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Machine Learning Driven Seismic Reservoir Characterization Guides 3D Static and Geomechanical Model Building

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Abstract

One of the key objectives of seismic reservoir characterization is to predict and map the distribution of reservoir properties in a 3D sense. Appropriate use of supervised artificial Intelligence (AI)/machine learning techniques can do a considerably good job in this aspect. However, to make the property estimation more robust, suitable attributes need to be fed into the AI training process. Pre-stack seismic inversion provides relevant elastic attributes, which are better correlated with the desired reservoir properties. Therefore, an integrated workflow consisting of pre-stack seismic inversion and a robust supervised machine learning technique, when implemented judiciously, will help in accurately predicting the petrophysical and rock-mechanical reservoir properties away from the drilled well locations.

The study area is an unconventional tight reservoir in the Cambay basin of India. Due to the tightness of the reservoir, hydraulic fracturing was planned. Therefore, apart from the prediction of the reservoir properties such as Porosity, Rock mechanical properties such as Young's modulus and Brittleness Index were also estimated using Machine Learning techniques to aid the fracking. In this study, we have carried out a thorough step-by-step analysis and proper integration of the available well and seismic data in hand for effective reservoir characterization and bringing out a robust predictive model of the subsurface.

Introduction

The study area is an unconventional tight sand reservoir in the Cambay basin of India. In unconventional reservoirs such as tight sand reservoirs, optimized hydrocarbon production requires effective hydro-fracking of the reservoirs. Here, the identification of sweet spot for the new well location is the combination of better reservoir properties as well as rock mechanical properties to make it favorable to hydraulic fracturing.

Seismic reservoir characterization and identifying sweet spot in tight sand reservoirs require both the distribution of reservoir properties such as Porosity and the rock mechanical properties such as Young's Modulus / Brittleness Index.

Supervised Machine Learning techniques such as Artificial Neural Network (ANN) can help in predicting the reservoir and rock mechanical properties effectively, away from the well. ANN derives a non-linear relationship between seismic data and its various attributes with the Reservoir properties such as Porosity (Russel et al, 2001; Leiphart and Hart, 2001). A few recent studies have used ANN techniques to successfully predict the reservoir properties away from the well with good accuracy (Othman et al., 2021; Sang et al., 2021).

As the tight sand reservoirs require hydro-fracking for sustained hydrocarbon productivity and brittle rocks aids in effective hydro-fracking of the reservoir, the understanding of brittleness plays a critical role in the development of the tight sand reservoir. A few authors (Zhang et al., 2016; Chopra et al., 2015) have discussed the relationship between brittleness and Young's modulus. Chopra et al., (2015) have also discussed seismic characterization of the brittle zones. Guo et al. (2012) discussed the relationship between the brittleness index and the Lamé parameters of incompressibility (λ) and rigidity (μ). In this study, Young's modulus, a measure of the brittleness of the rock, has been derived from the well log data.

Subsequently, Porosity, Young's modulus, and Brittleness Index volumes were generated using multi-Attribute analysis and Artificial Neural Network (ANN) techniques. The Porosity and Brittleness Index maps generated from these predicted volumes at the reservoir level were useful in identifying the sweet spots with respect to better reservoir quality and favorable to hydraulic fracturing.

Theory and/or Method

The study area is an unconventional fractured reservoir in the Cambay basin of India. The integrated workflow for Artificial Intelligence (AI)-assisted enhanced reservoir characterization is given in Figure 1. It is a two-step process - (i) Pre-stack inversion and computation of inversion-derived relevant elastic attribute volumes (ii) Artificial Neural Network (ANN)-based supervised machine learning technique for predicting reservoir petrophysical property such as total porosity (PHIT) and rock-mechanical properties such as young's modulus (E) and brittleness index (BI). For the present study, these reservoir properties were required for effective reservoir characterization and supporting further studies for the Static model and 3D Mechanical Earth Model (MEM) building.

The brittleness index was computed using normalized values of Young's modulus and Poisson's ratio (Rickman et al., 2008).

$$BI = 0.5 * \left(\left(\frac{E - E_{min}}{E_{max} - E_{min}}\right) + \left(\frac{\nu - \nu_{max}}{\nu_{min} - \nu_{max}}\right)\right)$$

Where, E is Young's modulus; Emin and Emax are its minimum and maximum values in the studied interval; ν is Poisson's ratio; νmin and νmax are its minimum and maximum values in the studied interval.

