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Low Frequency Model enhancement using Multi-Attribute Regression & Probabilistic Neural Network methods for Pre-stack Simultaneous Inversion – A case study from Krishna Godavari Basin, East Coast India

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Key Words:

Multi-attribute regression, Probabilistic Neural Network, Non-linear transforms, Low Frequency Model, Prestack Inversion.

Abstract:

Seismic inversion is an inevitable tool for reservoir characterization jobs during hydrocarbon exploration and development. To understand reservoir facies, Geoscientists often generate relative acoustic impedance and absolute acoustic impedance 3D volumes using seismic data. Relative acoustic impedance may not be sufficient to reveal the reservoir rock properties completely; quantitative interpretation requires a fair knowledge of absolute impedance inversion of the seismic data. Workflow of prestack deterministic inversion comprises of wavelet extraction, well-to-seismic tie, low frequency model (LFM) building, parameterization and inversion. As seismic data is band limited; during quantitative reservoir studies, an accurate low frequency model is essential to reveal the information related to geological structure. In practice, LFM is built using well logs (elastic properties to propagate), horizons and faults (structural trends for property propagation).

Multi-attribute regression methods are now widely used to train the log / rock properties at the well location and predict the same at the prospect locations away from the well positions. This method, unlike other conventional methods of interpolation, renders results equivalent to geostatistical methods to predict and generate elastic rock property volumes. Conventional techniques of interpolation which mainly uses well logs, are mostly based on the distance between the sample points and this sometimes may lead to artifacts if the sample points are inadequate or sparsely located. Multi-attribute regression methods which use seismic data and the derived attributes, give a plausible trend for interpolation between sample points. In this work, pre-stack simultaneous inversion was carried out using a robust low frequency model generated using the multi-attribute regression and probabilistic neural networks methods.

The current study demonstrates better delineation of reservoir geometry brought in the inversion output by the enhancement in the LFM generated using EMERGE algorithm - which provides a better geological model integration in the LFM building process.

Introduction:

Krishna-Godavari (KG) sedimentary basin, in the East coast of Indian peninsula, has got considerable hydrocarbon potential under the Yet-to-Find (YTF) category. Exploration in synrift plays is always challenging as the basin witnessed polycyclic rifting. Rift sediments approx. 900m are present in the areas where exploratory wells are drilled. Conventional core studies and the geological understanding of the area suggests that the deposition during the Jurassic – Cretaceous rift is occurred mainly in the fluvial environment. The study area falls in the shallow waters of the offshore block with a bathymetry range of 10m to 200+m **(Fig. 1)**.

A prestack deterministic inversion was carried out using CGG Jason Geoscience Workbench to bring out the hydrocarbon prospectivity within rift fill in the area. In this work flow, LFM was built in Jason platform using well logs and horizons only. However, in order to refine the inversion output, the LFM was further improved using HRS-EMERGE multi-attribute PNN method. The LFM thus generated was used as an input to carry out prestack simultaneous inversion which resulted in a better geological understanding.

Methodology:

Multi-attribute regression is an interpolation technique that uses both well log and seismic data to establish a relationship between various attributes and the available log curves (Hampson et.al., 2001). During the study, Hampson-Russell EMERGE module was utilized for generating the low frequency models for elastic properties P-impedance, Vp/Vs and Density. EMERGE module analyzes and uses several attributes to predict one variable by using multivariate geostatistics. In this process, software analyses a set of available attribute volumes to determine a group of attributes for an effective interpolation using a process called stepwise regression (Draper and Smith, 1966).

