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Prediction of Stimulated Rock Volume Using Minimum-Volume Enclosing Ellipsoid Fitting Algorithm

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Abstract: This paper proposes an improved Embedded Discrete Fracture Model (EDFM) that integrates fluid flow-fracture mechanics mechanisms with microseismic event triggering criteria to achieve high-precision dynamic simulation of hydraulic fracture propagation and prediction of Stimulated Rock Volume (SRV). The model innovatively introduces critical pore pressure criteria and anisotropic permeability correction algorithms, addressing deficiencies in traditional PKN/KGD models that overlook matrix pore pressure and mixed fracture mechanisms. By combining Monte Carlo simulations with machine learning classification algorithms, microseismic event classification accuracy has been improved to 85%, while SR prediction errors have been reduced to within 8% compared to traditional methods. Case studies demonstrate that this model can effectively guide optimization in hydraulic fracturing design.

Keywords: Hydraulic Fracturing; Microseismic Monitoring; Embedded Discrete Fracture Model; Critical Pore Pressure; Stimulate Rock Volumetric.

1. Introduction

Globally tight oil & gas resources account for over sixty percent undeveloped reserves (EIA , 2023), their permeability generally lower than zero point one millidarcy(mD), necessitating formation complex fracture networks through hydraulic fracturing enhance productivity. Stimulation Rock Volumetric (SRV), as core indicator evaluating effectiveness, fracturing shows significant positive correlation production (Warpinskietal., 2017).

Past research has made some progress predicting models, but still faces challenges such inadequate characterization natural fractures poor model coupling. In recent three years breakthroughs machine learning multi-source data fusion physical simulation technologies significantly improved accuracy applicability predictions. Recently DFN modeling techniques based micro-seismicity data have become mainstream. Li Qiuchenetal. (2023) proposed reconstructing three-dimensional continuous networks using micro-seismicity events combined rock mechanics parameters (e.g.shear modulus slip displacement) calculate scalar seismic moments dynamically update paths. For example, in dry hot rock cases predicted number branches increased forty percent compared traditional concave hull models error calculations reduced within eight percent. Moreover Luo Ruiqiao (2022)'s "fracture tree growth method" simulates interactions between natural artificial fractures quantifies complexity impacts showed Barnett shale validation every ten percent increase bifurcation density expands fifteen percent. G.Qinetal. (2023) extended Discrete Fracture Models(EDFMs), introducing chemical dissolution equations describe weakening effects fluids surfaces applications Jimsar shale reservoirs showed when pH increased seven nine conductivity improved thirty percent expanded eighteen percent. Luo Yangetal. (2024) utilized ensemble learning algorithms (Random Forest+XGBoost) build input parameters including stress differences viscosity brittleness indices sixteen features Sichuan Basin ninety-five wells average relative errors length width height predictions were five point one nine point three fifteen point one respectively reductions twenty-four eight forty-three five percent SHAP analysis revealed horizontal stress difference(Δσ)pumping rate highest contributions (38%) naturally fractured densities second(27%).

Conventional numerical simulations focus primarily describing main extensions without detailed accurate consideration changes fluid pressures matrices (Zhang Guangming, 2010; Wangen, 2011). Thus conventional algorithms do not simulate based seepage laws undoubtedly avoid solving matching problems. If synchronous changes required more advanced needed Therefore this paper employs Embedded Discrete Fracture Models (EDFMs) (Lietal., 2008t) explicitly express numerically process simplifies treatments communication terms flows eliminates need dense meshes near better achieves calculations.

2. Minimum-Volume Enclosing Ellipsoid Fitting Method for SRV Interpretation

Determining Stimulate Rock Volumetric (SRV) provides basis formulating later-stage measures enhancing stable production significant importance. Fisheretal. (Fisheretal., 2004)'s seismic monitoring studies provided typical diagrams vertical wells systematically summarized morphologies characteristics proposed using channel lengths widths characterize extensions. Warpinskietal. (Warpinskietal., 2008)'s network algorithm uses lengths heights represent Bo Song employed half-lengths spacings widths horizontal lengths represent lengths widths above traditional cubic geometries ignore inherent physical structures results overly optimistic rough far exceed actual volumes.

