PROCEEDINGS, 51st Workshop on Geothermal Reservoir Engineering
Stanford University, Stanford, California, February 9-11, 2026
SGP-TR-230

Machine Learning-based History Matching of Discrete Fracture Network Fields at Utah FORGE Enhanced Geothermal System

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Keywords: Enhanced Geothermal System, Utah FORGE, Diffusion Model, ES-MDA, Latent space-based data assimilation

ABSTRACT

Accurate subsurface characterization of Enhanced Geothermal Systems (EGS) is essential yet challenging due to structural complexity and data scarcity. We propose a data assimilation framework combining a deep generative denoising diffusion implicit model (DDIM) and Ensemble Smoother with Multiple Data Assimilation (ES-MDA) for characterization at the Utah FORGE site. Our ES-MDA approach utilizes permeability fields upscaled from Discrete Fracture Networks (DFNs) to train the DDIM and a surrogate model for efficient thermal-hydraulic simulation using permeability fields as input. Using pressure data from the April 2024 circulation test at the Utah FORGE site, we estimated the permeability field with calibrated permeability ensemble fields and subsequentially conducted a one-month performance simulation as a validation way against pressure and temperature data at the injection and production wells from the Aug. – Sep. 2024 recirculation test. The results demonstrate that our framework accurately predicts injection pressures and production temperatures consistent with field measurements. Due to its modular framework, machine learning-based history matching approach can be utilized to characterize stimulated enhanced geothermal systems.

1. INTRODUCTION

The efficiency and longevity of Enhanced Geothermal Systems (EGS) depends on the effective stimulation of hot, dry rock to create permeable fracture networks (e.g., Ghassemi, 2012). Because subsurface data is often sparse, data assimilation methods like the Ensemble Smoother with Multiple Data Assimilation (ES-MDA) are essential for integrating dynamic pressure and temperature data to reduce model uncertainty (Emerick and Reynolds, 2013). However, in EGS both natural and stimulated discrete fracture networks exhibit strong non-Gaussian characteristics. Hence, standard ES-MDA formulations that rely on Gaussian priors (Ghorbanidehno et al., 2020) may not be properly applicable for fractured geothermal reservoirs. Deep generative learning approach provides a pathway to overcome these limitations by learning complex, non-linear geological priors (Kim et al., 2021, Bao et al., 2024, Bao et al., 2025). Among various deep generative models, Denoising Diffusion Implicit Models (DDIM) (Song et al., 2020) have recently demonstrated superior stability and fidelity in generating realistic subsurface structures.

This paper presents a novel application of DDIM coupled with ES-MDA to characterize the permeability field at the Utah FORGE site. We leverage pressure data from a short-term and long-term circulation tests in April and Aug.-Sep. 2024, respectively, at the Utah FORGE site (Xing et al., 2025) for data assimilation. This approach demonstrates a robust workflow for characterizing complex EGS reservoirs beyond the limitations of Gaussian-based inversions.

2. METHOD

We characterize the permeability and porosity of the FORGE site as spatially heterogeneous fields significantly influenced by both natural and stimulated fractures embedded within the background rock matrix. Our initial DFNs are based on recent conceptual models at the Utah FORGE site (Finnila and Jones, 2024). To represent the complex distribution of the subsurface permeability fields, we generate an ensemble of probable property fields using a Discrete Fracture Network (DFN) tailored to site-specific parameters. These realizations serve as training data for a deep generative model. This approach not only significantly accelerates the generation of fractured permeability fields but also encodes key geological structures into a representative latent feature space.

2.1 Discrete Fracture Networks

DFN models have been widely used to represent fractures as discrete planar features with realistic geometry and properties. In this work, DFN models are used to capture the heterogeneity and connectivity of fracture networks and assess fracture-matrix interactions. dfnWorks (Hyman et al., 2015) was used to generate background natural fractures, and the up-to-date model parameters from Finnila and Jones (2024) were used for generating the fractures at the Utah FORGE EGS site. A total of 500 DFNs consisting of natural and induced fractures were generated with the size of 200 m × 200 m × 200 m, and the upscaled permeability fields on a 500 m x 500 m x 500 m domain were used for training the generative diffusion model explained in the Section 2.2. Generated DFN fields are upscaled to produce permeability fields at the grid system using an upscaling method from Sweeney et al. (2020) as described in Bao et al. (2025) (see Figure 1).

