Facies modeling in unconventional reservoirs using seismic derived facies probabilities

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Summary

We present in this paper a methodology to use prestack seismic inversion results to constrain facies modeling in unconventional reservoirs. The fact that the exploitation of unconventional reservoirs typically relies on the use of large numbers of long, closely spaced, data poor horizontal wells creates challenges in petrophysical analyses, rock physics diagnostics, seismic scale calibrations and stochastic facies modeling that do not exist in conventional reservoirs. We address these challenges and propose solutions that result in geological facies models that closely follow horizontal and vertical well facies data, vertical proportion curves and selected seismic constraints that are treated as hard data. We illustrate this methodology using data from a carbonate rich unconventional reservoir in Texas.

Introduction

The development of unconventional reservoirs requires large numbers of closely spaced horizontal wells aimed to maximize recovery in rocks of very low permeability that can produce commercial hydrocarbons only after hydraulic stimulation. Log data available in horizontal wells typically consists of Gamma Ray (GR) and mud logs obtained while drilling to steer the well path along the target and are therefore biased by design towards sampling the good rock while the wells are in zone. The proportion of vertical wells with modern and less biased sets of logs is much smaller than the horizontals since vertical wells are mainly used to identify the target depth for future horizontal wells and monitor pressure. These data disparities between horizontal and vertical wells create a new set of challenges for facies mapping using seismic data and geological modeling that are not common in conventional reservoirs where vertical or deviated wells are the norm for reservoir development.

Facies mapping in unconventional reservoirs is important for a variety of reasons. Facies not only help to map variations in matrix properties such as porosity and permeability but also help to assess whether a rock will fracture under hydraulic stress (brittleness) and control the variability and intensity of existing natural fractures relative to faults.

The geophysicist's workflow for facies mapping in conventional reservoirs using seismic data starts by performing crossplots of elastic properties at log scale colored by petrophysical properties that help to create probability density functions (PDFs) for different facies at log scale (Mukerji et al., 2001). These PDFs are then used in seismic scale crossplots of elastic properties to estimate facies probabilities in the volume of interest. Besides the possible limitations of assuming that log scale derived PDFs are also valid at seismic scale, another limitation of this approach is that resulting discrete facies do not necessarily honor either the facies flags along the well paths or the facies vertical proportion curve (Ravenne et al., 2000) in the interval of interest. In contrast, the geomodeler's workflow for facies mapping in conventional reservoirs focuses on honoring well facies data and vertical proportion curve (VPC) but leave the lateral variability in the interwell region to conceptual geological trends.

The application of these workflows in unconventional targets is not straight forward. Since the geophysicist's workflow requires collocated, log scale elastic and petrophysical information to generate PDFs and this information is usually not available along horizontal wells, they are forced to leave behind useful and abundant GR and mud log data that carry information about the target interval along possibly tens of miles of lateral sections. By doing so, the seismic calibration with log data is then limited to whatever can be extracted from a few hundreds of feet of log data along the vertical pilot well which may or may not be representative of the variability observed along the laterals. For geomodelers the situation is not any easier. Facies information cannot be honored along horizontal wells simply because this information is not commonly extracted from GR and mud log data. Even if facies data were available, VPCs cannot be generated from horizontal wells and the lateral continuity of the facies between undulating horizontal wells is hard to determine. Under these circumstances, geomodelers are only left with the facies data along the pilot well and possibly conceptual geological trends to constrain their facies models.

We present in this paper a workflow to perform seismic constrained facies modeling in unconventional reservoirs that attempts to overcome these difficulties. We start by calibrating the GR log along the pilot well with facies information derived from a complete set of logs. This calibration is then used to extract facies information along the horizontal wells that may be coarser (but still useful) than the facies description along the pilot well. Since no elastic logs are available along the horizontal wells to make log scale rock physics crossplots and estimate PDFs, elastic information is extracted from prestack inversion results along the well trajectories and this information is used to estimate facies probabilities from crossplots of inverted elastic properties colored by facies flags. A byproduct of the facies probability estimation is a measure of reliability of the estimates. Probability and reliability information is then used to select points from the probability volumes that are used as hard constraints for geostatistical facies modeling that also attempts to honor the VPC at the pilot well and the dominant facies information along the horizontals. The application of the workflow is illustrated with a pad-scale example (1 pilot well plus 8 horizontal wells in its vicinity) from a carbonate unconventional reservoir in Texas.

