Application of Artificial Intelligence to Predict Permeability in Low Permeability Limestone Formation

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Abstract

Porosity (ϕ) and permeability (k) are two important rock properties used in oil, gas, and water resources calculations. The mathematical relationship between porosity and permeability is not easily demonstrated. Due to the heterogeneity of rock properties, there is no exact mathematical formula from which permeability could be calculated depending on porosity. Some researchers depend on the core analysis to introduce a general mathematical relation between ϕ and k, while others depend on the flow zone indicator (FZI) method to find such a relation. Recently, supervised machine learning has gained much popularity in establishing a relationship between complex non-linear datasets. This type of machine learning algorithm has shown its superiority over petroleum engineering regression techniques in terms of prediction errors for high dimensional data, computational power, and memory. In this work, the FZI method was applied to a data set for Khasib formation in the East Baghdad oil field to present a mathematical formula relating ϕ and k. In addition an AI algorithm was used to predict k depending on ϕ for the formation under study. Results proved that the predicted values of k had better agreement with the actual k values compared to the k values calculated using the FZI method. The accuracy of results is measured by calculating the coefficient of determination (R^2).

Key Words: Porosity, permeability, FZI, ANN, R^2.

1 Introduction

A petroleum reservoir is a heterogeneous geological system with large intrinsic complexity. Porosity and permeability are two important rock properties used in oil and gas reservoir and water resource calculations. The capability of a rock to hold fluids depends on its porosity while permeability controls the ability of fluids to flow into the porous rock. There is a relationship between porosity and permeability, but this relation is not easily demonstrated especially in carbonate rocks compared with clastic rocks [12, 15]. Sometimes there is a positive relation between them while on the other hand, there is low permeability with high porosity and vice versa. If the quality of the carbonate reservoir is merely evaluated by porosity, the results could be quite inconsistent with the actual production preference [11, 18-19].

For decades a considerable number of researches have been done trying to establish a mathematical relation between porosity and permeability. The traditional core analysis, well logs, and rock petrophysical properties such as pore geometry, capillary pressure, surface area, water saturation, and production data were used to find this relation. The Kozeny, Kozeny–Carmen (K–C) correlation and their modifications are the most widely accepted methodology in the oil industry. [6-7, 17, 22].

Amaefule et al. [3] presented a modification for K-C correlation by introducing the concept of the Reservoir Quality Index (RQI) and Flow Zone Indicator (FZI) to enhance their capability to capture the various reservoir flow behavior based on their respective characteristics. Yet, there are challenges in using the original correlation due to its inherent limitations and oversimplified assumptions that prevent accurate Hydraulic Flow Unit (HFU) definitions. [2-3, 8, 16]. Recently several researchers utilized different artificial intelligence methods to get a more accurate estimation of permeability in carbonate reservoirs such as fuzzy logic, genetic algorithm, PSO, and Artificial Neural Networks (ANNs) [9, 14, 23]. In this work, the FZI method and ANN were used for permeability estimation depending on porosity. The data was collected from the results of core analysis for one of the carbonate reservoirs in the east Baghdad oil field [20]. The accuracy of results is measured by calculating the coefficient of determination (R^2). Results demonstrate that the artificial intelligence algorithm predicts permeability more accurately than the FZI method.

2 Brief Background of Supervised Machine Learning Algorithms

The implementation of supervised machine learning methods to solve complicated problems has gained momentum in many

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industries including the petroleum industry. Most of these complex problems were impeding critical decision-making and enhanced advancement in the industry hence, researchers progressively moved from using empirical correlations and linear regression models to the application of AI techniques which have been welcomed due to their added value in the industry (Ali, [1]). The first pattern recognition algorithm was proposed by Fisher in the mid-1930s where two normal distribution populations were modeled indicating that the Bayesian solution is a quadratic decision function [10];

$$\mathrm{F}_{sq}(X) = sign\left[\frac{1}{2}(x-m_1)^T\sum_{1}^{-1}(x-m_1) - \frac{1}{2}(x-m_1)^T\sum_{2}^{-1}(x-m_2) + \ln\frac{|\Sigma_2 \quad |}{|\Sigma_1 \quad |}\right] \tag{1}$$

This formed the basis of many supervised machine learning algorithms in use today. Supervised machine learning algorithms can generally be put as machines, being trained to map input data (x) to output data (y) by learning from a set of target function (f) mathematically put as;

$$y = f(x) \tag{2}$$

The dataset is usually divided into a 70:30 or 80:20 ratio for training and testing. Predictive modeling or analytics is hence described as a supervised machine learning algorithm that learns certain hidden and complex features from the target function (f) that are otherwise invisible or complex to statistical methods to make predictions of the output data (y) during training and testing. The model is then applied to new and unseen data (X) to validate its prediction accuracy, efficiency, and errors. The main reason for further research in supervised machine learning is to improve prediction accuracy, minimize errors and enhance computational efficiency.

