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Permeability Estimation Using an Integration of Multi-Resolution Graph-based Clustering and Rock Typing Methods in an Iranian Carbonate Reservoir

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Abstract
Rock typing has been utilized in numerous studies where it has been proven to be a powerful tool for determining rock properties and estimating unknown parameters such as permeability. It can be performed based on routine core analysis (RCAL) or special core analysis (SCAL) data, and the accuracy of results could be different. Because of the high cost and time-consuming process of special core analysis, SCAL data are not available in all wells of a reservoir. Hence, in this study, a practical workflow is carried out using RCAL data. For this purpose, the data of four wells in a reservoir have been used. After utilizing three HFU (Hydraulic Flow Units), Winland r35 and lithology methods, the results showed that the best and the most accurate rock typing method is Winland r35 method. In the next step, several approaches were used to estimate permeability, and it was observed that the combination of the multi-resolution graph-based clustering (MRGC) method in GEOLOG software and Winland r35 method in this carbonate reservoir is the best estimation approach. The correlation coefficient (R^2), between measured and estimated permeability was approximately 0.96. Eventually, when the only available data are the RCAL data, the presented algorithm yields a high degree of accuracy.

Keywords: Rock Typing, Winland r35 Method, Permeability Estimation, MRGC Method, Carbonate Reservoir.

Introduction
Rock typing identifies the reservoir rocks that have similar geological, fluid flow, and reservoir characteristics and it is performed in a way that provides the best possible agreement of calculated properties with measured ones. In rock typing, individual groups of rocks should have similar characteristics and need to be evaluated accordingly [1-5]. Thus, rock typing should focus on objectives in reservoir modeling (i.e. correlating permeability or other unknowns with the available data related to rock characteristics) [6-10].
Rock typing is performed to help reservoir modeling, i.e. determining unknowns for each grid cell from the known parameters based on the established rock types. Rock typing requires the understanding of reservoir lithology (e.g. limestone, dolomite, shale, etc.) and physical characteristics (i.e. porosity, permeability, etc.) [9].There are different rock typing methods that may be used in reservoir studies. Rushing et al. presented a method for integrating different evaluations of rock typing at different scales (e.g., depositional, petrographic, hydraulic) based on drilling core data [11]. A new method called FZI-Star (FZI*) that utilizes the concept of hydraulic radius to identify hydraulic flow units was introduced by Mirzaei-Paiaman et al [6]. Static and dynamic rock types in PSRT and PDRT were distinguished by Mirzaei-Paiaman et al [7-8]. A PSRT is a group of rocks having similar primary drainage capillary pressure characteristics, whereas a PDRT is a class of rocks having similar fluid flow indicators.
One of the main objectives of rock typing is to estimate permeability [12]. Estimating permeability in reservoir rocks can be improved by involving different flow units based on geological characteristics [13-15]. During rock typing, rock units with some similar characteristics (i.e., porosity and permeability) will be determined, and thus, it is possible to predict permeability for unseen rocks. Due to the high cost and time-consuming procedure of obtaining the reservoir permeability directly from drilled wells, many researchers have tried to present new approaches for this purpose [16-17]. Such methods, which are basically an integration of conventional rock

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typing methods and even simulation techniques, were suggested by some researchers [18-20], and also, some methods have been presented based on defining new models for permeability estimation. For instance, mercury injection capillary pressure data were used to build a new carbonate and shale reservoirs model by Liu et al [5].

Some rock typing methods such as FZI are mainly based on fluid flow equations in simple capillary tubes. These methods are helpful, primarily for qualitative evaluations. In contrast, some rock typing methods that relate rock type with static rock characteristics such as grain density, lithology and log measurements are based on more physically meaningful properties; and therefore, they are more realistic for quantitative evaluations and modeling purposes. A practical rock typing method is one that is able to represent a realistic distribution of reservoir properties such as lithology, porosity, permeability, and saturation in the reservoir model. Hence, rock typing is usually a challenging step in reservoirs characterization [21-22].

