INL/CON-22-69697-Revision-0

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Prepared for the
U.S. Department of Energy
Under DOE Idaho Operations Office
Contract DE-EE0007080

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Keywords
Discrete fracture network, FALCON, MOOSE, FORGE, Optimization under uncertainty, Stochastic methods

ABSTRACT

Orientation and completion for well pairs that have been subjected to multi-zonal stimulation play a critical role in the long-term performance of an Enhanced Geothermal Reservoir. Enhanced geothermal systems often rely on preferential flow along fractures between well injection and production locations. Modeling this preferential flow using discrete fracture networks (DNF) relies on stochastic realizations of the DFN based on geological sampling. Here we present the development of a stochastic optimization methodology to determine well completion options in a discrete fracture network based on using parallel subset simulation. Stochastic optimization will provide insight into regions where placements of the injection and production wells are optimal. An example optimization of well-pair location optimization based on a deterministic-stochastic DFN model representing FORGE follows a discussion of the theory.

1. Introduction

Fracture networks dominate the hydrology of subsurface flow in deep crystalline rocks. Fluid flow through a dense fracture network will result in large scale anisotropies in the fluid transport due to the orientation and size statistics of the underlying fractures. These anisotropies are important to account for in the placement of injection and production wells in a geothermal systems and will influence both the short term flow through the connectivity of the fracture network and the long term operational conditions for energy extraction.

A discrete fracture network (DFN) is a discretized geometry of the fracture network used in simulations. In our work, the DFN is produced from a stochastic realization that deterministically match the fracture data collected along the borehole [Finnila et al. (2021)]. Simulations of flow from an injection location in the fracture network to the production location provides insight into the operation of a well-pairs. Optimizing the placement of well pairs within a DFN is difficult due to the complexity of flow paths through the DFN and the stochastic nature of the DFN. Each well pair simulation can also be computationally expensive and so the number of such simulations needs to be minimized. Global optimization methods including random sampling can overcome some of these issues but brute force approaches based strictly on Monte Carlo methods become too computationally expensive due to the number of required samples. Some other methods are better, including adaptive importances sampling.

In this work, we perform porous flow simulations and develop the parallel subset optimization algorithms using FALCON, a MOOSE (Multiphysics Object-Oriented Simulation Environment)

based application developed for geothermal systems framework [Podgorney et al. (2010), Permann et al. (2020)]. In the following section, we provide an overview of the flow equations being solved and the algorithms implemented for adaptive importance sampling. This is followed by an analysis for optimal well pair placement in a large DFN created from the geology of the FORGE site.

2. Stochastic Optimization

In this section, we provide an overview of the DFN simulation and stochastic optimization as implemented in FALCON. The MOOSE framework that FALCON is built on provides an interface for developing new methods for solving the differential equations that govern physical processes. This interface allows a user to focus on the implementation of methods required for solving the physics of the problem without having to deal with parallel communication, nonlinear solvers, and finite element discretization. Optimization algorithms built within the MOOSE framework have the flexibility to control the execution of the flow of simulations.

2.1 Discrete Fracture Network Simulation

In our work we simulate fluid flow using FALCON, a MOOSE application for fully coupled Thermal-Hydraulic-Mechanical-Chemical porous flow [Podgorney et al. (2010)], Wilkins et al. (2020), Wilkins et al. (2021)]. To simplify and speed-up the simulations, we only consider fluid injection into a fluid filled DFN with no transfer occuring between the DFN and matrix. We also do not consider heat and energy transport in the fluid. Under these conditions, the fluid flow in the DFN is captured by the Darcy flow equations for a single-phase system containing multiple fluid components given by

(1)

where P is the pressure, is the porosity, is the mass fraction of component i, k is the permeability, is the fluid density and is the viscosity. In this case, there are two fluid components (i=2); the fluid initially filling the DFN (Fluid A) and the fluid being injected (Fluid B). Point sources are used to inject Fluid B into the DFN and withdraw both fluids from the production point.

