INTEGRATION OF ROCK PHYSICS AND DEEP MACHINE LEARNING FOR RESERVOIR CHARACTERISATION OF A COMPLEX GEOLOGY OIL FIELD

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Abstract

The use of Supervised Machine Learning (ML) techniques in predicting reservoir properties from seismic and well log data has proven to be effective. In this method, neural networks are trained by using seismic data and well logs as inputs and reservoir properties as outputs. However, a significant number of training data is needed to optimize the parameters in the training stage. To overcome the shortage of training samples, the authors of this study synthesized training data based on available seismic data, well logs, and reservoir conditions. A hybrid Theory-Guided Data Science (TGDS) model, as described by Downton and Hampson (2019), was used to generate pseudo wells and synthetic seismic gathers that reflect different expected reservoir conditions. This synthetic seismic catalogue was used to train a supervised ML system, a Convolutional deep Neural Network (CNN), to estimate reservoir properties from seismic data. The trained CNN was able to produce comparable results to those obtained from deterministic seismic inversion, and in some cases, the estimates showed a higher correlation with existing well data. The study focused on an oil field with a complex lithology that included Sandstones, Coal, Carbonate, and Shale intervals. Lithology-specific rock physics models, layer-specific statistics, and systematic changes to expected reservoir conditions were used to generate the synthetic catalogue and train the ML system.

Method

The first step in implementing machine learning is to prepare a sufficient amount of training data. The TGDS method was used, and systematic variations were applied to the expected properties of the reservoir intervals such as thickness, porosity, fluid (oil) content, and clay content. Two wells, Well_B, Well_C, were available for the study, with three time seismic angle stacks of 10, 20, and 30 degrees.

Lithologies were identified based on previous petrophysical studies and included sandstones, carbonates, shales, and coal intervals. The oil-producing intervals were within the sandstone intervals. Five lithology-specific rock physics models, for Carbonate, Shale, Water Sand, Oil Sand and Coal, were established and validated using measured well log data, and there was a good match between the predicted and measured well logs.

Synthetic reservoir property well logs were generated by systematically varying porosity, clay volume, water saturation, and reservoir thickness, and statistics were extracted per facies and per layer. The vertical continuity and interdependence of expected reservoir properties were accounted for using cross-correlations and vertical variograms. The synthetic logs were passed through calibrated RPMs to calculate elastic logs, including P velocity, S wave velocity, and density.

A synthetic gather was calculated for each pseudo well using the elastic logs and wavelet extracted from the measured seismic data. The final synthetic catalogue included 225 pseudo wells and their corresponding synthetic seismic gather data. Seventy percent of the data was used to train the convolutional neural network, with the remaining data serving as a blind well test or validation. The network parameters were optimized over 50 epochs to minimize the error between the predicted values and existing data in the synthetic catalogue. Trained CNN was the used to estimate reservoir property from pre-stack seismic data. Estimated properties were Acoustic Impedance and reservoir properties of Porosity, Water Saturation and Volume of Clay.

This study demonstrates the efficacy of incorporating rock physics models in the training of Convolutional Neural Networks (CNNs). The results showed that this approach was able to accurately predict elastic and reservoir properties, with a close match to well data even in complex lithologies where well data is limited. The findings are comparable to those obtained through traditional inversion methods and display a higher contrast in Acoustic Impedance data.

Overall, the results of this study highlight the potential of using rock physics models in combination with CNNs for more accurate predictions of elastic and reservoir properties.