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Neural Network and Empirical Models of Mamuniyat Reservoir Permeability Prediction, Murzuq Basin-Libya

Bahia M. Ben Ghawar [1*], Fathi M. Salloum [2], Mahmud A. Al Tarhouni [3]

[1,3] *Geological Engineering Department, Faculty of Engineering, University of Tripoli, Tripoli, Libya.*
[2] *Earth Sciences Department, Faculty of Science, University of Benghazi, Benghazi, Libya.*

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Correspondence:
Name: Bahia M. Ben Ghawa

Email:

gloriamuftah@yahoo.com

ABSTRACT

Permeability (K) is a dominant property of the production and development planning strategy of oil fields. Thus, deriving and/or defining a suitable reservoir permeability model provides time and cost consumption. Most reservoir characterization studies were associated with the estimation of permeability. In the present work, three approved empirical model cases were employed by Wyllie and Rose (1950), Timur (1968), and Sheffield (1956). These models' worth utilization to predict the permeability property of the Mamuniyat reservoir (Upper Ordovician) in Murzuq Basin, SW Libya. In addition, derivation of the permeability model of the studied reservoir is based on routine core analysis (CCA) data of two oil wells. Also, a neural network (NNW) is applied to assess the prediction permeability, dependent on measurements of well logging data. Whereas validation of the predicted permeability model is taken into consideration when adding two more oil wells, which are producing from the same reservoir. In general, the predicted permeability values of the clastic Mamuniyat reservoir are greater than 0.1 mD and do not exceed 200 mD, with a good effective porosity ($Øe \approx 13\%$). However, correlation between the predicted permeability results by the empirical and derive models are satisfactory, with a significant level (P) equal to 0.000. Furthermore, a statistical analysis emphasizes both the Derived and NNW models, which hold a regression coefficient (R^2) close to 1. Moreover, the grain size and irreducible water (Swi) have an impact on the predicted permeability.

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نموذج الشبكة العصبية (NNW) والنماذج التجريبية لتقدير نفاذية صخر مكمن مومنيات، حوض مرزق– ليبيا

بهية بن غوار [*1]، فتحي سلوم [2]، محمود الترهوني [3]

[3،1] قسم الهندسة الجيولوجية، كلية الهندسة، جامعة طرابلس، طرابلس، ليبيا .

[2] قسم علوم الأرض، كلية العلوم، جامعة بنغازي، بنغازي، ليبيا .

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المراسلة:
الاسم: بهية بن غوار
Email: gloriamuftah@yahoo.com

الملخص

تعد النفاذية خاصية فيزيائية تلعب دور اساسي بالخطة الاستراتيجية لتطوير إنتاجية الحقول النفطية. عليه، اشتقاق او تحديد النموذج الرياضي يوفر الوقت والجهد. اغلب الدراسات المتعلقة بخصائص الصخور الخازنة تتطلب تقدير للنفاذية. بذلك تشمل هذه الدراسة، تطبيق ثلاثة نماذج شائعة الاستخدام منها ويلي وروز (1950) وتايمر (1968) وشيلفد (1956) لتقدير النفاذية لمكمن المومنيات النفطي (الاوردفيشن العلوي) المنتج بحوض مرزق، جنوب غرب ليبيا. بالإضافة الي ذلك اشتقاق نموذج يعتمد على قياسات النفاذية والمسامية من عينات لباب الصخري (CCA) لعدد بئرين. أيضا تطبيق المحاكاة بالشبكة العصبية (NNW) باستخدام بيانات مجسات الابار والقياسات اللبية لتقدير النفاذية. بالتالي تم استخدام بئرين من الابار المنتجة من نفس الخزان النفطي للتحقق من مصداقية النتائج وإمكانية تطبيق النماذج الرياضية المذكورة أعلاه. أظهرت النتائج لتقدير النفاذية لخزان المومنيات الفتاتي انها أكبر من 0.1 ملي دارسي ولم تتجاوز 200 ملي دارسي بمسامية فعالة (Øe) تقترب من 13%. في حين، بينت المضاهاة قبول نتائج النماذج المطبقة والمشتقة مستوى الموثوقية (P) مساوي 0.000. ايضا عززت المعالجة الإحصائية نتائج كل من النموذج المشتق والمستخرج من المحاكاة NNW بمعاملات الانحدار تقترب من 1. علاوة على ذلك، كشفت دراسة التوزيع الحبيبي لخزان المومنيات وقيم المياه الحبيسة (Swi) بتأثيرها على نتائج تقدير النفاذية.

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Introduction

Permeability definition and validation are very important elements for the productivity of hydrocarbons from the subsurface formations for both conventional and unconventional reservoirs (Frantz et al. 2005). Also, the significant reservoir characterization and stimulation. were normally properties usually directly produced from laboratory measurement of core samples or estimated from wireline data, and in turn compared with the core measures results. The permeability of reservoir rocks is subjected to some depositional processes and diagenesis factors such as pore space characteristics, clay mineral type, and distribution within a rock matrix (Balan, 1995). Hence, measuring the core permeability is mainly limited to the reservoir rocks of the exploration wells, particularly at certain critical depths. Whereas, wireline logs normally continuously measure exploration or developed wells. Therefore, the permeability estimation by the wireline is characterized by saving time and the coring operation cost of laboratory measurements. Accordingly, many studies have been carried out as empirical models to estimate the permeability, as related to petrophysical properties: porosity (Ø) and water saturation (Sw). Although worldwide published empirical equations, permeability estimation may or may not fit the measured core values of the same lithology of a reservoir rock (Babadagli and Al-Salmi 2004). Then, Kozeny (1927) presents the first correlation to predict the permeability, which depends on the Kozeny constant, porosity, and surface area, while Tixier (1949) has used resistivity gradients, which include water saturation and capillary pressure. Also, Tixier correlation has been subjected to modification in 1950 by Wyllie and Rose. In addition, Coates and Dumanoir (1973) had modified the Kozeny, Wyllie, and Rose model to satisfy the zero permeability conditions. Thus, Sheykhinasab et al. (2023) have applied some composite formulations to estimate the permeability of carbonate reservoirs using different techniques, which depend on the well logging data; interval time (ΔT), bulk density (ρb), Neutron porosity (Øn), and resistivity.

