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Articles

EXPERIMENTAL INVESTIGATION OF REINFORCED FLAT SLABS WITH TRUSS-SHAPED PUNCHING SHEAR REINFORCEMENT

Shamshinar Salehuddin, Shaharudin Shah Zaini*, Megat Azmi Megat Johari, Ahmad Nurfaidhi Rizalman, Nur Liza Rahim & Mustaqqim Abdul Rahim
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RESEARCH ARTICLE

AN INTEGRATED APPROACH OF PERMEABILITY DETERMINATION USING HYDRAULIC FLOW UNIT AND ARTIFICIAL NEURAL NETWORK METHODS IN THE KMJ FIELD

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ABSTRACT

This study discussed on determining of reservoir rock permeability in the challenging and heterogeneous of KMJ Oil Field. Through the integration of well log and core data, the difficulty of permeability determination in this field compared to more homogeneous reservoirs could be handled. The permeability determination is based on well log analysis, which is validated against permeability obtained from core analysis or well testing. Selecting the appropriate permeability method is crucial for accurately calculating reservoir rock transmissibility in dynamic models. The analysis begins with the calculation of physical properties, such as Vshale rocks and porosity, derived from well log analysis, which is further validated against mud log data and core porosity measurements. In core analysis, core porosity and permeability data were utilized to calculate essential parameters including reservoir quality index (RQI), Øz, and flow zone indicator (FZI) cores using the Hydraulic Flow Unit (HFU) method. To determine permeability in well intervals without core data, the Artificial Neural Network (ANN) method to predict the FZI log was used. By combining the HFU and ANN methods, then could be generated to permeability prediction values specific to the field conditions. In the case of the KMJ-105 well of KMJ field, the resulting permeability predictions exhibit a deviation coefficient of 0.85 and a gradient (m) of 0.94, with an error percentage of 9.81%. These findings demonstrate the effectiveness of the integrated of HFU and ANN methods in permeability determination and provide valuable insights for reservoir characterization and management.

Keywords: Permeability, Flow zone indicator, Hydraulic flow unit, Artificial neural network, Rock type

INTRODUCTION

Permeability is a fundamental property of reservoir rocks that governs the flow of fluids through porous media. Accurate determination of permeability is crucial for reservoir characterization and simulation studies, as it directly impacts the efficiency and productivity of hydrocarbon reservoirs. One effective approach to assess and predict permeability variations within a reservoir is by utilizing the concept of hydraulic flow units (Al-Ajmi et al., 2000; Amaefule et al., 1993). Hydraulic flow units are discrete rock intervals or zones within a reservoir that exhibit similar fluid flow characteristics, including porosity, permeability, and fluid saturation. These flow units are identified based on geological and petrophysical properties derived from well logs, core samples, and other data sources (Al-Ajmi et al., 2000). By grouping rock intervals into hydraulic flow units, reservoir engineers and geoscientists can gain valuable insights into the reservoir's heterogeneity and fluid flow behavior (Amaefule et al., 1993).

The determination of permeability using hydraulic flow units involves a systematic process that begins with the characterization of different rock intervals within the reservoir. This entails the analysis of core samples, well logs, and other geological data to identify distinct flow units based on lithology and petrophysical properties (Al-Ajmi et al., 2000). Permeability in reservoirs is difficult to predict because it is influenced by a high degree of heterogeneity (Jong-Se et al., 2006; Hamada et al., 2009; Singh, 2005; Al-Ajmi et al., 2000; Sheng et al., 2010; Kassenov et al., 2016). High heterogeneity factors occur at all observation and measurement scales related to lithology, mineralogy, pore type, connectivity, facies (physical, chemical and biological aspects) and texture. Each of these can be related to geological processes, the controlling factors for the original deposition and diagenesis.

One common approach to estimate permeability within each hydraulic flow unit is by using empirical correlations. These correlations establish relationships between permeability and petrophysical properties like porosity, grain size, and lithology (Al-Bazzaz et al., 2007). By applying these correlations to the properties of each flow unit, permeability values can be approximated. In Amaeful's research, a method was developed and successfully tested for diagnosing and measuring rock pore-throat sizes by simulating the transform process of the porosity-permeability equation of the Hydraulic Flow Unit (Amaefule et al., 1993; Xiao et al., 2013; Ngo, 2015; Svirsky et al., 2004).

This study shows how to obtain a permeability determination method that can be applied through integration and validation of small/micro (Core) – medium/meso (Wireline Log) – large/ macro-scale data. Integration of core data (Routine and SCAL), wireline logs and test data aim to obtain accurate permeability results (Al-Bazzaz et al., 2007). The Artificial Neural Network (ANN) method can be used to predict permeability at depth intervals or wells that do not have log data (Sokhal et al., 2019; Soares et al., 1996; Al-Bazzaz et al., 2007; Olayiwola, 2017; Maslennikova, 2013).

GEOLOGICAL SETTING

The KMJ field is an oil field located in the middle of the Barito Basin, which is a foreland basin that has undergone inversion and is of Tertiary age. The Barito Basin is bounded by the Adang Fault in the north, separated from the East Java Basin in the south, bordered by the Meratus Mountains in the east, and limited by the Sunda Shelf in the west (Kusuma and Darin, 1989; Satyana and Silitonga, 1994). The geological history of the Barito Basin's structural formation is characterized by the difference in alignment between the Paleogene and Neogene ages. The Rift phase of the basement rocks began to form in the Paleocene-Eocene age (Haris et al., 2019). The stratigraphy of the Barito Basin is closely related to the tectonic history that has occurred. The Pre-Rift phase comprises basement rocks of pre-Tertiary age. The Syn-Rift phase was deposited in the Late Paleocene to Middle Eocene and consists of the Lower Tanjung Formation. The subsequent phase is composed of the Upper Tanjung Formation and the Berai Formation, deposited during the regional loading phase of the Middle Eocene to Early Miocene age. The Post-Rift phase was deposited during the Middle Miocene to its peak in the Plio-Pleistocene, caused by the uplift of the Meratus Mountains (Satyana and Silitonga, 1994).

