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

Henry Morris,¹ Rod Christensen,² David Gawith,³ and Martyn Millwood Hargrave¹ present a novel approach, based on forward modelling, AVO, and inversion-of-inversion techniques, to identify/track interlocking Palaeocene sand and shale-filled channels in an appraised subtle Palaeocene deep-marine turbidite, Central North Sea.

Seismic attributes relate to physical phenomena, and can be modelled by theoretical rock physics methods. By calculating and quantifying lithological and fluid-fill variability, it is possible to take the well-based model forward into the seismic world of AVA (Amplitude Variation with Angle) and inversion. By using rock physics to bridge the gap between petrophysics and seismic, we can use a supervised neural network 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 processing to enhance the signal-to-noise ratio will improve our confidence that subtle changes observed in the seismic signal reflect changes in the subsurface environment.

AVA and inversion are gaining increasing importance at all stages of the exploration and production workflow. Here we identify how the results of some early rock physics can be used to define the properties of the Brenda Field, block 15/25b. The approach involves 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 processes guided the interpretation and increased confidence that the model could be used to drive the static reservoir model, rather than using conventional reservoir modelling techniques.

**Workflow**

The approach used was based on an understanding of solid rock physics, a combination of pre-stack zero phased seismic data providing a set of near and far stack gathers, and a composite log suite from 12 wells. Two slightly different routes were used and then compared. One involved an unsupervised neural net method based on rock physics modelling of shale volume variation; the other employed a supervised neural net method trained directly on porosity, which we call inversion-of-inversion, because it derives reservoir properties from results of conventional inversions.

The Palaeocene sediments, which comprise relatively high-porosity, shaley sands in a relatively shallow marine environment, allow these techniques to be used with confidence, especially with advances 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 applied with success to guide interpretation and refine the final reservoir model.

**Rock physics modelling**

An initial QC (Figure 1a and 1b) showed the data was of reasonable quality and provided a good fit to identified theoretical models, meaning that forward modelling techniques could be used to predict the unknown. The two main

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¹ Ikon Science.
² Oil & Gas North Sea.
³ G&G Research.

* Corresponding author: hmorris@ikonscience.com.
scenarios modelled were: What happens with variable fluid content? and What happens with lithological variation?

By bringing together a spectrum of rock-physics theories - including Greenberg-Castagna’s Vp/Vs relationship (1992); Batzle and Wang’s fluid properties (1992); Gassmann’s Fluid substitution (1952); and the Zoeppritz equation (1919) to tune thickness models and data-derived models - it is possible to calculate certain attributes and their sensitivity to lithology and fluid variations. These can then be taken forward to the seismic data.

Gassmann’s equation (1952) was used in the forward modelling to predict each well characteristic under variable fluid conditions, ranging from water-filled to an oil saturation of 80%. An example can be seen in Figure 2, tracks five to seven. The initial porosity and saturation can be seen in tracks three and four. The fluid substitution from hydrocarbon (green) to water (blue) shows the expected increase in compressional velocity and density, while shear velocity remains relatively constant. The first set of synthetics shows the AVA gathers for the initial hydrocarbon-filled scenario, while the second shows a water-filled scenario. There is a significant increase in amplitude where oil is replaced by water.

Xu and White (1995) developed a theoretical model for velocities in shaley sandstones. It 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 essential feature of the function is that the shape of the porosity inclu-
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 is that they simplify the seismic picture by removing the effect of the wavelet. This allows us to build a better understanding of the stratigraphic, lithological, and pore-fill variation. Impedances bridge the gap between petrophysical variation and seismic amplitudes. The contrasting impedances at an interface between two rock types create a surface from which we get a reflection. 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. The concept is relatively simple to understand and very powerful. The inputs required to generate the EI logs are Vp, Vs, and Rho. Where Vs was missing, a modified Greenberg Castagna methodology was used to predict it. This allowed the various partial stacks to be used in the inversion domain.

**Coloured inversion**
Lancaster and Whitcombe (2000) proposed the coloured inversion technique, which estimates relative impedance by spectrum shaping and integration. Its advantages are ease of interpretation and, being a seismic attribute, not adding artefacts which may be introduced by more advanced deterministic inversion techniques. Additionally, it is quick and easy to apply. The downside of the technique is that the results are relative rather than absolute, so cannot be used directly for quantitative interpretation of reservoir characteristics. This is partly because tuning effects are not addressed in areas of rapid lateral variation in impedances.

Coloured inversions of the near and far stack seismic volumes show a reduction in impedance when hydrocarbon-filled (Figure 5, highlighted areas). The results from early modelling (Figure 3) show that the gradient reflectivity changes with reservoir quality (shale content). Therefore an inversion of the gradient reflectivity to gradient impedance should similarly provide a volume which is indicative of the lithology. Further modelling showed that the gradient reflectivity was only subtly affected by the fluid fill. This was supported by the results of the relative gradient impedance (calculated from the near and far stack coloured inversions) as shown in Figure 6 in the highlighted area.

