Quantifying Seismic Reservoir Characterization with Rock physics-based CNN Approach: Insights from the West Tryal Case Study

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Abstract

Reservoir characterization relies on the integration of petrophysical and geophysical data in making accurate predictions regarding reservoir properties. Deep learning neural networks have emerged as a powerful tool for such seismic reservoir characterization, particularly in complex geological settings. These networks can offer several advantages over traditional theory-based methods. For instance, Convolutional Neural Networks (CNNs) can yield predictions that are as good as, or even better than, theory-based inversion techniques. Additionally, machine learning techniques have the capability to simultaneously predict multiple reservoir properties, resulting in significant efficiency gains.

The utilization of synthetic training data extends the accuracy of the training models and the applicability of deep learning networks to areas with limited well control. This is particularly advantageous as it allows for the exploration and characterization of reservoirs in scenarios where access to extensive well data is limited or inadequate. Furthermore, certain machine learning methods alleviate the need for extensive seismic data conditioning and advanced volume attribute calculations, resulting in time savings compared to conventional workflows.

This study employs the Rock physics guided CNN methodology to demonstrate techniques for numerically quantifying the application of deep learning in seismic reservoir analysis. This work focuses on leveraging the West Tryal dataset as a case study to assess the effectiveness of Rock physics-based CNN approach on pre-stack seismic data. The goal is to provide concrete methods for evaluating and quantifying predictions of P-Impedance, Porosity, Volume of Clay, Water Saturation and Net Pay property volumes.

Geology

West Tryal Rocks gas field is located offshore at the western margin of the Barrow Sub-basin in the Carnarvon Basin of Western Australia. The hydrocarbon bearing zone of West Tryal Rocks is situated approximately 3200 meters below the seabed, with a water depth of around 150 meters. For a comprehensive understanding of the area's geology, consult the publication by Meath and Bird, 1976.

Pre-stack data with a maximum angle is 38 degrees is shown in Figure 1. Two wells are present in the area with basic petrophysical interpreted logs such as porosity, water saturation and volume of clay along with elastic logs. Well_4A used in training of neural networks (Figure 2), while WTR_2 used for validation as a blind well. The average thickness of sands in the area is around 40 meters.

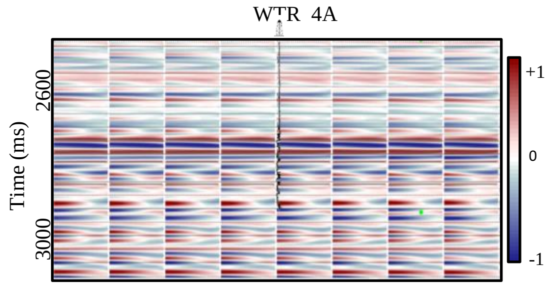

Figure 1. Input pre-stack seismic data around well WTR_4A.

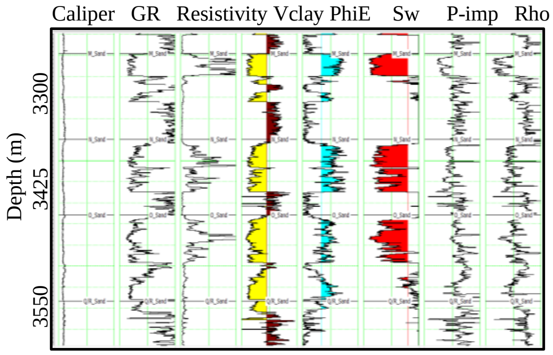

Figure 2. Measured and petrophysical logs available in Well_4A.

Methodology

The efficacy of CNNs relies on the availability of substantial amounts of well training data.

Synthetic data generation has been used to remedy for the lack of available wells. The adopted workflow involves the creation of an extensive library of synthetic wells, encompassing a diverse range of geological scenarios and reservoir properties. It requires the correct Rock Physics Model as per the depositional environment and can be applied to clastics, unconventionals (Downton, 2022) and carbonates (Allo 2021). Once the rock physics model is built and calibrated to the real well data, we generate hundreds of synthetic wells by perturbing Porosity, Sw, Vclay and reservoir thickness with the geological constrains of the rock physics model. For each synthetic well, we then generate synthetic gathers using the Zoeppritz equations.

