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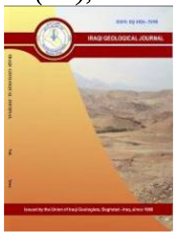

Artificial Neural Network Application to Permeability Prediction from Nuclear Magnetic Resonance Log

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Abstract

Reservoir permeability plays a crucial role in characterizing reservoirs and predicting the present and future production of hydrocarbon reservoirs. Data logging is a good tool for assessing the entire oil well section's continuous permeability curve. Nuclear magnetic resonance logging measurements are minimally influenced by lithology and offer significant benefits in interpreting permeability. The Schlumberger-Doll-Research model utilizes nuclear magnetic resonance logging, which accurately estimates permeability values. The approach of this investigation is to apply artificial neural networks and core data to predict permeability in wells without a nuclear magnetic resonance log. The Schlumberger-Doll-Research permeability is used to train the model, where the model prediction result is validated with core permeability. Seven oil well logs were used as input parameters, and the model was constructed with Techlog software. The predicted permeability with the model compared with Schlumberger-Doll-Research permeability as a cross plot, which results in the correlation coefficient of 94%, while the predicted permeability validated with the core permeability of the well, which obtains good agreement where R^2 equals 80%. The model was utilized to forecast permeability in a well that did not have a nuclear magnetic resonance log, and the predicted permeability was cross-plotted against core permeability as a validation step, with a correlation coefficient of 77%. As a result, the low percentage of matching was due to data limitations, which demonstrated that as the amount of data used to train the model increased, so did the precision.

Keywords: NMR Permeability; Permeability prediction; Artificial neural networks

1. Introduction

Permeability is a fundamental petrophysical characteristic of rocks that indicates the rock's capacity to allow the fluids to flow. It is the starting point for constructing any model to predict oil-well productivity (Mahdi and Farman, 2023a). Carbonate reservoirs exhibit complicated characteristics characterized by significant burial depth, diversified and complex pore space, and significant heterogeneity. The primary approaches for assessing reservoir parameters can be classified into two categories: direct measurement and indirect interpretation. The direct measuring approach is precise, requiring additional human resources and resources for material. Additionally, the quantity of rock samples acquired is often limited and influenced by many circumstances, which restricts the proper calculation of reservoir parameters. Obtaining well-logging data is typically more convenient and can

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be utilized to compute reservoir parameters for the entire oil well section. For 30 years, service organizations started commercializing a logging device called the nuclear magnetic resonance (NMR), which checks the entrained fluids' magnetic characteristics near the wellbore (Elsayed et al., 2021; Mitchell et al., 2014). The NMR logging can reveal pore space, permeability, and fluid characteristics without affecting the rock texture.

The permeability interpreted by NMR logging integrates two values that represent the pore size and shape together. It eliminates the drawbacks of the conventional techniques that deal only with porosity and excludes the role of pores size and shape effects on permeability. Based on NMR technology, the Schlumberger-Doll-Research (SDR) model was proposed by Kenyon et al. (1988), which is a standard and familiar method used to calculate permeability.

In a study conducted by Xiao (2007), it was discovered that the permeability of typical reservoirs with a straightforward pore structure, as calculated by the present model, closely matched the results of core experiments. Permeability models are extensively done utilizing characteristics collected by NMR measurements, such as porosity and relaxation durations. However, the traditional models could fail to estimate core permeability correctly, mainly when applied to heterogonous rocks (Fordham et al., 1999; Godefroy et al., 2001; Westphal et al., 2005). Thus, a more robust strategy has to be suggested for better usage of the NMR data to increase permeability estimations.

The pioneering study by Seevers (1966) and the commentary effort by Kenyon et al. (1988) confirmed that rock permeability can be calculated using the logarithmic average of the T2 relaxation time distribution assuming a fast diffusion regime where the protons are assumed to diffuse through the entire pore. These models are designated commercially as SDR, which is supplied by equation1 below:

$$KSDR=C*(T2LM)\ m*(ØNMR)n \tag{1}$$

T2LM represents the logarithmic average value of the T2 relaxation time distribution. To reflect the reservoir's lithology, the factors C, m, and n should be calibrated using core plug records. These coefficients can be obtained using multiple regression.

