PROCEEDINGS, 48th Workshop on Geothermal Reservoir Engineering
Stanford University, Stanford, California, February 6-8, 2023
SGP-TR-224

Understanding of Naturally Fractured Geothermal Reservoirs Using Data Assimilation

Gabriel S. Seabra[1,2], Stephan de Hoop[1], Denis Voskov[1,3], Femke. C. Vossepoel[1]

TU Delft, Department of Geoscience and Engineering, The Netherlands[1], Petrobras, Brazil[2], Energy Resources Engineering, Stanford University[3]

g.serraoseabra@tudelft.nl; de.hoop.stephan@gmail.com; d.v.voskov@tudelft.nl; f.c.vossepoel@tudelft.nl

Keywords: Data assimilation; Geothermal; Discrete fracture model; Naturally fractured reservoirs

ABSTRACT

Naturally fractured reservoirs can pose challenges for geothermal energy production where a clear understanding of mass and heat transfer is essential for developing and managing operations. The dynamic behavior of these reservoirs is greatly affected by fracture properties such as orientation and aperture, whose magnitude is mainly influenced by the stresses on the reservoir rocks. Methodologies for accurate modeling of thermal multiphase flow within fractured reservoirs are limited. Therefore, simulating fractures and their behavior tends to be computationally intensive, which often limits the use of data assimilation methods for uncertainty quantification. However, recent advances in Discrete Fracture Models (DFM) have successfully decreased computational costs and allow for the explicit inclusion of discrete fractures in reservoir simulations. This study explores data-assimilation techniques to help quantify uncertainties of energy production from naturally fractured reservoirs. We combine a recent implementation of DFM in the Delft Advanced Research Terra Simulator (DARTS) with both ensemble and gradient-based data-assimilation methods. The data-assimilation workflow, first developed with a synthetic naturally fractured reservoir for two phase flow, is extended in this study and applied to a real outcrop-based geothermal reservoir model. Our results show that data assimilation can help to characterize the main dynamic processes of geothermal energy production from fractured reservoirs. Using this technique, we obtain a more accurate representation of the stresses acting on the reservoir and how they affect the fracture aperture. This information is essential for the accurate representation of fractured reservoirs and their efficient reservoir management

1. INTRODUCTION

Geothermal energy has the potential to provide a renewable and sustainable source of power. However, extracting energy from naturally fractured reservoirs can be challenging due to the complexity of the rock structure and the resulting heat and mass transfer processes. Accurate modeling of these processes is important for the successful development and management of geothermal operations, but existing methodologies for simulating thermal multiphase flow in fractured reservoirs are limited and computationally intensive. An advanced methodology for accurately modeling fractured reservoirs is the Discrete Fracture Model (DFM), proposed by Karimi-Fard et al. (2004). In DFM, fractures are explicitly represented by individual elements in the reservoir grid, and fracture apertures can be computed using fracture orientation-dependent formulation (Barton & Bandis, 1980).

This approach has been successfully tested by Boersma et al. (2021) and de Hoop (2022) for geothermal production in Delft Advanced Research Terra Simulator (DARTS), which is a multi-physics python/C++ based simulator. DARTS relies on Operator Based Linearization (OBL) formulation to solve the governing equations (Khait & Voskov, 2018; Wang et al., 2020) and is capable of simulating a wide range of geothermal energy production scenarios in a computationally efficient way. However, there are still challenges in understanding the uncertainties that affect the thermal behavior of fluids in fractured reservoirs due to limitations in quantifying fractures properties accurately. Data assimilation can help understand the uncertainty of states and parameters usually predicted by numerical models, incorporating observations into the model.

Data assimilation is often used in fields such as meteorology, oceanography, and geoscience to improve the accuracy of weather and climate forecasts, ocean state prediction, and subsurface flow modeling, respectively. There are various methods of data assimilation, that can be divided in ensemble-based methods and gradient-based methods. Ensemble-based data assimilation methods, such as the Ensemble Kalman Filter (EnKF) and ES-MDA, are Monte Carlo based techniques that use a set of model simulations, known as an ensemble, to represent the uncertainty in the model and approximate the sensitivity of the unknowns in respect to the objective function avoiding the calculation of gradients. Gradient-based data assimilation methods, such as the RML and 4DVar methods, use variational optimization techniques to update the model's initial conditions based on the difference between the model's predicted output and the observations (Evensen et al. 2022). Ensemble-based and gradient-based data assimilation methods are widely used in geoscience applications to improve the accuracy of numerical models by incorporating observations from various sources, such as satellite data, in situ observations, and remote sensing data.

In this work, we explore the potential of data assimilation techniques to help understanding the effect of in-situ stresses, initial fracture, and matrix permeability on the thermal behavior of naturally fractured geothermal reservoirs. We apply ES-MDA and RML, an ensemble- and a gradient-based method, respectively (Evensen et al. 2022). We follow a similar integrated workflow proposed by Seabra et al. (2022), where data assimilation was applied to a synthetic reservoir with a naturally fractured network with two phase isothermal flow and maximum in-situ stress angle and initial fracture aperture were considered as the unknown parameters for the data assimilation.

However, we extend the workflow to thermal effects and include the matrix permeability as one of the unknown properties. We also use a real outcrop based reservoir model to test the data assimilation workflow.

To account for a realistic representation of the reservoir, we use a real outcrop based reservoir model, the Whitby Mudstone Formation. Boersma et al. (2015) interpreted aerial images of the outcrop in the aspect of its fractures orientation, length and density. In this study, a digital map of individual fractures was constructed. Based on this map of the Whitby Mudstone, de Hoop (2022) built the DARTS dynamic model used to simulate geothermal energy production, and performed sensitivity analysis on the effect of fractures discretization on energy production. The present study extends de Hoop (2022) sensitivity analysis, performing the described data assimilation workflow for uncertainty quantification. The succeeding sections of this paper first describe the reservoir model and the data assimilation workflow. Then, we present the results of the data assimilation workflow for the Whitby Mudstone reservoir model. Finally, we discuss the results and conclude

2. METHODOLOGY

2.1 Forward Modeling

The DFM scheme implemented in DARTS is utilized to accurately capture the pressure response triggered by flow in fractured networks. The following subsections describe this aspects of the study.