Consequently, permeability, as an essential physical property of reservoir rock, could be estimated for enhanced oil recovery. However, the Ordovician sequence of the Marzuq basin includes the Mamuniyat reservoir (Upper Ordovician) rock within many oil fields. Thus, the prediction of the permeability property of this reservoir rock has been considered by many techniques. Recently, intelligent tools or machine learning techniques were utilized to estimate the rock permeability of the Hawaz Formation of the D oil field, Murzuq basin (Arwini 2024). Whereas, quality control by Global Hydraulic Element (GHE) of Ordovician Sandstone reservoir (Mamuniyat) of seven oil wells at the northwest Murzuq basin, Libya (Salaheddin, 2010). In addition, the solution seems to influence the horizontal and vertical permeability of the Mamuniyat reservoir (Shararah Oil field) (Mohammed et al. 2002).

Aim of the study

The main aim of this study is to define a suitable applicable model in order to estimate the permeability of uncored reservoir rocks of the Mamuniyat reservoir (Murzuq basin, Libya). Also, the derivation of the permeability model is based on the core data, as well as on available and continuous logs of the reservoir rocks, based on the wireline data of wells 1 and 2. Furthermore, the application of the neural network (NNW) technique to predict the permeability of the studied reservoir, based on the comparison with the above computed permeability. Whereas, the validation process and uncertainty of the permeability models by using test wells 3 and 4, which are producing from the Mamuniyat reservoir. It is sensible to enhance the productive property of reservoir rocks (permeability) with an easier and simpler technique.

Geological background

Murzuq Basin is an intracratonic basin located on the North African platform. It is separated from Al Kufra Basin by the Tibesti Uplift, and narrows towards the south to the Niger. Also, it is bounded from the North by the Grgaf Uplift, and to the west by the Tihemboka Arch (Fig. 1a). Caledonian (late Silurian-early Devonian), Hercynian (end Carboniferous-Permian), and Alpine (early Tertiary) are the main tectonic orogens, which controlled the structural and stratigraphy of the Murzuq basin. Whereas the Hercynian compressional movements show the present-day influences of regional lineaments (NW-SE) of the basin (Hallett and Clark-Lowes 2016). Hence, the Murzuq basin has a maximum thickness of about 400 meters, that comprised a predominantly marine Paleozoic sequence overlain by a continental Mesozoic sequence (Echikh and Sola 2000). Also, the Silurian age includes a principal source rock (Tanezzuft Formation), while the Ordovician age comprises Hawaz and Mamuniyat Formations that are principal reservoir rocks. Sedimentology of the Mamuniyat Formation has been studied in detail by many authors, such as (McDougall and Martin 2000; Shalbak 2015; Fello 2001; Fello and Turner 2004) (Fig. 2). Periglacial and postglacial fluvial and marine environments gave rise to heterogeneity in the Mamuniyat reservoir character. Then, the distribution and thickness of the Mamuniyat reservoir facies of the Murzuq basin are changing, where it may be subdivided into two upward-coarsening cycles based on outcrop studies (Shalbak 2015). The lower part of each cycle is represented by widespread, fine-grained (shaly) marine facies representing a transgressive phase (Aziz 2000). These coarsen upwards into progradational high stand deposits in which facies become increasingly isolated (channelized). However, four oil wells (1, 2, 3, and 4) are used in this study that are producing from the Mamuniyat Formation with an average thickness of 129 feet. The studied wells are located between latitudes 26º and 27º North and longitudes 12º and 13º East (Fig. 1b).

