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Permeability and Hydraulic Flow Units Prediction Using Neural Network Technique of the Clastic Mamuniyat Reservoir (Upper Ordovician), Murzuq Basin-Libya

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ABSTRACT - Delineation of the hydraulic flow unit (HFU) and a petrofacies parameter (R_{35}) are essential reservoir characteristics, which are functions of the routine core analysis (CCA) and well log data. Thus, this work has been carried out with the Neural Network (NN) application to predict the HFU, pore size radius (R_{35}), and permeability (KHFU) in uncored well 3 within an average thickness of 133 feet of the clastic Mamuniyat reservoir Murzuq basin (Libya). This prediction is based on data of two wells (1 and 2) producing from the same reservoir. Hence, log analysis demonstrates about 12% effective porosity (Øe) and not exceeding 14% of the shale content (V_{sh}). Also, 11% and 96 mD are averages of core porosity (Øcore) and permeability (Kcore), respectively. Whereas micropores, mesopores, and macropores are three pore throat radius (R_{35}) classifications recognized in the reservoir and six HFUs in well 1 and five in well 2. Furthermore, gamma ray (GR) logs correlate among three wells and reveal a similarity between wells 1 and 3 that sustain the HFUs of well 3 by using the NN model. Whereas, the comparison between the predicted KHFU and two approved empirical permeability Equations manifests furnishing high agreement results with some exceptions. However, the NN provides predictions supported by data of Mamuniyat reservoir quality (HFU, R_{35}, and K) within the uncored reservoir section from the nearby wells that reveal consistent and reliable results.

Keywords: neural network; permeability; sandstone; mamuniyat; hydraulic flow unit.

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INTRODUCTION

The Reservoir characterization plays an important role in the distribution of formation and fluids properties within the heterogeneous reservoirs. Defining of rock types and pores geometry are essential part of reservoir characteristic. Also, both the deposition environment and diagenetic history have mainly impact on the pore geometry, which in turn controls on effective porosity and permeability of reservoir rocks. However, core samples and well logs are considerable source data for storage and flow capacity assessment of reservoir rocks in oil fields. Thus, hydraulic flow unit (HFU) is a technique concept introduced by (Ebanks Jr 1987) who has defined a hydraulic unit as a mappable portion of reservoir within the geological and petrophysical properties of other reservoir volumes. Whereas, Hearn et al. (1984) has defined a flow unit as, a reservoir zone that is laterally and vertically continuous and has similar permeability, porosity and bedding characteristics. Gunter et al. (1997) has defined a flow unit as stratigraphically continuous interval of similar reservoir process that honors the geological framework and maintains the characteristics of rock types. Moreover, flow zone indicator (FZI) is another unique parameter that includes the geological attribution of the texture and mineralogy of distinct pore, with geometrical filling materials. Furthermore, Winland correlation is another technique to classify reservoir rock based on pore size radius (R_{35}) (Winland 1972). Also, this petrofacies parameter (R_{35}) perfectly correlate with the HFU. Hence, these techniques essentially depend on the porosity (Ø core) and permeability (K core) that are measured by core samples, which may not be available in all the exploration and development wells. On the other hand, artificial intelligence tools (neural networks, NN) are a good alternative technique that has made a significant contribution to oil fields' performance in the petroleum industry in recent decades. The NN is based on supervised training algorithms (Mohaghegh 2000) that provides a high uncertainty and without consumption of time and costing to predict a property. Therefore, application of the NN technique has been applied by many researchers such as (Hamzah et al., 2021; Usmanet al., 2010; and Wahyudi et al., 2025). In the same manner, many published studies have been carried out, and described the rock type that defines HFU by Global Hydraulic Elements (GHE). Ha et al. (2021) present the same GHE work of a deltaic facies (Miocene formation) at Eastern Poland. Whereas, Khalid et al. (2020) utilized the hydraulic flow unit (HFU) to predict the permeability of un cored wells of JG field (Abu El-Gharadig basin), and enhanced the reservoir characteristics by integration between core and well logs data. Accordingly, Mamuniyat Formation (Upper Ordovician) is a clastic potential reservoir rock in the intracratonic Murzuq basin (southwest Libya), which subjects to describe the rock type as the HFU by Global Hydraulic Elements (GHE) by (Salaheddin 2010; and Castro et al., 2012). Also, These HFU's of the Mamuniyat reservoir were defined within wells have core and logs data. It worth mentioning that the Castro et al., 2012 have documented that the Mamuniyat reservoir illustrates changing of the porosity and permeability, with their impact on the global hydraulic elements (GHE) that have low porosity and permeability.

Consequently, our present work will utilize Interactive Petrophysics software (version 2018) to build NN model that provide the hydraulic flow units (HFU), and predict the permeability (K HFU) of the Mamuniyat reservoir in un cored well 3. This NN model is based on two wells (1 and 2), that have core and log data. In addition, defined the studied reservoir quality assessment by hydraulic pore radius (R_{35}).

Geological setting

The present geologic borders of the Murzuq basin are delimited by tectonic uplifts. The present-day structural framework is a consequence of the cumulative tectonic movements ranging from Palaeozoic through to Tertiary times. The main tectonic events are related to the Caledonian (late Silurian-early Devonian), Hercynian (end Carboniferous-Permian) and Alpine (early Tertiary) orogenies. Although the present-day structuring is related mostly to Hercynian compressional movements and the later tectonic activity, the regional lineaments (NW-SE) are probably related to late Precambrian Pan-African fault systems, which largely controlled the early Palaeozoic structural and depositional evolution of this basin (Hallett & Clark-Lowes 2016).

Mamuniyat Formation complex interplay between eustatic and isostatic controls (El-ghali 2005). Periglacial and postglacial fluvial and marine environments gave rise to heterogeneity in reservoir character (Figure 1b). Distribution and thickness of the Mamuniyat reservoir facies in the Murzuq basin are poorly defined (Cubitt et al., 2011). Previous drilling together with rock outcrops studies suggests that the clastic formation may be sub-divided into two upward-coarsening cycles. The lower part of each cycle is represented by widespread, fine-grained (shaly) marine facies representing a transgressive phase (Shalbak 2015). These coarsening upwards into progradational highstand deposits in which facies become increasingly isolated (channelised). However, three oil wells (1, 2 and 3) are utilized within this work, they are belonging to an oil field NC186, located in the south-west side of Murzuq Basin, Libya (Figure 1a).

