Journal of Petroleum Science and Technology 11(1): 29, 2021, Pages 2-10
DOI:10.22078/jpst.2021.3953.1627

Journal of Petroleum Science and Technology

https:///jpst.ripi.ir/

Cluster Analysis to Use a New Method for Permeability Estimation in Carbonate Reservoirs by Using NMR T2 Distribution Parameters in the South of Iran

Shahin Parchekhari[1,2], Ali Nakhaee*[1,3], Ali Kadkhodaie[4]

[1] *Department of Petroleum Engineering, Kish International Campus, University of Tehran, Iran*

[2] *Research and Technology Department, National Iranian Southfield Oil Company, Ahvaz, Iran*

[3] *Department of Petroleum Engineering, University of Tehran, Tehran, Iran*

[4] *Earth Sciences Department, Faculty of Natural Sciences, University of Tabriz, Tabriz, Iran*

Abstract

In particular, quantitative laboratory measurements are challenging to perform due to their costs and time consumption. So, the need to explore other available data interconnectivity to permeability is of great importance. One of these data is NMR (Nuclear Magnetic Resonance) log data which have been used frequently in recent studies. It is considered to segregate different groups, which can be obtained through cluster analysis. Using reliable parameters in the cluster analysis helps to segregate different rock units which can be used in the permeability models. To select reliable parameters, cross plots of the permeability versus extracted features from the NMR T2 distribution curve were plotted. Results indicate that TCMR, peak reading amplitudes, and T2Lm are the best permeability indicators, respectively. Cluster analysis was performed on T2LM, TCMR and Peak reading amplitudes, which showed the highest consistency with core derived data compared with other parameters. The crucial step is to determine the best estimate of the number of clusters. It is usually taken as a prior in most clustering algorithms. In this research, Davies-Bouldin criterion values versus the number of clusters were used to obtain the optimal number of clusters. The knee method, which finds the "knee" in many clusters vs. clustering evaluation graph, was used. A clustering model with the number of clusters from 2-100 was created. It showed the five is an optimal number of clusters. Subsequently, the Schlumberger-Doll-Research (SDR) coefficients for each cluster were modified using a curve fitting tool in the Matlab software. Results indicated that calculated permeability using cluster analysis showed a higher correlation by core derived permeability than the original SDR permeability model. Since this is the core part of the group attempt to use extracted T2 distribution features in permeability estimation in carbonate reservoirs, more investigation is required to attempt satisfactory results to standardize the value of the coefficient of the permeability models in carbonate rocks with different petrophysical properties.

Keywords: NMR; Peak Analysis; Clustering; Timur-Coates; SDR.

Introduction

Permeability is of great importance for formation evaluation and deliverability prediction. It is a rock property that relates to the rate of hydrocarbons that can be recovered. It is common to estimate permeability using a simple porosity-permeability correlation [1]. However, the porosity-permeability relationships in carbonate reservoirs are not well. It showed there are other affecting parameters in permeability correlations [1]. A variety of methods has been established to measure permeability. These methods of the direct and indirect permeability measurements of rocks exist. Direct measurements are obtained in the laboratory on core samples. However, in many cases, permeability measurements are not possible. The core samples limit the precise determination of each value due to rock properties, consumption time of the drilling rig and their expenses.

On the other hand, indirect permeability measurements may allow greater control of cost and time consumption, enabling to use of well log data for quantitative estimation of permeability. NMR log data is one of the best well log data widely used in the recent indirect permeability estimation. Wei et al. estimated the permeability from NMR logs based on the formation classification method in tight gas sands [2]. Xinmin et al. proposed an improved method for permeability estimation of the bioclastic limestone reservoir based on NMR data [3] (Xinmin et al., 2017). And Aghda et al. adjusted porosity and permeability estimation by nuclear magnetic resonance [4].

**Corresponding author:* Ali Nakhaee, *Department of Petroleum Engineering, Kish International Campus, University of Tehran, Iran*

E-mail addresses: *anakhaee@ut.ac.ir*

Received 2019-10-05, Received in revised form 2021-03-10, Accepted 2021-03-13, Available online 2021-10-10

The basis of NMR measurement on the fluid bearing rock is that the decay or relaxation time of the NMR signals is directly related to the pore size. The detected signals contain T2 components from various pore sizes of the measured volume [5]. Some of the petrophysical properties such as porosity, permeability, and free to bound fluid ratio could be inferred from T2 distribution [6]. So, NMR logging does not provide a direct measurement of permeability; rather, a formation-permeability estimate, or index, is calculated from the spectral-porosity measurements using conventional permeability models that are based on a combination of empirical and theoretical relationships. Several permeability models have been developed. The main two famous accepted mathematical models are:

- The free-fluid (Timur-Coates or Coates) model
- The mean-T2 (the Schlumberger-Doll-Research (SDR)) model.

