

Mapping of Shale Volume using Neural Network Modelling in part of Upper Assam Basin, India

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Keywords

Seismic inversion, Acoustic impedance, Neural Network, Volume of shale

Summary

In petroleum exploration, seismic amplitude information is used to delineate the lithology type and the presence of fluid. To infer the detailed rock and fluid properties, well data has to be carefully and closely integrated with the seismic data. A successful reservoir characterization mainly includes derivation of rock properties from the seismic data and relates them to reservoir properties and mapping their distribution within the reservoir. Post-stack seismic inversion has been carried out to understand various rock properties from the seismic section. To delineate and resolve sand reservoirs accurately, an approach has been made here to extract the reservoir properties utilizing Multilayered Feed Forward Neural Network (MLFN) technique. This technique is applied in geologically challenging Upper Assam basin of North-East India for estimating volume of shale (V_{sh}). By knowing the V_{sh} distribution, other reservoir properties can be properly estimated in the reservoir. The method is proven successfully in this study area with better correlation results between the actual and predicted V_{sh} .

Introduction

Understanding the lateral variation in reservoir quality using seismic data is essential for reservoir characterization study. Neural networks (NN) are now being used frequently for quantitative analysis of reservoir properties. It is used to predict log properties from seismic data away from well locations. MLFN analysis is carried out to establish a nonlinear relationship between seismic attributes and reservoir property at well locations provided an improved correlation between the predicted and the actual logs (Das et al., 2017, Das and Chatterjee, 2016, Kumar et al., 2016, Singha et al., 2014). The main objective of this study is to develop MLFN model for estimation of V_{sh} using acoustic impedance

(AI), shear impedance (SI), porosity (ϕ) and density (ρ) derived from post-stack seismic data. The model based post stack inversion section is used to predict V_{sh} section in Upper Assam reservoir. By knowing the amount of clay present within a reservoir, better estimations of effective water saturation and effective porosity can be obtained. For reservoir characterization, porosity and water saturation are the crucial factors in quantifying producible hydrocarbon. Shale volume could also be used as an indicator of zone of interest.

Geologic background of the Study area

The present study deals with the Upper Assam Basin, located in northeastern India, which constitutes one of the most important onshore petroleum provinces in India. Important hydrocarbon-producing strata include: Eocene Sylhet and Kopili, the upper Eocene-Oligocene Barail Group, and Miocene Tipam and Girujan group. The main target in this study is the Barail Group of Oligocene age which is the main producing reservoir of this basin. The Barail units can contain interbedded coals, sandstones, and shales. Sylhet formation mainly consists of limestone with alternation of shale and sandstone which is deposited in a shallow marine carbonate environment. The Eocene and Oligocene Barail group comprises as much as 900 m of sands with minor shales deposited in a delta front environment. The Lower Miocene Tipam Formation sandstone is largely of fluvial origin and the heavy mineral content of the unit indicates derivation from the rising Himalayas, with depositional transport towards the south (Mathur et al., 2001). The overlying Girujan formation consists of more than 1300 m of mottled clays containing minor sandstone lenses (Wandrey, 2004) deposited in a lacustrine to fluvial environment. Current oil and gas production in the region occur mainly in the south of the Brahmaputra River and north of the Naga thrust belt (Figure 1).

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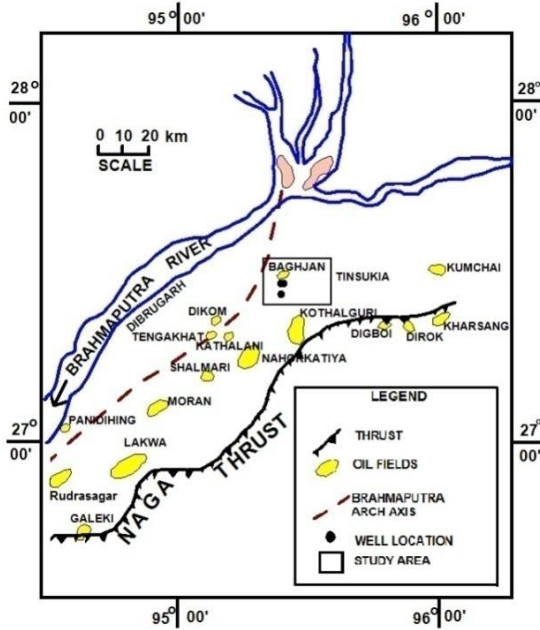


