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A Physical-based Model of Permeability/Porosity Relationship for the Rock Data of Iran Southern Carbonate Reservoirs

S. Gholinezhad and M. Masihi*

Department of Chemical and Petroleum Engineering, Sharif University of Technology, Tehran, Iran, P.O. Box: 11155-9465

Abstract

The prediction of porosity is achieved by using available core and log data; however, the estimation of permeability is limited to the scare core data. Hence, porosity and saturation data through the framework of flow units can be used to make an estimation of reservoir permeability. The purpose of this study is to predict the permeability of a carbonate gas reservoir by using physical-based empirical dependence on porosity and other reservoir rock properties. It is emphasized that this new relationship has a theoretical background and is based on molecular theories. It is found out that if rock samples with different types are separated properly and samples with similar fluid-flow properties are classified in the same group, then this leads to finding an appropriate permeability/porosity relationship. In particular, the concept of hydraulic flow units (HFU) is used to characterize different rock types. This leads to a new physical-based permeability/porosity relationship that has two regression constants which are determined from the HFU method. These coefficients, which are obtained for several rock types in this study, may not be applicable to other carbonate rocks; but, by using the general form of the model presented here, based on the HFU method, one may obtain the value of these coefficients for any carbonate rock types. Finally, we used the data of cored wells for the validation of the permeability results.

Keywords: Permeability, Porosity, Irreducible Water Saturation, Hydraulic Flow Units, Regression

1. Introduction

Reservoir characterization is one of the important aspects of petroleum engineering studies. An effective management strategy can be applied only after obtaining a detailed and close-to-reality "image" of the spatial distribution of rock properties (Balanand Ameri, 1995; Babadagliand Al-Salmi, 2002; Lopez and Davis, 2010). Porosity, permeability, and fluid saturations are the key variables for characterizing reservoirs (Bhatt et al., 2001; Babadagliand Al-Salmi, 2002; Lopez and Davis, 2010). Among these, the most difficult property to be determined is the reservoir permeability (Balanand Ameri, 1995).

Permeability is a measure of the capability of a porous medium to transmit fluid. It is expected that permeability is a complex function of several interrelated factors such as lithology, pore fluid composition, and porosity (Bhatt et al., 2001). The absolute permeability of a porous medium varies with grain size, sorting, cementing, direction, and location. Absolute permeability is a dynamic flow

*Corresponding Author:
Email: masihi@sharif.edu

property, while porosity is a measure of the storage capacity of a rock, or a static rock property (Basbugand Karpyn, 2007). It is possible to have very high porosity without having any permeability at all, as it is in the case of clays and shale rocks. On the other hand, high permeability with low porosity might also be true, as it happens in micro-fractured carbonates. But, if such relations are not seen in a rock, usually the higher the porosity of a rock is, the higher the permeability becomes (Davies and Vessell, 1996; Tiab and Donaldson, 2004; Akam et al. 2010).

Extensive investigations have been conducted on the permeability/porosity relationship of sandstone reservoirs and some of them showed reasonable results. In carbonate reservoirs, however, permeability description is difficult. One reason is that the porosity and permeability creation system and the texture of carbonate rocks are much more complex than sandstone rocks. Another reason is that the carbonate reservoirs are more heterogeneous; in other words, rock properties and particularly permeability varies sharply. Observations show mismatch between porosity and permeability in carbonate reservoirs; that is to say regions with low permeability exhibit high porosity and vice versa (Perez et al., 2003). These factors have resulted in few relations for carbonate reservoirs. On the other hand, there are many carbonate reservoirs in the world and carbonate reservoirs are very important in petroleum industry. Therefore, the experimental investigation of the permeability/porosity relationship for carbonate reservoirs can be essential in the characterization of reservoirs.

