Fuzzy logic in the simulation of sonic log using as input combinations of gamma ray, resistivity, porosity and density well logs from Namorado Oilfield

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Abstract

The main premise of this work is to consider that any geophysical well log may be derived from combinations of two other logs measured at the same depth, even if its physical principles are very different. Thus, our proposal is to simulate the sonic log (DT), because it is not always present on the set of logs, it may present problems in its measurement and it is very useful in the oil industry activities. To achieve these objectives, the basic suite of well logs from Namorado Oilfield was analyzed: DT, gamma ray (GR), resistivity (RT), porosity (NPHI) and density (RHOB). The results show a high correlation between DT-GR, DT-NPHI, DT-RHOB, GR-NPHI, RT-RHOB and NPHI-RHOB pairs, meanwhile, low correlations between DT-RT, GR–RT, GR-RHOB and RT-NPHI couples. The couples DT-NPHI and DT-RHOB reveal linear relationships, potential relationship for DT-GR, GR-NPHI, GR-RHOB and NPHI–RHOB pairs, and logarithmic ones for the couples RT – RHOB, RT – NPHI, GR – RT and DT- RT. In the simulation, it was found low fit errors regarding real data ranging between 5% to 7% for all the pairs, showing this that the utilized approach functioned very well, even in the presence of low correlations and non linear relationships between logs, caused by a clayey sandstone reservoirs present in Namorado Oilfield.

Introduction

Generally, the rocks are classified according to their mineralogical, lithological, paleontological or physical characteristics. The different types of physical properties can be electric, acoustic, radioactive, mechanical, thermal, etc., which can be measured with the continuous shift of sensors inside the wells. These registers are known as geophysical well logs, being graphic representations of these properties regarding depth. Thus, a simple way to understand the petrophysical evaluation performed through logs, it is using the Archie´s Law:

$$S_W^n = \frac{aR_W}{\Phi^m R_t}, \qquad (1)$$

where S_w is the water saturation in the reservoir (%); R_w is the resistivity of the water bearing geological formations (ohm.m); R_t is the volumetric rock resistivity measured in logs (ohm.m); Φ is the porosity (%); a is the tortuousity coefficient; m and n are the porosity and saturation exponents (dimensionless), respectively. The application of this equation needs at least the determination of three parameters derived from logs or laboratory tests. Thus, R_w can be obtained from the potential spontaneous (SP) log or derived from laboratory measurements in water samples, obtained from production or formation evaluation tests. On the other hand, R_t can be obtained from resistivity log (RT), while Φ can be obtained from sonic (DT), density (RHOB) or neutron (NPHI) logs. The parameters m and n should be derived from laboratory tests, the area experience or from the own logs, whose values, found by Archie, were around 2, for most of analyzed rocks, while a is generally used with the value of 1. Thus, the simplest of logging programs, for S_w determination should bear RT log and, at least, one of Φ logs (Hearts & Nelson, 1985).

In this form, the main purpose of this article is to use combinations of RT, GR, RHOB and NPHI logs of a borehole of Namorado Oilfield to simulate DT log. This oilfield was chosen because in it exists the basic suite of logs and the data are public. The interest in simulate this log is due to the fact that it is not always present on the set of logs and, it can show any problems in their measurements caused by defects in the tools, as well as cycle skipping derived of the presence of caves, gas zones with high porosities, horizontal fractures bearing by fluids, secondary porosity, high concentration of clay, etc. Also it should be considered its great utility of the information derived from this log in the characterization of reservoirs, determination of the reservoir porosity and elastic constants, supporting the seismic interpretation and well drilling, calibration of interpreted sections, etc. (Hearts & Nelson, 1985).

