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Petrophysical evaluation of thin laminated sands using SOM

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Introduction

From time to time the petrophysical interpreter is faced with the challenge that an evaluation of a reservoir is struggling to deliver credible results owing to the individual layers of the reservoir being thin and beyond the resolution of the petrophysical tools. The tools see a mixed bag of lithologies and fail to detect the individual layers of interest, let alone resolve the petrophysical parameters of same. When the reservoir layers are thin - from 2-3 decimeters and below - the summary of an evaluation is often associated with significant – and in some cases - massive uncertainty.

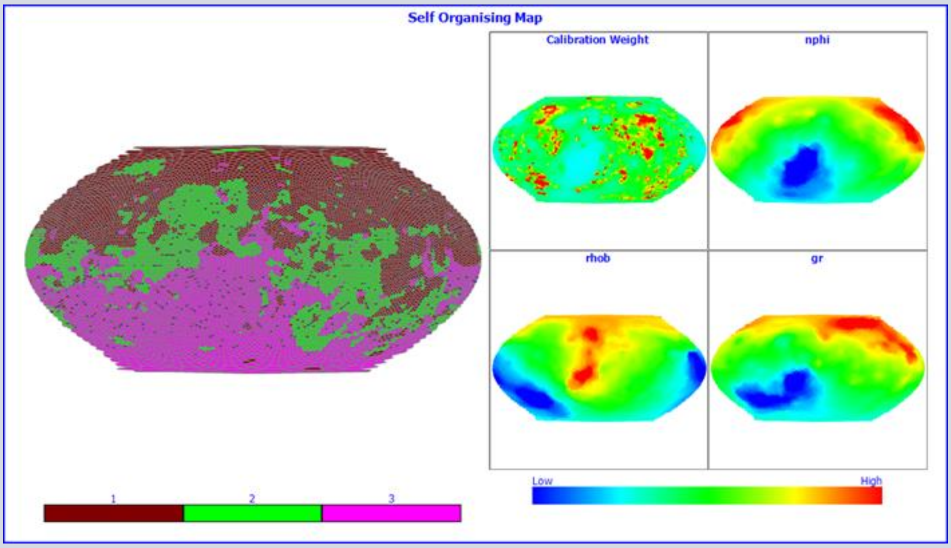

Figure 1. Example of Self Organising Maps (SOM) based on the spherical map geometry. The large map shows the SOM established from mapping of the three lithologies (shale, silt, sand) we want to predict. Maps of the three input vaiables used are shown also. The "Calibration Weight" map is established when calibrating the trained SOM to the facies data we want to predict. When performing this step we go from an un-superivised to a supervised SOM.

In a recent deterministic study carried out for OMV Norge it was concluded that the deterministic petrophysical summary simply was not credible. We concluded the evaluation was probably significantly underestimating the volume of sand in the Paleocene deep marine turbiditic fairway system under scrutiny. For that reason, it was decided to undertake an analysis based on the Machine Learning (ML) technique referred to as Self Organising Map (SOM). The outcome is a completely revised understanding of the volume of sand in the reservoir.

This article describes – in brief – the use and outcome of the SOM methodology applied in the evaluation of this highly laminated deep marine turbiditic sand system on the Norwegian Continent Shelf. It is very much a case story and the objective is to convey understanding of the capabilities of this Machine Learning technique when applied correctly to complex thin layered reservoirs.

At WellPerform we us the Interactive Petrophysics™ (IP) package from LR-Senergy for petrophysical interpretation and the work presented here is carried out using IP's SOM module.

The Self Organising Map (SOM) technology

The Self Organising Map (SOM) methodology uses a mathematical technique to enable data to be organised into groups to produce a map. SOM's are a form of neural network but are self-trained whereas normal neural networks are trained on a calibration curve. The SOM is subsequently calibrated so it can be used to produce either a discrete curve – in this case a facies curve – or to predict a continuous varying curve like permeability.

