Permeability Prediction Using Advanced Magnetic Resonance Tools and Hydraulic Reservoir Units Techniques for the Pliocene Sand Reservoirs, Sapphire Offshore Gas Field, Mediterranean, Egypt

Ahmed A. Baghdadi 1,*, Abdullah M. El-Sayed 1, Abdel-Khalek M. El-Werr 1 and Ali E. Farag 2

1 Geophysics Department, Faculty of Science, Ain Shams University, Cairo 11566, Egypt
2 Faculty of Petroleum Engineering, British University in Egypt, Cairo, 11837, Egypt
* Correspondence: aabaghdady12@gmail.com

Abstract
Permeability derived from magnetic resonance advanced logging tools was used to unlock the Pliocene sandstone reservoir heterogeneity. Permeability prediction from well logs is a significant target due to the unavailability of core data. The hydraulic flow unit approach is used to classify the reservoir rocks according to their porosity-permeability relationship. The predicted permeability is calculated using Sapphire-Dh magnetic resonance porosity and permeability relationship for each flow unit. Flow Zone Indicator and the quality flow unit have a direct proportion relationship. For the model’s verification, the predicted permeability is plotted against the measured resonance permeability in Sapphire-Dh as a reference studied well, showing highly matching results. Accordingly, the applied approach is implemented in the other three wells, which have neither core samples nor advanced logs measurements.

Keywords: Magnetic resonance; Hydraulic flow units; Flow zone indicator; Reservoir quality index; Permeability prediction; Sapphire gas field

1. Introduction

Sapphire gas field (Fig.1) is located at the offshore concession of West Delta Deep Marine (WDDM), Egypt, where the water depth ranges from 200 to 2500 m. It encompasses 8050 km² of the Nile Delta cone’s western border. These WDDM fields provide two-thirds of the gas production in Egypt (Ismail et al., 2020). The Pliocene slope-channel play has been the focus of recent exploration, with several exploration and appraisal wells successfully drilled in recent years.

The sapphire field was explored in 1975 by the Esso NDOA-1 well, targeting the Miocene level. In order to establish the Sapphire field’s economic viability, the Sapphire-1 and Sapphire-2 wells were drilled in 2000. Sapphire-3 well drilled in August-September 2001, showing the lateral continuity of the reservoir sands. Formation pressures and gas/liquid sample compositions demonstrated that the Sapphire sands were in communication. Sapphire-4 was drilled in 2002 to appraise the structurally more complex field extension to the northeast of the Saffron gas chimney. This well proved the presence of gas in this region and the continuation of reservoir sands. Sapphire-Dh was the second out of eight in Phase I development wells to be drilled into the Sapphire field. The Phase I development area includes part of the field located to the southwest of the main Scarab-Saffron gas chimney and north of the NDOA extensional fault.

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Fig. 2 shows the Nile Delta stratigraphic column and hydrocarbon system (Rio et al., 1991). This study focuses on Kafr El Sheikh Formation, which comprises shale and a relatively enormous fining upward trend of sand channels (Maguire et al., 2008). Kafr El Sheikh Formation represents the thickest rock unit deposited during the Pliocene times. Such a rock unit consists mainly of intercalated sand and shale, which indicates sea-level transgression (EGPC, 1994).

The hydrocarbon production is mainly controlled by pore throat size, which affects the permeability values for many clastic and carbonate reservoirs. Conventional electric logs cannot predict permeability directly. The measurement depth into the formation allows you to see beyond the data quality problems associated with rugose boreholes, mud cake, and fluid invasion. Regardless of hole size, deviation, or temperature (Banavar, 1989). Nuclear magnetic resonance (NMR) logs effectively predict permeability (Coates et al., 1999; Dunn et al., 2002) but still need calibration and several correlations to validate their results. The magnetic resonance tool makes simultaneous multifrequency measurements using NMR at multiple depths of investigation (Allaud, 1977). A single pass in the wellbore provides total and effective porosity, permeability, and fluid identification and characterization. NMR measurements are made independently of other logging outputs and are unbiased by the formation water salinity or the rock matrix (Segesman, 1980). This avoids the ambiguity introduced by shale, thin beds, or low resistivity contrast to conventional measurements (Kenyon, 1988).

