

# Multiple history-matched models for Teal South

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Over the next few years, practicing reservoir engineers will have to cope with a vast increase in data describing field performance. This will come from operational deployment of time-lapse seismic and fully instrumented wells providing real-time pressure and rate information.

The current approach to history matching of reservoir models usually involves time-consuming adjustments of simulator input parameters by an engineer. These adjustments, based on the difference between the predictions of the reservoir simulator and observed field production and pressure data, can involve several man months of effort.

Reservoir model history matches are almost always nonunique—more than one combination of reservoir model input parameters (porosity, permeability, transmissibility barriers, etc.) will match observed production data.

Recently, commercial aids to history matching have been developed. These programs compute gradients of reservoir models response with respect to model input parameters. The codes have the ability to automatically generate a history matched model but do not guarantee that it is the correct “global optimum” solution.

**Generating multiple history matched models.** Our approach is to develop multiple history-matched models and use the range of possible models to quantify the uncertainty in future performance. By generating many possible solutions, the task of updating the history match when new data come in should be reduced to selecting the models that match the new data.

The approach we use is a stochastic sampling program originally developed for earthquake seismology. The algorithm, known as the Neighborhood Algorithm, uses information obtained from previous runs to bias the sampling of model parameters to regions of parameter space where a good fit is likely. In this way it attempts to overcome a main concern of stochastic sampling—poor convergence. A full description of the algorithm is given by Sambridge (*Geophysical Journal International*, 1999).

Quantitative probability estimates using a stochastic sampling algorithm depend critically on accurate estimation of the likelihood. This depends on both errors in the data and errors in the modeling.

Errors in time-lapse signal can be due to survey repeatability, for example variations in source-receiver positions, shot-to-shot repeatability, ambient noise such as wave action or tide-induced noise in marine seismic, or different processing decisions and interpretations such as picks of individual horizons.

Generally, cross-equalization is carried out to remove as many of these differences as possible. Filters are designed to minimize differences in regions assumed to have no changes due to production and to warp the data volumes to align amplitudes or attribute distributions on horizons.

The two principal errors in reservoir simulation are numerical diffusion, which is an artificial smearing of sharp fronts, and cell-aspect ratio errors, where the results of a simulation are sensitive to the ratio of cell height to cell thickness. Numerical diffusion means that it is impos-

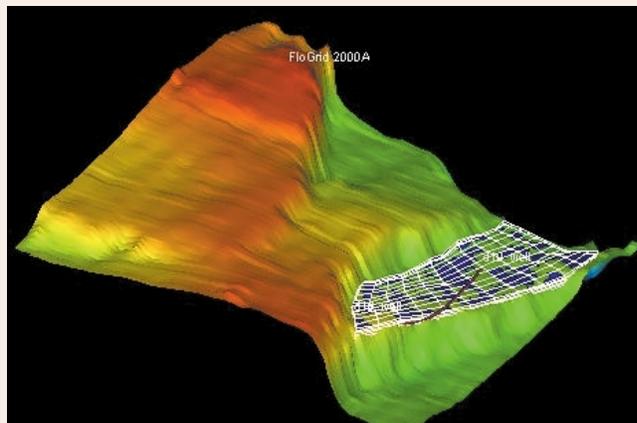


Figure 1. Teal South 4500-ft sand structure map and simulation grid.

sible to resolve a front over fewer than three cells, and generally fronts might be smeared over four or five cells and perhaps more. For a relatively coarsely gridded model, this raises the question of how quantitative we can be in comparing seismic with simulation.

**Application to Teal South.** Teal South is a reservoir in the Gulf of Mexico that has been the subject of a number of time-lapse surveys managed through Energy Resources Clearing House (ERCH) in Houston. Many institutions have been using the data to test and develop processing techniques for time-lapse seismic. At Heriot-Watt, we have used Teal South as one example data set in the Edinburgh Time-Lapse Project, which focuses on developing seismic processing and interpretation methods, and the Uncertainty Project, a reservoir engineering project to develop prediction methods for uncertainty quantification.

