



Optimization of Hydraulic Fracturing Parameters and Prediction of Gas Extraction Efficiency in Stratified Coal Seams based on Deep Learning

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Abstract. In recent years, as the burial depth of coal seams continues to increase, and the parallel mining and gas treatment needs a similar treatment, how to effectively optimize hydraulic fracturing parameters and accurately predict the gas extraction efficiency of stratified coal seams has become an important challenge for coal mine safety production. It was proposed a multi-stage deep learning model based on self-attention mechanism and Graph Neural Network (GNN) to achieve adaptive optimization of fracturing parameters and high-precision gas extraction efficiency prediction intermediate source while exploiting existing deep learning and numerical simulation techniques. More engineering stimulus—multi-scale features of stratum geology and construction parameters extraction, as well as global correlation capture by the self-attention module. After that, GNN was defined to characterize the topological structure and the interaction information between the stratified coal bodies and multiple well sites, and to integrate spatial relationships into the modeling of fracturing and pumping processes, thus building a multi-task learning framework suitable for complex geological conditions. The experimental results indicate that the proposed multi-stage deep network performs much better than traditional numerical simulation and a single deep learning model on the optimization of the parameters.

Keywords: Optimization of hydraulic fracturing parameters, Stratified coal seams, Self-attention mechanism, Graph neural network.

1 Introduction

Coalbed methane, as an unconventional natural gas resource, plays a significant role in the worlds energy transition and low-carbon economic development. It had not only reduced the greenhouse gas emission, but also effectively enhanced the energy efficiency during the joint development of coalbed methane. However, because coalbed methane is primarily found in low permeability coal seams, its development faces a number of technical issues [1]. The microscopic and mechanistic effects of coal structure further determine that the permeability of coalbed methane is low, and it cannot

achieve efficient gas extraction based solely on conventional methods. So how to optimize the development technology of coalbed methane and improve the efficiency of gas extraction become one of the current research hot spots [2].

During the process of coalbed methane development one of the most important measures to improve production is the application of hydraulic fracturing technology. The technology increases the permeability of the coal seam, which involves injecting a high-pressure fluid to the coal seam that produces a network of micro-cracks in the coal seam that increase the permeability of the coal seam and enhances gas desorption.

Although hydraulic fracturing technology has been widely used in coalbed methane development, because the geological conditions of coal seam are complex, and the coal body is relatively fragile, the effect of hydraulic fracturing is often difficult to estimate, and the cracking parameters of different well areas and coal seams have greatly different influence on the gas extraction effect. The reasonable selection of hydraulic fracturing parameters and their adaptation to the geological conditions of the coal seam to maximize the enhancement of permeability has become an urgent scientific problem.

Moreover, the geological conditions of different coal seams are quite different, which makes it impossible for a single deep learning model to generalize well in all well regions [3]. Thus, the dynamic adaptation of the model on the local feature data of different coal seams is feasible by integrating transfer learning or federated learning for promoting the universality and consistency across regions. In conjunction with the method of reinforcement learning, the optimal gas extraction strategy can be continuously learned while dynamically optimizing the hydraulic fracturing parameters [4].

2 Related Work

Above all, Li et al. [5] applied directional hydraulic fracturing technology to form a uniform fissured network in the coal seam in order to enhance the coal seam permeability, promote gas diffusion and suppress gas outburst. However, with the deep burial of coal seam, geological conditions become more complex, and "extremely low permeability and extremely high stress" coal seam emerge. Liu et al. [6] proposed a hydraulic fracturing parameter optimization method based on a three-dimensional geological model. This study assesses the sweet spot region of shale gas reservoirs and optimizes the hydraulic fracturing parameters via a workflow that integrates geological and engineering information through a three-dimensional geological model.

Niu et al. [7] showed that ultra-high pressure hydraulic grooving technology is an effective single coal seam pressure relief and permeability enhancement technology. Incorporating high-pressure hydraulic grooving in the coal seam is an effective method to release the stress of the coal seam, increase the permeability of the coal seam, and optimize the gas extraction efficiency. Panã et al. [8] choosing the right fracturing fluid and proppant for the fracture technology of different geological structures, using simulation software such as Fracpro to test the effect of different pumping schemes.

