Shale Characterization and Well Correlation by Competitive Neural Networks

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Abstract

The lithological characterization of a rock layer crossed by a borehole and its identification in the neighbor wells (well correlation) in an oil field are of great importance for reservoir studies that aim to improve the volume of oil recovered. In spite of the actual drilling technology is not usual to core all boreholes in a field and an alternative manner to deal with it is to use well log data. Thus, we present a new method to produce the lithological characterization and well correlation from well log data, using competitive neural networks, immerse in the context of interpretative algorithm, which can simulate the log analyst behavior, associating one formation evaluation method with core data and geological information. We show an evaluation of this methodology to shale characterization and well correlation with two boreholes from the Namorado oil field, Campos basin, Brazil.

Introduction

The lithological characterization of rock layers crossed by a borehole and its identification in the others boreholes in the neighborhood (well correlation) has a fundamental role in oil reservoir modeling and in the development of production strategies that aim to improve the oil recovery.

Usually, the lithology identification is obtained from core analysis. The cores are not deformed rock samples and are obtained, in the subsurface, from complex drilling operations. However, just a few boreholes are cored in an oil field, principally for economic reasons. Well logging, in the other hand, is a common technique, applied in all boreholes in an oil field, which measure the physical properties of rocks surrounding the borehole and permits to geologist handle with the lack of core data.

The lithological characterization using well log data is realized from rock physical properties, different from that one performed by core data, which is based on geological features in the rock sample. A common method in formation evaluation to lithological characterization is the M-N plot, which integrates three physical properties (density, neutron porosity and acoustic transit time) that enhance the rock composition sensibility and avoid the porosity influence in these measures individually.

Well correlation, or the transport of geological information from one borehole to another, is usually performed with well log data. It is a way to extend laterally the local information produced by well logging and permits the definition of lateral continuity and geometric disposition of rock layers that are crossed by different boreholes (cored or non-cored). The spatial and temporal geological information and its transport from cored wells to non-cored wells are fundamental geological activities to improve the oil reservoir model. This kind of work is deeply affected by geologist experience and dependent of his interpretative criterions to read and choose the correct log readings. So, the success of well log interpretation is subjective and the minimization of subjectivity is, nowadays, indispensable to oil industry (Luthi, 2001).

Here, we present a new look in conventional M-N plot by the development of an interpretative algorithm (Fischetti & Andrade, 2002), based on competitive neural networks. It is able to accomplish the well correlation, based on objective criterion as core analysis in a reference cored well, to produce the transport of geological information to another non-cored borehole. Our principal intention here is to transform the raw well log data in geological information useful to oil industry.

We show an evaluation of this methodology for one particular shale layer presents in two cored boreholes in Namorado oil field, Campos basin, Brazil, producing a cross section, which extend the visualization of subsurface.

The shales in Namorado oil field

The Namorado oil field is located in the central part of Campos basin (Figure 1) and composed by a sequence of clastics and carbonatics rocks (conglomerates, sandstones, shales, marls and diamictites) of transgressive characteristic (Guardado et al., 1990).

The fundamental element for oil occurrence, in significant amount, in a sedimentary basin is the existence of organic material in great volume, accumulated when fine sediments were deposited. This sedimentary rock is denominated as generating rock, which submitted to temperature and pressure appropriated generates the oil in subsurface.

The source rocks are, usually, formed by clastic material with very fine grain size (clay fraction), as the shales. In the Namorado oil field, down the Jiquiá formation, the shales with high content of organic material and suitable grade of thermal evolution originate the hydrocarbons discovered up to now.

As a function of its particular low energy depositional environment and occurrence in a large area inside the basin, the shales are a natural reference of the ancient topography and a good correlation datum, with high probability to be crossed by different wells in an oil field.

