Integration of lithology uncertainties in net volume prediction using Democratic Neural Network Association

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Summary:

From the prospect evaluation, to the development of a field, the understanding of lithology types and their distributions contributes a lot to the optimization of production. The use of all available data becomes then critical to assess with a maximum of confidence lithology descriptions of the fields. Techniques described in (Hami-Eddine et al., 2009) have shown the advantage of describing lithology kind and distribution using a probabilistic model. The probabilities estimated from well lithofacies can now be used for uncertainty estimation and generation of several lithology models. The uncertainty analysis using Democratic Neural Network Association (DNNA) results are there emphasized to estimate the potential variation of the net reservoir volume.

Introduction:

The amount of geological and geophysical data that can be available on a field becomes incredibly huge. Therefore creating comprehensive earth models catching the maximum of the information become challenging. Adding to that the uncertainty associated with each data recording, it gives the possibility to generate an almost as huge number of equi-probable models.

The integration of well data for lithology analysis at the prospect scale brings more robustness to generation of models. Taking into account uncertainties all along the process assesses model reliability.

As detailed in (Hami-Eddine et al., 2011), DNNA is designed to create a relationship between well determined facies groups and seismic attributes. DNNA propagates a probabilistic lithology model that allows us to generate different models taking into account wells and seismic data in a consistent way.

Uncertainty determination using DNNA results

The challenge of determining uncertainty based on well data and seismic data simultaneously brings a question about how to manage different data resolutions, and different extensions.

The use of DNNA has shown that the probabilistic approach to integrate multiple types of data creates results geologically meaningful. The fact that DNNA is based on probability computations adds another possibility to the use of DNNA results previously detailed in (Hami-Eddine et al., 2009) and (Hami-Eddine et al., 2011).

From DNNA probability estimation, several scenarios can be generated using stochastic simulations.

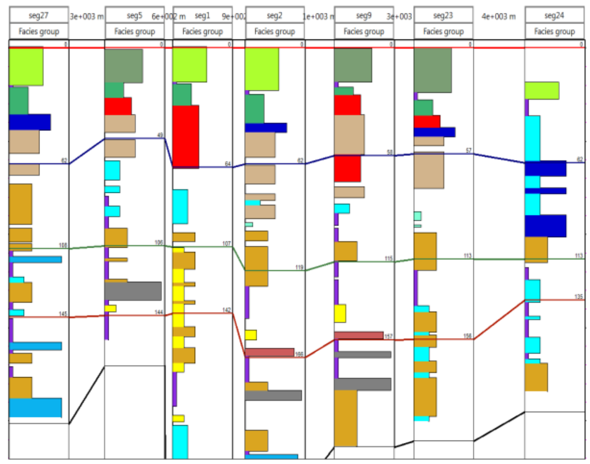


Figure 1: Facies groups have been determined using rock typing methodology. Fluid content have been taken into account when defining the groups. Red facies visible on top of the tracks and yellow on bottom are good oil reservoir facies groups.

Application and results: net prediction on a carbonate data set

Seismic data on this project is really low frequency (~20Hz). Observing well data and cross sections, we observe that reservoir intersected by wells show exaggerated continuity on seismic attribute responses.

Attributes that seems correlated to reservoir anomalies, extend somehow to wells that do not intersect the reservoirs. The poor lateral continuity observed at wells is not honored by seismic attribute analysis.

The proposition is then to use DNNA to bring in an alternative workflow using directly interpreted facies groups at wells (Figure 1), and prestack data. Therefore, the probability estimation from DNNA for each facies group will be used to perform uncertainty analysis on net rock volume.

DNNA workflow steps were carefully executed in order to predict uncertainty on net rock volume.

- Calibrate wells to seismic data
- Identify facies group using rock typing techniques and electro-facies analysis
- Run DNNA with prestack data and facies groups as input

- Run simulations based on probability outputs from DNNA
- Combine reservoir parameters observed at wells for each facies with probability densities from DNNA for scenario based analysis and net volume estimation

DNNA estimates at each (X,Y,Z) location of the cube a probability of facies group presence. Based on these probability values, several facies cube scenarios can be derived: optimistic, most probable, and most pessimistic for example.

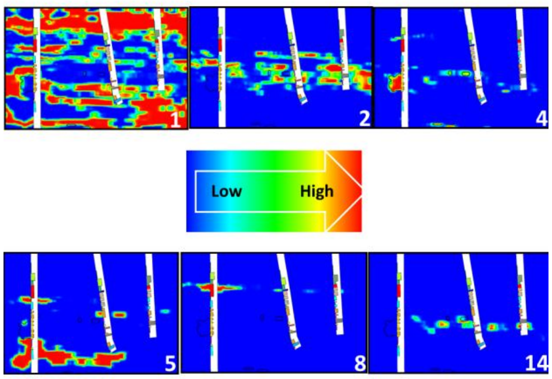


Figure 2: Probabilities from main facies described in Table 1, shale (top left) to facies group 14 Biostrom water (bottom right). In red we can observe some high confidence area. Facies lateral continuity can be analyzed on probability sections. Good reservoir facies (4 and 8) probabilities confirm the poor continuity observed at wells.

