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A Microseismic Events Cluster Analysis-based Method for Modelling Complex Fractures in Geothermal Reservoir

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ABSTRACT

Proper characterization of fractures is critical for evaluating the effectiveness of fracturing jobs and optimizing well performance in geothermal energy production, unconventional reservoirs, and other areas. However, accurately determining the size, shape, and orientation of these fractures solely from microseismic events is challenging due to weak signals and noise. To address this challenge, this study proposes a novel workflow that directly builds accurate fracture models from microseismic events using the DBSCAN clustering algorithm and BiLSTM-ESMDA. The first step is to filter the noise in microseismic events using the DBSCAN clustering algorithm. Next, a 3D planar equation is employed to construct the fracture plane in each perforation segment. Based on the results of this step, reservoir simulations are performed iteratively using PEBI grids and a BiLSTM surrogate model. Multiple representation models are obtained to capture calibration uncertainty and enable subsequent studies of long-term well performance, such as history matching for production. Finally, the ES-MDA history auto-fitting algorithm is utilized to find the most appropriate fracture model for matching production data through iterative processes. The developed inversion method was implemented on a representative geothermal model with a complex fracture network. The results demonstrate that the DBSCAN clustering algorithm effectively reduces noise in microseismic activity and ensures the accuracy of fracture geometry. A large number of different fracture models can be quickly generated by the surrogate model to capture calibration uncertainty. ES-MDA is utilized to optimize the fracture model and identify the optimal solution. The fracture models constructed using this method exhibit fracture half-lengths that are 20%-30% smaller than those estimated by microseismic monitoring. Furthermore, the high level of historical fit for this horizontal well indicates that the complex fracture model is realistic for the mine site. This study introduces a new approach to building a complex fracture network. By using microseismic data and BiLSTM-ESMDA, this method provides a practical solution. The proposed workflow significantly improves the accuracy of fracture network prediction and computational efficiency compared to traditional fracture inversion methods, which are often plagued by high multi-solution, high computational cost, and difficulties with convergence.

1. INTRODUCTION

Geothermal energy stands out as a fundamental and highly promising clean energy source, drawing increasing attention in recent years due to its abundance, stability, and renewability on Earth (Randolph and Saar, 2011; X. Bu et al., 2012; X. Song et al., 2018; Q. Zhang et al., 2019). The development of geothermal energy plays a pivotal role in mitigating energy shortages and addressing environmental concerns arising from the use of fossil fuels. Typically, geothermal energy development involves circulating working fluids (such as water, CO2, etc.) through geothermal reservoirs to extract heat from the fluid. This extracted heat can be subsequently converted into electricity on the Earth's surface. Over the past few decades, the geothermal engineering industry has achieved substantial advancements, with the successful application of Enhanced/Engineered Geothermal Systems (EGS) marking a significant breakthrough (Huenges E., 2016). Before the advent of EGS, geothermal energy extraction was confined to naturally permeable fractured hydrothermal reservoirs. However, with the advent of hydraulic fracturing, geothermal resources can now be harnessed from hot dry rocks, predominantly composed of impermeable granite or other low-permeability rocks.

Hot dry rock reservoirs, characterized by high density and extremely low permeability, require careful remodeling to facilitate sufficient heat exchange between injected fluid and reservoir rock. This remodeling aims to establish well-connected, high-conductivity flow channels, thereby improving reservoir permeability and enabling smooth fluid circulation through the production well. However, the common occurrence of a single high-permeability fracture during reservoir remodeling can lead to fluid short-circuiting and premature thermal breakthroughs, posing challenges to the sustainable development of Enhanced Geothermal Systems (EGS). Therefore, the accurate prediction of hydraulic fracture patterns and effective control of fracture network structure is pivotal for establishing a complex artificial fracture network and enhancing the heat extraction efficiency of EGS (Grant and Bixley, 2011; Park et al., 2017; Yoshioka et al, 2019; and Cheng et al., 2020).