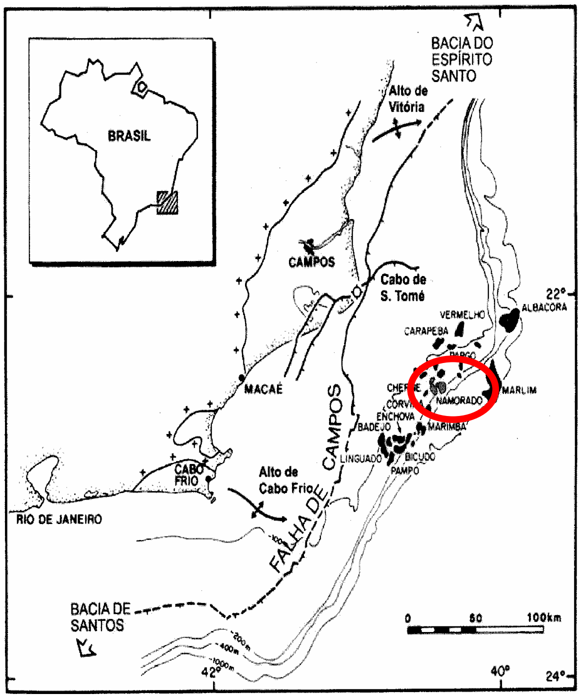

Figure 1- Campos basin map. The Namorado oil field location is highlighted by a red circle.

Competitive neural network

The classical architecture of a competitive neural network shows two full connected layers (Figure 2): the first, called input layer is composed only by sensorial units, which receive the input patterns and the second – The competitive layer, is the only processing layer in the network and is formed by competitive neurons, which exhibit feed forward and lateral connections. The lateral connections permit the competition among the competitive neurons. These neurons compete for the opportunity to produce the effective output (non-null) for an input pattern applied in the first layer and the winner neuron represents the classification category of input pattern.

The learning capacity is the most important characteristic of a neural network and occurs basically, through an iterative process of synaptic weights adjustments. Actually, there are very sophisticated learning (or training) processes that are able to adjust, not only the synaptic weights, but even its architecture and neuron activation functions.

In the competitive learning, the processing neurons compete among them to be active. Just one competitive neuron will be activated in each time. This characteristic turns this kind of neural network appropriated to discovery relevant statistical characteristics that may be used to classify the input patterns (Haykin, 2001).

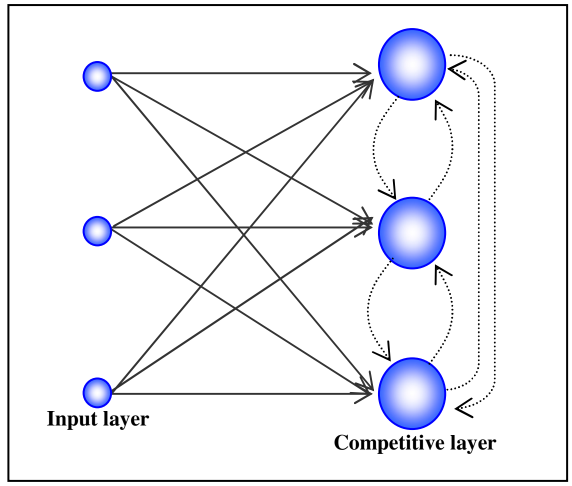

Figure 2- Competitive neural network with feed forward (solid arrows) and lateral connections (dotted arrows).

The common competitive learning rule establishes as winner neuron the one that most resembles to input vector, and has its synaptic weights moved close to input vector. So, each competitive neuron has its synaptic weights migrated to near of input vectors group that it represents. After network stabilization, the synaptic weights of each competitive neuron migrate to nearby the gravity center of input vectors cluster. If one neuron does not answer to a particular input vector, no learning will occur or its synaptic weights will not be moved (Haykin, 2001).

For a competitive neuron *k* to be the winner, its output signal y_k, regarding to one input vector *x*, might be the highest of whole competitive layer. The output signal y_k of winner neuron *k* is set to 1 (one), and the output signal of all others neurons is 0 (zero), thus, we have

$$y_k(t) = \begin{cases} 1, \; se \quad y_k(t-1) > y_j(t-1), \forall \, j \neq k \\ 0, \; otherwise \end{cases} \quad . \qquad (1)$$

Here, y_k represents the combined action of feed forward and lateral connections.

The M-N plot

The M-N plot is a method for mineral identification from well log data.

The porosity logs (density, neutron porosity and acoustic transit time) are used to determine the M and N parameters expressed in the metric units as (Ellis, 1987):

1) The M parameter

$$M = \frac{\Delta t_w - \Delta t}{\rho_b - \rho_{bw}} x 0.003 \qquad (2)$$

2) The N parameter

$$N = \frac{\phi_{N_w} - \phi_N}{\rho_b - \rho_{b_w}} \quad , \qquad (3)$$

where Δt and Δt_w are, respectively, log readings and water transit time, ρ_b and ρ_{bw} are, respectively, log readings and water density and ϕ_N and ϕ_{Nw} are, respectively, log readings and water neutron porosity.