Sixteen facies groups, taking into account lithology and fluid content are defined on 17 wells. The main facies groups are colored and named according to Table 1.

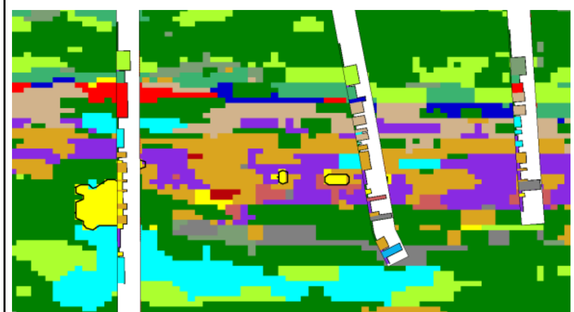
Table 1: Main facies group color coding.

1 - Shale
8 - Bioherm oil
4 - Biostrom (oil good quality)
2 - Biostrom (tight)
14 - Biostrom (oil medium quality)
5 - Biostrom (water)

DNNA probabilistic model is catching the detailed facies group description at well location to build a consistent probabilistic model at the prospect scale.

Figure 2 shows the results of probability estimation for the main facies along a cross-section.

From computed probabilities, DNNA estimates the most probable repartition of facies groups. The comparison between lateral facies group distribution results and probability density information at wells gives a first insight of the quality of the result. Main reservoir from base formation (yellow facies group) are detected and circled in black.



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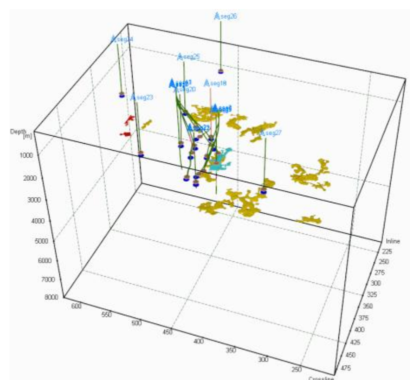

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Figure 3: a) DNNA section result with producing wells overlaid. We clearly see the accurate prediction of DNNA most probable model. Lateral extension of the bodies are consistent with expected geology. In addition, fluid content is predicted in a consistent way as water saturated carbonates are clearly distributed below supposed hydrocarbon ones. b) 3D repartition of good HC reservoirs in most probable scenario.

The probability cubes are used to generate the most probable scenario of facies group distribution as shown in the cross-section in Figure 3. Most probable facies group volume fits at wells at top and bottom formations. The prediction of reservoir thickness in the cubes confirms what is observed at wellbore. The repartition of detected reservoir geobodies confirms the poor lateral continuity observed on cross-sections.

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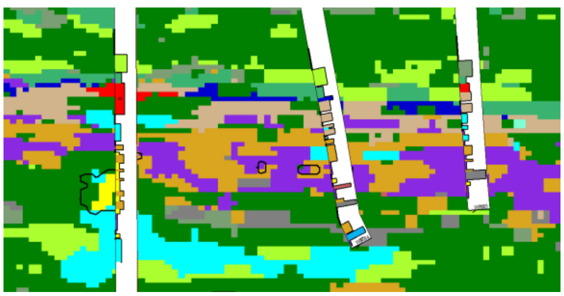
The next step consists in using the probability cubes to generate several scenarios of facies group repartition.
As explained in Figure 2 multiple realizations can be derived through a combination of probability. Randomization based on probability distribution of facies groups generates a series of models.

Most pessimist scenario generated using DNNA probability estimations.
Reservoir bodies are drastically diminished, as we can see as they do not fill the bodies. QC at well locations confirms that this scenario is more uncertain to happen than most probable model. The main reservoir bodies detected on most probable facies are circled in black to compare lateral extension differences between both hypotheses.



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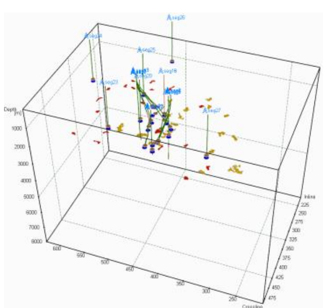

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Figure 4: a) DNNA section result with wells overlaid. This prediction corresponds to the most pessimistic scenario using the probabilities from DNNA. b) 3D repartition of good HC reservoirs is clearly reduced in the most pessimistic scenario.