Figure 1: Showing distribution of oil fields and well locations in study area of Upper Assam Basin.

Methodology

Post-stack seismic inversion is carried out and results used to derive SI, ρ and ϕ using transform on AI volume. The seismic attributes AI, SI, ρ and ϕ are used as input in computation of V_{sh} value in MLFN model. This methodology is applied to three wells (M1, M2 & M3) and 2D post stack seismic section from parts of Upper Assam basin (Russel and Hampson, 1991). Two wells (M2 and M3) are used as training well and M1 well is used to validate the result. Trained neural network from two of the wells is applied to the 2-D seismic section to generate V_{sh} distribution and validate the results using the third well. Finally the trained network is used to generate subsurface V_{sh} distribution map on the seismic section within a time interval of 1550–2250ms. The low values of training error and validation make reliable V_{sh} prediction.

Figure 2 is showing the procedure for estimation of V_{sh} from post-stack seismic section (Figure 3) crossing three wells. Actual values of shale volume at the three well locations have been evaluated from

gamma ray readings using the following relation (Bateman, 1985)

$$V_{sh} = \frac{GR_{log} - GR_{min}}{GR_{max} - GR_{min}} \quad (1)$$

Where,

V_{sh} = volume of shale

GR_{log} = gamma ray reading of formation

GR_{min} = minimum gamma ray reading (clean sand)

GR_{max} = maximum gamma ray reading (shale)

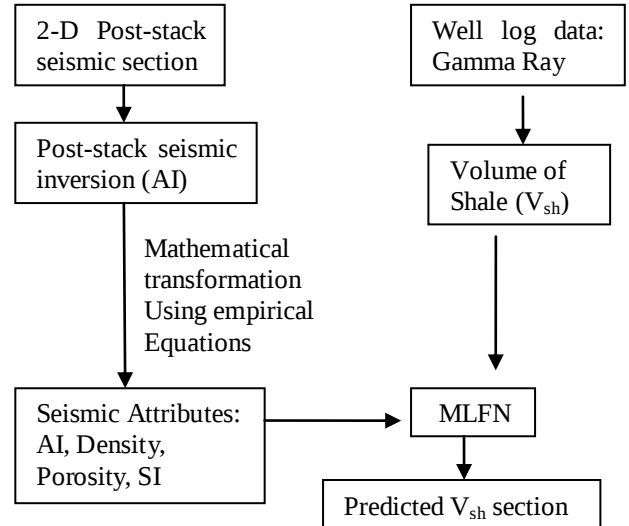


Figure 2: Flowchart showing methodology for prediction of volume of shale using MLFN model.

Using acoustic impedance (AI) inversion from post-stack data the seismic amplitude is transformed to its layer properties (Figure 4). AI, SI, ρ and ϕ sections have been used to train the MLFN model for mapping V_{sh} obtained from well logs in part of Upper Assam basin. SI, density and porosity sections are generated by mathematical transformation from inverted AI section. An empirical relation is carried out between SI and AI for well M1 of Upper Assam

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basin as shown in Figure 5(a). The transformation equation is obtained as $SI = 0.75AI - 1936$ with a coefficient of determination (R^2) = 91%. Using this transformation, SI section is generated from inverted AI section. Similarly, an empirical equation of

Porosity and AI ($\phi_D = -0.00005AI + 0.51$) is established (Figure 5.b). Using this relation, porosity section is created by transforming inverted AI section (Figure 6). Density section is derived from the inverted AI and P-wave velocity (V_p) sections.

