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Discrete Fracture Network Simulation of Shale Reservoir

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Abstract

Shale reservoirs are characterized by low porosity, low permeability, and extensive natural fractures, where fluid migration and storage primarily depend on complex fracture networks. As the primary flow channels in shale reservoirs, natural fractures not only directly govern hydrocarbon migration and distribution but also significantly influence the expansion of hydraulic fracturing fracture networks and fracturing effectiveness. Given the pronounced heterogeneity, anisotropy, and fractal characteristics of shale fractures, traditional equivalent continuum models struggle to accurately describe their intricate geometry and flow behavior. This study employs a discrete fracture network (DFN) simulation method to model spatial parameters including fracture orientation, inclination angles, and lengths. The results provide a realistic representation of natural fracture distribution in shale reservoirs, offering enhanced structural foundations for reservoir evaluation, fracturing design, and flow simulation. Therefore, DFN modeling of natural fracture systems in shale reservoirs serves dual purposes: it provides crucial insights into storage mechanisms and flow processes, while also constituting a pivotal element for optimizing shale hydrocarbon development efficiency and fracturing operations.

Keywords

Shale Reservoir; Geometric Parameters; Natural Fractures; Discrete Fracture Network.

1. Introduction

Shale oil is a typical unconventional petroleum resource with abundant reserves and enormous exploration and development potential in China. In recent years, with the maturation of technologies such as horizontal drilling and fracturing, shale oil extraction has become a crucial direction in the global oil and gas industry. According to statistical data, China's technically recoverable shale oil resources amount to approximately 4.393 billion tons, ranking third globally [1], demonstrating significant resource advantages and development prospects.

Shale reservoirs are characterized by low porosity, low permeability, and strong heterogeneity. However, natural fractures are widely distributed in these formations, not only providing primary pathways for hydrocarbon accumulation and migration but also significantly influencing the formation and propagation of fracturing fractures. Studies have demonstrated that the spatial structure and connectivity of fracture networks critically determine reservoir flow capacity, fracturing effectiveness, and ultimate recovery rates [2]. Therefore, accurately simulating the development characteristics of natural fractures in shale reservoirs is crucial for understanding flow mechanisms and optimizing extraction strategies. Natural fractures typically exhibit pronounced randomness and spatial disorder in their overall distribution, yet their geometric parameters—including length, orientation, inclination angles, and spatial positions—often follow specific statistical patterns [3]. Given that shale fractures span multiple orders of magnitude from micrometers to kilometers in scale, and unconventional logging methods like imaging logging are prohibitively expensive for widespread regional application, core or outcrop data alone cannot comprehensively capture fracture geometry. In this context, statistical-based numerical simulation has emerged as a crucial approach for studying fracture systems in shale reservoirs. Current numerical simulations of reservoir fracture seepage primarily employ two approaches: the Equivalent Continuous Medium (ECM) model and the Discrete Fracture Network (DFN) model. The ECM model, which uses equivalent permeability to describe fracture effects, offers high computational efficiency but tends to over-idealize fracture geometry, failing to capture the actual complexity of fracture networks. In contrast, the DFN model explicitly represents fracture geometry, spatial distribution, and connectivity, making it particularly suitable for structural characterization and seepage analysis in strongly heterogeneous reservoirs like shale formations [4]. Consequently, the DFN model has been widely adopted for studying the spatial characteristics of fracture systems and their regulatory role in seepage processes.

In the construction of DFN models, the Monte Carlo random sampling method serves as a commonly used and effective approach. It generates fracture geometric properties according to statistical distribution patterns, achieving a harmonious integration of randomness and statistical characteristics in fracture systems [5]. Research indicates that rock fracture length distributions typically follow log-normal or power-law distributions [6], while fracture orientation can be characterized using the Fisher distribution [7]. These statistical principles provide theoretical foundations and parameter specifications for numerical simulations of natural fracture networks in shale reservoirs.

In conclusion, the discrete fracture network simulation of natural fracture network in shale reservoir can not only make up for the deficiency of field observation and logging methods, but also reveal the influence law of fracture geometry structure on seepage characteristics, providing scientific support for the efficient development of shale oil.

2. Mathematical Model of Two-dimensional Discrete Fracture Network

2.1. Natural Fracture Length Distribution

Terrestrial shale oil reservoir typically exhibit strong heterogeneity and complex stress field characteristics, with their natural fracture geometric parameters displaying distinct self-similarity and fractal properties across different scales. The geometric parameters of natural fractures demonstrate distinct self-similarity and fractal features across different scales. Extensive exposure, core analysis, and imaging logging data indicate that fracture length distribution follows power-law patterns more closely than normal or log-normal distributions, as shown in Table 1, highlighting the advantages of power-law distributions. Therefore, incorporating power-law distribution functions into fracture network modeling can more accurately reflect the statistical patterns and formation mechanisms of fracture systems. Typically, the power-law exponent α for fracture network lengths ranges from 1.5 to 3. The probability density function is expressed as [8]:

$$P(l) = C \cdot l^{-\alpha} \tag{1}$$

In the above equation, α is the power-law exponent; C is the normalization constant, ensuring that the integral of the probability density function over its domain equals 1; l is the fracture length.

