Application of Stochastic Inversion for Reservoir Connectivity Analysis with Uncertainty

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Summary

Over the past two decades, the overall trend has been for a more quantitative use of seismic in building geomodels and interpreting subsurface data. Assessing static reservoir connectivity is a key element in the characterisation of recoverable reserves. This is sometimes based on 3D facies or "geobody" models defined by combining well data and inverted seismic impedances. However, connectivity analysis is mostly performed from deterministic inversion results that provide limited information on uncertainty and may yield biased estimates of connected reservoir volume. On the other hand, stochastic seismic inversion has been designed to overcome the band-limited nature of deterministic inversion methods by generating multiple realisations of elastic properties in fine-scale stratigraphic grids. The availability of multiple high frequency realisations, consistent with the seismic data serves as a base for assessing the impact of inversion uncertainty on reservoir connectivity.

The workflow adopted in this paper to exploit the stochastic inversion for sub-surface facies characterisation and reservoir connectivity analysis with uncertainty of a sandstone reservoir is divided into four stages. In first stage pre stack stochastic inversion carried out to generate inverted elastic attributes. In second stage, seismic facies classification was performed based on cross-plots of inverted elastic attributes. Applying the classification to all impedance realisations, multiple seismic sand facies models were generated that can be averaged to produce a sand probability cube, reflecting the level of uncertainty in the inversion process. In third stage all connected sand "geobodies" in each realisation was identified and the facies realisations were ranked based on computed geobody statistics. Finally, the geobodies from all realisations were combined to calculate the probability of connection to given wells and the uncertainty in connected sand volume.

Introduction

There are many methods available for the accomplishment of simultaneous seismic inversion and, consequently, the attainment of Acoustic Impedance (Ip), Shear Impedance (Is) and other different Elastic Attributes. They can be classified into two groups: the deterministic methods, which generate a single acoustic impedance model, and the stochastic methods, which result in multiple equiprobable models. The deterministic methods are generally cheaper in terms of computation time and disk space, with the vertical resolution of the results being constrained by the seismic bandwidth. The deterministic inversion is suitable for deriving general trends and highlighting large-scale features at the exploration stage, but in a depositional environment where fine-scale heterogeneities impacts on the problem are being addressed, stochastic approaches offer higher resolution. In order to overcome the band-limited nature of deterministic inversion methods, stochastic approaches have been proposed as a way of generating multiple high frequency realisations of elastic properties from seismic data. Stochastic elastic inversion generates a large number of impedance models, or realizations, all constrained by the seismic data, the well logs and some spatial correlation parameters. This robust mathematical framework allows taking into account uncertainties from all types of input data, such as wells, geological property distribution, in addition to the uncertainty on the seismic data itself. The availability of multiple realisations of elastic parameters becomes a significant advantage when using inversion results for reservoir modelling and uncertainty analysis. A mapping can often be done between elastic attributes derived from inversion and geological facies in the reservoir. With stochastic inversion, it becomes possible to not only build facies models but also estimate their uncertainty/non-uniqueness of the results through statistical analysis of many equiprobable models. With multiple facies models, stochastic reservoir connectivity analysis can also be applied to assess uncertainty in drainable reservoir volume for given well trajectories and the fine scale makes stochastic inversion results very well suited to integration in a reservoir model, since the need for downscaling of the results is reduced. Therefore, the aim of this work was to show how stochastic inversion has been used for facis classification and probability of reservoir connectivity with uncertainty for a sandstone reservoir pertains to offshore area.

Methodology

Figure-1 schematically depicts the workflow. The methods were divided into four stages. In the first stage, pre-stack stochastic inversion and different inverted elastic attributes were generated. In the second stage, seismic facies classification was performed based on cross-plots of inverted elastic attributes, calibrated to log data. Applying the classification to all impedance realisations, multiple seismic sand facies models were generated that can be averaged to produce a sand probability cube, reflecting the level of uncertainty in the inversion process. In the third stage, all connected sand "geobodies" in each realisation was identified and the facies realisations were ranked based on computed geobody statistics. Finally in the fourth stage, the geobodies from all realisations were combined to calculate the probability of sand connection to given wells and the uncertainty in connected sand volume.

