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Levenberg-Marquardt algorithm neural network for clay volume estimation from well-log data in an unconventional tight sand gas reservoir of Ahnet basin (Algerian Sahara)

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ABSTRACT The main goal of this paper is to show the contribution of artificial intelligence, namely a neural network, in reservoir characterisation to predict the clay volume in an unconventional tight sand gas reservoir. Clay volume is usually estimated using the natural gamma ray log, which can give bad results if non-clayey radioactive minerals are present in the reservoir. Our purpose is to implement a multilayer perceptron neural network machine to predict the clay volume using the conventional well-log data as an input and the measured mineralogical component, as desired output with a Levenberg-Marquardt algorithm. Application to two Ordovician reservoir intervals of a borehole located in the Ahnet basin in the Algerian Sahara shows the contribution and the efficacy of the implemented neural network machine in unconventional tight sand reservoirs characterisation.

Key words: clay volume, tight sand, well-logs, MLP, Levenberg-Marquardt algorithm, Algerian Sahara.

1. Introduction

With the increase of global demands for oil and gas, unconventional gas resources offer significant gas production and growth potential in the coming years. However, the cost-effective production of tight sand gas is very challenging as it exists in reservoirs with low porosity and permeability. In addition, the complexity of the tight sand gas is given by its heterogeneity in vertical and horizontal directions and the presence of clay minerals, such as illite, kaolinite, and micas in pores. Consequently, tight sand formation evaluation presents a difficult problem where the determination of petrophysical properties solely using conventional logs is very complicated (Hamada, 2009).

The clay volume is very useful in unconventional reservoirs characterisation. It can be used to estimate porosity, to locate the sweet spots (Aliouane *et al.*, 2013), to make completion decision and for the hydraulic fracturing.

Using conventional logs data alone to estimate clay volume suffers from uncertainties (Moore *et al.*, 2016). However, the interpretation can be enhanced by core data or mineralogical well-logs such as neutron spectral mineralogical recordings (Everett, 2014). In the case these latter are not available, a neural network can be proposed as an alternative, which is very popular in geosciences and in petroleum reservoirs characterisation (Aliouane *et al.*, 2012, 2018).

In this paper, we propose the use of artificial intelligence by implementing the multilayer perceptron neural network machine with the Levenberg-Marquardt algorithm, able to predict the clay volume. The network crossed the Ordovician tight sand gas from the Ahnet basin located in the Algerian Sahara.

A set of well-log data from one well are exploited with two Ordovician intervals (I and II), where the first is used for training as the supervised learning phase and the second interval for the generalisation phase.

2. Geological setting and Ordovician reservoir description

The Ahnet basin is one of the gas-producing Palaeozoic basins running along the northern flank of the African Craton. The first well to penetrate the stratigraphic column of the basin was realised the 1950s. Eploration was focused on the Ahnet basin, where several gas accumulations were discovered in various reservoir formations of several ages like the Ordovician Lower Devonian and Tournaisian - Strunian (Boukhallat and Rahmani, 2005).

