Net-to-gross from Seismic P and S Impedances: Estimation and Uncertainty Analysis using Bayesian Statistics

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Summary

Net-to-gross (*N/G*) is a measure of the amount of sand or pay in the overall reservoir and is used to appraise reservoir quality and the economics associated with reservoir development. As seismic based reservoir characterization technology is advancing in many cases lithology and porosity information derived from seismic inversion can be used to derive an estimate of *N/G*. In many cases this problem is non unique due to accuracy of seismic inversion and the rock physics nature of the lithology and porosity prediction. Thus as N/G estimates are often used for economic decision-making it is important to associate expected risk or confidence associated with the prediction. In this paper we we present a workflow to compute quantitative estimates of N/G, along with associated uncertainties, from well-log calibrated pre-stack seismic inversion attributes. The main tools we use in this workflow are Seismic (AVO) Inversion, Rock Physics, and Bayesian Statistics. We estimate the N/G from the seismically derived rock properties. We derive the uncertainty in net-to-gross from uncertainties in seismic inversion, reservoir properties, and geologic interpretation.

Introduction

Some authors (Vernik et. al., 2002, Engelmark, 2004) define net-to-gross (*N/G*) as the fractional volume of sand in the entire reservoir. It may be useful to estimate the fractional volume of hydrocarbon reserves (pay) in the reservoir. In this paper, we estimate two quantities – (1) the volume fraction of sand in the reservoir (V_{sand} or *N/G*), (2) the volume fraction hydrocarbon reserves (pay) in the reservoir (V_{Pay} or *PVF*). In each block, or "seismic pixel" within the reservoir, the volume fraction of hydrocarbon is given by the following equation:

$$v_{Pay} = \phi\left(1 - S_W\right) \qquad (1)$$

In the above equation, ϕ represents porosity, and S_W represents water saturation. To compute the volume fraction of hydrocarbon in the reservoir, we compute v_{Pay} at each seismic pixel that indicates sand, and then sum over the entire reservoir.

Sources of Uncertainty

The major sources of uncertainty in estimating net-to-gross and pay volume fraction are as follows:

(1) Measurements – The measured data, both seismic and well-log data are noisy. The seismic signal-to-noise is generally lower than the signal-to-noise of the well-log data, because of acquisition geometries. Especially at the higher frequencies, the seismic data quality is poorer than the corresponding log data quality. In calibrating the seismic to the well-log data, we account for the log-to-seismic discrepancy in data quality.

(2) Inversion – Apart from the measurement errors in the seismic data, there are errors in the inversion results, These source of these errors can be categorized as follows: A. Errors resulting from various processing sequences (e.g., gather flattening or multiple attenuation before AVO inversion). B. Model approximations (e.g., a 2 vs 3 term AVO is or approximate inversion process that ignores some second-order wave-propagation effects such as mode conversion etc.). and C. errors associated with filling of the inversion null space (this is specifically important when using convolutional forward model as the basis for the AVO inversion, which explicitly place all the low frequencies in the null space of the inversion process. Low frequency compensation is then needed to fill up the low frequency part of the reflectivity spectrum). We note that although these uncertainties are not easy to quantify, one should try to include a measure of these uncertainties resulting from inversion when estimating the uncertainty in net-to-gross from seismic.

(3) Rock Properties – Rock properties such as clay content, porosity, and fluid saturation are often correlated with seismic properties such as moduli, velocities, and densities. However, due to the complexity of the rock microstructure, mineralogy and digenetic process, it is difficult to derive a deterministic rock model that will capture the full complexity of the rock. Furthermore, we often do not have a complete knowledge of the rock mineralogy, fluid properties etc. Thus, rock models exhibit a certain amount of "scatter" or "uncertainty" around them. This rock physics uncertainty is a significant source of uncertainty in predicting lithology, fluids, and net-to-gross. In this paper, we account for uncertainties in clay content, porosity, and fluid saturation. The fluid properties themselves can be uncertain – however, we did not consider their contribution to be significant in estimating the net-to-gross.