2.1.2 Discrete Fracture Model simulation with DARTS

In order to accurately predict the behavior of mass and heat flow in fractured geothermal systems, a suitable fracture model is essential to reflect the reservoir response. Among several existing methods, the discrete-fracture model (DFM) accurately and reliably captures the pressure response triggered by flow in fractured networks by explicitly characterizing the fracture networks via individual control volumes (Karimi-Fard et al. 2004). Wang et al. (2021) presented the framework for the simulation of DFM with DARTS, where after selecting a fracture network configuration, the apertures are distributed using an empirical relationship of the mechanical closure of initially open fractures due to applied normal stress to each fracture (Barton & Bandis 1980). This stress-to-aperture mechanical relationship is described in Boersma et al. (2021), the fracture aperture is computed as a hyperbolic function as described as follows:

$$e_n = e_0 - \left(\frac{1}{v_m} + \frac{K_{ni}}{\sigma_n}\right)^{-1} \quad (1)$$

where e_n is the fracture mechanical aperture, e_0 the initial fracture aperture, σ_n is the in-situ stress normal to the fracture plane, and two empirical measured parameters, v_m the maximum fracture closure and K_{ni} the fracture stiffness, which are functions of material parameters and e_0 (de Hoop, 2022). Then, a power law model is applied to account for fracture permeability as a function of fracture aperture:

$$K_{frac} = \frac{e_n^2}{12} \quad (2)\text{a}$$

Note that the resulting permeability of each fractured segment is highly dependent on the stress acting normal to the fracture plane. Therefore, the in-situ stress directions will have an effect on the flow along each fracture plane, fractures parallel to the maximum in-situ stress directions will have bigger permeability than those normal to it. Finally, fractures are included in DARTS model as additional elements with the correspondent permeability. The DARTS framework for geothermal modeling of fractured systems has been validated against commonly used numerical simulators in the geothermal industry, and details about the governing equations for this problem can be found in Wang et al. (2020) and Wang et al. (2021). De Hoop (2022) conducted an analysis of grid optimization and heat transfer dynamics in a synthetic fracture model, as well as in models based on outcrops.

2.1.2 Model Description

All simulations in this study are based on a model of the Whitby Mudstone Formation. The Whitby Mudstone Formation is a sedimentary rock formation located in the northeast of England. It is composed mainly of mudstone, a type of fine-grained sedimentary rock formed from consolidated mud, and is known for its rich fossil content. The outcrop is a popular site for geothermal research due to its properties and geology, which make it suitable for studying geothermal energy production. (de Hoop, 2022), which uses a direct heat production strategy commonly employed in low enthalpy geothermal doublets. For a period of 20 years, cold water is injected into the reservoir at a temperature of 308.15 K, while the temperature of the reservoir is 348.15 K. During this time, hot water is produced to generate energy. The positions of the producer and injector wells, as well as the Whitby fracture network, are depicted in Figure 1.

2.2 Data Assimilation

Data assimilation is a process that combines observed data with a physical model in order to estimate the state of a system. To perform data assimilation, the first step is to sample the prior distribution, which represents the range of possible values for uncertain parameters. This is done by generating an ensemble of samples from the prior distribution, which allows for a representative sample of the uncertain parameters to be obtained. Observed data is collected through measurements that provide information on the dynamics or mechanics of the system. Finally, a data assimilation workflow is constructed, typically involving the use of a data assimilation method such as ES-MDA or RML, to compute the objective function and update the model based on the observed data. The updated model can then be used to make more accurate predictions about the system. The performance of a data-assimilation scheme can be tested by assimilating synthetic data, that is, data created from a model simulation.

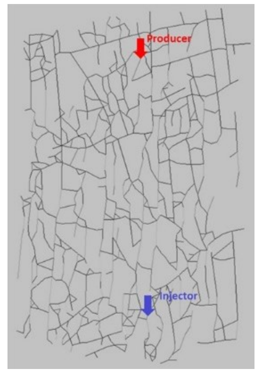

Figure 1 – Geothermal simulation model configuration with doublets position and Whitby fracture network configuration.

2.2.1 Sampling the prior

Sampling the prior distribution is an important step in data assimilation because the samples selected (i.e., the specific parameter values chosen) reflect the prior understanding of the uncertainties held by the user. This is achieved by generating an ensemble of samples from the prior distribution, which are expected to represent the uncertainty in the parameters. By forward simulating the state based on the prior choice of parameters, we can also better understand how the parameter uncertainty may affect the model predictions.

In this study, we investigate two different sets of prior unknown parameters. The first set consists of the maximum in-situ stress angle and initial fracture aperture, similar to the approach taken by Seabra et al. (2022). To sample the prior distribution for these uncertain parameters, we generate an ensemble of 100 members. The maximum in-situ stress angle is uniformly distributed from 0° to 90°, while the initial fracture aperture is normally distributed with a mean of 0.15 mm and a range from 0.10 mm to 0.25 mm. The second set of prior unknown parameters includes the matrix permeability, which is normally distributed with a mean of 100 mD and a range from 10 mD to 1000 mD. Figure 2 shows the histogram of the three prior unknown parameters.

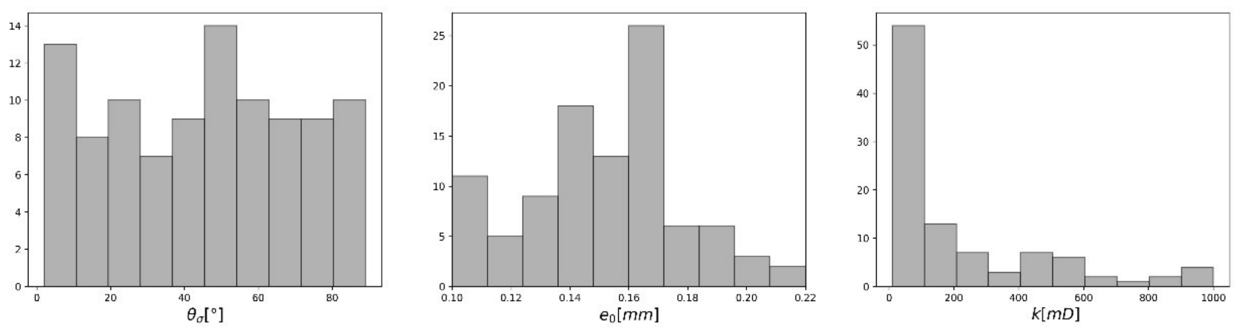

Figure 2 - Prior distributions of unknown parameters

2.2.2 Reference cases for the Data Assimilation

In this study, we selected three scenarios with three distinct stress angles from the ensemble members to generate synthetic data (reference cases) to evaluate the performance of the data assimilation method. These different values of the chosen stress angle are: 0°, 45°, and 90°. The reference models for these scenarios all have the same initial fracture aperture and permeability values, which are set to 0.15 mm and 100 mD, respectively. The results of the analysis show that the temperature drop in the producer well is highly influenced by the direction of the maximum horizontal stress (Figure 3). For instance, in the 0° reference case, the temperature drop occur after only 4 months of cold water injection, while in the 45° and 90° cases, the temperature drop occur after 105 months and 143 months, respectively.