3 Artificial Neural Network (ANN)

3.1 Concept and Theoretical Framework

Artificial Neural Networks (ANNs), a biologically inspired intelligence model, gained major attention in the ’80s when the neuroscience industry clocked some important advancements in its use leading to high interest in understanding the importance of NN models [21]. The brain’s neuron functions are replicated by large sets of algorithms representing the ANNs which are capable of establishing relationships amongst highly anomalous nonlinear variables and producing sophisticated, accurate, and reliable results to complex problems through learning and training [1].

There are generally two types of neural networks with the most rudimentary and straightforward ANN paradigm being the Feed-Forward Neural Network (FFNN) which is a multilayer interconnection of perceptron where the output layer does not form a loop for feedback connections or recurrent networks but in a forward unidirectional flow [24]. A simplified neuron network model can be represented mathematically as;

$$h_\theta(x) = \frac{1}{1+e^{-\theta x^T}} \tag{3}$$

Where $h_\theta(x)$ is referred to as the output, x is the input but x and θ are the parameter vectors. A typical FFNN architecture is shown in Figure 1 below. The other type of ANN is the Feedback Neural Network (FBNN) popularly called the Back-Propagation ANN (BPANN) which is widely used in supervised learning. This type of neural network is of a similar architectural structure to the FFNN but allows the creation of a loop where erroneous information is sent back for the iterative altering of weight values until error can no longer improve to achieve a more accurate output variable. A typical BPNN archetypal structure is shown in Figure 2.

The ANN works like the neuron connections in the brain with multiple interconnections where each node (point) is linked to the other in the form of a pathway for interaction with each other. The ANN can work with a single hidden layer to assign weights to each node in a neural structure [13]. The training phase feeds the input data as vectors through a NN framework. The output error is computed and looped back, for a BPANN, into the network for the iterative altering of the weights using gradient descent to be done to reduce the error based on experience until it can no longer be improved. This process is repeated until a bias value that gives a more accurate prediction is obtained. The mathematical equation of the error function derivative used to update the weights by gradient descent is represented as [4].

$$\Delta \mathrm{w}(\mathrm{t}) = \omega \nabla \mathrm{E}(\mathrm{T}) + \alpha \Delta \mathrm{e}(\mathrm{t}-1) \tag{4}$$

Where Δw is the weight update, E is the error observed between the predicted and actual output, ω is the learning parameter, and α is the momentum parameter (<1). With each increase in hidden layers depending on the complexity of the problem being worked on, we will be entering into the realms of deep learning [23].

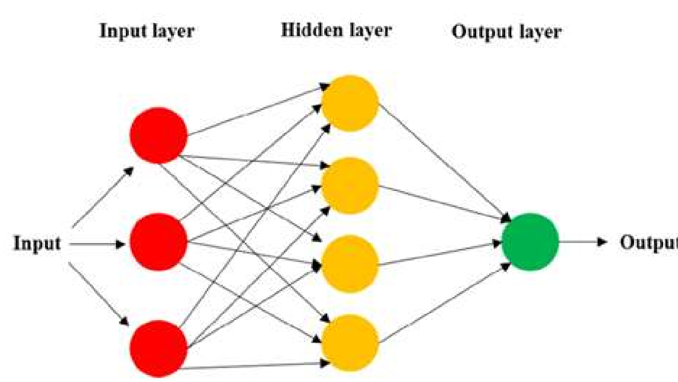


Figure 1: A typical feed-forward neural network architecture (Saggaf et al., 2003)

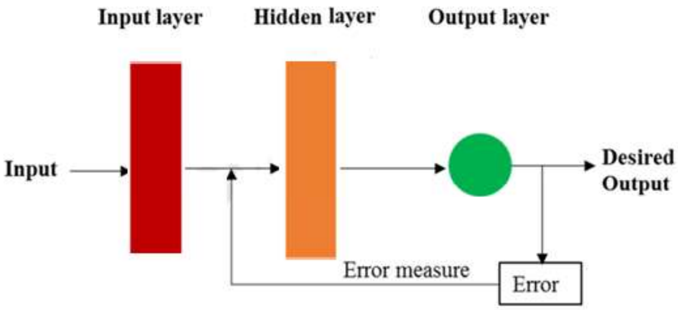


Figure 2: A back-propagation neural network architecture (Saggaf et al., 2003)

Within the scope of reservoir characterization, NNs are commonly used as a highly effective supervised machine-learning technique for classification problems. This is mainly attributed to the unique ability of a neural network to mimic the human way of thinking [5] to solve classification problems by creating complex dynamic estimation functions that offer improved performances over other algorithms. Given adequate computational power, ANN can theoretically learn the shape of any function necessary for classification. Regression analysis helps to model the relationship that exists between a dependent and one or several independent variables showing significant relations between them and the change of the dependent value as a result of a change in the independent variables.