When acquiring specific parameters of hydraulic fractures, the primary source of information is hydraulic fracture monitoring technologies, with microseismic monitoring being a predominant method employed during the hydraulic fracturing process. The creation of microseismic event maps plays a crucial role in delineating the extent of fractures (Barree et al., 2002; Fisher and Warpinski, 2012). Rock fracturing during hydraulic fracturing generates seismic waves, detectable by sensors either on the surface or downhole. Analyzing seismic wave data through surface systems allows for the generation of a distribution map of seismic sources, offering specific parameters related to hydraulic fractures. As early as 2000, microseismic technology demonstrated success in the Barnett oil field in the United States, producing post-fracturing microseismic source images (Maxwell et al., 2002). Consequently, microseismic monitoring technology has evolved into a mature commercial tool in U.S. hydraulic fracturing operations, facilitating the monitoring of hydraulic fracturing effectiveness and the extraction of hydraulic fracture parameters. Through microseismic monitoring technology, approximate ranges of parameters such as length, dip angle, azimuth, height, and stimulated reservoir volume (SRV) of hydraulic fractures can be obtained. However, owing to the typically weak signals of microseismic events, prone to noise interference, reliance solely on microseismic events poses challenges in accurately determining the size, shape, and orientation of fractures. This limitation complicates the depiction of the fine morphology of hydraulic fractures through microseismic monitoring (Wang et al., 2021).

In recent years, researchers have endeavored to construct hydraulic fracture models utilizing microseismic data, yielding notable outcomes. Li et al. successfully calibrated a complex network of discrete fractures using microseismic data, effectively modeling fractures in shale gas horizontal wells and conducting reservoir production simulations (Li et al., 2022). Han Bach et al. corrected the geometric shapes of fractures based on microseismic data, subsequently integrating the fracture model into a reservoir model for reservoir production simulation and forecasting (Bachi et al., 2023). Additionally, Liu et al., incorporating natural fractures, employed microseismic data to extract morphological information about hydraulic fractures (Liu et al., 2022). They iteratively updated the reservoir model with the assistance of an automatic history-matching algorithm to determine fracture parameters. While these methodologies deliver relatively accurate fracture parameters, their application in the geothermal field is limited, and they necessitate a substantial number of reservoir numerical simulations. The repetitive nature of these simulation computations results in a computation speed that falls short of meeting the practical requirements of real-world problems. This is a critical challenge that current research must address.

Surrogate models offer approximations of the relationship between well operational parameters and production data, replacing the direct numerical computation of a set of partial differential equations involved in the thermo-hydro-mechanical-chemical coupling processes. These surrogate models have found application in problems related to geological fluid flow and geothermal energy. In recent years, deep learning algorithms have gained prominence for modeling challenges in underground energy development. For example, deep learning models can be trained using available data to predict pressure fields, temperature fields, stress fields, etc., within geothermal reservoirs (H. Aydin et al., 2020). Bassam et al. introduced a novel Artificial Neural Network (ANN) technique for determining pressure drops between inclined and vertical geothermal wells (A. Bassam et al., 2015). Haklidir developed a Deep Neural Network (DNN) model to predict geothermal fluid temperatures based on hydrogeochemical data from the geothermal reservoir (Haklidir and Haklidir, 2019). However, it is still challenging to construct reasonable surrogate models to characterize complex hydraulic fracture parameters.

To address the aforementioned issues, this study introduces a novel workflow for the inversion of hydraulic fracture parameters in geothermal development. The process is initiated by constructing an initial hydraulic fracture model based on microseismic data. Subsequently, a Bidirectional Long Short-Term Memory (BiLSTM) model is employed to establish a surrogate model. The Ensemble Smoother-Multiple Data Assimilation (ES-MDA) algorithm is then applied, utilizing production data such as temperature changes in production wells as benchmarks, to achieve accurate inversion of hydraulic fracture parameters. This method offers a practical and feasible solution for precisely determining the size, shape, and orientation of hydraulic fractures.

