**Introduction**

Natural fractures are ubiquitous in carbonates; they provide high permeability pathways and reduce sweep efficiency. Fractures, matrix heterogeneity and wettability, and the interactions of these properties, not only reduce the recovery, but these are also primary uncertainties. These features are multi-scale, often sparsely sampled and their distributions can vary significantly well to well and across the reservoir, leading to significant uncertainty in the static and dynamic characterization of the reservoir. Ideally, we should consider different reservoir concepts of possible models to provide a robust production forecast capturing the impact of uncertainties (cf. Scheidt & Caers 2002). Full-physics simulation is still the most common tool used to compare reservoir models. However, for large complex models the simulation time can be long. Typically only a small subset of scenarios are considered, which may collapse into a single base case, which robustly quantify uncertainty and provides little confidence in the decision-making process (cf. Ringrose & Bentley 2015).

Flow diagnostics can rapidly approximate the reservoir dynamics is seconds providing dynamic metrics such as the dynamic Lorenz and dimensionless sweep efficiency (Shook and Mitchell 2012, Moyner et al. 2014) that can be used to rank and compare geological models and select models for forecasting.

We present an extended case study from Spooner et al. (2019) which compares the flow diagnostic response to the full-physics simulation results for the Teapot Dome, a naturally fractured reservoir located in Wyoming. A previous study noted that despite relatively good data for the fractures in the Teapot Dome there is still a high degree of uncertainty in the distribution of fractures between the wells (Ahmed Elfeel et al. 2013). The correlation of the fracture intensity between the wells affects the flow paths at the field scale and hence the flooding patterns and well connectivity. The simulation run-time for each model is around 2 hours, hence simulating the number of models required to quantify the impact of uncertainty would require a very large time investment.

**Teapot Dome Case Study**

The Teapot Dome is an elongated north–south-trending anticline located at the SW edge of the Powder River Basin. The Pennsylvanian Tensleep formation forms the main reservoir in the Teapot Dome, consisting of consists of aeolian sands, interbedded with sabkha and marine dolomites (Ouenes et al. 2010). The uppermost unit is fractured sandstone, Unit 2 consists of fractured dolomites and Unit 3 is a sandstone. The rock matrix is hard, tight and water-wet. A single relative permeability and capillary pressure curve describes the wettability of the rock matrix.

Firstly, we can assess the distribution of the transfer rate coefficients and their impact on the idealised Aronofsky recovery (Aronofsky 1958). The transfer is computed assuming spontaneous imbibition is the dominant recovery mechanism via Schmid and Geiger (2012). Figure 1 shows the distribution of the computed recovery curves for different orders of magnitude of $\beta$. The line thickness indicates the proportion of cells in the reservoir model with a transfer rate of that order. In this case most of the cells have transfer rates of the order of $10^{-8}$ to $10^{-6}$ m$^2$s$^{-2}$, which represents a recovery of 3 to 30 years to maximum recovery. As long as the fractures are well swept, recovery from the matrix will be slower as the Aronofsky model does not account for saturation differences.

![Figure 1: Transfer rate coefficient for the Teapot Dome (a) and recovery predictions for the transfer rates possible (b). Line thickness indicates the frequency of cells with a particular transfer rate.](image-url)
Having computed the transfer we can assess the flow through the fractures while accounting for the impact of fracture-matrix transfer using the dual porosity TOF, which models the delay of water breakthrough due to transfer during the passage of injected fluid through the reservoir as follows

\[
\tau^* = \int_0^s \frac{R \phi}{|v|} ds \quad \text{where} \quad R = 1 + \Gamma_\infty \left(1 - e^{-\beta T}\right), \quad \text{where} \ T \text{ is the grid cell residence time.}
\]

Figure 2 shows the flooded reservoir volumes for each injector after 365 days of water flooding. There are some notable differences in the flood fronts between the flow diagnostics and full-physics simulation. In the simulation the flood fronts preferentially travel eastwards down dip whereas the flow diagnostics flood fronts spread more uniformly. The difference can be attributed to the fact that flow diagnostics do not account for gravity. The greater the impact of gravity (i.e. the greater the reservoir thickness and the larger the vertical permeability and fluid density contrast) the greater the discrepancy between diagnostic results and simulation. The Teapot Dome is a relatively thin reservoir (36ft thickness), therefore we can use flow diagnostics with the caveat that we expect some degree of error due to gravity effects.

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**Figure 2:** Simulated fracture oil saturation showing the location of the flood fronts at 10 years (a) compared to the diagnostic swept volumes for each injectors threshold at 10 years (b).

Despite the fact the diagnostics do not capture the gravity effect, the dual porosity TOF provides a good approximation to the breakthrough for each producer. Figure 3a compares the simulated breakthrough with the diagnostic single porosity and dual porosity breakthrough. The dual porosity TOF overestimates the actual breakthrough, providing an upper limit, whilst the single porosity TOF underestimates the breakthrough providing the lower limit. Overall the diagnostic breakthrough range agrees well with the simulated results, accurately identifying the early breakthrough wells. For the wells where breakthrough occurs much later the diagnostic is less reliable. The exaggeration on the dual porosity TOF is exacerbated over greater distances since we do not capture the reduction in the retardation factor due to saturation changes behind the flood front.

