

Joint Rock Physics Model and Facies Classification Optimisation via Rock Physics Machine Learning – A North Sea Example

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Abstract

Rock Physics modelling and petrophysical facies interpretation form crucial foundation stages within the framework of quantitative interpretation.

A contemporary application of Machine Learning (ML) algorithms is their employment for automating petrophysical facies interpretation; however these ML implementations can fall short in fully capturing geological compaction trends. Understanding and incorporating these depth-varying trends across various rock types and regions is essential for accuracy in subsequent seismic inversion and reservoir characterisation stages.

We present a novel technique (Rock Physics Machine Learning (RPML)) that simultaneously derives optimized interpretations of petrophysical facies logs, petro-elastic depth trends, and rock physics parameters directly from well log data.

We support our proposition with a case study set in the Forties Field, Central North Sea, and demonstrate the versatility of our technique, its alignment with manual facies interpretation, and the value it may bring through cross-disciplinary integration.

Introduction

Geoscientists understand that there are depth trends in subsurface data arising from various inter-related geological and physical processes such as compaction, lithology, diagenesis, and pressure. Geoscientists also commonly apply standard ML techniques for the automation of petrophysical facies interpretation. What may frequently be seen after the application of standard machine learning techniques is that the output electrofacies need significant additional interpretive review. This is because the clustering algorithms used aren't aware that the data

contains depth trends; They don't understand compaction.

They may capture some depth related information, but they don't understand why – they are not aware of physics. There are also de-trending algorithms, and these are the least desirable since they completely remove the essential compaction related depth trend information.

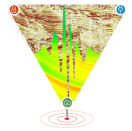
RPML turns this traditional shortcoming of automation to a strength by incorporating an expectation-maximization algorithm to simultaneously derive consistent interpretations of petrophysical facies logs, petro-elastic depth trends, and rock physics parameters. These may form inputs for facies-based inversions, providing reduced interpreter bias whilst significantly speeding up the well log interpretation process.

The toolkit facilitates the storage of both prior, regionally bound models and posterior calibrated rock physics models. Furthermore, the regional prior model can undergo rigorous testing, approval, and application in different areas within the same region, ensuring consistency and accuracy across various projects.

Method

The RPML methodology leverages the Expectation-Maximization (EM) algorithm in conjunction with petrophysical and rock-physical models to infer facies and determine the most suitable rock physical model parameters across a range of depths, within one or multiple boreholes.

To initiate the workflow, prior conditions must be established including Rock Physics models, facies definitions, and facies proportions. Since depth trends play a pivotal role in RPML the workflow



commences with the depth datum, which serves as the reference point. The datum is utilized to compute or model the lithostatic pressure (P_c) and normal pore pressure (P_p) using a depth trend model as specified by the user. Subsequently, the effective stress is modeled and optimized by incorporating the Biot coefficient (α) parameter from the model specification, along with the lithostatic and pore pressure, following the equation: $\sigma = P_c + \alpha P_p$.

Based on the effective stress, the compaction porosity trend is modeled. Petrophysical properties are then modeled as a function of porosity, utilizing logs such as resistivity, density, neutron porosity, gamma ray, and photoelectric factor. These properties are weighted based on optimized mineral volumetric fractions in a linear combination mixture model. Resistivity is interpreted and optimized using Archie's equation for non-shale lithologies or delta log resistivity in the case of shales.

To compute elastic properties the classified Rock Physics models come into play. The EM algorithm is employed to optimize this system. In this algorithm, each facies is represented by a multivariate Gaussian distribution with depth-dependent means for each dimension. This statistical model represents the most probable condition for a given facies. A sparsity parameter is employed to eliminate statistical models that poorly fit the data. The inversion process involves alternating optimization between facies classification and model calibration until convergence criteria are met. Figure 1 illustrates the corresponding schematic.

Further details regarding the EM algorithm as implemented in RPML can be found in the work of Beloborodov et al. (2021),

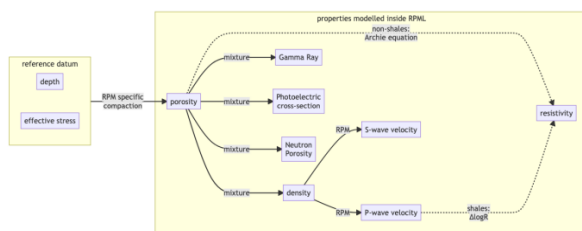


Figure 1: Schematic for the RPML algorithm internal workflow.