A small two component DFN simulation is shown in Figure 1. Initially, the DFN only contains Fluid A. Fluid B (tracer) is pumped into the DFN at the injection point and slowly saturates the DFN. Figure 1b shows the change in Fluid B mass fraction over time at the production point and at a test location. The test location only samples the mass fraction of Fluid B. The test location is close to the injection point and this location is quickly saturated by Fluid B, the red line showing the mass fraction of Fluid B in Figure 1b quickly goes from 0 to 1. Both Fluid A and B are being withdrawn from the production point. Initially, only Fluid A is available for withdrawal from the production point as shown by the blue line in Figure 1b with an initial value of 0 for the mass fraction of Fluid B. As the simulation progresses, Fluid B begins to saturate the DFN and makes its way to the production point where a mixture of Fluid A and Fluid B then starts to be withdrawn. As the simulation continues, the mass fraction of Fluid B being withdraw from the production point increases as most of Fluid A is either withdrawn or pushed away from the production.

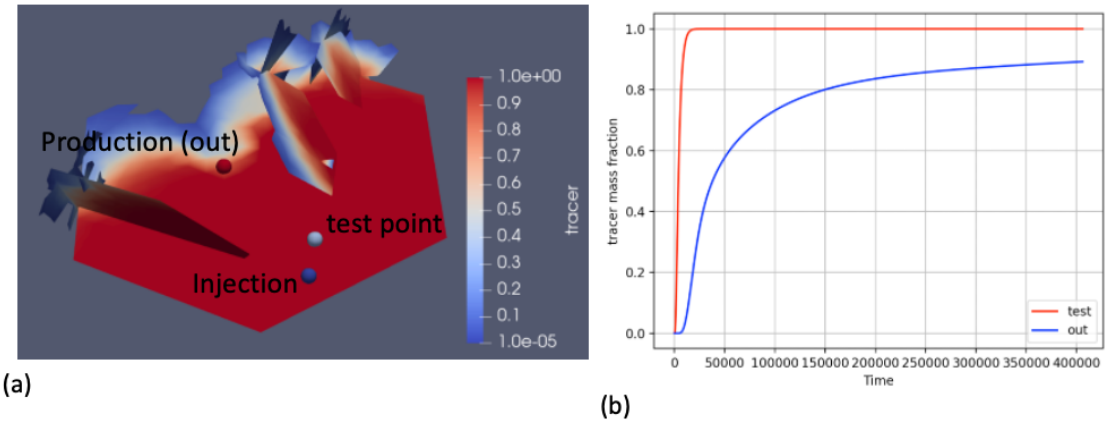

Figure 1: (a) Fluid B (tracer) flow in the DFN. A point source injects the tracer at the injection point and pressurizes the DFN. A sink is placed at the production point that pulls out Fluid A and Fluid B (tracer). (b) Fluid B (tracer) mass fraction versus time as measured at two points. The test point is close to the injection location and Fluid B quickly displaces the Fluid A and reaches a mass fraction of 1. At production location, the sink pulls in both Fluid A and B, leading to a more gradual increase in Fluid B (tracer) mass fraction.

2.2 Subset Simulation for Stochastic Optimization

We use the subset simulation algorithm to stochastically optimize the well completion options. Subset simulation [Au and Beck (2001)] is a stochastic algorithm which provides us with the ensemble of well completion options that are all similarly admissible. As presented in Figure 2, the algorithm starts with a regular Monte Carlo which randomly samples production locations and simulates the tracer output values. This is subset 1 of the algorithm. An intermediate failure threshold is picked which is percentile value of the tracer outputs. is usually set anywhere between 0.5 and 0.9. Then, numerous Markov chains are simulated such the corresponding tracer output values always exceed . These Markov chains again give use\ production locations and corresponding tracer outputs (which are greater than). This is subset 2 of the algorithm. Another intermediate failure threshold is picked which is percentile value of the tracer outputs in subset 2. Again, numerous Markov chains simulated for subset 3 whose tracer output values always exceed and the algorithm proceeds in this fashion. As the algorithm proceeds towards higher subsets, the tracer output values are stochastically optimized. In the final subset, the outcome is an ensemble of production locations and corresponding tracer outputs, all of which have a similar admissibility of being the best values.