On the other hand, Namorado Oilfield is located in Campos Basin, which has a tectonic - sedimentary evolution very similar to other marginal sedimentary basins of east coast of Brazil (Figure 1). These basins are defined by three distinct stratigraphic sequences: continental, transitional and marine, which represents the main former and modifier geological events of these basins. In this basin there are dozens of oil producer fields, among them the Namorado Field (Figure 1). This field was the first giant of Brazilian continental shelf to be discovered in 1975 by pioneering well 1-RJS-19. It is within the intermediary zone of the basin, which is in north-central portion of lineament accumulations of oil, at 80 km from the coast, in bathymetric quotas ranging between 110 and 250 m. This field presents as its main reservoir the Namorado sandstone, which has turbidite origin and lower Cenomiana age. This unit consists of sediments to the upper portion of Macae Formation and, in the area of the field, it occurs at varying depths between 2.900 and 3.400 m (Meneses & Adams, 1990).

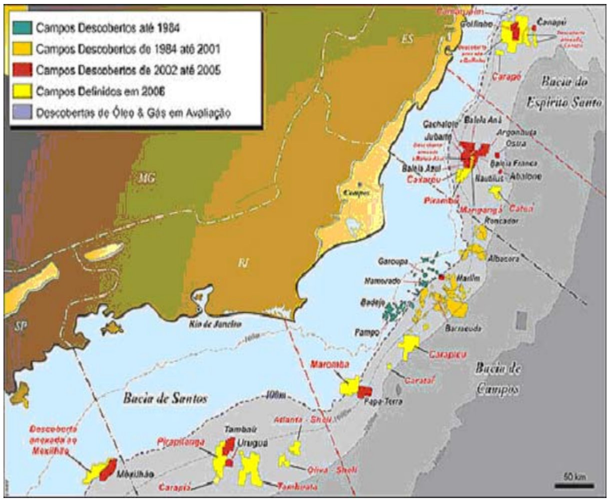

Figure 1: Main oil fields in Campos Basin, Southeast Brazil, including Namorado Oilfield (Fonte: site ANP)

Theoretical Aspects

To simulate the sonic log, it was used fuzzy logic concepts. Fuzzy logic was first developed by Zadeh et al. (1975) for representing uncertain and imprecise knowledge, providing an approximate but effective means of describing the behavior of systems that are too complex, ill-defined, or not easily analyzed mathematically, being thus considered as systems that are not easy to describe precisely. Zadeh argued that the attempts to automate various types of activities from assembling hardware to medical diagnosis have been impeded by the gap between the way human beings reason and the way as computers are programmed. Fuzzy logic uses graded statements rather than ones that are strictly true or false. It attempts to incorporate the “rule of thumb” approach generally used by human beings to make decisions. Fuzzy logic controllers, for example, are extensions of the common expert systems that use production rules like “if-then.” With fuzzy controllers, however, linguistic variables like “tall” and “very tall” might be incorporated in a traditional expert system. The result is that fuzzy logic can be used in controllers that are capable of making intelligent control decisions in sometimes volatile and rapidly changing problem environments. In this form, fuzzy variables are processed using a system called a fuzzy logic controller, which involves fuzzification, fuzzy inference, and defuzzification. The fuzzification process converts a crisp input value to a fuzzy value, while the fuzzy inference is responsible for drawing conclusions from the knowledge base. The defuzzification process converts the fuzzy control actions into a crisp control action. (Wang & Fu, 1998). More explanations of the use of fuzzy logic to geophysics studies can be consulted in Leite et al. (2008).

On the other hand, in order to assess the usefulness of our estimator, it is necessary to have some criteria to measure the performance, as bias and mean squared error. The bias is an estimator gives a measure of how much error we have, on average, in our estimative when we use T to estimate the parameter Θ, being defined as:

$$Bias(T) = E(T) - \Theta \,. \qquad (2)$$

If the estimator is unbiased, then the expected value of our estimator equals the true parameter values, so E(T) = Θ. If Θ denote the parameter we are estimating and T denote our estimative, then the Root Mean Squared Error (RMSE) of the estimator is defines as:

$$RMSE = \sqrt{\left(Var(T) - [Bias(T)]^2\right)}, \qquad (3)$$

where Var means the variance of the parameter T. Hence, RMSE is the most common method of evaluating how accurate model estimation, and, between two competing models, one may select the better model as that model with the lower RMSE. Because it combines the complementary relationship between bias and variance, RMSE is a function of the estimation error and the model complexity (Martinez & Martinez, 2002).

