Characterization of Lithostratigraphic Units using Neuro Fuzzy System Analyses Applied to Rock Magnetic Data

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Abstract: In this work we employ the Neuro Fuzzy System hybrid algorithm to infer $S-ratio$ through the experimental magnetic susceptibility (χ) data measured in 90 samples, from a 670 meters - thick sedimentary sequence, at the stratigraphic well Saltarin 1A (Colombia). The method is applied here as a means for pattern recognition of the major lithostratigraphic units encompassed by this well (i.e. Guayabo, Len and Cabonera Miocene Formations). The sets of fuzzy rules obtained work well only when used to infer $S-ratios$ within the same Formation from which they were derived. This is particularly noticeable in Guayabo, with lithological characteristics different to those of Len and Carbonera. The contrasts between these three Formations seem to be responsible for the inability of finding a unique set of fuzzy rules that could properly infer $S-ratio$ over the whole well using χ data only as the input variable.

1 INTRODUCTION

Geophysical and geological problems commonly involve systems with a large number of parameters interacting in a complex way. These interactions are mostly non-linear and non-random resulting in an increasing scatter of experimental data points that blurs up any likely associative trend among them. The Neuro Fuzzy Systems is a hybrid algorithm that combines fuzzy logic with neural networks, The hybrid describes these variables in natural and rigorous way. Based on an automatic pattern recognition technique, the fuzzy logic method searches for the different sets of data involved in a complex system and for the empirical relationships between them.

The Neuro Fuzzy Logic (NFL) method, a hybrid algorithm that combines fuzzy logic with neural networks, has been previously used in the prediction of complex petrophysical (Hurtado et al., 2009) and in paleoclimatic (Da-Silva et al., 2010) parameters. In most situations the results obtained have given rise to a set of numerical connections between the different variables involved as well as additional lithological information about an area of particular interest (Finol et al., 2001).

The $S-ratio$, a rock magnetic index that accounts for the relative contributions of low and high coercivity material to the total saturation isothermal remanent magnetization in a sample, has been determined here according to the definition (Bloemendal et al., 1992). By obtaining empirical relationships that correlate $S-ratio$ with magnetic susceptibility we are actually exploring how this magnetic parameter is tied up to the concentration of ferromagnetic minerals in the different strata analyzed. Our goal is to apply the Neuro Fuzzy logic technique as a unbiased quantitative tool for pattern recognition of the major stratigraphic units involved. The Saltarín 1A seems to be an ideal natural scenario for such a purpose since it shows numerous lithological contrasts that give rise to a complex geological system (Bayona et al., 2008).

In this work we have used the Neuro Fuzzy logic technique to infer $S-ratio$ from magnetic susceptibility (χ) data from 90 different depth levels (670 meters) of the stratigraphic well Saltarín 1A (Colombian Llanos foreland basin, fig.1). We employ this technique to find a set of fuzzy patches, with their corresponding mathematical relationships, that come close to the possible connections between $S-ratios$ and χ for the major geological units encompassed by the well.

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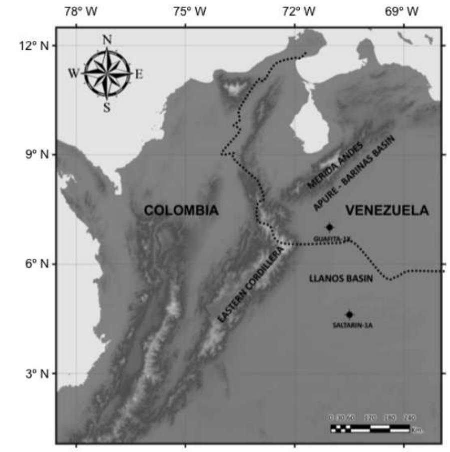

Figure 1: Geographical setting of the stratigraphic well Saltarín 1A in Colombia (Llanos Foreland Basin)

2 STRATIGRAPHIC SETTING

The deepest formation studied in stratigraphic well Saltarín 1A is Carbonera that includes a lower sandstone unit (654.6 to 670 m) accumulated in a fluvial system, a middle mudstone unit accumulated in a lacustrine system (608.2 to 654.6 m), and an upper sandstone unit that records sedimentation in a fluvial-deltaic system (546.9 to 608.2 m). Overlying Carbonera is the León Formation (441.8 to 546.9 m), a muddy sequence of sediments from a fresh-water lacustrine system.

On top of León lies the Guayabo formation that was divided in 6 lithological units (Bayona et al., 2008): G1 (388 to 441.8 m) and G2 (312.9 to 388 m), the two lower units, consist of green-colored laminated mudstones grading to sandstones interbedded with light-colored massive mudstones with ferruginous nodules. These lithologies were interpreted as the sedimentation from a fluvio-deltaic system changing to more continental sediment accumulation in fluvial floodplains. G3 (271.5 to 312.9 m) and G4 (205.5 to 271.5 m), the overlying units, are dominantly mudstones and siltstones that accumulated in fluvial flood plains. The unit G3 has more evidence of subaerial exposure (light-colored mudstones, formation of ferruginous nodules), whereas preservation of coal beds and laminated mudstones in unit G4 indicates less subaerial exposure of the flood plains. G5 (81.6 to 205.5 m) consists of feldspar-rich sandstones that record the filling of fluvial channels. G6 (0 to 81.6 m), the uppermost unit of the Guayabo formation, records a change to floodplain with evidence of subaerial exposure.

3 METHODS

For the characterization of the different lithostratigraphic units, through the inference of $S-ratio$, we used a hybrid Adaptive Neuro Fuzzy Inference System (ANFIS) with five layers that can be interpreted as a neural network with fuzzy parameters. ANFIS is equivalent, under some constrains, to a Takagi, Sugeno, Kang (TSK) model (Finol and Jing, 2002). To train our ANFIS we used $S-ratio$ ($IRM_{-0.03T}/SIRM_{+3T}$), as output and χ as input variable.