Salazar and Romero (2001) employed traditional logs as input and NMR data as output to evaluate porosity and permeability using artificial neural networks (ANN). Their approach accurately predicted both porosity and permeability compared to the laboratory data. By using both T2 and open-hole log data as input, Hamada and Elshafei (2009) also utilized the ANN algorithm in a gas and oil reservoir to forecast permeability and porosity. Consequently, the suggested model demonstrated an R2 value of 0.97 and high agreement with core measurements for both porosity and permeability. (Huang et al., 2020) used logging data to build a permeability forecasting algorithm based on a back-propagation artificial neural network (BP-ANN), and they demonstrated the effectiveness of BP-ANNs as a way to generate multi-variate, nonlinear equations for challenging issues. To increase the accuracy of permeability prediction in low-porosity and low-permeability reservoirs based on NMR data, (ZHU et al. (2017) suggested a permeability prediction approach merging Deep Belief Network (DBN) and Kernel Extreme Learning Machine (KELM) algorithm. Additionally, Zhou et al. (2012) used an ANN and genetic algorithm to estimate permeability based on NMR results.

This study presents building an ANN model to predict permeability in the reservoir using permeability calculated from NMR log with the KSDR method for training the model while using conventional well logs including (Bulk density, Gamma Ray, Photoelectric factor, Shear slowness, Thermal neutron porosity, Deep and shallow resistivity) as input parameters for the network, finally the validation of the predicted permeability accomplished with core permeability.

2. Geological Setting

Halfaya oil field is located in the Missan province, southeast of Amara city, about 35 km Fig. 1. The field is 12 km wide and 38 km long, NW-SE direction of anticline structure and belongs to the Tigris sub-tectonic formation of the Mesopotamian basin. Regression and Transcreation of the sea level resulted from the tec tonics of the Late Cretaceous. They represent many deposition cycles in Sa′di-B3 and a diversity of inner ramp microfacies. While middle ramp facies develop in Sa′di-B2 formations, outer ramp facies develop in the uppermost Sa′di-B1 and Sa′di-A formations to represent a transition from ramp to basinal conditions. In 1976, Sa′di reservoir was discovered within the Halfaya oil field in Iraq. The Late Cretaceous Sa′di Formation overlies the Tanuma Formation and the Hartha Formation. The average thickness of the Sa′di Formation is 120m to 130m (Hashim and Farman, 2023).