So far, many researchers have tried to introduce new approaches for rock typing based on various data such as SCAL, RCAL, seismic attributes, geology, and recently artificial intelligence algorithms. FZI parameter was introduced by Ameafule and coworkers [13]. One of the other basic parameters is PRT; the PRT classes are, in essence, units of rocks (consisting of multiple facies) with similar petrophysical correlations and common porosity-permeability bins in the poro-perm domain [3]. Kelishami et al applied petrophysical rock typing (PRT) method to evaluation of Cenomanian–Santonian lithostratigraphic units in southwest of Iran [23]. Moreover, some methods are an extended and improved iteration of the already existing methods like FZI* [6], FZI** [24]. Some of them suggest new parameters for rock typing, such as the true effective mobility (TEM) function [7, 25]. TEM-function converts relative permeability data to fluid flow indicators for dynamic rock typing. Mirzaei et al divided rock typing into petrophysical static rock typing (PSRT) [7] and petrophysical dynamic rock typing (PDRT) [22] and even improved PSRT to gain PSRTI. But performing the existing SCAL-based methods using RCAL data as inputs has not been considered [26-29].

In this study, we have introduced a hybrid algorithm that integrates MRGC and Rock Typing methods to improve reservoir permeability estimation. We have proposed the following workflow; first, rock typing, using RCAL data is carried out based on three rock typing methods (hydraulic flow units, Winland r35 and rock typing based on lithology). Rock typing results, in conjunction with log data, are then fed to MRGC, where permeability is estimated based on the input data. Estimated permeability associated with each rock typing method is compared with the measured permeability and consequently, the best rock typing method is chosen and permeability derived from this method is chosen as the final estimation.

The only available data were RCAL data, and therefore, a workflow has been designed to determine rock types and predict permeability, accordingly. In this workflow, various rock typing methods including hydraulic flow units, Winland r_{35} method and rock typing based on lithology have been applied on mentioned data.

Materials and Methods

Study Data and Framework

Our study has been carried out on a carbonate reservoir containing fractures located in southwest Iran. The available data are the results of RCAL of samples taken from four wells in this reservoir. Input data consist of porosity, permeability and grain density, and the rock typing and permeability estimation methods are performed based on these data. The main framework of this research is shown in Figure 1.

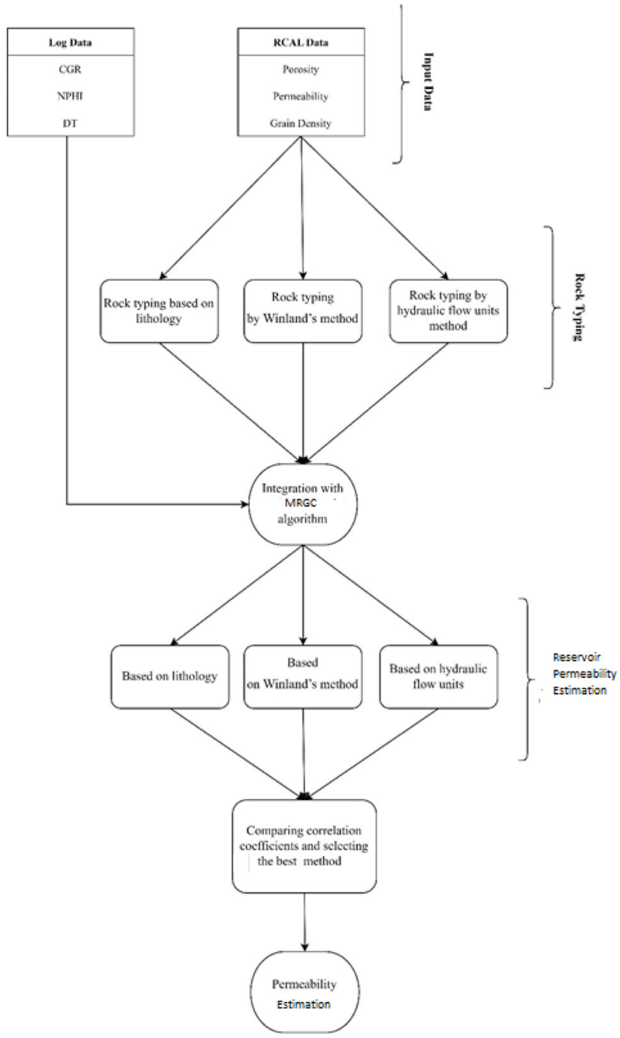

Fig. 1 The schematic framework of this study.

