Neural network computing for lithology prediction of carbonate- siliciclastic rocks using elastic, mineralogical and petrographic properties

Adrielle Silva, Irineu Lima Neto, Abel Carrasquilla, Roseane Misságia, Marco Ceia and Nathaly Archilha.
Laboratório de Engenharia e Exploração de Petróleo (LENEP) – Universidade Estadual do Norte Fluminense (UENF)

Abstract

The lithology identification has a great importance to petroleum reservoir characterization and wellbore economic viability analysis, and it is usually made from core and geophysical log analysis. However, the process of coring is costly and well log analysis is a task that takes time and requires highly specific knowledge. Thus, there is a great interest in the ability to predict the lithology behavior of a wide area from a small number of samples. Artificial Neural Networks (ANN) is a computational method based on human brain function, extremely efficient in recognizing patterns previously trained. This paper proposes a siliciclastic and carbonate lithological classification with backpropagation neural network algorithm supported by petrophysical, mineral and elastic information, from a well dataset located in the South Provence Basin, at the southwest of France. The great accuracy in the simulation leads to suggest that ANN application can be an auxiliary tool for lithological identification based on well data, specially for prediction intervals in the well that has not sampled or adjacent wells.

Introduction

One of the most important contributions to the geological and geophysical studies is the well lithology identification. However, this is also one of the most difficult tasks because the measurements, that are able to identify the rock physical properties change, do not necessarily reflect the lithological variations (Flexa et al., 2004).

The lithology identification is usually performed by core samples or cuttings analysis and borehole log, a direct and indirect method, respectively. Core samples are taken from well drilling process and can be analyzed by experts, such as geologists and paleontologists. This technique demands high costs. Well-logs and seismic imaging are applied to rock characterization with substantially lower costs and do not need necessarily to interrupt the well drilling process. However, being an indirect method, do not obtain the same accuracy as the core samples analysis (Schmitt, 2009). Hence, there is a real necessity to find alternatives for reservoir characteristics interpretation in order to minimize the time spent by specialists and improve the results confidence degree.

In the last two decades, several studies have demonstrated solutions for reservoir characterization problems from various perspectives using computational methods that simulate human intelligence (Nikravesh and Aminzadeh, 2001). Artificial Neural Network (ANN) is a computational approach that simulates the human nervous system activities and consists of an input layer, hidden layers and an output layer (Fausett, 1994). Each of these layers is composed of processing units, called neurons, which perform math functions aiming to solve problems, with ability to learn and generalize the information through samples. These units are interconnected through synaptic weights, storing the knowledge acquired by the network (Braga et al., 2000).

This study demonstrates the lithology classification from a well in South Provence Basin applying Artificial Neural Networks. This classification is based on mineralogical, petrographic and elastic data information obtained from Fournier and Borgomano (2009).

Method

The studied well is located within the South Provence Basin in the vicinity of La Ciotat and its data are available in Fournier and Borgomano (2009), who analyzed elastic, mineralogical and petrographic properties from carbonate and siliciclastic rocks. The work was based on core plugs and well logs analyses including gamma-ray, P- and S-wave sonic, density, and resistivity data. The ultrasonic P- and S-wave velocities were measured on dry samples as a function of effective pressure, and the porosity was derived from measured density. The rock minerals were quantitatively determined on whole-rock samples using XRD. Then, the study classified the samples based on seven petrographic classes, showed in Table 1.

Table 1: Petrographic classes proposed by Fournier and Borgomano (2009).

1	Limestone (grainstone)
2	Quartz-rich limestone (grainstone)
3	Quartz-rich limestone (wacke-packstone)
4	Limestone (wacke-packstone)
5	Slightly argillaceous quartz-rich limestone
6	Clean sandstone
7	Sandstone with carbonate matrix

Figure 1 illustrates the data properties distribution from La Ciotat-1 on classes along the depth.

The La Ciotat-1 dataset was evaluated using the tool called WEKA (Waikato Environment for Knowledge Analysis), which is part of the WEKA Machine Learning

Project of Waikato University. This tool offers several standard data mining tasks, including data preprocessing. The dataset were converted to standard ARFF and applied to the tool using the ID3 algorithm. This algorithm is based on decision trees technique and was used to calculate the information gain of each attribute. The information gain allows the group selection of attributes that best predicts the petrographic class target. Thus, it was identified the most relevant attributes to the lithological and petrographic classification. The ID3 application showed that “Calcite” is the first best attribute to classification, and after “S-wave velocity” and “Clay”. This allows us to verify that the best petrographic class factor differentiation is due to the presence, absence or variations of calcite in the sample, and both elastic and mineralogical properties have great importance for the correct data classification.