The classic SOM is a square map where each node is connected to its neighbours in a square grid. One of the drawbacks of this arrangement is known as the "border effect". This effect causes nodes along the border of the grid to be more poorly trained compared to nodes in the centre. In order to mitigate and indeed remove this effect a spherical- or toroidal geometry as SOM can be used. IP offers the spherical SOM as well as the classic ones. The sphecical map geometry is used in this study. We plan to investigate the use of the toroidal map geometry also to see how the results compare.

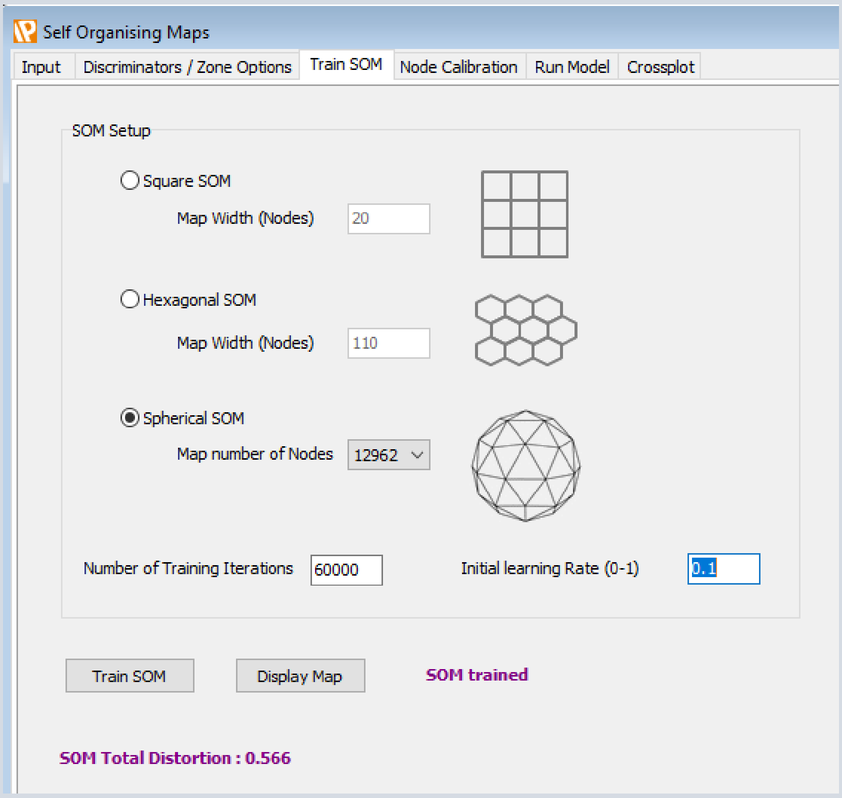

Figure 2. The various geometrical map types as discussed in this article and available in IP.

The spherical geometry maps a SOM onto the surface of a tessellated sphere. The geometry of the nodes is different to that of the classic square and hexagonal SOM and further there is no border effect. This is because the nodes which would be border-nodes in the other two geometries now wrap around the sphere and all nodes have the same number of connections. This essentially removes the inaccuracies of the border effect and greatly improves the quality of the final trained SOM. The spherical SOM works best using a high number of grid nodes and a high number of iterations.

The SOM workflow is as follows:

1. The SOM is trained using the input data (curves) selected. The inputs and mapping settings are explored until the lowest possible "SOM Total Distortion" number is achieved. This number reflects the quality in the training.
2. The trained SOM is calibrated towards the data/curve that we want to predict. By doing that the SOM becomes a Supervised SOM.
3. The model is run, and the methodology predicts the data/curve over the entire interval in the well(s) of interest.
4. The quality of the results is investigated and iterations to the training and calibration are carried out if desired and re-examined to find the best result and establish the best model with the optimum ability to predict the calibration data.

Evaluation of thinly laminated deep marine turbiditic sands

In a study for OMV Norge we performed a deterministic petrophysical evaluation of two deep-marine turbiditic sand systems encountered by the wells X-1 and the side-track X-1 T2. These wells are drilled in a well-known Paleocene sand fairway system. In the X-1 T2 well two cores were acquired – one from each of the two sand systems. In addition, conventional LWD data is acquired in both wells over the reservoir interval.