Methods

Rock Typing Using Hydraulic Flow Unit, Winland r35 and Lithology

The hydraulic quality of the rock is controlled by pore geometry which is a function of mineralogy and texture. Various permutations of these geological attributes often indicate the existence of distinct rock units with similar pore throat attributes. Determination of these pore throat attributes is central to accurate zoning of reservoirs into units with similar hydraulic properties [13].

In the hydraulic flow unit method, rock types are classified using the following three equations:

$$RQI = 0.0314\sqrt{\frac{K}{\phi}} \tag{1}$$

$$\Phi z = \frac{\Phi}{1-\Phi} \tag{2}$$

$$FZI = \frac{RQI}{\Phi z} \tag{3}$$

where K, φ, RQI, φZ, and FZI are permeability (mD), effective porosity (fraction), rock quality index (μm), normalized porosity (fraction) and flow zone indicator, respectively.

Core samples of the same rock type will have similar FZI values. Furthermore, on a plot of RQI versus φZ (Figure 2a), samples which lie on the same straight line constitute a hydraulic unit (Ameafule et al). The corresponding plot of horizontal permeability versus porosity is shown in Figure 2b.

Additionally, in the Winland r35 R_{35} method, rock types are calculated using the Equation 4 as follows:

$$Log\left(R_{35}\right) = 0.732 + 0.588\log\left(K\right) - 0.864\log\left(\Phi\right) \tag{4}$$

where R_{35} is the calculated pore throat radius at 35% mercury saturation from a mercury injection capillary pressure test (μm). Core samples of a given rock type will have similar R_{35} values [30].

For the mentioned formation, a plot of horizontal air permeability versus porosity and the straight lines related to R_{35} (microns) for each of the specified rock types are shown in Figure 2c. As can be seen, five specified groups of data are observed based on the Winland r35 rock typing concept.

The key properties for lithology-based rock typing include core porosity and lithology (or grain density) available from both log and core data. In this study, for lithology-based rock typing, core samples with more than 65% of limestone were defined as limestone-dominated rock types, core samples with more than 65% of dolomite were defined as dolomite-dominated rock type, and core samples with less than 65% of dolomite and 65% of limestone were defined as mixed rock. In Figure 2d, the defined rock types for all core samples based on lithology are shown. Therefore, three different rock types are considered in this field.

Ye and Rabiller in 2000 introduced a new clustering algorithm called MRGC (Multi-Resolution Graph based Clustering) that did not have the problems of previous methods (such as Dynamic Clustering (DC), Ascendant Hierarchical Clustering (AHC), Self-Organizing Map (SOPM), and etc.) in log data processing [31-33]. Further studies by Mohebian et al in 2018 also indicated the effective application of RVM in classifying anomalous seismic data to determine gas-bearing zones in an oil field [34].

Multi-Resolution Graph-based Clustering (MRGC) is an approach that gathers its knowledge by recognizing patterns in well logs using non-parametric K-nearest-neighbor and graph data representation. It allows the system to learn through experience how to log measurements related to important petrophysical parameters (e.g. porosity, water saturation, and permeability) [35].

This method is one of the few non-parametric methods in which logs data are evaluated by two indexes, i.e. NI (Neighboring index) and KRI (kernel representative index). NI indicates that each point in a data set is close to the peak or bottom of the probabilistic data density function. KRI determines the points prone to representation as to the core or center of the cluster. If NI(x) is the value of NI in x point, and y is the first neighborhood of x with NI(y) > NI(x) condition, the KRI at point x is calculated using the following equation:

$$KRI\left(x\right) = NI\left(x\right).M\left(x,y\right).D\left(x,y\right) \tag{5}$$

which is, M(x,y)=m, y is the m-neighbor of x, and D(x,y) is the distance between x and y.

