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Linking Microseismicity, Characterization of Pre-Exisiting Fractures and Geomechanical Models in Hydraulic Stimulation

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Introduction

Geomechanical modelling of hydraulic stimulations in unconventional reservoirs require data to build and calibrate models in order to predict decline curves and other aspects of long-term reservoir performance. The initialization of these models requires knowledge of the pre-existing fracture and other geological properties of the media. Orientations of different fracture sets at different scales, their intensities and spacings of these sets together with a characterization of their size scales (power law) critically impacts the geomechical predictions of both the stimulations in terms of proppant and fluid placement, but also the decline of the reservoir.

Much insight can be gained on the properties of the fracture network through analysis of the microseismic data that is generated from the stimulation. The frequency response of the waveforms corresponds to the size of the rupture necessitating wide band recording of these spectra in order to constrain a variety of scales. In fact, supplementing low frequency sensors to the traditional monitoring geometries of high frequency sensors allows for the extension of this resolvable bands to larger scale lengths. In these scales, with a sufficient sampling of azimuths around the stimulation, the mechanisms and associated fracture planes can be reconstructed though seismic moment tensor inversion (SMTI).

At the smaller scale lengths, events can occur at lower signal to noise ratios, and may not be observed at high enough quality on the multiple array geometries necessary for SMTI. So to extend the characterization of these fractures to smaller scales, we use a stochastic optimization algorithm designed to search for optimally placed fractures in the reservoir that intersect with the event locations, constraining their orientations to be drawn from the same distribution observed at the larger (SMTI resolvable) length scales. Effectively, this technique allows further extensions of the power laws governing the fracture distributions in the reservoir to smaller scales. In turn, the further characterizations of the wider band of fractures in the reservoir provided necessary inputs into geomechanical models to predict the fluid and proppant distributions.

Problem Statement

We model fracture planes on which microseismic events occur by penny-shaped cracks, and a DFN, for our purposes, is the collection of these features. Seifollahi et al [**1**] considered the following question: Given only a pointcloud of events, can a DFN be constructed that is better than randomly assigning orientations and midpoints to a predefined number of ellipses? They treat the problem of defining a DFN as a purely geometric optimization problem. They introduce fractures according to a lognormal distribution of fracture lengths with arbitrary orientation and midpoint. Their solution uses a simulated annealing protocol to refine the orientations and midpoints of the ellipses; their solution also splits and joins fractures based on certain similarity criteria. They minimize the orthogonal distance of events to the nearest ellipse, as well as maximize both the number of events with a "close" ellipse and the number of events per ellipse. Their conclusion is that they can construct a DFN that adequately improves the fitness of the model; further, their splitting and joining criteria means that they need not assume a predefined number of fractures.

Here we address a related question: does the Seffolahi et al approach allow extending a DFN determined from SMTI, to smaller scales that is fit and maintains the distribution of orientations? We identify an instability in the Seifollahi et al approach, especially in light of SMTI data: that the distribution of orientations varies considerably from run to run; moreover the distribution of orientations obtained from a pure stochastic simulation does not align with the distribution of orientations obtained from SMTI. We propose a change to Seifollahi's algorithm regarding the selection of orientations during the initialization of simulated annealing. Finally we evaluate our modelling approach and show that it avoids this problem.

Method

Our algorithm uses SMTI to derive an initial DFN; the orientations and lengths are taken from the SMTI and the determination of the source radius respectively. We then use a simulated annealing protocol to refine and extend the model. The algorithm for DFN construction breaks naturally into three main pieces: initialization, annealing, and fitness evaluation.

In the initialization phase, SMTI data is used to produce a DFN that is completely deterministic. This yields a DFN that contains the correct orientation distribution. We then extend this DFN to more events and sample from this distribution to derive the orientations for an initial guess of the right number of fractures. This procedure gives an initial model to be annealed.

We use a non-heterogeneous simulated annealing protocol to refine the model, continually testing various proposals to shifting the midpoints and swapping two fractures' orientations for acceptance against an acceptance probability that is controlled by "temperature" (a variable from the simulated annealing procedure). We also propose the introduction and removal of certain fractures when a fracture can be explained by two clusters, or when a fracture is redundant quite similarly to Seifollahi (respectively).

