Journal Homepage: http://ijcpe.uobaghdad.edu.iq
Iraqi Journal of Chemical and Petroleum Engineering
Vol. 25 No. 4 (December 2024) 49 – 60
EISSN: 2618-0707, PISSN: 1997-4884

Reservoir permeability prediction based artificial intelligence techniques

Hayder Mahdi Ghargan [a], Omar Al-Fatlawi [a, b, *], Yasir Bashir [c]

a Department of Petroleum Engineering, College of Engineering, University of Baghdad, Baghdad, Iraq
b WASM: Minerals, Energy and Chemical Engineering, Curtin University, WA, Australia
c Department of Geophysical Engineering, Faculty of Mines, İstanbul Technical University, İstanbul, Turkey

Abstract

Predicting permeability is a cornerstone of petroleum reservoir engineering, playing a vital role in optimizing hydrocarbon recovery strategies. This paper explores the application of neural networks to predict permeability in oil reservoirs, underscoring their growing importance in addressing traditional prediction challenges. Conventional techniques often struggle with the complexities of subsurface conditions, making innovative approaches essential. Neural networks, with their ability to uncover complicated patterns within large datasets, emerge as a powerful alternative. The Quanti-Elan model was used in this study to combine several well logs for mineral volumes, porosity and water saturation estimation. This model goes beyond simply predicting lithology to provide a detailed quantification of primary minerals (e.g., calcite and dolomite) as well as secondary ones (e.g., shale and anhydrite). The results show important lithological contrast with the high-porosity layers correlating to possible reservoir areas. The richness of Quanti-Elan's interpretations goes beyond what log analysis alone can reveal. The methodology is described in-depth, discussing the approaches used to train neural networks (e.g., data processing, network architecture). A case study where output of neural network predictions of permeability in a particular oil well are compared with core measurements. The results indicate an exceptional closeness between predicted and actual values, further emphasizing the power of this approach. An extrapolated neural network model using lithology (dolomite and limestone) and porosity as input emphasizes the close match between predicted vs. observed carbonate reservoir permeability. This case study demonstrated the ability of neural networks to accurately characterize and predict permeability in complex carbonate systems. Therefore, the results confirmed that neural networks are a reliable and transformative technology tool for oil reservoirs management, which can help to make future predictive methodologies more efficient hydrocarbon recovery operations.

Keywords: Quanti-Elan; Artificial Neural Networks; Data-Driven Approach; Permeability.

Received on 26/01/2024, Received in Revised Form on 12/05/2024, Accepted on 12/05/2024, Published on 30/12/2024

https://doi.org/10.31699/IJCPE.2024.4.5

1- Introduction

The implication of reservoir characterization techniques lies in their ability to present sophisticated interpretations into the flow properties and storage capacity of petroleum reservoirs, specifically those that are heterogeneous carbonate reservoirs [1-3]. Permeability is regarded as an essential characteristic of reservoir rocks, signifying the capacity of the rock to allow fluids (including oil, gas, and water) to flow through its pore spaces. It is a critical factor. Permeability data is generally acquired via laboratory core analysis, performed on core plug dimensions of (1 in × 3 in) as well as sidewall core samples. However, predicting permeability in uncored units is considered essential, as most wells do not undergo the coring process. This is primarily due to the challenges encountered during the coring process and the increased costs involved [4].

Permeability is defined as a measure of the ease of fluid flow through pore spaces, and it is an inherently complicated petrophysical property to quantify accurately. It is considered to be an important petrophysical attribute as it plays a significant role in reservoir characterization, flow unit identification, design and development well completion, production strategies, estimation of ultimate recovery factor (EURF) and also for reservoir management [5]. Well tests and core data are the traditional means of establishing permeability [6, 7]. However, the availability of closely spaced core permeability data is often limited due to adverse borehole conditions and the high costs associated with coring. Additionally, well-test data are not effective in providing spatially continuous permeability estimations [6]. As one of the essential properties of a petroleum deposit, permeability may be evaluated both in the laboratory setting and in situ, using core samples or well-test data. Recognized as a primary parameter influencing well completion, production strategies, and reservoir management obtaining an accurate estimation of permeability is critical [8-10].

Several studies have explored permeability prediction based on well logs using artificial intelligence techniques.

*Corresponding Author: Email: Omar.Al-Fatlawi@coeng.uobaghdad.edu.iq

Multiple wireline logs are utilized, including gamma ray, bulk density, neutron porosity, sonic, resistivity, spontaneous potential, and various other logs [11]. Researchers suggest that artificial intelligence applications contribute to reducing costs, time, and effort in the oil and gas sector while minimizing technical errors by improving forecasting accuracy [12-15]. In the fields of gas and oil, the use of artificial intelligence software is recommended to optimize operations and enhance decision-making processes [16].

The primary objective of this paper is to utilize neural networks for permeability prediction in oil reservoirs. This involves examining the current state of the field, identifying key challenges associated with traditional permeability prediction methods, and demonstrating the potential of neural networks in addressing these challenges. The paper aims to offer a comprehensive understanding of the methods employed in training neural networks for permeability prediction and their effectiveness in practical applications.

2- Conventional methods for permeability prediction

In oil reservoirs, the prediction of permeability utilizes various conventional methods, each characterized by distinct methodologies. The Core Analysis Method is regarded as the most accurate technique, involving the extraction of core samples from the reservoir, with permeability determined through laboratory experiments. However, this is costly and time-intensive due to core drilling. An alternative is the Empirical Correlations Method, which estimates permeability using correlations with measurable well log properties such as porosity, water saturation, and clay content; however, it is limited in applicability to heterogeneous reservoirs [17]. Well Test Analysis approximates permeability by analyzing well test data, providing an average value for the tested zone [6]. Petrophysical Models integrate well log and core data to predict permeability using tools such as neural networks, regression models, and rock physics models[18]. Finally, Production Data Analysis derives permeability distribution by matching production data with reservoir simulators, which requires long-term data [19].

2.1. Challenges or limitations of conventional method of permeability prediction

Heterogeneity in subsurface rock formations poses an enormous project for traditional permeability prediction methods [20-22]. The complicated and diverse nature of subsurface geology is often not correctly captured via these techniques, which can cause an oversimplification and convey predictions that are not totally reliable. Additionally, conventional methods like core analysis normally require invasive and costly facts series, a technique which limits the accessibility of records and might not be realistic for all reservoirs, specifically the ones going through value or logistical [23-25].

The time-ingesting nature of obtaining, processing, and deciphering conventional data is recognized as another drawback. In the context of fast-paced drilling operations and reservoir management, it is frequently discovered that delays in acquiring estimates of permeability can result in extensive monetary losses. It is usually located that conventional techniques depend on simplifying assumptions approximately rock properties and conduct, which won't be applicable in every geological placing. This reliance can result in inaccuracies in permeability predictions. An excellent difficulty is the sensitivity of some techniques to the unique rock kinds within the reservoir. When the reservoir contains a number of rock sorts, its miles stated that traditional strategies can also face demanding situations in providing correct predictions. Additionally, the inability of conventional methods to effectively address the anisotropic nature of certain reservoirs, where permeability varies in different directions, is often highlighted [26].