METHODOLOGY

Many scientists and engineers have dedicated extensive efforts to developing models for predicting the permeability of reservoir rocks, often integrating well logs (continuous data) with core data. This integration provides continuous predicted permeability for uncored depth intervals of potential hydrocarbon-bearing reservoir sections (Zhang et al. 202; and Mahmoud et al., 2019). Also, Mohamed & Kashlaf (2016) had adopted and made a quick petrophysical interpretation of the Hawaz formation (Middle Ordovician) by using logs and core analysis data, leading to the prediction of more than one HFU. However, well logs and routine core analysis (CCA) are essential data utilized to estimate the permeability of reservoir rocks (Yogi 2018). Hence, well logs package and CCA data of two wells have been analyzed to define the hydraulic flow unit (HFU) of the Mamuniyat reservoir, and utilized to predict permeability in the unscored well No 3. These

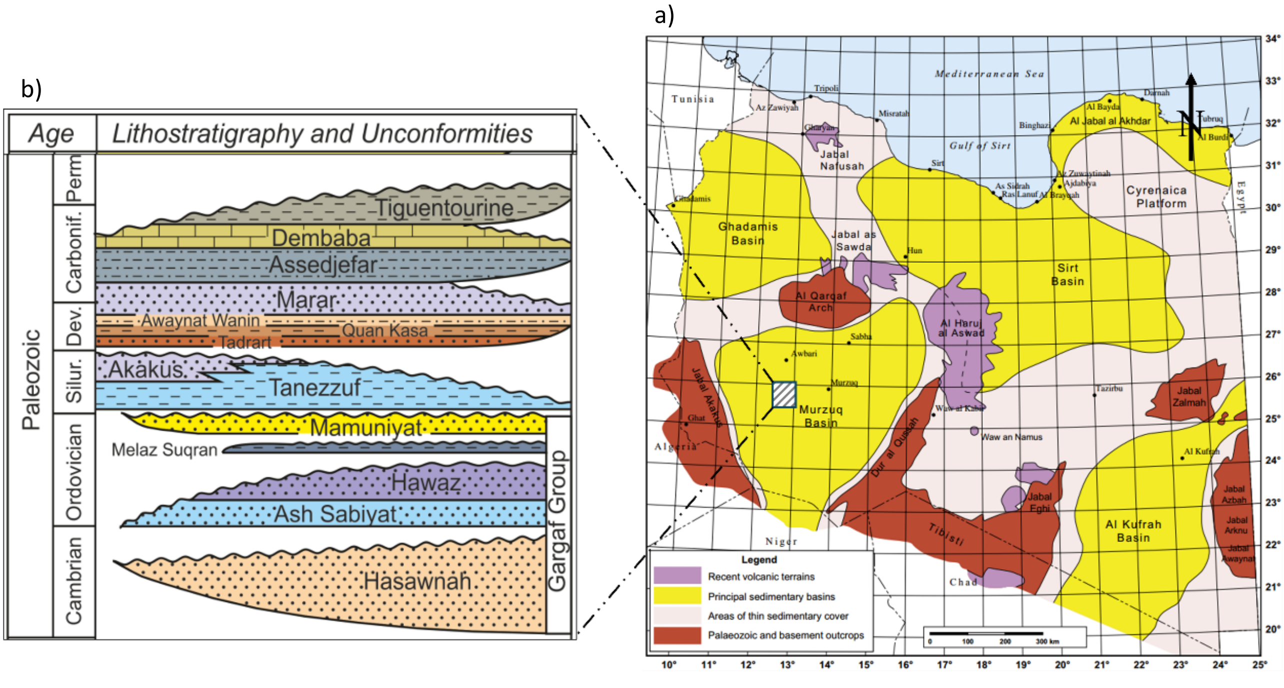

Figure 1. a). Location map of Murzuq basin, and b). Sequence stratigraphy of the Mamuniyat Formation (after Shalbak 2015; Hallett & Clark-Lowes 2016).

wells are producing from the Mamuniyat reservoir (Upper Ordovician) that has a thickness of 40.6 meters (133.33 feet). Also, the measured well logs package are including; Gamma Ray (GR), spectmetry (NGS), neutron porosity (Øn), bulk density (ρb), and interval travel time (ΔT). Therefore, the basic petrophysical evaluation is dependent on both the processed logs and core data to assess any reservoir rocks (Novita et al. 2022. Thus, in order to predict the required permeability (k) there would be a basic petrophysical evaluation, including shale volume (Vsh), effective porosity (Øe), water saturation (Sw), and permeability (k). Whereas, the CCA data are also processed to provide the HFU and pore throat radius (R_{35}) of the studied reservoir. Thus, Figure (2) summarizes the workflow of this study.

Petrophysical evaluation

The shale volume (V_{sh}) is an essential estimation parameter used for porosity correction and delineating the net pay thickness of reservoir rocks. The GR logs are the most providing shale content parameter, and define the clay minerals that may exist in the rock composite as may explored by the spectrometry (NGS) logs. Therefore, Equations 1 and 2 (Asquith and Gibson 1982a were used to process the measured GR logs and calculate the volume of shale (V_{sh}) as follows:

$$IGR = {(GR_{log} - GR_{min})}\big/{(GR_{max} - GR_{min})} \quad (1)$$

$$V_{sh} = 0.33 \times [(2^{2\times I_{GR}}) - 1] \quad (2)$$

where: GR_{log} = gamma-ray log value for shaly sand API; GR_{min} = gamma -ray minimum value for clean sand API; GR_{max} = gamma-ray maximum value for shale zone API; and V_{sh} = volume of shale for older formations (fraction).

Porosity gives an important physical rock property, and it gives an idea about a storage capacity of reservoir rocks that required to reserve estimation of oil fields in static and dynamic status. Hence, total and effective porosity are two distinctive porosity types, which has controlled flow capacity of the reservoir rocks. The porosity could be measured from core samples or different wire lines techniques. The neutron (Øn), bulk density (ρb) and interval travel time (ΔT) are three wirelines porosity indicators. In addition, the neutron (Øn) log is a direct measured porosity values of rocks, which is sensitive to the presence of shale content by an increasing log reading. While the bulk density (ρb) and interval travel time (ΔT) are indirect porosity logs that use Equations to calculate the density and sonic porosity, also to demonstrate the clayey content influence and rocks overburden. Therefore, Equations 3 and 4 (Asquith and Gibson 1982b are used to calculate the density porosity (Ød) and total porosity (Øt). Further, the permeability (K) is another significant physical property of rocks that describes the ability of fluid flow through the effective porosity (Øe). Accordingly, elimination of the shale content from the calculated total porosity (Øt) or density porosity (Ød) will provide the effective porosity (Øe) by Equation 5 (Asquith and Gibson 1982a. However, there are many published empirical Equations can be used to assess the permeability

