Comparing different Artificial Neural Network algorithms to estimate the lithology of Albian carbonate reservoirs in Campos Basin – Brazil

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Abstract

In this study, we proposed a procedure to discover the connection between the lithology of the carbonate reservoir rocks in Campos Basin - Southeast of Brazil and the response of geophysical well logs through numerical simulations. To answer this, we use an Artificial Neural Networks (ANN) back - propagation approach which uses different functions of Matlab´s module, beside geophysical well logs and a priori textural information derived from geological interpretation of core samples. The outcomes indicate that the Traingdx function has a better public presentation, with less fit error, reasonable training time, but with several iterations to make out the simulation. The study also shows that increasing the number of layers in the algorithm setting the error decreases, but increases the number of iterations of the training time. At the end, we discovered an excellent agreement between the facies derived from geological interpretation and the simulation obtained from ANN, existing only important differences when the lithology is cemented.

Introduction

This study was performed in a carbonate reservoir of Campos Basin, which is located along the continental shelf of Southeast Brazil. These rocks were deposited in an extensive carbonate platform environment, with more than 1500 km of extension along the Campos and Santos Basins (Figure 1, left). The sedimentary evolution of this platform was conditioned by pre-Albian section structures (Sao Tome Low, internal and external highs, NW and NE lines). The evaporites movement was influenced by the sediment load, substrate slope and reactivation of faults (direction NW/SE), controlling the geometry and distribution of facies. These reservoirs are represented by isolating structures, which correspond to shallow platform carbonate deposits that were formed during a transgressive Lower/Middle Albian regime (Torrez, 2012).

In this work, we studied carbonate reservoirs of Quissama Formation, which belong to the Cretaceous, Albian of age, with a nature marine sedimentation and transgressive depositional environment of shallow platform (Carrasquilla et al., 2012). According Guardado et al. (1990), this formation consists of carbonate banks dominated by grainstones and packstones stacked on sea level change cycles and composed of ooids, oncoids, peloids and bioclasts, which were deposited in a marine environment with high to moderate energy (Figure 1, right). The grainstone is considered the reservoir in this oilfield because has the higher values of porosity and permeability (Bruhn et al., 2003).

The study proposed to evaluate the lithology of these reservoirs using an ANN back-propagation algorithm, which is accompanied by a textural interpretation from core samples and log data set (Knecht et al., 2004). Although well logging is a method widely used to reservoir characterization, it is still a limited and an indirect measure (Luthi, 2001). On the other hand, ANN is an additional computational method to characterize and to estimate rock petrophysical properties capable to recognize previously trained patterns (Finol & Buitrago, 2002). Thus, together with this, it was used Interactive Petrophysics (Senergy, 2014) software to interpret of geophysical logs and to compare the simulations with the geological interpretation derived from core samples.

Method

The construction of the ANN was performed using geophysical logs (gamma ray, neutron porosity, density, resistivity and sonic) data set as input data for two drilled wells: training well (A10) and blind-test well (A3).

Six training functions from Matlab´s ANN Toolbox were used, namely Traingd, Traingdm, Traingda, Traingdx, Trainim and Trainrp (Matlab. 2014). The best performance of each was based on the Pearson correlation number (R), and, on the other hand, the sensitivity analysis (SA) determined the number of hidden layers more appropriate to use in the network (Nikravesh & Aminzadeh, 2003). The choice of the best algorithm was made based on the best performance in training and blind-test wells in the estimate of texture, i.e., the network output parameter. All tests were conducted using the same computational settings.

In brief, the methodology proposed in this work allows to assess the lithology in the reference well, even as to characterize the reservoir rocks in adjacent wells starting from well logs and facies description, evidencing the potential of ANN as a tool for developing new models that intend to describe heterogeneous systems, such as carbonate rocks (Silva et al., 2015).

Results

The results obtained in this work indicates that the Traingdx function had the best performance (Table 1) among all those tested in Matlab software, because, despite not having the best R in the pit of training (90.08), had the best R in the blind test (67.51), with a high number of iterations (10^5) as the other functions, with a low MSE (0.50) and a reasonable amount of training time (00:19:57 hours).

The accuracy of the ANN training using the well logs data set after SA network enabled the selection of the 20 layers as the optimal number of the network hidden layers (Table 2). The A10 well network training identified the textures satisfactorily (R = 90.29%), reaching the number of times equal to 10^5. For the blind-test, was used the neighbor well, 700 m distance from the training well, in which was demonstrated that the ANN method was efficient (R = 79.16%) to estimate well texture A3 from geophysical log data.