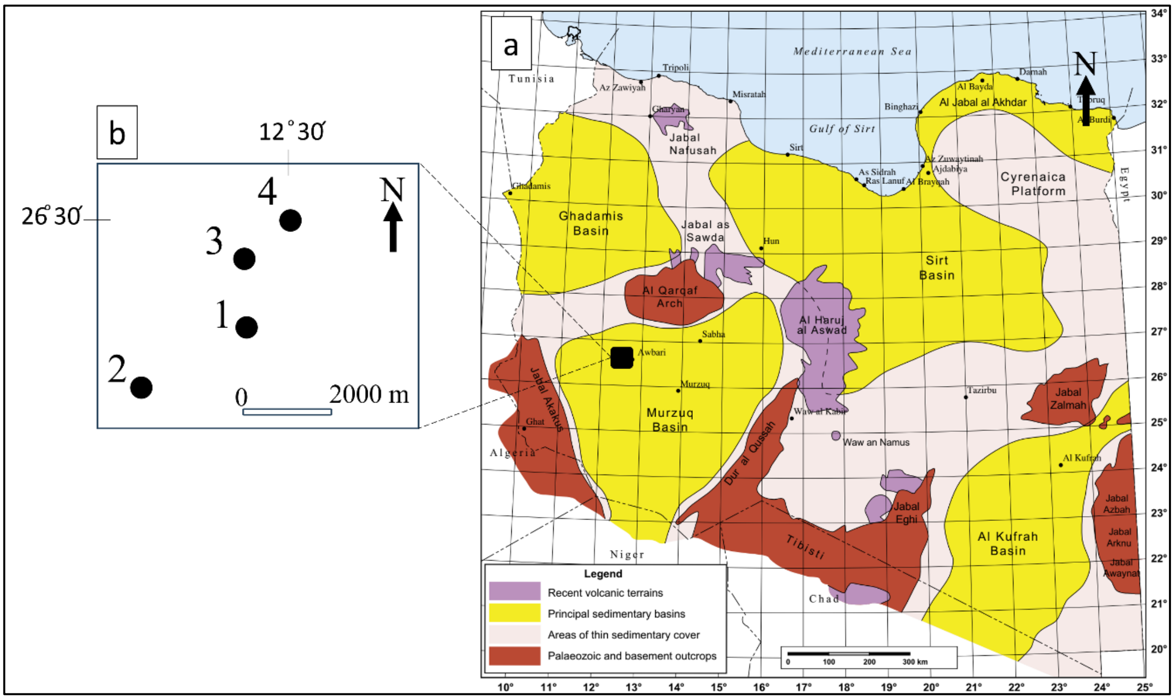

Fig. 1. a) Geology Map of Libya, shows the main sedimentary basins and studied area (after Hallett and Clark-Lowes 2016), and b) Location map of studied wells

Era	Period	Formation	Environment
Ordovician	Upper	Bi'r Mamuniyat Tasghart	Glacial/periglacial
		Melaz Shuqran	Glacio-marine
	Middle		
		Hawaz	Shallow marine
	Lower	Ash Shabiyat	Shallow marine

Fig. 2. General Ordovician Era sequence (after Hallett and Clark-Lowes 2016)

Materials and Methods

The Porosity and water saturation are two main key properties required for several known empirical equations, in order to evaluate the reservoir permeability using well logging data. Hence, neutron porosity (Øn) is a direct porosity log, while both bulk density (ρb) and interval travel time (ΔT) logs are indirect porosity assessments. Equation (1) is applied to compute density porosity (Ød), and equation (2) (Bateman 2012) for neutron-density porosity as a total porosity of the Mamuniyat reservoir. Whereas, shale content (Vsh) of rocks could be estimated by many logs, such as Spontaneous potential (SP), gamma ray (GR), and neutron - density porosity (Ønd) cross plot. Then, equations 3 and 4 (Bateman 2012) process the gamma ray log to compute the volume of shale (Vsh). In turn, Vsh is utilized to estimate effective porosity (equation 5) (Bateman 2012). Further, the water saturation could be calculated by several formulas, as functions of the resistivity, porosity, Archie parameters, tortuosity (a), cementation factor (m), and saturation exponent (n). These Archie parameters are measured by special core analysis of reservoir rocks, while they could use general values if the core samples are unavailable. It is worth mentioning that irreducible water saturation (Swi) is the amount of water saturation associated with the hydrocarbon depth interval, and a considerable parameter of the empirical equations of permeability estimation. Then, the following formula (6) is used to calculate the Swi (Asquith and Gibson 1982) of the Mamuniyat reservoir.

$$\boldsymbol{\emptyset_d = \frac{\rho ma - \rho b}{\rho ma - \rho fl}}$$ Equation (1)

$$\boldsymbol{\emptyset_{nd} = \frac{\emptyset_n + \emptyset_d}{2}}$$ Equation (2)

$$\mathbf{IGR} = \frac{\mathbf{GR_{log} - GR_{min}}}{\mathbf{GR_{max} - GR_{min}}}$$ Equation (3)

$$\mathbf{Vsh} = \mathbf{0.33} \times [(\mathbf{2}^{2\times I_{GR}}) - \mathbf{1}]$$ Equation (4)

$$\emptyset_e = \emptyset_{nd} - (1 - \mathrm{Vsh} \times \emptyset_{ndsh})$$ Equation (5)

$$\mathrm{Swirr} = \sqrt{\frac{a/\emptyset^m}{2000}}$$ Equation (6)

Where: Ød = density porosity (fraction), Ønd = neutron-density porosity (fraction), ρma = matrix density, g/cc (= 2.65 g/cc of Sandstone rock type), ρb = measured bulk density log value, g/cc, and ρf = density of drilling fluid, g/cc (= 1 g/cc of fresh mud type), Øe = effective porosity, fraction, and Sw = water saturation, fraction.

As mentioned above, the most published permeability models depend on the petrophysical properties (Ø, Swi, and Vsh). These models were selected because it requires the most recorded oil or gas well logs input data. Hence, the following models 1, 2, and 3 (Equations 7, 8, and 9) Wyllie and Rose (1950), Timur (1968), and Sheffield (1956) (Balan et al. 1995; Hashan et al. 2022) respectively are applied to estimate the Mamuniyat reservoir permeability. Moreover, validation of the suitability of these permeability models is done by measuring core permeability (K Core) of the studied wells, as well as the validation of the computed porosity with the measured core porosity (Øcore).

Model 1, $k^{1/2} = \frac{250\,\emptyset^3}{Swi}$ Equation (7)

Model 2, $K^{1/2} = \frac{100*\emptyset^{2.25}}{Swi}$ Equation (8)

Model 3, $K = \frac{1}{2F}\left(\frac{\emptyset}{1-\emptyset}\right)^2 \frac{1}{Swi^2}$ Equation (9)

Where: F = formation factor, a = tortuosity, and m = cementation factor.

The Neural Network (NNW) technique provides a valuable contribution to the oil industry that helps to build reservoir characteristic models (Alkinani et al. 2019). Thus, the NNW technique is utilized to predict the Mamuniyat reservoir permeability by Interactive Petrophysics software (IP), which is based on the well logs data (GR, Øe, ρb, PEF, and Kcore).

