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Using fluid-induced seismicity to infer permeability

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SUMMARY

For engineering applications involving fluid flow through porous rocks underground, the permeability of a rock mass is an important parameter. Imaging of the 3D permeability distribution is generally done by a history-matching approach: fluid pressure due to injection in a well with known pressure and flow rates is numerically simulated, and the rock permeability is adjusted so as to match predicted pressure values to measured observations. These pressure observations are made at producing wells. Because there will normally be few wells, the observations, while being dense in time, are spatially sparse. The idea of this paper is to augment these downhole pressure measurements by using microseismic data to infer pressure at seismic event locations.

The mechanism of pressure-induced seismicity is the reduction of effective normal stress across a plane of weakness. The rock strength can be represented as a critical pressure – the pore pressure above which the rock will fail. The rock strength is highly heterogeneous, because of the existence of weaknesses such as joints, bedding planes, and clay bands, and stronger regions such as sandstone channels. So the rock strength will be random. We model the rock strength as a Weibull-distributed critical field. A microseismic event occurs where pressure exceeds this critical field, and so is effectively a point pressure measurement, with an uncertainty given by this Weibull distribution. The idea is to augment the well-pressure observations with these "virtual" pressure measurements at seismic event locations.

We model pressure diffusion using a finite volume approach, and examine the inversion, for permeability, of two different types of data, (1) pressure measurements in boreholes, and (2) virtual pressure measurements at seismic event locations. We show that the two types of data provide complementary information.

Key words: microseismic, fluid injection.

INTRODUCTION

Permeability of a rockmass is an important parameter for any fluid-pumping engineering applications, whether they be extraction of gas or oil, underground storage of carbon dioxide, or high-pressure fluid injection for fracturing of unconventional reservoirs. Permeability is, however, a tricky parameter to determine, and current methods typically use a history-matching approach, where known fluid injection rates and pressures are used as sources in a numerical model, and rock parameters such as permeability are adjusted to match pressures measured at producing wells. A good recent review is (Oliver & Chen, 2011) who discuss many of the issues involved, such as how to parameterize the model, different optimization algorithms, computation of gradients, quantification of uncertainty, etc. The spatial sparsity of pressure and flow measurements in wells, however, limits the resolution that can be obtained.

Injection of fluid into the rock (or extraction from the rock) results in a pressure change which diffuses away from the injection point. There is also a change in stress distribution in the rock, because the rock is compressible, and fluid pressure changes induce changes in pore size. This fluid pressure and rock stress change triggers microseismic events at scales ranging from grain-boundary size upwards. Since these microseismic events occur throughout the rockmass, and are caused by pressure changes which are related to the permeability structure of the rock, their location should provide information on the permeability. This idea has been explored by (Shapiro, Rothert, Rath, & Rindschwentner, 2002) who find that the distance, r, from the injection point to a seismicity triggering front is given by

$$r = \sqrt{4\pi D t}$$

where t is the time, and D is a diffusivity. This provides a means of estimating the diffusivity, or, equivalently, the permeability, by estimating the shape of a fracture front curve in distance-time space, and finding a best-fit D value.

There have been numerous attempts to simulate seismicity induced by stress or pressure changes. For example, (Angus et al., 2010) use a coupled fluid flow and geomechanics model to simulate microseismic events due to fluid injection. Most models deal with seismicity by seeding the rock volume with points of weakness, and then testing after each time step to see whether the stress and pressure values at each point are such that the rock would have failed.

In this paper, we wish to use the locations of fluid-pressure-induced microseismic events to provide information on the permeability of the rock through which the fluid is flowing. In order to do this, we need to have a model that can predict seismicity, given rock permeability and injection parameters. There are two components to this: First, the modelling of pressure diffusion through the porous rock, and, second, the modelling of rock fracturing due to pressure changes.