The values of M and N parameters are quite porosity independent. The substitutions in equations (2) and (3) of log readings for correspondent matrix values (sandstone, limestone, etc) get the fixed points or matrix points in the M-N plot (Figure 3).

In the M-N plot, the M and N values for each depth point in a logged interval will be located close to correspondent matrix point, facilitating the lithology identification.

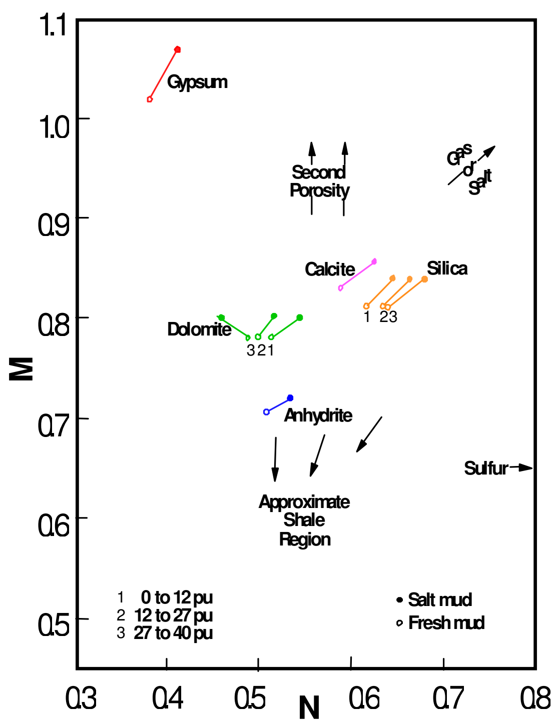

Figure 3- The M-N plot.

Methodology

The lithological identification of sedimentary rocks, in a complex depositional setting requires special attention when it is performed from well log data by the use of M-N plot, which shows more complexity than core analysis, due to sensibility and non-linearity of logging tools with the mineralogical variations in the rock constitution. So, the principal mineral or one that presents the greater volume in the solid part of rock constitution will be used to identify the lithology by well log data. This premise creates a particular problem in relation to shale identification in reason of its variable mineral constitution. We can observe in Figure 3, the absence of a specific shale point.

On the other hand, for well correlation purposes, a shale layer shows a good behavior as correlation datum. As the shale layers are a natural reference of the ancient topography, with high probability to be crossed by different wells in an oil field and considering the absence of important tectonic events, the mapping of shale layers facilitates a good estimative of reservoir rocks depositional geometry.

Our goal here is the development of an interpretative algorithm to produce the shale lithological characterization and map a chosen shale layer, integrating well log data, core data, M-N plot and geological information.

Shale characterization

Usually, the lithological identification methods developed in borehole geophysics have focus only on reservoir rocks. We present an adaptation of M-N plot to shale characterization using competitive neural networks, as the kernel of an interpretative algorithm. We show here, only the neural networks details.

As pointed out early, there is not a specific fixed point for shales in the M-N plot. Thus, our first step in the lithological characterization is the shale identification or the definition of its fixed point in the M-N plot. We start from the choice of a cored borehole – The reference well. In this borehole, we take the log readings to calculate the M and N values in a depth interval dominated by shale, as indicated in the core analysis. In Figure 4, we show the natural gamma ray log (GR), a good shale indicator and the core analysis of selected interval. The pairs (N, M) in the M-N plot create a cluster of points representing the shale and will be used as training set.

We construct a competitive neural network, with two neurons in input layer, which receive the M and N values, respectively, and three competitive neurons. The choice of three neurons in competitive layer has the intention to capture the spread of shale points.

An important point to note is the representation of a competitive neuron in the M-N plot. If we take its synaptic weights as M and N values, we can represent a competitive neuron as a point in M-N plot (Andrade & Fischetti, 1999). So, after the training, we retain as winner neuron, the one that has the smallest pair of synaptic weights or the competitive neuron nearest to shale direction, as shown in the M-N plot (Figure 3), to represent the shale. In Figure 5, we show the M-N plot with the fixed points marked by blue circles, the training set by red crosses and the competitive neurons, in their final position in the M-N plot after training, by green circles. The winner neuron, i.e., the competitive neuron that is shale representative will be marked by a green dot.