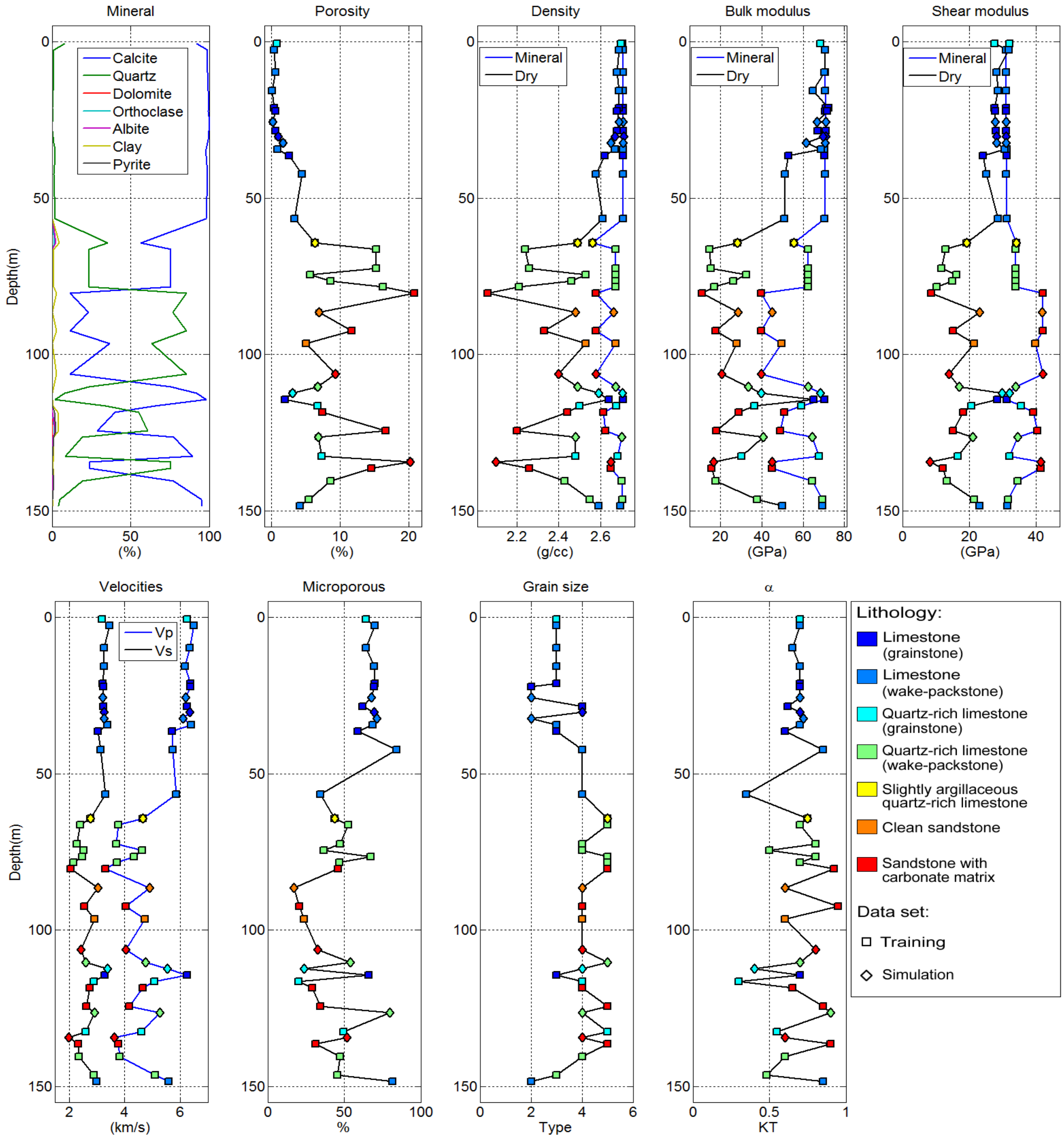

Figure 1: Dataset with laboratory and petrophysical measurements of porosity, compressional and shear velocity, quantitative mineralogy, aspect ratio and lithological interpretation of well La Ciotat-1.

Artificial Neural Networks

One of the characteristics of ANN is its capability of learning and internally organizes itself to be able to reproduce the presented patterns, observations or concepts. In addition, a neural network is capable of the following: (1) Generating correct responses when presented with partially incorrect or incomplete information; and (2) generalizing rules from the cases on which they are trained and apply these rules to new information (Garrett et al., 1992). These characteristics result to the information classification through learning. An artificial neural network learns by adjusting the weights between the neurons in response to the errors between the actual output values and the target output values.

The method used in this study, the backpropagation training algorithm, is the most frequently used neural network method. It is based on the heuristic of learning by error correction, where the network operates in a sequence of two steps: forward and backward (Azevedo et al., 2000). In the forward step, the input set is presented to ANN and the answer is propagated between the layers until the output layer, where the response is obtained and the error is calculated. After, the backward step changes the synaptic weights from the output layer to the input layer based on the error previously calculated. The structure of the backpropagation algorithm can be seen below:

Step 1: Randomly initialize the weights.