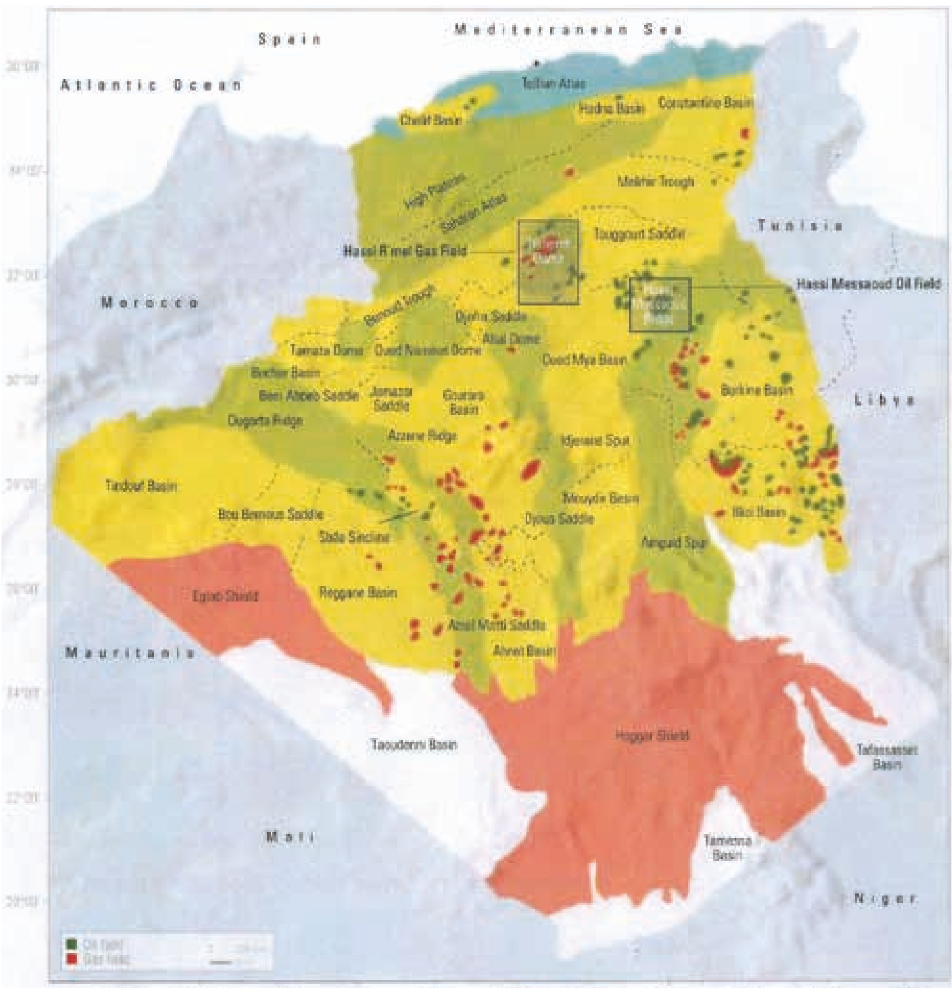

Fig. 1 - Location of the Ahnet basin in the Algerian Sahara (Sonatrach and Schlumberger, 2007).

The Ahnet basin is located in the western province of the Algerian petroleum Sahara platform, in the central-west of southern Algeria (Fig. 1). This province has garnered the interest of oil companies, which are engaging in more intense exploration. This follows on from very positive results for the whole province over the last few years where significant gas potential is associated with both conventional and unconventional traps, and particularly targets associated with tight reservoirs (Sonatrach and Schlumberger, 2007).

2.1. Stratigraphy of Ordovician interval

Van Dijk and Guney (2019) have described the stratigraphy of the Palaeozoic of the Ahnet basin in detail (Fig. 2). As is known, the objective of this study concerns the Ordovician interval, thus, only the stratigraphy of the Ordovician interval has been presented below (Ait Kaci and Moussine-Pouchkine, 1987; Zielìnski, 2011; Van Dijk and Guney, 2019):

- **Argiles D’El Gassi**: this formation is present only in part of the basin. It is absent in the southern part of the basin probably due to non-sedimentation. The maximum thickness of 207 m was penetrated. The lithology consists of shales, which are black, grey-dark grey, silty, hard, micaceous, and slightly pyritic with some intercalation of white, grey coloured sandstones;
- **Gres D’El Atchane**: this formation consists of quartzic and quartzites sandstones, which are dark grey coloured, very fine grained, glauconitic, and show intercalations of shales and black silty-siltstones. This series is characterised by the presence of strong radioactive peaks in the gamma ray (GR);
- **Quartzites De Hamra**: the Hamra quartzites have been penetrated by many wells in the basin. The well log response is characterised by low radioactivity and transit time values. The formation consists of a very homogenous quartzitic sandstone and quartzites body with some interlayered shale/claystone. The sandstones are grey-white coloured and bioturbated (tigillites), very fine to medium grained, occasionally coarse grained, subangular to subrounded, moderately sorted, with siliceous cement and grain contacts (quartzitic), hard, and showing abundant very fine to fine loose quartz grains, and frequent pyritic elements;
- **Argiles De Tiferouine**: this formation is present in almost all the basin except for the northern part where it was eroded by the Taconian unconformity. This series has a maximum thickness of around 90 m (AFF-1 well) and is conformably overlain by the Quartzites De Hamra. The formation mainly consists of shales, grey-black coloured, silty, micaceous, hard and very well-defined in GR log response. The lower boundary with Quartzites De Hamra is very clear. The formation has fair organic material content and can be considered as secondary source rock in the Ahnet basin. These shales also represent the cap rock and lateral seal for the Quartzites De Hamra;
- **Argiles D’Azel**: this shaly formation is present in the whole basin apart from some local area where it was eroded during the Taconian phase. The formation overlies the Argiles De Tiferouine formation. The log character is represented by GR and sonic values that are relatively lower than the underlying Argiles De Tiferouine formation. The lithology consists of shales, which are dark grey, grey-black, hard, silty, micaceous, sometimes carbonatic with intercalations of sandstones, which is fine to very fine grained, and siliceous to quartzitic;
- **Gres D’Oued Saret**: this formation is present almost all over the basin, but in certain areas it is more or less intensely affected by the Taconian erosion. The maximum thickness of the formation is assumed to be around 150 m. The lithology is represented by alternations of shale and sandstones. Shales are black, silty, micaceous, slightly carbonaceous with traces of pyrite. Sandstones are characterised as grey to light grey coloured, fine grained and quartzitic. The