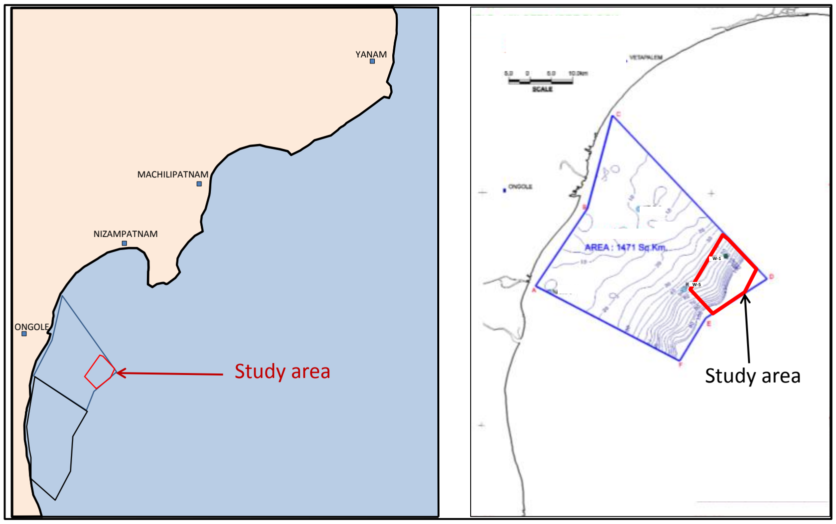

Fig.1: Location map showing the study area (red polygon) in the east coast of India (on left). Zoomed based map with bathymetry contour overlaid (on right)

As the low frequency information is vital in extracting reservoir parameters, an accurate interpolation is required to predict the same away from drilled wells. The missing low frequency part of the inverted impedance data can be predicted by distance based lateral interpolation methods. Quite often this may lead to artifacts and non-geological interpretations **(Fig.2)**. To generate model/trend data corresponding to P-impedance, Vp/Vs and Density, three EMERGE projects were created using target logs viz., P-impedance, Vp/Vs and Density using 3D Pre STM data, RMS velocity, Relative Acoustic Impedance (RAI) attribute volume generated using the post stack seismic data, Discontinuity attribute and Low Frequency Model (LFM) built using single well data. The LFM generated using single well curves (P-impedance, Vp/Vs and Density) can be treated as a representative compaction trend in the area of study.

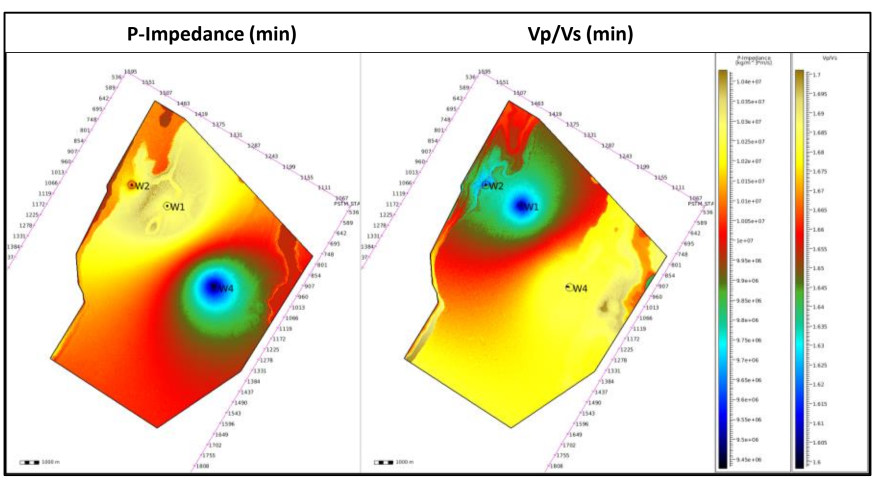

Fig.2: Window attribute for P-impedance and Vp/Vs extracted from the respective LFMs generated using inverse distance interpolation method

During the multi-attribute training process, various attributes were generated using seismic as internal volume, RAI and single well LFM as external volumes. It is observed that with increased number of attributes, training error is getting reduced, however, the validation error shows ups and downs with increasing number of attributes. Validation error was tested for different operator lengths (using 1,3,5,7 & 9 attribute sample points) and the number of attributes and operator length corresponding to the lowest validation error was chosen to avoid over-training of the attributes (as described by Hampson et.al., 2001). Cross plot between the target log vs. predicted log curve were analyzed for scatter points and correlation. Subsequently, the optimized multi-attribute list with suitable operator length was chosen as one of the inputs for Probabilistic Neural Network (PNN) interpolation along with target log curves. Representative validation plots (curve view & crossplot) for P-impedance and Vp/Vs are given in **Figure 3a & 3b**.