The constraint of conventional methods is further compounded by a lack of real-time data. Primarily dependent on historical data, these methods face challenges in adapting to changing reservoir conditions as they occur, which in turn impedes the ability to make decisions and optimize processes in real-time [27].

3- Artificial neural network

An artificial neural network model is a versatile mathematical structure capable of describing intricate, non-linear relationships between input and output data sets. The design of ANN models draws loose inspiration from the biological nervous system. Within a neural network, numerous processing elements, termed neurons, work in parallel. Each neuron connects to others via links characterized by variable weights, which represent crucial information used by the network to address specific problems [16].

Essentially, there exist several types of ANNs based on their architecture, with two common categories being recurrent and feed-forward. Beyond architecture, three distinct learning paradigms have been developed, each catering to a specific abstract learning task. These paradigms encompass unsupervised, supervised, and reinforcement learning. In unsupervised learning, the ANN is exposed to data without the guidance of a teacher, commonly employed for data clustering and analysis. In supervised learning, data is presented alongside teacher information to establish associations between data and the teacher signal, frequently used for classification and function approximation. In reinforcement learning, data is usually not provided but is generated through an agent's interactions with its environment [28].

One of the most popular ANN architectures is the multilayered perception (MLP) usually trained using the Backpropagation (BP) set of rules. An MLP community accommodates an enter layer, one or more hidden layers of computational neurons, and an output layer. The quantity of enter and output neurons aligns with the amount of input and output variables. The willpower of the wide variety of hidden layers and neurons includes an ordeal-and-mistakes system, contingent upon the complexity of the problem handy. A visual representation of a three-layer MLP is provided in Fig. 1.

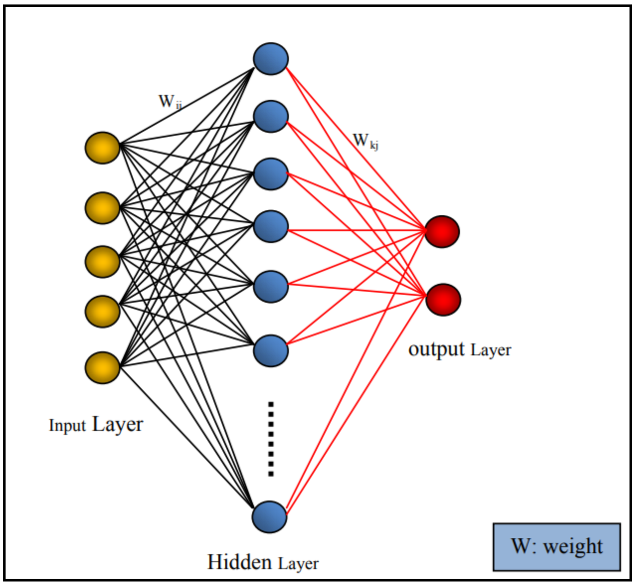

Fig. 1. A Simple multilayered perceptron with one hidden layer

Each neuron within a layer receives weighted inputs from the previous layer and transmits its output to the subsequent layer.it can be shown in Fig. 2. The calculation of the weighted input signal summation is accomplished using the following equation [28]:

$$y_{net} = \sum_{i=1}^{n} x_i w_i + w_b \tag{1}$$

The results from Equation 1 are transformed by a non-linear activation function given by the following:

$$y_{out} = f_{(net)} = (1 + e^{-y_{net}})^{-1} \tag{2}$$

This method can be used to calculate permeability in un-cored intervals which reduced costs. The responses of neural network system are compared with the target values through an error statistic namely mean square error given by:

$$\text{MSF}=\tfrac{1}{2}\sum_{i=1}^{n}(y_i^{obs} - y_i^{out}) \tag{3}$$

In the realm of Artificial Neural Networks (ANNs), often referred to as learning, the training process entails the input of sample vectors into a meticulously designed network. The error of the output layer is subsequently calculated by the network, and adjustments to the weights are made as necessary with the objective of minimizing this error. The training procedure is considered complete when the error of the network falls below a predetermined threshold.

Artificial Neural Networks [16] models leverage multiple inputs, such as mineral composition, porosity, and other logs, to predict permeability where core measurements are not available. Permeability is highly variable and depends on complex interactions between porosity, grain size, mineral content, and diagenetic features, which ANN can model effectively. Permeability affects fluid flow in subsurface formations, critical for hydrocarbon production and reservoir management. By using ANN, geologists can predict permeability at unsampled depths, enabling continuous reservoir characterization without extensive and costly core sampling. Core measurements are accurate but sparse and expensive. ANN models can fill in the gaps by providing continuous predictions, allowing for better reservoir modeling and simulation.

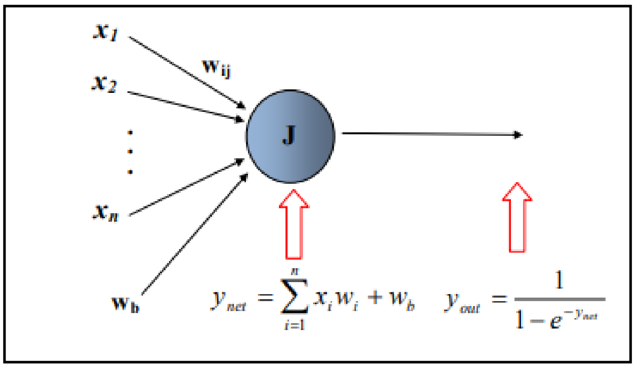

Fig. 2. The schematic representation of a neuron

In petroleum engineering, a significant emphasis has been placed on the prediction of permeability in oil reservoirs, with a particular focus on evaluating effective permeability. The realm of Artificial Intelligence has emerged as a crucial field in the last two decades, especially for modeling complex non-linear systems. Neural networks, an integral part of AI technology, have had a substantial impact in this area. These networks are inspired by the structural complexities of the human brain, notably in aspects related to perception, memory, and recognition [29]. Within the sphere of oil engineering and permeability prognosis, advancements have been made considerably through AI applications [30].

Different methodologies for predicting oil reservoir permeability had been explored by means of researchers in plenty of research, using a number of artificial intelligence and computational techniques. Valuable insights into the evaluation of permeability in diverse geological settings had been yielded by those investigations. Presented below is a summary of a few tremendous contributions in this field [31].

AI techniques, in conjunction with seismic statistics, had been done by Joonaki et al. To estimate oil reservoir permeability, focusing mainly on the characterization of reservoir residences based totally on seismic elastic properties.

Alfaaouri et al. employed a stochastic approach for estimating reservoir permeability, counting on a three-dimensional geological model and a -step modeling technique [32]. Helmi et al. Adopted a hybrid computational approach, integrating Support Vector Machine (SVM) and Fuzzy Logic (FL) to make unique predictions about oil reservoir permeability. SVM, grounded in the precept of structural risk minimization, has received prominence as a flexible device for data analysis and knowledge discovery [33]. Kaydani et al. delved into the prediction of oil reservoir permeability via a hybrid neural genetic algorithm, in particular focusing on heterogeneous reservoirs segmented into homogeneous components based totally on geological traits [34]. Gholami et al. additionally harnessed SVM for forecasting hydrocarbon reservoir permeability, demonstrating its efficiency in contrast to the General Regression Neural Network (GRNN) in phrases of both pace and accuracy [35]. Mohebbi et al. hired synthetic neural network methods for reservoir permeability estimation, with a focal point on segmenting the reservoir into homogeneous segments due to its inherent heterogeneity [36].