First, we carried out the rock physics-based cross-plotting analysis to identify the suitable elastic attributes, which correlate better with the desired reservoir properties. For effective pre-stack inversion, the initial key steps are proper gathers conditioning in order to make the gathers amenable to pre-stack inversion and AVO analysis to make sure the conditioned gathers agree with the modelled gathers in terms of AVO gradient response, at the well locations in the zone of interest. Next, pre-stack inversion was carried out using the conditioned gathers to derive P & S-impedance volumes and then other elastic attributes such as Vp/Vs ratio, Poisson's ratio, Lambda-rho, Mu-rho, E-rho (Young's modulus*Density) etc. were computed. In the next step, a robust ANN algorithm was adopted for predicting the reservoir properties.

Selection of the relevant attribute for the ANN training is critical and a key step to avoid any over-training in the analysis. For this purpose, cross-validation based multi-attribute regression (Hampson et al., 2001) was performed for the selection of optimum attributes in the ANN training process, separately for PHIT, E, and BI properties. A multi-attribute stepwise regression analysis was performed using the Porosity, Young's Modulus, and Brittleness Index log at the well locations. The optimum convolution operator length was chosen using the cross-validation criteria. This average validation correlation is equivalent to the average cross-correlation between well log and predicted reservoir properties, while using the available wells as blind wells, by taking out the wells one-by-one from the training dataset (blind well analysis) and then averaging the cross-correlations for all these available wells after repeating the procedure for all the wells.

The minimum validation error for Porosity was achieved with 10 attributes. Whereas the validation errors for Young's Modulus and Brittleness Index were achieved with 9 attributes each. Based on the cross-validation criteria, the optimum attributes used for predicting Porosity, Young's Modulus, and Brittleness Index are summarized in Table 1. Subsequently, these attributes along with the log PHIT from the key wells, were fed to the ANN training process. Similar procedures were followed separately for predicting E and BI properties. After completing ANN training and validation processes separately for PHIT, E and BI, the non-linear training networks were applied to the optimum attribute volumes to generate the pseudo volumes of these reservoir and rock mechanical properties.

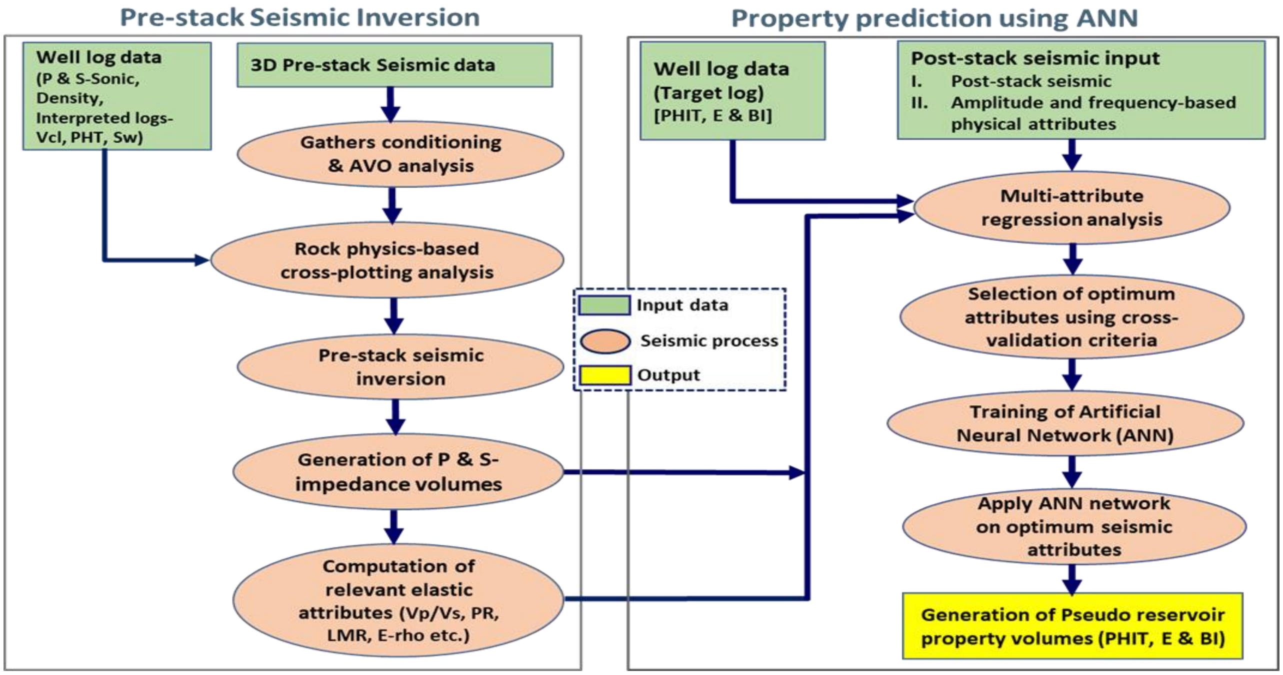

Figure 1: Integrated workflow for reservoir and rock mechanical property prediction

