Determination of mineral composition of reservoir rocks by expert system and genetic algorithm

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Abstract

The information about mineral composition of reservoir rocks is important to obtain more realistic porosity estimative. The log analysts usually consider a reservoir rock composed by a solid portion (matrix) and a fluid portion (pore). The fluid portion or porosity determination is fundamental to obtain the reserve potential and reservoir qualification.

We present the GEN-MN method to identify three minerals and their respective volumetric fractions present in the reservoir rock matrix, based on M-N plot interpretative criterions, expert system and genetic algorithm. Thus, we present a study about the influence of solid portion (matrix effect) on the porosity estimative from well logs.

We show its application on synthetic data and actual well logs from Namorado oil field, Campos basin, Brazil.

Introduction

The lithologic characterization of a hydrocarbon reservoir is a decisive step to geological model development and for the definition of exploitation strategies of an oil field (Luthi, 2001).

The determination of mineral composition of a sedimentary rock is done, usually, from macroscopic and microscopic analysis of outcrop and cores. Due the large number of minerals present in the sediments this kind of result can not be obtained from well log.

The lithological identification of reservoir rocks, made from measures and interpretative methods of borehole geophysics, uses several tools that are sensitive to the presence of some minerals found in sedimentary rocks like: natural gamma ray spectroscopy, pulsed neutron spectroscopy and aluminum activation (Ellis, 1987; Luthi, 2001). However, the use of these tools is not common and, thus, is adopted a simplified procedure based on individual or joint interpretation of porosity logs (bulk density, sonic transit time and neutron porosity) that identify only the principal mineral, i.e., the one with largest volumetric proportion in the rocky matrix composition.

We present the GEN-MN method, based on the M-N plot interpreted by an expert system that indicates which three minerals compose the rocky matrix and calculate the actual mineral composition by genetic algorithm (Tettamanzi & Tomassini, 2001). With the GEN-MN method results we obtain a better porosity estimative of rock, what makes possible a more realistic calculation of oil saturation and reserve potential. In the next sections, we discuss and present an application of this method to synthetic data and actual well logs from Namorado oil field, Campos basin, Brazil.

Methodology

The porosity tools are sensitive to fluid in the pore space as well as to minerals that form the rock structure. The basic concept in formation evaluation starts that sensitization of each logging tool is proportional to the volumetric fraction of each rock component. Thus, several techniques were presented to interpret porosity logs. We take the M-N plot. The definition of M and N parameters may minimize the fluid effect on the logging readings; emphasizing the effect of the solid portion of rock. Considering the interpretative criterion of the M-N plot, we propose a methodology, which is able to extract from the porosity logs the volumetric fractions of three minerals that compose the rock. The problem treated here is described as an inverse problem and the search in the solutions space will be realized by genetic algorithm. We present the fundamentals of GEN-MN method and make some comments about mineral composition of sedimentary rocks.

Mineral composition of sedimentary rocks

About ¾ of the surface of continental platform and a portion relatively greater of the oceanic basin bottom are covered by sediment beds. The sedimentary rocks have a great economic importance once they have the major part of the world mineral resource like oil, natural gas, coal, nuclear fuel, aluminum, iron and manganese minerals, etc. (Ernst, 1971).

The sediments show a surprising and wide composition (Figure 1), due erosion, mechanical effects and chemical reactions (Ernst, 1971).

Different mixture of minerals affects the log readings and may produce a misinterpretation of petrophysical properties of reservoir rocks. The actual interpretative rock model used in formation evaluation consider the matrix (solid) and pore (fluid), where the matrix is designed by a single mineral (principal mineral).

M-N plot

Several methods were developed to recover the lithology information from logging readings of porosity tools. We explore the M-N plot (Burke et al., 1969), which tries to remove the fluid effects and emphasizes the effect of rocky matrix. The porosity logs (bulk density, sonic transit time and neutron porosity) are used to determine the M and N parameters expressed in the metric units as (Ellis, 1987):

$$M = \frac{\Delta t_w - \Delta t}{\rho_b - \rho_{b_w}} x 0.003 , \tag{1}$$

$$N = \frac{\phi_{N_w} - \phi_N}{\rho_b - \rho_{b_w}} , \tag{2}$$

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.