(4) **Interpretation** –When trying to solve non-unique problems such as N/G one can further constrain the problem by using geological interpretation as prior information. It is important to note that interpretation is also subject to uncertainty. In our workflow, the reservoir sands are delineated based on a shale probability threshold. The shale threshold is determined in an interpretative step, and determines the volume fraction of sand in the reservoir. The uncertainty in the volume fraction of reservoir sand contributes to the uncertainty in net-to-gross estimation.

(5) **Scale issues** – The seismic scale is significantly larger than well-log scale, while the seismic frequencies are lower than the logging frequencies. The seismic resolution is an order of magnitude lower than the well-logging resolution. Therefore, the well-log data need to be suitably up-scaled in the process of calibration with seismic. The up-scaling procedure is a potential source of uncertainty, and contributes to the uncertainty in net-to-gross.

Workflow and Examples

To estimate net-to-gross and its associated uncertainty, we use a Bayesian approach for identifying and quantifying rock properties from seismic inversion results. The data required for this workflow are well log data (containing sonic, shear, density, clay content, porosity, and saturation information) and pre-stack seismic data. The well-log data are required for initial calibration of rock-properties to seismic attributes. The seismic data is subsequently used for facies classification and porosity-saturation estimation, based on the calibration that was done using well-logs. The workflow consists of the following major steps: (1) Lithology estimation, (2) derivation of sand Indicator from lithology probability maps, (3) Joint porosity Saturation inversion,

Net to Gross is estimated using the results of the above. We will next show how uncertainty in N/G can be derived after quantifying the expected uncertainty associated with steps 1,2,3 above.

Step 1: Lithology identification

The first step in our post-inversion workflow is lithology identification from seismic. The purpose is to infer litho-facies (such as sand, shaly sand, shale, etc.) from the seismic impedance and density (if available) data. First, we will discuss the class definition (calibration), followed by the class identification (classification). We used data from 6 wells in this step. (a) Litho-classes and well-log data (b) Contour plots of 2-dimensional PDF's

(a) Class definition

Class definition is done using well-log data. The number of "interesting" litho-facies is determined by detailed analysis of well log data, based on rock properties (clay content, porosity, saturation) and their seismic properties (sonic, shear, and density logs). Typical litho-facies can be shale, shaly sand, brine-saturated sand, and hydrocarbon-saturated sand. The number and type of litho-facies (or classes) can vary from one reservoir to another. Figure (1) shows well-log data for each litho-facies and the probability density functions (PDF's) derived from the log data. Avseth et. al. (2005) provides a good overview of the statistical technique (non-parametric PDF estimation) that is used for this purpose. We obtained a theoretical success rate of 66% in detecting pay sands, using log quality data.

Class probability

We then use the PDF's, and the seismic attribute (impedance, and density) volume, to generate posterior probability volumes using Bayes' rule (Takahashi, 2000, Avseth et al, 2005). Each class has a posterior probability volume associated with it.

Figure(2) shows relative probability maps obtained from seismic impedance and well-log-derived PDF's using Bayesian classification.

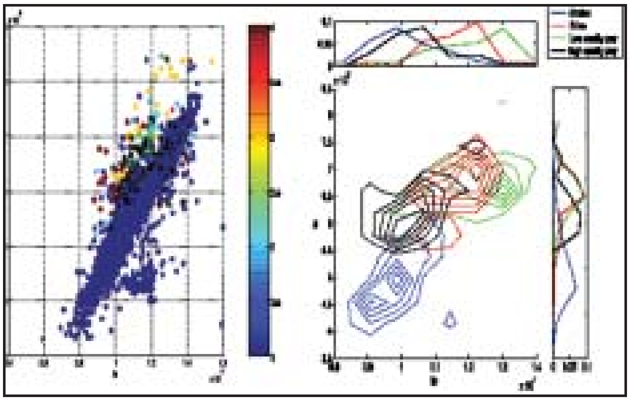

Fig. 1: (a) Ip and Is computed from sonic, shear, and density logs, color-coded by "class", where Class 1 is Shale, Class 2 is Brine sand, Class 3 is Low quality pay and Class 4 is High quality pay. (b) Contour plots of 2-D probability density functions corresponding to the log data.