Example

The case study focuses on the Forties Field, situated in the UK North Sea. The study employs simultaneous inversion on seven wells: App.3, App.4, Echo 1, Echo 2, Exp.1, Exp.2, and Exp.4.

This dataset was specifically chosen due to the presence of challenging-to-capture tuffs and the noteworthy reservoir sands found in the Forties Field, which exhibit average porosities of 33% and permeabilities of up to 10 Darcies (Newman et al., 1993; Timbrell, 1993).

Three working intervals were identified with lithologies and associated prior Rock Physics Models (RPM) as shown:

Overburden:

- Overburden shale: Silty shale RPM (Pervukhina et al., 2015)
- Soft shale: Silty shale RPM (Pervukhina et al., 2015)
- Tuff with clay: Silty shale RPM (Pervukhina et al., 2015)

Reservoir:

- Brine sand: Variable cement (Avseth et al., 2010)
- Oil sand: Variable cement (Avseth et al., 2010)
- Reservoir shale: Silty shale RPM (Pervukhina et al., 2015)
- Chalk: Hertz-Mindlin using Voigt bound.

Underburden:

- Chalk: Hertz-Mindlin using Voigt bound.
- Cemented carbonate: Variable cement (Avseth et al., 2010)

The selection of these prior models was based on available geological and stratigraphic information for the field, with RPM parameters optimized through testing within geophysically plausible value ranges.

Following the RPML joint inversion, the output RPML facies log is compared with the facies log obtained from previous petrophysical studies. Figure 2 demonstrates a favorable agreement between the two, even for challenging facies such as tuff sands and oil reservoir sands.

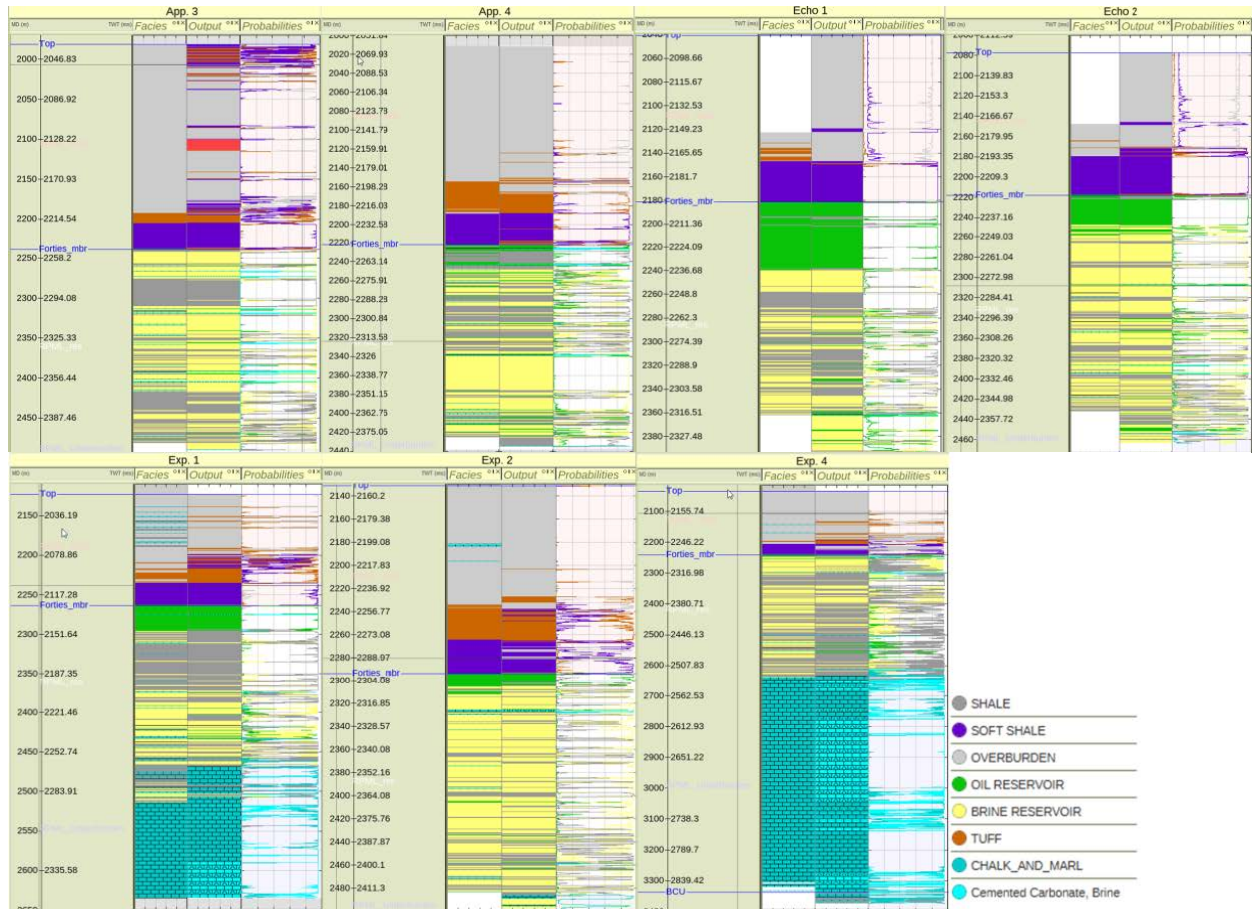
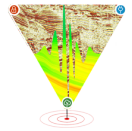