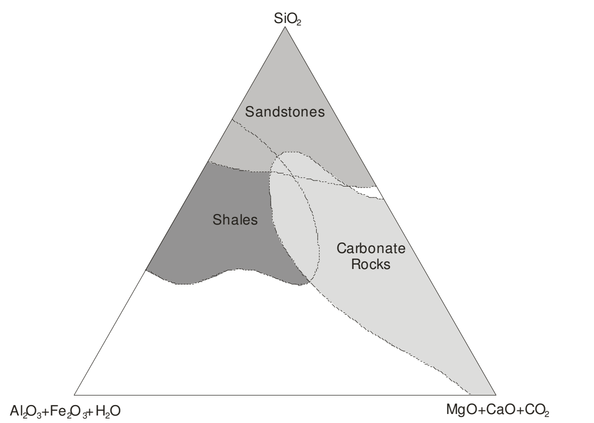

Figure 1- Variation in sedimentary rocks composition by different minerals proportion.

The substitutions in equations (1) and (2) of log readings for correspondent matrix values (sandstone, limestone, etc) get the fixed points or matrix points in the M-N plot.
The M and N values for each point in a logged interval when plotted in the M-N plot will be located close to correspondent matrix point, facilitating the lithology identification.
The Table 1 shows the M and N values for some common minerals considering freshwater (ρ_f = 1.0 g/cc). These minerals represent over 90% of the minerals occurring in all hydrocarbon reservoirs (Luthi, 2001).

Expert system & Genetic algorithm

The expert system is a branch of artificial intelligence (AI), which basic premise is to furnish solutions from a prior knowledge, transferred from human (log analyst) to computer. This prior knowledge stays stored, allowing for computer its use during the process with the goal of to provide a satisfactory conclusion. The kind of problem to be solved, its difficulty degree and the truthfulness of conclusion are directly associated with data quality and the techniques used to achieve the solution.
The genetic algorithm is a stochastic search method and an optimization technique based on principles from evolutionary theory (Holland, 1975; Romero & Carter, 2001; Tettamanzi & Tomassini, 2001; Tzeng, 2004). The genetic algorithm was inspired in biology, particularly those biological processes that describe the growth of organism populations adapting to their environment: genetic inheritance and survival of the fittest. In recent years, genetic algorithms have received considerable attention regarding their potential as a novel optimization technique. The genetic algorithm acts similarly to the evolutionary cycle, where a group of possible solutions is put to develop through selection, crossover and mutation operators.

Mineral	Composition	M	N
Quartz	SiO_2	0.81	0.64
Orthoclase	$KAlSi_3O_8$	0.79	0.68
Albite	$NaAlSi_3O_8$	0.88	0.64
Anorthite	$CaAl_2Si_2O_8$	0.83	0.59
Illite	$K_{1-1.5}Al_4(Al_{1-1.5},Si_{7-6.5})O_{20}(OH)_4$	~0.6	0.49
Kaolinite	$Al_2Si_2O_5(OH)_4$	~0.6	0.45
Smectite	$R^b_{0.33}Al_2Si_4O_{10}(OH)_2 . nH_2O$	~0.6	0.5
Calcite	CaCO3	0.83	0.59
Dolomite	$CaMg(CO_3)_2$	0.78	0.49
Anhydrite	$CaSO_4$	0.70	0.50
Gypsum	$CaSO_4.2H_2O$	1.01	0.30
Halite	NaCl	1.27[a]	1.09[a]

Table 1: The M and N values for some common minerals.
[a] In salt mud [b] R can include Na, K, Mg and Ca

An important aspect of genetic algorithm is the representation of complex models by simple encoding. The encoding initially considered by Holland (1975), and probably the simplest, is the representation of a model by binary digits or bit strings. There are many other types of encoding, which incorporate higher cardinality than binary (e.g. real numbers) or rely on ordering rather than direct representation of parameter values. As stated by both Goldberg (1989) and Davis (1991), the best encoding is problem-specific and may require some experimentation and modification of the crossover and mutation operators.
In genetic algorithm the reproduction may occurs simulating the sexual reproduction (crossover) and/or the asexual reproduction (mutation). In the sexual reproduction the crossover between two individuals happens by the exchange and recombination of parts of each individual structure, generating offspring with new characteristics. In asexual reproduction the individual will pass for random perturbations (mutation) in its structure, generating another individual with new characteristics.
The models with more characteristics in common with the correct solution, i.e., the fittest, would tend to survive during the evolutionary process, whereas the less fit would die off in a similar way to the survival of the fittest in nature. To achieve this model it is necessary to develop a suitable encoding and a method of evaluating the success of an individual model. In terms of optimization problem, the advantages of genetic algorithm are that the general implementation is independent of the nature of both the forward problem and the form of objective function. This way we avoid the need to calculate partial derivatives or

perform matrix inversion (Gallagher and Sambridge, 1994).

