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Perspective

Fracturing and thermal extraction optimization methods in enhanced geothermal systems

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Abstract:
Fracture networks, fluid flow and heat extraction within fractures constitute pivotal aspects of enhanced geothermal system advancement. Conventional hydraulic fracturing in dry hot rock reservoirs typically requires high breakdown pressure and only produces a single major fracture morphology. Thus, it is imperative to explore better fracturing methods and consider more reasonable coupling mechanisms to improve the prediction efficiency. Cyclic fracturing using liquid nitrogen instead of water can generate more complex fracture networks and improve the fracturing performance. The simulation of fluid flow and heat transfer processes in the fracture network is crucial for an enhanced geothermal system, which requires a more comprehensive coupled thermo-hydro-mechanical-chemical model for matching, especially the characterization of coupling mechanism between the chemical and mechanical field. Based on the results of field engineering, laboratory experiments and numerical simulation, the optimum engineering scheme can be obtained by a multi-objective optimization and decision-making method. Furthermore, combining it with the deep-learning-based proxy model to achieve dynamic optimization with time is a meaningful future research direction.

1. Introduction

Enhanced geothermal systems (EGS) stand out as efficient means to harness hot dry rock resources (Slatlem Vik, et al., 2018; Shi, et al., 2019). Fracture networks, fluid flow and heat extraction within fractures constitute central elements of EGS advancement (McClure and Horne, 2014; Shi, et al., 2018). Conventional hydraulic fracturing in hot dry rock (HDR) reservoirs typically requires high breakdown pressure and only produces a single major fracture morphology, increasing the concerns of seismic events and the environmental burden of freshwater sourcing/treatment. In addition, deep geothermal resources typically exhibit high temperature, pressure and stress, compounded by intricate hydrochemical environments. Consequently, interactions emerge among fluid flow, heat transfer, mechanical deformation, and chemical reactions within fractured geothermal reservoirs. Long-term injection and production induce discernible alterations in reservoir properties, productivity and lifespan. Therefore, it is imperative to achieve the efficient and accurate prediction of productivity by using better fracturing methods and more reasonable coupling mechanisms. Traditional prediction can obtain the influencing mechanism of subjective factors to optimize the injection-production scheme of main control factors by multi-objective optimization; however, it is unable to realize the dynamic optimization with time. Thus, artificial intelligence can be considered for the prediction of production capacity and obtaining the optimal injection-production scheme, thus promoting geothermal development. In recent researches, a new reservoir stimulation technique called cyclic liquid nitrogen (LN_2) fracturing was explored, and the aforementioned complexities could be addressed when combined

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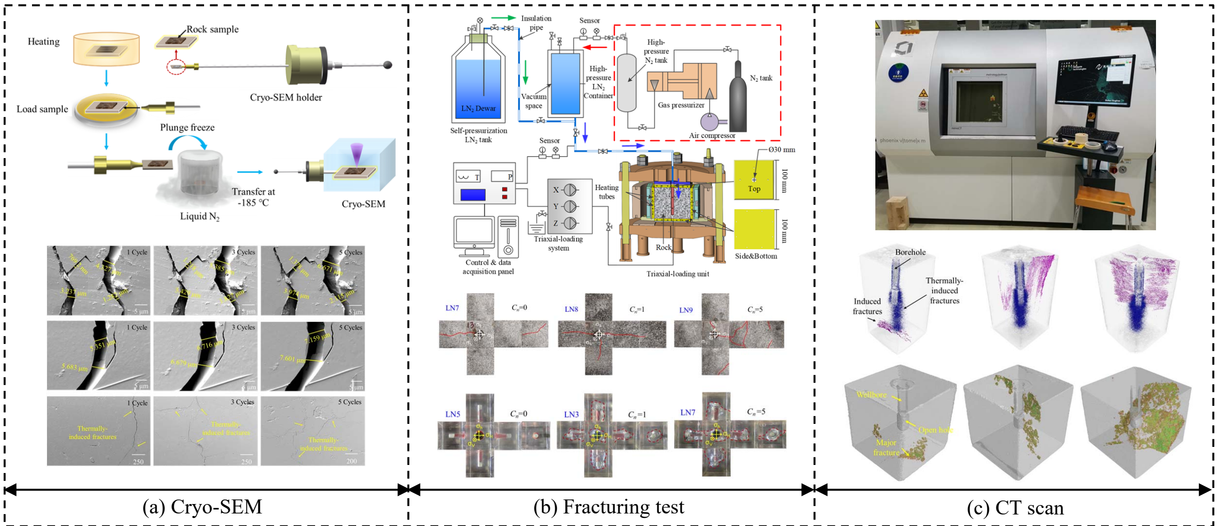