Ahmadi et al. Incorporated neural networks with hybrid genetic algorithms and particle swarm optimization to predict oil reservoir permeability, showcasing the ability of metaheuristic strategies like particle swarm optimization [16]. Rafik et al. Expected reservoir permeability by using leveraging nonparametric multivariate regression and neural networks, the use of properly logging information from an Algerian oil reservoir [37]. Yan et al. focused on estimating permeability in fractured carbonate reservoirs using micro-resistivity imaging logging. They applied an upscaling method to derive equations for calculating a variable parameter within the permeability version, with outcomes indicating the prevalence of their method over conventional permeability fashions, in particular in multiscale rock settings. This approach changed into effectively carried out in micro resistivity imaging logging interpretation [38].

Kaydani et al. predicted permeability in heterogeneous oil reservoirs with the use of a multi-gene genetic programming algorithm. Their method was compared with Adaptive Neuro-Fuzzy Inference System (ANFIS) and Genetic Programming (GP) fashions, highlighting the effectiveness of the Multi-Gene Genetic Programming (MGGP) version in permeability prediction, mainly for its low computational time. The MGGP version was also applied to generate an equation primarily based on well log and middle experimental records for predicting permeability in porous media [34].

Salman et al. focused on predicting permeability in a Mishrif reservoir in Iraq, utilizing various methods such as flow units and Artificial Neural Network analysis. The study cases show the effectiveness of the Flow Zone Indicator (FZI) method in predicting permeability compared to other conventional methods, providing valuable insights for reservoir characterization in carbonate reservoirs. The research contributes to enhancing permeability prediction accuracy in oil and gas reservoir management, production, and well-completion strategies [39].

These researches collectively underscore the diverse range of AI and computational procedures hired in the prediction of oil reservoir permeability, supplying treasured contributions to the field of petroleum engineering and reservoir characterization. The main benefits of neural network to predict permeability

Neural networks provide numerous advantages when used to expect permeability in geological and reservoir engineering packages [40, 41]:

a. Non-linearity: Neural networks can seize complicated, non-linear relationships among enter variables and permeability. This is mainly beneficial in geology and reservoir engineering, in which rock homes can exhibit problematic and non-linear interactions.
b. Data-Driven Approach: Neural networks can study from information, making them appropriate for instances wherein the underlying relationships between variables won't be well understood. They can adapt to the available facts and perceive patterns that may be tough to version using traditional strategies.
c. Feature Extraction: Neural networks can mechanically extract applicable features from the data, decreasing the desire for manual feature engineering. This is valuable in instances wherein the selection of informative features can be challenging [42].
d. Handling Large Datasets: Neural networks are capable of managing massive datasets, which can be common in reservoir engineering programs in which substantial proper statistics and geological facts are to be had.
e. Spatial Relationships: Convolutional neural networks (CNNs) may be used to analyze spatial relationships in geospatial statistics, allowing them to capture patterns in rock homes that are motivated by using region and neighboring data factors.
f. Anisotropy: Neural networks can be designed to account for anisotropy in permeability through directional, that is critical for correctly modeling reservoirs with anisotropic condition [43].
g. Real-Time Adaptation: With the availability of actual-time statistics, neural networks may be updated and pleasant-tuned to evolve to changing reservoir conditions and improve prediction accuracy through the years.
h. Integration of Multiple Data Types: Neural networks can seamlessly integrate special sorts of information, such as well logs, seismic facts, core samples, and geophysical measurements, to provide complete know-how of reservoir homes.
i. Reduced Assumptions: Neural networks can reduce the need for simplifying assumptions approximately the reservoir, making them extra adaptable to numerous geological settings.
j. Model Generalization: Well-trained neural networks can generalize well to unseen records, which is vital for making correct predictions in new geological environments or for new reservoirs.
k. Continuous Improvement: Neural networks can continuously examine and improve as more facts

become available, improving the accuracy of permeability predictions through the years.

l. Automation: Once trained, neural networks can automate the permeability prediction method, saving time and assets as compared to traditional techniques that require guide intervention.

4- Case study: permeability prediction of "Well-X"

In the oil and gas industry, the accurate prediction of permeability in hydrocarbon reservoirs is an essential undertaking, crucial for green useful resource exploitation and reservoir control. In this educational case study, we delve into the complex manner of permeability prediction for "Well-X," a representative well in an oil reservoir. This study employs advanced Artificial Neural Networks (ANNs) to predict permeability. It incorporates a multifaceted evaluation, protecting the significance of input parameters, the iterative education process, and a comprehensive assessment of the ANNs' predictive abilities in comparison to center permeability measurements.

4.1. The main benefits of neural network to predict permeability

The first section of the research centers on the selection and importance of input parameters. In our study, these parameters include the volume of limestone, the extent of dolomite, and effective porosity. These three elements are foundational to our reservoir characterization and permeability prediction model.

They represent the geological composition of the reservoir, reflecting the intricacies of lithological constituents and porosity, which determine the available pore space for fluid flow. By considering these specific input parameters, we can build a holistic understanding of the geological features influencing permeability within "Well-X". Each parameter uniquely contributes to the overall reservoir characterization, making the input data rich in geological information. Fig. 3 and Fig. 4 illustrate the input parameters and the extent of each, respectively.