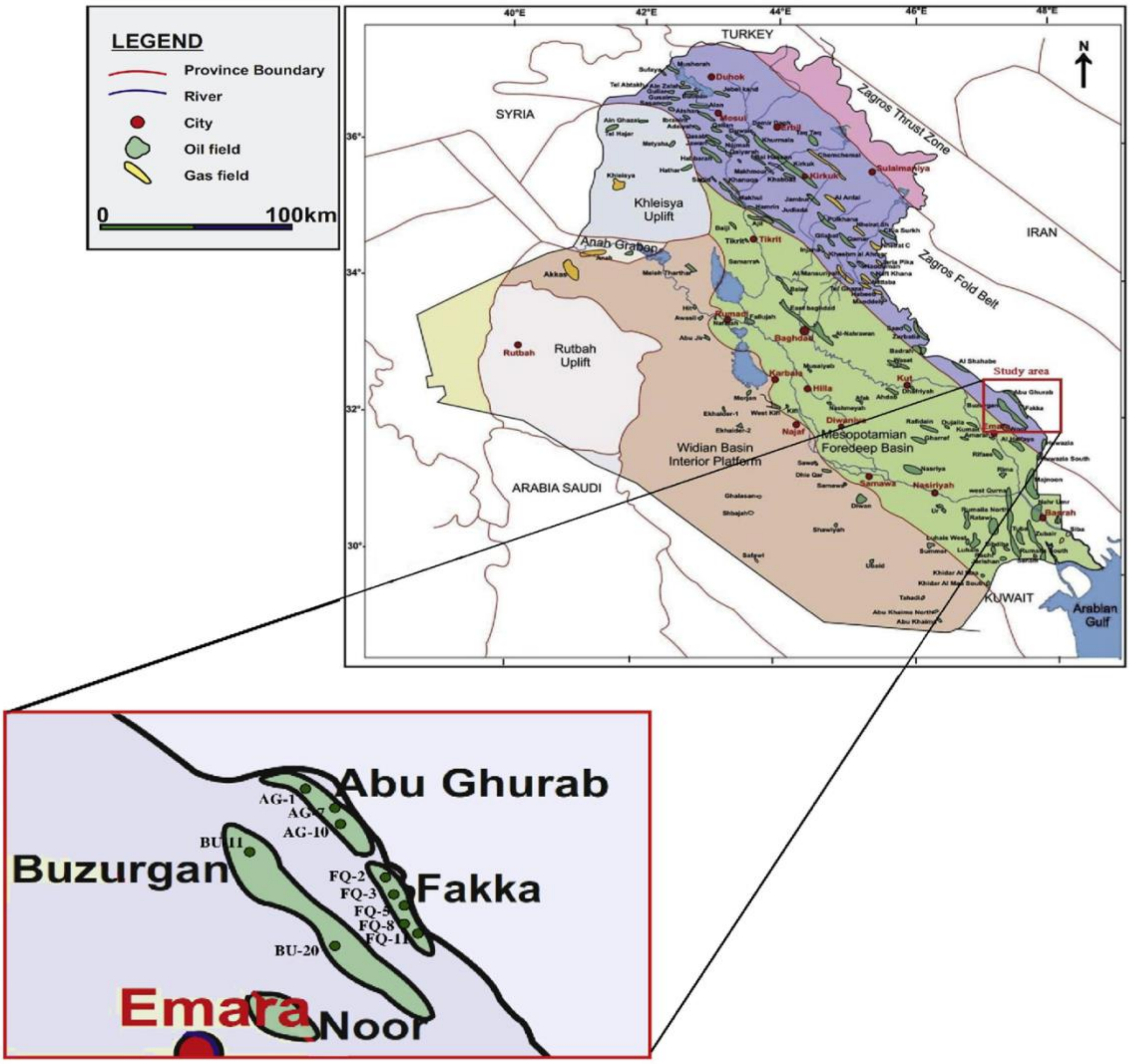

Fig. 1. Halfaya oil field location (Hakimi and Najaf, 2016)

3. Materials and Methods

3.1. NMR Permeability Calculation

Permeability is a crucial characteristic of reservoirs that directly impacts oil production (Awadh et al., 2014). The permeability of a reservoir is regulated by the decrease in pressure that occurs when fluids flow through pore throats (Mahdi and Farman, 2023b). Hence, the pore throat's magnitude, a characteristic that can be inferred from the NMR examination of pore body dimensions, governs permeability. Thus, reliable NMR measurements can be utilized to create an uninterrupted permeability log. The determination of permeability using NMR relies on establishing a clear relationship between the size of the pore throat and the pore body. The permeability can be determined by utilizing the relationship between NMR relaxation time and permeability. The interrelationship of SDRs is shown in Equation 2:

$$K_{SDR}=7.24*(T_{2LM})^{0.63}*(\text{Ø}_{NMR})^{2.57} \quad (2)$$

when T2LM is the T2 relaxation time distribution's logarithmic average value. However. The porosity component (Ø_{NMR}) modifies the size of pores from the pore throat up to the pore body.

3.2. Artificial Neural Networks (ANN)

(ANNs) Artificial neural networks are computational algorithms that, in most cases, are not task-specifically designed; instead, they are trained to forecast the output of a collection of previously identified inputs given a known desired variable or variables (Jreou and Farman, 2024). The model was developed to predict permeability in a carbonate reservoir. The model was tested within the NMR permeability and validated within the core permeability. Techlog software (K-mod module) is used in prediction. The software runs at different numbers of input parameters, neurons, realizations and hidden layers for the prediction model optimization by improving the "R" and error minimization.

Using inputs of seven oil well logs including Bulk density, Gamma Ray, Photoelectric factor, Shear slowness, Thermal neutron porosity, and deep and shallow resistivity. The optimization was done with one hidden layer, 13 neurons, and 70 realizations to achieve a good result in the dataset. The ANN model topology is shown in Fig 2.

4. Results

4.1. NMR Permeability Calculation

The T2 logarithmic mean value (T2LM) is the predominant parameter used to represent the T2 relaxation distribution. This quantity is the primary determinant for computing NMR-derived permeability using the SDR model. The parameter is significant since it considers the various identified pore sizes, even if its contribution to the overall pore volume is minimal.

The KSDR is validated with the core permeability, as shown in Fig. 3, which illustrates that calculated permeability matches core permeability. As seen in Fig. 4, the correlation coefficient of the cross-plot core and KSDR permeability is 0.82.