Reservoir Permeability Estimation

Permeability Estimation Based on Hydraulic Flow Unit, Winland r35 Method and Lithology

Permeability can be determined as a function of porosity for each rock type if FZI is known by relating it to some rock characteristics. Permeability from the FZI method is as follows.

$$K = 1014FZI^{2} * \frac{\Phi^{3}}{\left(1-\Phi\right)^{2}} \tag{6}$$

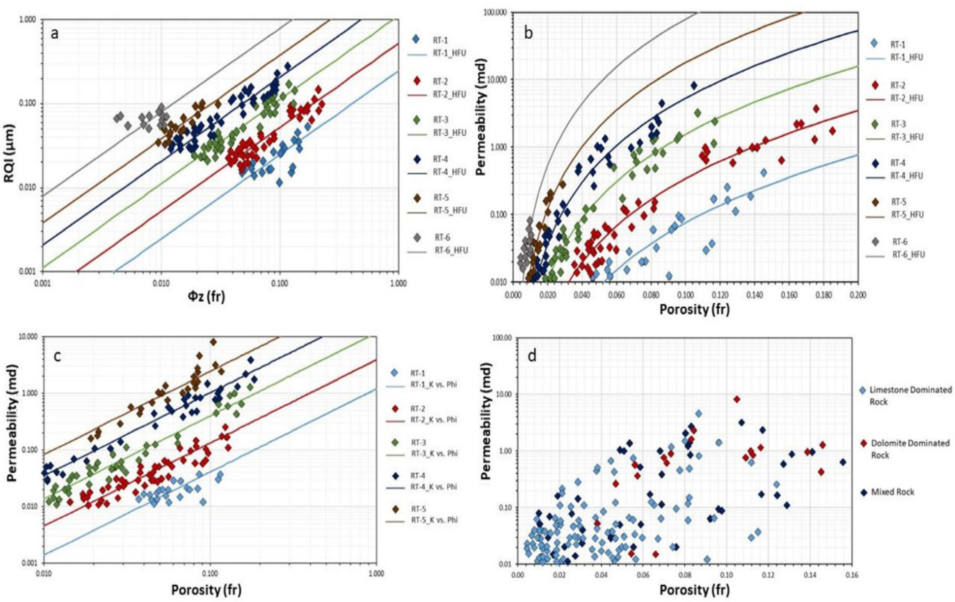

Fig. 2 Rock typing (a), (b) based on flow zone indicators (c) based on Winland r35 method (d) based on lithology.

Since the preferred method of permeability estimation is field-based (not well-based), FZI values for all core data from all the wells have been correlated together. This is because using the same FZI values in all wells is more applicable in reservoir modeling than determining it for each well individually. Based on the plot of permeability versus porosity which is shown in Figure 2b, permeability relations for the identified rock types are as follows (Table 1).

As discussed, calculated FZI (from core permeability and core porosity) cannot directly be used in the reservoir simulation model to estimate permeability because FZI is not a known physical characteristic. It is a function of permeability itself. To use rock types from the hydraulic flow unit method, FZI should be correlated with log measurements with satisfactory results. Suppose calculated FZI can be introduced to the reservoir simulation model by linking it to a known physical characteristic of the rock (such as their response in petrophysical log data). In that case, permeability can be determined using this rock typing approach.

Beside the HFU approach, based on Winland r35 method, permeability and porosity can be correlated with other rock characteristics using Equation 4. In the case of 35% mercury saturation, Equation 4 for determining permeability is written as follows:

$$K_{Air} = 10^{-1.244898} (R_{35})^{1.70068} \phi^{1.469388} \tag{7}$$

According to Equation 7, core data for different rock types would follow different straight lines in which each rock type would have its own parameters. Once these parameters are defined, then permeability for each rock type can be determined from MICP data. Based on the plot of permeability versus porosity which is shown in Figure 2c, permeability relations for the identified rock types are as follows (Table 2).

