A new technique for lithology and fluid content prediction from prestack data: An application to a carbonate reservoir

Kamal Hami-Eddine¹, Pascal Klein², Loic Richard³, Bruno de Ribet⁴, and Maelle Grout²

Abstract

One of the leading challenges in hydrocarbon recovery is predicting rock types/fluid content distribution throughout the reservoir away from the boreholes because rock property determination is a major source of uncertainty in reservoir modeling studies. Spatial determination of the lateral and vertical heterogeneities has a direct impact on a reservoir model because it will affect the property distributions. An inappropriate determination of the facies distribution will lead to unrealistic reservoir behavior. Because these data can take different forms (lithologs, cuttings, and for seismic, poststack, and prestack attributes) and have different resolutions, the manual integration of all the information can be tedious and is sometimes impractical. We developed a new neural network-based methodology called democratic neural network association (DNNA). The DNNA method was trained using lithology logs from wells simultaneously with prestack seismic data. This technique, using a probabilistic approach, aims to find patterns in seismic that will predict lithology distribution and uncertainty.

Introduction

The economic viability of a field is dependent on the quality and accuracy of lithology distribution prediction, as well as by the heterogeneity of a potential reservoir. These components are the keys to successful hydrocarbon exploration and production. The rise in unconventional resource prospecting and the increasing complexity of conventional plays have made accurate lithology prediction even more critical. All relevant data must be used optimally to determine lithology at the prospect scale with the highest degree of resolution, resulting in the most geologically meaningful lithology distribution. Risk increases with complexity, however, and the probability of success and the integration of uncertainty into the nature and distribution of lithology must be taken into account in any approach that tries to predict lithology.

Conventional approaches are mainly based on 2D or 3D analyses of inverted data to describe the elastic properties of the reservoir. However, precise lithology description in such attribute spaces often overlaps. This makes it difficult to clearly differentiate, for example, intermediate-type facies such as thin interbedded layers. The result is nonunique and highly sensitive to facies interpretation. It, therefore, becomes critical to estimate reservoir connectivity, as some lower quality or intermediate-type facies could improve understanding of the reservoir’s development.

Democratic neural network association (DNNA) is a new methodology to be considered alongside acoustic, elastic, and stochastic inversion methods. It allows for the generation of lithology probabilities from a combination of quantitative rock typing analysis at wells and seismic data at the well location (Hami-Eddine et al., 2009). The validity of the method has been demonstrated through the direct use of angle gathers (representing the seismic data) combined with well facies analysis, to predict the lithology and fluid content.

This methodology will be applied to a carbonate reef data set, in which conventional attributes and inversion have shown limitations when describing reservoir heterogeneities.

Methodology for predicting lithology from well data and seismic

Well data analysis and facies definition

Well log information is the main source of information for lithology and fluid content. Therefore, a key step in lithology and fluid prediction is precise and careful analysis of the well data. DNNA is designed to use lithology logs or facies determined using petrophysical properties calibrated to cores.

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Combining rock typing and multiresolution graph-based clustering (MRGC) (Ye and Rabiller, 2000) brings two different aspects to lithology prediction using log data. The first approach is mainly based on crossplot analysis, in a multi-2D manner. The simplicity of the tools used for rock typing makes facies estimation quality control understandable and easily reproducible. However, plot analysis is limited, in that it cannot catch subtle variations that MRGC electrofacies will identify in a multilog analysis study. DNNA input facies logs are determined through the calibration of rock-typing lithology and fluid estimation with electrofacies (Figure 1).

**Seismic data as a propagation guide for lithology prediction**

Well analysis is considered to be reliable information when describing the reservoir; however, well data are generally too sparse of a data set to adequately describe a prospect. Attributes derived from prestack seismic data analysis (e.g., amplitude variation with offset [AVO] inversion or inversion results) are typically used to predict the lithology of reservoirs and their fluid content, but separation of facies is hard to define clearly on 2D log crossplotting (Figure 2). Alternatively, raw data such as gathers bring a huge quantity of highly valuable, but often subtle, information, which is difficult to handle without making approximations.