Measurements on the core samples are needed in these models to optimize their coefficient values to develop a modified model for local applications. These models assume that there is a good correlation between porosity, pore-throat size, and pore connectivity. This assumption is generally acceptable in sandstones, but they may not be reliable in carbonates [7, 8, 9, 10]. However, the Coates model and the SDR models cannot be directly used in the carbonates due to the complicated pore types, structure, and a high degree of heterogeneity.

In this study, a new approach has been introduced to cluster reservoirs into units of high similarity. To do this, feature extraction analysis on NMR T2 distribution was performed to extract parameters showing the highest relationship with permeability. So, peak analysis on NMR log data using MATLAB programming software was employed. Relevant attributes of the T2 distribution affecting permeability extracted to use in permeability clustering model. For this purpose, T2Lm, TCMR, number of peaks, peak prominence, peak width at half prominence, kurtosis, standard deviation, and skewness were taken. Each parameter versus permeability was plotted in the studied well to make logical correspondence to clusters. Then, the interrelationship between directly derived permeability in the laboratory and indirect relevant NMR data were correlated. This technique can be used in other investigations, including optimization, prediction, and classification tasks.

Geological Setting

The studied oil field is located in NW of the Persian Gulf, about 80 km west of Kharg Island. Oil is mainly produced from the Albian Burgan Formation (Fig. 1) in this field. The Persian Gulf is divided into five zones based on the stratigraphic, structural, and petroleum systems. The studied field is located in the most prolific area. During the Albian time, Persian Gulf was a part of the Neo-Tethys Ocean in which the steadily subsiding basement developed significant carbonate-dominated successions. In this study, Dariyan Formation (in the studied field) is investigated. At the Early Cretaceous, a shallow carbonate platform was expanded in the Persian Gulf area [11]. The carbonate interval of the Dariyan (named as Shu'aiba in Arabian province) Formation was deposited on this platform during the Aptian [12, 13. 14]. In the Persian Gulf, the upper and lower contacts of Dariyan Formation are with Kazhdumi (shale) and Gadvan (marly limestone) formations, respectively (Fig. 2). In this oil field, a shaly zone separated the Dariyan Formation into two members, which are known as the Lower and Upper Dariyan [15, 16].

Material and Method

Material

In this study, a well from a studied oil field was used for the permeability estimation by using NMR log data. The NMR log was CMR type for the well. In this field, Darian Formation was studied. Totally 387 core-derived permeability data were used.

Fig. 1 The studied oil field location Soroosh oil field is located in Western Persian Gulf [21].

