Hydraulic flow units and ANFIS methods to predict permeability in heterogeneous carbonate reservoir: Middle East gas reservoir

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Abstract

Permeability is one of the key parameters in the characterization and modeling of the hydrocarbon reservoirs, which has an important effect on optimal production and field management. Permeability is directly obtained from the core data and indirectly from the well testing data. Determining permeability by using core is the most accurate and expensive method in the industry, also core information may only exist in some wells. Therefore, it is necessary to use methods that can determine permeability without core data. Use of hydraulic flow units (HFU) concept is one of the methods for estimate permeability. HFUs are a function of flow zone indicator (FZI), in which each flow unit has a unique FZI. Due to the fact that permeability estimation in wells without core data is one of the important issues in the oil industry, the purpose of this study is to estimate permeability in one of the southern Iranian carbonate gas fields. In this field, core data only exists in one of the wells; therefore, we used an integrated approach of HFUs and adaptive network fuzzy inference system (ANFIS) to estimate permeability. Subsequently, the values of FZI, RQI (reservoir quality index), and ϕ_Z (normalized porosity) were calculated for core samples, and six HFUs were identified by different methods which showed a high value of the correlation coefficient in each HFU. Based on HFU and FZI, permeability was estimated and compared with core permeability data. The average relative error between the core permeability and the estimated value is 1.83%. Eventually, based on conventional well log data and ANFIS, permeability values were estimated in un-cored wells. The average relative error between core permeability and ANFIS calculated has shown 5.21%. So it can be concluded that this method can be used in all un-cored wells by just using log data of high accuracy.

Keywords Hydraulic flow units · Estimate permeability · ANFIS · Middle East gas reservoir

Introduction

Collection of various reservoir data is critical for engineering evaluation, monitoring, and management of hydrocarbon reservoirs (Karimian Torghabeh et al. 2014). As the amount of data and information increases, knowledge about the reservoir and plans for optimal production increases. Permeability is one of the key factors in reservoir management. Permeability of rock is the ability of transmitting the fluid flow through the rock body and is measured by core analysis experiment and well test methods (Behnoudfar et al. 2017; Tadayoni and valadkhani 2012). Permeability data are often only available in a few wells as core data; therefore, the use of other methods that can predict permeability in un-cored wells is quite necessary. Permeability is generally obtained from core data, well test analysis, and log data. Estimation of permeability in a carbonate reservoir is difficult due to its high heterogeneity.

In the literature, adaptive network fuzzy inference system (ANFIS) has been used to estimate permeability (Handhal Amna 2016). Although other methods such as well testing are also used to determine permeability, however, it is time-consuming and costly. The use of HFUs is one of the most common techniques used to describe and classify rock types according to petrophysical properties such as core permeability and porosity (Abbaszadeh and Fujimoto 1996; Amaefule et al. 1993; Enayati-Bidgoli et al. 2014). HFUs are defined as units of rock with similar petrophysical and lithological

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attributes that are different from properties of other rock volumes (Jr Ebanks 1987; Mahjour Seyed et al. 2016). HFUs, which give a better description of the reservoir and can be used as inputs for reservoir modeling, are strongly dependent on flow zone indicator, which is a function of reservoir quality index. RQI and FZI are related to the petrophysical properties of cores such as porosity and permeability. Different methods such as probability plot, Log-Log plot of RQI versus Φ_z, and histogram analysis have been applied to characterize and classify HFUs from FZI. Mean FZI values determinate from the Log-Log plot of RQI versus Φ_z yield a unit slop trend line. If the reservoir is subdivided into different flow units, in each flow unit, permeability can be estimated with a high precision (Borhani Tohid and Emadi Seyed 2011; Kharrat et al. 2009). In the past, porosity with linear regression analysis in un-cored wells has been used to estimate permeability. Due to the fact that two samples with the same porosity can have different permeability, this method may result in a high error (Soto et al. 2001). In ANFIS model, fuzzy logic with mathematical models are generally applied on an inference process which can be designed either from expert knowledge or from data. An ANFIS is a combination of fuzzy logic systems and neural networks (Soto et al. 2001).

In the literature, several permeability predictive models have been used by using conventional well log data (Balan et al. 1995; Zhang et al. 2019). Recently, machine learning models such as artificial neural network and fuzzy systems have been widely used to enhance the reliability and accuracy of the models (Kharrat et al. 2009; Shahvar et al. 2009). In addition, permeability predictive models based on HFU were presented by many researchers (Abbaszadeh and Fujimoto 1996; Soto et al. 2001; Elnaggar Osama 2017). With artificial neural network application in cored wells, the connection between log and core data to expand the predictive permeability model was determined and then used to develop the flow units prediction in un-cored wells (Charkhi Amir et al. 2019).

