# Bayesian Sand-shale Reservoir Quality Indicators

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## Abstract

This work illustrates a methodology for reservoir inference in a siliciclastic oil field. The goal of this methodology is to produce an indicator of good reservoir cells inside of a 3D oil field volume. To create this indicator, we consider porosity, clay volume and saturation.

The degree of confidence that we have regarding these reservoir properties depends on current state of information. The sources of information are prestack seismic data, petrophysical and geological information from well data and rock physics models (empirical and theoretical). The seismic data has been pre-processed in an amplitude-preserved fashion.

These data sets are used to construct local probabilities representing each piece of information and associated degree of confidence, regarding the reservoir parameters. These probabilities are then combined by application of the Bayes theorem. As a result, we obtain a collection of posterior distributions probability density functions (PDF) covering each cell of the reservoir. The desired measures inferences can be computed from the distributions (e.g., estimates and associated uncertainty) and presented as reservoir inference cubes for further analysis. In particular, it can be used to delineate reservoir conditions for a risk analysis workflow associated with time-lapse and reservoir development projects.

## Introduction

The point of view taken herein is that determination of reservoir properties is essentially an inference problem. Geophysical data (seismic data and well data) – the main source of information used in a reservoir characterization work – are experimentally acquired and subjected to error disturbances. Also, the theory involving the data signal processing and the reservoir characterization process usually introduce additional uncertainty into the calculations. How the data and the theory affect the final uncertainty involved in reservoir description is a key ingredient to be considered in the evaluation of the exploitation risk for the oil industry.

This paper develops a methodology to provide an inference framework targeted for porosity, lithology and saturation from geophysical and petrophysical data. This work has been developed in a long-term project and is based on an extension of previous work. In the work presented by Loures and Moraes (2003) the final solution is a set of PDFs for porosity from which desired inferences can be drawn. Usually the median and an associated length of a probability interval (e.g., 0.95) are respectively used as estimator and measure of uncertainty.

Later, Loures and Downton (2004) implemented a methodology incorporating AVO inversion and modified the rock physics model to jointly infer porosity and clay volume for each reservoir cell. In this case, the joint posterior probability can be computed with greater reliability than the PDFs for individual parameters. The joint PDF is also useful for mapping good reservoir quality sandstones (i.e., high porosity and low clay volume).

Here, we take a step forward by including saturation on the inference workflow, after the porosity and clay volume PDFs have been computed. Analysis of the posterior distributions shows that conventional surface seismic data do not contain enough information for producing reliable estimates of saturation. It may, however, be used to discriminate fluid content and as indicator of quality reservoir, when used in combination with porosity and clay volume.

## Methodology

Here we present principal aspects of the methodology and the main steps used in our workflow.

<u>Bayes Theorem:</u>

The main task is to compute posterior PDFs for parameters, given the available data sets and prior information. The basic formulation, which is derived using Bayesian probability theory, has been previously presented by Loures and Moraes (2003). It essentially consists of a joint posterior distribution for the parameters under investigation $p(\mathbf{m}|\mathbf{d})$, where **m** represents the unknown parameters vector and **d** is the data-set. According to Bayes theorem, this joint PDF can be written as

$$p(\mathbf{m} \mid \mathbf{d}) = q(\mathbf{m}) l(\mathbf{d} \mid \mathbf{m}), \quad (1)$$

where $q$ is the prior distribution, which represent the data independent information, and $l$ is the likelihood function – the data distribution.

Work flow:

From seismic data to the joint conditional posterior PDF for porosity ($\phi$), clay volume ($\chi$) and saturation ($Sw$) the methodology follow a hierarchic workflow, which can be described by the following steps:

i- *Seismic inversion*: the first step is to compute, for each reservoir cell, a local posterior distribution for elastic velocities, given the seismic data and prior information $p(Vp, Vs \mid \mathbf{d})$. This PDF represents the information regarding $Vp$ and $Vs$ that is contained in seismic data and from prior information. It therefore incorporates uncertainties related to the seismic recorded signal (acquisition) and related processing and elastic inversion. The inversion for the elastic attributes is based on the AVO theory, using prestack data. Detailed information and bibliographic review for understanding of the AVO theory can be found in Castagna (1993).

ii- *Lithology inference:* here we compute a posterior distribution for porosity and clay volume $p(\phi, \chi \mid Vp, Vs)$, given the information provided by $p(Vp, Vs \mid \mathbf{d})$ obtained in the previous step. A petrophysical analysis is the framework to construct the empirical rock physics models capturing the correlations, which exist between the lithological parameters and the elastic impedances used in the Bayes theorem for this application. Additional information on the AVO inversion and petrophysical analysis is, respectively, given by Loures and Downton (2004) and Loures (2003).

iii- *Reservoir quality inference:* as a final step, we compute the posterior distribution for porosity, clay vollume and saturation $p(\phi, \chi, Sw \mid Vp, Vs)$ for each reservoir cell, using all the information gained from previous steps, as provided by $p(Vp, Vs \mid \mathbf{d})$ and $p(\phi, \chi \mid Vp, Vs)$. Fluid substitution theory is used as a mathematical relationship relating the petrophysical properties to the elastic velocities in the likelihood function.

An important feature of the above workflow is an inference work driven by $p(\phi, \chi \mid Vp, Vs)$ aimed on discriminating sandstone and shale lithologies (item ii). When the state of information described by $p(\phi,\chi \mid Vp, Vs)$ indicates sandstone as the most likely proposition for reservoir lithology at a particular cell, we promptly revise this PDF according to a more specialized petrophysical model. This is another empirical rock physics model calibrated, using only intervals corresponding to sandstone samples. The result is a more accurate PDF $p(\phi, \chi \mid Vp, Vs)$. This process of revising a PDF associated with new propositions in face of the available information is the essence of learning experience (see e.g., Zellner, 1996).

Once the conditional posterior PDF $p(\phi, \chi, Sw \mid Vp, Vs)$ is computed, one can infer the reservoir quality condition associated with a given reservoir cell. The conditions for a good quality reservoir are: i- minimun porosity value $\phi > \phi_{\min}$, ii- maximun clay volume value $\chi < \chi_{\max}$ and iii- oil saturation $Sw < 0.2$. The probability measure associated with the event $\{\phi > \phi_{\min}, \chi < \chi_{\max}, Sw < 0.2\}$, as computed from the posterior PDF $p(\phi, \chi, Sw \mid Vp, Vs)$, provides the information necessary for deciding as to whether reservoir quality is good or not. For that a decision criterion needs to be set. This criterion can be just semi-quantitative (higher than other possibilities) or a fixed probability value, such as 0.5 or 0.95. Other opposing events can be defined to check on the reliability of the discrimination between good reservoir to no reservoir within the sandstone sequences. A possible reliability measures can be given by the distance between the probabilities associated with the two events representing the quality. This would be an important input to risk analysis.

## Conclusion

The problem of reservoir characterization has being carried as an inference work, considering uncertainties associated with each data set. During the course of this research, we have observed that the information from conventional seismic data and well log is not sufficient for quantitatively describing lithology, porosity and saturation. This ill-posed problem has being avoided by reducing the amount of information being extracted from the posterior distribution to a compatible level. This is achieved by setting up a proposition and as a decision criterion representing good reservoir quality. An associated measure of reliability can be further obtained by making comparisons with probabilities of contrasting propositions.

## References

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