We introduced the χ training data in either semilogarithmic or direct form (i.e. $log(\chi)$ or χ respectively). Tests were also carried out using different combinations and numbers of fuzzy rules. Membership functions employed in all the trials were either linear, triangular, bell, pi, or gaussian. In each case inferred $S-ratio$ values were compared with their experimental counterparts. To quantify the performance of the inference, we applied the R^2 between inferred and experimental $S-ratio$ data, and the Root Mean-Square Error (RMSE) values.

4 RESULTS

For to ANFIS training we use a Gaussian membership function, the fuzzy rules was adjusted from 2 to 4, in order to monitor a possible improvement of the inference. Also we pruve that non-linear mathematical form of the function that relates the value of S-ratio to the magnetite weight percentage for a array of synthetic samples systematically mixed from magnetite and hematite (Heslop, 2009; Frank and Nowaczyk, 2008).

We trained the ANFIS separately with the χ and $S-ratio$ experimental values from Guayabo, Len and Carbonera and assessed the set of fuzzy rules obtained in each case in all the three formations involved (see Table 1). The figure 2 shows the results of some of these inferences, for the first case in which the ANFIS was trained using the experimental data from the Guayabo sandstones only. The qualitative examination of figure 2a shows that the fuzzy rules, obtained by training the ANFIS with Guayabo's data, give a reasonably good inference upon this Formation itself. However, that is not true when these same rules are applied to León and Carbonera (figures 2b and c respectively). The RMSE and R^2 values (Table 2) confirm this observation.

Similar tests were repeated by training the net only with experimental data from the mudstones of León and Carbonera .These results are summarized in Ta-

Table 1: Parameters of the Gaussian membership functions and fuzzy rules obtained by training the Neuro Fuzzy net using $S-ratio$ and χ data from the three Formations.

With data from and Range	Fuzzy rules
Guayabo (G)	
[16.80 −40.19]	$S-ratio = -1.63\chi - 0.82$
[65.35 +89.57]	$S-ratio = 0.0013\chi + 0.82$
León (L)	
[05.46 −17.26]	$S-ratio = 0.0067\chi + 0.84$
[01.47 +30.52]	$S-ratio = 0.002\chi + 0.87$
Carbonera (C)	
[02.21 −07.99]	$S-ratio = -0.027\chi + 0.93$
[01.27 +10.68]	$S-ratio = 0.0016\chi + 0.95$

Table 2: The RMSE and R^2 values obtained after applying, in each case, the fuzzy rules to their own data and to those from the other two Formations.

Evaluated data from	RMSE / R^2
G	0.17 / 0.33
L	0.01 / 0.54
C	0.03 / 0.80
G	0.56 / 0.04
L	0.07 / 0.13
C	0.32 / 0.10
G	0.50 / 0.06
L	0.22 / 0.00
C	0.07 / 0.27

bles 1 and 2. Once more, the minimum number of fuzzy rules obtained from either León or Carbonera, allows a reasonably good inference over each of these Formations themselves but it does not seem to provide a good inference when applied to the other two.

5 CONCLUSIONS

In this work we have used the Neuro Fuzzy logic technique to infer $S-ratio$ from magnetic susceptibility (χ) data from 90 different depth levels (670 meters) of the stratigraphic well Saltarín 1A, Colombian Llanos foreland basin.

Training the ANFIS with only experimental χ and $S-ratio$ values implies the assumption that magnetic susceptibility by itself can identify all the behavioral

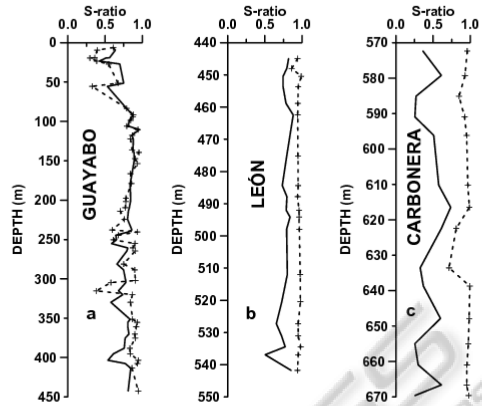

Figure 2: $S-ratio$ inference using an adaptative neuro fuzzy inference system (ANFIS), training the network with the $S-ratio$ and χ data of the Guayabo Formation only, and two fuzzy rules. Solid lines stand for the inferred data whereas the crosses and dashed lines represent the experimental data. Results of the inference are shown for the three Formations involved: a) inference for Guayabo Formation itself b) inference for León Formation c) inference for Carbonera Formation (Table 2)

patterns of the $S-ratios$ contained in a set of data. Namely it should be a univocal correlation between these two parameter, and equal χ values could not be linked to different $S-ratios$. However, although it is particularly noticeable the ability of the ANFIS to infer for the major changes of $S-ratio$ values within the first 300 meters of this well, beyond such a depth level the fuzzy rules seem to be less sensitive to predict $S-ratio$ changes.

This depth coincides with the transition zone from alluvial plains sediments deposited in a reducing environment, and oxidized paleosols, to lacustrine settings where other magnetic minerals (i.e. Fe sulphides and hematite) appear to be as important mineral phases. Thus, we argue that an improvement of the inference beyond 300 meters would be only possible by using, as input experimental data, not only χ values, but also other magnetic and non magnetic parameters that could account for all sorts of lithological changes throughout the whole well. Such parameters should provide information not only for the different types of mineral assemblages, but also for changes in grain size distributions and variable fractions of paramagnetic minerals.

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