Bulk Gas Volume Estimation Using Multi-Attribute Regression and Probabilistic Neural Network (PNN): A Case Study in a Gas Field from East Coast of India

Amit K Ray and Samir Biswal, Reliance Industries Ltd., Mumbai, India*

Summary

Effective porosity and hydrocarbon saturation prediction away from the well is essential to characterize reservoir effectively. Precise prediction of those parameters is a challenging task because of the non-uniqueness in its relationship with conventional seismic attributes. Again quantitative prediction of hydrocarbon saturation from seismic is ambiguous because of their independent nonlinear relationship particularly with amplitude, impedance etc. However, a property which is product of effective porosity multiplied by hydrocarbon saturation, named as 'Gas Volume' or 'Bulk Gas Volume', has a major effect on seismic amplitude than individual effect. In a complex geological setup with greater degree of heterogeneity in reservoir properties further intensifies the challenge of characterizing the reservoir based on individual seismic attribute. In the present case, major channel-levee complexes associated with smaller episodes of channel-cut-fill and migration has made the study area a geologically complex one. In the present study, a special approach has been adopted which combines multi-attribute linear regression with Probabilistic Neural Network (PNN) technology to predict Gas Volume. The predicted property has been found to contain finer detail amenable not only for better delineation of hydrocarbon saturated reservoir in 3D space but also its usage as an input for further quantitative reservoir characterization.

Introduction

The study area is a gas field in clastic reservoir situated in the deep waters of east coast of India. The reservoir stratigraphy comprises a heterogeneous succession of sandstones and mudstones organized into a composite upward fining profile. Component sand bodies are dominated by laterally amalgamated channels, sinuous channels and channel with splays, and are interpreted to be the products of deepwater, gravity-flow processes. Above a basal incision surface, the reservoir is highly sand-prone and comprises laterally amalgamated channels. The medial section of the reservoir is more aggradational and exhibits laterally isolated and sinuous channels. Within the upper part of the reservoir, channels are smaller, straighter and built of individual channels with frontal splay elements. Shale and thin-bedded facies become an increasingly important component of the stratigraphy in the upper parts of the reservoir. The main channel is buried by a prograding slope succession.

In this complex geological setup both horizontal and vertical heterogeneity has been observed to a great extent. So the challenge in this field was to capture the reservoir heterogeneity efficiently. Any direct method of determining the reservoir property using transform based on single property viz., amplitude, sweetness, P-Impedance etc. generates only an average outcome, devoid of finer details.

Effective porosity and hydrocarbon saturation are two important parameters in contributing to the impedance contrast and seismic amplitude. However, rather than individually the combined effect of both the properties has the stronger influence to the seismic anomaly. Therefore, to enhance the effectiveness of the analysis a special attribute which is a product of effective porosity and hydrocarbon saturation, named as 'Gas Volume', was predicted. Bulk Gas Volume is the fraction of rock volume composed of gas and is analogous to gas-in-place per unit rock volume. A method comprising of multi-attribute linear regression combined with Probabilistic Neural Network (PNN) was used for this study. The method derives a non-linear relationship between seismic data and its various attributes with Gas Volume (Russel et al, 2001; Leiphart and Hart, 2001). The applicability of the Gas Volume predicted using this method is found to be quite effective for further reservoir characterization and production planning operations.

Method and analysis of results

The input data used in the study were the effective porosity logs of 15 wells after converting them from depth to time at 2-ms sampling interval, full-stack seismic data volumes of 3-35º and seismic inversion volumes. Seismic inversion volumes were P-impedance and Vp/Vs ratio volumes obtained from simultaneous angle dependant inversion result.

The cross-plot between Effective Porosity and P-impedance shows a correlation coefficient of 0.5 (fig.1) while that of Gas Volume and P-impedance shows a correlation coefficient of 0.58 (fig.2). As the Gas Volume exhibit enhanced interdependence with seismic and superior ability to delineate hydrocarbon saturated sand, the authors attempted to estimate the Gas Volume in 3D space away from the well.

