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STOCHASTIC INVERSION FOR HIGHER RESOLUTION IN RESERVOIR CHARACTERIZATION, ABU MADI FORMATION, SALMA FIELD, NILE DELTA EGYPT

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الانقلاب العشوائي للحصول علي دقة أعلي في توصيف الخزان بتكوين ابوماضي في حقل سالمة بدلتا النيل، مصر

الخلاصة: الهدف من هذا البحث هو مقارنة العديد من طرق النمذجة السيزمية لعكسية العشوائية وتحليل شدة الانعكاس مع المسافه (AVO) في حقل سلمى دلتا بمنطقة إمتياز غرب القنطرة، دلتا النيل، مصر. تعتبر حسابات إحتياطيات الغاز من تفسير البيانات السيزمية التقليدية أمراً عسيراً وذلك لعدم تجانس توزيع صخور الخزان تحت سطح الأرض والتراكيب الجيولوجية المعقدة. نتائج النمذجه السيذميه العكسيه مختلفة اظهرت بوضوح انخفاض الممانعه الصوتيه للخزان داخل قناه الترسيب. يعطي الانعكاس العشوائي أفضل نتيجة؛ على وجه الخصوص، يوفر الانعكاس العشوائي صورة دقيقة و صورة قريبة لحساب الغاز الكامن من المحسوب بواسطة نموذج التوازن المادي الهندسى.

ABSTRACT: *The Nile Delta is one of the main hydrocarbon provinces in Egypt. It has already a lot of discovered hydrocarbon fields. The reserve calculation and the original oil and gas in place (STOIIP/GIIP) determination has been a problem. Abu Madi Formation is one of the main gas bearing formations in the Nile Delta. Salma Field has been producing gas from Abu Madi Formation for the Past seven years, in which the gas is present in two thin sand bodies separated by thick shale interval. By using conventional seismic techniques, it was found that both sand bodies are existing within the same seismic loop that made them undetectable. Deterministic inversion was applied and was not able to distinguish between both sand bodies. Stochastic inversion was tested in turn giving different results. A comparison is carried out between the deterministic and stochastic inversion results. The inverted Zp from stochastic inversion mean (P50) realization is found to be of more resolution than inverted Zp from deterministic inversion. Also, the inverted lambda-Mu from stochastic inversion has detected the thin reservoirs in well SD-5, in addition to the stratigraphic edge between SD-1 and SD-3 wells, as well as the separation between the two sand bodies in SDN-1 well. Where, the inverted lambda-Mu from deterministic inversion has failed to show neither the separation between the two sand bodies nor predict their stratigraphic edges in SDN-1 well.*

INTRODUCTION

Natural Gas is one of the main sources of energy in the modern world. Finding gas is crucial for survival of world economy.

Exploring gas fields in Estuary reservoirs, such as the Nile Delta, are usually stratigraphically unconnected. Compartmentalization and reservoir boundaries are hard to get from conventional seismic data interpretation and conventional attribute analysis. Seismic inversion is one of the most useful techniques to detect the gas signature in sand reservoirs.

The present paper is focus on the application of new advanced seismic methods and techniques to analyze the petroleum system and evaluate the hydrocarbon reserves of the study area.

Two techniques for pre-stack seismic inversion are used; deterministic and stochastic, trying to detect the gas reservoirs extension and limits in Salam Delta field, Nile Delta, Egypt.

Theoretical Principals

Today, AVO analysis and inversion of seismic data are routinely used to derive seismic attributes which are used as hydrocarbon indicators. Such attributes usually are: the acoustic impedance ($ZP = AI= \rho Vp$), shear impedance ($ZS = \rho Vs$), elastic impedance (EI), Lamé parameters (LMR) and the ratio of compressional- and shear-wave velocities (VP/VS) (Singh, 2007). The elastic impedance is defined as an extension of the convolutional model to non-zero incident angles (Connolly, 1999). The LMR attributes attempt capturing the intrinsic mechanical properties of the rock, such as the products of their elastic modules ($\lambda$and μ) with density (ρ). From these attributes, we can derive the P- and S- wave velocities and densities which can be further used to describe the properties of rock matrix and pore fluid. Thus, from true-amplitude processing of seismic traces, we can extract the reflectivity and impedances, and by adding the measured velocities, the density can be further estimated.