MODELLING OF PRESSURE DIFFUSION

The fluid pressure obeys a conservation equation,

$$\frac{\partial}{\partial t}(\phi\rho) + \nabla \cdot (\rho\vec{v}) = q$$

as well as Darcy's law, a constitutive equation describing the flow of fluid through a porous medium,

$$\vec{v} = -\frac{K}{\mu}\left(\nabla p - g\rho\nabla z\right)$$

Here, φ is the porosity, p is pressure ρ is the fluid density, q is an injection source term, $\vec{v}$ is the fluid velocity, K is the permeability, μ is fluid viscosity, g is the gravitational constant, and z is elevation. Note that both porosity and fluid density can be functions of pressure, meaning that the fluid or rock mass are compressible. The speed at which pressure diffuses through the model depends critically on these compressibilities. We have chosen, for this paper, to model the fluid as incompressible, as is commonly done in reservoir simulations, but to include a pressure-dependent form for the porosity.

We use a finite-volume method to solve the pressure-diffusion equations. Pressure, permeability, and porosity are defined at cell centres, while velocity is defined on cell faces. The gradient operator maps quantities from cell centres to cell faces, while the divergence operator does the reverse. The implementation was done in MATLAB®, based on the open-source MATLAB Reservoir Simulation Toolbox (Lie et al., 2012)

PRESSURE-INDUCED SEISMICITY

Rock failure is commonly modelled using the Mohr-Coulomb criterion, which relates the shear strength of a plane of weakness in the rock to the normal stress across that plane,

$$\tau = (\sigma_n - p)\tan(\theta) + c,$$

where τ is the shear strength, σ_n is the normal stress, p is the pore fluid pressure, and the rock strength parameters are θ, called the angle of internal friction, and c, the cohesion. When the shear stress exceeds the quantity on the right hand side, the rock fails. The actual values of shear and normal stress across a given plane depend on the orientation of that plane with respect to the tensor stress field. The effect of fluid pressure is to act as a negative normal stress, thus reducing the shear stress required for the rock to fail. It is this reduction in normal stress across planes of weakness that causes microseismic fracturing to occur during fluid injection. If we knew the rock strength parameters, the stress tensor, and the fracture plane orientation, therefore, then the location of a fracture from microseismic data would enable us to determine the fluid pressure at that point,

$$p = \sigma_n - \frac{\tau - c}{\tan(\theta)}.$$

We can model the stress state reasonably well. Fracture orientation could be inferred from the microseismic moment tensor, or from knowledge of joint and bedding plane orientations, but rock strength is highly variable on a local scale, and can only be determined statistically. We replace the rock strength parameters with a "critical pressure field" defined, as above, by the pressure which would be required to induce fracturing. The actual value of this rock strength critical field will be a random variable, defined by the variability of the rock, especially the distribution of weaknesses in the rock.

Rock is a complex material of highly-variable strength due to the geological processes through which it was formed. Microcracks and grain boundaries, bedding planes, joints, and pre-existing fractures all form planes of weakness over a large range of scales; differences in mineralogy, chemical weathering due to fluid movement through cracks, clay-filled seams and sandstone channels in sedimentary layers all result in strength variation. Measurements of joint spacing and orientations in the field, combined with lab measurements of rock strengths can give some idea of the statistical distribution of rock strength, which is commonly described using the Weibull distribution,

$$f(\sigma) = \frac{m}{\sigma_0}\left(\frac{\sigma}{\sigma_0}\right)^{m-1}\exp\left[-\left(\frac{\sigma}{\sigma_0}\right)^{m}\right]$$

where $f(\sigma)$, the probability distribution of our "critical field" rock strength, σ, is parameterised by a shape parameter m, and a scale parameter, σ_0.

