A Bayesian approach to identify clay minerals from petrophysical logs in Gonbadly Gas field, northeastern Iran

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Received: 17 April 2013 / Accepted: 5 June 2013 / Published online: 8 June 2013

Abstract

More often clay matrix is the major factor to reduce the porosity and permeability in sandstone facies. Consequently determination of clay minerals is of prime importance in reservoir quality assessment. The present study aims to identify four different types of clay mineral namely kaolinite, illite/cholorite, halloysite, and montmorilonite from Petrophysical Logs (PLs) using Cation Exchange Capacity (CEC) parameter. In this regard, PLs related to two wells of Shurijeh Formation (Early cretaceous) in Gonbadly gas field, Northeast of Iran, were used. Utilizing measured CEC data and proper PLs, the CEC log were generated by employing MLP neural network. Relying on this fact that clay minerals can be classified based on their CEC value, the formation under study were divided into five zones by implementing four cut offs on CEC log. Finally, Bayesian classifier was applied on PLs to identify the desired zones. According to the obtained results, the method proposed in this study is able to identify desired clay types with average accuracy of 68.5% in single well analysis step and 65.75% for generalization step.

Keywords: Clay minerals, Cation Exchange Capacity (CEC), MLP neural network, Bayesian classifier, Gonbadly oil field, Iran.

1- Introduction

Reservoir characterization is a considerable process whose main objective is identification and assessment of reservoir productive zones and its heterogeneities. Heterogeneities occur at various scales because of variability in lithology, pore fluids, clay content, porosity, pressure and temperature (Avseth *et al.*, 2005). One of the main items in reservoir characterization is identifying clay minerals (Josh *et al.*, 2012). Today, various applications for clay minerals has been found such as ceramics and building materials, paper industries, oil drilling, foundry moulds, pharmaceuticals, and as adsorbents, catalysts or catalyst supports, ion exchangers, and decolorizing agents (Zhang *et al.*, 2010). There are wide verity of methods for clay mineral identification such as X-Ray-Diffraction

(XRD), Scanning Electron Microscope (SEM) and Cation Capacity Exchange (CEC). In this regard, CEC as an effective method has not received much attention yet and most studies related to its performance are limited to agricultural engineering. Nevertheless, CEC is impressively employed in reservoir water saturation estimation studies.

Hill and Milburn (1955 and 1979) were the pioneers in this endeavor that showed the excess conductivity caused by clay minerals is related to cation capacity exchange. Furthermore researches in this area have led to providing a group of formula for estimating of water saturation, called CEC models. These models consider the electrical conductivity of clay minerals (Worthington, 1985), such as the Waxman and Smits and dual water models (Clavier *et al.*, 1984). The identification of the clay minerals can take the form of multiple classification process and their advantages. Different classification methods can be easily trained with known examples of previous patterns and put to effective use of solving unknown or untrained instances of the problem.

The present study aims to identify different clay minerals utilizing experimental measurements of CEC and Petrophysical Logs (PLs) from Shurijeh reservoir formation (Early cretaceous) in Gonbadly gas field, north-east Iran. For this purpose available PLs (i.e. LLD, RHOB, NPHI, PEF, CAL, DT and GR) related to two wells were used to produce CEC log and then the formation under study was categorized into five classes according to CEC values. Afterwards, the Bayesian classifier was employed to classify each depth of reservoir in five defined classes.