In the AVO analysis, pre- and post-stack techniques should be carefully differentiated (Russell, 1988). Post-stack seismic inversion methods use stacked (zero-offset) seismic data to produce images of the AI in depth or time. Pre-stack (AVO) inversion uses the variations of reflection amplitudes within the individual Common Midpoint Gathers (CMP) in order to determine the complete set of elastic properties (VP, VS, ρ), or equivalently, elastic constant properties (lambda (λ), Mu(μ), Rho(ρ)) of the subsurface, where the lambda is elastic parameter related to rock resistance to compression (sensitive to pore fluid) while the Mu is the share modules measure resistance to shear deformation, sensitive to rock matrix(litho. identification).

From these properties, the petrophysical properties and fluid/gas saturation may be further inferred. In addition, CMP gathers can be used to directly invert for the P- and S-wave impedances and to extract other attributes such as VP/VS ratios. Both of these methods depend on the theoretical relationships between the physical properties and the seismic amplitudes. In summary, variations of the amplitudes of post and pre-stack seismic data are valuable for hydrocarbon investigation, especially in relation to gas reservoirs.

Geological Overview

The Nile Delta Basin experienced a major regression during the upper Miocene time along with the rest of the Mediterranean, with deposition of evaporitic deposits of Rosetta Formation and fluvial to marginal marine facies deposited in deep incised valleys as the Abu Madi Formation. During the Lower Pliocene time, the sea level started to rise giving way to a generalized transgression bringing bathyal facies above the restricted Messinian units all along the Egyptian continental shelf (Fig. 1).

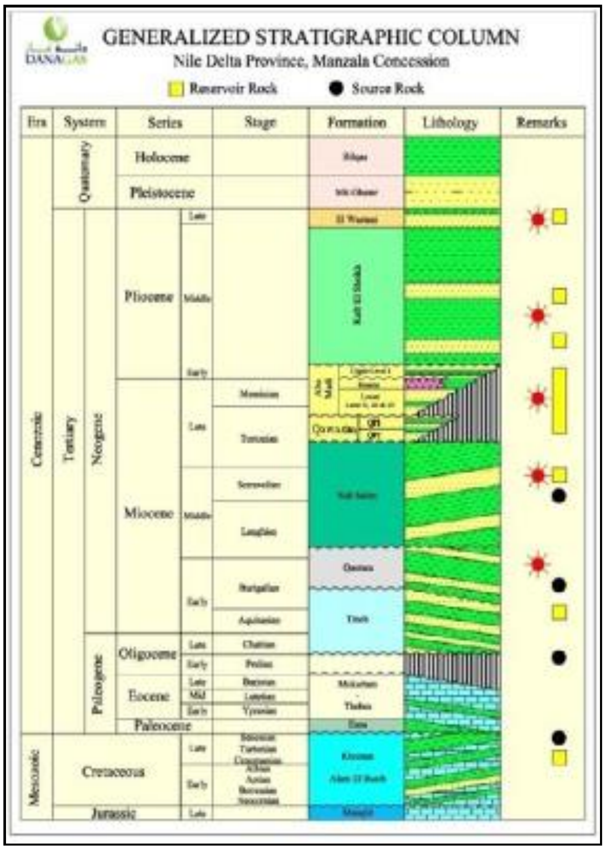


Fig. 1: Generalized Stratigraphic Column.

One of the main reservoirs in Nile Delta is Abu Madi Formation sandstones that have consistently proved to be the best reservoirs in the Nile Delta, as they have a high porosity with an average of (21%). The majority of fields are producing from Abu Madi Formation.

The study area is located at the eastern part of the Onshore Nile Delta in West El Qantara development license. (Fig. 2).

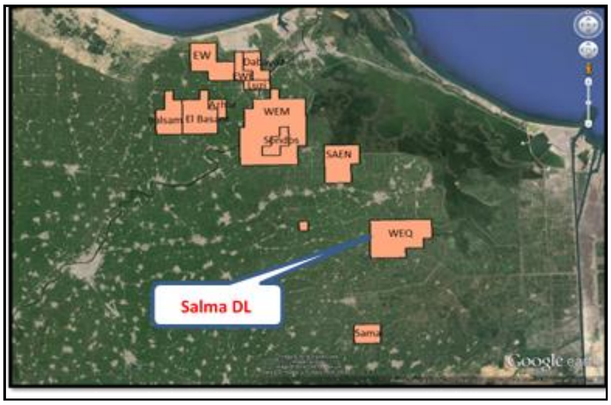


Fig. 2: Salma Field Location Map.