The GEN-MN method

The porosity determination involves the matrix effect on the log readings, it can be extended to determine other reservoir petrophysical properties in an oil field and the results may be not satisfactory due the poor matrix information.
To obtain the minerals volume by the solution of simultaneous log equations (Crain, 1986), where the number of equations depends on the number of well logs available on a borehole has some limitations, because if more well logs (known data) are available than unknowns (rock volumes), the case is called overdetermined, i.e., more than one reasonable answer could be found. If there are fewer equations than unknowns, the case is called underdetermined; it cannot be solved by conventional matrix method. If the number of equations and unknowns is equal, the case is determined, but this is not always true that N equations are sufficient to give N unknowns: the equations may be mutually contradictory or they may be consistent but contain insufficient information to separate N unknowns. Thus, all this suppositions are valid because the inversion in borehole geophysics is characterized like an ill-posed problem once the solutions of this problem do not present uniqueness and stability.
The GEN-MN is a hybrid method based on M-N plot. It is composed by an expert system and a sequential computational procedure involving genetic algorithm. The expert system is constructed to determine which minerals participate in the rocky matrix composition, and the genetic algorithm is designed to determine the volume fractions of each one mineral. At this point of its development the GEN-MN is able to identify up to three minerals in the rock composition. The genetic algorithm starts with the parent population that is obtained from the generation of random volumes for the mineral group obtained by expert system. Starting with the random volumes is calculated the theoretical values of ρ_b, Φ_N and Δt log and the M-N parents points. The evaluation of population evolution is obtained by its fit to a fitness function. We take as fitness function the Euclidean distance, in the M-N plane, between the M-N points calculated with log readings and M-N parents points. The offspring population is obtained from small mutations of the fittest parent. This approach aids to improve the process convergence. The evolution dynamic takes for each time step the offspring population as parent for the new generation. Thus, the GEN-MN operates for each logged point with a reduced computational time.

Results

In the first example of GEN-MN method, we deal with synthetic data, to get a better control in the validation of the method. We create nine aleatory rock samples, where for each one was attributed values of porosity (Φ) and, for the matrix, we take arbitrary mineral composition involving three minerals (V_{m1}, V_{m2} and V_{m3}).

Here, we consider only clean lithologies ($V_{SH} = 0$). Thus, the M and N equations are porosity independent. We calculate, for each sample, ρ_b, Φ_N and Δt values considering the matrix mineral composition through the log equations:

$$\left.\begin{aligned} \rho_b &= \phi\rho_f + (1-\phi)\sum_{i=1}^{3} V_{mi}\,\rho_{mi} \\ \phi_N &= \phi\phi_{Nf} + (1-\phi)\sum_{i=1}^{3} V_{mi}\,\phi_{N\,mi} \\ \Delta t &= \phi\Delta t_f + (1-\phi)\sum_{i=1}^{3} V_{mi}\,\Delta t_{mi} \end{aligned}\right\} \qquad (3)$$

From the synthetic log values we calculate the M and N parameters (equations 1 and 2) for each sample. We plot the coordinate pairs in the M-N plot, as shown in Figure 2, where the red crosses represent each sample of synthetic rock and the blue circles represent the matrix fixed points. From each one of these M and N values we start the process to determine the mineral composition by GEN-MN method. The mineral composition of each one synthetic data is reported in Table 2. We show for each sample the synthetic mineral composition and the estimated mineral composition determined by GEN-MN method. We can observe that the GEN-MN method defines which minerals and their volume fraction involved in the rocky composition.