Using this rock strength distribution means that a seismic event is effectively a point pressure measurement; at that point, the pressure has just exceeded the critical field. The uncertainty in the pressure measurement is therefore equal to the uncertainty in the value of the critical field, which is just the uncertainty in the rock strength. At all points where the rock has yet to fail, the pressure lies below the critical value, so the probability distribution for the pressure there is given by the integral

$$
\begin{aligned}
P\left(p\right) &= \int\limits_{\sigma=p}^{\sigma=\infty} \frac{m}{\sigma_0}\left(\frac{\sigma}{\sigma_0}\right)^{m-1} \exp\left[-\left(\frac{\sigma}{\sigma_0}\right)^{m}\right] d\sigma \\
&= \exp\left[-\left(\frac{p}{\sigma_0}\right)^{m}\right]
\end{aligned}
$$

This expression gives a kind of soft upper bound on the pressure in regions where the rock is still intact. This relationship between pressure and the rock strength critical value is illustrated schematically in `Figure 1`.

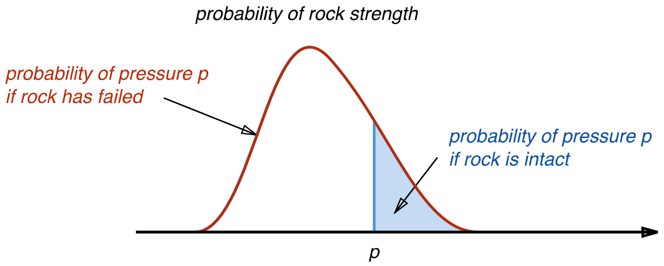

Figure 1: A microseismic event yields a point pressure measurement. The pressure probability distribution is equal to the rock strength distribution.

SYNTHETIC INJECTION-INDUCED SEISMICITY

To simulate seismicity, we assign a random rock-strength critical value, drawn from the Weibull probability density described above, to each cell in the model. We then simulate the pressure diffusion as fluid flows from an injection point through a model defined by rock porosity, permeability, and compressibility. Where the pressure exceeds the critical value, the rock is deemed to have failed. An example is shown in `Figure 2`, where the pressure field due to an injection at a well is shown at times, after start of injection, of 1, 164, and 511 days. The simulated seismic events are shown as black circles. The geology consists of two relatively permeable layers sandwiched between lower permeability units, all dipping and faulted.