A neural network application through the use of DNNA offers the possibility of inferring facies defined at wells using prestack seismic data. The probabilistic approach of DNNA combines all seismic-related information to build facies probability cubes.

**Neural network predictive aptitudes and evaluation of probabilities**

The prediction of lithology at the prospect scale is strongly limited because the inversion workflow is a seismic data-driven process that provides few attributes derived from impedance contrasts, and spatial lithology separation becomes a challenge if performed with a limited number of attributes. The goal of using a methodology based on neural network techniques is to enable the addition of more inputs and eventually use the complete information contained in a full set of seismic gath-

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**Figure 1.** Carboniferous interval facies description at the well bore are defined through the combination of rock typing and electrofacies analyses. (a) Interbedded facies, (b) good-porosity biostrom (oil), (c) medium-porosity biostrom (oil), and (d) medium-porosity biostrom (water). Each facies group shows a different type of log response.
classes often overlap with one another. The use of several neural networks running simultaneously as an associative combination is preferred (Tetko, 2002b).

With regard to the data, different approaches can be considered to simultaneously train several neural networks. Usually, multiple-view learning methods are used (Gao et al., 2010). By definition, this approach requires multiple independent sets of attributes. The application of this kind of approach to facies prediction is not optimal in a reservoir characterization sense because seismic data are interdependent, as in the case of near- and far-angle partial stacks, for example.

The second approach is to simultaneously run different neural networks to be trained with the same hard data set (Zhou and Goldman, 2004). This single-view co-learning approach provides the ability to handle the training of associative neural networks (ASNNs) with a unique set of seismic data attributes that are not necessarily independent, paired with the well information. This is the approach we prefer.

Defining an ensemble of networks with different learning strategies helps to compensate for the existing bias when using only one network. The ASNN explicitly corrects the bias of the neural network ensemble and leads to an improved prediction ability (Gao et al., 2010). This has been demonstrated (Hami-Eddine et al., 2011) in the case of lithological facies prediction based on prestack amplitudes.

Democratic learning concepts

The multistrategy learning ASNN performance is limited by the number of hard data samples in the training set. If the volume of data is too small, it is probable that the training set is too limited in terms of diversity as compared to the population to qualify. The risk of over-learning is significant in that case, and the predictive properties of the networks are seriously reduced and unreliable.

The combination of hard and soft data in the learning phase (Figure 3) improves the training data set (Guillaumin et al., 2010). In the case study developed further in this paper, hard data $X: (x_w, c)$ comprise prestack amplitude values and a facies index $c$, whereas soft data are limited to $(x_w, ?)$. Soft data provide information

Associative neural networks

Many limitations are clearly identified for discrete prediction using seismic data. Lithological information, interpreted and gathered at wells, is not linearly correlated with seismic data. Facies are not ordered, and there is no notion of mathematical separation between them. Each neural network is designed to learn in a specific way. Using only one supervised neural network tends to bias the results of the training (Tetko, 2002a). A network is built to reach one objective, which is usually to approximate data or class densities (Kohonen, 2001). The problem of “well-to-seismic” data classification renders this one-goal approach unsatisfying because classes often overlap with one another. The use of several networks running simultaneously as an associative combination is preferred (Tetko, 2002b).

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![Figure 2](Interpretation_Figure2.png)

Figure 2. Multiwell crossplots of standardized gamma and density logs with facies group color coding (Table 1). Two-dimensional facies analysis shows interesting grouping; however, clear limits between identified facies groups are hard to identify.
on seismic prestack amplitude values, but they give no information about the nature of the facies.

We can summarize the training steps of the democratic ASNN as follows:

- Define a number $p$ of neural networks.
- Apply learning over the $p$ neural networks with each training set and examine the training quality by analyzing misclassification rates at well locations.
- Enrich training set: Apply a democratic vote system over a user-defined set of soft data and add the ones that pass the majority vote test as training data, with a lower weight than hard data.
- Apply learning over $p$ neural networks using the expanded training set now containing hard and soft data.

