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Original Research

Advanced Permeability Estimation in Heterogeneous Carbonate Reservoirs: Integrating Machine Learning and Petrophysics in the Kangan Formation, Iran

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Abstract

Permeability estimation in carbonate reservoirs remains challenging due to heterogeneity. This study aims to present the most comprehensive flowchart possible for permeability estimation using well-logging data. This study evaluates five permeability estimation methods Artificial Neural Network (ANN), FZI-Stoneley (FZI-ST), improved FZI-ST, Timur-Coates, and SDR for the Kangan carbonate reservoir in Iran. The improved FZI-ST method achieved superior accuracy (R^2 = 0.88) by addressing reservoir heterogeneity through multi-resolution graph-based clustering (MRGC), outperforming traditional methods (Timur-Coates: R^2 = 0.36; SDR: R^2 = 0.27). ANN also showed strong performance (R^2 = 0.86). NMR-based methods underperformed due to T_2 cutoff instability in carbonates. Our workflow offers a cost-effective, log-based solution for complex reservoirs, with global applicability. It can be applied to other heterogeneous carbonate reservoirs, such as those in the Middle East or North America, where similar diagenetic processes (e.g., dolomitization, fracturing) are prevalent. This broad applicability makes the method a valuable tool for global reservoir characterization.

Keywords: Kangan reservoir, permeability, NMR and DSI, FZI-ST method, MRGC method, ANN model

1. Introduction

Production, development, and exploitation of hydrocarbon reservoirs properly require an accurate and true understanding of the basic properties of reservoirs such as permeability (Rezaei and Chehrazi, 2010; Javanbakht et al., 2020 ; Mateus et al., 2022). Permeability is the amount of empty and free space where the rock allows the fluid to flow and transfer (Sarhan and Selim, 2023). In the oil industry, permeability measurement is a matter of great importance for identifying the characteristics of reservoirs, finding the optimal location of development well drilling, recovery enhancement, constructing a static model, and estimating the production volume (Rezaei and

Chehrazi, 2010). Fluid mobility in a porous medium can be determined by permeability calculation and estimation playing a significant role in reservoir management and how to extract hydrocarbon fluids (Jamalian et al., 2018 ; Farhadmehr et al., 2024). As permeability is one of the most complex concepts in evaluating the petrophysical properties of rock and fluid, it is difficult to calculate and estimate accurately (Rafik and Kamel, 2017). Various methods including direct laboratory measurements (core analysis), well-testing (pressure tests), seismic data, empirical relationships, a complete set of typical and specific logs such as nuclear magnetic resonance (NMR) and dipole shear sonic imager (DSI), or a combination of these and artificial intelligence are presented to calculate and estimate permeability in hydrocarbon reservoirs (Rafik and Kamel, 2017; Soleimani et al., 2018). Traditional methods such as NMR face challenges in heterogeneous carbonate reservoirs due to unstable T_2 cutoff values, highlighting the need for more robust approaches like the improved FZI-ST method proposed in this study. Core analysis and well-testing are conventional methods of calculating permeability, but the direct laboratory measurement of permeability using core analysis in all field wells is a time-consuming and costly process and also impossible in some wells like horizontal ones (Rezaei and Chehrazi, 2010). Factors such as high costs make well-testing operations in all wells of a field impossible. The great importance of permeability estimation in the oil industry necessitates finding a cost-effective appropriate way to estimate it. Empirical relationships are also one of the methods for calculating the permeability of reservoirs, which are invalid because their reliability is limited to the location under study. Due to the low costs, comprehensiveness, and availability of logging operations, log data is available for nearly all wells of a field. Therefore, it appears reasonable to develop and apply well-logging-based methods for permeability calculation. Permeability can be predicted by discovering the complicated relationship between input data or well logs through artificial neural networks, intelligent algorithms, and artificial intelligence as solutions inspired by the human brain that is to learn. Artificial neural networks have a great ability in data prediction, classification, and matching. Following patterns of the human brain and mathematical relations, they are seeking to discover the complicated relationship between the input data so that they can correctly predict the output with a minor error (Mohaghegh et al., 1995; Mohaghegh et al., 1997; Elkatatny et al., 2018). Nuclear magnetic resonance (NMR) log and Stoneley waves obtained from DSI log have also proven to be useful, practical, and accurate tools for permeability estimation in hydrocarbon reservoirs (Coates et al., 1999; Al-Adani and Barati, 2003; Stefanelli et al., 2023;Tiab and Donaldson, 2024). Recent advances in machine learning, such as deep learning models (e.g., Elkatatny et al., 2021), have shown great potential for permeability prediction in heterogeneous reservoirs. These methods could be integrated with the improved FZI-ST method to further enhance accuracy.

The application process of Stoneley waves was presented by (Biot, 1956) based on the theory of propagation of waves in a porous medium containing fluid. (Williams et al., 1980) showed a good correlation between permeability and Stoneley wave attenuation in well-logging data derived from a field. (Cassell and Zemanek, 1980) used the variations of Stoneley waves at a specific frequency as an indicator for permeability determination. (Al-Adani and Barati, 2003) showed that the permeability index included the tortuosity factor of flow paths and the pore geometry of rock. It was therefore a direct measurement of the flow zone indicator (FZI) (Al-Adani and Barati, 2003).

(Vardian et al., 2016) used the neuro-fuzzy system to predict the porosity and permeability of Khuff formation in a fractured gas-condensate reservoir of southern Iran. (Amaefule et al., 1993) and (Rafik and Kamel, 2017) used petrophysical logs to predict permeability from MRGC analysis. (Elkatatny et al., 2017) showed that the results from data classification based on electro-facies were more accurate than other methods. (jamalian et al., 2018) predicted the permeability of a heterogeneous carbonate reservoir by developing an artificial neural network model using only 3 different logs (resistivity, density, and neutron). (Soleimani et al., 2018) estimated the permeability and facies of reservoir rock of the Bangestan Group in the Mansouri oil field using Stoneley waves obtained from the shear bipolar sonic log. Their results showed a high correlation between permeability predicted from the Stoneley wave and core permeability. (Jamalian et al., 2018) used an artificial neural network and support vector machine to estimate and calculate permeability from core and well logs in one of the Iranian oil fields.

