Comparing Bayesian and neural network supported lithotype prediction from seismic data

Sabine Klarner[1]*, Dmitriy Kirnos[1], Natalya Ivanova[1], Aleksey Gritsenko[1] and Olga Malinovskaya[2] benchmark advanced neural network algorithms against standard probabilistic lithology classifications from seismic data to find out which approach works best and under which circumstances.

Introduction

In the past few years there has been increasing interest in the application of machine learning in the industry, and specifically in its application to seismic interpretation. In this work, we benchmarked advanced neural network algorithms against standard probabilistic lithology classifications from seismic data, calibrated to well information to understand their benefits and limitations, and to check which approach works best under which circumstances. We tested the approach in various clastic and carbonate environments; the conclusions are presented in this paper. The workflow itself (Figure 1) is presented using part of the public F3-Netherland data set[1]. The interval of interest comprises a Tertiary progradational clastic unit, which is penetrated by four wells.

Conceptual geological model

In order to perform any property prediction from seismic data, a conceptual geological model is required. The model describes the expected lithotypes, their proportions, geometries and principal rock properties. The more well data available, the more detailed the model becomes. If fewer well data are available, the model is built on analogies. In the current study, we use the general

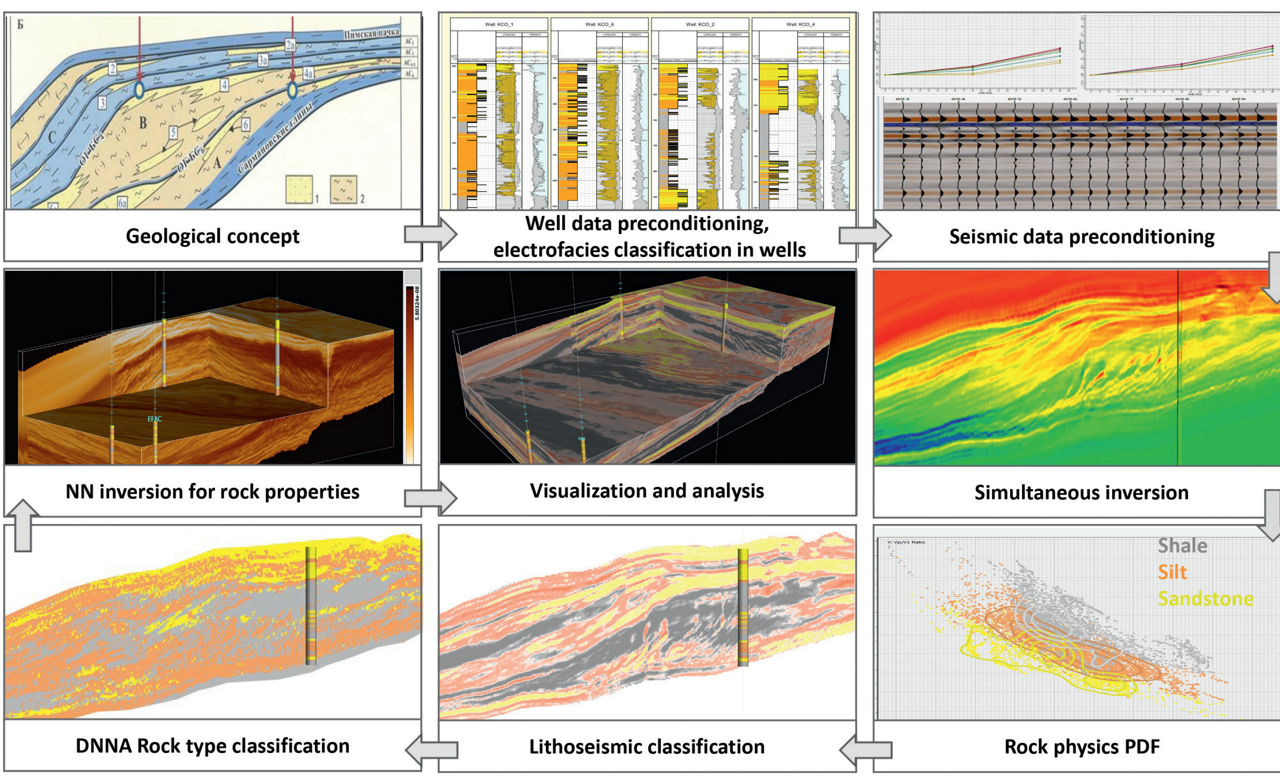

Figure 1 A rock type classification workflow from well and seismic data using various algorithms.

[1] https://terranubis.com/datainfo/Netherlands-Offshore-F3-Block-Complete

[1] Klarenco LLC | [2] Emerson
* Corresponding author, E-mail: sk@klarenco.com
DOI: 10.3997/1365-2397.fb2020053

model of prograding clastic clinoforms. The intrinsic lithology distribution in this depositional setting is well understood and extensively described in the literature (Kos et al., 2004). Well sorted sandstones are usually found in shelf edge and basin floor positions. The slope sediments are predominantly fine grained, channels are sometimes observed which distribute the shelf edge sands into basin floor fans. The sedimentation takes place in cycles, with the individual cycles often being separated by the shales of a maximum flooding event.

