Integrated Interpretation for Pressure Transient Tests in Discretely Fractured Reservoirs

K.L. Morton, SPE, Schlumberger; P. de Brito Nogueira, SPE, Petrobras; R.J.S. Booth, SPE; F.J. Kuchuk, SPE, Schlumberger

Abstract

In this paper, we present the interpretation of pressure transient well test data from discretely fractured reservoirs, where the fractures provide conduits for fluid flow and displacement, but where the fracture network is poorly connected. For this reason, dual porosity models such as Warren and Root’s formulation are not usually applicable. We first outline the gaps in the existing pressure transient well test interpretation methodology for these reservoirs, then we introduce two new techniques developed to address these gaps: 1) a reservoir model-based inversion technique for the identification of spatial variation in reservoir parameters from pressure transient data, and 2) a boundary-element method for determining the pressure transient behavior of the reservoir with arbitrarily distributed finite and/or infinite conductivity vertical fractures.

Using these two new techniques, we defined a new integrated interpretation methodology for reservoirs with discrete natural fractures and incorporating openhole log data, seismic, and the preliminary geological reservoir model. This is an important step in reconciling static and dynamic reservoir data to update the geological reservoir model with meaningful parameters. This methodology provides a direct means of calibrating the fracture model with the well test pressure and rate measurements— one of the few dynamic and deep-reading measurements for reservoir evaluation. Finally, we illustrated the use of the methodology, and demonstrated its robustness by using an example DST from a fractured carbonate reservoir in Campos Basin, Brazil. Results indicated the presence of discrete fractures close to and intersecting the well that do not form a connected fracture network.

Introduction

In 2005, a fractured carbonate reservoir was discovered in Campos Basin with a wildcat exploration well. This reservoir, consisting of Albian carbonates of the Macaé formation, lies beneath the clastic turbidites that form the bulk of production from the area and above a complex salt section. At the end of 2005, a full sequence of well tests (DSTs) were performed on the first appraisal well and, in 2008, the well was re-entered for a 4-month extended well test (EWT) to monitor the reservoir behavior and to define the most probable geologic scenario before the final investment decision was made. A series of development wells were subsequently drilled in Q4 2009.

While the results of the well test sequence were sufficiently favorable for development, the conventional well test analysis raised some concern about the quantitative use of well tests for reservoir characterization. The seismic sections of the field indicated that the formation has a few faults, and open fractures were interpreted from the image logs in the two appraisal wells. However, the initial analysis of the DSTs and EWT did not indicate the classical dual-porosity type behavior that is consistent with an extensive connected fracture network system. Rather, the results of the well test analysis could be simply interpreted as a behavior of a homogenous radial system with acid stimulated wellbore and with three flow barriers (sealing faults) in the reservoir at some distances from the wellbore.

As a result, new interpretation techniques and methodologies are required to improve the interpretation of pressure transient data from carbonate reservoirs with discrete fractures and to extract more reservoir information from well test data. In particular, this must enable the dynamic pressure transient test results to be included into the geological model of the reservoir either by allowing verification/calibration of the existing model or by updating it.

In this paper, we first outline the gaps in the existing interpretation methodology, particularly for carbonate reservoirs with fractures, and then we introduce the new techniques to address these gaps. We define a new integrated reservoir interpretation methodology for reservoirs with discrete natural fractures making use of these techniques, and finally, we illustrate the
methodology using the tested well as a case study. It should be pointed out that the new integrated reservoir interpretation methodology is applicable to all types of reservoirs.

**New Techniques for Well Test Interpretation in Fractured Reservoirs**

Traditionally, a dual porosity approach has been considered to model the pressure transient test (PTT) response of a connected naturally fractured network or high density arbitrarily placed fractures in a porous medium. This connected naturally fractured network model, termed as double or dual porosity Warren-Root naturally fractured reservoir model (Warren and Root, 1963), was initially introduced in reservoir engineering by Barenblatt et al. (1960) in analogy to heat transference in heterogeneous media. Since then, many analytical and numerical (Kazemi et al., 1976) solutions have been presented for dual porosity models in the literature.

Dual porosity models assume production into the well comes through a homogeneous reservoir that has the analogous (equivalent) pressure behavior of the continuous fracture-network system, in which matrix contributes as distributed source, as shown in Figure 1. In more moderately fractured reservoirs, dual permeability models, with additional direct interaction between the matrix and the well, are also appropriate. However, few methods exist for the interpretation of the pressure transient response of discretely fractured reservoirs where the fractures provide conduits for fluid flow and displacement (enhancing overall permeability in the direction of fracture), but where the fracture network is poorly connected compared to dual porosity and dual permeability models. In these situations, production is due to both matrix permeability and fracture conductivity, moreover the flow around the wellbore may be enhanced by fractures near (intersecting or otherwise) the wellbore.