Following careful depth-shifting to accurately match core- and log data, the core image data was parametrised and converted into a facies log of discrete values. This was done in two steps. First, two sets of intensity image logs were created; an Intensity image which takes the maximum value of the RGB components at every element of the image as well as a single-valued intensity image curve along an 180^0 slice angle intensity image log. Secondly, these image logs are used to discriminate between shale, silt/fine sands and good quality sands by performing a careful breakdown of the single-valued intensity curve spectra into three bins that each represents one of the three facies. The discrete facies log that enters the SOM analysis has the following values: 1 = shale, 2 = silt/fine sand and 3 = good quality sand. Figure 3 provides a flavor of the scale of the reservoir sands in relationship to the log curves and show the core image, the intensity images and the final discrete facies curve.

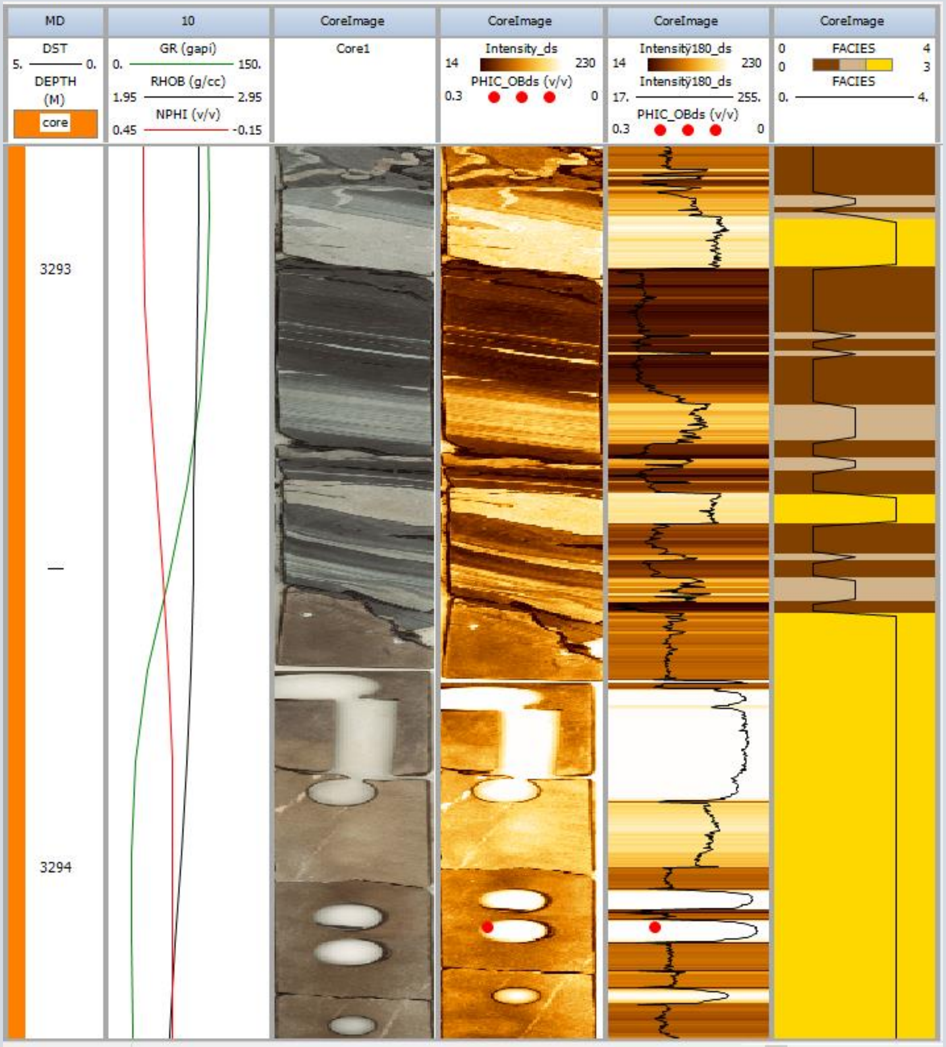

Figure 3. The core image, the intensity images and the final discrete facies log used in SOM. The three LWD log curves used as input to SOM evaluation are also shown and the challenge in terms of log resolution can be seen.