**Validation of network prediction by bootstrapping**

Cross validation is a well-known technique that measures prediction quality (Hastie et al., 2009). This method was used in the project, but experiments resulted in the use of the bootstrapping method. This method is more robust and less time-consuming for large data sets (Efron and Gong, 1983). The learning process can be halted, for example, by setting a maximum bootstrap error or a few iterations. The performance of democratic ASNNs has to be measured to avoid erroneous prediction capabilities as well as the overlearning phenomenon.

The bootstrap error is computed by taking the “.632+” estimator (Hastie et al., 2009):

$$\hat{\text{Err}}^{.632+} = (1 - \delta)\text{Err} + \delta\hat{\gamma} + \omega,$$

where

- $\text{Err}$ is the misclassification rate
- $\delta$ is a weighting factor: $\delta = .632/(1 - 0.368\hat{\gamma})$
- $\hat{\gamma}$ is the no-information rate:

$$\hat{\gamma} = \sum_{i=1}^{C} \hat{p}_i(1 - \hat{q}_i),$$

with $\hat{p}_i$ being the observed proportion of responses, $y_j$ equaling $i$, $\hat{q}_i$ is the observed propor-

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**Figure 3.** Description of DNNA training steps: Initial training data, from well facies groups and seismic prestack data, are used as hard training samples for the first supervised learning stage, whereas the democratic contribution (voting system) involves only soft data (seismic prestack) to enrich the final training data set for the second supervised learning stage.
portion of predictions $\hat{f}(x_i)$ equaling $i$, and $C$ is the number of classes.

The value $\overline{\text{Err}}^{(1)}$ is the bootstrap error in which only predictions from bootstrap samples that do not contain the $x_i$ observation are kept (Figure 4) as

$$\overline{\text{Err}}^{(1)} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{|C_{-i}|} \sum_{j \in C_{-i}} 1 - \delta y_i \hat{f}(x_j).$$  \hspace{1cm} (1)

Here, $C_{-i}$ is the set of indices of bootstrap samples that do not contain observation $i$ and $|C_{-i}|$ is the number of such samples. Terms for which $|C_{-i}| = 0$ are left out; $\hat{f}(x_i)$ is the class prediction made by the network trained with the $l$th bootstrap set; and $y_i$ is the expected answer. The bootstrap error $\overline{\text{Err}}^{(632+)}$ gives a robust estimation of the prediction error committed using DNNA. Our experiments have led us to adopt heuristics: A value of less than 0.3 means that the prediction quality is satisfying.

**Propagation of network properties using a weighted k-nearest neighbor algorithm**

When the DNNA learning has reached a satisfying bootstrap error value, we then predict facies values for the full amount of unlabeled data. The extrapolation of the network properties is based on a Bayesian approach using the a priori defined by the DNNA. The inference of classes performed by the DNNA is used to compute an a posteriori probability based on an a priori defined by the network.

The weighted $k$-nearest neighbors (WKNN) algorithm is a local version of the probabilistic neural network (PNN) (Specht, 1990), which computes a posteriori probabilities of class labels.

Figure 4. (a) Bootstrap set contains the same number of data as the original set. Consequently, some repetitions are observed as well as some missing data. (b) Each bootstrap set is used to train one DNNA entity. (c) Points missing in a bootstrap set because of repetition of other points. Missing points are used to validate predictive DNNA aptitudes.
According to the Bayes formula, we can define the a posteriori probability that \( y \) belongs to class \( c \) by
\[
P(c \mid y) = \frac{P(y \mid c)P(c)}{\sum_{c=1}^{C} P(y \mid c)P(c)}.
\]
(4)
The PNN makes the assumption that the probability \( P(y \mid c) \) is modeled by a multivariate Gaussian distribution kernel:
\[
P(y \mid c) = \frac{1}{n_c} \sum_{k=1}^{n_c} \exp \left( -\frac{\|y - x^c_k\|^2}{2\sigma^2} \right),
\]
(5)
where \( n_c \) is the number of elements of class \( c \), \( \sigma \) is a smoothing parameter, and \( x^c_k \) is the \( k \)th neuron of class \( c \). The nonlabeled vector \( y \) is assigned to class \( c \) for which \( P(c \mid y) \) is maximal. In the case of WKNN, the computation of \( P(y \mid c) \) is restricted to the \( k \) first nearest codebook vectors. Let us note \( n_{kc} \) — the number of codebook vectors of class \( c \) in the \( k \)-size neighborhood; we can then write
\[
P(c \mid y) = \frac{1}{n_{kc}} \sum_{i=1}^{n_{kc}} \exp \left( -\frac{\|y - x^c_{(i)}\|^2}{2\sigma^2} \right),
\]
(6)
where \( x^c_{(i)} \) is the \( i \)th nearest training sample of class \( c \) to \( y \).

