ADN method: simultaneous determination of porosity and shale content.

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Abstract

A key step in petrophysical formation evaluation is the determination of porosity values corrected by the effect of shale content (shaliness) and consequently to produce a better estimate of oil saturation. Here, we present the ADN method as a methodology to simultaneous determination of corrected porosity values, the shale content and additionally, it may estimates the principal mineral (matrix) for a single mineral rock model. The ADN method uses the three porosity logs (**a**coustic transit time, bulk **d**ensity and **n**eutron porosity) as input for an interpretative algorithm, based on competitive artificial neural network concept. It is able to treat conveniently a great data set, without core calibration and interpret intervention and may produce more realistic values for shale content and porosity than conventional methods as neutron-density cross-plot and consequently, improve the processes of reservoir characterization. We show an application of this methodology with synthetic and actual well log data from the Namorado oil field in the Campos basin, Brazil.

Introduction

The great majority of commercial methods to estimate oil saturation need a prior determination of porosity values and many methods are available for this purpose. All require some assumptions about matrix, fluids and shale properties. One can estimate porosity from individual logs or combinations of two or more logs. Two-log combinations are termed cross-plot methods, since the log data can be plotted on the *x* and *y* axes of a graph. Three or more log combinations require solution by linear simultaneous log equations (Crain, 1986).

To get more realist porosity values, we consider the integration of three logs, introducing the concept of 3D cross plot, where each orthogonal axis is represented by one porosity log (acoustic transit time, bulk density and neutron porosity), called ADN plot, this spatial distribution of log readings makes possible a better separation of porosity and shale influences on the log readings and for a single mineral log model, the matrix effect is also exhibited. Of course, a simple spatial display of log readings does not motivate any new interest and we do not aim to it. We developed the ADN method, a computational tool able to explore the interesting characteristics exhibited by ADN plot using the concepts of competitive neural networks to produce a simultaneous determination of shale volume and porosity, corrected by shale effect – the effective porosity without the need to solve any linear simultaneous log equations.

The application of techniques as neural computation, fuzzy logic and genetic algorithms for data analysis and interpretation come being more important in the science and engineering areas, transforming data in information and information in knowledge (Nikravesh, 2004). Those techniques have found application in petroleum industry: contributing for exploratory risk reduction, the improvement of oil recovery, the increase of overall oil production efficiency and finally, promoting the exploration and production costs reduction (Nikravesh, 2004; Fischetti & Andrade, 2002; Saggaf & Nebrija, 2000; Crocker et al., 1999).

An interpretative algorithm (Fischetti & Andrade, 2002), is an example of those computational tools. An interpretative algorithm that makes possible the determination of effective porosity and shale content by an computational interpretation of neutron-density cross-plot to the whole logged interval and weakly dependent of analyst intervention was presented (Fischetti & Andrade, 2002), but it depends on a external matrix identification. An approach to automatic matrix identification (Fischetti & Andrade, 2002) by an interpretative algorithm, improves the matrix recognition, but needs a prior shale correction of log readings.

The amount of logging data, its different physical nature, scales and considering the geological uncertainty associated with them are factors that induce the use of no conventional computational tools, as the interpretative algorithm. In this sense, the ADN method is presented as one with a competitive neural network as kernel and may be more efficient than traditional cross-plots, as neutron density. The ADN method overcomes the need for a prior matrix knowledge in the evaluation of effective porosity and shale content, considering three independent measurements of three different physical properties.

The performance of ADN method is shown with synthetic and actual well log data from Namorado oil field in the Campos basin, located offshore Rio de Janeiro in southeastern Brazil. The Campos basin covers an area of about 100,000 Km^2 from the coastline to the 3400-m isobath (Mello et al, 1994). The Campos basin presents an evolutionary sequence of a rift to drift basin and it is part of the Atlantic Ocean passive margin and presently, is the mostly productive and prolific offshore Brazilian hydrocarbon province.

Methodology

In this section, we start with some comments about porosity determination by the neutron-density cross-plot, the basis of competitive neural network and finally, we describe the fundaments of the interpretative algorithm called ADN method.

