Generation of Pseudo-Log Volumes from 3D Seismic Multi-attributes using Neural Networks: A case Study

V.B.Singh, S.P.S.Negi, D.Subrahmanyam, S.Biswal & V.K.Baid

G&G Group, MH Asset, SPIC, ONGC, Mumbai

ABSTRACT : Multi-attribute and neural network analysis was attempted with the help of EMERGE™ software of Hampson-Russell for generation of pseudo log volumes with integration of seismic and petrophysical properties. Neutron porosity log was taken in first phase as target and window of A1 layer of LIII reservoir was taken for analysis. Multi-attributes were generated from 3D seismic volume including inversion of seismic data and it was found that multi-attributes are useful for the improvement in the correlation factor. Cross-correlation was established between log based neutron porosity and seismic derived neutron porosity using multi-attributes and it was applied to complete volume of seismic data of ZA area of Mumbai High field for converting it into neutron porosity volume. The slice for porosity was generated for A1 layer and it was found that it is matching with porosity measurements at wells satisfactorily. Neural networking method has also been attempted. Encouraged by the result, pseudo log volume for DT (sonic), LLD (resistivity), GR (Gamma Ray) and RHOB (density) were also prepared applying the same methodology. Predictions of reservoir properties as porosity, shale volume, water saturation, fluid content, etc in 3-D volumes based on these pseudo log volumes have also been discussed using basic formulas to generate petrophysical properties from logs. Average prediction error and validation error were found within tolerance limit. It can be utilized in identification of sweet zone, preparation of prognosis for multilateral horizontal well and volumetric computation.

INTRODUCTION

The injection and production wells must be optimally placed for efficient oil recovery. Change in lithology, presence of shale and fault can hamper the free flow of oil and/or gas and reduce productivity. Therefore, subsurface must be well understood.

Wells drilled into the reservoir to test stratigraphy are primary tool for this investigation, but these wells are mostly away from the proposed location of the development wells. On the other hand, seismic traces are available at close grid interval and contain all the information contained in petrophysical logs. Seismic data can help to resolve the reservoir characteristics by analyzing the depth, thickness of the reservoir layer and petrophysical property such as porosity, shale volume, and water saturation of the layers in the form of pseudo-well logs. Volumes of NPHI, RHOB, gamma ray, resistivity and sonic logs have been generated using relation between seismic and log properties. Area around ZA platform was taken considering the importance of the area for upcoming horizontal wells and ZB platform. Finally, attempts have been made to compute the reservoir properties from pseudo log volumes generated from 3-D seismic volume.

STUDY AREA

The ZA platform area falls within one of the oil field of western offshore basin. The main carbonate reservoir L-III (Early Miocene) is divided into ten layers from A1 (top of reservoir) to C layer. The reservoir has a series of stacked limestone and shale with excellent reservoir quality in limestone. The layers have been deposited under intra tidal to supra tidal environment. The upper layer contributing to production was selected for the study. The area was selected excluding the gas cap area so that fluid effect on seismic property could be avoided during attribute analysis. New platform ZB is likely to be taken up in northern part of ZA platform area.

The area under investigation has the size of roughly 200 km^2 as shown in Fig1. Most of the wells have sonic, gamma ray, resistivity and density logs. The area is covered by good quality OBC seismic survey with close grid of 12.5x25mts. VSP data is available in BH-61 for depth to time relationship.

METHODOLOGY

Synthetic seismogram generated from sonic and density log were correlated with seismic data as shown in Fig 2 and good correlation was established for prediction of log property based on seismic data. Reference horizon A1 top and some lower horizons were mapped. Neutron log is more sensitive to porous formation and useful for quantification of porosity—the important factor for good reservoir. In this case study for carbonate reservoir of ZA area of Mumbai High field we have preferred NPHI log as target for the transformation of 3D seismic data in to pseudo NPHI log.