The created training dataset of synthetic wells and synthetic gathers captures the heterogeneity we expect as per our geological understanding. It offers increased diversity of training examples, enabling the machine learning model to have more geological awareness and improving the model's ability to make accurate predictions throughout the seismic survey (Downton, 2020).

An important differentiator of our CNN implementation to the typical approach is our use of the transfer learning technique. The CNN operator is initially trained on the images extracted from the synthetic gathers. For 200 synthetic wells with a 200 ms time length synthetic at 2ms sample interval this results in about 10,000 training images for the CNN. After training solely on synthetic data, the derived operator (model) is updated using transfer learning incorporating the real well control. The updated model leverages the knowledge learned from the large amount of synthetic data used to train the pre-trained model, resulting in improved performance.

Once the CNN is trained on the synthetic seismic gathers and updated using the transfer learning technique, the results are applied to real wells and actual pre-stack seismic data for the reservoir property volume predictions such as P-impedance, Density, Porosity, V Clay and other. This approach can also be run in the classification mode to do facies volume classification.

Quantitative Evaluation and Results

To optimize the CNN parameterization and to quantitively evaluate the model predictions, we employ metrics that indicate the accuracy of predictions at various stages. The quantitative evaluations These quantitative evaluations build upon the prior research conducted on the West Tryal dataset by Jyoti and Ting (2022).

First, by analyzing the training loss versus the number of epochs, we make decisions regarding training model convergence, overfitting, underfitting, and learning rate adjustment. The number of epochs act as a regularization parameter similar to the prewhitening in deconvolution or inversion. As shown on Figure 3, increasing the number of epochs improves the fit to the training data but at the risk of overfitting, therefore, it is important to choose the maximum number of epochs in conjunction with the validation data. In addition, the CNN employs other regularization strategies such a drop-out.

Figure 3. Number of epochs vs training and validation loss.

Next, we use the common evaluations for regression tasks such as correlation and the NMSE (normalized mean square error) values. Correlation value measures the proportion of variance of the target variable that is explained by the model. NMSE computes the average absolute difference between the predicted and actual values.

These numbers give an indication of the model's overall accuracy in predicting continuous variables and are summarized in Table 1. The initial model shows poor match for Water Saturation Prediction.

Transfer learning is especially useful when there is limited training data available as in this case. In the first step of transfer learning, the CNN is trained with the synthetic wells and synthetic gathers. In the next step, we introduce the real seismic data and freeze the convolutional layers, updating only the fully connected layer weights at the end of the process. The resulting operator is then applied to real seismic gathers to estimate the desired reservoir properties.

This improved the model fit at the well location is also demonstrated numerically in table 1.

Property	Correlation Value		NMSE	
	Initial Model	Improved Model	Initial Model	Improved Model
Pimpedance	56%	74%	0.89	0.76
Porosity	57%	78%	1.19	0.78
Water Saturation	15%	93%	10.18	0.93
Volume of Clay	49%	80%	1.71	0.81

Table 1: Correlation and NMSE values for the WTR_4A well show improvement after Transfer Learning.

The CNN property predictions at the well location are illustrated in Figure 3 showing a good fit between the well and CNN estimations:

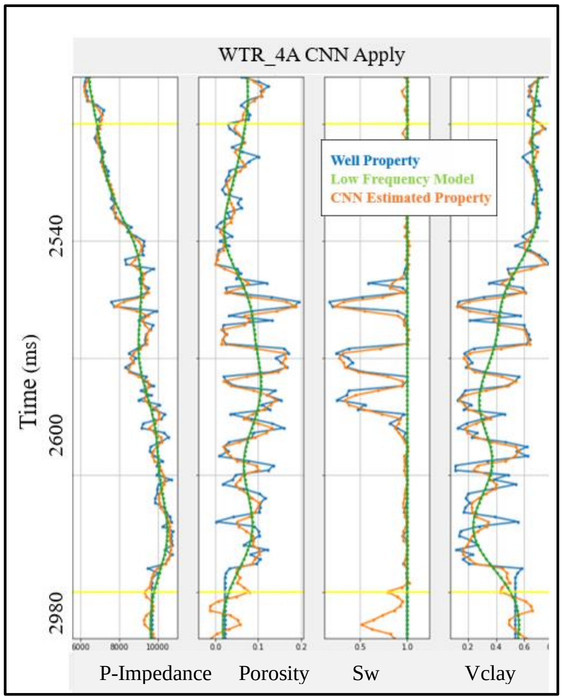

Figure 3. CNN predicted curves at the well location compared to the original well properties.

