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MACHINE LEARNING PREDICTED S-SONIC LOG AND FACIES DRIVEN MODELLING: A SEISMIC RESERVOIR CHARACTERIZATION APPROACH

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EXTENDED ABSTRACT

OBJECTIVE

Modelling of reservoir properties and their facies dependency go together and solving this challenge gets further complicated in areas with sparse well control. In our case study, we use a dataset from the Gulf of Mexico and create a “what-if-missing-log” scenario, thereby taking the advantage of the existing log data in a few wells to confirm the validity of the results by comparing to real log data. The machine learning can aid in predicting missing Shear-Sonic (S-sonic) data. We then take the results of the predicted S-sonic log to carry out Pre-Stack Seismic Inversion. Low frequency modelling is the “backbone” of the inversion results, and an inadequate low frequency model can potentially have detrimental effects due to usage of interpolation methods that are not representative of the geological variations, both laterally and vertically. To overcome this issue of interpolation, we demonstrate the impact of a completely data-driven modelling approach by creating facies driven-low frequency models for seismic inversion. The image below shows a simple workflow of the study conducted (Figure 1).

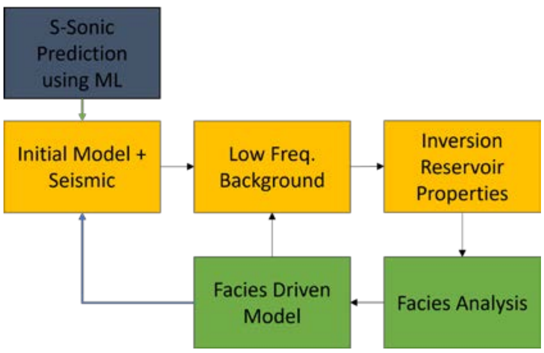

Figure 1. A simple diagrammatic view of the workflow applied during the project: Machine learning predicted S-sonic log being used for facies-driven seismic inversion

METHODS, PROCEDURES, PROCESS

A pre-stack seismic inversion estimates compressional-Impedance, shear-Impedance and Vp/Vs ratio. These seismic driven properties are useful to estimate key engineering properties like lithofacies, etc. A pre-stack seismic inversion demands S-sonic (or S-velocity) logs or their derivatives as input. These are often not acquired or, if acquired, may be of sub-optimal quality. Commonly, theory-based methods are used to estimate shear sonic logs. Alternatively, machine learning methods are also appropriate for the complex task of non-linear log predictions.

This case study used seven wells and five seismic angle stacks from the Gulf of Mexico, where two reservoir levels are known. The available input well log data were density, gamma ray, porosity-neutron, effective porosity, resistivity, water saturation, volume of clay, P-sonic and S-sonic. The following method (Melo et al., 2022) was applied: a) The dataset was divided into “training” and “test” sets b) Pearson correlation plot analysis was performed on the training data to check feature redundancy; c) The training data was sub-divided into training & validation data sub-sets; d) A gradient boosting-based machine learning method was trained for prediction of missing S-sonic logs in the test wells. The result of the S-sonic prediction at test wells shows a good match between the true and predicted S-sonic logs, with a score of 93% (Figure 2) In fields with sparse well data, the formerly described process of S-sonic prediction contributes to a reliable S-sonic data.

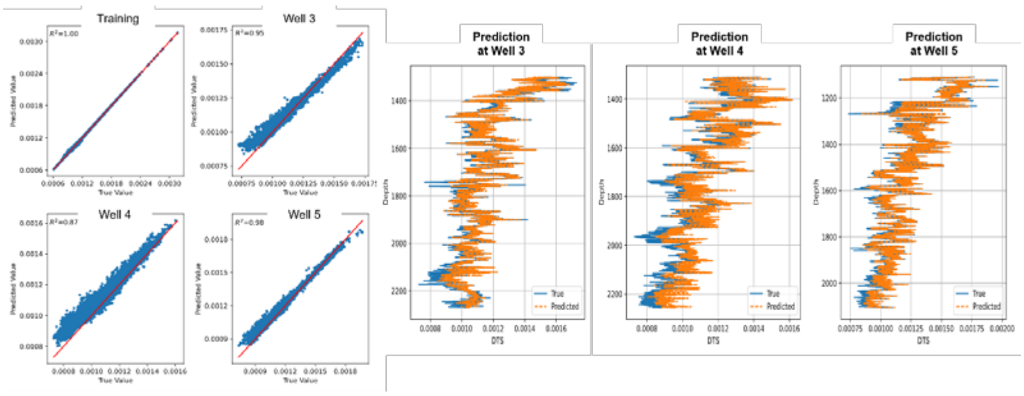

Figure 2. Correlation cross-plots on training and test data (left-hand side) and log display at test wells (right-hand side) to review the match between machine learning between the predicted S-sonic log (in orange) and the original S-sonic log (in blue). Overall, the average correlation in test wells is 0.93.