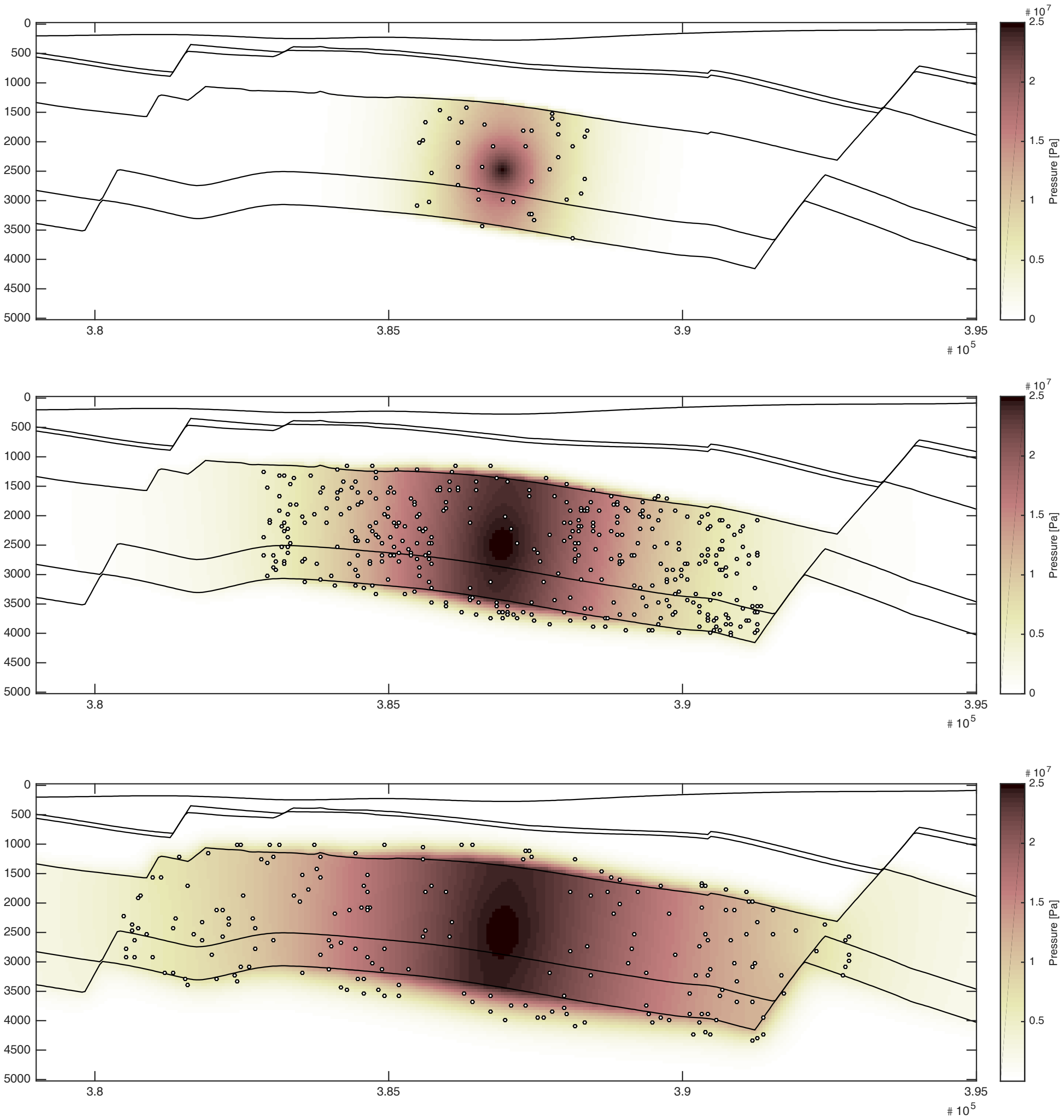

Figure 2 Pressure field computed at three different times (1, 164 and 511 days) in a sedimentary earth model, along with synthetic induced microseismic events. The seismic events are generated by assigning random rock strength critical values, following a Weibull distribution, to each cell of the model, and taking the rock to have failed when the pressure exceeds this critical value.

INVERSION OF PERMEABILITY

We use a quasi-Newton method to invert for rock permeability values, by minimising an objective function consisting of a least-squares fit error along with any prior information we have. (Currently, the rock porosity and compressibility values are held constant.) This requires that we are able to compute a gradient of the objective function with respect to the permeability values, which we do using an adjoint method (Jansen, 2011). Computing the adjoint of the pressure diffusion equations involves solving a time-reversed version of the same equations, with the pressure observations taking the place of sources, so the same code can be used for both forward and adjoint computations. The advantage of using the adjoint method is that only one forward and one reverse run of the model is required in order to compute the derivative of the objective function with respect to all of the model parameters (i.e. the permeability values in this case.) The observed data is then either actual pressure measurements made in boreholes, or pressure inferred at the locations of seismic events.

To illustrate the additional information that can be obtained from the seismic event locations, Figure 3 shows the gradient of the objective function with respect to the permeability values in the grid. This is computed at the first iteration of the inversion, starting from a uniform model, so the colours show the change in model permeability required to improve the data fit. The top example shows the gradient when the data to be fit consists of pressure measurements taken down two vertical boreholes, one on either side of the injection point. The bottom example uses "virtual pressure measurements" at seismic event locations, inferred from the rock strength distribution. Both of these calculations are done using data collected over the first 10 days of the injection. It can be seen that the information from the seismic events is complementary to that from the borehole pressure measurements.

