Stochastic seismic inversion for static reservoir modeling

S. K. Mekap, Paritosh Chaturvedi, P Vidyasagar, Ashish Kumar, Tanmaya Bhanja & Babita Tiwari, IRS, ONGC, Ahmedabad. Mr. Akash Mathur & Ms. Jyoti Malik, M/s CGG, Mumbai*

sk_mekap@yahoo.com

Keywords

Elastic inversion, Rock physics inversion, Stochastic Inversion and Bayesian Classification

Summary

Deterministic pre-stack Seismic inversion brings elastic properties which depend on the rock and fluid properties. However, this lacks resolution (band limited seismic) and issue of non-uniqueness remains unsolved. The stochastic seismic inversion technique integrates the fine vertical sampling of the log data with the dense areal sampling of the seismic data to create detailed, high resolution elastic property (elastic impedance, density or velocity) models utilizing geostatistical techniques. Multiple solutions address the issue of non-uniqueness and highlight the uncertainty associated with inversion. In the next step, reservoir properties are computed/inverted from elastic attributes. In the present study, a deep water gas field in Pliocene sands of KG basin was taken up to bring out seismic-guided static reservoir model. The Vp/Vs volume, realized from the stochastic inversion that represents the most probable hydrocarbon sand facies is used for porosity prediction using Probabilistic Neural Network (PNN). Subsequently, the porosity cube is input to Petrel (Schlumberger) for static reservoir modelling.

Introduction

Seismic data is now routinely being used for the characterization of complex reservoir geometry, their internal distribution and is often used for monitoring of reservoir changes between wells during production. However, deriving any reservoir information quantitatively from these attributes is far more complex in practice because of (1) the band limited nature of seismic data mired in various noises, (2) the forward-modelling simplifications needed to obtain solution in a reasonable time, and (3) the uncertainties in well-to seismic ties (depth-to time conversion), in estimating a proper wavelet, and in the links between reservoir and elastic properties. Over last one and half decades, seismic inversion techniques have evolved and various geostatistical techniques are in use to solve its inconsistencies and incompleteness by integrating with various hard well data. Thus, to successfully address complex reservoir challenges, seismic study needs to be extended from conventional qualitative interpretation to quantitative interpretation.

In the present study, a Pliocene clastic gas charged reservoir (ABC field of KG offshore), is taken as a pilot project to bring out seismic guided static reservoir model. General inversion theory is a mathematically rich discipline and beyond the purview of the study. The paper, however, presents a case study of stochastic inversion and its integration into static reservoir modelling using geostatistics. It briefly discusses various seismic inversion techniques and highlights the concepts of rock physics.

Status of reservoir modelling

For the past few years, oil industry is engaged in the preparation of static models (Geocellular Modeling), which are input to the Dynamic Modeling process. The most common approach is to use well data for either deterministic or stochastic interpolation of properties within the structural framework defined from seismic data. This method works fine in case of abundance of well data. In case of sparse well data, the accuracy of reservoir properties generated by such an approach decreases rapidly away from well control points. Particularly, frequently used Kriging approach has the tendency to provide a smooth geological model away from the wells. In reality, however, geology has no reason to be smoother away from the wells.

Data Integration

Reservoir characterization requires the construction of detailed petrophysical property models contained within a geological framework. The reservoir is unique and deterministic. But, only sparse and incomplete information is available. Use of geo-statistics integrates both the hard and soft data, exploiting on the vertical resolution of the hard well data and dense spatial sampling of soft seismic data. **Bayesian approach directly integrates the probabilities (and the uncertainty) from the independently estimated properties from various sources. Thus, integration of different geoscientific data reduces geological uncertainties**.

Generally, the above task is implemented in two steps. In the first step, called **elastic inversion**, elastic attributes (such as, P- and S-wave velocities, or P- and S-impedances) are estimated from seismic data. In the second step, reservoir properties are estimated from elastic attributes by **rock-physics inversion**.

Seismic Inversion Techniques

Seismic inversion technique is classified into two types: Deterministic and Stochastic. Deterministic inversion can be further divided into post Stack (full stack) and pre stack inversion (partial stack). With post-stack inversion, only one elastic property (P-impedance) can be estimated, and does not say anything about reservoir fluid and lithology. Whereas, pre-stack seismic inversion obtains other elastic properties such as P-reflectivity, S-reflectivity and Vp/Vs ratio. Relation between Poisson's ratio & Vp/Vs is the link between rock physics & seismic reflection. However, because the number of seismic attributes is usually smaller than that of the desired rock properties, these transforms cannot be uniquely inverted. Thus in case of deterministic inversion, two main issues remain unsolved, the first one is the problem of resolution constrained by the band limited nature of seismic data and the other one is the non-uniqueness. This is further discussed below.