Step 2: Feed the training sample.

Step 3: Propagate the inputs forward; compute the net input and output of each unit in the hidden and output layers.

Step 4: Back propagate the error to the hidden layer.

Step 5: Update weights and biases to reflect the propagated errors. Training and learning functions are mathematical procedures used to automatically adjust the network's weights and biases.

Step 6: Terminating condition.

The backpropagation-ANN used in this study (Figure 2) consisted of three layers. The input layer, where the neurons were elements of a feature vector (mineralogical, petrographic and elastic properties, according to Figure 1). The second layer is the internal or hidden layer, which contains 400 neurons. The third layer is the output layer that presents the output data, in this case, corresponding to the petrographic class estimated. Each neuron in the hidden layer is connected to neurons in both the input and output layers by weighted connections (Atkinson and Tatnall, 1997).

Results

The dataset was divided into two parts called training and simulation set. The training set is used to develop the network, where the desired output in the training set is used to help the network adjust the weights between neurons. After the ANN learns the information, the simulation set is applied to the ANN.

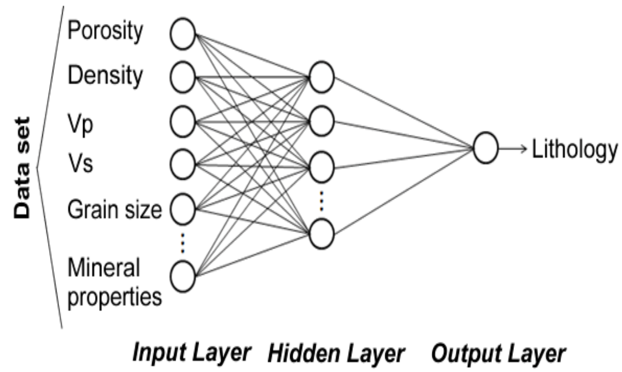

Figure 2: Architecture of a Backpropagation-ANN with 20 neurons in the input layer, 400 neurons in the hidden layer and 1 neuron in the output layer.

The ANN input parameter was training on simulation dataset for expected lithological classes, as shown in Figure 1. In the training, ANN output is an equivalence relation between lithology and input samples. This output is compared with the set of expected lithology, allowing checking the network error and analyzing the efficiency of the configured network.

During the training phase, a variation of the backpropagation algorithm called “Gradient Descent With Adaptive Learning Rate” was used, and showed the best success rates during training when compared to other five backpropagation variations. The transfer function used in the input layer was “Tan-Sigmoid Function” and in the output layer was “Linear Function”. The verification of the performance of ANN learning is given at each epoch by applying the function “Mean Squared Error” (MSE), taking as limiting the maximum epochs (10^5) and error rate goal (10^{-3}). Stabilization of ANN learning (Figure 3a) occurred at around 10^4 epochs, verifying a slow minimization error and a better synaptic weights calibration of the RNA until it reached the target error rate at the 74720 epoch.

The simulation was performed after ANN training with the same set used for training. As seen in Figure 3b, the simulation resulted had a high success rate because the ANN already knows these data. Then, the ANN predicted the samples lithology according to trained dataset, as expected. The ANN accuracy is given by A (%) = 100% - E (%), where E is the mean error calculated.

Figure 3c displays the results using the simulation dataset, identified in Figure 1. The lithology recognition was best adapted to class 5 since this class has a low frequency in dataset. Then, the pattern 5 is repeated in both sets to form training and simulation dataset.

For other lithology, the class 7 showed the highest error rate while the other classes had approximately the same error rate. The ANN accuracy was 84.52%, which demonstrates a good equivalence between the petrographic classes descriptions from Fournier and Borgomano (2009) and interpretation performed by the neural network.