RESEARCH METHODOLOGY

This analysis uses log data such as gamma ray, resistivity, neutron porosity, bulk density and petrophysical analysis of several wells in KMJ Field. Analysis of rock properties (Vsh, porosity, water saturation, and permeability) from well logs, special/routine core laboratory tests and rock visual porosity based on pore and matrix relationships based on the integration of core data, wireline logs and test data (Al-Ajmi et al.,2000). This analysis is expected to obtain variations in porosity values, especially permeability from log readings. Detailed of the flowchart research methodology is shown in Figure 1 (Modified from Amaefule et al., 1993).

3.1. Log Analysis (Vsh and PHI Calculation)

The determination of V-shale in well log analysis relies on the identification of clean-baseline and shale-baseline lines. The withdrawal of these two curves is based on the magnitude of GRmin and GRmax values (David et al. 2015). The accurate determination of V-shale is crucial as it directly impacts the calculation of effective porosity in rock layers.

Porosity analysis plays a significant role in evaluating subsurface formations. Several methods are commonly used to determine porosity based on well log measurements, including Density, Neutron, Sonic, Neutron-Sonic, and Neutron-Density methods. The porosity values obtained from these methods are then compared with the porosity values derived from core samples taken at corresponding intervals (Albeyati et al. 2021).

To assess the validity of the porosity analysis methods, a comparison is made between the log-derived porosity values and the porosity values obtained from the core samples (Albeyati et al. 2021). This is often done using a log vs core cross plot, which allows for a visual representation of the correlation between the two data sets. The reliability of the comparison is determined by evaluating the deviation value (r^2) and the gradient value (m).

The most valid porosity analysis method is typically the one that exhibits a deviation value (R^2) close to 1, indicating a strong correlation between the log and core porosity values. Additionally, a gradient value (m) close to 1 suggests a consistent relationship between the two datasets. This method aligns closely with the porosity values derived from the core samples and thus provides reliable results (Delfiner, 2007). In conclusion, accurate determination of V-shale and valid porosity analysis methods are essential in well log analysis. The V-shale determination directly affects effective porosity calculations, while the comparison of log-derived porosity values with core porosity values allows for a reliable assessment of subsurface formations. Utilizing methods that demonstrate high correlation and consistency with core data enhances the accuracy of porosity analysis and improves the understanding of rock properties in subsurface environments.

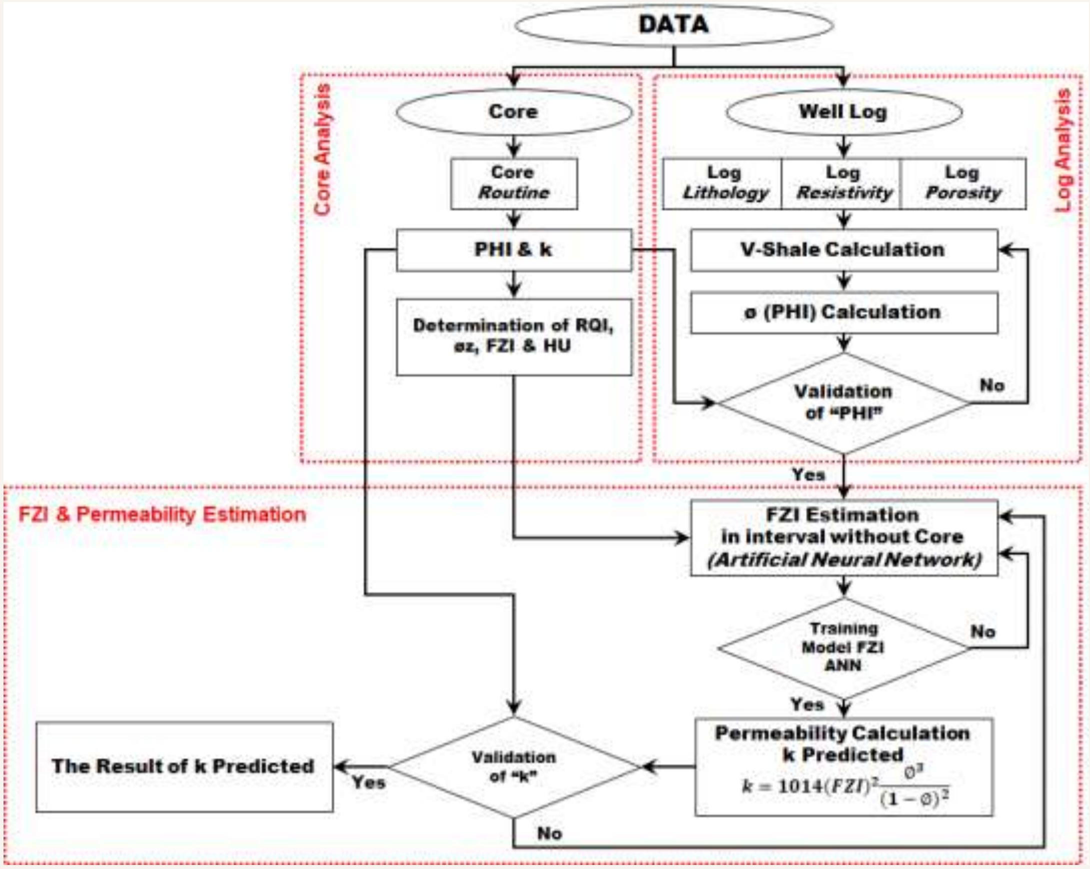

Fig. 1. Research methodology in the KMJ Field

3.2. Hydraulic Flow Unit Calculation (Core Analysis)

The initial data that must be prepared to carry out a transform permeability analysis using a hydraulic flow unit is the availability of core analysis data (Ø and k). Clustering analysis and permeability calculation using the equation developed by Kozeny – Carmen (Amaefule et al., 1993; Xiao et al., 2013;