Stochastic Inversion

Deterministic inversion result produces an average effect of thick strata, whereas, stochastic inversion **simulates** small scale variability that cannot be detected from seismic data, but seen on the well log data. The issue of **non-uniqueness** is addressed by delivering multiple realizations consistent with available well and seismic data. Stochastic techniques are capable of producing many plausible outcomes. Reservoir performance prediction becomes more accurate when all possible reservoir heterogeneity is input to a simulation process. **Geo-statistical inversion is stochastic inversion where a prior elastic property model with a plausible bedding geometries and facies succession (geologically consistent) is updated constrained by seismic.** The algorithm is a conditional simulation, an extension of Sequential Gaussian Simulation (SGS).

Rock Physics

The link between seismic derived elastic attributes and rock properties, such as porosity, mineralogy and fluid is governed by rock physics. A rock physics model is established at the well by geostatistically correlating depth trends of both the properties for different lithologies and pore fluids, taking burial and compaction history into consideration. This model is used to arrive at the spatial distribution of rock properties from seismic-derived elastic properties. The well data is used independently to derive a facies classification based on the bulk transport properties rather than elastic properties. The process of extraction of rock properties from elastic properties is called **rock physics inversion**. However, its implementation requires continuous updating of local geological and petrophysical data. In this study, **Probabilistic Neural Network** (PNN) was used to predict the porosity from elastic attributes.

General Geology of the Area

KG basin (Figure-1) is located along the east coast of Indian Peninsula. Post Oligocene, the Krishna-Godavari River started depositing huge piles of sediments on the shelf and in the deep water basin. Three major events (Figure-2) are evident as follows. 1- Mid-Late Oligocene growth faulting and resultant toe thrusting. 2- Widespread Early Pliocene Mass Transport Complex (MTC) which occurred in stages. 3- Late Pliocene to recent growth fault development and toe-thrusting.

The main reservoir comprises of slope and intra-slope basin facies, primarily incised channel and deep-water channel-levee complexes with submarine fans overlying Late Pliocene MTC. The study area (ABC field) is a four way closure in deep water, depth ranging between 150m to 500m. Figure-3A shows vertical disposition of three sand bodies A, B and C as high amplitude bursts in seismic. In the well A-9, four hydrocarbon bearing sands, subunits of A-sand pack

(1 to 4, from bottom to top), were encountered. These four subunits are believed to be in communication with each other. Sand-5 and sand-6 are other two independent sand subunits, just above the A-sand pack in the main ABC field. To the west, two wells (B-1 and B-2) flowed gas from deep water channel sands (B-sand), just above A-sand pack. Well C-1, drilled to test the amplitude anomaly (C-sand) towards the top of Pliocene, close to the eastern boundary of the block, indicated gas on mini DST. Figure-3B shows spatial distribution of Acoustic Impedance (AI) of these three sand bodies A, B & C.

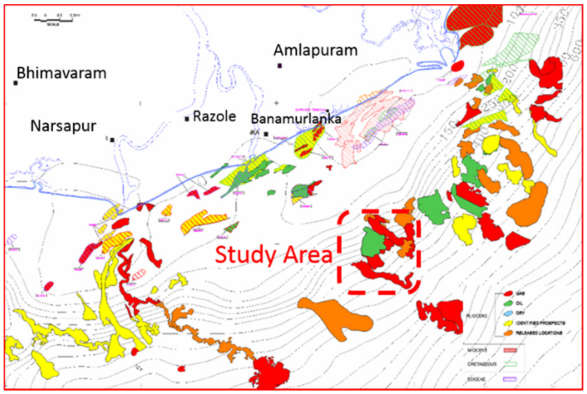


Figure-1: Location of the study area

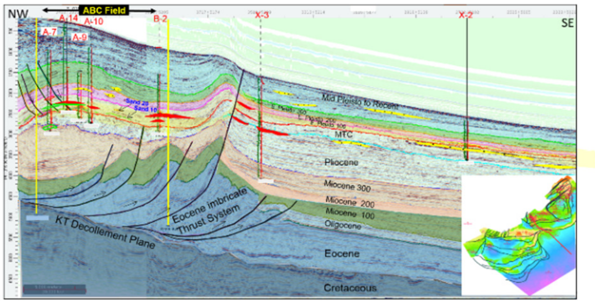


Figure-2: Regional seismo-geological section (from unpublished report, KG basin)

In this study, stochastic inversion was carried out for A-sand pack and overlying snd-5 & 6 only.