In all methods used, 80% of the core data were used as training data, and 20% of the data were used as validation data (unseen data). Figure 3 shows the relationship between estimated and actual permeability for the available core samples using the Winland r35 method in the unseen section of the interval. Overall, the agreement between actual and estimated data from low permeability to high permeability data is satisfactory, with a correlation coefficient (R2) of more than 0.96.

In order to perform permeability estimation based on lithology, a corresponding rock type was assigned for each valid core sample based on the given lithology or grain density. For each group of data separated based on lithology, a relation between permeability and porosity was determined.

Table 1 The porosity-permeability relations for the identified rock types based on the FZI method.

Rock Type	FZI range	Average FZI	Porosity-Permeability relations
RT-1	FZI<0.34	0.25	$K = (1014)(0.25)^2 \frac{\varphi^3}{(1-\varphi)^2}$
RT-2	FZI<0.75≥0.34	0.52	$K = (1014)(0.25)^2 \frac{\varphi^3}{(1-\varphi)^2}$
RT-3	FZI<1.5≥0.75	1.11	$K = (1014)(1.11)^2 \frac{\varphi^3}{(1-\varphi)^2}$
RT-4	FZI<2.94≥1.5	2.06	$K = (1014)(2.06)^2 \frac{\varphi^3}{(1-\varphi)^2}$
RT-5	FZI<5≥2.94	3.78	$K = (1014)(3.78)^2 \frac{\varphi^3}{(1-\varphi)^2}$
RT-6	FZI≥5	7.93	$K = (1014)(7.93)^2 \frac{\varphi^3}{(1-\varphi)^2}$

Table 2 The porosity-permeability relations for the identified rock types based on R35 method.

Rock Type	R_{35} range	Average R_{35}	Porosity-Permeability relations
RT-1	R_{35}<0.15	0.113	$K_Air = 10^{(-1.244898)} (0.113)^{1.70068} \varphi^{1.469388}$
RT-2	R_{35}<0.3≥0.15	0.225	$K_Air = 10^{(-1.244898)} (0.225)^{1.70068} \varphi^{1.469388}$
RT-3	R_{35}<0.55≥0.3	0.431	$K_Air = 10^{(-1.244898)} (0.431)^{1.70068} \varphi^{1.469388}$
RT-4	R_{35}<1≥0.55	0.75	$K_Air = 10^{(-1.244898)} (0.75)^{1.70068} \varphi^{1.469388}$
RT-5	R_{35}≥1	1.249	$K_Air = 10^{(-1.244898)} (1.249)^{1.70068} \varphi^{1.469388}$

