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Predicting Electrical Anisotropy in the Barents Sea Using Multivariate Statistics

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SUMMARY

Electrical anisotropy provides key information that can be used to understand regional variations in rock physics properties. Most standard well log suites include only measurements for horizontal resistivity, and vertical resistivity is unknown. The available data from 7220/8-1 (Skrugard) in the Barents Sea, including three-component resistivity measurements were analysed to determine which well logs best characterize the electrical anisotropy in the borehole and determine the relationship between these logs and the vertical resistivity. Using a subset of the data measured at the Skrugard borehole as a training dataset, a nonlinear regression model was found which uses commonly collected well properties to predict vertical resistivity, from which a prediction of electrical anisotropy can be made. Application of the model to the full and offset wells elsewhere in the Barents demonstrates that nonlinear regression modelling provides a good first-order approximation of electrical anisotropy.

Introduction

Electrical anisotropy provides key information that can be used to understand regional variations in rock physics properties. A poor understanding of the electrical anisotropy will lead to misleading Controlled Source Electromagnetic (CSEM) survey feasibility studies and inaccuracies in CSEM data analysis, resulting in erroneous estimations of hydrocarbon saturations (Ellis *et al.,* 2011). Most standard well log suites include only measurements for horizontal resistivity, and electrical anisotropy is unknown. Three-component resistivity tools can be used to measure vertical resistivity in the borehole, providing a calibration point for the interpretation of CSEM data, but this type of data is rarely available.

Investigating electrical anisotropy variations across the Barents Sea was one of the main goals of the ERA Consortium. The work primarily involved deriving bulk anisotropy values from CSEM data for each of the major stratigraphic units across the Barents Sea. This was achieved by performing 1D anisotropic modelling of the CSEM data. (Bouchrara *et al.*, 2015)

An alternative approach is to use a standard well log suite and attempt to predict the vertical resistivity statistically. Using training data from the Skrugard well (7220/8-1) in the Barents Sea (*Figure 1*), we have used a multivariate statistics approach to attempt to understand which of the standard log measurements best characterise the vertical resistivity measured at the borehole, then predict vertical resistivity through nonlinear regression modelling. In conjunction with the standard horizontal resistivity measurement, the predicted vertical resistivity can be used to estimate electrical anisotropy. This methodology has been validated using statistical methods as well as through application of the model to offset wells elsewhere in the Barents, including the Wisting Central well (7324/8-1) where measured three-component resistivity data are available, and additional wells for which EM inversion results are available, but a wellbore vertical resistivity measurement is not.