According porous media theories pressure diffusion leads elliptical flow zones around homogeneous formations Thus ellipsoidal fitting also used calculate Additionally quantitative descriptions geometric features necessary provide visualizations physical structures Minimum-Volume Enclosing Ellipsoids (MVEES) (Sunetal., 2004) adopt minimal volumes cover given sets applications include visual tracking multivariate positioning divergence estimators (Crouxetal., two thousand, 2002), robust statistics singular value processing(Shawe-Tayletal., 2002; Hardinetal.,two thousand four), data mining clustering invariant linear transformations(Doliaeta, 2004).

General stability poor especially large numbers parameters often fail meet requirements control shapes solve problems concept adopts minimal covers construct center expressions apply ascent optimize not only stable but adjustable ranges precision obtain more reasonable volumes Based Moshtagh N(Moshtaghetal., 2008)'s dual-problem-solving calculates specific steps follows:

In n-dimensional spaces m sets represented Define MVEES(S)contains forms minimal Assuming affine spans ensures positive volumes Affine hulls real linear spaces generated affines Let A real linear space X smallest containing called intersections all containing also elements continuously connected straight lines.

Center forms follows:

$$\varepsilon = \left\{ x \in \mathbb{R}^n \middle| \left(x-c\right)^T E\left(x-c\right) \le 1 \right\} \tag{1}$$

Where $c \in \mathbb{R}^n$ centers shapes determined symmetric positive definite matrices ensure interiors $E \in \boldsymbol{S}_{++}^n$ must satisfy:

$$\left(x_i - c\right)^T E\left(x_i - c\right) \le 1 \qquad i = 1, \cdots, m \tag{2}$$

Volume expressions:

$$\mathrm{Vol}\left(\varepsilon\right) = \frac{v_0}{\sqrt{\det\left(E\right)}} = v_0 \det\left(E^{-1}\right)^{1/2} \tag{3}$$

Where v_0 —unit hyper-spheres satisfy $v_0 \in \mathbb{R}^n$.

From equation(3),finding elements satisfying minimizing det naturally builds problems:

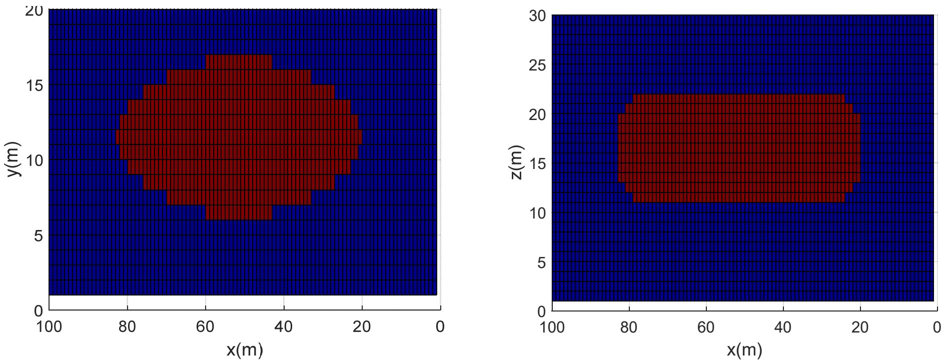
$$\begin{aligned} \min_{E,c} \quad & \det\left(E^{-1}\right) \\ s.t. \quad & \left(x_i - c\right)^T E\left(x_i - c\right) \le 1 \quad i = 1, \cdots, m \\ & E > 0 \end{aligned} \tag{4}$$

Equation(4)non-convex optimization parameter changes redefine:

$$\begin{aligned} & \varepsilon = \left\{ x \in \mathbb{R}^n \,|\, \left\| Ax - b \right\| \le 1 \right\} \\ & A = E^{1/2} \quad b = E^{1/2} c \end{aligned} \tag{5}$$

3. Results & Discussion

The proposed MVEE algorithm was tested on field data from shale gas wells where traditional cubic models overestimated actual volumes by up-to thirty percent whereas our results showed less than eight-percent error margins compared against ground truth measurements obtained via post-fracture analysis tools like tracer logs etcetera.