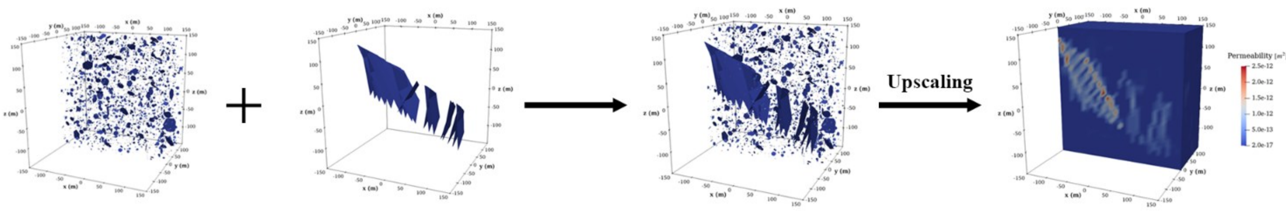

Figure 1: Schematic of permeability field generation. A generated DFN filed is combined with an indued fracture network to construct DFNs at the Utah FORGE. The combined DFN field is then upscaled to generate permeability field (right).

2.2 Denoising Diffusion Implicit Model

We utilize the Denoising Diffusion Implicit Model (DDIM) (Song et al., 2020) to capture the underlying generative mechanism of the FORGE site permeability fields, using the dataset of 500 realizations described in Section 2.1. The DDIM framework operates through two coupled processes: (1) a forward process that systematically adds noise to a fractured field sample until it converges to an independent and identically distributed (i.i.d.) Gaussian random field; and (2) a reverse process that reconstructs a coherent, fractured permeability field by denoising the random Gaussian input using a neural network model (Figure 2). The forward process is mathematically defined as (Song et al., 2020):

$$x_t = \sqrt{\alpha_t} x_0 + \sqrt{1-\alpha_t}\epsilon \tag{1}$$

where x_0 is the original image, and x_t is the generated image. α_t is a decreasing sequence and $\alpha_t \in (0,1)$. $\epsilon \sim N(0,I)$ is the normal noise used to perturb the image and the noise in the generation is estimated using a neural network ϵ_θ given the noised image x_t. Then the reverse problem reconstructs the targe image x_0 from the random noise field x_t with trained neural network ϵ_θ as:

$$x_0 = \frac{x_t - \sqrt{1-\alpha_t}\epsilon_\theta}{\sqrt{\alpha_t}} \tag{2}$$

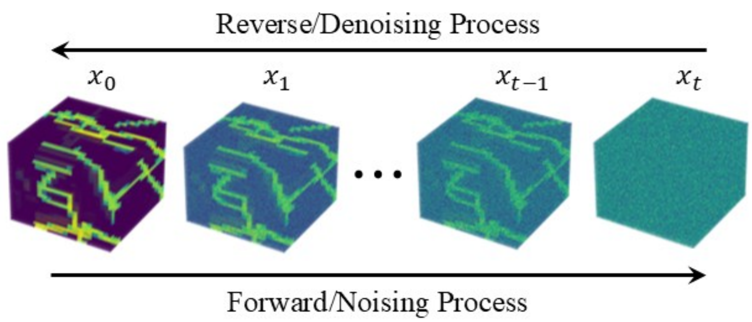

Figure 2: The forward and reverse processes of the Denoising Diffusion Implicit Model (DDIM).

2.3 Ensemble Smoother with Multiple Data Assimilation

The forward model MALAB Reservoir Simulation Toolbox (MRST) (Lie, 2019) is used for simulating thermal-hydraulic(-mechanical) (THM) processes. The pressure and temperature fields from MRST simulations using input of permeability fields and injection/production configurations at the Utah FORGE are used to develop a deep learning surrogate model as described in Bao et al. (2025). An UNet-based neural network is trained to predict pressure and temperature over time at 3D numerical grid as a function of permeability fields. At the Utah FORGE site, the observed data includes pressure and temperature profiles at injection and production wells. We aim to estimate permeability and porosity distribution of the FORGE site using observed data and the identification of unknown permeability field is performed by ES-MDA (Emerick and Reynolds, 2013) where we use the latent space of the DDIM to update the permeability field. Specifically random values are sampled from a Gaussian distribution in the latent space, and then the trained DDIM is used to generate multiple realizations from the latent variables. Prediction of pressure and temperature fields are performed using the UNet-based surrogate model as the forward model, and the latent variables are updated using ES-MDA based on the mismatch between the simulated and observed data as shown in Figure 3.