Seismic Attributes used used in ANN training		
Porosity	**Young's Modulus**	**Brittleness Index**
P-impedance	Mu-Rho	E-Rho
Poisson Impedance	E-Rho	Poisson’s Ratio
Lambda-Rho	Poisson Impedance	Mu-Rho
Poisson’s Ratio	Poisson’s Ratio	Lambda-Rho
Coherent Energy	Spectral decomp magnitude 25 Hz	Amplitude strength
Spectral decomp magnitude 25 Hz	Coherent Energy	Spectral decomp magnitude 25 Hz
Spectral decomp magnitude 15 Hz	Amplitude strength	Coherent Energy
Derivative instantaneous Amplitude	Derivative instantaneous Amplitude	Derivative instantaneous Amplitude
Amplitude weighted frequency	Amplitude weighted frequency	Frequency filter seismic(20/25-30/35)
Second Derivative		

Table 1: Seismic attributes used for predicting Porosity, Young’s Modulus and Brittleness Index

Examples / Results

Excellent match between inverted and well log P & S-impedances were achieved at the blind wells and this indicated a high-quality pre-stack inversion process.

Figure 2 shows the plot of average validation error vs number of attributes during the multi-variate regression analysis for the Porosity prediction process. Figure 3 shows the crossplot of actual well log Porosity vs predicted porosity for training (left) and validation (right). The color code is given based on different wells. High training correlation of 0.977 and validation correlation of 0.88 are achieved considering the available wells in the study. The plot of Avg. validation error vs number of attributes during the multi-variate regression analysis for the Young's Modulus (left) and Brittleness Index (right) prediction processes is given in Figure 4. Figure 5 illustrates the crossplot of the actual well log Young's Modulus vs predicted Young's Modulus for training (left) and validation (right). High training correlation of 0.96 and validation correlation of 0.875 are achieved. The crossplot of the actual well log Brittleness Index vs predicted Brittleness Index for training (left) and validation (right) is given in Figure 6. High training correlation of 0.95 and validation correlation of 0.852 are achieved.

It is observed that very high average cross-correlation of 0.95 - 0.975 was achieved between well log and predicted reservoir properties (PHIT, E and BI). Importantly, very good validation correlation of 0.85 - 0.88 between the well log and predicted reservoir properties (PHIT, E, and BI) was achieved in the available wells. Hence, high validation correlations lent credence to the predicted pseudo property volumes for further using them in reservoir characterization and supporting the Static Model and 3D MEM building.

Thereafter, the interval property maps were generated at the reservoir levels using the interpreted horizons. Porosity maps extracted at different levels within the reservoir clearly brought out the porosity distribution and helped in delineating the areas of better revoir quality within the study area. Due to its high fidelity, the predicted Porosity volume could be used effectively to guide the reservoir property propagation during static model building. Brittleness maps extracted at different levels within the reservoir depicted the distribution of Brittleness property distinctly and helped in identifying the favorable areas for hydraulic fracturing. Due to its high credence, the predicted pseudo Brittleness volume could be used effectively in the 3D MEM building process. Porosity along with Brittleness property distribution helped in identifying the better-producing sectors within the study area.

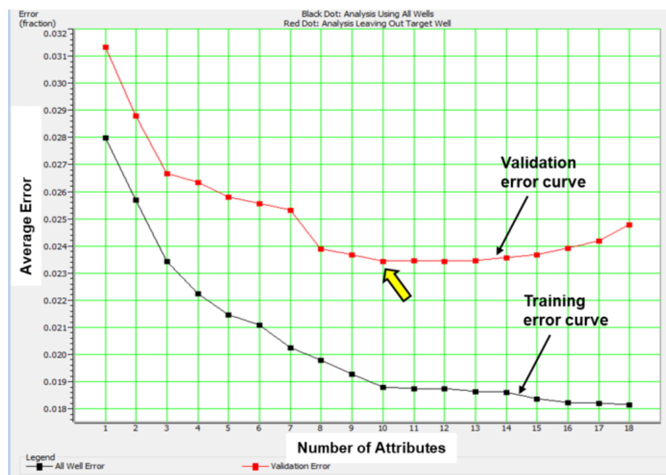

Figure 2: Plot of average validation error vs number of attributes during the multi-variate regression analysis for the Porosity prediction process