Accurate permeability estimation is crucial for effective reservoir management and hydrocarbon production, especially in complex carbonate reservoirs like Kangan. Traditional methods such as core analysis and well-testing are often impractical due to their high costs and time-consuming nature. This study aims to address these challenges by evaluating and improving well-logging-based permeability estimation methods, offering a cost-effective and reliable alternative for reservoir characterization. Our results align with those of (Soleimani et al., 2018), who also found that Stoneley wave-based methods perform well in carbonate reservoirs. However, our improved FZI-ST method outperforms traditional approaches, demonstrating the value of incorporating MRGC clustering. The novelty of this study lies in the improved FZI-ST method, which incorporates multi-resolution graph-based clustering (MRGC) to address reservoir heterogeneity. This approach enhances permeability estimation accuracy by considering rock texture variations, offering a more reliable solution for complex carbonate reservoirs like Kangan. High-resolution logs (NMR, DSI) and core data were quality-checked for consistency (e.g., depth-matching, outlier removal).

2. Case study

The Kangan Formation (Late Permian–Early Triassic) is part of the Zagros Fold-Thrust Belt, influenced by the Neo-Tethyan rifting and subsequent compressional regimes. Reservoir heterogeneity stems from diagenetic processes (dolomitization, fracturing) and depositional facies variations.

The Kangan Formation, as part of the reservoir rocks of these fields, has long been of interest to geologists due to its reservoir capabilities and hydrocarbon production potential (Fig.1). The present study was conducted on Kangan carbonate formation as one of the main gas reservoirs in Iran (Motiei, 1993; Aghanabati, 2004). : Dominated by limestone, dolomitic limestone, and dolomite. The most important diagenesis processes affecting this formation include Key processes including dissolution (enhancing porosity) and anhydrite cementation (reducing permeability) (Jafarian et al., 2018). Data are from a complete set of cores, typical logs, and Stoneley wave from Well A (2873–2918 m depth), South Pars Gas Field taken. Porosity and permeability at depths of 2873-2918 m for well A in one of the Iranian gas fields were used.

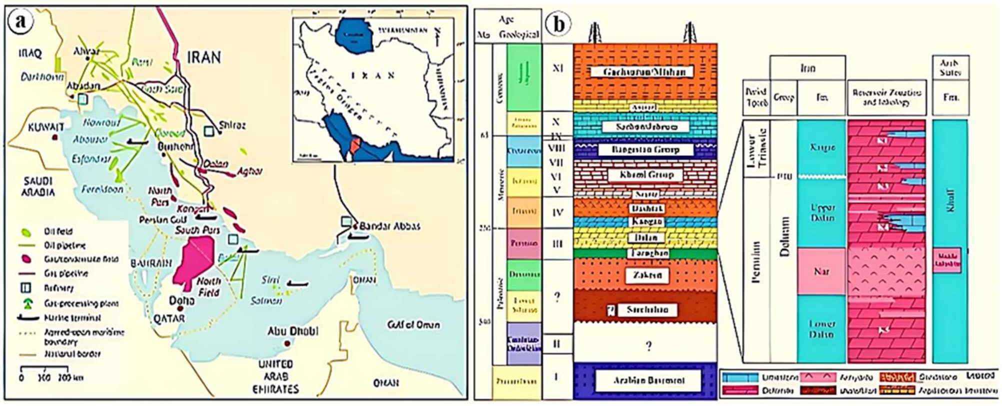

Figure 1. a) Geographical and geological location of the Persian Gulf and the South Pars gas field, along with the location of some major cities and major hydrocarbon fields (Kakemem et al., 2020). b) Stratigraphic column of the South Pars gas field including the Triassic Kangan Formation and Permo-Triassic reservoir stratigraphy including lithology and reservoir zones (Mehrabi et al., 2016).

3. Methodology

Data from Well A (2873–2918 m depth), in the Kangan Formation were used for this study. The dataset included well-log data (NPHI, RHOB, PHIE, DTCO) and core permeability measurements. Descriptive statistical analysis was performed to characterize the dataset, including the mean, standard deviation, and range for each variable. First information Depth alignment and normalization were collected then petrophysical data was interpreted. Software used Geolog1.0 (ANN) and Techlog 2022 (MRGC). Logs used were NPHI, RHOB, DTCO, PHIE, NMR T_2, Stoneley wave, and Permeability (Al-Adani and Barati, 2003). Permeability logs include ANN (70/30 train-validation split, 4 input neurons), FZI-ST (Equations 1–6 (cite Al-Adani and Barati, 2003), Improved FZI-ST (MRGC clustering (6 hydraulic units)), NMR Models (Timur-Coates (Coates et al., 1999), SDR (Schlumberger, 2015)). MRGC was selected for its ability to handle complex, non-linear relationships without requiring predefined cluster numbers, making it more adaptable to heterogeneous reservoirs compared to K-means, MRGC does not require predefining the number of clusters, making it more adaptable to varying reservoir conditions.

In the present study, attempts are made to present a comprehensive bank of permeability estimation methods based on well logs for the Kangan Formation (one of the gas fields in southern Iran). In this study, permeability was calculated by 5 methods. In the first stage, permeability obtained from the Neutron porosity hydrogen index log (NPHI), SONIC Compressional Delta Time log (DTCO), effective porosity log (PHIE), and density log (RHOB) were estimated using Artificial Neural Network (ANN). In the second stage, due to the critical role of the Stoneley wave in permeability estimation and the fact that this wave was accessible in this well, permeability estimation was carried out using the Stoneley wave. In the third stage, to increase the accuracy of the calculations and provide a new method to estimate the permeability in carbonate gas reservoirs (due to the poor performance of the Stoneley wave in the previous stage) attempts were made to improve the ST-FZI method by introducing the characteristics of rock texture in the Rock Typing permeability estimation calculations to overcome reservoir heterogeneity.

