Back Propagation and Hidden Weight Optimization Algorithms Neural Network for Permeability Estimation from Well-Logs Data in Shaly Sandstone Petroleum Reservoirs: Application to Algerian Sahara

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Abstract

In this paper, we present an inexpensive approach based on a multilayer neural network, using two different algorithms to estimate permeability in petroleum reservoirs from well-logs data. In a supervised learning, the Back propagation (BP) and Hidden weight optimization (HWO) are tested in order to determine the best algorithm for better permeability predictions. The application to real data has been realized in the Algerian Sahara, exploiting data of several petrophysical parameters of Triassic reservoirs of two wells. The data of the first well are used to train the neural network machine as a pilot well, while the second well data were used for generalization to predict permeability. The obtained results are compared with permeability from core data.

Keywords

Shaly sandstone reservoir • Neural network
Permeability • Training algorithm

1 Introduction

Permeability estimation is a key parameter in reservoir engineering; it depends on its effective porosity and the type of clay or cementing material between sand grains [1].

Routinely, this parameter is obtained through core analysis, well testing, or by correlation to other more easily measured rock properties such as porosity from several empirical petrophysical models. The empirical models may not be applicable in regions with different depositional environments without making adjustments in the model, mainly, in shaly sandstone reservoirs [2].

Artificial Neural Network (ANN) is becoming very popular in geosciences and in petroleum reservoirs characterization from well-logs data [3].

The objective of this paper is to improve permeability predictions in shaly sandstones reservoirs through two kinds of neural networks techniques, which are the learning algorithms Back propagation (BP) and Hidden weight optimization (HWO). We have applied the proposed techniques to Triassic reservoirs of two wells located in the Algerian Sahara, where several petrophysical data are used. Data of the first well are used to train the neural network machine, and the second well data for permeability prediction. Results will be compared with permeability from core data.

2 Reservoir and Data Description

The presence of shale in sandy reservoirs can provide erroneous results of permeability, and Triassic reservoirs are generally shaly sandstone (Fig. 1a). The raw well-logs data of two wells located in the Algerian Sahara have been exploited. The raw well-logs data are: Natural gamma ray (GR), bulk density (RHOB), neutron porosity (NPHI), photoelectric absorption factor (PEF), and sonic transit time (DT). Core permeability data are also available for the two wells. Figure 1 shows the composite log of raw logs data of one borehole; Well-A.

3 Permeability Estimation Problem and Neural Network

The permeability estimation is a hard task; the presence of shale in sandy reservoirs is the main ambiguity, where all the relationships that provide permeability cannot be applied

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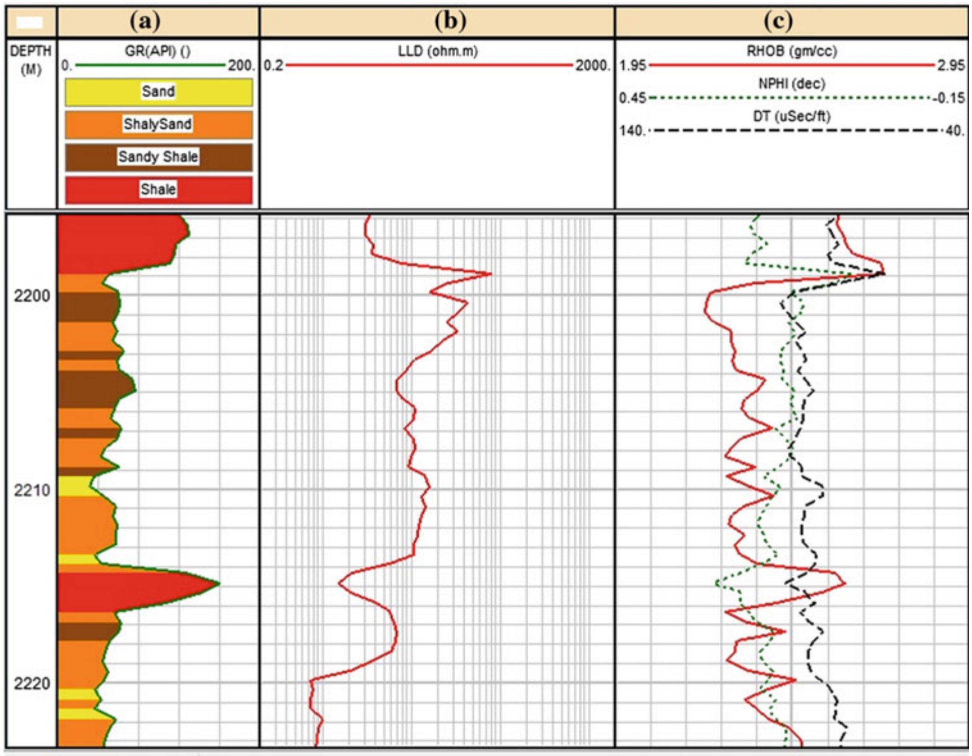

Fig. 1 Petrophysical parameters recordings of Triassic reservoir; Well-A

Fig. 2 MLP neural network architecture

[4, 5]. An artificial neural network can be applied in this case to resolve this ambiguity [6].

