Supporting critical well delivery decisions by utilising machine learning to aid interpretation of wellsite XRF data

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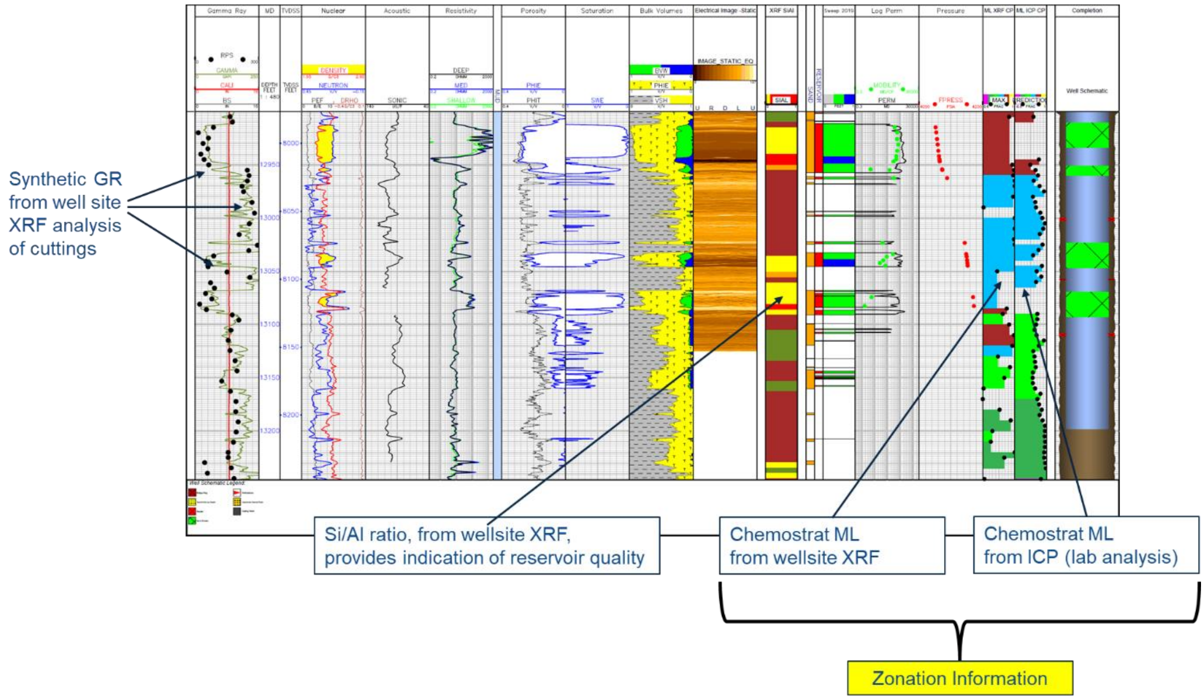
Abstract

The success of a recent infill drilling campaign on a major UK North Sea oil field required a real time assessment of which reservoir units had been encountered, and an indication of reservoir quality. This was necessary in order to decide whether and how to complete each well. Wellsite XRF data was acquired as a critical component of the formation evaluation programme to address both of these uncertainties. This paper describes how a machine learning algorithm was developed to provide a robust interpretation of the encountered stratigraphy from XRF data.

The oil field that forms the case study of this paper is composed of sequences of erosive channel complexes that have produced sandstone and mudstone units with very little well log character that can be used to distinguish between the sand units. Production performance is however strongly dependent on which of the sand units are encountered. Chemostratigraphy is a technique that addresses this issue by characterising sedimentary rock successions using inorganic geochemical data. Elemental abundances measured on core or cuttings have proved useful in identifying subtle differences between the mudstone and sandstone units, and this data is currently used as the basis of the reservoir correlation. Achieving successful production performance from the current drilling campaign involved making operational decisions (with timeframes measured in hours) based on criteria that included the sand unit encountered. These decisions included whether to complete the well, to side-track to an alternative location, and how to complete the well. Manual (expert) interpretation of the wellsite XRF dataset was not optimal either for meeting decision time-frames or for providing a robust measure of interpretation uncertainty. Data Science methods were applied to address this challenge because it was anticipated they had the potential to evaluate the subtle relationships in the geochemical dataset in a rigorous and consistent fashion.

A machine learning algorithm was developed that took as input the wellsite XRF data from cuttings and provided an interpretation of clay and sand units, with associated uncertainty. There were several challenges which needed to be addressed, caused by biases and inconsistencies in the field database of elemental data, such as differences between the type of elemental analysis and fundamental differences between data acquired from core and cuttings. Limitations in the strength of the interpretation were clearly identified so that decisions could be made with full knowledge of the inherent uncertainty. The algorithm was further improved by post-processing the results and applying stratigraphic rules – in effect developing an electronic geologist.

In this instance machine learning has proved its utility in application to a subsurface interpretation challenge. As well as improving on an existing process, the application of data science techniques provided significant insight into the dataset and previous interpretation biases.



Speaker's Bio:

Robert Webber is a Petrophysicist with a strong petroleum industry background of 24 years.
His experience has been gained across a variety of basins and continents, and through working for several consultancies and a couple of major operators. He was lucky enough to spend a few years in Rio de Janeiro working the pre-salt carbonate mega-fields in Brazil and then a few more years in Brisbane working on an Unconventional mega-project, the first Coal Seam Gas to LNG development in the industry. Since returning from Australia in 2016 he has been focused on UK oilfield developments; working for the operator of the Buzzard, Golden Eagle and the Scott Telford fields, and leading the UK petrophysics team at CNOOC International.
His specialist experience includes QI Petrophysics and Production Surveillance; and Robert enjoys applying an innovative and scientific mindset to mid/late life assets to maximise value.