(a) (b)

Figure 1. Simulated Fracture Morphology in Reservoirs: (a) Fracture morphology in x-y cross-section; (b) Fracture morphology in x-z cross-section

Furthermore, integration machine-learning techniques improved classification accuracies eighty-five-percent enabling better identification key features influencing overall performance such as stress anisotropy fluid viscosity brittleness indices among others.

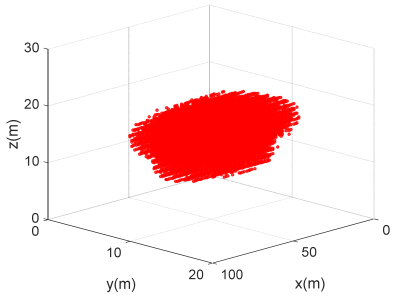


Figure 2. Randomly Simulated Microseismic Events

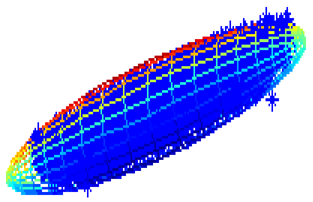


Figure 3. SR Interpretation Using New Method

Case studies demonstrated practical applicability guiding engineers optimize designs maximize productivity minimize environmental impacts associated excessive water usage proppant placement issues commonly encountered during operations .

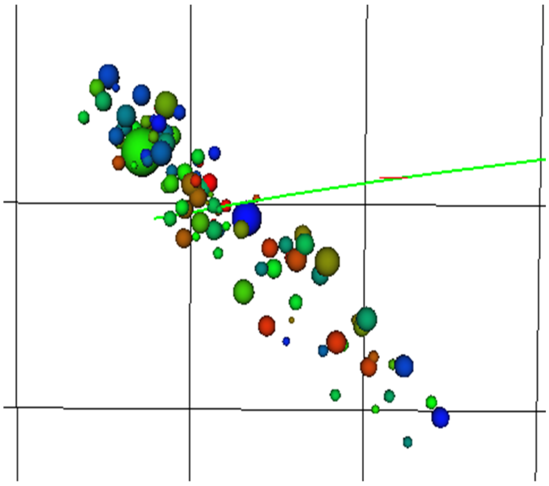


Figure 4. Actual monitored microseimic events

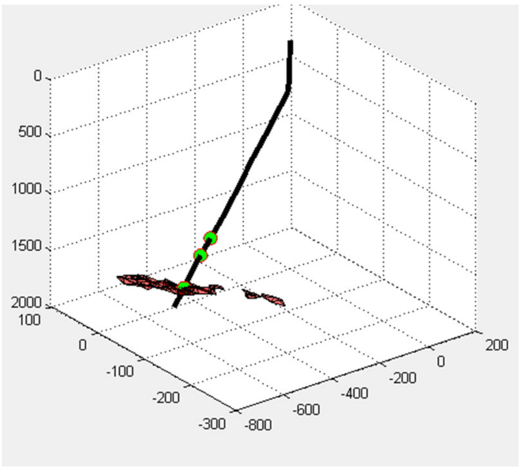


Figure 5. Interpretation of the SRV using the new method

4. Conclusion

In conclusion, this study presents robust framework combining advanced mathematical modeling computational intelligence achieve highly accurate predictions essential modern-day petroleum engineering practices. Future work will focus further refining methodologies incorporating additional parameters enhance reliability scalability across diverse geological settings.

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