Figure 4 presents the temperature distribution in the reservoir at these times for all three reference cases and suggests that the direction of the maximum horizontal stress has a significant impact on the temperature drop in the producer well. This difference occurs because when the stress angle is 0°, the temperature tends to flow directly towards the producer well, leading to a faster temperature drop. On the other hand, when the stress angle approaches 90°, the temperature tends to flow in a direction perpendicular to the producer well, causing a dispersion effect that delays the temperature drop. This is due to the fact that the path of flowing in a direction perpendicular to the producer well has a higher conductivity. Overall, the map illustrates how the direction of the maximum horizontal stress can have a significant effect on the temperature distribution in naturally fractured reservoirs.

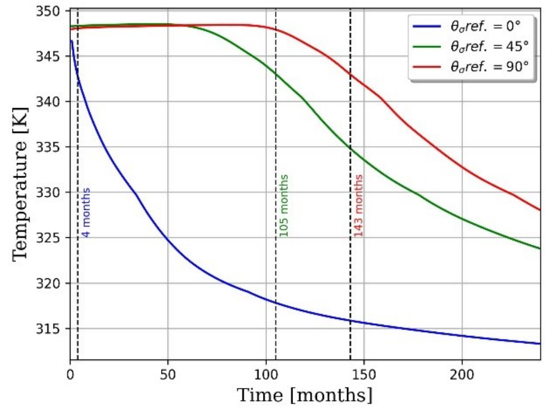

Figure 3 - Bottom hole temperature for the three reference cases, highlighting the time for a 5degrees temperature drop in each case.

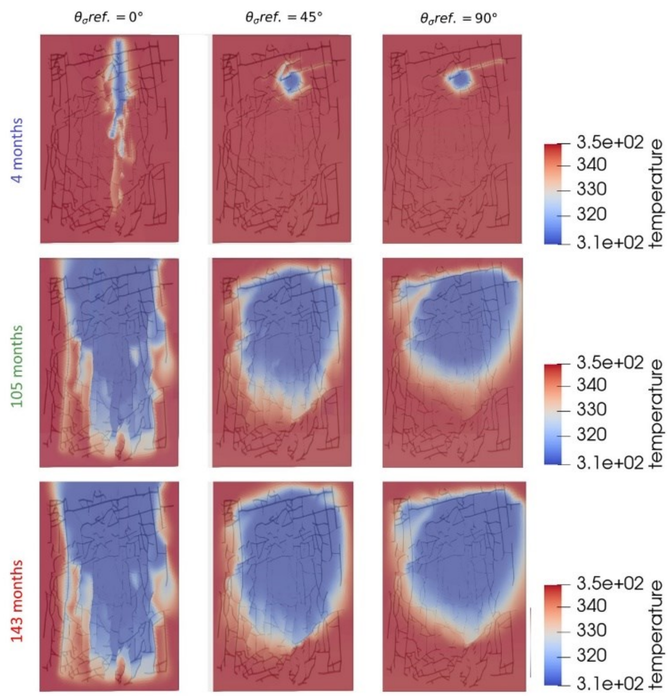

Figure 4 -Reservoir temperature distribution, in Kelvins, for the three reference cases for 4, 105 and 143 months after the start of injection

2.2.3 Data Assimilation workflow

Our work follows an integrated data assimilation workflow similar to that proposed by Seabra et al. (2022), where both ES-MDA and RML were applied to a naturally fractured reservoir. DARTS is used to compute the simulated data. In the first moment, we used the same workflow for the geothermal simulations, then we added matrix permeability to the list of unknown properties. Observed data, generated by a synthetic case are assimilated with the framework presented in Figure 5 to evaluate the capability of two data-assimilation methods (ES-MDA and RML) to quantify uncertainties in the unknown parameters.

It is important to highlight that different data assimilation methods compute the objective function in different ways which are characteristic of each method. ES-MDA and RML, for example, compute the objective function based on their own distinct premises. A unified formulation for various well-known data assimilation methods, including ES-MDA and RML, can be found in Evensen et al. (2022). In the next section, we will present the results of our proposed data assimilation framework applied to geothermal simulations of the Whitby model, where we evaluate the performance of ES-MDA and RML in quantifying uncertainties in the unknown parameters.

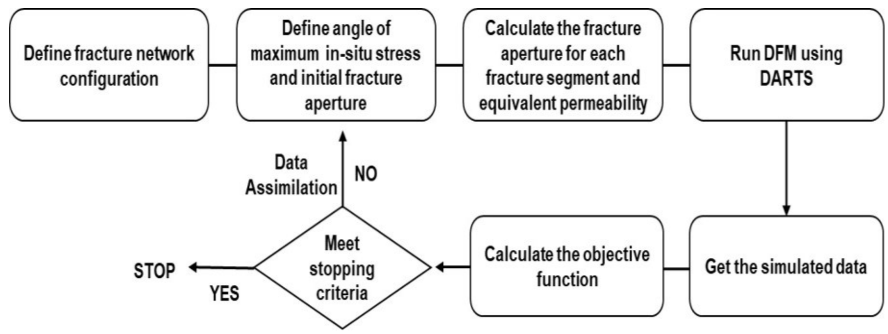

Figure 5: Data-assimilation workflow proposed by Seabra et al. (2022).

3. RESULTS

3.1 Evaluation of the Data Assimilation workflow with ES-MDA

First, the ES-MDA method is applied in the data-assimilation process to perform history-matching on the models. This process involves using synthetic observations, generated from three reference cases, to perform the history of the prior ensemble. To make the process more realistic random noise is added to the bottomhole temperature data collected during the first 15 years of production, which is used as the observed data. The last 5 years of production are then used to evaluate the behavior history- history--matched models during the extrapolation period.