Although picking of facies from core image data is carried out on a 1 cm scale all curves entering the SOM analysis were re-sampled into a data set with a sampling rate of 5 cm which constitutes a compromise balancing the need for a high resolution data set as well as the need of a data set that is not too excessive in size.

The SOM analysis and prediction of facies

Figure 4 shows all the inputs for training and calibration of the supervised SOM. Although the five curves - Bulk Density (RHOB), Neutron Porosity (NPHI), Medium Depth Resistivity (RESM), Normalized Gamma ray (GR_N) and Compressional Sonic (DT) - were all used initially as inputs, the best result was achieved using the RHOB, NPHI and GR_N only. Normalized GR is used because GR is the single most important input variable and by using a normalized curve the GR input used in both the wells become unified and the methodology get more information to work with.

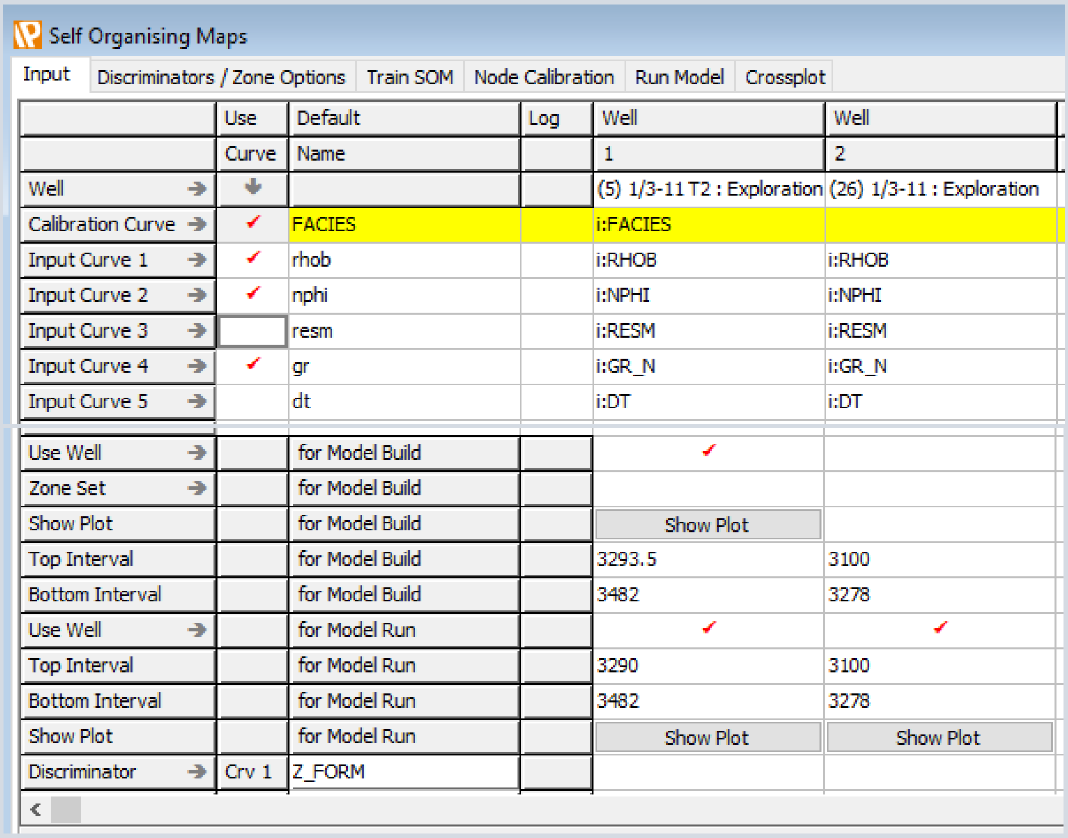

Figure 4. All the inputs for training and calibration of the methodology.

