Introduction

Today, seismic interpretation often requires compromise. It is mostly accepted that there will rarely be enough time available for geoscientists to perform several interpretations to provide alternative scenarios to better understand the subsurface. Hence, by accelerating the seismic interpretation, artificial intelligence presents a huge opportunity to change this paradigm, mainly if it is used to complement classical techniques. It has the power to improve the quality, speed and understanding of subsurface data.

In 2018, TOTAL launched the GAIA project to explore and assess oil & gas fields faster and more efficiently. After one year, we obtained very encouraging results with the development of an A.I. fault model and proceeded to its deployment in TOTAL’s internal geosciences and reservoir integrated platform, SISMAGE, within a dedicated user interface.

During summer 2019, a TOTAL asset team performed autonomously its first operational interpretation study with the assistance of an A.I. fault model. As a new seismic processing was received on the study area, the team performed a new manual interpretation. In parallel, an A.I. assisted interpretation was carried out to compute the efficiency gain using this new A.I. product on an operational study before deploying it into production.

Study context

The field study area is located in the southern part of the Niger Delta in deep offshore Nigeria. The field lies 200 kilometres southeast of Port Harcourt and around 140 kilometres offshore in water depths ranging from 1100 meters to 1300 meters.

A dual-azimuth anisotropic PSDM processing was recently carried out in this area. The objectives were first and foremost, to enhance the signal to noise ratio, to better illuminate the faults, and to better understand the structural definition of the study area. The quality of this new dataset is good, and it is considered as the best existing data on this field. This new processing has been used to interpret again the structure and update the existing reservoir model.

Figure 1 Coherency map of reservoir 1: Good signal to noise ratio with enough structural complexity to serve as a test study.

The target area is a 4-way dip affected by complex and highly dense faulting, especially in the Central crestal area. Previous interpretations have shown that there are three main fault families, such as:
• **Outer arc faults:** they are the most common faults in the field, preferentially oriented NW – SE. The outer arc faults are NW-SE trending faults, related to the collapse of the structure’s graben.

• **Radial faults:** Observed at the steeply dipping flanks. In terms of compartmentalization, they appear to impact the younger reservoir series.

• **Collapse faults:** Located up-dip on the southern flank of the structure and are rooted in the shaly beds.

### A.I. fault model

Detecting faults using A.I. has been largely demonstrated over the past few years. However, using such models in production is a challenging task due to the difficulty to properly build a robust training set. The training set used has been optimized following the methodology described in [1] & [2] in 2019. In total, 34 seismic training datasets with different structural & seismic quality have been prepared. The validation set is composed of 11 datasets coming from different areas, on which ones the faults have been perfectly interpreted. Data augmentation and synthetic seismic generation techniques were used to obtain the best training set, hence the best model.

### Benchmark standard seismic interpretation versus A.I. assisted seismic interpretation

During this study, 94 faults were used as a reference for the machine learning prediction and for computing the productivity gain. Measuring gain for interpreters is a difficult exercise as it is highly dependent on available tools allowing fault extraction from attributes. Nevertheless, in order to face it, we take the problem form the angle of fault sticks extraction.

---

**Figure 2** Raw seismic inline (PSDM – Vertical scale in metres) with (a) manual fault interpretation, (b) Generic fault extracted from the A.I. fault model, (c) Individual faults after manual assignment and adjustment of generic fault extracted from the A.I. fault model
One of the main goals of standard seismic interpretation is the extraction of objects from seismic data (for instance fault surfaces) that can be directly used to compute volumes or create a 3D reservoir model. In order to compare the standard seismic interpretation and the A.I. assisted seismic interpretation, our goal with the two methods was to extract exactly the same set of 3D individual faults.

For both seismic interpretations (standard and A.I. assisted), we used the raw seismic data, i.e. without applying any filter or attribute. On one hand, we interpreted manually 94 faults and measured for each fault the time needed to perform the interpretation ($T_{\text{interpretation}}$). On the other hand, we computed first the A.I. fault attribute (the A.I. fault model provides in output a probability dataset) using our fault model, then we extracted all the fault sticks in a generic fault, and finally we assigned individually each fault and adjusted them in order to get exactly the same 94 faults. This time needed to assign individually each fault and adjust them to get the same interpretation as the reference ones was also recorded ($T_{\text{assisted}}$).

The productivity gain is defined by the following formula:

$$\text{Productivity Gain} = \frac{T_{\text{interpretation}} - T_{\text{assisted}}}{T_{\text{interpretation}}}$$

![Relative Productivity Gain](image)

**Figure 3** Histogram showing the productivity gain on using the A.I fault model for the three kind of faults

It appears that it is faster to extract and adjust individually the faults from the A.I. fault attribute in comparison with the standard manual interpretation in order to obtain the same interpretation. An interesting point that should be noted is that productivity gain is quite different according to the different types of faults. Supervised learning assumes that the training data and the target production data at inference time have a similar distribution. This result shows that we need to get more faults diversity and smaller faults in complex areas (collapsing faults are quite small and located here in a part where the seismic is of lower quality) in our training dataset.

An A.I. training pipeline has been put in place to allow us to train new models to continuously improve our prediction in the future. We have been using our first trained A.I. fault model so far and we will train and deploy our second A.I. fault model during the second quarter of 2020.

We have tested other post-processing methods (for instance point set segmentation) but we did not get a higher productivity gain for the moment. It is working well where the seismic is of really good quality and the structure is quite simple, but it needs to be improved in complex areas.
Conclusions

In this field located in Nigeria, an important finding to emerge is that it was demonstrated that the classical fault interpretation together with the A.I. fault model has the power to improve the efficiency and understanding for the geoscientists in an operational study.

Other post-processing methods could bring potential upside and we need to continue to explore the extraction of individual fault surfaces with deep neural networks, as opposed to traditional post-processing. Finally, the A.I. fault model trained by TOTAL will be continuously improved by adding new datasets in our new training pipeline available this year.

This first operational A.I. interpretation study at TOTAL is the beginning of a new era where the implementation of artificial intelligence into geoscience will assist all geoscientists to focus on high added value tasks and improve the subsurface understanding.

Acknowledgements

TOTAL E&P Nigeria would like to thank our partners Nigerian National Petroleum Corporation (NNPC), South Atlantic Petroleum, CNOOC E&P Nigeria Limited for their permission to publish this work. We also would like to thank Julie Boyer, Laurent Castanie, Genquan Duan, Jonathan Gallon, Sebastien Guillon, Frederic Joncour, Paramjit Sandhu and Victor Martin.

References