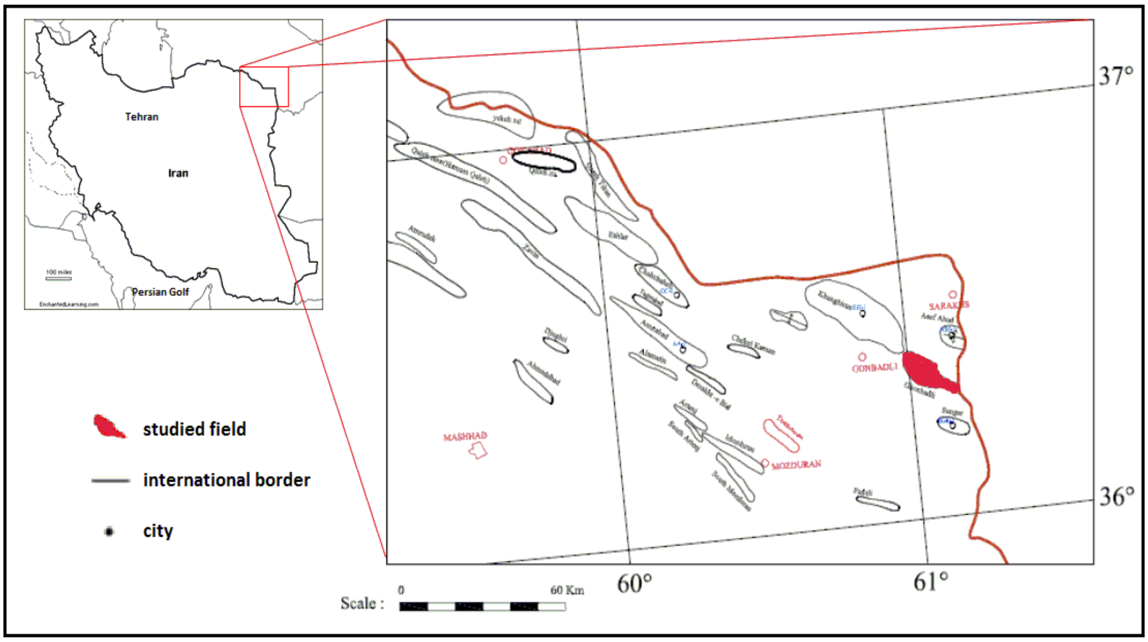


Figure 1) Geographical location of studied area.

2- Geological setting

The study area, Gonbadly Gas Field is part of the Kope dagh tectono-sedimentary unit and located in northeastern Iran (Stoklin, 1968). The Kope dag range is a 700 km-long structure that stretches from the Caspian Sea in the west along the Iran-Turkmenistan border to Afghanistan in the east (Fig. 1).

It forms the Iranian part of Alpine-Himalayan mountain belt and consists of a thick Tertiary-Mesozoic sedimentary sequence, deposited in a deep and narrow through. The whole complex was folded in young alpine Neogene-Quaterner phases (Eftekharnejad *et al*., 1991). Cretaceous stratigraphic sequence in study area is summarized in Table 1 as follow:

Table1. Cretaceous stratigraphic sequence.

Era	Period		Formations
Mesozoic	Cretaceous	Upper	Kalat Nayzar Abtalkh Abderaz
		Lower	Atamir Sanganeh Sarcheshmeh Tirgan Shurijeh

Shurijeh Formation as main reservoir in Gonbadly gas field consists of red continental sediments (sandstone, siltstone and claystone). This formation can be divided into 3 parts:

1- The upper part consist of red brown to chocolate brown and white gray to blue gray c coarse to medium grained sandstone and siltstone alternating with thin beds of red brown and green grey partly gypsiferous, silty clay to claystone.
2- The middle part of this formation is composed of red brown and grey to white grey hard quartzitic sandstone interbeded with thin layers of reddish brown siltstone and silty clay stone.
3- The lower part of this formation consists of red brown to chocolate brown gypsiferous claystone alternating with thin beds of red brown to chocolate brown and green grey very fine grained partly glauconitic sandstone and white hard anhydrite.

The Shurijeh Formation is barren of fossils but this formation should be of Neocomian.

3- Data Set

3.1- Petrophysical Logs (PLs)

Data related to two wells of the Gonbadly gas field have been used. The petrophysical interpretation was made on input: NPHI, RHOB, GR, DT, CAL, LLD, and PEF for Shurijeh Formation. Figure 2 displays the probabilistic analysis results in well No.2.

3.2- Core description studies

In order to identify the type of clay minerals in selected intervals, an extensive core description studies were conducted on 25 samples. Cores are depth matched against wireline logs using a combination of lithological and core analysis data. These studies include thin section petrography, XRD analysis, and SEM studies (Fig. 3).

3.3- Cation Exchange Capacity (CEC)

Cation Exchange Capacity (CEC) is an innate property of shale representing the ability of clay minerals to conduct electricity. As an important part of this study, the CEC parameter was also measured for total of 20 samples by bower method in laboratory (Richards, 1954).

