Improved carbonate reservoir characterization using formation density derived from pre-stack simultaneous inversion: a case study in West Kuwait

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Summary

Seismic reservoir characterization for carbonates is a very difficult task due to its complexity in internal pore structure and depositional environment. The present case study involves seismic reservoir characterization of a carbonate reservoir in the West Kuwait area, using density and other properties estimated from pre-stack simultaneous inversion. In this study we used density from inversion results to directly predict lithology and other properties, such as porosity and water saturation. The main inference from the current study is that the use of density from pre-stack inversion results can significantly reduce the uncertainty in lithofacies prediction which is very important in mitigating exploration risk in carbonates. Also, by combining seismic inversion with Bayesian facies classification leads to significant improvements in reservoir characterization.

Introduction

In the last few decades, the oil industry has focused on better methods to solve current characterization problems, such as the modeling of carbonate reservoirs in Marrat formation, Kuwait. Post-stack, pre-stack and elastic seismic inversions are among those methods that aid to characterize hydrocarbon reservoirs. Latimer et al. (2000) point out that it is common to find empirical relationships between P-impedance and rock properties such as lithology and porosity. Even though the P-impedance model can offer such information, it does not discriminate porosities between carbonates and shales (Li et al., 2003). However, when we analyze P-impedance, S-impedance, and density models together, we can reinforce this hypothesis because multiple elastic properties obtained from seismic data enhances in the categorization of different rock types (King et al., 2007).

The pre-stack inversion emerges from the need for extracting more information from seismic results to solve geological problems that are not answered by post-stack inversion. The Vp/Vs and density information obtained from pre-stack seismic inversion can solve, e.g., the duality between porosity in carbonates and shales, in which P-impedance alone cannot solve. Therefore, the S-impedance and density are crucial to discriminate among reservoir and non-reservoir rocks. In this context, density is the important factor that combines petrophysical data with seismic inversion techniques. One of the obstacles in carbonate rocks is that, in contrast with sandstones, these lithotypes are vertically and laterally heterogeneous and represent a complex challenge of reservoir characterization. Being mainly of biological origin, carbonates have complex textures and are susceptible to diagenesis changes, leading to mineralogy and pore structure changes that make these rocks more difficult to model (Eberli et al., 2003).

An understanding of carbonate reservoirs can be enhanced by the use and understanding of density volumes estimated through the simultaneous inversion of pre-stack P- wave seismic data, as described by Hampson et al. (2005). Although it has been stated that density estimates for limited far angles of incidence are difficult to obtain, we present a rationale and an example of where it is possible to obtain useful density estimates from low angles. However, the density model should be interpreted with caution, because the pre-stack data used in this work does not have incident angles higher than 38°. In most cases, this is not enough to solve density models with reliability. Seismic data has a low signal/noise when registered at high angles. Shi et al. (2010) point out that the near offset seismic amplitudes are mainly controlled by velocity, and that only the far offset amplitudes may record density information.

The key steps in the prestack inversion workflow include well-to-seismic calibration, wavelet extraction, prior model building and finally, the inversion. This litho-facies discrimination cannot be achieved using the conventional P-impedance and Vp/Vs cross plots. The illite-rich carbonate facies and the porous carbonates have a similar range for P-Impedances and the Vp/Vs ratio also tend to be on the lower side similar to porous carbonates. So these two litho-facies overlaps in the Vp/Vs and P-impedance domain. So it is almost impossible to discriminate these facies unless we introduce the density parameter for classification. The illite-rich carbonate facies shows lowering of P-velocity but the density of the rock does not lower to the extent of P-velocity as illite-rich clay has a density of 2.78 g/cc rather than normal clay which has a density of 2.35 g/cc. So overall there is a lowering of P-impedance due to porous nature of the shale which has a porosity of about 24 pu, whereas in the porous carbonate the average porosity is only a maximum of 14 pu.

Geological Setting

The Kra Al-Maru area lies to the south west of Kuwait and includes four main structural trends. The Kra Al-Maru Kahlaluh trend in the west; Rahiya-Umm Rus trend in the east; Riksa trend in the north and North Minagish trend in
Improved carbonate reservoir characterization using formation density

The Marrat formation is considered to be one of the most important carbonate oil reservoirs in West Kuwait. The Marrat formation was divided into three main para-sequences, upper, middle and lower. The Middle Marrat was further subdivided into sub-layers. The lithology is derived from electro-logs calibrated with cores. Detailed Rock typing was accomplished using neural network technique that resulted in identification of five main litho-facies viz. limestone (LST), dolomite (DOL), mudstone (MUDS), porous limestone (Pay) and anhydrite (ANHY).

Porosity in Marrat reservoir is linked with the environment where the rock was developed; so, the porosity in several cases will be produced by diagenesis and in many cases the pore spaces will be not be connected; the connection between different pores generally is produced by fractures, dissolution (vuggy porosity), or both.

Methodology and Results

An elastic impedance (EI) curve as a function of offset angle is computed for each well. This log is derived with an Aki-Richards algorithm which analyzes the P-impedance and S-impedance logs with respect to incident angle (Connolly, 1999).