Well log data preparation and facies classification

For the well data interpretation, GR, Sonic and Density logs were used. The well log data preconditioning included editing and normalizing the logs, followed by the calculation of volumetric fractions for each well. From the volume fractions, a synthetic shear wave log from Vp was calculated using the Greenberg and Castagna empirical relationships for shales and sandstones (Greenberg and Castagna, 1992). Our experience is that in most cases these relationships give a good approximation, which can be used to build a starting rock physics model, with some exceptions only in very complex reservoirs.

The first step in the workflow was the facies classification from well log data. To ensure that we were able to identify facies classes, which can be predicted by seismically effective parameters, the input for the electrofacies classification was limited to AI, Vp/Vs and Density, with the Vshale log as lithology control. The algorithm used – Multi-Resolution Graph-Based Clustering (MRGC) - automatically defined an optimum number of 15 electrofacies. This is, of course, too detailed for a seismic classification. We decided to regroup the data into three main facies types: clean sandstones (potentially good reservoir), clean shales (non-reservoir) and a transition facies, conditionally called siltstone and including shaly sandstones and sandy shales (potentially non-reservoir). The sandstones tend to have lower impedances and a lower Vp/Vs ratio than the shaley facies types, but in the crossplot domain and in the probability density functions of the elastic properties, we see a significant overlap of the facies types (Figure 2).

Seismic data preconditioning

An important step in any QI workflow is seismic data preconditioning, preferably done through close cooperation between data processers and interpreters. It can be done either on postmigration gathers or on angle stacks, and along with tools for noise reduction, may include steps like parabolic radon de-multiple, residual moveout, and HTI anisotropy analysis. Each of these tools can significantly affect the quality of the stacks and the distribution of amplitudes. Parasitic amplitudes of multiples distort the real

