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NEURAL NETWORK AND LOGICAL FUZZY APPLICATION IN BRAZILIAN CARBONATE FORMATIONS USING CONVENTIONAL WELL LOGGING, NMR AND CORE DATA FOR PERMEABILITY PREDICTION

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ABSTRACT. Petrophysical information, such as permeability and porosity, is of great importance for oil reserve evaluation. Rock petrophysics measurements involve some degree of uncertainty because conventional well logging and nuclear magnetic resonance data are indirect measurements. Data from core samples are more accurate, depending on the laboratory conditions, but this information belongs to a specific depth and does not represent an entire formation, especially when carbonate formations are present. Carbonate formations are characterized by their variation in porosity systems. Such porosity can be defined as intercrystalline, intergrain, moldic, vuggy and fracture and this parameter is linked with permeability values in different ways. In this work we compare the results obtained from the applications of neural network and fuzzy logic using conventional well logging, nuclear magnetic resonance data and information from core samples for permeability prediction. After using these two techniques, which can be considered efficient tools for uncertainty evaluation, a statistical coefficient called R^2 shows better results when using logical fuzzy.

Keywords: intelligent systems, reservoir evaluation, petrophysics.

INTRODUCTION

Although significant progress has happened in modeling problems about porous structure obtained from physical properties of rocks, factors such as multiplicity of responses, computational stability, and availability of core analysis information limit their reliable petrophysical characterization (Wu and Chen, 2014). The studied field is a heterogeneous carbonate reservoir located in the southwest of Brazil and corresponds to the Barra Velha Formation. Geologically, it is divided into three supersequences: rift, postrift and drift. The postrift phase is composed by two sequences: the lower sequence of Aptian age, characterized by the deposition of microbial limestones, stromatolites and laminites with grainstones and packstones composed of stromatolites and bioclasts. The upper sequence is composed of stromatolites, limestones and dolomitized microbial laminites (Moreira et al., 2007). The lithology of the reservoir is mainly limestone. Permeability in carbonate formations is not only related to porosity, but also depends on grain size, sorting, pore throat sizes of intergranular pore space, the amount of vugs (formed by solution cavities), fractures and the presence or absence of connected vugs, as discussed by Lucia (2007).

The data for this study are composed by a set of openhole logs for a depth interval of 5580 – 5820 m and a group of 81 permeability core data. As shown in Figure 1, the group of input well logging data consists of: gamma ray (GR, track 2), deep resistivity log (AT90, track 3) showing high values at 5580 – 5750 m, permeability data (track 4), and porosity data (sonic - DTCO, density - RHOZ

