Permeability Prediction and Facies Distribution for Yamama Reservoir in Faihaa Oil Field: Role of Machine Learning and Cluster Analysis Approach

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Abstract
Empirical and statistical methodologies have been established to acquire accurate permeability identification and reservoir characterization, based on the rock type and reservoir performance. The identification of rock facies is usually done by either using core analysis to visually interpret lithofacies or indirectly based on well-log data. The use of well-log data for traditional facies prediction is characterized by uncertainties and can be time-consuming, particularly when working with large datasets. Thus, Machine Learning can be used to predict patterns more efficiently when applied to large data. Taking into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method. Taking time into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method. Taking into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method. Taking into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method. Taking into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method. Taking into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method. Taking into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method. Taking into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method. Taking into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method. Taking into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method. Taking into account the electrofacies distribution, this work was conducted to predict permeability for the four wells, FH1, FH2, FH3, and FH19 from the Yamama reservoir in the Faihaa Oil Field, southern Iraq. The framework includes: calculating permeability for uncored wells, using the classical method and FZI method.

Keywords: Permeability prediction; FZI method; Self-organizing map (SOM); Machine learning; Cluster analysis

1. Introduction
The permeability is the most significant rock property that influences the flow of fluids in a reservoir from the perspectives of reservoir engineering, reservoir management, and enhanced recovery schemes. It is vital to understand the geographical distribution of rock permeability throughout the reservoir (Saemi et al., 2007). In 1856, Darcy defined rock permeability as a property that determines how well the fluids pass through porous media, it is measured by Darcy (D) or millidarcy (md) (Hubbert, 1956). Knowledge of permeability distribution is essential for accurate reservoir characterization which depends on the ability to generate three-dimensional representations of reservoir petrophysical properties including shale volume, porosity, permeability, and saturation (Ali et al., 2021; Al-Mashhdani and Al-Zaidy, 2023; Al-Obaidi et al., 2019). Moreover, a reservoir’s permeability is crucial in defining many operations for the reservoir such as formation evaluation and reservoir quality processes that are used in oil field exploration, production, and development to decide whether a possible oil field is financially feasible (Debel et al., 2020). The pursuit of achieving unparalleled precision in permeability modeling has emerged as a paramount challenge within the domain of well-logging studies. It is a fundamental component of the dynamics of fluids and consequently reservoir simulation. The accuracy of permeability calculations is critical during reservoir development and production phases, as it directly impacts productivity estimation and facilitates a thorough examination of reservoir heterogeneity (Al-Mudhafar et al., 2021; Al-Obaidi and Al-Jawad, 2020). It is essential to accurately predict the permeability of uncored wells. However, for carbonate reservoirs, this task remains problematic due to

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the inherent heterogeneity. The carbonate reservoirs typically have lower homogeneity as compared with clastic reservoirs. Additionally, it is composed of limestone and dolomite with a broad spectrum of particle sizes (Lazim et al., 2018; Tali et al., 2023). Due to this heterogeneity and their propensity to be tight, resulting from depositional and digenetic processes, carbonate reservoirs present difficulties in terms of characterization (Alobaidi, 2016; Haghighi et al., 2011; Tawfeeq and Al-Sudani, 2020). There are numerous ways to predict permeability, however, the two most used direct methods are the Routine Core Analysis (RCA) and the Special Core Analysis (SCAL). Since not every well is cored, permeability can be determined by using well tests, and well logs. Predictions are typically made using porosities and other derived parameters from the well logs (Abdulateef et al., 2014). Kohon, 2001, used a neural network based on a Self-Organizing Map (SOM) which is an unsupervised learning model to perform the clustering analysis of wireline logs, that is applied in this work.

Yamama reservoir in the Faihaa Oil Field consists primarily of interbedded limestone, dolomite, and shale at particular depths (Handhal et al., 2019). Ahmed et al.(2020) classified Yamama as a diagenetic reservoir that is affected by dissolution and fractures, especially in the upper Yamama Formation. While cementation and compaction had devastating consequences on reservoir quality, particularly in the lower Yamama Formation (Ahmed et al., 2020).