At first, the flow units were specified using the MRGC method. In this part, to increase the accuracy of the calculations, NDS artificial log was created and introduced to the model as one of the model inputs along with CGR, PHIE, and DTCO logs. In the next step, the ST- FZI method was separately applied to each flow unit, and finally, the calculated permeability levels were merged to obtain an accurate permeability log in well A. The proposed method was able to improve permeability calculation accuracy by 0.54%. In the fourth stage, (as the NMR log was also available in this well) attempts were made to estimate permeability using SDR concerning the NMR log to address all the conventional and special methods relying on the well-logging method (Barakat et al., 2017) In the fifth step, permeability was computed using the Timur-Coates model with the help of the NMR logs.

An uncertainty analysis was performed to quantify the variability in permeability estimates. The results show a 95% confidence interval of ±0.1 MD, indicating a high level of precision in the improved FZI-ST method. Cross-validation was used to ensure the robustness of the ANN model. Abdullah et al. (2021) The dataset was split into training (70%) and validation (30%) sets. The model's performance was evaluated using R^2 and RMSE, demonstrating high accuracy and reliability. While this study focuses on data from a single well, future research should include data from multiple wells across different fields to validate the robustness of the improved FZI-ST method. This would help generalize the findings and ensure the method's applicability to a wider range of reservoir conditions.

4. Results

4.1. Permeability estimation using artificial neural network (ANN)

The purpose of the first stage is to use an artificial neural network model for estimating the permeability from well-logging data (as input data) and data from core analysis (as output data). This section seeks to construct a model for permeability estimation from logs of the well under study using the ANN part embedded in Geolog software. Therefore, after training the network and validating it by the existing permeability of core analysis, a model is obtained from well-logging and core data, which can be used only with several well logs and no need for coring in all wells to estimate the permeability of formations at locations where core permeability is unavailable. To assess the permeability using an artificial neural network model, 70 and 30% of the data were applied to the network as training and verification data, respectively. NPHI, RHOB, PHIE, and DTCO logs were selected as the best input variables to construct the neural network model in a stepwise analysis. In the next step, the input and output data were normalized between 0 and 1. Then, the selected inputs were controlled by cross-plots for the last time to eliminate unrelated inputs. Finally, the optimal parameters of the neural model (the number of neurons and iterations) were specified by a trial-and-error approach (Tahmasebi and Hezarkhani, 2012). Fig.2 indicates the correlation coefficient between ANN estimated and core permeability ($R^2 = 0.86$). Fig.4. shows a comparison between ANN estimated (red continuous curve) and core (black pointed curve) permeability at the second track from the right.

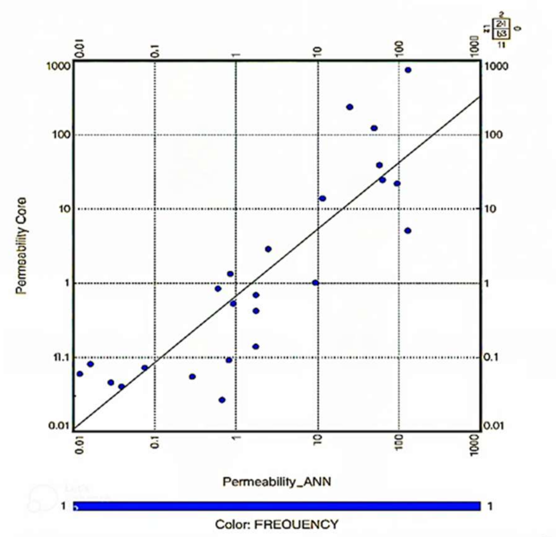

Figure 2. The Correlation coefficient of ANN estimated permeability.

4.2. Permeability estimation from shear Dipole sonic imager (DSI) using FZI-ST

Stoneley wave includes extraordinary information about hydrocarbon reservoirs. It is used to estimate the permeability from the DSI log, which saves both time and cost compared to other methods. A continuous curve of permeability variations along the entire length of the well can be created by recording the inherent property of the Stoneley wave and quantifying the relationship between its petrophysical parameters and permeability (Al-Adani and Barati, 2003). Estimating and calculating permeability through a continuous process and under reservoir conditions is a unique feature of Stoneley Wave (Wu and Yin, 2010). Today, sonic well-logging is both less expensive and faster than other permeability measurement techniques. Stoneley wave has scattering properties and it propagates at the between fluid-formation interface (Ye and Rabiller, 2000). Stoneley wave attenuation and slowness are a function of frequency so an increase in permeability increases the scattering and therefore attenuation and slowness of Stoneley wave.

Factors affecting Stoneley wave slowness are as follows:

Mud filtrate often produces a fixed shift along the well, taking into account its thickness and uniformity. Constituent material of the particles is one of the most essential effective factors so a change from pure calcite to dolomite or a siliceous rock in the lithology causes a change in slowness (lithology). Stoneley wave is also affected by fluid modulus. That is, a change from liquid to gas in the fluid causes an increase in the predicted permeability by about 20 times (fluid) (Al-Adani and Barati, 2003).

A set of data necessary for estimating the permeability using the FZI-Stoneley method is as follows.

Shear wave slowness, Stoneley wave slowness (DTST), Stoneley wave slowness in non-permeable zone (DTSTE), Core permeability, Effective porosity resulting from petrophysical evaluation, Volume of each mineral, Density and index match factor for all constituent minerals of lithology.

Given that the porous space affects the Stoneley wave, the permeability index can be calculated from the ratio of measured Stoneley slowness to model one that is Stoneley slowness in the non-permeable zone (Winkler and Johnson, 1989):

$$KIST = \frac{DTST}{DTSTE} \tag{1}$$

Where, $KIST$, $DTST$, and $DTSTE$ are Stoneley permeability index, Stoneley wave slowness in the whole formation, and Stoneley wave slowness in non-permeable or elastic zone, respectively.