2. METHOD AND WORKFLOW

This section provides a concise overview of the methodology and workflow associated with hydraulic fracture parameter inversion. Firstly, it is essential to establish the equation for the hydraulic fracture model. Due to the phased implementation of downhole microseismic monitoring in practical operations, the microseismic events in different stages often overlap in the plane. Therefore, it is necessary to redivide the microseismic events based on the perforation section positions. Here, we use the principle of image segmentation algorithms in computer vision, taking the boundary lines of each perforation section as segmentation lines, considering microseismic points as pixels, and recognizing pixels in the rectangular area enclosed by every two boundary lines. This step avoids cumbersome calculations, ensuring that there is no overlap between microseismic points in each stage, and preparing for the subsequent clustering analysis. Microseismic events are weak signals susceptible to noise from various sources, requiring further data filtering. Experimental studies have found that most hydraulic fractures exhibit a "cluster expansion" trend, and density clustering thinking should be used for analysis. The Density-Based Spatial Clustering Algorithm with Noise (DBSCAN), recognized for its ability to manage noise, can partition regions with sufficiently high density into clusters (Ester et al., 1996). It defines clusters as the largest collection of points connected by density and can implement clustering in spatial databases containing noise. This algorithm is used for clustering analysis of microseismic point sets in three-dimensional space for each perforation section, determining the required microseismic points set for modeling. A three-dimensional plane equation is constructed to characterize hydraulic fractures, obtaining accurate hydraulic fracture models for each perforation section. The complete process for this part is shown in Figure. 1 and the detailed work in this part has been discussed in our previous papers (Sun et al., 2023).

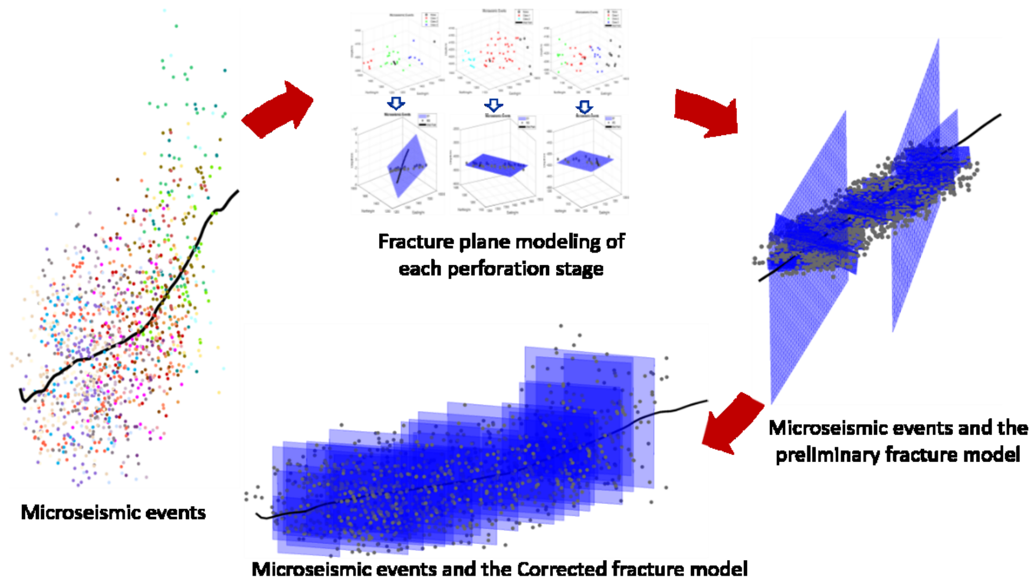


Figure 1: Workflow of the fracture model construction method based on DBSCAN.