1- Neutron-density cross-plot

The porosity (ϕ) is the volume of nonsolid portion of the rock (V_{ns}) that is filled with fluids divided by the total volume of the rock (V_t),

$$\phi = \frac{V_{ns}}{V_t} \,. \tag{1}$$

Porosity derived direct from well log without correction for shale content is termed apparent or total porosity. If the zone has no shale, the total porosity equals the effective porosity. Should the zone contain shale, corrections must be applied to obtain the named effective porosity.

The use of cross-plots or interpretative charts in borehole geophysics was developed in 60-70 years as an appropriate form to represent the solution of two linear simultaneous log equations (Crain, 1986).

The neutron-density method is one of the most used of them and calculates the effective porosity (ϕ) and shale content (V_{sh}) considering the effect produced by fluids and clays, present on reservoir rocks pores, over the bulk density and neutron porosity. The log readings are related to those petrophysical properties by the following linear simultaneous log equations for a single mineral rock model, expressed in porosity units as

$$\phi_N = \phi\phi_{Nw} + V_{sh}\phi_{Nsh} + (1 - \phi - V_{sh})\phi_{Nm} \tag{2}$$

$$\phi_D = \phi\phi_{Dw} + V_{sh}\phi_{Dsh} + (1 - \phi - V_{sh})\phi_{Dm} \tag{3}$$

Where ϕ_D is the bulk density porosity, ϕ_N is the neutron porosity log reading; ϕ_{Dw} and ϕ_{Nw} are respectively density porosity and neutron porosity for fluid (fresh water); ϕ_{Dm} and ϕ_{Nm} are respectively density porosity and neutron porosity for matrix. The solution of this linear simultaneous log equation gives the shale content as

$$V_{sh} = \frac{\phi_N - \phi_D}{\phi_{Nsh} - \phi_{Dsh}} \,. \tag{4}$$

The effective porosity is given by

$$\phi = \frac{\phi_D\phi_{Nsh} - \phi_N\phi_{Dsh}}{\phi_{Nsh} - \phi_{Dsh}} \,. \tag{5}$$

In the expressions (4) and (5), the term ϕ_{Dsh} is the apparent shale density porosity or

$$\phi_{Dsh} = \frac{\rho_m - \rho_{sh}}{\rho_m - \rho_w} \,. \tag{6}$$

The term ϕ_{Nsh} is the apparent shale neutron porosity, given by

$$\phi_{Nsh} = \frac{\phi_{sh} - \phi_m}{\phi \;\; - \phi_m} \,. \tag{7}$$

The terms ρ_{sh} and ϕ_{sh} in expressions (6) and (7) are respectively bulk density and neutron porosity log readings in 100% shale.

The neutron-density method has a graphical representation or cross-plot, as shown in Figure 1. Two straight lines characterize the density-neutron cross-plot. The line 1 represents the clean lithology ($V_{sh} = 0$), connection the matrix point (0,0), by construction, and fluid point (1,1), with porosity equal 100%. So, naturally, we have determined a porosity scale. The line 2 is the shale line and is scaled on clay volume values, from the connecting the matrix point to the shale point (ϕ_{Nsh}, ϕ_{Dsh}), with clay volume equal 100%

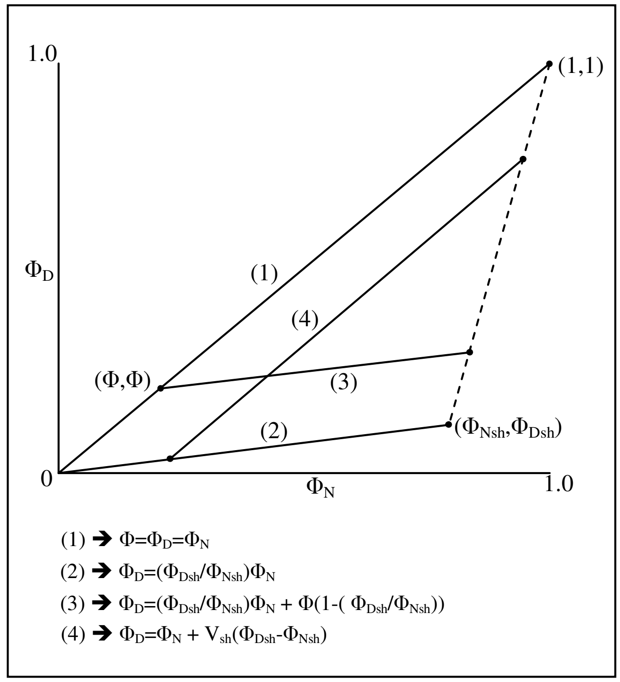

Figure 1: The neutron-density cross-plot.

