Fast track reservoir characterisation of a subtle Palaeocene deep marine turbidite field using a rock physics and seismic modelling led workflow.

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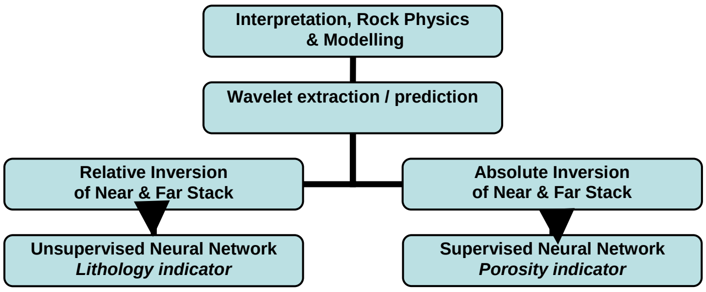
Abstract
This paper presents a novel approach to identifying/tracking interlocking Palaeocene sand and shale filled channels (based on forward modelling, AVO classification, inversion of inversion techniques for an appraised subtle Palaeocene deep marine turbidite, Central North Sea.

Introduction
Geophysical analysis methods and seismic attributes are built on physical phenomena, and can be modelled by certain theoretical rock-physics methods. By calculating and quantifying lithological and fluid fill variability it is possible to take the well based modelling forward and then apply to the seismic world of AVA and inversion. By using rock-physics to bridge the gap between petrophysics and seismic we can us an inversion of inversion technique to quantitatively predict reservoir properties (such as porosity, shale volume and saturation) away from the well. Without the use of rock physics seismic is incapable of measuring any of these parameters directly. Improvements being made in the processing world to enhance the signal to noise ratio will mean that the geoscience community can gain confidence that any subtle changes that are observed in the seismic signal are true artefacts of the subsurface environment.

AVA and inversion is becoming an ever-increasing part of the workflow within all stages of Exploration and Production. Here we identify how the results of some early rock-physics can be applicable to defining the properties of the Brenda Field, block 15/25b. The approach involves using rock-physics analysis and modelling, an improved interpretation on a pseudo volume, relative and absolute inversions, and comparison of a supervised and unsupervised neural network. The integration of these guided the interpretation and gave an ever increasing confidence that the model can be used to drive the static reservoir model rather than using more conventional reservoir modelling techniques.

Workflow



The approach used was based around a solid rock physics understanding a combination of pre-stacked zero phased seismic data providing a set of near and far stack gathers, and a composite log suite from 12 wells. Two slight different routes were used and then compared; an unsupervised neural net method based on rock physics modelling of shale volume variation; and a supervised neural net approach (inversion of inversion) method trained directly on porosity.

The Palaeocene sediments with relatively high porosity shaley sands in a relatively shallow marine environment allow such techniques to be used with confidence, especially with improvements in acquisition and processing techniques which continue to improve the signal to noise ratio. The Brenda Field is a working example where relatively modern techniques can be used and applied with success, to guild interpretation and the final reservoir model.

Rock physics modelling

An initial QC (figure 1a & 1b) of the data shows that the data is of reasonable quality and fits identified theoretical models previous recognised. Based on the understanding that our lithologies conform to models proposed and trends were apparent forward modelling techniques could be used to predict the unknown. The two main scenarios that were modelled were; what happens with variable fluid content; and what happens with lithology variation.

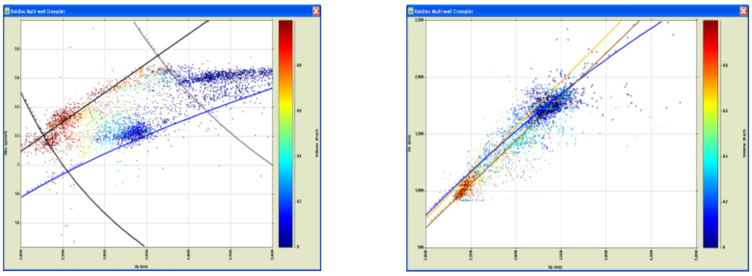


Figure 1a) Vp/Rho crossplot Initial logged data from12 wells from the Brenda area over the interval of interest. b) Vp/Vs crossplot from wells with logged data available over the interval of interest.