Rock typing is essential for reservoir characterization to classify the reservoir into different rock units with different porosity and permeability relations using porosity permeability cross-plots that affect the hydrocarbon flow profile (Amaefule et al., 1993; Elnaggar, 2018). Flow Zone Indicator (FZI) and Winland’s approach (1972) are two techniques utilized in petrophysical analysis. They are employed to classify facies that exhibit comparable porosity and permeability relationships. This allows for identifying facies with similar geological origins and depositional environments. Therefore, these techniques can help to provide valuable insights into the properties and behavior of subsurface rocks. Zayed et al. (2019) reported that the Pliocene sands in the neighboring field (Baltim field), offshore Nile Delta, have four hydraulic flow units depending on the approach of Winland (1972).
The permeability calculation was a big challenge in the sapphire field due to the core data's unavailability. The available magnetic resonance permeability in the reference Sapphire-Dh well was used to characterize the reservoir into four different rock units according to permeability values. As permeability was unknown in the other three blind wells, we used artificial intelligence (neural network) to predict these four rock units using the conventional logs (Gamma ray, neutron porosity, density, and resistivity). Then we applied the permeability equations for each rock unit to calculate the permeability in the other three wells.

The aim of this study is two-fold. Firstly, to characterize the sand facies into unique rock units by utilizing the Sapphire-Dh magnetic resonance porosity and permeability advanced logging tool and establish different permeability-porosity equations for each unit. This will be beneficial in understanding the variations in permeability and porosity across the Pliocene sand reservoir. Secondly, the study aims to predict the permeability in three blind wells, namely Sapphire-1, Sapphire East-Da, and Sapphire South Central-1, which have neither magnetic resonance porosity and permeability logs nor core data. To achieve this, the calculated effective porosity in the Pliocene sand reservoir was utilized in porosity-
permeability established equations for each rock unit in Sapphire-Dh, which will assist in predicting the permeability in the other three blind wells and provide valuable insights for future exploration and production activities.

2. Methodology

2.1. Data Preparation

Before conducting a petrophysical evaluation, it is necessary to undertake quality control measures and perform data editing as part of the current study. These measures include the removal of constant values at the first reading of the logs, cleaning all logs affected by casing over the cased zones, and correcting for gas effects. Correction is required due to the borehole effect on the density and neutron porosity curves. These corrections were made with respect to the corrected fluid density before any deterministic or probabilistic interpretation. In addition, the neutron porosity should be corrected due to the low hydrogen index of gas, which can lead to an underestimation of measured porosity. Failure to make these corrections could impact calculations of shale volume and effective porosity.

2.2. Conventional Logging Data

The magnetic resonance porosity correlates well with the calculated porosity in Sapphire-Dh well. Three blind wells were selected for the present study, which have no magnetic resonance porosity and permeability (Sapphire-1, Sapphire East-Da, and Sapphire South Central-1).

The electric logs, such as the gamma-ray, density, neutron, and resistivity, were used to predict the rock units using a neural network algorithm and test them against the rock types in Sapphire-Dh well. Then all the porosity-permeability relationships from the reference well were applied to the other three wells.

2.3. Petrophysical Parameters

Petrophysical evaluation is performed for all the wells (Asquith & Krygowski, 2004). This analysis includes a calculation for shale volume and effective porosity (Schlumberger, 1974), which is calibrated with the magnetic resonance porosity in Sapphire-Dh well. The same porosity calculation method was applied for each rock unit in the other three wells where there is no magnetic resonance log, water saturation, net sand thickness, net pay thickness, and lithology volume.