4- Methodology

4.1- Bayesian classifier

The Bayesian classifier, developed based on Bayes' theorem is an effective probabilistic algorithm, assigns the most likely class to a given data. This classifier uses the complete probability distribution functions of the input features, and assumes that all the Probability Density Functions (PDFs) are known. In practice, they should be estimated from the training data. Bayes' formula allows us to express the probability of a particular class given an observed x as following (Duda and Hart, 1973; Theodoridis and Koutroumbas, 2003):

$$P(c_j|x) = \frac{P(x, c_j)}{P(x)} = \frac{P(x|c_j)P(c_j)}{P(x)} \quad \text{Eq.1}$$

Where x denotes the univariate or multivariate input that could be well log parameters (e.g. Vp or gamma ray). Let cj, with j =l,...,N, indicates the N different states or classes. P(x,cj) expresses the joint probability of x and c and P(cj) is the "prior probability" of a particular class before having observed any x. P(cj│x) known as "posterior probability", estimated from the training data or a combination of training and forward models (Duda and Hart, 1973).

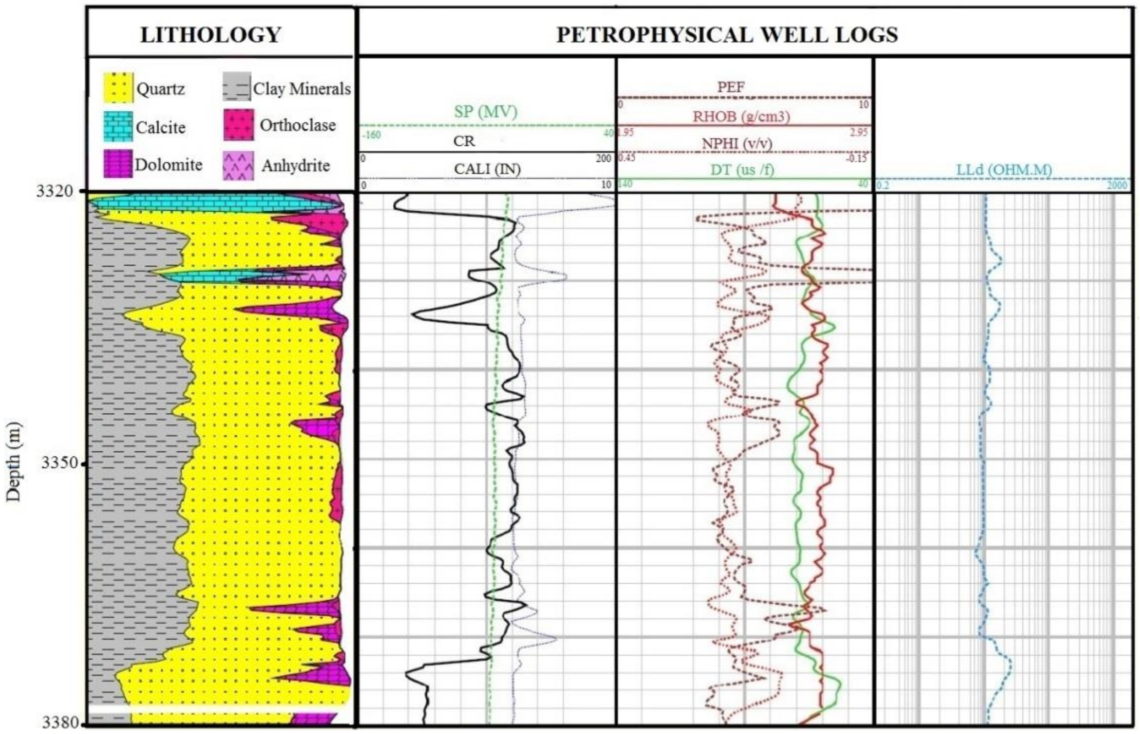


Figure 2) Bulk mineralogy and PLs in well No. 2 for depth interval 3320 (m) to 3380 (m).