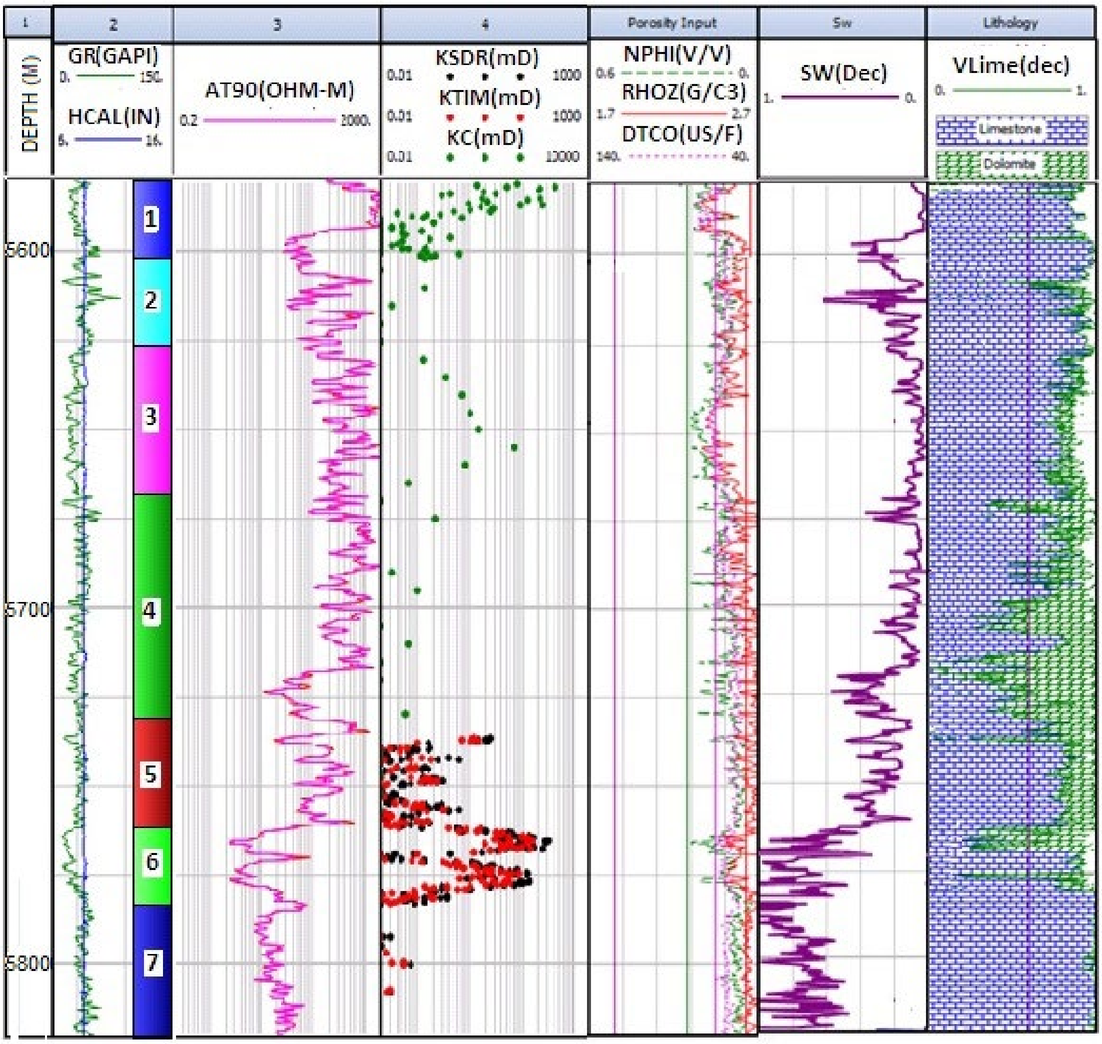

Figure 1: Well input data.

and neutron - NPHI, track 5). Permeability data are composed by core information (green points, KC) and nuclear magnetic resonance (NMR) permeability obtained from two equations: the model SDR (Schlumberger-Doll-Research) in black points (KSDR) and the Timur-Coates model in red points (KTIM).

A preliminary interpretation was performed based on information from these logs, which allowed defining seven zones as shown in Figure 1, column 2. The sixth column shows the water saturation after applying the Archie equation (a=1.14, m=1.95; obtained from data core), and the last column shows a graphic representation of the lithology (limestone in blue and dolomite in green). In this figure there is a great variation in permeability values in zone 1. Zones 3 and 6 are characterized by high permeability values, and zones 2, 4 and 7 by having low permeability values. Most of core data were taken from the hydrocarbon bearing layer (zones 1 to 4); the NMR permeability data belong to the transition and water zone (zones 5, 6 and 7).

There are some research works where fuzzy logic was efficiently used to obtain responses taking different parameters as reference. These permeability values are difficult to predict for the entire carbonate formation; then, fuzzy logic and neural network were used to obtain these values, taking core and NMR data as reference. Finally, both responses were compared.

METHODOLOGY

For permeability prediction, core and NMR permeability data were joined into the same track called KCKTIM, because there is no superposition between these two data groups.

