Studying the Effect of Permeability Prediction on Reservoir History Matching by Using Artificial Intelligence and Flow Zone Indicator Methods

Mustafa R. Abdul Hameed¹,* and Sameera M. Hamd-Allah ²

¹ Petroleum Research and Development Center, Iraqi Oil Ministry, Baghdad, Iraq
² Petroleum Engineering Department, College of Engineering, University of Baghdad, Baghdad, Iraq

* Correspondence: m.abdul-hameed1308d@coeng.uobaghdad.edu.iq

Abstract
The map of permeability distribution in the reservoirs is considered one of the most essential steps of the geologic model building due to its governing the fluid flow through the reservoir which makes it the most influential parameter on the history matching than other parameters. For that, it is the most petrophysical properties that are tuned during the history matching. Unfortunately, the prediction of the relationship between static petrophysics (porosity) and dynamic petrophysics (permeability) from conventional wells logs has a sophisticated problem to solve by conventional statistical methods for heterogeneous formations. For that, this paper examines the ability and performance of the artificial intelligence method in permeability prediction and compared its results with the flow zone indicator methods for a carbonate heterogeneous Iraqi formation. The methodology of the research can be summarized by permeability was estimated by using two methods: Flow zone indicator and Artificial intelligence, two reservoir models are built, where the difference between them is in permeability method estimation, and the simulation run will be conducted on both of the models, and the permeability estimation methods will be examined by comparing their effect on the model history matching. The results showed that the model with permeability predicted by using artificial intelligence matched the observed data for different reservoir responses more accurately than the model with permeability predicted by the flow zone indicator method. That conclusion is represented by good matching between observed data and simulated results for all reservoir responses such for the artificial intelligence model than the flow zone indicator model.

Keywords: Artificial intelligence; Flow zone indicator; History matching; Permeability, Artificial Neural Networks; South Iraq

1. Introduction
The field development plan is conducted on a calibrated reservoir model which mimics the fluids’ transmission through porous media in the actual reservoir. History matching (HM) is the process that works to validate the dynamic model by matching observed data and estimated results so that it can be relied upon to conduct development strategy plans to study future forecasting with reliable and accurate results (Carter et al., 1974). The HM workflow is based on tuning the parameters which have uncertain values so that the HM process's difficulty comes from the reservoir's uncertain parameters (Kabir et al.,
2003). The petrophysical properties are considered the most parameters that are tuned during the HM process to replicate the actual dynamic modeling due to its governing fluid flow in the reservoir.

The permeability is considered the most crucial petrophysical property that is tuned through the HM process. The importance of permeability is due to its governing the fluid flow through the reservoir which makes it the most influential parameter on the HM than other parameters. The tuning of properties to get on HM for the reservoir model is highly time-consuming and exhausting effort labor. For that, the reduced errors in the property values by a reliable estimation method will speed up the HM process by decreasing the iteration runs of the simulation.

Reducing the errors in the permeabilities’ values represent the major challenge in permeability estimation. This uncertainty comes from the measurement method. Unfortunately, there is no direct method to measure permeability values (except core analysis, which is expensive and doesn’t cover the whole reservoir) therefore indirect methods were developed to predict it. The sources of data measurement errors are attributed to (1) human or device errors when getting results from direct measurements (e.g., core plug data from the laboratory) and (2) inherent errors by indirect measurements (e.g., well log data) (Hutahaeean, 2017).

As mentioned above, the direct measurement represented by the coring process is difficult and very expensive therefore doesn’t cover the whole reservoir for that indirect measurements are developed to estimate the permeability. Well-tests data such as build-up and drawdown predict average reservoir permeability value so that it could not be applied to the whole reservoir due to permeability heterogeneity along the reservoir. While correlations methods where static information about rock properties is used in permeability prediction can be grouped under two categories: (a) pore (micro) scale data or properties, and (b) field (core or macro) scale data or properties (Babadagli & Al-Salmi, 2004).

As the reservoir is the result of geologic deposition processes and is not randomly generated, the Hydraulic flow units (HFUs) method was developed. The HFU is defined as the lateral continuity of reservoir units with consistent geological features governing fluid flow behavior in porous media (Amaefule et al., 1993). in heterogeneous reservoirs, The HFU can Estimation of Permeability with high accuracy (Ismail et al., 2017). Hydraulic flow unit and electrofacies (EF) methods give a good estimation for permeability with less distance offset wells when a limited number of data are available (Bhatti, et al., 2020).