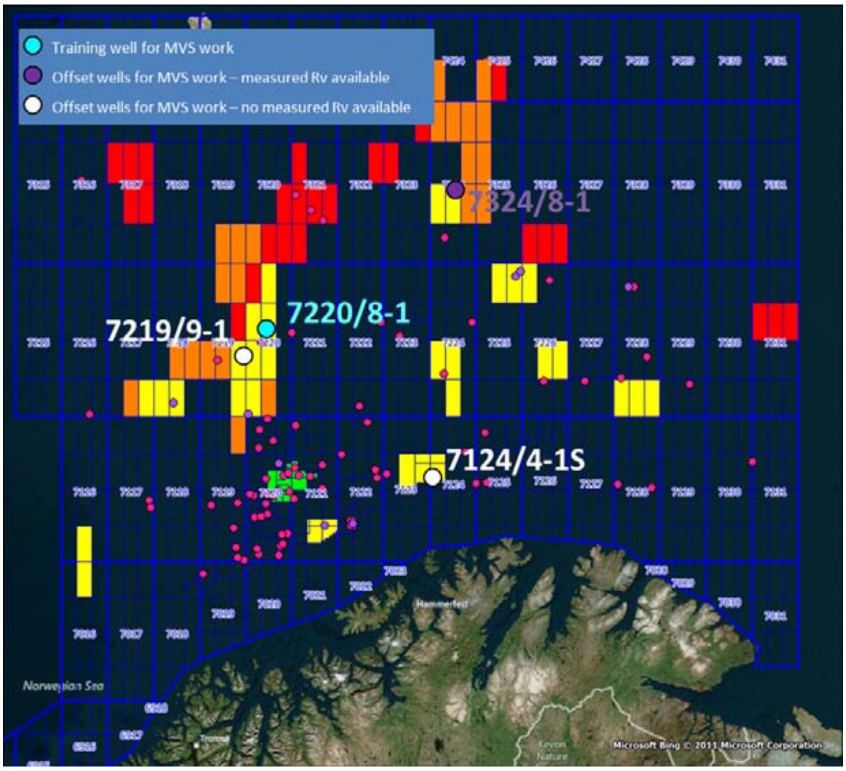

Figure 1 *Map of the Barents Sea. Large dots highlight the locations of the well data considered in this analysis. Coloured squares show CSEM survey areas (as of 2012), small dots show additional well locations.*

Analysis and Preparation of Input Data

The multicomponent resistivity data (acquired) and other fundamental logs were analysed to determine which well logs best characterise the electrical anisotropy in the Skrugard borehole and determine the relationship between these logs and the vertical resistivity. Correlation values and crossplots were examined to obtain a first-order understanding of the relationships between the well attributes and to identify outliers in the input data to be excluded from further analysis. In order to obtain a mechanism for predicting background electrical anisotropy, data points from hydrocarbon-saturated samples were also excluded from the modelling.

Nonlinear Regression Modelling

Nonlinear regression (NLR) is a statistical technique in which a dependent variable (also called the response) is modelled by a function of a combination of nonlinear model parameters and one or more independent variables (called predictors). As most of the logs exhibit nonlinear relationships with the observed vertical resistivity, the nonlinear regression method is being applied to predict the logs which are driving the vertical resistivity in this particular borehole.

A training dataset randomly sampled from the available data measured at Skrugard was used. VP (p-wave velocity), RHOB (density), PHIE (effective porosity), NPHI (neutron porosity), RESD (deep resistivity), VClay (clay volume), AI (acoustic impedance), GR (gamma ray), and VCalcite (calcite volume) were considered as possible predictor variables for use in the nonlinear regression modelling performed. Modelling was performed iteratively, to choose the most appropriate model which provides the most robust results. The preferred model used VP, RHOB, PHIE, and RESD as predictor variables.

To examine the modelled relationship between each predictor variable and the response variable, simulations of independent variable values through the NLR model were carried out. These simulations used a Monte Carlo approach, computing conditional probability distributions for the fixed independent variable values and from previously randomly drawn values from the independent variables that are allowed to vary.

Application of the Nonlinear Regression Model

The preferred model was applied to all non-hydrocarbon bearing zones within the full Skrugard well for comparison with measured vertical resistivity (*left set of plots in Figure 2)*. Anisotropy ratios have been calculated using the RESD measurement (for horizontal resistivity) with both predicted and measured vertical resistivity. These measured and predicted anisotropy ratios were then differenced to determine the accuracy of the prediction.

Overall, the character of the electrical anisotropy is being well-captured by the nonlinear regression model – the predicted vertical resistivity is not a simple linear relationship with RESD, but honours the different anisotropy ratios measured in the well. For all non-hydrocarbon-bearing sediments in the well, the predicted and measured vertical resistivity curves demonstrate the same trends, with no obvious intervals of systematic misfit.

The model was then used to make predictions for vertical resistivity and electrical anisotropy at other Barents Sea wells. The vertical resistivity measured in the Wisting well (7324/8-1) is well-predicted in most intervals (*right set of plots in Figure 2*). Intervals of systematically poor prediction exist where the Wisting well penetrates intervals not well-described by the training dataset – for instance, the lower Fuglen just above the reservoir at Wisting is more calcareous than any interval measured at Skrugard. A richer training dataset which included additional wells with vertical resistivity measurements would allow for a better and more general prediction model.