2.4. Advanced Logging Data

Using the effective resonance porosity and permeability data, which is calculated using Timur-Coates method by applying the following equation, from the Sapphire-Dh well, FZI was calculated according to Ebanks (1987). Applying this approach resulted in the differentiation of the Pliocene sand into four hydraulic flow units (HFUs), as described by Amaefule et al. (1993).

\[ K_{\text{Timur}} = a' \cdot 10^{4 \cdot b'} \cdot (\Phi b' \cdot (\text{FFV/BFV})^c' \]

\[ \Phi = \text{FFV} + \text{BFV} \]

\[ a' = \text{prefactor, } \sim 1 \text{ for sands} \]

\[ b' = \text{porosity exponent, } \sim 4 \]

\[ c' = \text{ratio, } \sim 2 \]

\[ \text{FFV} = \text{free fluid volume} \]

\[ \text{BFV} = \text{bound fluid volume} \]
2.5. Reservoir Characterization

The Pliocene sand reservoir's magnetic resonance porosity and permeability differentiated the sand reservoir into four different rock units with significant porosity and permeability characteristics.

2.6. Rock Typing

The rock typing approach is a commonly used technique to differentiate the reservoir facies based on their porosity-permeability relationship, and it relies on measurements of core porosity and permeability. However, this approach could not be used in the studied wells due to the unavailability of core data. Instead, a different workflow relied on the available magnetic resonance porosity, permeability data, and calculated porosity from logs. The calculated permeability was then validated against reference magnetic resonance permeability data from Sapphire-Dh well as shown in Fig. 3, and the high validation confirmed the accuracy of the workflow. This alternative approach demonstrates the importance of adapting methods to account for variations in data availability and the need to validate results against established benchmarks. The whole workflow was implemented using Techlog software.

![Fig. 3](image-url) Accuracy (R²=0.86) of permeability predictions by HFU technique VS the resonance permeability, Pliocene Sand Reservoir in Sapphire-Dh Well.

The workflow started by running the FZI interactive charts to help identify resonance porosity-permeability trends. After that, Reservoir Quality Index (RQI) was plotted against normalized porosity (PHIZ) for each FZI given a distinct color. Then, porosity-permeability regression equations were established. Later, a model was created from the reference well to predict permeability, and based on that model, the permeability was obtained for the other wells. Finally validated, the results by comparing the calculated porosity from the conventional logs with the one we had from the magnetic resonance for different rock units showed a good match as shown in Fig. 4.
**2.7. Permeability Prediction using Neural Network**

Neural networks have been applied extensively in solving regression problems, where the goal is to predict a numerical value or target variable based on a set of input variables or features. The neural network is a computational model consisting of interconnected processing nodes or neurons that simulate the function of biological neurons. The neural network structure comprises an input layer, one or more hidden layers, and an output layer (Hadi et al., 2022). The input layer receives the input data, which is then propagated through the hidden layers, where the neurons apply a series of mathematical operations to transform the input data. The output layer produces the final prediction or estimate. The training process involves adjusting the weights and biases of the neurons to minimize the difference between the predicted and actual output values. Using neural networks in regression problems has shown significant promise in achieving accurate predictions and has found applications in various fields, including petroleum engineering (Mohaghegh, 1995).

Each layer connects to the other layer and has an associated weight and threshold that will affect the final output. If the output of any single node is above the specified threshold, this node will be activated and send data to the next network layer. Otherwise, no data is passed along to the next layer of the network as shown in Fig. 5. A supervised data and a driven approach are utilized to train the model, which used the electric logs to estimate the rock units as an output (Alfonso et al., 2021).
This is a prediction algorithm for the qualitative (rock units) or quantitative (permeability) data (Sapphire-Dh well). This algorithm allowed classification and data clustering using the available log data.

3. Results and Discussions

3.1. Geological Significance of HFU & Permeability-Porosity Relationships:

Reservoir discrimination was based on porosity and permeability relation reflecting different flow units and could unlock the reservoir heterogeneity. The FZI is a special parameter that represents the quality of the reservoir (Amaefule et al., 1993; Abdul Hameed & Hamd-Allah, 2023), which is equal to 0.0314 √K/Φ. The RQI is calculated by dividing the FZI by the normalized porosity. It is a distinct parameter for each hydraulic unit, as depicted in Fig. 6. Finally, FZI is associated with various combinations of logging tool responses to create regression models for the permeability estimates in the reference well "Sapphire Dh" and other intervals or wells. Each rock unit with the same FZI range has similar pore geometry, rock textures (i.e., grain size, sorting, diagenesis), and fluid flow characteristics.
Fig. 6. Reservoir Quality Index (RQI) VS Normalized Porosity (PHIZ) intersecting the FZI probability for each rock type (4 Rock types) in Sapphire-Dh Well.