Facies estimation along horizontal wells

The interval of interest for this study (~ 200 feet) consisted mostly of carbonate facies (porous packstone, porous mudstone and tight carbonate) with a small proportion of kerogen rich clay layers. These facies were defined by petrophysical modeling calibrated with core data. Since brittleness estimates derived from dipole sonic data did not help in this area to separate these four facies into brittle and non-brittle categories, we created a brittleness indicator based on the relative fractions of each facies per interval. This indicator assumes that clay is non-brittle and tight carbonate is the most brittle facie followed in descending order by packstone and mudstone respectively. A crossplot of the dipole derived brittleness estimation versus the lithology based brittleness colored by the different facies is shown in Figure 1a. We then colored this crossplot by the GR log and tested different GR cutoffs until we obtained brittleness regions similar to those obtained from the lithology brittleness estimate. The result of applying a 70 API cutoff to the GR log to separate brittle from non-brittle facies is shown in Figure 1b. This cutoff may be later adjusted to make sure the facies model shows a similar proportion of brittle/non- brittle facies compared to the original facies. The brittle/non-brittle facies that result after applying this GR cutoff to the GR logs along the horizontals and pilot well is shown in Figure 2.

Calibration of inverted elastic properties

Once facies have been defined along the horizontal wells, we need to understand their relation with the elastic properties of the reservoir before we use seismic data to map the variability in the interwell region. In the absence of dipole sonic data, the only elastic information available along the horizontal wells was the acoustic impedance and VpVs ratio from prestack inversion of seismic data. We extracted this information along the well paths from depth converted inversion results using the same sampling interval of the GR logs.

Since inverted elastic and log facies data are now collocated, we can make seismic scale rock physics crossplots to understand the relation between acoustic properties and facies along the horizontal wells for different GR log cutoffs. An example of this crossplot is shown in Figure 3. This result shows that less abundant non-brittle facies tend to cluster in areas of lower acoustic impedance.

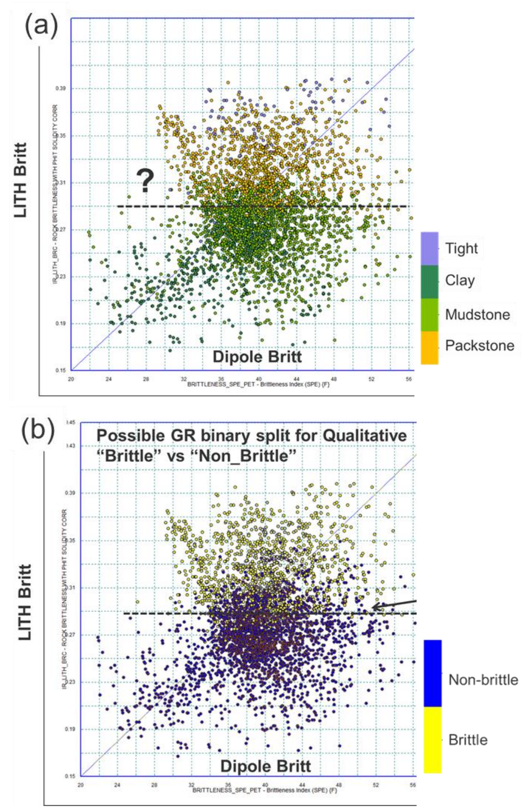

Figure 1: Crossplots of dipole derived brittleness versus lithology based brittleness at the pilot well. (a) Original facies. (b) Brittle/non-brittle separation using a 70 API GR log cutoff.

Facies probabilities from inversion results

Since brittle and non-brittle facies tend to cluster in different regions in the crossplot of inverted elastic properties, we can translate this observation into quantitative information by gridding the crossplot (with different cell sizes) and estimating the probability of brittle facies within each grid cell. For each cell in the crossplot, the algorithm conducts a poll in the population (points in the cell) about which candidate (facie) may win. Like in any opinion poll, our algorithm yields the favorability (probability) of the candidates, the margin of errors for a given confidence interval (assuming random sampling as a first approximation) and the sample size. Probabilities with large margin of error and small sample size are considered less reliable than probabilities with small error and large sample size. The method for probability estimation from prestack inversion results is described in Michelena et al. (2011).

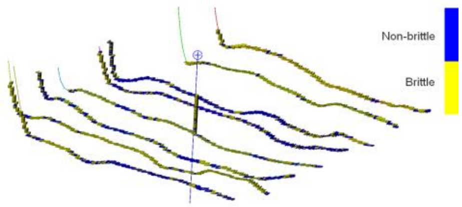

Figure 2: Brittle and non-brittle facies extracted from calibrated GR logs. The lateral sections range between 6,000 and 7,300 feet. The pilot well is indicated by a "+". Notice how some wells navigate along large portions of brittle rock whereas others don't.