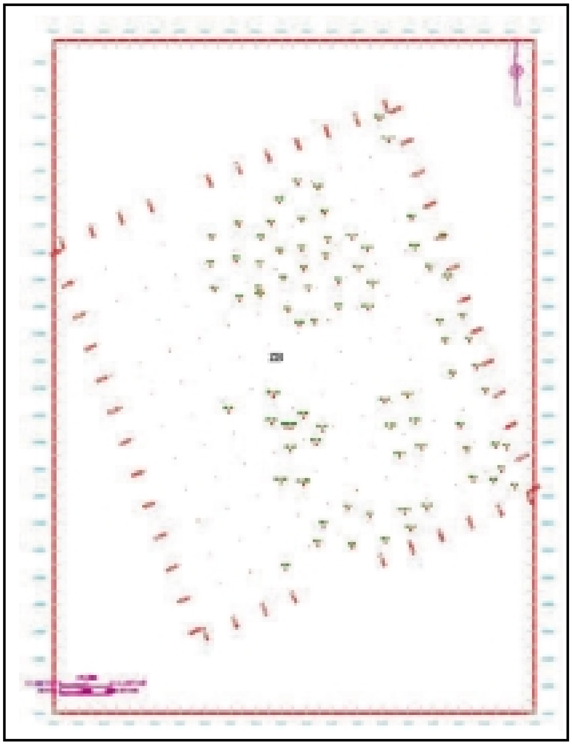

Figure 1: Location Map of ZA area

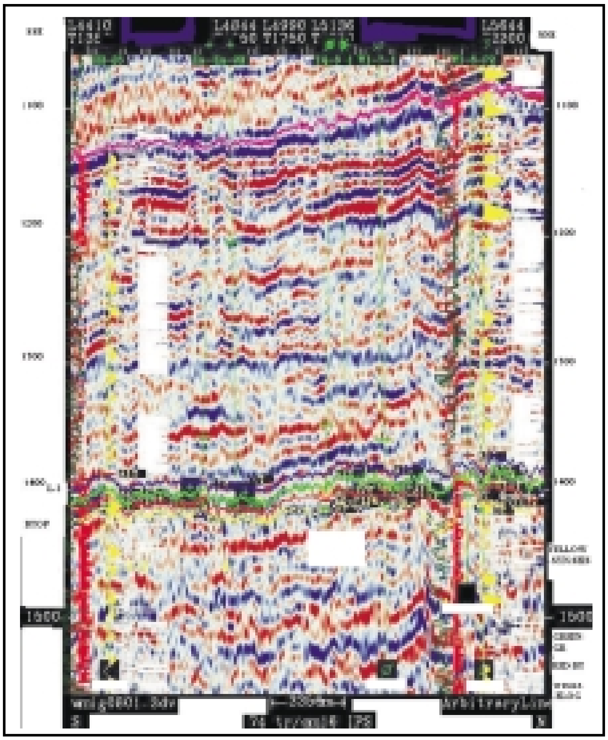

Figure 2: Seismic line superimposed with Synthetic seismogram and logs

The well data are key to establish the relationship between NPHI and seismic data. Used together with gamma ray log it helps to define shale, limestone and porous formation. In combination with density and /or sonic log it is useful in determining lithology and fluid type. Neutron log, despite being primarily a porosity tool, are also able to distinguish shale from limestone especially in situation when sonic and density logs are not available. Encouraged by the result, the gamma ray, DT and resistivity volumes have also been generated by establishing the relationship between seismic and wells.

All the three available processes such as single attribute regression, multi attributes correlation and neural network were tried in the study and finally multi-attribute and neural networking process was focused.

Single Attribute Analysis

In the first process, seismic attributes were extracted for each seismic trace near well. Nine traces surrounding well were taken to avoid the risk of taking noisy traces. Cross correlation between neutron log (NPHI) and single seismic attribute shows low correlation of 54 % and it fails to establish any relationship. Similarly acoustic impedance (external attribute) values were also tried without success.

Multi-Attribute Analysis

In the next step of analysis, five attributes namely acoustic impedance, amplitude weighted cosine phase, average frequency, instantaneous absolute amplitude and trace integrate were taken in combined way on the basis of their correlation with target log NPHI. Fig 3 shows the target log (red) of well X with few of the attributes. Cross correlation as shown in Fig 4 indicate a better correlation of 68%. By editing 2 or 3 samples, correlation improves to 70%. Five attributes were selected according to its correlation coefficient with target log. As shown in cross validation test (Fig 5) for attribute analysis, increase in number of attributes does not improve the correlation after certain limit. Validation and prediction analysis carried out for wells is shown in Fig 6.

Neural Networking Analysis

In the final step, neural networking approach was attempted .Validation test is critical part of the study .The key well of the area were divided into training and validation wells for acid test. Eight wells were selected for training process