Svirsky et al., 2004). The available of Ø and k data used to calculate the Reservoir Quality Index (RQI) as follows:

$$RQI = 0{,}0341\sqrt{\frac{k}{\text{Ø}}} \quad (1)$$

The normalized porosity (Øz), as the ratio between the pore and grain volumes calculate using equation as follows:

$$\text{Ø}z = \text{Ø}/ (1-\text{Ø}) \quad (2)$$

and, the Flow Zone Indicator (FZI) calculation can be performed for each depth as follows:

$$\text{FZI} = \text{RQI} / \text{Ø}z \quad (3)$$

hence, the Hydraulic Flow Unit (HFU) value as grouping based on HFU calculate as follows:

$$\text{HFU} = \mathit{Round}\,[2\ln(\text{FZI}) + 10{,}6] \quad (4)$$

finally, determine of the permeability (k) for each depth based on the HFU method, using equation

$$k = 1014(FZI)^2\left(\frac{\text{Ø}^3}{(1-\text{Ø})^2}\right) \quad (5)$$

3.3. Prediction of Flow Zone Indicator (FZI)

The Artificial Neural Network (ANN) method builds relationships between predictive data, automatically obtaining non-linear solutions to the problems at hand (Soares et al., 1996). In this case, the ANN method utilizes well-log data to determine the FZI (Formation Factor Index) log. The well-log data includes Gamma Ray log data, Resistivity log data, and Porosity log data. It is crucial to normalize all the log data so that the data to be tested or predicted has a uniform range (Sokhal et al., 2019; Singh, 2005).

The training process involves training the network to recognize patterns in the input data. The network then produces output that is compared with the target data, specifically the FZI core (Sokhal et al., 2019; Singh, 2005). Through this training process, the weighting value of each input data can be determined, highlighting the factors that have the greatest influence on predicting the FZI value.

The next step involves network testing to assess whether the network can generalize to new data. In this scenario, the data used for FZI log prediction relies on log porosity data, which has been correlated with core porosity data. The accuracy of the network in recognizing test data demonstrates its capability to make predictions (Singh, 2005).

For testing purposes, the best network architecture obtained from the porosity log network training results is utilized. This architecture is controlled by weighted log data. Finally, the FZI log predictions are made based on the optimal network architecture, providing permeability prediction results that can be compared with the evaluation of log and core data formations under actual field conditions.

3.4. Determination of Permeability (Based on Well-Log)

The results of the FZI predictions (based on well-log) that have been validated against core data will be used to calculate permeability using equation 2 through equation 5 (Amaefule et al., 1993; Xiao et al., 2013; Svirsky et al., 2004). The results of the log permeability calculation must be validated against core permeability with a deviation (R^2) and gradient (m) value close to 1 (>0.8).

RESULTS AND DISCUSSION

4.1. Determination of V-Shale and Porosity

Withdrawal of GR clean and GR shale in the Sand C and D Unit differs from the withdrawal trend in the Sand A and B Unit. Core-plug data in Figure 2 shows that the lithology in the KMJ Sand C and D Unit Field is dominated by sandstone with intercalated clay with a conglomerate at the bottom of the Sand Unit C. In contrast, Sand Units A and B are dominated by conglomerates, with the grain size of Sand Unit A being larger than that of Sand Unit B. Volume shale in conglomerate rocks refers to the proportion or percentage of shale or fine-grained sedimentary material present within the rock formation. In conglomerates, the matrix material between the clasts is typically finer-grained, often consisting of silt, clay, or shale particles. Estimating the volume shale in conglomerates involves identifying and quantifying the amount of fine-grained matrix material within the rock.

Determining the volume shale in conglomerates can be challenging due to the presence of clasts and the variable nature of the matrix material. Petrophysical analysis, including visual inspection of core samples and thin sections, as well as well log interpretation, can be utilized to estimate the volume shale. Well logs that provide lithology information and measurements of gamma-ray response and resistivity can assist in identifying shale-rich intervals and estimating the volume of shale.

The porosity in conglomerates can vary depending on factors such as clast size, sorting, compaction, cementation, and diagenetic processes. In general, conglomerates tend to have lower porosity compared to well-sorted sandstones, as the clasts occupy a significant volume of the rock. However, certain conglomerates with well-developed intergranular porosity and limited cementation can exhibit relatively high porosity values

To determine porosity in conglomerates, core analysis, laboratory measurements, and well logging techniques are commonly employed. Core samples are analyzed to measure the porosity directly, while well logs such as density logs and neutron porosity logs provide indirect estimates of porosity based on the response of the rock to specific measurements.