The permeability index of the formation can be calculated from the relation above. It should be noted that the index is not a measure of mobility and permeability and in fact it indicates the flow of fluid around the well. Since the fluid flow is a function of the size, shape and distribution of pore throats in the formation, the permeability index can be considered as an indicator of tortuosity.

According to the relationship between tortuosity and flow zone indicator, finally, the Stoneley flow zone indicator is proportioned to FZI (Wu and Yin, 2010):

$$FZI \propto KIST \tag{2}$$

Since $KIST$ tends to be one in the non-permeable zone, FZI must tend to zero, and vice versa. When permeability becomes infinity, both the permeability index and FZI must be infinite, therefore the proportion above is as follows (Wu and Yin, 2010):

$$FZI \propto (KIST - 1) \tag{3}$$

For converting proportion to equality, the index match factor is defined as follows:

$$FZI = IMF(KIST - 1) \tag{4}$$

The factor is the only correlation between the Stoneley permeability index, FZI, and true permeability for calibrating and it is determined by the equation below based on the volume of constituent minerals of the formation under study(Nabeed and Barati, 2003).

$$IMF = \sum IMF_i V_i \tag{5}$$

where, IMF and V_i are the index match factor and volume of each mineral, respectively, and i represents each mineral. After calculating the values of FZI, Stoneley permeability is finally obtained from the relation below(Winkler and Johnson, 1989)

$$K = 1014FZI^2 \left[\frac{\varphi^3}{(1-\varphi)^2}\right] \tag{6}$$

where, K, φ, and FZI are Stoneley permeability, effective porosity, and flow zone indicator, respectively (Al-Adani and Barati, 2003).

There are two methods for calculating Stoneley wave slowness in the non-permeable zone:

1- Calculating the average of Stoneley wave slowness in non-permeable zones (it was 185 in this study).

2- Using a cross-plot showing Stoneley wave versus effective porosity (in this study, it was compared to the first method, and Stoneley slowness in the non-permeable zone was determined to be 187) (Fig. 3).

After calculating the $Stoneley$ permeability index from Equation (1), the index match factor or IMF is determined by equations (4), (5), and (6) for constituent minerals (dolomite: 31 and calcite: 3.58) of the Kangan formation. Values of the flow zone indicator (FZI) are calculated by placing core permeabilities in the relation. Then, the total value of the index match factor is calculated by the factor relation at different depths to make the best match between the permeability and permeability index.

Fig. 4. shows a comparison between Stoneley wave estimated permeability (red continuous curve) and core (black pointed curve) permeability at the first track from right, and Fig. 5. indicates the correlation coefficient between Stoneley wave estimated permeability and core permeability (R^2 = 0.34).

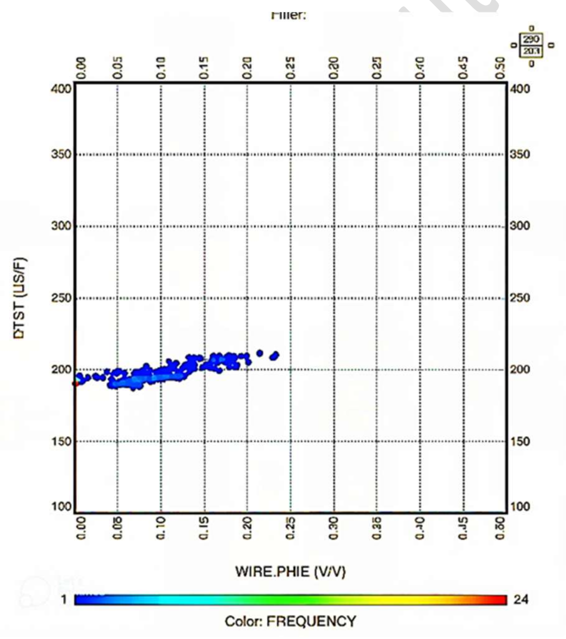

Figure 3. Cross-plot of Stoneley wave slowness versus effective porosity in Well A. The red line represents the regression fit, showing a strong correlation (R^2 = 0.85) between the two variables