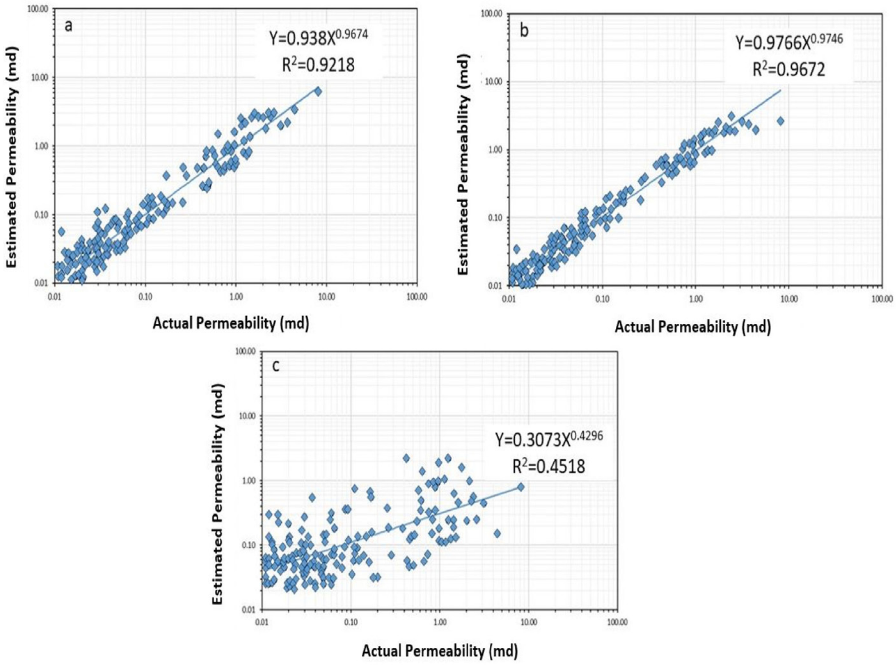

Fig. 3 Estimated versus actual permeability for the available core samples in the unseen section of well (a) using hydraulic flow unit method (b) using Winland r35 method, and (c) using lithology method.

Considering that the dominant lithology in each well is also different based on core data in wells 004, 011 and 017, the data indicate a significant effect of formation heterogeneity across the reservoir area and in the vertical direction. Based on the best possible curve-fitting of the data, the relationship between permeability versus porosity for each lithology group was determined (Table3).

In order to correlate FZI, R_{35} and lithology with log measurements and prepare permeability logs based on the aforementioned methods for different wells in the reservoir formation of the understudied field, a nonlinear regression analysis was performed among calculated parameters (as dependent variables) and corresponding petrophysical log data (DT, CGR and NPHI as independent variables) for the cored intervals using multi-resolution graph-based clustering (MRGC) method in GEOLOG software. The estimated FZI, Winland r35 and lithology logs for different wells using the MRGC method as well as effective porosity logs and the mentioned permeability correlations for different rock types were used to prepare corresponding permeability logs for different wells in the mentioned field. These permeability logs can be propagated later in the geological model to prepare 3D horizontal permeability model for the matrix system.

Table 3 The relationship between permeability versus porosity for each lithology group.

Rock Type	Lithology	Porosity-Permeability relations
RT-1	Dolomite dominated (more than 65% of dolomite)	$K = 0.05633e^{25.10052}\varphi$
RT-2	Limestone dominated (more than 65% of limestone)	$K = 0.01914e^{25.10052}\varphi$
RT-3	Mixed (less than 65% of limestone and 65% of dolomite)	$K = 0.03547e^{25.10052}\varphi$

Results and Discussion

To understand the accuracy of each method for permeability estimation, the results of permeability estimation have been validated with real permeability data and Figure 3a, Figure 3b, and Figure 3c show the relationship between estimated and actual permeability for the available core samples in the unseen section of interval using mentioned methods with correlation coefficients (R2) of around 0.93, 0.96 and 0.45, respectively.

Thus, the preferred and more accurate approach for permeability estimation under studying reservoir is the integration of Winland r35 with MRGC method.

In order to validate the permeability estimation results, core actual and estimated permeability should be compared based on correlation coefficient (R2) as well as on a plot versus depth. It is important to get satisfactory matching results on the plot of permeability versus depth. If productive intervals (pay zones) have good prediction of permeability, then it can be acceptable in terms of prediction of well production performance.

Using Winland r35 method (and correlating R_{35} with log measurements) for permeability estimation, the best match of estimated versus actual permeability for the available core samples was optained. Also, the hydraulic flow unit and lithology-based methods have been employed, and the correlation coefficients are displayed in Table 4.

Table 4 Correlation coefficients and root mean squared error values for each method.

Permeability estimation method	R^2	RMSE
Winland r35 method	0.96	0.018
Hydraulic flow unit method	0.93	0.032
Lithology-based method	0.45	0.120

Estimated permeability logs for wells 004, 011 and 017 based on different Permeability estimation methods, including lithology (Lith, using petrophysical evaluated porosity and lithology logs), hydraulic flow unit (HFU, using estimated FZI and petrophysical evaluated porosity logs) and Winland r35 (using estimated R_{35} and petrophysical evaluated porosity logs) are shown in Figure 4 to Figure 6, respectively. As shown in the figures, the Winland r35 method offers the best match of estimated versus actual core sample permeability and provides more reasonable permeability values for dense and porous intervals of reservoir formation in the studying field than other methods. Its results are demonstrated by red rectangular.

