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Reservoir characterization and porosity prediction of carbonate reservoir using stochastic inversion

Abstract

Present study deals with carbonate reservoirs of a field. Predicting porosity in carbonate reservoir has always been a daunting task. Due to high velocity of carbonates and the limited band width of seismic data, the vertical resolution gets severely impeded, thereby calibration exercise with well data may not serve the purpose to delineate thin pay zone. Attempt has been made in present study to assay an integration of well data and seismic data in a coherent manner to create a robust three-dimensional (3D) reservoir model. To overcome the challenge of poor vertical resolution, post stack stochastic inversion was carried out by incorporating well data, seismic volume and geo-statistical information to generate high frequency non-unique fine layered impedance realizations. These realizations were subsequently tested at blind wells to understand predictability. Validated realization was preferred to leverage strong correlation of well level acoustic impedance and neutron porosity. Probability density function based on Bayesian approach has been exploited to extract lithology information from neutron porosity. Further, regression at well level led to transformation of acoustic impedance into effective porosity within carbonates. Aim of this paper is to elucidate process of utilizing high density lateral samples of impedance cube along with fine vertical well point in building a high-resolution high-predictability reservoir model.

Introduction

Well based petrophysical properties population using geo-statistical algorithm brings in fair amount of lateral uncertainties. Extent of pay zones are overtly decided by variogram parameters which might deviate static model from actual depositional pattern. Problem gets aggravated in case of carbonate reservoirs due to large and abrupt variation in rock properties caused by diagenetic processes. This brings in requirement of a secondary attribute that can assimilate lateral rock type distribution and translate the same for reservoir characterization.

Seismic inversion is therefore needed to help estimate the spatial variation of rock type and properties. Stochastic inversion on 3D PSTM volume was carried out by integrating geological & petrophysical parameters for reservoir characterization in a complex carbonate reservoir. Stochastic impedance cube was judiciously employed to ensure effective calibration with well points for reservoir characterization in a complex carbonate field.

General geology of the field

The study field is located 70 Km SW of Mumbai City in western offshore of India, at a water depth of 50 meters (fig-1). Heera formation overlies the Mukta formation, is developed in entire field. It consists of 40-50 m thick alternations of limestone and shale. Mukta formation (10-15 m in thickness) is developed in entire field. This formation is relatively tight as compared to the Bassein formation but better developed in crestal part of the field. The Mukta formation overlies the Bassein formation with an unconformity. The Bassein formation is well developed except in the crestal part of the field. It overlies the clastic Panna formation, which is also developed in entire field but is better developed in South- Eastern part of the field overlying the basement rock. The Mukta and Bassein formations have thin shale layers. The present study has been carried out for the Mukta and Bassein carbonate pays. The main producing formations are the Bassein and Mukta limestone of Middle Eocene to Lower Oligocene ages. General stratigraphy of the western offshore is given in fig-2.

Methodology

Employed methodology attempts to integrate high vertical resolution of log data and lateral sampling of seismic data beyond the well. Available data for the study consists of 3D PSTM volume, interpreted surfaces and complete set of logs including density and sonic logs in few wells. Inverse relation between neutron porosity and impedance at wells was observed as shown in fig-3. Extracting the wavelet for inversion process was the first step so seismic well tie process was carried out in multiple wells distributed throughout the field.