Fuzzy logic is an extension of the conventional Boolean logic (zeros and ones) developed to handle the concept of partial truth - truth values between "completely true" and "completely false". It was introduced by Dr. Lotfi Zadeh of UC/Berkeley in the 1960's as a means to model uncertainty (Cuddy, 1997). In the petroleum industry, the reservoir characterization process involves quantifying uncertainties and building complex correlations among rock properties. Hence, for this type of problem, fuzzy logic coherently tolerates and interprets subjective concepts such as 'very high permeability'; efficiently fills missing information gaps; allows a mathematical formulation of the problem; and carries the inherent error term through the calculation rather than ignoring or minimizing it (Cuddy, 2000).

For application of the fuzzy logic, permeability core data may be classified as excellent, good or poor with respect to the cutoff values. Using fuzzy sets, each value will be a member of each fuzzy set with a membership degree. For permeability prediction, the interval core and NMR permeability data and the well logging data were used as data input (density, neutron, sonic, resistivity and gamma ray data). The permeability data are sorted in an increasing order and then the other input curve data will be assigned according to their permeability values in each bin. Different bin numbers can be assigned, and the result will be dependent on the amount of bins. The number of bins depends on the number and the range of the input data (Ghafoori et al., 2008). In Figure 2, the vertical lines in the cross plot represent one standard deviation either side of the mean (central point). Using Fuzzy logic, the data were sort into four groups as input data and were expressed as a bin number. Different bin numbers can be assigned, and the result will be dependent on the distribution.

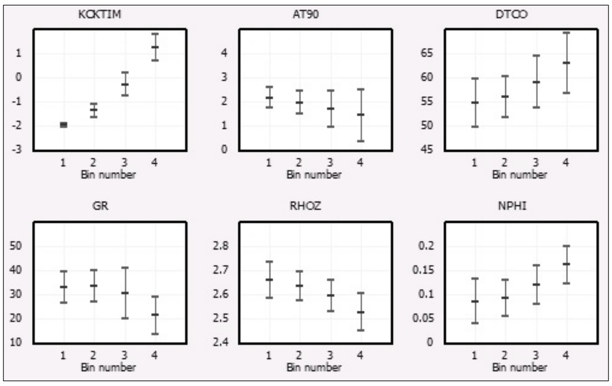

Figure 2: Cross plot of the curve bin distribution for fuzzy logic.

To make the prediction, the Interactive Petrophysics software (IP) first calculates the fuzzy probability that an input log is in a certain bin. The following equation 1 is used for this:

$$P(C_b) = \sqrt{n_b} \times e^{\frac{-(C-\mu_b)^2}{2\sigma_b^2}} \qquad (1)$$

where P(C_b) is the probability that curve C is in bin 'b'; n_b is the number of samples in bin 'b'; C is the input values for curve C; μ_b is the mean value for curve C for bin 'b'; and σ_b is the standard deviation for curve C and bin 'b'. The probabilities for all the input curves are then combined as follows in equation 2:

$$\frac{1}{P_b} = \frac{1}{P(C1_b)} + \frac{1}{P(C2_b)} + \frac{1}{P(C3_b)} + \ldots + \frac{1}{P(Cn_b)} \qquad (2)$$

where P_b is the probability for bin 'b'; and P(Cn_b) is the probability for curve Cn for bin 'b'. The most likely solution will be the bin with the highest probability (Senergy, 2014).

Data histograms are shown in Figure 3 for each input data. The logarithmic function was applied to the permeability (KCKTIM) and resistivity data AT90.

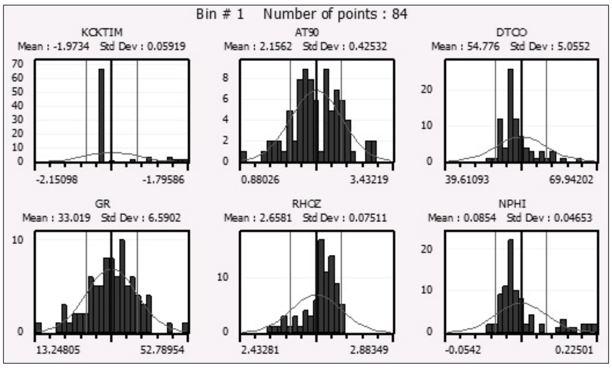

Figure 3: Cross plot of the curve bin distribution for fuzzy logic.