Well correlation

The well correlation can be decomposed in two stages: the first, achieves the datum identification in the

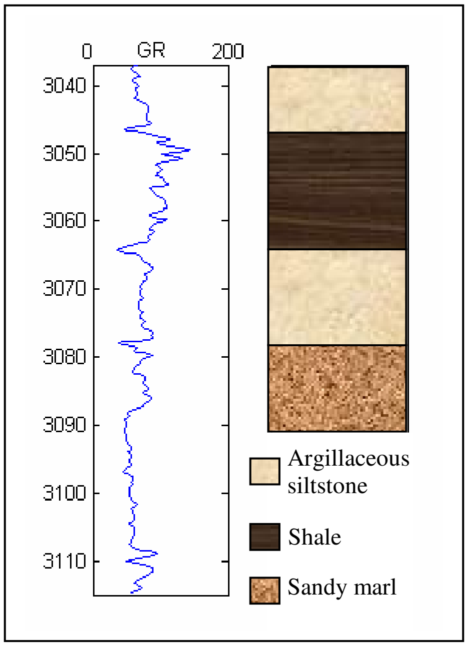

Figure 4- The GR log and core analysis of selected shale layer.

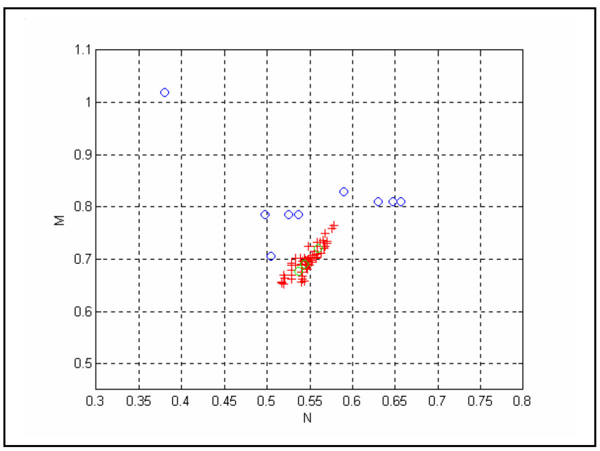

Figure 5- The final position of competitive neurons (green circles) in the M-N plot.

well logs from a reference borehole, and the second, achieves the datum lateral continuity identification in the other wells (Andrade & Fischetti, 1999).

Considering the fact that a competitive neuron, in a competitive neural network with two sensorial units can be represented as a point in the M-N plot, we construct such architecture, with two sensorial units, which receive the M and N values, as input and one competitive layer, with ten neurons, where each neuron is associated to one fixed point in the M-N plot, including the shale point. Thus, no training is need, once the network synaptic weights were established. The operation occurs with presentation of M and N pairs, calculated from the whole logged interval. Thus, the neurons compete for each input pair. The winner neuron indicates the lithology of this point.

Now we can see the capacity of this competitive neural network architecture to handle with well log data. We show a new utilization of M-N plot with the shale point, to lithological characterization of shales in other boreholes. In other words, we transport the geological information acquired in one borehole to another. It is well correlation.

We take the well logs of another well (the test borehole) in the same oil field of reference well. The test well can or cannot be cored, but we must have geological information about the nonexistence of relevant tectonic events between them.

We calculate the M and N values for the test well and make it as input in the competitive neural network. Our intention is to investigate the lateral continuity of the shale layer chosen early, in the reference borehole, as correlation datum. So, we retain only input points that produce as winner neuron the shale neuron (test points).

We show in Figure 6, the M-N plot with the training set marked by red crosses, the competitive neurons (as fixed points) marked by blue circles, the shale neuron marked by green dot and the test points marked by cyan crosses. We can note the proximity between the training set and the test points with the shale neuron. It means that the same material in different locations sensitized the logging tools in the same way. In this way, we have characterized the occurrence of the same shale layer in different wells.

In Figure 7, we show the shale characterization in the test well. As shale reference, we show the natural gamma ray log (GR) (Figure 7-A) and the results of interpretative algorithm. In Figure 7-B, we show a computed log obtained attributing the GR value of each depth point, which M and N values activate the shale neuron or a log presentation of test points. We can note the good agreement of shale layer identification as indicated by the GR log.