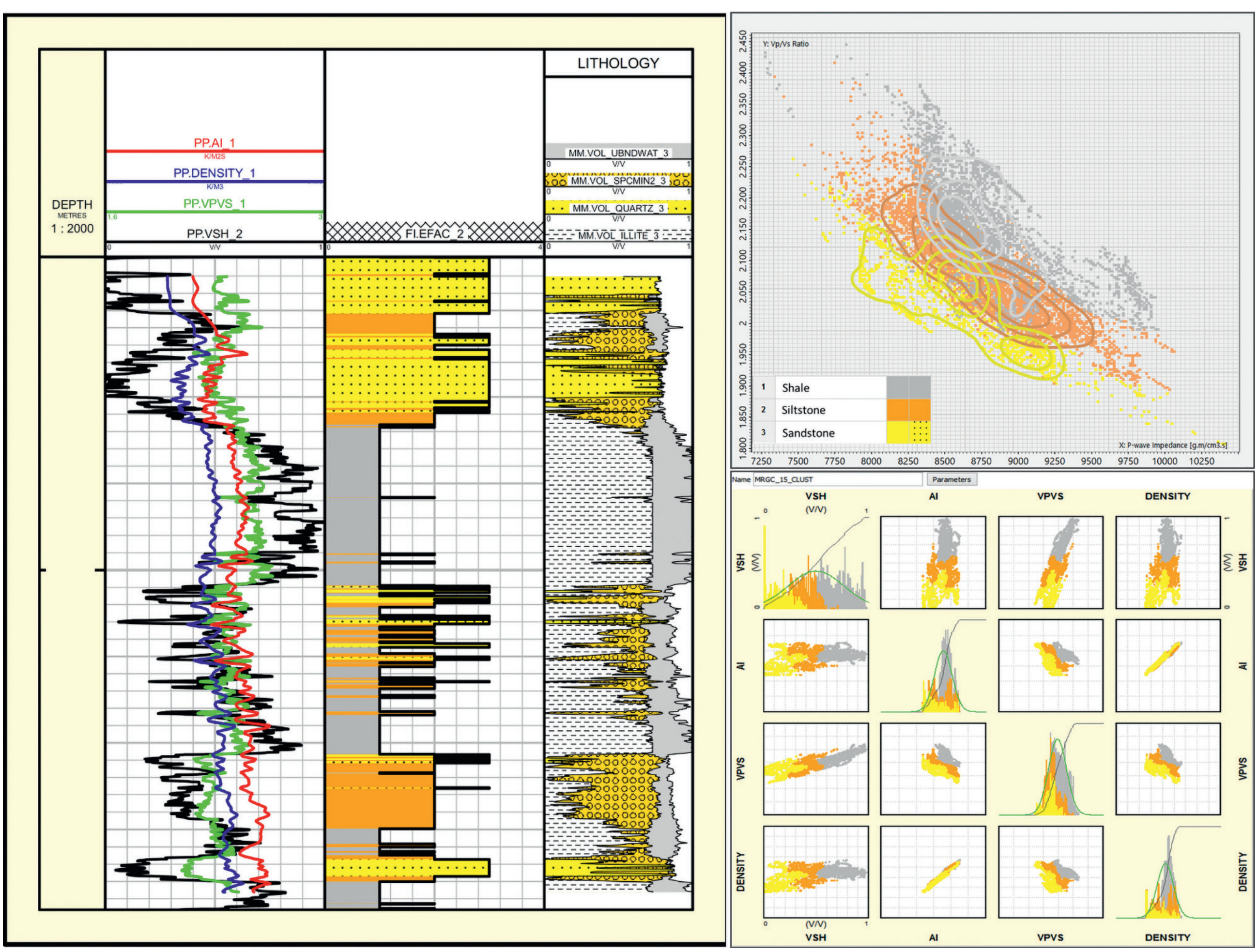

Figure 2 Example of facies classification in one of the wells, cross plots from all four wells.