Depending on the available data, permeability can be determined by analyzing well test, core, or well log data. Well test interpretation provides an in situ measure of average permeability. When no well test data are available, analyzing the core in a laboratory is another way to estimate the reservoir permeability (Ratchkovski et al., 1999; Elarouci et al., 2010; Chenand Lin, 2006). If core data are not sufficient, one can use well log data as a secondary variable. Moreover, intelligent methods such as neural networks and fuzzy logic are very successful in the estimation of permeability. Furthermore, in recent years, some new methods such as committee machine and fuzzy-neural methods have been proposed and it has been shown that their results are more accurate than the former methods. However, these new methods as well as the primary neural networks and fuzzy logic methods are time-consuming and difficult to implement and cannot be used in all cases. The aim of this work is to use a simple efficient method requiring little time and work, while providing reasonable results. Hence, the relationships between permeability and other properties of a porous medium are of great importance for reservoir engineering (Basbugand Karpyn, 2007; Izadiand Ghalambor, 2012).The determination of the correct value of permeability makes it possible to design the field development plan properly (Lopez and Davis, 2010). The proper management of a reservoir requires thorough knowledge of permeability map (Abbaszadeh et al., 1996; Babadagliand Al-Salmi, 2002).

2. Available empirical relationships

For sandstone samples, there are many proposed permeability/porosity relationship in the literature. Among them are Carman-Kozeny, Tixier, Wyllie and Rose, Sheffield, Pirson, Timur, Coates and Dumanoir, Coates, Archie, and Armstrong correlations. The details of these models can be found elsewhere (Balan and Ameri, 1995; Babadagli and Al-Salmi, 2002; Lopez and Davis, 2010). However, carbonate rock samples have a more complex structure, and thus there are fewer proposed empirical correlations in the literature. These models include Wyllie and Rose, Archie, and Armstrong correlations as follows:

2.1. Wyllie and Rose model

This model for carbonate reservoirs has been proposed as (Armstrong, 2003):

$$k = \left(79 \frac{\varphi^3}{S_{wi}}\right)^2 \tag{1}$$

where, k is permeability (millidarcy, mD); φ stands for porosity (fraction) and S_{wi} represents connate water saturation (fraction).

2.2. Archie models

The permeability formulas proposed by Archie are:

$$k = 2.55(10\varphi)^{5.65} \qquad \text{archie 1} \tag{2}$$

$$k = 9.35(10\varphi)^{5.65} \qquad \text{archie 2} \tag{3}$$

where, k is permeability (millidarcy, mD) and φ represents porosity (fraction).

2.3. Armstrong model

The model proposed by Armstrong is given by:

$$k = a\varphi^{1.5}\left(\frac{1}{S_{wi}} - 1\right)^{1.5}; \qquad a = \begin{cases} 10 & k < 200 \\ 1 & k \geq 200 \end{cases} \tag{4}$$

where, k is permeability (millidarcy, mD); φ stands for porosity (fraction) and S_{wi} represents connate water saturation (fraction).

3. Comparison of existing models

The laboratory measurements of the studied reservoir (samples are dolomite rocks extracted from the depth of 2793-2867 meters in one of the Iran southern carbonate reservoirs) are presented in Table 1. It should be mentioned that the average initial water saturation (S_{wi}) of the core samples for the studied depths obtained from well log analysis and capillary pressure determination was 10.1% with 1% fluctuations about this average value. Our studies showed that none of the existed correlations could precisely predict the permeability of the studied reservoir. Among the above models, Wyllie and Rose model and Armstrong model showed better results when the predicted permeability were compared to the laboratory permeability. For the studied reservoir, the permeability values estimated by these correlations were not accurate enough and there was a significant difference between the permeability predicted by these models and the laboratory permeability. For example, the permeability predicted by Armstrong model and the experimentally measured permeability at special depth intervals is shown in Figure 1. As can be seen, the difference between the permeability predicted by Armstrong model and the laboratory permeability is very important. Therefore, it seems reasonable to find an alternative model based on a theoretical background to estimate the permeability.

4. The proposed model

Based on the works done by some researchers and the physical reasons that will be mentioned later, the model proposed in this paper is expressed as follows (Balanand Ameri, 1995; Armstrong, 2003):

$$k = a \times 10^{b\left[\frac{\varphi_e}{1-\varphi_e} \times \frac{1-S_{wi}}{S_{wi}}\right]} \tag{5}$$

where, φ_e is effective porosity in fraction and S_{wi} stands for irreducible water saturation in fraction. *a* and *b* are constants that should be specified for any reservoir under study.

Table 1

Experimental data for the studied reservoir, permeability calculated from Armstrong model and calculated HFU parameters.