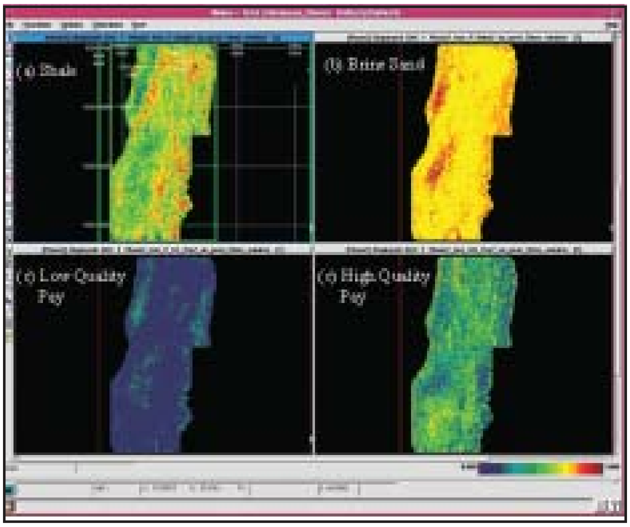

Fig.2: Relative probability maps of (a) Shale, (b) Brine-sand, (c) Low quality pay, and (d) High quality pay obtained using Bayesian classification.

Step 2: Sand Indicator

Shale threshold

After we have derived the litho-facies probability map, our next step is to assign a sand indicator. The sand indicator is used for the following tasks: A. to estimate porosities in the sands. (Shale porosities can be high, but do not contribute to the net-to-gross). B. To derive expected volume of pay , i.e., we define our expectation in terms of the lithology threshold. We note that the choice of this threshold is interpretive. This is illustrated in figure 3. In figure 3a we present a shale probability map we will use. Because the depositional environment is dominated by sand and shales, we assign a shale probability cut-off, such that, a given point in the reservoir is determined to be sand if the Probability of Shale at that point is lower than the cut-off probability.

As we have noted earlier, choosing this cut-off is an interpretive step, and can be somewhat subjective, as shown in Figure (3). A benefit of this interpretation is that one can use a quantitative threshold number such that the sand layer continuity and overall depositional character will be maintained. This can be done by changing the probability threshold associated with the sand indicator at a given section and looking wether the general expected character is maintaind. In figure 3a we present a sand indicator map associated with a P(shale) threshold of 60% and in figure 3b we present the sand ndicator map associated with P(shale) threshold of 75%. The shale probability cut-off should ideally be 0.5, but in our experience, can be anywhere between 0.35-0.75. The sand indicator ranges are the uncertainty we associate with the indicator because classifying a point as shale or sand can make the net-to-gross estimates more or less conservative respectively. These ranges will be propagated later in the uncertainty analysis. We define the ranges between 0.35-0.75 as ΔV_{sand}.

Step 3: Joint Porosity-Saturation estimation

After the sand indicator has been mapped, we can move forward and estimate the porosity and saturation within the sand zones. We use a Bayesian estimation

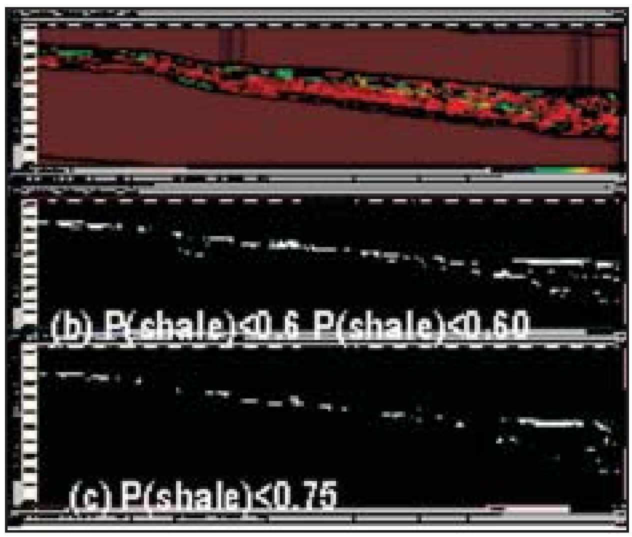

Fig. 3: Choosing a Sand Indicator based on Probability of Shale (a) P(Shale) along a seismic line, (b) Sand Indicator = P(Shale)<0.6, (c) sand Indicator = P(Shale)<0.75

approach, described in detail by Bachrach (2005), for the porosity and saturation estimation. Using this approach, we can obtain the estimated porosity and saturation, along with the uncertainties associated with the porosity and saturation values at each pixel.

