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Permeability Prediction in One of Iraqi Carbonate Reservoir Using Statistical, Hydraulic Flow Units, and ANN Methods

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Abstract

Permeability is an essential parameter in reservoir characterization because it is determined hydrocarbon flow patterns and volume, for this reason, the need for accurate and inexpensive methods for predicting permeability is important. Predictive models of permeability become more attractive as a result.

A Mishrif reservoir in Iraq's southeast has been chosen, and the study is based on data from four wells that penetrate the Mishrif formation. This study discusses some methods for predicting permeability. The conventional method of developing a link between permeability and porosity is one of the strategies. The second technique uses flow units and a flow zone indicator (FZI) to predict the permeability of a rock mass using data from cores and well logs. The approach is used to predict the permeability of some uncored wells/intervals. The flow zone indicator is an efficient metric for calculating hydraulic flow units since it is based on the geological properties of the material and varied geometries pore of rock mass (HFU) and Artificial Neural Network (ANN) analysis is another way for predicting permeability. The result shows the FZI method, gave acceptable results compared with the obtained from core analysis than the other methods.

Keywords: permeability, FZI, Artificial Neural Network, Mishrif formation.

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1- Introduction

Reservoir characterization approaches are important to provide a better indication of the flow capabilities and storage of petroleum reservoirs [1], especially for heterogeneous carbonate reservoirs [2]. Permeability which reflects the rock's capacity to transmit fluids (oil, gas, and water) through pore spaces, is one of the essential properties of reservoir rocks. Laboratory core analysis can get permeability data on (1.5) in core plugs and sidewall core. However, permeability prediction in uncored sections is crucial because most wells do not core because of challenges during coring and more significant expenses [3]-[5].

One of the essential properties of a petroleum deposit is its permeability. Permeability can be assessed in the laboratory or the field by using core samples or other well-test information [6]. You need to know how permeable the rock is to write an effective reservoir description [7].

Because permeability is recognized as a fundamental quantity that influences reservoir management, well completion, and production methods, it's vital to get it right [8].

Flow zone indicators (FZIs), one of the most used approaches for permeability prediction, identify flow units (groups of rocks) whose elements have particular flow characteristics that are different from those of other units in the rock volume [9].

Artificial Neural Network (ANN) which is the most often used since it does not require any correlations between variables, and neural networks offers a flexible technique to generalize linear regression [10], [11].

Three different methods are used in to estimate permeability Flow Zone Indicator and classical approaches rely on relationship between porosity-permeability, and an artificial neural network (ANN) is using traditional well log and core data to predict permeability [12].

The approach is demonstrated by applying it to one of Iraq's oil fields. Four wells were chosen from field as located at east south of Iraq (XX 1, XX 2, XX 3, XX 4) because they were evenly distributed across the Mishrif formation to assess the reservoir's properties and rock type.

The field is one of Iraq's most important oil fields in the southeast. Seismic tests undertaken between 1973 and 1988 discovered the field in the Dhi Qar city. The field is 34 kilometres long and 17 kilometres wide, implying the presence of unfaulted underlying fold structure with a general northwest – southeast trend [13]. The shallowest of Iraq's X field's hydrocarbon-bearing formations is the Mishrif reservoir. Fine to coarse bioclastic limestones exhibit a shallow depositional domain, the average

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thickness of this formation is about 170 m. Mishrif formation consists of two parts: upper part (MA) unit and lower Mishrif (MB) separated by shale. The lower part also subdivided into two reservoir subunits (MB1 and MB2) [14].

2- Methodology

2.1. Classical method

The permeability-porosity relationship is found through core analysis and turned into well-log data. Using the equation below, log-derived porosity in uncored wells or zones is used to figure out empirical permeability [15], [16].

$$K = a * exp(b\phi) \tag{1}$$

Where: K: is the permeability (md), ϕ: is the porosity (fraction), and, a and b: are the constants to be fitted to the case study.

