrates mechanical-geometric criteria (FNMmg) to address these limitations.

A distinguishing feature of FNMmg is its construction of fracture networks by fusing numerous small fracture elements under dual criteria of geometric similarity and mechanical/diagenetic principles. This process allows the hierarchical organization and growth of fracture networks to be represented more consistently with tectonically controlled fracture development. Complementary strategies include: (i) orientation simulation using a cumulative probability curve, which avoids errors arising from arbitrary fracture group partitioning; (ii) scale-weighted orientation statistics to capture the role of longer fractures; and (iii) dip angle simulation with respect to bedding-normal directions, improving the representation of stratabound fractures.

Application to the Triassic Chang 6 tight sandstones in the Ordos Basin of China demonstrates that the method can reproduce multi-scale fracture systems and maintain computational feasibility. The validation against tracer monitoring across 34 well pairs yielded a connectivity consistency rate of about 91%, including 86% consistency for fracture-related connections and 93% for pore-related or unconnected cases.

Overall, FNMmg provides a more geologically constrained and dynamically representative framework for DFN modeling in tight reservoirs. By explicitly incorporating mechanical origin, geometric growth, and data-driven statistical treatments, it offers a practical basis for improving fracture characterization and reservoir simulation workflows. Future work will focus on refining fracture fusion criteria and improving computational efficiency to support transferability at larger reservoir scales.

CRediT authorship contribution statement

Shao-Qun Dong: Writing – original draft, Funding acquisition, Formal analysis, Conceptualization, Software, Methodology. **Lian-Bo Zeng:** Writing – review & editing, Writing – original draft. **Le-**

Ting Wang: Visualization, Formal analysis, Data curation. **Fu-Yu Zhang:** Software, Methodology, Investigation. **Shao-Peng Song:** Visualization, Validation, Data curation. **Bao-Yu Liang:** Writing – review & editing, Resources, Methodology. **Xiang-Yi Du:** Validation, Resources, Formal analysis. **Xu Yang:** Writing – review & editing, Software, Investigation. **Zi-Yi Yang:** Writing – review & editing, Visualization, Data curation.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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