Neural Network analysis of lithofacies from logs in carbonate reservoirs

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This paper was prepared for presentation during the 15th International Congress of the Brazilian Geophysical Society held in Rio de Janeiro, Brazil, 31 July to 3 August, 2017.

Abstract

Lithofacies determination from well logs is of great importance for carbonate reservoir characterization. Costly coring processes induces normally a lack of geological data over the reservoir. For this, geophysical logs analysis is central for the development of reservoir models capable to distinguish different geological facies. The Artificial Neural Network (ANN) are considered as a suitable tool for the identification of facies and an efficient method for quantitative analysis. The aim of this study is analyze and compare the Artificial Neural Network with the Back-Propagation approach (ANN-BP) to support the lithofacies classification from two carbonates well data sets, located in the Campos Basin (in the continental margin of Brazil) and at the Ses Sitjoles experimental site (in the south-east part of the Mallorca Island, Spain), near the city of Campos, Baleares. The accuracy of training and blind tests suggests that ANN-BP application for two different carbonate reservoirs offers an auxiliary tool for lithofacies classification based exclusively on well data.

Introduction

An Artificial Neural Network (ANN) is a mathematical tool inspired from human brain functions, and designed to perform complex pattern recognition tasks (Parra and Ursula, 2014) and they have been applied as a classifier to quantify patterns and estimate different parameters in geophysical data (Mohaghegh et al., 1994; Gonçalves, 1995; Benaouda, 1999; Nikravesh and Aminzadeh, 2001, 2003; Bhatt and Helle, 2002; Haykin and Lippmann, 1994). A good reason to use an ANN in petroleum engineering is due to the strength of this technique which is capable to learn and self-adjust after training. It provides thus a powerful tool for solving pattern recognition problems through the processing units nested in the hidden layers (Mohaghegh et al, 1994).

The adaptability of the ANN is crucial. This feature allows the ANN to respond as humans brains, learning by experience. Neural networks need a reasonable amount of information to learn and adjust the links and connections between different neurons by training, storage, recognition and estimate sampled function when the output of the functions is unknown. Rumelhart at al. (1986) developed the back-propagation algorithm which is the most used in neural networks training.

In this context, the objectives of this work were to demonstrate the ability of ANN-BP to learn and replicate different classifications of lithofacies. The study is based on two carbonate reservoirs, considering that carbonates may have heterogeneities that can be difficult to describe, and consequently difficult to encompass.

The first reservoir studied is part of the Llucmajor carbonate platform, in the SE part of the Mallorca Island (Spain). It is composed of complex prograding limestones affected by a freshwater reservoir overlying a sea water intrusion (Hebert, 2011). The Ses Sitjoles site is located near the local city of Campos, 6 km inland from the mediterranean coastline (Figure 1). It belongs to the inland part of the Llucmajor reef-rimmed platform set up during Miocene age. According to Pomar (2001b), the complexities on the platform facies architecture were the result of changes in carbonate production and accommodation related to high-frequency sea-level fluctuations. The lithology of the Ses Sitjoles site is characterized by upwards reefs to lagoonal depositional environments (Hebert, 2011).

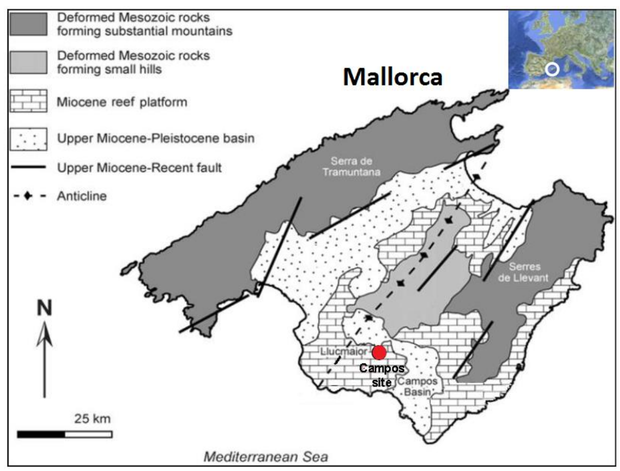

***Figure 1 –** Geological and structural mal of the Island of Mallorca, Baleares, Spain (modified from Hebert, 2011); a red dot locates the experimental site near Campos.*

The second reservoir studied here is made of carbonate rocks from Macaé Group (Albian) in Brazil. Named "Campo A" for confidentiality reasons, the site is located in the Campos Basin on the northern coast of the Rio de Janeiro state, Brazil (Figure 2). The tectono-sedimentary evolution of this basin occurred in three different phases: rift, post-rift and drift, which gave origin, respectively, to continental, transactional and marine super sequences. The reservoir studied belongs to the Quissamã formation, which took place as part of a carbonaceous platform, with homoclinal ramp morphology (Guardado et al., 1989).