By bringing together a spectrum of Rock-physics theories; such as Greenberg-Castagna's Vp/Vs relationship (1992); Batzle and Wang (1992) fluid properties; Gassmann's Fluid substitution (1952); Zoeppritz (1919) equation; tuning thickness models; and numerous others, along with data derived models, it is possible to calculate certain attributes and there sensitivity within the reservoir of lithology and fluid variations and take these forward to apply to the seismic data.

Gassmann's (1952) equation was used in the forward modelling to predict each well characteristic under variable fluid conditions, ranging from water filled to a high oil saturation of 80%. An example of which can be observed in tracks 5-7, figure 2, whilst the initial porosity and saturation can be seen in tracks 3 and 4.The results of the fluid substitution from the initial logs (green) and the pseudo water filled (blue). The substitution from hydrocarbon (green) to water (water) shows the expected increase in compressional velocity and density, whilst shear velocity remains relatively constant. The first set of synthetics show the AVA gathers for the initial hydrocarbon filled scenario, whilst the second set is for a water filled scenario. There is a significant increase in amplitude where there is substitution to water from oil.

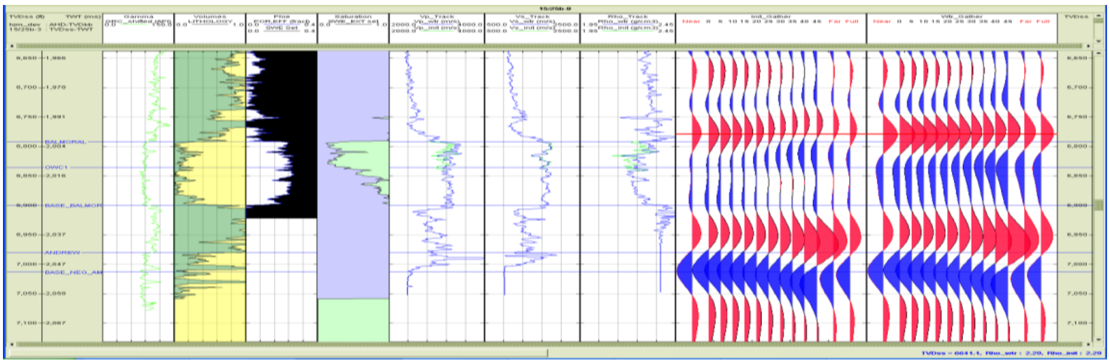


Figure 2) Well data and synthetics for the initial lo (green) scenario and the pseudo water wet (blue) scenario.

Xu and White (1995) developed a theoretical model for velocities in shaley sandstones. It was stated that clays introduce bias and scatter into standard porosity-velocity models, because they normally form pores with much smaller aspect ratios than those associated with sand grains. The Xu-White model was used to derive VP, VS and density using the Xu and White (1995) clay-sand mixture model and the Kuster and Toksöz (1974) differential effective medium (DEM) equations (Keys and Xu, 2002). The essential feature of the function is that the shape of the porosity inclusions can be specified using a shape factor. Therefore the effect of changing pore geometry on VP, VS and density, and hence the seismic response, can be investigated.

The Xu-White methodology (1995) was used to calculate a predictive Vp, Vs and Rho, these were then optimised on the logged data and then perturbations were calculated to find the quantitative effects of increasing the volume of shale within the Forties interval. The Xu-White methodology uses water wet lithologies so where hydrocarbons were present Gassmann's equation was used to back then out and substitute to water prior to lithology modelling.