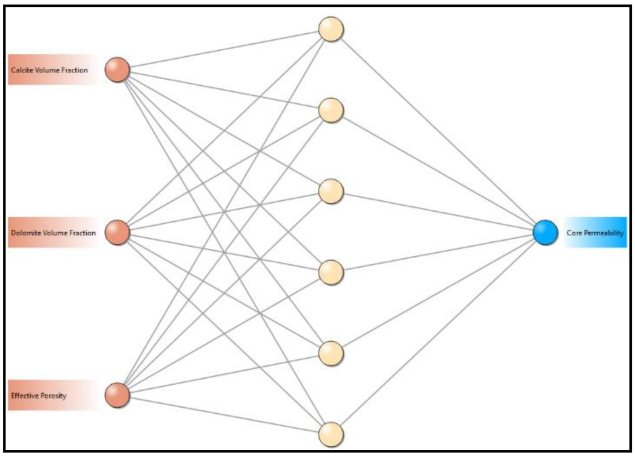

Fig. 3. Input parameters used for permeability prediction

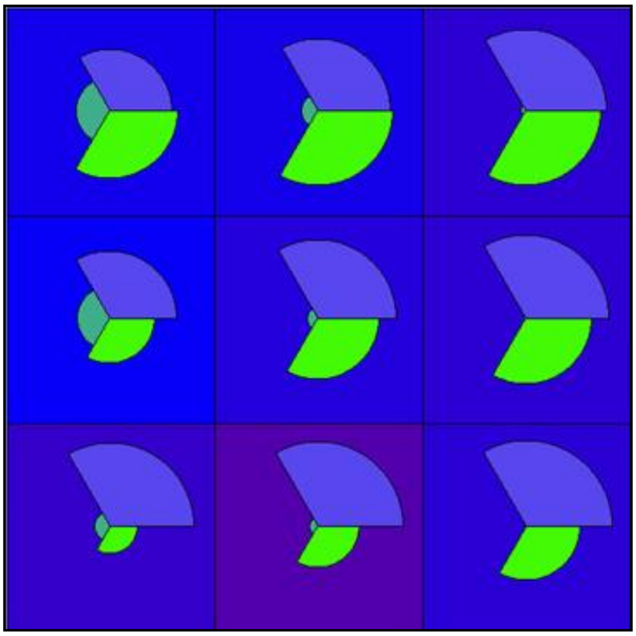

Fig. 4. The volume of input components

4.2. Convergence and training: fine-tuning the neural networks

The second size of the case looks at focuses on the education of the ANNs. Training ANNs involves a method of iterative learning and adjustment, driven with the aid of the minimization of prediction errors. To reap the most fulfilling predictive accuracy, ANNs require a couple of education attempts. This is performed by iteratively feeding the input parameters into the community, calculating the mistake within the expected permeability values compared to actual center records, and then adjusting the community's weights and parameters. The convergence error, which quantifies the disparity between expected and actual values, provides insight into the version's learning behavior.

Moreover, it informs us of the wide variety of training iterations necessary for the model to attain a fine degree of predictive accuracy. Observing the convergence dynamics at some stage in the schooling process is essential in knowledge of how well the ANN adapts to the precise traits of "Well-X". Fig. 5 illustrates Convergence and Training.

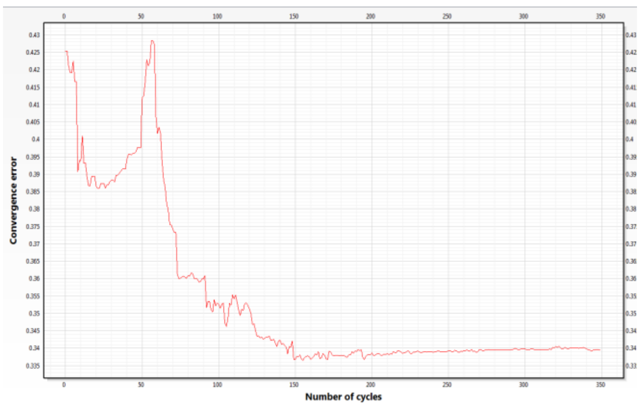

Fig. 5. Convergence and training

4.3. Comparative analysis: ANNs vs. core data - A robust benchmark

The third section of the case study presents a thorough comparative evaluation. The permeability predictions are evaluated against core permeability measurements obtained from “Well-X”. The fundamental data, regarded as ground truth and reliably reflecting the actual permeability characteristics of the well. This comparative analysis is essential for evaluating the accuracy and reliability of the ANN version by measuring it against this rigorous reference. Comparisons between the ANN predictions and this reliable reference yield strong conclusions regarding the robustness of the ANN model in replicating reservoir conditions. This confirms the predictive capability of ANN in estimating permeability, establishing its reliability for application in reservoir engineering programs.

Furthermore, the use of Artificial Neural Networks for permeability prediction, vital for robust reservoir characterization, is examined. The capability of ANNs to process complex geological statistics and generate accurate permeability estimations is compared with the core data from "Well-X", an extended-status benchmark within the petroleum industry. This evaluation assesses whether or not present-day computational strategies compete with or improve typical techniques in petroleum engineering. The reliance of petroleum engineers on center information, its acclaimed accuracy, and the ability paradigm shift initiated by means of ANNs in geological predictions are considered. The comprehensive methodology of comparative analysis includes:

a. Data Harmonization and Integrity: This involves the selection of data and preprocessing for each center and ANN data, which includes data cleaning, managing missing values, and detecting outliers. Normalization and standardization are essential for eliminating biases, ensuring that the representativeness and integrity of data is vital, particularly in relation to cross- validation involving diverse datasets or historical records.
b. Expanded Statistical Analysis: Regression analysis is conducted to establish the relationship between actual and predicted permeability values. Residual analysis is necessary to understand error patterns. Advanced statistical metrics, nonparametric tests, and sensitivity analysis are incorporated to assess the predictive accuracy of the ANN.
c. ANNs' Capacity to Replicate Core Data Trends: Advanced visualizations, including three-dimensional plots and Cumulative Distribution Functions, are employed to provide a comprehensive interpretation and visualize complex interactions and patterns.
d. Quanti-Elan application from Schlumberger’s Techlog software. Quanti-Elan is an application that optimizes simultaneous equations comprising multiple interpretation models. Log measurements and tool response parameters are used together in response equations to compute the volumetric results for formation components, including lithology, oil, gas and water saturations [44]. The program is one section of the three-way relationship among tools, response parameters, and formation components (Fig. 6).

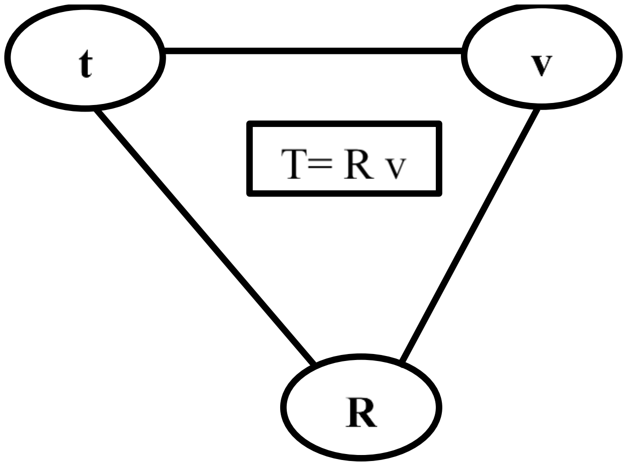

Fig. 6. Quanti-elan response parameters [44]

Where “t” represents the logging tool data, “v” represents formation component volumes, and “R” represents the response matrix (the expected tool readings given 100% presence of each specified formation component) (Eq.4).

$$v = \frac{t}{R} \quad (4)$$

For the purposes of this research, the inverse problem, where “t” and “R” are used to compute “v”, is employed to initially determine the volumes of components. For the Quanti-Elan model, the lithology components are calculated and used as input data. Fig. 7 illustrates a comprehensive multi-track well log that integrates various petrophysical measurements to evaluate the subsurface geology, porosity, resistivity, and fluid content, specifically within the Mishrif formation. Below is a detailed breakdown and discussion of the figure's components:

1. Track 1: Density (RHOB)
   - RHOB (Red curve): The bulk density curve measures the formation's density, reflecting its mineral composition and porosity. In Figure 7, RHOB varies from approximately 1.95 g/cm³ to 2.95 g/cm³, which suggests changing lithology (e.g., limestone, dolomite, or shales).
2. Track 2: Neutron Porosity (NPHI)
   - NPHI (Blue curve): Neutron porosity shows variations in hydrogen content. It reflects the porosity and type of fluids present (gas, oil, or water). Divergence between RHOB and NPHI curves indicates possible gas zones or lithology changes.
3. Track 3: Total Porosity (PHIT)
   - PHIT (Yellow curve): This represents total porosity derived from density and neutron logs. Zones with higher porosity indicate potential reservoirs, while low porosity suggests tight formations or non-reservoir lithology.