In the late 90ths of the last century, the artificial intelligence (AI) approach started to be used in petroleum engineering when researchers started to investigate the ability of machine learning to solve some issues (Al-Kaabi & Lee, 1990) (Zhou et al., 1993). So, machine learning was used in many fields, especially in petrophysical properties prediction such as permeability, porosity, and water saturation. The most powerful tool of AI techniques in the prediction of reservoir properties using well logs is neural networks and fuzzy logic. They can make more accurate and reliable reservoir properties estimation compared with conventional methods (Mohaghegh et al., 1994) (Lim & Kim, 2004) (Al-Alwani et al., 2019). The artificial intelligence is used to estimate the Hydraulic flow unit and then predict the permeability by estimated HFU. The results show that AI with HFU gives good permeability estimation (Alobaidi, 2016).

In this paper, the research objective is to examine the effect of the permeability estimation method on the history-matching process by reducing the mismatch between observed data and simulation results. The methodology of the research can be Summarization by (1) permeability values were estimated by using two methods: Flow zone indicator and Artificial intelligence (2) two reservoir models are built, where the difference between them is in permeability method estimation. (3) the simulation run will be conducted on both of the models, and the permeability estimation methods will be examined by comparing their effect on the model history matching where the more accurate method will give less gap between the observed data and simulation results for the reservoir models.
2. Area of Study

This study is conducted on the West Qurna 2 oil field which is considered one of the supergiant oils fields in Iraq. It is located in Basra governorate about 70 km towards the northwest of the city as shown in Fig. 1. West Qurna oilfield is located within the ancient platform where the main oil-bearing formations are Yamama and Mishrif. Yamama Formation belongs to the lower Cretaceous system, while the Mishrif Formation belongs to the upper cretaceous system. This study targets the Mishrif reservoir which is a carbonate formation. Carbonate formations are more difficult to characterize than sandstones, but they contain more than 60% of the world's hydrocarbon reserves. Carbonate reservoirs show a high degree of heterogeneity at each scale (Abdulelah et al., 2020).

The Mishrif Formation comprises the major producing reservoir of the West Qurna-2 field (Yose et al., 2012). The Mishrif oil reservoir includes the Mishrif and Rumaila formations. The top of the Mishrif Formation is unconformably overlaid by the Khasib carbonate-terrigenous formation. Fig. 2. shows the Stratigraphic column for southern Iraq oil fields. This field is considered a green oil field because the exploitation began at the end of 2014. The data are extracted from three cored wells. The number of plugs that have porosity and permeability after filtration is 289.

Fig. 1. West Qurna oil field location. (Awadh et al., 2018)
Fig. 2. The stratigraphic column of the southern Iraqi oilfields (Mahdi and Aqrawi, 2018)

3. Materials and Methods

The permeability is calculated by two methods as presented below:

3.1. Permeability Prediction by Flow Zone Indicator (FZI)

Information-relevant borehole log data or reservoir properties can be correlated using statistical techniques. This method is used to describe or detect zones within a reservoir to determine reservoir behavior. (Abdul Majeed et al., 2022)

In this method, the Amaefule et al. technique was used to divide the reservoir into several units depending on porosity and permeability cores. These units indicate the existence of distinct rock units with similar pore throat attributes (Amaefule, et al., 1993). The process to find out the reservoir units is as follows:

1. Calculate Reservoir quality index RQI:

   \[ \text{RQI} = 0.0314 \times \frac{k}{\sqrt{\phi_e}} \]

2. Calculate \( \phi_z \):

   \[ \phi_z = \frac{\phi_e}{1 - \phi_e} \]
3. Calculate permeability $K$:

$$K = 1014 \times FZI^2 \times \frac{\phi^3}{(1-\phi)^2}$$

RQI vs. $\phi_z$ should be plotted on log-log paper, samples that have similar FZI values will lie on a straight line and have a unit slope because they have similar pore throat attributes. The intercept of that unit slope straight line at $\phi_z = 1$ can be used to calculate the value of the constant FZI.

To generate permeability distribution for the reservoir by using the FZI method, first, a hydraulic unit log (hydraulic unit vs depth) should be estimated for cored wells, and then it should be input and distributed along with the porosity into the geological model. By using these properties, permeability values for uncored wells can also be estimated.

Fig. 3. shows that there is no relationship between porosity and permeability of the core which indicates the formation is heterogeneous. The values of core porosity and permeability were used to find out the number of hydraulic flow units for the reservoir. Eight hydraulic flow units were obtained by applying the FZI method as shown in Fig. 4. This dividing of hydraulic flow units gives a clear relationship between permeability and porosity contrary to the whole formation relationship as shown in Table 1. Fig. 5. shows a comparison between the results of permeability prediction by the FZI method and core permeability.
Table 1. Flow units’ equations and coefficients of determination.