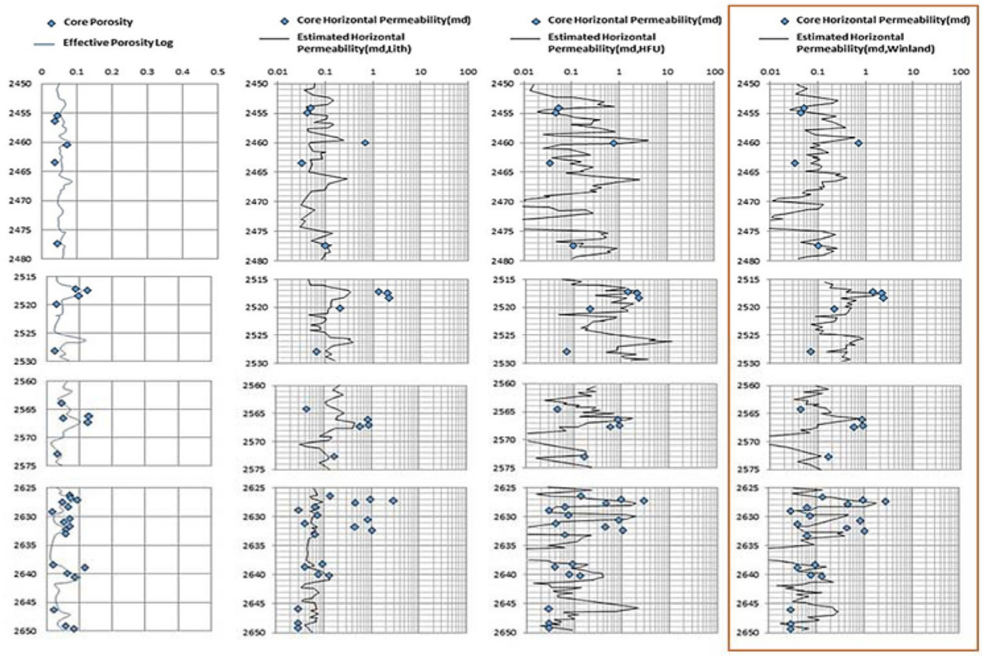

Fig. 4 Estimated permeability logs for well-004.

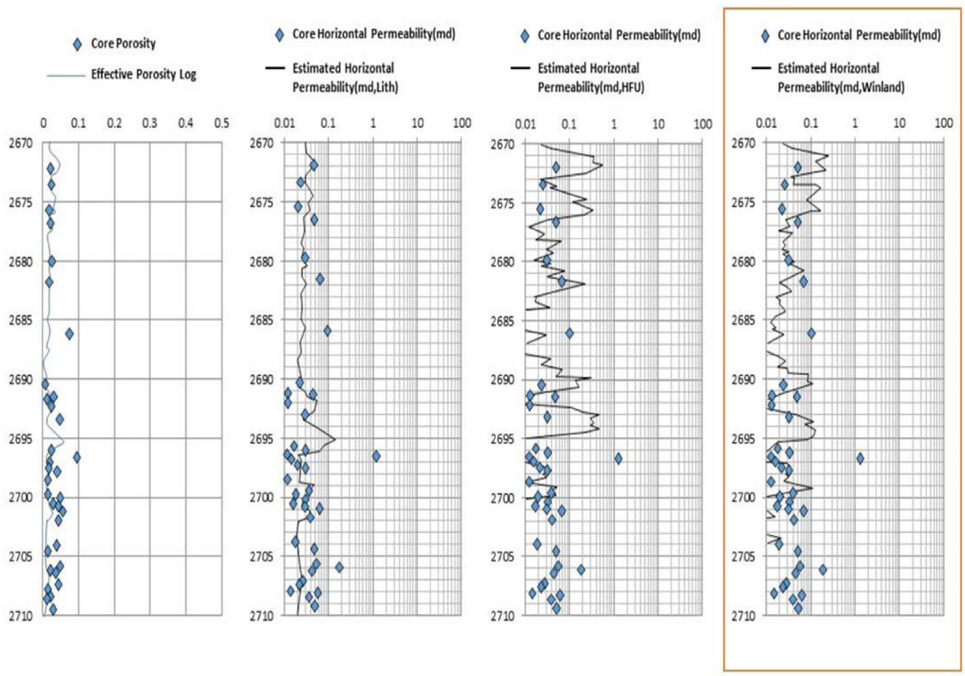

Fig. 5 Estimated permeability logs for well-011.