Reservoir parameters have been estimated along well-bore per facies and correlated with the facies groups used for DNNA analysis. These parameters have been estimated using a deterministic approach. The use of facies group volume simulations using DNNA probability cubes helps to generate scenarios from best to crash case. The most pessimistic scenario (P10) is shown in Figure 4. The extracted geobodies for good quality reservoir are smaller and show less continuity.As a comparison, most probable scenario in Figure 3 shows bigger reservoir in bottom formation.
The position of water contact is as precise on both cubes. This position corresponds to what is observed at wells.

The computation of net rock volume can be estimated as a scenario-based process using stochastic simulations. For confidentiality reasons, the net volumes will not be discussed in this paper. Net to gross will be used to illustrate the case (Figure 5 and Figure 6), and show how sensitivity to lithology variation can impact reservoir volume estimation.

Example of the net to gross variation provided by simulations. Probabilities for each facies group are used to compute it for each formation.

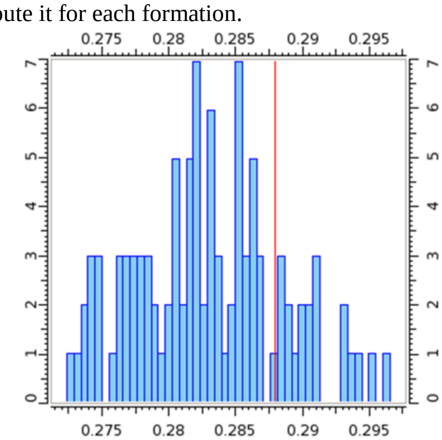

Figure 5: Average net to gross histogram versus number of realizations. Most probable realizations confirms net to gross values ranges of approximatively 0.28.

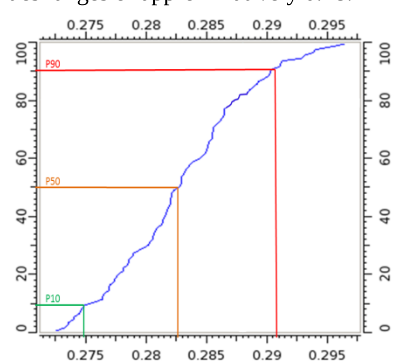

Figure 6: Cumulative distribution function of average net to gross in top and bottom formations based on 100 stochastic realization. From P10 to P90 we observe a 7% variation of this estimation.

Reservoir heterogeneities are kept in the multi-scenarios realizations. The net to gross variation ranges from 0.27 to 0.29 which is relatively stable.
In that particular study, the net volume is also impacted by the detected body continuity as expected through well section analysis.

The addition of petrophysical uncertainty as described in (McLean et al., 2012) is the next step to enhance the uncertainty management based on facies groups. This result can be integrated in a sequence that would qualify and quantify reservoirs (Figure 7) from wells and prestack seismic data to flow simulation grids (Gringarten, 2012).

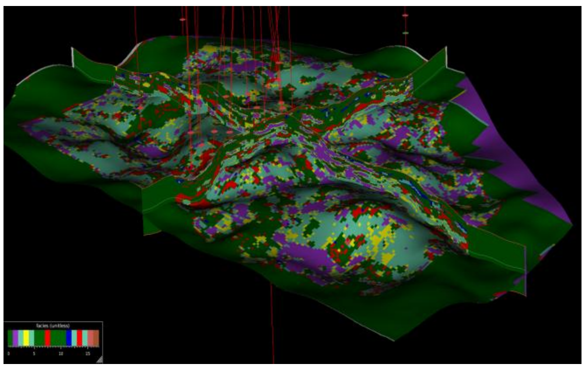

Figure 7: Integration of facies group volume to reservoir model. Net volume and reservoir properties can be determined using facies infilling.

Conclusions

The prediction of lithology distribution is an addition to techniques such as inversion for reservoir property estimation. Using the lithology and fluid content observed at wells jointly with seismic data brings to lithology prediction using DNNA a way to assess the reliability of the generated models. The neural network approach of this technique simultaneously used with a Bayesian prediction method gives a great possibility to deal at the same time with well data and a large amount of prestack data to infer lithology and at large, facies groups.
This methodology brings another aspect to uncertainty management as it adds the possibility to directly integrate discrete information interpreted at wells in an uncertainty workflow at reservoir scale. Facies groups can be used as lithological and fluid content information despite the fact that they may not be ordered, and are discrete by nature. The use of facies group probabilities gives the opportunity to integrate much more than a few numbers of facies scenarios.

As experienced on this case study, the probability cubes generated by this process contain a lot of information about uncertainty of facies group nature at each location of the area of study. The consistency of this information is found again in net to gross and net sensitivity to facies group variations.
The example taken for net volume uncertainty estimation could be extended to reservoir parameters such as porosity, permeability, saturation and gross control during depth transformation. Each of these parameters could be integrated in the uncertainty study, based on each facies group repartition, and estimated parameters along well path.

Acknowledgments

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