Method

To simulate DT from combinations of other logs in wells of Namorado Oilfield, well Na04 was selected to develop the proposed approach. Firstly, it was create log data sets from two well groups, calling the first one as offset well (Na04), and, the other, as validation wells (NA01, NA03D, NA05, NA09D, NA011, NA12, NA17, RJS-19, RJS-42, RJS-234), all of them from Namorado Oilfield.

Initially, statistical concepts were utilized to determine the level of correlation between pair of logs, and, after that, the mathematical relationship between pair of logs (for example, RT - GR, RT – NPHI, etc.) was determined. Immediately, the simulation of sonic log was made, using combinations of couple of logs of well Na04 measured at the same depth (GR, RT, NPHI and RHOB), even if their physical principles are different. For the simulation, Fuzzy Logic concepts (FCM – Fuzzy C-Means) were used, beside the second group of logs to validate the estimatives. FCM is a function of the MATLAB scientific engineering software, which was also used to implement this methodology, and, to develop the calculations and the code of the algorithms. Finally, to measure the performance of the estimative, we used the RMSE index (MATLAB, 2003).

Results

In Figure 2, different logs of well Na04 were plotted, showing clearly the presence of a high resistivity layer in the RT log at 3.040 and 3.100 m, which is also registered in RHOB log with low density values at the same depths.

Meanwhile, in a strange form and differently of common well logs, DT, GR and NPHI do not show clearly the presence of this reservoir, possibly caused by the high concentration of clay in its composition. On the other hand, these three logs, plus RHOB one, show a lithological change above 3.120 m of depth, caused mainly by the presence of limestone in these depths, as shown in the stratrigraphic column at the left of the Figure 2. But, RT log do not register this layer at this depth.

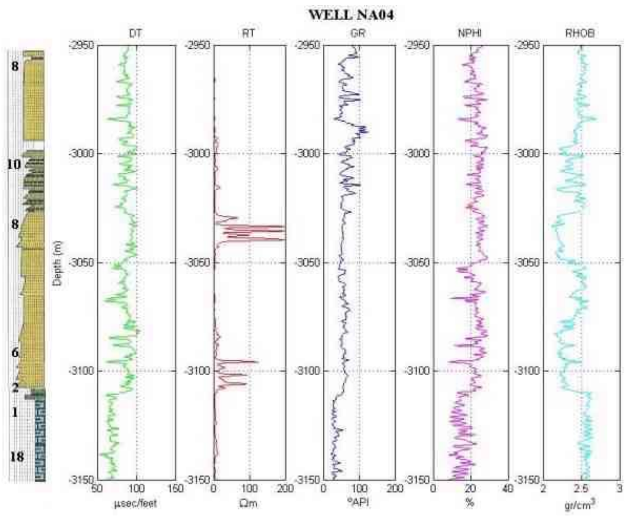

Figure 2: Stratrigraphic column and well logs (DT, RT, GR, NPHI and RHOB) of well Na04. 1=calcilutite, marl and shale intercalations; 2=conglomerate and carbonatic breccias; 6=amalgamated coarse sand; 8= massive medium sand; 10=sand with shale intercalations, and 18=ritmite.

Figure 3 shows that it exists a strong correlation (above 50%) between pairs DT-NPHI, DT-RHOB and NPHI-RHOB, average correlation (30 to 50 %) between pairs RT-RHOB, DT-GR, GR-NPHI and GR-RHOB, and, low correlations (below 30%) between pairs RT-GR, DT-RT and RT-NPHI. On the other hand, in Figure 4, it is possible to observe a linear relationship between DT-NPHI and DT-RHOB pairs (above); polynomial relationships between NPHI-RHOB, DT-GR, GR-NPHI and GR-RHOB pairs (middle); beside a logarithmic relationship between the pairs DT-RT, RT–RHOB and RT-GR (below).