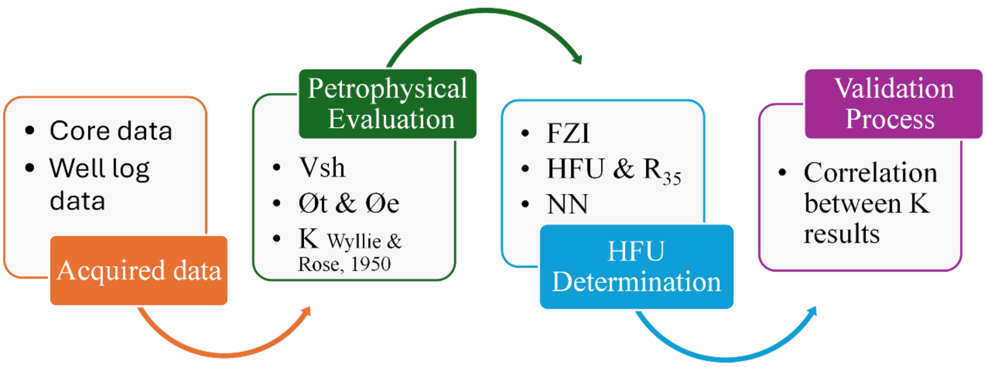

Figure 2. Workflow chart of the study procedures.

(K). Babadagli & Al-Salmi 2004 have summarized methods applied to estimate the permeability in carbonate reservoir rocks. Also, Ahmed et al., 1991; and Alkinani et al., 2019 present a literature review of different permeability estimation techniques and discussed most most influencing factors. Whereas, Mohammed 2020 illustrates Tiny Permll device techniques for permeability determination, and diagenesis process that affecting the physical property of sandstone reservoirs, as well as a Permian Rotliegend Sandstone Formation as a case study. In general, Wyllie & Rose 1950 have applied permeability empirical Equation 6 that depend on well logs data, that are functioning on rock properties such as porosity, Archie parameters; tortuosity factor (a) and cementation factor (m), and irreducible water saturation (Swirr). On the other hand, Ghawar et al., 2026 is another attempt applying an empirical Equation 7 of the Mamuniyat reservoir (Upper Ordovician).

$$Ød = (ρb_{ma} - ρb_{log})/(ρb_{ma} - \rho_f) \tag{3}$$

$$Øt = (Øn + Ød)/2 \tag{4}$$

$$Øe = Øt \times (1 - Vsh) \tag{5}$$

$$k^{1/2} = \frac{250\, Ø^3}{Swirr},\ \mathrm{Swirr} = \sqrt{\frac{a/Ø^m}{2000}} \tag{6}$$

$$\mathrm{K} = 4 \times 10^7 \times Ø^{7.2044} \tag{7}$$

where: $ρ_{ma}$ = apparent matrix density for sandstone (equal to 2.65 g/cc), $ρb_{log}$ = bulk density log reading (g/cc), $ρ_f$ = fluid density (equal to 1 g/cc for fresh drilling mud), Øn = neutron porosity log reading (fraction), Ød = density porosity (fraction), Øt = total porosity (fraction), Øe = effective porosity (fraction), Swirr = irreducible water saturation, fraction, a = tortuosity, and m = cementation factor.

Statistical analysis is necessary for the uncertainty evaluation when applying any empirical Equation, which provide a confidently and widely utilization of this Equation. Thus, average values of the calculated petrophysical properties (V_{sh}, Øt, Øe, and, Øcore) of each well could be calculated by Equation 8.

$$Xaverage = \frac{\sum(X \times h)}{\sum h} \tag{8}$$

where: Xaverage = average of the petrophysical property, X = calculated petrophysical property, h= thickness of each property, and Σ is the summation of property value.

Hydraulic flow unit (HFU) and R_{35} determination

The routine core analysis (CCA) is a principle measured data of the HFU and Winland parameter (R_{35}) determination of the Mamuniyat reservoir rock. including the porosity (Øcore), horizontal and vertical permeability (Kh and Kv), respectively. Hence, Equations 9 and 10 were applied to calculate Rock quality index (RQI) and flow zone index (FZI) of the studied reservoir within the wells 1 and 2. Where the FZI is a function of normalized porosity (Øz), which is a pore volume to grain volume ratio. Then, reordering Equation 10 by picking the logarithm of both sides, as a linear Equation form (Equation 11). Thus, cross plot between the RQI and FZI produce multi-straight lines that have the same pore throat. These lines provide an empirical Equation to predict the permeability for each FZI value of each HFU zone. Furthermore, Winland parameter (pore throat radius, R_{35}) is another technique used to discriminate and classify lithofacies within the reservoir rocks based on the pore size. Also, Equation (12) could be used to calculate the pore throat radius (R_{35}) of the Mamuniyat reservoir.

$$\mathrm{RQI} = 0.0314\sqrt{\mathrm{K}/Ø} \tag{9}$$

$$\mathrm{FZI} = \mathrm{RQI}/Øz;\ Øz = \frac{Ø}{(1-Ø)} \tag{10}$$

$$\mathrm{Log\ (RQI)} = \mathrm{Log(FZI)} + \mathrm{Log}(Øz) \tag{11}$$

$$\mathrm{Log}\ R_{35} = 0.732 + 0.588\ \mathrm{Log\ K} - 0.864\ \mathrm{Log}\ Ø \tag{12}$$

where: Ø = porosity (fraction), K = permeability (mD), FZI is flow zone indicator (μm), Øz = normalized porosity, and R_{35} = Winland parameter (μm).

Neural network technique application

The neural network (NN) technique, invented by McCulloch & Pitts (1943) on the basis of a simplified biological process, is a flexible mathematical structure capable of describing complex non-linear relations between input and output of the data sets. Supervised and unsupervised are two categories of NN based on training methods. All applications of NN in the oil and gas industry are based on supervised training algorithms, which are divided into three main steps: training, calibration and verification (Mohaghegh 2000). However, in the Mamuniyat reservoir the NN model is constructed by the IP Software with one input layer, one hidden layer and one output layer. The trial zones were selected in front of input data curves; GR, Øe, Øcore, Kcore, FZI, HFU, Øn, and ρb at different depths of the studied reservoir within two trail wells 1 and 2. Training passes, epoch per pass and cross-validation percentage are three training settings of the NN technique. The training passes specify how many times the NN will be trained each time, and in this case, it was 3. The epoch per pass shows how frequent training data will be interpreted in this case, it was found to be 100. The cross-validation percentage of the input data defines how much the training data cross-check to process, and this was 5%. Epochs trained, the epoch of best cost and raw sensitivity are four outputs of the training settings. Therefore, after training the tool many times, resulted building the NN model. Then, this created NN model will run automatcialy to yield the HFU in the wells.