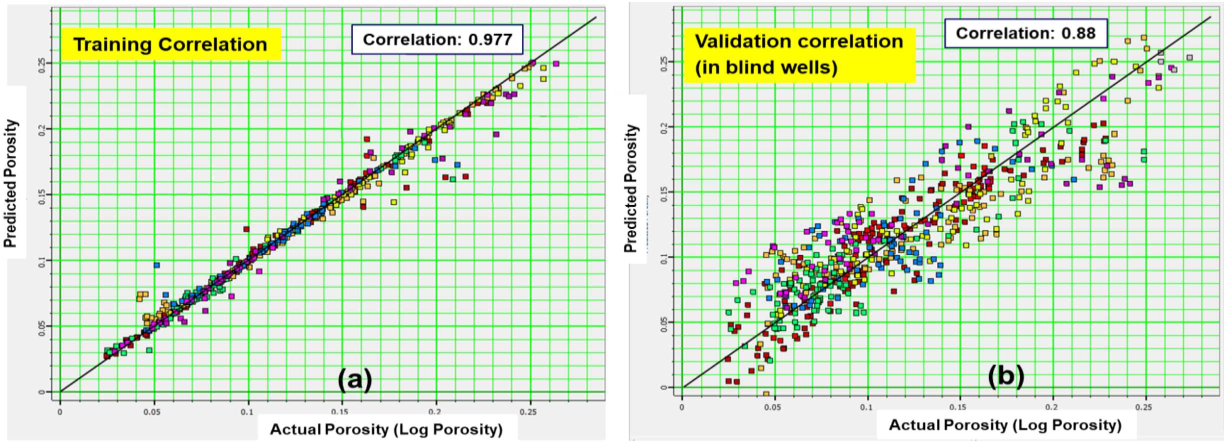

Figure 3: Plot of actual well log Porosity vs predicted porosity for training (left) and validation (right). High training correlation of 0.977 and validation correlation of 0.88 are achieved.

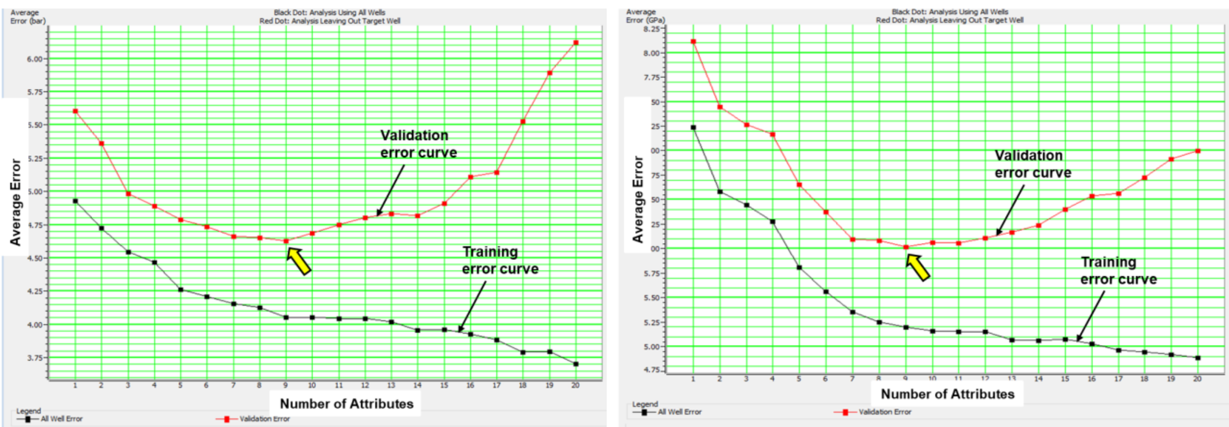

Figure 4: Plot of average validation error vs number of attributes during the multi-variate regression analysis for the Young's Modulus (left) and Brittleness Index (right) prediction processes.