Petrophysical Study & Well Log Conditioning

Raw logs were processed in GeoFrame (Schlumberger) and the extracted reservoir properties, such as water saturation, effective porosity and shale volume were input for property propagation.

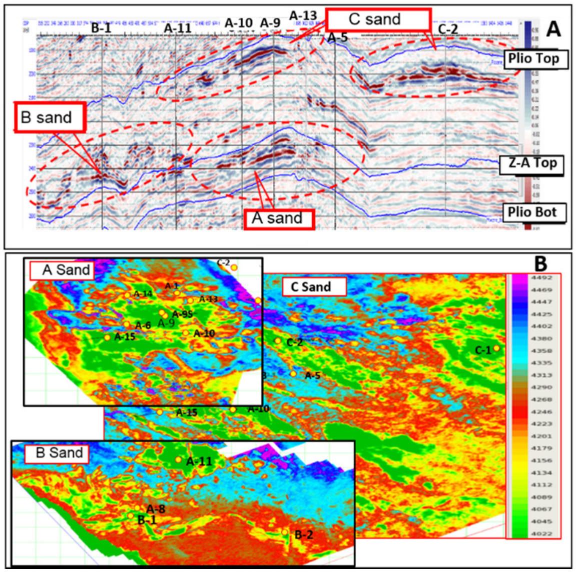


Figure-3: A. Amplitude bursts (Pliocene sand bodies) in seismic. B. AI showing spatial distribution of different sands.

Good quality well log data is essential for high quality seismic reservoir characterization. Hence, the well logs were conditioned in Powerlog, corrected and synthesized to provide complete and reliable input. Bad and missing portions of Density, P-Sonic and S-Sonic logs were predicted using multi-linear regression making use of GR and Resistivity logs as these are less affected by borehole rugosity.

For more detailed analysis, however, further investigation may be required to eliminate the post-depositional effects such as compaction, lithification and digenesis.

Seismic data conditioning & partial stack

For quantitative study, gather conditioning is a prerequisite to pre-stack inversion and AVO studies. Hampson-Russell suite of software was used to generate three partial angle stacks (ranges 6-17, 17-32 and 32-42, Figure-4) which were subsequently input to the deterministic inversion/stochastic inversion process. Classical AVO technique shows sands are of **class-II** type, impedance very close to that of shale. Presence of gas lowers the sand impedance.

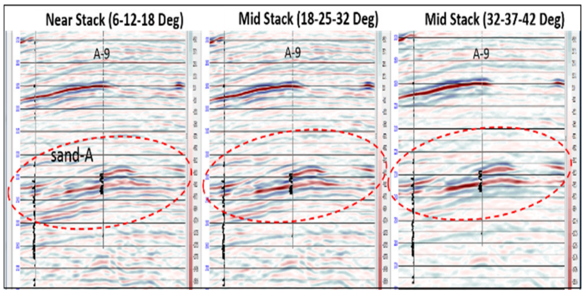


Figure-4: Partial angle stacks (range 6-17, 17-32 and 32-42)

Pre-Stack Simultaneous Inversion

Pre-Stack Simultaneous Inversion in Hampson Russell is based on three assumptions. 1- Linearized approximation of reflectivity 2- PP and PS reflectivity is a function of angle, given by the Aki-Richards equations. 3-Linear relationship between the logarithm of P-impedance (Ip) and both S-impedance (Is) and density holds good for the background wet lithologies.

Given these three assumptions, we can derive a final estimate of P-impedance, S-impedance and density by perturbing an initial P-impedance model. This theory has been published by Hampson et al. (2005) which is built on the work of Simmons and Backus (1996) and Buland and Omre(2003). In Hampson Russell module (STRATA), partial stacked data are simultaneously inverted into elastic property volumes such as Ip, Is, Density & Vp/Vs (Workflow in Figure-5).

Final processed well logs along with conditioned seismic data are used for well to seismic ties and three independent wavelets for respective angle stacks are extracted. Kriging process creates low frequency initial P impedance models. Initial models for S-impedance and Density are also created using respective transforms. Thus, the initial models, the angle stacks and their respective wavelets are used for deterministic simultaneous inversion and subsequently for stochastic inversion too.