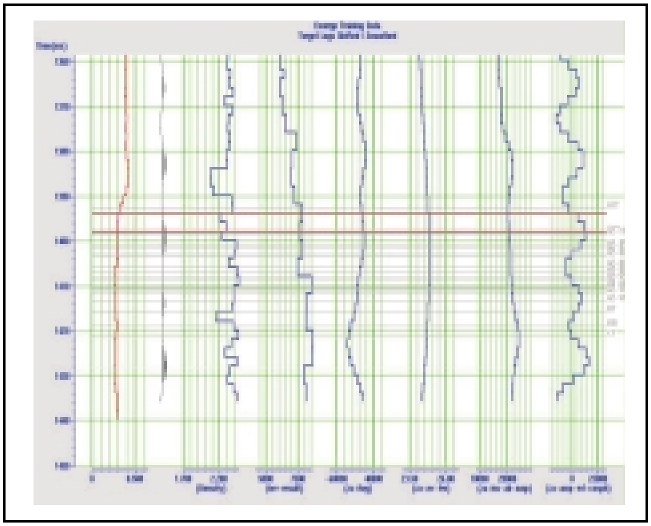

Figure 3: Target log NPHI with seismic attributes

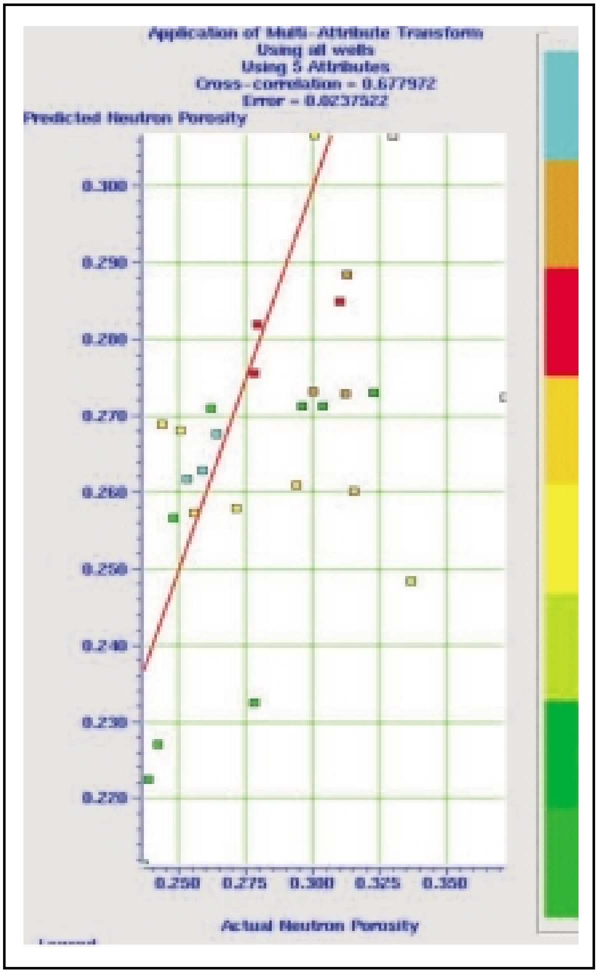

Figure 4: Cross plot of predicted and actual NPHI with multi-attributes

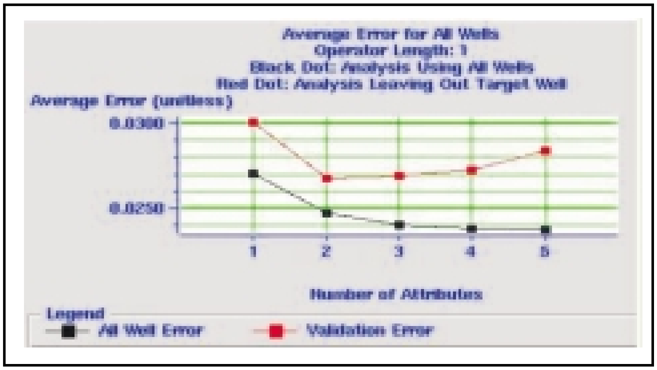

Figure 5: Prediction and validation error for seismic attributes

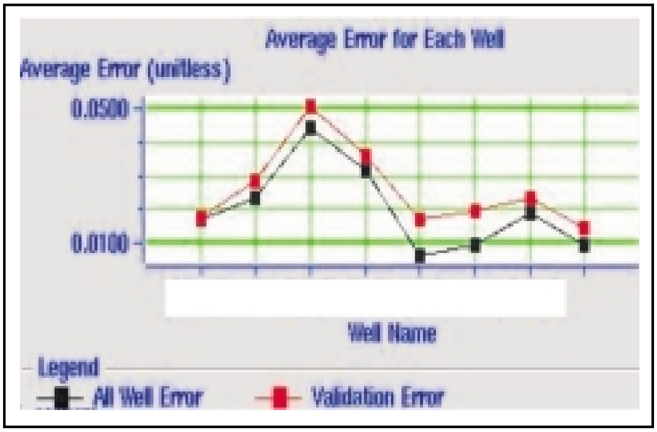

Figure 6: Validation and prediction error for wells

and other wells were kept aside for validation test. Since rock property influences the seismic property at the particular time and also values above and below due to nature of seismic wave convolution, a time window of one to three samples were taken for analysis one by one. One sample each was taken from above and below the time window to avoid the uncertainty of horizon mapping. The predicted and actual log value of NPHI is plotted in Fig 7, which shows increase in correlation up to the order of 70%. It indicates that neural network does not improve correlation much from multi attribute analysis particularly in this case. The modeled and actual log of each well as plotted in Fig 8, are superimposed with each other. Horizontal lines (blue), depicts the target zone A1 layer. Once excellent correlation was achieved between actual and predicted NPHI log values, the seismic 3-D volume was converted into 3-D log volume of NPHI with the help of EMERGE™ application of Hampson-Russell™ .In the same fashion, cross correlation between Sonic (DT), Resistivity (LLD), Gamma Ray (GR), Density (RHOB) log with seismic multi attributes were established individually and seismic volume was converted