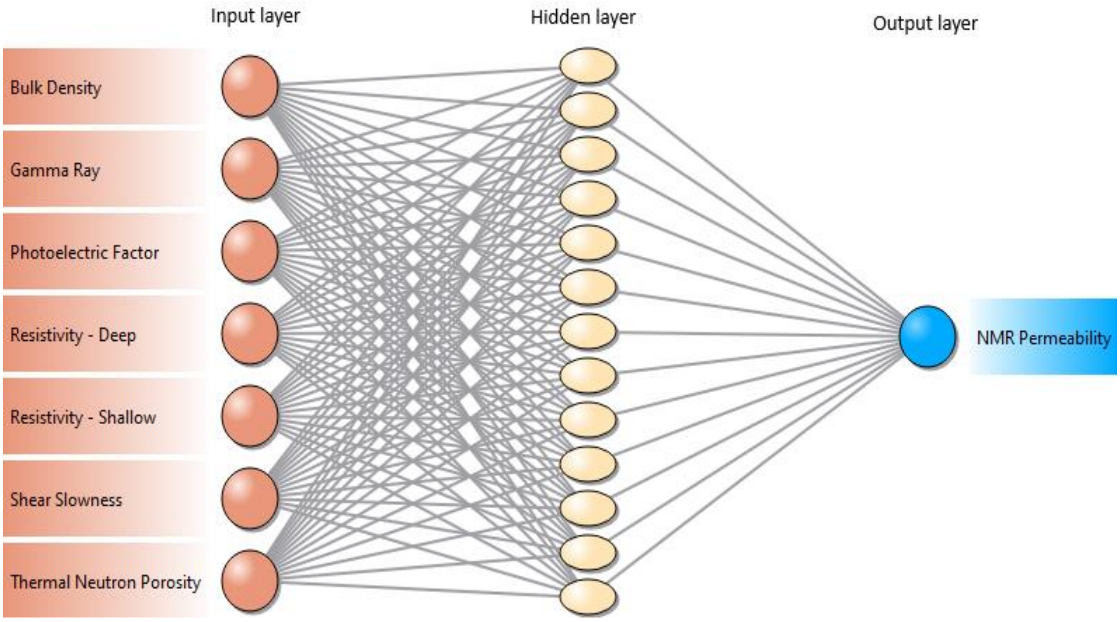

Fig. 2. Network schematic for the well logs used with NMR permeability model

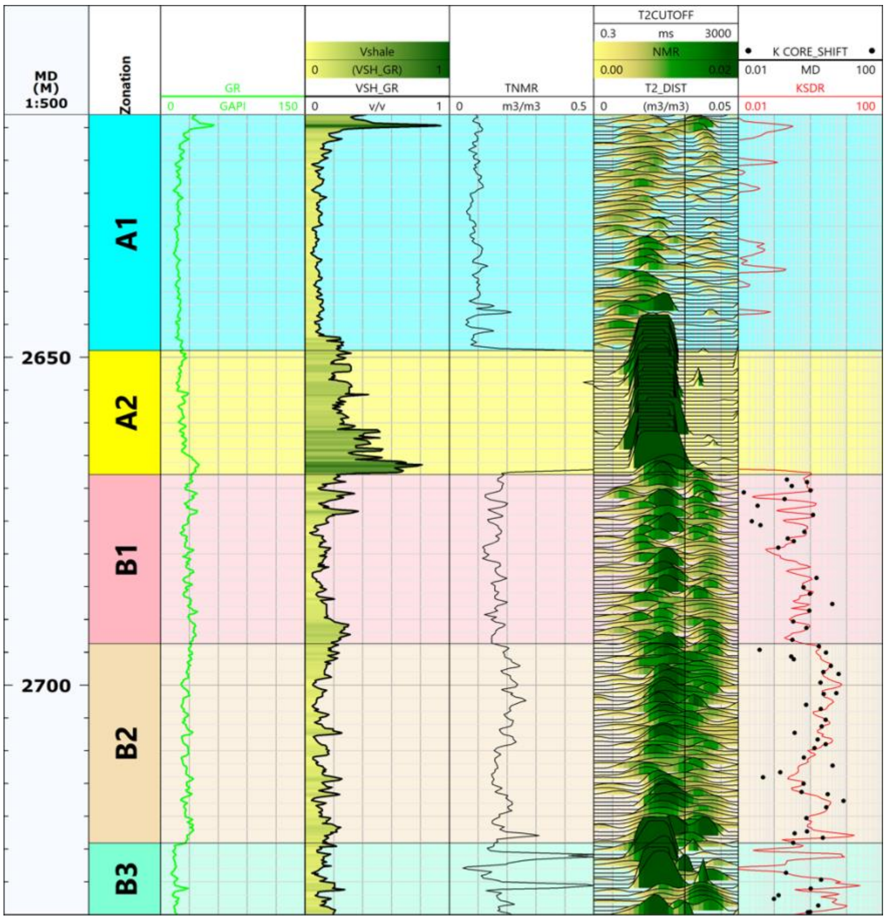

Fig. 3. HF005 SDR permeability match with core permeability

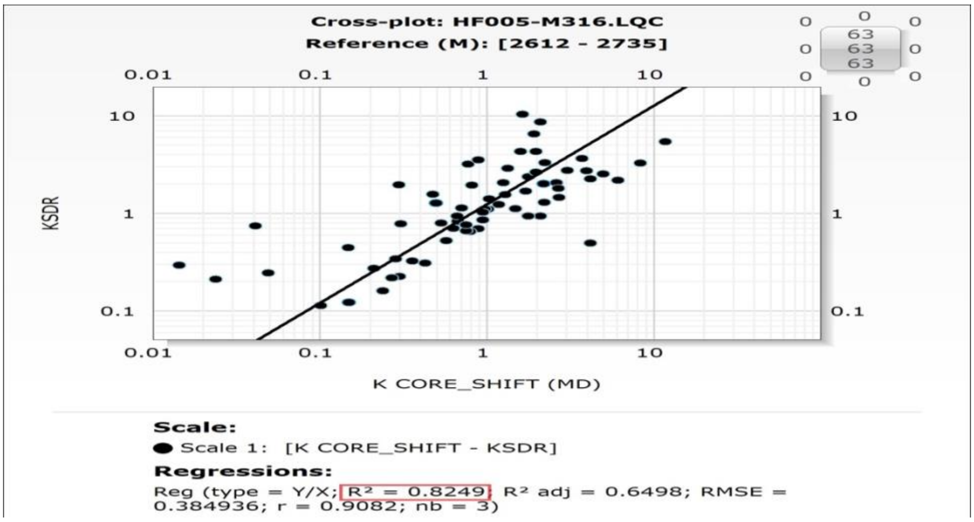

Fig. 4. Comparison of core permeability and SDR permeability for HF005-M316

4.2. Neural Network Training

4.2.1. Permeability Training Model

The computed NMR permeability was used to forecast the permeability into the fourth well, which lacks an NMR log. Seven well logs characteristics, namely GR (gamma ray), RHOB (bulk density), PE (photoelectric effect), DT (sonic travel time), LLD (deep resistivity), LLS (shallow resistivity), TNPHI (Thermal neutron porosity), were used to forecast the permeability of the rock. Fig. 2 depicts the network design created in this study to forecast the permeability using the information obtained from well logs. The constructed ANN model comprised one hidden layer of 13 neurons. Furthermore, Fig. 5 illustrates the relationship between KSDR permeability and the predicted permeability from the ANN model built in this study. The data utilized for the training phase is the calculated SDR permeability. The implemented ANN model demonstrated high accuracy in forecasting rock permeability. This is evident from the strong correlation, as shown by the close alignment of data points along the 45°-line. The cross plot has an R2 (0.94), as shown in Fig. 6. The correlation coefficient (0.8) between the predicted permeability and the core permeability of well HF005-M316 represents a good match (Fig. 7).