The pair (ϕ_N, ϕ_D) of neutron porosity and bulk density log readings represents a point in the neutron-density cross-plot The points representing shaly lithology will be distributed in the area delimited by straight lines 1 and 2. Tracing by any point in this area a straight line parallel to line 1, we have the shale content of this point read on the clay volume scale in the crossover of this line with line 2. The effective porosity can be read in the porosity scale on line 1 by the same process, tracing a straight line by the point (ϕ_N, ϕ_D) parallel to line 2.

The neutron-density is simple and precise, but it is extremely dependent of log analyst intervention to supply adequate values for matrix, fluid and shale parameters and cannot be applied to the whole logged interval.

2- Competitive neural network

The simplest architecture of an artificial neural network with competitive layer corresponds to one input layer composed only by sensorial units full connected with one processing layer composed by competitive neurons. Each

competitive neuron is connected with all sensorial units by synaptic weights (weight connections), which will be changed in the network training process.
In competitive learning, the competitive neurons compete with each other for each input data to produce a winner, which carries the output signal, and at a given time, only one competitive neuron is active (Haykin, 2001). The output signal corresponding to the winner neuron is assumed to be 1 (one) and the output signal of all other competitive neurons is null. If a neuron does not answer to a particular input vector, then no learning will happen in that neuron or its synaptic weights are unchanged.
The most common competitive learning uses the Kohonen training rule (Kohonen, 1989), where the competitive neuron that most resembles the input vector wins the competition and has its synaptic weights moved closed to the input vector. Thus, each competitive neuron has its synaptic weights progressively migrated close to a group, or cluster of input vectors and after some iterations, the network stabilizes, having the weight connections of each competitive neuron close at the center of each cluster in the input space. These connections produce a direct association between the competitive neuron and the cluster that it represents.
The data analysis realized by this type of artificial neural network is commonly called feature-discover scheme, which performs clustering or quantization of the input space and can be used to detect statiscally significant patterns in the input space and to classify them (Haykin, 2001). If the input is not randomly permuted before presentation to the network, then the method always converge to the same network after training. In other words, given exactly the same training set to the method, the network obtained is always the same (Kohonen, 1989). Also, once the network is obtained, its output is always reproducible, no matter how many times this is repeated, because the process is deterministic, particularly in its learning rules.

3- ADN method

To show the steps involved in the development of ADN method, we start commenting about the construction of ADN plot, the special characteristics of competitive neural network used and finally, the design of interpretative algorithm called ADN method.
The ADN plot is a graphical representation of spatial relations among porosity values obtained by each one porosity log (acoustic transit time, bulk density and neutron porosity). The ADN plot cannot be confused with conventional Z-plots due the fact that the Z-plots show the third parameter numerically on the crossplot and the ADN plot constructs planes regarding the each matrix (quartz, calcite and dolomite). In this case, the logged points are distributed in the ADN space forming clusters located near to the matrix plane and fairly distant of shale point. We show in Figure 2, the ADN plot. The blue, red and green circles represent, respectively quartz, calcite and dolomite points. The magenta circle is the shale point. The blue, red and green lines represent the porosity scale and the magenta lines represent the shale content scale, respectively, for each lithology. The fluid point is not show in Figure 2. The crosses in black represent logged points in porosity units, obtained considering the same neutron porosity lithology calibration as matrix to permit comparisons.
Now, we are interested in look for angular relations among the points representative of matrix, fluid and shale in the ADN plot. Thus, we construct a competitive neural network with *instar* neurons (Grossberg, 1982) to handle with it.