φ_e	k_{lab}	$k_{armstrong}$	φ_z	*RQI*	*FZI*	*DRT*	*PS*	*log* (k_{lab})
0.053854	7.0	7.957093	0.056919	0.356897	6.27028	12	0.506634	0.842441
0.058607	0.2	9.033419	0.062255	0.052558	0.844243	10	0.554132	-0.78463
0.106818	0.3	22.2281	0.119593	0.052715	0.440788	10	1.064498	-0.52134
0.030188	0.8	3.339573	0.031128	0.166342	5.343795	12	0.27707	-0.07202
0.075122	0.2	13.10939	0.081224	0.049756	0.61258	10	0.72297	-0.7244
0.081652	0.1	14.85544	0.088912	0.036099	0.40601	10	0.791407	-0.9669
0.10389	0.5	21.32034	0.115935	0.07188	0.620002	10	1.031932	-0.26407
0.108561	0.5	22.77417	0.121782	0.065886	0.541014	10	1.083976	-0.32061
0.088661	0.2	16.80864	0.097287	0.04748	0.48804	10	0.865947	-0.69311
0.077244	0.1	13.66889	0.083711	0.030536	0.364781	10	0.745107	-1.13637
0.171686	2.1	45.29346	0.207272	0.108567	0.523791	10	1.844924	0.312273
0.187177	4.1	51.55973	0.23028	0.147491	0.640487	10	2.049718	0.615925
0.136791	0.6	32.21219	0.158468	0.064361	0.406143	10	1.410525	-0.24056
0.275373	32.0	92.00582	0.380021	0.338639	0.891108	10	3.382561	1.505537
0.261207	20.3	84.99836	0.35356	0.277083	0.783695	10	3.14703	1.308345
0.176512	5.0	47.2165	0.214347	0.167112	0.779636	10	1.907897	0.698931
0.02266	0.2	2.171746	0.023185	0.084195	3.631476	12	0.206368	-0.78803
0.163354	0.1	42.03673	0.195249	0.024602	0.126001	9	1.737913	-0.9988
0.15367	0.5	38.35457	0.181572	0.057204	0.315046	10	1.616174	-0.29242
0.209653	0.3	61.11997	0.265266	0.035311	0.133115	9	2.361136	-0.57654
0.138965	0.1	32.98302	0.161393	0.024571	0.152246	9	1.436557	-1.0701
0.316982	1	113.6276	0.464089	0.057104	0.123044	9	4.13086	0.020502
0.099717	0.1	20.04857	0.110761	0.02649	0.239165	9	0.985886	-1.14892
0.059543	6.7	9.250874	0.063313	0.333292	5.26417	12	0.563551	0.826623
0.185382	0.1	50.81995	0.227569	0.022516	0.098943	9	2.025594	-1.02079
0.178911	0.3	48.18258	0.217895	0.038363	0.176064	9	1.939487	-0.57339
0.193591	0.3	54.23261	0.240066	0.040658	0.169363	9	2.136823	-0.48868
0.256637	0.8	82.77729	0.345237	0.055655	0.161207	9	3.072958	-0.09354
0.191568	0.3	53.38494	0.236963	0.038182	0.16113	9	2.109208	-0.54782
0.179605	0.1	48.463	0.218925	0.019867	0.090748	9	1.948651	-1.14327
0.18643	0.1	51.25161	0.229151	0.023172	0.101123	9	2.039673	-0.9934
0.240123	0.3	74.91739	0.316002	0.032383	0.102476	9	2.812733	-0.5928
0.157051	0.1	39.62717	0.186311	0.022323	0.119816	9	1.658353	-1.10023
0.198857	0.1	56.46061	0.248217	0.026048	0.104939	9	2.209382	-0.86378
0.02943	0.7	3.2146	0.030323	0.15247	5.028231	12	0.269903	-0.15869
0.044863	7.8	6.050222	0.046971	0.414993	8.835151	12	0.418086	0.894115
0.120349	1.1	26.58269	0.136815	0.095279	0.69641	10	1.217789	0.044583