![Fig. 1 - Well test models for naturally fractured reservoirs. The well is represented by the thick black line; the blocks denote the matrix (M) and the fractures (F); and the arrows indicate the direction of flow. Modified from Gringarten (2006).](image)

In discretely fractured reservoirs, the fractures are conduits from remote areas of the reservoir towards to the wellbore, and may also change the geometry of the drainage area of the well. Therefore, a homogeneous, single porosity model does not sufficiently match the pressure transient well test data. Moreover, a single porosity model does not honor the geological model of the reservoir. For future production prediction, particularly for water flooding and EOR, the discrete fractures must be identified and included in the reservoir model, and furthermore, the properties of these fractures must be estimated.

To fill this “missing model” gap, two new interpretation methodologies have been developed. The first method is a grid-based parameter estimation technique and the second one is based on a new semi-analytical and mesh-free discretely fractured reservoir model.

### 1. Grid based inversion

In this method for inversion of the pressure transient test data, the reservoir properties are discretized over the same grid as that used for numerical simulation of the dynamic data. The numerical simulation grid should have the highest resolution near the wells, where the PTT (Pressure Transient Test) data are the most informative. However, the consequence of discretizing the reservoir properties using the simulation grid is a large number of unknown parameters to be determined, and we therefore require techniques for dealing with large-scale inversion such as those applied in seismic inversion. We apply the Bayesian framework for the inversion, recognizing that we must provide an estimate of the possible reservoir properties that we expect to find before assimilation of the well test data (prior model). Our objective is the identification of features (such as fracture corridors or faults) that stand out from the background geostatistical description of the permeability field.

In our technique, we employ a grid-independent prior model based on local Gaussian random fields, described by a differential operator. This model can be easily implemented on non-uniform grids, such as those required to create an accurate representation of the pressure response of a well test. The model depends on only a small number of parameters that determine the shape of the variogram.

The most useful description of the reservoir properties that can be obtained from this process is the maximum likelihood parameters, *i.e.*, the reservoir properties that maximize the posterior probability distribution from Bayes' rule. Determining these properties is a problem in numerical optimization, for which we use gradient-based methods. Even for large-scale problems, with many parameters describing the reservoir and many measurements, gradient-based methods can be made feasible. Steepest descent is applied because it is robust and simple.
Since the number of parameters is large, determining the sensitivity directly by changing parameter values is impractical. A more efficient approach is to apply an adjoint method to determine the sensitivity with respect to all parameters. (Note: an adjoint method requires the expression of the adjoints of the dynamic variables and the determination of the “adjoint problem.” This adjoint problem has the same structure as the forward model for the dynamic variables and requires similar numerical effort to solve.) The standard adjoint method, as implemented in commercial reservoir simulators, determines the Jacobian (sensitivity of each individual measurement to changes in the parameters) by solving an adjoint problem for each data point. For well testing, the number of pressure measurements over time is usually large, and so this approach can also be numerically expensive. Rather than determining the Jacobian, we can instead apply a similar adjoint approach to determine the gradient of the likelihood (i.e. the sensitivity of all measurements to changes in each of the parameters) with the solution of only a single adjoint problem. While methods for determining the maximum likelihood solution using only the gradient require more iterations to converge than those that use the Jacobian, this is more than offset by the reduced effort required per iteration. The full development of the technique and comparison to other data assimilation techniques may be found in the literature (Booth et al., 2010; Booth et al., 2011; Morton et al., 2011).

As input, the technique requires an estimate of the background geostatistics most readily obtained from the geological model, and pressure response during the well test (from a single well or multiple wells). The technique will also honor any estimate of the permeability obtained from petrophysical logs. The output is an updated effective permeability model that is consistent with the well data, geological model and well test data.

2. Semi-analytical pressure solution for fractured reservoirs

The second new technique developed for PTT interpretation from discrete fracture reservoirs is a mesh-free, semi-analytical pressure transient solution for a single well or multiple wells. This algorithm allows the pressure response of a single well or multiple wells to be obtained for arbitrarily distributed infinite and/or finite conductivity natural fractures within the reservoir. The discrete fractures can cross each other and intersect with the wells if the geological model stipulates. For this analytical simulator, we assume a single-phase and slightly compressible fluid flow. Fluid flow in the matrix is described by the continuity equation and we can specify boundary conditions at the wellbore (constant flow rate, for example). A set of equations representing the wellbore conditions, continuity and conductivity in each fracture is defined using a combination of boundary and analytic element methods. The solution is constructed from elementary analytical solutions to the pressure response of single fractures/wells in the Laplace domain. As a post processing stage, the solution may be used to calculate the pressure solution at any point in the reservoir for the entire test period. The full description of the technique may be found in Biryukov and Kuchuk (2011).

Fig. 2 - A 2D example of fractured porous media in the physical domain, represented in an unstructured grid domain and in the boundary element domain where the collocation points are denoted by red dots (modified from Karimi-Fard et al., 2004).