Artificial fractures exhibit a wide range of planar extensions, vertically traversing multiple small layers, with permeability significantly higher than that of the matrix and natural fractures, exerting robust control over the direction and scale of fluid flow. Particularly in proximity to artificial fractures, the dynamics of fluid movement undergo rapid changes. The production well capacity proves highly sensitive to factors such as the distribution, geometric dimensions of artificial fractures, and the positional relationship between fractures and wells, necessitating a detailed characterization of these features. In this study, PEBI grids are employed to represent the true morphology of the artificial fracture network and the grids are densified in the modified area to refine the flow characteristics near the fractures. Given that fractures in geothermal reservoirs are primarily vertical or approximately vertical, during the grid division, the fractures are initially projected onto the plane. Wells, fractures, and reservoirs are then gridded separately, constructing a 2D PEBI grid. Subsequently, a 3D PEBI grid is obtained based on depth (Figure.2). This study utilizes the geothermal simulation module in the MATLAB Reservoir Simulation Toolbox (MRST) to simulate the production of fractured reservoirs. The detailed implementation process of the model is described in the reference (Lie 2014).

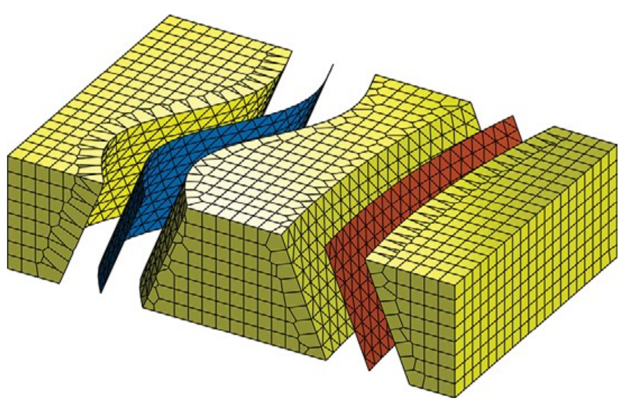


Figure 2: The 3D PEBI grid (yellow) conforms to two triangulated surfaces (red and blue): The grid is shifted away from the surfaces in the illustration to visualize the conforming faces (Lie, 2014).

Following this, the Bidirectional Long Short-Term Memory (BiLSTM) neural network is utilized to construct a surrogate model. Hochreiter and Schmidhuber (1997) introduced a Long Short-Term Memory (LSTM) network to address time series problems. LSTM, an advanced Recurrent Neural Network (RNN) architecture extensively applied in deep learning, diverges from traditional RNNs by incorporating gate structures within each recurrent unit. These gates closely emulate the information transmission patterns of biological neurons, enabling the network to retain longer-term sequential information without necessitating additional adjustments. More recently, BiLSTM has been introduced to further amalgamate information from both directions. Specifically, we integrate information from backward (from future to past) and forward (from past to future) directions for predictions. As shown in Figure.3, the fundamental units of BiLSTM resemble those of ordinary LSTM and encompass input gates, forget gates, candidate units, and output gates. In this study, a total of 7 input parameters, including fracture half-length, fracture porosity, fracture permeability, initial reservoir temperature, thermal conductivity, rock heat capacity, and time step, are considered. The output is the temperature change in the production well.