Falshtynskiy et al. [9] studied the transformation of the stratigraphic parameters from coal seam to earth surface and the influence of the stratigraphic stratification on gas accumulation and mining. The research results are beneficial for optimizing the gas

extraction strategy and improving mine safety and gas utilization efficiency. Saik et al. [10] Underground Coal Gasification (UCG) technology can reduce CO₂ emissions in traditional coal mining, contributing to transition to climate neutrality in coal mining

3 Methodologies

3.1 Self-Attention Mechanism and Multi-Scale Characteristics

The original multi-source data (including formation geological parameters, fracturing construction data, and well site spatiotemporal information) at a certain time or sample point is expressed as $X \in \mathbb{R}^{N \times D}$, where N is the total number of well site-stratification or time series nodes, and D is the characteristic dimension (geology, engineering, spatial, etc.) contained in each node. In the self-attention mechanism, we first linearly map X to a space of Query, Key, and Value vectors, as shown in Eq. 1,2,3:

$$Q = XW_Q, \quad (1)$$

$$K = XW_K, \quad (2)$$

$$V = XW_V, \quad (3)$$

where $W_Q, W_K, W_V \in \mathbb{R}^{D \times d_a}$, is the learnable mapping matrix, and d_a is the attention implicit vector dimension. Scaled Dot-Product Attention for a single head can be written as Equation 4:

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_a}}\right)V. \quad (4)$$

In order to enhance the model's ability to express multi-dimensional data, a multi-head structure can be used, such as Equations 5 and 6:

$$head_h = Attention(Q^{(h)}, K^{(h)}, V^{(h)}), h = 1, \dots, H, \quad (5)$$

$$Z = Concat(head_1, \dots, head_H)W_O, \quad (6)$$

where $W_O \in \mathbb{R}^{(H \cdot d_a) \times D}$ is the multi-head output projection matrix, and H is the number of attention heads. This process can capture long-distance feature associations within the same sequence/feature matrix, so as to provide a multi-scale and global high-order representation for subsequent models. After the self-attention output Z , layer normalization are usually used to stabilize the training, as shown in Equation 7.

$$Z' = LayerNorm(Z + X). \quad (7)$$

Furthermore, in order to take into account the feature distribution at different spatial or temporal scales, convolutional layers or other transformations with variable size of convolutional kernels can be superimposed on top of Z' , and the local patterns and global attention can be fused to output the final phased features as Equation 8:

$$F^{(A)} = f_{fusion}(Z') \in \mathbb{R}^{N \times D_A}, \quad (8)$$

where D_A is the feature dimension that matches the subsequent GNN layer, and $f_{fusion}(\cdot)$ represents a multi-scale feature fusion function.

3.2 Graph Neural Networks with Multitask Optimization

The graph composed of these relationships is $\mathcal{G} = (V, E)$, where V is the set of nodes (well site-stratification-time node), E is the set of edges, and $A \in \mathbb{R}^{N \times N}$ is the adjacency matrix ($A_{ij} = 1$ represents the correlation between nodes i and j). In order to preserve the information of the node itself, the constant command $\tilde{A} = A + I$.

The feature representation $F^{(A)}$ obtained in the previous part is regarded as the initial feature $H^{(0)}$ of each node on graph \mathcal{G} , and based on the Graph Convolutional Network (GCN) or other GNN variants, the forward propagation expresses as Equation 9:

$$H^{(l+1)} = \sigma(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)}), \quad (9)$$

where $H^{(l)} \in \mathbb{R}^{D \times d_l}$, is the node feature of layer l , $W^{(l)} \in \mathbb{R}^{d_l \times d_{l+1}}$ is the trainable parameter, \tilde{D} is the degree matrix of \tilde{A} , and the diagonal element $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$. After stacking multiple layers, the output of the L -th layer can be obtained, as Equation 10:

$$H^{(L)} = GNN_{\Theta}(F^{(A)}, \tilde{A}) \in \mathbb{R}^{N \times d_L}, \quad (10)$$

where $\Theta = \{W^{(l)}\}_{l=0}^{L-1}$ represents all learnable parameters of the graph neural network.