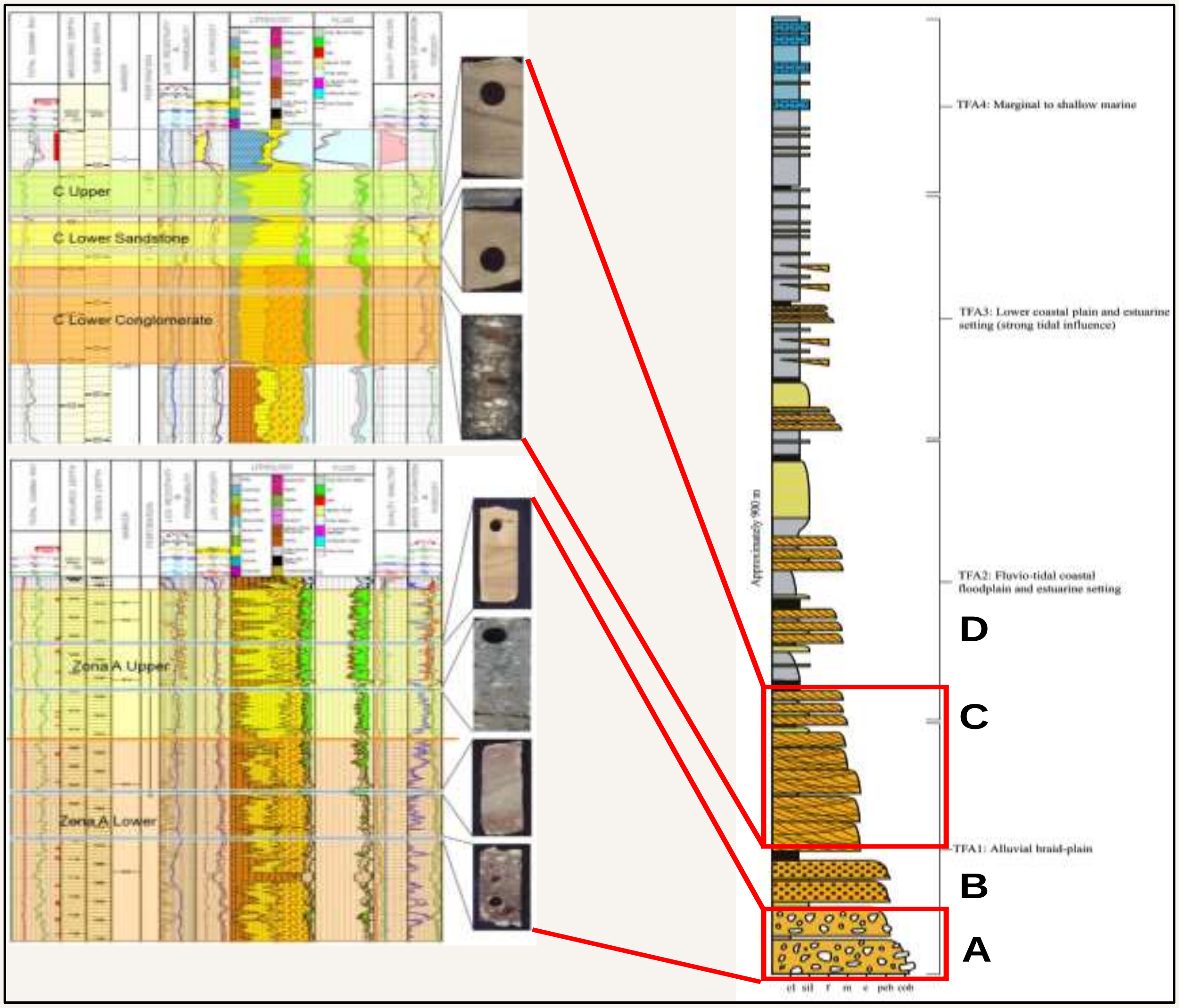

Fig. 2. Integration of core-plug and well log data to determine the lithology of sand units ABCD

The KMJ Field Porosity was calculated using the Neutron–Density (N-D) method. Figure 3 shows a comparison of the results of the porosity calculation at the KMJ-105 Well, which has been validated with the porosity of the core data. Figure 3 shows an example of a cross-plot between log porosity and core porosity. Phi-core-Phi-log Regression is a method used to compare the porosity values obtained from core samples (Phi-core) with those derived from well log measurements (Phi-log). One approach to assess the agreement between these two porosity values is through cross plotting. By plotting log porosity against core porosity, we can visually examine their alignment on the y = x line.

Figure 4 shows a cross plot, consisting of 249 data points, along with its associated linear trend line. The regression analysis reveals that the plotted points demonstrate a significant correlation. The fraction of variance explained, represented by the deviation value (R^2) value of 0.872, indicates that 87.20% of the variation in porosity can be attributed to the linear relationship between core and log porosity. The high correlation coefficient of 0.872 further supports the strong agreement between core and log porosity values. This coefficient indicates a robust positive correlation between the two sets of porosity data. Therefore, we can conclude that there is very good agreement between the porosity values obtained from core samples and those derived from well log measurements. This Phi-core-Phi-log regression analysis serves as a valuable tool in validating the accuracy of log porosity measurements. The close alignment between core and log porosity, as demonstrated by the linear trend line and high correlation coefficient, enhances our confidence in the reliability of well log data for assessing subsurface porosity.

In conclusion, the cross-plot analysis and regression results illustrate the excellent agreement between core and log porosity values. This finding reinforces the utility of the Phi-core-Phi-log regression method as a means of validating the accuracy of well log measurements.