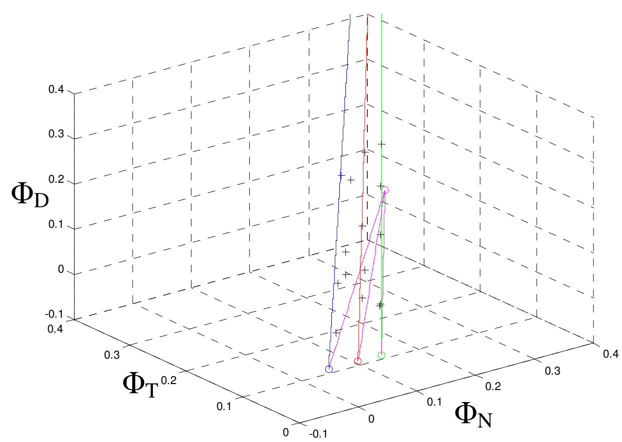

Figure 2: The ADN plot – Synthetic data

The interpretative algorithm is a computational tool that seeks the integration of the whole information available of the geology, geophysics and well logging, to produce an autonomous and geologically plausible interpretation of these data on a field wide-basis (Fischetti & Andrade, 2002). The use of an interpretative algorithm simulates the decision process involved in the log interpretation tasks in complex depositional sets.
We aim to construct an interpretative algorithm based on such competitive neural network. The ADN method can be separated in four steps. The first one is the shale point identification, which is performed by a specific competitive neural network with 30 instar neurons designed to find the center of the clusters formed by the logged points. The net input is the dot product of unit vector of each line from matrix point to fluid point with a unit vector of each line from matrix points to each logged point. The competitive criterion termed the winner neuron as the one with largest weight connection. The position vector associated with winner neuron is termed as shale point.
The second step is the matrix identification. The fluid, shale and each one of matrix points define three lithological planes (Fischetti & Andrade, 2003). We construct a competitive neural network with three instar neurons to represent each lithology. The net input is the dot product of the orthogonal unit vector of each lithological plane with a unit vector of each line from matrix points to each logged point. The competitive criterion termed the winner neuron as the one with smallest weight connection. This procedure associates each logged point to correspondent matrix, considering the single mineral rock model.
The third step is the effective porosity determination. We construct a competitive neural network with a number of

instar neurons dependent of the precision required for porosity values. To each neuron is associated a point (porosity point) over the line from matrix point to fluid point. The net input is the dot product of unit vector over the line from the porosity point to logged point with a unit vector over the line from matrix point to fluid point. The competitive criterion termed the winner neuron as the one with closest to zero difference among its weight connection and the dot product of unit vector over the line from matrix point to fluid point with a unit vector over the line from matrix point to shale point. The ratio among the modulus of the vector associated with the winner neuron and the modulus of the vector associated with the line from matrix point to fluid point gives the fractional effective porosity value.

The last step is the shale content determination. We construct a competitive neural network with a number of instar neurons dependent of the precision required for shale content values. To each neuron is associated a point (shaly point) over the line from matrix point to shale point. The net input is the dot product of unit vectors over the line from shaly point to logged point with a unit vector over the line from matrix point to shale point. The competitive criterion termed the winner neuron as the one with closest to zero difference among its weight connection and the dot product of unit vector over the line from matrix point to fluid point with a unit vector over the line from matrix point to shale point. The ratio among the modulus of the vector associated with the winner neuron and the modulus of the vector associated with the line from matrix point to shale point gives the fractional shale content value for each logged point.

Results

We start the ADN method results with synthetic logged points, shown in Figure 2. Each black cross represents a logged point with coordinates (ϕ_N, ϕ_T, ϕ_D) and adopting the single mineral rock model, can be obtained by the following expressions:

$$\phi_D = \frac{\rho_m - \rho_b}{\rho_m - \rho_w}\ ; \quad \rho_D = \phi\rho_w + V_{sh}\rho_{sh} + (1 - \phi - V_{sh})\rho_m$$

and

$$\phi_T = \frac{\Delta t - \Delta t_m}{\Delta t_w - \Delta t_m}\ ; \ \Delta t = \phi\Delta t_w + V_{sh}\Delta t_{sh} + (1 - \phi - V_{sh})\Delta t_m$$

In the above expressions, ρ_b is the bulk density logging reading; Δt is the acoustic transit time logging reading. Both expressions are calculated with matrix parameters equal to neutron porosity lithology calibration.