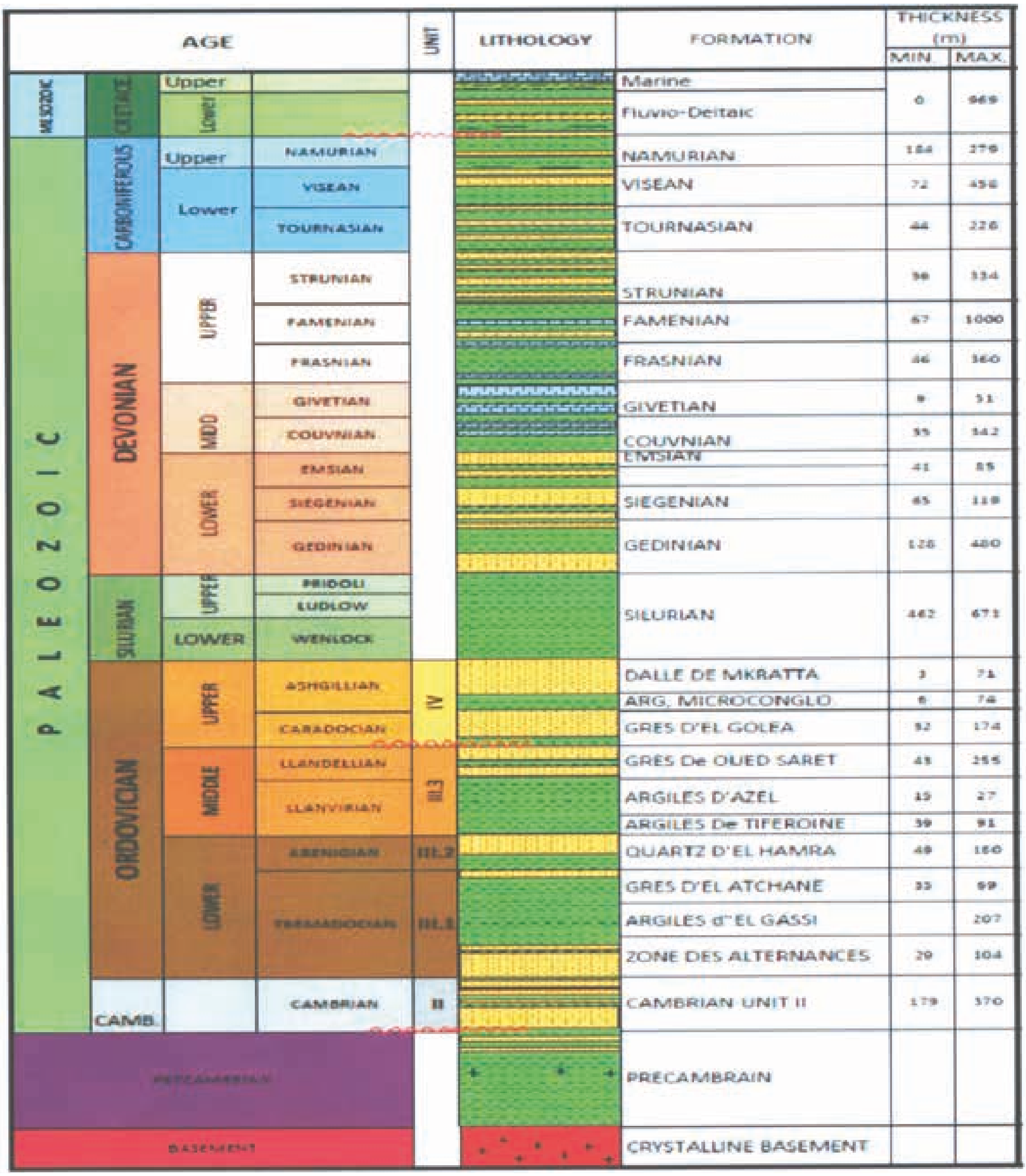

Fig. 2 - Paleozoic stratigraphy of the Ahnet basin (Van Dijk and Guney, 2019).

lower boundary with the Argiles D'Azel is well- defined with the GR log response. Due to high argillaceous content, this formation is not considered as a reservoir in the basin;