The objective of this study is to present two ways for calculating permeability for four wells (FH1, FH2, FH3, and FH19) of the Faihaa oil field using porosity-permeability correlations established from core data of well FH2. The classical method FZI and the electrofacies method. The electrofacies in reservoir investigations are determined using clustering.

1.1. Geological Background of Faihaa Oil Field

Faihaa Oil Field is situated in the eastern portion of the Mesopotamian Zone within the Zubair Subzone (stable shelf) and located within the exploration area (Block-9) in southeastern Iraq, about 25 kilometers north of Basra city, near the Iraq-Iran border (Fig.1). Faihaa Field structure is about 20 km long and 8km wide and it is the west flank of the same anticline of the Yadavaran field, in Iran. The structural average dip is around 2.5° on Yamama. The Faihaa Oil Field is surrounded by several oil fields such as Majnoon from the north, Sindibad from the south, Nahr Umr, and the Iranian Yadavaran Field from the north and east, respectively (Fig.1). Twenty-six fields in southern Iraq alone have hydrocarbons in the carbonate reservoir of the Yamama Formation including the large fields such as Majnoon, Rumaila, and Qurna (Al-Ibrahim and Al-Ameri, 2015). Yamama Formation is one of the largest reservoirs in the southern portion of Iraq. It is a heterogeneous carbonate reservoir with a thickness of up to 400 m deposited throughout the Lower Cretaceous period during the major retrogressive depositional cycles (Berriasian-Aptian) (Al-Jawad et al., 2020; Chafeet et al., 2019; Kareem et al., 2021). It is conformably underlain by the Sulaiy Formation and overlaid by the Ratawi Formation (Fig.2).

bioclastic/coral/stromatoporoid packstone-wackestone, and an outside ramp cycle base made up of a thin bed of shale with a string of chalky micrite (Sadooni, 1993). Yamama Formation is divided into Yamama Upper and Yamama Lower. Yamama Upper appears to be located in a protected marine environment where the shoals and local formations provide suitable reservoirs, whereas Yamama Lower is distributed steadily across the surrounding areas, and the relatively poor reservoir characteristics indicate a deeper and more stable depositional situation (Fig.3).
2. Materials and Methods

The current study is based on data from four wells (FH1, FH2, FH3, and FH19) for Yamama Reservoir in Faihaa Oil Field supported by Basra Oil Company, which included well-FH2 core samples. There are many methods to predict permeability using cores, well tests, and logs which can supply permeability information. The least expensive way is to calculate permeability using well logs. Data from wireline logs can offer a continuous permeability profile over a given period. Various machine learning (ML) methods have been successfully used to classify facies in many different types of reservoirs to model facies distributions as a function of well-log data (Abbas and Al Lawe, 2019; Abbas et al., 2023; Abed and Hamd-Allah, 2019; Hamd-Allah et al., 2016; Yunjiang et al., 2018; Albuslimi et al., 2021; Ali et al., 2023; Al-Mudhafar, 2020; Al-Mudhafar and Wood, 2022; Al-Mudhafar et al., 2022; Hussain et al., 2022; Puskarczyk, 2020; Salman et al., 2023).

In this research, the Classical and the FZI methods are used to estimate the formation permeability for the Yamama reservoir in the Faihaa oilfield. After calculating the permeability, the application of SOM facilitated the establishment of Cluster analysis to make predictions regarding the number of electrofacies present in the reservoir. As well as the determination of permeability for each electrofacies is achieved by employing the appropriate correlation derived from the FZI method.
Fig. 2. Stratigraphic section and the major tectonic phases relevant to the Jurassic through the Tertiary Total Petroleum System (Al-Ameri et al., 2009)

1.2. The stratigraphy of Yamama Reservoir

Yamama Formation (Lower Cretaceous) is deposited in the oolitic shoal-inner shelf habitats and is primarily composed of limestone and some dolomitic limestone with shale (Al-Jawad et al., 2020). In southern Iraq, it consists of three significant depositional periods. The cycle tops are composed of oolitic grain stone, with an inner ramp descending into fine-grain peloidal facies, a middle ramp formed of
2.1. Classical Method

Permeability can be derived directly from porosity by using an empirical correlation between permeability and porosity derived from core data. The conventional form for the relationship between permeability and porosity is typically expressed from equation 1 as follows:

\[ \log(k) = a\phi + b \]  

(1)

Where

- \( k \): permeability (md)
- \( \phi \): porosity (%)
- \( a \) and \( b \) are coefficients to be fitted to the case study.