So, where the near and far stack inversion results are affected by fluid fill, the gradient inversion is virtually independent of the fluid and more indicative of lithology.

**Model-based inversions**
In order to derive absolute impedances from relative impedance trace inversions, a low-frequency model must be added to the relative impedance inversion. This comes from a simple interpolation of well log data in our case, or it could be derived from stacking velocity data. The relative impedance reflects the variation at the interface, and hence can be affected by the variation in shale overburden, while the absolute impedance should, in theory, account 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 the calculated AI and EI impedance logs). This model is con-
structured using the maximum-likelihood deconvolution algorithm, which works on the basis that the wavelet is known and uses a low-frequency impedance model as the starting point. A broadband reflectivity is created and modified gradually until the resulting synthetic matches the real trace at each sample. An optimum impedance volume is then calculated by comparing the synthetic volume to the real seismic. This is achieved by minimizing the difference between the two sets until an optimum volume is found.

Cross-plotting the well data can help identify the elastic properties of the different lithologies and fluid fills. By using specific cut-offs we can clearly separate sands from shales (Figure 7). Oil and water sands overlap. However, if a given point falls in an area of high data density, we can confidently discriminate between oil and water sands, or at least assign it a probability.

The absolute acoustic impedance and elastic impedance volumes (Figures 8a and 8b) show a large degree of similarity to the relative (coloured) impedance volumes (Figure 6). However, the values shown are absolute to each loci and independent of the overlying lithology, although the values are similar to those observed in the cross-plot. Also, no tuning effects should distort the results. The target locations were then drilled to hit the proposed anomalies and to delimit the extent of the accumulation: the impedance volumes predicted were confirmed. The solid lines (Figure 8a and b) represented targets where there was low risk oil to be found. This was eventually supported by the results of the drill bit. Where the anomalies were not so distinguished (dotted lines), the results were found to be thinner pay as expected, but important in defining the limits and extents of the reservoir.

Neural nets

Neural nets act as a pattern-recognition tool, similar to the human brain. Characteristics are identified on the cross-plot and then searched for within the attribute data. We describe the methodology and present the results of two slightly different approaches: one ties well properties to seismic attributes (a supervised neural net); the other uses clustering patterns which can be related...
to rock physics models (a form of unsupervised neural net). The eventual aim is to predict reservoir characteristics separately from the wells based on the seismic attribute.

**Supervised neural nets**

The supervised neural network used here works as a multi-layer perceptron (MLP). This network works by building up a number of small processing units. The nodes in an MLP are broken down into three sub-processing units - inputs, hidden, and 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 net is to find the best non-linear relationship between porosities taken from the real wells and the attributes extracted from the seismic at those locations. The network starts training from a random surface and a 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 applies an error for the weights applied. These are 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 to a sigmoidal-shaped surface by changing the 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. The final product is an effective porosity cube which can be used to drive the reservoir simulation model.

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

**Unsupervised neural nets**

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, Zoeppritz equation, and basic first principles of rock physics).

The results show that by increasing the shale content of the reservoir channel sands we see a change from a negative to a positive gradient. This is shown by the synthetics modelled in Figure 3 and the AVA plots 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 consistent velocities and density in the area of interest.

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

Figure 9 Relative Gradient impedance (RGI) age slice through the reservoir, with the yellow indicating the main sand fairway enclosed in shale background (brown).
2.) The hydrocarbons only have a minor effect on the gradient, in comparison to shale variation. This can be seen by modelling a fluid substitution. A comparison of the water-wet scenario and the hydrocarbon-filled sands shows that whilst the amplitude decreases with hydrocarbon saturation, the gradient only changes marginally. Because the gradient is 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 a relative gradient impedance (RGI), whereby the seismic amplitude represents reservoir properties rather than the interface above. The channel sands can be seen clearly on an age slice (Figure 9), with additional overbank and splay deposits being visible.

A comparison of the supervised (inversion-of-inversion) and unsupervised neural net approaches (Figure 10) shows a good correlation between both results, even though the technical approaches are different. In Figure 10a the red represents high effective porosity, while the blue represents a low porosity lithology. In figure 10b the sands are coloured yellow and the shales brown.

Conclusions
Understanding the characteristic of the reservoir’s variability via forward modelling allows the interpreter to rapidly build knowledge of the signature of the seismic data involved. The combination of 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) which the interpreter struggles to use intuitively.

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 networks can be applicable in areas of limited well data.

References

Figure 10a and b) Depth slices through the reservoir: a) Porosity cube generated using the inversion-of-inversion technique (neural net trained on porosity logs and AI and EI impedance volumes); b) Unsupervised neural net lithology indicator (Relative gradient impedance).