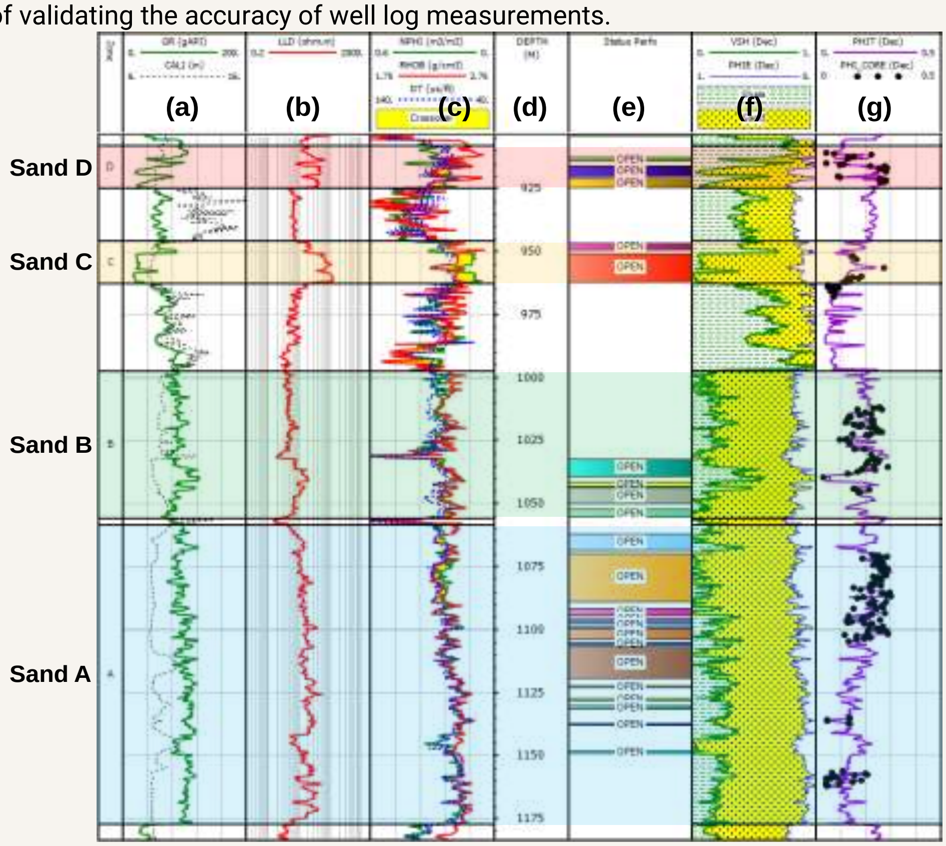

Fig. 3. Vshale calculation results, log porosity validated against core data of KMJ-105: (a) Lithology logs: GR log and Caliper log, (b) Resistivity log, (c) Porosity logs: NPHI, RHOB and DT logs, (d) Measured depth, (e) Perforation, (f) Volume shale, (g) Comparison of log porosity with core porosity

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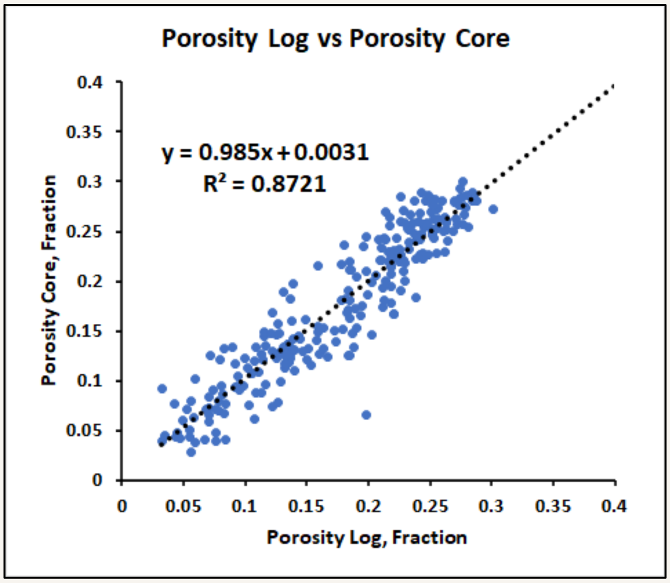
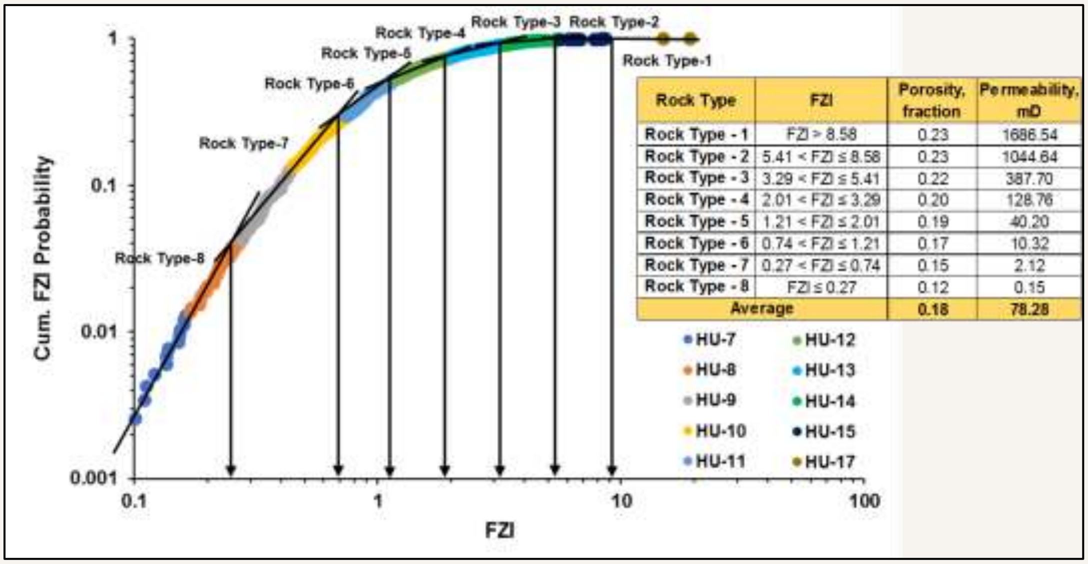


Fig. 4. Cross plot of log porosity vs core porosity of KMJ-105

4.2. Calculation of HFU (Core)

The division of the hydraulic unit (HU) begins with calculating the reservoir quality indx (RQI) and normalized porosity (øz) values. After obtaining the RQI and øz values, the flow zone indicator (FZI) values are calculated, plotting the HU distribution on the porosity versus permeability graph. Smaller HU values indicate rock groups with smaller pore throat sizes. The division of rock type considers changes in the FZI trend for each cumulative FZI probability value so that the reservoir rocks in the Sand ABCD Unit of the KMJ Field can be classified into eight (8) rock types. Furthermore, the maximum and minimum FZI value limits are determined for each change in trend, as shown in Figure 5. FZI provides a quantitative measure of fluid flow potential at specific rock intervals, while Cumulative FZI Probability analyzes the overall distribution of FZI values across the reservoir. FZI is focused on individual flow zones, while Cumulative FZI Probability provides a broader perspective on the reservoir's fluid flow behavior and connectivity.



Rock Type	FZI	Porosity, fraction	Permeability, mD
Rock Type - 1	FZI > 8.58	0.23	1686.54
Rock Type - 2	5.41 < FZI ≤ 8.58	0.23	1044.64
Rock Type - 3	3.29 < FZI ≤ 5.41	0.22	387.70
Rock Type - 4	2.01 < FZI ≤ 3.29	0.20	128.76
Rock Type - 5	1.21 < FZI ≤ 2.01	0.19	40.20
Rock Type - 6	0.74 < FZI ≤ 1.21	0.17	10.32
Rock Type - 7	0.27 < FZI ≤ 0.74	0.15	2.12
Rock Type - 8	FZI ≤ 0.27	0.12	0.15
Average		0.18	78.28

Fig. 5. Distribution of rock types based on the ABCD sand units routine core data

In Cumulative FZI Probability analysis, FZI values are sorted in ascending order, and the cumulative probability of occurrence is calculated. This probability represents the likelihood of finding a specific FZI value or lower in the reservoir. The resulting cumulative FZI probability curve provides a graphical representation of the FZI distribution. The Cumulative FZI Probability curve can reveal valuable insights about the reservoir's flow characteristics. It allows reservoir engineers and geoscientists to understand the percentage of the reservoir volume associated with different FZI values. By examining the shape and slope of the curve, one can infer the dominant flow behavior, identify flow barriers or conduits, and assess the reservoir's heterogeneity and connectivity.