There is no rigorous theoretical support for the conventional cross-plot of the logarithms of permeability against porosity. The log-normal distribution of permeability is considered when plotting permeability versus porosity data. However, the correlation between two variables with normal distributions does not necessarily establish causality, as porosity, unlike permeability, is typically independent of particle size (Amaefule et al., 1993).

The available core data for one well which is Faihaa-2 is used in this study. Plotting between the core plug porosity values and the permeability on the logarithm scale for the Yamama reservoir is done as shown in Fig.4. They are subjected to linear regression, following equation 2:

\[ k = 0.0682e^{2.4\phi} \]  

(2)

The regression coefficient (R2) is found as 42.73%. The heterogeneity of rocks is responsible for this low (R2) coefficient percentage (Fig.4). Both high and low permeability zones with the same porosity values can exist in the same reservoir. The increase in permeability does not necessarily translate to an increase in porosity, and vice versa.
As a result, the reservoir exhibits random correlation. Therefore, the studied field is interested in the necessity to improve permeability estimation.

2.2. Flow Zone Indicator Method (FZI)

2.2.1. FZI background

Rock types with comparable flow capacities are grouped to identify reservoir flow units. Instead of focusing on the distribution of lithologies, the Hydraulic Flow Unit (HFU) idea differs from lithofacies in that it seeks to group similar fluid pathways in the reservoir (Abdulah et al., 2018).

This method is based on sensible geological parameters and the mechanics of flow at the pore scale, which are derived from the Flow Zone Index (FZI) and Rock Quality Index (RQI) calculations. The key concept is to classify data based on flow zone index values. It relies on the idea of a modified Kozeny–Carmen equation and the mean hydraulic radius notion. This method may organize conventional core data into groups based on rock type, yielding excellent permeability-porosity relationships. The FZI equations can be derived under the premise that a porous material can be represented as a network of capillaries. Equation 3 is a straightforward equation that links the porosity and permeability of materials using Darcy’s law and Poiseuille’s law of straight cylindrical tubes. Their main premises are that "the travel time of a fluid element in a capillary tube is equal to that in a reservoir" and "porosity is effective" (Amaefule et al., 1993).

\[ K = \frac{r^2}{8} \phi_e \]  

The aforementioned formula establishes a connection between the geometrical properties of pore size (radius) and pore shape. Kozeny and Carmen adjusted the preceding equation to take into consideration realistic porous media using a tortuosity factor and the mean hydraulic radius, yielding the generalized version seen in Equation 4.

\[ K = \frac{\phi_e^3}{(1 - \phi_e)^2} \frac{1}{F_S \tau^2 S_{go}} \]  

Where

- \( K \) : in \( \mu m^2 \)
- \( \phi_e \) : effective porosity, fraction
Fs : shape factor  
τ: tortuosity  
\(svg\): surface area/unit volume, \(L^2/L^3\)

Fs\(τ^2\): Kozeny constant, which varies between hydraulic units but is constant within a given unit.

Defining flow zone indicator FZI, which includes all major geological and geometrical characteristics of a porous medium as follows by applying the equations 5 to 11:

\[
FZI = \frac{1}{FS \tau^2 S_{gv}} \quad (5)
\]

So

\[
K = \frac{\phi_e^3}{(1 - \phi_e)^2} \frac{1}{FZI} \quad (6)
\]

Dividing both sides by porosity \((\phi_e)\) and taking the square root of both side results is:

\[
0.0314 \sqrt{\frac{K}{\phi_e}} = \frac{1}{1 - \phi_e} \frac{1}{FZI} \quad (7)
\]

Where the constant (0.0314) is the permeability conversion factor from \(\mu m^2\) to \(md\). Then the following parameter can be defined:

Reservoir quality index RQI as:

\[
RQI(\mu m) = 0.0314 \sqrt{\frac{K}{\phi_e}} \quad (8)
\]