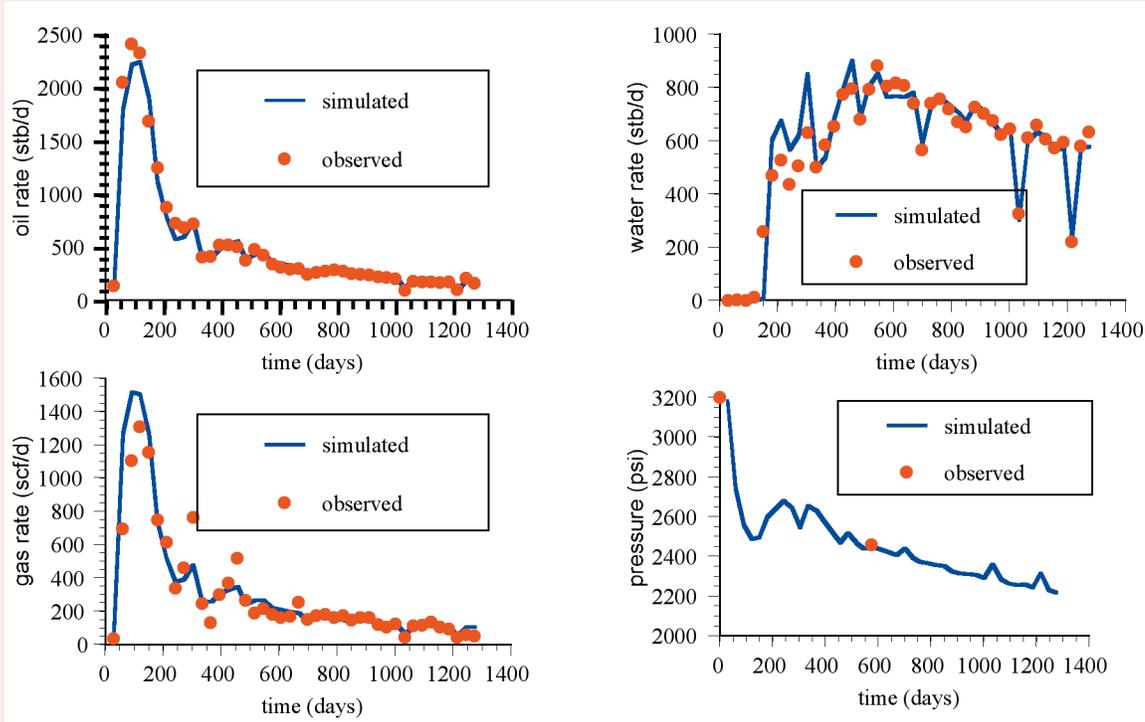
Figure 1 shows the 4500-ft sand, which is bounded on three sides by faults and closed by dip to the north. A single well penetrates the sand, which is initially overpressured at 3096 psi. Monthly production rates of oil, water, and gas are available; there are only two pressure data points—the initial pressure of 3096 psi and a measurement of 2458 psi after 570 days of production. Pennington (*TLE*, 2001) analyzed some time-lapse results and cross-equalization issues were described by Druzhinin et al. (*SEG 2001 Expanded Abstracts*).

Data available to aid the history matching study included a depth-converted top-structure map of the 4500-ft sand, pvt data, and estimates of reservoir thickness. We had no access to relative permeability data.

We set up a history matching process using production data only. Key unknowns in our history matching procedure were horizontal and vertical permeabilities, water-oil and gas-oil relative permeability, rock compressibility, water-oil contact, and aquifer strength.