Borhani Tohid and Emadi Seyed (2011) used ANFIS and HFU to estimate the permeability in southern parts of the reservoir in Iran (Borhani Tohid and Emadi Seyed 2011). Elkatatny et al. (2018) developed an artificial neural network model which was utilized to anticipate the permeability of heterogeneous reservoir based on well logs. Also, they introduced a new term which is effective in estimating permeability (Elkatatny et al. 2018). All of these approaches have used indirect methods for estimating permeability.

The objective and innovation of this study is to estimate permeability in wells without sampled core data with high accuracy by using ANFIS model, which has not been applied before for predicting the permeability in a carbonate reservoir based on HFU. The main advantage of the artificial neural network method lies in the high accuracy and less needed information in comparison with other methods. The requisiteness for this research is the lack of permeability information in un-cored wells, as well as the accuracy improvement of neural network improvement in comparison with previous research approaches.

Geological setting

The Kangan and Upper Dalan formations, which is equivalent to the "Upper Khuff reservoirs" in the Arabian Plate, include the most important reserves in the Middle East region. The study area is an Iranian natural gas field which was discovered in 1967 and is considered one of the largest gas fields not only in the Middle East but also all over the world. Kangan field is located in the south of Iran (Fig. 1). Kangan and Dalan formations represent the two most important formations of the Deh-Ram group in the Kangan field, as well as the most important gas reservoirs in the Persian Gulf region. The Deh-Ram group is subdivided into three formations, which are, in stratigraphic order, the Kangan, Dalan, and Faraghan formations (Fig. 2). The Kangan formation is of early Triassic in age, which is characterized by alternating dolostone, limestone, evaporites, and shale sequence. The study area is considered being a part of the largest carbonate gas reservoir in the Persian Gulf region (Insalaco et al. 2006; Zamannejad et al. 2013). The main deposits of this formation are shallow-marine sediments that underwent intense near-surface diagenesis and restricted carbonate ramp platform with minor burial modification (Zamannejad et al. 2013).

Carbonates and evaporates are two major lithologies in Dalan formation (Motiei 2003). It comprises a lower limestone succession, a middle section of anhydrides, and an upper carbonate succession consisting of limestones and dolomites and is classified into one formal and two informal members:

The upper Dalan member It consists of three main layers, from base to top, Oolitic limestone, Micritic limestone, and dolomite, and few stringers of anhydrite and dolomites.

Nar member It consists mainly of massively bedded anhydrites, anhydrite and dolomite stringers, and Oolitic limestone.

The lower Dalan member This layer has been deposited from the Permian Sea as the first carbonate beds, containing abundant macrofossils, such as crinoids, corals, bryozoan, and gastropods with sand and silt grains and sandstone beds near the base. According to Insalaco et al. (2006) and Motiei (2003), the lower Dalan member is made up of fossiliferous limestone and dolomites and oolitic and pelletoidal limestones with a few beds of completely dolomitized limestone and dolomitized oolitic limestone.

The stratigraphic column of the region Fig. 2 shows the Kangan formation and the Dalan formation with its three members.

Fig. 1 Map showing the location of the Kangan gas field located in south Iran (modified from Faraji et al. 2017)

Methodology

In this study, permeability's prediction follows two-step procedure. Core data only exist in one well. So the first step was the implementation of the HFU method to predict permeability in this well, and second, the ANFIS method was used to calculate the value of the FZI in un-cored well to predict permeability by well logs data.

Permeability prediction using HFU

Petrophysical properties are very important parameters to define the distribution of different rock types and reservoir modeling. Reservoir porosity and permeability are two major parameters in reservoir studies. On the other hand, permeability measurements, unlike porosity, may not exist in all the wells of the field; in addition, the interval of core data is usually limited. The HFU represents a reservoir zone, which has lateral continuity. Incorporation of HFUs and rock typing is a key element of an integrated reservoir description. HFU uses core porosity and permeability, which are crucial parameters for the identification of different reservoir rock types and evaluation of formation storability. The HFU concept was selected for classifying the reservoir into distinct petrophysical properties. Each distinct petrophysical property has a unique FZI value. FZI is determined from log analysis (porosity and permeability) and is calculated using the rock quality index (RQI) and the normalized porosity (PHIZ) (Amaefule et al. 1993).