- Gres D'El Golea: this formation is present in most of the basin except some locations due to non-deposition. The maximum thickness is around 174 m. The lithology consists of sandstones, which are grey and dark grey coloured, fine grained, hard, siliceous to quartzitic, sometimes carbonatic, with shale layers, which are black, silty, micaceous, hard, and with traces of pyrite. The depositional environment is considered as marginal marine;

- Argiles Microconglomeratiques: this formation is common in the basin except for some locations of the basin due to non-deposition. The maximum thickness is around 74 m. This formation is represented by black shales that are hard, micaceous, pyritic, with quartz grains, angular and sub-angular, and some intercalations of sandstones, which are grey, fine grained, ranging from siliceous to quarzitic. The upper boundary and lower boundaries are clearly marked by log responses;

- Dalle De M'Kratta Sandstone: this formation is present in almost the whole basin. The maximum thickness is around 75 m. The series represents the top of the Ordovician succession and is characterised by arenaceous and quartzitic facies. The sandstones are grey, white coloured, fine to medium and sometimes coarse grained, subrounded, poorly sorted, hard, and show intercalations of shales, which are dark grey to black coloured, silty and micaceous. The depositional environment is considered as a marginal marine environment.

3. Ordovician tight sand gas description and data analysis

All the Palaeozoic sandstones can be regarded as potential reservoir rocks, and the main gas-producing levels are the Ordovician, Gedinnian, Siegenian, Emsian and Tournaisian (Sonatrach and Schlumberger, 2007).

The Ordovician sandstones consist of low-porosity, low-permeability tight gas reservoirs. The porosity ranges from 3% to 12% and permeability is much less than 0.1 mD with high capillary pressure greater than 1000 psi. These apparent low-quality reservoir properties are essentially related to the depositional conditions and the diagenetic alterations (mechanical and chemical compaction and quartz overgrowths cement (Mokhtari, 2003).

The El Goléa sandstones are of shallow marine fluvio-glacial type. The grains are fine to coarse and well-cemented. This unit is marked by major variations in facies and thickness. Porosities vary from 5% to 14%.

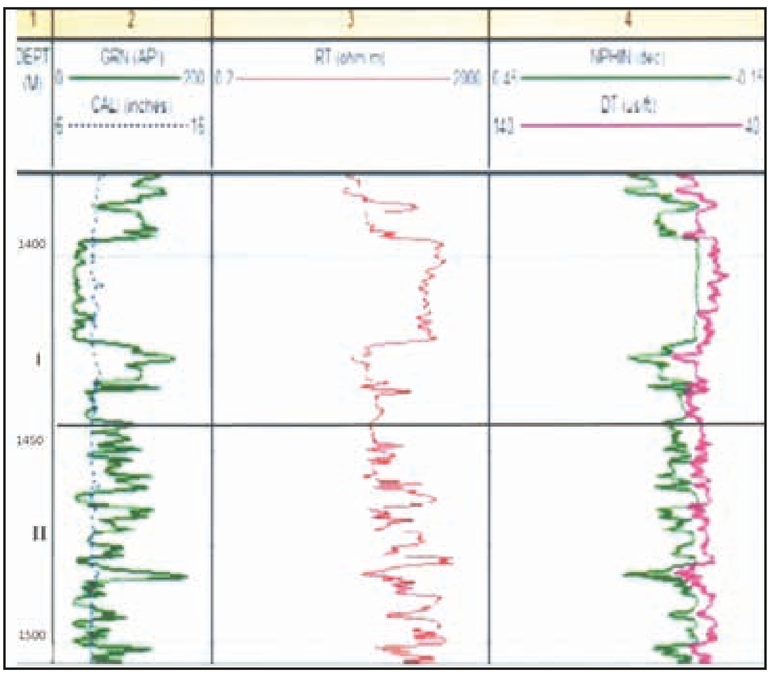

Fig. 3 - Petrophysical recordings crossing the Ordovician tight sand gas (interval I and II) of a well-A from the Ahnet basin (Algerian Sahara).

The Hamra quartzites are of a shallower marine fluviatile type, very fine to coarse with porosities of 3% to 8%. Fracturing is the key factor controlling Ordovician reservoir qualities.

A set of petrophysical recordings, sensitive to clay, of two intervals (I and II) crossing the Ordovician tight sand gas reservoir of one well (well-A), located in the Ahnet basin, have been exploited for clay volume estimation (Fig. 3).

These are: total natural GR, deep resistivity (RT), neutron porosity (NPHI), and transit time of P wave (DT).