And \(\phi_z\) can be normalized as following:

\[
\phi_z = \left[ \frac{1}{1 - \phi_e} \right] \quad (9)
\]

By simplified (FZI) in the following terms:

\[
FZI = \frac{RQI}{\phi_z} \quad (10)
\]

Substituting these variables into equation 5 and taking the logarithm of both sides results in using equation 11:

\[
\log RQI = \log \phi_z + \log FZI \quad (11)
\]

On a log-log plot of RQI versus \(z\), all samples with similar FZI values will lie on a straight line with a unit slope, and samples with the same FZI values that are substantially different from the preceding sample will lie on parallel lines with the same slope. This indicates that all rock samples with similar FZI values and pore throat characteristics comprise a single, straight flow unit. Consequently, the prevalence of distinct straight lines indicates distinct rock types. Each of these rock categories is denoted by its \(\phi_z = 1\) intercept (Al-Ajmi et al., 2000).

2.2.2. Permeability prediction by HFU

The porosity-permeability relationship of each HFU can be determined based on FZI values after the porosity data were normalized using Equation 9 and calculating RQI and FZI from core data using Equations 8 and 10. Fig.4 shows the HFU approach applied to Yamama Formation in the studied Faihaa Oil Field where five types of rocks or groups can be determined from core data depending on a particular value of FZI for each rock type. The values of mean FZI vary from 0.322 to 2.549 corresponding to the five flow units.
Fig. 4. Hydraulic flow unit for prediction using Intractive petrophysics (IP) software

Accordingly, the porosity-permeability relationships for each hydraulic flow unit of carbonate rocks were estimated by using core permeability (K core) versus core porosity (∅ core) on a log-log scale for a specific value of FZI for each group as shown in Fig. 5.

Fig. 5. Core porosity Vs. core permeability plot using IP (Intractive petrophysics) software

A comparison between core permeability and the permeability calculated by using the HFU method is made afterward. The outcome demonstrates good matching between the calculated and core permeability, indicating that the hydraulic flow unit is still an effective tool for predicting permeability on carbonate rocks as shown in Fig. 6.
2.3. Cluster Analysis

Cluster analysis is a multivariate technique that attempts to divide a sample of subjects measured on a particular variable into several groups in which subjects with similar characteristics are grouped. The objective of cluster analysis is to arrange data points into groups known as electrofacies by searching for similarities and differences between them in the multivariate space of logs (Cornish, 2007). According to the cluster analysis, Electrofacies are defined by the specific features of well-log data that represent minerals and lithofacies within the logged interval (Alameedy et al., 2023; Perez et al., 2005). Defining facies distribution based on well-log records has tremendous value as they represent the most accessible and broad dataset since engineers and geologists frequently experience difficulties linked to the lack of Core Data (La Croix et al., 2019).

The outcomes of the clustering method are affected by many factors such as the criteria of the clustering, the algorithm’s parameter settings, and other factors such as finalization criteria. This is since it is crucial to assess the clusters’ goodness of fit to the data's natural partitions without the aid of extra information. There are many types of clustering methods such as k-means, hierarchical clustering, density-based clustering, spectral clustering, nonparametric clustering, and Self-Organizing Maps, each method has its own set of benefits and drawbacks (Delgado et al., 2017).

In this study, a self-organizing map (SOM) neural network method is used to reduce the uncertainties and analyze the clustering. SOMs are unsupervised artificial neural networks that map the input space into topological structures whose organization is related to the input data's trends (Chang et al., 2002). SOM units, also known as neurons, construct maps with their nearby structures by connecting to them. These maps are usually hexagonal or rectangular in shape, as illustrated in Fig.7.