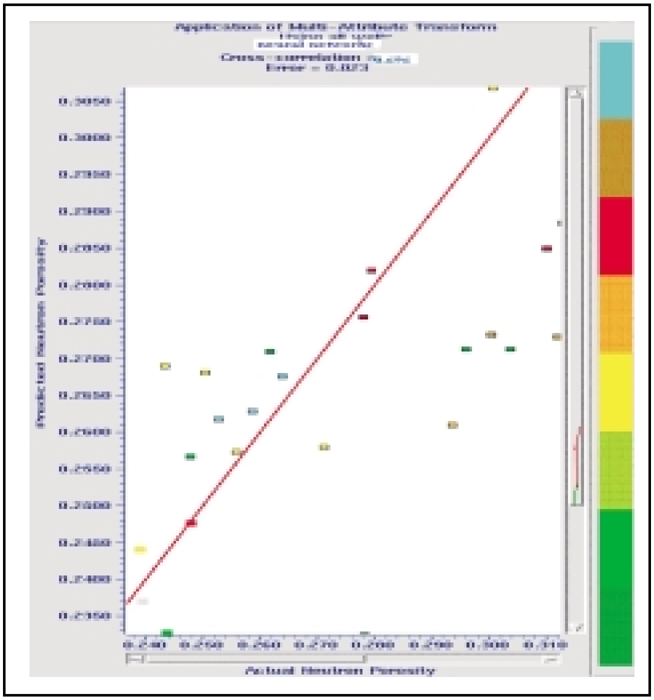

Figure 7: Crossplot of predicted and actual NPHI with neural network

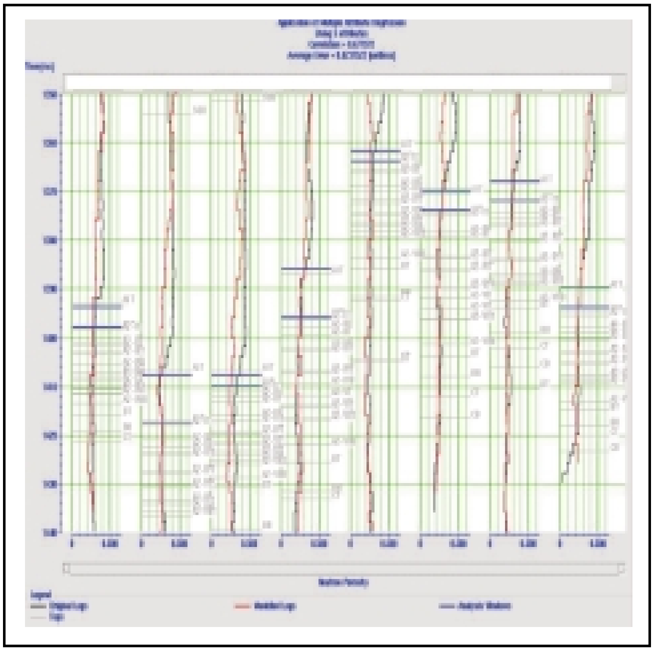

Figure 8: Actual NPHI log superimposed with predicted log

into pseudo log volumes. Reservoir properties such as shale contents, effective porosity, water saturation and permeability can be computed using the basic formulae from logs and taking these properties as target log, 3-D volume of seismic can be converted into 3-D volumes of rock properties with the help of EMERGE software application. Also, it can be done with the help of SeisWorks™ computation utility.

DISCUSSION

It has been observed that cross correlation was above 65% with all wells and improves to above 70% with editing and removing the spurious data. Cross correlation, as shown in Fig 9, 10 and 11, between computed and actual GR, resistivity and density data indicate correlation up to 90%, 77% and 84% respectively, with multi attribute analysis. Fig 12 and 13 are maps of pseudo NPHI values of A1 layer based on multi-attribute and neural network analysis. Neural network based map shows more variability in comparison to multi-attribute neutron PHIE map.

Although non-linear estimation may be able to increase the resolution in some cases, we should not expect to obtain a transformation as well log resolution because spectral content of log data is much broader than seismic. However, up scaling and smoothening of the log data, the problem is solved up to some extent. The standard linear regression based on single attribute method is not adequate to predict neutron porosity and other petrophysical properties. The difference