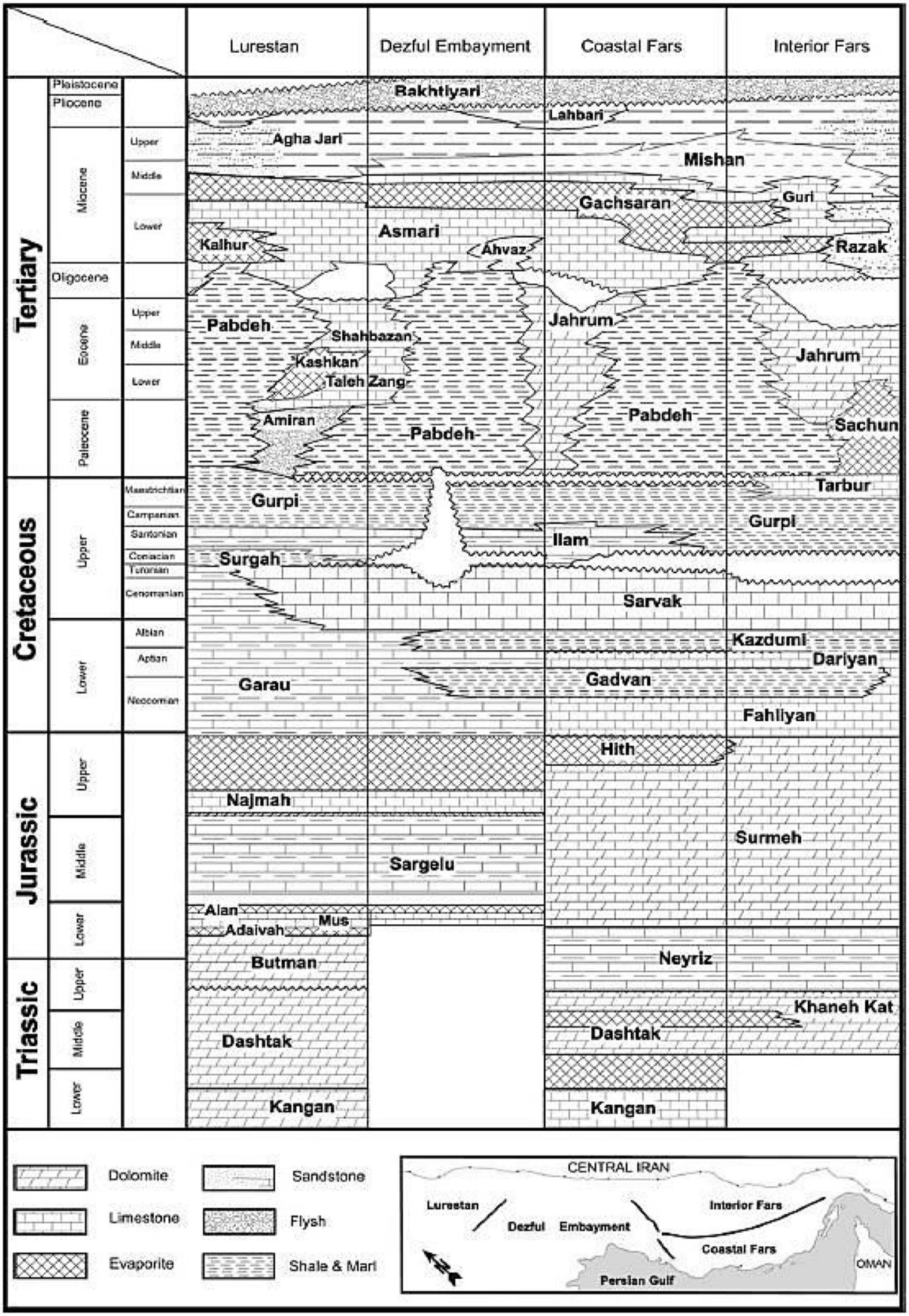

Fig. 2 The Asmari and Dariyan formations location in the stratigraphic column of Zagros [22].

Method

The extraction of relevant peak parameters (i.e. position, area) from a measured spectrum was performed using MATLAB software, providing automatic detection and analysis of multiple, non-overlapping, signal peaks in acquired waveforms. The extracted attributes from T2 distribution are:

• **Peak Count**: The Peak Finder function counts the number of local extrema in each row of the real-valued input signal giving the number of local extrema as outputs.

• **Amplitude**: The amplitude of a periodic variable is a measure of its change over a single period

• **Width**: It is the extent of a function between the two extreme values of a variable at which the dependent variable is equal to half of its maximum value

• **TCMR**: total CMR porosity, which comes from the area below the NMR T2 peaks.

• **T2lm**: T2 Logarithmic Mean.

• **Prominence**: the height point of a peak's crest above the lowest contour line encircling it but containing no higher crest in it (Fig. 3).

• **Standard deviation**: the standard deviation is used to show the amount of variation of the values of a data set.

• **Skewness**: in a set of statistical data, the asymmetry from the normal distribution is defined as skewness.

• **Kurtosis**: a statistical measure that is used to describe the distribution of data around the mean (Fig. 3).

Extracted relevant peak parameters were stored in the separate matrixes to perform cross-plot analysis of the features versus core derived permeability values to find reliable parameters to group rock units.

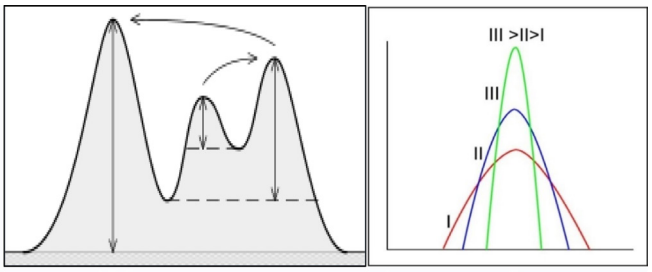

Fig. 3 The Prominences of the NMR T2 Distribution (left) and its Kurtosis (right).

Clustering Algorithm

Cluster analysis is a popular unsupervised categorizing technique. It is recognized as an important area of data mining in geosciences. The basic objective of clustering is to discover uncovered relationships within data. It gets the data and divides data elements into different groups (known as clusters). In such a way, the elements within a group possess high similarity but differ from those in the other group. There are some clustering techniques available. The focus here is on the K-means method, as one of the popular unsupervised data clustering algorithms.