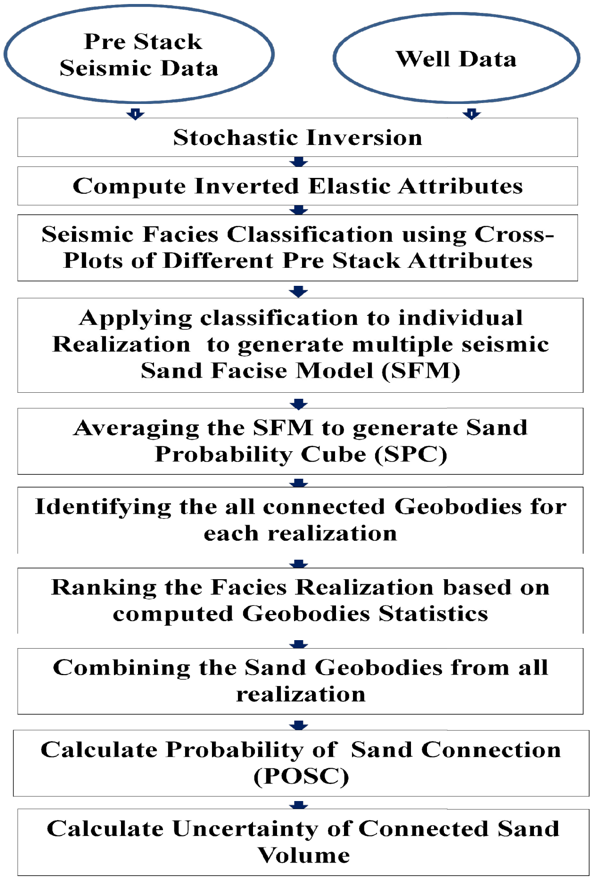

Fig-1: Work flow

Data Preparation

PSTM 3-D seismic volume, three angle stacks (16°, 30° and 40°), sonic and density logs of four wells and four interpreted seismic horizon were available for deterministic and stochastic seismic inversion. Two pseudo markers, 100 ms above the top interpreted horizon and 100 ms below the base interpreted horizon, were also used as the upper and lower limits of seismic inversion. The seismic data contained a frequency bandwidth of 8 to 67 Hz.

a. Noise Cancellation

The S/N ratio of the data was improved through application of structure orient filtering along the structure. Enhancing the image quality by removing of noise was important, in order to generate attributes of the highest possible resolution and which had the best chance of capturing subtle strati-structural details.

b. Low Frequency Background Model Building

A background low frequency model typically contains frequencies in the 0 – 15Hz range was generated. This is a straight forward process, where well properties are now interpolated with accurate structural control. Lateral interpolation algorithm like inverse distance had been used. The main geologic input in the model building was supplied in the form of seismic horizons to guide the interpolation algorithm.

