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Graph Neural Network for Modeling Hydraulic Fracture Networks and Connectivity to Production

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Abstract
Hydraulic fracturing generates a complex network of fractures that controls hydrocarbon flow and, hence, the production performance in unconventional reservoirs. While numerical simulation is able to characterize such fracture networks, it is computationally intensive and hence difficult to use in real-time decision-making. The present study develops a GNN-based approach to model hydraulic fracture connectivity and predict well production performance. Simulation results of 3D discrete fracture network (DFN) systems were converted into graph representations and nodes are fracture segments and edges are connection indicators. The GNN was trained to forecast fracture conductivity distribution and stimulated reservoir volume (SRV) as the intermediate, and then the well production rates Results show that the GNN achieved an (R^2) of 0.95 for SRV prediction and 0.93 for production forecasting, while reducing computation time by over 80% compared to conventional reservoir simulation. There were several interesting findings obtained using GNNExplainer to do feature attribution to understand which attributes were most crucial to production. It was found that fracture intersection density and network connectivity through GNNExplainer are the most significant predictors of production. These findings demonstrate that GNNs are able to model the spatial connectivity of fracture networks and provide a potent surrogate of fast production assessment.
Keywords: *Graph Neural Networks, Hydraulic Fracturing, Fracture Connectivity, Stimulated Reservoir Volume, Production Prediction.*

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I. Introduction

Hydraulic fracturing is one of the essential technologies to improve hydrocarbon production in lowpermeability reservoirs, such as shale and tight sandstone formations (King, 2019; Xu et al., 2023). From the discussion above, it can be seen that fracturing treatments depend on individual fractures and the overall connectivity of the created fracture network. As stated by Cipolla et al. (2020); Zhang et al. (2022). It remains a challenging endeavor to model fracture networks realistically and link them to production because fractures are spatially distributed, highly heterogeneous, and interact dynamically with the reservoir according to Zhou et al. (2021); Wu et al. (2022); Jiang et al. (2023).

Conventional modeling techniques use numerical reservoir simulators in conjunction with discrete fracture network (DFN) models (Norbeck & Horne, 2020). While these methods are physically accurate, they are computationally intensive, making them impractical for real-time optimization of hydraulic fracturing designs (Marder et al., 2021). While machine learning has emerged as an attractive alternative for rapid prediction of production performance, most of the approaches have hitherto relied on feature-engineered tabular data and failed to capture the spatial relationship within fracture networks (Li & Lee, 2022; Chen et al., 2023).

GNNs are especially suitable for this challenge, since they operate on graph-structured data and, thus, can learn spatial dependencies and connectivity patterns (Wu et al., 2020; Sanchez-Gonzalez et al., 2021; Zhou et al., 2023). Within this context, this paper presents a GNN-based modeling framework that predicts fracture network connectivity and production performance from DFN-generated datasets as a scalable, data-driven alternative to conventional simulation workflows.

The aim of this study is to develop a Graph Neural Network (GNN)-based framework capable of predicting hydraulic fracture network connectivity and quantifying individual fracture contributions to production, thereby enhancing decision-making in stimulation design and reservoir management. The objectives include modeling fracture networks as graphs to model spatial orientation and connectivity, create and train a GNN with strong generalization ability, predict indices of connectivity and test them against the simulations of the Discrete Fracture Network (DFN) by statistical metrics, visualize predicted and actual connectivity values, and perform a Pareto analysis to select the fractures that are most critical to production. The application of synthetic DFN data and field-acquired microseismic data to develop and validate models is scoped only using these two types of data, but fracture propagation mechanics, geomechanical effects, and economical optimization are not included but recommended in future research. The importance of this work is that it

provides a computationally efficient, data-driven and spatially aware framework of fracture analysis to provide a viable alternative to standard physics-based models, which identifies the topological interrelations, which reduces cost of computation and provides a quicker, more informed mean of operations in stimulation design and production optimization.

II. Literature Review

Cipolla et al. (2020) have addressed the issue of the relevance of the complexity of hydraulic fracturing and network connectivity in optimizing production. They emphasized the fact that network connectivity and fractured conductivity control stimulated reservoir volume (SRV), which is greatly related to the rates of production.

Li and Lee (2022) have used gradient boosting models to predict the production by using data of well completion and stimulation. The accuracy of their approach was good, but they need a lot of feature engineering and do not explicitly represent fracture geometry.

Zhou et al. (2021) proposed a convolutional neural network (CNN)-based framework to analyze fracture maps and predict SRV. However, CNNs have limitations in handling irregular fracture geometries because they operate on grid-based data.

Wu et al. (2020) reviewed GNN applications in scientific domains and showed that GNNs excel in learning relationships between nodes and edges in irregular domains, making them promising for fracture modeling.