The RQI was calculated using Eq. (1):

Fig. 2 Chronostratigraphic of study interval. Permian numerical ages (modified from Farrokhrouz and Asef 2010)

$$RQI = 0.0314\sqrt{\frac{K}{\varphi_e}} \qquad (1)$$

where permeability is in MD and RQI is reservoir quality index (μm). The core porosity was converted to normal porosity Φ_z as defined in Eq. (2).
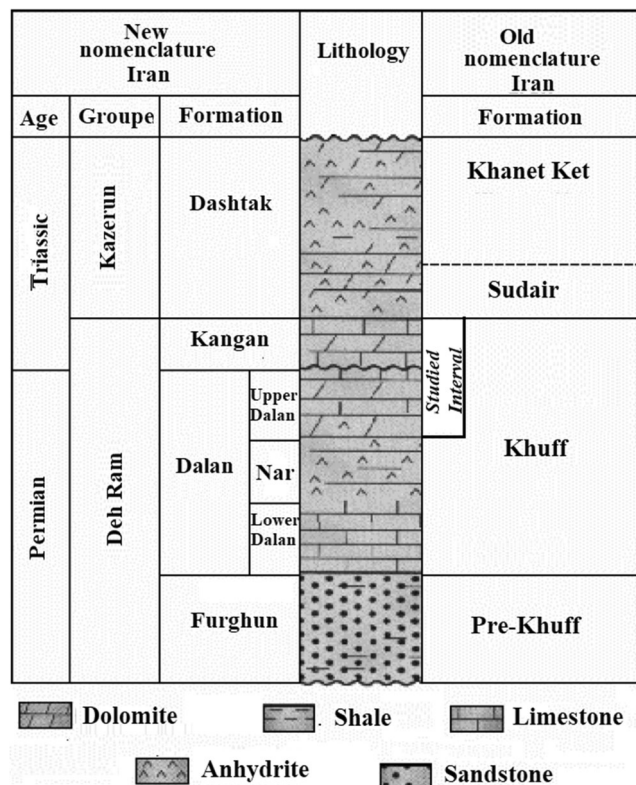
$$\varphi_z = \frac{\varphi_e}{1-\varphi_e} \qquad (2)$$

By simplifying Eq. (2), FZI can be defined as:

$$FZI = \frac{RQI}{\varphi_Z} \qquad (3)$$

Finally, by taking the logarithm of Eq. (3), the following equation is obtained:

$$Log(RQI) = Log(\varphi_z) + Log(FZI) \qquad (4)$$

To identify each flow unit in log-log plot of reservoir quality index versus normalized porosity, the line with unit slope is known as a flow zone indicator. In this plot, samples with similar value of FZI lies on the similar line. These samples are supposed to have the same pore throat and petrophysical properties, which can be considered a unique flow unit (Abbaszadeh and Fujimoto 1996; Amaefule et al. 1993). Also, samples with different FZI value will lie on other lines and are considered different flow units. RQI, FZI, and ϕ_z were used for HFU classification, which is discussed in the following sections. After determining the flow units, a relation based on FZI obtained to estimate the permeability is shown in Eq. (5).

$$K = 1014 * (FZI)^2 \left(\frac{\varphi_e^3}{(1-\varphi_e)^2} \right) \qquad (5)$$

To determine flow units in a reservoir, porosity and permeability values were used. In this study, the optimum number of HFU in Kangan and upper Dalan formations was identified by using RQI vs normal porosity, histogram analysis, and probability plot methods. The histogram of FZI was first calculated, which is the simplest method to get a quick identification of HFUs. Then, the reservoir quality index and normal porosity were calculated by Eqs. (1) and (2). This simple method is found to be not sufficient to distinguish different units, and other methods must be used to increase confidence. Finally, a probability plot of FZI data was used. This method is found to be more suitable to determine the optimum number of HFUs, because the identification of HFUs becomes easier and more reliable.

In the histogram method, a histogram of log FZI data was used to recognize the number of HFUs. Each normal distribution of logarithm flow zone indicator shows a different HFU. In this method, it is hard to recognize the optimal number of flow units existing in these formations.

So using one method cannot predict the exact number of existing flow units.

## Permeability prediction in un-cored wells

Estimating permeability in un-cored wells depends on the determination of FZI in these wells. So, by using FZI and effective porosity, permeability can be calculated in each hydraulic flow unit with high accuracy. There are various methods used for calculating FZI. In this study, an ANFIS model was used to calculate the value of the FZI in un-cored wells. In this method, the parameters of the method are chosen to tailor the membership functions to the input/output data in order to find out calculation for all the alterations in the data values, which is known as neuro-adaptive learning and is similar to that of neural networks (Soto et al. 2001; Jang 1993). The basic idea for neuro-adaptive learning techniques is simple. These techniques provide a method for the fuzzy modeling procedure to learn information about a dataset. Neural networks, according to input and output data, try to identify and adapt the behavioral pattern between input and output data by modifying and adjusting mathematical models. Therefore, to use this method first, a suitable model should be established between the log data and FZI in cored well, and then the obtained model should be generalized to estimate the FZI in un-cored wells. In this work, permeability was calculated by ANFIS and HFU methods, and then these results were compared with the core permeability in cored well.