The use of WKNN allows the determination of probabilities associated with each facies. Each location in the prospect area will be evaluated by the DNNA and probabilistically estimated from facies and seismic data learning process.

**Reservoir prediction in a carbonate reef**

The challenge in evaluating the quality of a carbonate prospect is not limited to understanding facies distribution. Carbonate reservoir properties are directly impacted by the depositional environment, but they are also highly dependent on chemical processes, such as diagenesis or karstification, which occur after deposition. As a consequence, this case study will focus not only on predicting facies, but also on facies groups. These take into account facies as well as rock properties due to rock evolution through time (Table 1). The ability to use all the available seismic information and facies calibrated to wells makes the DNNA methodol-

![Figure 5. Simplified stratigraphy column showing depositions throughout epochs. The Carboniferous and Permian intervals are our zones of interest and show biostrom and bioherm depositions, respectively.](image)
ogy an ideal candidate for carbonate reef studies through the multidimensional approach.

**Geologic context**

We focus on limestone carbonate reservoirs (Figure 5). Subaerial exposure in terrestrial and coastal environments has initiated a series of physical, chemical, and biological processes that have modified the carbonate rocks. The related karstic process is of paramount importance for reservoir enhancement, particularly within Palaeozoic rocks. The setup of potential reservoirs distributed through karstic galleries is not clearly identifiable on seismic data due to seismic resolution limitations.

The major trapping mechanism involved in the region is stratigraphic, with the top and lateral seals provided by overlying shale. Existing wells have shown an oil presence at the Permian and Carboniferous levels.

The description of the 16 facies groups is shown in Table 1. They are derived from facies (e.g., limestone, siliciclastic, bioherm, and biostrom rocks) groups based on porosity variation and fluid contents.

Combining prestack data and observation at wells in a heterogeneous environment to predict facies groups, where no wells are drilled, is challenging. We can observe AVO effects on carbonates, but these are generally more subtle (Li et al., 2003) than in a clastic-type reservoir due to the lower sensitivity of the response of carbonate rocks to porosity and fluid. In the selected data, the dominance of class I (Rutherford and Williams, 1989) anomalies can also make the interpretation difficult.

The DNNA methodology was applied to carbonate reefs in two layered reservoirs. Although the basin of interest is known for containing good-quality, proven oil and gas reservoirs, the geologic setting has a signifi-
Figure 7. (a) Seismic data are of low frequency in the area of interest. Separation of the reservoir units is unclear. Seismic reflectors show high energy across the whole section, with no apparent direct hydrocarbon indicator. (b) The seismic spectrum calculated in the dotted window visible on the I-J section. The central frequency is 20 Hz. The seismic resolution is highly limited. (c) Structural map of the top Carboniferous with section line I-J projection.

Figure 8. The reef shape (circled in green) in the Carboniferous interval is identified in green through proportional slicing on the signal envelope attribute. Lateral continuities are highly exaggerated, however.
cant impact on risk evaluation and control of the exploration and development of a field.