Consequently, validation of the predicted permeability models requires comparison with the measured permeability (Kcore). Thus, the SPSS program is utilized to determine a significant level (P) and regression coefficient (R^2), while equation (10) is used to calculate the Root Mean Squared Error (RMSE) (Hodson 2022).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{Kcore_i} - \mathrm{Kpredicted_i})^2}$$ Equation (10)

Results and Discussion

The Assessment of the petrophysical characteristics of the Mamuniyat reservoir rocks demonstrates a decent reservoir quality, whereas the average effective porosity is about 13 %, 13 % of the Vsh, and 13 % of the Swi. Accordingly, the calculated effective porosity (Øe) and irreducible water saturation (Swi) are required for the permeability models (Wyllie and Rose, Timur, and Sheffield). Whereas the routine core analysis (CCA) data of the studied reservoir, wells 1 and 2, were used to derive an empirical equation of the Mamuniyat reservoir permeability. Therefore, Figure (3) displays a cross plot between core permeability (Kcore) and porosity (Øcore), where equation (11) is a derived model. In addition, well logs (GR, Øe, ρb, PEF, and Kcore) are training zones (Neural Training) input data to run the NNW model by the IP software, which also utilizes the same wells 1 and 2. The training passes of the Neural training are 3, the Epochs per Pass are 100, and Cross-validation is 5%. Thus, application of different models (Wyllie and Rose, Timur, Sheffield, derived, and NNW) results have been compared with the measured core permeability (Kcore) as shown in Figures 4 and 5 of wells 1 and 2.

In addition, the GR log and both the calculated effective (Øe) and core (Øcore) porosities correlation are also displayed within Figures 4 and 5. The figures present a high agreement between the Øcore and calculated Øe of the clean Mamuniyat reservoir depths with a less than 50 API of the GR. Also, Abukliesh et al. (2024) has determined similar results among the core and calculated porosity. Moreover, the reservoir has permeability values ranging from 0.01 mD to 1000 mD, whereas the porosity does not excess 18 %.

$$\mathbf{K} = \mathbf{4} \times \mathbf{10^7} \times \emptyset^{\mathbf{7.2044}} \qquad \text{Equation (11)}$$

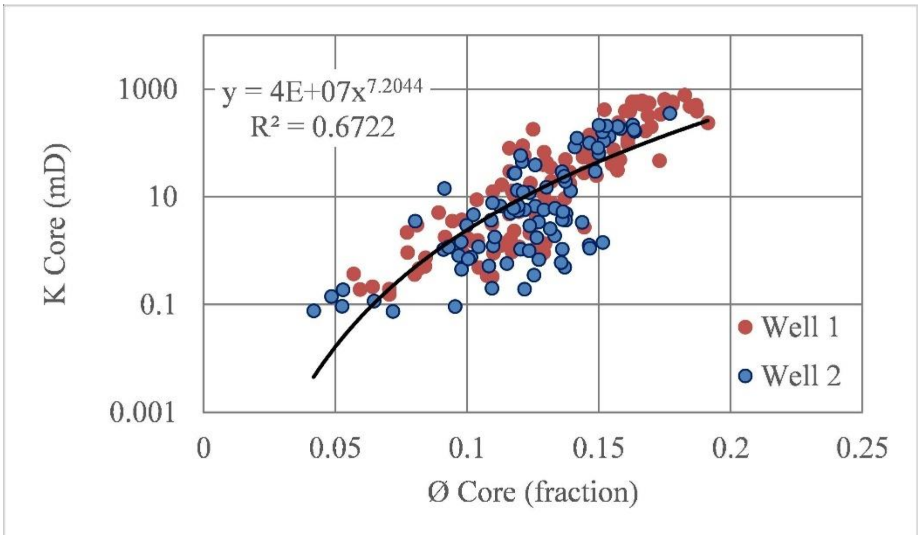

Fig. 3. Core permeability and core porosity cross plot of the studied wells

Generally, the permeability correlation in both Figures 4 and 5 reveals an alteration between approving and conflicting with the measured core permeability (Kcore) and the results of the models. Hence, the Timur, Sheffield, Derived, and NNW models illustrate evidently a greater conformity with the Kcore values than the Wyllie and Rose model. Also, the Derived model is closer to the measured core permeability and Neural Network models than others, with an exception below the depth 4870 feet interval of well 2 (Fig. 5). Moreover, the core and models result values of the permeability illustrate a response to the gamma ray fluctuation as well as the porosity. Then, reducing of the permeability values is followed by a decrease in the porosity and increasing of the GR. Accordingly, the predicted permeability results from the different applied models are acceptable.