***Figure 2 –** Campos Basin to the north of the Rio de Janeiro coast, Brazil, where "Campo A" is located.*

This study aims to demonstrate that lithofacies classification by application of the ANN-BP method using wireline logs is a valid tool to describe the inner geological structure of carbonate reservoirs.

For the Mallorca site (Spain), the facies texture is described by Hebert (2011). For the Campos Basin data (Brazil) and the facies texture description was provided by PETROBRAS S/A. The output classification from ANN-BP is based on a combination of logs to reproduce lithofacies description using the Multilayer Perceptron approach. The main purpose of the ANN-BP structure presented aims to analyze the accuracy of the methods at the two sites.

Methods

In order to obtain the results presented in this paper, two different approaches were used. The first application of Artificial Neural Network is to estimate the texture facies (target) using all logs (inputs) available for each reservoir. The second application seeks to evaluate the ability of ANN-BP to match the facies texture for the same logs either present at the Mallorca or the Campos A sites. The data set used in the input layer to train the ANN-BP is composed by downhole geophysical measurements such as travel time (DT), gamma ray (GR), neutron porosity (PHIN), effective porosity (PHIE), deep resistivity (Rt), shallow resistivity (Rxo), water saturation (Sw) and bulk density (RHOB) from Campos A. For the Llucmajor reservoir, the gamma ray (GR), uranium concentration (U), compressional wave velocity (Vp), formation Factor (F), reflectance of rock (R), bulk density (ρ_r) and impedance (Z) were used. These downhole geophysical measurements feed the ANN-BP input layer (Figure 3) to obtain facies texture (output).

The Waikato Environment for Knowledge Analysis (WEKA) (Hall et al., 2009) is a software from the WEKA Machine Learning project of Waikato University (Hamilton, New Zealand) that offers different tasks to work with data mining, as pre-processing of the data. The data set was converted to the standard file, called Attribute Relation File Format (ARFF), normalized and analyzed using the Artificial Neural Network type Multilayer Perceptron.

A Summary of downhole geophysical data from borehole MC10 series of the Llucmajor sequence, between 43 and 95 m is presented (Figure 4). The experimental site is set in a karstic carbonate context and located 6 km off the coastline, to the south of Campos city. It penetrates the Miocene Llucmajor reefal carbonate platform. Hole MC10 penetrates the carbonated shelf down to 100 m depth into the inner platform, reefal and slope units. The three hydrological systems are found from top to bottom with fresh water on top, mix water and salt water at the base. The upper sequence, assigned to the Messinian, consists of a variety of lithologies controlled by the response of the system to changing sea level (Pomar, 1991). The set of 100 m-deep boreholes reveals a simplified facies succession of bioturbated fine grained packstones and algal grainstones to rudstones (81 - 95 m; Figure 4), skeletal packstones – grainstones (59 - 81 m), coral-rich zone (boundstones, coral floatstones, rudstones), grainstones and skeletal rudstones (43 - 59 m). Globally, the grain size is medium to coarse. Mudstones (Figure 4, in *blue*) and wakstones (Figure 4 in *pink*) are deposited in low energy environments and typically higher gamma-ray activity (Lucia, 2007).

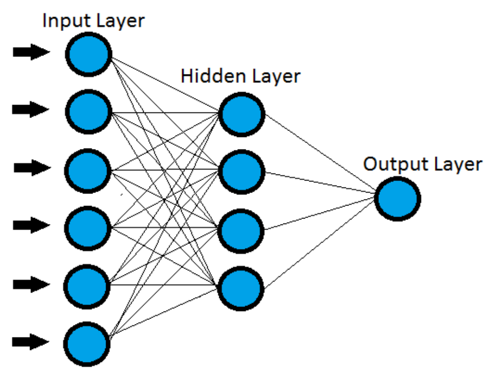

***Figure 3 –** Architecture of ANN. Example with 6 neurons in the input layer, 4 neurons in the hidden layer and 1 neuron (output) in the output layer.*