4. Track 4: Sonic Log (DT)
   - DT (Pink curve): The sonic travel time measures acoustic velocity through the rock. Lower DT values suggest denser rocks (e.g., limestone or dolomite), while higher values indicate porous or shaly formations.
5. Track 5: Resistivity Logs (Deep and Shallow)
   - Resistivity Logs (Green curves):
     - Deep resistivity (LLD): Reflects the formation's true resistivity, indicating fluid types.
     - Shallow resistivity (LLS): Represents invasion zones, where drilling mud affects the resistivity reading.
   - High resistivity zones (e.g., >200 ohm-m) often indicate hydrocarbons, while low resistivity (<10 ohm-m) suggests water saturation.
6. Lithology Model (Far Right Track)
   - This portion integrates the Quanti-Elan model, which combines log data to determine lithology and volumetric composition. The bar chart identifies lithology components (e.g., sandstone, limestone, dolomite, or shale).

Based on the Quanti-Elan model illustrated in Fig. 7, zones dominated by blue or green blocks may indicate carbonate rocks such as limestone or dolomite. Gray or darker tones suggest shale or argillaceous content. The identified Mishrif zone reflects a carbonate formation, commonly found in the Middle East, with variable porosity and hydrocarbon potential. Fig. 7 indicate that high porosity zones (PHIT > 0.2) coupled with high resistivity (e.g., >200 ohm-m) are likely hydrocarbon-bearing zones. Density and neutron crossover may indicate gas presence, especially where RHOB and NPHI curves separate significantly. Additionally, Fig. 7 shows that zones with low resistivity (e.g., <10 ohm-m) and high porosity are likely to contain water. High resistivity zones with moderate porosity suggest presence of hydrocarbons (oil or gas). Finally, Fig. 7 identifies depth intervals with favorable reservoir properties (e.g., high porosity, high resistivity), which should be further analyzed for hydrocarbon potential. Low DT values, high RHOB, and negligible NPHI suggest tight zones or non-reservoir rock.

Fig. 8 shows the permeability match between ANNs and core measurements. Figure 8 comprises four main tracks displaying key reservoir parameters: Mineralogy Tracks (Calcite_QE and Dolomite_QE), which indicate the volume fractions (v/v) of calcite and dolomite, reflecting the rock's mineralogical composition and its influence on porosity and permeability. Porosity (PHIE_D) represents the effective porosity (v/v) derived from well logs, denoting the fraction of the rock's volume capable of holding fluids, with higher porosity typically signifying better reservoir quality for fluid storage. Core Permeability and Predicted Permeability (PERM_C and ANN Prediction) compare core analysis-measured permeability (PERM_C) with predictions from Artificial Neural Networks (ANNs), providing insights into the rock's ability to allow fluid flow, a critical parameter for assessing reservoir performance and production potential. The ANN predictions (blue line) closely follow the trend of the core-measured permeability (red dots), demonstrating a good match. Some discrepancies are observed in certain zones, likely due to heterogeneity in rock properties or limitations in the input parameters to the ANN model. In regions with higher porosity (PHIE_D), permeability is generally higher. Zones dominated by calcite and dolomite (as seen in the first two tracks) exhibit varying effects on permeability, depending on their distribution and pore connectivity.