<table>
<thead>
<tr>
<th>No. of Hydraulic Flow Unit</th>
<th>Permeability Prediction for unit</th>
<th>coefficients of determination ($R^2$)</th>
<th>Color of Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$k = 14.36 \Phi - 1.3271$</td>
<td>0.4984</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>$k = 2661.7 \Phi^{3.4557}$</td>
<td>0.6296</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>$k = 9917.1 \Phi^{3.3074}$</td>
<td>0.8022</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>$k = 29631 \Phi^{3.3133}$</td>
<td>0.8143</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>$k = 37672 \Phi^{2.8162}$</td>
<td>0.8589</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>$k = 4880.2 \Phi - 243.82$</td>
<td>0.7461</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>$k = 483449 \Phi^{3.0643}$</td>
<td>0.9772</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>$k = 4748.6 \Phi - 123.45$</td>
<td>0.8841</td>
<td></td>
</tr>
</tbody>
</table>

3.2. Permeability Prediction by Artificial Intelligence

Artificial neural networks (ANNs) are a type of machine learning that is used in deep learning techniques. Their name and structure are derived from the human brain, and they resemble the way biological neurons communicate with one another. It's a parallel adaptive information processing system that can create associations and change data between input and output (Onerous, 2002) (Mohaghegh, 2000).

3.2.1. Artificial neural networks performance steps

1- Data processing: is an important step in ANN performance which is featuring with the consumption of time compared with other steps of ANN performance. It is characterized by

- Identification of the objective of the ANN: the objective of ANN will help us to choose the type of data and select which data will be independent variables (input) and which data are the dependent variable (output). In this study, the input data are represented by Depth, porosity, and shale volume while the core permeability is the output variable.
- Scaling (normalization) of input data in the range 0 to 1 or -1 to 1. This step is very important because it is considered preprocessing data. Its main goal is to preprocess the data to be more...
adequate for machine learning algorithms to faster training, computational stability, and speed up the convergence of the gradient descent algorithm which represents the basis of most machine learning applications. The process of this step depends on neglecting the effect of range variance of the inputs data because a large range will take large weight in the calculation than variables with a small range, for example, depth range from 2250 to 2700 while porosity range from 0 to 0.4 for that depth will take weight large than the porosity (Pandey et al., 2020) (Cranganu et al., 2015). The formula that is used in this study is:

\[ X' = \frac{(X - X_{\text{min}})}{(X_{\text{max}} - X_{\text{min}})} \]  

(4)

2- ANN structure: This step is represented by building the structure of ANN which consists of three parts which are:

- Input layer which is representing independent variables data.
- Hidden layers which are containing neurons.
- Output layer which is representing dependent variables data.

A neural network executes in two phases: The feed Forward phase and the Back-Propagation phase. The steps of executing are:

- The values in the input nodes and the weights are used to make predictions in the feed-forward phase of ANN. The formula for this step is

\[ X.W = x_1.w_1 + x_2.w_2 + x_3.w_3 + b \]

- To predict output as same as actual output, the activation function is used. The predicted output for the input features is the result of the activation function. The selection of activation function type is considered a critical step in neural network design. The activation function type choice depends on the target variable to predict such as for real target variables, then it makes sense to use the identity activation function while it makes sense to use a sigmoid activating function to predict a probability of a binary class (However, it is possible to have other types of situations where different target variables may be predicted.) (Aggarwal, 2018). In this study, two activation functions were used to predict porosity and permeability which are the sigmoid function for the first three hidden layers and the identity function for the last hidden layer as shown in Fig. 6. and Fig.8.