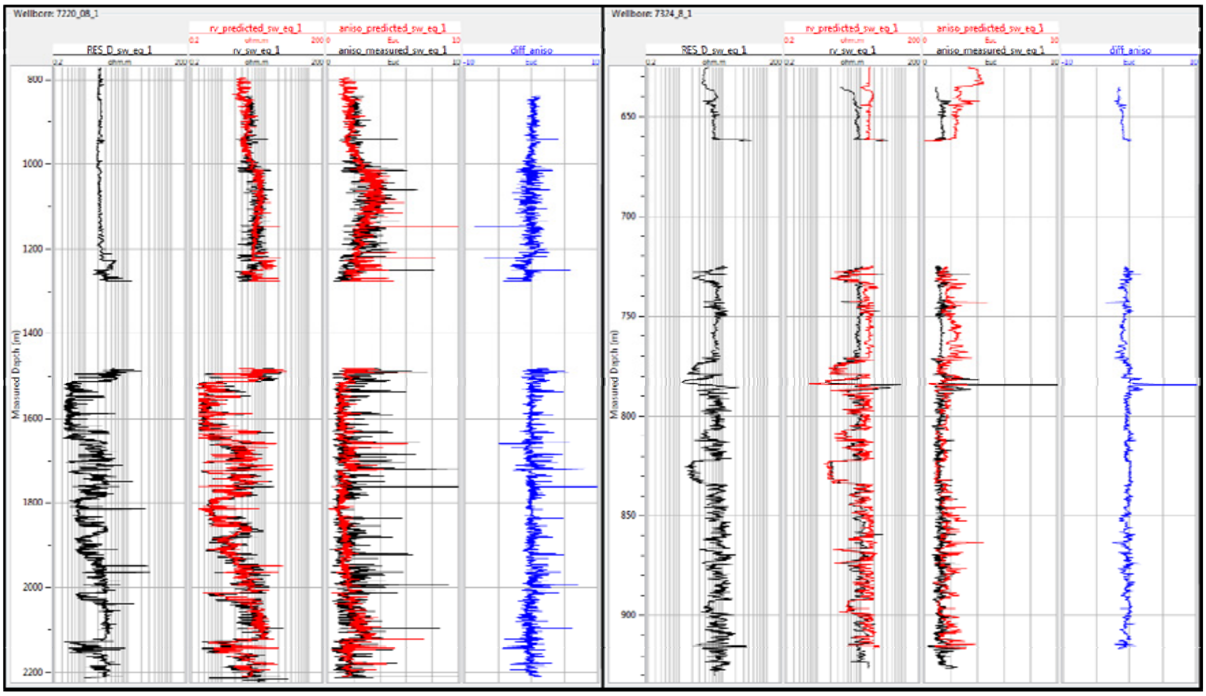

Figure 2 *Comparison of measured and predicted resistivities and anisotropies at Skrugard (left) and Wisting (right). Each set of four well tracks shows (from left) measured RESD, measured (black) and predicted (red) vertical resistivity, measured (black) and predicted (red) electrical anisotropy, and the difference between measured and predicted electrical anisotropy (blue). Hydrocarbon-bearing zones are excluded from plotting.*

The model was then used to make predictions for vertical resistivity and electrical anisotropy at other Barents Sea wells, where no borehole measurements of these properties are available. To examine the validity of the use of the model at the offset well locations, the vertical resistivity prediction and measured RESD were upscaled for comparison with the results of anisotropic 1D CSEM inversions of data collected from receivers surrounding each well location, carried out earlier in the ERA Consortium project. For comparison, the same was done at Skrugard. The plots in Figure 3 show results for Skrugard, 7219/9-1 and 7124/4-1S. At Skrugard, the measured RESD and vertical resistivity curves are in close agreement with the result of 1D CSEM inversion above the hydrocarbon-bearing zone. Beneath the hydrocarbon-bearing zone, the CSEM inversions carried out recovered higher resistivities (both horizontal and vertical) than were measured in the well. This may be due to the regularization of the Occam inversion routine, scaling issues, higher dimensional effects, decrease in sensitivity below the resistive reservoir, and/or non-uniqueness in the EM results. Centre plots show the upscaled results of applying the non-linear regression model to predict vertical resistivity at the 7219/9-1 well. In this dry well near Skrugard, the vertical resistivity prediction is reasonably consistent with CSEM-derived vertical resistivity in most intervals. The intervals with the greatest misfit are the two thin low resistivity intervals between about 2 km and 2.5 km measured depth, where the smoothness requirement of the inversion of the CSEM data makes accurate recovery of the true resistivity structure unlikely. Right plots show the comparison for 7124/4-1S. Horizontal resistivity recovered by inversion matches the upscaled RESD and predicted vertical resistivity very well. Note that high confidence cannot be placed in the results for the intervals shaded due to the predictor values in the offset wells going out of range of the Skrugard training dataset.