Figure 2: Original interpreted petrophysical facies log (left track), RPML predicted output facies log (center track), RPML output facies probabilities (right track) for all the wells in the case study.

The fine alternation of brine sand and shale facies observed within the reservoir interval appears to be a product of human interpretation, as the petrophysical logs display ambiguity in the shale/sand trends. This leads to RPML facies logs presenting more distinct facies definitions, as illustrated in well Exp. 1, particularly in the shale at 2300m MD, where a "bulkier" facies definition is observed.

Additionally, RPML provides accurate petrophysical trend logs, as depicted in Figure 3, capturing finer details such as the resistivity log. The inverted critical porosity value for brine sand is determined to be 32.2%, aligning closely, albeit slightly lower, with the average estimated porosities of the Forties Field (33%).

Conclusions

The RPML methodology is shown to define petrophysical facies and depth trends accurately across multiple wells. Notably, challenging facies like tuff and chalk are correctly identified and their petrophysical and elastic properties are accurately inverted with good detail.

Supporting the underlying philosophy, depth trends are shown to play a vital role in quality control with Figure 4 clearly demonstrating the separation in the resistivity log of the oil sands which has been accurately recognized by RPML.

In summary, the RPML approach efficiently defines and optimizes facies in terms of lithology, saturation fluid mixture, and the parameters of the rock physics model.