After application of the fuzzy logic, a curve was created in the last column of Figure 4. In this column, permeability core data (KC) and NMR permeability data (KTIM) are also shown in dark points. Permeability NMR data are located in the lower part of the seventh log.

The neural network technique was applied for these same groups of data, and the algorithm used was the back-propagation neural network, which is probably the most well-known and widely used feedforward neural network system. The term back-propagation refers to the training method by which the connection weights of the network are adjusted. During operation, all information flow is feedforward.

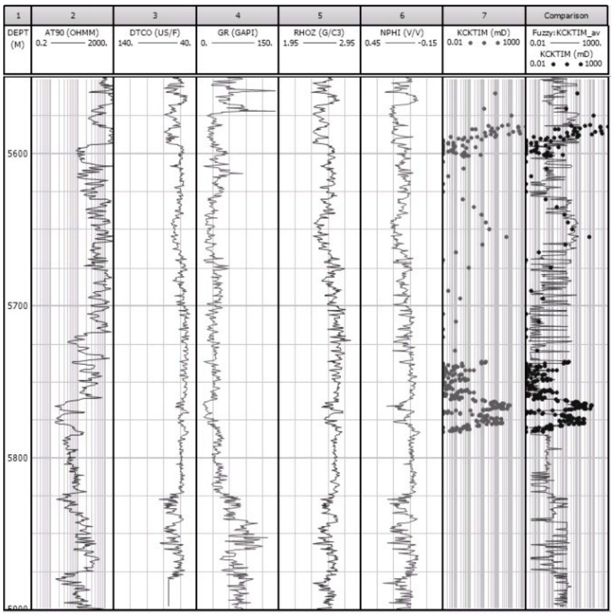

Figure 4: Permeability values from fuzzy application.

Figure 5 shows the basic structure of the back-propagation network, showing a group of neurons called input neurons which receive information from the real world.

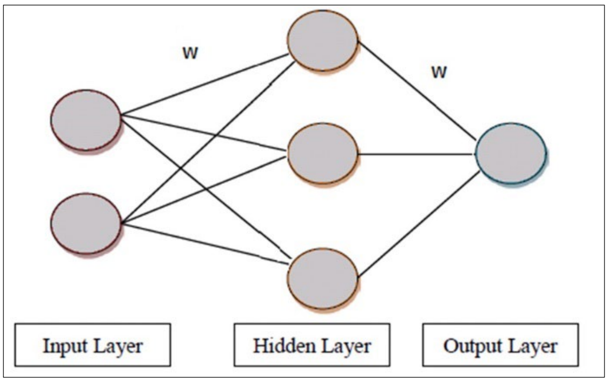

Figure 5: Basic structure of a back-propagation network (Kohli and Arora, 2014).

These neurons are interconnected to another layer, called the hidden layer, and, in turn, they are interconnected to output neurons. Each interconnection has a numerical value, called weight (W); depending on the weights; different input patterns can result in the firing of one or more output neurons. Through training, the output neurons are taught to give the correct answer. The output pattern is then compared to the desired output, and an error signal is computed for each output unit (Ali, 1994).

Two training zones were used as shown in column number 2 (Figure 6). The upper training zone is characterized by core values of variable permeability in the zone containing hydrocarbons. The percentage of samples used for training this upper section was 91%. However, the lower training zone has little core permeability data (3%) and more permeability values obtained from NMR at the bottom of this section. This lower training zone corresponds to an aquifer. Through training, the output neurons are taught to give the correct answer. The output result is shown in the red curve of the last column (Figure 6).