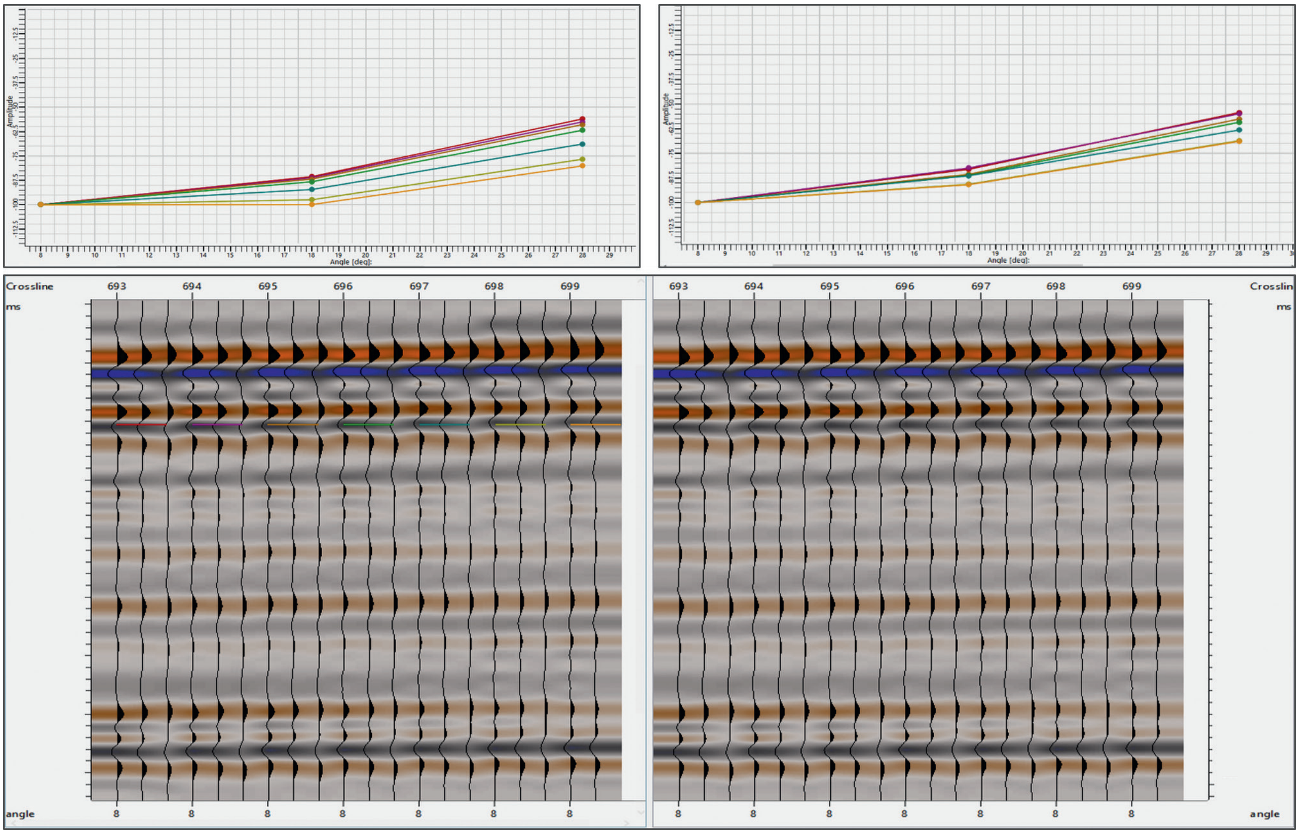

Figure 3 QC of AVO response before (left) and after (right) noise removal.

image, generate false reflections, or cancel real events. Due to the large number of traces stacked, on a full stack section they are usually less harmful than on selected angle stacks, and a parabolic Radon filter can effectively suppress this regular noise. While migration is usually an iterative process aimed at refining the velocity model during each iteration, it is sometimes necessary to apply one more velocity refinement after migration to remove minor non-flatness of the reflections on the gathers or super-gathers collected from angle stacks. If wide or full-azimuth data are available, HTI anisotropy analysis or at least QC of possible HTI anomalies should be performed to make sure the HTI ripples on mid and far offsets are correctly kinematically compensated. This analysis also helps to identify the direction of the fast axis, which should be consistent with the isotropic media properties that we are trying to estimate. To avoid amplitude distortions, after each step the AVO response has to be controlled.

