

## Reservoir characterization using electrofacies analysis: application to the Norne Field (Norway)

[Gil Correia](#)

*"This text shows the generation of an electrofacies database base in Artificial Neural Networks integrated with geostatistical modelling methods in order to improve the geological characterization of the Norne Field reservoir"*

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### Introduction

The Norne pilot project is a benchmark case based on real field data established between the IO Center, NTNU, and Norne Field Operations (Statoil, ENI & Petoro). The main goal is to provide a real dataset to different research groups in order to evaluate and compare different methods for history matching and ultimately closed-loop reservoir management.

It was necessary to generate new models because the deterministic model provided in the Norne Field benchmark case was not adequate to be used in current probabilistic history matching procedures.

This text describes the detailed characterization of the geological heterogeneities through the electrofacies analysis together with the simulation grid refinement that has been used to derive new facies and petrophysical models. These high resolution datasets improve the geological characterization of the Norne Field and provide better control and understanding of these properties on the reservoir flow behavior.

### Methods

The methods used in this study are part of a geological modelling workflow that resulted in new information to the Norne Field reservoir. The major steps are (Figure 1):

1. Data preparation involves: (1) gathering all the available geological information regarding the reservoir or analogues; (2) a common suite of logs in all the wells used as input data; (3) rigorous quality control of those datasets; (4) depth matching of various logs; (5) creation of a *diff* curve for each well:

$$\text{diff} = n_{phi} - \text{phif}$$

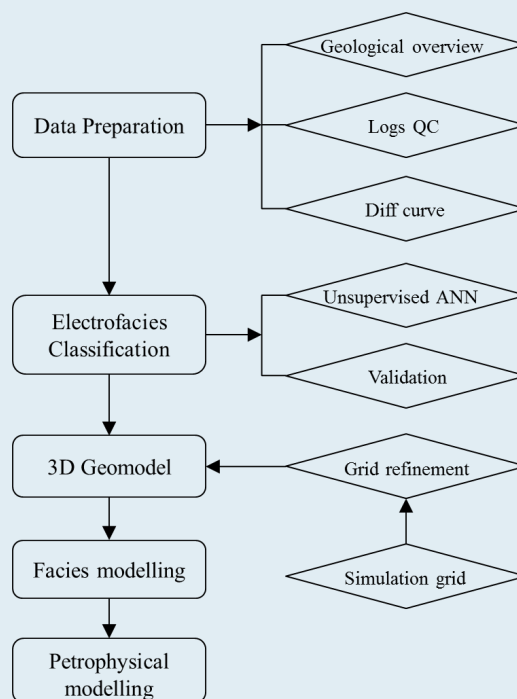
where  $n_{phi}$  is the neutron porosity and  $\text{phif}$  the density porosity;

2. Electrofacies classification based in the artificial neural networks algorithm (ANN). The unsupervised ANN was used because no core data was available to train the neural network. For quality control purposes, the obtained electrofacies were compared with the simplified lithological column that was available in some of the geological well reports. The ANN should be used with caution when constructing 3D models, due to over an under-training problems, being more useful when integrated with statistical methods;
3. Simulation grid refinement in order to maintain as much as possible the fine scale heterogeneities seen in the well logs, namely the thin carbonate and the shale layers that could act as vertical stratigraphic barriers due to their low permeability;
4. Upscale well logs and the created electrofacies to the high resolution geomodel grid to be able to generate 3D facies and petrophysical models through geostatistical methods. This high resolution grid should maintain as much as possible the fine scale heterogeneities seen in the well logs;
5. Generation of 3D facies and petrophysical models (porosity, permeability and NtG) using stochastic methods able to generate multiple realizations under certain uncertainty ranges. The 3D models of each petrophysical property were restricted by the 3D facies distribution and by correlation factors between each property obtained from the data analysis process.

### Application

The methods were applied in the real dataset, the Norne Field benchmark case, which includes: a reservoir simulation model with grid cell sizes of 60 x 60 x 8 m, 44927 active cells, subdivided in 22 reservoir zones; 48 wells most of all including gamma-ray (*gr*), bulk density (*rhob*) and neutron porosity (*nphi*) logs and

density porosity (*phif*), permeability and Vshale calculations, with a sampling rate of 0.125 m; production data and 4D seismic data.



**Figure 1:** Workflow scheme of the electrofacies analysis integrated with the 3D modelling phase

### Results

Due to the fact of being a real dataset, some errors were found when analyzing the different datasets, such unrealistic porosity and permeability log values that could have a significant impact during the modelling stages. For this reason, a rigorous quality control of all data is very important, prior to any subsequent stage, in order to correct these errors and also to understand the weaknesses and strengths of our datasets. The different electrofacies were recognized by grouping distinct well-log clusters on multiple log cross-plots (*gr* vs. *diff* and *rhob* vs. *nphi*) (Figure 2). The final electrofacies classification comprehending a total of six classes has been resolved down to a sampling rate of 0.125 m thick allowing a better interpretation and comprehension of the geological framework of the reservoir, namely, the occurrence of thin shale and carbonate layers, with low permeability, could act as stratigraphic barriers to the fluid flow.

The electrofacies classification based on ANN becomes more useful when integrated with statistical modelling methods and geological and reservoir knowledge. The electrofacies were upscaled to a high resolution grid (2.066.642 active cells with 0.5 to 1 m thick) forming the basis for building high resolution 3D reservoir facies and petrophysical models (Figure 3). This high resolution grid was obtained through the refinement of the reservoir simulation grid available in the Norne database, keeping the reservoir geometry and taking into account that most facies thickness was below 1m.