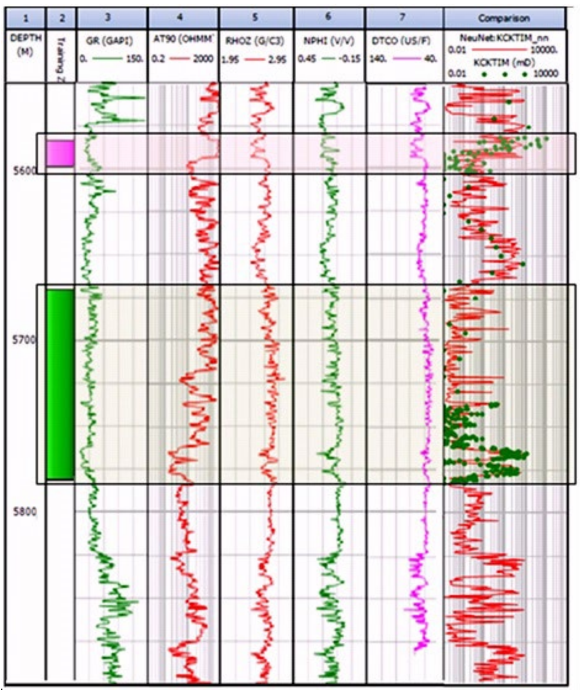

Figure 6: Basic structure of a back-propagation network (Kohli and Arora, 2014).

RESULTS

Considering the results obtained after the application of both techniques, we can note that fuzzy logic and neural network techniques have proved to be efficient tools for the study of complex data, as shown by both curves in columns 3 and 4 of Figure 7. As seen in this figure, it is possible to notice that there is a lot of consistency between the results obtained using these two methods.

A depth separation into 7 zones was performed based on the preliminary interpretation, considering the radioactivity level of the formation and permeability characteristics of the samples, as shown in track 2 of Figure 7.

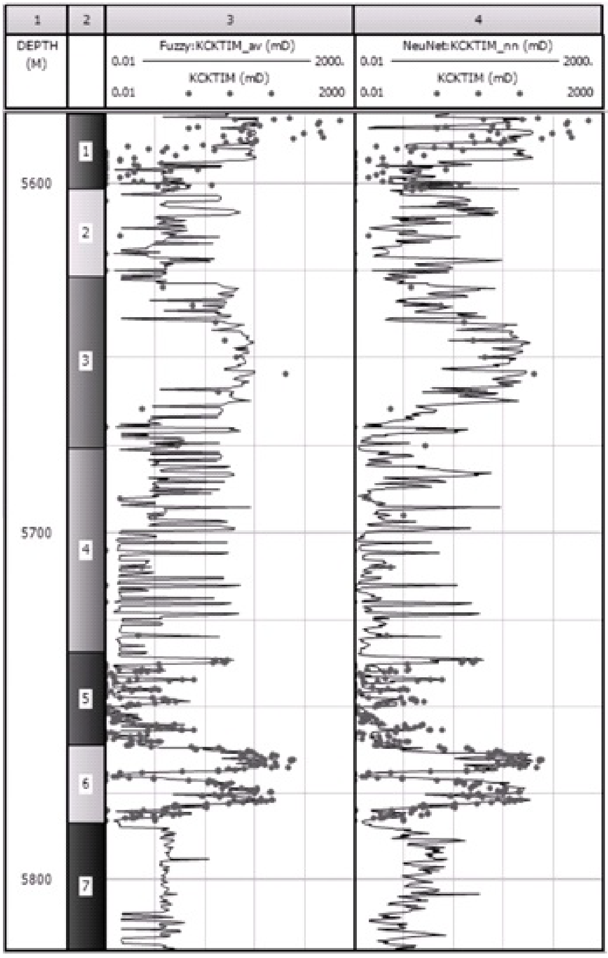

Figure 7: Fuzzy and Neural Network results.

Thus, we find that only in zone 1 there is a poor response using both techniques, because of the great variation in permeability values; however, there are better responses in the remaining zones. The fuzzy logic results are in column 3 and the neural network ones in column 4.