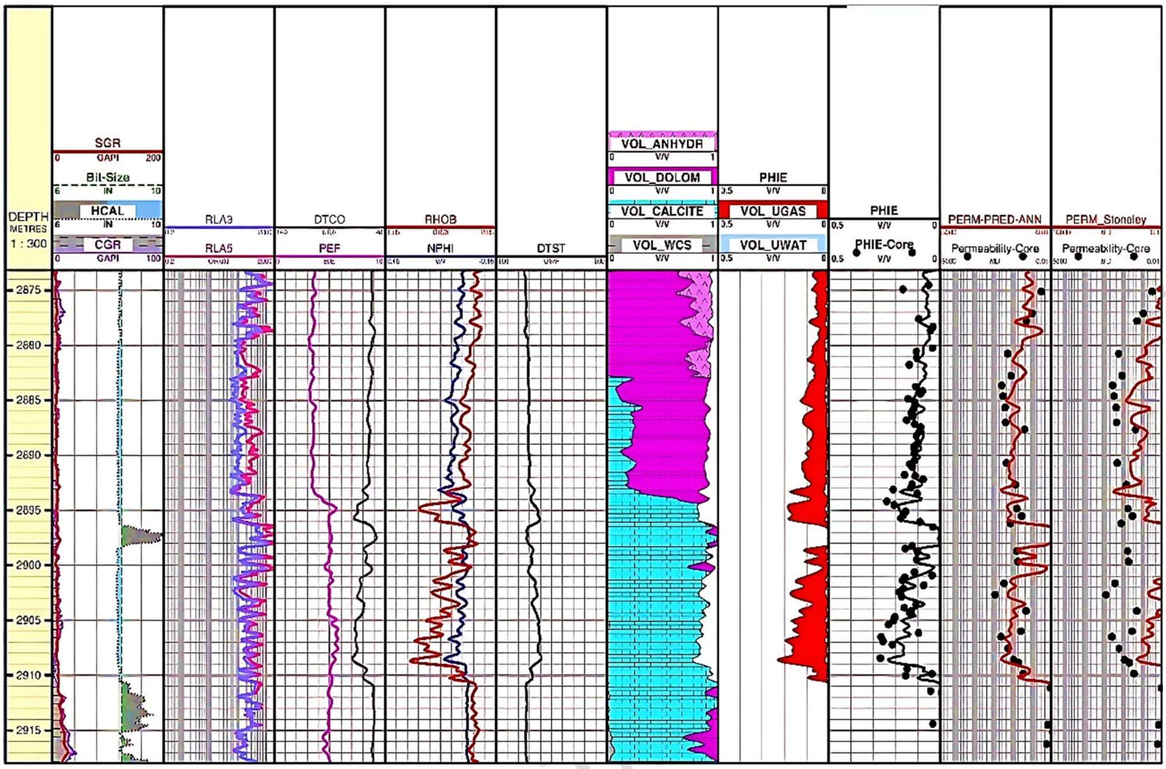

Figure 4. Stoneley wave estimated permeability at the first track from right vs. core permeability in well A.

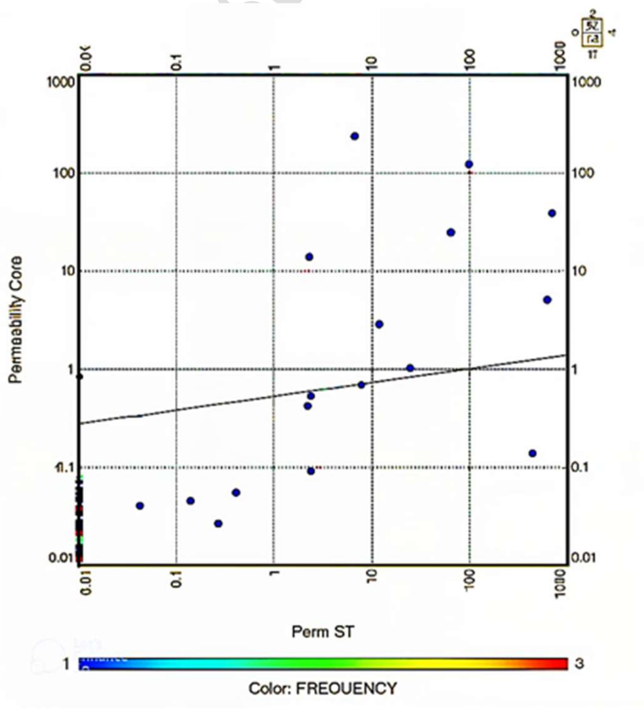

Figure 5. correlation coefficient of FZI-ST estimated permeability.

4.3. Multi-resolution graph-based clustering (MRGC) to improve FZI-ST calculated permeability

In the previous stage, permeability was calculated through the FZI-ST method. In this stage, to overcome the reservoir heterogeneity, flow units were identified and the FZI-ST method was separately implemented for each of them, and finally, an accurate permeability in well A was estimated by merging and combining the calculated permeability. Given that the purpose of this stage was to improve FZI-ST estimated permeability, the properties of rock texture were applied in the calculations to calculate the permeability more precisely. Since the porosities may be connected in an interval, but a few meters lower they are non-connected, and consequently permeability is low, in this stage, sections of the reservoir with the same lithology in terms of texture, certainly affecting the permeability are clustered in terms of their specific characteristics. Because the Kangan reservoir in the studied well is reservoir complex in terms of lithology and diagenesis, only one Index Match Factor should not be determined for each mineral. Because the mineral texture (meaning the texture of the grain size, grain shape, sorting, and how the particles are placed next to each other) may change at different depths. Therefore, in this study, electrical facies were used to classify the types of rocks according to the flow properties based on hydraulic flow units to identify high permeability intervals and to overcome the problem of heterogeneity and effective factors of diagenesis in permeability. For this purpose, to apply the rock texture more accurately in the calculations of artificial logs, Neutron Density Separation (NDS) was calculated from the difference between neutron logs and density (Ohen et al., 1996). Then, using CGR, NDS, DTCO, and PHIE logs, the number of electrical facies was calculated by graph-based multivariate clustering (MRGC) method (Perez et al., 2005), and then for each group Separately permeability was estimated and finally the calculated permeability for each group was merged and the permeability was calculated very accurately in the reservoir. Finally, the Kangan carbonate reservoir was divided into 6 groups, which are shown in Fig. 6. (sixth track from right). After the groups were identified, the permeability of the FZI-ST relationships described in detail in the previous step was calculated separately for each group. That is, first KIST was calculated, then FZI was obtained using kernel data, and finally IMF was calculated separately for each group. Table 1. shows the characteristics and values of the compliance index for the minerals that make up the Kangan Formation.

For groups 1 and 4, the Index Match Factor was not calculated because in group 4 it is a non-reservoir zone and in group 1 lithology has some anhydrite. Finally, for the other 4 groups, the Permeability was calculated separately by the FZI-ST method and then merged and a very accurate log of permeability was obtained in the study well. Fig. 7. shows the permeability coefficient improved by the Stoneley method with the permeability obtained from the core analysis (R^2 = 0.88).