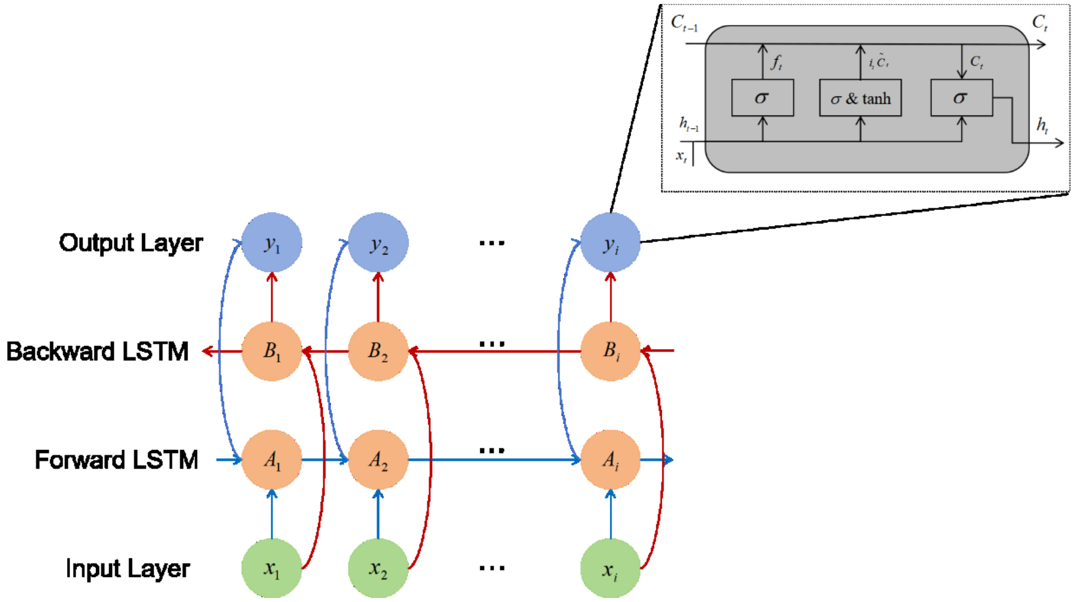


Figure 3: The structure of Bidirectional Long Short-Term Memory.

Lastly, the Ensemble Smoother for Multiple Data Assimilation (ES-MDA) algorithm is applied for the inversion of fracture parameters. ES-MDA, recognized as a prevalent data assimilation method, is esteemed for its simplicity, user-friendly nature, and effective performance. It can achieve relatively accurate historical data fitting.

The inversion process is depicted in Figure.4, encompassing four main steps. Initially, uncertain fracture parameters and their prior information, including ranges and distributions, are identified based on microseismic monitoring data. Following this, Latin hypercube sampling is employed to sample the training and testing sets. High-fidelity simulations (MRST) are conducted to gather input and output data. Subsequently, the collected data is utilized to train the BiLSTM surrogate model. Then, ES-MDA is applied to invert the uncertain fracture parameters, utilizing the trained BiLSTM as the forward model to reduce computational complexity. Finally, the inverted uncertainty parameters are input into the high-fidelity model for comparison. If the predicted values exhibit a sufficiently small error compared to the actual response, the inversion is considered accurate. Otherwise, the accuracy of the BiLSTM surrogate needs examination, and a revisit to the previous information may be necessary.

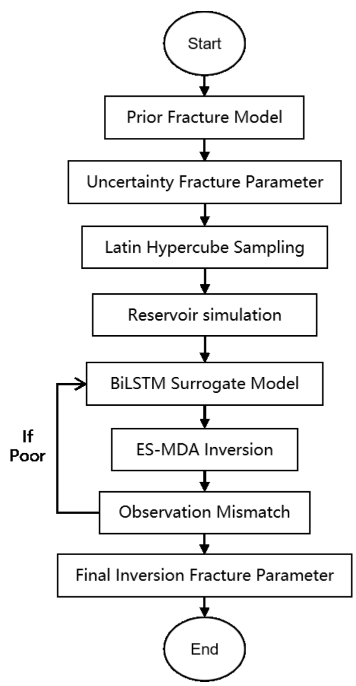


Figure 4: Fracture parameter inversion workflow based on BiLSTM-ESMDA.

3. APPLICATION

To illustrate the effectiveness of the aforementioned method in the inversion of uncertain fracture parameters during geothermal exploitation, we employed an Enhanced Geothermal System (EGS) provided by MRST as a reference model (Lie, 2019). As shown in Figure.5, this model was established through the fracturing of underground low-permeability, high-temperature rocks. It comprises an injection well and a production well, with cold water primarily injected, flowing within the fractures. These fractures function as heat exchangers, facilitating the extraction of heat from the reservoir. Figure.6 shows the temperature distribution at different time steps of water injection. The detailed parameters of the geothermal reservoir are outlined in Table 1. Before training the Bidirectional Long Short-Term Memory (BiLSTM) surrogate model, we normalized the uncertain parameters to the range [0,1] to enhance accuracy.

