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Permeability Estimation in a Multi-fractured Top Seal

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SUMMARY

Permeability of fracture media is one of the most important parameters characterising fluid flow, but it requires a detailed knowledge of fractures and fracture networks distribution.
The unique exposures north to Santa Cruz represents a rare opportunity to observe and fully investigate a recently active bitumen-bearing fractured top seal.
Permeability of a fracture network depends on the statistical distribution of fracture length, aperture, orientation, and density. Those fracture attributes are related to the permeability properties though a tensor (the Permeability Tensor). The statistical methods presented here for collecting and analysing fracture attributes shows how to obtain a more accurate data set directly collecting fracture attributes from fields, and how those features are fundamental for estimating permeability in a multi-fractured system.

Introduction

The upper part of the Earth's crust is highly fractured on all scales ranging from microcracks to large-scale joints, from tens of microns to hundreds metres. Fractures and joints are well known for their effects on the mechanical properties of rocks (e.g. bulk elastic constant and shear strength), but they also control the permeability of crystalline and tight sedimentary rocks, such as shales and mudstones (*Brace*, 1980). They can make major flow paths when they are connected in networks. Fluid flow in fractured rocks is therefore of primary importance for hydrocarbon production from fractured reservoirs, reservoir stimulation by hydrofracturing, hazardous waste isolation, and geothermal energy extraction (*Brown*, 1987). For these reasons an effort has to be placed on characterisation (*Aydin*, 2000) and modelling (e.g. *Oda*, 1986; *Brown & Bruhn*, 1998) of fractures and fractured systems. Unique outcrops around Santa Cruz (California, USA) gave us the chance of observing in the field a recently active bitumen-bearing fractured top seal, which can be used as a natural example to build a general model for permeability estimation. The fracture network is represented by tensional fractures most of which contain some bituminous material. Through a detailed collection of fracture attributes (e.g. length, aperture, orientation) we have obtained the key parameters that allow us to estimate the permeability of this fracture network, as well as their statistical distribution. The main objective of this preliminary work is to understand if permeability of 'multi-fractured' and 'multi-component' systems can be predicted with reasonable uncertainties, and if field measurement of fractures could be used directly to build quantitative models for the estimation of permeability.

Geological Setting

The outcrop areas (Panther Beach and 4 Mile Beach) are located on the South-West flank of the Ben Lomond Mountains, along the coast to the north of Santa Cruz, California. The Salinas Block consists of Palaeocene to Pliocene marine and non-marine deposits which lie disconformably on the pre-Tertiary granitic and metamorphic basement (*Boehm & Moore*, 2002). As described by *Clark* (1981), unconformably overlying the middle-Miocene sequence is a late-Miocene sedimentary sequence consisting of a shallow water transgressive sandstone unit, the Santa Margarita Sandstone, a deeper water biosiliceous mudstone unit, the Santa Cruz Mudstone, and a shallow-water unit, the Purisima Formation. It is believed that the Santa Margarita Sandstone served as a migration path or reservoir for the hydrocarbons sourced in the underlying Monterey Formation (*Phillips*, 1990). In the study area the entire outcrop of the Santa Cruz Mudstone is characterised by a pervasive dilatant fracture system. Fractures form a joint set striking predominantly towards N-W, having all the features of tensile failure, such as plumose structures, hackles and hackles fringes (en-echelons fractures). Numerous fractures in the area show infill and stains of bitumen. Therefore, dilatant fractures represent pathways for hydrocarbon migration, from the source rock (the Monterey Formation) to the surface.

Permeability Estimation

In a series of papers written by *Oda* and coworkers, and by *Brown & Bruhn*, a statistical approach has been used to describe and model the elastic deformation and fluid flow properties of fractured rocks (*Oda*, 1986; *Brown & Bruhn*, 1998). In these works permeability properties are related to the fracture network through a tensor. *Oda* (1986) developed a tensorial model for fluid permeability of fractured rocks. He assumed that fractures are bound by smooth parallel plates with constant aperture (t). Therefore, fluid flow is described by a parallel plate model, where the volumetric flow rate (q) is proportional to the aperture raised to the third power (t^3). Given this assumption the permeability tensor k_{ij} is found to be:

$$k_{ij} = \lambda(P_{kk}\delta_{ij} - P_{ij}) \qquad (1)$$

Where:

$$P_{ij} = \rho\frac{\pi}{4}\int_0^{t_m}\int_0^{r_m}\int_\Omega r^2 t^3 n_i n_j E(\mathbf{n}, r, t)\, d\Omega\, dr\, dt \qquad (2)$$

and where δ_{ij} is the Kronecker delta function. In equations (1) and (2), the permeability of a fracture network depends on the statistical distribution of Length (r), Aperture (t), Orientation (μ), and Density (ρ). Equation (1) is based on the assumptions that: 1) each crack is idealised by a set of parallel plates with uniform aperture; 2) the solid matrix is impermeable (which is a reasonable assumption considering that the Santa Cruz Mudstone is a biosiliceous mudstone). The permeability tensor has been calculated using a new custom MATLAB™ function whose input is a list of fracture apertures, densities, lengths, and fracture direction cosines. The function outputs the values of the P_{ij} tensor used to calculate the permeability tensor, the direction cosines, and k_{ij}, the permeability tensor (Fig. 1).