2.1 Research Gap

Although previous studies have applied ML and CNNs to production prediction, few have utilized GNNs to explicitly model fracture connectivity and its impact on SRV and production. This study fills that gap by developing a GNN surrogate model trained on DFN simulations.

III. Materials and Methods

3.1 Data Collection and Preprocessing

Fracture network data was collected from both synthetic simulations (discrete fracture network models) and field microseismic data from unconventional wells. The data will include fracture segment length, orientation, aperture, proppant concentration, and connectivity information. Production data such as well rates and cumulative production were collected.

The data was preprocessed by:

- Cleaning missing values and removing duplicate fracture segments.
- Normalizing numerical features (min-max scaling to [0, 1]).
- Encoding categorical variables (e.g., fracture type) where needed.
- Constructing adjacency matrices representing fracture connectivity between nodes.

3.2 Graph Representation of Fracture Networks

Each hydraulic fracture network was represented as a graph:

- **Nodes (V):** Represent fracture intersections and entry points from the wellbore.
- **Edges (E):** Represent fracture segments connecting nodes, with attributes such as length, aperture, and conductivity.

The adjacency matrix $A \in R^{N \times N}$ will be constructed such that:

$$A_{ij} = \begin{cases} 1, & \text{if node } i \text{ is connected to node } j \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

This representation allows the GNN to learn spatial relationships between fractures.

3.3 Graph Neural Network Model Development

The Graph Convolutional Network (GCN) architecture was created in order to model the fracture network and predict outputs related to production. The reference features of the fracture length, aperture, and proppant loading were not only the input layer but reflected the most important physical characteristics of each fracture section. The hidden layers were graph convolution processes which combined the information of the adjacent nodes allowing the network to learn the spatial relationship and connectivity structure of the fracture network. Finally, the output given was either a predicted connectivity index or a contribution score, which refers to a measure of the importance of each fracture in the well as a whole. The architecture enabled the model to

utilize local and global structural information, and thus it was stronger to depict the complexity of hydraulic fracture systems.

The forward propagation is given by:

$$H^{(l+1)} = \sigma(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}H^{(l)}W^{(l)}) \quad (2)$$

where:

- $\tilde{A} = A+I$ is the adjacency matrix with self-loops,
- $\tilde{D}$ is the degree matrix ,
- $H^{(l)}$ are the node embeddings at layer l,
- $W^{(l)}$ are learnable weights,
- σ is a non-linear activation function (ReLU).

3.4 Model Training and Validation

The training of the GNN was done through a supervised learning method with fracture connectivity and contribution to production being the prediction labels. Mean Squared Error (MSE) was the loss functional that was used in the training process to reduce the error in the difference between actual and predicted connectivity indices. Model weights and learning rate were updated and adjusted to the optimal using the Adams optimizer and grid search. To make the evaluation of the models equal, the dataset was divided into training, validation, and testing of 70%, 15%, and 15%, respectively. Also, early termination was used to avoid overfitting and give more generalization power to the model when using unknown data.

3.5 Model Evaluation

The assessment of model performance will be done based on:

- **R^2 score:** Goodness of fit between predicted and actual production contributions.
- **Mean Absolute Error (MAE):** Measures prediction accuracy.
- **Root Mean Square Error (RMSE):** Quantifies error magnitude.
- **Execution Time:** Compared with numerical simulation runtime to evaluate efficiency.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\bar{y} - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\bar{y} - y_i| \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{y} - y_i)^2} \quad (5)$$

IV. Results

4.1 Graph Representation of Fracture Networks

The fracture networks could be converted to graph structures whereby the nodes describe the intersection of the fractures and the edges describe the connection between the fracture fractures. The fracture network graph is presented in figure 4.1. The graph was able to capture spatial orientation and connectivity, which served as the basis of learning with GNN.