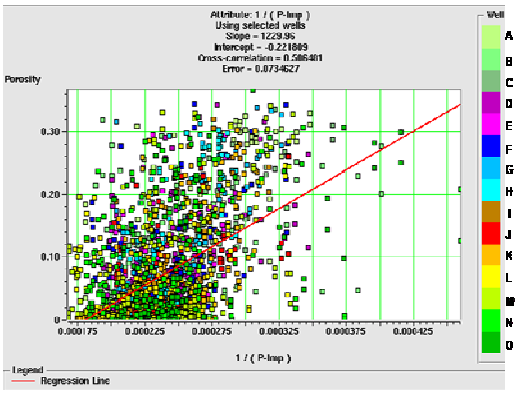

Fig 1: Cross plot between effective porosity and P-impedance

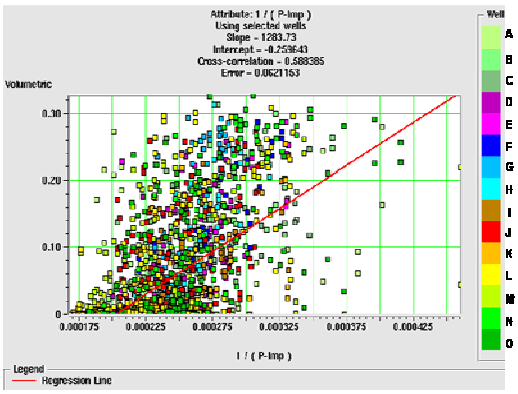

Fig 2: Cross plot between Gas Volume and P-impedance

Presently, there are several methods available in the industry for predicting different reservoir properties, namely single-attribute regression, multi-attribute regression, Probabilistic Neural Network (Russel et al., 1997; Liu and Liu, 1998; Hampson et al., 2001; Leiphart and Hart, 2001; Walls et al., 2002) etc. In this present study, it has been observed that multi-attribute regression and PNN was more effective in predicting Gas

Volume over single attribute regression. The following steps illustrate the effectiveness of multi-attribute regression and PNN in predicting the Gas Volume away from the well with greater accuracy.

First, single-attribute regression was performed to the data. Out of all the attributes, inverse of Vp/Vs ratio gave highest correlation with Gas Volume with a coefficient of 0.64. Cross plot between Vp/Vs ratio and Gas Volume is shown in fig 3. It is observed that there is a large scatter of data points and the correlation coefficient is not good enough for further analysis.

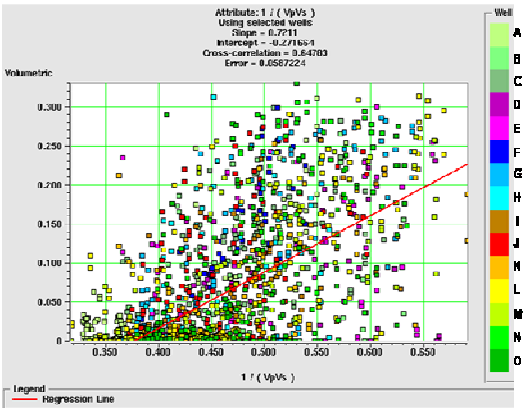

Fig 3: Crossplot between Gas Volume and Vp/Vs ratio

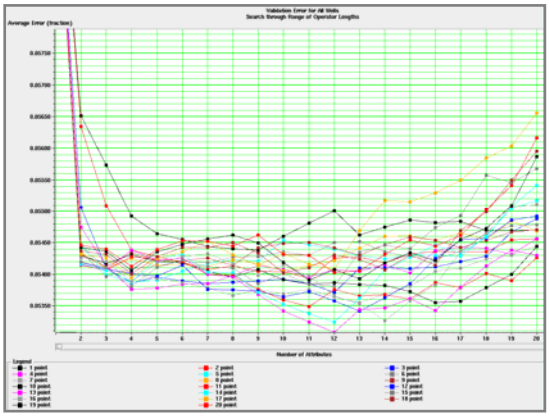

Fig 4: Plot of validation error vs attributes for different operator length

Then a method was adopted that combines multi-attribute regression and probabilistic Neural Network (PNN) to derive a suitable relationship for predicting Gas Volume (Hampson et al., 2001). A multi-attribute stepwise linear regression analysis was performed using Gas Volume log at fifteen well locations. Convolution operator length has been chosen using the cross-validation criteria. Validation correlation is computed by excluding one well at a time from the training data set, calculating correlation at that well and making average of the correlations after repeating the procedure for all the wells.