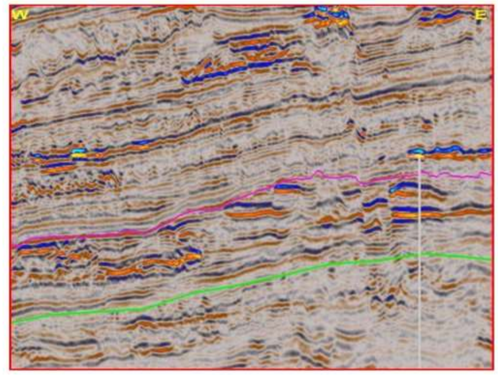

Fig-2: Original Seismic Section

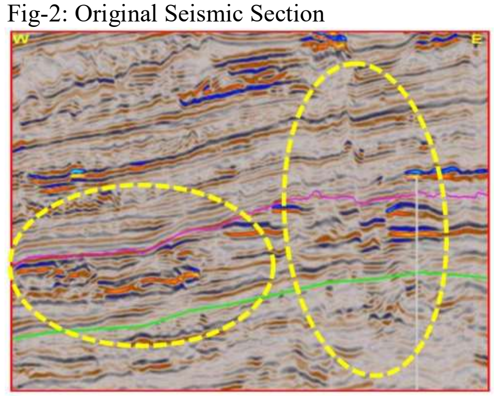

Fig-3: Noise cancelled seismic section by applying structure orient filter

Deterministic Inversion

The model based deterministic inversion was then performed by spectrally combining the inverted balanced reflectivity trace and the low-frequency background model. The inversion starts by evaluating the error between the synthetic trace and the input seismic trace. If the error between these two terms is not small enough, the algorithm will update the synthetic trace and put it into the next iteration and keep this process until the error meets the exit threshold.

Stochastic Inversion

It had been used a Bayesian formalism and a linearised, weak-contrast approximation of the Zoeppritz equation to construct a log-normal joint posterior distribution for P- and S-wave impedances. The basis of the stochastic inversion was geo-statistical. A variogram analysis was necessary before running the stochastic inversion to simulate the spatial variation at each direction. Due to non-uniqueness, a large number of realizations were generated during the inversion. Each realization was the same at the well locations, but the inversion results were increasingly different further away from the well. The final stochastic inversion model that was used in this study to predict the attributes, reservoir properties, facies classification, sand facies model, sand probability cube, sand cube connectivity and uncertainty of connected sand volume was the average of all hundred realizations obtained.

Result and Discussion

The inversion was run in a fine-scale stratigraphic grid with about 180 layers of 1 ms each, and constrained with three wells in addition to the prestack seismic data. Several hundred of impedance realizations were generated from elastic pre-stack stochastic inversion like Vp/Vs as illustrated in Figure 4. Low Vp/Vs indicated the sand facies.

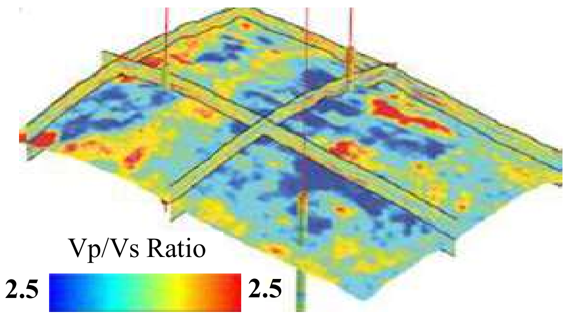

Figure 4: 3D view of a single realisation of Vp/Vs

After inversion, seismic rock facies were defined using cross-plots of elastic attributes calibrated to well logs. Considerable sand / shale discrimination was achieved through a simple cross-plot of P-impedance versus Poisson's ratio as illustrated in Figure 5 where the color was coded according to Vsh. Points having low Vsh within the polygon were assumed as sand facies and points having high Vsh outside the polygon were shale facis.

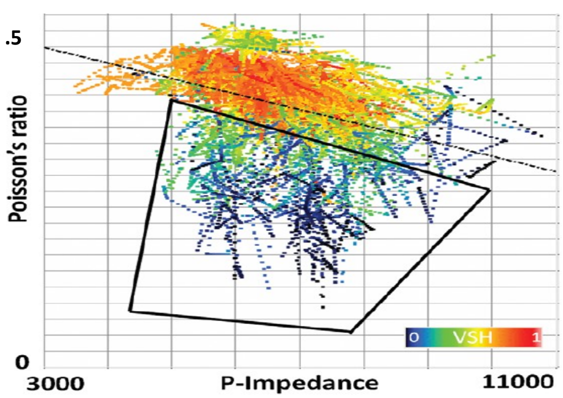

Figure 5: Cross-plot of P-impedance vs. Poison's ratio

Cross-plot-based lithology classification as defined in Figure-5 had been used to transform the each realization into seismic facies model. This resulted in multiple facies models as illustrated in Figure 6.