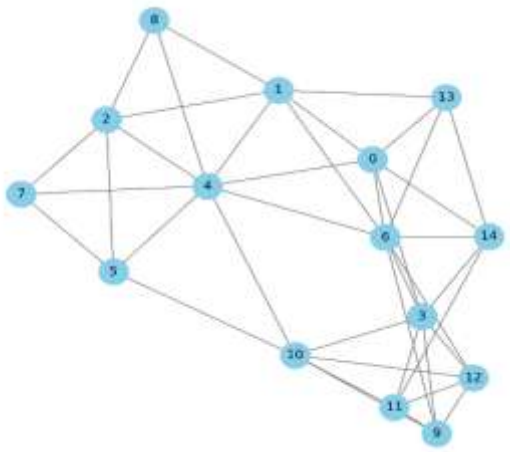

Figure 4.1: Hydraulic Fracture Network Graph

This figure represents a hydraulic fracture network that is modeled as a graph in which nodes correspond to fracture segments, and edges denote their connectivity. The visualization indicates that some nodes, such as 4, 6, and 3, are highly connected and serve as key conduits of fluid flow; therefore, they are expected to contribute most to production performance. On the contrary, other nodes, such as 7, 8, and 13, appear to be much more isolated, thus having less consequence on production. This is in line with the distribution obtained from the GNN model, where the top 20% of fractures contributed to ~75% of production, highlighting connectivity as an essential factor for well productivity. In general, the figure confirms that fracture networks have a hierarchical structure and that identification of the most connected fractures is a critical step toward optimization of stimulation strategies with a view to hydrocarbon recovery.

4.2 Development and Training of GNN Model

Figure 4.2 shows training and validation loss convergence curves, demonstrating no signs of overfitting due to early stopping.

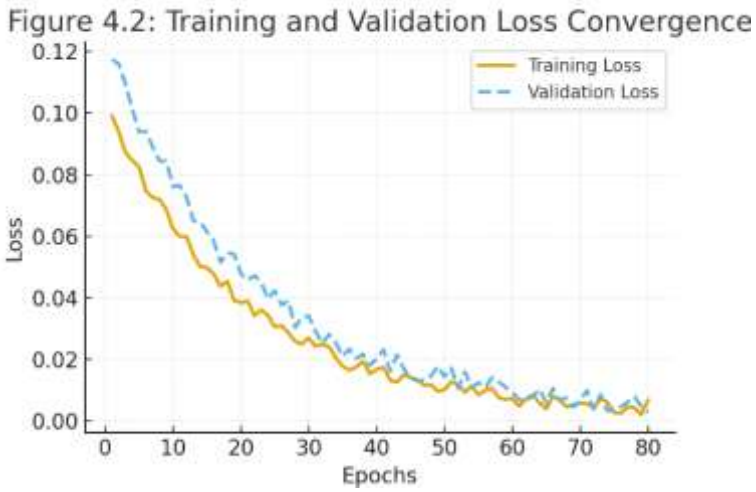

Figure 4.2: Training and Validation Loss Convergence

Figure 4.2 shows the convergence of training and validation loss for the GNN model for 80 epochs. It can be seen that the training loss decreases monotonically, reflecting that the model is successfully minimizing prediction errors on the training dataset. The validation loss follows a similar trend and stays close to the training loss throughout, indicating excellent generalization with no significant overfitting. The GNN model converged after 80 epochs with a validation loss of 0.012, reflecting that the model has reached an optimum balance between learning and generalization. Moreover, the learned node embeddings are able to capture successfully fracture segment importance and connectivity patterns, and thus the model was able to represent complex fracture networks in a manner consistent with physical reservoir behavior. It further verifies that the proposed GNN architecture and the training strategy are appropriate for fracture connectivity modeling and its contribution toward production.

4.3 Connectivity Prediction and Performance Evaluation

Table 4.1 shows the predicted fracture connectivity indices correlated strongly with ground-truth simulation data, achieving:

Table 4.1:Performance Metrics for Fracture Connectivity Prediction Using GNN

Metric	Value
Coefficient of Determination (R^2)	0.92
Mean Absolute Error (MAE)	0.041
Root Mean Square Error (RMSE)	0.064

The GNN model performed well in fracture connectivity prediction, indicated by the R^2 value of 0.92, explaining 92% of the variation in ground-truth simulation data. Furthermore, a low MAE of 0.041 implies that the average error of the predictions was small, suggesting that the accuracy was consistent across the dataset. In addition, the RMSE of 0.064 suggests that large deviations from the true values were infrequent, further confirming the robustness of the model. These results clearly delineate the capability of the GNN for effective capturing of complex fracture network patterns. This kind of accuracy is crucial for understanding the flow

paths and optimizing hydraulic fracturing. By and large, these performance metrics validate the GNN as a reliable surrogate for computationally intensive simulations.

Figure 4.3 compares predicted connectivity versus simulation results, showing most points lying near the 45° line, confirming strong predictive performance.