RESULT AND DISCUSSION

Processing of well logs and CCA data provide a set of results required to predict the permeability from the HFU. Therefore, Table 1 summarized the average values of the essential calculated petrophysical properties (V_{sh}, Øt, and Øe) of the Mamuniyat reservoir. Generally, the percentage of the volume of shale does not exceed 20%, and Well 3 has a higher average value of the V_{sh} than wells 1 and 2. This variety of the shale content has the material caused the average total porosity (Øt) does not reach 20%, and the effective porosity is about 15%. Also, the comparison procedure between measured core and calculated log porosity is an important step for reservoir evaluation. Hence, Figure 3 displays an accepted match of the measured core porosity (Øcore) and the calculated total and effective porosity results of well 1 and 2. As earlier stated, no core data for well 3. Thus, generation of relationship between the core permeability and porosity of well 3 is helpful to predict permeability of un cored reservoir depth intervals. Therefore, Figure 4 displays a cross plot between the measured core permeability (Kcore) and the porosity (Øcore) of wells 1 and 2 which do not exceed 70% of regression coefficient (R^2).

Table 1. Summary of avalues of the petrophysical properties of the Mamuniyat reservoir.

	Wells			Average
	1	2	3	
h (ft)	181	99	120	133.33
V_{sh}, %	13.7	12.00	14.61	13.46
Øt, %	11.3	11.04	13.56	11.96
Øe, %	11.5	11.39	12.08	11.68
Øcore, %	13.1	10.85	UC	10.87
Kcore, mD	116.7	75.83	UC	96.29

UC = Un cored

Application of the Kolodzie (1980) to estimate the Winland parameter (R_{35}), provide a contribution indicator of the HFU of the Mamuniyat reservoir. Hence, the reservoir includes three pore throat sizes classification; micropores, mesopores, and macropores based on the results of the pore size radius (R_{35}). The micropores and macropores classification are presented in well 2, as well as the minor presence of the mesopores pore throat sizes, while well 1 concerned with the three pore throat radius classifications. Thus, two reasons could be referred to the minor presence of the mesopores pore throat sizes in well 2, that may be attributed to depositional heterogeneity of the Mamuniyat reservoir as reported by Castro et al. (2012); Fello (2001); Fello & Turner (2004); Salaheddin et al. (2010); and (Shalbak 2015). Also, a rich quartz mineral in the Mamuniyat sandstone (El-ghali et al. 2006 may cause the elimination of the mesopores pore throat sizes. However, the pore size radius (R_{35}) versus core permeability is widely

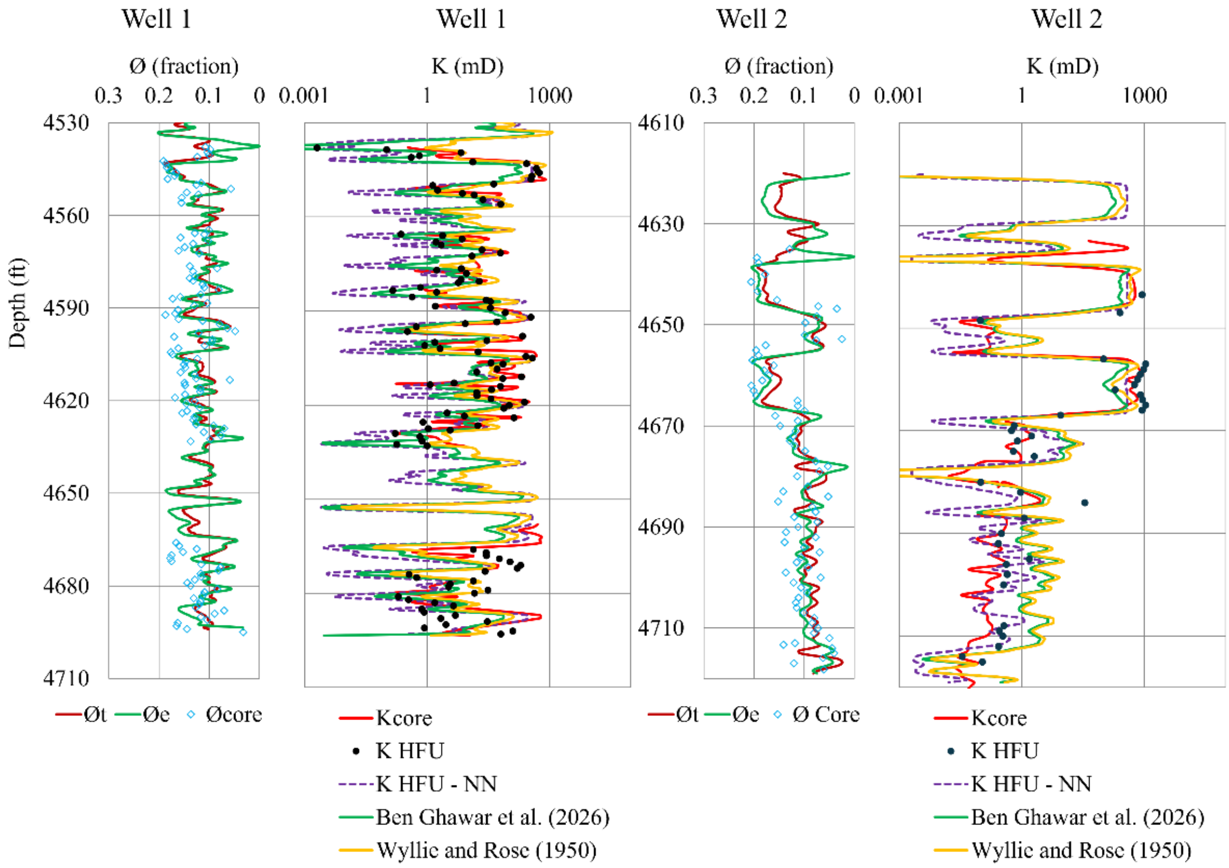

Figure 3. Overlay between the core (Øcore) and calculated porosity (Øt and Øe) of wells 1 and 2.

applied in limestone and sandstone reservoir rock several local oil field, this provides a linear empirical Equation (Lala and El-Sayed 2017. Accordingly, Figure 5 discloses a good linear relationship between the core permeability and pore throat radius of wells 1 and 2, with a high regression coefficient (R^2) equal to 0.9806 of the Mamuniyat reservoir. Also, on Figure 4 manifests a combined correlations of wells 1 and 2 between the Kcore, Øcore, and R_{35} of the Mamuniyat reservoir. These correlations disclose and conformably emphasis between the permeability ranges and the pore throat sizes classification in wells 1 and 2. On the same procedure, cross plot between the core porosity and R_{35} of well 1 and 2 reveals more scatter plotting points of well 2 than well 1 (Figure 6). This high linearity of plotting points in well 1 yield an ability to derive an empirical Equation for predicting the R_{35} in well 3.