In Eq. (1), P(x) is probability of belongings of each test data to each possible class is calculated as follow (Duda and Hart, 1973):

$$P(x) = \sum_{j=1}^{N} P(x|c_j)P(c_j) \qquad \text{Eq.2}$$

Based on this method, if P(ck│x) > P(cj│x) for all j≠ k, x will assign to class of ck. It should be noted that, prior probabilities P(cj) of a particular class can be determined by counting number of occurrences, divided by all training samples.

4.2- Back- propagation neural network

Multi-layer Perceptron (MLP), is the most commonly used networks, consists of three layers namely: input layer, hidden layer(s) and output layer. The number of hidden layers and neurons depends on complexity of the problem to be solved. The feed-forward back-propagation algorithm is the most unsupervised learning method for training MLP neural networks. In this technique signal flow from input layer to the output layer (forward pass) and then the difference between resulted output and desired (target) values is computed. This difference or error propagate back through the network (backward pass) updating the individual weights. This procedure is repeated until the error is converged to a certain level defined by a proper cost function such as root mean square error (RMSE) (Demuth and Beale, 2002).

5- Results and discussions

The algorithm proposed in this study consists of three main steps: generating a log which continuously gives the value of CEC through the well, defining clay minerals as different classes based on their CEC value, and identifying the desired classes using Bayesian classifier from proper PLs.

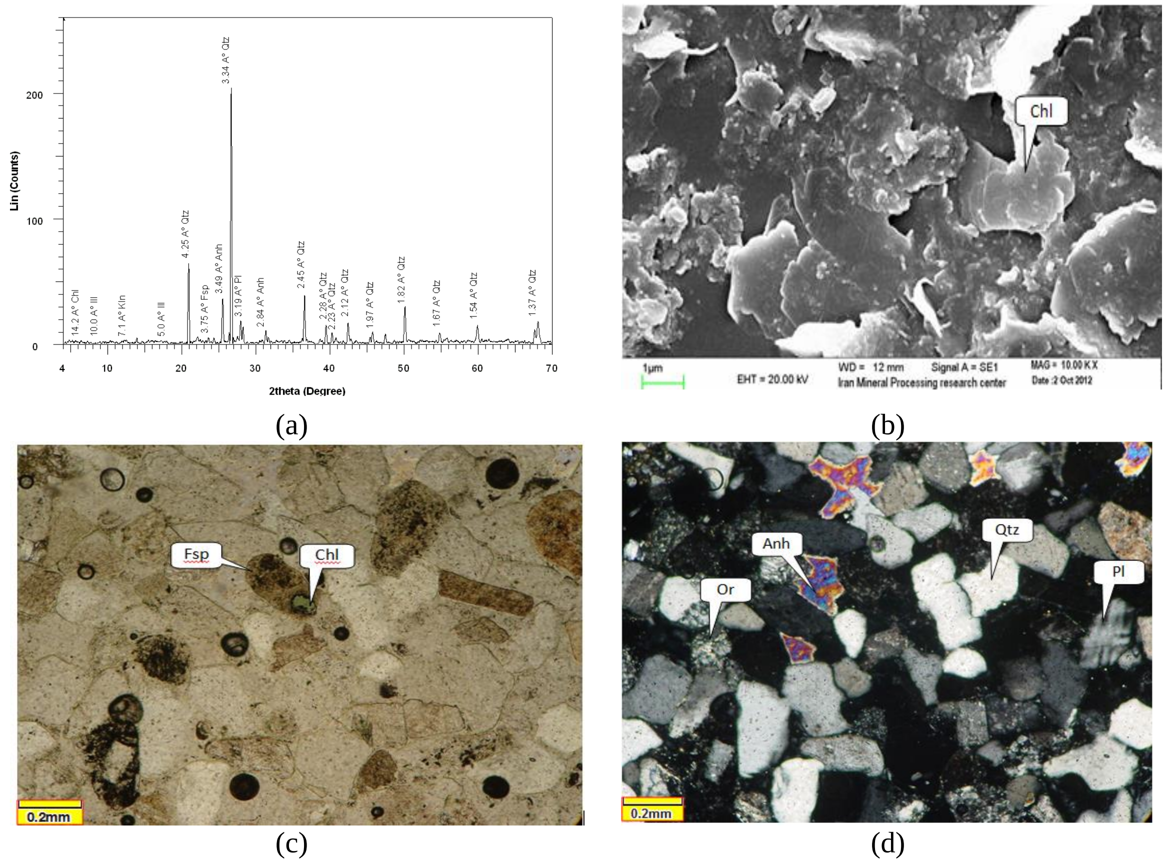
In the following sections, the above mentioned steps are described.