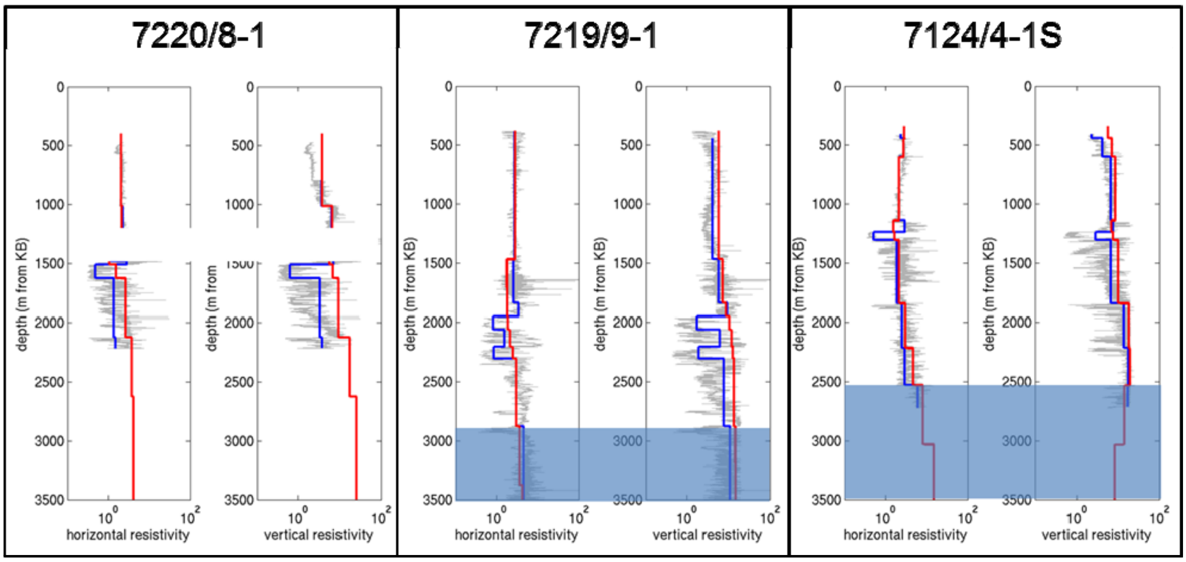

Figure 3 *Comparison with CSEM modelling results. For each pair of plots, the grey curve in the left plot is measured RESD, blue is the upscaled RESD and red is the CSEM inverted horizontal resistivities. In the right plot, the grey curve is the predicted vertical resistivity, blue is the upscaled predicted vertical resistivity and red is the CSEM inverted vertical resistivity.*

Conclusions

Using a subset of the data measured at the Skrugard borehole as a training dataset, a nonlinear regression model was found which uses commonly collected well properties to predict vertical resistivity, from which a prediction of electrical anisotropy can be made. The model, when applied to the complete Skrugard dataset, produces vertical resistivity and electrical anisotropy predictions which are broadly consistent throughout the well (excluding hydrocarbon bearing zones) with the vertical resistivity measured by the three-component tool at the wellbore, and with the electrical anisotropy calculated used measured vertical resistivity and RESD. Application of the model to offset wells validates both the model found (when it is applied to data represented within the training dataset), and the overall approach. Inclusion of additional wells with vertical resistivity measurements in the training dataset would allow for refinement of the model.

Nonlinear regression modelling provides a good first-order approximation of electrical anisotropy. The existence of statistical relationships may suggest underlying mechanisms linking anisotropy and the parameters considered that could be modelled deterministically.

Acknowledgements

The authors would like to thank the sponsors of the ERA Consortium for funding and donating data to this project. We would also like to thank Rob Keirstead, Alberto Rusic, Paola Vera de Newton, Slim Bouchrara, and Sriram Nanduri for their efforts supporting this work.

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