The K-means algorithm takes the input parameter k, the number of clusters and partitions a set of n objects into k clusters. The main idea is to define k centroids, one for each cluster. These centroids should be placed cunningly because of different location causes different results. So, the better choice is to place them as much as possible, far away from each other. The next step is to take each point belonging to a given data set by associating it to the nearest centroid. When no point is pending, the first step is completed, and an early groupage is done. At this point, new K centroids are recalculated. A new binding must then be done between the same data set points and the nearest new centroid. A loop has been generated. The K centroids change their location step by step in the loop until no more changes happen. In other words, when centroids do not move anymore, clustering is completed. Finally, this algorithm aims at minimizing an objective function, in this case, a squared error function.

The objective function is:

$$j = \sum_{j=1}^{k} \sum_{i=1}^{k} \left\| x_i^{(j)} - c_j \right\|^2 \quad (1)$$

Where $\left\| x_i^{(j)} - c_j \right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster center c_j, is an indicator of the distance of the n data points from their respective cluster centers.

The formal algorithm is:

1. Select K points as initial centroids
2. Repeat
3. Form K clusters by assigning all points to the closest centroid
4. Recompute the centroid of each cluster
5. Until the centroids do not change

The K-Means is a simple algorithm adapted to many problem domains and is a good candidate to work for log data points. K-Means is based on minimizing the average squared Euclidean distance between the data items and the cluster's center (called centroid).

Results

The core part of this study is to optimize the statistical parameters (m, n, and C) of the SDR model. To calculate the permeability, empirical values of 4, 2, and 10 are assigned in the SDR model for m, n, and C, respectively. Results were plotted against core derived permeability values (Fig. 4). Unlike sandstones, carbonate rocks have very complex pore systems. Therefore, applying constant statistical parameters in the SDR model will cause miscalculation of the permeability in the carbonate rocks. Figure 4 illustrates that to calculate permeability from NMR logs using the SDR model, m, n, and C values must be determined for each rock type to get appropriate results. It means that permeability may be overestimated or underestimated from NMR logs using the unified calibrated SDR model (Fig. 4). To overcome this issue, the clustering method was applied for adjusting different statistical parameters for different rock types. In this study, for improving the applicability of the SDR model, the K-Means clustering method was used to classify the interval into several rock types. As it is mentioned previously, the first step in clustering analysis is to define the optimal number of clusters. For this purpose, selected input data was clustered from two to one hundred clusters, and data of each cluster evaluated using the criterion of the Davies-Bouldin value. Then, the number of optimal clusters is defined by an evaluation graph where the criterion of the Davies-Bouldin value (y-axis) is plotted versus the number of clusters (Fig. 5).

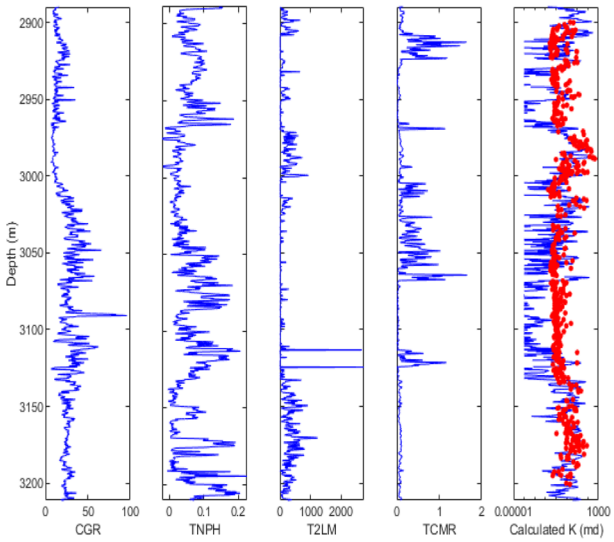

Fig. 4 calculation of the permeability using SDR method.

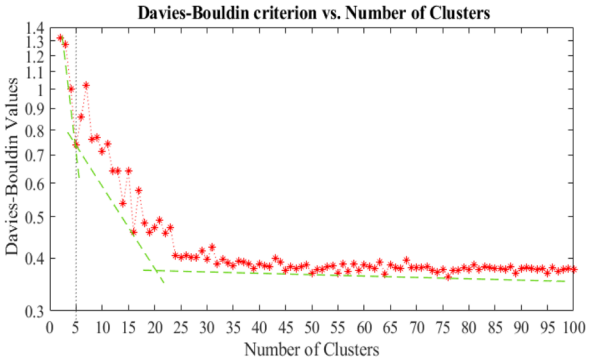

Fig. 5 Davies-Bouldin values versus the number of clusters where using the knee method that finds the "knee" in some clusters vs. clustering.

According to this plot, the optimal number of clusters in our case is five. So, the results of the k-means clustering with five clusters were used in this study. Then, appropriate values of m, n, and C of the SDR model in every cluster of the reservoir were calculated (Fig. 6). These values are obtained using the curve fitting tool in Matlab (Table 1).