The uncertainty in porosity, in this case was about 0.05 (5%), while the uncertainty in saturation was about 0.30 (30%). Porosity estimation is significantly more accurate than saturation estimation, because the rocks are more sensitive to porosity differences in terms of change in seismic response. Even though we cannot reliably quantify saturation differences to less than 30% accuracy, it is still sufficient for identifying zones of high pay versus low pay.

Net to Gross estimation and Uncertainty analysis

From Steps 1,2 and 3 above, , all the required ingredients for computing the net-to-gross are available. V_{sand} is directly related to the sand indicator and the uncertainty around is defined as the interpretational uncertainty associated with the sand indicator. Porosity and saturation estimation can be directly used with equation (1). Next we derive the uncertainty associated with the prediction.

The uncertainty (fraction) in net-to-gross is given by . The uncertainty in volume of pay is given by $\Delta V_{Pay} / V_{Pay}$. (Note that v denotes volume fraction at a pixel while V denotes volume fraction in the reservoir). The uncertainty in Pay volume fraction is clearly expected to be larger than the uncertainty in net-to-gross because it additionally includes the uncertainties in porosity and saturation. Within each seismic pixel, it is straightforward to compute the pay volume fraction using Equation (1). The uncertainty or "error" in each seismic pixel is defined by the complete differential associated with Equation(1).

$$\Delta v_{Pay} = \Delta \phi (1 - S_W) + \phi \Delta S_W \qquad (2)$$

Given that we have already obtained the porosity and saturation values, along with the associated uncertainties at every seismic pixel, we can estimate the uncertainty in the pay volume fraction using Equation (2). If we divide Equation (2) by Equation (1), we can clearly see that the uncertainty in pay volume fraction is a sum of the uncertainty in porosity and the uncertainty in saturation at each pixel. In our data example, the saturation contributes 4 times as much as porosity to the total uncertainty in pay. Finally, the total uncertainty in pay volume fraction ($\Delta P/P$) is given by:

$$\frac{\Delta P}{P} = \frac{\Delta V_{Pay}}{V_{Pay}} + \frac{\Delta V_{sand}}{V_{sand}} = \frac{\Delta \phi}{\phi} + \frac{\Delta S_W}{(1 - S_W)} + \frac{\Delta V_{sand}}{V_{sand}}, \qquad (3)$$

where V_{pay} denotes the summation of the hydrocarbon volume-fraction in the reservoir sands.

Results and discussions

In this example we used seismic inversion, rock physics modeling and interpretation based on geology-based sand continuity criteria to predict net to gross. We derived a measure of uncertainty associated with each prediction and propagated it to derive a total measure of uncertainty in the net-to-gross prediction. Shale probability map was used to derive a sand indicator and the uncertainty associated with the indicator have been derived by defining a geological criteria and purterbing the threshold. We note that the interpretational criteria is many times be subjective, however we emphasize that it is not unique. The method we present in figure 3 allows us to explore the ranges of interpretation associated with posterior lithology classes.

The Pay volume fraction (PVF) can be a very useful quantity for estimating hydrocarbon reserves. To give a simple illustration, if the *PVF* of a reservoir is 0.01 (1%) by volume, the reservoir is 50m thick, and extends laterally over 100 square km, the total estimated reserves (*PVF* times Reservoir Volume) will be about 31.4 million barrels. In our workflow, we compute the net reserves in a much more rigorous fashion, by computing pay volume fraction in each seismic pixel and then summing over the entire seismic block. We can estimate the net hydrocarbon reserves in a seismic data volume, along with the uncertainty in the estimation.

Conclusions

Using Bayesian statistics, we were able to predict the success rate of hydrocarbon identification. The estimation of net-to-gross is computationally easier and more reliable than the hydrocarbon volume fraction in the reservoir. However, the sand net to gross alone cannot provide an estimate of the net hydrocarbon reserves in a reservoir. The Pay volume fraction is expected to be less accurate, but it is useful for economic evaluation of a reservoir. The uncertainties is Pay volume fraction can be quantified using Monte-Carlo techniques for estimating uncertainties in porosity and saturation, and then performing a weighted summation in the reservoir zone.

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