The differences presented by the lithology training of ANN have also agreed with the gamma ray log and fits variations in the ambient energy level at the time of deposition, both in the reference well as in the blind test. As can be seen in these figures, there is not a very good match between the geologic descriptions and the simulations when lithologies are cemented packstones and grainstones. But it exists a good correlation in the case of not cimented grainstones, packstones and wackstones lithologies, probably due to poor log responses in front of cemented lithologies (Figures 2 and 3).

Conclusions

ANN was able to estimate the texture with high reliability, both in reference well (R = 90.29%) and the borehole used as a blind test (R = 79.16%), demonstrating potential in this kind of geological description of carbonate reservoirs. Although it is necessary to use a priori lithological information to assist well logs and ANN algorithm, this approach showed good performance in blind test when using the same conditions of simulation as those used in the reference well. Some contradictions pointed out by the ANN indicate the necessity of additional input data, enabling better differentiation of lithologies and draws the attention of interpreters for pointing out patterns and trends of lithological interpretation based on log data.

Acknowledgments

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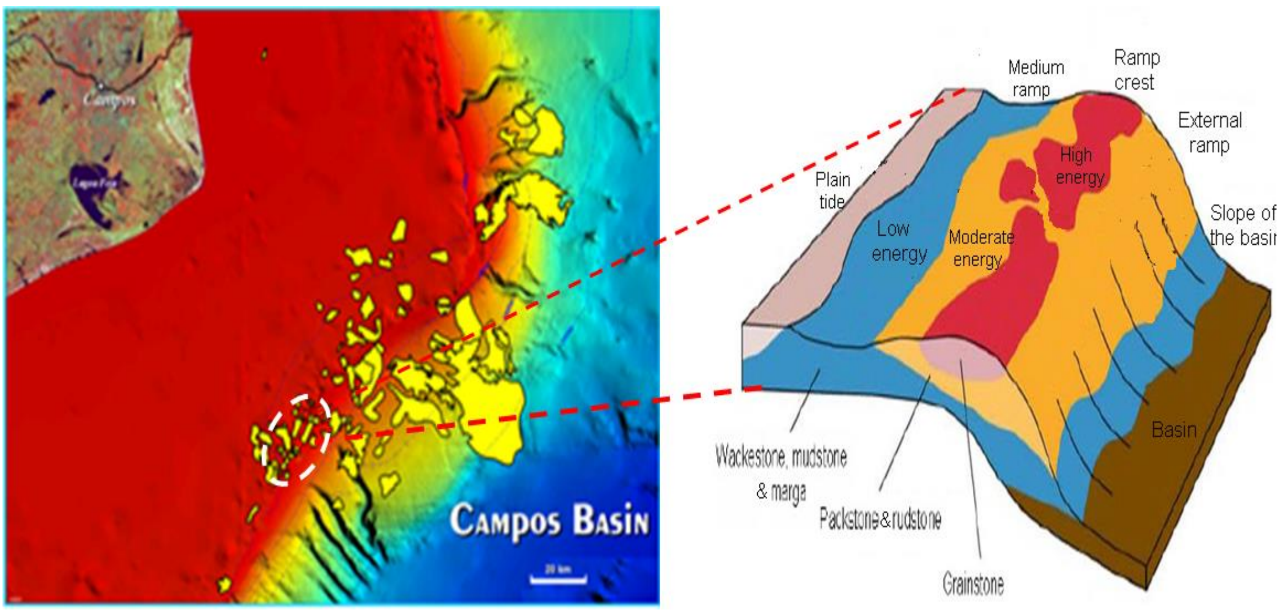