- network performance should be checked by finding out the divergence between the predicted and the actual output data. For this purpose, the mean squared error or MSE cost function is used

\[ \text{MSE} = \frac{1}{n} \sum_{o=1}^{n} (\hat{Y}_o - Y_o)^2 \]

Where: \( Y_o \): the value of actual output, \( \hat{Y}_o \): the value of predicted output, and \( n \): observations number.
- To reduce the error percentage between the actual data and the predicted one, a Backpropagation error is used. That is a technique used to update the input data weights by using gradient descent. Gradient descent is an iterative algorithm of optimization to find the function minimum, in this study, it aimed to minimize the error function (Fausett, 1993).

\[ w_x^* = w_x - \left( \frac{\partial \text{Error}}{\partial w_x} \right) \]

3.2.2. AI method application

Porosity values that are estimated from the wells’ logs should always be corrected for core porosity to increase its accuracy. In this work, the log porosity values were corrected based on the core porosity by using an artificial neural network. The input data were depth, log porosity, and shale volume. Then
the corrected porosity values had relied upon as input data in permeability prediction. The Matlab software is used to build the ANN model Fig. 6. shows the structure of the ANN model to predict corrected log porosity. This ANN model gives a good correlation of coefficient results for training, validation, and test stages. Consequently, a good coefficient of determination for correct log porosity is gotten which was \( R^2 = 0.85 \) as shown in Fig. 7.

The resulting values of predicted porosity were used as input data along with depth and shale volume to predict permeability where the output of the ANN model was core permeability. The structure of ANN shown in Fig. 8. gives a good model to predict permeability with a coefficient of determination \( R^2 = 0.74 \) as shown in Fig. 9. This ANN model can estimate the permeability of un-cored wells using their porosity, depth, and shale volume logs.
Effect of Permeability Prediction Method on History Matching (HM)

This section deals with studying the permeability prediction method's effect on the reservoir's history matching. Two models were built to show that effect. The first model includes permeability values that are predicted from the hydraulic unit flow method while the second model includes values predicted by ANN. Taking into consideration that other parameters were fixed by considering them controlled.

Figs. 10 and 11 show the comparison in the HM of the two models according to oil production rate, water production rate, and the bottom hole pressure. The figures illustrate that the model with the AI permeability prediction method matched the observed data better than the model with the HFU permeability prediction method for all response features. Fig. 12. indicates the same thing for the entire field oil production rate. The summarization of these figures is the AI method is better than HUF in the
permeability characterization that clear through reducing the mismatch gap between the simulation results and observed data.

**Fig. 8.** Comparison between the two models in Oil production rate, water cut, and bottom hole pressure history matching for well WQ2-167.

**Fig. 9.** Comparison between the two models in Oil production rate and Bottom hole pressure history matching for well WQ2-198.
5. Discussion

Although the coefficient of correlation and coefficient of determination for the HFU method is higher than those for the ANN, the permeability predicted by the ANN method is more accurate to represent the actual reservoir permeability than that of FZI. Which is a result of:

- FZI method is done by dividing the reservoir into units depending on the relationship between core porosity and core permeability. And because the core extraction process is limited to only a few wells for specific depths of the reservoir because it is highly expensive. This leads to missing permeability values for the interval of depth which is uncored. Consequently, the FZI method neglects the uncored depth in its correlation.

- The FZI method is unable to estimate the distribution of heterogeneity through the reservoir. Fig. 13. shows the distribution of the hydraulic flow units vertically and horizontally through the reservoir which emphasizes the presence of vertical and areal heterogeneity in the reservoir. While the ANN method depends on training the input data (which are logs data) and their relationship with output data (permeability). For that, the ANN method will give a model for predicting the permeability for any specific interval of depth, and at the same time, the model interacts with the heterogeneity of the reservoir.
6. Conclusions

The study was conducted on a heterogeneous carbonate reservoir in the southern part of Iraq. The prediction of permeability faces the issue of the heterogeneity of the reservoir. To overcome this issue, two methods were used: FZI and AI methods. The integrated analysis of the HFU method proves its capability to develop the porosity-permeability relationship equation to estimate the permeability where the coefficients of determination $R^2 = 92\%$ for permeability prediction vs. core permeability. Also, it succeeded to divide the reservoir into 8 units depending on the same pore-scale properties and generate a good equation for each unit to estimate the permeability precisely in terms of porosity. AI method is used to predict the corrected porosity and then used as input in permeability prediction. The ANN creates a model to predict permeability based on the other reservoir parameters with coefficients of determination less than the FZI method. Two reservoir model simulation runs (different in permeability prediction method) were conducted; the results show that the model with permeability predicted by using ANN matched the observed data for different reservoir responses more accurately than the model with permeability predicted by the FZI method. The coefficients of determination may not be evidence for the best method in the petrophysical properties characterization, especially for heterogeneous reservoirs because the FZI is based on all data to generate the equation of permeability in terms of porosity while the AI method validates and tests the model on random data to increase the accuracy of the permeability prediction model.

Acknowledgements

The authors would like to thank the Petroleum Research and Development Center for contracting with the College of Engineering, university of Baghdad and funding this study.

References