In the current data set, the input data are three angle stacks with centre angles at 8, 18 and 28 degrees, respectively. We applied dip-steered filtering to each of the angle stacks to remove incoherent noise and stabilize the AVO response. To ensure that the amplitude response is not deformed, we usually apply QC plots of super-gathers collected from angle stacks (3) and compare the consistency of the amplitudes with neighbouring traces.

Simultaneous inversion of angle stacks

Because our aim was quantitative property mapping and prediction, the seismic reflectivity data needed to be transformed into cubes of elastic properties by simultaneous inversion of angle stacks. For the inversion, low-frequency models for Vp, Vs and density were built to compensate for the lack of low frequencies in the seismic data. Our models are usually an interpolation of the well log data, following the top and bottom horizon geometry of the target interval and with interval velocities derived from seismic velocities by a constrained velocity inversion as a background trend.

For the inversion we applied the prestack constrained stratigraphic inversion algorithm developed by IFP Energies Nouvelles, because it uses dip and azimuth cubes for stabilization, which is an advantage in data sets with tilted reflections like in the progradational foresets in this study. The results of the inversion were P-impedance and S-impedance cubes, from which the Vp/Vs ratio was calculated, and a density cube. The inversion QC (mainly the residuals, calculated from input data minus synthetic angle stacks) showed that almost all the seismic energy had been inverted, except for a small amount of energy around 5-10 Hz, which was attributed to the relatively smooth low-frequency model used.

Probabilistic lithoseismic classification

The standard probabilistic lithoseismic classification approach is based on probability density functions (PDF) created for each of the identified lithotypes. Using a Bayesian approach, pairs of elastic attributes (like acoustic impedance and Vp/Vs ratio, LambdaRho and MuRho, or Young's modulus and Poisson's ratio) were applied to define the probability of a data point to belong to one of the predefined facies types. The PDFs are usually built from well log data, but there is the possibility of increasing the deviation range for each parameter. This gives us the opportunity to cover a broader extent of geological values than the specific range encountered in the wells. It is one of the significant advantages of this approach, especially if there is only a limited amount of well data available.

For the test, we used the acoustic impedance and Vp/Vs ratio cubes to create probabilistic facies cubes for sandstones, 'siltstones' and shales. The resulting geometries, especially of the reservoir facies, fit the conceptual geological model very well, with cleaner sandstones located at the shelf edge and in basin floor fans (Figure 4).

DNNA rock type classification

The machine learning algorithm used in this case was a Democratic Neural Network Association (DNNA) from Emerson. It employs several neural networks running in parallel that simultaneously learn from the same data set using different strategies. The outcome of this workflow is a probabilistic facies model that predicts the most likely facies distribution and associated maximum probability, as well as the probability relative to each facies (Hami-Eddine et al., 2013). After upscaling the well data to 2 m, the DNNA was trained to use acoustic impedance, Vp/Vs ratio, and density traces extracted at well locations to predict the three facies types. Three of the wells were used for training, with one left as a blind test. The DNNA was applied to perform the classification over the whole cube, with a subsequent smoothing filter applied to create connected geobodies. Only the three attributes were used to ensure a fair comparison with the results of the probabilistic lithoseismic classification. The DNNA classification had significantly higher resolution. The facies distinction was sharper with less overlap than in the lithoseismic classification, and this sharpness was preserved even after smoothing. Again, the cleaner sandstones are predominantly located at the shelf edge and in the basin floor fans (Figure 4).

In other projects, we used significantly more poststack and even prestack attributes, which eventually resulted in a more detailed while still stable classification result. However, in heterogeneous data sets, a larger number of wells is required to provide a statistically valid basis for training, which is one of the obvious limitations of the approach.