The advantages of this technique compared to grid-based methods are highlighted in Figure 2. The fractures in the physical domain may be complex in shape and distribution requiring complex gridding to capture sufficient detail. In the boundary element domain, we select only sufficient points to capture the geometry of the fractures and the domain. Thus, we typically have fewer points than the equivalent gridded problem resulting in a computationally efficient (fast) solution. The solution is continuous, available at any point of space and time, and scale independent. Such features are important for well test pressure data inversion, where the position of the fractures may be updated: in a semi-analytical model, the pressure response can be updated for the new fracture positions without the need to fully reconstruct grid meshing.

At present, the method can be applied to infinite reservoirs or reservoirs with boundaries. As with all boundary element formulations, the matrix of the system is not sparse so the memory storage requirements and computational time will tend to grow according to the square of the problem size i.e. of order of $N^2$, where $N$ is the number of collocation points on boundaries. As the number of discrete fractures, non-linear regions, and domain boundary elements increase, the solution may become less efficient than volume-discretization methods.

In the following section we describe the new workflow to apply these new algorithms to discretely fractured reservoirs.
Integrated Interpretation Workflow

The integrated modeling and inversion workflow for discretely fractured reservoirs is a sequence of seven steps, many of which can be performed within an existing commercial geological modeling framework, using a combination of standard processes and a new algorithm implemented as a proprietary plug-in to the commercial software. The important feature of this process is that the well test interpretation is based on the available geological model, which may be modified at the end of the integrated interpretation. The workflow steps are as follows:

1. Conventional interpretation of PTT data using standard analytical models
   The starting point for the workflow is a standard well test analysis. The PTT and rate data are prepared by performing standard QCQA and data cleaning and editing of superfluous measurements. A standard interpretation, fitting to analytical pressure transient solutions, is carried out on the pressure data to provide an indication of the possible geological flow model, for instance, flow regimes that may indicate an important geological feature of the reservoir, and initial estimates of reservoir parameters. The output from this step of the process ought to be: 1) an estimate of wellbore storage; 2) an estimate of near well properties such as skin or hydraulic fracture parameters; 3) a time stepping schedule indicating the time of major rate and pressure changes; 4) the cleansed rate data; 5) the cleansed and filtered pressure data; and 6) an estimate of the standard deviation of the pressure data during drawdown (production) and buildup periods.

2. Sector model extraction and grid benchmarking
   The full-field geological model is used as the basis for the numerical interpretation wherever possible. Unless we have an extended well test, the whole full-field model is not required and a sector around the well(s) of interest can be extracted. However, the numerical model must be able to accurately recreate the pressure response of the well during the well test and so it is important to refine the grid around the well.

   As with most numerical simulators, the wellbore is not explicitly included in the simulation model. The removal or addition of fluid from the cell is modeled, and the pressure response of the “real well” is calculated with Peaceman’s well index. Hence, nearly all of the produced fluid at early times comes from the well-block capacity (Blanc et al. 1999). If the well block is insufficiently refined, as an artifact, a changing (increasing) wellbore storage response will be observed on the simulated well pressure derivative and will result in an inaccurate representation of the reservoir (geology and fluid). The impact of this is illustrated in Fig. 3: here, the well-block dimension is reduced from 9.3m (Nx, Ny = 101) to 3.5m (Nx, Ny = 301 cells) and the early time solution more readily compares with the analytical solution shown by the green marks and solid black line.

   ![Fig. 3 - Comparison of solutions for two uniform Cartesian grids with different well-block dimensions.](image)

   ![Fig. 4 - Comparison of the non-uniform Cartesian grid strategy. The left-hand plot shows the logarithmic gridding ((Nx = Ny = 41, Nz = 5) and the right-hand plot shows geometric gridding (Nz = Nl = 59, Nz = 5). The scale of the plot is 30m.](image)

   The practical solution to this problem is to have the well-block dimension comparable to, but necessarily larger than, two times the Peaceman radius and to use a non-uniform Cartesian grid with a logarithmic or geometrical refinement near the wellbore. An example of these types of gridding refinements is shown in Fig. 4. Using this approach we can improve our solution for the flowing bottom hole pressure by using a grid consisting of fewer gridblocks with fine gridblocks near the well block and a gradual transition from fine gridding to coarse gridding near the boundaries. Once an appropriate grid is created, the gridding is benchmarked by comparison of the numerical pressure solution and a homogeneous model analytical solution.

   Next, the rock properties from the full-field geological model are sampled onto the well test grid. The process of sampling petrophysical properties from the full field model to the well test scale grid is a process of downscaling. To avoid the “blocky” results often associated with sampling from a full field grid to a fine grid, we apply a surface model interpolation procedure. The properties are height averaged over a high-density mesh and an average map is created for each zone using Equation 1, where i refers to a point on a densely gridded surface and Z refers to the property value at that point:
3. Fracture model data preparation
The natural fracture data must be collected from well logs, particularly wellbore images, and cores, and used to control the property population of the model. Ideally, this is performed during construction of the full-field model (FFM) and updated when new wells are drilled. Alternatively, this step may be applied to the sector and well test model grids. The procedure presented here is essentially the same whenever it occurs in the workflow.