The final stage of this work comprising the generation of high resolution 3D facies and petrophysical models (porosity, permeability and NtG) highlighted the importance of generating an electrofacies scheme (Figure 3). The histograms of porosity (permeability) within the different facies add a significant control on the distribution of those properties, reducing uncertainties and resulting in models with more predictive power. The definition of the reservoir and the connectivity estima-

*"These high resolution datasets will form the working basis in the integration with a probabilistic history matching guided by production and 4D seismic data"*

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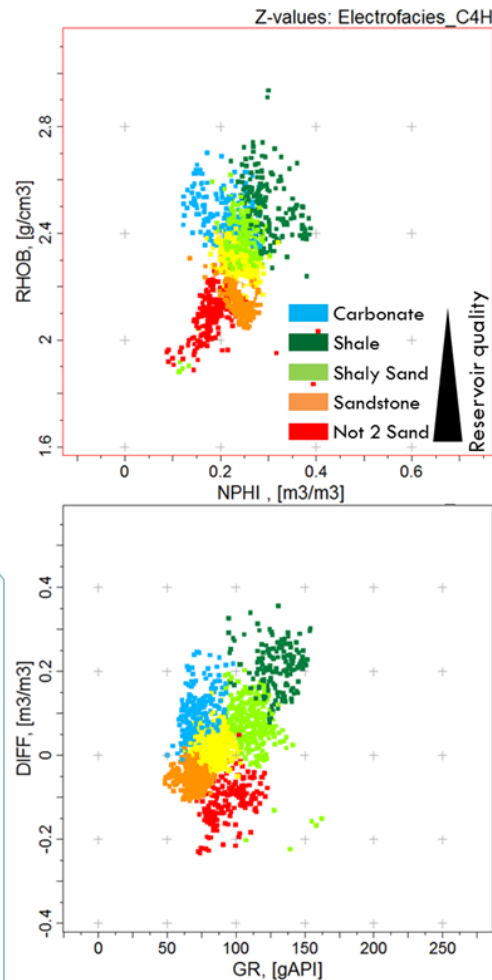


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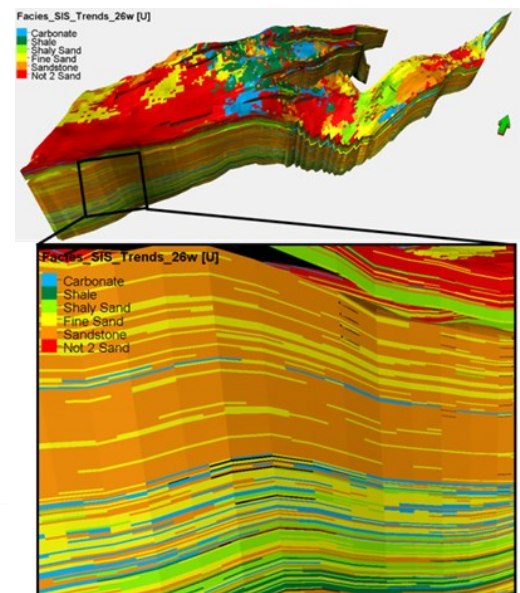
**Figure 2:** Electrofacies display on two-dimensional cross plots (example from the well 6608/10-C-4 H). The carbonates and shales have the worst reservoir properties and the sandstones the best reservoir quality.

tion through the NtG becomes directly related to the electrofacies by defining specific ranges of uncertainty to each electrofacies instead of using the frequently problematic permeability cut-offs and  $V_{shale}$  curves. To the sandstones (facies 3, 4 and 5) was assigned a NtG = 1, to the shaly-sandstones (facies 2) an intermediate NtG (mean 0.5) and for the carbonate and shale horizons it was assumed that the grid cells were practically disconnected (NtG < 0.2).

Finally, 200 facies and petrophysical models were generated using different petrophysical ranges to each electrofacies (in each of the 22 reservoir zones), different NtG values attached to each facies, and the variograms. Stochastic methods were used for this purpose. The pore volumes of each realization were analyzed, being in agreement with the deterministic pore volume informed in the Norne Field benchmark case ( $673 \times 10^6 \text{ m}^3$ ) however, with a wider range.

#### Final Remarks

Besides the absence of a geological model, the Norne database provided only a deterministic solution based on kriging methods applied into a low resolution grid.



**Figure 3:** 3D facies model obtained using the sequential indicator simulation (SIS) algorithm. The black circle highlights a particular region where this influence is most evident. The detached region (black square) shows the location, thickness, extent and frequency of decimeter shale/cemented layers that could act as vertical barriers to fluid flow displacement.

The electrofacies scheme and the high resolution models obtained in this study allow a refined comprehension of the geological framework. Also help to identify and characterize small variations in the reservoir quality and are essential in recognizing the location, thickness, extent and frequency of decimeter scale shale and cemented layers that could act as vertical barriers to fluid flow, having a significant impact in the estimation of the effective vertical permeability and in the reservoir behavior.

These high resolution models give also a better control on the upscaling methods to the coarser simulation grid, allowing us to understand, quantify and minimize the information that is lost due to the smoothing effect.

The stochastic methods used in the modelling stages allow us to work with uncertainties, forming the working basis in the integration with a probabilistic and multi-objective history matching approach using both production and 4D seismic data, and assisted by geostatistical parameterization techniques.

#### References

Correia, G.G., and Schiozer, D.J. 2016. Reservoir characterization using electrofacies analysis in the sandstone reservoir of the Norne Field (offshore Norway). *Petroleum Geoscience*, V. 22, pp. 165-176. DOI: 10.1144/petgeo2015-056.

#### About the author:

Gil Correia graduated in Geology and M.Sc. in Petroleum Geology from the University of Coimbra. Since 2012, is a researcher at UNISIM Group and Ph.D. student in Petroleum Science and Engineering at Unicamp.

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