The FZI and RQI values are calculated for clustering the reservoir into different rock units according to the porosity and permeability values. Four permeability equations were established from the porosity-permeability cross plot for Sapphire-Dh, as shown in Fig. 7. Data filtering was done to normalize the data distribution and reflect the various rock units. RQI and FZI are crucial in establishing a representative simulation model for actual reservoir behavior. Horizontal permeability distribution is usually estimated from advanced tools such as magnetic resonance. However, most wells are not cored and rely on magnetic resonance porosity and permeability analyses. As a result, permeability in other sections/wells is predicted using permeability versus porosity relationships developed using statistically insignificant data sets.
Fig. 7. Four permeability equations derived from Permeability-Porosity relationship (four rock types), Pliocene Sand Reservoir in Sapphire-Dh Well.

Each rock unit was assigned a unique FZI value (R2 = 73, 84, 76, and 81%, Fig. 8). The FZI values were then utilized to establish a porosity-permeability relationship and identify the dominant pore throat size (R35) for each of the four rock units. Four equations were developed to represent these units, as demonstrated in Fig. 7.

Fig. 8. FZI probability plot (4 Rock types), Sapphire Sand Reservoir in Sapphire-Dh Well.
3.2. Neural Network in Rock Units Prediction:

The model predictions data show a high correlation with the reference data in Sapphire-Dh (R2=0.91), and this proves that we can use this method for rock units’ prediction, as visualized in Fig. 9.

![Contingency table](image)

Fig.9. Magnetic Resonance rock units versus Neural Network prediction (R2=0.9099), Pliocene Sand Reservoir in Sapphire-Dh Well (C: Regression coefficient, ■1: rock unit 1, ■2: rock unit 2, ■3: rock unit 3, ■4: rock unit 4)

3.3. Wireline Data Selection for Petrophysical Evaluation, Rock Units Prediction, and Permeability Calculation:

The permeability cannot be directly calculated from the conventional logs. There was a high match between the magnetic resonance porosity and the density-neutron calculated porosity for calibration (R2=0.82). The high match allowed these calculated porosity curves to be used as input in the permeability equations, as shown in Fig.10. The permeability logs are then calculated using transform equations with the chosen electric log data as variables. Wireline electric logs in a set (Gamma Ray, Neutron, Density, and Resistivity) were used for the rock unit prediction in the test well (Sapphire Dh) and then applied to the other three blind wells.

![Cross-plot](image)

Fig.10. Magnetic Resonance-Log porosity relationship (R2=0.82), Pliocene Sand Reservoir in Sapphire-Dh Well.
The neural network prediction approach employed a different algorithm to produce the results. It relies only on the findings of statistical inferences that were carried out independently on each blind well without making any assumptions. Therefore, this deterministic approach enhances the reliability of the prediction because it offers a trustworthy and sound inference database from a mathematical perspective.

Nearby wells were correlated with Sapphire-Dh well to identify the probability of sharing the same hydraulic unit within a prediction window. Sapphire-Dh well served as a reference point for this analysis. The permeability equations from the Winland plot are now applied for each rock unit, including the FZI values as presented in Fig. 7. The predicted permeability in the reference well compared to the calculated permeability shows a validation (R²=0.86) as illustrated in Fig. 3. The rock units have been established for all sand intervals across all wells, and the corresponding permeability equations have been applied to each rock unit. This has enabled the characterization of variations in rock units based on FZI values as shown in Table 2. Fig. 11 illustrates the petrophysical evaluation of Sapphire-Dh well, and Table 1 shows the petrophysical evaluation results of all four wells. Moreover, a comparison between magnetic resonance permeability and rock typing permeability showed a good match in Sapphire-Dh well, as depicted in Fig. 12.

### Table 1. Summary of Petrophysical Parameters (PHIE: effective porosity, SW: water saturation, Vsh: Shale Volume) for the Studied Wells.