Fig. 1. Research framework of cyclic LN_2 fracturing on HDR: (a) Cryo-scanning electron microscopy analysis to analyze the fracture initiation behavior of HDR after cyclic/single LN_2 cooling treatment under cryogenic conditions (Yang et al., 2021), (b) true-triaxial fracturing test to evaluate the cyclic/single LN_2 fracturing performances on high-temperature granites (Cha, et al., 2018; Hofmann, et al., 2018; Hong, et al., 2023), (c) CT scan to observe and analyze the fracture-network patterns after the fracturing tests (Yang et al., 2023).

with this fracturing method and a fully coupled thermo-hydro-mechanical-chemical (THMC) model. In the optimization phase, a multi-objective optimization and decision-making approach is utilized for balanced geothermal development optimization. Considering the limitation of computation efficiency, proxy models for the fast prediction of dynamic temperature and pressure fields is another research trend; a well-trained proxy model is used for various issues in geothermal reservoir engineering to improve computation efficiency.

2. Cyclic LN_2 fracturing

Conventional hydraulic fracturing in HDR reservoirs typically requires high breakdown pressure and only produces a single major fracture morphology, which also increases the likelihood of seismic events and the environmental burden of freshwater sourcing/treatment. Cyclic LN_2 fracturing, which combines cyclic soft stimulation and LN_2 fracturing, can address these limitations. The relevant research framework is shown in Fig. 1. In cyclic LN_2 fracturing, low-temperature LN_2 is injected in a cyclic manner, i.e., alternating between high injection rate and low injection rate (or stop injection). This cyclic LN_2 injection causes fatigue damage in the formation rocks due to the alternating thermal stress and fluid pressure, leading to the initiation, propagation and bifurcation of fractures, which ultimately results in the formation of complex fracture networks and improves the stimulated reservoir volume. Cryo-scanning electron microscopy can be applied to study the fracture initiation behavior of HDR after cyclic/single LN_2 cooling treatment under cryogenic conditions. The study of cyclic/single LN_2 fracturing performance on high-temperature granites needs to implement a self-developed true-triaxial fracturing equipment. Additionally, CT scan is suitable for observing and quantitatively describing the three-dimensional fracture-network patterns after fracturing tests.

Cyclic LN_2 fracturing has 21.3% to 67.2% lower breakdown pressure than cyclic water fracturing under the combined action of alternating thermal stress and fluid pressure. The phase transition of LN_2 inside the fractures promotes fracture propagation, and the low viscosity and interfacial tension of LN_2 assists in reducing the fracture initiation pressure and promoting the formation of complex fracture networks. Cyclic LN_2 fracturing generates complex fracture networks characterized by “thermally-induced fractures + major fractures + branching fractures”, while cyclic water fracturing mainly produces single major fractures. Cyclic LN_2 fracturing can significantly increase the fracture length, tortuosity, area, and volume by 210.8%, 19.6%, 143.6%, and 142.6%, respectively. Complex fracture networks are still achievable with cyclic LN_2 fracturing under higher horizontal stress differences. Increasing the initial rock temperature, cycle numbers, cooling treatment time, and cooling pressure contributes to lower breakdown pressure and the formation of complex fracture networks. However, when the cycle number is 0, a single major fracture is formed and the breakdown pressure might be even higher than that in water fracturing. This indicates that cyclic LN_2 cooling pretreatment is crucial for enhancing LN_2 fracturing performance. The alternating thermal exchange between LN_2 and high-temperature rock during cyclic loadings results in more significant thermal fatigue damage, facilitating the reduction of breakdown pressure and improving the fracturing performances. Furthermore, the cyclic LN_2 injection will cause the coupled hydraulic-thermal stress to intensify and relax periodically, leading to the periodic opening and closing of fractures. The exposure of high-temperature reservoirs to freeze-thaw cycles, stress oscillation and fatigue damage potentially enhances the stimulated reservoir volume. The above

