Shear Log Estimation by Rock Physics Assist Machine Learning Approach An Offshore Abu Dhabi Case Study

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ABSTRACT

Shear log estimation is one of the essential steps during a seismic reservoir characterization study. It is common that limited shear log acquisitions were implemented in the brownfields. Recently several approaches to log estimation by machine learning (ML) were published. However, it is well known that ML techniques don't have the capability to estimate outliers. To fill this gap, a combination of fluid substitution and ML was implemented to predict elastic log at the reservoir, which is one of the largest oil reservoirs at offshore Abu Dhabi.

In this carbonate reservoir, it was known that low frequency model is principal information to characterize a fluid distribution by AVO inversion based on the current 3D seismic vintage. Because the wells with shear log data were only limited within the oil pool and also in various acquisition years, it is not simple to predict elastic log at the aquifer and historical mid-dip water injection regions and in seismic acquisition year. To solve it, we implemented two ML steps (ML algorithm: LightGBM) within conventional fluid substitution steps i.e. ML prediction for elastic log in in-situ, and then in dry conditions along with saturation log in seismic acquisition year from history matched reservoir simulation model.

Through this workflow, the predicted elastic property is reasonably matched to input data in dry condition confirmed by a blind well test. Hence a total of 65 wells of elastic logs in dry condition and in target reservoir condition was predicted. Predicted P-impedance and Vp/Vs crossplot suggests elastic properties of brine as well as oil saturation condition were reasonably estimated as per rock physics analysis from other carbonate fields in Abu Dhabi. We demonstrate this workflow and the impact of low frequency model generation, and discuss the benefit and pitfalls compared to empirical equations and model-based methods like Xu - Payne model.

EXTENDED ABSTRACT

Introduction

In matured oil and gas fields, the opportunity for shear log acquisition is generally limited due to the usage of conventional formation evaluation. However, it is essential data to implement reservoir characterization studies using seismic data. While several empirical equations and model base methods were available for shear log estimation, rock properties such as porosity, pore aspect ratio, fracture etc. are identical in each reservoir and then several geological assumptions are required to implement these. Recently several approaches to log estimation by machine learning (ML) were published. However, it is well known that ML techniques don't have the capability to estimate outliers.

The subject field of this study is located offshore Abu Dhabi ranked as one of the biggest offshore oil fields and has been producing oil for over 60 years. The total thickness of this ZOI is about 250 ft associated with 30-40 ft of multiple high porous limestone reservoirs and dense zones over the field (Ikawa et al., 2009). In this ZOI, it was known that low frequency model is the principal information to characterize the fluid distribution by seismic inversion based on the current 3D seismic vintage. Because the wells with shear log data were only limited within the oil pool, it is not simple to predict shear log at the aquifer and historical mid-dip water injection regions. In addition to this, oil and water saturations differ from log data and seismic data acquisition timing. Therefore, it is difficult to estimate shear and other elastic logs directly by ML because training data don't have several target properties i.e. outliers. To fill this gap, rock physics assist machine learning approach was implemented in order to use this outcome for AVO seismic inversion study.

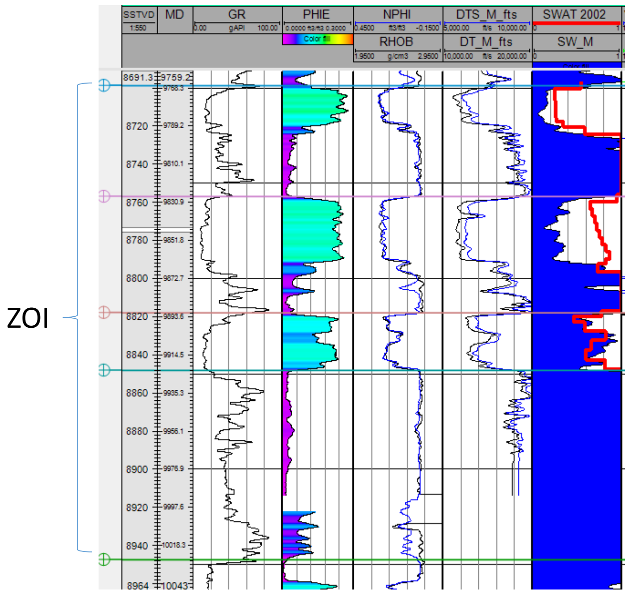

Figure 1. ZOI and log data in this study. Two water saturation logs are in-situ condition (blue) and reservoir condition (red) when seismic data was acquired, respectively. At this well, water saturation was changed due to the combination of oil sweeping and water injection at the middle zone.