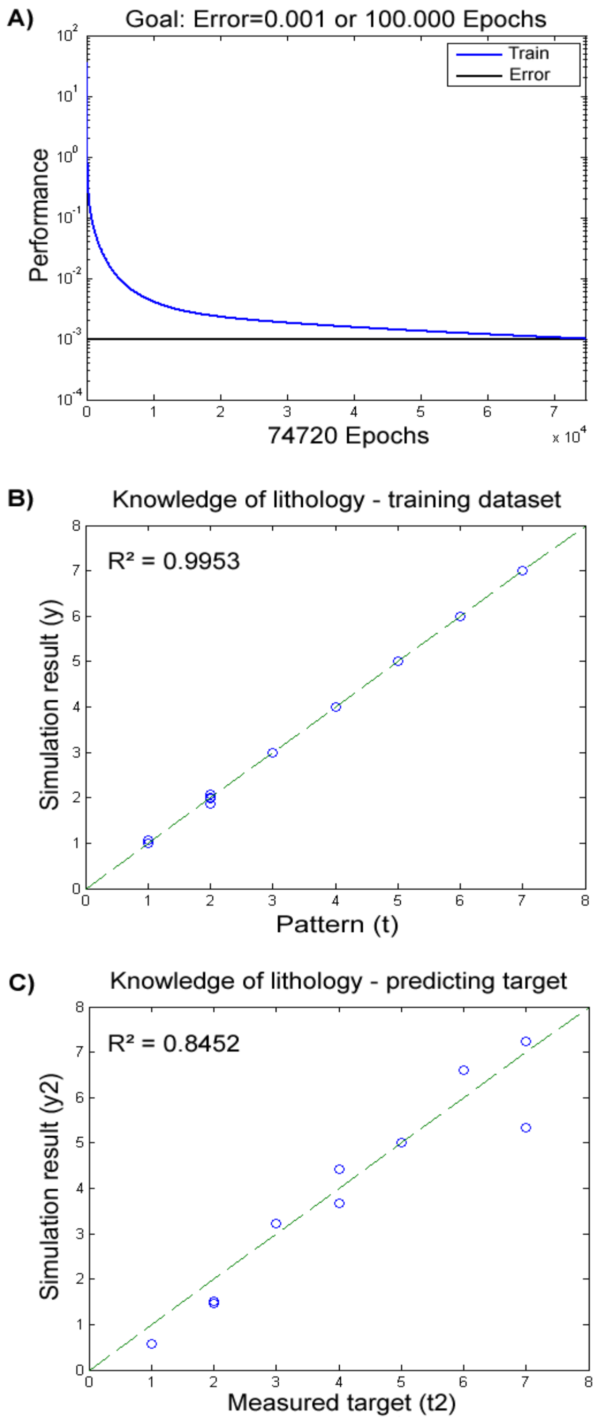

Figure 3: (A) ANN learning evolution. (B) Result for training dataset input. (C) Result for simulation dataset input.

Conclusions

ANN techniques have been proven as a useful tool for predicting, classifying and approximating functions in various fields. The proposed method improves the performance of the geology expert to find quickly the lithology of a given well, simplifying many studies and analyzes. The results obtained shown that the ANN application were efficient to predict petrographic classes.

The great accuracy in the simulation leads to employ ANN method for prediction intervals in the well that has not sampled or adjacent wells, respecting the necessary representativeness of the data used in the training set.

The WEKA tool allowed evaluation of the dataset and relevance of each attribute, showing the importance of use a single set with petrographic, mineralogical and elastic properties instead of use tree isolated sets of properties.

Finally, the ANN application can be an auxiliary tool for lithological identification based on well data.

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References

Atkinson, P.M. and A.R. Tatnall, 1997, Introduction: Neural networks in remote sensing: Int. J. Remote Sensing 18, 699-709.

Azevedo, F. M., L. M. Brasil and R. C. Oliveira, 2000, Redes neurais com aplicações em controle e em sistemas especialistas: Florianópolis, Visual Books.

Braga, A., T. B. Ludermir, and A. C. Carvalho, 2000, Redes Neurais Artificiais: Rio de Janeiro, LTC.

Demuth, H., and M. Beale, 2002, Neural Network Toolbox User's Guide: The MathWorks.

Fausett, L. V., 1994, Fundamentals of neural networks: Architecture, algorithms, and applications: Englewood Cliffs, N.J., Prentice Hall.

Flexa, R. T., A. Andrade, and A. Carrasquilla, 2004, Identificação de liotipos nos perfis de poço do Campo de Namorado (Bacia de Campos, Brasil) e do Lago Maracaibo (Venezuela) aplicando estatística multivariada: Revista Brasileira de Geociências, 34, 571-578.

Fournier, F., and J. Borgomano, 2009, Critical porosity and elastic properties of microporous mixed carbonate-siliciclastic rocks: Geophysics.

Garret, J. H. Jr., J. Ghaboussi, X. Xu, and S. Ranjithan, 1992, Neural networks and their application to civil engineering: Expert systems in civil engineering – knowledge representation, R. H. Allen, ed., Expert Systems Committee of ASCE.

Haykin, S., 2009, Neural Networks: A Comprehensive Foundation, Prentice Hall.

Nikravesh, M., and F. Aminzadeh, 2001, Past, present and future intelligent reservoir characterization trends (editors' view points): Journal of Petroleum Science and Engineering, 31, pp. 67-79.

Schmitt, P., 2009, Redes Neurais Artificiais aplicadas na classificação litológica das formações Palermo e Rio Bonito na jazida Leão-RS, com base em perfis geofísicos: M.Sc. thesis, Universidade do Vale do Rio dos Sinos.