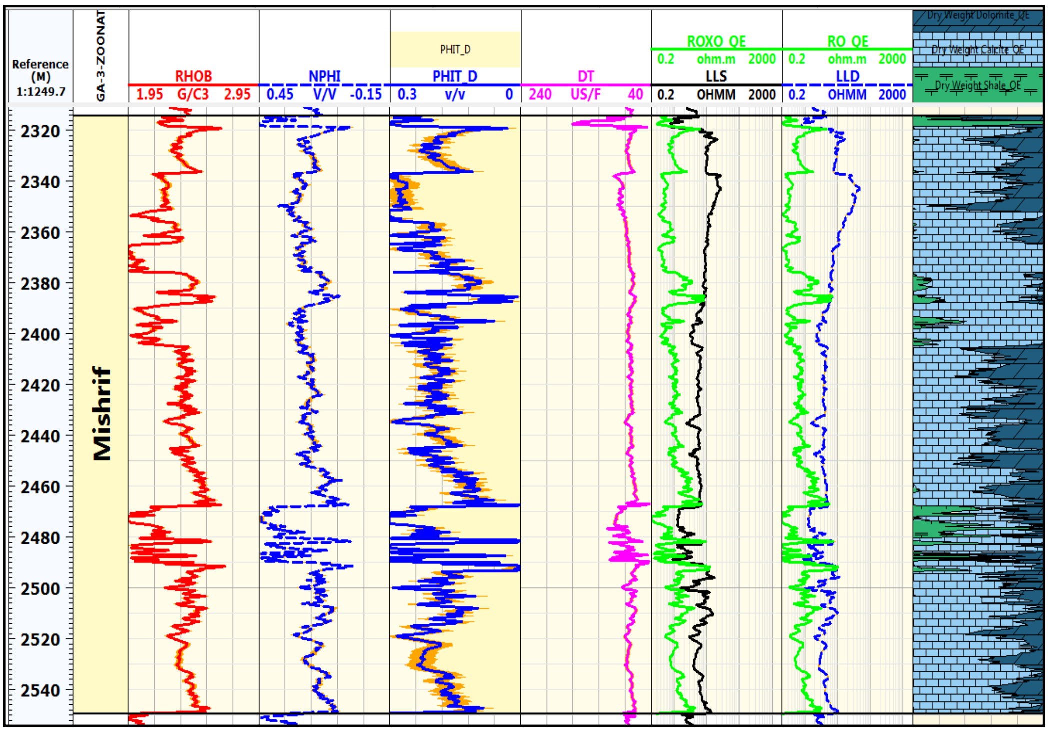

Fig. 7. Lithology by Quanti-Elan model

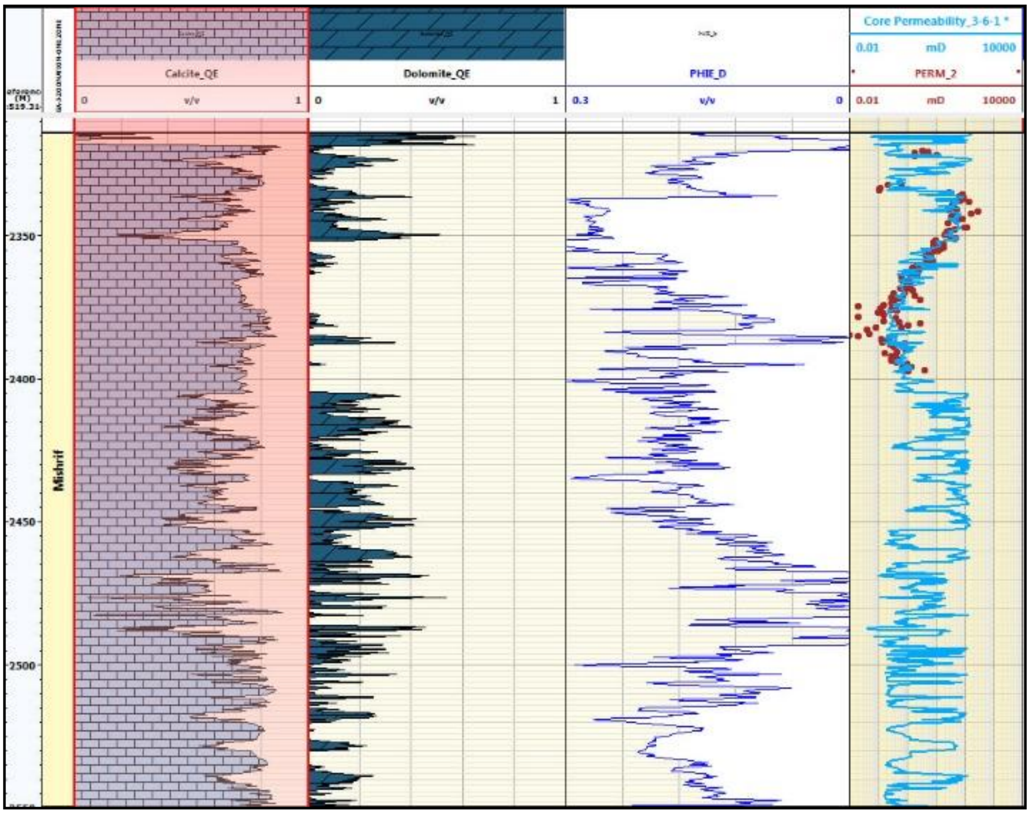

Fig. 8. Permeability match of ANNs vs. core

The ANN model demonstrates a strong predictive capability, capturing trends and magnitudes of permeability at different depths as shown in Figure 8. This highlights the robustness of the input data and the ANN's ability to generalize from training. Minor deviations may result from small-scale heterogeneities not captured by the input logs, limitations in the ANN model's training data, and measurement errors in the core data. The strong agreement between ANN predictions and core data implies confidence in using ANN results for permeability mapping. This data can be used to design production strategies, enhance recovery efficiency, and reduce costs associated with core sampling.

5- Conclusion

The Mishrif Formation is mainly composed of limestone with notable dolomite content and minor shale. Using the Quanti-Elan model, lithological variations were effectively outlined, revealing distinct reservoir zones. High-porosity zones were found to be heterogeneously distributed, aligning with areas of reservoir potential. These variations are attributed to diagenetic processes and facies distribution, which play a critical role in controlling reservoir quality and heterogeneity.

Hydrocarbons in some intervals are confirmed by integrating density, neutron and resistivity logs through the Quanti-Elan model. Many of these intervals demonstrate a relatively wide amount of high resistivity and porosity with clear density-neutron crossover signatures identified as potential hydrocarbon-bearing zones. On the other hand, high porosity with low resistivity is indicative of water saturation. It allows for identification of hydrocarbon zones and characterization of fluid distribution through this detailed integration of log data.

The Quanti-Elan model is proven to effectively assimilate complex logs while providing thorough lithology and fluid property interpretations. This allows for greater detail in the interpretation of formation properties than what can be accomplished by log analysis alone, thereby increasing the value of reservoir characterization from this model.

The use of artificial neural networks (ANNs) in this study further underscores their potential in predicting permeability across depths. The ANN model exhibited a strong correlation between predicted and actual permeability, replicating trends in core data even when such data were sparse or unavailable. With further optimization and robust training strategies, ANNs could become powerful tools in petroleum engineering, transforming reservoir management and improving hydrocarbon recovery operations through reliable and efficient predictive modeling.

Nomenclature

n	Number of examples (instants).
W_b	Bias
W_i	Weight associated with each neuron input
X_i	Neuron input
γ_{net}	The non-linear activation function
Y_{out}	Response of neural network system

y_i^{obs}	Observed values
y_i^{out}	Predicted values

References

[1] D. J. Sadeq, A. Almomen, H. H. Hamad, and U. Alameedy, "Exploring the Impact of Petrophysical Uncertainties on Recoverable Reserves: A Case Study," *The Iraqi Geological Journal*, vol. 57, no. 1C, pp. 47-61, 2024, https://doi.org/10.46717/igj.57.1C.4ms-2024-3-16

[2] Z. A. Hadi, O. F. Al-Fatlawi, and A. Kadkhodaie, "Estimation of the Petrophysical Properties of the Lower Cretaceous Yamama (YC) Formation in Siba Field," *Iraqi Journal of Chemical and Petroleum Engineering*, vol. 24, no. 4, pp. 47-57, 2023, https://doi.org/10.31699/IJCPE.2023.4.5

[3] S. A. Jassam, A.-F. Omer, and C. H. Canbaz, "Petrophysical Analysis Based on Well Logging Data for Tight Carbonate Reservoir: The SADI Formation Case in Halfaya Oil Field," *Iraqi Journal of Chemical and Petroleum Engineering*, vol. 24, no. 3, pp. 55-68, 2023, https://doi.org/10.31699/IJCPE.2023.3.6

[4] Z. Zhang, H. Zhang, J. Li, and Z. Cai, "Permeability and porosity prediction using logging data in a heterogeneous dolomite reservoir: An integrated approach," *Journal of Natural Gas Science and Engineering*, vol. 86, p. 103743, 2021, https://doi.org/10.1016/j.jngse.2020.103743

[5] O. F. Al-Fatlawi, "Numerical simulation for the reserve estimation and production optimization from tight gas reservoirs," PhD, WA School of Mines: Minerals, Energy and Chemical Engineering, Curtin University, 2018.

[6] M. M. Hossain, O. Al-Fatlawi, D. Brown, and M. Ajeel, "Numerical approach for the prediction of formation and hydraulic fracture properties considering elliptical flow regime in tight gas reservoirs," in *Offshore Technology Conference Asia*, 2018: OTC, p. D021S007R004, https://doi.org/10.4043/28418-MS

[7] D. Sadeq, S. Iglauer, M. Lebedev, T. Rahman, Y. Zhang, and A. Barifcani, "Experimental pore-scale analysis of carbon dioxide hydrate in sandstone via X-Ray micro-computed tomography," *International Journal of Greenhouse Gas Control*, vol. 79, pp. 73-82, 2018/12/01/ 2018, https//:doi.org/10.1016/j.ijggc.2018.10.006

[8] S. Sen *et al.*, "Petrophysical heterogeneity of the early Cretaceous Alamein dolomite reservoir from North Razzak oil field, Egypt integrating well logs, core measurements, and machine learning approach," *Fuel*, vol. 306, p. 121698, 2021, https://doi.org/10.1016/j.fuel.2021.121698

[9] H. M. Alrekabi and O. F. Al-Fatlawi, "Integrating Rock Typing and Petrophysical Evaluations to Enhance Reservoir Characterization for Mishrif Formation in Garraf Oil Field," *The Iraqi Geological Journal*, vol. 57, no. 1D, pp. 131-152, 2024, https://doi.org/10.46717/igj.57.1D.12ms-2024-4-22