The tight character is shown with low NPHI logs and low DT. This kind of reservoir can be radioactive where these radiations are not necessarily related to clay content (Ma *et al.*, 2014). In addition, due to shallow invasion in many tight gas sands, NPHI low values can be a very good indicator of gas formation.

4. Clay volume estimation by conventional methods

The traditional method is to calculate effective porosity corrected from clay volume in tight gas sandstones. Through diagenesis, the primary porosity may be reduced in the primary pore system by quartz, and secondary porosity may be produced in feldspars or clays (Moore *et al.*, 2016).

Total porosity from log interpretations in tight gas sandstones can appear to be high due to the effect of clay on the NPHI and sonic velocity measurements. In many areas, washouts and rugose boreholes resulting from over or under pressure can affect the log readings and make interpretation difficult, especially for density porosity (Holditch, 2006; Moore *et al.*, 2016).

Eslinger and Pevear (1985) established a model showing the different fractions of solids and fluids as well as clay volume (or shale volume). Fig. 4 summarises the general relationships between log measurements, core measurements, pore types, clay and fluid types.

When clay content is low, the total porosity calculated from logs is usually higher than measured core porosity and the effective porosity calculated from logs can be a little higher than measured core porosity. When the clay content (feldspar, illite, chlorite and swelling clays) is high, the total porosity calculated from logs tends to be much higher than the measured core porosity and the effective porosity calculated from logs may be higher than the measured core porosity (Moore *et al.*, 20016).

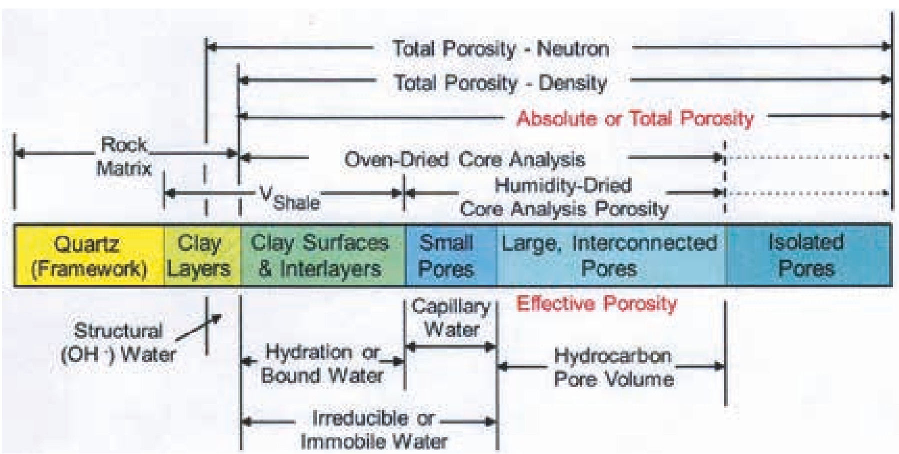

Fig. 4 - Porosity relationships among log measurements, core, clay and fluids (Eslinger and Pevear, 1985).