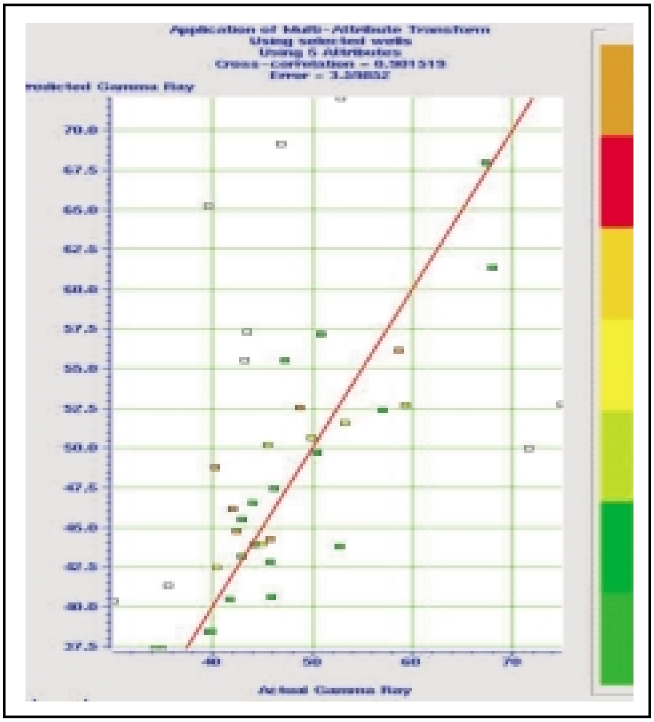

Figure 9: Cross Plot of predicted and actual Gamma ray

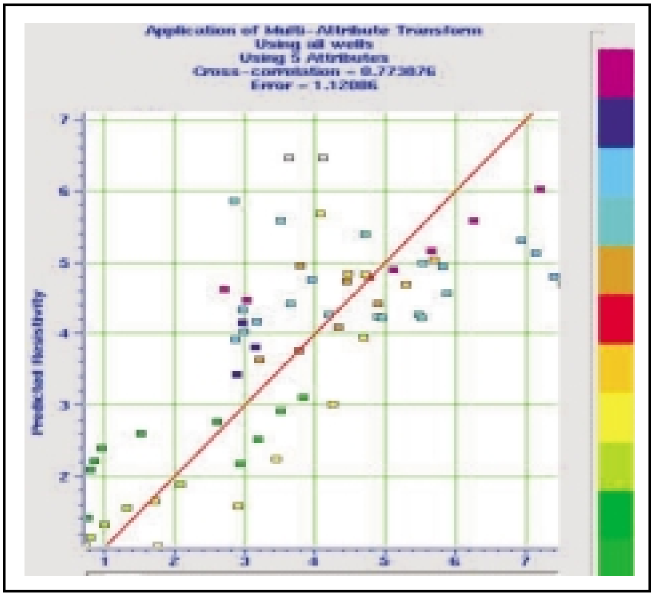

Figure 10 : Cross plot of predicted and actual resistivity value

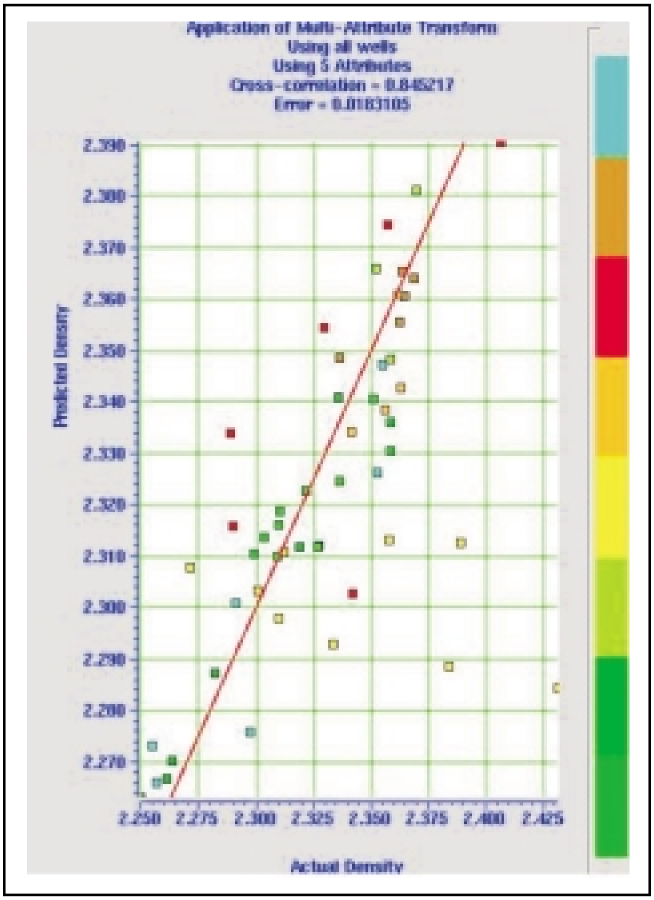

Figure 11: Cross plot of predicted and actual RHOB values

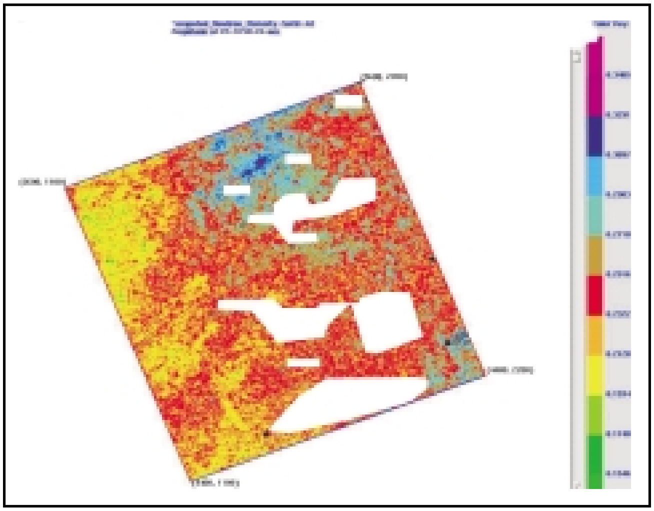

Figure 12 : Computed NPHI slice for A1 Layer (with multi attributes)

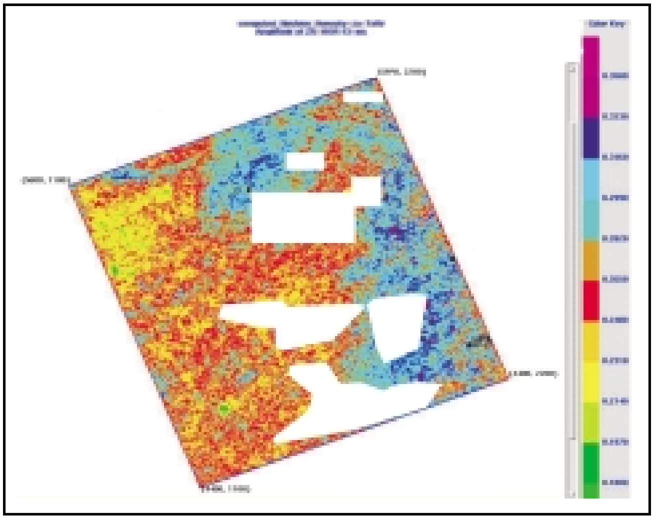

Figure 13: Computed NPHI map for A1 layer (neural network)

between predicted and actual neutron porosity is of the order of 3%. The multi attribute analysis improves the correlation coefficient and computed petrophysical properties become closer to log derived properties. Fig 5 indicates the average prediction error (black curve) around 0.024 (in fraction) and validation error (red curve) around 0.028. Validation error has been calculated by hiding each of the well and predicting its values using rest of the wells It represents the error we could expect if new well is predicted . Analysis as shown in Figure 6 for validity check for well shows that error is within 0.03 except well Y. On an average prediction and validation error is of the order of 3%.

The Probabilistic Neural Network (PNN) was trained to find best non-linear relationship between five attributes and log curve value. The results were improved over the regression model. PNN was only applied for neutron porosity computation. Other log curves were derived from multi-attribute analysis only. It has been observed that prediction becomes erroneous where well control is not available. PNN method works satisfactorily for interpolation but it fails where extrapolation is required and the prediction depends on the well situated at the edge of field.

In general, the increase in gamma ray value in map indicates the increase in shale content or more radioactive minerals. Increase in RHOB and resistivity values shows the decrease in porosity whereas increase of transit time value in sonic log (DT) indicates the development of good porosity or increase in shale content. In combination with GR log data it differentiates between porosity and shale. NPHI log value predicts directly about porosity in absence of shale. Considering all the maps it seems that ZA and ZB area falls in the good reservoir zone. Gamma ray, resistivity and DT maps of A1 layer as shown in Fig 14, 15 and 16 indicate the low Gamma, high resistivity and high velocity in North-west corner of the area. It indicates tight limestone having low porosity (ϕ). Fig 17 showing the map of density slice for A1 layer indicate low density near ZA area caused by good porosity. 3-D volume of Pseudo density derived from seismic is shown in Fig 18 and it is superimposed with RHOB (density) log of Y, one of the trained (reference) wells.