Method

4 wells were acquired with shear and other Openhole logs to be used for training data (800 ft). And a total of 61 wells were used for prediction data (60000 ft). To estimate shear and

elastic logs in the reservoir saturation condition in seismic acquisition period, three steps were implemented as follows:

1. Predict shear log under in-situ condition by ML and estimate elastic logs in dry condition by Gassmann's equation
2. Predict Vp/Vs ratio in dry condition by ML and calculate other elastic properties
3. Estimate elastic logs in specific saturation conditions by Gassmann's equation

In step 3, recent history matched reservoir simulation data was used to estimate the water saturation log. It is worth noticing that one of the essential parts of this workflow is rock physic part i.e. Gassmann's equation. In this ZOI, the study of laboratory rock physics core measurement has confirmed a practical usage of this equation (Kato et al., 2013).

Only conventional openhole logs were selected in each ML because historical wells are also targeted in the prediction (Table 1). For training and prediction data, outliers such as the edge between porous and dense reservoirs were eliminated to avoid resolution differences in each log.

Table 1. Input log and data for ML

Step1	GR, NPHI, PHIE, NDS, SW, RHOB, DT, TVDss- top reservoir depth
Step2	GR, NPHI, PHIE, NDS, RHOB dry, DT dry, TVDss- top reservoir depth

LightGBM (Ke et al., 2017) and Optuna were selected for ML algorithms and automated hyper-parameter tuning, respectively. In addition to the conventional train and test data splitting, blind well test was carried out in each well in order to evaluate overfitting by individual well trends. For the feature engineering part, TVDss - top reservoir depth was used as a common practice for other similar ML workflows in this region because the total thickness in this reservoir is not drastically changed (Voleti et al., 2017). Because other tree based learning algorithms such as random forest, XGBoost and CatBoost did not show clear improvement, this combination was selected in view of minimum calculation time including hyper-parameter tuning.

During blind well test, porous intervals showed poor prediction only at high inclination well geometry (Figure 2). While this could be explained by velocity anisotropy, this is very difficult to capture via this workflow due to limited inclination varieties in training data. Given this observation, only wells with limited inclination geometries were selected for training and prediction dataset.

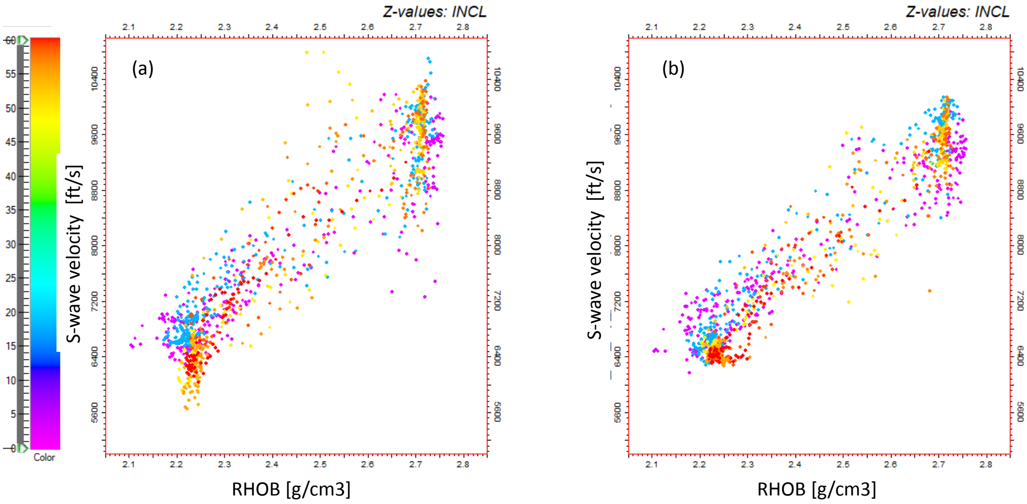

Figure 2. S velocity and RHOB crossplot coloured by inclination. (a) input well for training wells (20> degrees) and blind wells (>40 degrees). Velocity anisotropy was observed only at the porous zone. (b) Prediction result of step 1. The velocity anisotropy trend was not captured for this prediction.

Result and Discussion

As highlighted earlier, these outcomes will be used for AVO inversion i.e. applying bandpass filter. Therefore, the evaluation criteria of this prediction are not only depth by depth prediction error but also a vertical trend of prediction accuracy within ZOI. On the other hand, extremely high accuracy is not required because of this filtering. Figure 3 shows one of the blind well tests during step 1 and step 2. Both RMS and STD errors are minimum and predicted Vs (dry) and Vp/Vs (dry) in ZOI show reasonable matching in view of geological trend and these criteria. The results of other blind well also show a similar range of error as this well. Figure 4 shows training data and prediction data through all steps. It demonstrates that porous reservoir zones (low acoustic impedance interval) with high water saturation were captured well in this prediction result. Rock physics analysis from other carbonate fields in Abu Dhabi (Al Naqbi et al., 2021) also supports this value range of acoustic impedance and Vp/Vs ratio in this ZOI. As explained above, training data don’t have this water saturated reservoir zone. Thus rock physics can predict such outlier. As an alternative workflow, it could be worked well that a large amount of synthetic log with several saturation logs after fluid substitution step could use for training data. However, in view of the decision tree algorism, it is unclear how much data we need to feed into ML algorism to make it sensitive to saturation log i.e. high rank in the feature importance.