In the un-cored wells, the log data is the only available data to determine FZI. An ANFIS is based on adaptive neural networks, hybrid soft computing techniques, and fuzzy inference systems (FIS), and in this study, it was used for permeability predictions (Soto et al. 2001). ANFIS is a category of adaptive networks that the parameters are chosen so as to functions to the input/output data to compute for all the variations in the data values. Relationships between input and output data was carried out through a set of fuzzy if-then rules. Normally, these rules came from the fuzzy clustering procedure. Subtractive clustering is one of the best methods for constructing a fuzzy model (Chiu 1994). The adequacy of a fuzzy model is related to the search for the optimal clustering. More clusters may complicate the system behavior and reduce the performance and search lower clusters increase the error because this search does not cover the entire area (Kadkhodaie-Ilkhchi et al. 2010). To predict permeability,

Table 1 Core well porosity and permeability data

	N	Mean	Minimum	First quartile	Median	Third quartile	Maximum	StDev
Permeability	490	18.96	0	0.11	0.35	2.33	2649	148
Porosity	490	0.077	0	0.019	0.064	0.12	0.31	0.067

Fig. 3 Cross plot of porosity versus permeability for cored well
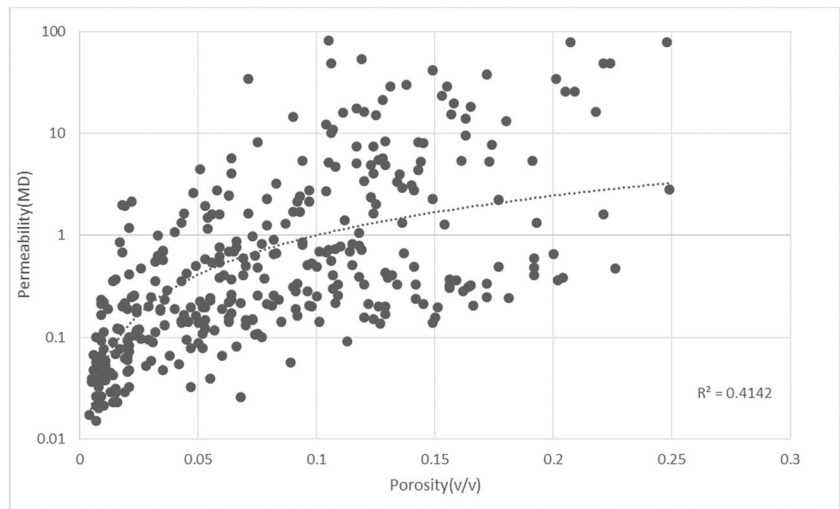
first, the FZI value must be calculated. The advantage of neural networks is that it does not require the definition of a specific mathematical model to estimate permeability. In this method, the network parameters can be estimated through a training or learning procedure. In this way, the behavior of the system can be predicted according to the pattern generated by the neural networks (Soto et al. 2001). Fuzzy logic acts based on fuzzy theory. For permeability estimation at first, determine a suitable model for log data in cored well. Then based on this model and log data, FZI is determined. In this study, NPHI, RHOB, PHIE, and GR logs were used as inputs and the log FZI (calculated in cored well) is used as the system output for ANFIS. In Eq. (7), relationship between core FZI and log FZI is shown.

$$FZI_{core} = 1.002*\left(FZI_{\log}\right)^{1.01} \tag{7}$$

Finally, permeability can be estimated from log data by substituting Eq. (7) in Eq. (5).

$$K = 1018*\left(FZI_{\log}\right)^{2.02}\left(\frac{\varphi_e^3}{(1-\varphi_e)^2}\right) \tag{8}$$

Results and discussion

Data analysis

In this study, 490 porosity and permeability measurements from core data and well log data were used to predict permeability in a carbonate reservoir located in Iran.