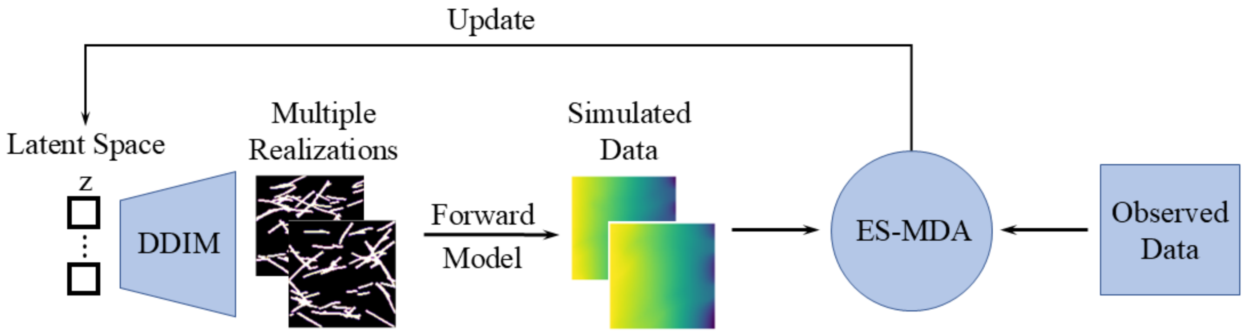

Figure 3: The workflow of coupling DDIM and UNet-based forward model with ES-MDA.

3. RESULTS

3.1 Circulation Test Data and Forward Model setup

We consider the April 2024 9-hour circulation test between wells 16A (78)-32 and 16B (78)-32 for the validation of our proposed framework at the Utah FORGE site (Xing et al., 2025). The simulation domain was chosen within the granitoid layer of the FORGE native state model with corresponding boundary conditions of 2596 psi and 171 ˚C at the top boundary and 3292 psi and 213 ˚C at the bottom boundary. The injection schedule included a peak rate of 16.5 bpm and a scheduled shutdown at 310 minutes for tool adjustments as described in Xing et al. (2025). The well operations, including a brief shutdown after 310 minutes of pumping with injection rates varying between 13.5 and 16.5 bpm, were incorporated into the model. The simulation took about 30 minutes using MRST and such computation time prohibits the direct use of MRST in the data assimilation, which would require more than 1,000 forward model runs to characterize the permeability field. A surrogate TH model using the UNet was considered to accelerate the data assimilation and MRST simulations were executed using 500 permeability field scenarios to obtain pressure and temperature responses. Figure 4 below shows an example of the surrogate model. The permeability field in Figure 4 (a) was not included in training and Figure 4 (b) shows the comparison of the simulated injection pressure obtained from the surrogate model and MRST indicating that the surrogate model.

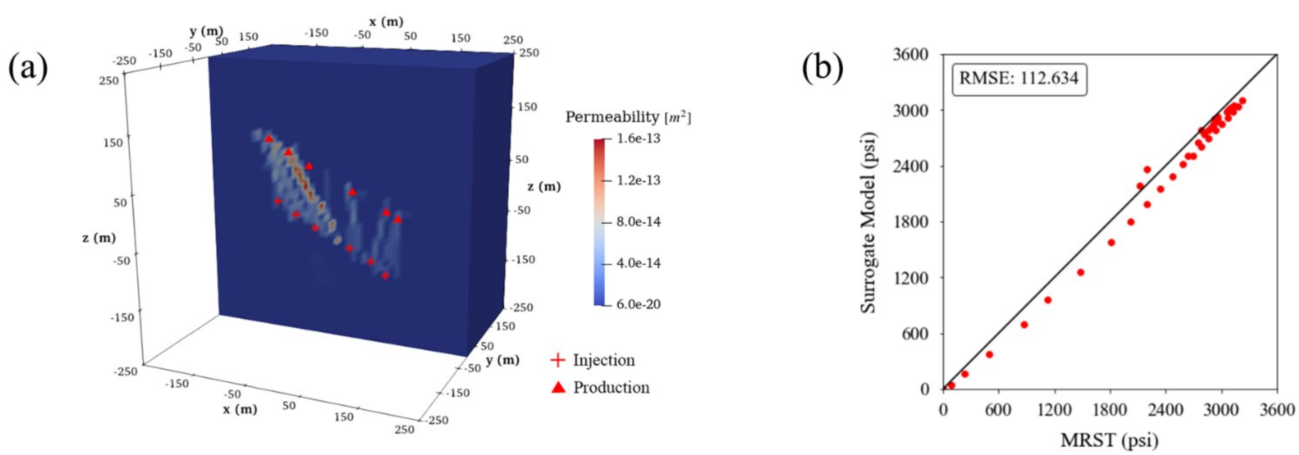

Figure 4: Example of surrogate model training result. (a) permeability field with well locations that was not used in the surrogate modeling construction. (b) the simulated pressure at the injection wells from the trained surrogate model and MRST.