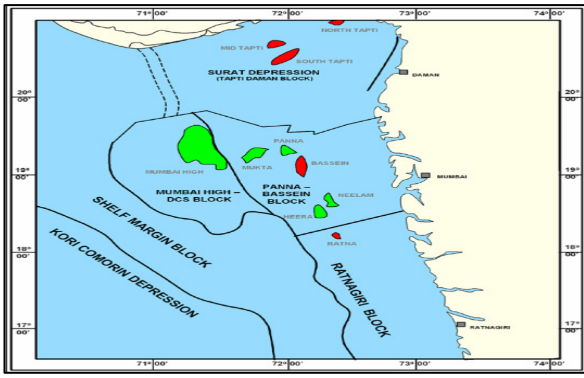


Fig-1 Location map of western offshore

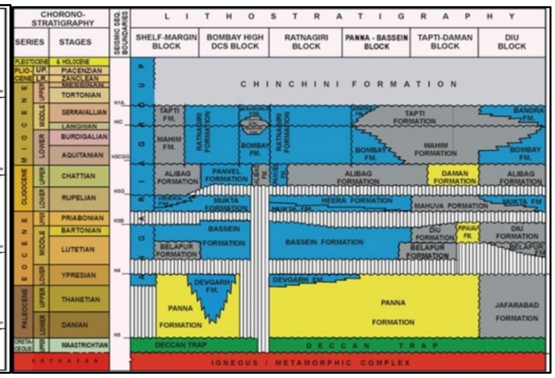


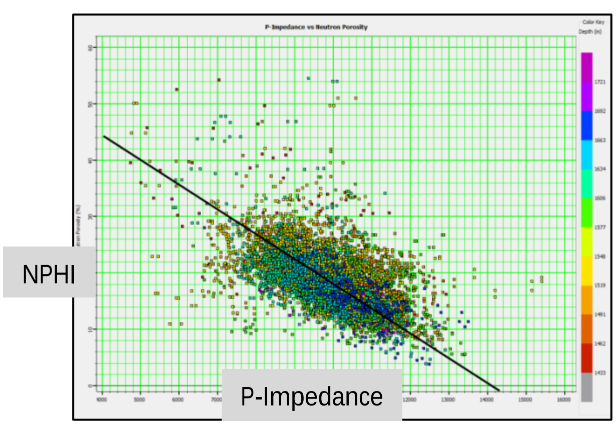
Fig-2 General Stratigraphy of western offshore

Deterministic inversion was performed to generate acoustic impedance. Deterministic inversion ignores the non-uniqueness problem of seismic inversion as it produces single and best least square solution within seismic bandwidth. It computes average of rock layer property and a broad understanding of lithological variations, though not suitable for finer reservoir characterization. Stochastic inversion was attempted to generate high frequency impedance realizations. The realization with highest correlation at blind well was used for porosity prediction.

Thin shale layers within the Mukta-Bassein formation lead to aberration in the prediction of effective porosity, necessitating shale-carbonate differentiation. Litho logs obtained from well data were used to generate 1-D probability distribution function (PDF) from neutron porosity log. This PDF is then applied using populated neutron porosity volume to generate seismic lithology.

The effective porosity had strong inverse correlation with impedance in carbonates. Compartmentalization of facies (Shale-Carbonate) was carried out to allow different mechanisms of populating effective porosity based on facies distribution.

Post Stack Inversion



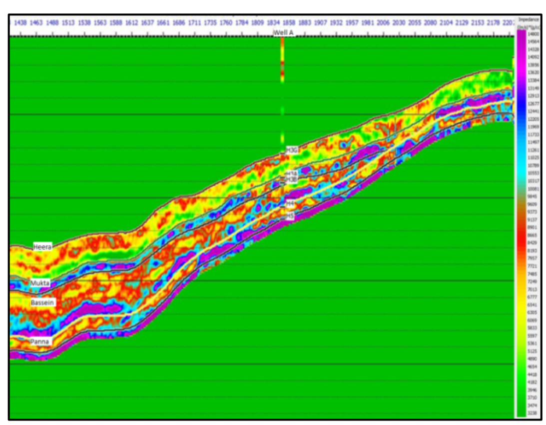


Fig-3 Log Nphi and P-Impedance cross plot

Fig-4 Deterministic acoustic impedance section

Total 15 wells having sonic and density logs were used for deterministic inversion. Horizon guided low frequency model was built by applying 10/15 Hz high cut filter on log data. Composite wavelet was used for carrying out deterministic inversion. The inverted acoustic impedance clearly demarcates the lithological boundaries of Mukta, Bassein and Panna formations (Fig-4).

Stochastic Inversion

Stochastic inversion uses Stratigraphic grid based initial model. Stratigraphic grid was built by using horizons as guide. Five horizons namely Heera, Mukta, Bassein, Panna and Basement were used. Proportional layering method was used for layering. The thickness of each stratigraphic grid layer is given 1ms. This stratigraphic grid combined with low pass filtered impedance logs, gives initial model. Stochastic inversion is performed by populating well data using Sequential Gaussian Simulation algorithm with initial model as a trend. Populated equi-probable impedance realizations are optimized to fit the seismic data through forward modeling approach.