Figure 1 shows the SOM's that are established from the training part. The map showing the calibration weight assigned to each grid node is added during the following step of calibration. After having done the calibration against the discrete facies log the model is run to create the predicted facies curves in both wells over the entire interval being evaluated.

Figure 5 shows exactly how successful the model is at predicting the data provided for the calibration. 84.7% of calibration data is correctly predicted by the model which is a quite good result considering that the method is asked to predict thinly laminated facies with many sands being significantly thinner than log resolution.

The contingency table show how many data points are used in the calibration – in total and for each facies – as well as the success of the model at predicting the calibration inputs.

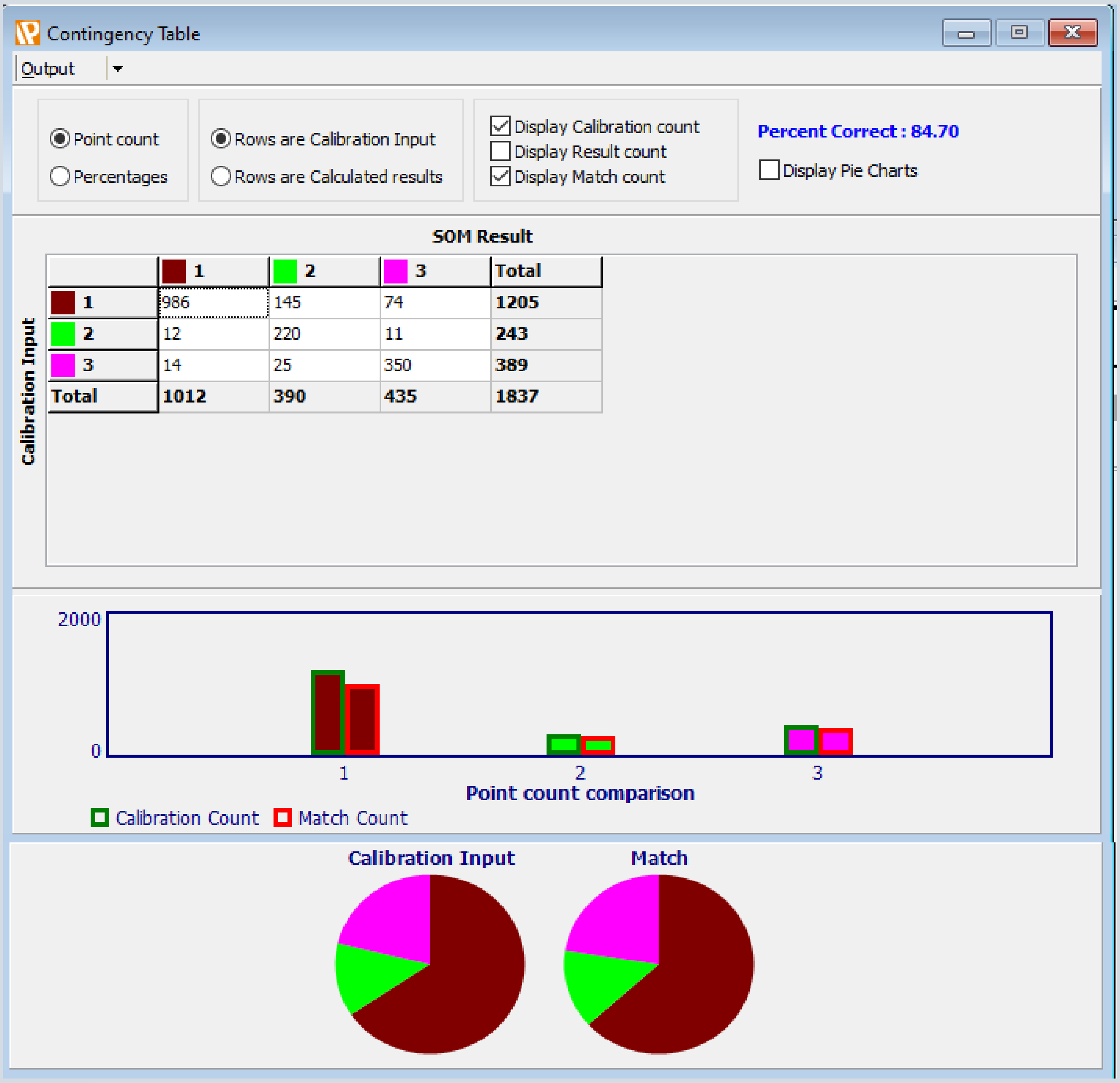

Figure 5. The Contingency Table used to assess the quality of the prediction.

The figures 6 to 8 show the predicted results as well as the calibration inputs for the X-1 T2 well. The predicted results for the X-1 well are excluded here since there is not calibration data to compare with. The text associated with figure 6 explains the plots. It is obvious that the technique can predict even very thin sands that are not readily seen in the input logs of RHOB, NPHI and GR_N and would never be identified in a deterministic evaluation.

Figure 6. Well X-1 T2. The figure shows all input data as well as predicted facies from SOM analysis over the upper part of core 1 covering the upper sand. ***The Facies Calibration*** *track shows the input calibration data from core and the other tracks show the results of the SOM analysis. In track 3 to 5 the SOM results are imposed on top of the input log data.* ***Facies Percent Curves*** *is a set of curves, one per facies and these curves give the weighting of each facies at each depth level and allows the user to see how confident the facies selection is at each depth level. The* ***Fit Flag Curve*** *is a flag curve which is 1 if the input calibration curve value matches the output facies curve value otherwise a value of 0 is output.*

