Integrating prestack inversion, machine learning, and forward seismic modelling for petrofacies characterization: A Barents Sea case study.

Honoré Yenwongfai [2,1], Nazmul Mondol [1,3], Isabelle Lecomte [4,1] ,Jan Inge Faleide [1], Johan Leutscher [5]
[1] *University of Oslo*, [2] Statoil ASA, [3] Norwegian Geotechnical Institute, [4] University of Bergen, [5]Eni Norge.
Contact email: hyen@statoil.com

Introduction

The Barents shelf has been explored for hydrocarbons during the past three decades with a dominance of gas discoveries over oil. This area has a complex burial history with differential amounts of uplift in the different basins, platform areas, and local highs. Uplift in this area has devastating consequences for the petroleum system elements such as the cap rock integrity, source rock maturation, and overconsolidation of the target reservoirs at their respective present day burial depths. Stiffening of the rock framework is known to reduce the seismic sensitivity to pore fluid changes.

The main objective of this study is to discriminate and map out clean reservoir sands within a Triassic reservoir unit using a cascaded multidisciplinary workflow. The target formation in the study area has relatively poor reservoir properties compared to the primary producing formations in this field. Initial rock physics feasibility indicate that acoustic impedance (AI) and the ratio of P-wave velocity to S-wave velocity (V_p/V_s) attributes are not efficient in discriminating the defined petrofacies of interest. On the other hand, combining acoustic impedance and effective porosity show clear trends in the estimated shale volume. This observation is the primary motivation for integrating prestack inversion and machine learning to estimate the effective porosity (PHIE) for further quantitative interpretations.

Database and Methods

High quality long offset multi-azimuth (MAZ) partial angle stacks, prestack depth migration velocities (PSDM), horizon interpretations, and a suite of six exploration wells with standard formation evaluation petrophysical logs have been used. Two of the available wells have measured shear wave logs. A summary methodology is shown in Figure 1a. The low frequency model input to the inversion has been built by horizon guided co-krigging of the well velocities with the PSDM velocities. A deterministic simultaneous inversion (Hampson et al., 2005) has been performed for AI, SI (shear impedance) and bulk density. Lambda-mu-rho (LMR) attributes (Goodway et al., 1997) are then computed from the inversion outputs. These inversion products are input into a machine learning training network from which the effective porosity is estimated. Probability density functions (PDFs) obtained from the well logs for each petrofacies class is subsequently applied to the inverted AI and PHIE volumes. Geobodies are then extracted following the Bayesian sand probability estimates. Finally point spread functions (PSFs) are used to simulate PSDM seismic images from the AI model in selected areas with a high probability of clean sands. Resolution and illumination effects are also assessed in order to constrain the petrofacies interpretations.

Results and discussion

Figure 1b shows the difference between the validation error (red curve) and average training error (black). Five optimum attributes have been selected based on the turnaround point within increasing validation error. The inverted bulk density showed the greatest individual correlation to PHIE. A correlation of ~0.8 is obtained between the inverted and actual porosity for 5 wells (Figure 1c). For a final quality control, a good match is obtained between the actual and predicted result for PHIE (Figure 1d) at a blind well. Combining seismic inversion with machine learning provides the opportunity to explore multilinear and nonlinear relationships between several attributes.

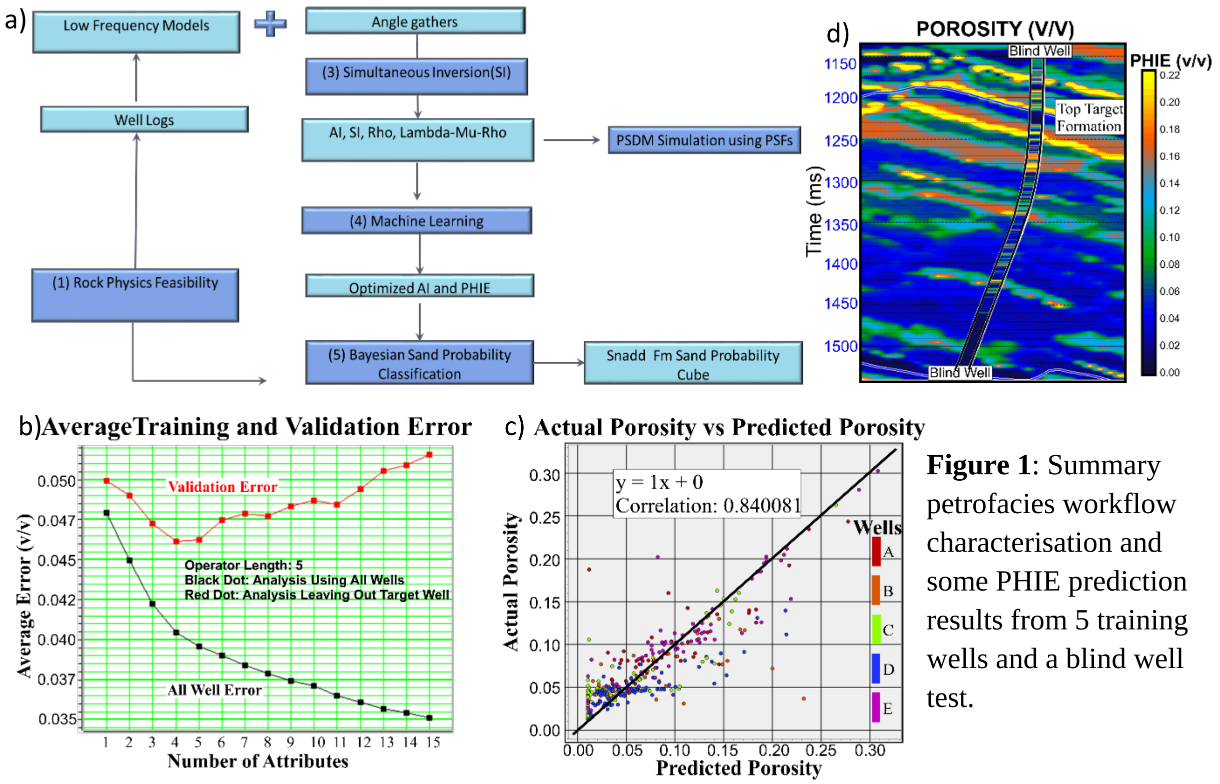

Figure 1: Summary petrofacies workflow characterisation and some PHIE prediction results from 5 training wells and a blind well test.

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