Log-Log plots of the reservoir quality index (RQI) and normalized porosity (Øz) of the Mamuniyat reservoir within the two wells 1 and 2 are shown on Figures 7a and 8a. These plots are constructed by the Interactive Petrophysical (IP) Software that reveal well 1 has six hydraulic flow unit (1, 2, 3, 4, 5, and 6), while well 2 contains five (1, 2, 3, 5, and 6) of HFUs. Therefore, reconstruction of the core permeability (Kcore) and porosity (Øcore) cross plots (Figs. 7b and 8b) were based on the HFU of each well. Thus, the lines of each HFU that has an empirical Equation as summarized in Table (2) for permeability prediction against the hydraulic flow unit in wells 1 and 2. However, the Castro et al. (2012 have documented heterogeneity of the Mamuniyat formation due to variation in vertical and lateral depositional flow regime resulting variations in porosity, permeability and regional hydraulic element (GHE) distribution.

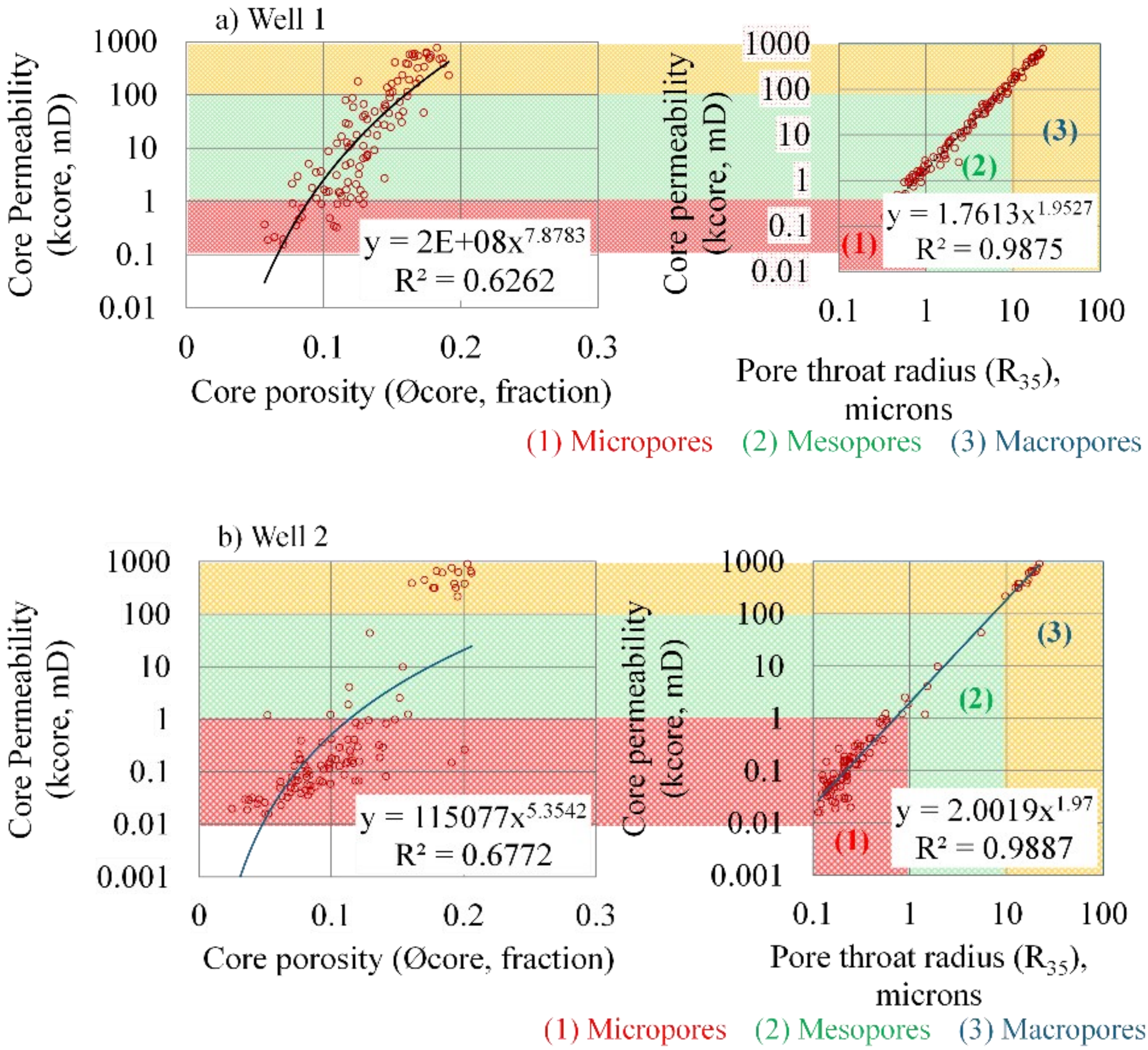

Figure. 4. Core permeability versus core porosity and permeability versus pore throat radius (R_{35}) of the Mamuniyat reservoir, a). Well 1, and b). Well 2.

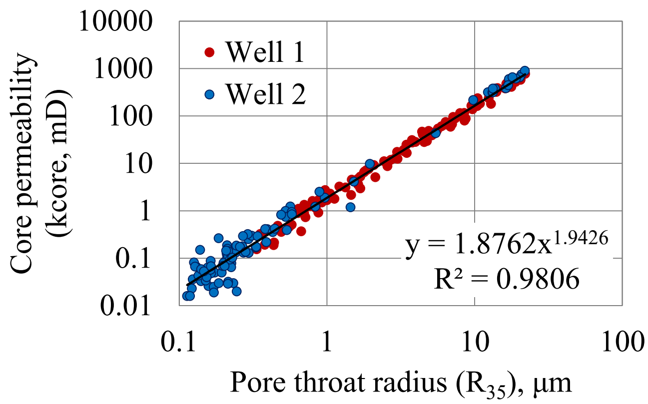

Figure 5. Core permeability versus pore size radius (R_{35}) of wells 1 and 2 of Mamuniyat reservoir

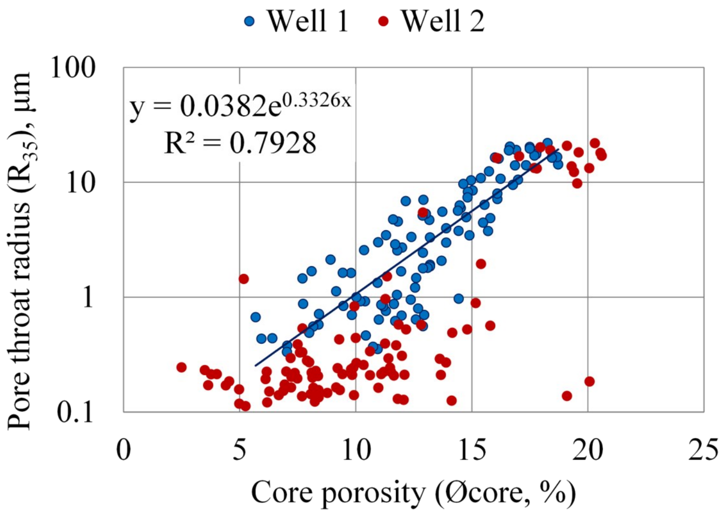

Figure 6. Core porosity versus pore size radius (R35) of wells 1 and 2 of Mamuniyat reservoir.