3.1.1 – Considering maximum in-situ stress angle ($\boldsymbol{\theta_\sigma}$) and initial fracture aperture ($\boldsymbol{e_0}$) as unknown parameters

As described in section 2.2.1, the initial set of prior unknown parameters consists of the maximum in-situ stress angle and initial fracture aperture. The results show that the posterior distribution of rates, as determined by the ES-MDA method, is closer to the observed data than the prior distribution of rates in all three stress angle scenarios (as shown in Figure 6). The posterior distribution of the maximum in-situ stress angle and initial fracture aperture is also significantly narrower than the prior distribution after assimilating data (Figure 7) for all reference cases. This indicates that the applied data-assimilation framework is successful in creating a posterior with less uncertainty than the prior, and identifying what would be the dominant stress angle acting on the fractures of the reservoir. Figure 8 illustrates the evolution of the objective function for each of the four ES-MDA iterations needed to achieve good history-history--matching results.

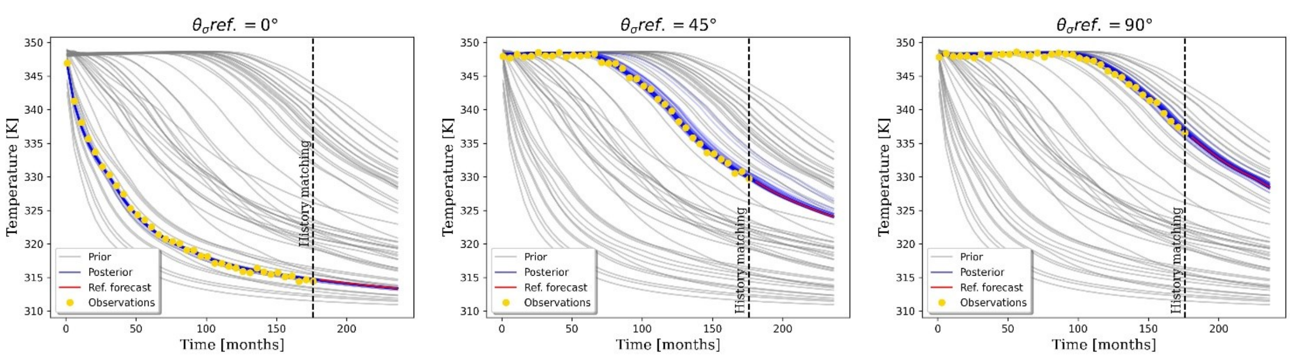

Figure 6 - Comparison of posterior and prior distributions of rates for different stress angle scenarios using ES-MDA method when maximum in-situ stress angle ($\boldsymbol{\theta_\sigma}$) and initial fracture aperture ($\boldsymbol{e_0}$) are considered as unknowns.

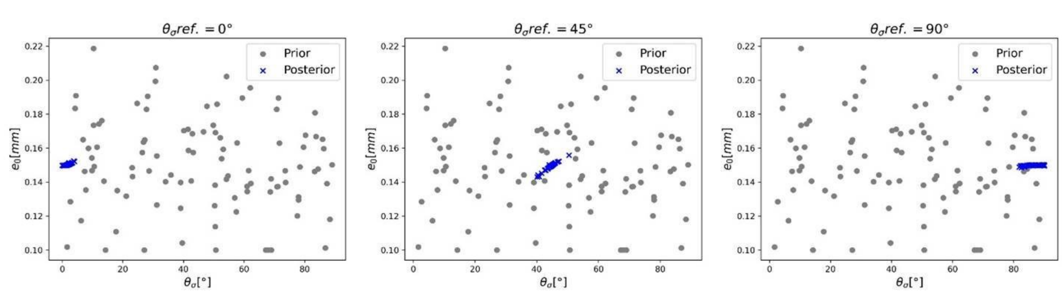

Figure 7 - Comparison of posterior and prior distributions of maximum in-situ stress angle and initial fracture aperture using ES-MDA method when maximum in-situ stress angle ($\boldsymbol{\theta_\sigma}$) and initial fracture aperture ($\boldsymbol{e_0}$) are considered as unknowns.

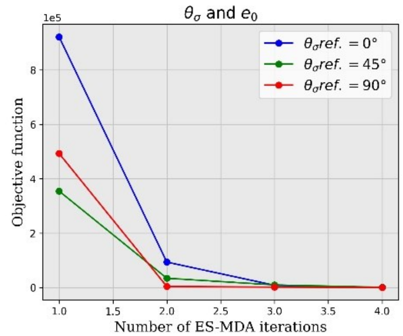

Figure 8 - Evolution of ES-MDA objective function for all three reference cases when maximum in-situ stress angle ($\boldsymbol{\theta_\sigma}$) and initial fracture aperture ($\boldsymbol{e_0}$) are considered as unknowns.

3.1.2 – Considering maximum in-situ stress angle ($\boldsymbol{\theta_\sigma}$), initial fracture aperture ($\boldsymbol{e_0}$) and matrix permeability ($\boldsymbol{k}$) as unknown parameters

The incorporation of permeability as an additional unknown factor significantly enhances the complexity of the problem and presents a greater challenge for the data-assimilation algorithm. In an effort to address this challenge, the ES-MDA framework was initially implemented with four iterations. Many studies in the literature have found that this number of iterations is effective for addressing subsurface problems (Canchumuni et al., 2021). However, the outcomes of this initial approach are not satisfactory, as illustrated in Figures 9 and 10. Thus, we obtain better results (smaller error for the history--matching) increasing the number of iterations from four to eight, as illustrated in Figures 11 and 12. This decision was taken taking into account our previous experiences and the additional unknowns present in this case. . It is worth noting that increasing the number of iterations in the ES-MDA method requires starting the process from the beginning, as it is not possible to increment the number of iterations one by one. The reduction of the ES-MDA objective function for the different numbers of ES-MDA iterations is illustrated in Figure 13.

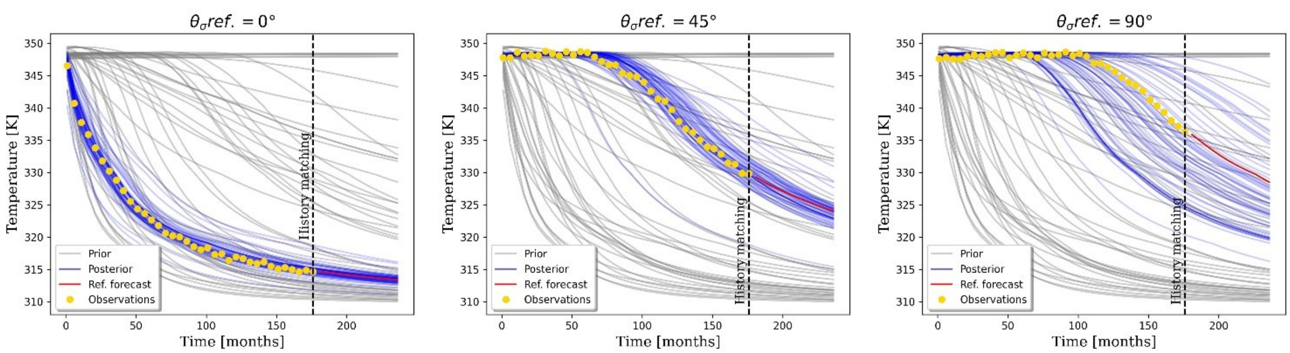

Figure 9 - History- matching for the three reference cases when permeability is added as an unknown parameter and with four ES-MDA iterations.