4 The FZI Method

Kozeny [17]: concluded one of the important formulas to estimate permeability

$$K = a\,(\emptyset/S) \tag{5}$$

Where, s is the surface area per unit bulk volume (L^2/L^3), Carmen [6]: changed the Kozeny formula and introduced permeability in packs of a uniform size.

$$K = (\frac{1}{f_g\tau\ S^2})(\frac{\emptyset^3}{(1-\emptyset)^2}) \tag{6}$$

Where f_g is the shape factor, dimensionless and τ is the Tortuosity (dimensionless).

Amaefule et al., [3]: suggested two known methods to estimate permeability and indicate hydraulic units for uncored wells, first method is reservoir quality index (RQI) and the second is flow zone indicator (FZI), where the hydraulic unit will be introduced as a unit of reservoir rock which given a special relationship between porosity and permeability. A lot of mathematical resolutions are applied to equation (2) to become as follows:

$$0.0314\sqrt{\frac{k}{\emptyset}} = \left[\frac{1}{s\sqrt{f g\,\tau}}\right]\left[\frac{\emptyset}{1-\emptyset}\right] \tag{7}$$

Surface area, tortuosity, and shape factor could be measured differently in the reservoir so that term of the Kozeny-Carmen formula $\frac{1}{s\sqrt{f g\,\tau}}$ is assumed by the square root of FZI^2.

RQI can be introduced as the following term:

$$RQI = 0.0314\sqrt{\frac{k}{\emptyset}} \tag{8}$$

And $\emptyset_z$ can be normalized as follows:

$$\emptyset_z = \emptyset/(1-\emptyset) \tag{9}$$

So FZI will be:

$$FZI = RQI\ /\ \emptyset_z \tag{10}$$

Then RQI vs. $\emptyset_z$ can be plotted on (log–log) paper, where similar FZI values of the core sample will appear as a straight line, while various FZI values of the core sample show on other parallel straight lines [3].

4.1 Coefficient of determination (R^2)

The coefficient of determination, or R^2, is a measure that provides information about the goodness of fit of a model. In the context of regression, it is a statistical measure of how well the regression line approximates the actual data. It is therefore important when a statistical model is used either to predict future outcomes or in the testing of hypotheses.

$$R^2 = 1 - \frac{sum\ squared\ regression\ (SSR)}{total\ sum\ of\ squares\ (SST)} \tag{11}$$

5 Data Set

The data set was for the Khasib formation, which is one of the reservoir rocks in the East Baghdad (EB) oil field in Iraq. It is a low permeability porous limestone from the upper cretaceous age with shelly lime and chalky lime in some sections. The data are from core analysis for the cored intervals in wells EB- 4, 11, 12 and 16 [20]. The porosity range is (6 to 29.24%) and the permeability range is (0.1 to 28.9) md. Figure 3 shows porosity – permeability plot for the data.

6 Methodology

Two methods were utilized to predict core permeability depending on its porosity. The first is the FZI method in which FZIs were calculated from equation 6 for each core data and rounded to the nearest integer (0, 1, 2, etc.). The similar FZI value of the core sample will have appeared as a straight line on a log-log plot of RQI vs $\emptyset_z$, while various FZI values of the core sample show on other parallel straight lines. From each straight-line equation, a relation between porosity and permeability was deduced, then used to calculate permeability for the set