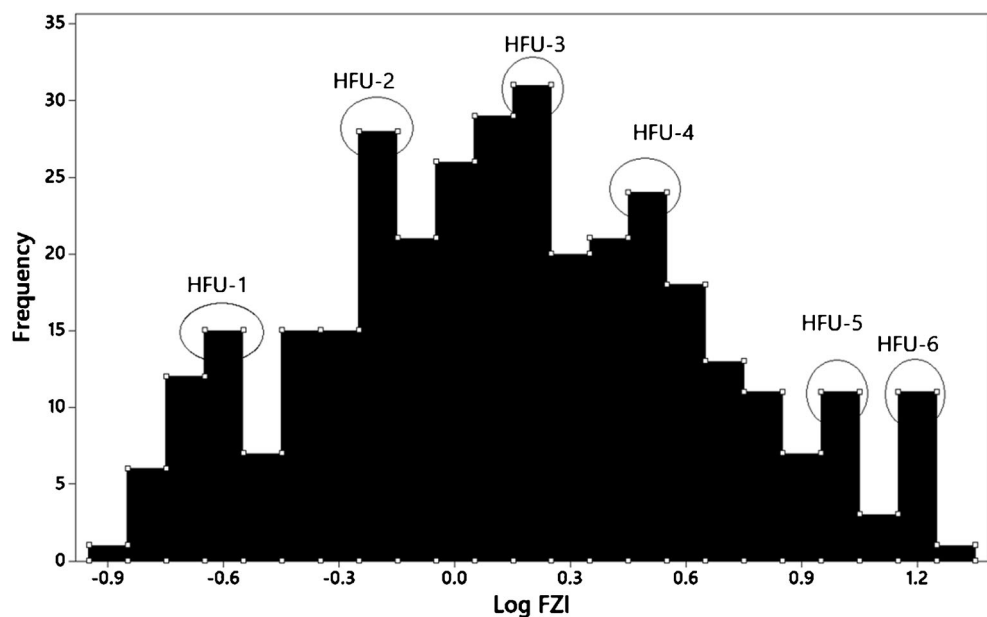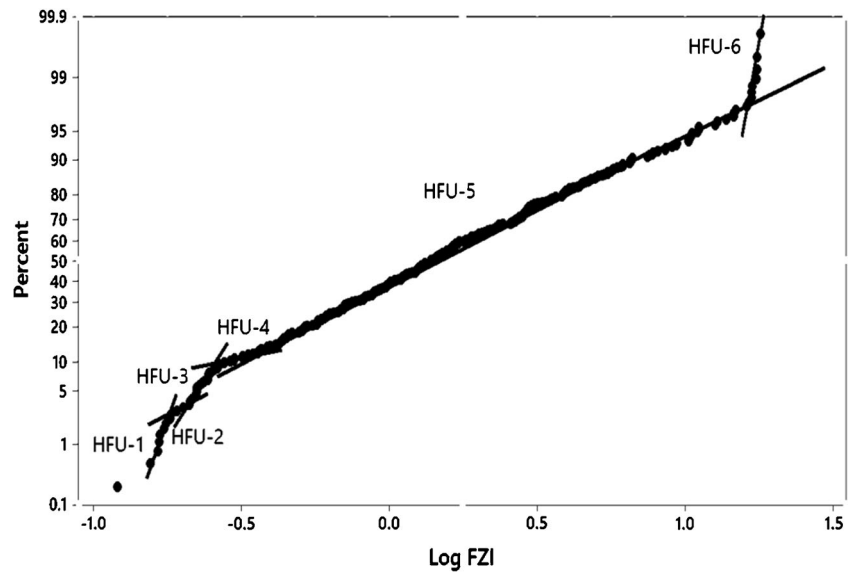**Fig. 4** Histogram of flow zone indicator

Fig. 5 Normal probability plot of log FZI

The core information of this field is shown in Table 1. Figure 3 illustrates the permeability distribution versus cores porosities. The high scatter of the porosity and permeability data by a correlation coefficient of 0.41 indicates that the formations are highly heterogeneous, and several rock types with different petrophysical properties exist. Therefore, only porosity cannot be used to explain and investigate permeability variation.

Identification of hydraulic flow units

According to the normal distribution in Fig. 4, six HFUs can be identified. However, to confirm the boundaries of each one

of the HFUs with high confidence, it is essential to use a probability plot. A second method was used, in which the normal probability of Log FZI data was plotted. In this plot, any change in the slope and fracture that can be represented as straight lines will reveal the optimum number of HFU. For histogram and probability plotting, Minitab software and EXCEL were used. The probability plot is smoother than the histogram method, so it is more suitable to specify the optimum number of HFUs. Probability plot in Fig. 5 shows six HFUs in this field. The last method to identify HFUs in this field is the plot of RQI vs Φz. In this method, samples with similar FZI will lie on a straight line with a slope equal to one which have a similar pore throat. Each straight line with