In this reservoir, fractures and microcracks are not developed confirmed by dozen of core data and image log data. Therefore microcracks which are essential parameters for Xu - Payne model (Xu and Payne, 2009) could be ignored. However, this carbonate reservoir has a variety of rock types and these pore geometries, and these are indeed difficult to simplify. Some prediction errors could be explained by not only ML prediction error but also this heterogeneity. However, one of the benefits of this machine learning is data-driven approach. Such theoretical rock physics relation can be skipped by ML approach although it has a risk of oversimplifying its geology.

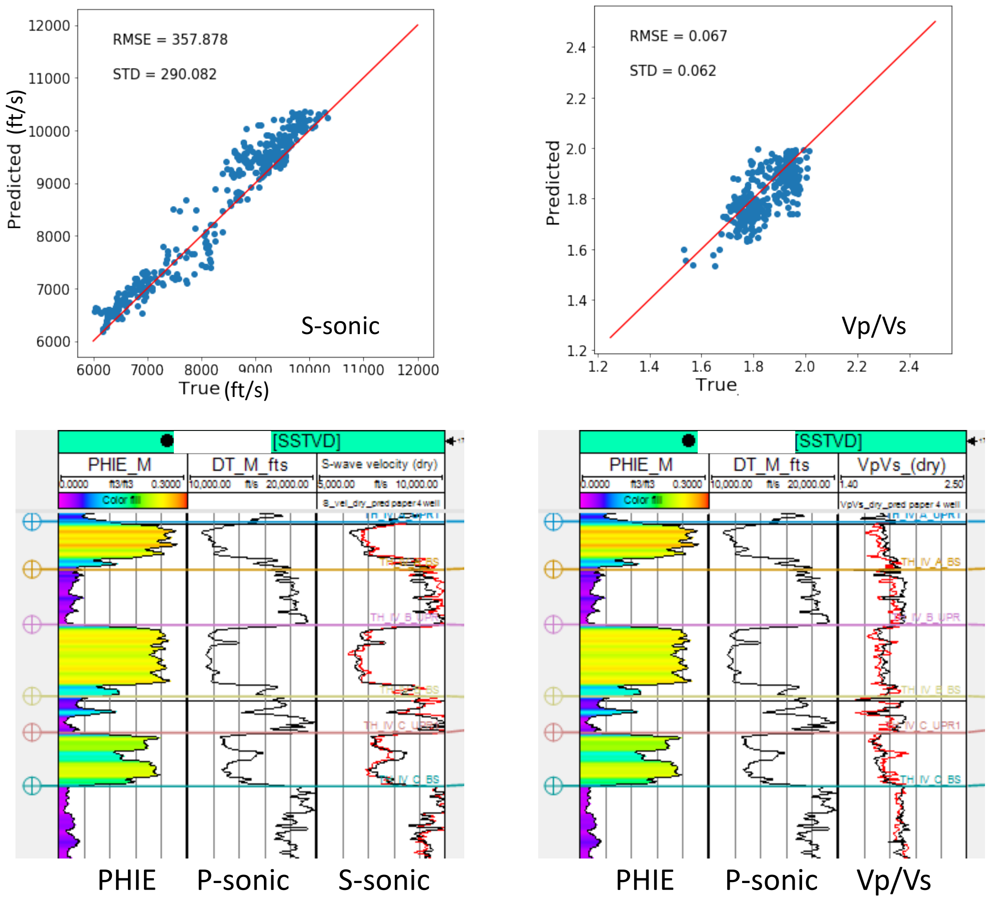

Figure 3. One of blind well test result during step 1 and step 2 (above figures). Well section views of this test result (below figures). Black and red lines indicate training and prediction data, respectively.