The main hydrocarbon-bearing reservoir in the study area is the Abu Madi Formation.

Seismic Inversion

To achieve the goal of the current study, the following steps have been consequently conducted.

Two types of seismic inversion algorithms were used to derive Elastic Impedance seismic data (EI), the EI data was converted to reservoir properties including but not limited to: porosity, permeability and lithology.

The seismic inversion requires the initial value of the acoustic impedance (Z), wavelet extraction and sensitivity analysis to be well performed.

Wavelet Sensitivity Analysis

Extracting seismic wavelet is the first step and is one of the most important keys in seismic inversion. As it used to provide the time-depth relationship and the seismic wavelet for the specific reservoir. First, statistical wavelet is calculating using the seismic trace at the well location. Secondly, the extracted wavelet, the P-wave velocity, and the density logs are combined to generate a synthetic seismogram. Third, correlate the generated synthetic with the seismic trace to get the best match by time shifting the synthetic. Finally, and after well tie, a deterministic wavelet, which represents the recorded reservoir wavelet to be extracted.

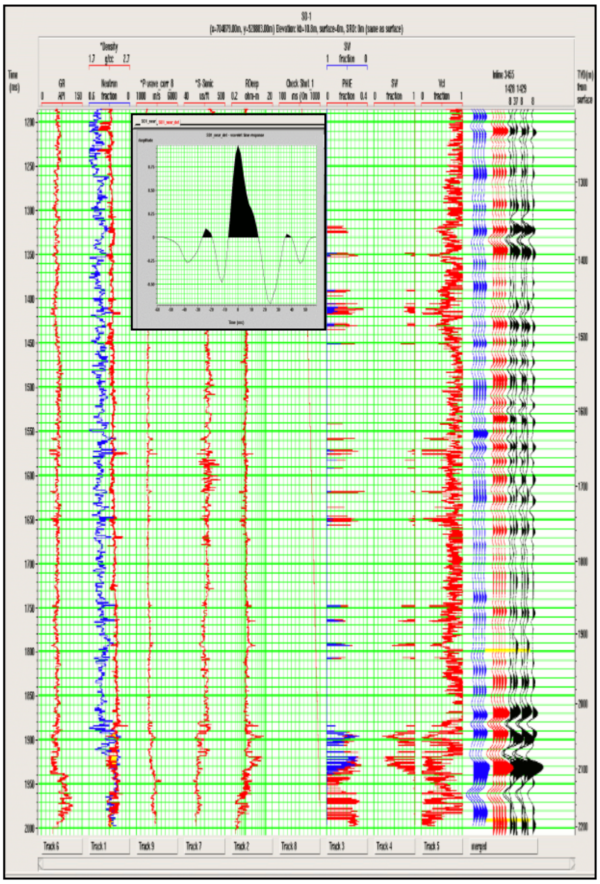


Fig. 3: SD-1 Synthetic using deterministic wavelet with the Near angle 8.