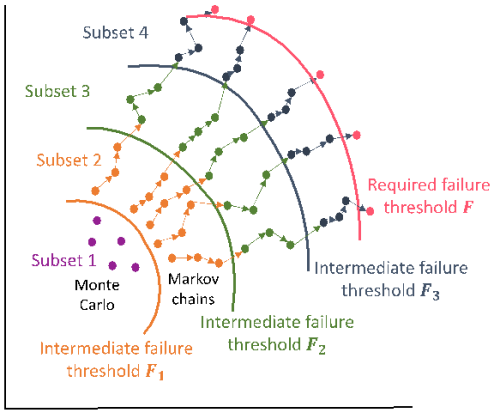

Figure 2: Schematic of the subset simulation algorithm used for conducting stochastic optimization of the well completion options based on the tracer output values. This figure is adapted from [Dhulipala et al. (2022)].

3. Optimization of Well Pairs in FORGE DFN

The above stochastic optimization algorithm and two component DFN flow simulation is applied to a large DFN representative of FORGE Well 16(A and B)-78(32) [Finnila et al. (2021)], shown in Figure 3. In this analysis, we assume the following:

- the physics is fully-saturated, two component, single phase porous flow;
- the pore pressure is initially hydrostatic, around 10MPa corresponding to a depth of around 1km;
- injection of tracer fluid is into the fracture network only, through a fixed point at the DFN's centroid, at a rate of 10kg.s^{-1};
- production is from the fracture network only, at locations determined by the optimization alogorithm, at a rate of approximately 10kg.s^{-1} for both fluid A and tracer;

3.1 DFN Simulation

The DFN contains 4320 individual fractures shown in Figure 3, meshed with three-noded triangular elements at 5m resolution. These meshes were created from the injection stimulated XSite simulations [Xing et. Al. 2021] of the stochastic DFN [Finnila et al. (2021)]. Results for a simulation are shown in Figure 3 with the injection and production wells labeled in Figure 3(b). This simulation contains 738,420 elements and 403,755 nodes and requires 5 hours of wall clock time on 48 processors for the 20-day simulation.