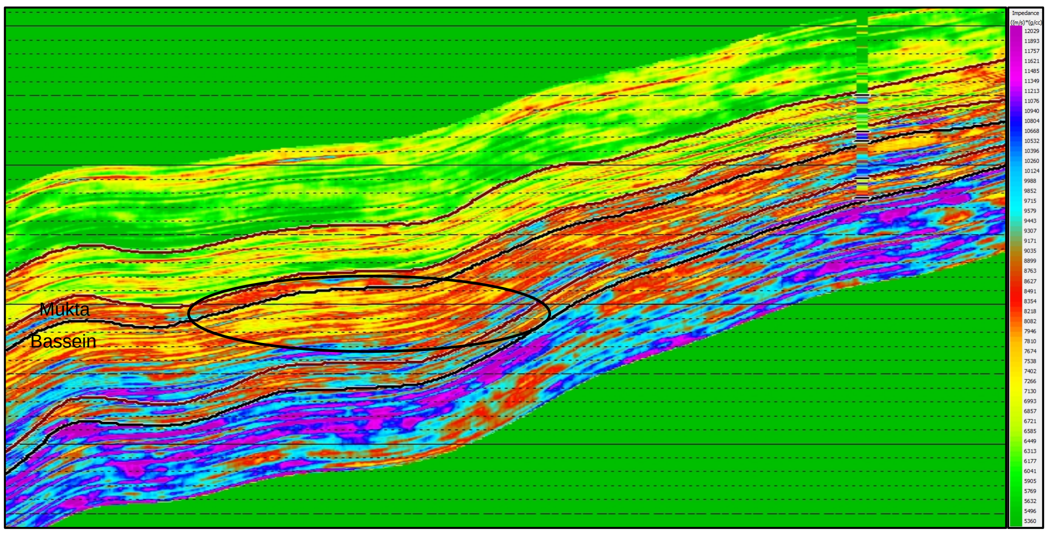
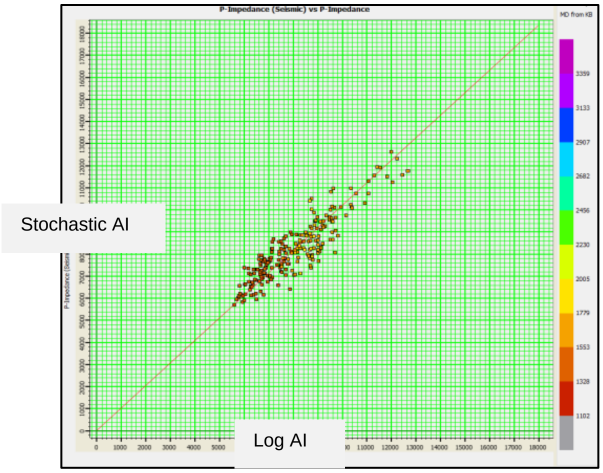


Fig-5 realization, selected for characterization

Despite the significant variation between the realizations, their forward convolutions are similar and have good match with the seismic. Total of 50 realizations were generated having 75% convergence with seismic data. For reservoir characterization purpose, we selected the realization based on blind well test, one that showed highest correlation and least error. Vertical section of the selected realization reveals thin laminations as shown in fig-5.



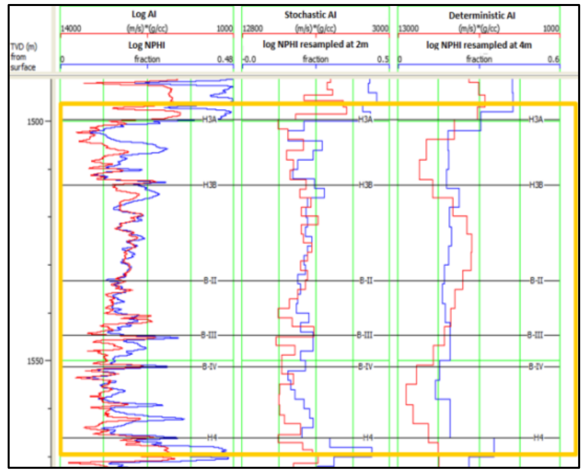


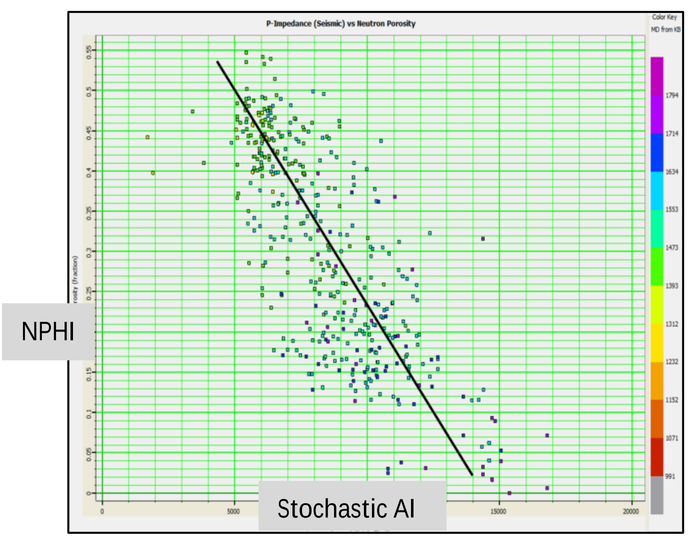
Fig-6 Stochastic AI v/s Log AI (Blind well)