The fitness evaluation that drives the annealing consists of four goals. Minimize distances of events to their closest fracture; maximize the number of points per fracture; maximize the number of events with a close fracture; minimize the distance to the power law distribution of fracture lengths (needed due to splitting and joining fractures).

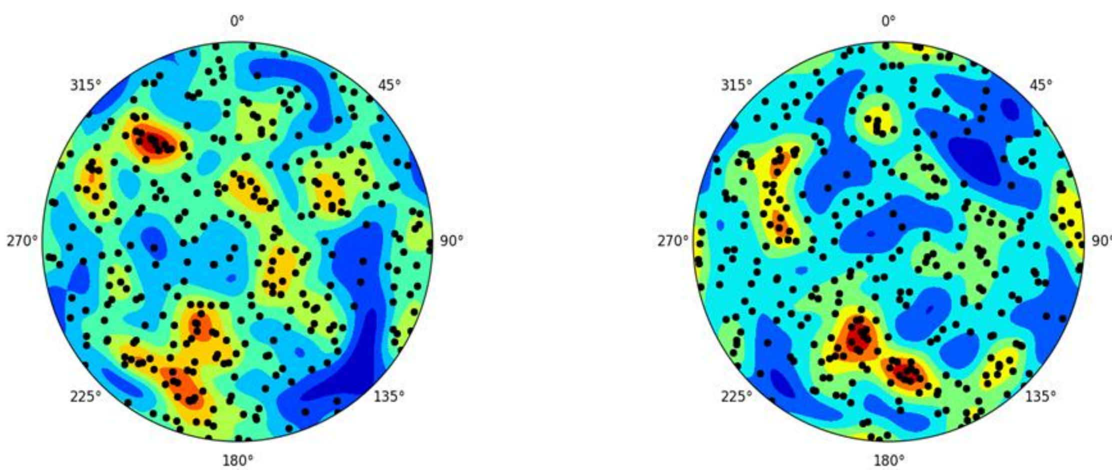

Figure 1: (left) Stereonet of orientation from a run of Seifollahi on the Nexen d-E37-h stage 17 data set. 0 is North and clockwise runs N,E,S,W. The altitude follows meridian and parallel lines that intersect at right angles. From blue to red indicates a shift from low to high density. (right) Stereonet of a second run of Seifollahi on d-E37-h. Note the differences between the two runs.

Results

We first identify an instability in the Seifollahi et al approach: each time the algorithm is run, the distribution of orientations changes. Consider the two stereonets of orientation distributions of two different runs of the Seifollahi algorithm applied to a set of locations recorded during a stage of a hydraulic fracture completion of a multi-well pad in figure 1.

On one hand, figure 1 showcases some consistency in the orientation distributions; both have clusters of orientations near the 180 degree line and the 315 degree line. However, there is large discrepancy between the two as well; the highest density in the left picture is along the 315 degree line while the highest density in the right picture is along the 180 degree line. Further the largely unoccupied orientations in the distributions do not align.

Moreover, the distribution of orientations does not reflect the orientation distribution that is determined from SMTI. Figure 2 depicts the actual orientation distribution from SMTI.

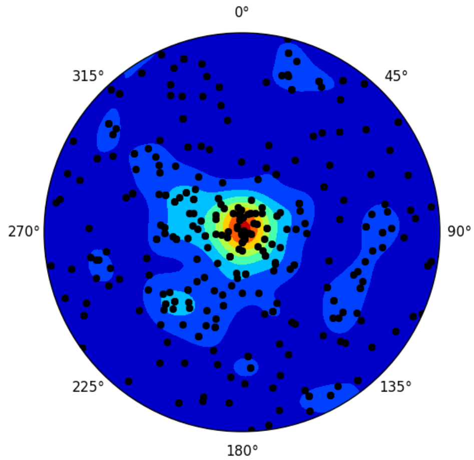

Figure 2: Stereonet of orientations of pure SMTI DFN on d-E37-h stage 17.