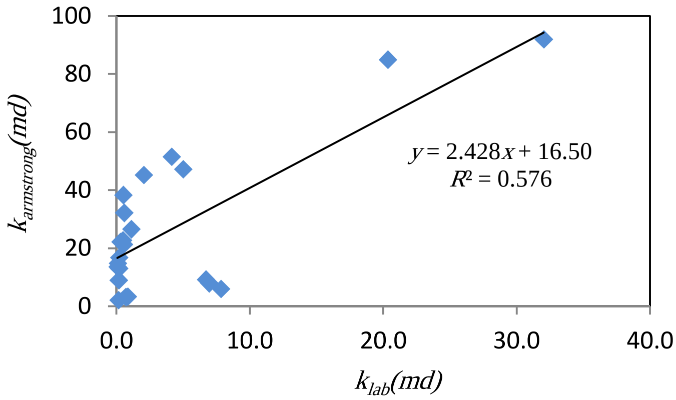

Figure 1
Permeability calculated using Armstrong model versus the experimental permeability

Regarding the theoretical background of the above correlation, as it can be seen, this correlation is in the general form of $k = a \times 10^{f(\varphi, S_{wi})}$. In other words, $log(k)$ depends on $f(\varphi, S_{wi})$ and not k itself. There is no strong theoretical reason for this idea. Statistically, the range of variations of k is very wide, whereas φ_e varies in a relatively narrow range (between 0 and 0.4). Therefore, we use $log(k)$ to resolve this problem and make the range of variations of k comparable with the other parameters.

In addition, instead of using φ_e as used in previous models, we use $\frac{\varphi_e}{1-\varphi_e}$ that is called normalized porosity index. The reason is that if we use φ_e (with a power of 1), with small changes in the value of φ_e, permeability will change very slightly, which is not supported by the experience. Theoretically, in the case of very large porosity values (when φ_e is equal to 1), a small change in φ_e results in a significant variation in the normalized porosity index, namely $\frac{\varphi_e}{1-\varphi_e}$.

Moreover, in this model instead of using S_{wi}, we use $\frac{1-S_{wi}}{S_{wi}}$ is employed. As emphasized by Armstrong, according to molecular theories for both sandstone and carbonate rock samples, total pore diameter is in proportion to $\frac{1}{S_{wi}}$, whereas the effective pore diameter, which influences permeability, is in proportion to $\frac{1-S_{wi}}{S_{wi}}$ (Armstrong, 2003). As a result, models using $\frac{1}{S_{wi}}$ cannot show good results, while the models like Armstrong one that employs $\frac{1-S_{wi}}{S_{wi}}$ give better results.

It should be noted that any permeability/porosity correlation that is obtained for a specific rock type may only be applicable to that rock type. In other words, for different rocktypes, we may find different permeability/porosity relationships. We used hydraulic flow units to separate the rocks with different types from each other.

5. Results and discussion

5.1. Hydraulic flow units (HFU)

Before using this method, it should be introduced in a concise way. Generally, four relationships are used for the discrimination of different rock types in this method. These relationships are:

$$\varphi_z = \frac{\varphi_e}{1-\varphi_e} \tag{6}$$

$$RQI = 0.0314\sqrt{k/\varphi_e} \tag{7}$$

$$FZI = \frac{RQI}{\varphi_z} \tag{8}$$

$$DRT = Round\left[2Ln\left(FZI\right)+10.6\right] \tag{9}$$

In the above relationships, φ_e is the rock effective porosity in fraction and k stands for rock permeability in millidarcy (mD). φ_z is called normalized porosity index that will be introduced later. Furthermore, *RQI*, *FZI*, and *DRT* are called Reservoir Quality Index, Flow Zone Indicator, and Discrete Rock Type respectively. The unit of *RQI* and *FZI* is micrometer and *DRT* is dimensionless. The last correlation is a simple equation that converts *FZI* (which is a continuous variable) to *DRT* (which is a discrete variable). More information about the method of hydraulic flow units can be found elsewhere (Al-Ajmi and Holditch, 2000; Aggoun et al., 2006; Bagciand Akbas, 2007; Orodu et al., 2009; Elarouci et al., 2010; Sheng et al., 2010; Izadiand Ghalambor, 2012; Nooruddinand Hossain, 2012).