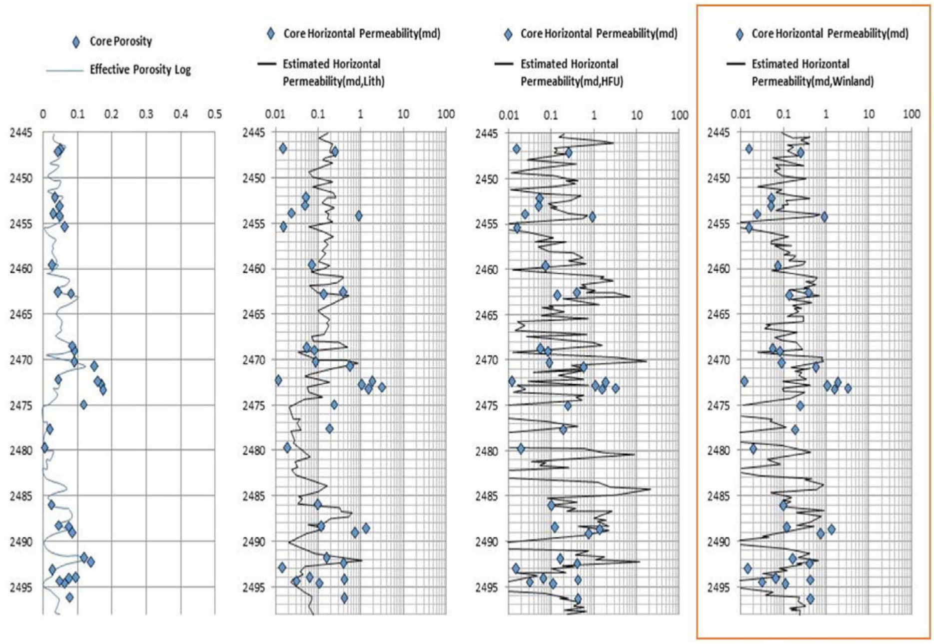

Fig. 6 Estimated permeability logs for well-017.

Conclusions

This study presented a framework of rock typing and, therefore, permeability estimation based on the RCAL data and applying conventional rock typing approaches.

Different RCAL rock typing methods were examined based on the available data, including rock typing based on hydraulic flow unit, Winland r35, and lithology. Also, permeability estimation based on hydraulic flow unit, Winland r35 and lithology were performed , and the following results have been concluded:

• By using Winland r35 method (and correlating R_{35} with log measurements) for permeability estimation, the best match of estimated versus actual permeability for the available core samples (with a correlation coefficient (R2) of 0.96) was obtained.

• Winland r35 method is capable of matching core sample data with high and low permeability values.

• The correlation coefficient values for hydraulic flow unit and lithology-based methods are 0.93 and 0.45, respectively.

• The value of RMSE for the Winland r35 method is 0.018, confirming this method is the most accurate one for permeability estimation.

• The FZI and lithology-based methods showed RMSE values of 0.032 and 0.12.

Declarations

Conflicts of interest/Competing interests: On behalf of all the co-authors, the corresponding author states that there is no conflict of interest.

Authors' contributions: **Reza Mohebian**: Supervision, Conceptualization, Methodology, Writing- Original draft preparation. **Hassan Bagheri**: Methodology, Data curation, Reviewing and Editing. **Mahdi Kheirollahi**: Data curation, Writing- Reviewing and Editing, Results correction. **Hassan Bahrami**: Validation, Reviewing and Editing.

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