Initial model serves two purposes in Hampson Russell software 1-Filling the lower end of spectrum created by absence of low frequency in seismic data. 2-Acts as a starting point for inversion scheme and helps to converge the solution in solution space.

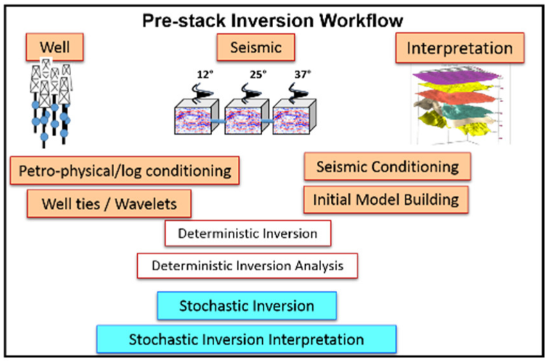


Figure-5: Pre-stack Seismic Inversion workflow (CGG)

The inverted Ip and Is output (Figure-6, in inversion analysis at well A-9) reasonably resemble log independently, however, their ratio Vp/Vs often fails to match well log trend due to issue of scale factors. The deterministic pre-stack inversion (Figure-7), results in very poor resolution in comparison to stochastic one, which is to be discussed later. The quality of deterministic inversion depends on the quality of seismic input, quality of well logs, well tie and choice of wavelets. This subsequently controls the quality of stochastic inversion process.

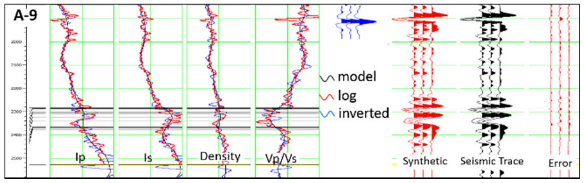


Figure-6: Inversion analysis at A-9

Stochastic Inversion using GeoSI (HR)

The method is developed by TOTAL and CGG that combines geostatistical stochastic inversion (which was slow and did not converge well to an answer) and a multivariate **Bayesian approach** by Buland and Omre (2003). GeoSI is a layer based approach that works in fine **stratigraphic grid** (workflow in Figure-8), typically much smaller than the seismic resolution, with horizontal sampling fixed by the seismic bin size and vertical columns of cells of varying thickness defined by the stratigraphic layers. GeoSI uses the same initial low frequency models, used in deterministic inversion, however, with certain modifications. The seismic horizons are used to make thinly layered, of the order of 1 to 2 ms, stratigraphic grid, which is consistent with the resolution in the well logs and stratigraphic layering of the area. At this fine-scale, inversion is highly **non-unique**, but GeoSI generates multiple high-frequency realizations to explore this non-uniqueness. **Posterior uncertainty** increases as the thickness of the layers decreases.

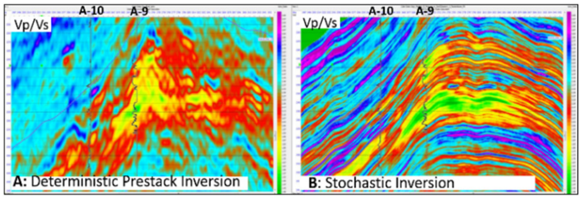


Figure-7: Resolution of Vp/Vs; pre-stack Deterministic (A) vs stochastic Inversion (B). Sw curve overlaid.

Figure-9 illustrates workflow for stochastic inversion to generate the multiple realizations of elastic attributes P-impedance and S-impedance. The GeoSI method requires three input data types' i.e 1-**Prior model** (initial Ip, Is & Density model with mean and standard deviation 2-Seismic (partial angle stack data with uncertainties), 3-Wells (well curves, Ip, Is and Density data with uncertainty along with variograms, both vertical as well as horizontal.

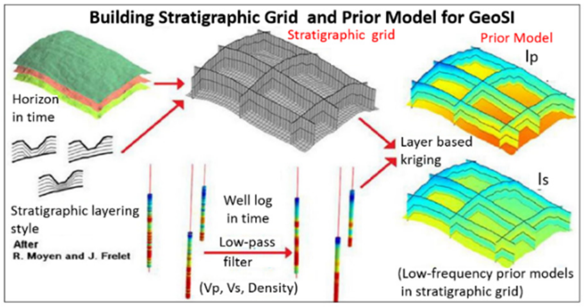


Figure-8: Work flow for building Stratigraphic Grid & Prior Model for GeoSI (CGG)

These three data types can be viewed as a **trade-off triangle** (Figure-10). The standard deviations of the prior model and the uncertainties of the seismic and well data will control where the result falls in the triangle. Increasing the results match to one type of data results in decreasing the results match to other two types.