Validation process

Identification of the hydraulic flow units of the wells 1 and 2 within the Mamuniyat reservoir rocks, provides and drive to delineate hydraulic flow units in uncored well 3. Hence, the availability of core data of well 3 is essential to HFU of the Mamuniyat reservoir section, which is suitable to estimate HFU in terms of permeability empirical Equations, adjacent well 1 or well 2. In order, predicate permeability in well 3 may be subjected to verification procedure, also requires another permeability source to enhance uncertainty in Mamuniyat reservoir permeability evaluation. Accordingly, Wyllie and Rose (1950 have approved an empirical Equation applied to estimate the permeability of the Mamuniyat reservoir (Upper Ordovician) in well 3. However, utilizing of Neural Network (NN) technique by Interactive Petrophysics (IP 2018) to generate the HFU in well 3 based on the HFU in well 1 that is in turn to predict the permeability (K HFU). Therefore, the gamma ray (GR) logs of the studied wells (Figure 9) illustrate high matching between wells that is used to create the HFU in well 3, in the Neural Network training process. Then, Figure 10 Reservoir Quality Index (RQI) and normalized porosity (Øz) and permeability- Porosity cross plotting of well 3, by predicated the HFU's. Figure 10 manifests three hydraulic flow units (4, 5, 6) within the Mamuniyat reservoir. In addition, Figure 11 demonstrates two different approved empirical Equations, predicated permeability by HFU Equations and R_{35} classification with the GR and porosity logs. Although the predicated permeability by HFU (K HFU) of well 3 furnish higher values than the Wyllie & Rose (1950) and (Ben Ghawar et al., 2026), it has a good fluctuation pattern between the predicated permeability results. Meanwhile, both Wyllie & Rose (1950); and (Ben Ghawar et al., 2026) furnished high agreement results with some exceptions. These exceptions are disconformable results of the predicated permeability of well 3, retracted between the depths 4700 and 4810 foot, which could attribute to limited number of the predicted HFU4, HFU5, and HFU6 though this depth interval may attribute to be changed from fine- to medium-grained sands into coarse-grained to pebbly sands of a braided system as reported by (Salaheddin et al., 2010).

CONCLUSION

The petrophysical evaluation of the Mamuniyat reservoir, is characterized by an approximate thickness of 133 feet and a low shale content (V_{sh}) of 13%, effectively addresses the inherent challenges of reservoir heterogeneity and pore geometry distribution within the Murzuq Basin. By establishing a high convergence between total and effective porosity, and a strong correlation between core-measured and calculated porosity, this study provides a fine assessment of storage capacity. The integration of the Flow Zone Indicator (FZI) and the Winland parameter (R_{35}) successfully delineated five distinct hydraulic flow units (HFUs) categorized into micropores, mesopores, and macropores, thereby honoring the geological framework and depositional history essential for

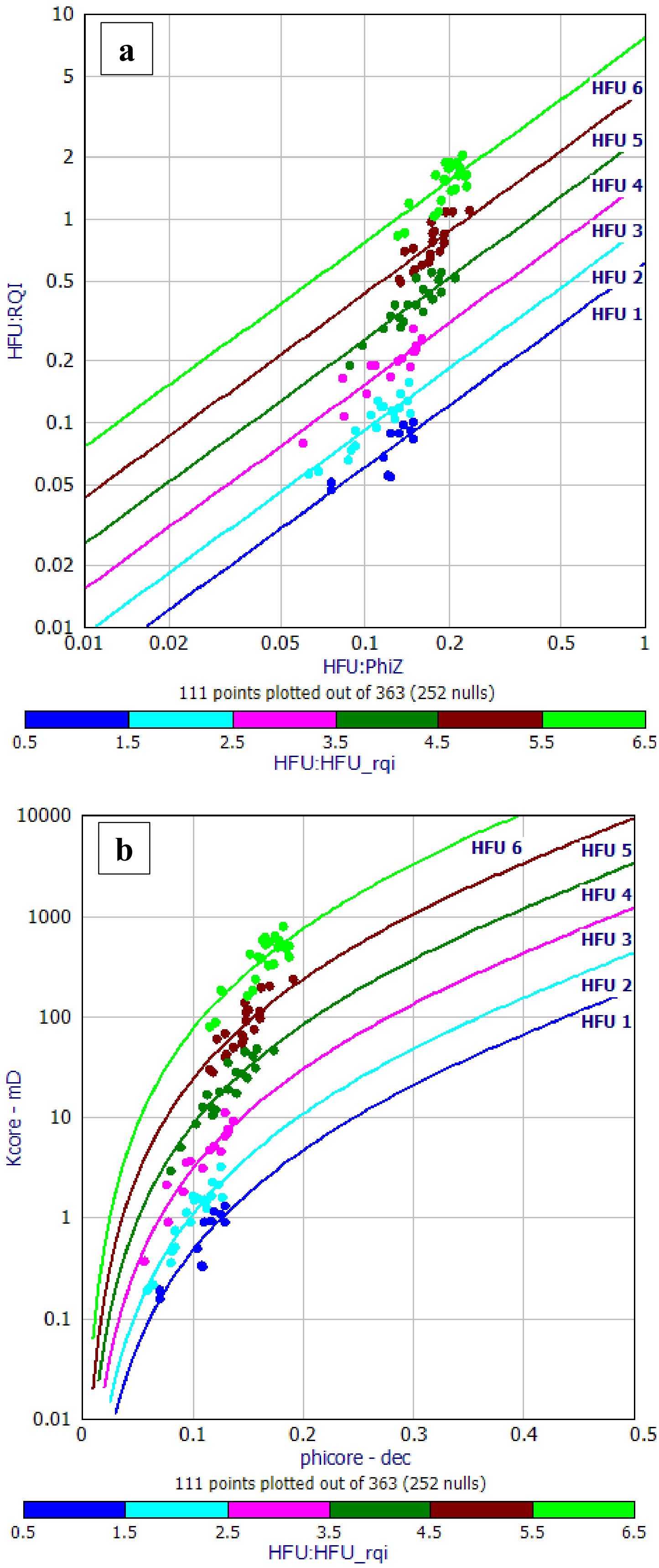

Figure 7. a). Reservoir quality index (RQI) and normalized porosity (Øz), b). Permeability- Porosity cross plotting and the different HFU'S of two wells 1, Mamuniyat reservoir.