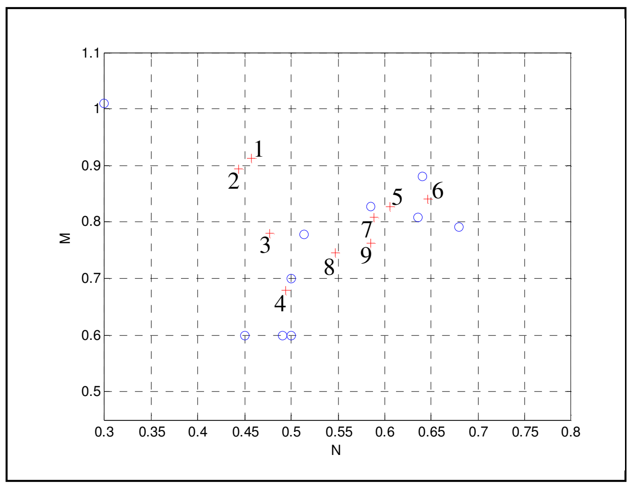

Figure 2- The M-N plot showing the nine synthetic samples represented by red crosses.

To show the matrix effect on petrophysical properties estimative from well log data we perform the porosity determination of synthetic data from two approaches to the matrix. The first one take as matrix the mineral defined in the M-N plot (Figure 2). The second one takes the matrix obtained from GEN-MN method. The results of this evaluation are presented in Table 3. In the second column of Table 3 are shown the porosity values adopted in the equations 3. The methodology to calculate the porosity was the ρ_b x Φ_N method or the following expression:

$$\phi = \frac{(\rho_m - \rho_b) + (\phi_{Nm} - \phi_N)}{(\rho_m - \rho_f) + (\phi_{Nm} - \phi_{Nf})}, \quad (4)$$

where the index *m* represents the matrix adopted, the index *f* represents the fluid and ρ_b – Φ_N the log readings. Thus, we obtain the remaining columns of Table 3. The third column shows the influence of an incorrect matrix estimative on porosity calculus and the last column shows the exactly porosity determination when the log analyst has the mineral composition knowledge.

After the GEN-MN method validation with synthetic data, we apply it in six samples of two boreholes in the Namorado oil field, Campos basin, Brazil. The first three samples have the depth between 3037.0 and 3037.4m having, in agreement with core description, a matrix composed by graded medium sandstone. The others three samples are located between the depths 3359.0m to 3360.2m having, in agreement with core description, mud-sandy siliciclastic matrix, gravel fraction of lithic nature (quartz, granite, calcilutite and shale).

From ρ_b, Φ_N and Δt log readings of each sample were calculated M and N parameters. We plot the coordinate pairs in the M-N plot (Figure 3), where the green crosses represent the first three samples and the red crosses represent the following samples.

We start the process to determine the mineral composition, by GEN-MN method, observing the results in Table 4. We note that the minerals fractions found by GEN-MN method agree with the core description.

We continue the process determining the porosity taking into account the minerals composition. We use two methods to determine the porosity. The first considers just the principal mineral obtained in agreement with M-N plot interpretative criterions (Table 5 – second column); and the second considers the mineralogical composition obtained by GEN-MN method. In a similar way to synthetic data, the method selected to determine the porosity was ρ_b x Φ_N method.

Table 3- Comparison between porosity values from synthetic data obtained with principal mineral and mineral composition.

Sample	$\Phi_{Synthetic}$ (%)	$\Phi_{Estimated}$ (%)	
		f(principal mineral by M-N plot)	f(mineral composition)
1	18	6	18
2	15	19	15
3	20	17	20
4	13	21	13
5	22	28	22
6	17	21	18
7	12	13	13
8	10	17	10
9	14	11	13

Table 2- The mineral composition by GEN-MN method – Synthetic data.