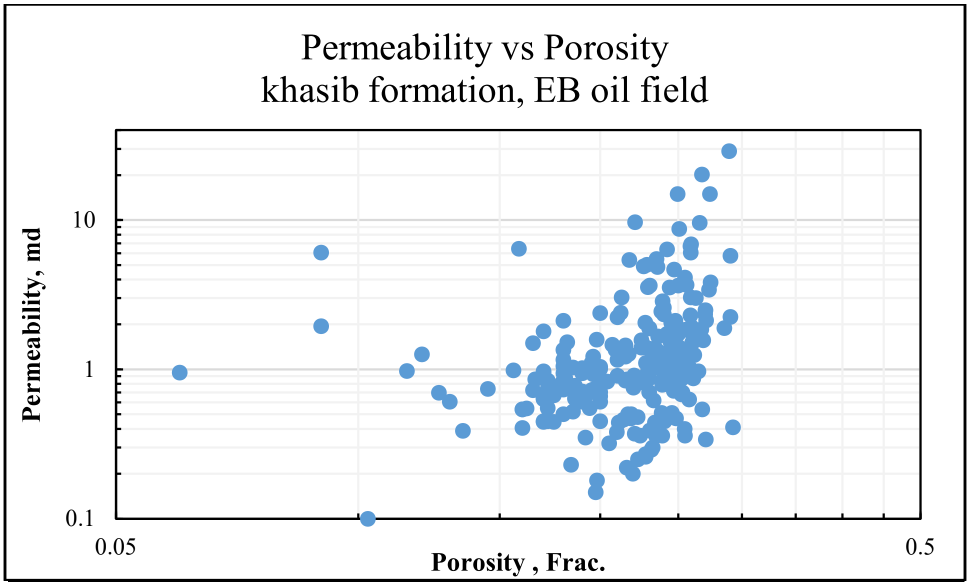


Figure 3: Porosity permeability plot

having the same rounded FZI value. The second method is using one artificial intelligence algorithm. Usually in these algorithms data set is split up into two groups.

One of these groups is used as input training data for the algorithm, while the second one is for comparison between the predicted and the original values. More than one algorithm had been adopted to perform permeability prediction depending on the location, depth, and porosity of the data used. Part of the data is fed for training and the remaining data is compared with that predicted by the algorithm. Finally, the algorithm that has the best regression values were selected to perform the work.

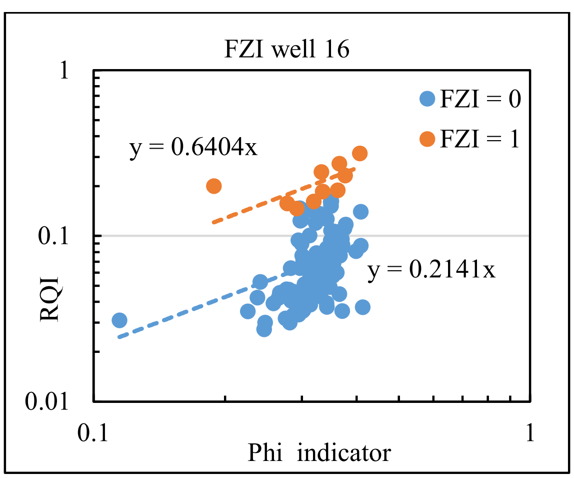
7 Results and Discussion

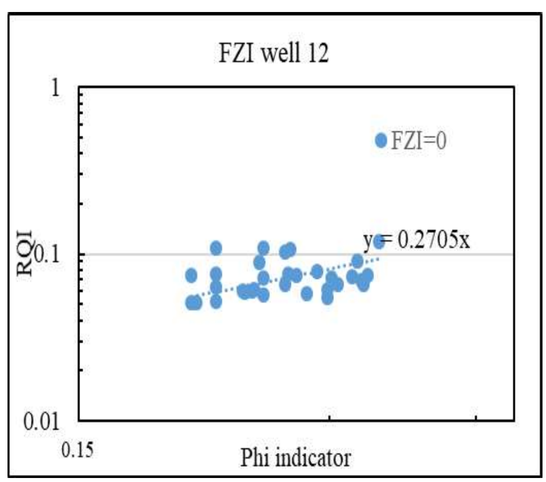
Applying the FZI method to the data of the four wells under study shows that most zones identified with FZI = 0, with some points having an FZI value of 1 which is attributed to low permeability values. The FZI plots for the four wells are shown in Figure 4.

The equations relating porosity with permeability resulted from the FZI relations used to calculate the core permeability. Application of the ANN algorithm resulted in predicted permeability values for each corresponding porosity. To get a better comparison, plots of measured core permeability against calculated permeability using the FZI method and plotted against predicted permeability by ANN for each well are given in Figures 5 and 6.

The coefficients of determination (R^2) in Figures 5 and 6 were better for permeability predicted by the ANN methods in comparison with that calculated using the FZI method as shown in Table 1.

The plot of measured core permeability, calculated permeability using the FZI method, and that predicted by the ANN algorithm versus depth for the four well in Figures 7 and