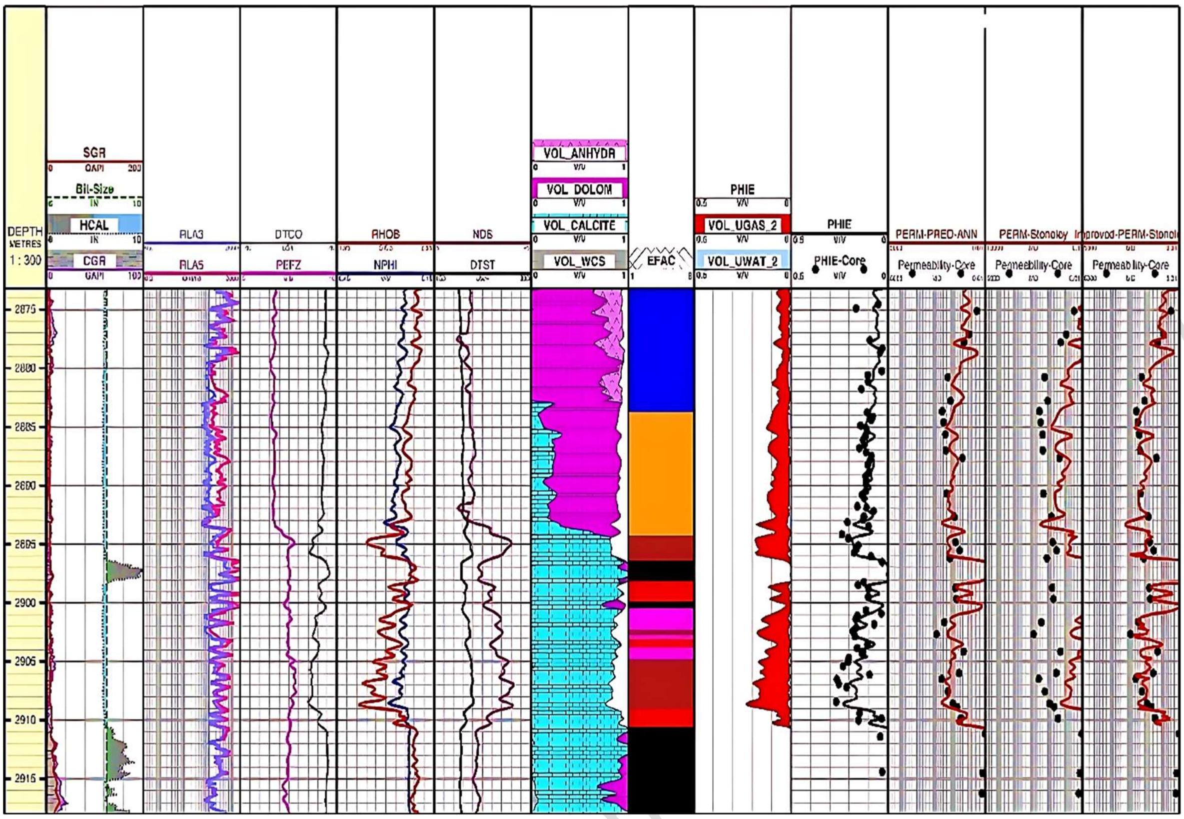

Figure 6. PermeabilityPermeability calculated from the improved FZI-ST method at the first track from right with red color, permeability calculated from the FZI-ST method at the second track from right in red, Permeability calculated from the ANN method at the third track from the side Right with red versus core permeability in well A.

Table 1. Determination of index match factor for constituent minerals of formation in each group

Color (class) and EFACT	IMF For Calcite	IMF For Dolomite
Blue (EFACT1)	…..	…..
Orange (EFACT2)	16	3/2
Brown (EFACT3)	68	2/7
Black (EFACT4)	…..	…..
Red (EFACT5)	30	9/6
Magenta (Efact6)	32	4/5

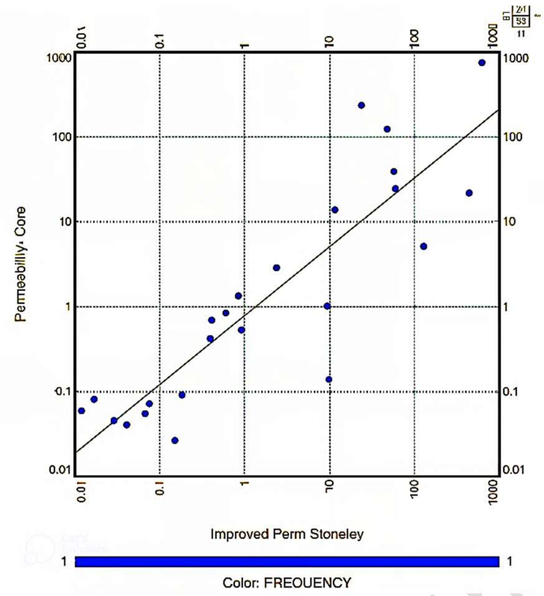

Figure 7. Improved permeability correlation coefficient of FZI-ST versus core permeability.

As can be seen from Fig. 6. The similarity between (the first track of right) obtained from the improved FZI-ST method and core permeability (fourth track of right), is very high which is proof of the high accuracy of the method proposed and introduced in this study. Therefore, the method has a very high accuracy in estimating permeability in carbonate gas reservoirs (Anifowose et al. 2013, Sarhan and Salim, 2023).

4.4 Permeability estimation from nuclear magnetic resonance imaging (NMR) log using Timur-Coates

At this stage, the study of the Timur-Coates equation (K_{TIMUR}) has been used to estimate permeability and compare it with the improved permeability of FZI-ST and other methods, the relationship of which is as follows (Coates et al., 1999). In this method, the useful fluid volume index or BVI, which is equal $BVI = \emptyset S_{wirr}$, and the free fluid index, which is equal $FFI = \emptyset.(1 - S_{wirr})$, are used. In this method, the permeability is obtained from equation (7) (Coates et al.,1999):

$$k_{NMR} = a.10^4.(\emptyset_{PMR})^4.\left(\frac{FFI}{BVI}\right)^2 \quad (7)$$

Where the constant expression a is equal to 1 $millidarcy$. Fig. 8. shows the permeability coefficient estimated by the Timur-Coates method versus the core permeability (R^2= 0.36).