In this paper, a Multilayer Perceptron (MLP) has been implemented. It is constituted by three layers where the input layer has four neurons corresponding to gamma ray (GR), Transit travel time (DT), bulk density (RHOB) and neutron porosity (NPHI). The output layer has one neuron corresponding to permeability and one hidden layer (Fig. 2).

3.1 Back Propagation Algorithm

The first training algorithm is the back propagation, which is based on the minimization of the root mean square between the calculated and the desired output. More detailed explanation of the BP algorithm can be found by Aqil et al. [7]. Obtained results (Perm_BP) using this kind of learning algorithms are shown in Fig. 3.

3.2 Hidden Weight Optimization Algorithm

The hidden weight optimization (HWO) training algorithm alternately solves linear equations for output weights and reduces a separate hidden layer error function with respect to hidden layer weights [8].

4 Results Interpretation

The obtained results (Fig. 3b, d) clearly show that the HWO algorithm predicts permeability in a better way, compared to the BP algorithm. Thus, the HWO results are very close to

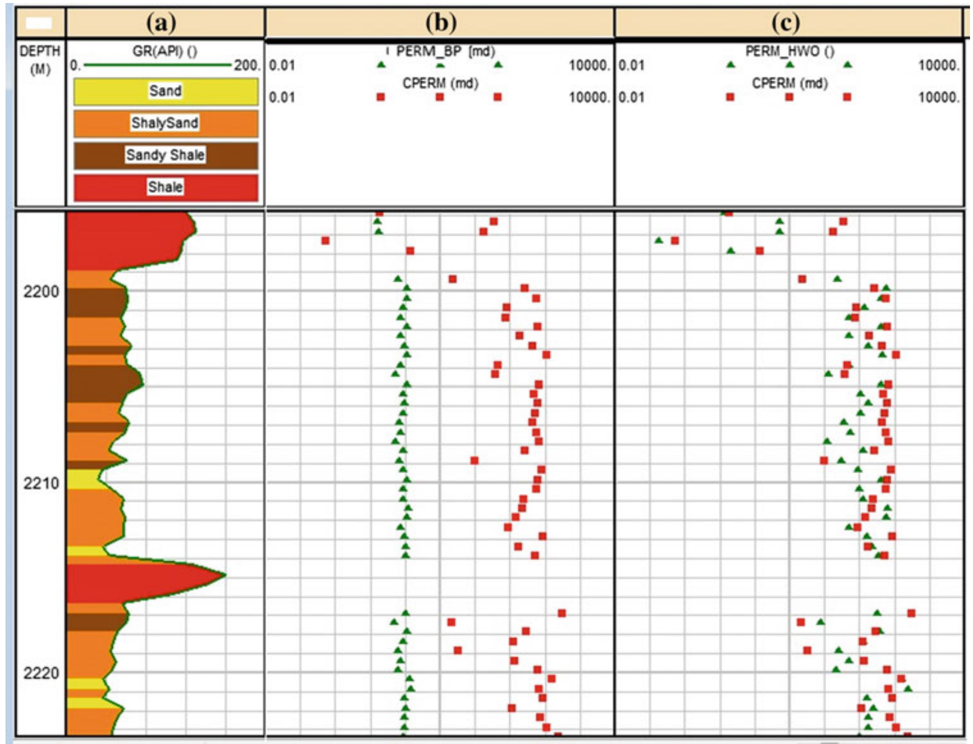

Fig. 3 Permeability predicted from BP and HWO algorithm of Triassic reservoir, Well-B

core permeability (CPERM). Consequently, the HWO algorithm can be used to train the multi-layer neural network rather the BP algorithm for a better permeability estimation, to enhance the petroleum reservoir characterization.

5 Conclusions

Permeability is a key parameter in reservoir characterization, empirical models cannot be applied in shaly sandstone reservoirs, because they suppose that the reservoir is "clean". The artificial neural network can be greatly used to predict permeability from well-logs data; the Hidden Weight Optimization training algorithm is highly recommended compared to the back propagation.

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