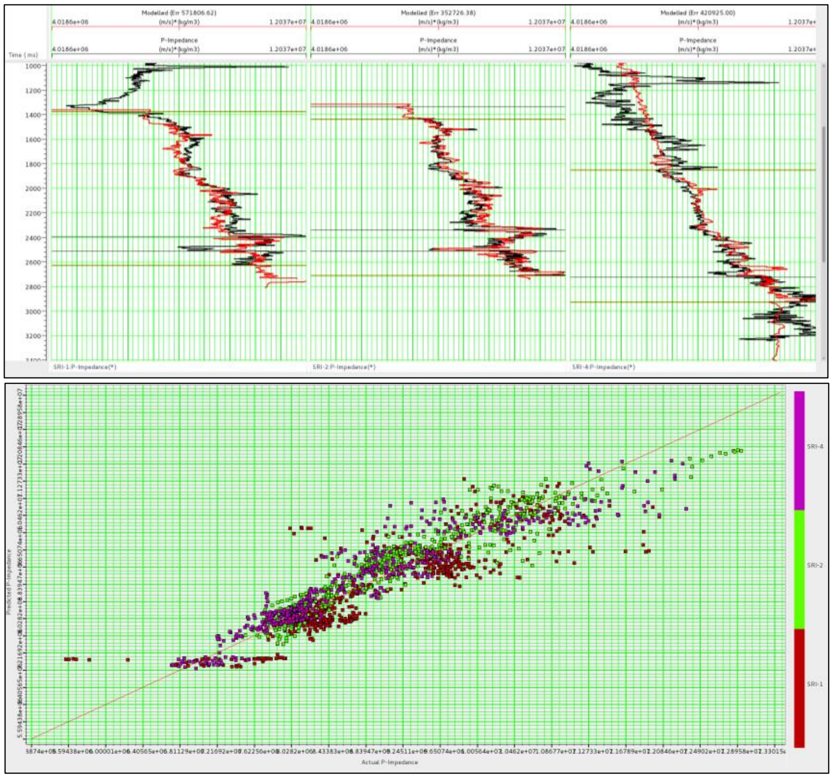

Fig.3a: P-impedance validation curve view after multi-attribute regression (top) and the validation crossplot (bottom) in the zone of interest

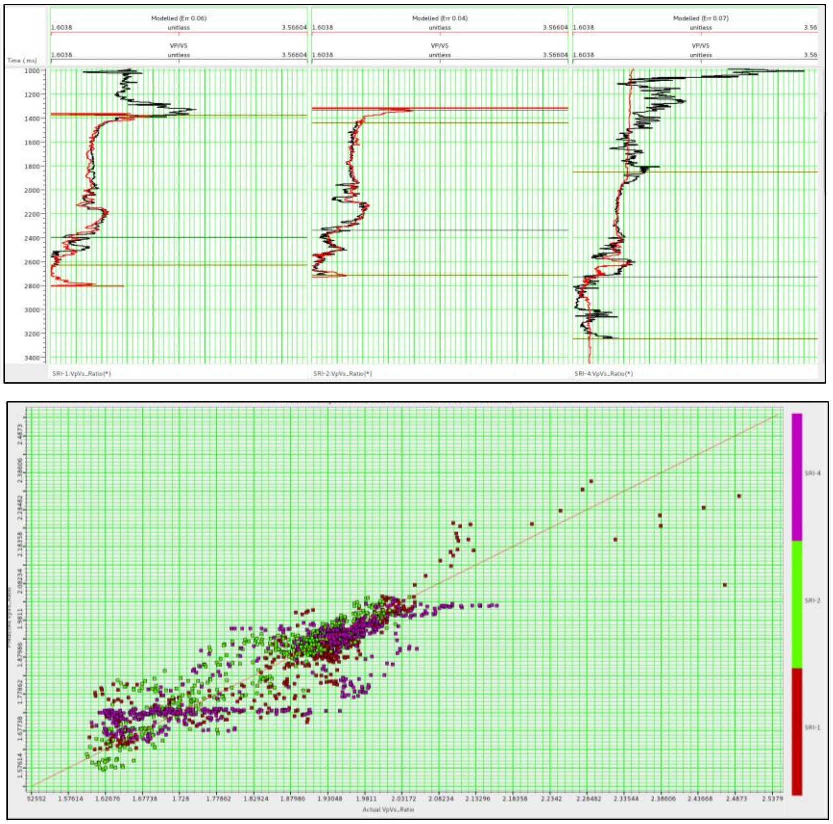

Fig.3b: Vp/Vs validation curve view after multi-attribute regression (top) and the validation crossplot (bottom) in the zone of interest

After neural network training and validation is done, both training and validation errors were reduced and correlations were found to be improved. On application of PNN with selected attribute list, elastic property volumes were generated for P-impedance, Vp/Vs and Density. Model data thus generated was analysed and quality checked using horizon slices in the zone of interest **(Fig.4)**. Subsequently, property volumes of P-impedance, Vp/Vs and Density were incorporated as an LFM in the Pre-stack deterministic inversion.