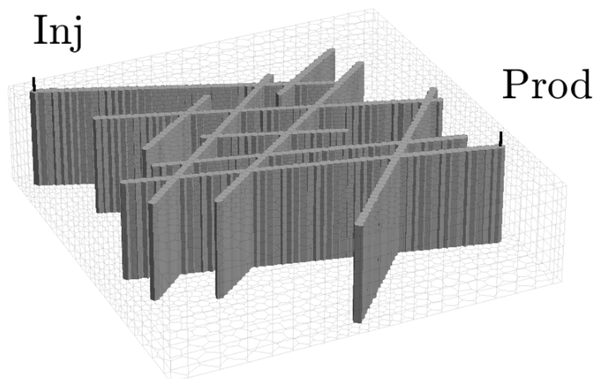


Figure 5: Utilizing PEBI to characterize fracture model.

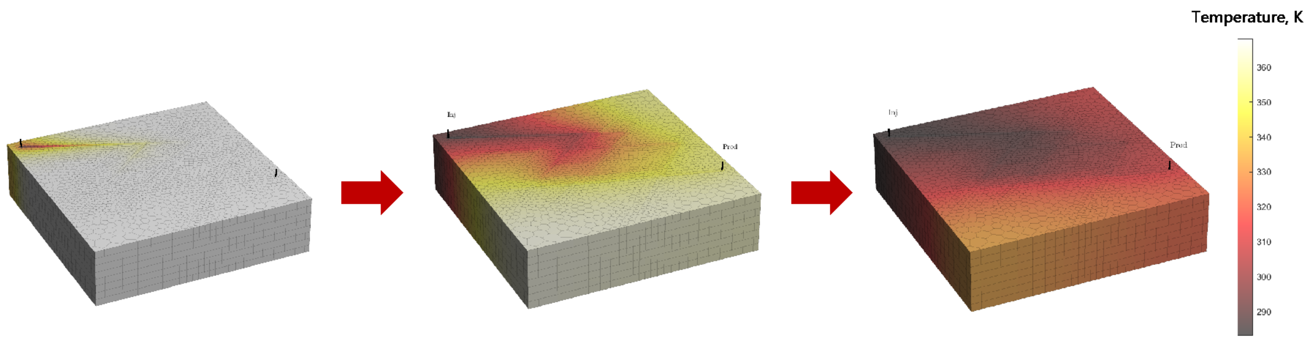


Figure 6: The change of the geothermal reservoir temperature distribution at different times.

Table 1: Basic geothermal reservoir parameters used in the case.

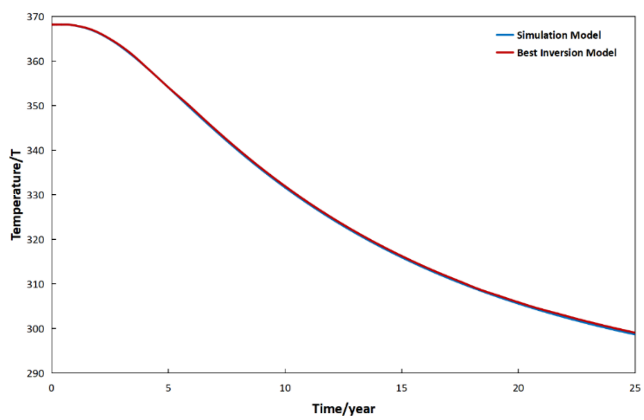
Model Parameter	Value	Unit
Model dimension	50x50x15	m
Matrix porosity	0.05	-
Matrix permeability	0.1	mD
Initial reservoir temperature	358.15	K
Rock heat capacity	1400	J/(g·K)
Rock thermal conductivity	3	W/(m·K)
Injected water temperature	283.15	K
Water injection rate	30	m^3/day
Water heat capacity	4.2	J/(g·K)
Water thermal conductivity	0.6	W/(m·K)

Utilizing microseismic monitoring data, we developed a precise model for hydraulic fracture networks. Parameters associated with fractures, such as half-length, porosity, and permeability, were chosen as uncertain fracture parameters, and their ranges are outlined in Table 2. Employing Latin Hypercube Sampling, we generated 500 sets of parameter combinations as the initial model. From these, 450 models were designated as training samples, while the remaining 50 were assigned as validation samples for training the Bidirectional Long Short-Term Memory (BiLSTM) network. The neural network structure underwent adjustments to bolster its feature extraction capabilities.