The following method was employed, after predicting the S-sonic logs:

1) First pass inversion with constant, structurally compliant low frequency model:

   Using the resultant predicted S-sonic logs along with other existing elastic P-impedance, Density logs, a first pass pre-stack seismic inversion was carried out. This first pass pre-stack seismic inversion used a structurally-compliant constant trend low frequency model averaged over the wells but with no well log interpolation (Figure 3).

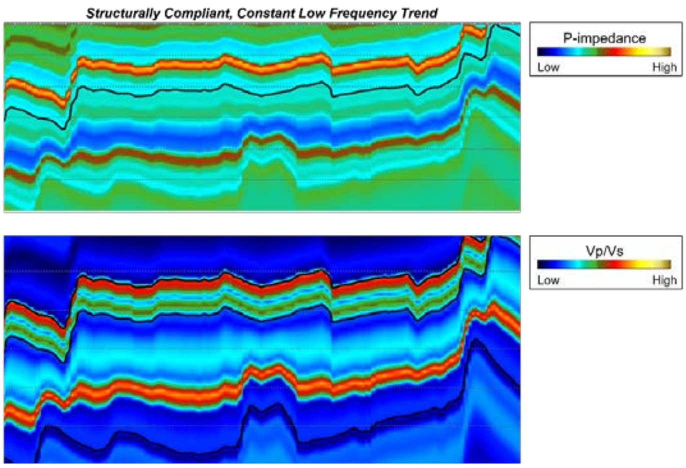

Figure 3. Structurally compliant, constant low frequency trend (Top- P-impedance, Bottom- Vp/Vs)

2) Facies Probability Estimation and Facies Driven Modelling of Elastic Properties:

   This step is to identify facies from first-pass seismic inversion. Using the inverted outputs of the first pass seismic inversion, a Bayesian-based probabilistic estimation of facies (Pendrel et al., 2006) was applied to estimate probabilistic volume estimates of three types of Shale, Pay and Silty facies (Figure 4).

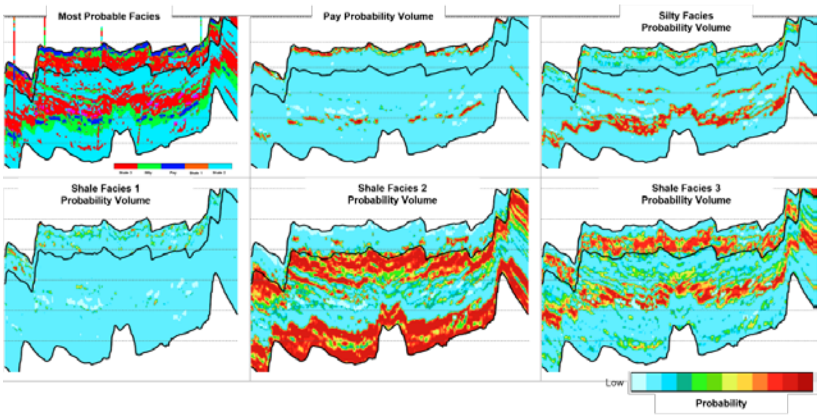

Figure 4. Identification and estimation of facies using Bayesian facies discrimination approach from first pass seismic inversion and probability volumes estimated per facies.

The facies probability volumes were used to derive relationships between the elastic properties per facies and per reservoir layer by construction of probability density functions (PDFs) in the elastic domain (Figure 5).

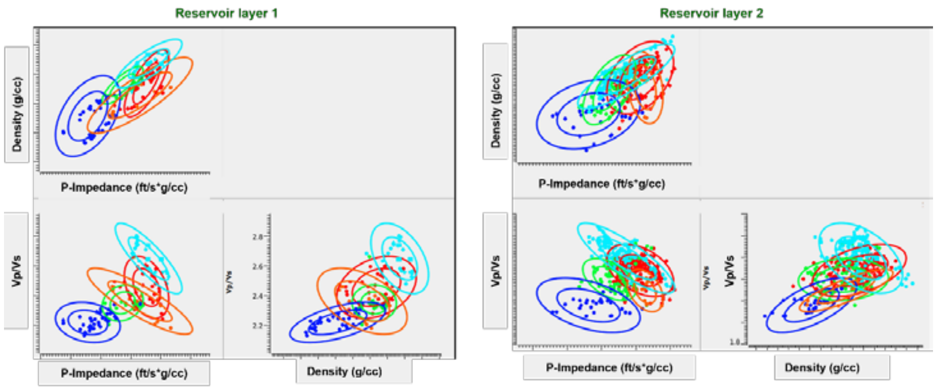

Figure 5 The PDFs constructed for five facies (three types of Shale, Silty and Pay) in elastic domain to estimate elastic property volume for input to second pass inversion. Also, input to this process are the probability volumes derived from Bayesian estimation of facies in the previous step shown in Figure 4.