Fig-7 Comparison of Log, Stochastic/deterministic AI

At blind well X, the correlation between stochastic acoustic impedance and log impedance is 89% at 2ms sampling interval shown in fig-6. A comparison of acoustic impedance (red color) and neutron porosity (blue color) is shown in fig-7. Left track shows actual log impedance and porosity, middle track shows stochastic impedance and neutron porosity (resampled at 2m) and the right track shows deterministic impedance and neutron porosity (resampled at 4m). This profile clearly shows that deterministic impedance is not capable of capturing fine change in porosity. While stochastic impedance appears to be in tandem with neutron porosity at finer scale (resampled at 2m).

Porosity prediction

The stochastic impedance shows good correlation with neutron porosity. Cross plot between stochastic impedance and neutron porosity (resampled at 2m) shows 76% correlation (fig-8).



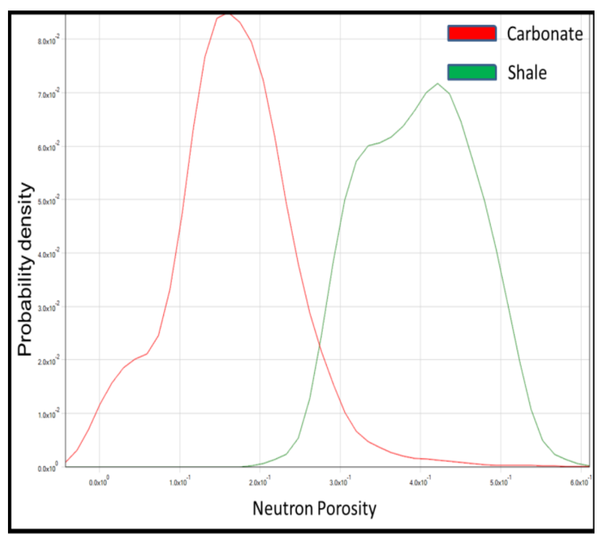


Fig-8 cross plot of stochastic impedance-Nphi

Fig-9 Probability density function

To generate neutron porosity volume, log of 15 wells were populated by co-kriging Nphi log with stochastic impedance.

Seismic lithology prediction

The presence of thin shales in Mukta-Bassein formation distorts correlation between effective porosity and acoustic impedance. This observation emphasized the importance of facies modeling prior to porosity population. Lithology variation was observed to be captured by neutron porosity at log level. Rather than giving cut-offs based on qualitative judgment, 1-D probability density function (PDF) were generated based on Bayesian approach. As shales had much higher neutron porosity than carbonates, well level PDF was able to discern thin-layered & scantly present shale from carbonates (fig-9). The PDF was then applied on predicted neutron porosity volume to generate seismic lithology volume.

Estimation of effective porosity

Shale being segregated from carbonates through facies model, next step was to exploit strong correlation of effective porosity and impedance within carbonates to carry out petrophysical modeling. The effective porosity revealed inverse correlation of 64% with acoustic impedance. Porosity log data of 15 wells was upscaled and populated by co-kriging with stochastic impedance within carbonate facies. Porosity cutoff for shale had been assigned to 6%. Average map of populated porosity is then compared with average porosity map of well guided static model (more than 100 wells were used to generate this model). Average porosity maps from both mentioned approach has been shown in Fig-10 and Fig-11 respectively. It can be observed that seismic guided porosity map captures lateral variations of porosity in an efficient manner. In contrast to well based model, which fails to capture trends and instead create localized pay zones. Beyond oil water contact well guided static model reveals arbitrary extrapolated porosity that is not the case in seismic guided model.