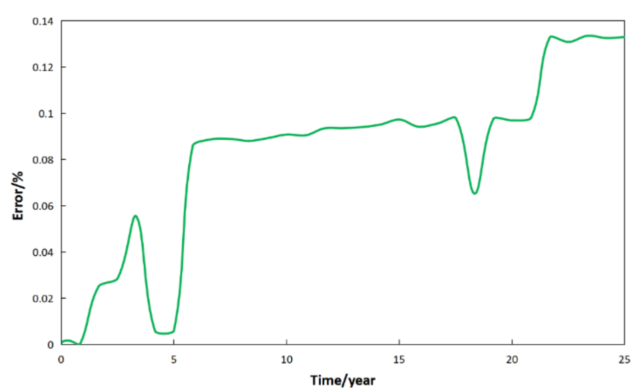
Table 2: The range of the uncertain fracture parameters.

Fracture Parameter	Min	Max	Mean	Unit
Fracture half-length	6.49	22.41	15.41	m
Fracture porosity	0.6	1	0.8	-
Fracture permeability	0.01	0.15	0.1	mD·m

The trained Bidirectional Long Short-Term Memory (BiLSTM) served as a surrogate model, and the Ensemble Smoother with Multiple Data Assimilation (ES-MDA) method was employed to conduct a history matching inversion for the temperature changes in the production well. The inversion aimed to obtain hydraulic fracture parameters, covering a simulation period of 25 years with a total of 38-time steps. The results of the inversion of uncertain fracture parameters were then fed into a high-fidelity model, and the temperature changes were compared with the inverted values. As depicted in Figure. 7a and illustrated in Figure. 7b, the error between these two sets of values was minimal, affirming the feasibility and effectiveness of this approach for hydraulic fracture parameter inversion in geothermal reservoirs.



(a)



(b)

Figure 7: Comparison between the Simulation model and the best inversion fracture model: (a) The temperature change between the high-fidelity simulation and the BiLSTM-ESMDA inversion; (b) The errors between the two sets of values.

4. CONCLUSIONS

This article introduces a novel approach for inverting complex hydraulic fracture parameters in geothermal reservoirs. The initial hydraulic fracture model is constructed based on microseismic data, and high-fidelity numerical simulation models are executed to obtain training data. The Bidirectional Long Short-Term Memory (BiLSTM) is then employed to establish a surrogate model, and the Ensemble Smoother with Multiple Data Assimilation (ES-MDA) algorithm is applied to accurately invert the hydraulic fracture parameters, utilizing the temperature changes in the production well as a benchmark. In conclusion, the key findings of this study are as follows:

(1) In the hydraulic fracturing process of hot dry rock, injecting thousands of cubic meters of fracturing fluid is required to form a complex fracture network. Microseismic monitoring offers a preliminary range of fracture parameters, such as the half-length. However, these values are generally inaccurate and tend to be overestimated. Particularly in geothermal reservoirs, the actual modification range is smaller than anticipated.

(2) The proposed BiLSTM-ESMDA method efficiently and accurately achieves hydraulic fracture parameter inversion. Given the complex morphology of hydraulic fractures, representing the fracture network with PEBI grids results in the slow execution of high-fidelity models. The introduced inversion method reduces the single numerical simulation run time from five minutes to around ten seconds, significantly improving computational efficiency for practical applications. The inversion results of uncertain fracture parameters align well with the actual temperature responses, demonstrating the robustness of the method.

(3) The paper focuses solely on the inversion of three uncertain fracture parameters, such as the half-length of hydraulic fractures, without exploring the uncertainty of fundamental parameters in geothermal reservoirs, such as porosity and permeability. Subsequent research could extend this method to invert more uncertain parameters.

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