The derived CNN model is applied to the pre-stack seismic to make reservoir predictions for the entire area within the zone of interest. The derived reservoir properties along the arbitrary line passing through the well locations are show in Figure 4.

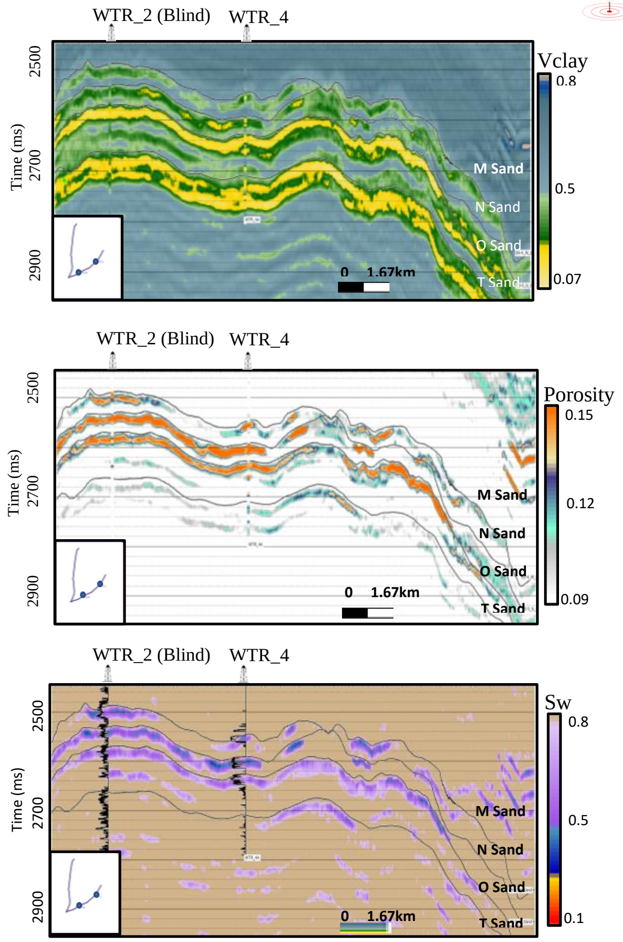

Figure 4. CNN predictions of Porosity (top), Vclay (middle), Sw (bottom). The well on the left is a blind well and was not used in training.

Seismic observations in the O sand reveal higher amplitudes, indicating the presence of hydrocarbon saturation (refer to Figure 5). However, in the case of the M sand, the bright amplitudes observed in the upper zone do not align with the hydrocarbon-saturated reservoir (refer to Figure 6). For the maps, the maximum amplitudes for porosity and the mean amplitudes for the V Clay and Sw maps are used. To highlight the zones of interest we created polygons depicting the bright seismic amplitudes.

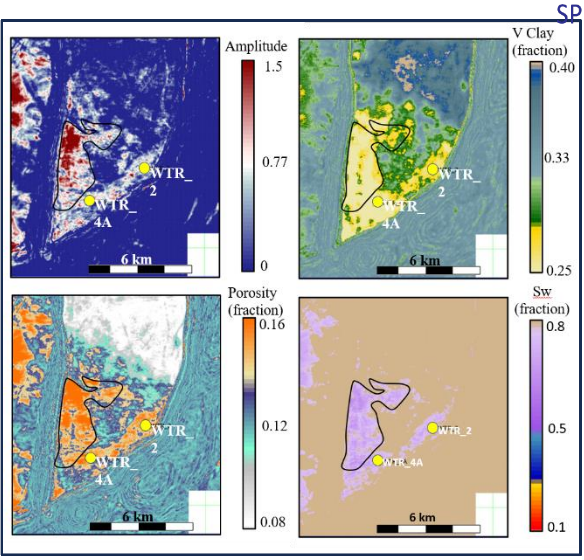

Figure 5: Maps for the estimated properties extracted at the O sand plus 40 ms below.