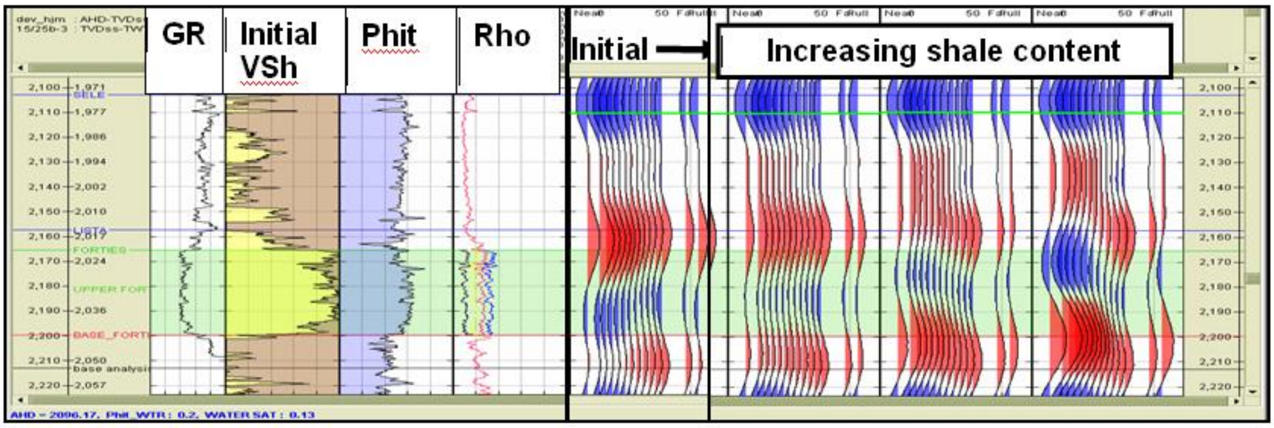


Figure 3) Well tracks represent a mixture of logged and pseudo logs. Track one holds the gamma log, track two is a representation of the clay and sand volume fractions, track three is the total porosity, track four shows a set of pseudo Density logs for water substituted logs and variable shale content (blue=initial volume fraction & water) (black= 60% increase in shale) over the reservoir interval. Track 5 synthetic a represents the initial synthetic over an angle range of 0-50 degrees. Tracks 6, 7 & 8 represent synthetics using pseudo well data using logs constructed for an increasing content of shale from left to right over the reservoir zone.

The pseudo logs were then used to create sets of synthetics for differing shale contents. The results of which can be seen in figure 3, where there is a significant, change in seismic signature. Where we have a hemipelagic shale overlying a clean channel sand, we see a negative gradient and as more shale is added to the sands the gradient increases and eventually becomes positive. Figure 2 show irrespective of pore fill if the shale content is low then the gradient is negative. Although fluid fill does effect the gradient is only small relative to the lithological affect. Also hydrocarbon presence increases the gradient.

Seismic Attributes

There are many different types of seismic inversion; we hereby show two types of pre-stack inversion, a coloured inversion and a model-based inversion.

Both methods used here exploit the AVO effects in the pre-stack domain and uses Vp, Vs and density information. Where the P-wave is greatly affected by the pore fill the S-wave is better at showing variation in rock framework The strength of inversions are that they simplify the seismic picture by removing the effect of the wavelet, which there by allows us to build a better understanding of the stratigraphic, lithological and pore fill variation. It is impedances, which bridge the gap between petrophysical variation and seismic amplitudes. The contrasting impedances at an interface between two rock types create a surface from where we get a reflection. Therefore by estimating and extracting the wavelet from the seismic data we get a cube of impedance, which has slightly more geological relevance.

Connolly (1999) introduced elastic impedance (EI) as the equivalent to acoustic impedance (AI) but at an angle of incidence. It is relatively simple in its understanding and very powerful. The inputs required to generate the EI logs are Vp, Vs and Rho. Where Vs was missing the Greenberg Castagna's methodology was used to predict. This allows the various partial stacks to be used in the inversion domain.

Coloured Inversion

Lancaster & Whitcombe (2000) proposed the coloured inversion technique which is a simpler approach to estimate relative impedance by trace integration. Its advantages are ease of interpretation and being a seismic attribute, it does not add artefacts, which may be introduced by more advance deterministic inversion techniques, and it is quick and easy to apply. The downside is data is relative property rather than absolute, an attribute, so it cannot be used for quantitative interpretation of the reservoir characteristics. The reason for this is that tuning effects are not addressed in areas of rapid lateral variations in impedances.