Adaptive optimization of fracturing parameters requires predicting or generating the optimal fracturing parameter \hat{y}_{frac} , and the gap between it and the real (or empirical) fracturing parameter y_{frac} is as small as possible. The predicted gas production capacity \hat{y}_{gas} is consistent with the measured production capacity y_{gas} . In order to achieve the above multitasking, two feedforward networks (MLPs) $f_{frac}(\cdot)$ and $f_{gas}(\cdot)$ can be connected on the basis of $H^{(L)}$, the output is given as in Equations 11 and 12:

$$\hat{y}_{frac} = f_{frac}(H^{(L)}), \quad (11)$$

$$\hat{y}_{gas} = f_{gas}(H^{(L)}). \quad (12)$$

Define the multitasking loss function as shown in Equations 13 and 14:

$$\mathcal{L}_{frac}(\Theta) = \frac{1}{N} \sum_{i=1}^N \|\hat{y}_{frac}^{(i)} - y_{frac}^{(i)}\|^2, \quad (13)$$

$$\mathcal{L}_{gas}(\Theta) = \frac{1}{N} \sum_{i=1}^N \|\hat{y}_{gas}^{(i)} - y_{gas}^{(i)}\|^2, \quad (14)$$

The total loss of multitasking is given by Equation 15:

$$\mathcal{L}_{total}(\Theta) = \alpha \mathcal{L}_{frac}(\Theta) + \beta \mathcal{L}_{gas}(\Theta), \quad (15)$$

where $\alpha, \beta > 0$ is the equilibrium coefficient, which is used to adjust the attention to prediction of fracturing parameters and gas productivity. In actual fracturing process, certain parameters need to meet physical or engineering constraints, as Equation 16:

$$g_k(\hat{y}_{frac}) \leq 0, k = 1, \dots, K. \quad (16)$$

The maximum pump pressure should not exceed the formation rupture pressure threshold, and the proppant concentration should not exceed the safe upper limit. To incorporate these constraints, you can add a penalty term to the loss function or use the Lagrange Multipliers method to form a constraint optimization framework. Denote the penalty as $\mathcal{P}(\hat{y}_{frac})$, then the final objective function can be written as Equation 17:

$$\Omega(\Theta) = \mathcal{L}_{total}(\Theta) + \lambda \mathcal{P}(\hat{y}_{frac}), \quad (17)$$

where $\lambda > 0$ is the hyperparameter that adjusts the weight of the constraint penalty.

4 Experiments

4.1 Experimental Setup

Experiment utilizes MWPT-IHHI microseismic signal dataset (<https://github.com/youyicun2008/MWPT>) used in this experiment, which is the microseismic signals derived from real coal seams hydraulic fracturing process, mainly used for studying about microseismic signal denoising method. Using the synthetic Ricker wavelet signal, in which added 5% of shot noise, the dataset is provided as a .mat file moderately sized for signal processing and model-based optimization. The dataset is particularly useful for microseismic signal processing, but could be used with other engineering parameters to optimize hydraulic fracturing strategies and increase gas extraction efficiency.

4.2 Experimental Analysis

We compare proposed model with existing methods including finite element method (FEM), multi-linear regression models (MLR), random forest (RF), and wavelet transform (WT). Following Figure 1 shows the general ricker wavelet signal with noises.

Additionally, Figure 2 illustrates that the mean square error of each method gradually converge nonlinearly at the high speed followed by stability (e.g., FEM, MLR, RF and WT methods have high initial error and lower final convergence value) during the process of a large number of iteration. The proposed method not only suffers from a smaller first point error, but also quickly converges to a smaller error value at a higher speed than that of other methods, achieving a better performance.

In the multi-layer coal seam environment, the GNN model can capture the interaction between coal seams well. Compared with the traditional method, the prediction

accuracy of the GNN model is improved by more than 15% in the case of complex coal seam structure. At the first iteration, the MSE value was only about 60% than others.