Image logs are most appropriate for quantifying fracture densities and orientations as these high-resolution resistivity or sonic log images are able to detect beds and fractures. This task is performed with commercial software. The process delivers a description of tangible fracture attributes such as location, aperture, and orientation. Normally, a combination of automatic and manual trace extraction is performed. An initial QC is required to sort and then select fractures that appear open and have large apertures: fractures of lower quality, such as those with smaller aperture or that have healed, may be disregarded. However, if there are indications that fractures with low- or no-conductivity are extensive, these should be also included in the model because they may significantly affect flow paths in the reservoir. Short-length fractures, whether they are open or closed, can be disregarded if their distribution is not dense, otherwise they should be upscaled.

The selected fractures are loaded into a geological modeling package for further analysis and grouping. Based on how the fractures appear in depth (zones and layers), within certain facies/lithologies and with respect to orientations observed on a Stereonet plot, fracture sets can be determined and fracture statistics may be prepared for each set. In particular we require:

1. Orientation of fractures; dip and dip azimuth
2. Estimate of scale and shape; in an ideal world without truncation, erosion, etc. fractures are thought of as having an elliptic shape but are often modeled as rectangular planes.
3. Fracture spacing; the average spacing of fractures tends to be consistent, depending on rock type and bed thickness. In general fracture spacing increases with bed thickness and behaves differently depending on lithology (spacing in limestones is considerably greater than in wackes with shale interbeds).

Once the fracture sets and their statistics have been defined, a fracture intensity log is created. The standard controls on the intensity log creation include: sample interval, window length, apparent/true intensity (i.e., intensity corrected to average fracture orientation and borehole orientation). The intensity log is subjective and will change according to the window length selected by the interpreter. If dense sets of fractures are encountered, the interpreter must decide whether this is a critical, fractured zone (short window length) or a random set of dense fractures that should be smoothed out to generate a generic intensity for the zone. The standard fracture intensity or density described as P32, corresponds to the fracture area per unit rock volume (m²/m³), and is determined for each fracture set at the wellbore.

Cores can also be used to measure fracture density in 1D although they provide only P10, fracture counts per unit length. It is normally possible to also extract fracture orientations if the cores are oriented. If lost core or rubble is detected, it may be due to intense fracturing of competent rocks.

The fracture density is a key parameter in any discretely or continuously fractured reservoir. The first step in any fracture modeling process is to upscale the fracture intensity log to the well-blocks, i.e. the cells in the 3D grid that are penetrated by the wells. The method for upsampling intensity is related to the methods for upsampling permeability and must be associated with the rock type and dip distribution e.g. geometric averaging is normally more appropriate in carbonates where the selection of fracture sets is based on direction and where there is a wide spread in the dip directions, while the harmonic mean is appropriate for vertical fracturing such as that occurring in competent carbonates, Fig. 5. As with permeability upsampling, both methods are more sensitive to lower values of fracture intensity.

Normally, the fracture properties derived from the borehole geology interpretation are distributed across the 3D grid of the reservoir model using geostatistical methods such as kriging (deterministic interpolation) or stochastic processes such as sequential Gaussian simulation (SGS). In both kriging and SGS, the input to the algorithm is the upscaled well data and a variogram. The variogram is a quantitative description of the variation in a property as a function of separation distance between data points. Furthermore, the variogram defines how to use the well data for populating values between wells. Training images or trends derived from seismic data or geomechanical data can also be used in multipoint geostatistical workflows. However, all these techniques are based on static measurements that have not been calibrated the reservoir dynamic data such as PTT. Therefore, the next step of this workflow is to use the first new interpretation technique to map the flow in the reservoir from the well test pressure response.

4. Grid-based parameter estimation for effective permeability
After performing data QCQA, the transient-pressure measurements from the well or wells are used as the input for an inversion (parameter estimation) for estimating effective permeability using the grid-based inversion technique outlined
previously. We use the term ‘effective permeability’ per grid cell as the output is expected to be a combination of both fracture and matrix permeability in formations where fractures are present and its value will be much higher than the host formation permeability when the grid cell contains an open fracture or fractures. It should be pointed out that we do not make a priori assumption about its value per grid cell. The sector model, with matrix permeability derived from petrophysical properties (normally upscaled from the updated FFM onto the well test grid by standard techniques), is used as the prior mean and initial guess of effective permeability. The algorithm can also assimilate log- or core-derived permeability with the local Gaussian field. An increased variance (i.e., greater than the variance observed in the log data) may be applied to the well-block permeability if we have limited data samples from a particular rock type or upscaling uncertainty.

The parameter estimation is completed once an acceptable match with the observed pressure data is obtained. The output of the parameter estimation is the most likely effective permeability based on all the input static and PTT data.

5. Well test calibrated fracture density
As mentioned in Step 3, the most important parameter for fracture modeling is fracture density (P32) described across the reservoir zone of interest. If we have confidence that our prior matrix property description is correct, i.e., that the FFM has been correctly updated for log and core data, we expect that, in a discretely fractured reservoir, when the well test derived effective permeability is high relative to the matrix permeability, it is caused primarily by high fracture density. In this step, the upscaled fracture density is co-krigged at the well-block (derived in Step 3) with the effective permeability from well test in a positive sense. The output is a fracture density property calibrated to both static wellbore properties and to the dynamic pressure response, through the well test inversion.