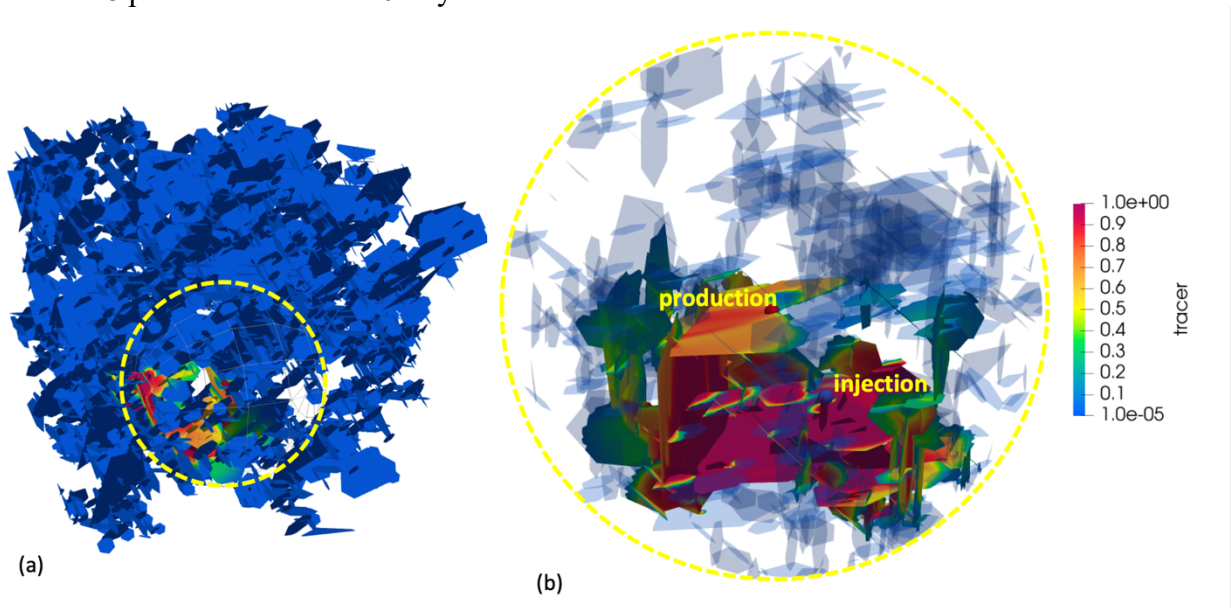

Figure 3: (a) Entire DFN colored by tracer mass fraction after 20 days of simulation time. Radius of yellow dashed circle is 170m. (b) Close-up of circled region showing well pair. Injection point shown by blue sphere and production point shown by red sphere and labels.

3.2 Parallelized Subset Simulation in Falcon/MOOSE

The subset simulation algorithm for conducting stochastic optimization has been implemented in Falcon/MOOSE [Dhulipala et al. (2022)]. MOOSE supports a massively parallel computing environment. As such, the subset simulation algorithm is implemented in way that it leverages MOOSE's massively parallel computing capabilities using the MOOSE MultiApp System [Gaston et al. (2015)]. The MultiApp System provides us with the ability to create a main application that runs the subset simulation algorithm which controls the execution of multiple DFN simulations and the data each simulation returns to the main application. The numerous Markov chains in subset simulation are independent of each other and can be executed in parallel.

Below, we give a brief syntax description of the MOOSE input file to use subset simulation with parallel computing. There are three components: (i) Samplers block; (ii) Reporters block; and (iii) Executioner block. The Samplers block specifies the parallel subset simulation algorithm and the associated parameters: distributions of the production coordinates which follow a uniform distribution with upper and lower bounds, output_reporter which is the tracer output value from the simulation, num_samplessub which specifies the samples in each subset, num_parallel_chains which specifies the number of parallel Markov chains to execute in parallel; and subset_probability which specifies the value. Listing 1 presents the Samplers block. The Samplers block proposes new production coordinates for running the DFN simulations.

```
[         ]
  [       ]
    type =
                  = 'xcoord ycoord zcoord'
                    = 'Tracerout_storage/Tracerout:int_tracer:value'
                    = 'adaptive_MC/inputs'
               = 'PRE_MULTIAPP_SETUP'
                   = 200
                       = false
                        = 100
                       = 0.5
          = 1012
  []
[]
```

Listing 1: Samplers block in the MOOSE input file specifying the ParallelSubsetSimulation sampler and the required parameter inputs.

The Reporters block then decides on whether to accept the production coordinates sampled by the Samplers block. In a Markov chain, there is a proposal step and a accept/reject step. The Samplers and Reporters blocks replicate these two steps. The Reporters block has two components: StochasticReporter stores the output value from the DFN model sub-application; and AdaptiveMonteCarloDecision takes the output value from StochasticReporter and decides on whether to accept the production coordinates. The StochasticReporter also requires the sampler as an input. Listing 2 presents the Reporters block.

```
[          ]
  [                ]
    type =
               = 'timestep_end'
  []
  [            ]
    type =
                  = 'Tracerout_storage/Tracerout:int_tracer:value'
           = 'inputs'
            =
  []
[]
```

Listing 2: Reporters block in the MOOSE input file and the required parameter inputs.

The Executioner block specifies the total number of samples for the stochastic optimization. Listing 3 presents the Executioner block. For the present paper, we used three subsets in the subset simulation algorithm, each having 200 samples. We have used 1000 processors to run the stochastic optimization with 100 parallel Markov chains in each subset. This means that an individual DFN evaluation is made by 10 processors. Also, since 100 parallel samples are simulated per subset and there are three subsets, to total number of steps (i.e., num_steps) in the Executioner block is 6.

```
[            ]
  type =
               = 6
[]
```

Listing 3: Executioner block in the MOOSE input file and the required parameter inputs.