We created a corner point grid using FloGrid. Initially we set up a model with three layers and sampled for relative permeabilities, water-oil contact, and constant values of horizontal and vertical permeability. We used this

**Figure 2.**  
History match for most likely model.



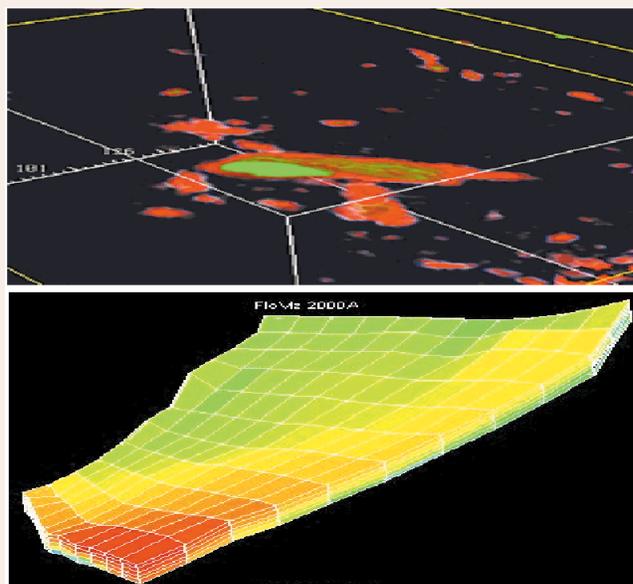
initial model primarily to determine a reasonable set of relative permeability data and a good estimate of water-oil contact. The water-oil contact was consistent with data acquired subsequent to these initial runs.

A more detailed reservoir model was then set up on an  $11 \times 11 \times 5$  corner point grid. We allowed horizontal and vertical permeability of all five layers to vary in addition to rock compressibility and aquifer strength.

Figure 2 compares production data from the maximum likelihood model obtained from the sampling algorithm with observed data. The match was obtained by fixing the total production of the model to be that observed; comparing individual oil, water, and gas rates with observed data; and ensuring that pressures matched the two observed data points.

Figure 3 shows a plot of synthetic stacked amplitude computed directly from the simulation model and the observed time-lapse response. The overall behavior is similar, but there are differences in detail. The first point that stands out is that the areal resolution of the seismic response is significantly greater than that of the simulation model. All reservoir models need at least two cells to locate fronts such as a gas-oil contact. For displacement processes the number of cells needed can be significantly higher. The second point is that vertical resolution is much higher in the reservoir simulator. Figure 3 shows amplitude computed from the top layer of the reservoir model. The amplitude was computed by taking pressure and saturation from the reservoir model, computing elastic properties using petrophysical relationships developed at Heriot-Watt, and then calculating reflectivity using the Zoeppritz equations to give a stacked response for a range of near-offset angles.

When matching seismic and simulation, we have to remember that each process produces an approximation to true reservoir behavior. In the case of simulation, two features can cause errors in prediction. The first is that the solution of the difference equations has not converged, and hence numerical errors exist. The second is that the variation in porosity and permeability is not captured on coarse



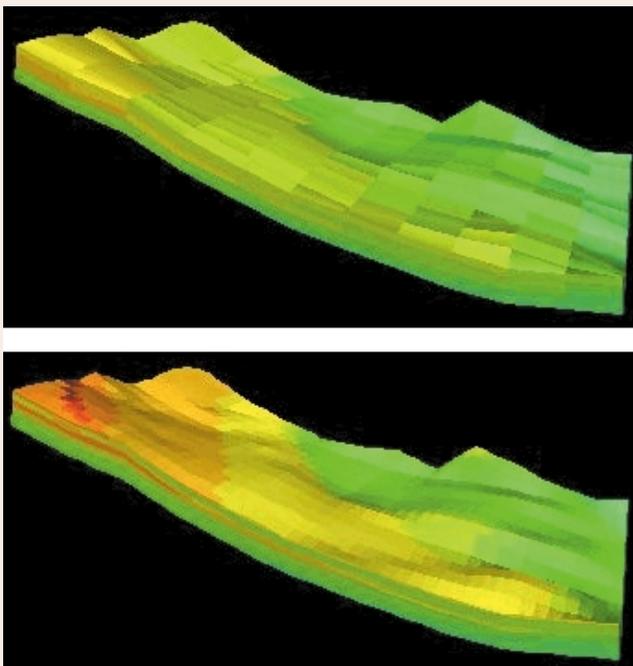
**Figure 3.** Comparison of observed (top) and simulated (bottom) reflectivity.

grids, and errors due to upscaling exist.