<table>
<thead>
<tr>
<th>Wells</th>
<th>Zone</th>
<th>Net Sand (m)</th>
<th>Net Pay (m)</th>
<th>PHIE (%)</th>
<th>SW (%)</th>
<th>Vsh (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sapphire</td>
<td>East Da</td>
<td>28</td>
<td>23</td>
<td>28</td>
<td>36</td>
<td>2</td>
</tr>
<tr>
<td>South Central-1</td>
<td>Pliocene Sand</td>
<td>77</td>
<td>41</td>
<td>25</td>
<td>46</td>
<td>4</td>
</tr>
<tr>
<td>Sapphire-1</td>
<td></td>
<td>64</td>
<td>47</td>
<td>29</td>
<td>32</td>
<td>5</td>
</tr>
<tr>
<td>Sapphire Dh</td>
<td></td>
<td>71</td>
<td>42</td>
<td>28</td>
<td>37</td>
<td>3</td>
</tr>
</tbody>
</table>
Fig. 11. Pliocene Sand petrophysical evaluation (PHIE: effective porosity, SW: water saturation, Sg: gas saturation) (Sapphire-Dh) Well.

Table 2. Pliocene sand reservoir characteristics, four rock units

<table>
<thead>
<tr>
<th>Rock Units</th>
<th>Porosity (V/V)</th>
<th>Permeability (mD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Avg.</td>
</tr>
<tr>
<td>RU1</td>
<td>0.15</td>
<td>0.26</td>
</tr>
<tr>
<td>RU2</td>
<td>0.13</td>
<td>0.23</td>
</tr>
<tr>
<td>RU3</td>
<td>0.11</td>
<td>0.2</td>
</tr>
<tr>
<td>RU4</td>
<td>0.08</td>
<td>0.15</td>
</tr>
</tbody>
</table>
Fig. 12. Magnetic Resonance Permeability (CMR: Perm) versus Calculated Permeability using Rock Units Porosity-permeability Relationships, Pliocene Sand Reservoir in Sapphire-Dh Well.

In the other three blind wells (Sapphire-1, Sapphire East-Da, and Sapphire South Central-1), the varied hydraulic unit profiles are predicted using the suggested methodology. Also, the regression equations are assigned for permeability estimates based on electric logs as seen in Figs. 13-15.

Fig. 13. Predicted Rock Units versus Calculated Permeability in Sapphire South Central-1 Well.
Fig. 14. Predicted Rock Units versus Calculated Permeability in Sapphire East Da Well.

Fig. 15. Predicted Rock Units versus Calculated Permeability in Sapphire-1 Well.
4. Conclusions

This paper uses advanced magnetic resonance tools and hydraulic reservoir unit techniques to predict Pliocene sand reservoirs’ permeability for the first time in Sapphire Offshore Gas Field, Mediterranean, Egypt. The study represents a workflow to challenge the fields that do not have core data.

Four reservoir rock units were identified in the Sapphire Pliocene sand reservoir using Sapphire-Dh well magnetic resonance porosity and permeability as a reference for predicting reservoir rock units in the other three wells, which did not have permeability data. The Neural Network approach characterized all the reservoir rock units by generating the prediction model using gamma-ray, density, and neutron porosity logs.

Conventional logs were used to calculate the effective porosity of the Sapphire-Dh well. After that comparison of the magnetic resonance and the calculated porosities for each rock unit showed a regression coefficient of 0.82. Hence, effective porosity calculation was performed for the other three wells, which had neither magnetic resonance nor core data.

The RQI and FZI techniques were applied for permeability prediction. Finally, the porosity-permeability transform was applied to all wells. The final permeability prediction models were selected based on the prediction match quality with the magnetic resonance permeability in blind test wells. A total of four porosity-permeability trends were obtained for four rock unit definitions. High correlation trends were obtained for all the rock units. The porosity-permeability observed on RQI-FZI cross-plots.

This study recommends acquiring conventional or sidewall cores over the Pliocene sand reservoir for more reservoir characterization study and to compare with the magnetic resonance rock typing. Moreover, compare the calculated permeability with each well's production profile or the available production logs for flow rate validation.

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References