Our changes to the Seifollahi algorithm force the initialization of stochastic fractures to be sampled from the distribution of SMTI orientations; there is a small loss in the distribution expected here. Then, once the initial orientation distribution is set, the annealing of the model strictly preserves the orientation distribution. Consider figure 3:

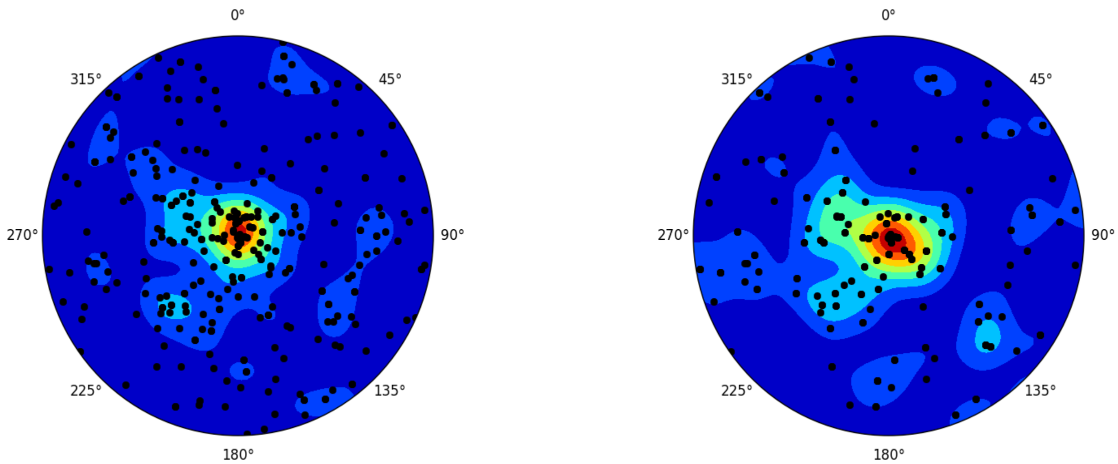

Figure 3: (left) SMTI+Optimization orientations for d-E37-h. Note that the orientations are almost identical to the above pure SMTI orientation distribution. (right) Crippled SMTI+Optimization orientations for d-E37-h. Even with less SMTI data, we construct the correct orientation distribution.

The left picture displays the full model from our approach. Note it preserves the orientations of the true SMTI distribution (figure 2) almost precisely. On the right, we have crippled our approach, we sampled just under half of the SMTI events, and we nearly recreate a DFN with the correct orientations. Thus, not only do consecutive runs produce DFNs with very similar orientation distributions, they do so even on a sparse sampling of orientations, and further they correctly reflect the SMTI DFN. We also see adequate improvements in fitness. In ten runs, the average fitness drop for our approach was not significantly different from Seifollahi. A typical graph of fitness with respect to "temperature" is given in figure 4.

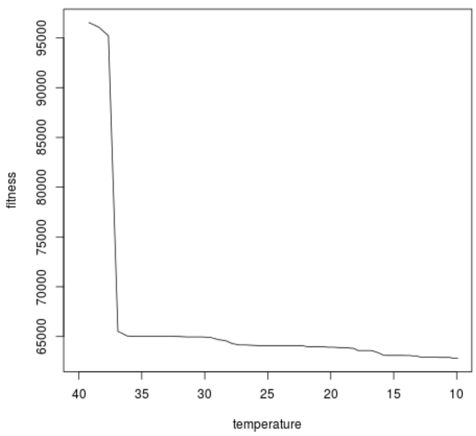

Figure 4: Plot of Temperature (horizontal) versus Fitness (vertical). Lower fitness is better. Temperature lowers as the algorithm runs, and is proportional to the number of refinements made.

Anecdotally, one typically sees large improvements in fitness near the beginning where exploration is high (due to higher "temperature"), and slow and gradual improvement until the algorithm halts. We see smaller but continual improvements the longer the algorithm is run.

Conclusions

We have seen that a stochastic approach to DFN construction based on simulated annealing allows the improvement of a DFN when no other criteria are available. We have seen that such a purely stochastic algorithm has an instability in the distribution of orientations it outputs. We have shown that in light of microseismic and SMTI data, the stochastic approach can be modified to avoid these instabilities quite well; in fact, we can even remove more than half of the SMTI events, and still produce a DFN with strikingly similar orientations to the SMTI DFN.

This approach thus allows more safely extrapolating a DFN derived from SMTI to more events. It also allows extending the DFN to smaller scales than would be available from SMTI alone.

References

1. S. Seifollahi, P. Dowd, C. Xu, and A. Fadakar. "A Spatial Clustering Approach for Stochastic Fracture Network Modelling." Rock Mechanics and Rock Engineering. Volume 47. pp. 1225 – 1235. 2014.