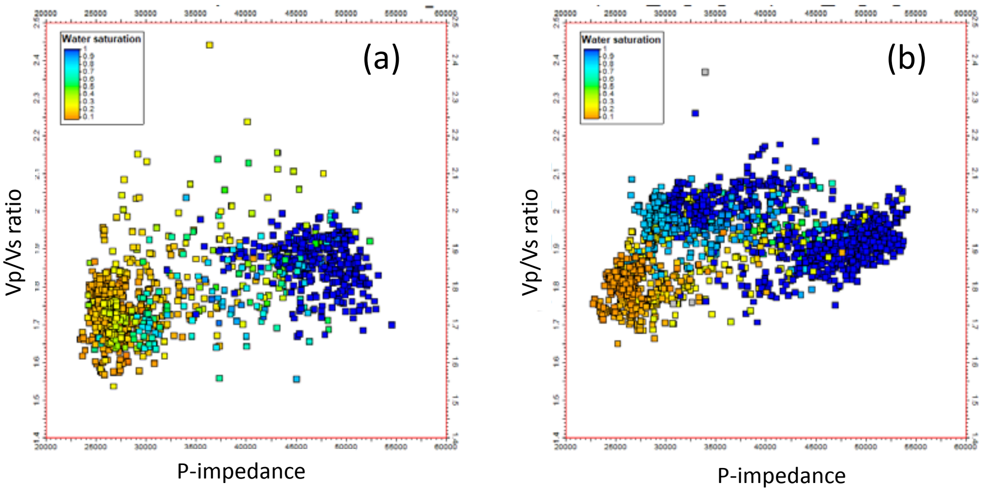

Figure 4. (a) Training data coloured by in-situ water saturation. (b) Prediction data (5 wells) coloured by the specific water saturation condition.

To see the impact of the outcomes, low frequency model (LFM) was generated based on training well data only, and training and prediction well data to adjust the current low frequency range in recent seismic re-processing data (Figure 5). This averaged map indicates low Vp/Vs ratio in the region above initial oil-water contact while a high Vp/Vs ratio near this contact. And some minor Vp/Vs ratio changes can be seen at the crest area where historical mid-dip water injections were implemented. Because the separation of Vp/Vs ratio between oil and water is about 0.2-0.3 in this reservoir (Figure 4), this predicted shear and elastic logs show a strong contribution to making a realistic LFM.

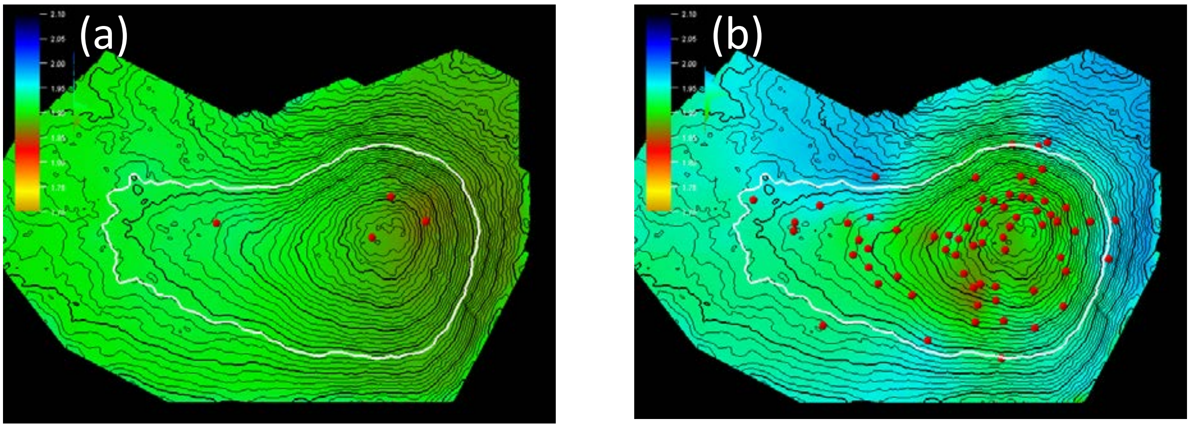

Figure 5. Vp/Vs ratio maps (time contour as black, original oil-water contract as white polygon and well location as red points) by low frequency model at ZOI. Log data are interpolated by kriging with 13 Hz high cut filter. (a) training well data only, (b) training and prediction well data.

In this study, shear and elastic log changes by pressure have not studied. However, input log data was acquired in the various reservoir pressure condition. One of the benefit of this workflow is to estimate shear and elastic logs including such pressure effect. Because the equations of elastic property change by pressure was established in this laboratory rock physics core measurement (Kato et al., 2013), this pressure effect can be considered in a future study.

Conclusions

This paper demonstrates shear and elastic log estimations via rock physics assist ML approach to predict these in various reservoir conditions at offshore Abu Dhabi giant oil fields. One of the benefits of ML approach is data-driven approach which has apparently superior rather than empirical equations. Meanwhile, rock physics base approach can estimate target rock properties which is sometimes categorized as outliers by ML. The combination of ML and rock physics can overcome weaknesses and strengthen the benefits.

Acknowledgements

The authors would like to acknowledge the management of ADNOC (Abu Dhabi National Oil COMPANY), ADNOC offshore, INPEX/JODCO and other concession folders for their support and permission to publish this paper.

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