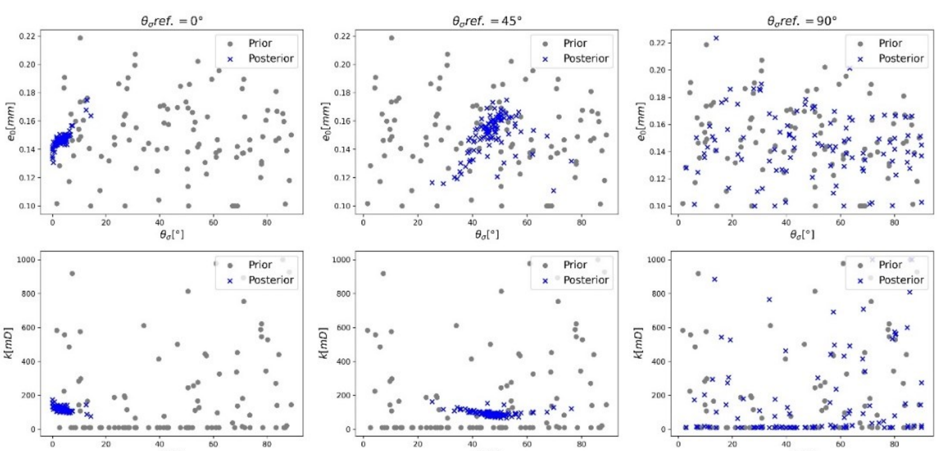

Figure 10 - Prior and posterior distribution of initial fracture apertures and stress angle for the three reference cases when permeability is added as an unknown parameter and with four ES-MDA iterations.

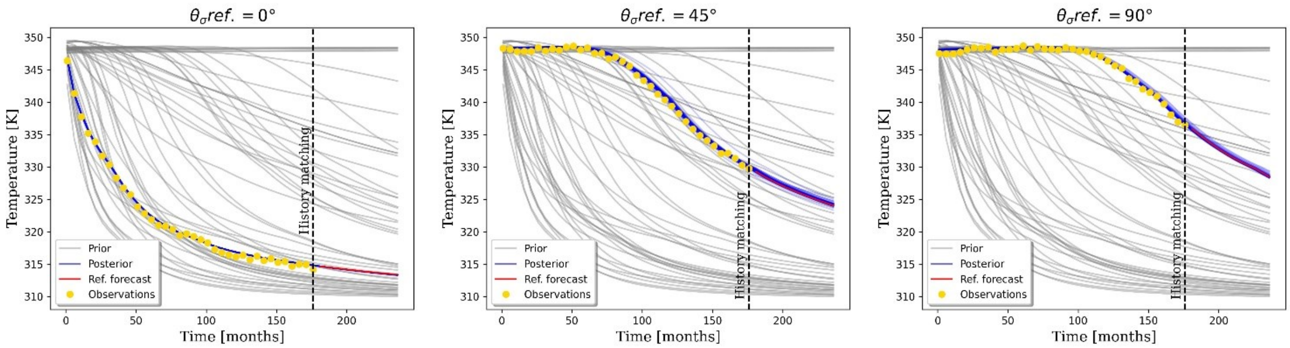

Figure 11 - History- matching for the three reference cases when permeability is added as an unknown parameter and with eight ES-MDA iterations.

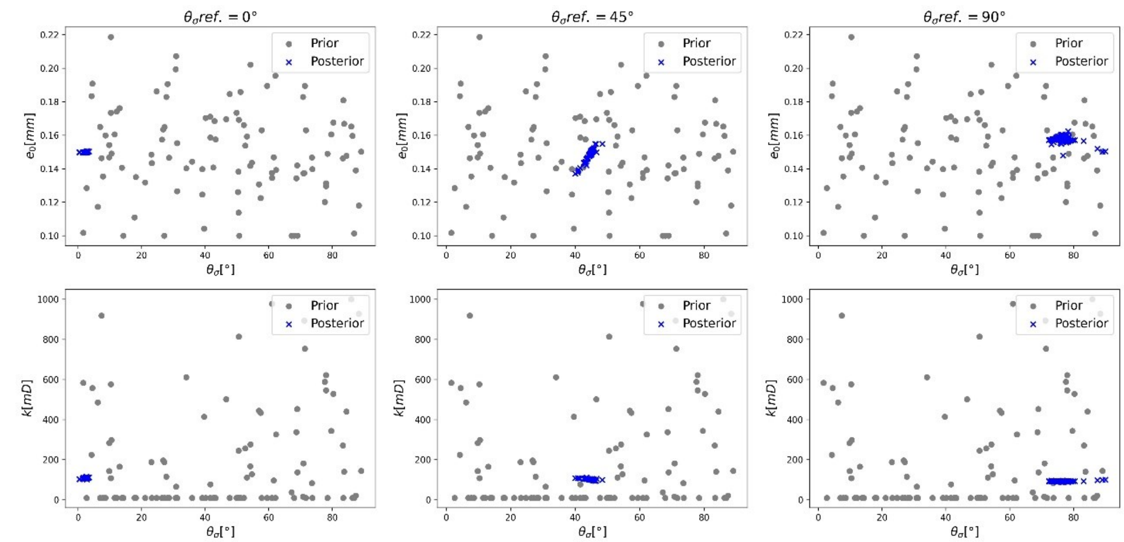

Figure 12 - Prior and posterior distribution of initial fracture apertures and stress angle for the three reference cases when permeability is added as an unknown parameter and with eight ES-MDA iterations