**Figure 3:** Simulated breakthrough compared to the diagnostic breakthrough range (a) the ranking for the simulated well cum. oil production compared to the diagnostic drained volume (b).

The diagnostics are also effective in determining the best and worst performing wells in terms of oil production. There are some differences in the ranking for the mid performing wells (5_62, 2_63, 1_43-...
We attribute these differences to the differences in the predicted flood fronts (Figure 2). The simplifications in the physics manifests as differences in water breakthrough times and drained volumes.

An ensemble of Teapot dome models was created that explores different uncertainties in the fracture network related to the lithology (i.e. increased fracturing in dolomite or sandstone units). From a set of 30 DFN models, multipliers were applied to the fracture permeability to produce a set of over 400 realisations. Flow diagnostics were applied to the ensemble and k-means clustering was then performed on the Lorenz and Sweep Efficiency. The cluster centre models and the two models at the upper and lower limit on the Ev-Lc plot were selected (Figure 4a). For each model, a full-physics simulation was performed to assess the range of outcomes and diversity in response across the entire ensemble.

The models in the first cluster (green) are models where the fracture scenario features long fractures; these models have increased permeability and produce more strongly than the others. The other clusters contain a variety of fracture scenarios. The Model 6 has the most heterogeneous sweep (indicated by Lc) and poor sweep efficiency; the production for this model is hence poor compared to others. The poorest performing model in terms of the simulation results is Model 3; in this case the maximum length of the fractures is much smaller than for the models in cluster 1. This model and the Model 6 do have reduced permeability multipliers applied which do slow down the production in the model.

![Figure 4: Crossplot of metrics Lc and Ev for the ensemble of the Teapot Dome Models showing the 6 selected models from the clusters (a) and the corresponding simulated FOPT for each model (b).](image)

Finally, we demonstrated the use of flow diagnostics for fast stochastic optimisation. We have adjusted well controls to minimise the dynamic Lorenz based on the dual porosity TOF with the aim to improve the flow heterogeneity. In approximately 7 hours, 2000 flow diagnostic runs were performed concurrently across 4 cores on a standard desktop PC; this is equivalent to 50 seconds per model which includes setup and exporting results after each run. The optimal case was simulated and compared with a base case. The optimised production design yields a drastic improvement in total oil production (Figure 5a). It should be noted that the base case design was chosen arbitrarily. Nether the less the speed at which flow diagnostics can be used to identify preferable production controls is significant.

Optimisation was also performed for Models 1 and 6 (the extremes) from the ensemble. The optimal production design is not the same across the three models considered as the different fracture scenarios impact the connectivity and pairing of the wells between scenarios. There are, however, some similarities; a significantly reduced pressure is predicted to provide optimal Lc* across all three models for the well 6_72 which is furthest from the injectors. For the wells that lie closest to the injectors (1_43-2, 2_63, 4_73 and 5_62) overall increasing the injection pressure to close to the reservoir pressure aids the flow heterogeneity. We note that this very simple exercise by no means identifies the optimal well control design across all scenarios but it does demonstrate that flow diagnostics can be used effectively as a fast tool to quickly test different optimisation scenarios. Additional consideration of the individual well metrics such as breakthrough, drainage region and well allocation could be expected to provide further insight into choosing an optimal scenario.
Conclusion

Flow diagnostics offer a key benefit in that they provide key information about the reservoir dynamics under different production mechanisms in seconds. Flow diagnostics are not a replacement for reservoir simulation but offer a natural pre-processing step that complements modern uncertainty quantification, and optimisation workflows, especially for naturally fractured reservoirs where fracture conductivities are difficult to constrain but are a first order control on reservoir performance.

Our new dual porosity flow diagnostics identify and quantify the interplay of fracture-matrix transfer and advective flow, providing insights into the interaction between the rock matrix and the fractures, which is a key uncertainty in naturally fractured formations. We have applied dual porosity flow diagnostics to a real fractured reservoir, the Teapot Dome. The dual porosity flow diagnostics can be used effectively to predict approximate breakthrough times, particular for well close to injectors at risk of early breakthrough, and rank wells based on overall production via the drained volumes. We have demonstrated the use of flow diagnostics to distinguish between members of a model ensemble based on their dynamic response and select a small but diverse set of models for further study. A simple example also demonstrates the use of flow diagnostics as a fast optimization tool.

Flow diagnostics offer geoscientists a tool to quickly assess the reservoir dynamics directly from the geomodel. This provides a unique opportunity to understand the flow behavior of the system early and explore the impact of different geological scenarios prior to full flow simulation, helping geoscientists and engineers select the most important features and cases to consider for forecasting.

References


Ringrose P., and Bentley, M., [2015], M., Reservoir Model Design: A Practitioner's Guide. Springer Verlag