The link between porosity and permeability was determined from core for MB1 and MB2 Units from four of the wells studied; However, in some cases, the association between core analysis results and porosity and permeability is low because of the heterogeneity of rocks as shown in Fig. **1** and Fig. **2**. In the same reservoir, can exits both high and low permeability zone with same porosity values. That requires accurate alternative methods to predict permeability in uncored intervals.

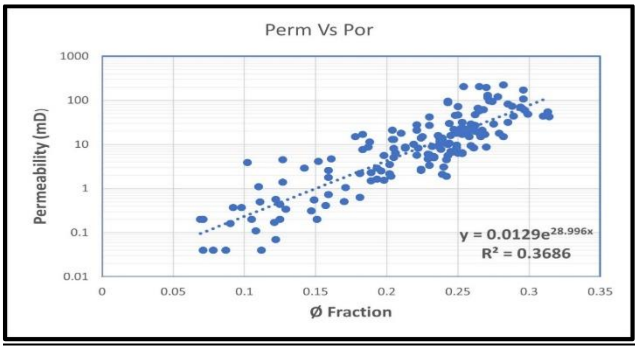

Fig. 1. Permeability vs Porosity Cross Plot for MB1 Unit

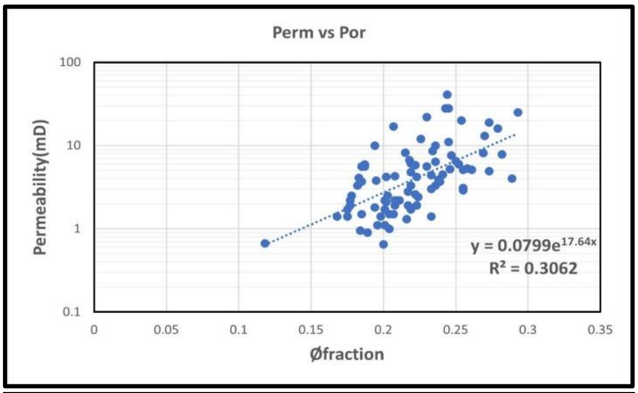

Fig. 2. Permeability vs Porosity Cross Plot for MB2 Unit

The results of the correlation between permeability - porosity of Mishrif formation obtained from core analysis are shown in Table **1**.

Table 1. Classical Permeability Formulas

Unit Name	Formula	Number of core samples (N)	(R^2)
MB1 for all wells	**K = 0.0129*exp(28.9996*Ø)**	**201**	**0.368**
MB2 for all wells	**K = 0.0799*exp(17.64*Ø)**	**87**	**0.3062**

2.2. Flow Zone indicator

This technique is advised for determining the permeability of the reservoir. Based on the hydraulic flow units, core data was categorised by the slope of the linear fitted line between porosity and permeability. This revealed that geological conditions corresponded to each other [16], [17].

The equation is simplified if permeability and porosity are measured in millidarcy and fraction, respectively [18].

$$RQI = 0.0314 * \sqrt{K/_{\text{Øe}}} \tag{2}$$

It is possible to express the normalized porosity index (Øz) in terms of the porous volume to grain volume ratio (fraction).

$$Øz = \frac{Øe}{1-Øe} \tag{3}$$

FZI is given by:

$$FZI = \frac{RQI}{Øe} \tag{4}$$

RQI vs Øz log-log plots show that the slope of a line connecting all samples with identical FZI values is one, and that the slopes of lines connecting samples with FZI values that are significantly different from the preceding one are all equal to one. It is possible to create a single hydraulic flow unit by aligning samples in a straight line that all have the same pore throat characteristics. For each Hydraulic Flow Unit (HFU), the intercept of this line with Øz = 1 reflects the mean FZI value [19].

Mishrif formation was divided into four HFU or FZI, and four porosity-permeability relations are applied by different equations with powerful correlated factors for each one, as in in Fig. **3** and Fig. **4**, the equation results of the regression analysis for the hydraulic flow units are given in Table **2**.