**Results**

Facies group determination was performed using only 13 of the available 22 wells because the method requires having a full suite of electric logs available for facies determination purposes. The group of 13 wells was used to analyze lithology distribution as well as fluid content when reservoirs intersect. In the Permian, bioherm-type depositions have occurred, whereas in the Carboniferous, we observe biostrom-type deposition. Combining density and neutron porosity logs, gamma ray and sonic, and as M-N plots, allowed the separation of shale, carbonates of various types, and their discrimination by porosity. A parallel study was performed at multiwell scale using MRGC to generate electrofacies. The same logs used for rock typing were integrated into the MRGC workflow. The result was integrated with crossplot analysis to determine facies based on lithology type and porosity. The MRGC approach constitutes a multivariate approach, whereas rock typing is a multilog pair analysis method. An additional MRGC was completed using SP logs and resistivity ratios to integrate fluid content information (Table 1). This fluid version of electrofacies was compared to pay flags on existing wells.

As shown in Figure 6, the final facies logs consist of low-resolution groups, taking into account lithology type and fluid content. Well sections such as the north–southeast (Figure 5) show relatively poor lateral continuities in reservoir bodies and sharp terminations, as expected in this type of environment. As mentioned, Table 2. Facies group prediction at the well bore. High reconstruction rates show the good match at the well after DNNA training.

<table>
<thead>
<tr>
<th>Well name</th>
<th>Reconstruction rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEG1</td>
<td>90.63</td>
</tr>
<tr>
<td>SEG17</td>
<td>73.45</td>
</tr>
<tr>
<td>SEG18</td>
<td>61.95</td>
</tr>
<tr>
<td>SEG2</td>
<td>74.05</td>
</tr>
<tr>
<td>SEG20</td>
<td>91.89</td>
</tr>
<tr>
<td>SEG22</td>
<td>74.78</td>
</tr>
<tr>
<td>SEG23</td>
<td>71.05</td>
</tr>
<tr>
<td>SEG25</td>
<td>73.56</td>
</tr>
<tr>
<td>SEG27</td>
<td>80.99</td>
</tr>
<tr>
<td>SEG3</td>
<td>90.11</td>
</tr>
<tr>
<td>SEG4</td>
<td>81.48</td>
</tr>
<tr>
<td>SEG5</td>
<td>80.43</td>
</tr>
<tr>
<td>SEG6</td>
<td>75.34</td>
</tr>
<tr>
<td>SEG8</td>
<td>98.31</td>
</tr>
</tbody>
</table>

![Figure 9](image_url)

**Figure 9.** (a) The seismic section on the left shows a projected gather position in blue. Corresponding gathers on the right show a large variation in frequency with angle. The green line corresponds to the top of the Carboniferous reservoir. (b) Amplitude versus angle response at the green line location shows the unclean class I effect. (c) 1D elastic modeled response based on well information. The expected response is materialized at the green arrow position. The class I effect is visible but subtle. This behavior explains the dimming of amplitude and phase reversal observed on stacked inline. AVO effects are consistent with modelization, despite the fact that they are subtle.
Figure 10. Reconstruction rates are high, as shown in Table 2. (a) Gamma ray track, (b) neutron-density crossing track, (c) interpreted facies group log, (d) predicted facies group log, and (e) probability log. Associated maximum probability values are displayed in last track, showing how confident the prediction is.

Figure 11. (a) P-impedance section: As expected, acoustic inversion does not detect contact. (b) Full-stack amplitude section: Seismic section shows dimming responses at the reservoir. The seismic vertical and lateral resolution makes estimating the reservoir extension difficult. (c) DNNA facies group prediction: The result of the prediction, using the DNNA approach, is a volume of the most probable facies. It clearly shows the water contact proven at well 1. The resolution of the facies cube is higher than for poststack seismic data. The subtle extra information contained in prestack angle gathers has been extracted by DNNA. (d) Map of top Carboniferous showing cross section A-B projection.
seismic data have low frequencies; therefore, the vertical resolution does not allow for the separation of different deposition units (Figure 7).

An initial study would consist of performing a seismic attribute analysis from seismic volumes. Computations of signal envelope, instantaneous frequency, and frequency-weighted amplitudes have helped map the lateral extension of the reef. However, the inner composition of the reef is not detailed and it would not allow the derisking of any well plan. The lack of reservoir continuity observed at wells is not honored by seismic attributes, which show either exaggerated continuities (Figure 8) or dimming responses due to class I reservoir type (Figure 9). Seismic attributes and inversion have proved to be of limited use in describing the bodies of interest, because amplitude and frequency do not significantly vary laterally in the area of interest. Detailed facies differentiation was not possible; therefore, uncertainty about reservoir extension and connections, thickness, and gross volume remains high. In the rest of the article, we demonstrate the use of DNNA that will add the ability to correlate the full collection of gathers with facies groups and extrapolate them at the prospect level, with an estimated probability of success.