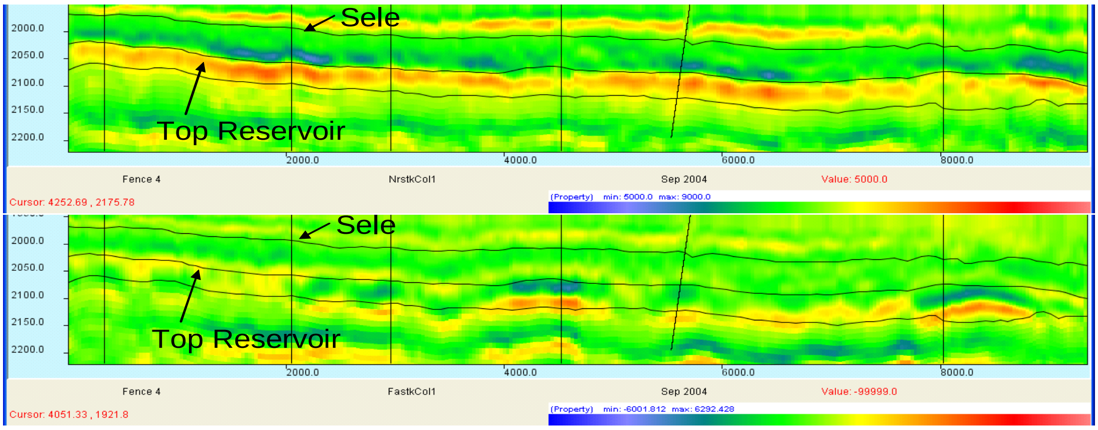


Figure 5a) Near Stack coloured inversion & b) Far stack coloured inversion

By looking at the various impedances in figures 5, in the inverted near stack low impedances are shown in the highlighted areas, however in the gradient impedance in figure 6, which is indicative of sands, as there is still a strong negative gradient. This supports benefits of using the gradient stack to represent the reservoir system rather than solely using the inverted near stack to represent lithology.

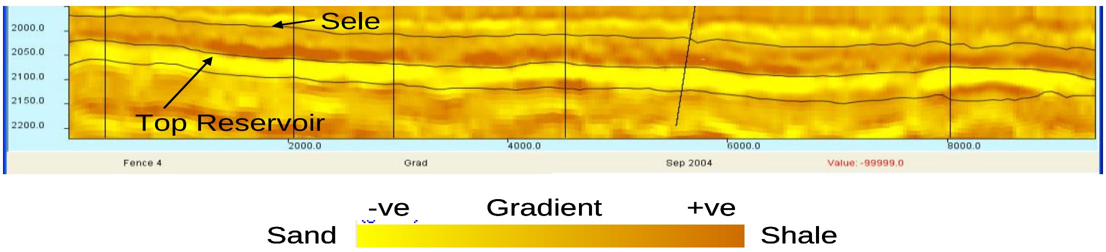


Figure 6) Gradient impedance section

Model-based Inversions

In order to derive absolute impedances from relative impedance trace inversions, a low frequency model is needs to be added to the relative impedance inversion. This comes form a simple interpolation of well log data in our case or it could be derived from stacking velocity data. Whereas the relative impedance reflects the variation at the interface, hence can be affected by the variation in shale over burden, the absolute impedance in theory should accommodate for this.

The aim of the seismic inversion here is to relate the RMS amplitudes of the seismic data to an impedance model (derived from AI and EI impedance logs calculated).This was constructed based on the maximum likelihood deconvolution algorithm. It works on the basis that the wavelet is known and a low frequency impedance model acts as the starting point. A broadband reflectivity is created and modified gradually until the resulting synthetic matches the real trace at each sample. It then tries to find the optimum impedance volume which represents the seismic data, by comparing the synthetic volume with the real seismic. It works by trying to reduce the error or difference between the two sets until an optimum volume to represent the seismic is found.

Crossplotting the well data can helps identify the elastic properties for the different lithologies and fluid fills. By using specific cut-offs we can clearly separate out water sands, oil sands and shale (figure 7). Shale has a lower AI than oil sands which have a lower AI than water sands. With oil sands AI properties (values) overlapping into the shale and water sand it would be hard to separate out clearly. The EI volume however gives the shale and water sand higher values than the oil sands. Where we have a high density of points we can have confidence that a location with these values is either oil sand, water sand or shale. Moving away from the high density areas in the crossplot and in the attributes domain variation is occurring due to either a reduced saturation level or variable reservoir quality.