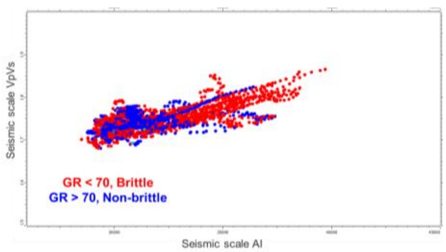

Figure 3: Crossplot of inverted acoustic impedance versus inverted VpVs ratio extracted along 8 horizontal wells and colored by facies generated from GR logs.

As Figure 4 shows, only a small fraction (yellow points) of the total population in the volume (blue points) participates in the poll. To fill the points in the whole volume with a probability estimate, we divide the crossplot in two regions (separated by the red rectangle in Figure 4). Inside the red rectangle, we estimate probabilities by polling the data within cells of different sizes that cover the entire region. Outside, we fill the voids not sampled by horizontal wells either by interpolation of probabilities in the space domain or by using conceptual, rock physics based end member facies. Figure 5 shows there is good agreement between estimated facies probabilities and expected facies flags along the horizontal well paths.

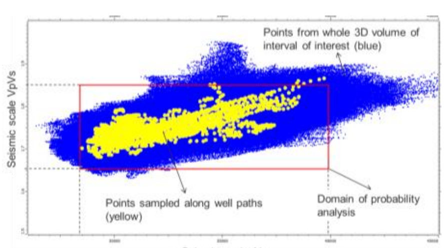

Figure 4: Domain of facies probability analysis (red rectangle) that includes all points sampled along the horizontal well paths (in yellow). Probabilities in (blue) points outside the rectangle are estimated by interpolation in the (x, y, z) space domain.

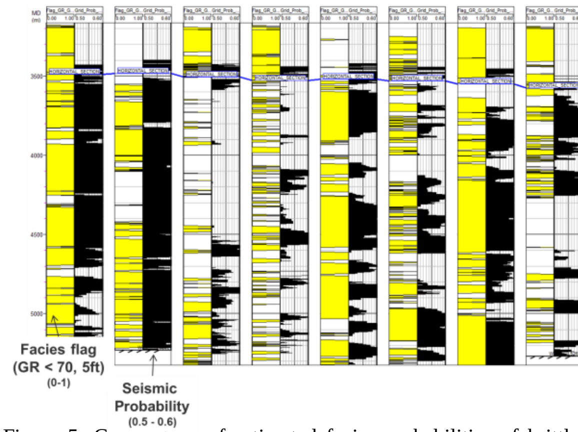

Figure 5: Comparison of estimated facies probabilities of brittle rock (black) versus expected brittle facie flags (yellow) derived from GR log along lateral sections.

The outputs of the facies probability analysis are volumes of probability of brittle/non-brittle rock, margin of error and sample size in each cell. Although these outputs can be used in different ways to guide stochastic facies modeling, our approach uses only the "best" points with high probability, small margin of error and large sample size as hard constraints.

Stochastic facies modeling

The input for stochastic facies modeling using Sequential Indicator Simulation (SIS) consists of facies flags along the horizontal wells, facies flags along the pilot well, VPC at grid resolution from the pilot well and seismic derived hard constraints from the facies probability analysis. The fact that we use more points as hard facies constraints than the original facies flags along the well makes the simulation results less dependent on the properties of the variograms and stochastic nature of the modeling. However, the results are strongly dependent on the cutoffs used to generate the hard constraints from the facies probabilities. The fewer the amount of points we use from the seismic, the easier it is to honor the well data and the VPC which means that only the most likely and most reliable facies information from the seismic inversion ends up being used.

Figure 6 shows an example of a volume of hard constraints for brittle and non-brittle facies if we keep only points with probability higher than 60%, margin of error less than 3% (assuming 90% confidence) and sample size greater than 135 points per cell. Only 3.5% of points in the volume meet all these requirements. The final selection of these cutoffs is performed iteratively by examining the fit between the expected VPC at the pilot well versus the VPC extracted from the grid after stochastic facies simulation. The selection of the points is also weighted by the expected proportion of brittle/non-brittle facies observed at the pilot well for each layer of the grid. Figure 7 shows this process in detail. By selecting only the most likely and reliable points and weighting their selection also by the VPC at the pilot well, we are able to impose the seismic trends in the result while still honoring both the horizontal and pilot dominant facies data in addition to the VPC.