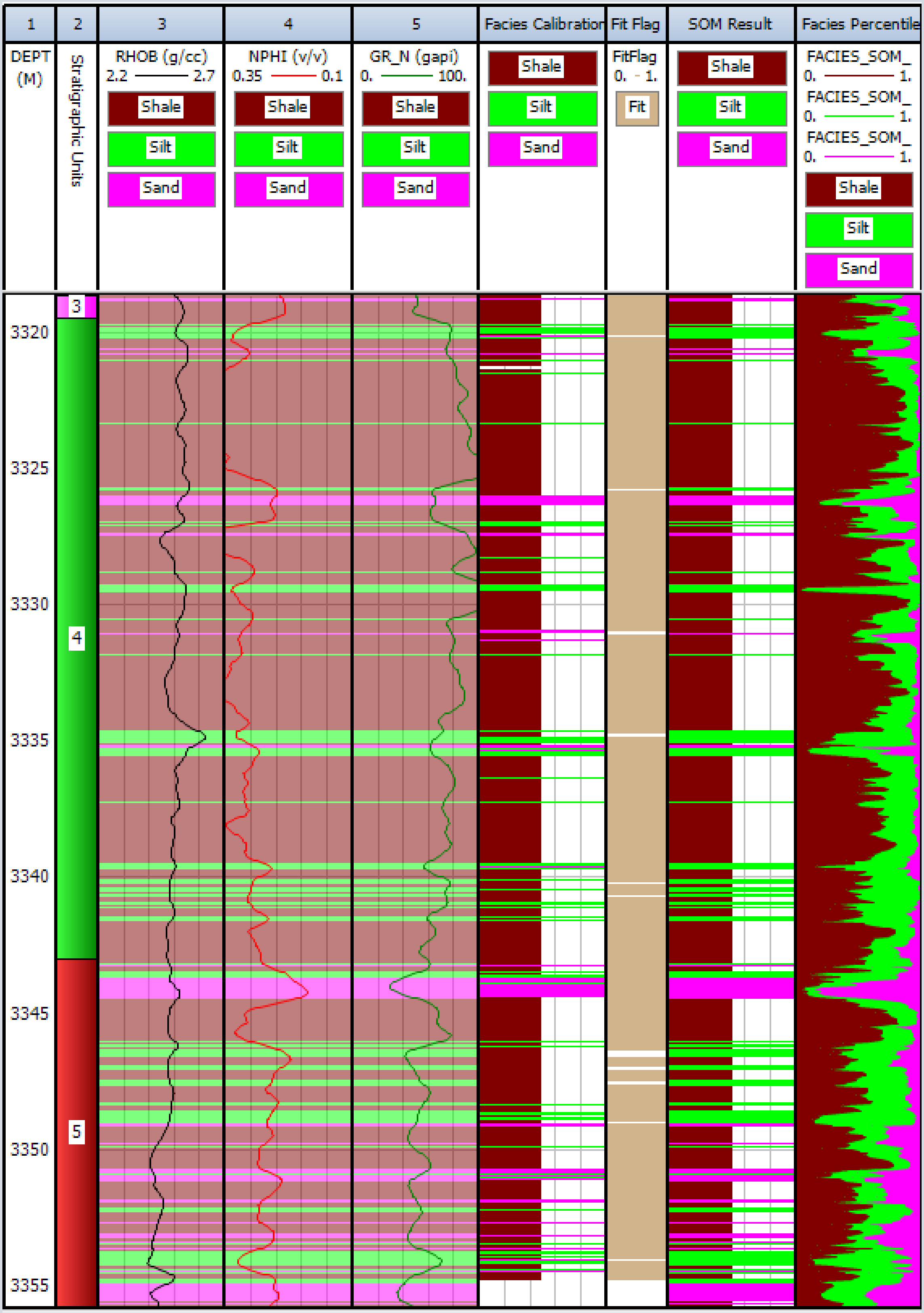

Figure 7. Well X-1 T2. The figure shows all input data as well as predicted facies from SOM over the lower part of core 1 covering mainly non-reservoir shale formations. Further explanation of the plot is found under figure 6.