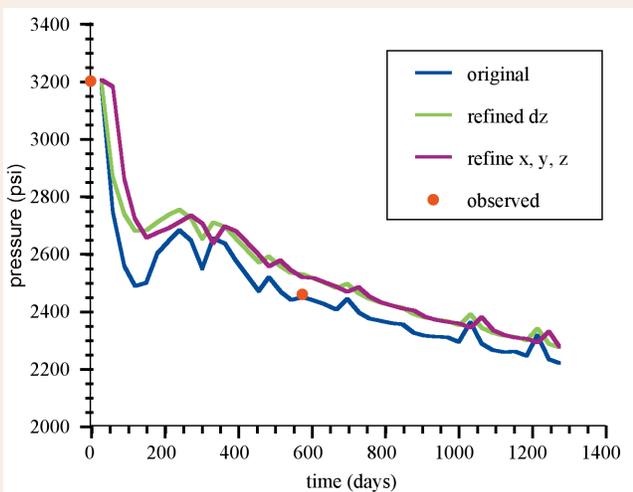
Figure 4 shows our best fitting model run on a refined grid with  $55 \times 55 \times 15$  cells. We took the five-layer description and refined uniformly, so that multiple layers now have the same property values. We can see that the increased resolution means the simulator can resolve the way the gas rises and is held up at layer boundaries. The best match is obtained with higher permeability toward the bottom of the reservoir.

Figure 5 shows reservoir pressure as a function of time for three grids: the coarse  $11 \times 11 \times 5$  grid, a vertically refined grid of  $11 \times 11 \times 15$ , and a refined grid of  $55 \times 55 \times 15$ . The change in simulated pressure at 570 days is almost 100 psi.

This pressure change with varying grid size points out the need for simulator error models in history matching.



**Figure 4.** Comparison of coarse grid (top) and fine grid (bottom) reflectivity.



**Figure 5.** Changes in simulated pressure response with grid refinement.

In the matching phase, we rejected models with pressure discrepancies less than the change we see here due to grid refinement. Some initial work on development of simulation error models has been published by Glimm et al.

We initially set up the model with no aquifer influx. Pressure support was provided by gas cap expansion and reservoir compaction. However, we found that it was virtually impossible to generate reservoir models where the pressure was as high as 2458 psi at the time of the second pressure measurement. When we added pressure support due to a limited aquifer, we were able to obtain good agreement.

This finding ties in with the observations by Pennington that a nearby reservoir is leaking, and pressure communication exists between it and the 4500-ft sand. The reservoir model alone is not able to identify the source of additional pressure support, merely that it is required for consistency with the observed pressure response.

**Summary.** We have presented some initial results showing generation of multiple history matched models linking reservoir simulation with time-lapse seismic. The role of errors in both the simulation and in the processing of seismic is key to understanding the impact of time-lapse data on uncertainty quantification.

**Suggested reading.** “Geophysical inversion with a Neighborhood Algorithm, Part 1: Searching a parameter space,” by Sambridge (*Geophysical Journal International*, 1999). “Geophysical Inversion with a Neighbourhood Algorithm, Part 2: Appraising the ensemble” by Sambridge (*Geophysical Journal International*, 1999). “Seismic time-lapse at Teal South: That little neighbor reservoir is leaking” by Pennington et al. (*TLE*, 2001). “Prediction of oil production with confidence intervals” by Glimm et al. (*SPE* 66350, 2001).  $\square$

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