To intuitively illustrate the improvement of permeability estimation, using the calibrated SDR models based on the clustering method, permeabilities acquired from 2 different kinds of methods are compared (Figs. 6 and 7). Calculated permeability matches the core derived permeability samples, as shown in Figure 6. It can be observed that the accuracy of the permeability estimation is not high enough from NMR logs using the unified SDR model (Fig. 7). Once the interval is classified and the above-mentioned parameters in the SDR model are calibrated separately, the predicted permeability is improved considerably (Table 2).

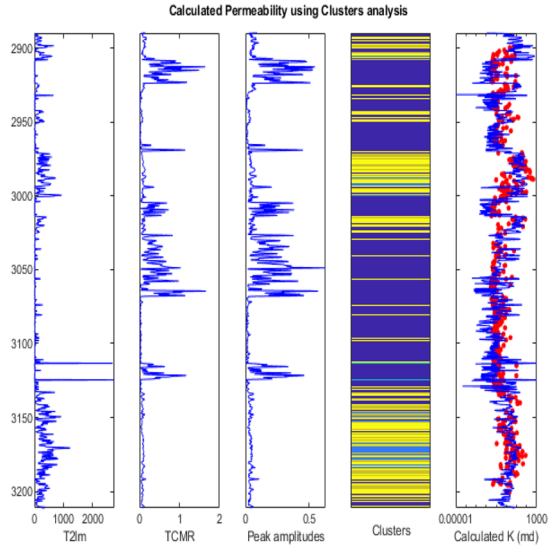

Fig. 6 clustering of the T2LM, TCMR and Peak amplitude and calculated permeability using clustering results.

Table 1 Constant of the SDR model calibrated for each zone.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
c	7.075e-05	1.62	0.016	4	22.09
n	2.736	1.55	1.68	2	0.402
m	0.3723	3.085	1.64	4	1.045

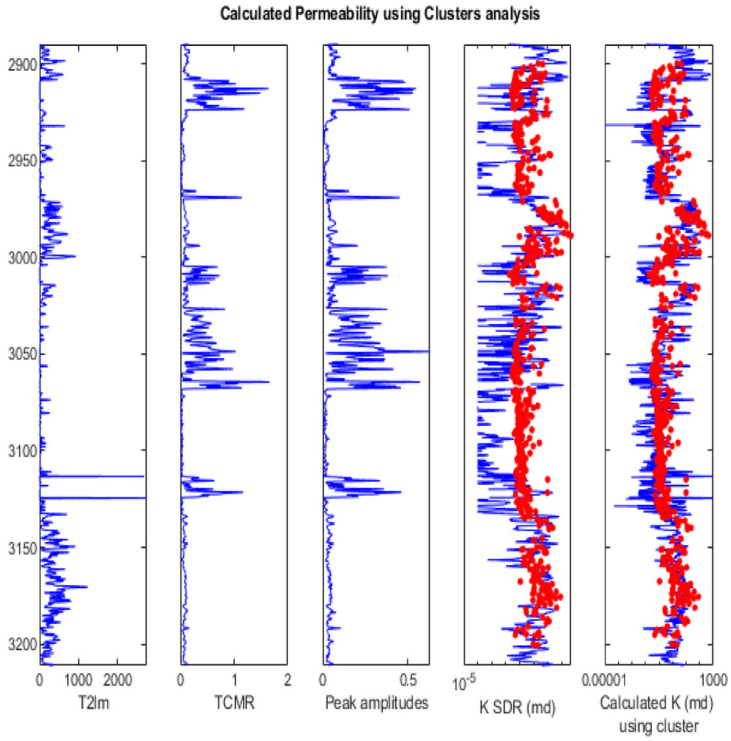

Fig. 7 calculated permeability using clustering results and SDR derived permeability.

Table 2 Comparison of results by statistical parameters.

	Mean	Meian
Core derived permeability	6.5312	0.2030
Cluster based permeability	31.5068	0.2568
SDR derived permeability	207.3692	2.1223

In Figure 8, the cross plot of the SDR permeability versus core permeability has been shown. The correlation coefficient is 15.11 %. However, the correlation coefficient of the clustered permeability versus core permeability increased to 24.09 % (Fig. 9).