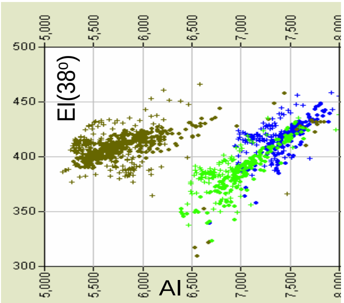


Figure 7) Acoustic impedance vs elastic impedance cross-plot. Brown = shale, Green = oil sands, Blue = water sands.

The absolute acoustic impedance and elastic impedance (figures 8a & b) volumes show a large degree of similarities to that of the relative (coloured) impedance volumes (figures 6), however the values shown are absolute to each loci and independent of the overlying lithology whilst at the same time the values represent values similar to those observed in the crossplot. Also no tuning effects should distort the results. The target locations were then drilled to hit the proposed anomalies and delimit the extent of the accumulation and confirmed the impedance volumes predicted properties.

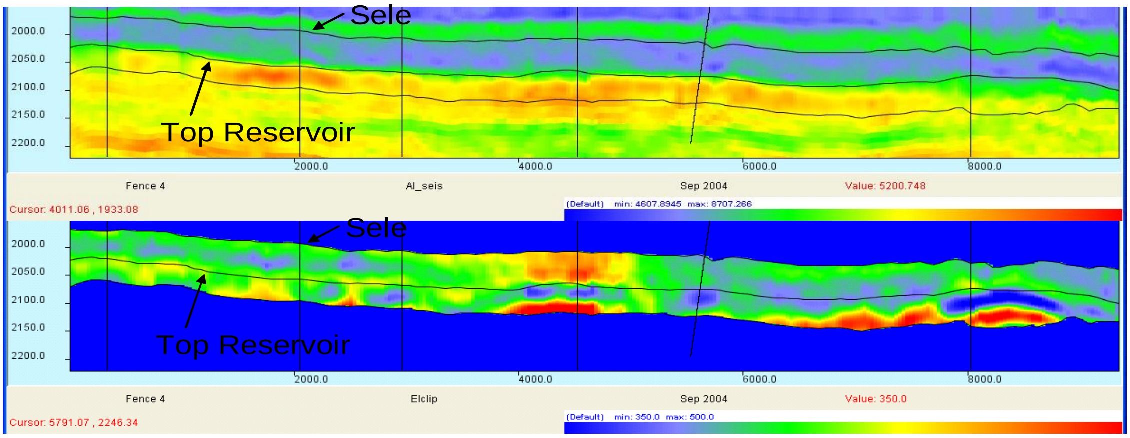


Figure 8a & b) Absolute Acoustic and elastic impedance section. Red solid lines represent low risk targets. Red dashed lines represent medium risk targets.

Neural Nets

Neural nets act as pattern recognition tool similar to the brain, similar to identifying characteristic on the crossplot and then trying to find those values within the attribute data. We describe the methodology and present the results of two slightly different approaches; tying well properties to seismic attributes, a supervised neural net; or clustering patterns which we can be related to rock-physic models, a form of unsupervised neural net. The aim is eventually to predict reservoir characteristics away from the wells based on the seismic attribute.

Supervised Neural Nets

The supervised neural networks used here works as a Multi-layer Perceptron (MLP). This network works by building up a number of many small processing units. The nodes in an MLP are broken down into three sub-processing units; the inputs, hidden and the outputs. The functionality of the MLP neural network is controlled by the user, who defines the inputs and the selected outputs, and the number of nodes in the hidden layer.

The aim of the neural is find the best non-linear relationship between porosities taken from the real wells and the attributes extracted from the seismic attribute at the locations. So how does it work? The network starts training from a random surface and set of weights, and then gives the surface an error in relation to the attributes at the well locations. The operator system then continues to create another surface and apply an error for the weights applied. This is then compared and training continues in a cycle of reducing the error with new weighting applied. In essence the neural net works by trying to find the optimal fit of sigmodal shaped surface by changing weights which stretch and squeeze the surface, trying to find the minimal amount of error. Once a best fit surface is found, it extracts the two input attributes at every trace location, and passes these through the network to obtain a predicted effective porosity. Thus the final product is a effective porosity cube which can be used to drive our reservoir simulation model.