For better comparison, correlations were used between permeability responses and core with RMN permeability data by using the statistical coefficient of determination R^2. So, we have that permeability prediction for this complex formation results in $R^2 = 0.758$ using neural network and $R^2 = 0.929$ using the fuzzy logic.

Figure 8 shows a correlation between permeability data (core and NMR) and the values predicted by using neural network. The approximate equation obtained between them is described by equation 3.

$$Log(KC)=0.000789763+0.947336*Log(Kcnn) \quad (3)$$

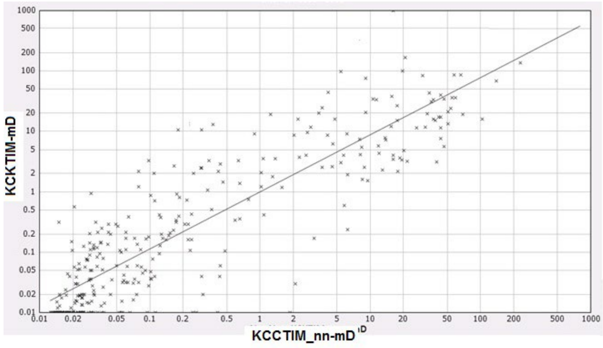

Figure 8: Comparison between permeability data and neural network results.

In the same way, Figure 9 shows a better correlation between permeability data (core and NMR) and the values predicted by using fuzzy logic. The approximate equation obtained is described by equation 4.

$$Log(KC)=0.257242+0.787801*Log(KCf)-0.119317*Log(KCf)^2 \quad (4)$$

Taking the average permeability values obtained by the fuzzy logic and neural networks for each previously defined zones, we obtain Table 1, showing in general that the permeability values obtained with the fuzzy logic are smaller than those obtained with neural networks, with the exception of zones 4 and 5, where the permeability values are lower.

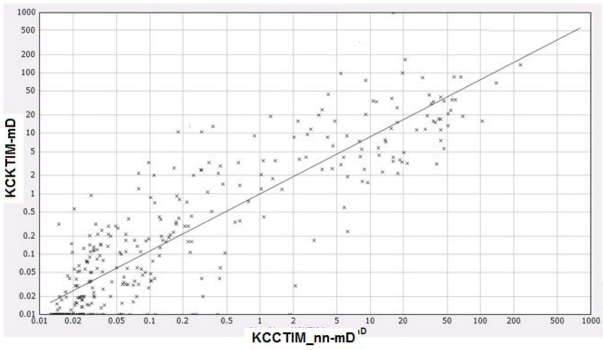

Figure 9: Comparison between permeability data and fuzzy logic results.

Table 1: Average permeability values.

Zone	Depth (m)	K - Fuzzy (mD)	K - Neural Networks (mD)
1	5580- 5600	4.55	14.42
2	5600 - 5626	0.86	1.51
3	5626 - 5675	4.89	9.91
4	5675 - 5723	0.97	0.37
5	5723 - 5760	0.38	0.22
6	5760 - 5775	6.81	14.77
7	5775 - 5825	0.69	1.38

CONCLUSION

Both fuzzy logic and neural network techniques have proved to be efficient tools for the study of complex data. The present work presented the use of two machine learning techniques to predict permeability in carbonate formations. Carbonate formations are characterized by their heterogeneity in permeability values, because of the presence of different types of porosity. For this case, Fuzzy logic responses showed better results than the neural network technique, given a statistical R^2 correlation of 0.929.

Using neural network, the amount of training data is an important fact for obtaining better results. In this work it was chosen two training zones with different characteristics.

Thus, permeability data were included as input data in discrete form to obtain the answers in continuous form. In neural networks the permeability input data are part of the input data to serve as a reference in the machine learning process.

Although different, both models exhibited the same behavior. This fact confirms the efficiency of the two techniques in predicting permeability. Therefore, it is concluded that the use of machine learning to estimate permeability in carbonate formations proved to be highly effective, being an easy-to-implement and low-cost option.

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