Table 2. Permeability Formulas for Each HFU

FZI	**Formula**	**R2**
FZI_1	**K= 710.23*Øeff$^{3.7475}$**	0.8889
FZI_2	**K= 1123.7*Øeff $^{3.3357}$**	0.9359
FZI_3	**K = 2624.9Øeff$^{3.1939}$**	0.8873
FZI_4	**k= 64471*Øeff$^{3.6175}$**	0.95

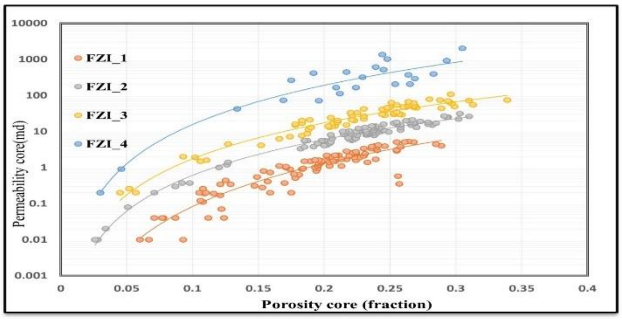

Fig. 3. Permeability vs. Porosity Cross Plot for Specific FZI

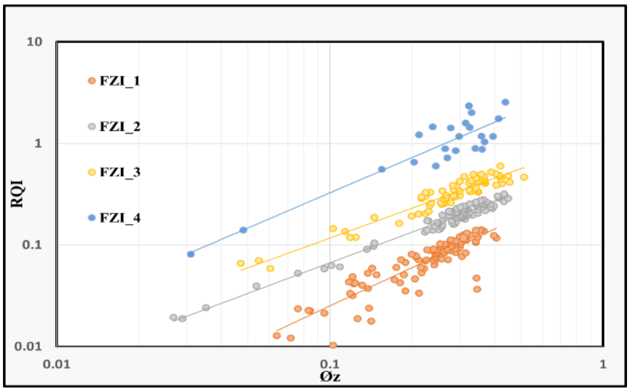

Fig. 4. RQI versus. Øz Cross Plot

2.3. Artificial Neural Network

An artificial neural network (ANNs) is a computer model that tries to mimic the basic biological learning process and the specialized function of the human nervous system. An adaptive parallel information processing system, it is capable of developing associations and transformations between input and output data input and output the In an ANNs analysis [20].

Artificial neural networks (ANNs) have proven to be an effective method for modeling generic relationships. They've been employed in remote sensing, biomedical engineering, and other fields [21].

ANNs are excellent predictors because they can learn a problem from a small number of samples and their generalizing ability allows them to make predictions based on data that was not included in their training set. ANNs are also stronger than typical prediction methods in dealing with incomplete or noisy data [22].

A training set is created using (water saturation SW, effective porosity PHIE, invasion depth Di, shale volume VSH, variables as inputs and their related permeability values (known from core analysis) as desired outputs to predict permeability by using the ANNs algorithm which build in interactive petrophysical software V4.5.

3- Results and Discussions

1. According to the classical technique and neural network, the permeability of the core data was much lower than the calculated permeability Because it is challenging to establish a simple correlation between porosity and permeability in these formations, it is challenging to identify the permeability of heterogeneous formations using well log data. However, none of these methods can be applied to every case as shown in Fig. **5** and Fig. **6** a plot of prediction permeability versus core permeability of MB1and MB2, which were applied the formulas in Table **1** and in Fig. **7** and Fig. **8** which is represented the permeability estimated by ANNs and permeability by core analysis.