CROSS VALIDATION

Under the redevelopment plan of the field, few horizontal wells from ZA platform were drilled in the porous lime stone layer with the help of analyzed data and 3D volume

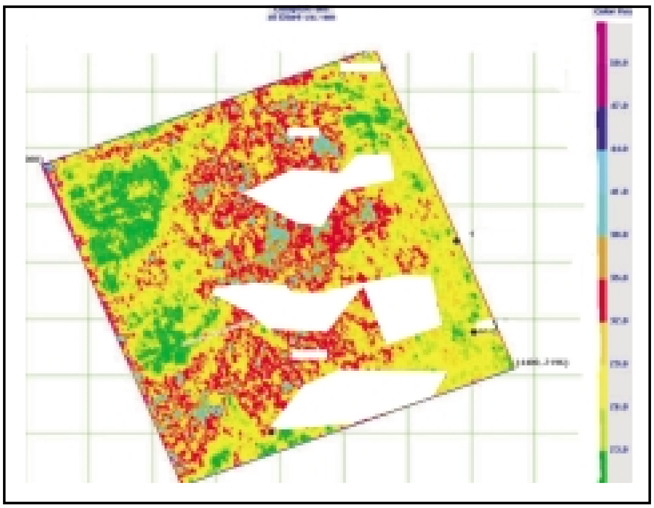

Figure 14: Computed Gamma ray map for A1 layer

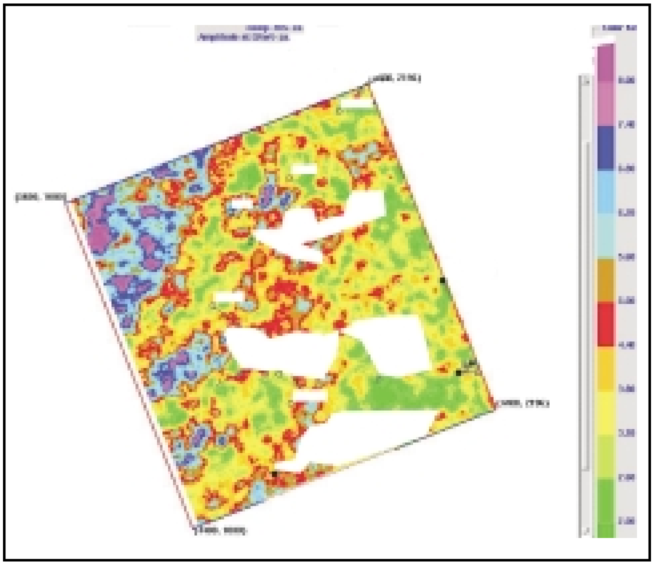

Figure 15: Computed resistivity slice for A1 layer

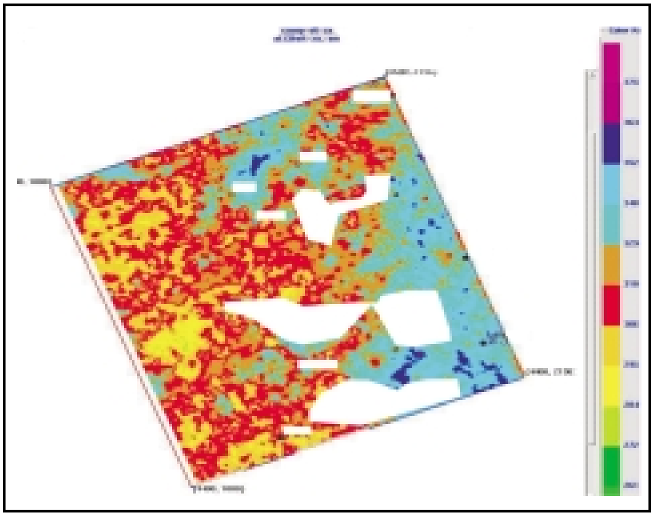

Figure 16 : Computed DT slice for A1 layer

of pseudo logs generated from seismic data. Fig 19 shows the successful encounter of reservoir layer having porosity range from 18% to 24% and shale layers were avoided. Fig19 shows seismic line passing through validation wells A, B and C. Scale of NPHI values for the superimposed wells is given at the top of wells. The predicted NPHI values were color coded and shown in vertical section superimposed with NPHI log of validation well. All NPHI anomalies were captured in the predicted pseudo-NPHI log profile.