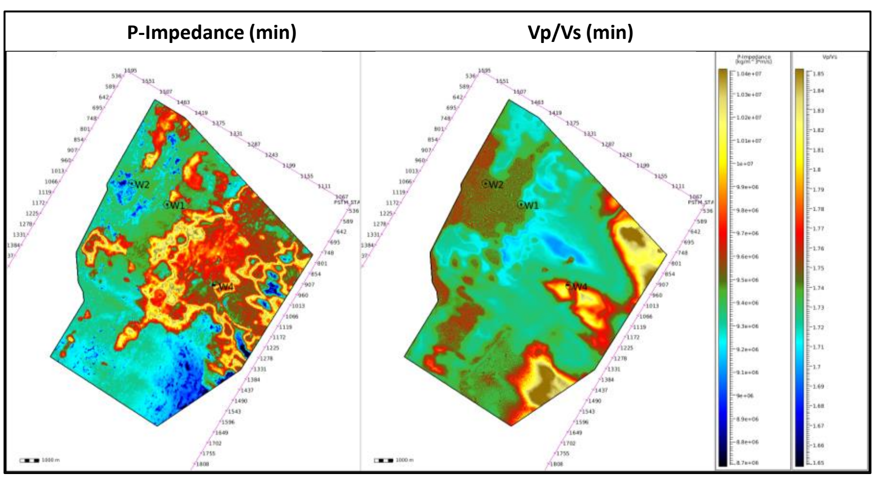

Fig.4: Window attribute for P-impedance and Vp/Vs extracted from the respective LFMs generated using EMERGE multi-attribute regression method

Probabilistic Neural network (PNN) property prediction:

Probabilistic Neural network (PNN) is widely used in classification and pattern recognition problems. PNN determines weightage of various attributes using a Gaussian kernel estimator based on the distance in the seismic attribute space from known point to an unknown point. In practice, PNN property prediction can be elaborated as follows.

1) Stepwise multi-linear regression analysis and validation.
2) Training of neural network to establish a non-liner relationship between seismic attributes and elastic properties at well locations.
3) Application of trained neural network to input data volumes.
4) Validation of results at well positions by dropping one well at a time and predicting it from other wells and attributes.

Multi-attribute property prediction: EMERGE property volumes of P-impedance, Vp/Vs and Density were generated using log data of three exploratory wells, PSTM data, RMS velocity, RAI, Discontinuity and single well based LFM. Application and validation error plots were analysed after the multi-attribute training performed with 15 attributes and 5 different operator lengths. Target logs (HC of 60Hz) overlain with predicted logs are showing a good match. Crossplots of target logs (P-impedance, Vp/Vs & Density) vs predicted logs (P-impedance, Vp/Vs & Density) show a linear fit. From regression analysis, correlation coefficients for P-impedance, Vp/Vs & Density are found to be 0.91, 0.89 and 0.82 respectively.

During the PNN training, multi-attribute list with least validation errors were chosen as one of the inputs along with property log at the well locations. It is observed that after PNN training and validation the correlation coefficients were improved, indicating a better prediction of log properties.

Results and Discussions:

In the conventional LFM, horizons and faults are used to provide the geological model whereas in EMERGE algorithm, multi-attribute interpolation of properties and the structural frame work provide a robust geological model for inversion process. This, in turn delivers a better interpretation of the properties for facies prediction.

Model files of P-impedance, Vp/Vs and Density were generated using the inverse distance interpolation method and EMERGE multi-attribute regression methods were utilized in two separate deterministic inversion workflows. Outputs of the inversion studies were compared by generating attribute slices for various windows and analysed for improvements. It is observed that the outputs of the inversion using multi-attribute regression had given better results compared to the one utilized conventional LFM. This also helped in better delineation of geobodies.