3.3 Preliminary Results: Optimal Production Locations

We used the parallelized subset simulation method in Falcon/MOOSE to estimate the best production well locations that minimize the time-integrated tracer output from the production well. By using an objective function that minimizes the tracer output, we are in effect finding production well locations that will increase the amount of time the fluid spends in the DFN, maximizing the amount of heat extracted from the geothermal system. The parameters used for running the parallelized subset simulation method in Falcon/MOOSE are described in Section 3.2. Figure 3(a) presents the DFN model mesh and the injection location. The random production coordinates are sampled within the spherical domain presented in Figure 3(b). Figure 4 presents the time-integrated tracer output for the three optimization levels. It is observed that as the level increases, the time-integrated tracer output is minimized. The production coordinates associated with the time-integrated tracer output in the optimization level 3 are the required coordinates. In the future, we will explore other optimization objectives which lead to a better selection of the production coordinates and consider production locations intersecting with multiple fracture planes along a long.

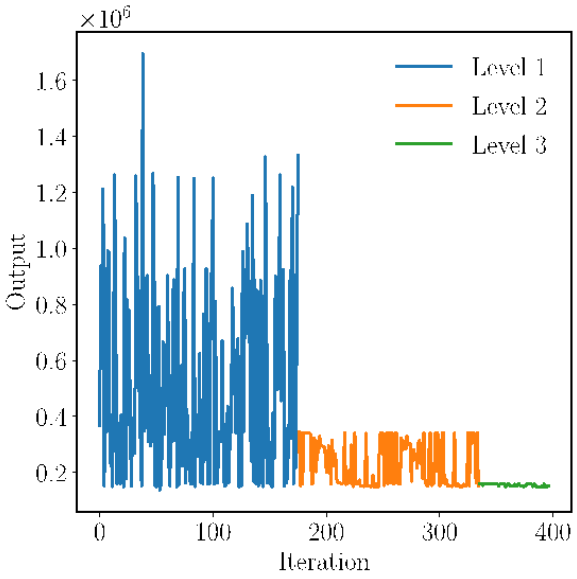

Figure 4: The integrated tracer output values during the stochastic optimization using the subset simulation algorithm. It is noticed as the optimization level increases from 1 to 3, the output value is optimized. The production coordinates corresponding to the outputs in level 3 of the optimization are the optimized production coordinates.

4. Conclusions and Future Work

In this work we presented two component flow simulations of a large DFN representative of the FORGE site. We also presented an adaptive sampling technique, termed parallelized subset simulation, to efficiently place 100's of well pairs in the DFN and determine an optimal placement based on a simple objective function. The objective function used for optimization was based on minimizing the mass flow rate of tracer at the production site. This resulted in distance from the injection site being the main factor in determining optimal well placement. This objective function allowed us to develop our stochastic optimization framework but, in the future, we will explore different objective functions. We would like the objective function to find production locations that will maximize the extent of tracer in the DFN and maximize the connectivity of the DFN between the well pairs. This work was also based on a single production point in the DFN. Our future work will build on this to allow for open hole production wells that will connect with multiple points on the DFN. The optimization algorithm and objective function would need to be changed to account for this type of flow pattern in the DFN.

Acknowledgement

Funding for this work was provided by the U.S. DOE under grant DE-EE0007080 "Enhanced Geothermal System Concept Testing and Development at the Milford City, Utah FORGE Site". We thank the many stakeholders who are supporting this project, including Smithfield, Utah School and Institutional Trust Lands Administration, and Beaver County as well as the Utah Governor's Office of Energy Development.
This research made use of the resources of the High Performance Computing Center at Idaho National Laboratory, which is supported by the Office of Nuclear Energy of the U.S. Department

of Energy and the Nuclear Science User Facilities under Contract No. DE-AC07-05ID14517.

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