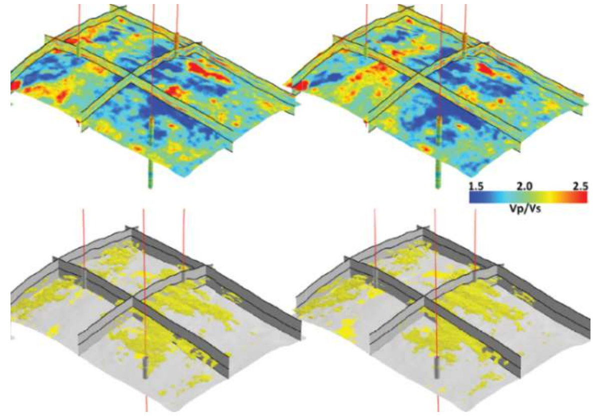

Figure 6: Two different Vp/Vs realisations (top) & the corresponding facies models (bottom) generated by applying the classification defined in Figure 5.

The channel architecture of the reservoir became visible in Figure 6, but there were significant variations between realisations, hinting at significant connectivity differences.

The multiple seismic facies models were summed together to produce a sand probability cube illustrated in Figure 7. This cube was used to assess the impact of inversion uncertainty on the lithology distribution in the reservoir. The low probability around the left most well illustrated the fragmented nature of the channel, whereas the higher probability in the middle indicated a probable connection between the two right-most wells. It also provided uncertainty information in each point. The sand bodies visible on the left in Figure 7 were not connected to any well and thus were not drainable from the current well configuration.

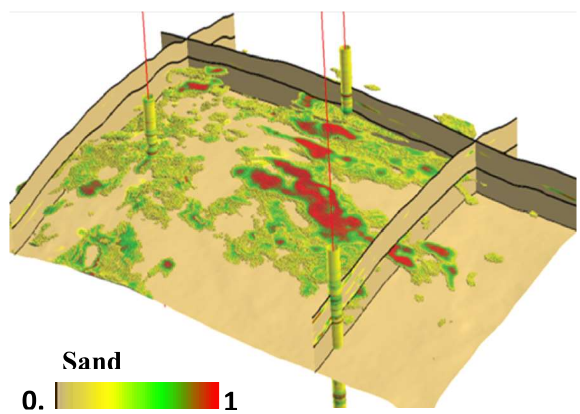

Figure 7: Sand probability cube derived by combining all facies models.

Each facies model derived from a single realization from inversion was processed. The connected sand bodies were identified as illustrated in Figure 8. Then, the connected sand bodies are filtered so that only the ones connected to the wells are kept illustrated Figure 9.

These individual connectivity models were summed together. This produced a probability cube of connection to the wells as illustrated in Figure 10, which clearly shows that one of the wells was not connected at all to the two others, confirming the visual analysis of the sand probability.

More importantly, the connected sand volume was used as a ranking criterion. This yielded a distribution of the connected sand volume across all the realizations as illustrated in Figure 11.

The bimodal nature of the distribution highlights two sets of realizations, differentiated by whether the large sand body in the middle is connected or not to the top-most well (blue arrow in Figure 9). This in turns depends on a very small bottleneck (black circle in Figure 9), which only becomes apparent from the connection uncertainty analysis.