The results of ADN method, effective porosity, shale content and matrix identification are showed in Table 1 and can be compared with ones adopted in the model.

To exemplify the behavior of ADN method with real well log data, we show in Figure 3, some points of a logged interval from a borehole in the Namorado oil field. These points were chosen randomly to get a clear figure. In Table 2, we show the results of ADN method. We also show the results of neutron-density cross-plot to compare.

Table 1: Synthetic data – Results of ADN method and rock parameters used in the model.

Sample	Synthetic data		ADN method	
	ϕ	V_{sh}	ϕ	V_{sh}
1	0.1500	0.0300	0.1505	0.0300
2	0.0100	0.2000	0.0105	0.2038
3	0.1000	0.0800	0.1000	0.0808
4	0.0400	0.1800	0.0400	0.1800
5	0.0700	0.0600	0.0705	0.0600
6	0.1700	0.1400	0.1705	0.1400
7	0.2300	0.1600	0.2305	0.1600
8	0.1100	0.0200	0.1105	0.0231
9	0.2200	0.1200	0.2200	0.1200
10	0.2400	0.1500	0.2400	0.1514

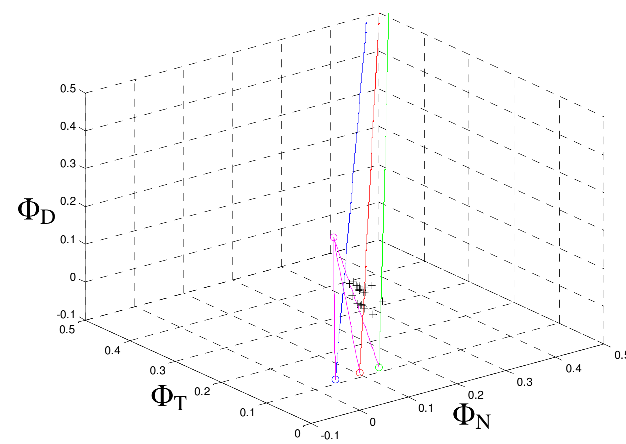

Figure 3: ADN plot – Real data.

Table 2: Real data – Results of ADN method and results of neutron-density cross-plot.

Sample	Real data		ADN plot	
	ϕ	V_{sh}	ϕ	V_{sh}
1	0.0910	0	0.1152	0.0232
2	0.0873	0.0360	0.1105	0.0307
3	0.0908	0.0945	0.1029	0.0027
4	0.0928	0.0036	0.1038	0
5	0.0859	0.0144	0.1029	0.0030
6	0.0848	0.0216	0.1038	0.0104
7	0.0896	0.0108	0.1067	0.0004
8	0.0851	0.0252	0.1086	0.0257
9	0.0718	0.0539	0.1000	0.0968
10	0.0758	0.1432	0.0876	0.0860
11	0.0782	0.1920	0.0952	0.0662
12	0.0484	0.0126	0.0857	0.2265
13	0.0352	0.0395	0.0571	0.1675
14	0.0680	0	0.0838	0
15	0.0670	0.0144	0.0819	0

Conclusions

We introduced the concept of 3-D cross-plot and explore the particular disposition of logged point that permits the separation of matrix points of the shale points. We introduced an automatic interpretation procedure, the ADN method, by the construction of convenient competitive neural networks embedded in the interpretative algorithm concept to produce the lithology identification and the determination of effective porosity and shale content. The ADN method involves all the information furnished by the three porosity logs in a way to avoid some misclassification commons in the use of classical well logs cross-plots. We present here one example of transformation of raw well log data in geological information useful to solve many problems in oil reservoirs characterization.

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Acknowledgments

The authors would like to thanks the support extended by CNPq and UFPa/ANP/PRH-06 for this work.