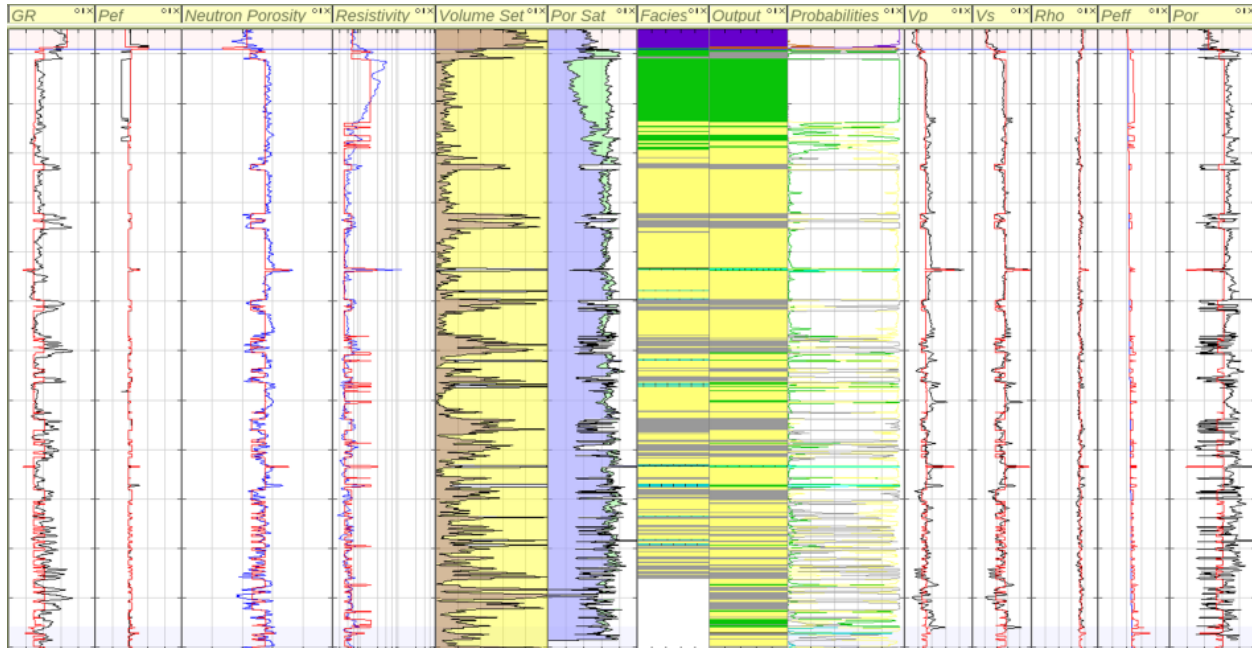
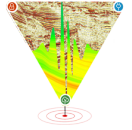


Figure 3 Well Echo.2: Log tracks from left to right: GR, PEF, neutron porosity, resistivity, clay volume, porosity, petrophysical facies, RPML output facies, Vp, Vs, Rho, effective pressure log. In black, the input data for the logs; in red, the RPML output logs.

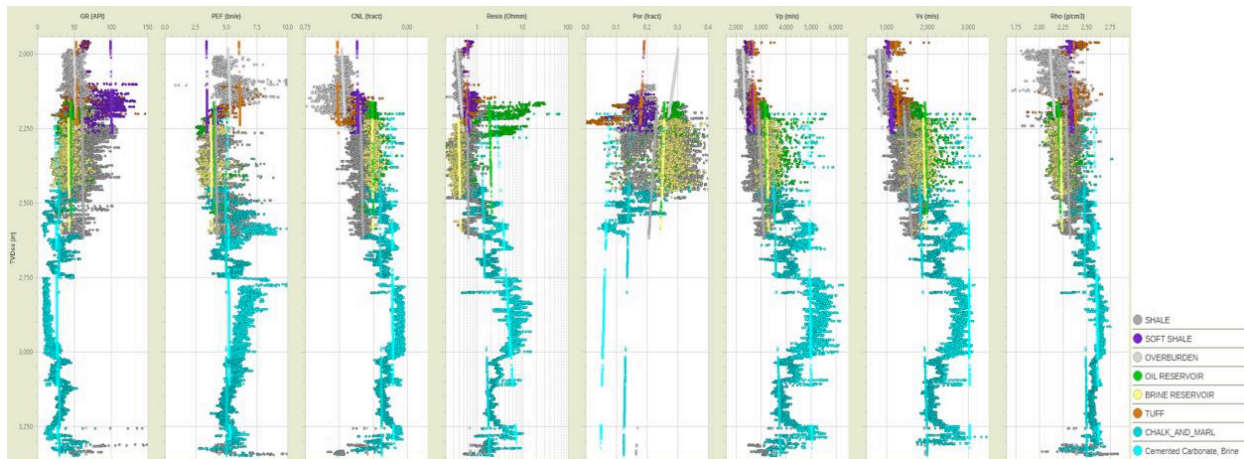
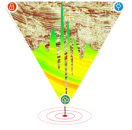


Figure 4 Depth trends with data points from all wells of the case study and with RPML inversion data points (vertically aligned). The color indicates the facies as outputted by RPML, legend on the right. From left to right: GR, PEF, neutron porosity, resistivity, porosity, Vp, Vs, Rho.

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