The results of stochastic inversion are of relatively higher bandwidth. The lower frequency comes from initial/prior model, intermediate frequencies are taken from seismic and high frequency are taken from well logs and variogram models (Figure-11).

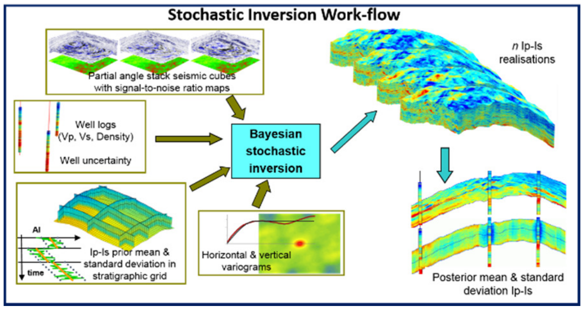


Figure-9: Work flow of Stochastic Inversion in GeoSI (CGG)

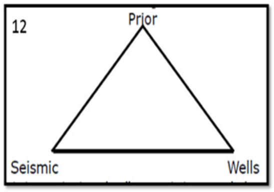


Figure-10 trade-off triangle

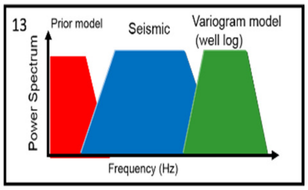


Figure-11 Stochastic Inversion Bandwidth Component (CGG)

Figure-12 shows comparison of deterministic and stochastic inversion results (P-Impedance and Vp/Vs ratio). Clear improvement in the resolution can be seen in stochastic inversion. Sands with thickness less than seismic resolution can also be resolved in stochastic inversion (Figure-13). The resolution of Vp/Vs trace extracted from stochastic inversion (blue, Figure-14) at well location is far better than of that of the deterministic inversion result (red), and is comparable with well log.

Figure-15 A shows net pay thickness (in time ms) for sand 5 (above A-sand pack) which is bisected by an N-S fault. Figure-15 B shows combined thickness of the A-sand pack and their inter-connectivity. A single geo-body (pink, Figure-15C), for sand A pack, could be picked in Geoprobe. Single hydrodynamic system confirms that the sand 1 to 4 are in communication with each other. Yellow geo-body corresponds to sand-5 which could be picked separately.

Interpretation of Stochastic Inversion

The Final output from stochastic Inversion are multiple realizations of Zp, Vp/Vs and Density. Cross plotting Vp/Vs versus Zp, realizations are classified into different predefined facies and probable HC sand volumes using two techniques i.e. polygon based method and **Bayesian classification** scheme. Polygon based method strictly requires accurate rock-physics model of the lithology of interest.

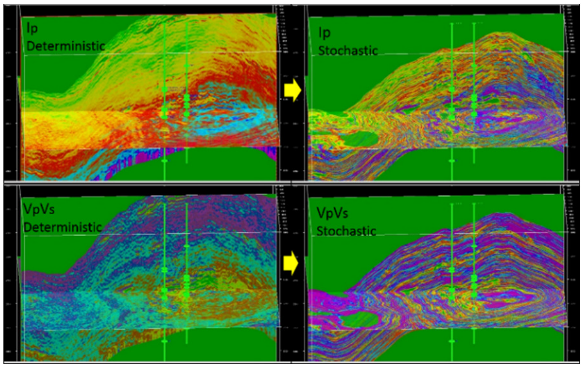


Figure-12: Ip-Deterministic Inversion vs stochastic Inversion, Vp/Vs-Deterministic Inversion vs stochastic Inversion.