To complete the well correlation, we must to avoid the miscorrelation among two or more shale layers and to determine the depths of top and bottom of correlation datum in the two wells. To avoid the miscorrelation, we need to find the gravity centers of all clusters of shale points in the test well that spread in the neighborhood of shale point. To achieve it, we constructed a competitive neural network, similar to the first one, with a greater number of competitive neurons, like 20, to permit redundancy and guarantee that all shale clusters will be identified. These N and M pairs will be the connections weight of neurons in another competitive neural network that will compete for the shale point. The winner neuron means a shale layer in the test well that is correlated with one in the reference well. In Figure 8, we show the depths of top and bottom of correlation datum in the two wells marked in the GR logs of processed boreholes and the correlation lines linking the shale layer. Here, we suppress the horizontal and vertical scales to get a clean figure. Observe that layers with different thickness can be correlated and that correlations lines indicate a presence of a geological fold between these boreholes.

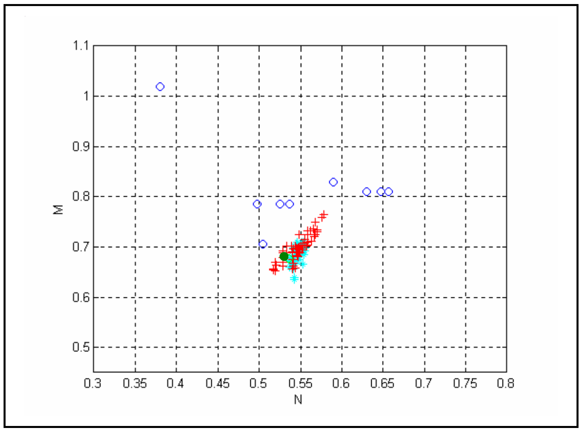

Figure 6- The M-N plot for the test well.

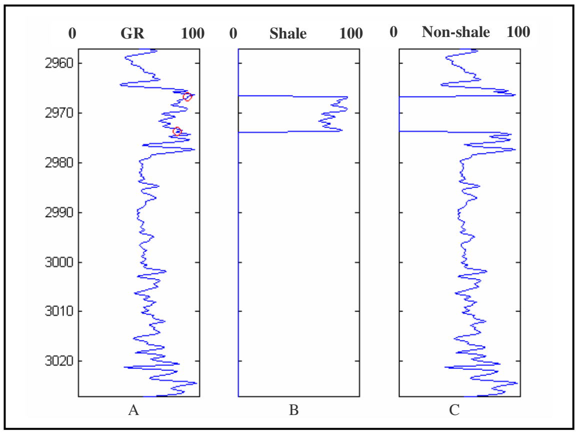

Figure 7- Shale characterization in the test well.

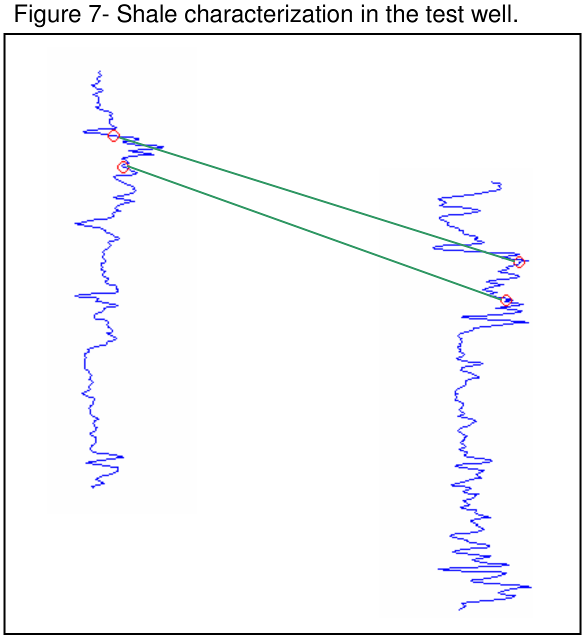

Figure 8- The well correlation. The green lines are the correlation lines linking the same shale layer in two boreholes.

Conclusions

We present here one example of transformation of raw well log data in geological information useful to oil industry. It is a broad research field in academia and oil industry about the applications of artificial neural networks and theirs capabilities, immerse in the concept of interpretative algorithm, to treat conveniently raw data, as well logs and soft data, as geological information and improve the use of some well log interpretation methods, which help us to solve many problems in oil reservoirs characterization.

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