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Predicting and Optimizing Fracture Growth Through the Integration of Microseismic and Seismic Data.

Samuel M. Muller, Marco Perez and Andrew Iverson
Velvet Energy Ltd.

Summary

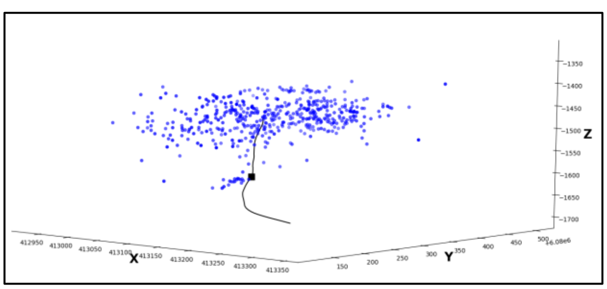
With a statistically significant set of microseismic data from hydraulically stimulated wells a correlation can be established between the microseismic estimate of stimulated rock volume (SRV) and well production. By correlating various microseismic patterns to a porosity volume, a relationship between “porosity class” and the expected microseismic response can be established.

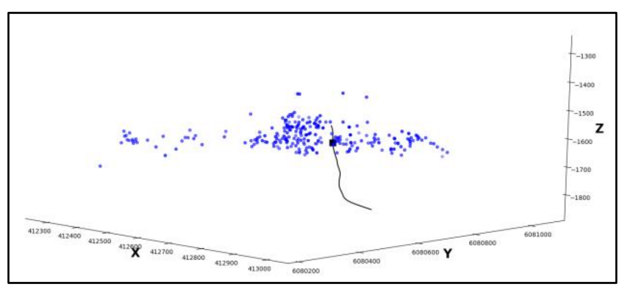
By analyzing how the microseismic cloud grows as a function of cumulative proppant tonnage, hydraulic fracturing can be optimized by maximizing the likelihood of achieving the desired microseismic response. Properly developing this workflow results in a data driven map that prescribes the tonnage that optimizes a stages stimulation.

Theory / Method / Workflow

The data used in this workflow consists of a set of seven wells that have microseismic data and production data. Additionally, inverted seismic provided porosity estimates at the locations of the microseismic wells and in the surrounding area.

The microseismic dataset used in this workflow contained the surface and depths (X, Y and Z) of each microseismic event as well as at what tonnage the event occurred at. As shown in the figures below, there can be large variations in microseismic response along a single well bore. To make meaningful associations and predictions with the microseismic data a quantitative method must be used to capture the inter-stage microseismic without smoothing over potentially significant outliers.





The metric chosen to characterize microseismic clouds was the fracture half length (Xf). Xf was calculated for four geologic intervals that contained microseismic data, providing four values that describe the length of the microseismic cloud perpendicular to the wellbore. The fracture half-length in each zone was estimated by first isolating the in-zone events, and then calculating the radius of gyration (Sayers and Le Calvez, 2010) based on their cumulative moment of inertia about a vector defined by the well bore.

Each stage, using its four calculated Xf values, can be associated to an SRV pattern using the K means clustering algorithm. The three resulting centroids represent the microseismic responses that describe the population with the least error (four-dimensional Euclidean distance). Plotting the lower zone Xf, mid zone Xf, and average of the two upper zone Xfs allows a simple visual of how the stages have been clustered through this algorithm. Figure 2 shows these clusters. Observe the differences between the pink class, and the blue and red classes. The pink class exhibits large lower zone stimulation and very limited stimulation in the upper zone. In contrast, the blue and red classes show ascending stimulation. Speculation can be made as to which class is 'optimal', but this will be statistically established later in the workflow.

The same clustering algorithm can be used on the inverted seismic data. Extracting the average porosity value in each of the four zones, a map can be produced that is populated by the discretized porosity interval at each X, Y location. Figure 3 shows the discretized porosity classes along with the stages colored by their microseismic classification. Notice how some porosity classes such as teal and blue show ascending porosity with depth, whereas the other classes show a more constant porosity structure.