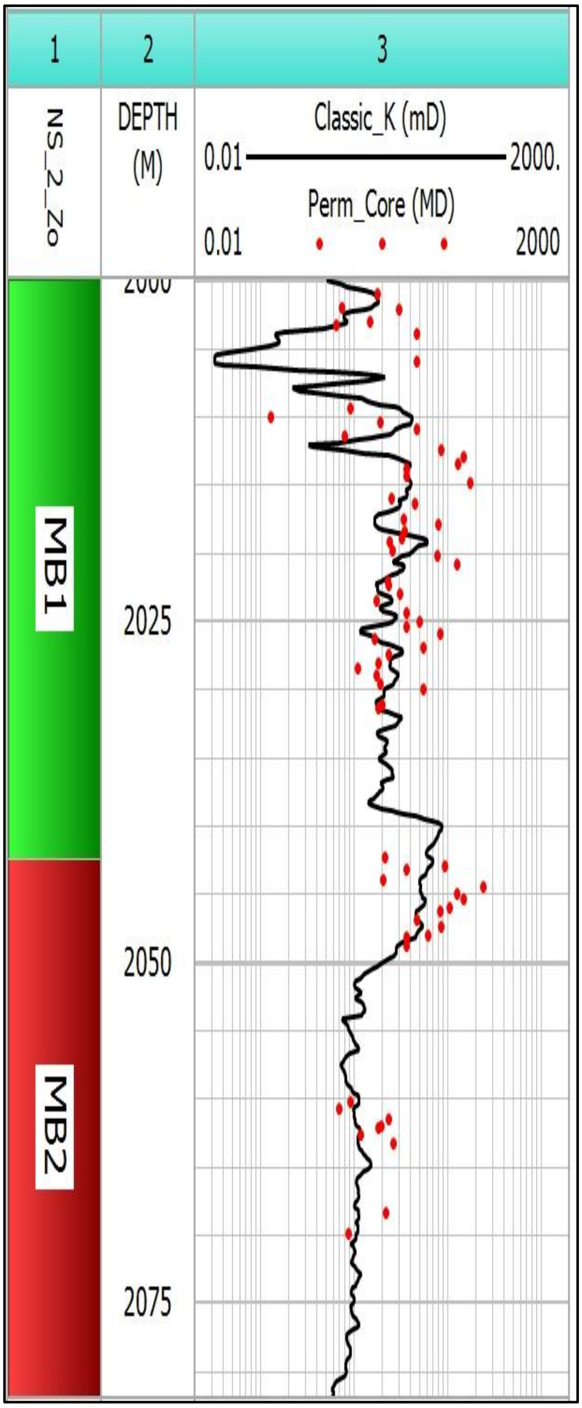

Fig. 5. K-core and K –classic for XX_1

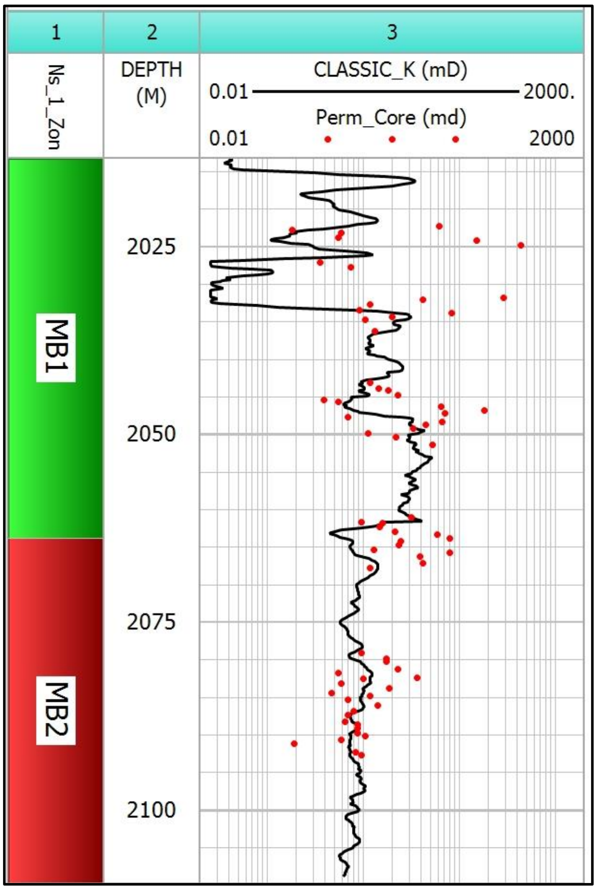

Fig. 6. K-core and K –classic for XX _2

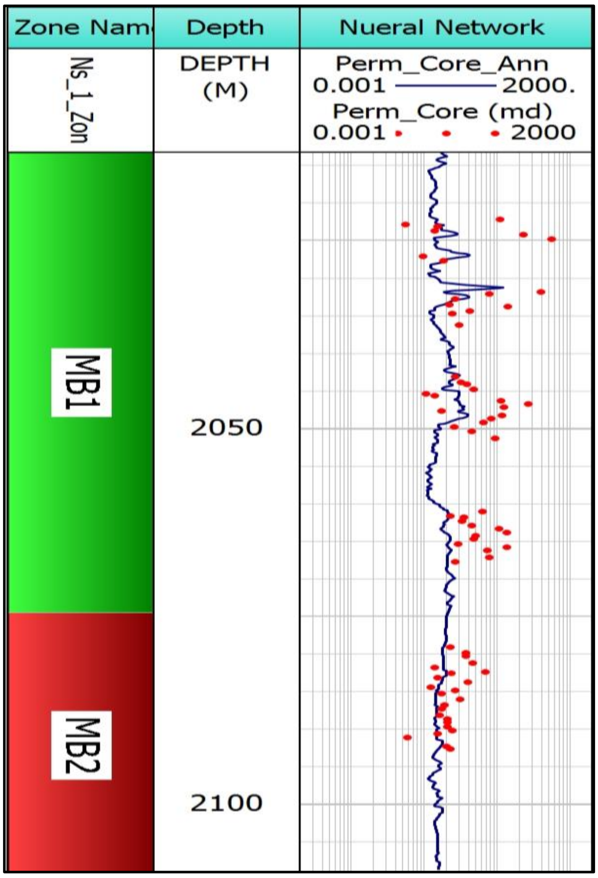

Fig. 7. K-core and K-ANNs for XX _1

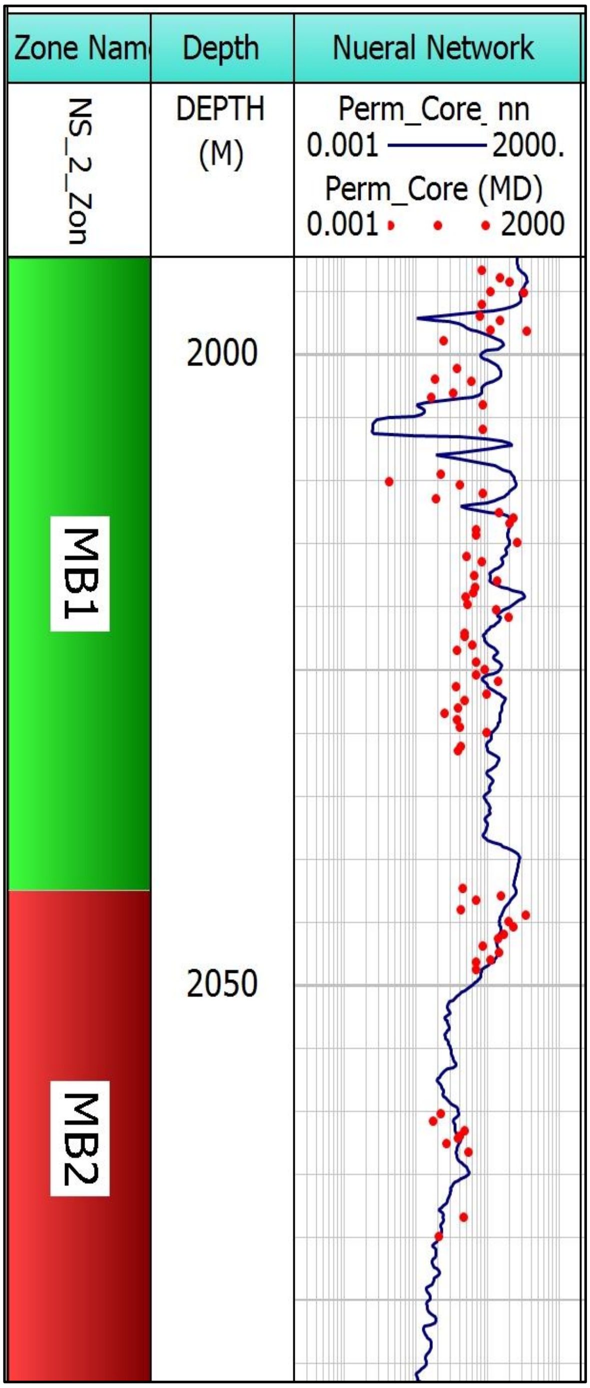

Fig. 8. K-core and K-ANNs for XX _2

2. According to values of FZI four groups were identified in permeability– porosity plot and permeability formula generated for each group. Each of them represent the different type of rock. The generated permeability formulas are applied in uncored wells and intervals depending on the porosity value from the logs.

The produced permeability formulas in Table **2** were used in the cored wells (xx-1, xx-2, xx- 3 and xx-4) to compare the estimated permeability values with the measured core values as illustrated in Fig. **9** to Fig. **12**.