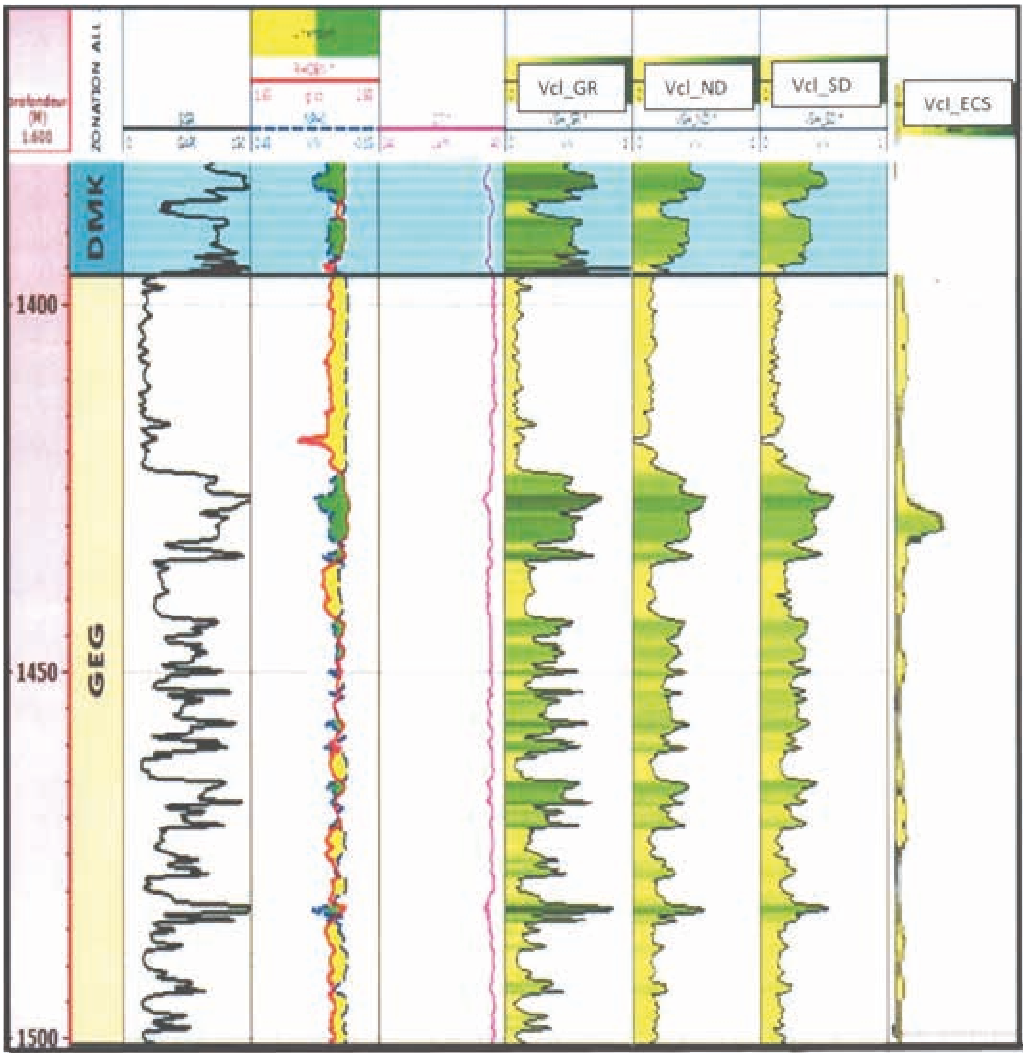

Fig. 5 - Vcl estimation by conventional methods and mineralogical well-log in Ordovician tight sand gas of the Ahnet basin (Algeria).

Usually, the clay volume is computed from GR, porosity logs, and a combination of logs (Moore *et al.*, 2016). Many analysts use density porosity alone calculated from the bulk density with a variable grain matrix to correct for mineral composition (pyrites and clay minerals) and a fluid density lower than 1 to compensate for incomplete flushing in the measurement zone.

Using conventional log data alone to estimate clay volume (Vcl), suffers from the uncertainties. To overcome this, Vcl core or mineralogical log-data can give the best value of Vcl. When mineralogical logs are available, such as spectral mineralogical neutron log, better Vcl can be acquired providing the percentage of aluminium (Al), which is the common element of all clay minerals (Everett, 2014). This is the case of ECS (Elementary Capture Spectroscopy) tool, which can estimate Vcl (Vcl_ECS) from Al, Ca, Si, and Fe (Everett, 2014).

In this case of Ordovician tight sand gas, conventional methods from well-logs, such as total GR, the combination of neutron-density and the combination of sonic-density, are used to compute Vcls, respectively, Vcl_GR, Vcl_ND, and Vcl_SD (Fig. 5).

5. Clay volume prediction by artificial neural network

When Vcl core and mineralogical well-logs are not available, we propose using artificial intelligence, such as an artificial neural network, which simply requires a kind of structure to be trained.

A neural network is inspired by human biology; each neural network is composed of a set of neurons. Each neuron is connected with some neurons in the network. Each neuron receives a signal from other neurons and transfers to outside using a transfer function. The Multilayer Perceptron (MLP) is a feedforward artificial neural network. The MLP is composed of a set of layers; the first one is called the input layer, while the last one is called the output layer. The set of layers between these two layers are called hidden layers. It has been shown that one hidden layer is enough for better approximations and the neural network will react better (Hagan and Menhaj, 2014). The MLP uses the supervised learning mode where the couple input-desired output is known.

Many training algorithms have been suggested in the literature, and the back propagation is one of the classical algorithms. Traditional back propagation algorithms have some drawbacks such as getting stuck in the local minimum and the slow speed of convergence. The Levenberg-Marquardt (LM) training algorithm is used to resolve these ambiguities.

5.1. The Levenberg-Marquardt training algorithm

The LM training algorithm is an approximation of Newton's method for artificial neural networks. The LM technique is known to be the best algorithm for optimisation problems applied to artificial neural networks.

When the performance function has the form of a sum of squares (typical in training feedforward networks), then the Hessian matrix can be approximated as (Lampton, 1997):

$$H = J * J^T \tag{1}$$

The gradient can be computed as:

$$g = J^T * e \tag{2}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases.