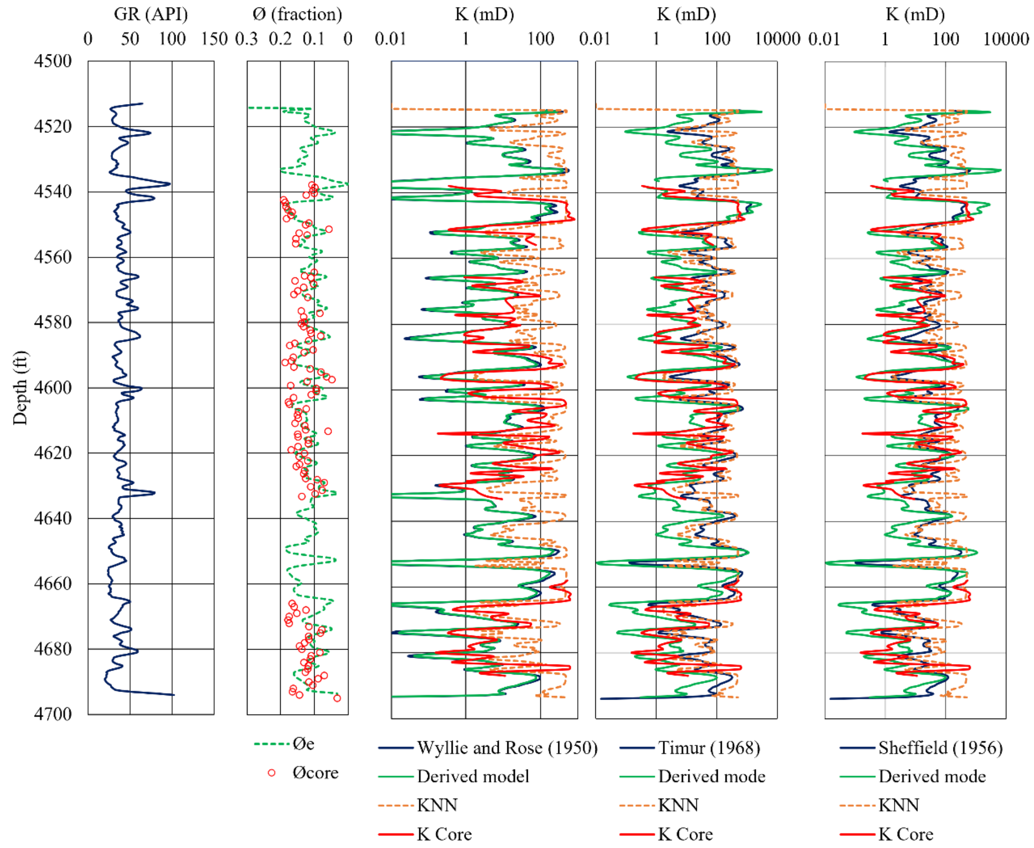

Fig. 4. Correlation of the core and predicted permeabilities by models of the Mamuniyat reservoir, well 1

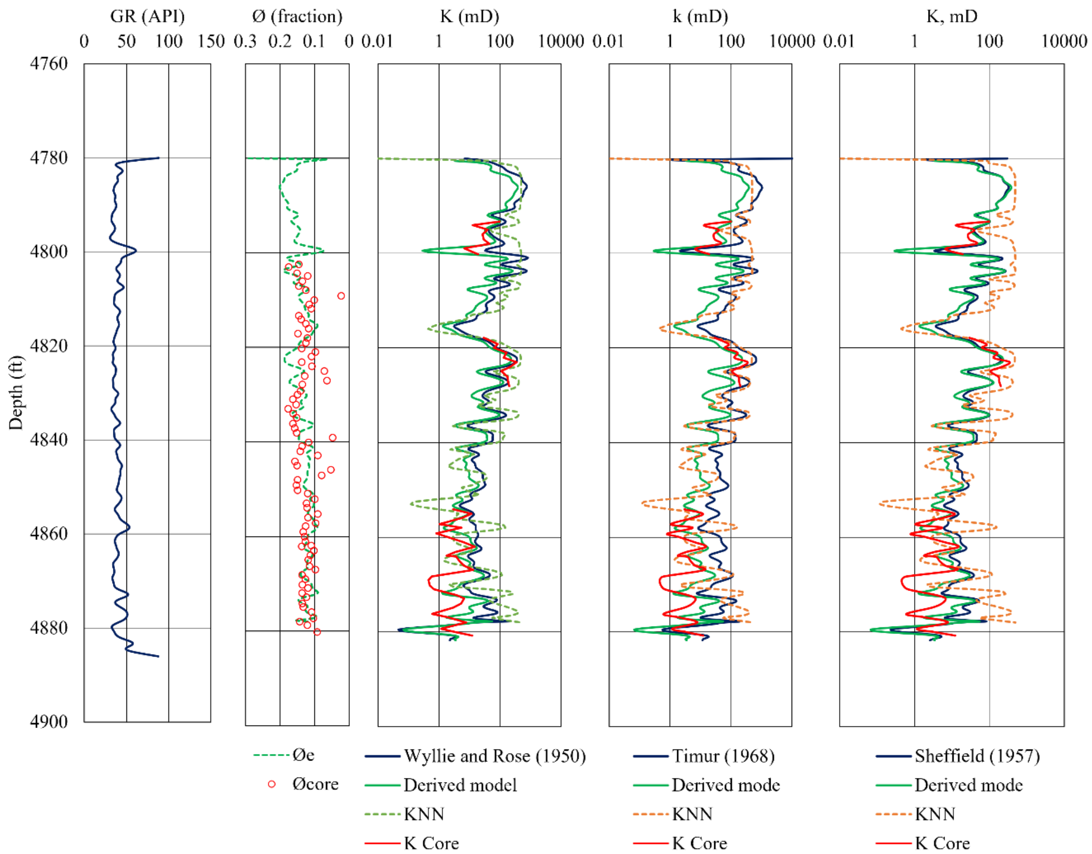

Fig. 5. Correlation of the core and predicted permeabilities by models of the Mamuniyat reservoir, well 2

Validation of models

The permeability estimation is one of the reservoir characterizations, and the suitability of any derived or published empirical models requires a validation process that gives confident application in the location area. Wells 3 and 4 are producing from the Mamuniyat reservoir, and have measured core permeability and porosity. These wells were used as test wells for the Derived, NNW, Wyllie, Rose, Timur, and Sheffield permeability models. Moreover, there are various factors affecting the permeability estimation. Thus, grain size is one of the main dominant factors on pore size, which in turn has an impact on the rock permeability (Pryor 1973). Also, Chilingar (1964) The chart illustrates the different grain size distributions affecting the permeability and porosity relationship. Accordingly, the grain size distribution of wells 3 and 4 is verified to have a similar grain size distribution to both wells 1 and 2, which are used for the Derived and NNW building Models. This process is as important as the permeability assessment validation. Therefore, the core permeability and porosity cross plot of wells 1, 2, 3, and 4 is superimposed with a standard permeability – porosity clastic rock of the Chilingar (1964) chart. Hence, Figure 6 displays plotting and demonstrates the Mamuniyat reservoir that has the same grain size range (coarse to clayey size). Furthermore, Figures 7 and 8 manifest a correlation of the permeability estimation results of the test wells (3 and 4). Well 4 illustrates better agreements between predicted permeability results by models than Well 3. In general, increasing of the gamma ray causes decreasing of the porosity and permeability. The Mamuniyat reservoir has a variety of grain sizes that in turn influence the porosity by increasing or decreasing the permeability. Then, increasing of core permeability (Kcore) and the NNW estimation below 4785 feet depth interval of well 3 (Fig. 7) is attributed to increasing of porosity, due to fine grain size as illustrates on the Figure 6. On the other hand, decreasing of the Kcore and NNW results less than the other models of well 4 (Fig. 8), is responding to fine and clayey grain size changing. This noticeable decrease in the permeability also could be referred to increasing of the irreducible water (Swi) of more than 20 % below 4785 feet. Accordingly, increasing of the Swi is related to the grain size, that silty and clayey size associated with the high-water percentage. Therefore, the Mamuniyat reservoir has two coarsening upward cycles.