Cumulative distribution function:

$$P(L \geq l) = \int_{l}^{\infty} P(l')dl' \tag{2}$$

In practical application, the length of fractures usually has upper and lower limits, so the formula needs to be truncated. Since the distribution probability integral of all fractures is 1, the following formula can be obtained:

$$\int_{l_{\min}}^{l_{\max}} P(l)dl = 1 \tag{3}$$

From the above equation, we can get:

$$C=\frac{\alpha-1}{l_{\min}^{1-\alpha}-l_{\max}^{1-\alpha}} \tag{4}$$

In the above equation, l_{max} represents the minimum fracture length; l_{min} represents the maximum fracture length.

From the above equation, we can obtain the revised probability density function [8]:

$$P(l)=\frac{1-\alpha}{l_{\max}^{1-\alpha}-l_{\min}^{1-\alpha}}\cdot l^{-\alpha} \tag{5}$$

In the above formula, α is the power law index. The larger the index, the fewer long fractures.

Table 1. Comparison and advantages of power law distribution with normal and log-normal distribution

	Power-law distribution	Normal distribution	Log-normal distribution
Distribution patterns	Long tail distribution, with a large number of small fractures and a few very long fractures.	Symmetrical distribution, the number of long and short fractures is close.	Medium length fractures are most common.
Physical significance	Reflect the multi-scale, self-similar and fractal characteristics of fractures.	Applicable to random independent processes.	Applicable to cumulative stochastic processes.
Geological adaptability	It conforms to the fractal distribution law of fracture system.	It is inconsistent with the heterogeneous growth mechanism of fractures.	Approximate medium scale fracture distribution, lack of power tail characteristics.
Long fracture contribution	The probability tail of retaining long fractures can reflect the connected channels.	Long fracture probability is low.	Long fracture probability is low.
Modeling effect	It can generate multi-scale through network and reflect the real seepage characteristics.	The model tends to be uniform, which is not conducive to connectivity research.	The network structure is simple.

2.2. Natural Fracture Location Distribution

In this paper, when the natural fractures are randomly generated, the position of the natural fractures is represented by the center point (x, y) of the fractures. The Poisson distribution is used to simulate the distribution of the natural fractures, and the probability density function describing the distribution of the fractures is obtained [9]:

$$P(x=\eta)=\frac{\lambda^{n}}{n!}e^{-\lambda} \tag{6}$$

In the above formula, n is the number of fractures, λ is the expected value.

2.3. Directional Distribution of Natural Fractures

The directional distribution of fractures can be characterized using the Fisher distribution and normal distribution. The Fisher distribution is commonly employed to simulate the spatial distribution of natural fracture orientations (tendency and dip angle). By applying integral methods and inverse functions, Fisher distribution random numbers are transformed into a " XOY " plane coordinate system. The distribution of fracture orientations is characterized by their degree of deviation from the main distribution direction, which better aligns with the natural fracture orientation patterns in shale reservoirs. Therefore, this study employs the random generation method of the Fisher distribution to produce natural fracture azimuth data, with its distribution formula as [10]:

$$f(\theta)=\frac{k\sin\theta e^{k\cos\theta}}{e^{k}-e^{-k}} \tag{7}$$

In the above formula, θ is the angular deviation from the main direction; k is the dispersion coefficient (k> 0, the larger the value, the more concentrated the direction).

3. Numerical Simulation of Two-dimensional Discrete Fracture Network

Based on the length, orientation, and spatial distribution of natural fractures, this study utilizes Monte Carlo random functions to generate a 2D discrete natural fracture network with varying geometric parameters and morphological distributions within a 100m×100m area. To simulate authentic shale reservoir fracture patterns, the simulation parameters were calibrated using small-scale natural fracture data from the 7th Longyan Shale Reservoir in the Ordos Basin, as detailed in Table 2. The parameter "a" represents the angle between the main fracture network direction and the horizontal plane. Using these calibrated parameters, we designed discrete fracture networks with distinct configurations, as illustrated in Table 3.

Table 2. Value range of fracture parameters

Parameter name	Symbol	Interval
fracture length /m	l	[5,60]
Number of fractures	n	[50,100]
Angle of main fracture direction	a	[0,90]
power law index	α	[1.5,2.5]
dispersion coefficient	k	[1,15]

Table 3. Simulation parameters of fracture group

Numble	n	$a/(°)$	k	l_{max}/m	l_{min}/m	α
F-1	50	45	3	30	10	2
F-2	150	45	3	30	10	2
F-3	100	0	3	30	10	2
F-4	100	90	3	30	10	2
F-5	100	45	1	30	10	2
F-6	100	45	10	30	10	2
F-7	100	45	3	30	10	2
F-8	100	45	3	60	10	2

Based on the design parameters in Table 3, we simulated two-dimensional discrete fracture networks (F-1 to F-8) with different parameter values, as shown in Fig 1. This simulation program allows adjustment of fracture geometric parameters to generate discrete fracture networks that conform to the natural fracture geometry distribution in shale reservoirs. Control parameters include fracture count (n), main orientation angle (a), dispersion coefficient (k), maximum length (l_{max}), minimum length (l_{min}) and power-law exponent (α). The simulation results for F-1 to F-8 under various control parameter settings demonstrate the high practicality of this program in modeling natural fracture network geometries.