Fig.4 shows the plot of validation error against the number of attributes for the different operator lengths. The plot illustrates that a thirteen-point operator gave the minimum validation error with 12 attributes. The attributes were 1/(Vp/Vs), 1/(P-impedance), Integrated absolute amplitude of seismic, Amplitude Envelope (P-impedance), Instantaneous Phase of seismic, Integrate (Vp/Vs), Average Frequency (Vp/Vs), Apparent Polarity (Vp/Vs), Instantaneous Frequency (P-impedance), Integrate (P-impedance), Cosine Instantaneous Phase of seismic and Amplitude Envelope (Vp/Vs). The network derived from the multi-attribute linear regression gave an average correlation of 80%. Fig 5 shows the cross-plot between the actual and predicted Gas Volume after multi-attribute regression. It is observed that scattering of the data points in the cross-plot has been reduced considerably compared to the single-attribute regression.

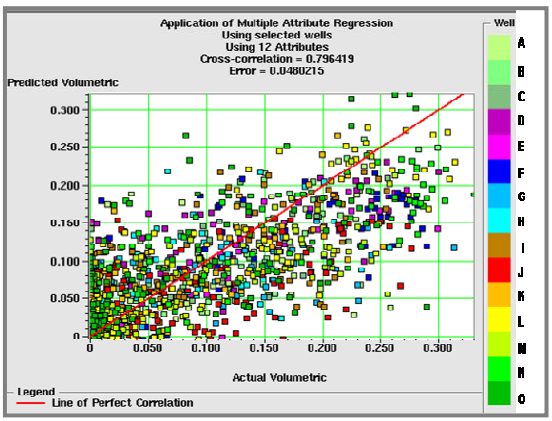

Fig 5: cross-plot between the actual and predicted gas Volume after multi-attribute regression

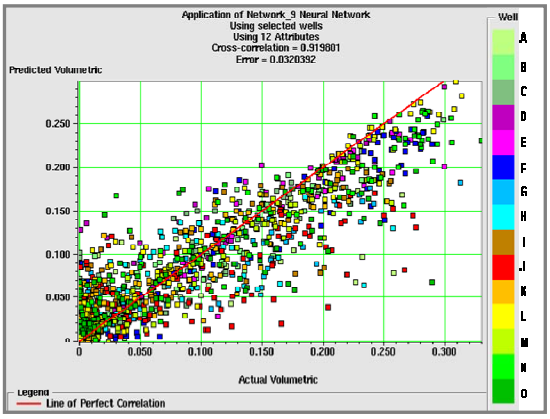

Fig 6: cross-plot between the actual and predicted Gas Volume after PNN

Then PNN was performed, cascading with the trend from the multi-attribute linear regression after applying a smoother length of 50 samples to the transform. After PNN, average correlation has been increased to 92% while validation correlation was estimated as 75%. Fig 6 shows the cross-plot between actual and predicted porosity at the well locations after applying PNN. It is observed that using PNN, scattering of the data points in the cross-plot has been further reduced compared to the multi-attribute approach.

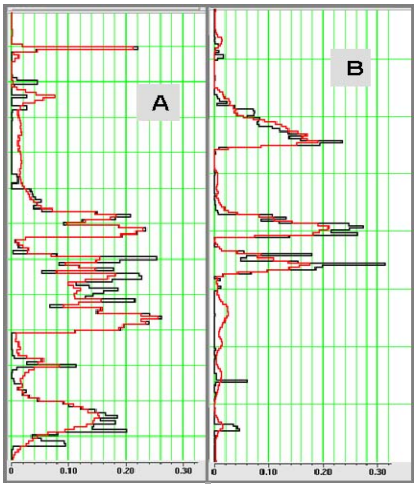

Fig 7: Match between actual (black) and predicted (red) effective porosity after PNN for the wells A and B

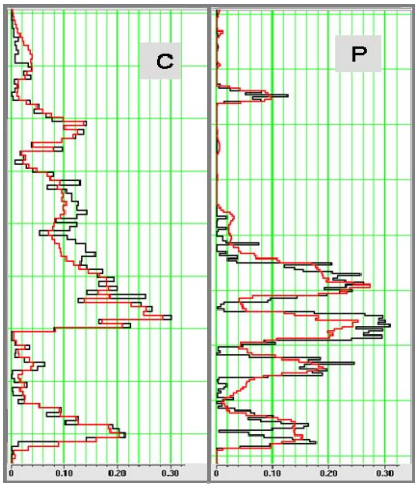

Fig 8: Match between actual (black) and predicted (red) effective porosity after PNN for the wells C and P

The match between actual and predicted effective porosity for the first 3 wells (A, B and C) and has been shown in fig 7 and fig 8. The well P has been used as a blind well. The match between actual and predicted Gas Volume at the well P is shown in fig 8. Gas Volume sections along the well A, B, C and P are shown in fig 9 -12.