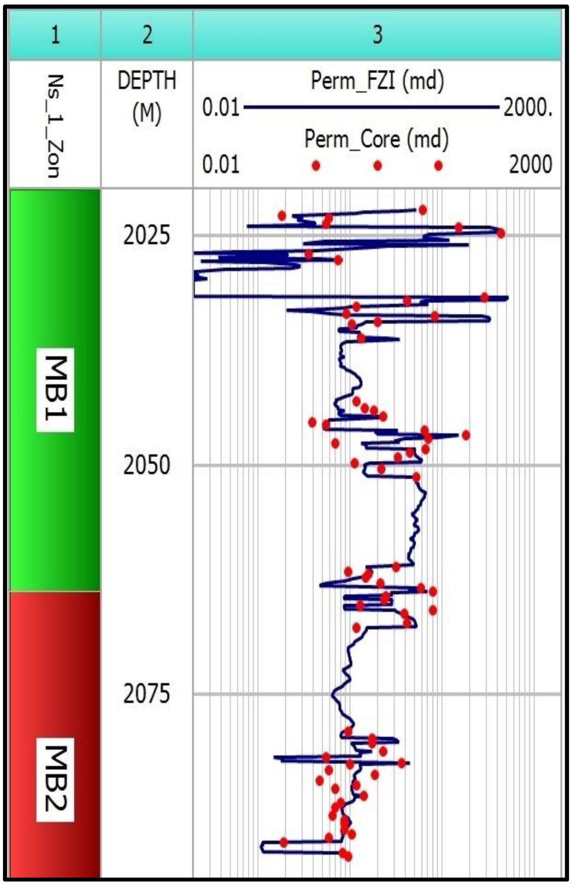

Fig. 9. K-core and K-FZI for XX_1

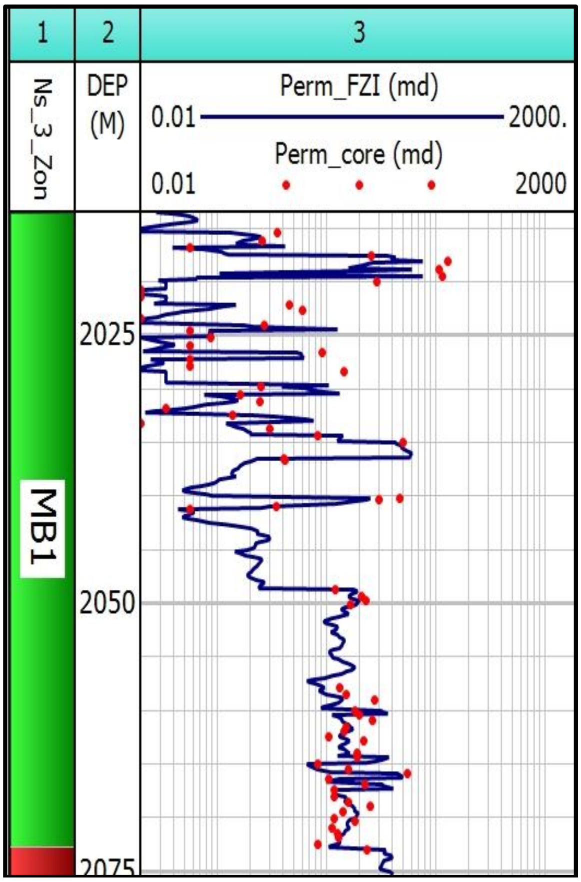

Fig. 11. K-core and K-FZI for XX_3

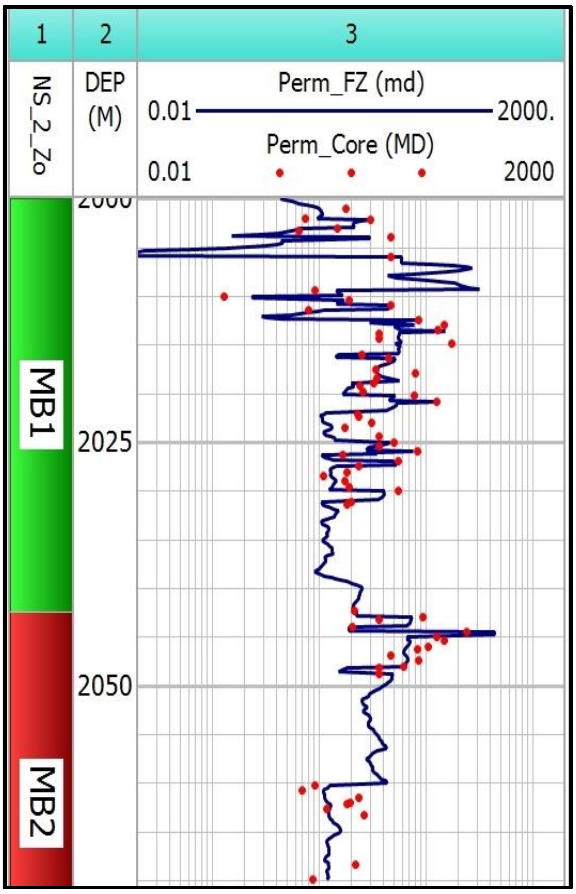

Fig. 10. K-core and K-FZI for XX_2

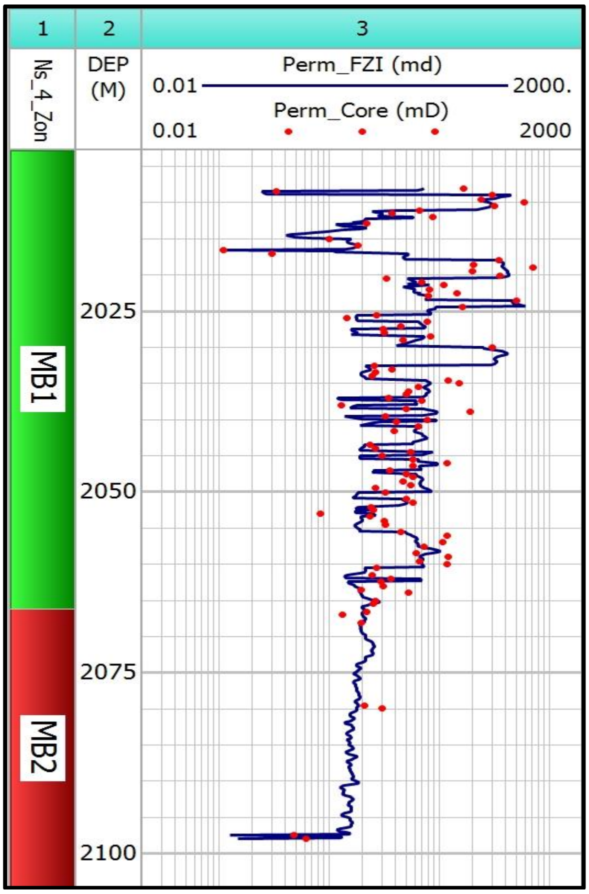

Fig. 12. K-core and K-FZI for XX_4

4- Conclusion

1. ANNs and classical methods failed to give a good match between calculated permeability and core permeability because due to heterogeneity and variation in pores geometry.
2. The (FZI) gives the best results for permeability prediction because it gave good agreement between the predicted and cored values at most depth intervals of the two units in the wells, so this study has adopted the Flow Zone Indicator (FZI) method to predict permeability in uncored wells/units.
3. Using the FZI approach, Mishrif reservoir is divided into s four HFUs groups with high correlation coefficient (R^2) for each (HFU) represents a different type of rock, which has a similar porosity and similar qualities.