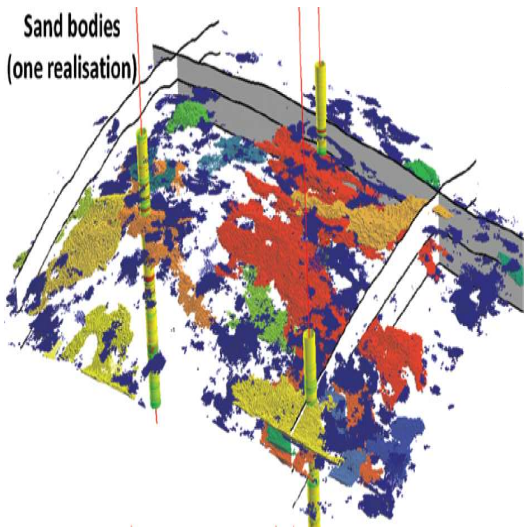

Figure 8: Identified continuous sand bodies from one realisation

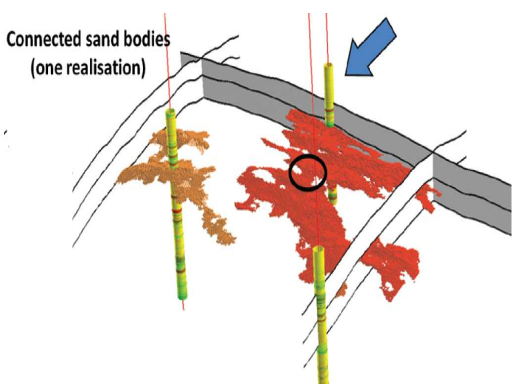

Figure 9: Connected sand bodies to at least one well

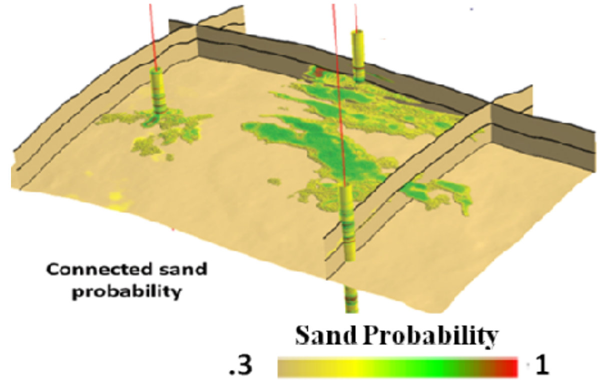

Figure 10: probability of sand connection to at least one well

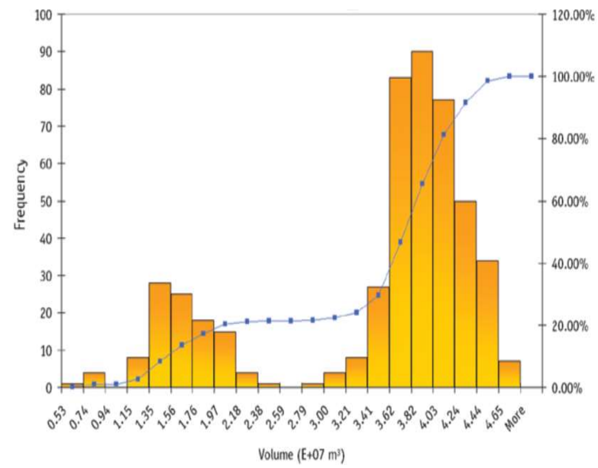

Figure 11: Corresponding sand probability distribution

Comparison with deterministic inversion

Compared to deterministic inversion, the stochastic approach has several advantages. First it can be readily used for subsurface uncertainty analysis. Second it removes the statistical bias which may occur when computing net sand volume or other statistics from deterministic inversion results. As an illustration of this "flaw of averages", it had been computed an estimate of sand volume from the mean P- and S-impedances, obtained by averaging all corresponding realisations. Figure 12 showed the facies model (bottom left corner) obtained by applying the sand cross-plot polygon to the inverted Ip and Is means. The corresponding sand volume was depicted just above (top left corner). This "deterministic" sand volume estimate was much lower than predicted from the range of histogram values corresponding to the multiple realisations (top right corner) and the geometry of the sand bodies was also very different. This apparent bias was a direct result of the smooth, band-limited nature of deterministic inversion compared to stochastic inversion.