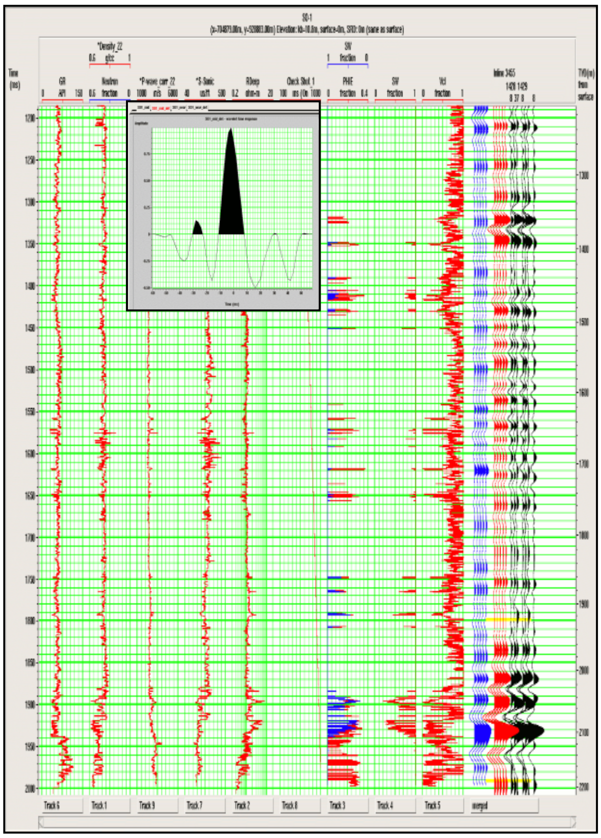


Fig. 4: SD-1 Synthetic using deterministic wavelet with the Mid angle 22.

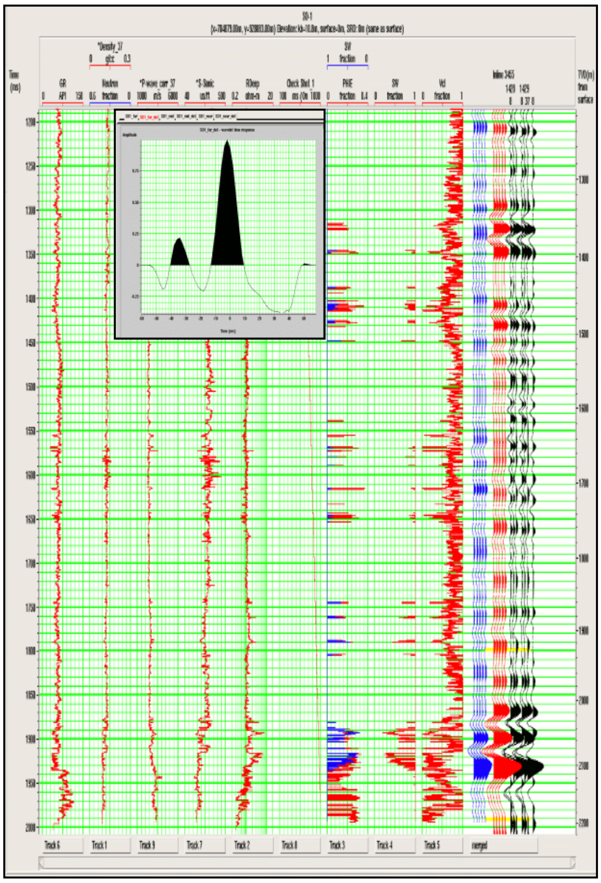


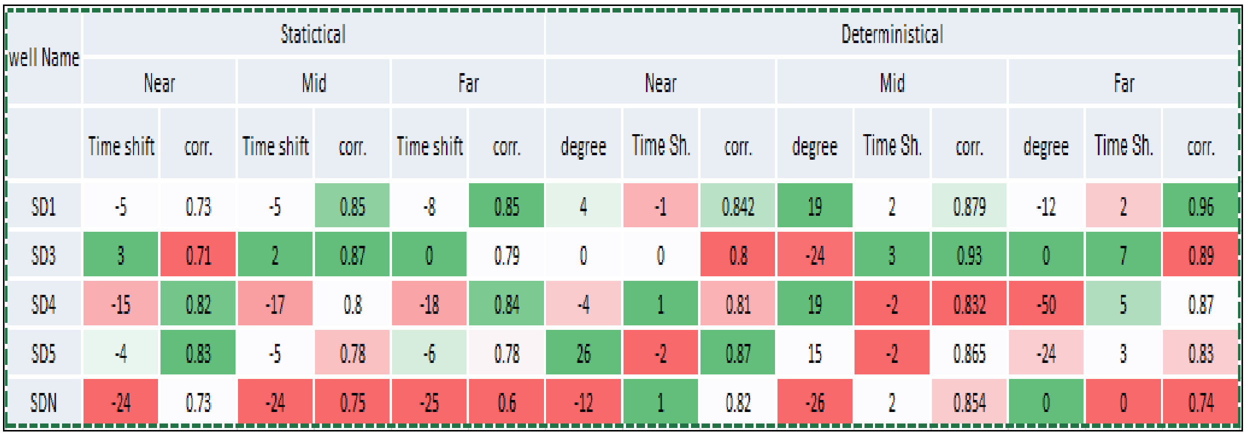
Fig. 5: SD-1 Synthetic using deterministic wavelet with the Far angle 37.