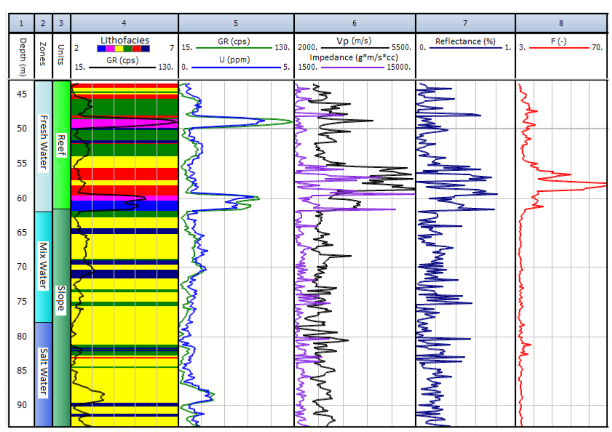

***Figure 4** Summary of downhole geophysical data from borehole MC10 series of the Llucmajor sequence, between 45 and 95 m. Description of columns: (1) Depth (m), (2) Pore fluid (fresh water, mix water and sea water), (3) Facies texture deduced from core description and thins section analysis according to Dunham's carbonate*

*classification (Dunham, 1962) with total gamma ray profile, (5) Gamma Ray (cps) and uranium (ppm) profiles displaying the natural radioactivity trend, (6) Ultrasonic P-wave velocity Vp (m/s) and Impedance (g*m/s*cc) extracted from Acoustic Borehole Wall Image (ABI) log, (7) Reflectance (%) computed from Luthi (2001) and (8) Formation Factor (F) computed from downhole geophysical pore fluid and formation electrical conductivities. Graphical display of lithofacies by depth for the six facies texture (blue = mudstone, pink = wackstone, yellow = packstone, green = grainstone, red = boundstone, dark blue = rudstone).*

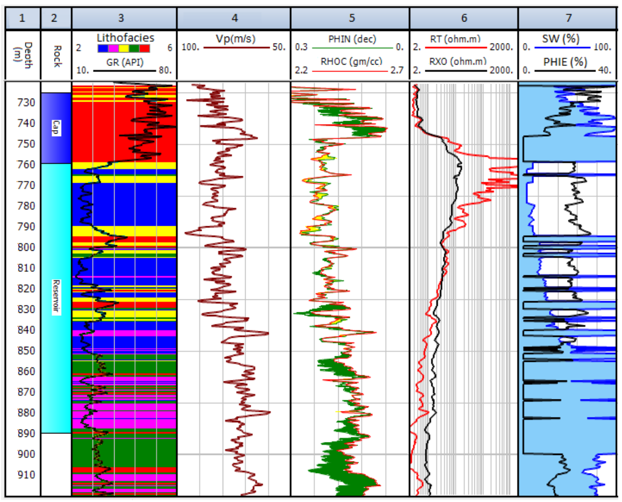

Figure 5 – *Graphical summary of downhole geophysical measurements from borehole X10 in the Campos Basin, Brazil, between 730 and 910 m. Descriptions of columns: (1) Depth (m), (2) Cap rock and reservoir localization, (3) Facies texture as determined by PETROBRAS from core description and thin sections analyses according to Dunham carbonate classification (Dunham, 1962) with Gamma Ray (API) overlaid and displaying the natural radioactivity trend, (4) Sonic log (DT) in µ*sec/feet, (5) Neutron porosity (PHIN) and bulk density (RHOC) logs showing the presence of oil and gas, (6) Electrical resistivity at depth in the formation (Rt) and in the invaded zone (Rxo), and (7) Effective porosity (PHIE) and Water Saturation (Sw). Graphical display of lithofacies by depth for the 5 facies texture (blue = grainstone, pink = cemented grainstone, yellow = packstone, green = cemented packstone, red = wackstone).*

Downhole geophysical data from borehole X10 series of the Campo A sequence, between 730 m and 910 m used to train and test the ANN-BP are also presented (Figure 5). Due to confidentiality issues, the depths and names of the wells are not directly reported. The lithofacies from borehole X10 are controlled by the response of the system to changing sea level. As a consequence, the rock texture changes due to depositional energy. For high sea level stands, mudstones and wackstones with carbonatic mud associated are found. The shallow and deep resistivity logs associated with density and neutron are suffisant to identify the reservoir (close to 750 m; Fig 5). The oil/water contact is identified at 820 m depth. This site is drilled into shallow water carbonates from the Quissamã formation.