The distribution of rock types considering the FZI Log value is used because FZI trends show more changes in flow units. The relationship between porosity parameters and permeability of routine core data for each rock type is shown in Figure 6. HFU can consist of a single dominant rock type or may comprise multiple rock types that exhibit similar fluid flow properties. The presence of different rock types within a HFU can affect the heterogeneity and connectivity of the reservoir, hence influencing fluid flow patterns.

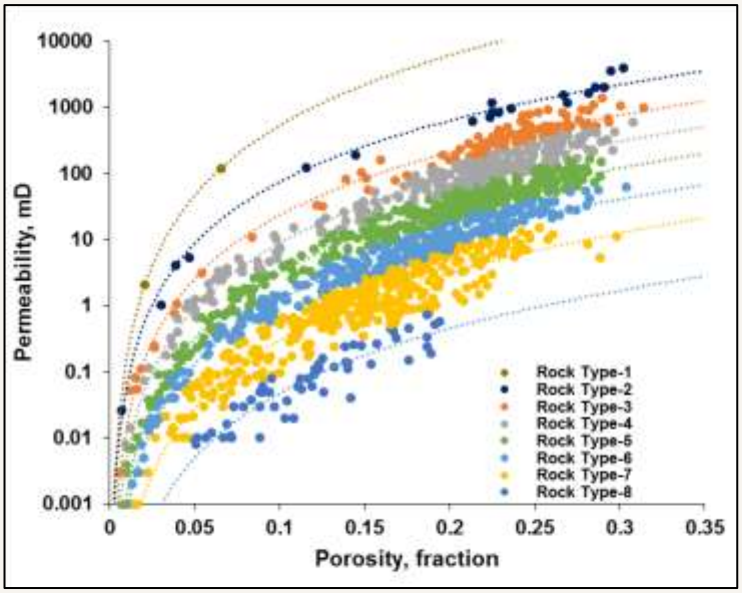


Fig. 6. The relationship between porosity and permeability for each rock type of sand units ABCD

4.3. FZI Log Prediction

The prediction of Formation Factor Index (FZI) is a crucial task in analyzing subsurface formations. It involves the analysis of various well log measurements and the calculation of specific petrophysical properties. This article explores the use of well logs and the Artificial Neural Network (ANN) method for predicting FZI values.

To predict FZI accurately, several well log measurements are commonly utilized. These measurements include volume shale, resistivity, and porosity-related parameters. By analyzing these logs, it becomes possible to estimate the FZI value for different well intervals. When core data is not available for a particular well interval, the ANN method proves useful for FZI prediction. Before applying the ANN method, it is crucial to test and identify the parameters that significantly influence the FZI value.

In the case of the KMJ Field, certain parameters have been identified as influential factors in FZI prediction. The Vshale curve, calculated from the Gamma Ray log, and the Porosity curve, calculated from the Neutron–Density log, have shown promising results in estimating FZI values. Figure 7, presents the predicted FZI results for the KMJ-105 well, specifically for intervals lacking core data. The ANN method was employed using the Vshale and Porosity curves as input parameters. The FZI Log vs FZI Core cross-plot demonstrates a deviation coefficient (R^2) of 0.86 and a gradient (m) of 0.96, indicating a reasonably accurate prediction as shown in Figure 8. Predicting FZI values using well logs is essential for understanding subsurface formations. The ANN method offers a reliable approach for estimating FZI when core data is unavailable. In the KMJ Field, the Vshale and Porosity curves have shown promising accurate results in FZI prediction.

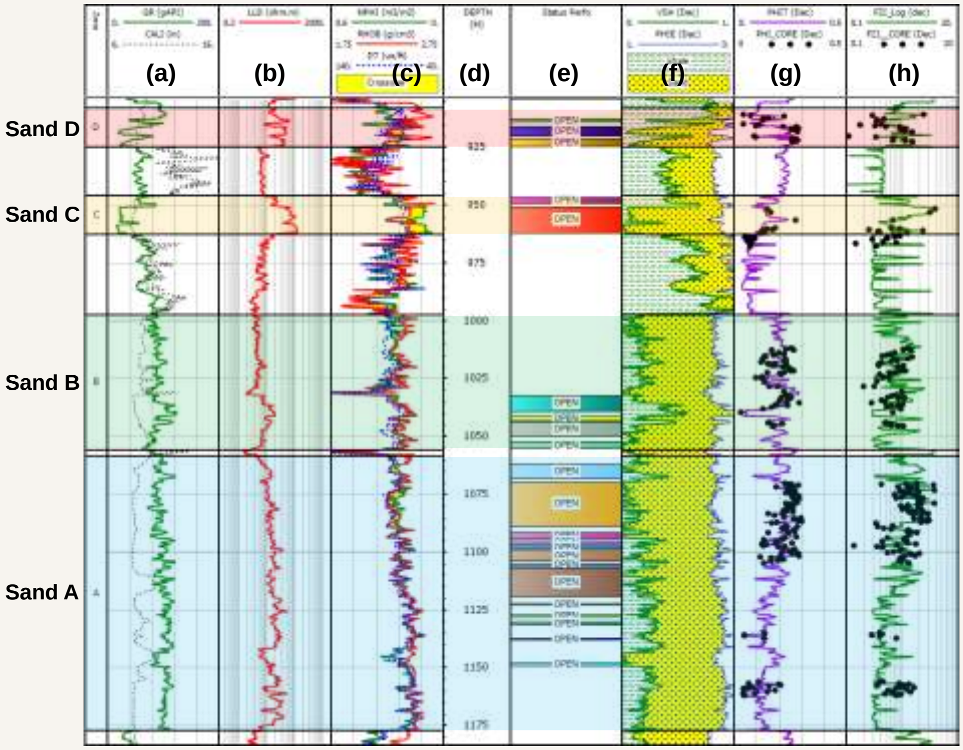


Fig. 7. Determination of flow zone indicator (FZI) of KMJ-105: (a) Lithology logs: GR log and Caliper log, (b) Resistivity log, (c) Porosity logs: NPHI, RHOB and DT logs, (d) Measured depth, (e) Perforation, (f) Volume shale, (g) Comparison of log porosity with core porosity, (h) Comparison of log FZI with core FZI