5.2. Rock typing

In the HFU method, rock samples with the same *DRT* values belong to the same rock type. This criterion enables us to separate various rock types. These calculations are shown in Table 1, columns 4-7. The data shown in this table are abridged, since we could not present all the data herein.

5.3. Determination of the coefficients of the suggested model

Now, for any rock type (any *DRT*) we need to determine the coefficients *a* and *b* and of Equation 5. First, *log*(*k*) is plotted versus $PS = \frac{\varphi_e}{1-\varphi_e}\times\frac{1-S_{wi}}{S_{wi}}$. According to the model, the result should be a straight line with an intercept of *log*(*a*) and a slope of *b*. For example, the results are shown in Figures 2 to 7 for *DRT*'s equal to 8 to 13 respectively. For a *DRT* value of 10, the coefficients of *a* and *b* and are 0.039 and 0.898 respectively. The values of *a*, *b*, and R^2 (determination coefficient) for *DRT*'s equal to 8 to 13 are presented in Table 2.

Table 2
Values of *a*, *b*, and R^2 for several *DRT* values

DRT	8	9	10	11	12	13
a	0.022	0.020	0.039	0.119	0.039	0.105
b	0.245	0.434	0.898	0.938	4.47	6.559
R^2	0.531	0.734	0.915	0.724	0.848	0.784

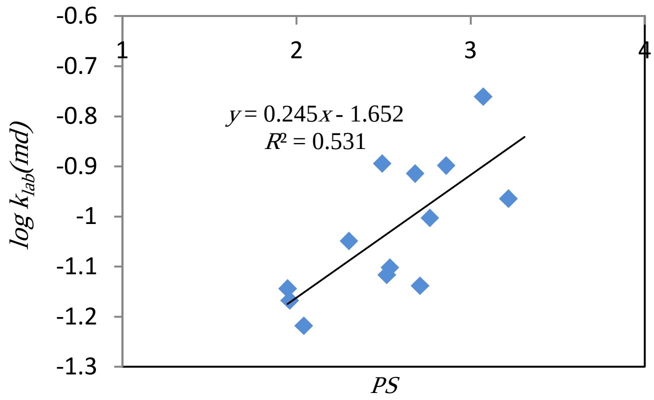

Figure 2

Experimental permeability versus $PS = \frac{\varphi_e}{1-\varphi_e} \times \frac{1-S_{wi}}{S_{wi}}$ for *DRT* equal to 8

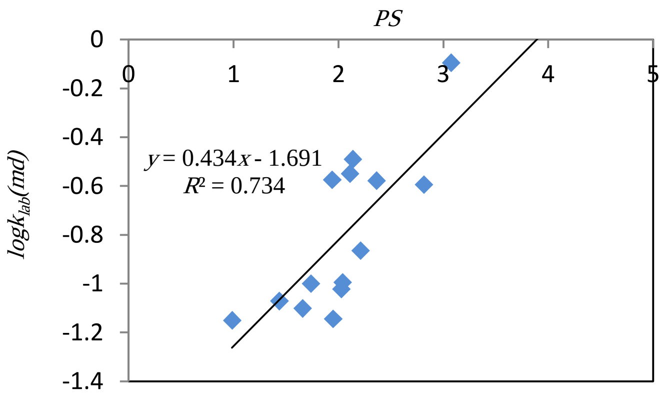

Figure 3

Experimental permeability versus $PS = \frac{\varphi_e}{1-\varphi_e} \times \frac{1-S_{wi}}{S_{wi}}$ for *DRT* equal to 9

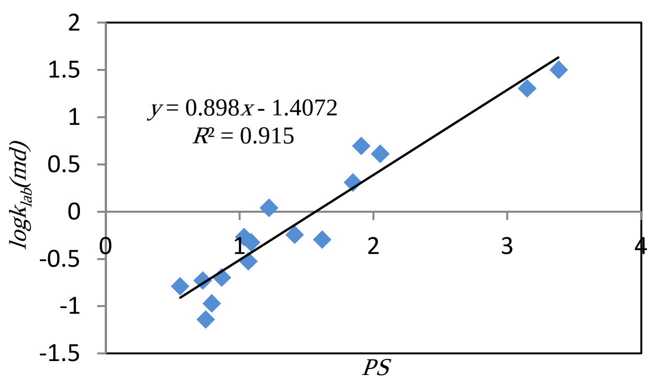

Figure 4

Experimental permeability versus $PS = \frac{\varphi_e}{1-\varphi_e} \times \frac{1-S_{wi}}{S_{wi}}$ for *DRT* equal to 10