Sample	Principal mineral by M-N plot	Volumes	Mineral composition by GEN-MN method (%)									
			Quartz	Calcite	Dolomite	Orthoclase	Albite	Illite	Kaolinite	Smectite	Anhydrite	Gypsum
1	Calcite	$V_{Synthetic}$	0	43,66	0	0	4,23	0	0	0	0	52,11
		$V_{Estimated}$	0	43,67	0	0	4,22	0	0	0	0	52,11
2	Dolomite	$V_{Synthetic}$	0	28,13	21,35	0	0	0	0	0	0	50,52
		$V_{Estimated}$	0	28,13	21,35	0	0	0	0	0	0	50,52
3	Dolomite	$V_{Synthetic}$	0	0	41,67	0	0	0	0	0	38,42	19,91
		$V_{Estimated}$	0	0	41,66	0	0	0	0	0	38,43	19,91
4	Anhydrite	$V_{Synthetic}$	0	0	0	0	0	0	15,38	14,42	70,20	0
		$V_{Estimated}$	0	0	0	0	0	0	15,39	14,41	70,20	0
5	Calcite	$V_{Synthetic}$	31,64	58,23	0	0	10,13	0	0	0	0	0
		$V_{Estimated}$	31,64	58,23	0	0	10,13	0	0	0	0	0
6	Quartz	$V_{Synthetic}$	31,31	0	0	19,20	49,50	0	0	0	0	0
		$V_{Estimated}$	31,32	0	0	19,19	49,50	0	0	0	0	0
7	Calcite	$V_{Synthetic}$	41,72	36,42	21,85	0	0	0	0	0	0	0
		$V_{Estimated}$	41,72	36,42	21,85	0	0	0	0	0	0	0
8	Dolomite	$V_{Synthetic}$	36,73	0	10,88	0	0	0	0	0	52,38	0
		$V_{Estimated}$	36,72	0	10,88	0	0	0	0	0	52,39	0
9	Calcite	$V_{Synthetic}$	49,55	0	0	13,51	0	0	0	0	36,94	0
		$V_{Estimated}$	49,56	0	0	13,5	0	0	0	0	36,94	0

Table 4- The mineral composition by GEN-MN method – Actual data.

Sample	Principal mineral by M-N plot	Mineral composition by GEN-MN method (%)									
		Quartz	Calcite	Dolomite	Orthoclase	Albite	Illite	Kaolinite	Smectite	Anhydrite	Gypsum
1	Quartz	85.67	14.19	0.14	0	0	0	0	0	0	0
2	Quartz	75.08	23.48	1.44	0	0	0	0	0	0	0
3	Quartz	80.29	11.61	8.10	0	0	0	0	0	0	0
4	Calcite	61.86	20.55	17.59	0	0	0	0	0	0	0
5	Calcite	53.79	17.50	28.70	0	0	0	0	0	0	0
6	Calcite	73.36	0	20.75	0	0	0	0	0	5.89	0

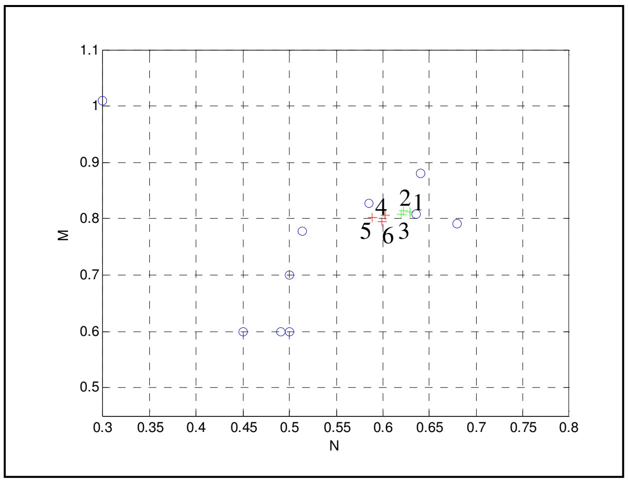

Figure 3- The M-N plot with six samples (green and red crosses) of actual data from Namorado oil field, Campos basin, Brazil.

Table 5- Comparison between porosity values from actual data obtained with principal mineral and mineral composition.

Sample	$\Phi_{Estimated}$ (%)	
	f(principal mineral by M-N plot)	f(mineral composition)
1	27	29
2	27	29
3	23	26
4	24	21
5	20	19
6	14	10

Conclusions

With the GEN-MN method we show the matrix effect in the porosity calculus. The analysis of presented results shows that for shaly lithologies, the shale content in the matrix or porous space exerts a relevant influence, which needs more refined studies.

However, for clean lithologies, the GEN-MN method describes with good accuracy the three minerals rock models producing more realistic porosity values.

We continue the studies to improve the GEN-MN method, making it able for identify four or more minerals in clean and shaly lithologies.

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