The Jacobian matrix determination is less computationally expensive than the Hessian matrix; e is a vector of network errors. Then, the update can be adjusted as:

$$X_{k+1} = X_k - [J^T * J + \mu * I]^{-1} * J^T * e \tag{3}$$

where * indicates the multiplication.

The parameter μ is a scalar controlling the behaviour of the algorithm. For $\mu = 0$, the algorithm follows Newton's method, using the approximate Hessian matrix. When μ is high, this becomes gradient descent with a small step size.

In practice, this algorithm, in particular in the case of neural networks, can converge with much less iteration. However, each iteration requires more calculations, in particular for the inversion of the matrix, and, therefore, its use is limited to cases where the number of parameters to optimise is not very high. Indeed, the number of operations required for a matrix inversion is proportional to the size of the matrix, and also to the size of the vector (Hagan and Menhaj, 1994).

5.2. The Multilayer Perceptron

An MLP neural network machine with a multilayer model has been implemented to calculate the clay volume using the whole well-log data of two intervals I and II (Fig. 3) of one part of the Ordovician tight reservoir of one well located in the Algerian Sahara (Well-A). Well-log data of the first interval (I) are used for learning and the second interval (II) for generalisation with a supervised learning using an LM algorithm.

The input layer is constituted by 04 neurons corresponding to 04 conventional well-log data: GR, NPHI, RT, and sonic DT. The output layer presents only one neuron corresponding to the Vcl (Vcl_ANN). The desired output is represented by volume computed by spectral mineralogical by ECS (Vcl_ECS) data. ECS tools can be used to determine the percentage of minerals in the rock composition so that porosity and clay volume can be calculated more accurately (Moore *et al.*, 2016). Fig. 6 shows the MLP structure for Vcl prediction.

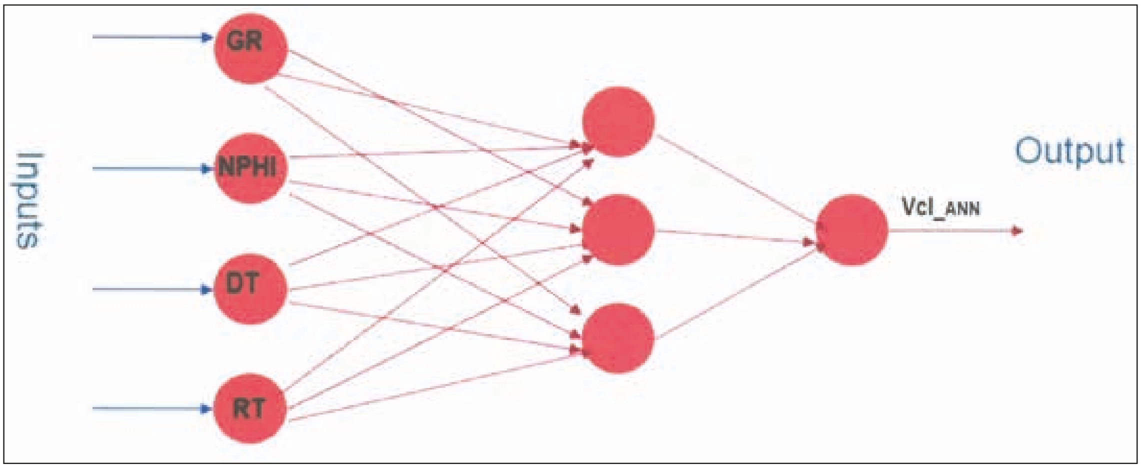

Fig. 6 - The MLP structure for Vcl prediction in the Ordovician tight sand gas of the Ahnet basin (Algeria).

6. Results analysis

Fig. 7 shows the Vcl computed from conventional well-log data: from GR, from neutron-density, from density-sonic, from the spectral neutron well-logs (Vcl_ECS), and neural network (Vcl_ANN**).** Obtained results show that this intelligent technique can be used to predict Vcl compared with the Vcl from ECS log (Fig. 7).

As is shown in Fig. 7, the Vcl obtained by the neural network is much closer to Vcl predicted from the spectral mineralogical log (ECS), mainly in the interval (430-435 m).