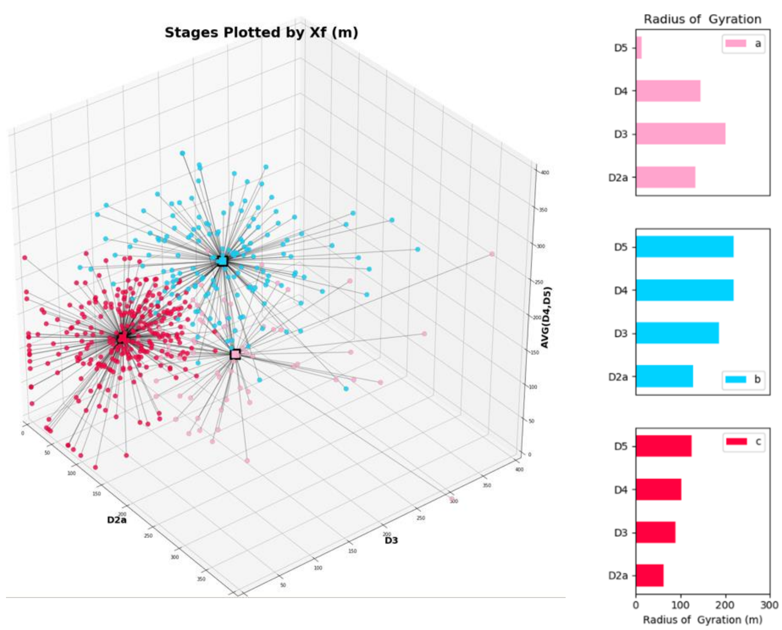


Figure 2

The relationship between porosity variation with depth and the microseismic response is explored in this workflow. It was explored due to the relationship between porosity in a rock media and the diffusion of pressure (Shaprio et al 2006) Permeability operates partly as a function of porosity, and the diffusion of pressure operates as a function of the permeability of the media. So, it would stand to reason that a statistical relationship could be found between porosity variations with depth and the variations of hydraulic stimulations operating in those same intervals.

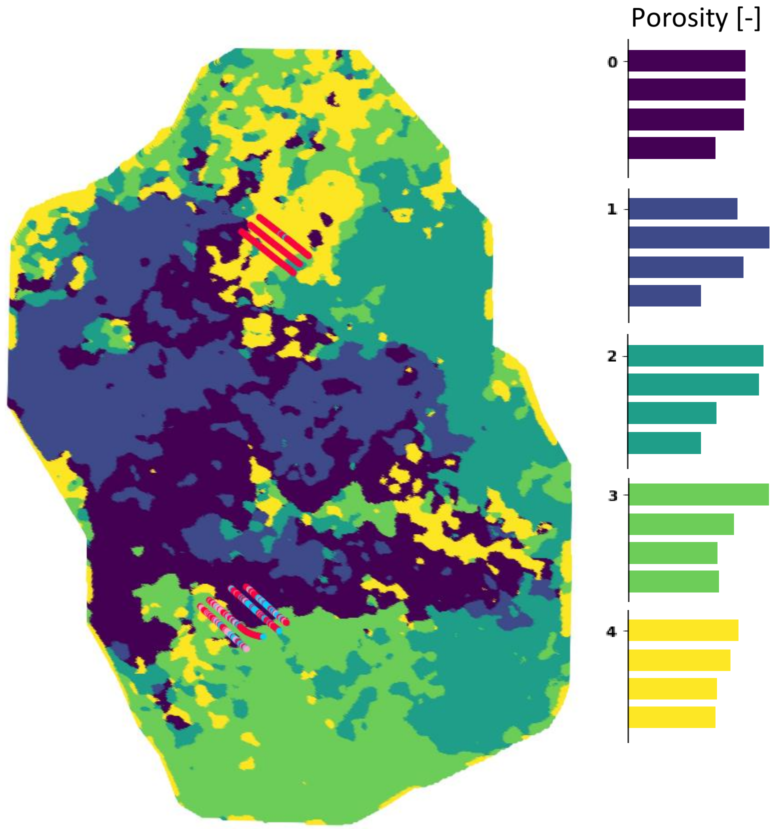


Figure 3

Each stage can be classified by its microseismic class, and a porosity class. By computing the conditional probabilities of achieving each microseismic class for a given porosity class, a stochastic matrix can be constructed. By normalizing the values along each of the 5 porosity classes a probability matrix is made that, when used in areas with no microseismic data provides the likelihood of achieving a certain microseismic class given a known porosity class.