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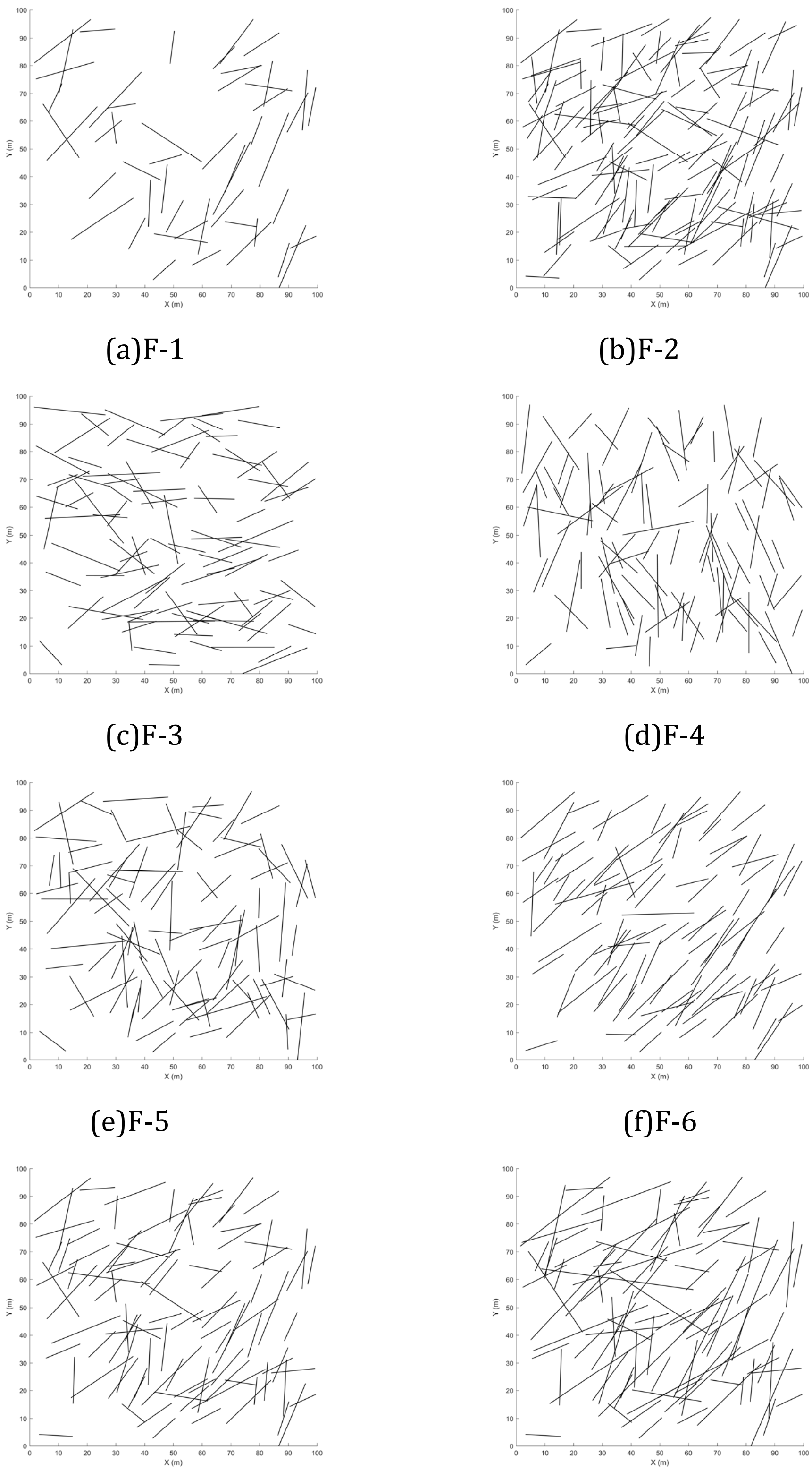

Fig 1. Simulation of two-dimensional discrete fracture network

4. Summary

Based on the power-law distribution of fracture network length, Fisher distribution of fracture angles, and Poisson distribution of fracture locations, we utilized Monte Carlo simulations to generate two-dimensional discrete fracture networks. This established a model that accurately reflects the natural fracture network geometry characteristics of $l_{max}l_{min}$shale reservoirs. The model allows parameter-controlled generation of fracture networks with distinct parameters including fracture count (n), main orientation angle (a), dispersion coefficient (k), maximum lengths (l_{max}), minimum lengths (l_{min}), and power-law exponent (α). These findings provide crucial guidance for determining hydraulic fracturing strategies and optimizing operational parameters in field applications, thereby enhancing sustained high production rates in shale oil reservoirs.

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