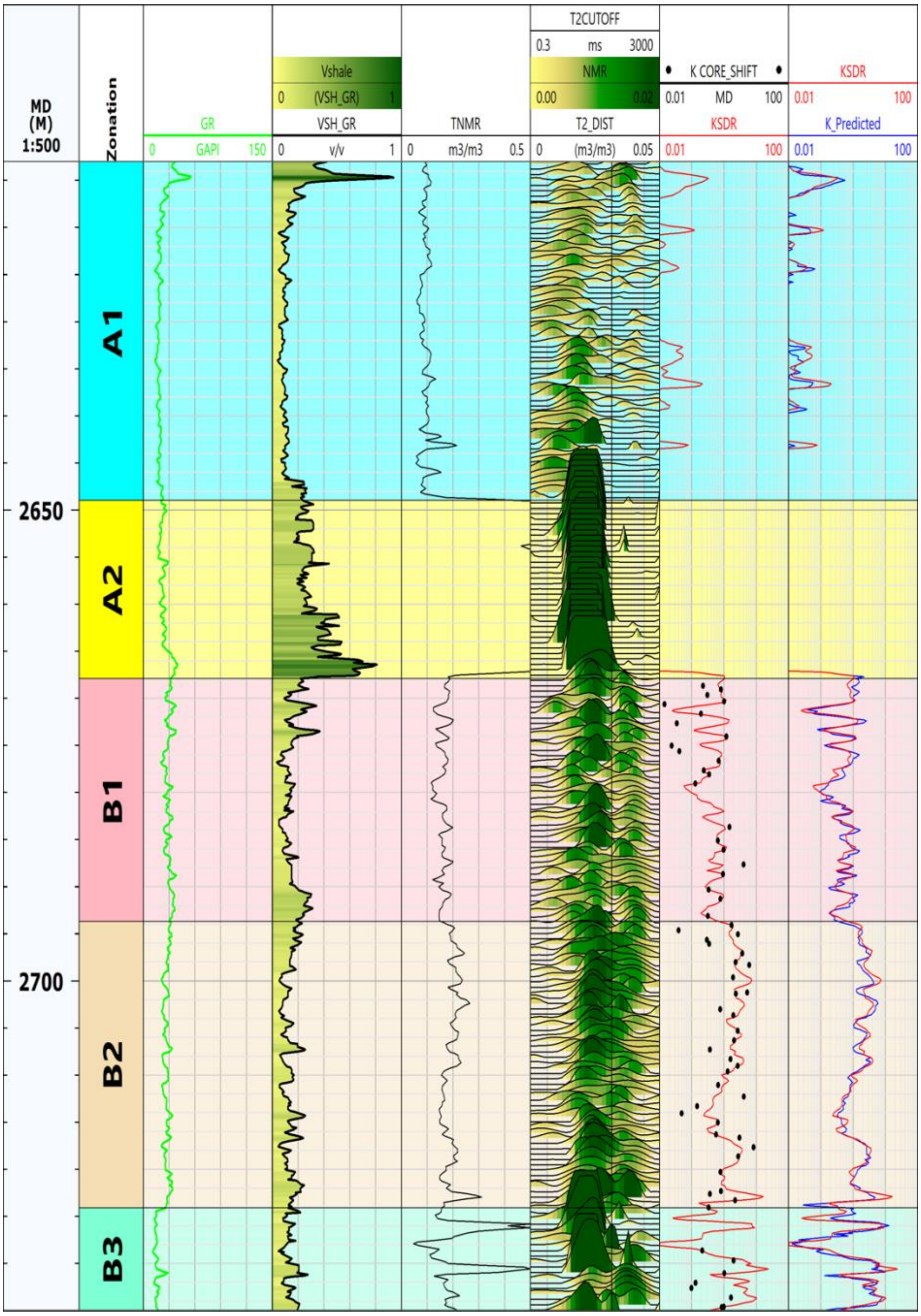

Fig. 5 Calculated permeability (KSDR) Vs Predicted permeability (ANN)