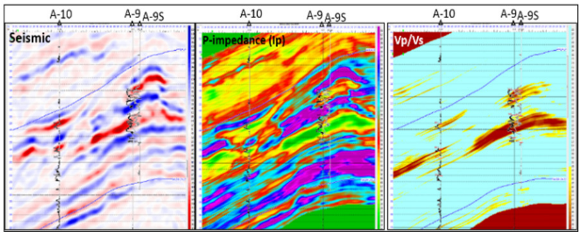


Figure-13: Stochastic Inversion result along line passing through well A-9 & A-10

Using Vp/Vs versus P-impedance crossplot in the well logs, discrete facies logs are created, color coded (gas sand-red, brine sand-blue and shale-green) and verified against well logs. We observe clustering of points based on lithology and then prepare **Probability density function** (Figure-16A) corresponding to each lithology (Bayesian classification scheme). Points falling in the center of the cluster are given high probability of occurrence and as we move away from cluster center the probability decreases. Black boundary define limit of classification. Each realization of Vp/Vs (B) of stochastic inversion is classified as litho-facies (C) and hydrocarbon sand probability volume (D).

Subsequently Vp/Vs realizations are classified into P10, P50 & P90 cases on basis of sand volume (sand volume histogram, Figure-17). The conservative result of P10 (90% probable) realization was directly input to the EMERGE (HR) software.

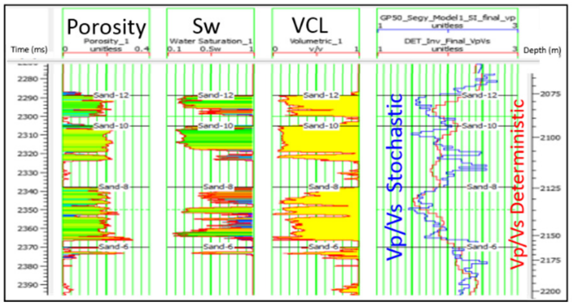


Figure-14: Comparison of extracted Vp/Vs trace, stochastic (blue) vs deterministic (red) inversion.

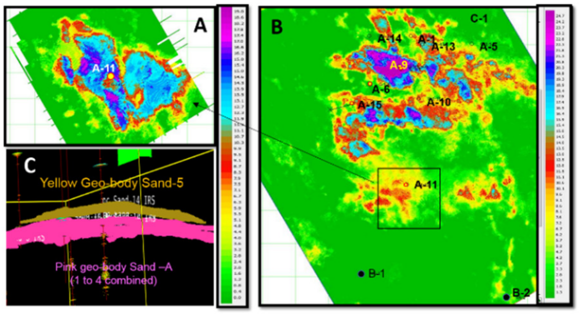


Figure-15 A: Net pay thickness (ms) for sand-5 & B: for sand 1 to 4 combined together (A-sand pack). C: Single Geobody (pink) shows sand pack-A. Yellow geobody corresponds to sand-5

Porosity Prediction in Emerge

Porosity (total porosity, $\phi_{total\ PNN}$) is predicted from Vp/Vs volume and other seismic attributes using multi-attribute regression (Emerge of HR). NPHI log is used as the target log, for building relationship. Maximum 81% correlation is achieved by further application of PNN (Figure-18A). B shows the validation plot, a well drop analysis. The cross-plot of predicted porosity vs actual NPHI log (C) shows good correlation. Similarly, VCL was predicted from Vp/Vs volume. Subsequently, effective porosity volume was calculated using equation $\phi_{eff\ PNN} = (1-VCL_{PNN})*\phi_{total\ PNN}$ and input to PETREL for GCM process after depth correction.

Figure-19 shows Vp/Vs, PNN predicted VCL and PNN predicted effective porosity along line passing through well A-9 respectively.

Figure-20 A & B show the comparison of log (red) and PNN predicted (blue) of effective porosity and water saturation at different well locations, respectively. A fairly good match can be seen at most of the wells. However, only effective porosity volume was input to Petrel after depth conversion.

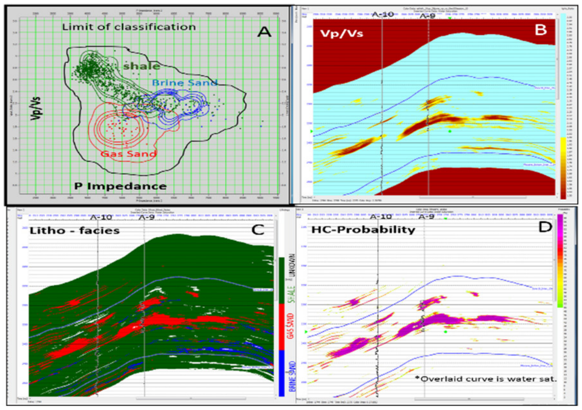


Figure-16: A. Probability distribution function. B. Vp/Vs, C. its classification result in lithofacies and D. Hydrocarbon sand probability volume.