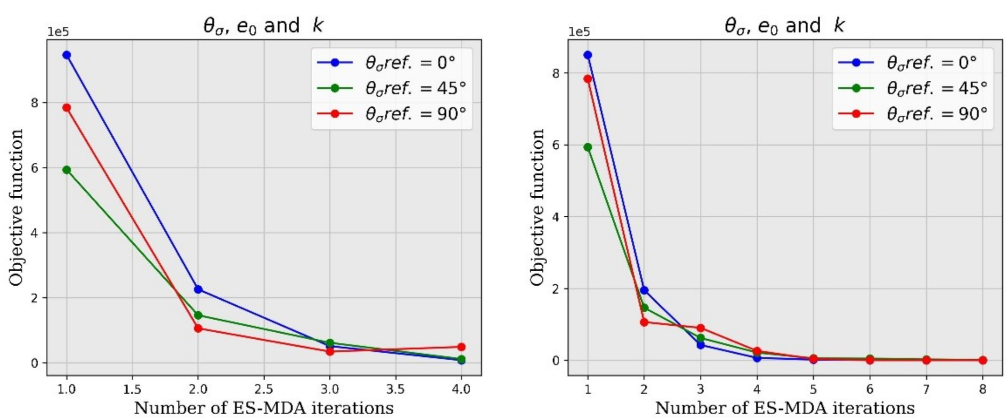

Figure 13 Evolution of the objective function for the cases: stress angle, initial fracture and permeability and four ES-MDA iterations (left), and, initial fracture and permeability and eight ES-MDA iterations (right).

Figure 14 depicts the evolution of two parameters (permeability and maximum stress angle) at each iteration of the ES-MDA algorithm for the reference case $\theta_\sigma=90^0$ when eight iterations are performed. Each point on the plot represents a set of parameter values, and the color of the point indicates the corresponding value of the objective function. As the algorithm progresses, the parameter values move towards values that minimize the objective function. The plot shows that the parameter values generally converge towards the optimal solution (θ_σ=90^0 and $k = 100\,mD$), indicated by the concentration of points near the reference value for each parameter where the objective function is at its lowest. However, during the initial steps, there are also some points scattered throughout the plot that do not converge towards the optimal solution , suggesting that the algorithm may get stuck in or oscillate around local minima. Overall, Figure 14 provides a visual representation of how the parameters evolve during the data assimilation process.

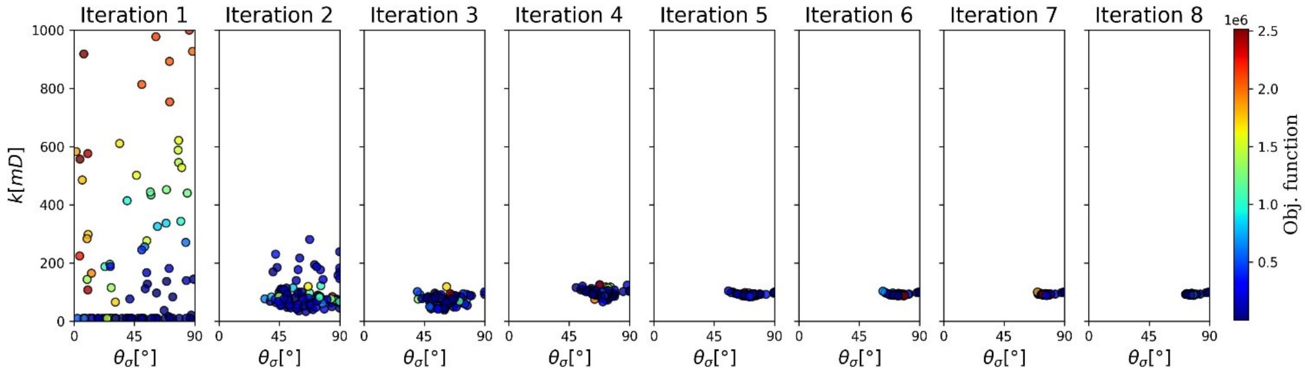

Figure 14 - Evolution of permeability and maximum stress angle for the reference case θ_σ=90^0 in the ES-MDA algorithm colored by the objective function.

Including the matrix permeability in the data assimilation problem is especially a challenge because matrix permeability and fracture conductivity are important factors in determining fluid conductivity. The temperature drop in the producer well is largely influenced by the connectivity between wells. When the stress angle is below 30 degrees, the matrix permeability does not significantly affect the temperature drop in the producer. However, when the stress angle is above 30 degrees, the matrix permeability becomes a dominant factor in the temperature drop, with high matrix permeability leading to an early temperature drop and low matrix permeability resulting in a later temperature drop (Figure 15).

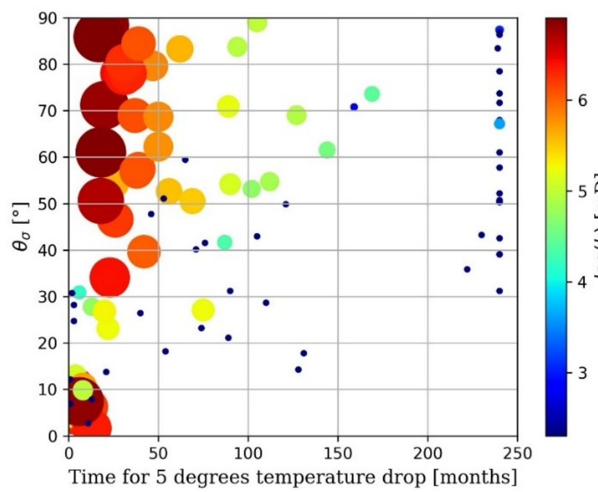

Figure 15 – Influence of maximum in-situ stress angle (θ_σ) and permeability on the time for temperature drop in the producer well for all 100 prior models. The size of the circles is the magnitude of permeability.

The results demonstrate the effectiveness of the ensemble-based data assimilation method in estimating the uncertainty of producer well temperature, stress angle, and initial fracture aperture. A key aspect of this method is its ability to use dynamic data from the reservoir, in this case the bottomhole well temperature, to constrain the in-situ stress angle. While incorporating additional unknown parameters, such as permeability, make the problem more complex, the ES-MDA framework is able to produce improved results with additional iterations.

