Use of classification technique to characterize porous carbonate reservoir in Machukhy field, onshore Ukraine

Introduction

Seismic reservoir characterization, following a seismic inversion, plays a key role to capture the vertical and lateral variations of matrix properties for advanced geosciences workflow. Geological constraint can be obtained by using a classification technique trained by well data samples such as discriminant analysis, which is a Bayesian supervised approach, to obtain probability of assignment into facies. Additional properties such as porosity can therefore be characterized depending on the predicted facies for more accuracy.

The present paper describes the work performed on the Machukhy field, focusing on the evaluation of Carboniferous carbonate reservoirs in the Ukrainian Dniepr-Donets Basin. The objective consists in performing model-based inversion (Aki and Richards, 1980) and reservoir characterization workflows in order to provide key elements to help predicting inter-well reservoir location, thickness and properties behaviour using inversion results and identifying possible drilling locations for development and exploration wells. The main targets are associated with the Tournaissian carbonate formation.

Reservoir characterization, following 3D PP surface seismic inversion, is performed to assess the reservoir potential of the area in term of facies and porosity distribution. A two-pass discriminant analysis is performed in order to first to isolate massive carbonate facies and predict the porous carbonate facies. Then, the porosity is predicted within the massive carbonate facies.

Context

The Dnieper-Donets basin is almost entirely in Ukraine, and it is the principal producer of hydrocarbons in that country (Ulimshek, 2001). A small part of the basin is in Russia. The basin is principally a Late Devonian rift that is overlain by a Carboniferous to Early Permian post rift sag. Sedimentary succession of the basin consists of four tectono-stratigraphic sequences: Upper Devonian syn rift sequence is composed of marine carbonate, clastic, and volcanic rocks and two salt formations, of Frasnian and Famennian age; post rift sag sequence consists of Carboniferous and Lower Permian clastic marine and alluvial deltaic rocks; Lower Permian interval includes a salt formation that is an important regional seal for oil and gas fields and post rift platform sequence includes Triassic through Tertiary rocks.

Several assessment units were identified in the Dnieper-Donets petroleum system. This is a prolific basin but still contains undiscovered resources, in particular gas. Amongst them, carbonate reef reservoirs contain resources that are under development and production since the last decades. These reservoirs are challenging as they exhibit strong lateral discontinuities, low porosity and layer mixtures.

Method

The Bayesian supervised seismic facies analysis is based on discriminant analysis (Nivlet et al., 2007). It aims at relating sonic and shear impedance (IP and IS) values to seismic facies. Available elastic parameters and facies logs are used first for value recognition and classification at well location (1) at log scale in the depth domain, to assess feasibility of facies discrimination from (IP, IS) variables (2) at seismic scale in the time domain, to assess feasibility of facies discrimination from upscaled (IP, IS) variables, and define the discrimination technique. This information, called training samples, is used as a priori information for 3D analysis. As it works in a probabilistic framework, this discriminant analysis provides cubes of probability of assignment into each facies, from which can be derived a most likely facies cube with its associated probabilities. As a control after propagating the classification in 3D, traces extracted from the facies probability cube at well positions are compared to initial facies log.

Effective porosity (PHIE) prediction is based on a law defined at the well using P-impedance. Similar to facies prediction, the work is performed first at log scale (depth domain) then at seismic scale (time domain) and is then extended in 3D using an optimized P-impedance cube resulting from inversion. Control is carried out at the well location to assess the predictability of the effective porosity.

Results

Facies prediction
Facies prediction is performed using samples from the targeted carbonate interval and overlying shale interval in order to increase the number of sample and the reliability of the prediction, in particular, shale facies presents a very different elastic impedance response (Figure 1 – a, b). Discriminant analysis is performed using computed P and S-impedance curves from wells where DTS has been recorded and not modelled to prevent any bias.

The result shows that the discrimination of the carbonate facies is driven by P-impedance (Figure 1 – c, d). Spatial organization of the samples after discriminant analysis is consistent with rock physics concepts: carbonate elastic answer is linked to higher IP and IS values. The score of reassignments are high: 99% of the samples assigned as carbonate were initially carbonate facies samples, meaning that the shale and carbonate facies were already well separated before discriminant analysis. Thereafter, discriminant analysis is carried out at seismic scale (after upscaling) in time domain in order to select training samples which allow an accurate discrimination between the facies, using both well-logs and inverted traces. Similar to discrimination before upscaling, the prediction is reliable.

To go further, porous carbonate facies is defined. A cut-off set on effective porosity at 0.04 is defined in depth domain, before upscaling. Porous samples (carbonate with PHIE >= 0.04) are associated to low IP and IS values after upscaling (Figure 2 – a, b). Discriminant analysis is performed using inverted IP and IS traces and the two carbonate facies within the target interval. It shows that the discrimination of carbonate facies is driven by both IP and IS. The distribution of samples after inversion in (IP, IS) space leads to a good discrimination between low and high porosity carbonate samples (Figure 2 – c, d).