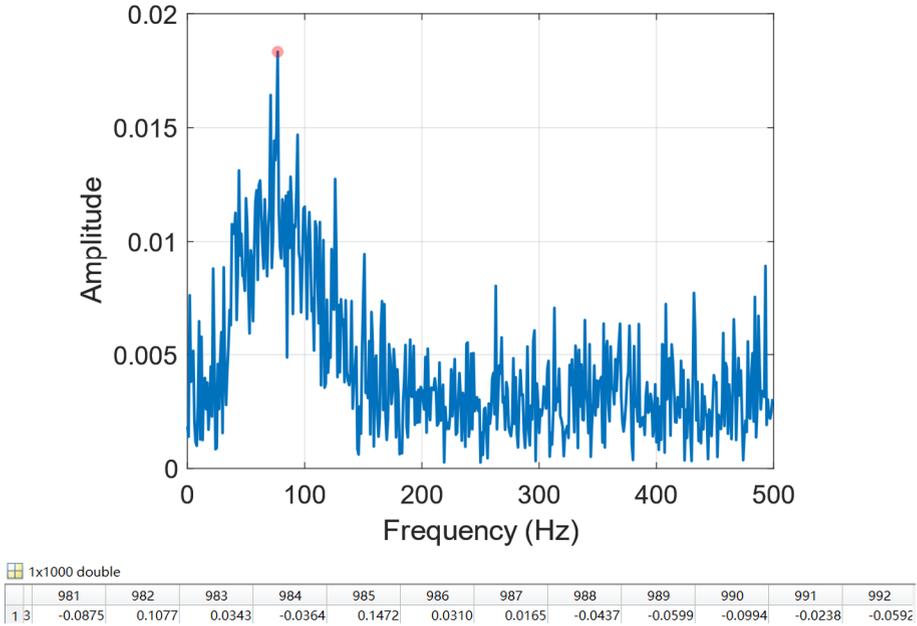


Fig. 1. FFT Spectrum of the Loaded Data.

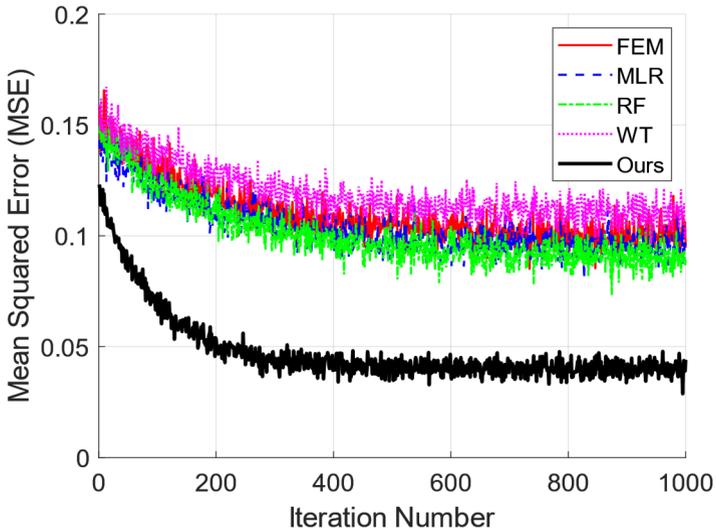


Fig. 2. Comparison of MSE for Different Methods

5 Conclusion

In conclusion, we propose a multi-stage deep learning model that integrates self-attention mechanism and graph neural network. The global and local characteristics in the well site and stratified coal spatio-temporal data are captured by multi-scale feature extraction together with spatial topological relationship modeling, while the multi-task learning framework is used to accomplish the simultaneous optimization of fracturing parameters and gas productivity. Future work will focus on enhancing the real-time adaptive optimization and prediction capabilities of the model in complex geological environments to offer more comprehensive technical support for deep coal seam mining and gas control. In the future, reinforcement learning can be integrated into the model, and dynamic learning and adaptive strategies can be used to further optimize the coal seam gas extraction process.

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