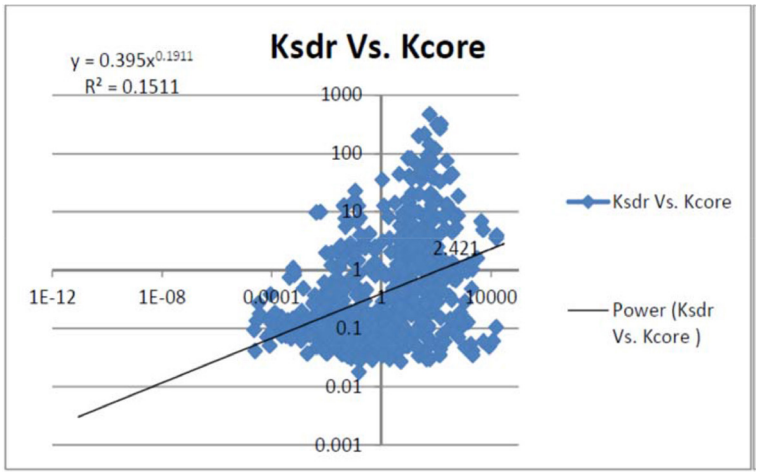

Fig. 8 SDR permeability versus core permeability.

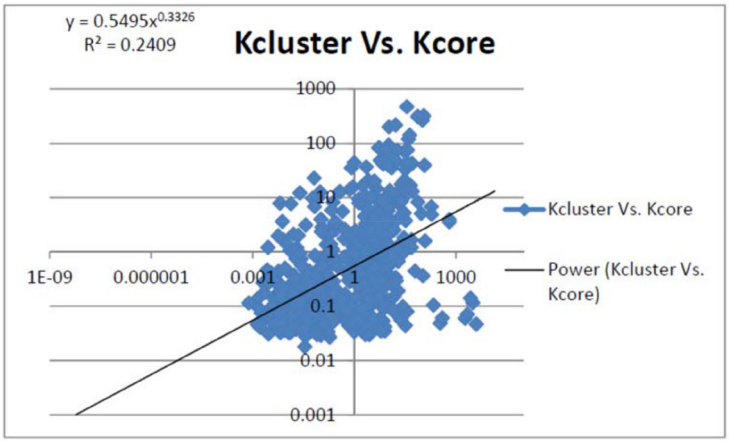

Fig. 9 SDR clustered base permeability versus core permeability.

Discussion:

In this study, the proposed predictor algorithm is presented for a well in the studied oil field to estimate permeability. To obtain appropriate permeability estimation, it is necessary to find high consistent and relevant input data. This study used cross-plot analysis input selection to identify appropriate input variables (Fig. 10). The analysis showed a correlation up to 0.47. Therefore, T2lm, TCMR, and peak amplitude variables were used as the input parameters for the permeability calculation model using the clustering technique (Fig. 10). In contrast, prominence, width, kurtosis, standard deviation, skewness, and peak counts were discarded due to their very weak association with permeability values and trial and error input selection.