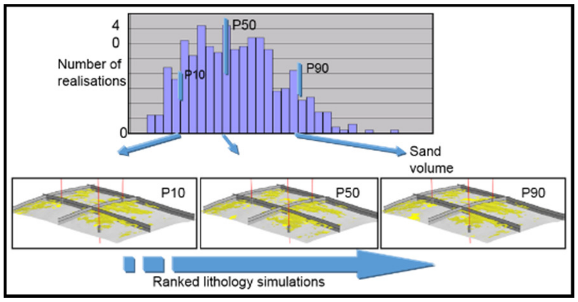


Figure-17: Ranking of GeoSI realizations based on facies volume (gas sand volume)

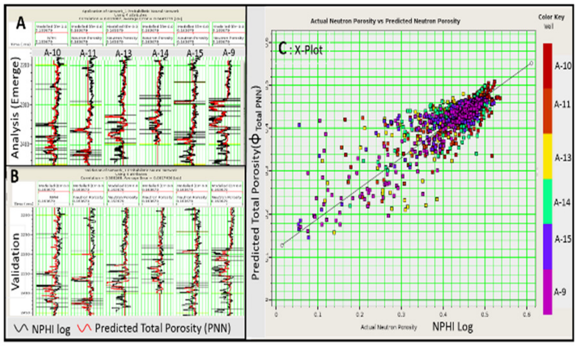


Figure-18: (A) Emerge Analysis, (B) validation & (C) X-plot of log porosity and predicted total porosity.

Velocity modeling for reservoir characterization purpose requires accurate and rigorous approach like grid tomography and depth imaging. However in the present study, it is carried out by conventional approach of vertical stretching of migrated seismic data.

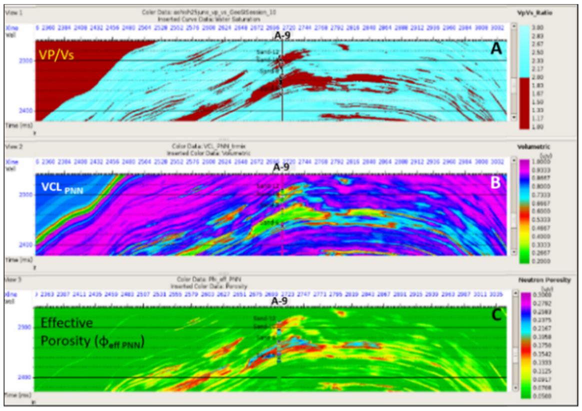


Figure-19: Vp/Vs, PNN predicted VCL & effective porosity along line passing through well A-9

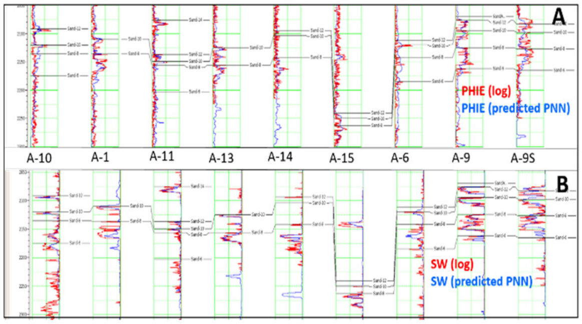


Figure-20 A: Actual log vs predicted effective porosity at different wells B: Actual log and predicted water saturation.

Geocellular Modeling in PETREL

Depth converted Vp/Vs and effective Porosity volumes, output from Emerge, are loaded into Petrel for Geocellular modeling. Pillar gridding of 12.5m X 12.5m grid size is chosen in order to preserve the resolution of stochastic inversion. The zone-A seismic reflector top, fairly consistent throughout the seismic volume, is used to create three vertical geological zones (Figure-21), sand pack-A (sands 1 to 4), sand-5 and sand-6. Each of these zones is sub divided proportionally into fine layers (total 257 fine layers) of one meter thick, in order to preserve heterogeneity.

The aim of the project is to capture the spatial reservoir continuity in inter well space, preserving heterogeneity, guided by the results of stochastic inversion. Cross-plots between scaled up log PIGN vs $\phi_{eff\ PNN}$ and up-scaled log PIGN vs Vp/Vs (Figure-22 A & B) show significant correlation. (C) Shows crossplot between processed well log porosity and modelled porosity and (D) shows histogram of model porosity.