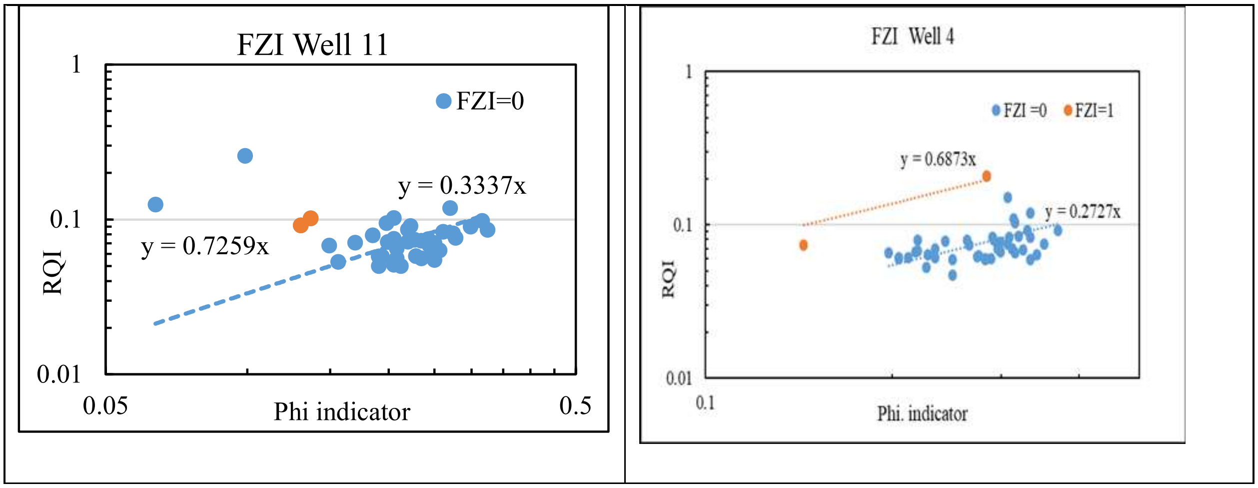


Figure 4: The FZI plot for wells EB- 16, 12, 11, and 4

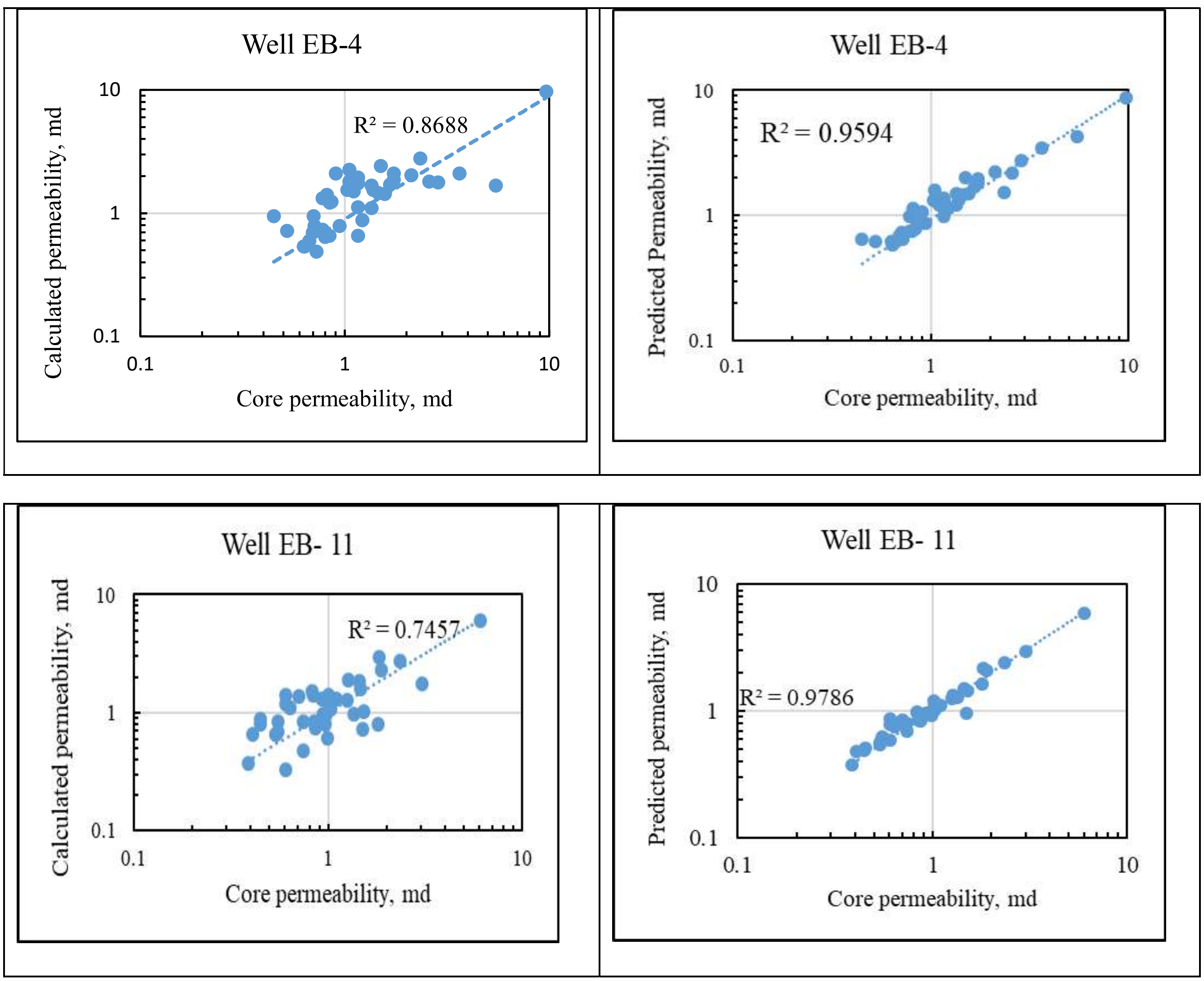


Figure 5: Calculated and predicted permeability vs core permeability wells EB-4 and 11