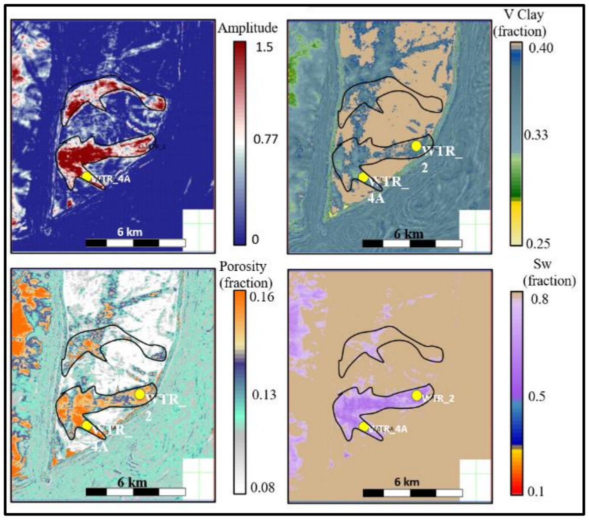

Figure 6: Maps for the estimated properties extracted at the M sand plus 30 ms below.

Another metric used for evaluation is the comparison of net pay values between well locations and predicted values (Figure 7). To assess the net pay intervals in logs and volumes, the following thresholds have been employed: Sw < 80%, PhiE > 10%, and Vclay < 45%.

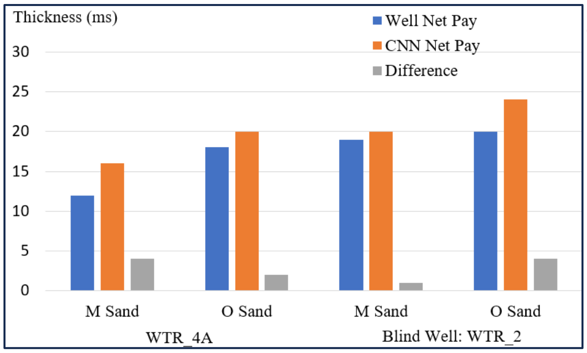

Figure 7. Well net pay estimation to the CNN Net pay for the WTR-4A and WTR_2 wells.

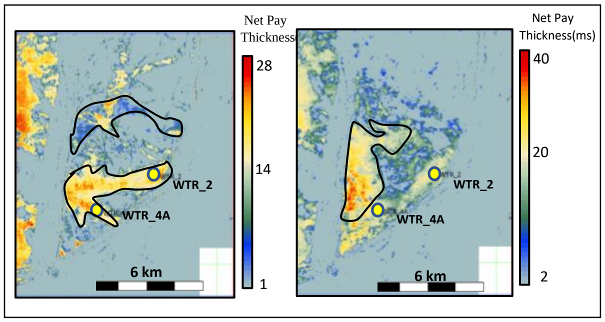

Figure 8: Maps for estimated Net Pay thickness for the M sand (left) and O sand (right).

In figure 8, it is observed that for the M sand, the bright seismic amplitudes in upper polygon have poor net pay thickness, whereas for the O sand, there is a new prospect in the polygon which has not been drilled so far.

Summary

The rock physics-based Machine Learning approach is used for the prediction porosity, P-impedance, Vclay and Sw properties. Along with the further evaluation of net pay, this methodology provides a comprehensive understanding of the reservoir. It can significantly help in adding a new dimension for seismic quantitative interpretation, specially in exploration areas with limited well control.

We demonstrate how the quantitative evaluation adds substantial value at each step of the analysis, allowing for a more precise understanding of the reservoir's characteristics.

This research contributes to advancing the field of seismic reservoir characterization, promoting the adoption of Rock physics-based CNN techniques, and enabling more accurate reservoir evaluations.

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