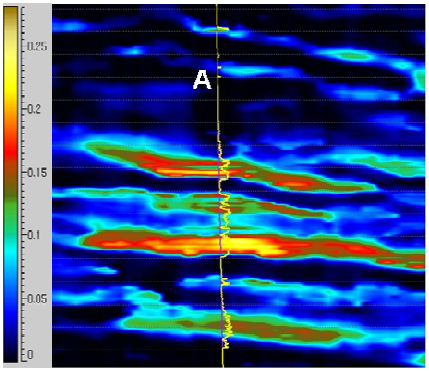

Fig 9: Section view of Gas Volume along with actual log at the well A after PNN

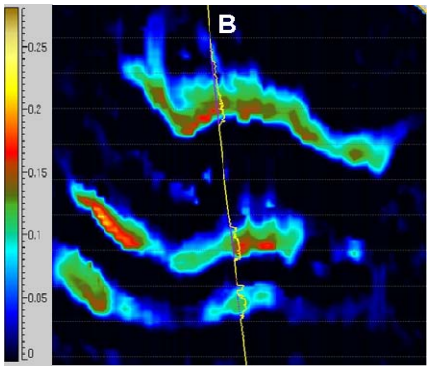

Fig 10: Section view of Gas Volume along with actual log at the well B after

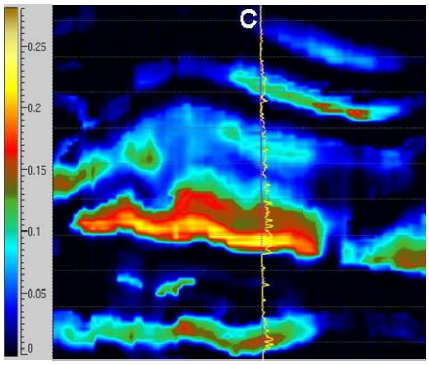

Fig 11: Section view of Gas Volume along with actual log at the well C after

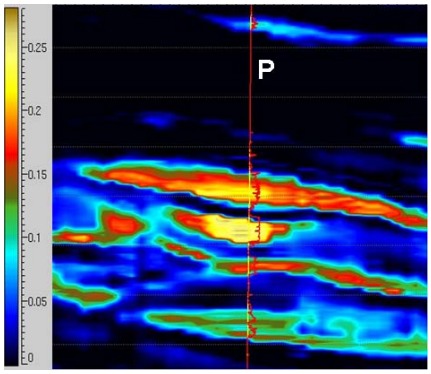

Fig 12: Section view of Gas Volume along with actual log at the well P after

Discussion

Gas Volume is a seismically well correlatable reservoir property, which is a good representation of hydrocarbon saturated sand. Multi-attrubute regression and PNN analysis has predicted the Gas Volume with good accuracy. Excellent match at the validation well P illustrates the superiority of this method. This Gas Volume has helped in delineating the reservoir away from the well in much better way and to place the infill development wells. Again, this attribute as an input has helped in further quantitative reservoir characterization.

References

Hampson, D., Schuelke, J., and Quirein, J., 2001, Use of multiattribute transforms to predict log properties from seismic data: Geophysics, **66**, 220–236.

Leiphart, D. J., and Hart, B. S., 2001, Comparison of linear regression and a probabilistic neural network to predict porosity from 3D seismic attributes in Lower Brushy Canyon channeled sandstones, southeast New Mexico: Geophysics, **66**, 1349–1358.

Liu, Z. and Liu, J., 1998, Seismic controlled nonlinear extrapolation of well parameters using neural networks: Geophysics, **63**, 2035–2041.

Russell, B., Hampson, D., Schuelke, J., and Quirein, J., 1997, Multiattribute seismic analysis: The Leading Edge, **16**, 1439–1443.

Walls, J. D., Taner, M. T., Taylor, G., Smith, M., Carr, M., Derzhi, N., Drummond, J., McGuire, D., Morris, S., Bregar, J., and Lakings, J., 2002, Seismic reservoir characterization of a U.S. Midcontinent fluvial system using rock physics, poststack seismic attributes, and neural networks: The Leading Edge, **21**, 428–436.