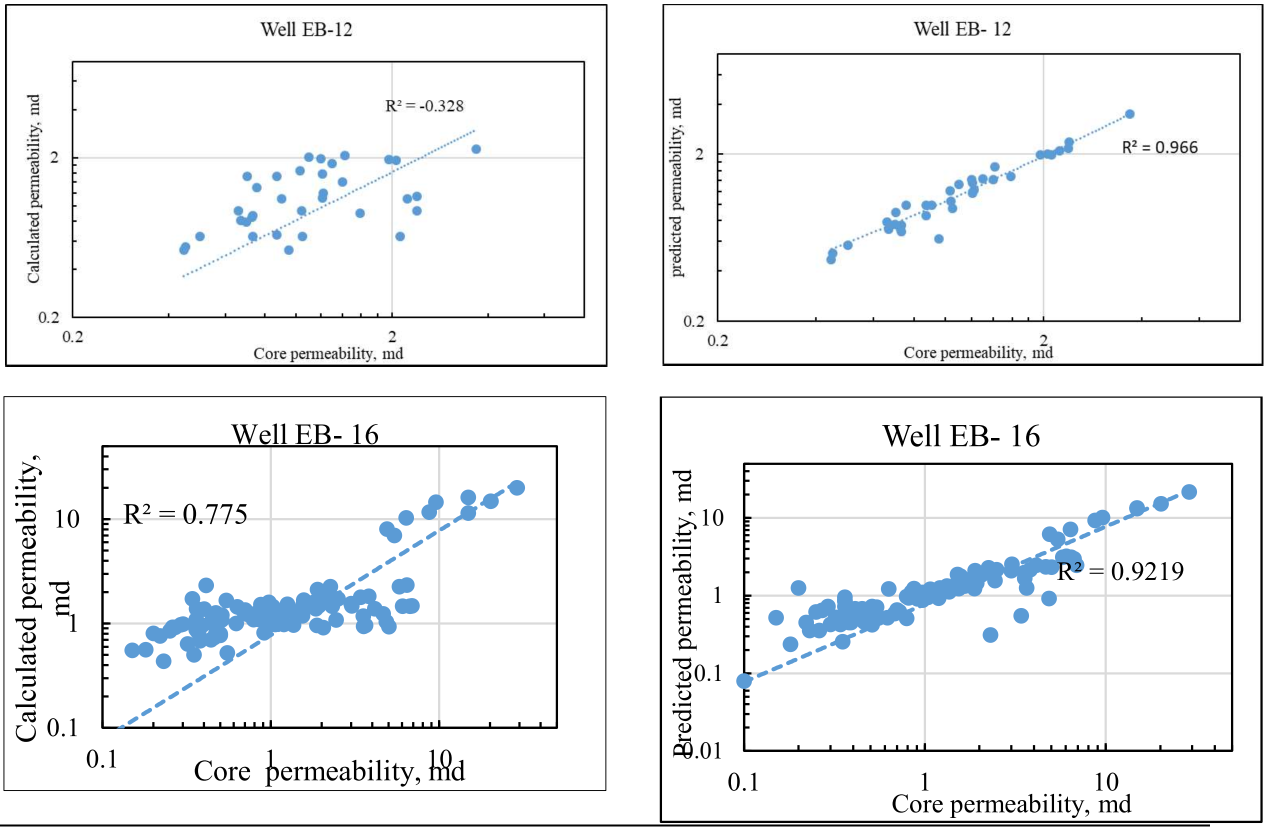


Figure 6: Calculated and predicted permeability vs core permeability wells EB-12 and 16

Table 1: Comparison between the R^2 values.

Well No.	Value of R^2	
	The FZI method	Predicted by ANN
12	0.328	0.966
16	0.775	0.9216
4	0.6953	0.9594
11	0.7457	0.9786

8 indicate that there is better agreement between the predicted and the measured values compared with the calculated ones.

Finally, Figure 9 presents a plot of the measured permeability for the four wells vs the calculated permeability shows that $R^2 = 0.7632$ while the plot vs the predicted permeability shows that $R^2 = 0.9188$.