Using this matrix, the expected number of each microseismic classes for the portion of the seven wells that did not have microseismic data can be determined. The collection of microseismic classes along the wellbore provides a general description of the well's stimulation in the four zones. It can be shown that the Total Fluids (water + oil) produced by a well is a function of the number of each of the three microseismic classes found along the well bore. Using the seven wells in the dataset, a Multi Linear Regression model was determined that expresses Total Fluids as a function of the number of each microseismic class.

Using the matrix to estimate the expected quantities of microseismic classes along a well bore and inputting these values into the MLR equation the Total Fluids of wells that fall within the bounds of the inverted seismic can be predicted for. Figure 4 below shows the strength of the correlation between predicated Total Fluids and the measured Total Fluids for that well.

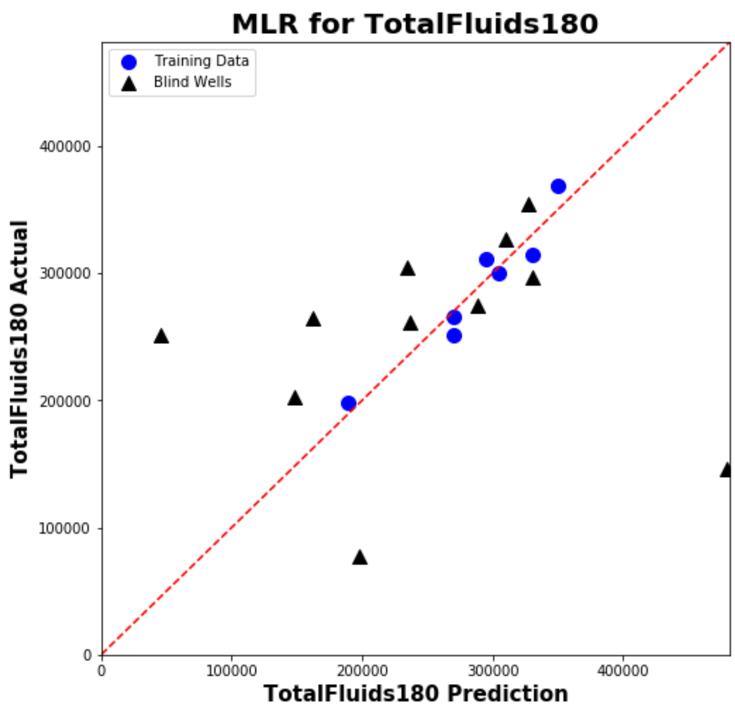


Figure 4

By analyzing the coefficients of the MLR equation it was determined that additional pink microseismic classes, characterized by large lower zone Xf and small upper zone Xf, have the most constructive effect on total fluids production.

This workflow can be carried out to assess the impact of tonnage. Smaller tonnage outputs can be simulated by varying tonnage cutoffs, that is, only including microseismic events that occur before the chosen tonnage. By recalculating the Xf values for each stage using only microseismic events that occur before the chosen tonnage a new probability matrix can be calculated at each tonnage increment. Analyzing the row of the probability matrices that represents a given seismic class the optimal tonnage can be determined that maximizes the MLR prediction of Total Fluids Prediction. The development of a production equation is not done to predict future tonnage, but to understand qualitatitvely which microseismic classes exhibit a constructive relationship to Total Fluids

Transforming each seismic class to its prescribed tonnage an optimal tonnage map can be created. The tonnage map offers a prescription of what tonnage will optimize the total fluids produced by a stage in a known porosity class.

Results, Observations, Conclusions

This workflow outlines a new way to combine microseismic, seismic and production data to be prescriptive of future completions strategies. By relating the instances of the desired microseismic response to the three-dimensional porosity model the probability of achieving the various microseismic responses within the boundaries of the inverted seismic can be statistically estimated. By analyzing how the microseismic responses vary with tonnage the affect that tonnage has on the microseismic cloud can be better understood, and ultimately prescriptions can be made for stages in the seismic survey boundary.

Acknowledgements

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