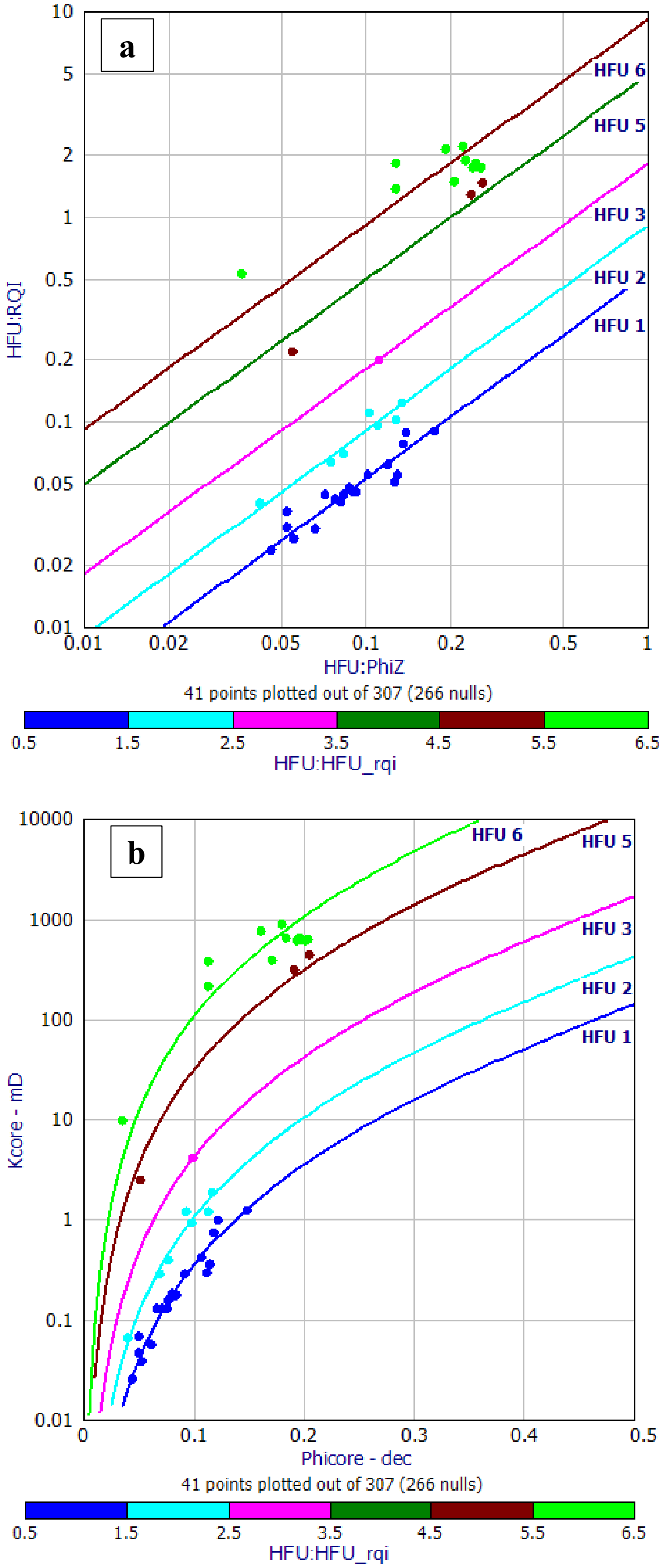

Figure 8. a). Reservoir quality index (RQI) and normalized porosity (Øz), b). Permeability- Porosity cross plotting and the different HFU'S of two wells 2, Mamuniyat reservoir.

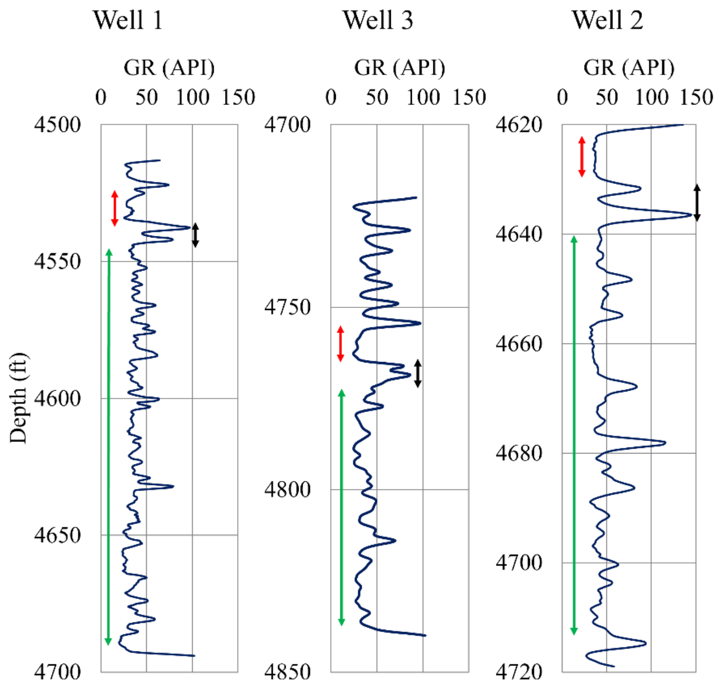

Figure 9. Gamma ray logs correlation between wells, of the Mamuniyat reservoir.