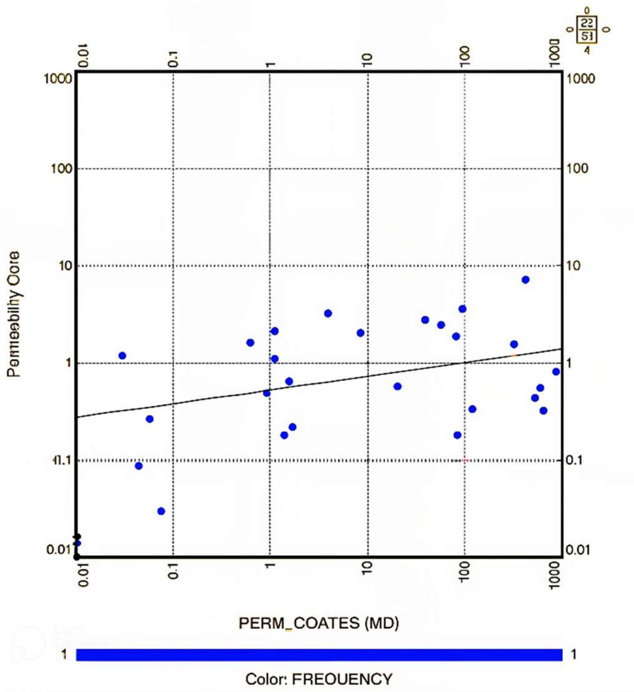

Figure 8. The correlation coefficient between $Timur$-Coates estimated permeability and core permeability.

4.5 Permeability estimation from magnetic resonance imaging (NMR) log using SDR

Another method that is often used today to estimate permeability is the SDR method of NMR logs, which has been introduced by Schlumberger's research center. This equation is obtained from the mean logarithm of T_2 relaxation time with porosity and is as follows(Barakat et al., 2017):

$$k_{PMR} = C.(\emptyset_{PMR})^4.(T_{2log})^2 \quad (8)$$

Where c is a constant coefficient and its value is 4 for sandstones and 0.1 $md/(ms)^2$ for carbonates. Both the Timur-Coates and SDR equations are in most cases similar and highly dependent on porosity Fig. 9. shows the permeability correlation coefficient estimated by the SDR method versus the core permeability R^2= 0.27.

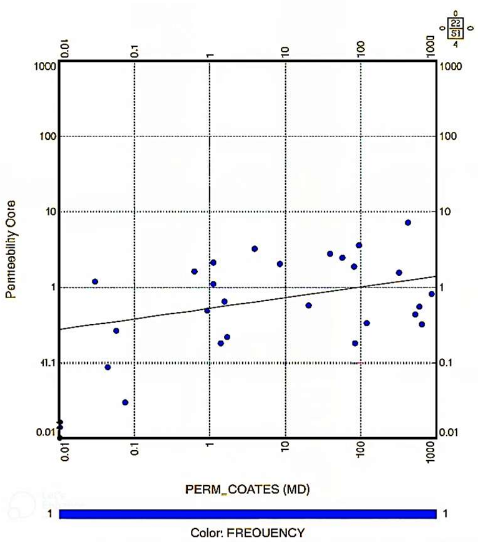

Figure 9. The correlation coefficient between *SDR* estimated permeability and core permeability.

Fig. 10 shows the permeability curve estimated by the Timur-Coates method with core permeability analysis at the first track from right and the permeability curve calculated by the SDR method shows the NMR log versus core permeability at the second track from right.

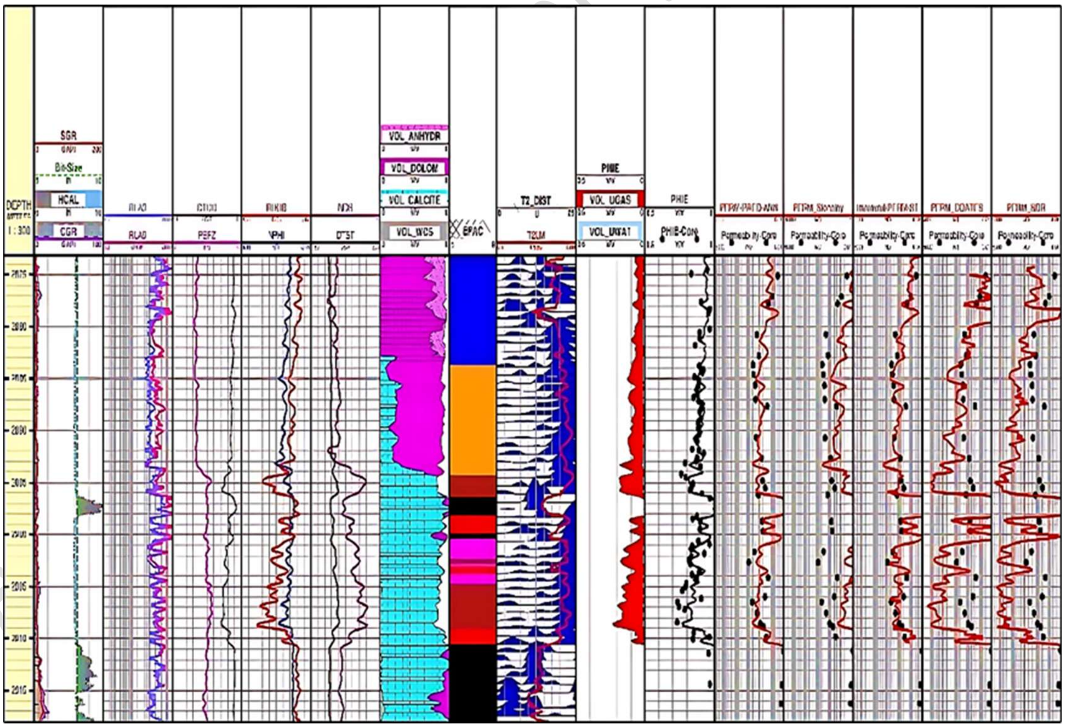

Figure 10. permeability estimation by *Timur*-Coates methods (first track red curve from right), SDR method (second track red curve from right), improved FZI-ST method (third track red curve from right), FZI-ST (fourth track red curve from right), ANN method (fifth track red curve from right) versus core permeability in well A.