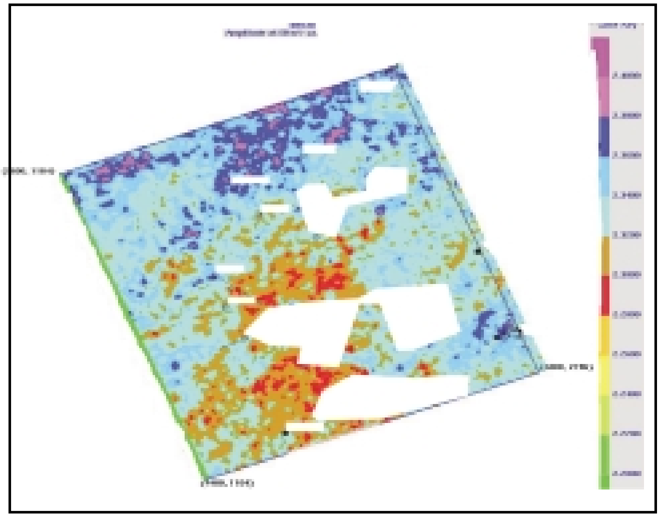

Figure 17 : Computed density (RHOB) slice For A1 layer

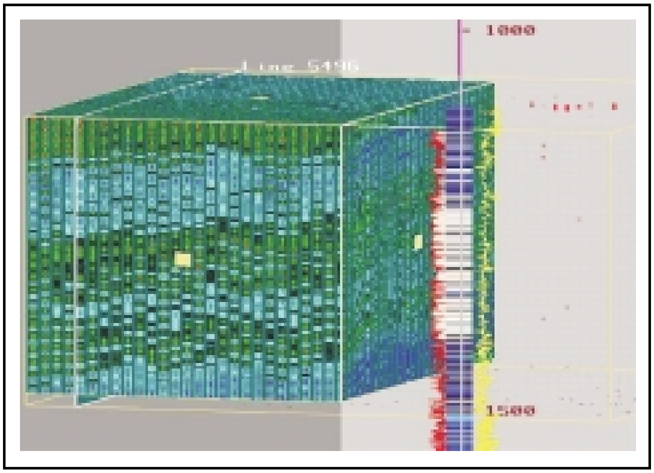

Figure 18 : Computed density cube with RHOB log of Y

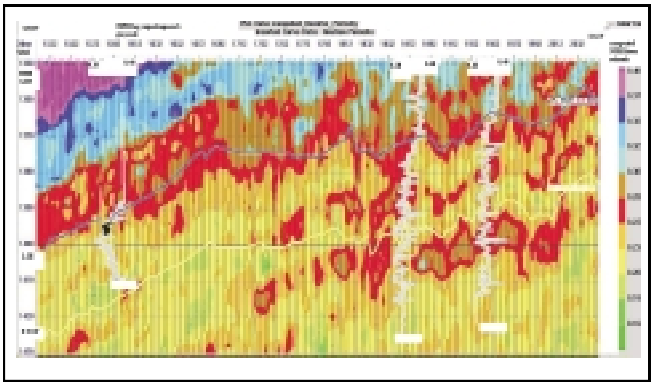

Figure 19: Neutron PHI profile superimposed with validation wells A, B and C.

COMPUTATION OF PETROPHYSICAL PROPERTIES BASED ON LOG VOLUMES DERIVED FROM SEISMIC

Generation of different log volumes and maps from 3-D seismic volume is not an end product. The ultimate goal is to predict petrophysical properties of reservoir .To paraphrase "A map is a poor model of reality if it does not depict the spatial distribution of rock properties which affect the reservoir". Mostly the petrophysical properties are derived from these logs either mathematically or graphically. Some of the computational method is given in brief as follows:-

Porosity Determination

(A) From Sonic log

$\Phi = (\Delta t-\Delta t_m) / (\Delta t_f-\Delta t_m)$

(B) From Density log

$\Phi = (\rho_m-\rho_b) / (\rho_m-\rho_f)$

1. Read Δt or ρ_b from sonic or density (RHOB) log in zone of interest.

2. Calculate ϕ using appropriate matrix and fluid as Δt_m (limestone) - 189 µsec/ft. (approx.), Δt_f (oil or water) = 47.6 µsec/ft. (approx.), ρm (limestone) = 2.71

Correction for compaction:-

$\phi = ((\Delta t - \Delta t_m) / (\Delta t_f-\Delta t_m)) \times (100/ \Delta t_{shale})$ if $\Delta t_{shale} > 100$

Correction for gas :-

Multiply estimated porosity by 0.7.Correction for oil:- multiply estimated porosity by 0.9 Correction for density derived porosity log as

$\phi_{corr} = \phi_{den} - (\phi_{sh} \times v_{sh})$ and $\phi_{sh} = (\rho_m-\rho_{sh}) / (\rho_m-\rho_f)$ for shaly formation.

(C) Neutron porosity log :-

$\phi = \sqrt{(\phi_n^2 + \phi_d^2)/2}$

ϕ_n = porosity value from neutron log, ϕ_d = porosity value from density log.

Water saturation and formation factor from Resistivity log:-

Water saturation, $S_w = \sqrt{R_o/R_t} = \sqrt{FR_w/R_t} = \sqrt{aR_w/\mathbf{\Phi^m}R_t}$

Farmation factor , $F = a/\Phi^m$

Oil Saturation $S_o = (1- S_w)$

R_o = Resistivity in water wet zone. R_t = Resistivity in oil zone.

Permeability $K = \sqrt{250 x \Phi^2 / S_{wirr}}$ for medium gravity oil
S_{wirrr} is irreducible water saturation

$K = \sqrt{79 x \Phi^2 / S_{wirr}}$, for dry gas

Shale volume from Gamma Ray log:-

Shale volume (shale content) $V_{sh} = (\rho_b xGR - GR_{clean}) / (\rho_{sh} xGR_{sh} - GR_{clean})$

ρ_b and ρ_{sh} are Observed from density log. GR_{clean} and GR_{sh} are observed from GR log for clean limestone and shale.

Graphically, cross plot can be generated between two porosity values derived from different log volumes as (1) Neutron – density cross plot (2) Density – Sonic cross plot and (3) Neutron – Sonic cross plot and appropriate value of porosity can be obtained.

Vertical sections or horizontal slices can be extracted from the generated pseudo log volumes at any proposed new location or zone of interest and petrophysical properties can be obtained simply by computation as above in advance before drilling wells and risk of drilling dry well or hazardous zone can be avoided.

Petrophysical properties such as V_{sh} (shale content) and effective porosity (Φ) for A1 layer computed from pseudo log volumes are given in fig.20 and 21.Shale content and effective porosity values are shown with color filled contour with color bar index. In effective porosity map, red color indicates 14% or less (low) and blue color indicates 28% (high) porosity values. In shale volume map, yellow color indicates 10% (low) and blue color shows 30% (high) shale content with interpolation of other values and gradation of colors. Average prediction error varies from 2 to 5% near wells. Most of the wells are deviated or horizontal well in the area and the actual petrophysical properties recorded at wells itself are affected by inclination. Prediction error is 5% only at one well, other wells are within error of 2 to 3%. Therefore prediction error upto 5% is considered tolerable for predicting the log properties or rock properties for future wells. Similarly, water saturation (S_w), oil saturation (S_o) and permeability (K) can also be computed from pseudo log volumes and calibrated with wells.