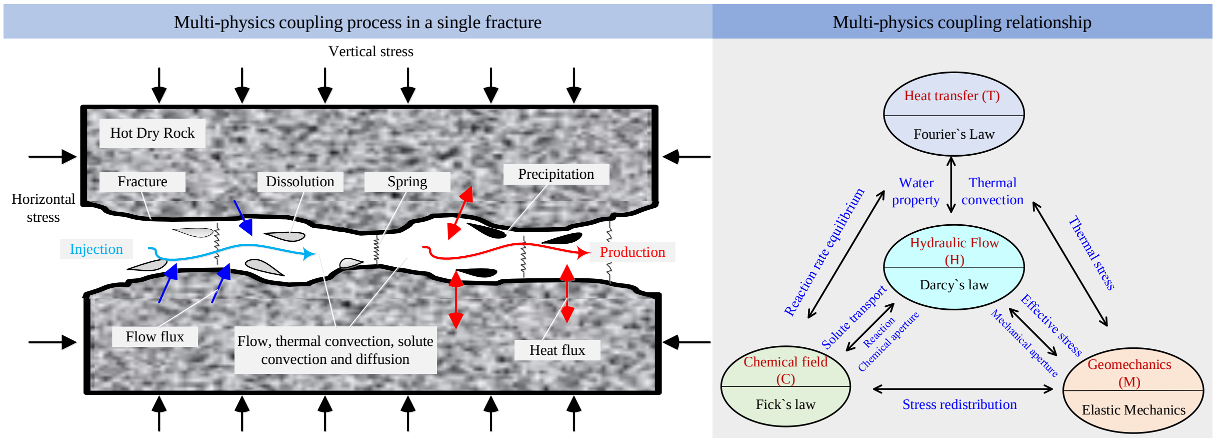


Fig. 2. The THMC coupling relationship (Song et al., 2022).

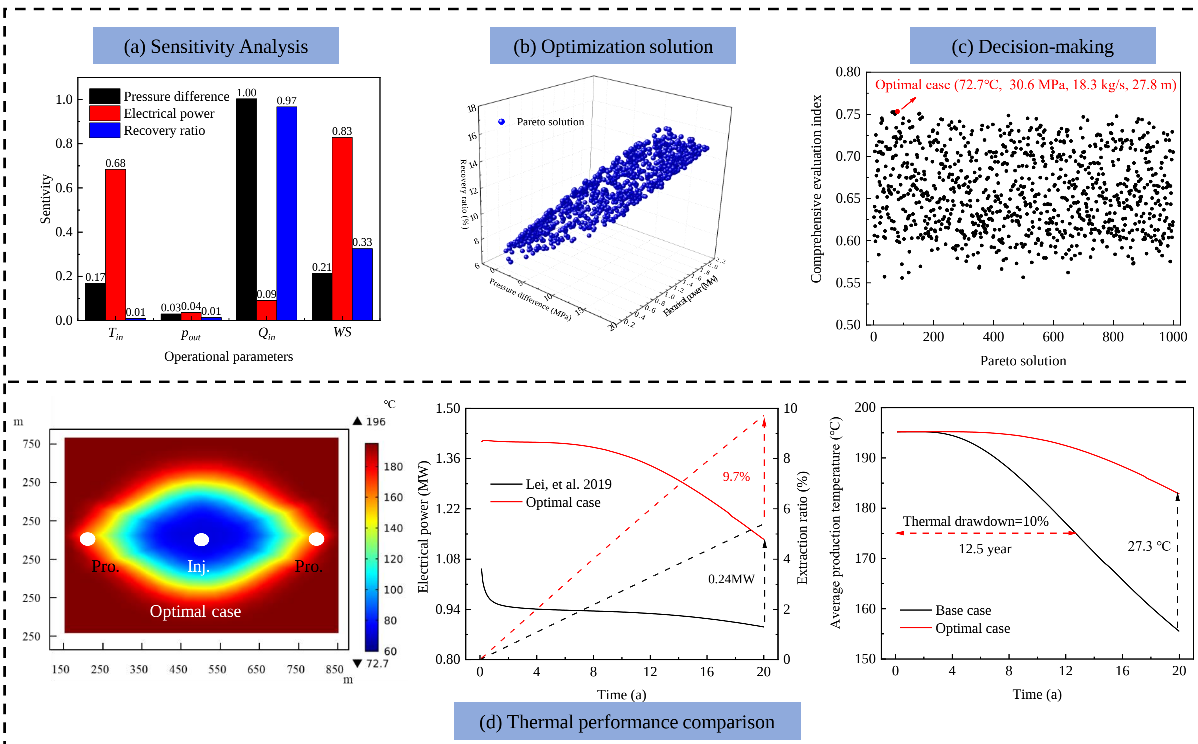
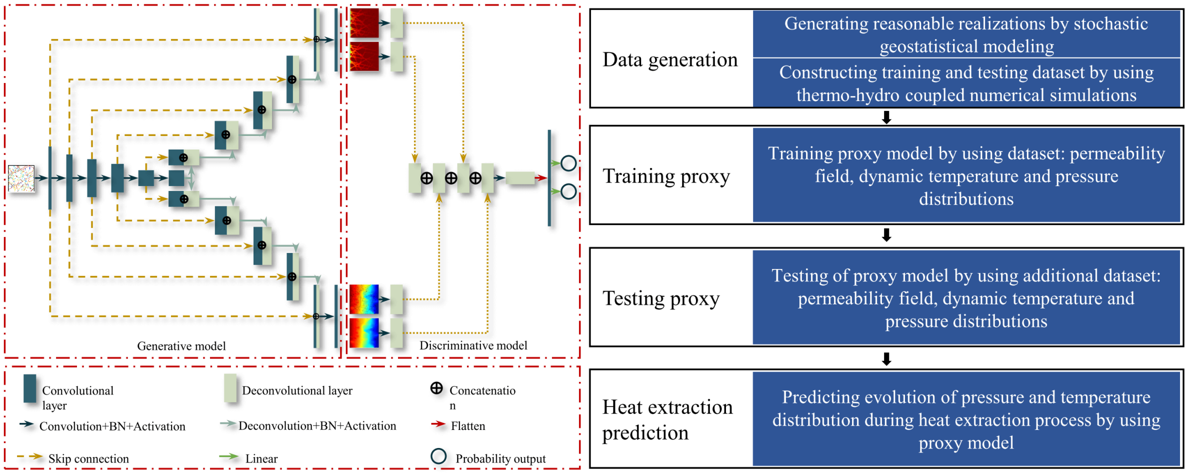