5. Discussion

In this study, one of the most complete and accurate flowcharts of various permeability estimation methods has been performed, which is based on all typical and specific well logs and with the help of intelligent algorithms and artificial intelligence. Which eventually led to the introduction of a new accurate method to improve the calculated permeability of the Stoneley wave. The methods used in this study to estimate permeability are: artificial neural network or ANN, using FZI-ST calibration from DSI log, Timur-Coates method from NMR log, and SDR method from NMR log and most importantly presenting a new method to improve the permeability calculated by the FZI-ST calibration method. Fig.10. shows the methods used in this study to estimate the permeability, Timor-Coates method (first crack red curve from right), SDR method (second track red curve from right), improved FZI-ST method (third track red curve from right), FZI-ST method (fourth track red curve from right), ANN method (fifth track red curve from right) and groups of the MRGC method (ninth track from right). What is clear is that the accuracy of NMR in estimating permeability in both Timur-Coates and SDR methods in carbonate reservoirs is very low. In carbonate reservoirs, instability at the T_2 cutoff threshold causes an error in the correct detection of free fluid volume (BVM) and band volume (BVI), which ultimately leads to incorrect and incorrect permeability estimates. In other words, the standard value for carbonate rocks is 92 ms, but the study shows that due to the presence of multiple pores and complex pore systems in rocks and carbonate reservoirs, this value can change in the range of 700 ms to 90 ms. Also, the presence of separate secondary porosities, including; moldic and vuggy in carbonate reservoirs causes this phenomenon to affect measurements such as NMR, which are static, but dynamic measurements such as core coronation or even Stoneley wave cannot be affected. This phenomenon. The artificial neural network method had a good performance in the Kangan carbonate reservoir of the studied well. Stoneley wave in the carbonate reservoir studied in the first series did not provide a good estimate of permeability, the main factor of which can be the existence of very complex lithology in the study field, so in this section to overcome the heterogeneity of the reservoir to classify rocks Regarding the flow properties based on hydraulic flow units, electrical facies were used to identify high permeability intervals and to overcome the heterogeneity problem and the factors influencing in permeability. First, the number of electrical facies was calculated by graph-based multivariate clustering (MRGC) method, and then for each of those groups, based on their specific properties, permeability was calculated by FZI-ST method, and finally permeability was combined and a very, very accurate log of permeability was obtained in this study reservoir. The method introduced in this study was the most accurate and best method for calculating permeability in the Kangan carbonate reservoir in the study field among other methods.

The improved FZI-ST method demonstrated superior accuracy ($R^2 = 0.88$) compared to traditional methods, aligning with findings from (Soleimani et al., 2018), who also highlighted the effectiveness of Stoneley waves in carbonate reservoirs. However, the lower accuracy of NMR-based methods (Timur-Coates and SDR) is consistent with observations by (Sarhan, 2021), who noted the challenges of NMR in heterogeneous carbonate reservoirs.

On the other hand, this study has several limitations. First, the improved FZI-ST method requires accurate recorded data, which may not always be available. Second, the accuracy of NMR-based methods is limited by the instability of T2 cutoff values in carbonate reservoirs. Future research should explore Integrate seismic attributes (Reda et al., 2024) to further increase the accuracy of permeability estimation. The improved FZI-ST method demonstrated superior accuracy (R^2 = 0.88) compared to traditional methods like Timur-Coates (R^2 = 0.36) and SDR (R^2 = 0.27). Cross-validation results confirmed the robustness of the ANN model, with consistent performance across the training and validation datasets and Test in clastic reservoirs (Azab et al., 2024).

6. Conclusions

Due to the very high importance of permeability parameter in hydrocarbon reservoirs, this study utilizes all available methods with a heavy reliance on intelligent ones for permeability estimation using a variety of petrophysical logs such as a complete set of typical logs, bipolar shear sonic log, and magnetic resonance log to provide a comprehensive description of well-logging-based methods determining to their advantages, disadvantages, accuracy, and performance. Finally, the best method for permeability calculation in carbonate gas reservoirs is introduced by presenting a new one. In the beginning stage, permeability was estimated using an artificial neural network model. In the second stage, permeability was calculated from the Stoneley log whose performance was unsatisfactory. In the next stage, FZI-Stoneley method multi-resolution graph-based clustering (MRGC) was used for overcoming reservoir heterogeneity and applying lithology type in the calculations in the third stage, to improve the permeability calculated by the FZI-ST method, the studied reservoir was grouped for a more accurate estimate. In the fourth and fifth stages, the permeability of the Timur-Coates method and SDR method of NMR log were evaluated. The correlation coefficient between calculated permeability and core permeability in artificial neural network methods, FZI-ST, improved FZI-ST, Timur-Coates, and SDR were 0.86, 0.34, 0.88, 0.36, and 0.27%, respectively. It was observed that the accuracy of the NMR graph in permeability estimation in both Timur-Coates and SDR methods in carbonate reservoirs is very low. in carbonate reservoirs, instability at the T2 cutoff threshold causes an error in the correct detection of bound (BVI) and free-fluid (BVM) volumes, which ultimately leads to incorrect permeability estimates. Also, the presence of separate secondary porosities, including; moldic and vuggy porosity in carbonate reservoirs causes this phenomenon to affect measurements such as NMR, which are static. In general, in this study, the improved ST-FZI method for calculating permeability in the Kangan carbonate reservoir is introduced as the most accurate and best method for calculating permeability. The improved FZI-ST method offers a cost-effective and reliable solution for permeability estimation in heterogeneous carbonate reservoirs. Its ability to accurately classify hydraulic flow units makes it a valuable tool for reservoir management and well placement. A sensitivity analysis was conducted to assess the impact of key input parameters (e.g., porosity, Stoneley wave slowness) on the permeability estimates. The results indicate that the method is most sensitive to changes in porosity, with a 10% variation in porosity leading to a 15% change in permeability estimates. While the improved FZI-ST method shows great promise, its practical implementation faces challenges such as the need for high-quality well-log data and computational resources for MRGC clustering. Future work should focus on optimizing the algorithm for faster processing and exploring its integration with real-time logging tools. Future research should explore the integration of seismic data and deep learning models to further enhance the accuracy of permeability estimation. Additionally, applying this method to other reservoir types, such as clastic or fractured reservoirs, would help validate its broader applicability.

7. References

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