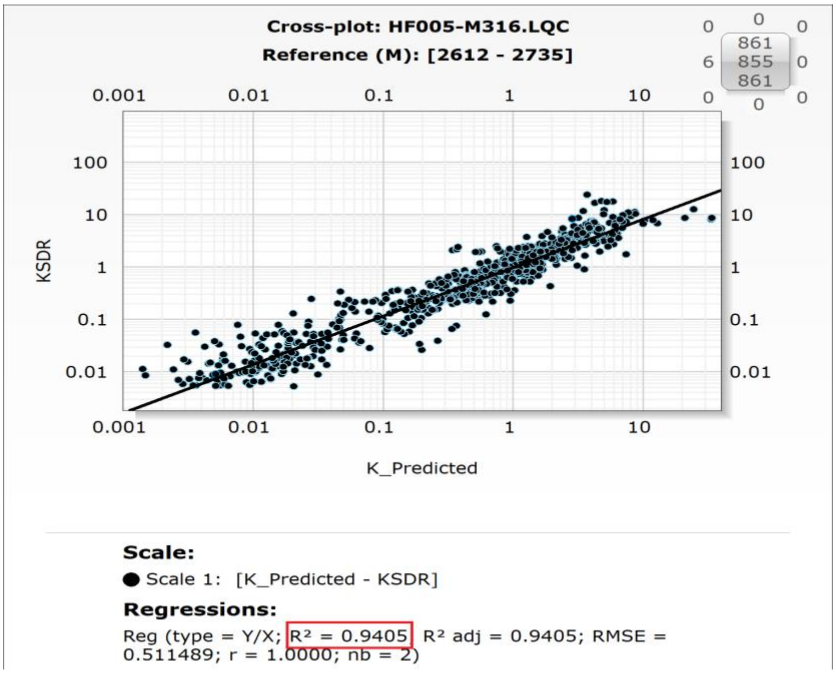

Fig. 6. HF005 Calculated permeability (KSDR) Vs K_Predicted Cross plot

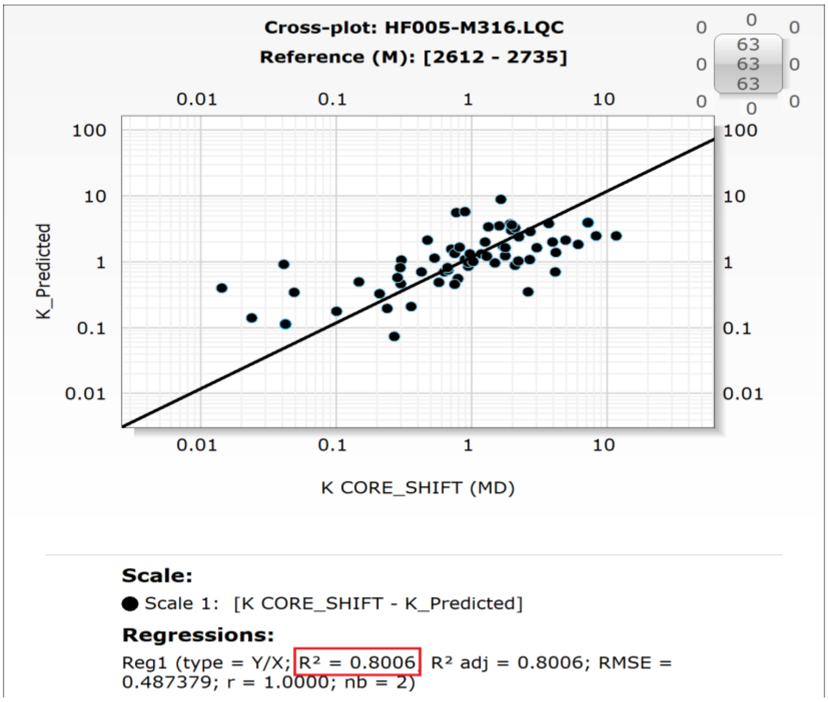

Fig. 7. Comparison of core permeability and predicted permeability of HF005-M316

4.2.2. Permeability prediction

Fig. 6 shows that it can be observed that the model of ANN can construct the complicated nonlinear connection among the petrophysical parameters, and it was additionally able to extrapolate the relationship amongst the attributes in various facies. The usage of artificial neural networks has addressed the issue of non-linearity, leading to underestimating and overestimation linked with the use of other existent empirical correlations. HF021 is without an NMR log; thus, permeability is estimated by the ANN model plotted in Fig. 8. As illustrated in this figure, the predicted permeability is validated with core permeability. The cross plot between predicted permeability using ANN and core permeability plotted in Fig. 9, has a correlation coefficient of 0.77, representing a good match of these parameters.