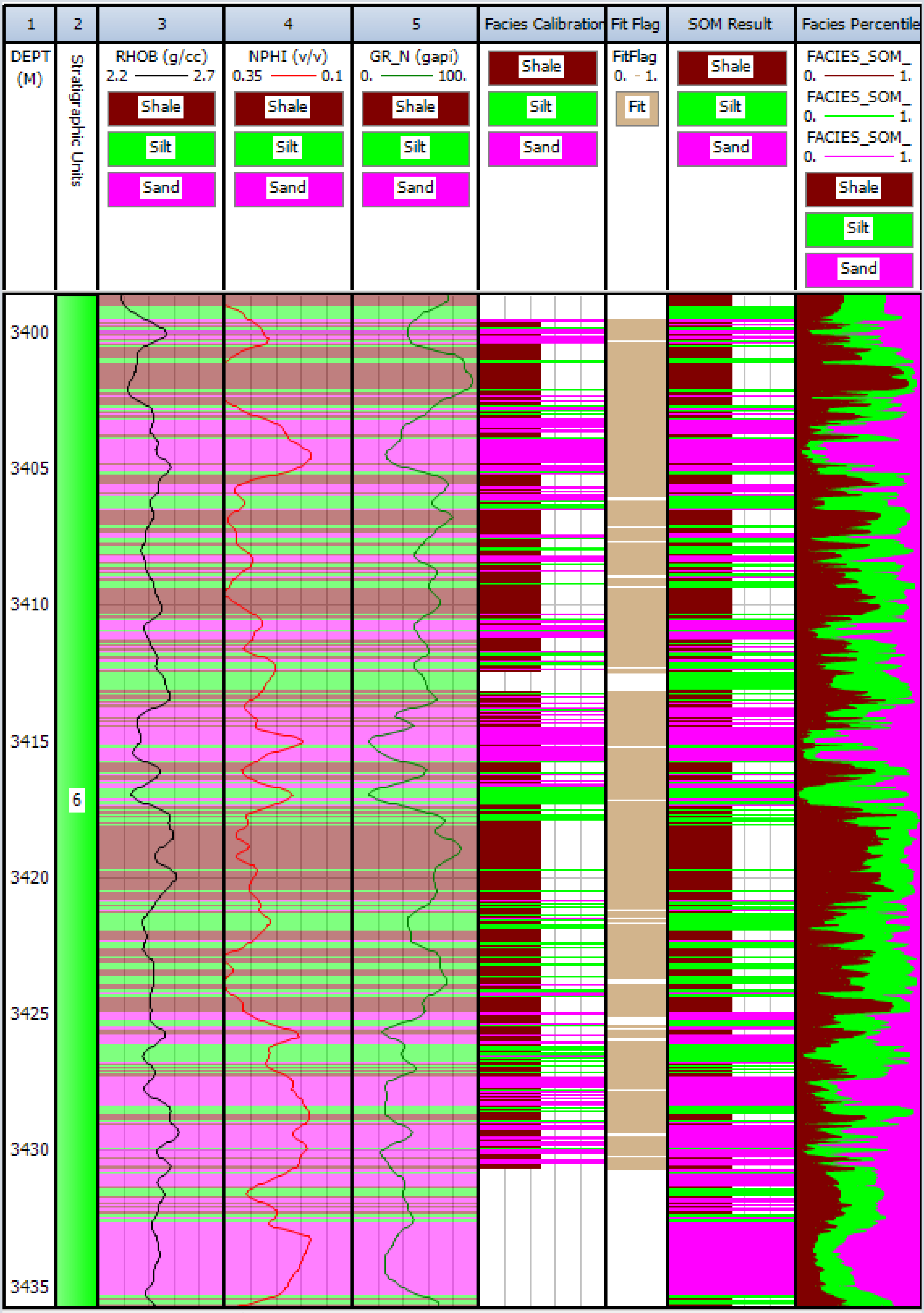

Figure 8. Well X-1 T2. The figure shows all input data as well as predicted facies from SOM over core 2 covering the major part of the deeper sand. Further explanation of the plot is found under figure 6.

Conclusions and remarks

The difference in the results between the conventional deterministic evaluation and the SOM analysis is significant – to say the least. The prediction delivered by the SOM methodology and verified against the input calibration data completely changed the view and perspectivity of the sand fairway system in the area being evaluated. Table 1 shows the results and the differences between the two methodologies in both wells. X-1 T2 is listed first because this is the calibration well.

Facies 2+3 (all sands)	SOM result (m)	Deterministic result (m)	Difference (SOM-Determ.) (m)	Difference (%)
Well: X-1 T2				
Upper sand	**19.6**	**7.3**	**+12.3**	**~170**
Lower sand	**86.1**	**14.6**	**+71.5**	**~490**
Well: X-1				
Upper sand	**3.1**	**0.3**	**+2.8**	**~930**
Lower sand	**56.2**	**21.0**	**+35.2**	**~170**

Table 1. Comparison of results of the SOM methodology and the deterministic evaluation. Facie no. 2 refers to silt/fine sand and facies 3 refers to good quality sand.

The supervised SOM methodology is a very strong tool in predicting a discrete variable like facies or hydraulic flow units. The method has demonstrated its capabilities in identifying patterns in data that are invisible to the eye. It allows to establish a model that can identify facies in a geological setting where the individual sands are very thin – down to centimeter scale - and significantly thinner than the resolution of the petrophysical logs trying to detect and resolve them.

If the objective is to predict a continuous curve like porosity or permeability SOM is not the best machine Learning technique to apply. In that case Deep Neural Network is a better methodology and that will be the subject of a coming article from us.

The above conclusions are equally important whether the reservoir under evaluation is an oil & gas reservoir or a geothermal reservoir - the task is the same. The next step in our work in this field will be to establish a model based on the toroidal map geometry to find out if a model can be established with even better predictive abilities. We will – in a not too far future - revert with a similar article covering the results of that analysis.

In addition, we will soon come out with an article sharing our results applying SOM to the Hydraulic Flow Units (HFU's) established from core data for these sands in these two wells. Again, SOM is showing to be a very powerful tool in predicting the HFU's away from intervals covered by core.

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