3) Second pass inversion with facies driven low frequency model:

In the next step, the facies driven elastic properties were used as inputs to a second pass pre-stack seismic inversion. The facies driven updated low frequency trend proved to be helpful in imaging the deltaic sand in the seismic inversion with better well ties and more consistent inverted P-Impedance and Vp/Vs ratio.

RESULT

We consider that the success of S-sonic prediction with only a few available wells is attributed to several factors:

- Thorough QC of input log data to check for outliers
- Pearson correlation plot analysis to recognize linear correlation trends between input logs and the target i.e., the S-sonic log
- Nested cross-validation for model selection and hyperparameter tuning
- Efficient cost function minimization at the machine learning step through the gradient boosting

In the second stage of the study, we demonstrated the value of the facies-driven low frequency model. On comparing the second pass and the first pass inversions, we observe the following improvements: 1) Overall improvement in imaging of deltaic sands with better well tie in the two reservoir layers due to the use of a more proper 3D low frequency model, 2) The inverted P-impedance and Vp/Vs ratio show more consistency in terms of resolution of the reservoir of interest in the second pass inversion, in this step the thickness of the deltaic sands are more comparable 3) We see slightly higher resolution achieved in the second pass inversion result due to reduction in destructive interference of the side lobe in the wavelet 4) Vp/Vs ratio which is more challenging to achieve from this dataset is better predicted with the second pass inversion result (Figure 6).

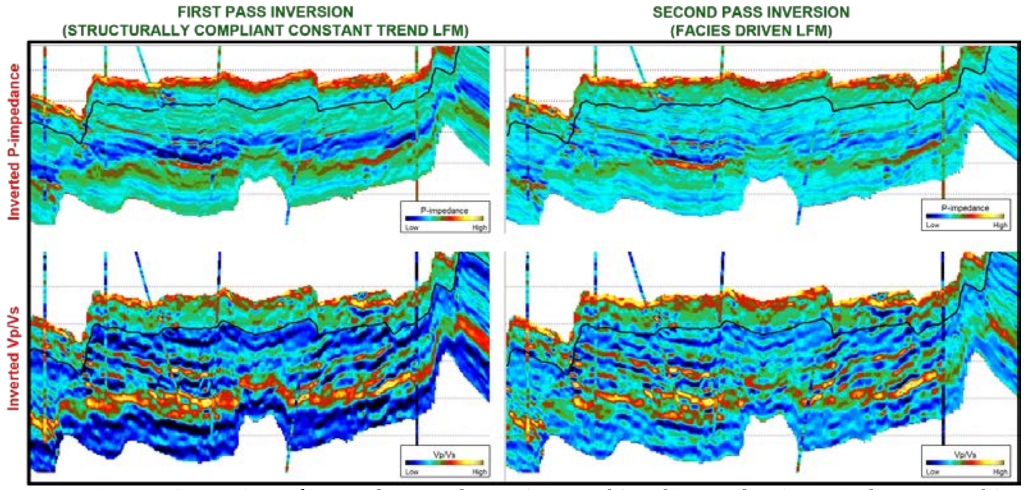

Figure 6. Comparison of inverted P-Impedances (top panels) and inverted Vp/Vs ratio (bottom panels) of first pass inversion performed with structurally-compliant, constant frequency trend (left-hand side)

and the second pass inversion performed with facies-driven low frequency model (right-hand side). All the section views have wells overlain on the inverted results for comparison.

NOVEL OR ADDITIVE INFORMATION

We have demonstrated two workflows through this case study. The first is aimed at predicting reliable shear-sonic logs for fields with fewer wells through a machine learning approach. The second uses the outputs of the first study and takes these as inputs into the seismic domain or truly speaking in the elastic domain. The objective is to estimate robust facies derived low frequency elastic models for a second pass of seismic inversion. The main advantage of the updated low frequency model is that it is free of well log interpolation, which is usually a factor that has the potential to obscure inversion results. Since the second method's elastic property estimation are through Bayesian inference methods, it is possible to understand the uncertainties associated with the through puts of the processes from one into the other along the workflow (Pendrel et al., 2022). Usually, it is seen that the observed uncertainties are facies-dependent and variable both laterally and vertically.

REFERENCES

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