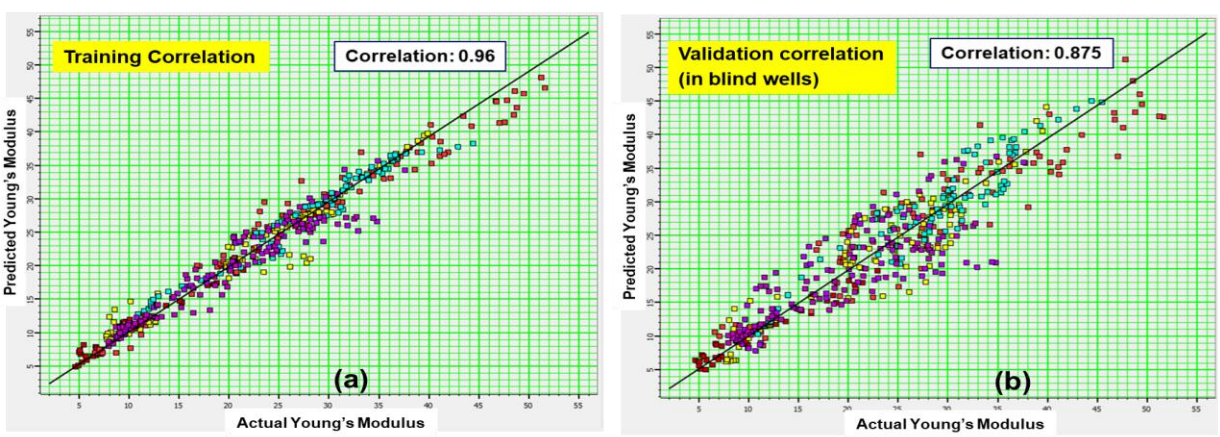

Figure 5: Plot of actual well log Young's Modulus vs predicted Young's Modulus for training (left) and validation (right). High training correlation of 0.96 and validation correlation of 0.875 are achieved.

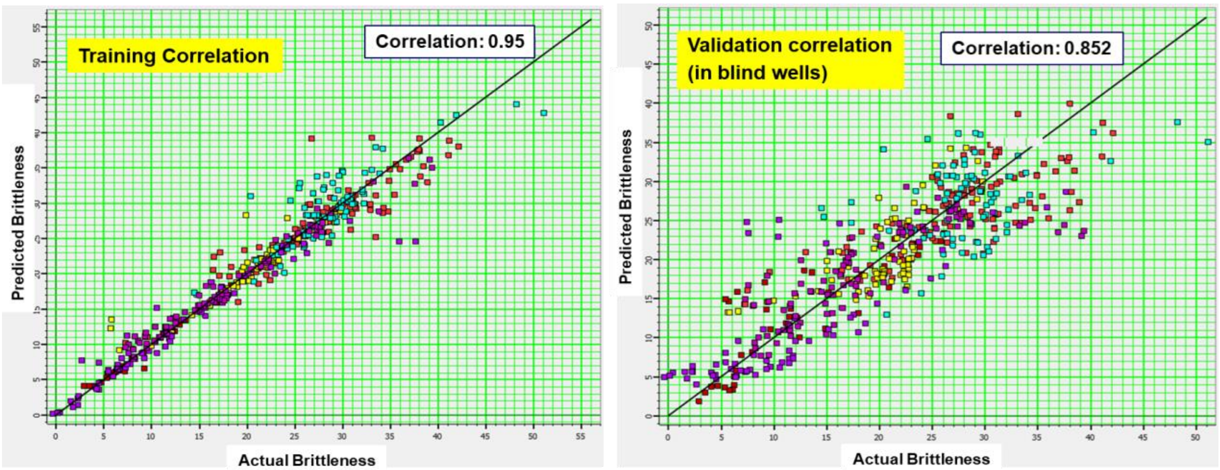

Figure 6: Plot of actual well log Brittleness Index vs predicted Brittleness Index for training (left) and validation (right). High training correlation of 0.95 and validation correlation of 0.852 are achieved.

Conclusions

In this study, we have carried out a thorough step-by-step analysis and proper integration of the available well and seismic data in hand for effective reservoir characterization and bringing out a robust predictive model of the subsurface. Moreover, adopting the advanced techniques judiciously to accomplish the objective, facilitated in considerable enhancement of our integrated workflow, and helped in predicting the desired reservoir property such as Porosity and rock mechanical properties such as Young's Modulus, Brittleness Index with high fidelity. Thus, we could identify the sweet spots with respect to better reservoir quality as well as favorable to hydraulic fracturing effectively.

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