Figure 5 shows the simulation for each couple of logs, evidencing a good fit between the estimatives and the real data, with RMSE errors of 5% for the simulated pairs GR – NPHI, 6% for GR – RHOB, RT – NPHI and NPHI – RHOB, and, 7% for RT – GR and RT - RHOB (above of 7%).

Finally, Figure 6 presents jointly all the 6 simulations, which have almost the same minimum and maximum limits, having, thus, a high confidence in the results. Some oscillations are clearly visible in this figure, which can be explained by the high concentration of clay in the reservoir. This plot also shows clearly the main reservoirs between 3.030 - 3.050 and 3.070 - 3.100 m of depth, and, important lithological changes registered in DT real log at depth above 3.120 m, causing by the presence of limestone.

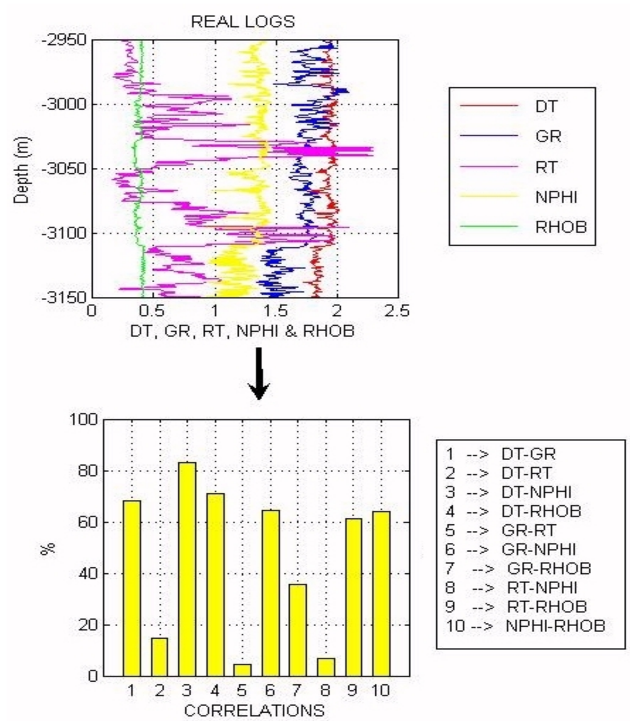

Figure 3: Correlations between couple of logs of well Na04.

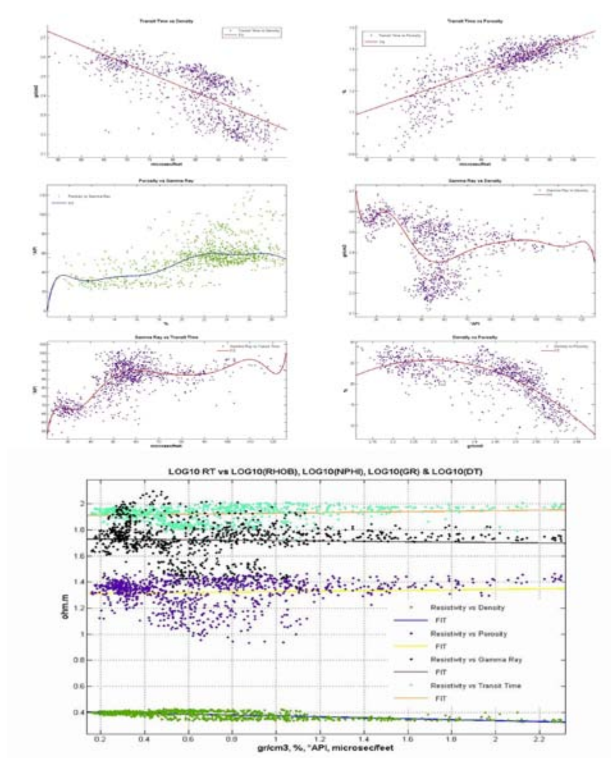

Figure 4: Mathematical relationships between pair of logs of well Na04.