LIMITATIONS AND PRECAUTIONS

Reservoir thickness, depth structure, seismic constrained porosity and gamma ray values may be wrong if seismic horizon are mapped incorrectly and seismic is not properly tied with log. Poor quality seismic especially in case of complex geology can hamper horizon tracking.

Calibration of seismic with well log or synthetic seismogram improves depth conversion to time and visa versa. Additional data as VSP improves the conversion. In structurally complex area depth based processing as PSTM or PSDM from raw seismic is preferable.

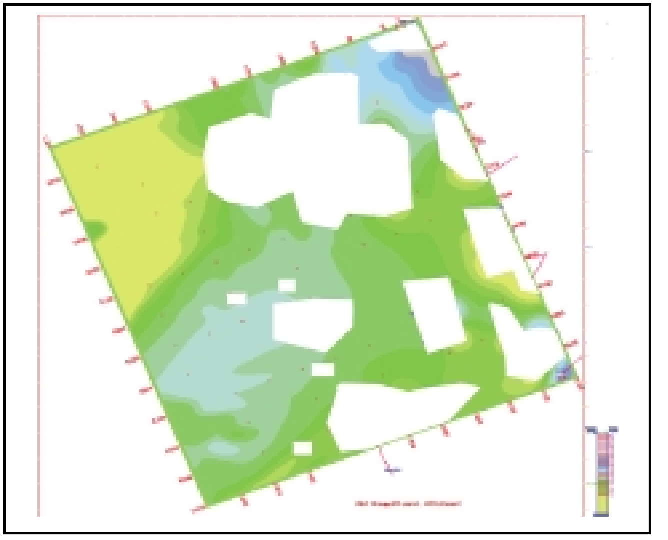

Figure20: Vsh (shale content) map of A1 layer derived from pseudo log

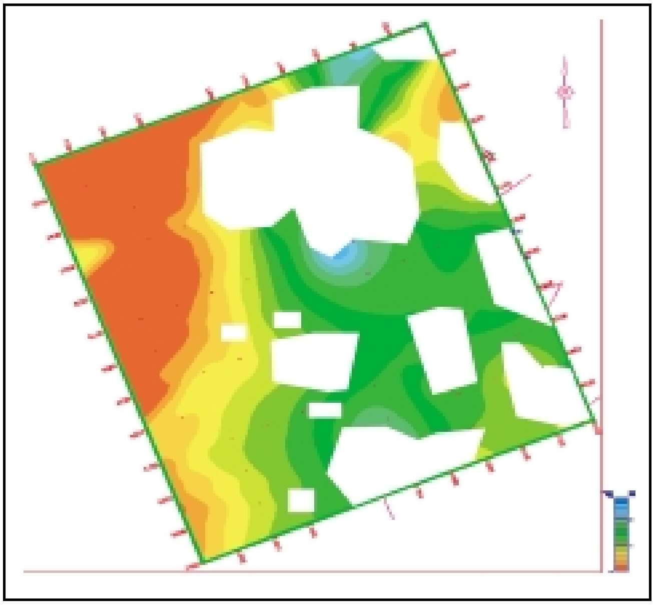

Figure21: Effective porosity map of A1 layer derived from pseudo log volume

Carbonates generally have higher interval velocity than inter-bedded shale. The high impedance contrast makes these interfaces strong contributor to multiple generations. Special data processing for multiple removals is very important in such cases.

We should not expect to obtain a transformation that goes all the way from seismic resolution to well log resolution because the spectral content of log is much broader than seismic data. Smoothing and re-sampling of log data is required but it will lose some details during this process which plays important role in simulation model.

CONCLUSION

Pseudo-log volumes derived from 3D seismic volume with the help of multi-attribute and neural network improves the reservoir characterization by providing information about petrophysical properties away from existing wells. Pseudo log volumes can be used as a steering component to derive deviation trends, identification of sweet zones and volume estimation. Risk of drilling dry holes and hazardous zones can be avoided by analyzing the log volume data at closed grid between wells. Vertical resolution required for reservoir simulation can be handled separately through stochastic or simulation techniques of geo statistical analysis with finer refinements.

Broadly ,the analysis indicate that proposed platform ZB and horizontal / multilateral wells fall in good reservoir zone having good porosity ,less shale contents and good oil saturation zone . Reservoir facies are equally good as ZA platform. Facies model can be generated with combination of pseudo log volumes and it can be visualized in 3D mode in Virtual Reality Centre (VRC) for details.

Multi attribute analysis and neural networking method is suitable for transformation of 3-D seismic volume into pseudo log volumes. Average prediction error for pseudo log volumes and derived reservoir properties volumes on the basis of 3-D seismic is within the tolerance level of 5% and it is considered good for predicting the reservoir properties of incoming wells. During the analysis it was observed that GR log have good correlation up to 90% with seismic especially in this case, after editing and removing spurious log data.

Vertical and horizontal sections or horizon slices extracted from pseudo log volumes or computed 3-D volumes of rock properties can provide a primary tool to constrain the stratigraphic correlation, if the wells are sparsely distributed.

In context of enhanced oil recovery by infill drilling and ongoing reservoir simulation of Mumbai High Field, the present study of ZA platform can be extended to other sector of the field for better understanding of the heterogeneity of the reservoir.

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