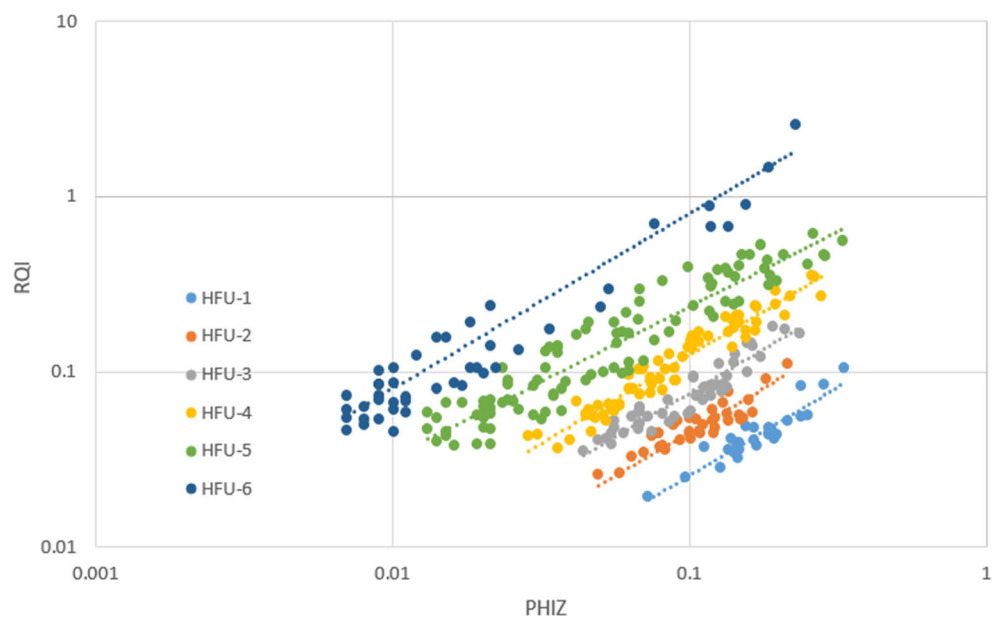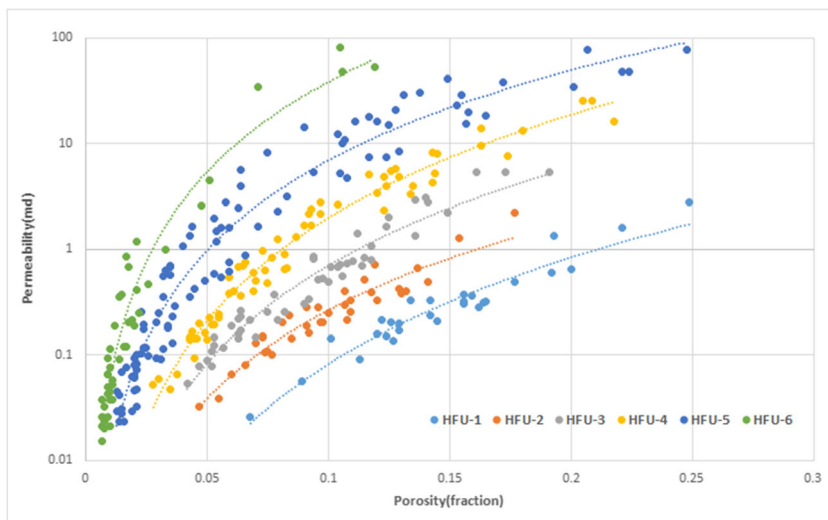**Fig. 6** The plot of RQI vs. normalized porosity

Fig. 7 Hydraulic flow units in relation to porosity and permeability data

similar FZI is considered one HFU. Also, the mean FZI values can be determined for all HFUs from the intercept of the straight lines that were used in permeability prediction Fig 6.

Finally permeability and porosity relationship were established from the HFUs as shown in Fig 7.

Permeability calculation based on HFU

The optimal number of HFUs was found to be six. This means that six rock types exist in this field. Six mean value of FZI is used to calculated permeability using Eq. (7). Table 3 shows the mean values of FZI for the six detected HFUs. By using the unequivocal value of FZI, the best permeability model can be reached. The best quality of petrophysical properties has the highest values of FZI, and the lowest FZI values show the HFUs with the lowest petrophysical properties (Tables 2, 3).

After calculating permeability, the results should be compared and validated with core permeability. Hence, the average relative error (ARE) between core permeability and the calculated ones was calculated as below:

$$ARE = \frac{1}{n} \sum_{i=1}^{n} \left[\frac{\text{Core permeability-calculated permeability}}{\text{Core permeability}} \right] \quad (6)$$

After determining the optimal number of HFUs and FZI values, permeability value was calculated in the cored well. According to Fig. 8, the correlation coefficient is 0.93 which shows an excellent linear relationship between the core and calculated permeability values. Also based on Eq. (6), the ARE result in this well was found to be 1.83%. Figure 8 shows the plot between core permeability vs calculated permeability as a comparison correlation between these two parameters. According to this plot, the high correlation coefficient (0.93) indicates the accuracy and high compliance of the results.