With these synthetic EI logs, a wavelet is estimated for each seismic data set. These wavelets match the phase, amplitude and frequency content of their respective offset data set. The offset volumes are then inverted with a Simultaneous Constrained Sparse Spike Inversion algorithm. This algorithm is an extension of the zero-offset CSSI method, in which a single volume of stacked seismic is inverted into a normal incident acoustic impedance (AI) data set (Pendrel et al., 2000). For this study, the Simultaneous Inversion (SI) algorithm simultaneously invert multiple seismic data sets with different angle ranges, where the objective function involves angle dependent reflection coefficients and data fit to all input stacks. The SI algorithm generates broadband elastic parameter results. In the inversion the low frequency component may be stabilized with a background model, typically derived from well logs or seismic velocity control. Generally, in SI algorithm the density component is poorly resolved from the input seismic data. To alleviate this instability, the Gardner equation is invoked as a soft constraint to the algorithm, and the output density volume is calibrated to well control. Additionally, the mudrock relationship was applied to stabilize the inversion further, but this relationship is generally not required. The inversion achieved several key results with respect to subsequent interpretation. The fact that the data sets are well log...
Improved carbonate reservoir characterization using formation density

calibrated, layer-based rock property volumes leads to the application of a very powerful, highly automated volume-based interpretation methodology. This procedure starts with a well log analysis (Figure 2) of the elastic and other petrophysical logs to determine how lithologies, fluid types and porosity ranges are discriminated from each other in the $Z_p-Z_s-\rho$ domain. The effectiveness of such an approach is enhanced by including the results of fluid substitution modeling. The methodology itself is typically achieved through cross plot analysis where zones of interest are examined. The relationships established through the well logs then are carried over to the 3D volumes to automatically find all points in space meeting the well log derived criteria, thus calibrating the seismic derived rock property cubes to well control. Subsequently the spatial points are analyzed for connectivity to generate geobodies of connected points.

Reliable facies prediction is a key problem in reservoir characterization. Using a statistical technique (Figure 3), we can calculate not only the best zone, but also the probability of occurrence of that zone. The underlying principle of Bayes’ theory that is normally used for probabilistic facies classification is illustrated in equations (1) and (2) and in figure 3. This theory primarily involves a prior to posterior updating technique. Mathematically Bayes theory is given by:

\[
P[A/B] = \frac{P[A/B] * P[A]}{P[B]} \tag{1}
\]

\[
P[\text{Facies (Pay)}] = \frac{[\text{Data Density of Elastic Property of Facies (Pay)}]}{[\text{Data density of Elastic Property of all Facies}]} \tag{2}
\]

Figure 3: (a) Data density of all Facies, (b) Data density of Facies (Pay) and (c) Probability of Facies (Pay).

Considering probability as data density, then on a cross plot of individual facies, Bayes theorem simply states that the probability at a certain facies at a particular point on the cross plot, is the data density of points of that particular facies divided by the data density of points from all facies for the property that is cross plotted. With those relationships established, an integrated seismic inversion and classification workflow utilizing multi-dimensional probability density functions (PDFs) for each possible facies and a supervised Bayesian classification scheme generates probability cubes for the distribution of the different facies that have been defined with lithology and fluid properties (Figure 4). This methodology, grounded with real-world petrophysical measurements, quantifies uncertainty in seismic lithology and facies prediction while providing a superior definition of the lithology classes in an elastic domain.

Figure 4: (a) Density vs P-impedance cross plot and (c) is its probable litho facies predicted from it and (b) Vp/Vs ratio cross plot vs P-impedance with (d) its probable litho facies predicted from it.

The density-porosity cross plot and the accuracy of the classified facies using this cross plot (Figure 4) clearly demonstrates the point, that formation density plays a major
Improved carbonate reservoir characterization using formation density

role in the characterization of pay zones within Marrat carbonates. The predicted facies are the foundation for advanced studies for lithology and fluids. For this study, the output acoustic and shear impedance and density volumes are used to compute litho-facies volume and facies-based porosities. As a final step, a new lithotype volume consisting of lithology and fluid information is generated, based on relationships between the P-impedance, S-impedance and density volumes derived from inversion. Simultaneous Inversion are analyzed sample by sample using this statistical classification approach, and a full lithotype volume incorporating rock type, porosity and fluid fill is generated to further enhance the reservoir description. The P-impedance, S-impedance and Vp/Vs ratio in Figure 5 shows that Well-B has considerable lowering of impedances and Vp/Vs also shows that Well-B should have better pay zone than Well-A. But in logs Well-A had very good reservoir facies and Well-B is very tight mudstone facies. This is clearly demonstrated in the density and the lithofacies. Also, from the density-P-impedance cross plot and Bayesian facies classification (Figure 4) it proves that density plays a major role in the characterization of Marrat carbonate reservoir facies as there is very less overlap between the facies in density vs P-impedance cross plot compared to Vp/Vs ratio vs density cross plot. Density derived from inversion should be used as an attribute for lateral variation in lithologies and fluids rather than using it as absolute property for petrophysical studies, as this density will not have that high degree of vertical resolution.

Conclusions

For seismic reservoir characterization, we provide a method to improve lithology classification and identify new exploration targets. In order to improve facies predictions using Bayes’ theory, we integrated petrophysical facies with elastic properties using Bayesian statistical techniques assuming that the prior probability represents our knowledge about rock properties and the prior probability is consistent with our geological knowledge. We showed Bayes’ prediction increases as we use density as property instead of Vp/Vs ratio. The prior probabilities from the probabilistic facies classification method provided in this study can be used for litho-facies classification for conventional and unconventional reservoirs and identification of future drilling locations.

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