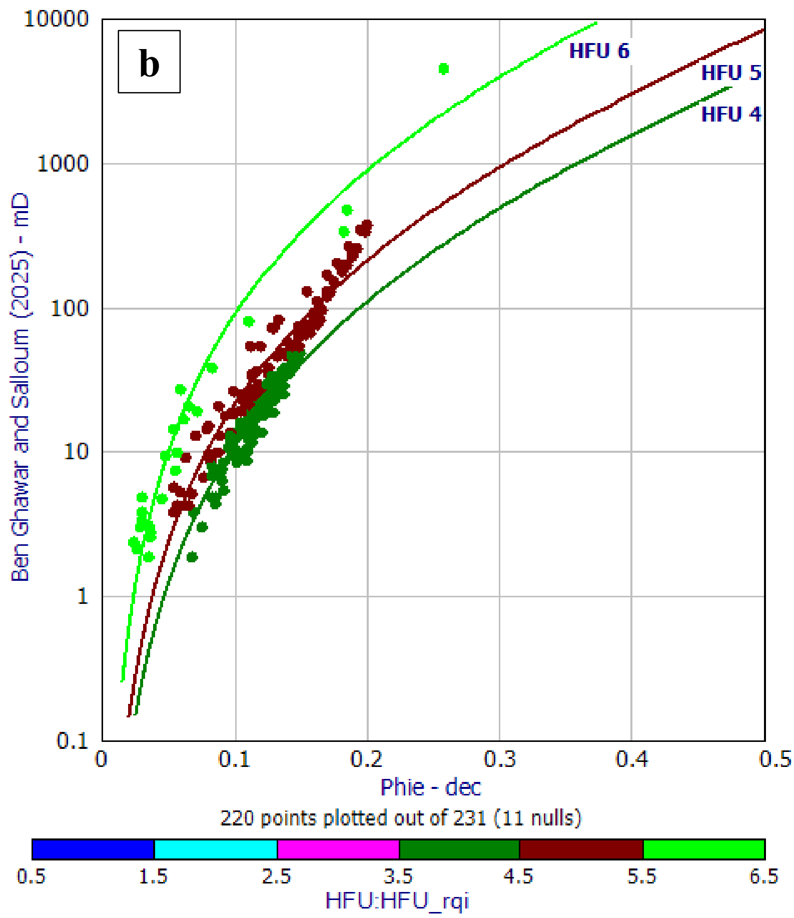

Figure 10. a). Reservoir Quality Index (RQI) and normalized porosity (Øz), b). Predicted permeability- Porosity cross plotting and the different HFU'S of well 3, Mamuniyat reservoir.

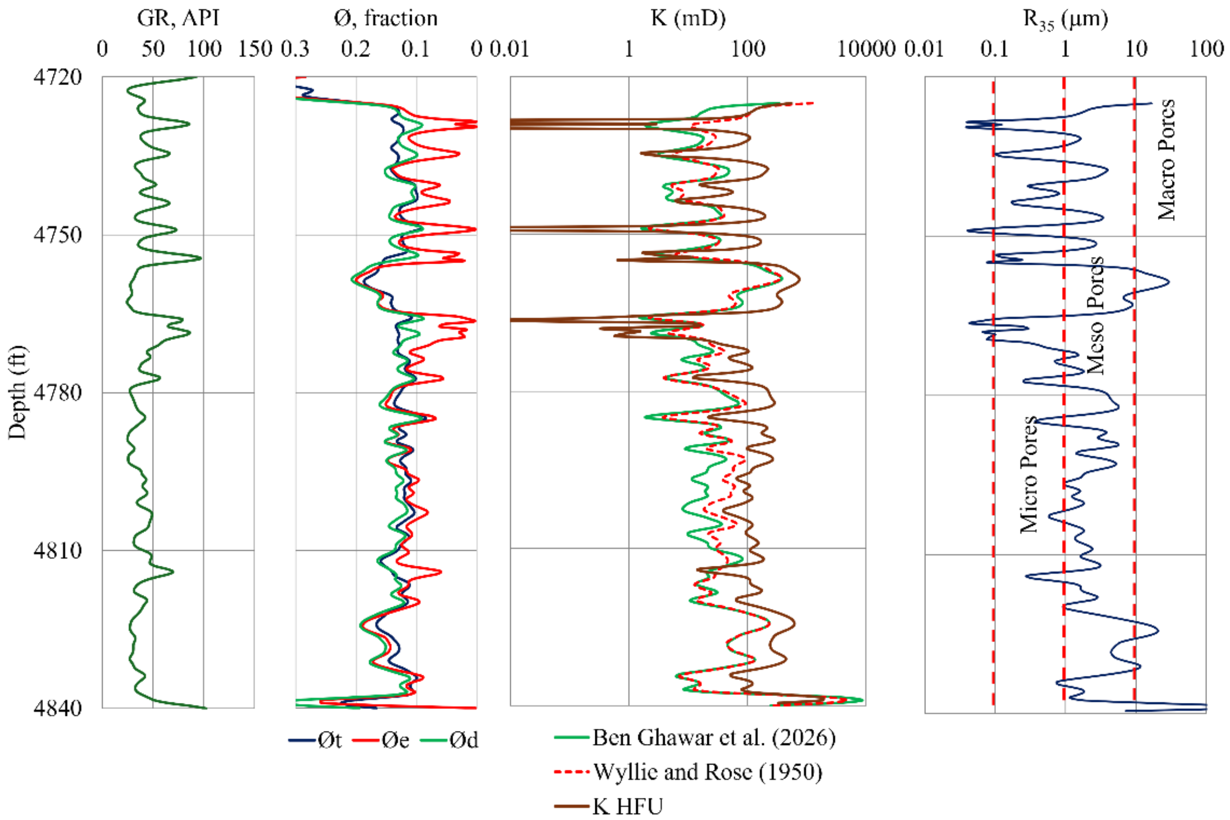

Figure 11. Gamma ray (GR) log, calculated porosity and permeability predication comparison of well 3, Mamuniyat reservoir.

flow capacity assessment. The primary novelty of this research lies in the application of the Neural Network (NN) technique to overcome the limitations of missing core data in exploration wells. By utilizing training algorithms based on Wells 1 and 2 (R^2 ≈ 70%), the NN model successfully predicted HFUs and permeability for the uncored Well 3. This approach yielded superior performance and reliability compared to traditional empirical models like Wyllie and Rose (1950 or Ben Ghawar et al. (2026. Ultimately, this study demonstrates that artificial intelligence tools offer a robust, cost-effective alternative for enhancing reservoir characterization and predicting hydraulic properties in complex clastic reservoir.

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DECLARATIONS

Author contribution

The authors contributions is perfectly lead by the first Author, in terms of working hard, getting the data, editing, revision, administration and supervision of this work.

Funding statement

None

Competing interest

None

The use AI or AI-assisted technologies

None

GLOSSARY OF TERMS AND SYMBOLS

Terms& Symbols	Definition	Unit
K	Permeability	mD
Øt	Total porosity	fraction
Øe	Effective porosity	fraction

Øcore	Core porosity	fraction
Kcore	Core permeability	mD
V_{sh}	Volume of shale	fraction
HFU	Hydraulic flow unit	-
FZI	Flow zone indicator	-
CCA	Routine core analysis	-
R_{35}	Pore throat radius	µm
NN	Neural network	-
GR	Gamma ray	API
IGR	Gamma Ray index	-
NGS	Spectmetry gamma ray	-
Øn	Neutron porosity	fraction
ρb	Bulk density	gm/cm^3
ΔT	Interval travel time	µs/ft
Sw	Water saturation	fraction
Ød	Density porosity	fraction
a	Tortuosity factor	-
m	Cementation factor	-
Swirr	Irreducible water saturation	fraction
RQI	Quality index	-
Øz	Normalized porosity	fraction

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