We can note that in the interval (425-435 m), the Vcl computed by conventional methods such as by GR and combinations of porosities, is estimated higher, probably due to the presence

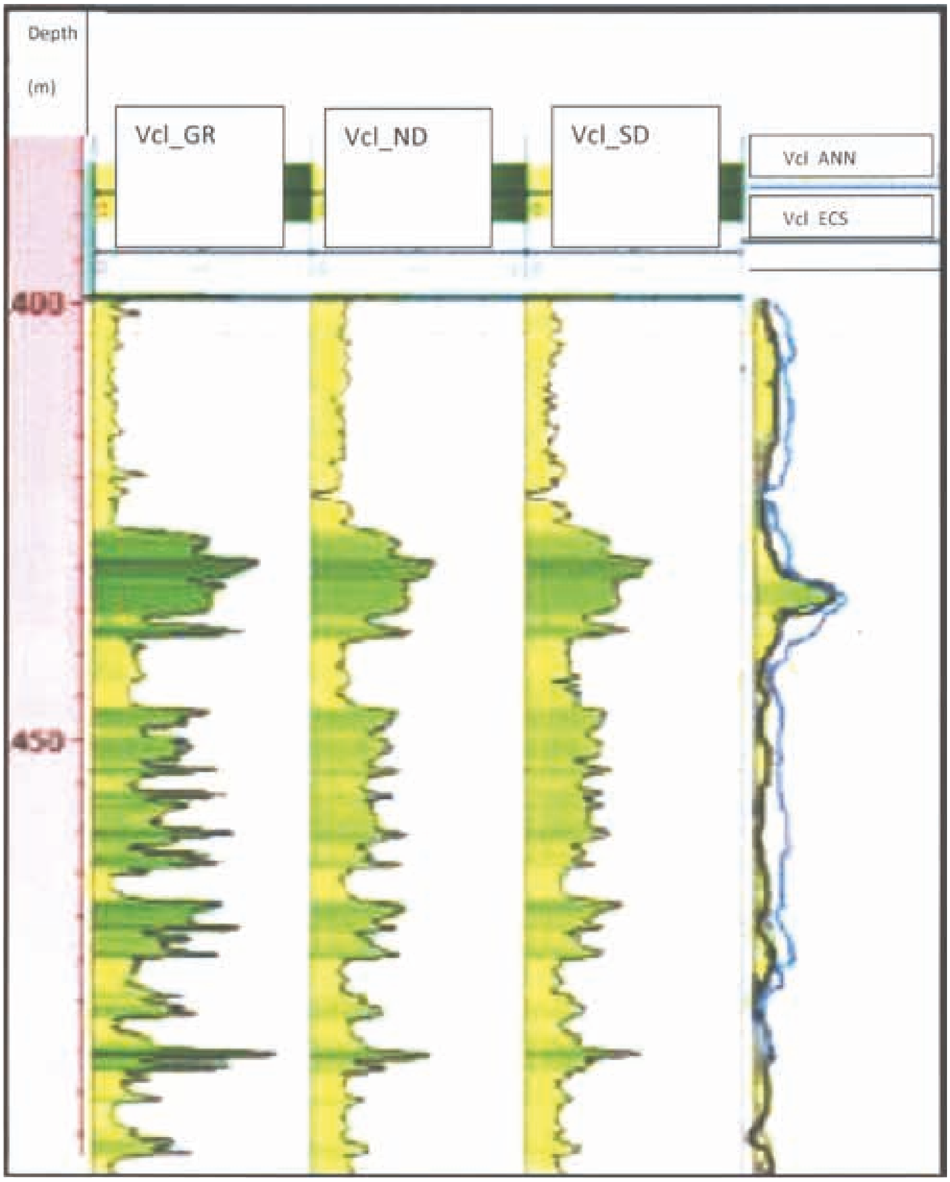

Fig. 7 - Vcl estimation from conventional methods and MLP neural network crossing the Ordovician tight sand gas from the Ahnet basin (Algeria).

of non-clayey radioactive mineral. In this case, in the Ordovician tight sand gas reservoir from the Ahnet basin, the MLP with LM has solved this problem and the Vcl has been estimated correctly compared with the estimated results by spectral mineralogical logs.

7. Conclusions

In this study, an MLP neural network with LM algorithm has been implemented for Vcl prediction to enhance tight sand gas reservoir characterisation. Indeed, the Vcl value is mandatory to deduce effective porosity, to identify the sweet spots and for hydraulic fracturing, and for this reason, this intelligent method can give better results than conventional methods. Advanced well-log data such as spectral mineralogical recordings, when available, provide better Vcl estimation. However, when advanced well-logs are not available, a neural network can provide good results.

In the Ahnet basin, Vcl obtained from the neural network with LM has given a good result.

By implementing our method, we have demonstrated that it is possible to provide an accurate petrophysical interpretation within a short time in order to enhance unconventional tight sand gas reservoir characterisation.

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