Fig. 3. Multi-objective optimization and decision-making for the efficient development of EGS (Song et al., 2021): (a) dimensionless sensitivities of production performance to different operation parameters, (b) pareto solution for the multi-objective optimization of geothermal field production, (c) decision making from the pareto solution, (d) temperature distribution for the optimal case after 20 years (left); production comparison among previous optimal and base case (middle and right).

observations provide a theoretical and experimental foundation for the development of HDR using cyclic LN_2 fracturing.

3. Multi-objective optimization and decision-making

The establishment of a fully coupled THMC model is imperative for EGS reservoir production with the fracture aperture as the coupling node. The THMC coupling relationship is shown in Fig. 2. This model introduces a novel mechanical-chemical coupling, wherein chemical deformation induces the redistribution of mechanical stress. This coupling is formulated through equations of chemical aperture and mechanical aperture. The distinct contributions of mechanical and chemical behaviors to the reservoir characteristics are quantified across temporal and spatial dimensions. Mechanical effects have a pronounced influence around the injection well in the early stage. In contrast, chemical effects assume dominance at greater distances from the injection well, with their impact spanning the later stage. There are mainly thermo-driven and chemical-driven regions during stable production.



(a) Architecture of the proxy model (b) Workflow of establishing the proxy model

Fig. 4. (a) Illustration of the proxy model architecture for the heat extraction process by interwell fluid circulation based on coupled generative adversarial network (Co-GAN). The interwell fluid flow pathways (e.g., permeability distribution or fracture network) and time are the inputs, and reservoir temperature and pressure distributions are the desired outputs. (b) Workflow of establishing the proxy model.

Exploring the THMC coupled process bears substantial significance for the profound comprehension of reservoir variations, production trends and the optimization of efficient operations.