[10] O. Al-Fatlawi, A. R. Vimal Roy, M. M. Hossain, and A. H. Kabir, "Optimization of Infill Drilling in Whicher Range Field in Australia," in *SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition*, Dammam, Saudi Arabia, 2017, vol. Day 3 Wed, April 26, 2017, D033S014R003, https://doi.org/10.2118/188085-MS

[11] M. H. Mahmood and D .J. Sadeq, "Study of petrophysical properties of a Yamama reservoir in Southern Iraqi oil field," in *AIP Conference Proceedings*, Pune, India, 2023, vol. 2839, no. 1: AIP Publishing, https://doi.org/10.1063/5.0167933

[12] M. AlJuboori, M. Hossain ,O. Al-Fatlawi, A. Kabir, and A. Radhi, "Numerical Simulation of Gas Lift Optimization Using Genetic Algorithm for a Middle East Oil Field: Feasibility Study," in *International Petroleum Technology Conference*, 2020, vol. Day 3 Wed, January 15, 2020, https://doi.org/10.2523/IPTC-20254-MS

[13] A. M. Ayal and D. J. Sadeq, "Prediction of Sand Production from Poorly Consolidated Formations Using Artificial Neural Network: A Case Study, Nahr Umr Formation in Subba Oil Field," *The Iraqi Geological Journal*, vol. 57, no. 2C, pp. 123-138, 2024, https://doi.org/10.46717/igj.57.2C.10ms-2024-9-18

[14] M. A. Al-Janabi, O. F. Al-Fatlawi, D. J. Sadiq, H. A. Mahmood, and M. A. Al-Juboori, "Numerical Simulation of Gas Lift Optimization Using Artificial Intelligence for a Middle Eastern Oil Field," in *Abu Dhabi International Petroleum Exhibition & Conference*, Abu Dhabi, UAE, 2021, vol. Day 2 Tue, November 16, 2021, D022S183R002, https://doi.org/10.2118/207341-MS

[15] M. A. Al-Janabi, H. A. Mahmood, O. F. Al-Fatlawi, D. J. Sadeq, Y. M. Al-Jumaah, and A. A. Essa, "Optimizing Gas Lift for Improved Oil Recovery in a Middle East Field: A Genetic Algorithm Approach," *Journal of Petroleum Research and Studies*, vol. 14, no. 3, pp. 52-74, 2024, https://doi.org/10.52716/jprs.v14i3.876

[16] M. A. Ahmadi, S. Zendehboudi, A. Lohi, A. Elkamel, and I. Chatzis, "Reservoir permeability prediction by neural networks combined with hybrid genetic algorithm and particle swarm optimization," *Geophysical Prospecting*, vol. 61, no. 3, pp. 582-598, 2013, https://doi.org/10.1111/j.1365-2478.2012.01080.x

[17] A. Esmailzadeh, S. Ahmadi, R. Rooki, and R. Mikaeil, "Oil reservoir permeability estimation from well logging data using statistical methods (A case study: South Pars Oil Reservoir)," *Civil Engineering Journal*, vol. 3, no. 10, pp. 831-840, 2017, https://doi.org/10.28991/cej-030918

[18] Y. Bashir *et al.*, "Cohesive approach for determining porosity and P-impedance in carbonate rocks using seismic attributes and inversion analysis," *Journal of Petroleum Exploration and Production Technology*, vol. 14, no. 5, pp. 1173-1187, 2024/05/01 2024, https://doi.org/10.1007/s13202-024-01767-x

[19] A. Tali, S. Abdulridha, L. Khamees, J. Humadi, G. Farman, and S. Naser, "Permeability estimation of Yamama formation in a Southern Iraqi oil field, case study," in *AIP Conference Proceedings*, 2023, vol. 2806, no. 1: AIP Publishing, https://doi.org/10.1063/5.0163281

[20] X. Bu, H. Saleh, M. Han, and A. AlSofi, "Permeability Prediction of Carbonate Cores With Gaussian Process Regression Model," in *SPE Reservoir Characterisation and Simulation Conference and Exhibition*, Abu Dhabi ,UAE, 2023: SPE, p. D011S001R002, https://doi.org/10.2118/212592-MS

[21] A. Sheykhinasab *et al.*, "Prediction of permeability of highly heterogeneous hydrocarbon reservoir from conventional petrophysical logs using optimized data-driven algorithms ",*Journal of Petroleum Exploration and Production Technology*, vol. 13, no. 2, pp. 661-689, 2023, https://doi.org/10.1007/s13202-022-01593-z

[22] L. Zhao *et al.*, "Modeling Permeability Using Advanced White-Box Machine Learning Technique: Application to a Heterogeneous Carbonate Reservoir," *ACS omega*, vol. 8, no. 25, pp. 22922-22933, 2023, https://doi.org/10.1021/acsomega.3c01927

[23] A. I. Al-Yasi and M. A. Jaed, "Using Computer Processing Interpretation (CPI) Technique to Evaluate Mishrif Formation in Garraf Oil Field, Southern Iraq," *Iraqi Journal of Science*, pp. 1469-1483, 2016.

[24] A. K. Neamah, A. J. Al-Khafaji, and F. N. Al-Sadooni, "Evaluation of Petrophysical Characteristics of Mishrif and Yamama Reservoirs, in Garraf Oil Field, Southern Iraq, Based on Well-Logging Interpretation," *Iraqi Journal of Science*, pp. 1115-1128, 2022, https://doi.org/10.24996/ijs.2022.63.3.19

[25] W. H. Al-Ateya, A. M. Handhal, and H. A .Hasan, "Well log interpretation and petrophysical modeling to evaluate Zubair Reservoir in North-Rumaila Oil Field," *The Iraqi Geological Journal*, pp. 208-219, 2022, https://doi.org/10.46717/igj.55.2A.15Ms-2022-07-31

[26] B. A. Al-Baldawi, "Evaluation of petrophysical properties using well logs of yamama Formation in abu amood oil field, southern Iraq," *The Iraqi Geological Journal*, vol. 54, no. 1E, pp. 67-77, 2021, https://doi.org/10.46717/igj.54.1E.6Ms-2021-05-27

[27] O. Salman, O. Al-Fatlawi, and S. Al-Jawad, "Reservoir characterization and rock typing of carbonate reservoir in the Southeast of Iraq," *The Iraqi Geological Journal*, pp. 221-237, 2023, https://doi.org/10.46717/igj.56.1A.17ms-2023-1-29

[28] A. Handhel, "Prediction of reservoir permeability from wire logs data using artificial neural networks," *Iraqi Journal of Science*, vol. 50, no. 1, pp. 67-74, 2009.