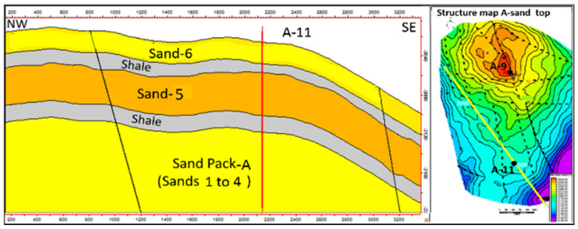


Figure-21: Cross section of the model through well A-11

Saturation modeling was carried out by propagating scaled up well log (SUWI) using modeled porosity volume as secondary attribute. A crossplot (Figure-23A) between well effective porosity PIGN and well saturation SUWI shows a strong negative correlation. The crossplot between processed well log (SUWI) and model saturation (Figure-23 B) shows very good correlation.

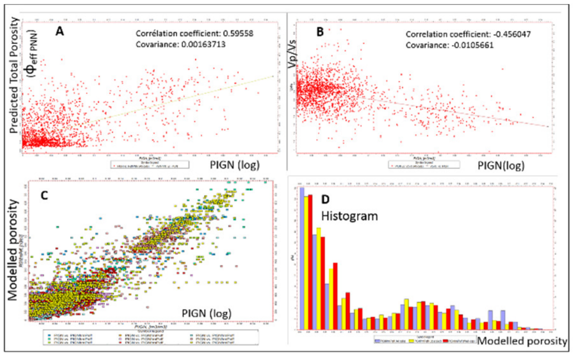


Figure-22: Crossplot A. scaled-up log porosity vs porosity generated using PNN; B. Up-scaled well log porosity vs Vp/Vs, C. well log porosity vs modelled porosity and D. Histogram of model porosity

Wells section (Figure-24) along wells A-9 and A-9S compares the modeled effective porosity (ϕ_e) and water saturation (Sw) with Vp/Vs, the input from stochastic inversion. Horizontal (K) sections (Figure-25) shows properties along a K section, layer within sand pack-A.

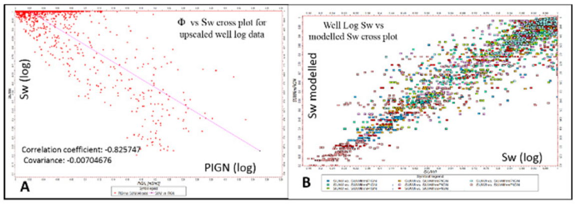
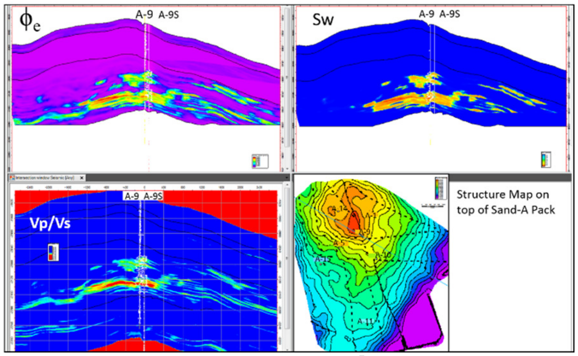


Figure-23: Crossplot A.scaled up log porosity vs water saturation B. processed log water saturation and modelled water saturation



Figures-24: Modeled effective porosity (ϕ_e), water saturation (Sw) and Vp/Vs (stochastic inversion).

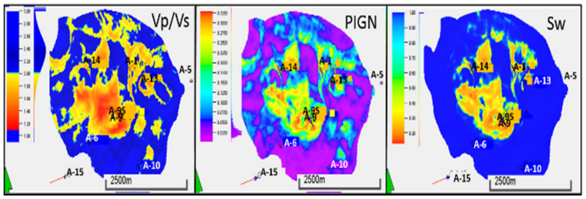


Figure-25:Horizontal(K)sections of properties, within Sand pack-A

Conclusion

The high resolution elastic rock properties derived from the stochastic inversion are incorporated in the study to prepare an integrated static reservoir model with increasing confidence in property distribution in the inter-well grid space. The use of geo-statistics has played a major role in solving problems of resolution and non-uniqueness of deterministic seismic inversion. The Bayesian framework has incorporated prior geological information into seismic inversion which has facilitated the process of multiple solutions that are consistent with both the seismic data and the prior probability distribution. The link between the elastic attributes and rock properties is governed by a rock physics, therefore rock physics inversion would have provided more meaningful insight into the reservoir behavior.

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