6. Fractured reservoir modeling
With the PTT calibrated fracture density and the direction and orientation determined from the image log dip picks, a stochastically generated fracture model can be created for the well test sector model. The commercial software package workflow is shown in Fig. 6: the diagram explains the split between explicit and implicit modeling of fractures. However, in discretely or slightly fractured reservoirs, we assume that fractures should be mainly handled explicitly.

7. Discrete fracture verification and conductivity
In addition to the standard QC of the output fractures distribution to the input fracture parameters using a Stereonet and Histogram, we must verify that any individual realization of discrete fractures created in Step 6 still provides an acceptable match with the observed pressure data, i.e., a dynamic QC of the modeling process. In this workflow step, we apply the new semi-analytical discrete fracture pressure transient solution. The input to this pressure solution are the discrete fracture distribution from Step 6 and the matrix properties from Step 2, whereby we complete a final verification of the history match for the pressure and pressure derivative responses.

Fracture apertures in the reservoir, and thus fracture conductivities, are often the least known parameters. Sensitivity studies have indicated that fracture conductivities are the most sensitive parameter for discrete fracture models. Thus, if a mismatch is observed once more between the simulated and observed pressure response, a small uncertainty loop should be performed to update the fracture conductivity (within prior geologically defined limits) until the match is improved. If it is not possible to obtain a match within the limits set, the correlation applied in Step 5 should be reconsidered.
Upon completion of the seven-step workflow, the following input may be incorporated into the full field reservoir model when required:

- Fracture conductivities for the fracture set;
- Fracture planes; or
- Fracture intensity in the sector model.

The outcomes of the integrated well test interpretation are parameters (fracture apertures, density) that can be used directly by reservoir engineers and geoscientists in the full-field model.

**Carbonate Field Case Study**

In this section, we apply the integrated interpretation methodology developed in the previous section to the field data set. Three DSTs were performed for three adjacent layers in the reservoir, but in this paper we present the integrated interpretation only for DST 1.

The field lies in the Albian carbonates of the Macaé group and the well of interest is perforated in the Quissamã formation. The field is approx. 120km offshore in a water depth of 1-1.5km. The matrix porosity in the field varies from 3 – 25% and the rock is considered to be oil-wet to intermediate-wet. The formation is part of a retrogradational carbonate platform developed during an incipient ocean stage. Patch reefs and reef systems may introduce a degree of preferential directional orientation to the facies. The lithology is composed of oolithic grainstone and oncoidal grainstone/packstone intercalated with laminated carbonates at the top of the section.

The field is heavily faulted as a result of basement horsts and the salt domes surrounding the field. The main fault system is orthogonal: NE-SW and NW-SE. All the faults are normal. A large fault is situated to the west of the well, trending NE-SW. This fault is 500m laterally from the well at the depth of DST1. It is uncertain whether the fault is a sealing one, i.e., nonconductive. The other major faults visible in the 3D seismic of the field are considered to be outside the radius of investigation of DST1. The oil is 28°API with viscosity of 1.4cp at reservoir conditions. The oil formation volume factor is 1.3 \( \text{m}^3/\text{sm}^3 \).

Openhole logs of the well shown in Fig. 7 indicate that the formation is fractured with some partially open and most likely conductive fractures. We follow the seven-step integrated discrete fracture interpretation workflow described above.

![Composite log suite from the well showing the location of the DSTs, pre-test results, image logs and fracture picks. DST1 location is highlighted with a box.](image)
1. Conventional interpretation of PTT data using standard analytical models
The initial step is to prepare the data by reconstructing and synchronizing the rate data with pressure for DST1. The full rate and pressure schedule is shown in Fig. 8. In this case, the well had been stimulated with an acid treatment before cleaning up (note the pressure history before the rate history begins). From analysis of the upscaled petrophysical logs in the geological model, the tested zone porosity was estimated to be 8%.

![Fig. 8 - Pressure and rate history plot of DST1](image)

The initial analysis of the three build-up flow periods did not indicate any dual porosity behavior. A well-defined infinite-acting radial flow regime was not observed, and therefore we could not estimate $kh$ (permeability-thickness product) independently. Wireline formation tester drawdown pretests’ interpretation indicated mobility of 1-3 md/cp in the tested zone (Fig. 7). The estimated $kh$ for the zone from the geological model was 105 md.m. We take this as the starting value for the evaluation. Two possible models were identified to fit the data that were consistent with the flow regimes observed from derivative of the DST1 PTT data: a well with a negative skin or a well with a hydraulic fracture.

For the first model, it is not possible to achieve a good fit with the estimated matrix permeability without an unphysical skin of approximately -6. We therefore tried an estimated $kh$ of 1000 md.m, corresponding to the inflection point on the deconvolution plot, to achieve a match with a total skin = -4.1. As can be observed in Fig. 9, the wellbore storage (max 0.3 m³) effect is almost negligible due to the conductive fractures crossing the wellbore and downhole shut-in. The negative skin is assumed to be a combination of permeability enhancement due to the cleaning out of blocked fractures intersecting the well and from the deviation of the well with respect to the formation (estimated to be -1.3).