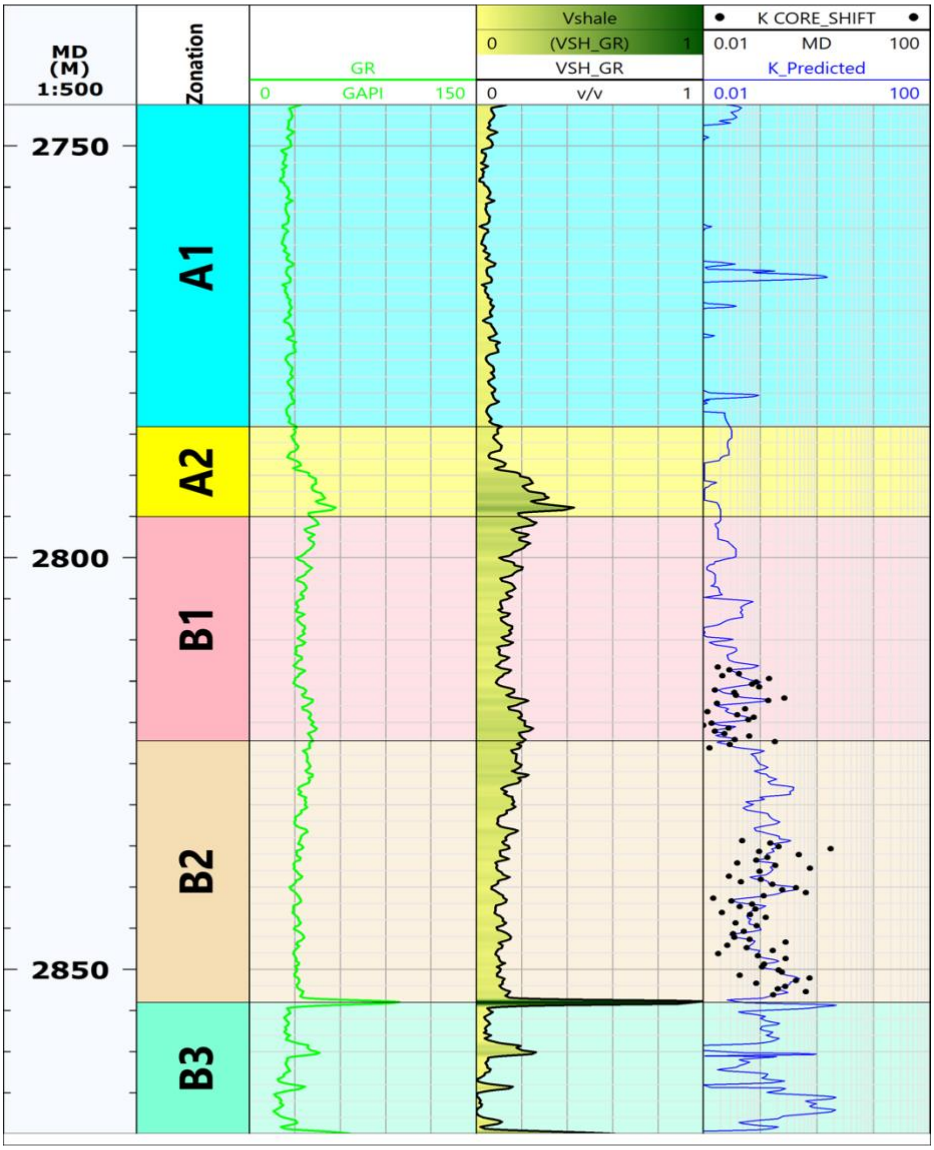

Fig. 8. HF021 predicted permeability match with core permeability

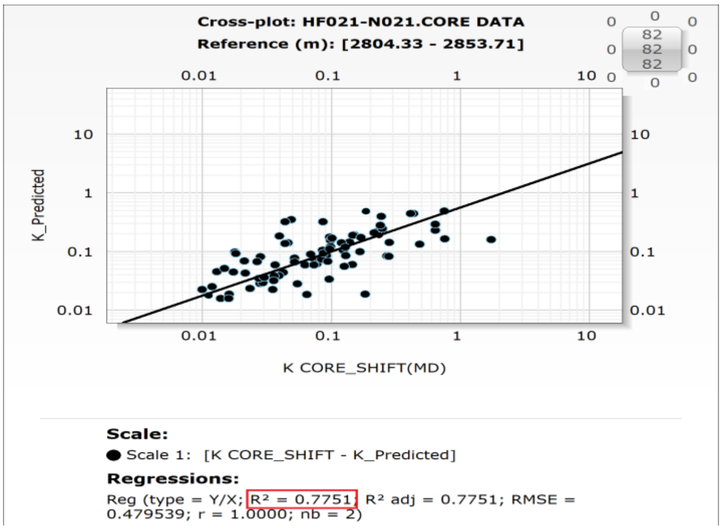

Fig. 9. Comparison of core permeability and predicted permeability of HF021-N0021.

5. Discussion

The data used to calculate permeability with the SDR approach is T2LM relaxation distribution and ØNMR; as T2LM considers the effects of pore size and pore shape, permeability calculated from the NMR log with this approach is more reliable than the classical method. Fig. 3 illustrates the permeability calculated with the SDR method, which is viewed in the same truck with the core permeability of well HF005-M316 for validation, which shows a good match between the calculated and core permeability. For more precise validation knowledge, the last mentioned permeabilities cross-plotted in Fig. 4 resulted in a correlation coefficient of 0.82.

Seven well logs, including bulk density, gamma ray, photoelectric factor, shear slowness, thermal neutron porosity, and deep and shallow resistivity, were used to construct the ANN model. A few scenarios were implemented to reach the optimal result from the available data, as seen in Fig. 2. The model's topology consists of 7 well logs (mentioned above) as input parameters in the input layer to give the optimal result.

With some prediction tests on the model, it was found that Gamma Ray and Thermal neutron porosity have more influence on the performance of the model, NMR permeability in the output layer used to train the model, which connected with the input layer by one hidden layer that has 13 neurons.

The predicted permeability is matched with KSDR (Fig. 3), which has a correlation coefficient of (0.94) as illustrated in Fig. 6. The validation of predicted permeability accomplished with core permeability of well HF005-M316 which is cross-plotted in Fig. 7 that resulted in a correlation coefficient 0.80, which is less precision than the match between calculated and predicted permeability.

The well HF021-N021 does not have an NMR log the model used to predict the permeability within the well as illustrated in Fig. 8. which is matched with core permeability in the same truck, the cross plot between predicted and core permeability shown in Fig. 9 that shows a correlation coefficient of 0.77, this low in precision between core and predicted permeability in well HF021-N021 due to the limitation of the data (number and quality of well logs used in prediction, number of NMR logs used for training, core data.

6. Conclusions

Based on the obtained result, the ANN has successfully developed a precise model for predicting the permeability of the reservoir. The cross plot of predicted and calculated permeability shows a high accuracy, with an R^2 value of 0.82. A strong correlation exists between the permeability computed by NMR and the permeability measured from the core of well HF005-M316. In addition, the permeability predicted by the artificial neural network (ANN) based on the nuclear magnetic resonance (NMR) decay time T2 closely matches the permeability of the HF021-N021 well core, indicating a moderate level of agreement with a correlation coefficient of 0.77. The advice is to research developing a new formula for calculating NMR permeability to achieve better alignment with core permeability. The created ANN model should also be utilized to estimate permeability from NMR data in additional wells. It is advisable to explore alternative ANN architectures to achieve better results than those obtained with the current one. Additionally, a substantial amount of nuclear magnetic resonance (NMR) data should be provided for further analysis, as NMR data provides a more accurate description of the hydrocarbon fluid in the oil and gas reservoir.

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