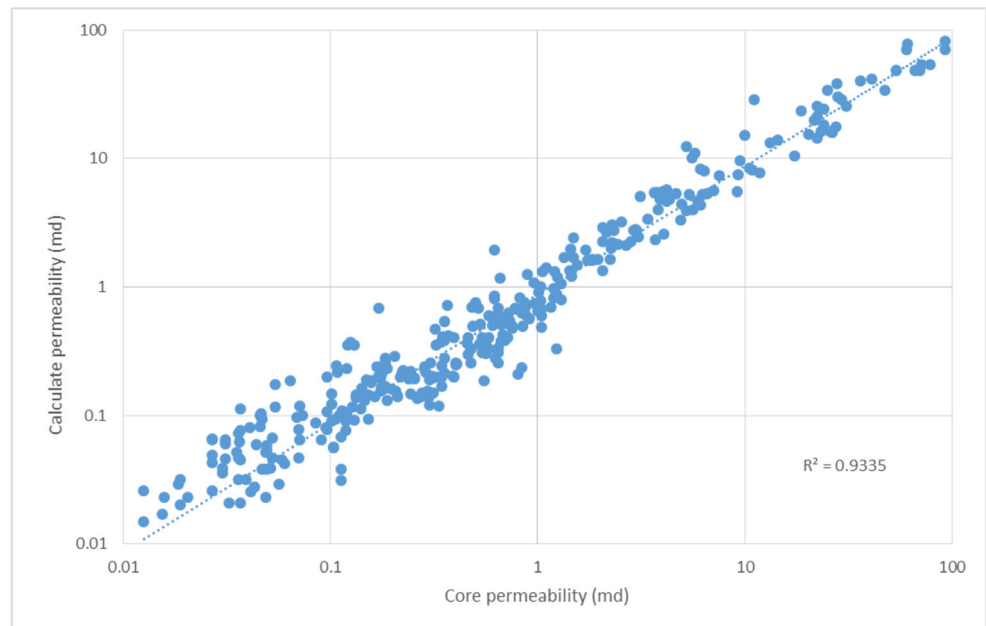## Permeability prediction in un-cored wells using ANFIS

Figure 9 shows the relationship between the FZI of ANFIS method vs the FZI obtained from core data. According to the correlation coefficient of (0.87), this model is considered the best method to predict permeability from log data in case of the absence of core data.

By using FZI value, permeability was determined in un-cored wells. Figure 10 shows the correlation between the values of permeability that were measured from core data and those that were predicted by ANFIS. The average relative error between core permeability and calculated permeability with ANFIS method is 5.21%. So with this validation, we can use this method to

Table 2 Reservoir rock classification

Layers	Minimum square	Relationship between k and φ
HFU-1	0.9141	$182.46 * \Phi^{3.3488}$
HFU-2	0.9041	$163.08 * \Phi^{2.7899}$
HFU-3	0.9389	$874.62 * \Phi^{3.0968}$
HFU-4	0.9689	$3496 * \Phi^{3.2461}$
HFU-5	0.9473	$4806.7 * \Phi^{2.8439}$
HFU-6	0.9341	$26430 * \Phi^{2.8354}$

Table 3 Mean values of FZI

HFU	FZI
HFU-1	0.2928
HFU-2	0.409
HFU-3	0.779
HFU-4	1.2254
HFU-5	1.9188
HFU-6	5.9715

Fig. 8 The relation between calculated permeability and core permeability

predict permeability in un-cored wells of the entire reservoir. By comparing and validating the results, it can be deduced that using this method can estimate permeability more accurately using log data in un-cored wells in this field.

permeability is using well log data, which are routinely available data in every well.

In this research, 490 core samples and log data (NPHI, RHOB, PHIE, and GR logs) were used to calculate permeability. The study consists of two steps:

Conclusions

Estimating permeability of hydrocarbon reservoir is an essential parameter to build a reservoir model which affects fluids flow. Well test and core data are two reliable sources of permeability determination. In fact, coring from all points of formation is not possible. So another way to estimate

1. Calculate permeability by HFU methods and then compare it with the core permeability. The optimal number of HFUs was found to be six with a different method, and mean FZI value has been used for the prediction of permeability in cored well. It was found that HFUs are strongly related to FZI. FZI is considered important parameter in estimating permeability in wells.