This cutting-edge map utilizes a highly adaptable grid system that seamlessly conforms to the inherent similarities within the data. According to this rationale, data near the entry space will exhibit a representation that is close to the exit space, thereby indicating its affiliation with either the same cluster or neighboring clusters. Because of this, SOM allows for the creation of a two-dimensional network that may be used as a visualization tool to display many characteristics of data, such as their possible clustering, by preserving the metric and topological links of entry space (Kuroda et al., 2012). The self-organizing map (SOM) can be described by Equation 12:

\[
W_{v+1}(s) = W_v(s) + \theta_{(u,v,s)} \cdot \alpha(s) \cdot [D(t) - W_v(s)]
\] (12)
Where
s : the current iteration.
t : the index of the target input data vector in the input data set.
D(t) : the vector of the target input data.
v : the node index in the map.
Wv (s) : the current weight vector of node v.
u : the best matching units (BMUs) index on the map (node in the SOM with the minimum aggregate distance to an input vector).
θ(u,v,s) : a restraint due to distance from BMU, usually called the neighborhood restraint.
α is a learning restraint on account of iteration progress.

Fig.7. Two grid configurations and neighborhood levels. (A) represents the hexagonal grid and (B) the rectangular grid (Kuroda et al., 2012)

The SOM methodology consists of two distinct components, namely mapping and training. The quantization is defined as the average distance between each data vector and its corresponding winning neuron that determines the map resolution. The training phase involves the initiation of the neuron square grid to facilitate the network's learning process. A weight vector with random values originally assigned to the weights represents each node and has the same dimension as the input vector. The network undergoes an iterative procedure wherein random input patterns are strategically introduced from the high-dimensional input space to the low-dimensional feature space (Pang, 2003).

3. Results and Discussions

3.1. Cluster Analysis Through the Self-Organizing Map (SOM)

The initial phase that pertains to a comprehensive and dispersed map was initiated as illustrated in Fig.8. The data from the wells used were effective porosity, water saturation, and clay volume.

The primary objective of SOM training is to achieve a state that aligns with a meticulously structured "topology conserving map" of the input space. This map shows all of the important facies characteristics of the input patterns in a way that is easy to understand. It is in a two-dimensional format. As the training commences, the neighborhood undergoes a significant expansion, prompting a
global initiation of the organizational process. As the training progresses, the radius of the neighborhood gradually decreases, and the weight update converges towards a smaller, more localized scale. Multiple nodes have the potential to function as the optimal matching unit for the patterns they are exposed to. The resultant map, which occurs after the training phase ends, seamlessly organizes itself in a topographical manner, thereby indicating the successful completion of network training. This signifies that the network is fully equipped to proficiently map all input data into the feature space of the SOM maps, as illustrated in Fig. 9.

**Fig. 8.** SOM results after the training phase

**Fig. 9.** Two-dimensional facies distribution and self-organizing maps after calibration and the color index demonstrating each log contribution

The findings of the self-organizing map (SOM) model reveal the presence of five distinct groups, as depicted in Fig. 9. The horizontal and vertical distribution functions are utilized to establish the facies description of the interpreted wells, with each type of facies being assigned a specific color code.
3.2. Cluster Analysis for Facies Distribution

The trained map is utilized as an input for the clustering process, which consists of two primary steps: In the initial stage, the entire number of nodes is partitioned into k clusters using the K-means algorithm. In the second stage, the k clusters are combined into 40 cluster groups by utilizing hierarchical clustering. The k-means statistical method is employed to assign input data to clusters by assuming an initial estimate of the mean value for each cluster of individual input log data and attempting to minimize the within-cluster variance. The hierarchical method involves the amalgamation of 40 clusters. This process entails calculating the interval between clusters and subsequently merging the two clusters that are closest in terms of this interval. The procedure is then repeated, with the interval being recalculated among the newly formed clusters and the two clusters that are closest in terms of this interval being merged. This iterative process continues until all clusters have been merged into a single cluster. The cluster randomness plot provides a straightforward means of assessing the relationship between the combination of clusters and the number of rock types by incorporating the random thickness of the plot. The computation of the average number of depth levels for each cluster allows for the evaluation of randomness, revealing the average thickness of the cluster layers. Subsequently, the theoretical mean random thickness is determined by assuming that the clusters are randomly distributed at each level of depth. The index of randomness quantifies the ratio between the average thickness of clusters and the mean thickness of randomly distributed clusters.

Yamama Formation randomness plot represents that five clusters can be dependent on types of rocks by gathering the number of the same peaks as represented in Fig. 10. The hierarchical clustering matrix for Yamama Formation is depicted in Fig. 11.