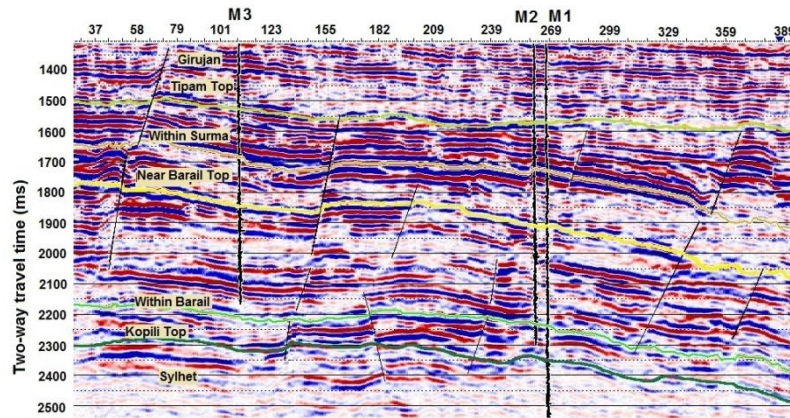


Figure 3: Seismic section of part of Upper Assam Basin

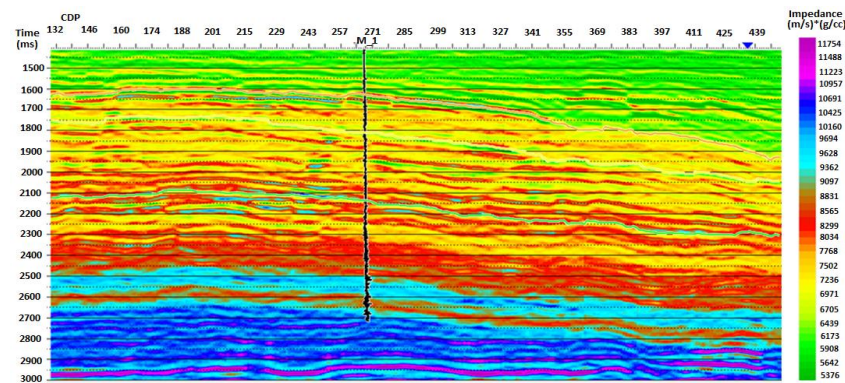


Figure 4: Inverted Acoustic Impedance section of the 2-D post-stack Seismic data.

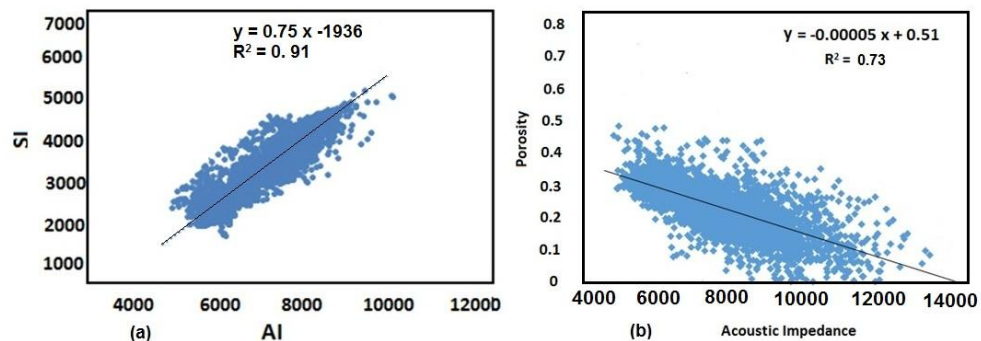


Figure 5: Empirical relation between (a) SI and AI & (b) Porosity and AI for well M1 of Upper Assam Basin.