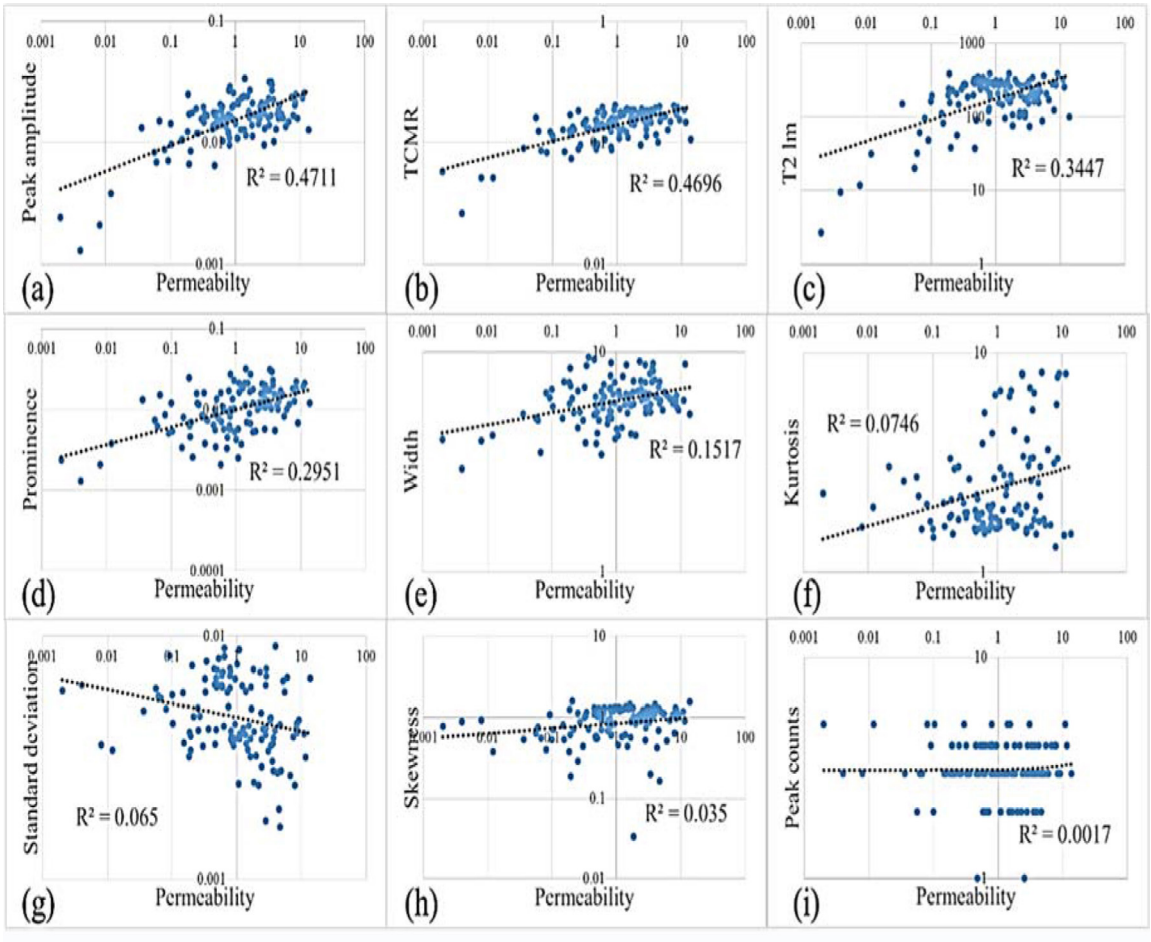

Fig. 10 Cross-plot showing the relationship between core derived permeability and peak amplitude (a), TCMR (b), T2lm (c), prominences (d), width (e), kurtosis (f), standard deviation (g), skewness (h) and peak counts (i) in training.

The MATLAB code used for K-means clustering and Davies-Bouldin values criterion is shown as follows:

MATLAB code used for K-means clustering and Davies-Bouldin criterion values.

```
%KMEANS K-means clustering.
%   IDX = K-means(X, K) partitions the points in the N-by-P data matrix X into K clusters.
%   This partition minimizes the sum, over all clusters, of the within-cluster sums of
%   point-to-cluster-centroid distances.  Rows of X correspond to points, columns correspond to
%   variables.  Note: when X is a vector, K-means treats it as an N-by-1 data matrix, regardless of its
%   orientation.  K-means returns an N-by-1 vector IDX containing the cluster indices of each point.
%    By default, K-means uses squared Euclidean distances.
clear all, clc
a=[];
b=[];
for  j=1:100
[idx,cmeans] = kmeans(X,j,'dist','sqeuclidean');
a1=[idx];
a=[a a1];
[DB, Dunn] = valid_DbDunn(X,idx);
b1=[DB];
b=[b b1];
end
plot (j,b)
```

Two proposed models can be used to calculate permeability from NMR logs. They have known as the SDR and Timur–Coates models [17, 18, 19].The SDR and Timur–Coates models are expressed as follows, respectively:

$$K=C*\phi^{m}*T2LM^{n} \quad (2)$$

$$K=(\phi/C)^{m}*(FFI/BVI)^{n} \quad (3)$$

Where K is the permeability (in mD); T2lm is the logarithmic mean of NMR T2 distribution (in ms); ϕ is the total porosity (in %); FFI is the free fluid bulk (in %); BVI is the bulk volume irreducible (in %); m, n, and C are the statistical constants of the model, whose values can be derived from lab experimental data sets of the core samples. When there is no recorded data available for m, n, and C, empirical values of 4, 2, and 10, respectively, are assigned to the model [20]. In the following study, the SDR model has been used to calculate permeability since the SDR model is very popular in permeability estimation in practical applications [20].

Conclusions

Unlike sandstones, carbonate rocks have very complex pore systems due to the digenetic overprint. It causes individual samples to have different proportions of primary and secondary porosities. Thus, the greater the porosity variety, the more complex the pore size distribution and the wider the NMR T2 spectrum. The behavior of the carbonate rocks is very complex and depends strongly on the proportion and size of the pores. Nonetheless, the TCMR, peak reading amplitude, and T2Lm might be a reliable way to group rock units. Cluster analysis performed a combination of these parameters, and an optimal number of five was chosen using a validation graph of Davies-Bouldin criterion versus the number of clusters. The results showed that the accuracy of permeability estimation is not high enough from NMR logs by using the unified SDR model. Once the interval is classified and the C, m, and n parameters in the SDR model are calibrated individually, the permeability prediction is improved considerably. This study is the first step of the group attempt to use T2 distribution features in permeability estimation in carbonate reservoirs. More investigation is required to reach satisfactory results to improve the value of the coefficient of the permeability models in the carbonate rocks with different petrophysical properties.