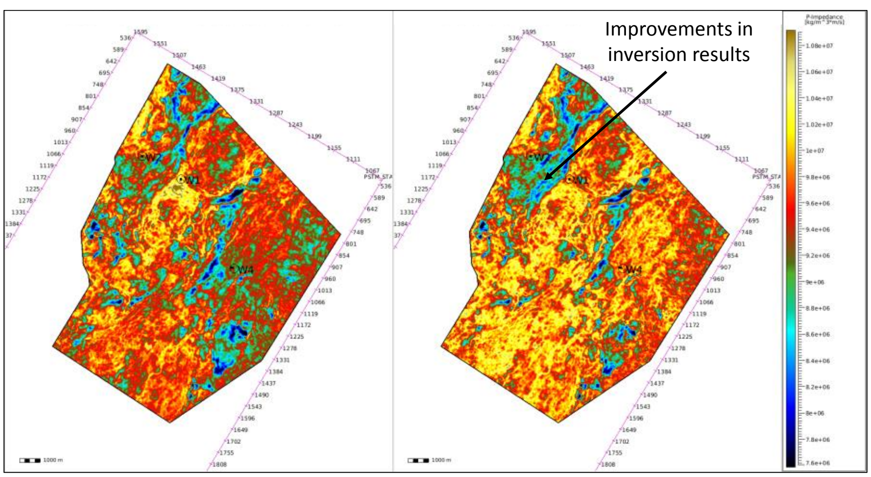

Fig.5: P-impedance slices from prestack inversion outputs generated using conventional LFM (left) and EMERGE multi-attribute LFM (right)

A representative attribute slice of P-impedance and Vp/Vs demonstrating the improvements in the inversion outputs are shown in **Figures 5 & 6** respectively. The inverted outputs thus generated may help geoscientists to perform interpretation of the subsurface reservoir properties with good confidence and may lead to better geological understanding of the area.

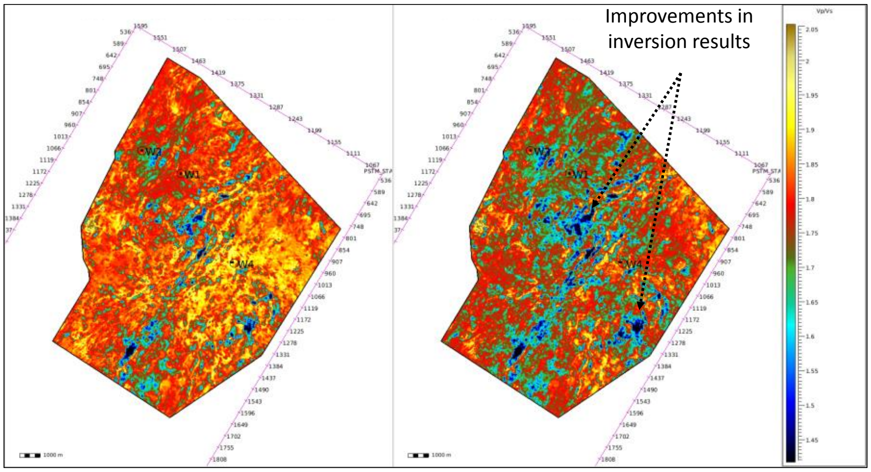

Fig.6: Vp/VS slices from prestack inversion outputs generated using conventional LFM (left) and EMERGE multi-attribute LFM (right)

Conclusion:

Multi-attribute regression and neural network are better methods of interpolation where sample data is inadequate or sparsely located. In the event of sparse point data, conventional methods of interpolation viz, inverse distance, triangulation, local/global weighted may lead to bull's eyes in the vicinity of the data. Conventional interpolation algorithms give maximum weightage to the sample point data and hence, the predictability at areas close to sample points are good. However, the predictability becomes poor with distance and this sometimes may lead to non-geological interpretations. Comparison of the P-impedance and Vp/Vs attribute slices corresponding to the rift sequences extracted using the inverse distance based LFM and the Multi-attribute and PNN based LFM show betterment in the property prediction away from the well positions. Further, this study vindicates the prestack inversion using these LFMs improved the quality of outputs, P-impedance, Vp/Vs and Density to characterize the reservoir facies.

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