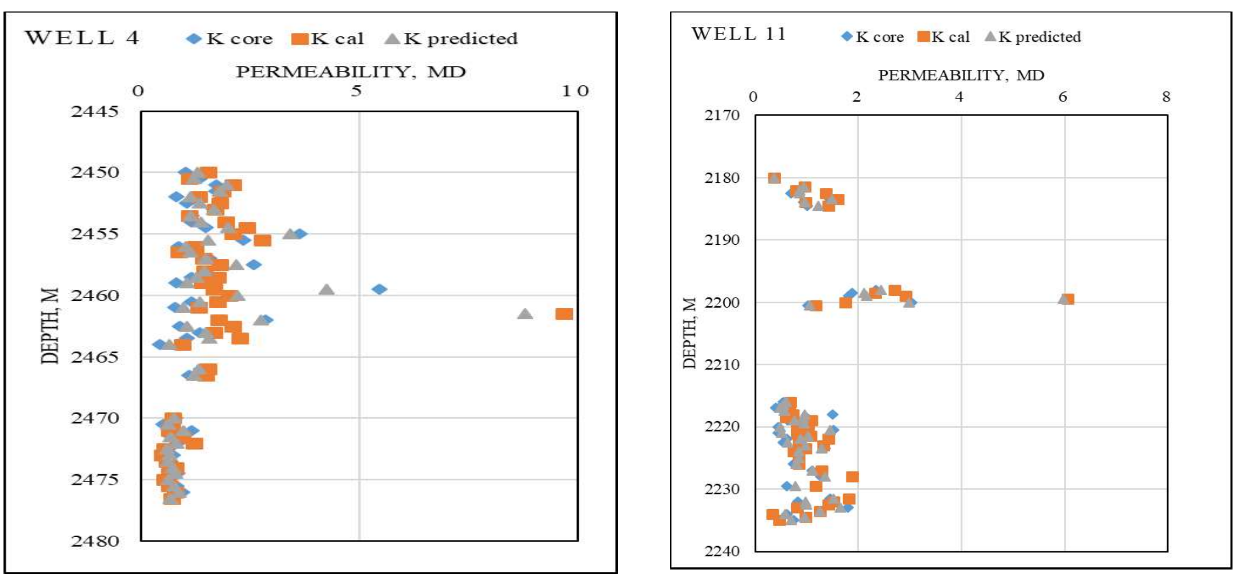


Figure 7: Permeability vs depth for wells EB-4 and EB-11

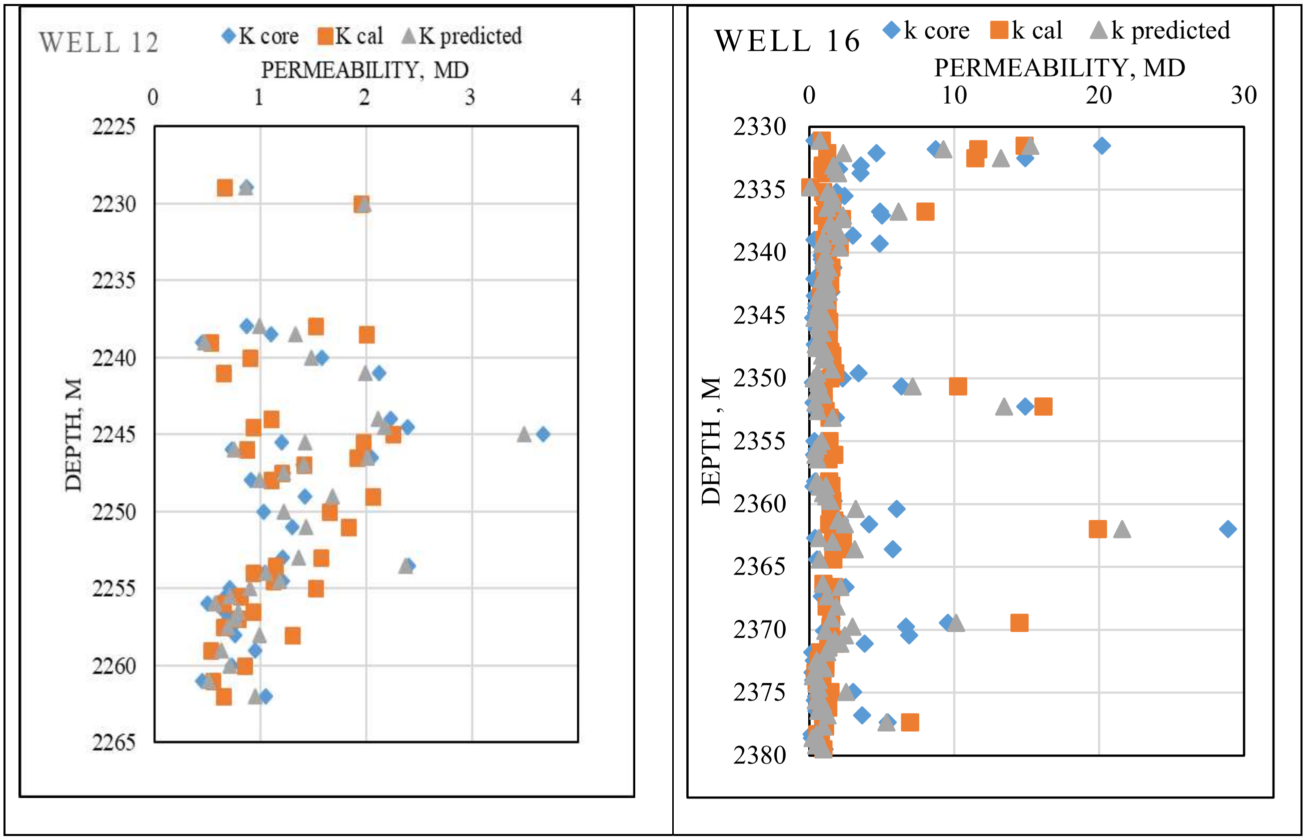


Figure 8: Permeability vs depth for wells EB-12 and EB-16

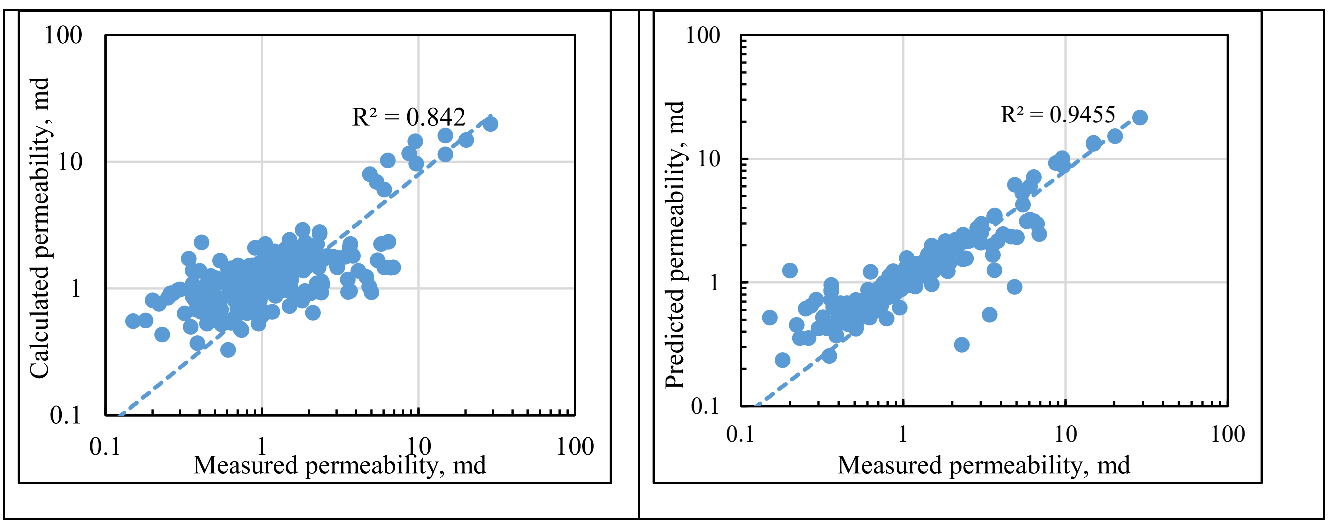


Figure 9: Calculated and predicted permeability vs measured permeability of the four wells

8 Conclusion

AI is being used more in exploration, development, production, reservoir engineering, and management planning to speed up decision-making, reduce cost, and save time. Supervised machine learning is popular for connecting complex non-linear datasets. This approach outperforms petroleum engineering approaches in prediction errors, computational power, and memory. Two significant rock qualities, porosity, and permeability are employed in estimations of oil, gas, and water resources. It is difficult to show the mathematical connection between permeability and porosity. There is no precise mathematical formula from which permeability may be determined relying on porosity due to the variety of rock qualities. This research utilizes one of the most popular artificial algorithms which is named Genetic Algorithm. The algorithm is used to predict and calculate the value of the porosity and permeability of the rock. The results revealed that the ANN approach is better than the mathematical approach. In finding the final solution based on all possible solutions that is produced in the search space, it consumes a high amount of time to find the optimal solution.

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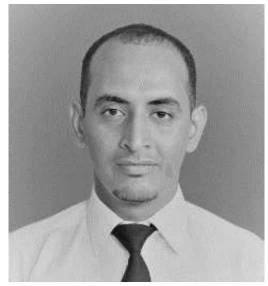

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