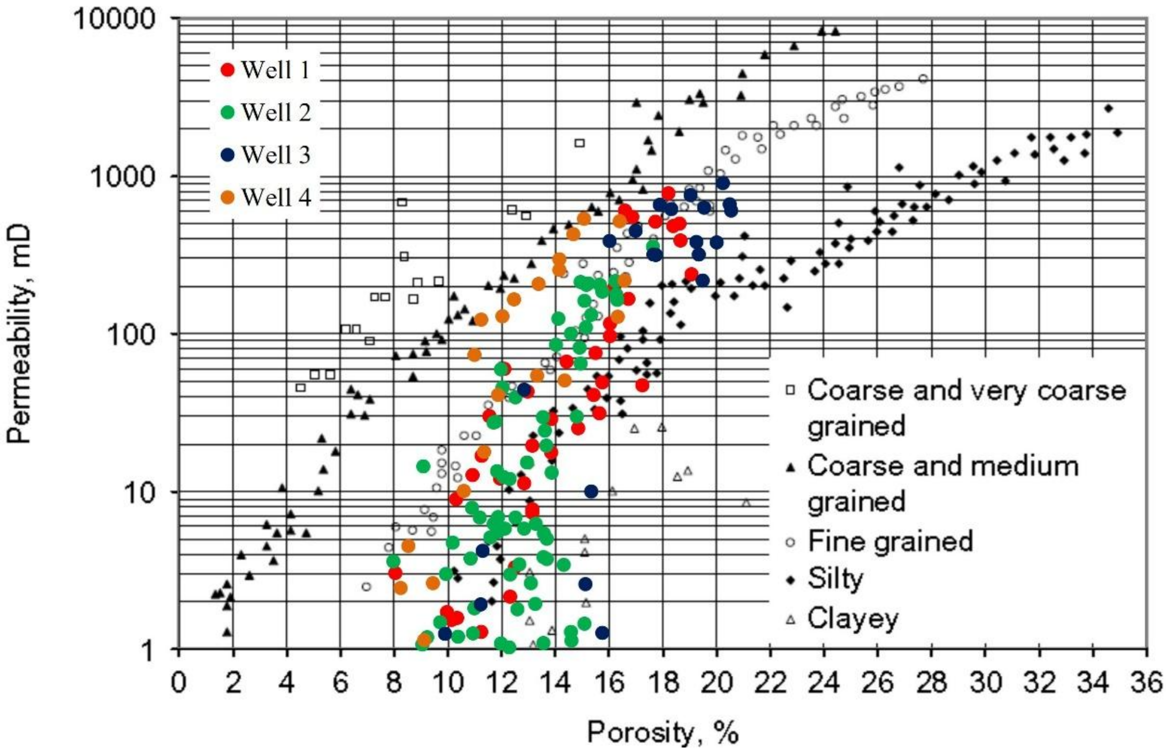

Fig. 6. Core permeability and porosity cross plot of the wells 1, 2, 3, and 4 (after Chilingar 1964)