3.2 Evaluation of the Data Assimilation workflow with RML

After conducting data assimilation with ES-MDA, we apply the RML method to perform history-matching. As a gradient-based approach, the RML method involves optimizing a set of parameters through an iterative process by following the gradient of an objective function (Evensen et al. 2022). While the overall data assimilation framework is similar, the RML method does not involve history-matching for an entire ensemble of models. Instead, a single prior model is selected on which history-matching is applied. We first evaluate the RML method using synthetic data in which the initial guess is randomly chosen from the prior ensemble described before and has stress angle of 40° and initial fracture aperture 0.138 mm. We perform data assimilation with the three different reference models with maximum in-situ stress angles of 0°, 45° and 90° and an initial fracture aperture of 0.15 mm. Similarly to the ES-MDA, the first attempt at history-matching only considers the angle of maximum in-situ stress and the initial fracture aperture. We allow the gradient to be calculated a maximum of 25 iterations of minimization of the RML objective function using Sequential Least Squares Programming (Kraft & Powell, 1994), a optimization algorithm from *scipy* Python package, to calculate the numerical gradients. Figure 16 presents the results of the three different history-matchings. The posterior values of the estimated parameters are presented in Table 1. It is noteworthy that the reference stress angle of the 90° in-situ stress angle case had the largest misfit of all of the cases. This may be due to the fact that models with higher stress angles exhibit similar temperature responses,, leading to similar objective function values, and this can pose challenges for gradient-based data assimilation methods.

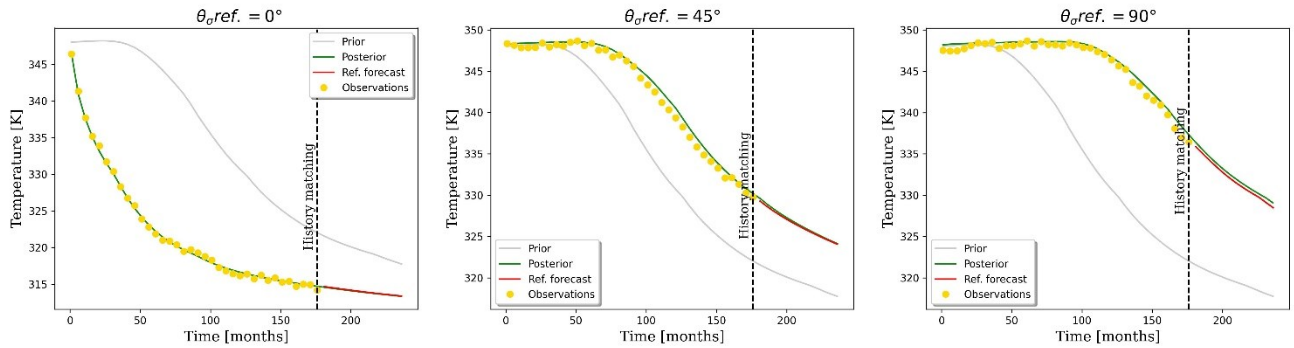

Figure 16 - Comparison of history-matching results for the temperature using the RML method for three reference cases. The red line indicates the reference forecast, and the dashed black line marks the end of the history-matching period.

Table 1 - Posterior values of the parameters for the three history-matching cases using the RML method for the first set of unknown parameters.

Parameter for history-matched model (posterior)	Reference $\boldsymbol{\theta_\sigma}$= 90°	Reference $\boldsymbol{\theta_\sigma}$= 45°	Reference $\boldsymbol{\theta_\sigma}$= 0°
Maximum in-situ stress angle ($\boldsymbol{\theta_\sigma}$) [°]	81.8	44.7	1.3
Initial fracture aperture ($\boldsymbol{e_0}$) [mm]	0.148	0.149	0.149

Next, we add permeability as a third unknown parameter in the data assimilation framework. This time, another prior model is randomly chosen from the prior ensemble and has a stress angle of 35°, while initial fracture aperture is 0.144 mm and matrix permeability 10 mD. All reference models have a matrix permeability of 100 mD. This time, the gradient calculation requires a maximum of 100 iterations for the minimization of the RML objective function for each case. Figure 17 presents the results of the three different history-matching, all with a good fit to the observations. The posterior values of these parameters are presented in Table 2. It is worth noting that when an additional parameter is included in the set of unknown parameters, it is necessary to increase significantly the number of maximum iterations to achieve a good fit to the data in the history-matching. One potential reason for this may be the use of numerical derivative methods to calculate gradients. However, there are more efficient methods for computing gradients analytically, such as the adjoint method, as described in Tian et al. (2021). While the adjoint method can be more efficient than numerical gradients, it requires additional implementation and changes to the code of the simulator, which is beyond the scope of this work.

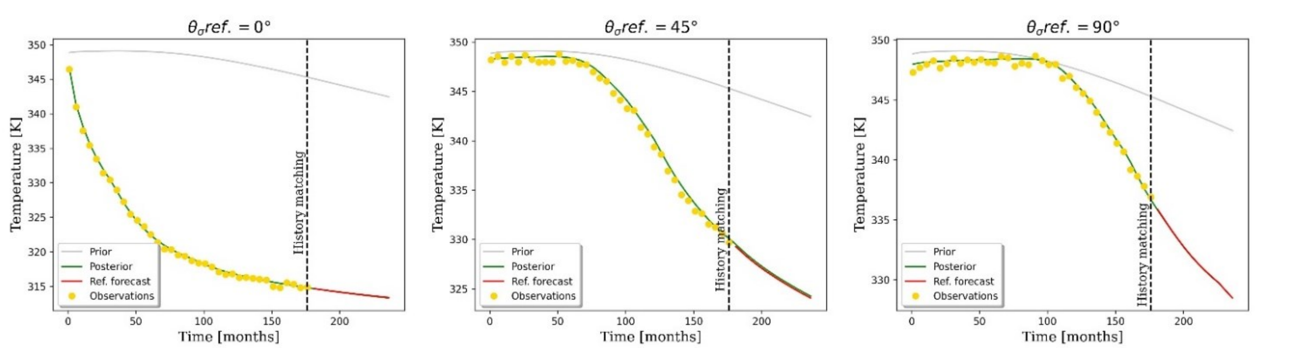

Figure 17 - Comparison of history-matching results for the temperature using the RML method for three reference cases when permeability is included as an unknown parameter. The red line indicates the reference forecast, and the dashed black line marks the end of the history-matching period.

Table 2 - Posterior values of the parameters for the three history-matching cases using the RML method for the second set of unknown parameters.

Parameter for history-matched model (posterior)	Reference $\boldsymbol{\theta_\sigma}$= 90°	Reference $\boldsymbol{\theta_\sigma}$= 45°	Reference $\boldsymbol{\theta_\sigma}$= 0°
Maximum in-situ stress angle ($\boldsymbol{\theta_\sigma}$) [°]	87.4	44.7	2.5
Initial fracture aperture ($\boldsymbol{e_0}$) [mm]	0.152	0.148	0.149
Matrix permeability ($\boldsymbol{k}$) [mD]	98.1	101.5	109.3

Overall, these results show that while the RML method can effectively perform history- matching, it is much more computationally intensive compared to the ES-MDA method. The ES-MDA method requires running 100 models for each iteration, providing a more comprehensive exploration of the parameter space and a better description of the uncertainty. In contrast, the RML method uses a sequential process and stops when the objective function is below a certain threshold, or a maximum number of iterations is reached (which was set at 100 iterations per model in this case). Figure 18 shows the evolution of the RML objective function, respectively, for the first (stress angle and initial fracture aperture) (left) and second (stress angle, initial fracture aperture and matrix permeability) (right) set of unknown parameters along the iterations of the optimization algorithm for each case.