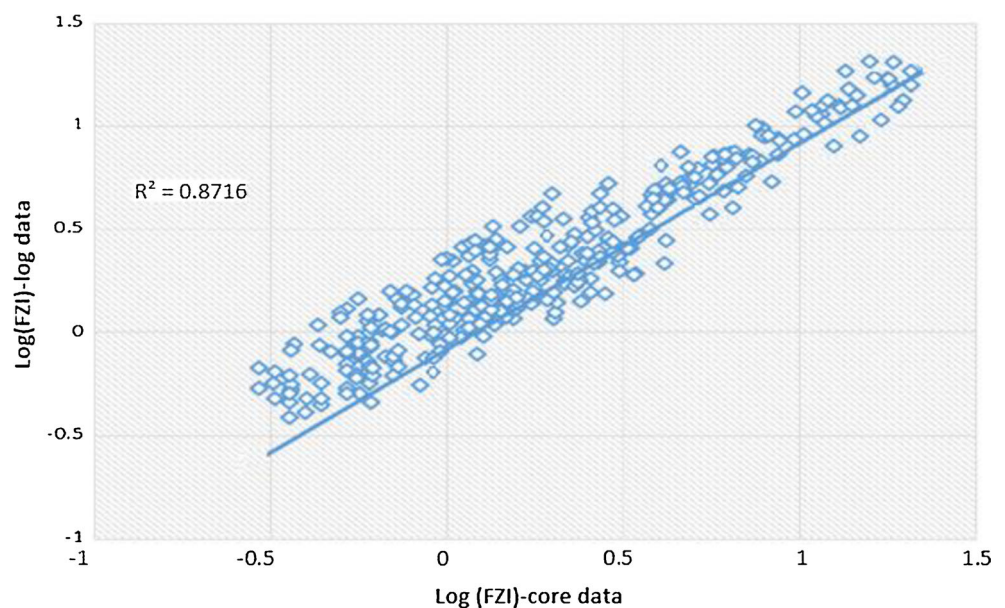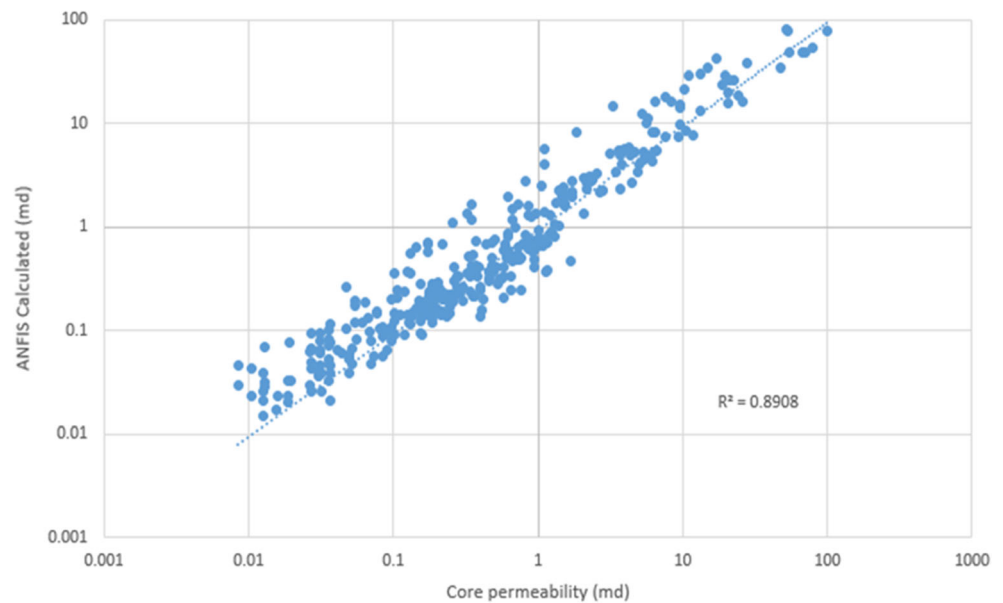**Fig. 9** The cross plot between FZI of core data and FZI of ANFIS method

Fig. 10 The relation between ANFIS permeability and core permeability

2. Estimate permeability with standard well logs data in un-cored wells. In un-cored wells, the FZI values were calculated with ANFIS method and log data.

The average relative error between the core permeability data and calculated permeability values was 1.83%, and the correlation coefficient was observed 0.93 which related to high precision. Finally with ANFIS and conventional log data, permeability was predicted. The average relative error between the ANFIS permeability and the cored permeability was obtained 5.21% and correlation coefficient found equal to 0.89. Although the results of this method show a lower correlation coefficient, it allows us to estimate the permeability with suitable accuracy without core data in the other wells of this field.

Declarations

Conflict of interests   The authors declare no competing interests.

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