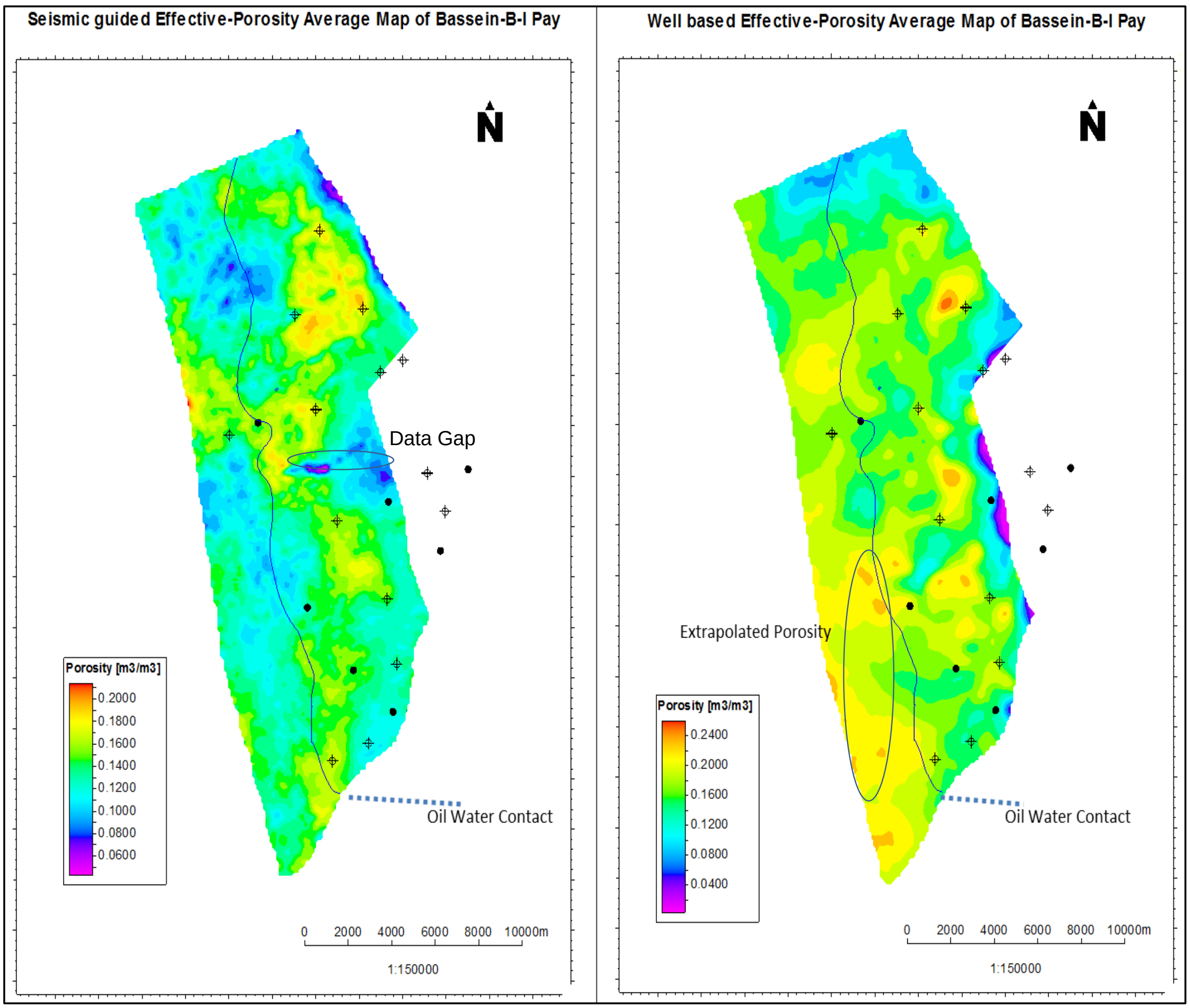


Fig-10 Seismic guided effective porosity map

Fig-11 well model based effective porosity map

Conclusion

The presented work focused on capturing strong correlation (>80%) at well level between neutron porosity and acoustic impedance for reservoir characterization. Correlation was replicated at model level by increasing resolution of acoustic impedance cube using stochastic inversion method. A probability density function exploiting neutron porosity-lithology relationship was used to generate seismic guided lithology volume. Strong correlation of effective porosity with acoustic impedance was leveraged within carbonates for porosity modeling. It has been observed that model generated in said manner captures 3D heterogeneity in detail as compared to well guided interpolation. Thus, increasing the confidence in computed property away from the well position. For porosity prediction and static modeling, post stack stochastic acoustic impedance inversion can be applied to similar fields where strong correlation between porosity and acoustic impedance is observed.

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