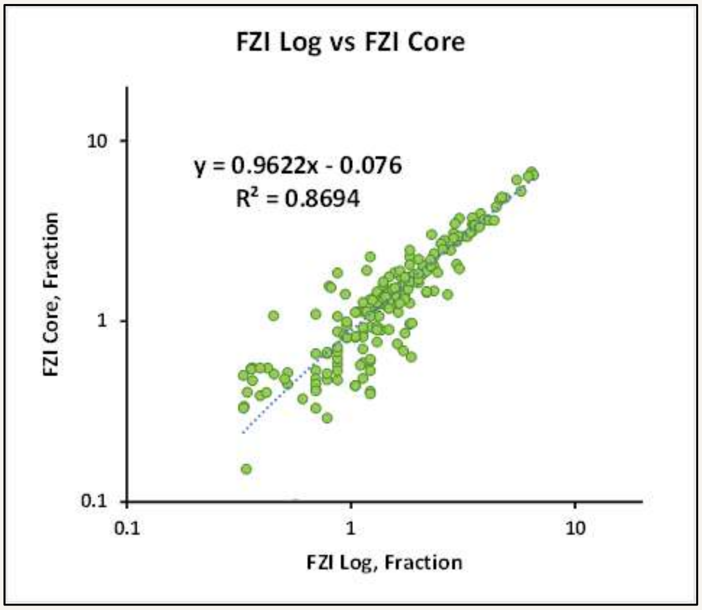


Fig. 8. Crossplot of FZI log vs FZI core of KMJ-105

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4.4. Permeability Determination at Depth Intervals without Core Data

Accurate estimation of permeability in subsurface formations is crucial for reservoir characterization and hydrocarbon exploration. However, in cases where core data is unavailable for specific depth intervals, log analysis techniques can provide valuable insights. This article focuses on the calculation of permeability at depth intervals without core data using log-derived parameters. To estimate permeability in depth intervals lacking core data, equation (3-5) is utilized. This equation incorporates the log Formation Factor Index (FZI) value and log porosity to produce a permeability value. The log permeability calculation process is illustrated in Figure 9.

The accuracy of the log permeability calculation is assessed by comparing the results with core permeability data. Figure 10 displays the cross-plot of log permeability against core permeability, revealing a deviation coefficient (R^2) value of 0.85 and a gradient (m) of 0.94. These metrics indicate a reasonably good agreement between the log-derived permeability and core permeability. To further evaluate the accuracy of the calculated permeability, percentage error calculations are performed. The percentage error is determined by comparing the calculated permeability values to the core permeability. Specifically, the analysis focuses on the percentage of data falling within the range of ±200% of the core permeability.

In the case of the KMJ-105 Well, the error analysis reveals a percentage error of 9.81% for the total dataset, indicating a relatively small deviation from core permeability values. Moreover, 90.19% of the data falls within the acceptable range, indicating a significant proportion of matched data, as depicted in Figure 11.