Figure 1 Discriminant analysis of massive carbonate facies before upscaling (a) Example of well curves (facies, IP, IS) (b) Well-log IP versus IS cross-plot coloured by facies before assignment (c) Well-log IP versus IS cross-plot coloured by the probability of good assignment into massive carbonate facies (d) Re-assignment histogram, giving the confidence in the classification with percentages of re-assignment within each cluster (i.e. facies)

Figure 2 Discriminant analysis of porous carbonate facies after upscaling (a) Inverted IP versus PHIE crossplot coloured by facies before assignment (b) Inverted IP versus IS crossplot coloured by facies before assignment (c) Re-assignment histogram (d) Inverted IP versus IS crossplot coloured by the probability of good assignment into porous carbonate facies.
Discriminant analysis is then applied in 3D using dedicated training samples (i.e. a priori information) for each interval using inverted impedance cubes. It shows that the entire interval is correctly predicted as massive carbonate facies. Based on well information, porous carbonate facies is more likely located in the upper part of the interval. In order to properly handle the identified uncertainties in the prediction of facies distribution, post-processing work is performed in a statistical framework: probability of assignment into each facies resulting from the discriminant analysis are used (Figure 3 – a).

Based probability of assignment into carbonate facies, the top and base of the massive carbonate have been tracked (Figure 3 – b). There is a high confidence on top reservoir tracking as it shows a binary pattern between high and low probability. There are some uncertainties for bottom reservoir edition, indeed it shows a less clear transition (mixed shale/carbonate facies in the bottom part).

Thus, carbonate facies are predicted with confidence using a statistical approach. Thicknesses observed at well and predicted thicknesses have been compared: for massive carbonate facies, average thickness percent error is 13% and for porous carbonate facies, 8.5%, showing the robustness of the prediction.

Porosity prediction

Porosity law is defined for the carbonate samples in depth domain, at log scale, considering the carbonate interval (Figure 4 – a). The global trend is fair. Two clusters are observed: a large pool of low porosity samples (~below 0.04) and a pool of higher porosity samples (~above 0.04). In order to match the high porosity samples, a polynomial trend is used. Then, porosity law is defined in time domain, at seismic scale (Figure 4 – b). Porosity prediction in time does not allow to retrieve higher porosity values as the trend is driven by low porosity samples (blue curve). After upscaling, high porosity samples are removed, and mainly low porosity samples are kept, so it is not possible to obtain a trend similar to the one before upscaling. Thus the trend define before upscaling is used as it is the one allowing to retrieve higher porosity values (black curve).

Predicted porosity are extracted at wells and compared to well-log effective porosity (Figure 5 – a). There is a good global match and the main variations are well retrieved. Mismatches are mainly linked to poorer well-to-seismic tie quality, even though the overall quality is satisfactory. In the lower part of
the carbonate interval, there is mixed shale and carbonate layers, as observed before upscaling. After upscaling, it is assigned as carbonate, and also predicted partially as carbonate after discriminant analysis. Here porosity tends to be overestimated, there is a change of the elastic answer (decrease of impedance) linked to the change of lithology, leading to this increase of porosity.

Average effective porosity is computed from well-logs and compared to average predicted effective porosity in the upper part, in order to focus on an interval where most of the porous carbonate samples are localized. (Figure 5 – b). It shows that the predicted porosity values are over-estimated compared to the petrophysical analysis. Nevertheless, there is still a linear trend (dotted line), which would mean that the overall porosities are higher, but variations are consistent with well data. Thus, in a qualitative view, effective porosity prediction works well: it is possible to distinguish zones with higher porosity values.

Based on observation at well, an additional surface is used to separate the upper porous carbonate, from the lower one which are actually not porous carbonate facies to use qualitatively the results.

![Figure 5](image)

**Figure 5 (a) First track corresponds to facies before upscaling, second track, facies after upscaling, third track, probability of assignment into porous carbonate facies and fourth track, well-log PHIE in black and predicted PHIE in red (b) average predicted effective porosity versus average well-log effective porosity after upscaling cross-plot**

**Conclusions**

Preliminary 3D elastic inversion have been performed and resulting inverted elastic parameters are used for further dedicated workflows. Carbonate facies prediction is based on discrimination analysis methodology. Both massive and porous carbonate predictions are reliable as demonstrated by well based QCs. The porosity cube is derived from the inverted P-impedance cube using a polynomial relationship. The prediction is satisfactory with more uncertainties in the bottom section where mixed shale/carbonate layers lead to higher predicted effective porosity values. Based on results, surfaces have been tracked to accurately isolate massive and porous carbonate facies.

In order to consider both simultaneously, a porous thickness map is computed using effective porosity and facies proportion maps. This map provides an insight on the prospectivity of the area, characterized by higher reservoir facies thickness and higher effective porosity, and can guide possible drilling locations for future wells targeting the main carbonate reservoir.

**Acknowledgements**

We would like to thank DTEK for the dataset and this project, as well as RPS for the support.

**References**