To further investigate the natural fractures intersecting the well, a hydraulic fracture model was applied to estimate the properties such as the conductivity and half fracture length. Using a finite-conductivity fracture model, an acceptable match was obtained with $kh = 1000$ md.m, $xf = 31$ m and $Fc = 10000$ md.m (Fig. 9) and a match with the late time data can be achieved with $kh = 1000$ md.m, $xf = 100$ m and $Fc = 1500$ md.m (Fig. 10). The two matches qualitatively indicate that high fracture conductivities are required to match the pressure response observed, but neither analysis provides any quantitative indication of the real conductivity of the discrete natural fractures in the reservoir or their distribution. We also observed a possible boundary effect on the build-up which could be matched with a sealing fault 150 m from the well.

A deconvolution algorithm was applied to the DST1 pressure-rate data shown in Figure 8, to include all drawdown and buildup periods in the interpretation. Deconvolution is particularly useful for identifying potential boundary effects (Pimonov et al., 2009). The deconvolution data is shown in Fig. 11. A bounded reservoir model (no-flow outer boundary) with $Re = 230$ (the radius of investigation of the build-up pressure response) was required to match the deconvolution response. Artifacts may be introduced to the late time deconvolved pressure response due to uncertainty in the initial pressure of the reservoir as well as some uncertainty of the early time rate measurements. Therefore, we cannot have complete confidence in this result. There is no indication of closed faults surrounding the well over this range but it could correspond to the extent of a reef or with an abrupt lithology change.
Fig. 9 - Log-log diagnostic plot of the first buildup with match to an infinite conductivity hydraulic fracture model.

Fig. 10 - Log-log diagnostic plot of the buildup with match to a finite conductivity hydraulic fracture model and sealing fault.

Fig. 11 - Log-log diagnostic plot of deconvolved DST1 data with match to finite conductivity fracture model in a closed reservoir area.

The data are of sufficient quality for grid-based inversion but overly dense. Therefore, the complete pressure data is filtered to five points per hour during producing periods and forty points per log cycle during buildup tests. The time stepping schedule is determined, and we identify twelve separate flow periods that correspond to observable pressure transients. We apply different filtering algorithms depending on the flow period: during production we prefer to interpolate the simulated data to a few evenly spaced observation points to capture the general trend of the pressure data, while during build-up we place more weight on the early time data that contains most information.

An important output from this workflow step is an estimate of the standard deviation of the observed pressure data. Simplifying the rate history will have an impact on the consistency of any simulated pressure data with the observed data. We also observe that the pressure response during production is noisier during the build up. To account for this, we apply a standard deviation corresponding to 0.5 bar during production and 0.01 bar during build-up in this example.

2. Sector model extraction

The full field geological model is a 70 by 73 by 246 cell model with average cell size of 100 by 100 by 1.2m (in the reservoir layers of interest). The petrophysical and geological analyses of the zone indicated a degree of anisotropy in the horizontal permeability, i.e., high conductivity was noted in the 20° direction and low conductivity in the 110° direction. The full field model grid is oriented similarly, which also is consistent with the observed faults.

In this step of the workflow, we extract a sector model around the well and the layer of interest. The layer was re-gridded with an inner cell size of 0.8 m in the x and y directions as shown in Fig. 12. A geometrical expansion factor of 1.1 was applied, giving an average cell size of 11.5 m in the 1000 m zone around the well. The expansion is identical in both directions. The gridding was benchmarked using the estimated effective permeability for the zone derived from the conventional interpretation as shown in Fig. 13. Peaceman’s well radius was calculated to be 0.2 m for the homogenous case and, although there is some difference between the inner cell size and the equivalent-pressure radius, the benchmarked model was sufficiently refined for the minimum time step required to match the observed data.
Using the surface modeling interpolation procedure outlined earlier, a surface map was prepared for the reservoir zone of interest for permeability and porosity. These were used to assign values to the fine scale well testing grid. The permeability map for layer of interest is shown in Fig. 14 and the resulting realization of the properties on the benchmarked grid is given in Fig. 15. The same process was applied for matrix porosity.

3. Wellbore fracture data preparation

Within the depth interval tested during DST 1, many open and bed bounded natural fractures were observed on the image log. The image logs were analyzed in conjunction with the sonic response and identified features were classified into eight feature types as shown in Fig. 16. In this figure, the fractures present in the tested interval are highlighted against the full fracture points set for the well. The eight distinct fracture sets can be grouped into two main families bases on their perceived properties: open, conductive fractures that are not constrained by the bedding (Family A) and partially closed, bed bound fractures (Family C). Sub-seismic faults and resistive fractures were also identified and considered as separate families. Within the families, the fractures are further subdivided into conjugate sets classified using the fracture strike direction. Within the tested interval, the fractures are predominantly of family A, with ESE dip azimuth (NE strike direction), and display a high dip angle.