Since different angle stacks have different seismic wavelets, the above-mentioned process needs to be repeated for the three angle stacks separately (Near, Mid &Far) to get the angle dependent seismic wavelet (Fig. 3-5). A wavelet sensitivity analysis is done using five wells (SD-1, SD-3, SD-4, SD-5 and SD-4) (Fig. 6).

Initial Model Constrain and the white Noise

The inversion requires the initial value of Z to be known. The inherent bandwidth characteristic of the seismic adds a limitation to this technique. The low-frequency component missing in the seismic must be added from another source, such as filtered sonic logs, to assure a more realistic result (Lindseth, 1979). Several authors have raised the importance of including an initial guess to accurately predict an impedance model.

The impedance model was generated by interpolating the impedance at the wells locations which is calculated from the sonic and density logs of SD-1, SD-3, SD-5 and SDN wells with a low-pass filter of 0-5-10-15 Hz. The interpolation algorithm is guided by using the four seismically picked horizons. The interpolation program uses a least square fit to determine a trend to use for the top and bottom of the well (Fig. 7).



well Name	Statictical						Deterministical								
	Near		Mid		Far		Near			Mid			Far		
	Time shift	corr.	Time shift	corr.	Time shift	corr.	degree	Time Sh.	corr.	degree	Time Sh.	corr.	degree	Time Sh.	corr.
SD1	-5	0.73	-5	0.85	-8	0.85	4	-1	0.842	19	2	0.879	-12	2	0.96
SD3	3	0.71	2	0.87	0	0.79	0	0	0.8	-24	3	0.93	0	7	0.89
SD4	-15	0.82	-17	0.8	-18	0.84	-4	1	0.81	19	-2	0.832	-50	5	0.87
SD5	-4	0.83	-5	0.78	-6	0.78	26	-2	0.87	15	-2	0.865	-24	3	0.83
SDN	-24	0.73	-24	0.75	-25	0.6	-12	1	0.82	-26	2	0.854	0	0	0.74

Fig. 6: Wavelet Sensitivity.

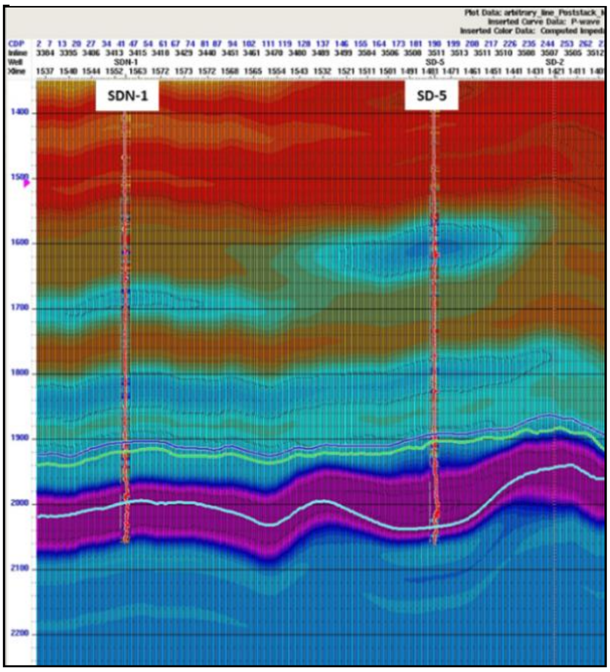


Fig. 7: Initial Zp Model.

Deterministic Inversion

Deterministic inversion gives a single solution using the inversion parameters, there are several equations used to invert the seismic data into impedance models, one of the most commonly used is Fatti et al. (1994) that re-expressed of Aki-Richards Equation as:

$$r_{pp}(\theta) = C_1 r_p + C_2 r_s + C_3 r_D \qquad (3)$$

Where

$$C_1 = 1 + \tan^2\theta\,,$$

$$C_2 = -8\left(\frac{V_s}{V_p}\right)^2 \tan^2\theta$$

$$C_3 = 0.5\tan^2\theta - 2\left(\frac{V_s}{V_p}\right)^2 \sin^2\theta$$

And the three reflectivity terms are given by:

$$r_p = \frac{1}{2}\left(\frac{\Delta V_p}{V_p} + \frac{\Delta\rho}{\rho}\right),\; r_s = \frac{1}{2}\left(\frac{\Delta V_s}{V_s} + \frac{\Delta\rho}{\rho}\right)\; \&$$

$$r_D = \frac{\Delta\rho}{\rho}$$

Fatti model was selected to perform the inversion as it gave the most accurate approximation to the impedance model generated.