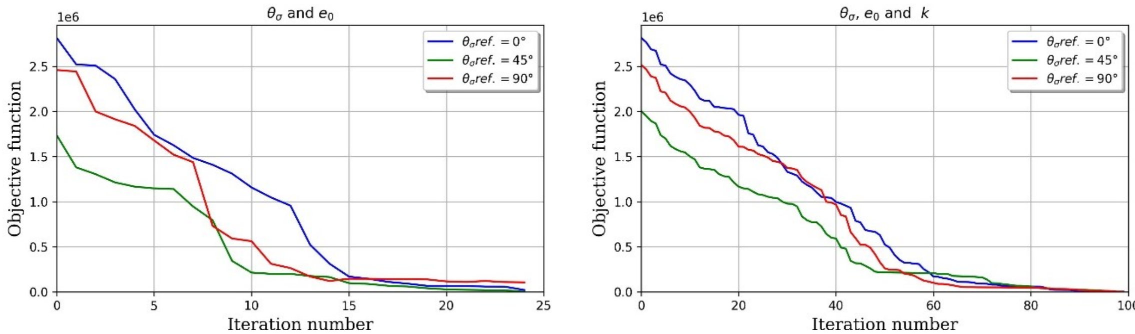

Figure 18 - Objective function values for 25 iterations of the RML algorithm for the first set of unknown parameters (left) and objective function values for 100 iterations of the RML algorithm for the second set of unknown parameters (right).

4. CONCLUSIONS

This study explores the use of data assimilation techniques to improve our understanding of geothermal energy production in naturally fractured reservoirs. It combines a recent implementation of the Discrete Fracture Model (DFM) in the Delft Advanced Research Terra Simulator (DARTS) with both ensemble and gradient-based data assimilation methods. The data assimilation workflow is applied to a real outcrop-based naturally fracture configuration to generate the geothermal reservoir model, the Whitby Mudstone Formation.

The main findings of the research can be summarized as follows:

1. Data assimilation can help to characterize the main dynamic processes of geothermal energy production from fractured reservoirs. Using this technique, we were able to obtain a more accurate representation of the stresses acting on the reservoir and how they affect the fracture aperture.

2. The ES-MDA method was able to achieve good results with relatively low computational costs, while the RML method was more computationally expensive but still able to achieve good results.

3. The inclusion of additional unknown parameters, such as permeability, can increase the computational demands of the data assimilation process. In this study, we found that the RML method required significantly more iterations to achieve similar results to those obtained with ES-MDA when permeability was included as an unknown parameter.

4. The data assimilation results showed that stress angle and fracture aperture have a significant effect on the temperature drop in the producer well. Specifically, when the stress angle is below 30 degrees, the matrix permeability does not significantly affect the temperature drop, while above 30 degrees the matrix permeability has a larger influence.

Overall, the study demonstrates that data assimilation techniques can be used for a more accurate description of of geothermal energy production in naturally fractured reservoirs. The results of this study provide valuable insights into the dynamic processes of these reservoirs, and highlight the importance of accurately representing the stresses acting on the reservoir and their impact on the fracture aperture. Further research could explore the potential of data assimilation techniques to improve our understanding of other types of naturally fractured reservoirs, with the aim to optimize geothermal energy production operations in naturally fractured reservoirs.

REFERENCES

Barton, N. & Bandis, S.(1980). Some effects of scale on the shear strength of joints. International Journal of Rock Mechanics and Mining Sciences 17: 69–73

Boersma, Q. D., Bruna, P. O., De Hoop, S., Vinci, F., Tehrani, A. M., & Bertotti, G. (2021). The impact of natural fractures on heat extraction from tight Triassic sandstones in the West Netherlands Basin: a case study combining well, seismic and numerical data. Netherlands Journal of Geosciences, 100.

Canchumuni, S. W., Castro, J. D., Potratz, J., Emerick, A. A., & Pacheco, M. A. C. (2021). Recent developments combining ensemble smoother and deep generative networks for facies history-matching. *Computational Geosciences*, *25*(1), 433-466.

de Hoop, S., Voskov, D., Bertotti, G., Barnhoorn, A. (2022) An Advanced Discrete Fracture Methodology for Fast, Robust, and Accurate Simulation of Energy Production From Complex Fracture Networks. Water Resources Research 58.5. Evensen, G., Vossepoel, F. C., van Leeuwen, P. J.(2022). Data Assimilation Fundamentals: A Unified Formulation of the State and Parameter Estimation Problem. Springer Textbooks in Earth Sciences, Geography and Environment. Cham: Springer International Publishing, 2022.

Khait, M., Voskov, D. (2018) Operator-based linearization for efficient modeling of geothermal processes”. Geothermics 74 (2018), pp. 7–18.

Kraft, D., & Powell, S. (1994). A software package for sequential quadratic programming. Argonne National Laboratory, Technical Report ANL-94-41

Seabra, G. S., De Hoop, S., Voskov, D., & Vossepoel, F. C. (2022). Improved Understanding of Naturally Fractured Reservoirs Using Data Assimilation. In *EAGE GET 2022* (Vol. 2022, No. 1, pp. 1-5). European Association of Geoscientists & Engineers.

Wang, Y., Voskov, D., Khait, M., & Bruhn, D. (2020). An efficient numerical simulator for geothermal simulation: A benchmark study. *Applied Energy*, *264*, 114693.

Wang Y, Hoop S de, Voskov D, Bruhn D, Bertotti G. (2021). Modeling of multiphase mass and heat transfer in fractured high-enthalpy geothermal systems with advanced discrete fracture methodology. Advances in Water Resources, 154:103985.

Karimi-Fard, M., Durlofsky, L. J., & Aziz, K. (2004). An efficient discrete-fracture model applicable for general-purpose reservoir simulators. SPE Journal, 9(02), 227-236

Tian, X., Blinovs, A., Khait, M., & Voskov, D. (2021). Discrete well affinity data-driven proxy model for production forecast. *SPE Journal*, *26*(04), 1876-1892.