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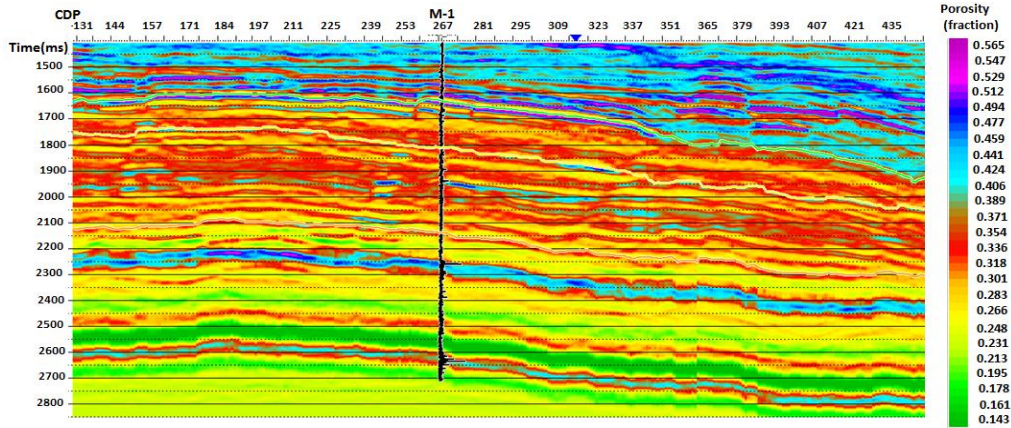


Figure 6: Porosity section of Upper Assam basin using transformation equation.

Results and Discussion

The training data set is used to derive the transform, while the validation data set is used to measure its prediction error. Figure 7 depicts the correlation between actual V_{sh} from well log data and predicted V_{sh} from neural network analysis. The training error and cross-correlation is found to be 0.039 and 0.72 respectively (Figure 8.a) within a time window 1700-1800ms. The validation error is 0.049 for the seismic section (Figure 8.b). The derived V_{sh} shows strong correlation with the actual volumetric logs, both at training and validation well locations. It suggests that V_{sh} can be estimated from seismic data using neural network analysis and thereby ease to understand the lateral variations of reservoir property away from the wells.

MLFN method	Cross Correlation	Training Error (fraction)	Validation Error (fraction)
V_{sh}	0.72	0.039	0.049

Table 1: Showing error in construction of MLFN model for predicted V_{sh} .

The predicted V_{sh} derived from MLFN analysis varies from 24% to 49% (Figure 9). Inverted Porosity value varies from 14% to 57% around well M 1 (figure 6).

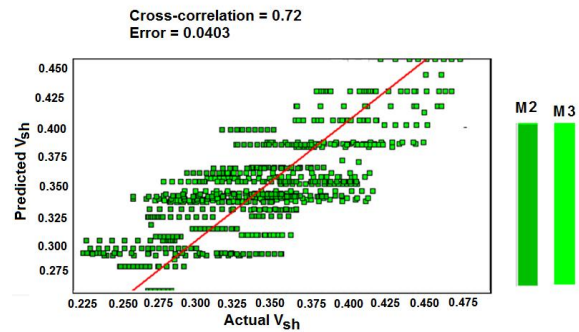


Figure 7: Cross-correlation between actual and predicted V_{sh} is 0.72.

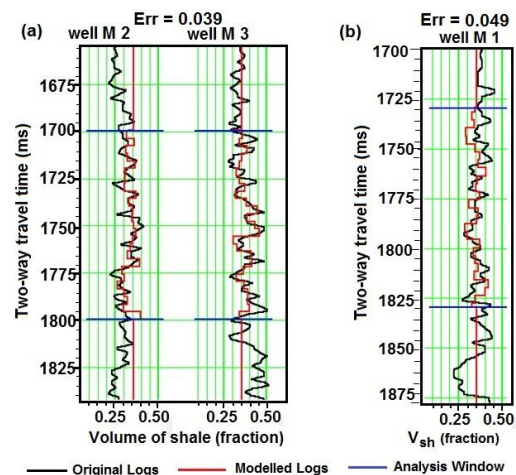


Figure 8: (a) Training error is 0.039 and (b) Validation error is 0.049 for the seismic section of Upper Assam basin.