Neural network inversion for rock properties

In order to diversify prediction techniques, in addition to the probabilistic prediction of lithotypes, which is based on AVA inversion results and corresponding probability distribution functions, a Neural Network Inversion (NNI) was applied. One of the benefits of neural network applications is that the inversion can be run directly to predict rock properties like effective porosity (PHIE), shale volume (Vshale) or even saturation from a set of input attributes. Unlike the seismic inversion, NNI is the process of spatial interpolation of well log data using a nonlinear operator which is built from well log data, and a set of seismic attributes derived from corresponding seismic volumes along well tracks (training data set). Here as well, it is possible to use not only pairs of elastic parameters, but also a large number of physically meaningful attributes. In this case, the training data set consisted of the smoothed porosity and shaliness logs, and a number of seismic attributes extracted along well trajectories: seismic inversion output – absolute and relative P- and S- impedances, Vp/Vs relation, density and other seismic attributes – rotated angle stacks (near, mid and far), and some frequency attributes. Our experience shows that the employment of inversion attributes constrained by a low frequency model, in addition to attributes created from the reflectivity data, increases the quality of the prediction because a priori information like the compaction trend or lateral facies changes can be taken into account.

Whereas one traditional way of porosity mapping is via (linear) regressions from impedance or density cubes, the use of multiple attributes enables a reliable prediction of nonlinear dependencies. For the current data set, we ran a few NN predictions for PHIE and Vshale (which always result in slightly different outcomes) and compared the results with the lithology probability cubes. Despite a general match, it gave us a good understanding of the dispersion of different property prediction approaches using the same input data set in each approach.

There are advantages and disadvantages to NNI. The large amount of seismic data involved – stack and prestack seismic data, seismic inversion results – makes it possible, if properly used, to obtain resulting volumes of shaliness and porosity with better vertical resolution than the volumes of predicted lithotypes. Also, the results of NNI are very close to the well log data in the vicinity of the wells. On the other hand, in the case of an over-trained NNI operator, the prediction could be unstable, as distance from the wells increases. To avoid overtraining, part of the training data needs to be excluded from the training process and used as a blind test.

Visualization of results and comparison of the approaches

The visualization and analysis of the classification results at the well locations and in 3D showed that all three tested methods

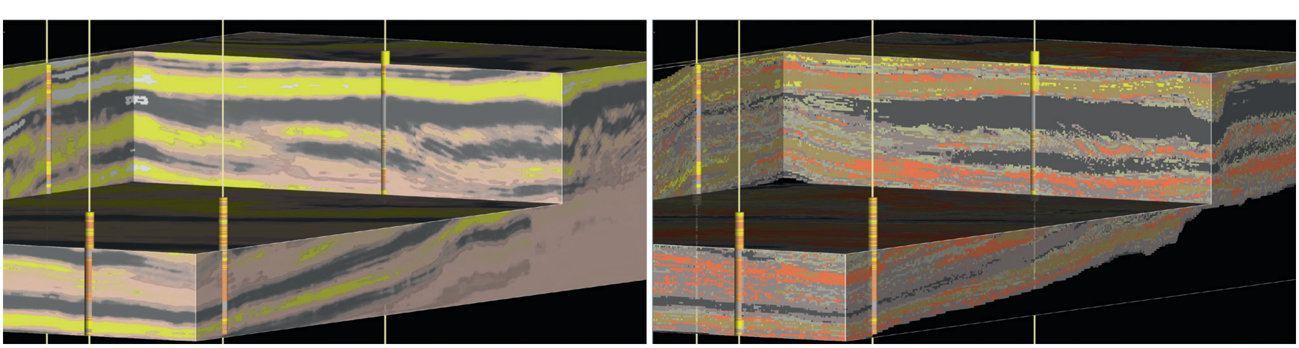

Figure 4 Facies probabilities from lithoseismic classification (left) and DNNA (right); greyish shale, orange siltstones, yellowish sandstones.