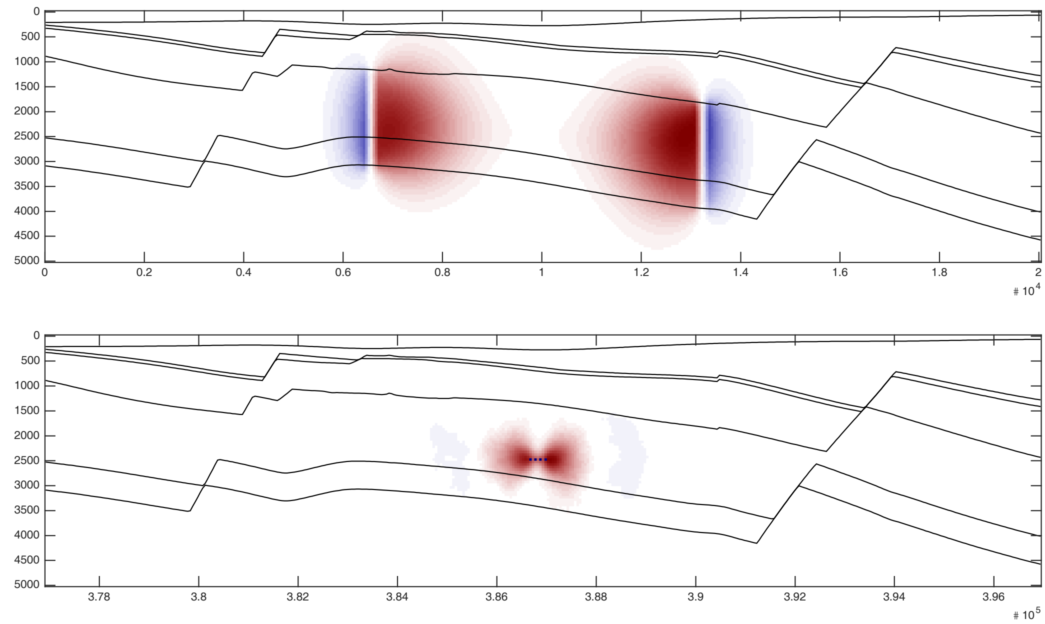

Figure 3 Information from seismic events complements that from borehole pressure measurements. The images show the gradient of the objective function with respect to permeability at the first inversion iteration, computed using the adjoint method, and starting from a uniform permeability. (top) The observed data consists of pressure measurements down two vertical boreholes. (bottom) The observed data is the pressure inferred from seismic events

CONCLUSIONS

We have shown how microseismic events induced by pressure injection can be used as virtual pressure measurements. This is based on the Mohr-Coulomb rock failure model relating shear and normal stress across a plane to the rock strength. Pressure acts by reducing the effective normal stress, thereby triggering rock failure. If a probability distribution can be obtained for rock strength, then the rock can be characterised by a random critical field, the value at any point being the fluid pressure at which the rock will fail. A seismic event then represents a point where the pressure has exceeded this field, so we have an effective pressure measurement, along with an uncertainty given by the rock strength distribution.

We used a finite volume technique to model pressure diffusion, and simulated microseismic events by generating a random critical field, following a Weibull distribution representing rock strength, and considering the rock to fail when the fluid pressure exceeds this critical value. Synthetic observations were computed in the form of pressure measurements down wells and simulated seismic events, and these were then used to invert for rock permeability. Gradients computed using the adjoint method illustrate the complementary nature of the information from the seismicity.

The biggest potential problem with the method is that rock strength distributions are not well known, and will have to be estimated from strength tests, and joint and fracture density estimates. These could possibly be calibrated for a given rock unit by retrospectively fitting a strength distribution once the pressure at the event locations is known, for example when seismicity reaches a well where pressure measurements are being made. In the absence of calibrated rock-strength curves, it is not possible to determine pressure, but the method should still allow for the prediction of future seismicity, because the critical field value, although unknown, is likely to be common to a geological unit.

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