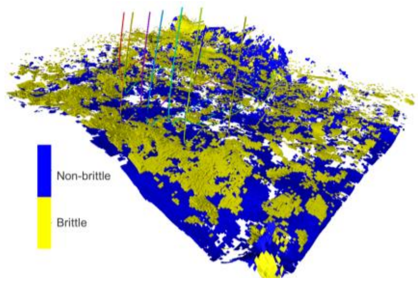

Figure 6: Hard constraints extracted from seismic probabilities that correspond to high probability of brittle or non-brittle facies, small margin of error and large population size. The selection of these points is also weighted by the relative facies proportions observed at the pilot well for each layer of the grid. See Figure 7.

Figure 8a shows one stochastic realization of the brittle/non-brittle facies model that results from this workflow. Since the final goal is to model the original packstone, mudstone, tight carbonate, and clay facies, we use the brittle/non-brittle regions in Figure 8a to guide the modeling of such original facies while still honoring their flags and VPC along the pilot well. The result is shown in Figure 8b.

Conclusions

We have presented a facies modeling workflow in unconventional reservoir that addresses the petrophysics, rock physics, seismic calibration and stochastic modeling challenges created by the abundance of long horizontal wells with limited types of log information. We start by defining facies using Gamma Ray logs along the horizontals that have been previously calibrated along the pilot well with core data and a full set of logs. The information needed to calibrate the facies along the horizontals to the elastic properties of the reservoir is extracted from the prestack inversion results along the well paths. By using crossplots of inverted elastic properties colored by facies, we estimate facies probabilities and their reliability for the volume of interest. Only the most likely and most reliable information from seismic is finally used to constrain the stochastic facies modeling while also honoring the dominant facies flags along the horizontals and the VPC along the pilot well. This workflow can be also applied to facies modeling in conventional reservoirs and the results can be used to constrain flow simulation models.

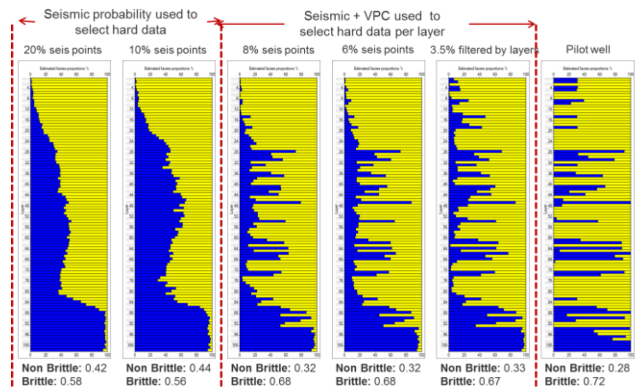

Figure 7: Vertical proportion curves (VPC) extracted from the grid after stochastic facies simulation using decreasing amounts (from left to right) of seismic derived hard constraints. The estimated VPC at the pilot well is shown at the right. Brittle/non-brittle proportions of facies for the whole grid are shown at the bottom of each VPC. The final iteration used only 3.5% of the points in the grid to constrain the facies model.

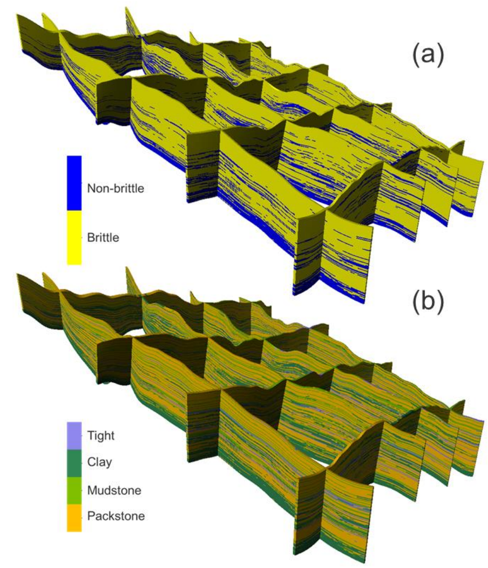

Figure 8: (a) Stochastic realization of brittle/non-brittle facies using the workflow presented in this paper. (b) Stochastic realization of original facies along brittle (tight, mudstone and packstone) and non-brittle (clay) regions of the model on (a).

Acknowledgments

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EDITED REFERENCES

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