3.2 Data Assimilation

With the developed surrogate model and proposed data assimilation framework, we characterized the permeability field from the available pressure data. Figure 5 presents the data assimilation results; Figure 5 (a) is the estimated permeability and Figure 5 (b) displays the pressure response over time, where the red line is the average pressure of the 6 injection points, simulated using the estimated permeability and the trained surrogated model. The black line is the injection pressure measured in the circulation test. The simulated pressure response is consistent with the measured pressure response. In Figure 5 (c), the simulated pressure and the measured pressure are presented in a parity plot and the RMSE is 284.671 psi, showing that the simulated pressure is in a good agreement with the measured pressure. Pressure values in the first 40 minutes and the last 10 minutes were considered outliers and were not included in the calculation of RMSE. The main discrepancy in the model fitting is shown in the shut-in event around 310 minutes after pumping started.

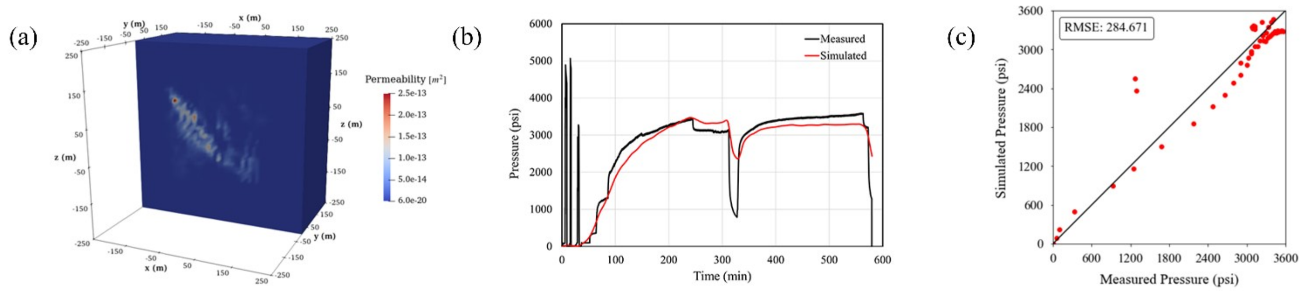

Figure 5: Example of surrogate model training result. (a) Estimated permeability field, (b) comparison of pressure response over time at the injection well between measured and simulated data, and (c) a parity plot between the measured pressure and the simulated pressure after ES-MDA calibration.

4. CONCLUDING REMARKS

In this work, a data assimilation framework combining deep generative model for permeability construction and surrogate TH model is applied to Utah FORGE site permeability characterization. The proposed framework can estimate a 500 m x 500 m x 500 m permeability field efficiently and effectively. The process took about 30 minutes using two NVIDIA RTX A6000 GPUs on a workstation equipped with 32 Intel CPUs and 128G RAM. To perform geothermal simulation faster, a deep learning surrogate model was trained, and the trained surrogate model can produce simulation results similar to MRST. Using trained surrogate models can significantly reduce the time of the data assimilation process, which requires hundreds of simulations per iteration. The estimated permeability using the proposed data assimilation method can produce similar pressure response as the measured data. The estimated permeability field was then used to conduct a one-month simulation to investigate the long-term performance of the geothermal system, with the simulated injection pressures and production temperatures consistent with the measured data.

Acknowledgement: This work was supported by a R&D award (5-2557) as part of funding provided by DOE EERE Geothermal Technologies Office to Utah FORGE and the University of Utah under Project DE-EE0007080. HY was also supported by the U.S. DOE Science Foundations for Energy Earthshots (SFEE) project - Advanced Multi-Physics Machine Learning for Subsurface Energy Systems Across Scales. Sandia National Laboratories is a multi-mission laboratory managed and operated by National Technology \& Engineering Solutions of Sandia, LLC (NTESS), a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration (DOE/NNSA) under contract DE-NA0003525. This written work is authored by an employee of NTESS. The employee, not NTESS, owns the right, title and interest in and to the written work and is responsible for its contents. Any subjective views or opinions that might be expressed in the written work do not necessarily represent the views of the U.S. Government. The publisher acknowledges that the U.S. Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this written work or allow others to do so, for U.S. Government purposes. The DOE will provide public access to results of federally sponsored research in accordance with the DOE Public Access Plan.

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