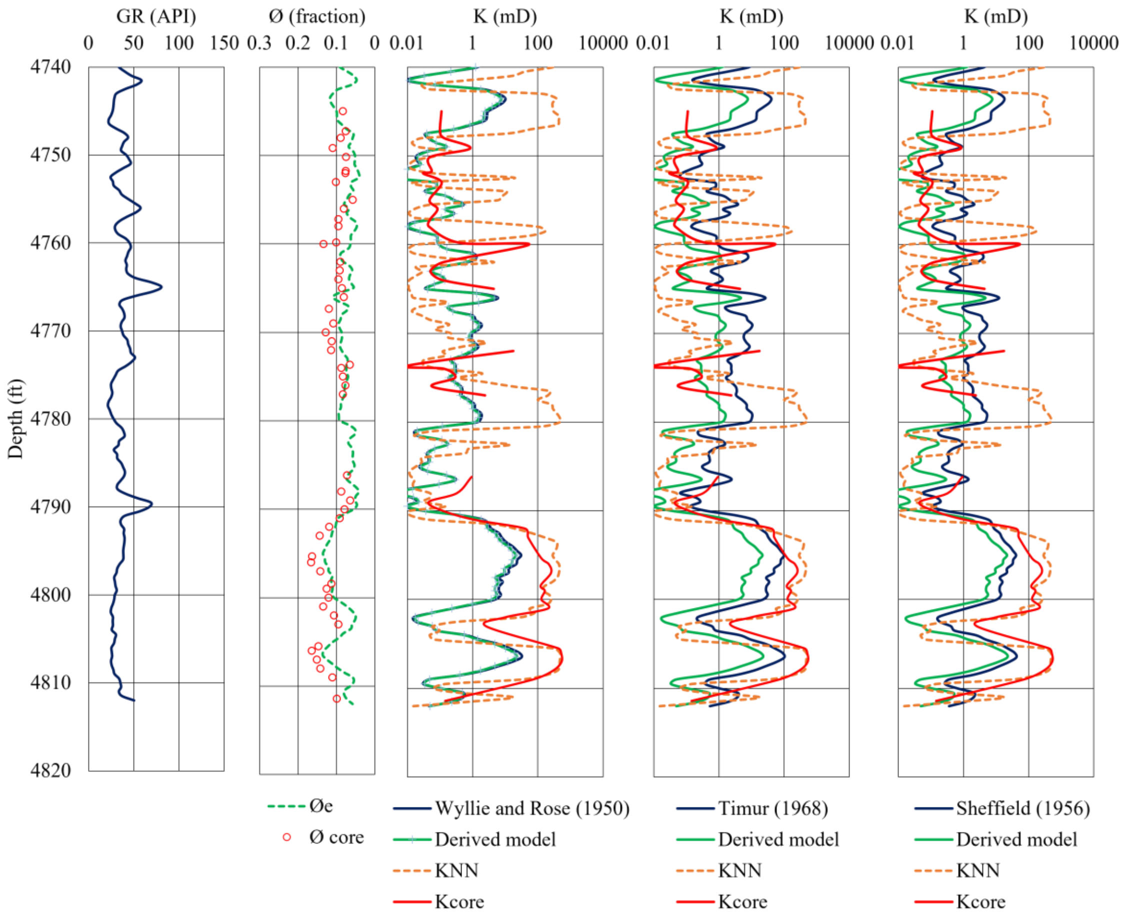

Fig. 7. Correlation between core measured and predicted permeability by the models of well 3

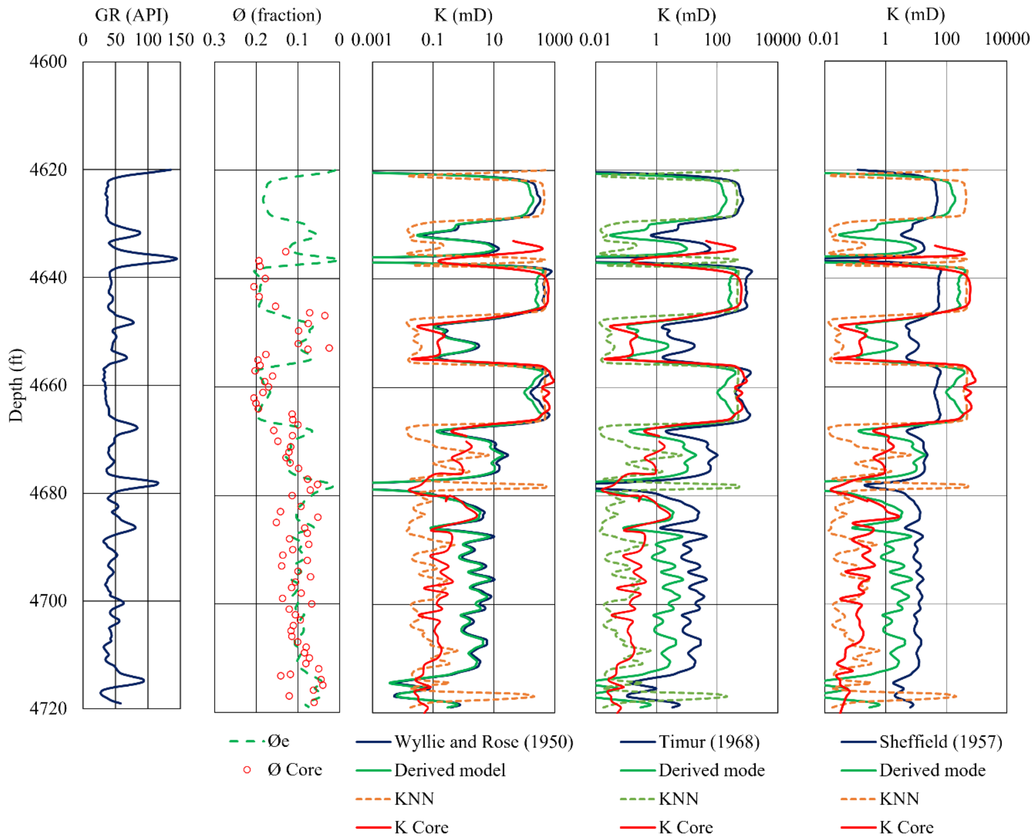

Fig. 8. Comparison of predicted permeability by models with the core permeability of the Mamuniyat reservoir, well 4

The average statistical parameters results of P and RMSE are summarized in Table 1. The significance level (P=0.00) is less than 0.005, which indicates the validity of the predicted permeability. Whereas the RMSE results detect that well 4 has a lower RMSE average result than well 1. Also, the NNW model presents lower values of the RMSE. Moreover, Figure 9 illustrates cross plots between the measured core and predicted permeability of two wells, 1 and 4. These cross plots give the regression coefficient (R^2) higher than 75% of the most models, and it reaches up to 90% of both the Derived and NNW models.