The efficient development of EGS necessitates thermal production optimization to fully harness the potential of high-temperature reservoirs. This optimization is a challenge due to the inherent trade-off between positive objectives, such as net heat power, electricity and extraction ratio, as well as that between negative objectives, such as lifespan, pressure differentials and human input (Samin, et al., 2019). This conundrum complicates the simultaneous optimization process that aims to define operational parameters including injection rate, injection temperature, production pressure, and well spacing. To address this complexity, multi-objective optimization and decision-making is a suitable approach for balanced geothermal development optimization, which is shown in Fig. 3. This approach combines multi-physics coupling modeling, multiple regression, the non-dominated sorting genetic algorithm, and the technique for order preference by similarity to the ideal solution with integrated weighting. Initially, parametric analyses are conducted by multi-physics coupling geothermal production models for the Gonghe field. The sensitivity analysis identifies injection rate as the most influential parameter on heat extraction, followed by well spacing and injection temperature, while production pressure has the least impact. Subsequently, multi-regression techniques establish a production proxy model linking operational parameters and production indices. These models are incorporated into the non-dominated sorting genetic algorithm to yield a Pareto set of potential optimal operations, which are further refined using the integrated weighting decision-making method. The ultimate optimal parameter combination can alleviate thermal breakthrough and reduce pressure differentials by 8 MPa compared to the basic case. Notably, this optimal scenario boosts a 50% higher energy extraction rate than a previous case (Lei, et al., 2019). Comparative analyses involving multi-objective, single-objective and parametric optimization have established the effectiveness of the proposed multi-objective optimization and decision-making approach, showcasing its capacity for balanced optimization. This can provide a valuable reference for the efficient development of EGS.

4. Deep-learning-based proxy model

The deep-learning-based proxy model is a highly attractive option that is capable of accelerating the simulation of geo-energy production process. Generative adversarial network (GAN) and its variants have become one of the most prevalent algorithms for the construction of proxy models (Zhong et al., 2020). In recent researches, the coupled generative adversarial network (Co-GAN) has been successfully applied to develop a proxy model to forecast the temporal and spatial evolution of formation pressure and fluid saturation in heterogeneous reservoirs during geo-energy production (Zhong et al., 2021). The Co-GAN model contains two pairs of generative and discriminative models for learning the joint distributions of the target high-dimensional image data. For the proxy model (i.e., the generative models of Co-GAN), the inputs consist of permeability field, injection rate and time, and the outputs are reservoir pressure and fluid saturation with respect to forecast time. Image data obtained from reservoir numerical simulations are used to train the Co-GAN model, then testing data are adopted to appraise the accuracy and generalization ability of the trained model.

The proxy model can predict the temporal and spatial evolution of formation pressure and fluid saturation with high accuracy. For the geothermal energy production process, the evolution of temperature and seepage fields between wells are the most concerning problems. Based on the aforementioned research, a framework is used for the construction of a proxy model for the fast prediction of dynamic temperature and pressure distributions during heat extraction via interwell working fluid circulation (e.g., water or CO_2), and the architecture of the proxy model is designed based on Co-GAN (see Fig. 4). The interwell fluid flow pathways (e.g., permeability distribution or fracture network) and time are the inputs, and dynamic reservoir temperature and pressure are the desired outputs. In addition, stochastic geostatistical modeling and full-scale thermo-hydro numerical simulations are adopted for the generation of training and testing data (Wang et al., 2022), and the Co-GAN model needs to be trained following the workflow as shown in Fig. 4. Subsequently, the well-trained proxy model can be used for various issues in geothermal reservoir engineering, such as parameter optimization, uncertainty analysis and inversion problem, in order to improve the computation efficiency.

5. Conclusions

Cyclic LN_2 fracturing features a lower breakdown pressure than cyclic water fracturing under the combined action of alternating thermal stress and fluid pressure. The phase transition of LN_2 inside the fractures promotes fracture propagation, and the low viscosity and interfacial tension of LN_2 assists in lowering the fracture initiation pressure and promoting the formation of complex fracture networks.

Thermal breakthrough is effectively alleviated by the ultimate optimal parameter combination obtained by the multi-objective optimization and decision-making approach. This strategy shows capacity for balanced optimization and provides a valuable reference for the efficient development of EGS. During the construction of the proxy model, the interwell fluid flow pathways and time are the inputs, and dynamic reservoir temperature and pressure are the desired outputs. The proxy model based on stochastic geostatistical modeling and full-scale thermo-hydro numerical simulation can be applied in various tasks in geothermal reservoir engineering to improve the computation efficiency.

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Conflict of interest

The authors declare no competing interest.

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