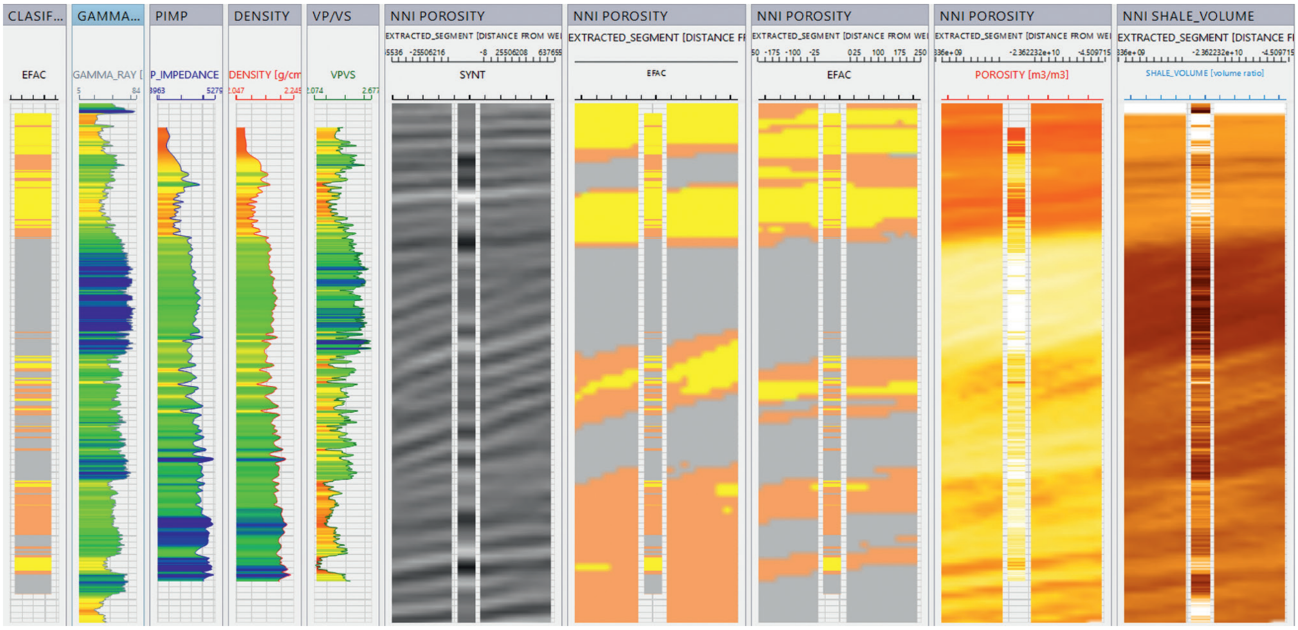

Figure 5 Example well with electrofacies from well logs, input data, well tie, and facies predictions from lithoseismic classification and DNNA and neural network property predictions.

have their pros and cons (Figure 5). The prerequisite for any classification from seismic data is the existence of certain rock physics dependencies for different lithotypes or reservoir parameters, which need to be established during the preparatory well data evaluation. The lithoseismic classification is based on a generalized rock physics model, usually involving only pairs of attributes (like acoustic impedance and Vp/Vs ratio, LambdaRho and MuRho, or Young's modulus and Poisson's ratio). It works well in a clastic setting and generally in data sets with sparse well information, but in cases of significant overlap of properties, such as in carbonates, it may have limitations. The DNNA classification requires significantly higher well data input. It reveals more details even for overlapping facies types, as more training attributes can be used (Klarner et al., 2019). However, after smoothing the results in the current test, results became close to the lithoseismic classification. Obviously, the neural network approach needs an experienced interpreter to understand how much information can be objectively extracted from the data set, and when the neural network becomes over-trained with no physical substantiation behind it. In the case of sufficient well data presence for training, the direct inversion for rock properties is an elegant solution for predicting and mapping them even if there is a nonlinear dependency on the elastic attributes. What is 'sufficient' depends on the degree of heterogeneity in the analysed data set.