Table 1. Statistical analysis results of the predicted permeability models

Well	Model	MSRE	P
1	Wyllie and Rose (1950)	196.35	.000
	Timur (1968)	155.5	.000
	(Sheffield 1956)	179.01	.000
	Derived	171.5	.000
	Neural Network	103.26	.000
4	Wyllie and Rose (1950)	136.24	.000
	Timur (1968)	215.43	.000
	(Sheffield 1956)	238.81	.000
	Derived	140.72	.000
	Neural Network	42.06	.000

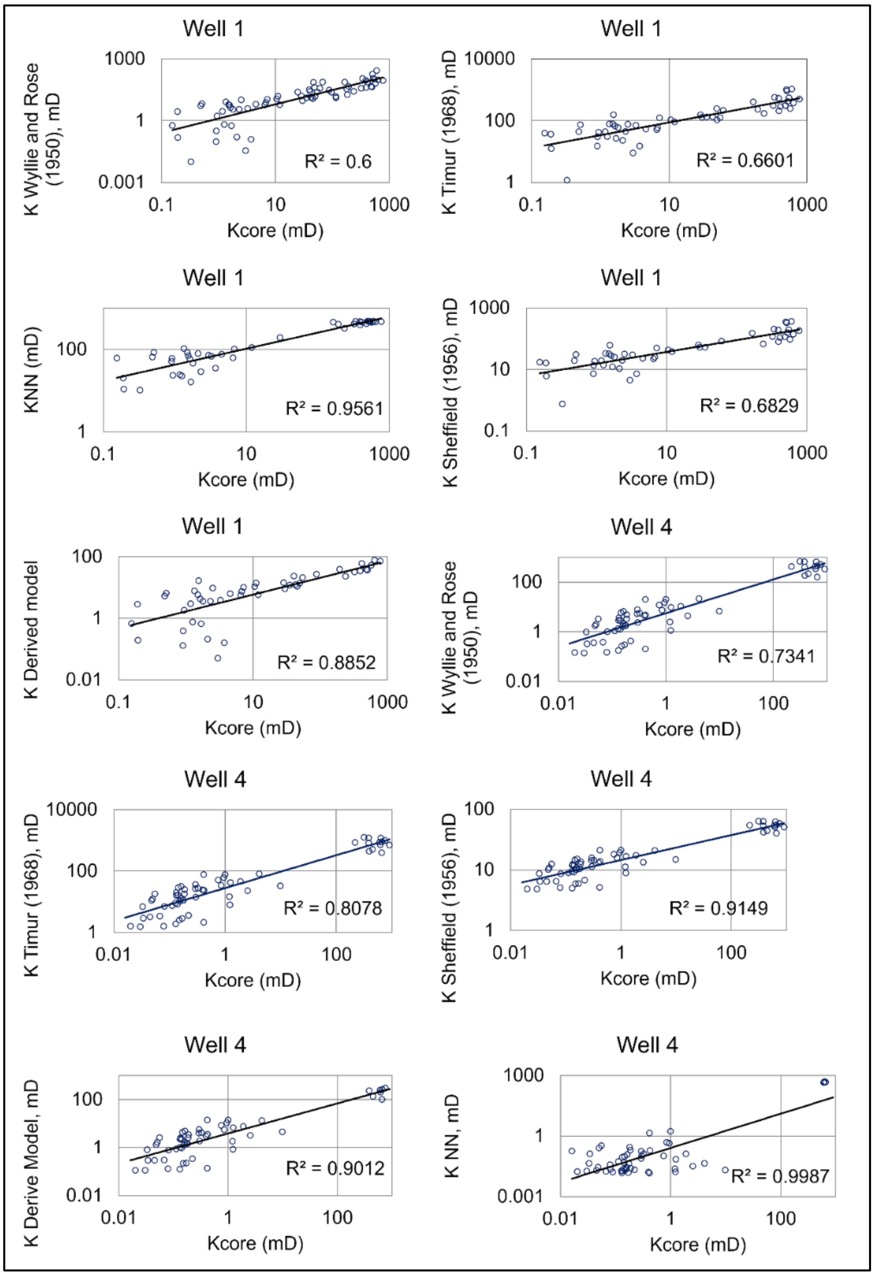

Fig. 9. Core permeability (Kcore) versus predicted permeability by models of wells 1 and 4

Conclusion

The Permeability is considered a principal physical property of reservoir rocks, which has a major contribution to oil field productivity. Hence, the routine core analysis (CCA) provides a good source of both measured permeability and porosity properties at the concerned depths of reservoir rocks, and as a tool to describe the grain size of these rocks as well. Also, measuring the wireline is a suitable tool to evaluate the permeability of the reservoir rocks. The wireline data is a more reliable tool than the core results, as it has a continuous measured depth interval. Hence, measured well logs of the clastic Mamuniyat reservoir are used to predict permeability by approved empirical models: Wyllie and Rose (1950), Timur (1968), and Sheffield (1956). While the routine core analysis (CCA) data is utilized to construct the Derived model, which has a regression coefficient equal to 67%. Also, both the well logs and CCA are processed by the Interactive Petrophysics software (IP) to generate the neural network (NNW) permeability model of the Mamuniyat reservoir. These different models provide acceptable predicted permeability results in four wells (1, 2, 3, and 4). The Wyllie and Rose, Timur, Sheffield, Derived and NNW models illustrate an alteration between approving and conflicting measured core permeability (Kcore). Both Derived and NNW models evidently show a greater conformity with the Kcore values than others, based on the regression coefficient (R^2), equal or close to 90%. In addition, the significance level (P=0.00) is less than 0.005, which allows the ability of utilization of these models for this reservoir. It is worth mentioning that these empirical models depend on the effective porosity (Øe) and irreducible water saturation (Swi), which in turn are influenced by the gamma ray (GR) log reading. Thus, all wells demonstrate high agreement between the core porosity and Øe. Generally, petrophysical evaluation of the 129 feet average thickness of the Mamuniyat reservoir demonstrates an average effective porosity (Øe) of about 13 %, 13 % of the Vsh, and 13 % of the Swi. Moreover, based on the Chilingar (1964) chart, the clastic Mamuniyat reservoir among the four oil wells has a grain size distribution ranging from fine to clayey. Also, the increasing of the Swi is related to the silty and clayey grain size of the lower deep intervals of the Mamuniyat reservoir, which emphasizes the reservoir coarsening upward-cycles.

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Conflict of Interest

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

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