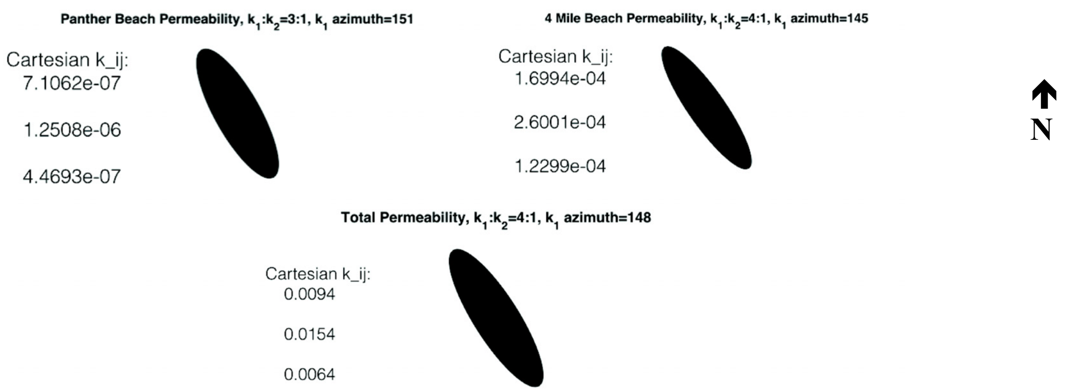

Figure 1 *Graphical overview of the MATLAB™ outputs. The ellipses on the top of the figure represent the 2D Permeability Tensors for Panther Beach and 4 Mile Beach, respectively. The bottom one shows the output for the totality of the fracture system. Permeability values are expressed in m^2. The ellipses are oriented relative to North.*

Fracture Attribute Acquisition and Data Analysis

According to *Oda*'s tensorial method we are interested in the distribution of the following fracture attributes:

- Length (r) expressed in m;
- Intensity (i) as fracture length per unit area, expressed in unit/m;
- Density (ρ) as the number of fracture per unit area, expressed in unit/m2;
- Aperture (a) as the distance between the wall of a fracture, expressed in m;
- Orientation (n_i, n_j... n_k) as direction cosines obtained from the pole to the planes of the fractures.

We collected fracture attributes using the 'circular estimator' method, a combination of circular scan-lines (simply represented by circles drawn on the rock surface) and windows (the region enclosed in the circular scan-line). It is a time-saving sampling tool, providing efficient estimates for fracture trace density, intensity and mean trace length that eliminate orientation bias, censoring and length bias with respect to measurement in a plane (*Mauldon et al*., 2001). It is defined as an 'estimator', because instead of directly sampling individual fractures and measuring their characteristics, parameters are estimated using statistical models (*Zeeb et al*., 2013). Fracture attributes are obtained by simply counting the number (n) of fracture traces intersecting the circumference and counting the number (m) of fracture traces terminating in the circle interior (*Rohrbaugh, et al*., 2013). However, this method does not provide information on important parameters such as fracture orientation and aperture. Hence, we add orientations and apertures data of each fracture inside the circular windows. Commonly the statistical distribution used to describe fracture attributes ranges from the 'normal distribution' (unskewed) to increasingly skewed distributions, such as log-normal, exponential, and power law (*Gillespie et al*., 1999). As suggested by *McCaffrey* and co-workers (2003), the simplest qualitative test to decide which of these distributions is appropriate for a given set of data is obtained by using a 'population plot'. Population plots are generated by ranking the attribute data in descending order, and then, plotting attribute against cumulative frequency (*McCaffrey* et al., 2003).