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In Figure 9, a high V_{sh} zone above 1500 ms corresponds to the Girujan clay formation. The same zone is clearly indicated by the low impedance (in Figure 4) and high porosity (in Figure 6) above 1500ms. The Tipam series includes sandstones that are somewhat coarser, mottled clays, and a few conglomerates. The Surma series consists of alternating beds of shale, sandy shale, shaly sandstone, sandstone, and conglomerate (Corps, 1949). The zone between 1550-1750 ms shows alternate layers of shale and sand (Figure 9), that corresponds to part of Tipam and Surma group. Comparatively low V_{sh} zone with shaly sand features is exhibited from 1800 to 2200ms (Figure 9), which is the Barail group of Oligocene age. The same

low values of training and validation error make reliable estimation of V_{sh} in this study area. The estimated MLFN predicted V_{sh} model follows the general geological trend of Upper Assam basin. Since presence of shale impact the reservoir quality, shale volume estimation is important parameter in log analysis. So it is important to determine the shaly sand analysis in reservoir characterization studies. Better estimations of hydrocarbon production can be achieved by understanding the shale distribution and knowing the volume of shale in the reservoir.

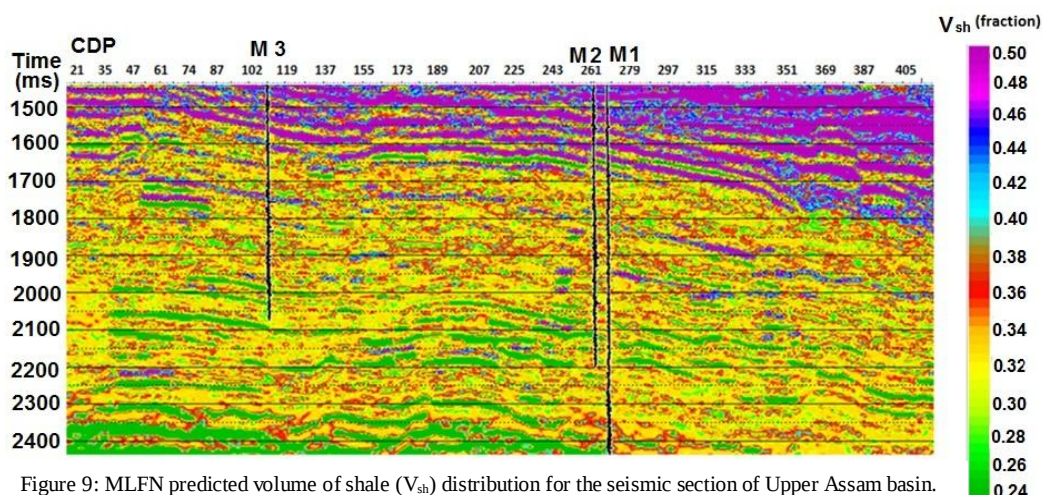


Figure 9: MLFN predicted volume of shale (V_{sh}) distribution for the seismic section of Upper Assam basin.

formation within 1800–2100 ms is characterized by a high value of porosity (27%-38%) in figure 6 and low AI value (in Figure 4) compared to its lower zone. This is the main producing reservoir in Upper Assam basin. This formation serves as a good shaly sand reservoir in this study area. A low V_{sh} , high AI and low porosity zone from 2350 ms characterizes the Sylhet limestone formation of middle Eocene age.

Conclusions

This new approach to shale volume prediction from post-stack seismic section using neural network proved to be effective in Upper Assam basin. The

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