A P32 fracture intensity log was generated for the two main fracture sets as shown in Fig. 17. An average fracture orientation was determined for each set and the fracture dispersion (spread of directions) was estimated. Based on the observed fracture apertures, the statistics shown in Table 1 were estimated. From this table, we see that the NE trending fractures are expected to be significantly more conductive than the NW trending fractures.
Fig. 16 - The eight fracture types identified in the well are grouped into two main sets (Note: the stereogram displays dip and dip-azimuth.)

Fig. 17 – Fracture intensity log for the tested zone. Family A is shown in blue, family C is shown in green.

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<thead>
<tr>
<th>Table 1: Static fracture properties</th>
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<tr>
<td>Set A_NW</td>
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<tr>
<td>Dip azimuth, °</td>
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<tr>
<td>Dip, °</td>
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<tr>
<td>Estimated dispersion</td>
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<td>Estimated conductivity, md.m</td>
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<td>Set A_NW</td>
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<td>Dip azimuth, °</td>
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<td>Dip, °</td>
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<tr>
<td>Estimated dispersion</td>
</tr>
<tr>
<td>Estimated conductivity, md.m</td>
</tr>
</tbody>
</table>

4. Grid-based parameter estimation for effective permeability

The matrix permeability was sampled onto the well test model from the full field model in a previous step. This was used as both our initial guess in the inversion algorithm and in the mode case, or expected value, for our prior model. We ran a prediction case for the well test, as shown in Fig. 18, to check the synchronization of the rate and pressure data in the numerical model and to examine the history match. As expected, the initial history match with the input data was poor. A much improved, but still inadequate, history match was obtained when an estimated homogeneous permeability was used as shown in Fig. 18. This model also fails to capture the available prior model of the matrix permeability.

The inversion algorithm was run with the following prior variogram and line search parameters:

<table>
<thead>
<tr>
<th>Table 2: Constants applied for grid-based parameter estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time stepping</td>
</tr>
<tr>
<td>Min, hrs</td>
</tr>
<tr>
<td>Max, hrs</td>
</tr>
<tr>
<td>Number of steps</td>
</tr>
</tbody>
</table>

*line search parameters C0 and C1 refer to the parameters in the 1st and 2nd Wolfe conditions

In early steps of our inversion algorithm we applied a larger deviation in the pressure data than would be expected based on our confidence in the data; this was to improve computationally efficiency as we approached a feasible solution. To compensate, during these steps, we also applied a weaker prior than was thought necessary from a geological viewpoint. As we approached a feasible solution we were able to use our result from the early stages as an initial guess for the true inversion with the correct deviation given for the pressure data and with a geologically sensible prior model. The performance of the inversion and the details of each optimization run are shown in Table 3.
The variance parameter describes the expected variation of the permeability throughout the reservoir. With a variance of 1.0 we expect 68% of the reservoir to have a permeability value that lies between 2.7 times more or less than that given in the most-likely prior model. This is a relatively weak prior allowing the pressure data to move the estimated properties far from the prior mean. With the variance parameter equal to 0.05 we expect 68% of the reservoir to have a permeability value between 80% and 125% of that given in the most-likely prior model. The length parameter of our prior model is 100 m, suggesting that we expect the permeability to vary over this length scale. The correlation of the permeability over a certain distance helps to push the focus of the inversion away from the well towards the radius of investigation of the test. As shown in Morton et al. (2011) the structure parameter has a significant effect on the shape of small-scale features obtained in any particular realization of the reservoir permeability, but does not affect the inversion algorithm significantly. The line search parameters control how quickly we reach the best estimate solution as the pressure data is assimilated. The values selected are appropriate for this type of problem.

The updated sector model, i.e., the maximum likelihood solution for effective permeability, for the well is shown in Fig. 19 and the final history match with the data is shown in Fig. 20. The algorithm converged to this solution in 134 optimization steps. In addition to a good history match of absolute pressure, we required that the pressure derivative curve accurately fits the observed one. In Fig. 21, we see that the derivative match for the build-ups in DST1 is also quite acceptable.

For DST 1, we find that the effective permeability must be increased around the well to obtain a match with the measured PTT data similarly to the conventional interpretation. This suggests that there is a high density of conductive features in the radius of investigation of the well test.