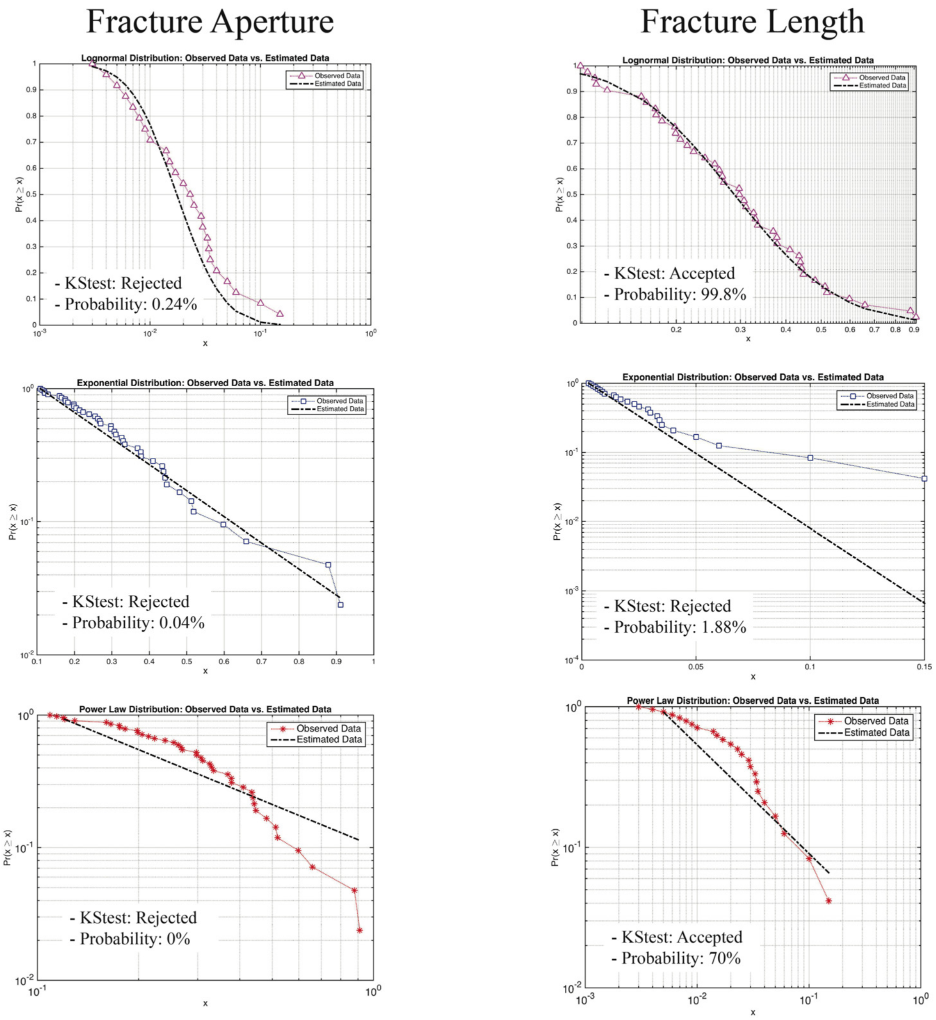

Figure 2 *Graphs showing the curve obtained with the MATLAB™ script comparing the observed data and the theoretical data for fracture aperture and length distributions.*

Then, the resulting function can be fitted to the linear form by least-squares regression. The slope of the fit is interpreted as the estimate of the scaling parameter. However, *Newman* (2005) and *Clauset et al*. (2007) explained that this procedure has several problems, which generates systematic errors under relatively common conditions (*Clauset et al*., 2007), resulting in imprecise prediction of fracture attributes. Therefore, following *Newman* (2005) and *Clauset et al*. (2007) approach to the problem, we were able to estimate the data set distributions through Maximum Likelihood Estimators (MLE). By a new custom MATLAB™ script, it has been possible to find the theoretical distribution (chosen between Power Law, Exponential, and Log-normal distributions) that can best fit apertures and mean trace lengths data. The script gave two different results for the two fracture attributes. It failed to compute a good fit for the apertures. An explanation for this misfit can be directly found in the way aperture data have been collected in the field. Using simply a ruler to measure fracture apertures, it was not possible to discriminate values that are not multiples of 1/2 of millimetre. This causes the data to be highly binned, and reduces the accuracy of the Maximum Likelihood. On the other hand, the script was able to compute and fit very well the fracture length data (with a fit of 99.8% accuracy to a Log-normal distribution) (Fig. 2).

Conclusions

The permeability of fracture networks is one of the most important parameters characterising fluid flow, and is crucial for modelling hydrocarbon migration. The unique exposure of the Santa Cruz Mudstone represents a rare chance to observe an exposed fractured top seal. The preliminary statistical methods presented here for collecting and analysing fracture attribute data could represent a more accurate approach to obtain useful, and more meaningful data from fields analogues, which usually lack of large data sets. Moreover, finding the best statistical distribution governing a data set is of critical importance when predicting the tendency of fracture attributes towards small and large scales, attributes that usually suffer censoring and truncation biases, and which are fundamental for estimating permeability in a multi-fractured system, as we suggest in this work.

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