**Training of democratic neural network association and quality control of predictive aptitudes**

Facies logs from 13 wells and time-migrated angle gathers are used for DNNA training. The quality control of DNNA predictive capabilities is showing promising results because it combines low bootstrap error values (0.3 ± 0.05) with good reconstruction rates at wells (Table 2). Thin beds are not reconstructed with exact thickness and become the main source of prediction errors along well bores. Reservoir facies groups are well reconstructed, as shown by associated probability values (Figure 10).
Probabilistic propagation of facies groups

The most probable facies distribution by DNNA is summarized in a lithology cube, in which each value at a given \((x, y, z)\) position corresponds to the most likely facies distribution predicted, i.e., each facies associated with its highest probability value.

Figure 11 shows the poststack seismic response and acoustic impedance compared to facies group prediction. Analysis of the results shows higher lateral and vertical detail than that provided by conventional attributes and seismic inversion. The distribution of Permian and Carboniferous facies groups is consistent with the structural interpretation, and the lateral discontinuities observed on cross sections such as the east–west (Figure 12) are respected in the DNNA facies group prediction. A water contact is clearly identified (Figures 11 and 12), and the reservoir position is consistent with AVO anomaly locations (Figure 11). The lateral continuity of reservoir bodies respects discontinuity observations. At the same time, the shape of the reservoir conforms to the karstic gallery hypotheses in the area.

As described in the methodology, DNNA outputs facies group probability values for each \((x, y, z)\) location (Figure 13). These probability values, calibrated to wells, can be used directly in a 3D geologic model to generate multiple realizations. Figure 14 shows the distribution of facies group four (good-porosity biostrom oil in the Carboniferous reservoir) for the most pessimistic scenario and the most likely scenario. The distribution of a good oil reservoir shows patches of high-porosity zones that can be detected using probability values and the most probable facies group volume. This confirms the initial geologic hypothesis about the zone. Reservoir properties can be modeled, taking into account seismic and well-based lithology and fluid definition. Therefore, the multiscenario-based approach is used for assessing uncertainty of facies distribution. This latter methodology was used to accurately estimate net volumes in this case study (Hami-Eddine et al., 2013).

Conclusion

The determination of reservoir extension and internal description is highly challenging in a carbonate environment. It is crucial to use all available data to extract maximum information. It is equally crucial to capture the geoscientist’s input and understanding of the geology. The DNNA approach combines the ability to perform a multidimensional analysis of seismic data with the analysis of well-based facies interpretation. We show that the introduction of soft data during the training process provides the ability to stabilize the result and reduce bootstrap error rates. The results obtained on this carbonate reef are consistent with geologic hypotheses and with wells that were used for blind testing. The most probable facies volume shows geologically reasonable facies group lateral distribution and thickness. The analysis of the probability distribution gives good insight into prospect uncertainty and seismic data reliability for prediction. The probability volumes can be used to evaluate risk on volumes and contribute to target rating.

In other words, DNNA performs facies inversion based on lithologs and seismic data, and is a robust alternative to conventional approaches. The addition of lithology probabilities directly based on well observations will help to reduce uncertainty in reservoir prospecting and qualification.
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Figure 14. Multiscenario realization of reservoir hypothesis based on probability distributions. The most probable scenario fitted at best the four blind well testing performed in this study. (a) The most pessimistic case in which only good-porosity oil reservoirs were kept if the probability value was greater than 0.9. (b) The most probable geobody detection for good-porosity oil reservoirs.
Pascal Klein received a Ph.D. (1986) in applied mathematics from the University of Grenoble and now serves in the research and development department at Paradigm. His research interests include development of tools and algorithms for seismic interpretation and unconventional reservoir characterization.

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