![Cluster Groups Randomness](image)

**Fig.10.** Cluster randomness plot analysis for Yamama Formation
Fig.11. Dendrogram grouping tree for Yamama Formation

With this approach, it would be a bit easier to see what the logs potential for grouping good or bad facies as shown in Fig.12.

Fig.12. Star plot for the electrofacies predicted by IP software

A cluster multi-curve cross plot of cluster analysis for studied wells is presented in Fig.13.
There may be a connection between the hydraulic flow unit and the five-rock types discovered by the cluster analysis technique employing facies star plot data illustrated in Fig.12.

Facies-1 (Yellow color): Represents the good reservoir quality rock properties, it is characterized by the lowest clay volume content with a mean value (about 0.153) with a relatively high porosity fraction with a mean value (0.09), and relatively low water saturation of a mean value about 0.426. This rock type represents the fourth hydraulic flow unit (HFU-4).

Facies-2 (Gray color): The rock qualities of this particular reservoir exhibit excellent quality, as seen by their low clay volume content, with an average value of approximately 0.265. Additionally, the rock displays high porosity, with a mean value of 0.154, and low water saturation, with a mean value of 0.276. The facies observed in this context are indicative of the fifth hydraulic flow unit (HFU-5).

Facies-3 (Pink color): This rock type represents very bad rock quality and corresponds to the non-reservoir units characterized by the high clay volume content of 0.587, low porosity of 0.006, and high water saturation of 0.979. This represents the first hydraulic flow unit (HFU-1).

Facies-4 (Green color): Represents the intermediate reservoir quality properties, it is characterized by clay volume content of 0.364, porosity of 0.056, and water saturation of 0.444. This represents the third hydraulic flow unit (HFU-3).

Facies-5 (Red color): This rock type represents the poor reservoir rock type units characterized by an average clay volume content of 0.214, porosity of 0.03, and water saturation of 0.929. And is defined as the second hydraulic flow unit (HFU-2).

The distributions of the SOM facies vertically in the zone of interest for the four wells (FH1, FH2, FH3, and FH19) for Yamama Reservoir in Faihaa Oil Field, used in this study are shown in Fig.14.
3.3. Facies and Permeability Upscaling

The initial phase of property modeling entails the strategic scaling up of petrophysical logs to meticulously structured grid-based model cells. Well-log upscaling is a process that entails utilizing algorithms to calculate the average value of each property, resulting in a precise assignment for every grid cell within a skeletal structure (Abd El-Gawad et al., 2019).

Various statistical techniques are commonly employed to do logarithmic scaling, depending on the nature of the data. These methods include arithmetic, harmonic, and geometric approaches, which are specifically tailored for continuous properties. Using different techniques and methods, the electrofacies and permeability logs were scaled up to cover the whole grid. For scaling up the discrete electrofacies data, the "Most of" method is used. For permeability log scaling up, the "Geometric" method was chosen as shown in Fig.15.
5. Conclusions

The significant heterogeneity of the Yamamam reservoir makes the established estimate of permeability correlation based on porosity ineffective only. Rocks with similar fluid-flow conductivity should be found and placed together to best accomplish the reservoir porosity permeability relationship. It was found that the FZI method’s prediction of permeability has the highest correlation coefficient (R² = 0.93) compared to the classical technique (R² = 0.42). Accordingly, FZI approach is a successful method for defining heterogeneous reservoir intervals for estimating permeability, especially in a carbonate environment with a high heterogeneity index such as the Yamamam reservoir. The utilization of a cluster analysis methodology has a significant impact on the assessment of major reservoir rock types. Additionally, establishing a connection between the electrofacies derived from this approach and the hydraulic flow units obtained through the FZI method gives a better understanding and more accurate results for permeability estimation. The Self-Organizing Map (SOM) is specifically intended to cluster the prominent confidential electrofacies of the reservoir. This approach demonstrates a high level of effectiveness in discerning the specific rock types of intricate geological structures. From this study, Yamama reservoir can be classified into five distinct electrofacies, each exhibiting varying levels of heterogeneity. Each group is known as a hydraulic flow unit.

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