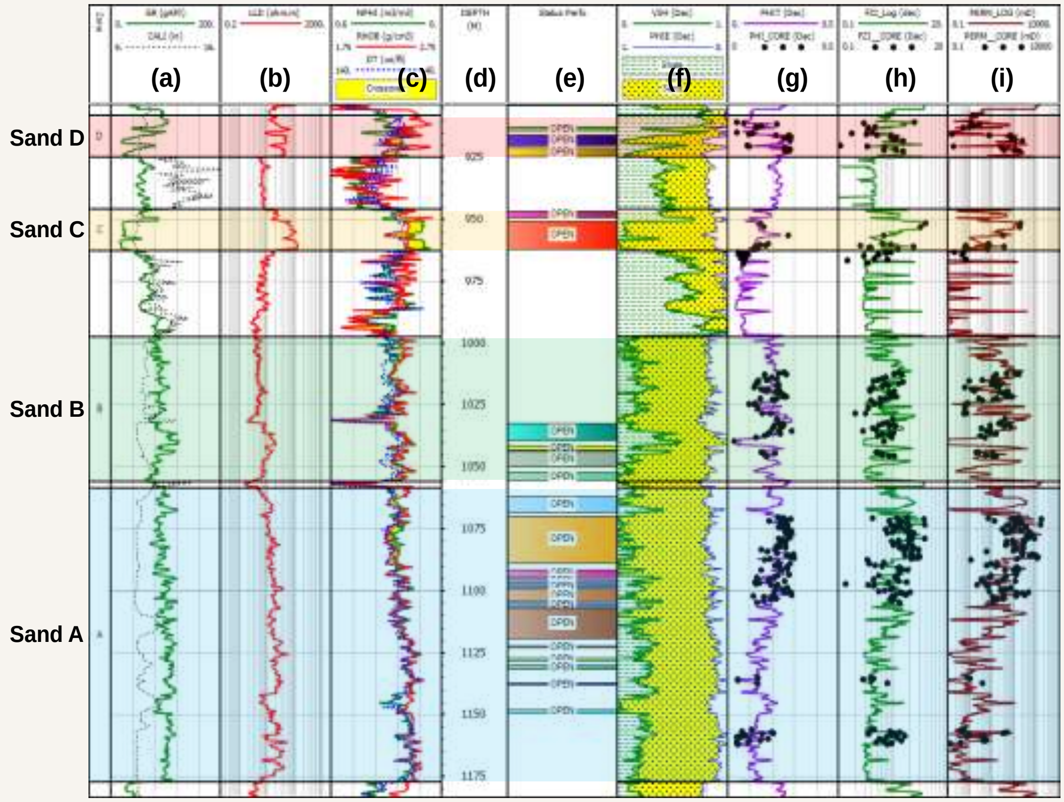

Fig. 9. Calculation of permeability of KMJ-105: (a) Lithology logs: GR log and Caliper log, (b) Resistivity log, (c) Porosity logs: NPHI, RHOB and DT logs, (d) Measured depth, (e) Perforation, (f) Volume shale, (g) Comparison of log porosity with core porosity, (h) Comparison of log FZI with core FZI, (i) Comparison of log permeability with core permeability

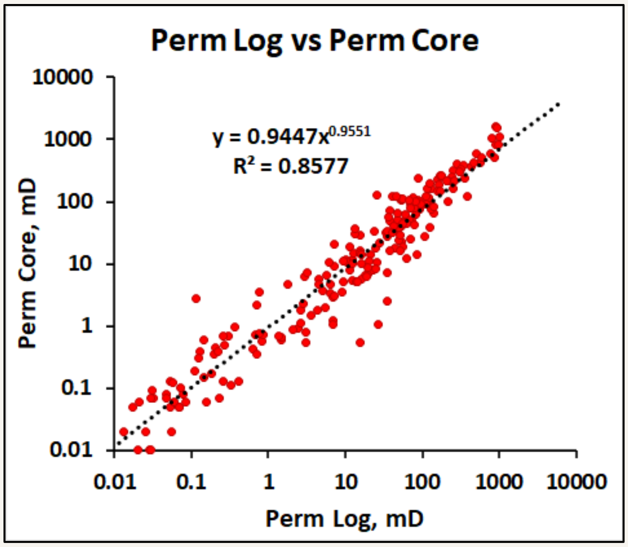

Fig. 10. Crossplot permeability log vs. permeability core of KMJ-105

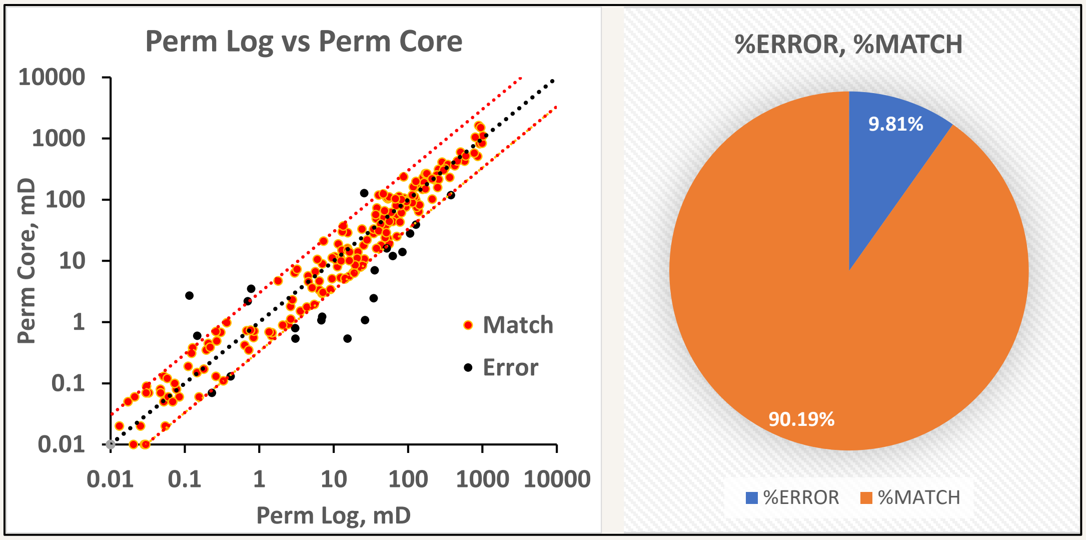

Fig. 11. Error percentage for permeability log vs. permeability core of KMJ-105

CONCLUSIONS

Porosity Influence: The porosity value of the reservoir rock was found to have a significant influence on permeability. Different permeability values were observed for the same porosity due to the presence of Vshale, which affects the size of the pore necks. This highlights the importance of considering both porosity and Vshale content in permeability calculations.

Flow Zone Indicator (FZI): The Flow Zone Indicator (FZI) derived from the analysis played a crucial role in understanding the flow characteristics of the reservoir. By grouping permeability values into different rock types based on the FZI using the Hydraulic Flow Unit (HFU) method, a better understanding of fluid flow behavior within the reservoir was achieved.

FZI Log Prediction: The FZI log prediction using the Artificial Neural Network (ANN) method provided valuable insights into permeability values in intervals without core data. By utilizing this prediction, valid permeability values could be obtained for these intervals. The ANN method demonstrated its effectiveness in estimating permeability and proved applicable in the case of the KMJ-105 well.

Evaluation Metrics: The permeability predictions based on the FZI log using the ANN method yielded favorable results. The deviation coefficient (R^2) of 0.85 and the gradient (m) of 0.94 indicate a reasonably accurate prediction. Although a percentage error of 9.81% was observed, the overall performance of the methodology suggests its reliability in permeability estimation.

The porosity value significantly affects the permeability of reservoir rocks, and the FZI determined through the HFU method, enables the classification of permeability values into distinct rock types. The FZI log prediction, facilitated by the ANN method, provides valid permeability values for intervals lacking core data. The combination of these methods enhances our understanding of reservoir properties and facilitates more accurate permeability estimation in the KMJ Oil Field.

It is important to note that these conclusions are based on the specific methodologies and data used in this study. Further research and validation are recommended to assess the applicability of these findings in other reservoirs with different geological characteristics.

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DECLARATION OF COMPETING INTEREST

The authors have no conflict of interest to declare.

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