5.1- Predicting CEC log

The CEC log was predicted by a three-layer MLP neural network on input logs: LLD, RHOB, NPHI, PEF, CAL, DT, GR and the CEC values measured from core analysis as output. To build the ANN predictor in most prediction problems, the dataset must be divided into two parts: the training set with 70% of the data points and testing data with the remaining 30%. However, the number of CEC measured from core analysis in our study was low (20 data), and information might have been lost by dividing the dataset.

Therefore, the Leave-One-Out (LOO) cross validation method as most useful method was used to overcome this problem. Through this method, 19 data point were used for training and the remaining one was used to validate the ANN predictor.

A Lenvenberg-Marquardt training method was used to optimize the weights. Table 2 displays the results of this stage.



(a) (b) (c) (d)

Figure 3) An example of studies have been done for XRD (a), SEM (b), thin section analysis at PPL light (c), and XPL (d)

Table 2) ANN CEC predictor model description

Model	Function	Number of neurons	RMSE
CEC predictor	TANSIG – LOGSIG – PURELINE	7-10-1	3.97

The result of selected ANN model for CEC prediction is shown in Figure 4.

5.2- Applying cut offs

To consider the performance of the algorithm proposed in this study, the formation under study was divided into five classes based on CEC values.

With respect to the range of the obtained CEC log (between 0 and 135), four cut offs were implemented by the use of the standard CEC values. The class in which the CEC value is below the limit of 3 was considered as clean zone with a low amount of V_{sh}. The applied cut offs are shown in Table 3.

Table 3) The applied cut offs.

Defined class	Applied cut off on CEC value
Clean zone	below the limit of 3
Kaolinite	between the limits of 3 and 15
Illite or Chlorite	between the limits of 15 and 40
Halloysite - $4H_2O$	between the limits of 40 and 70
Montmorillonite	above the limit of 70

5.3- Classification result

To apply the method, existing data were randomly divided into two data sets, training data, with 70% of the data points and the testing data with the remaining 30%. Confusion matrix was used to display the results of the classification.

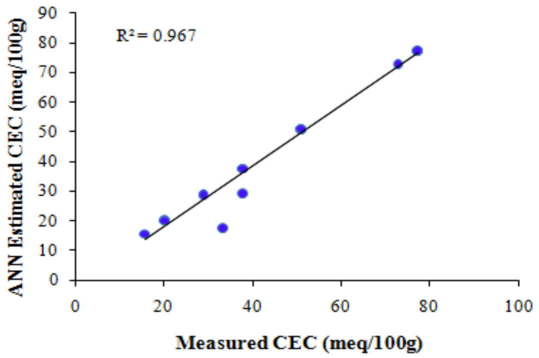


Figure 4) Results of selected ANN model for CEC Prediction.

Confusion matrix is a squared matrix (5×5 in this study), whose rows and columns represent decided and actual classes, respectively.

The trace of this matrix indicates the total accuracy of the method. The Classification Correctness Rate (CCR) was also calculated as an index by dividing trace of confusion matrix by number of classes. Classification was performed in two stages:

a) At the first attempt, capability of Bayesian classifier in identifying different classes was examined in each individual well separately (single well analysis).

b) At the second attempt, the generalization capability of the method was investigated, where input data from one of the wells were used as train data to identify the classes in the remaining well (multi-well analysis).

5.3.1- Single well analysis

Table 4 summarizes the results of Bayesian classification in two investigated wells. Based on this table, the Bayesian method showed a reasonable capability in identification of clean zone (class 1 with accuracy 69%) and class of kaolinite (class 2 with accuracy 63%) and a good accuracy in identification of halloysite and montmorillonite classes in well No.1. However, it doesn't show a salient success for class of illite. In well No.2, the situation is otherwise. In general, identification of clean zones and class of montmorillonite is more accurate than the other and the total accuracy for this well varies from 50% to 82% (average 65.8%) for different classes and is reliable.