Experimental design is used to assess the sensitivity of a few important parameters in pre-stack inversion, including seismic wavelet, geological models, ZP-ZS relationship, ZP-Density relationship and VS/VP ratio. As the seismic inverse problem always involves finding a model that either minimizes the error energy between the observed and the theoretical seismograms or maximizes the cross-correlation between the synthetics and observations (Sen and Stoffa, 1991), we first assess the sensitivity of seismic residual (error energy) to each parameter.

After performing the deterministic inversion, it was observed that the technique failed to predict the 2.5m of net pay present in SD-5 well and its extension and could not resolve the two gas sand reservoirs in (SDN-1well Fig. 8-9)

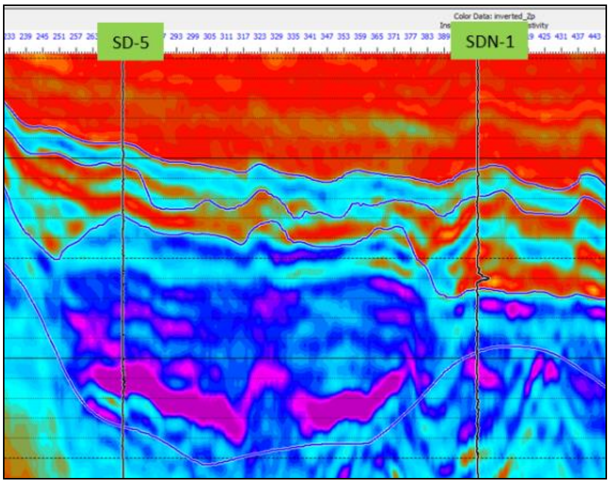


Fig. 8: Inverted Zp Volume.

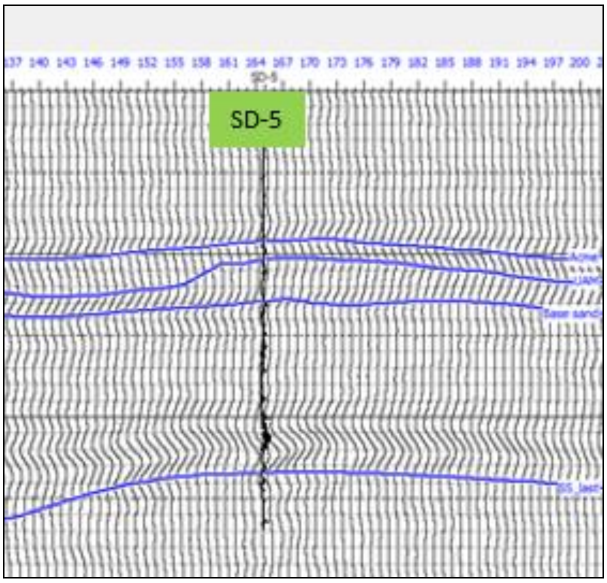


Fig. 9: Inverted Vp/Vs Volume.

Stochastic Inversion

To allow for the estimation of uncertainty in our inversions, the technique of stochastic inversion was developed in the 1990s. In stochastic inversion we produce many possible solutions, all plausible, which average to the deterministic solution. Stochastic inversion obtains a higher frequency result by using a vertical variogram model (Fig. 10)

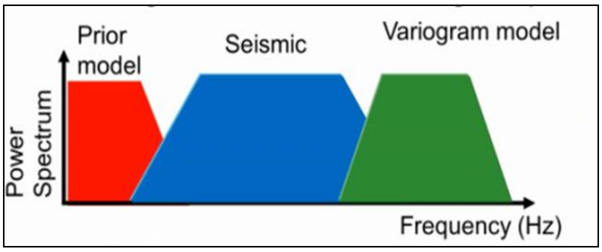


Fig. 10: Stochastic Inversion Work Flow Hampson and Russell Software manual guide v. 10 (2015).