References:

1. Lucia F J (2007) Carbonate reservoir characterization: an integrated approach, Springer Science and Business Media.
2. Wei D F, Liu X P, Hu X X, Xu R, Zhu L (2015) Estimation of permeability from NMR logs based on formation classification method in tight gas sands, Acta Geophys, 63: 1316–1338.
3. Ge, Xinmin, Fan Y, Liu J, Zhang L, Han Y, Xing D (2017) An improved method for permeability estimation of the bioclastic limestone reservoir based on NMR data, Journal of Magnetic Resonance, 283: 96-109.
4. Aghda S M F, Taslimi M, Fahimifar A (2018) Adjusting porosity and permeability estimation by nuclear magnetic resonance: a case study from a carbonate reservoir of south of Iran, Journal Petrol Explor Prod Technol, 8: 1113–1127.
5. Dunn K J, LaTorraca G A, Warner J L, Bergman D J (1994) On the calculation and interpretation of NMR relaxation time distributions, In SPE Annual Technical Conference and Exhibition. Society of Petroleum Engineers.
6. Jianwei D (2015) Permeability characterization and prediction in a tight oil reservoir" Edson Field, Alberta, PhD thesis, University of Calgary, 113.
7. Kaufman J (1994) Numerical models of fluid flow in carbonate platforms: implications for dolomitization. J Sediment Res 64, 1: 128–139
8. Lucia FJ (1995) Rock-fabric/petrophysical classification

of carbonate pore space for reservoir characterization. AAPG Bull 79, 9: 1275–1300.
9. [9] Amabeoku MO et al (2001) Calibration of permeability derived from NMR Logs in carbonate reservoirs. SPE Middle East Oil Show, Society of Petroleum Engineers.
10. Westphal H et al (2005) NMR measurements in carbonate rocks: problems and an approach to a solution. Pure Appl Geophys 162, 3:549–570.
11. Alsharhan A S, Nairn A E M (1993) Carbonate platform models of Arabian Cretaceous reservoirs, 173-184.
12. Schroeder R, van Buchem F S, Cherchi A, Baghbani D, Vincent B, Immenhauser A, Granier B (2010) Revised orbitolinid biostratigraphic zonation for the Barremian–Aptian of the eastern Arabian Plate and implications for regional stratigraphic correlations, GeoArabia Special Publication 4, 1: 49-96.
13. Droste H (2010) High-resolution seismic stratigraphy of the Shu'aiba and Natih formations in the Sultanate of Oman: implications for Cretaceous epeiric carbonate platform systems, Geological Society, London, Special Publications, 329, 1: 145-162.
14. Maurer F, Van Buchem F S, Eberli G P, Pierson B J, Raven M J, Larsen P H, Al-Husseini M I, Vincent B, (2013) Late Aptian long-lived glacio-eustatic lowstand recorded on the Arabian Plate, Terra Nova, 25, 2: 87-94.
15. Mehrabi H, Rhimpour-Bonab H, Hajikazemi E, Esrafili-Dizaji B (2015) Geological reservoir characterization of the lower cretaceous dariyan formation, (Shu'aiba equivalent) in the Persian Gulf, Southern Iran, Marine and Petroleum Geology, 68: 132-157.
16. Mehrabi H, Ranjbar-Karami R, Roshani-Nejad M (2019) Reservoir rock typing and zonation in sequence stratigraphic framework of the cretaceous dariyan formation, Persian Gulf, Carbonates and Evaporites, 34, 4: 1833-1853.
17. Kenyon W J T L A (1997) Petrophysical principles of applications of NMR logging, The Log Analyst, 38.
18. W. Kenyon P, Day C, Straley J, Willemsen A (1988) Three-part study of NMR longitudinal relaxation properties of water-saturated sandstones, SPE Formation Evaluation, 3: 622-636.
19. Coates G R, Xiao R, Prammer M G (1999) NMR logging principles and applications, Halliburton Energy Services, Houston.
20. Mao Z Q, Xiao L, Wang Z N, Jin Y, Liu X G, Xie B (2013) Estimation of permeability by integrating nuclear magnetic resonance (NMR) logs with mercury injection capillary pressure (MICP) data in tight gas sands, Applied Magnetic Resonance, 44, 4: 449-468.
21. Bordenave M L, J A Hegre (2010) Current distribution of oil and gas fields in the Zagros Fold Belt of Iran and contiguous offshore as the result of the petroleum systems, Geological Society, London, Special Publications 330, 1: 291-353.
22. Sepehr M, Cosgrove J W (2004) Structural framework of the Zagros fold–thrust belt, Iran, Marine and Petroleum geology, 21, 7: 829-843.