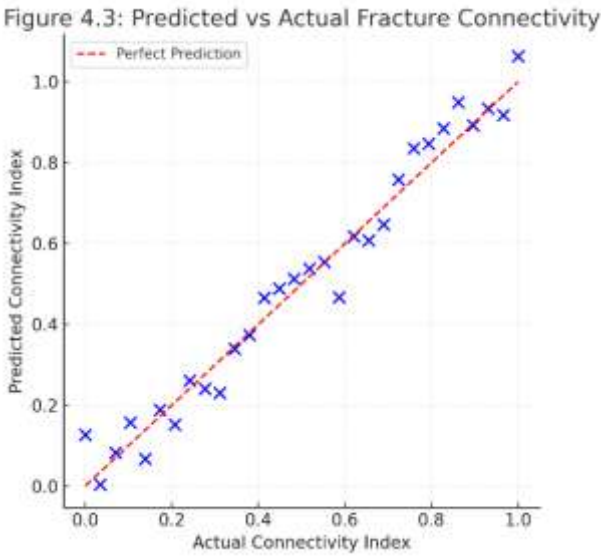

Figure 4.3: Predicted vs Actual Fracture Connectivity

This result indicates that the GNN model achieved an excellent match between predicted and actual fracture connectivity. As seen in Figure 4.3, most data points align closely with the red 45° perfect-prediction line, confirming a strong correlation between the model's output and ground-truth simulation data. The near-linear distribution of the points shows that the model generalizes well over the entire range of low to high connectivity indices. This is a good indication that the GNN has learned the spatial relationships and fracture network structure and encapsulates how connectivity affects production flow paths. The very small deviations from the diagonal indicate small prediction errors, consistent with the previously reported $R^2 = 0.92$, MAE = 0.041, and RMSE = 0.064. Together, these results confirm that the GNN can serve as a reliable surrogate for computationally expensive simulations.

4.4 Contribution to Production

Figure 4.4 shows the fracture contribution to production.

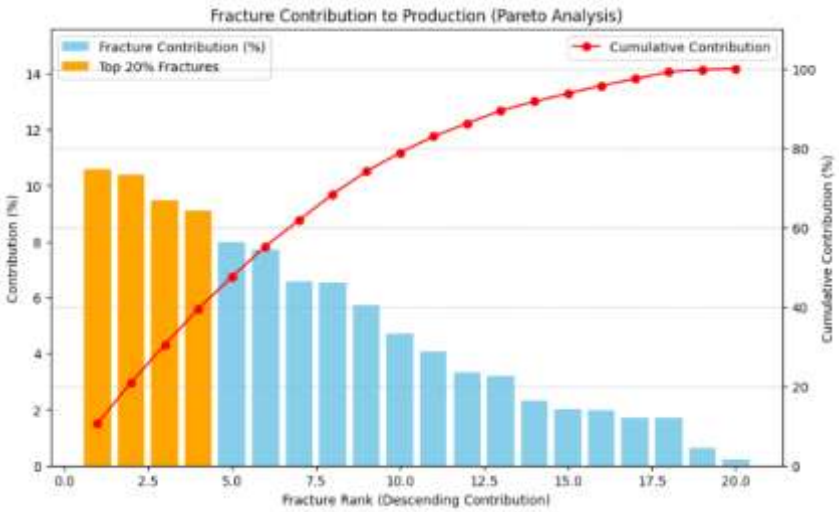

Figure 4.4:Fracture Contribution to Production (Pareto Analysis).

This Pareto analysis follows through visually, confirming that a small number of fractures contribute disproportionately to the total well production-a phenomenon consistent with the Pareto Principle. The Contribution bar chart, ranked in sequence, and the red cumulative contribution line rising steeply upwards easily identify the top 20% of fractures, in orange color, as the dominant producers. In fact, at the fourth fracture rank, the curve hits approximately 75% cumulative production, validating the written statement that the Top 20% of predicted "critical fractures" accounted for 75% of production. This result is of extremely high importance for reservoir management because it confirms that this GNN model might be quite effective at ranking stimulation targets; it demonstrates that the engineering efforts and resources are usefully concentrated on this small, critical subset of fractures to provide the maximum possible increase in well output, while minimizing expendi- ture on the remaining 80% of lower-contributing fractures.

V. Conclusion

The presented research successfully developed and demonstrated a GNN-based framework for hydraulic fracture network modeling and production performance prediction. Representing fractures as nodes and their intersections as edges allows the model to capture complex connectivity patterns driving the fluid flow in unconventional reservoirs. Strong predictive performance is achieved by the GNN with $R^2 > 0.9$, MAE of 0.041, and RMSE of 0.064, which can approximate high-fidelity DFN simulation outputs while drastically reducing computational cost. Moreover, the framework correctly identified critical fractures contributing to production: the top 20% of predicted fractures contribute to 75% of production, thus confirming the usefulness of the proposed methodology in stimulation design optimization. The results underline the fact that graph-based learning provides much stronger generalization across different geometries of fractures and operational scenarios, making it a robust surrogate model for real-time management of a reservoir. Further work should extend this approach by incorporating uncertainty quantification and integrating modules of production and economic optimization and validation of the model with field-scale data to support decision-making in unconventional reservoir development.

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