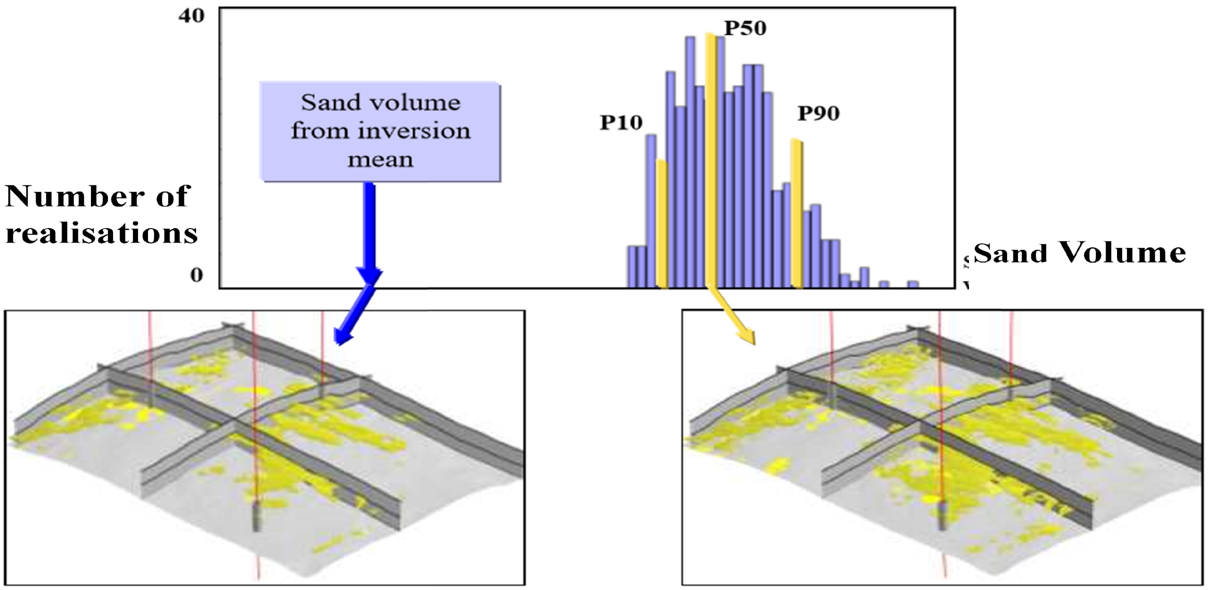

Figure 12: Comparison of the facies cubes derived from individual impedance realisations & from the mean of all impedance realisations, **Top**: histogram of the total sand volume constructed from multiple facies realisations. **Bottom**: facies cube derived from mean of all impedance realisations (left) & from one impedance realisation (right)

Conclusion

The paper deals with the advantages of stochastic seismic inversion over a deterministic pre-stack inversion.. it has also described the limitation of deterministic Pre-stack inversion. Deterministic inversion results produce an average effect of thick strata whereas stochastic inversion simulates small scale variability.

Stochastic inversion offers the opportunity to fully explore the probability space around a seismic inversion, or rather determine the extent of the uncertainty associated with it. It has been illustrated how multiple realisations of IP and IS produced by stochastic seismic inversion can be used for uncertainty analysis and cascaded stochastic simulation of facies. Facies probability cubes allow assessing not only the most probable facies distribution, but also the uncertainty on this distribution, coming from the inversion process.

The uncertainty on the well litho-classification could also be integrated. Moreover, connectivity analysis can be performed, based on the facies models derived from the individual impedances realisations. This analysis leads to ranking criterion closer to the ranking that could be obtained by performing full flow simulation. It is also possible to compute well connection probability cubes that provide information not only about the drainable reservoir volume, but also about the uncertainty on this volume.

The paper has brought out an integrated static reservoir model with better confidence in rock properties distribution in the inter well grid space.

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