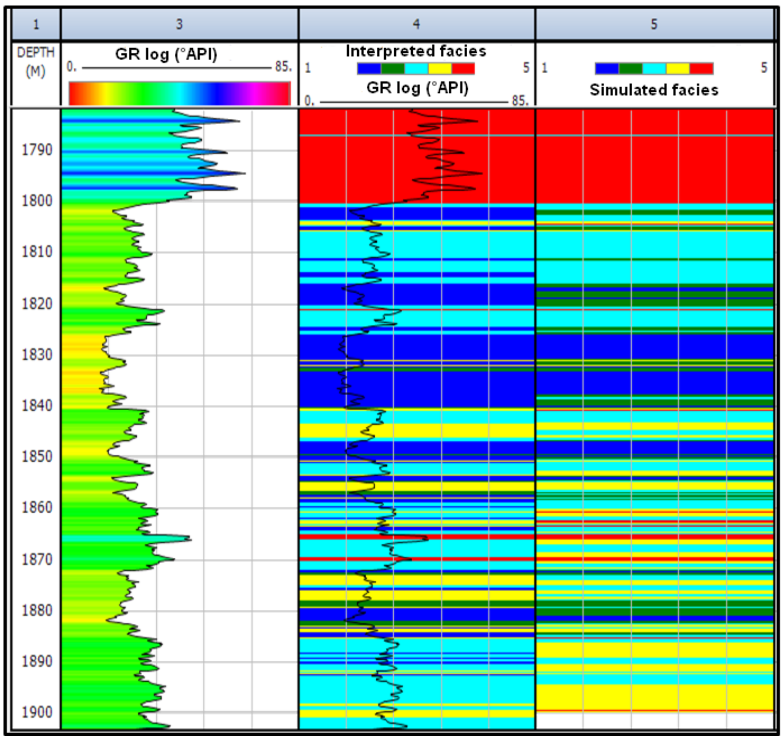
Figure 1. Campos Basin - Southeast Brazil at left and, schematic carbonate ramp platform at right (modified from Guardado et al., 1990).

Table 1. Comparison of the performance of different ANN Matlab´s functions

Algorithm	R (%) training	R (%) blind - test	Iterations	MSE	Training time
Traingd	62.69	61.62	10^5	2.32	00:24:47
Traingdm	62.60	62.26	242	2.39	00:00:04
Traingda	85.69	62.71	10^5	9.71	00:18:09
Traingdx	90.08	67.51	10^5	0.50	00:19:57
Trainlm	93.68	54.05	10^5	0.20	00:54:35
Trainrp	62.26	62.26	39	2.39	00:02:39

Table 2. Performance of the Traingdx ANN function.

Traingdx (layers)	R (%) training	R (%) blind - test	Iterations	MSE	Training time
20	90.29	79.16	10^5	0.25	00:17:27
25	89.36	68.74	10^5	0.29	00:19:40
30	88.73	35.36	10^5	0.21	00:20:45
35	89.41	36.86	10^5	0.23	00:22:23
40	90.66	53.40	10^5	0.17	00:22:43
50	89.25	64.82	10^5	0.23	00:31:31
100	90.39	53.10	10^5	0.18	00:37:42



Númber	Texture	Color
1	Grainstone	
2	Cemented Grainstone	
3	Packtsone	
4	Cemented Packstone	
5	Wackstone	

Iteractions: 105
R = 79.16%

Figure 2. Comparison between simulation and geological texture description for blind test well A3.

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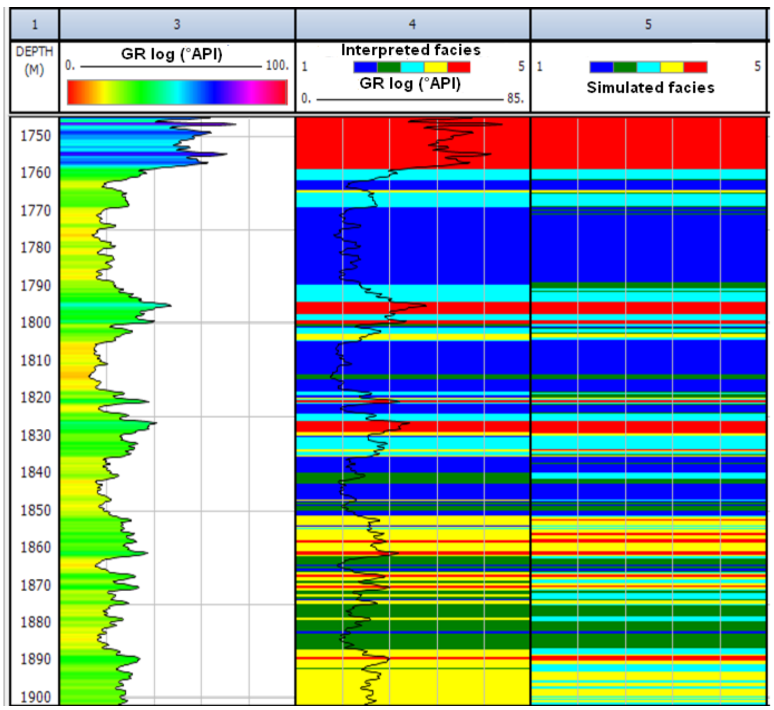

Number	Texture	Color
1	Grainstone	
2	Cemented Grainstone	
3	Packtstone	
4	Cemented Packstone	
5	Wackstone	

Iteractions: 105
R = 90.29%

Figure 3. Comparison between simulation and geological texture description for reference well A10.