[29] K. Wang, B. He, and R. Chen, "Predicting parameters of nature oil reservoir using general regression neural network," in *2007 International Conference on Mechatronics and Automation*, 2007: IEEE, pp. 822-826, https://doi.org/10.1109/ICMA.2007.4303651

[30] E. Artun, S. D. Mohaghegh, J. Toro, T. Wilson, and A. Sanchez, "Reservoir characterization using intelligent seismic inversion," in *SPE Eastern Regional Meeting*, Morgantown, West Virginia, 2005: SPE, https://doi.org/10.2118/98012-MS

[31] E. Joonaki, S. Ghanaatian, and G. Zargar, "An intelligence approach for porosity and permeability prediction of oil reservoirs using seismic data," *International Journal of Computer Applications*, vol. 80, no. 8, 2013, https://doi.org/10.5120/13881-1778

[32] S. Alfaaouri, M. Riahi, N. Alizadeh, and M. Rezaei, "Permeability prediction in an oil reservoir and construction of 3D geological model by stochastic approaches," *Journal of Applied Sciences*, vol. 9, no. 11, pp. 2016-2030, 2009, https://doi.org/10.3923/jas.2009.2016.2030

[33] T. Helmy and A. Fatai, "Hybrid computational intelligence models for porosity and permeability prediction of petroleum reservoirs," *International Journal of Computational Intelligence and Applications*, vol. 9, no. 04, pp. 313-337, 2010, https://doi.org/10.1142/S1469026810002902

[34] H. Kaydani, A. Mohebbi, and A. Baghaie, "Permeability prediction based on reservoir zonation by a hybrid neural genetic algorithm in one of the Iranian heterogeneous oil reservoirs," *Journal of Petroleum Science and Engineering*, vol. 78, no. 2, pp. 497-504, 2011, https://doi.org/10.1016/j.petrol.2011.07.017

[35] R. Gholami, A. Shahraki, and M. Jamali Paghaleh, "Prediction of hydrocarbon reservoirs permeability using support vector machine," *Mathematical Problems in Engineering*, vol. 2012, no. 1 ,p. 670723, 2012, https://doi.org/10.1155/2012/670723

[36] A. Mohebbi, R. Kamalpour, K. Keyvanloo, and A. Sarrafi, "The prediction of permeability from well logging data based on reservoir zoning, using artificial neural networks in one of an Iranian heterogeneous oil reservoir," *Petroleum science and technology*, vol. 30, no. 19, pp. 1998-2007, 2012, https://doi.org/10.1080/10916466.2010.518187

[37] B. Rafik and B. Kamel, "Prediction of permeability and porosity from well log data using the nonparametric regression with multivariate analysis and neural network, Hassi R'Mel Field, Algeria," *Egyptian journal of petroleum*, vol. 26, no. 3, pp. 763-778, 2017, https://doi.org/10.1016/j.ejpe.2016.10.013

[38] W. Yan, J. Sun, K. Liu, L. Cui, and H. Dong, "Fractured Carbonate Reservoir Permeability Estimation by Microresistivity Imaging Logging," in *79th EAGE Conference and Exhibition 2017*, 2017, vol. 2017, no. 1: European Association of Geoscientists & Engineers, pp. 1-5, https://doi.org/10.3997/2214-4609.201701391

[39] O. Salman, O. F. Hasan, and S. Al-Jawad, "Permeability prediction in one of Iraqi carbonate reservoir using statistical, hydraulic flow units, and ANN methods," *Iraqi Journal of Chemical and Petroleum Engineering*, vol. 23 ,no. 4, pp. 17-24, 2022, https://doi.org/10.31699/IJCPE.2022.4.3

[40] B. Mathew Nkurlu, C. Shen, S. Asante-Okyere, A. K. Mulashani, J. Chungu, and L. Wang, "Prediction of permeability using group method of data handling (GMDH) neural network from well log data," *Energies*, vol. 13, no. 3, p. 551, 2020, https://doi.org/10.3390/en13030551

[41] T. M. Olson, "Porosity and permeability prediction in low-permeability gas reservoirs from well logs using neura networks," presented at the SPE Rocky Mountain Petroleum Technology Conference/Low-Permeability Reservoirs Symposium, Denver, Colorado, 1998, https://doi.org/10.2118/39964-MS

[42] S. Chen, Y. Zhao, and Y. Bie, "The prediction analysis of properties of recycled aggregate permeable concrete based on back-propagation neural network ",*Journal of Cleaner production*, vol. 276, p. 124187, 2020, https://doi.org/10.1016/j.jclepro.2020.124187

[43] P. Bagheripour, "Committee neural network model for rock permeability prediction," *Journal of Applied Geophysics*, vol. 104, pp. 142-148, 2014, https://doi.org/10.1016/j.jappgeo.2014.03.001

[44] A. M. Al-Heeti, O. F. Al-Fatlawi, and M. M. Hossain, "Evaluation of the Mishrif Formation Using an Advanced Method of Interpretation," *Iraqi Journal of Chemical and Petroleum Engineering*, vol. 24, no. 2, pp. 41-51, 06/30 2023, https://doi.org/10.31699/IJCPE.2023.2.5

التنبؤ بنفاذية المكمن باستخدام تقنيات الذكاء الاصطناعي

حيدر مهدي غركان [١] ، عمر الفتلاوي[١، ٢، *] ، ياسر بشير [٣]

١ قسم هندسة النفط، كلية الهندسة، جامعة بغداد، بغداد، العراق

٢ مدرسة غرب استراليا للمناجم، المعادن، الطاقة والهندسة الكيمياوية، جامعة كيرتن، استراليا

٣ قسم الهندسة الجيوفيزيائية، كلية المناجم، جامعة اسطنبول التقنية، اسطنبول، تركيا

الخلاصة

في هندسة المكامن، يعد التنبؤ بالنفاذية أمرًا بالغ الأهمية حيث يلعب دورًا محوريًا في تحسين استراتيجيات استخراج الهيدروكربونات. تتناول هذه الورقة البحثية استخدام الشبكات العصبية للتنبؤ بالنفاذية في خزانات النفط، مسلطة الضوء على تزايد أهميتها في هذا المجال. يوضح القسم الخلفي التحديات والتعقيدات المرتبطة بتقنيات التنبؤ التقليدية بالنفاذية، مؤكدًا على الحاجة إلى حلول مبتكرة. تُعرَّف الشبكات العصبية، بفضل قدرتها على استيعاب العلاقات المعقدة ضمن مجموعات بيانات كبيرة، كبديل واعد. يحدد القسم الخاص بالطرق بإيجاز التقنيات الرئيسية المستخدمة في تدريب الشبكات العصبية للتنبؤ بالنفاذية، ويشمل معالجة البيانات، وهندسة الشبكة، واستراتيجيات التدريب. تعرض مراجعتنا نتائج دراسة حالة حيث تم مقارنة تنبؤات الشبكة العصبية بالنفاذية لبئر نفط محدد مع قياسات اللباب، وكشفت عن تطابق ملحوظ بين القيم المتوقعة والفعلية. تمثل هذه التحليلات المقارنة إمكانات الشبكات العصبية في نمذجة والتنبؤ بالنفاذية بدقة، حتى في الحالات الجيولوجية المعقدة. في الختام، نلخص النتائج الرئيسية ونبرز قابلية الشبكات العصبية كأداة قوية للتنبؤ بالنفاذية، مؤكدين على إمكاناتها في إحداث ثورة في إدارة وتعزيز كفاءة عمليات استخراج الهيدروكربونات. تعتبر هذه الورقة البحثية بمثابة دليل شامل للباحثين والممارسين الذين يبحثون عن حلول مبتكرة للتنبؤ بالنفاذية في خزانات النفط.

الكلمات الدالة: التنبؤ بالنفاذية، الشبكات العصبية الاصطناعية، النهج المبني على البيانات، توصيف المكمن.

.