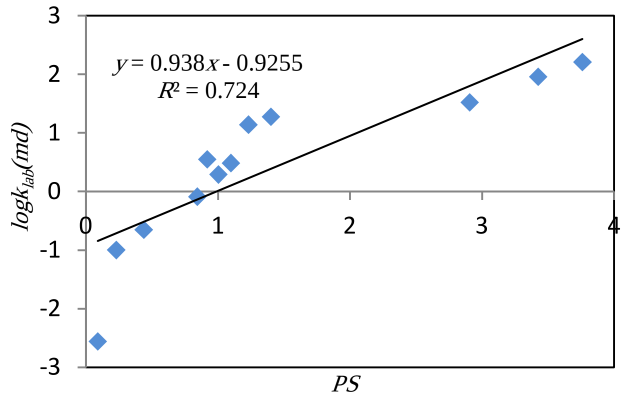

Figure 5

Experimental permeability versus $PS = \dfrac{\varphi_e}{1-\varphi_e} \times \dfrac{1-S_{wi}}{S_{wi}}$ for *DRT* equal to 11

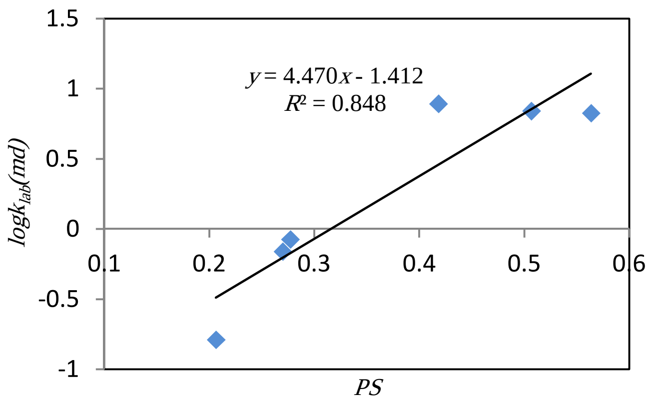

Figure 6

Experimental permeability versus $PS = \dfrac{\varphi_e}{1-\varphi_e} \times \dfrac{1-S_{wi}}{S_{wi}}$ for *DRT* equal to 12

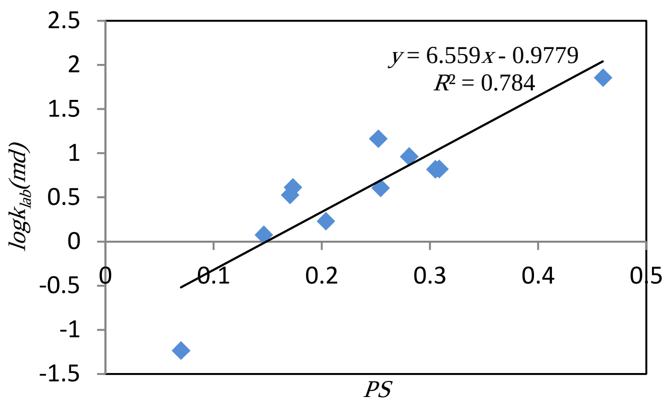

Figure 7

Experimental permeability versus $PS = \dfrac{\varphi_e}{1-\varphi_e} \times \dfrac{1-S_{wi}}{S_{wi}}$ for *DRT* equal to 13

According to Figures 2-7, there is a reasonable correlation resulting in a straight line at various *DRT* values. Thus, the condition might also be the same for other values of *DRT*. For all the rocks, the average value of the R^2 is 0.756.

However, it can be shown that if the existing empirical relationships are considered through the use of the HFU method, none of them show suitable results in comparison to the model suggested here.