Conclusions

Simultaneous seismic inversion is a method which solves the seismic inverse problem. It transforms the amplitudes of the interference seismic wavefield of partial angle stacks or even gathers into elastic properties (compressional and shear wave impedances and density) of the strata through which the seismic waves propagate. There are proven theoretical models (rock physics templates) which establish the relationship between elastic and reservoir properties of the layers. The main advantage of deterministic seismic inversion is that it makes it possible to use theoretical or empirical rock physics models to separate lithotypes, reservoirs and non-reservoirs, saturated and brine reservoirs, in a deterministic or probabilistic way. Thus, the inversion creates a spatial distribution model of the rock properties even at a distance from existing wells, and through stochastic rock physics models we can create probabilistic lithology and pore fluid cubes from the results of the simultaneous inversion. These cubes help to localize structural and stratigraphic traps and rank them through the predicted properties. The more wells available that can be tied to the seismic data set for calibration, the more quantitative the estimation becomes. However, even if there are no wells within the survey, it is still possible to localize 'sweet spots' and rank them, at least qualitatively. One limitation of deterministic seismic inversion is that the vertical resolution of the inversion results cannot be higher than that of input seismic data. For this and other reasons, such as noise in seismic data – multiples, acquisition footprints etc., the elastic properties obtained with seismic inversion at the points of the wells will always differ from the ones measured in the wells. This difference can be used as the measure of possible errors when moving away from the wells.

Neural network (NN) techniques are also often used to predict reservoir properties in the interwell space. The input for neural networks is well log data and a corresponding set of seismic attributes at well locations. While learning, the NN creates a nonlinear operator which interpolates the reservoir properties that were used for learning, between the wells. Modern neural networks are quite sophisticated, and if correctly used, allow us to obtain volumes of predicted reservoir properties which are accurate in the vicinity of the wells and can possess a higher vertical resolution than the input seismic attributes. There are two important considerations when working with the NNI – the neural network input must be representative and the neural network must not be over-trained. The results of an over-trained neural network will fit exactly to the training data set, but there will be unpredictable errors for features which were not represented in the training set. It is necessary to find a compromise between the accuracy and lateral stability of the NNI predictions. A possible limitation is the risk that geological bodies such as channels, fans, etc., may not be predicted by means of NNI if similar objects are not penetrated by the wells used for training.

In our best practice, especially in areas with a high heterogeneity of elastic properties and relatively low well coverage, the first step in quantitative seismic interpretation is still AVA inversion. Through the low-frequency model, important prior geological information can be integrated which makes the probabilistic seismic classification more reliable. If more well data are available to train neural networks, additional attributes can be used to provide a more accurate property prediction. In any case, the joint interpretation of AVA and NN inversion results improves the quality of the reservoir predictions and reduces the ambiguity. Thus, the advantages and limitations that we see in both NN and AVA inversions are our motivation for combining both.

Acknowledgement

We would like to thank Emerson's Seismic Quantitative Interpretation team for its assistance and helpful discussion during the development of the presented workflow.

References

Kos, I.M., Polyakov, A.A., Koloskov, V.N. and Bespalova, E.B. [2004]. Geological-geophysical prediction of oil saturation in the Neocomian; Sakhalinskiy licence block (W. Sibiria). *Geologiya Nefti I Gaza*, 2004/02.

Greenberg, M.L. and Castagna, J.P. [1992]. Shear-wave velocity estimation in porous rocks: theoretical formulation, preliminary verification and applications. *Geophysical Prospecting,* **40** (2) 195-209.

Hami-Eddine, K., Richard, L. and Klein, P. [2013]. Integration of lithology uncertainties in net volume prediction using democratic neural network association. *83rd SEG Annual International Meeting*, Expanded Abstracts, 2495–2499.

Klarner, S., Almoulani, G., Thampi, S., Alansari, Y. and Razin, A. [2019]. A NN supported seismic workflow to create new exploration concepts offshore Bahrain. *AAPG Middle East Geoscience Technology Workshop, Integrated Emerging Exploration Concepts*, Abstracts.