In respect to the Brenda field the network was designed to predict the average effective porosity and saturation from two seismic attributes. The results clearly show a correlation to a realistic geological model and are based on deterministic data rather the probabilistic modelling techniques.

Unsupervised Neural Nets

As well as the supervised neural networks we can also use unsupervised networks. The difference between supervised and unsupervised methodologies is the data supplied. The unsupervised method proposed here is based on forward modelling of well data and theoretical models (Greenberg/Castagna shear wave prediction, Gassmann’s equation, Zeopprittz equation and basic first principals of rock physics.

The results show that by increasing the shale content of the reservoir channel sands we see a change in AVA. Clean channel sand displays a negative gradient, however with increasing shale content we see a change from negative through to a positive gradient. This is shown by the synthetics modelled in figure 3 and the AVA plots below showing the response from the top of the channel sands. By inverting the gradient stack we then have a property which represents the characteristics of the reservoir rather than the interface.

This approach makes two simple assumptions:

1.) The hemipelagic shale properties above the channel sands remain constant. Fortunately all the wells showed the overlying shale has a consistent velocities and density in the area of interest.

2.) The hydrocarbons only play a minor affect on the gradient, in comparison to shale variation. This can be seen in modelling of a fluid substitution. A comparison of the water wet scenario and the hydrocarbon filled sands shows that whilst the amplitude decrease with hydrocarbon saturation, the gradient only changes marginally. Due to the gradient being affected by both the lithology and saturation when applying this to the seismic data the results were used as a sand/shale indicator. The results of such assumption are best seen when the gradient stack has been inverted to relative gradient impedance (RGI) and the seismic amplitude represents reservoir properties rather than the interface above. The channel sands can be clearly identified on an age slice (fig.9b).

A comparison in figure 9, of the supervised (inversion of inversion) and unsupervised neural net approaches shows that there is a good correlation between both results even though technical approaches are different. In figure 9a the red represent a high porosity (effective) whilst the blue represents a low porosity lithology. In figure 9b the sands are identified as yellow and the shales are brown.

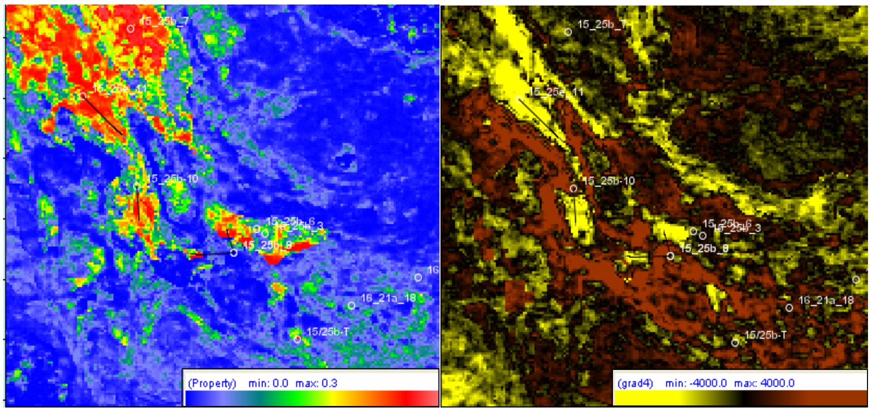


Figure 9a & b) Depth slices through the reservoir: a.) Porosity cube generated using the inversion of an inversion technique (neural net trained on porosity logs and AI and EI impedance volumes);b.) Unsupervised neural net lithology indicator (Relative gradient impedance).

Conclusions

Understanding the characteristic of the reservoirs variability via forward modelling allows the interpreter to build a rapid knowledge of the signature of the seismic involved.

The combination of the rock-physics, AVA analysis, partial stack inversions and neural nets can provide geological properties (e.g. shale fractions, water saturations) rather than specialist properties (e.g. Poisson's ratio, Lambda) that the interpreter struggles to use properly.

The Unsupervised Neural Network calibrations served as a health check and cross validation to enhance the Supervised.

Good correlation between unsupervised and supervised means that unsupervised neural network can be applicable to areas of limited well data.

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