4. A method based on HFUs has been developed for better permeability assessment in uncored wells or uncored intervals of otherwise cored wells. The method produces good results when its limitations and applicability range are acknowledged and considered.

Nomenclature

ANN: Artificial Neural Network
FZI: Flow Zone Indicator, µm
HFU: Hydraulic flow unit
PHIE: effective porosity, fraction
S_w: water saturation
Di: invasion depth
VSH: shale volume
RQI: Reservoir Quality Index, µm

Symbols

k: permeability, md
R^2: correlation coefficient
Øz: normalized porosity, fraction
Øe: effective porosity, fraction

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التنبؤ بالنفاذية في أحد مكامن الكاربونية العراقية باستخدام الطرق التقليدية ووحدات التدفق الهيدروليكي وطرق الشبكة العصبية الاصطناعية

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الخلاصة

النفاذيـة هـي مـن المعلومـات الأساسـية فـي توصـيف المكمـن لأن عـن طريقهـا يـتم تحديـد أنمـاط تـدفق الهيدروكربون وحجمه، ولهذا السبب، فإن الحاجة إلى طرق دقيقة وغير مكلفة للتنبؤ بالنفاذية مهمة للغاية. تم اختيار مكمن مشرف في جنوب شرق العراق لاتمام هذه الدراسة، واستندت الدراسة إلى بيانات من أربعة آبار تخترق المكمن. تناقش هذه الدراسة عدة طرق للتنبؤ بالنفاذية، الطريقة الاولى هي الطريقة التقليدية لتطوير الصلة بين النفاذية والمسامية هي واحدة من الاستراتيجيات. والطريقة الثانية هي بالاعتماد على كتلة الصخور ومؤشر منطقة التدفق باستخدام البيانات من اللباب وسجلات الآبار. وطريقة أخرى للتنبؤ بالنفاذية هي بالشبكة العصبية الاصطناعية.

أظهرت النتائج أن طريقة مؤشر منطقة التدفق هو مقياس فعال لحساب وحدات التدفق الهيدروليكي لأنه يعتمد على الخصائص الجيولوجية للمادة وهندسة المسام المتنوعة لكتلة الصخور مقارنة بالطرق الأخرى وقد اظهرت نتائج مقبولة لحساب النفاذية مقارنة بالطرق الاخرى.

الكلمات الدالة: النفاذية، مؤشر منطقة التدفق، الشبكة العصبية الاصطناعية.