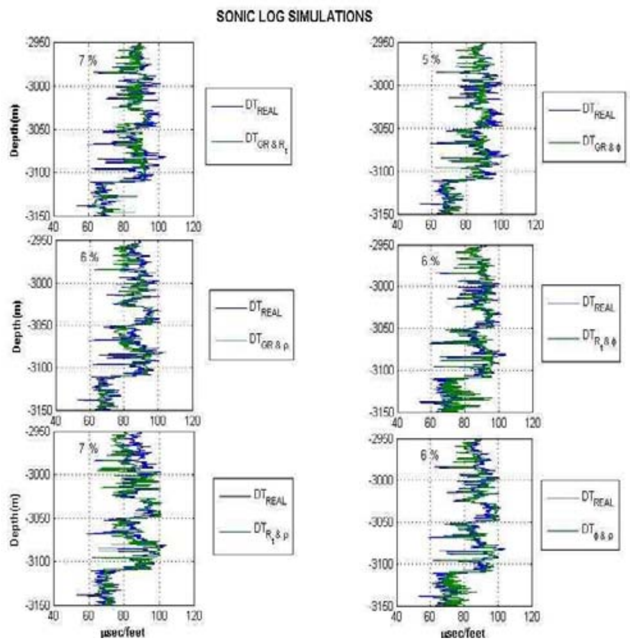

Figure 5: Simulations of DT log with fuzzy logic for each couple of logs of well Na04, calculating the fit error with RMSE index.

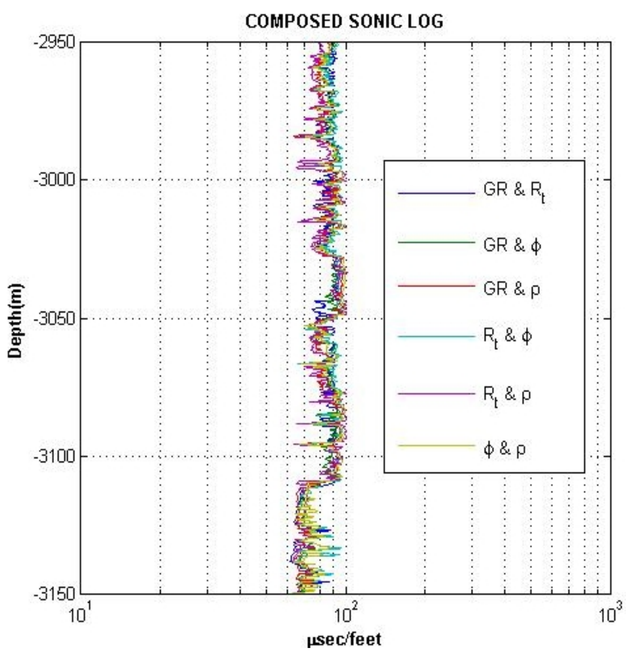

Figure 6: Joint plot of the simulations of DT log with fuzzy logic for each pair of logs of well Na04.

Conclusions

In this article, it was shown that, using fuzzy logic, it is possible to simulate the DT log in well Na04 of Namorado Oilfield, combining pairs of geophysical well logs, although with very different physical principles. The correlation between pair of logs was found especially high, when DT log is considered, and very low, when RT log is including in the analysis. Also, linear relationships exist between DT with another logs (NPHI and RHOB), meanwhile, logarithmic relationships exist between RT with other logs (DT, GR, NPHI and RHOB), and, potential ones between GR with others (DT, NPHI and RHOB), and between NPHI with RHOB. These results can probably be caused by the high content of clay in the reservoir. Moreover, the fuzzy logic proved to be efficient in the simulation of DT log, because it results in estimates with acceptable RMSE errors (5%) for logs with high correlation, and lower for logs with average to low correlations (7%). At the end, a plot with all the fuzzy simulations shows clearly the main lithological changes registered in the real DT log, mainly the reservoirs (at 3.030 - 3.050 and 3.070 - 3.100 m of depth) and the limestone (above 3.120 m), demonstrating, thus, the reliability of estimates, which can help in the reservoir characterization and drilling operations in this oilfield. The oscillations clearly visible in some estimatives can be explained by the high concentration of clay in the reservoir.

Acknowledgments

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