Results

The Artificial Neural Network with the Back Propagation approach (ANN-BP) was used to support the lithofacies classification for two data sets from carbonate reservoirs. The study was performed in two steps: data set training first, then blind test. The training phase provides an accuracy estimate for the ANN-BP. The blind test is aimed at demonstrating the ANN-BP capacity to identify lithofacies classification using different combinations of data sets. The first data set refers to all well data available while the second one is restricted to the same type of well data at both sites in petrophysical terms.

For both sites, the highest lithofacies determination accuracy is obtained using all well data (Table 1). The high success rate of 99,6% and 98,2%, for all logs and three logs respectively, accuracy for Campos Basin was expected due to familiarity of the ANN-BP with the data set during the training phase. For Mallorca data set the accuracy (79,8% and 69,1%) decreases (Table 1).

Subsequently, the blind test was performed using the two testing data set. The first one contains all downhole geophysical measurements for each site, and the second data set used is smaller, containing only three logs. This procedure was adopted to compare the training phase using the same logs available at both sites where different downhole geophysical measurements were recorded. The ANN-BP blind tests show, in both cases, that the blind test accuracy increases when the full data set is used.

Table 1 – *ANN-BP results from training and blind tests for the Mallorca (MC10 and MC2) and Campo A (X10 and X3) boreholes.*

	Training			Blind test	
	All logs	3 logs		All logs	3 logs
X10	99,6%	98,2%	X3	85,7%	54,9%
MC10	79,8%	69,1%	MC2	60,5%	44,4%

Figure 6 presents the ANN-BP accuracy for the training and blind test results for two groups of data sets from Mallorca. "Training 1" corresponds to gamma ray (GR), uranium concentration (U), compressional wave velocity (Vp), formation Factor (F), reflectance (R), bulk density (ρ_r) and impedance (Z) data. "Training 2" was performed using gamma ray (GR), compressional wave velocity (Vp), and bulk density (ρ_r). The blind test 1 (Figure 6, column 5) and blind test 2 (Figure 6, column 6) correspond to training 1 (Figure 6, column 3) and training 2 (Figure 6, column 4), respectively. Due to proximity of the training and blind test boreholes (2 m away from each other), the lithofacies core description was performed in MC10 and extended to MC2, as described by Hebert (2011). The general results provide the expected good agreement between lithofacies description based on Dunham (1962) classification. The analysis performed with the back propagation algorithm applied to both data sets (training 1 and 2) compare well with the lithofacies description. At the same time, the lithofacies recognition accuracy varies for the individual classes and appears as best adapted to packstones (in yellow). As the ANN-BP routine for carbonates was trained (and memorized) on the basis of a large number of packstone samples, which generates an “overfitting” problem in the context of this study. In this data set, the packstones represent 54,1% of all samples used in the training phase, which is also justified by input data set limitations due to low sample frequency of mudstones and wackstones. During the blind test process, the model was expected to behave in the same way. Grainstones were associated with the highest error because the lithofacies classification refers mostly to the packstones. For blind test 1 (column 5) the model is more generalist for packstones than in the blind test 2 (column 6). For the wackstones (in 49 m and 59 m) the ANN-BP predictions are in good agreement with the lithofacies description in both data set studied (Figure 6).

The ANN-BP model for the Campo A site shows the lithofacies description from X10 and X3 (column 2 and 5, respectively), training 1 and 2 (column 3 and 4, respectively) and blind tests (column 6 and 7, respectively; Figure 7). During the training tests, the sucess accuracy of ANN-BP is higher than 98% in both data set used in borehole X10. Cemented grainstones generate significant errors as they refer to cemented grainstones (in 775 m, 1805 m, 1845 m and 1873 m; Figure 7). The same situation occurred between wackstones (red) and packstones (yellow) in 1760 m. For blind test 2 (Figure 7 column 7), some of the grainstones were classified as packstones (1802 m, 1820 m, 1838 m) or as cemented grainstones (1832 m, 1848 m).