Table 4) Results of Bayesian classifier in two studied well.

Well No.	1	2
Confusion matrix	$\begin{bmatrix} 0.69 & 0.3 & 0 & 0.01 & 0 \\ 0 & 0.63 & 0.31 & 0.06 & 0 \\ 0 & 0.30 & 0.56 & 0.13 & 0.02 \\ 0 & 0 & 0.11 & 0.85 & 0.04 \\ 0 & 0 & 0 & 0.18 & 0.82 \end{bmatrix}$	$\begin{bmatrix} 0.75 & 0.19 & 0.06 & 0 & 0 \\ 0.38 & 0.50 & 0.12 & 0 & 0 \\ 0 & 0.32 & 0.68 & 0 & 0 \\ 0 & 0 & 0.17 & 0.54 & 0.29 \\ 0 & 0 & 0 & 0.18 & 0.82 \end{bmatrix}$
Trace of Confusion matrix	3.55	3.29
Accuracy of classification (%)	71	66

5.3.2-Multi-well analysis

To examine the generalization capability of the proposed method (multi-well analysis), one well was selected as test and data related to the remaining well as train. The results are shown in Table 5.

As it can be seen, having data in one well, the technique is able to identify five desired classes in other well with an accuracy between 64% and 67.5%. The higher accuracy belongs to class of clean zone for both two investigated case of generalization. The interesting point is that, in well No.2 the accuracy of identifying kaolinite, illite and montmorillonite has increased when data related to well No. 2 are used for training. In well No.1, the accuracy of identifying class 1 and class 5 is increased whereas the identification accuracy of other classes is decreased.

Table 5) Results of generalization investigation

Test well No. 1	
Training well No.	2
Confusion matrix	$\begin{bmatrix} 0.99 & 0.01 & 0 & 0 & 0 \\ 0.54 & 0.41 & 0.02 & 0.02 & 0.01 \\ 0.15 & 0.24 & 0.49 & 0.1 & 0.02 \\ 0 & 0.08 & 0.16 & 0.35 & 0.41 \\ 0 & 0.01 & 0 & 0.04 & 0.95 \end{bmatrix}$
Trace of confusion matrix	3.19
CCR (%)	64
Test well No. 2	
Training well No.	1
Confusion matrix	$\begin{bmatrix} 0.73 & 0.25 & 0.02 & 0 & 0 \\ 0 & 0.88 & 0.12 & 0 & 0 \\ 0 & 0.27 & 0.72 & 0.01 & 0 \\ 0 & 0.01 & 0.3 & 0.49 & 0.2 \\ 0 & 0 & 0.01 & 0.44 & 0.55 \end{bmatrix}$
Trace of confusion matrix	3.37
CCR (%)	67.5

In short, based on obtained results it can be said that the method is effectively able to identify the considered classes by the average accuracy of 68.5% .

One of the main points in application of classification methods is their high dependency on the number of data which restricts their general application. The total accuracy of these techniques decreases where the amounts of data decrease. Another disadvantage of these methods that come from their essence is that they may not produce good result in environments in which the numbers of observed /measured data are limited.

6- Conclusion

This paper presents a novel approach through the Bayesian method to identify four different types of clay minerals in a shaly-sand reservoir located in northeastern Iran. With the help of wire line logs related to two wells of the reservoir under study, it has been shown that:

a) The accuracy of the method is dependent on the proportion of each class.

b) Although CCR in multi-well analysis is lower than the single-well case, but it is still worthy of acceptance.

c) The CCR value of the classifier shows that this method has been able to identify desired clay types with average accuracy of 68.5% in single well analysis step and 65.75% for generalization step.

Acknowledgments

The authors would like to thank Dr. V. Tavakkoli and an anonymous reviewer for their comments that help improve the manuscript. They also would like to express their sincere thanks to the Exploration Directorate of National Iranian Oil Company (NIOC) for their assistance in providing data and information.

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