Another issue that should be addressed is to calculate *RQI* values when the value of *k* is unknown. By definition, *RQI* is a function of *k* and φ_e. In practice *RQI* is not calculated and *FZI* itself is calculated from the values of several logs. In this method, it is assumed that a modern collection of logs is available at the studied depth intervals for all wells and that the logs have consistently been interpreted. It should be noted that the concept of hydraulic flow units is usually applied to the wells where only well-log data are available (Desouky, 2005). Before presenting the relationship between *FZI* and the logs, we first define the normalized value of a log. The normalized value of any log at any depth is given by:

$$N\delta = \frac{\delta - \delta_{\min}}{\delta_{\max} - \delta_{\min}} \tag{10}$$

where, δ is the value of the studied log at the studied depth and $\delta_{\min}$ and $\delta_{\max}$ represent the minimum and the maximum values of the studied log respectively (Guo et al., 2007).

The relationship between *FZI* and the normalized values of logs is given by:

$$FZI = \lambda_0 + \lambda_1 NXRD + \lambda_2 NXRHO + \lambda_3 NXGR + \lambda_4 NXSP + \lambda_5 NXDT + \lambda_6 NXNPH \tag{11}$$

where, *NXRD*, *NXRHO*, *NXGR*, *NXSP*, *NXDT*, and *NXNPH* stand for normalized resistivity log, normalized density log, is the normalized gamma ray log, is the normalized spontaneous potential log, is the normalized sonic log, is the and normalized neutron porosity log respectively. λ is also regression coefficients. If the known values of *k* at specific depths are available, then the coefficients λ_0, λ_1, …, λ_6 can be determined by using multivariable regression. With these λ's, the values of *FZI* can be determined by Equation 11 at any depth that the logs are available, which could then be used for estimating the values of *k* parameters at the corresponding depths. In other words, at any depths that cores are available, one could calculate the *FZI* values. The calculated *FZI* values from the cored data are used as the anchor points for the rock type prediction. The values of the normalized logs are calculated at exactly the same depths as the core plugs. This will yield a matrix of the normalized logs and the calculated *FZI* values at all the core depths. A multivariate regression analysis is then performed to develop an explicit mathematical model for predicting *FZI* using the normalized logs.

It is notable that the reading values of logs must be corrected before being used in Equation 11. Also, any corrections usually performed in a well log analysis to make the values obtained from the logs more accurate should be applied to well logs; for example, if a well is cased hole, gamma ray log reading must be corrected for the effects casing.

6. Conclusions

The novelty of this study is that it suggests a porosity/permeability relationship that is physically-based and is not a correlation obtained only by pure regression. Moreover, this physically-based correlation is used together with hydraulic flow units, which increases the flexibility of the correlation and facilitates its application to permeability prediction. Some of the conclusions are as follows:

1. Reservoir porosity/permeability relationship is best developed if rocks with similar fluid-flow conductivity are identified and grouped together; each group is referred to as a hydraulic flow unit.
2. The reliability of the model presented in this work depends on the ability to predict the rock types accurately; in other words, it depends on the accuracy of the relationship between *FZI* and the normalized values of logs.
3. The presented method is particularly suitable for uncored intervals and its results are reliable.

Nomenclature

a	: Regression constant
b	: Regression constant
DRT	: Discrete rock type (dimensionless)
F	: shows a function
FZI	: Flow zone indicator (micrometer)
HFU	: Hydraulic flow unit
K	: Permeability (md)
$k_{armstrong}$	: Calculated permeability by using Armstrong model
k_{lab}	: Permeability obtained in laboratory
kr	: Relative permeability
$N\delta$	: Normalized δ log
NXDT	: Normalized sonic log
NXGR	: Normalized gamma ray log
NXNPH	: Normalized neutron log
NXRD	: Normalized resistivity log
NXRHO	: Normalized density log
NXSP	: Normalized spontaneous potential log
PS	: $\frac{\varphi_e}{1-\varphi_e}\times\frac{1-s_{wi}}{s_{wi}}$
Round	: Rounded value
RQI	: Reservoir quality index (micrometer)
S	: Fluid saturation (fraction)
S_{wi}	: Irreducible water saturation
δ	: Any log
δ_{max}	: Maximum reading of δ Log
δ_{min}	: Minimum reading of δ Log
φ	: Porosity (fraction)
φ_e	: Effective porosity (fraction)
φ_z	: Normalized porosity index (dimensionless)

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