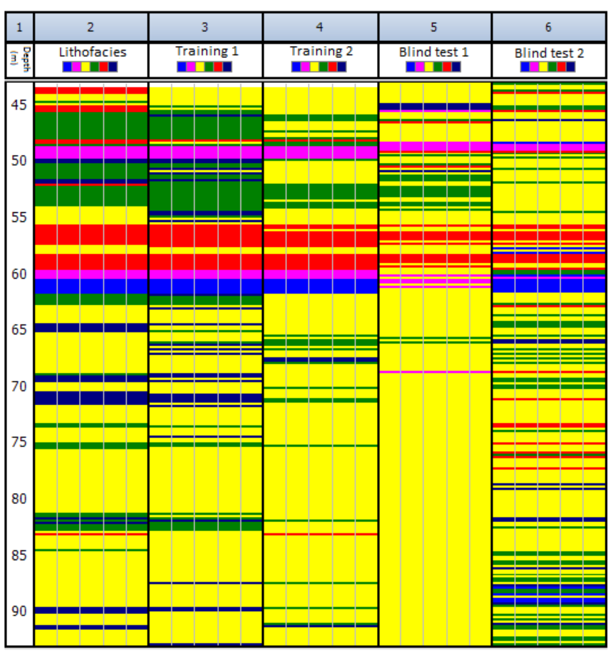

Figure 6 – *Mallorca ANN-BP training and blind test for two different data sets, using all data set and using 3 logs. Columns: (1) Depth (m), (2) Facies texture from MC10, (3) ANN-BP training using all logs available, (4) ANNBP training using 3 logs, (5) Blind test from training with all logs, and (6) Blind test from training with 3 logs. Graphical display of lithofacies by depth for the six facies texture (blue = mudstone, pink = wackstone, yellow = packstone, green = grainstone, red = boundstone, dark blue = rudstone).*

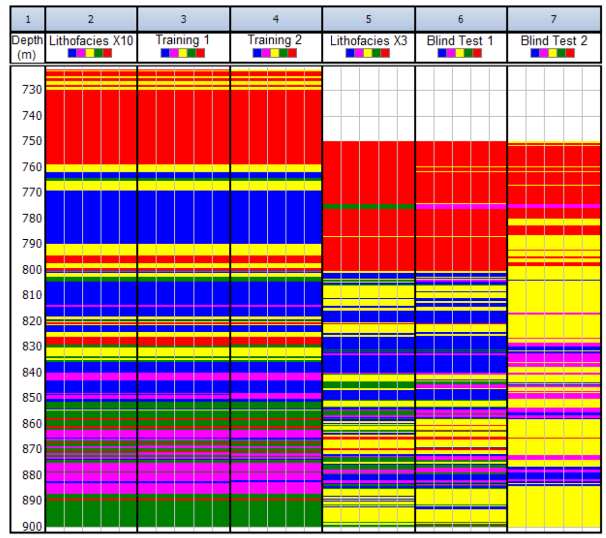

Figure 7 – *Campo A ANN-BP training and blind tests for two different data sets, either using all data set or using 3 logs. Columns: (1) Depth (m), (2) Facies texture from X10, (3) ANN-BP training using all logs available, (4) ANN-BP training using 3 logs, (5) Facies texture from borehole X3, (6) Blind test from training with all logs, and (7) Blind test from training with 3 logs. Graphical display of lithofacies by depth for the 5 facies texture (blue = grainstone, pink = cemented grainstone, yellow = packstone, green = cemented packstone, red = wackstone).*

Conclusions

This study demonstrates an approach for lithofacies classification from two different carbonate sites based on downhole geophysical measurements. This methodology can support decisions and perform rock characterization due to the ability of ANN-BP to perform a lithofacies classification for a given well, simplifying the process of study and analysis required in.

The ANN-BP method based on the WEKA routine, is proven to be useful tool to provide a lithofacies classification in different types of carbonate reservoirs. The results obtained using two different combination of data set are shown to be efficient in predicting lithofacies. The ANN-BP has some difficulties to distinguish lithofacies that were more trained than others, due the “overfitting” problem from neural networks that memorizes the training. For data sets with similar attributes, the ANN-BP can “memorize” the training phase and generalize to new situations. Some contradictions pointed out by the ANN-BP can indicate the necessity of additional input data.

The results show that the ANN-B based on the WEKA routine can help decisions in lithofacies classification in petroleum reservoir engineering using downhole geophysical measurements.

Acknowledgments

The authors thank CAPES for doctoral scholarship and the Université de Montpellier (UM), France, for use of the facilities provided to perform this work.

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