In stochastic inversion, the least-squares inversion method is extended by formulating the problem using a Gaussian or Log Gaussian posterior probability density function, or pdf (Tarantola, 1987). This allows us to sample various scenarios from the pdf using the Monte Carlo (MC) or Markov Chain Monte Carlo (MCMC) approach. The earliest approach to stochastic inversion was by Haas and Dubrule, 1994, in which Sequential Gaussian Simulation (SGS) is used. Buland and Omre (2003) developed a fast approach to stochastic linearized inversion which utilized a Bayesian statistics approach. The GeoSI method combines both the Bayesian approach and the SGS method (Doyen, Williamson et al., 2007).

After optimizing the correlation coefficient and variograms, the next step is to run the inversion at the wells.

Stochastic Inversion result at SD-5 well, where the black line is the recorded log and the red line is the mean solution showing an excellent match between the receded logs and the inverted ones and can predict the thin reservoirs encountered by the well.

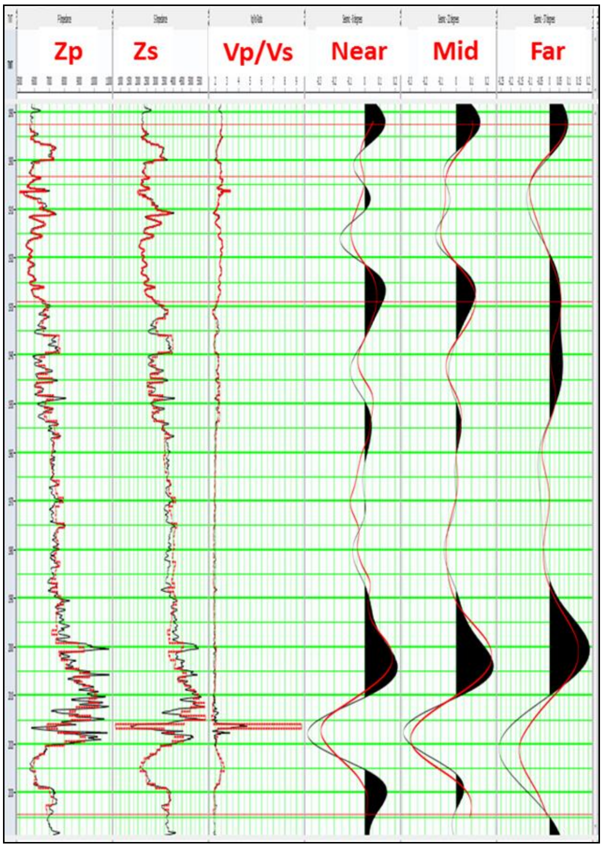


Fig. 11: SD-5 Stochastic Inversion.

Gas Sand probability Section showing separation two gas sand bodies in SDN-1and thin pay in SD-5 (Fig.12).

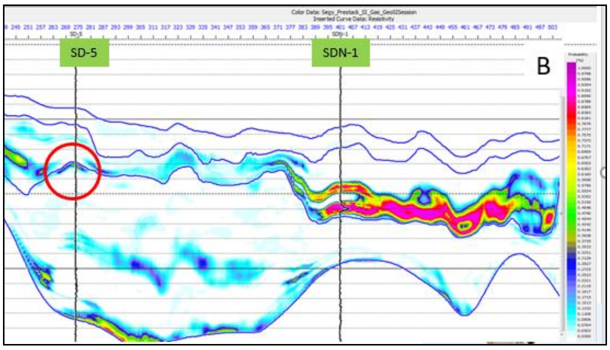


Fig. 12: SD-5 Stochastic Inversion.

As seen from figures (Fig. 11-12) the stochastic inversion was able to distinguish the thin Abu Madi sands gas reservoir and its lateral extension.

CONCLUSION

The inverted Zp from stochastic inversion mean (P50) realization has more resolution than the inverted Zp from deterministic inversion, also the inverted lamda-Mu which is sensitive to pore fluid from stochastic inversion were able to detect the thin reservoirs in SD-5 well, the stratigraphic edge between SD-1 and SD-3 wells, and the separation between the two sand bodies in SDN-1 well. Where, the inverted lamda-Mu from deterministic inversion could not separate the two sand bodies in SDN-2 well or predict their stratigraphic edges.

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