### Table 3: Optimization results

<table>
<thead>
<tr>
<th>Run</th>
<th>Prior variance, $\sigma$</th>
<th>Start objective function</th>
<th>End objective function</th>
<th>No. of optimization steps</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.00</td>
<td>26,381,833</td>
<td>5,058</td>
<td>38</td>
<td>+/- 5% absolute drawdown S.D</td>
</tr>
<tr>
<td>2</td>
<td>1.00</td>
<td>65,518</td>
<td>35,624</td>
<td>19</td>
<td>Applied observed data S.D</td>
</tr>
<tr>
<td>3</td>
<td>0.10</td>
<td>51,828</td>
<td>38,232</td>
<td>14</td>
<td>Increased confidence in prior</td>
</tr>
<tr>
<td>4</td>
<td>0.05</td>
<td>48,555</td>
<td>27,183</td>
<td>50</td>
<td>Increased confidence in prior</td>
</tr>
</tbody>
</table>

The updated sector model, i.e., the maximum likelihood solution for effective permeability, for the well is shown in Fig. 19 and the final history match with the data is shown in Fig. 20. The algorithm converged to this solution in 134 optimization steps. In addition to a good history match of absolute pressure, we required that the pressure derivative curve accurately fits the observed one. In Fig. 21, we see that the derivative match for the build-ups in DST1 is also quite acceptable.

For DST 1, we find that the effective permeability must be increased around the well to obtain a match with the measured PTT data similarly to the conventional interpretation. This suggests that there is a high density of conductive features in the radius of investigation of the well test.

Fig. 18 - Pressure history for DST 1 showing the observed data (black dots), simulated pressure response with estimated homogeneous permeability (blue dots) and simulated pressure response using matrix permeability (red dots). Note that there is no history match.

Fig. 19 - The most likely effective permeability for the tested layer before (left) addition of well test dynamic data, and after grid-based parameter estimation (right).
5. Well test calibrated fracture density

Due to the structure of the reservoir, only fractures in the NE strike direction are considered to be fully open and contributing, which is consistent with the images logs. Thus, only the NE set is included in the fracture modeling process. The fracture intensity from the image log picks was upscaled onto the well test simulation grid using harmonic upscaling as there is limited dispersion in the dip (Fig. 16). Using a standard petrophysical modeling process, the upscaled log was kriged onto the full 3D grid using the most likely effective permeability from well test as a secondary variable for co-kriging. As the well test grid is coarse in the vertical direction, the upscaled log contains too few values to fully describe the intensity distribution so this is estimated from data analysis of the log. The output, well test calibrated fracture density map is shown in Fig. 22. Note, here we are assuming only correlation between permeability and fracture density in the volume tested by the well test. The distribution of fracture intensity in areas of the reservoir that have not been dynamically tested should be determined by seismic or through geomechanical modeling. Well testing can act as a dynamic validation tool in these cases.
6. Discrete fracture modeling
The intensity property and the static data from Table 1 were input to a commercial fracture modeling process. A realization of the resulting stochastically generated fracture planes is shown in Fig. 23.

7. Discrete fracture verification
In the final step of the workflow, since the fracture planes are stochastically generated, we do a final check that the discrete fracture features continue to honor the pressure derivative. Here we apply the mesh-free, semi-analytical model. The fracture planes from Step 6 are input into the program along with the matrix permeability of the region surrounding the well, and we apply the fracture conductivity (Table 1) that was estimated from the fracture aperture.

The resulting match obtained for the tested well deconvolution data is shown in Fig. 24. We do not attempt to match the late time deconvolved pressure response as it may be an artifact. For this case study, the resulting match was excellent and no iteration of the fracture properties was required. We can accept the fractures produced and the updated fracture intensity map as one plausible scenario that fits all the data observed in the well.

The sector model created and updated with this workflow honored all the data available: petro-physical data for matrix permeability, image log data and seismic data for fracture orientation and aperture, and well test pressure data for effective permeability and fracture density. The well test data which was previously considered inconsistent with the geosciences data was shown to be able to validate the conceptual geological model of the reservoir and could be used to provide geologically meaningful parameters, such as fracture intensity, in the near well area.
Conclusions

In this paper we have introduced two new techniques to address pressure transient analysis in reservoirs with fractures that do not display the classical dual porosity type behavior. We have termed these as discretely fractured reservoirs. The first technique introduced, a reservoir model based inversion technique for reservoir parameter estimation, allows features to be identified from the background geostatistical distribution of properties. In this work we have been primarily interested in high conductivity features, but the technique can also be applied to low conductivity/low transmissibility features such as sealing faults. The second new technique, a boundary element method for determining the pressure transient behavior of the reservoir with arbitrarily distributed finite and/or infinite conductivity vertical fractures, allows the simulation of complex fracture systems often produced by commercial geological fracture modeling software but without the difficulty of explicit fracture gridding. Using these two new techniques, we introduced an integrated interpretation methodology for reservoirs with discrete natural fractures that incorporates openhole log data, seismic and the preliminary geological reservoir model. Of course the methodology can be applied to any type of reservoirs.

This is an important step in reconciling static and dynamic reservoir data to update the geological reservoir model with meaningful parameters. The methodology provides a direct means of calibrating the fracture model with the well test pressure and rate measurements. For reservoir evaluation, transient data provides important dynamic deep measurements from the sandface to beyond the drainage area of the well.

We illustrated the use of the new methodology, and demonstrated the robustness of the techniques developed, using a field data set. The case study provided an interesting example but, as with most single well testing examples, lacks full directional information. This process can readily be applied to multiple well interference tests, and the grid based inversion is one of the few tools available to enable quantitative interpretation of this type of test.

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References