Determining the petrophysical rock types utilizing the Fuzzy C-means Clustering technique and the concept of hydraulic flow units in the Asmari Formation, SW Iran

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Research Article

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Highlights:

Bullet Points

- A *flow unit* is defined as a reservoir zone with lateral continuity between wells and internally consistent characteristics that control fluid flow and are distinct from those of adjacent flow units.
- Utilizing hydraulic flow units (HFUs) in the reservoir rock and identifying areas with suitable reservoir quality could examine the distribution of porosity and permeability variables.
- Declustering and partitioning algorithms deal with hydraulic flow unit identification.
- Fuzzy logic applies constrained clustering approaches with different must-link hard constraints.
- The fuzzy c-mean method not improved the relationship between the petrophysical parameters of the reservoir in all hydraulic flow units and caused a decrease in the relationship between porosity and permeability.

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Abstract

Rock types are the reservoir's most essential properties and show special facies with a defined range of porosity and permeability. This study used the fuzzy c-means clustering technique to identify rock types in 280 core samples from one of the wells drilled in the Asmari reservoir in the Mansouri field, SW Iran. Four hydraulic flow units were determined for studied data after classifying the flow zone index with histogram analysis, normal probability analysis, and the sum of square error methods. Then the two methods of flow zone index and fuzzy c-means clustering were used to determine the rock types in given wells according to the results obtained from the implementation of these two methods in-depth, and continuity index acts, the fuzzy c-means methods with continuity number 3.12 compared to flow zone index with continuity number 2.77 shows more continuity in depth. The relationship between porosity and permeability improved using hydraulic flow unit techniques significantly. In this study, the correlation coefficient between porosity and permeability improves and increases in each hydraulic flow unit using the flow zone index method. So that in the general case, all samples increased from 0.55 to 0.81 in the first hydraulic flow unit and finally 0.94 in the fourth hydraulic flow unit. The samples were characterized by similar flow properties in a hydraulic flow unit. In comparison, the correlation coefficient is obtained less than the general case in the fuzzy c-means method in all hydraulic flow units.

Keywords
Asmari reservoir, Mansouri field, Hydraulic flow units, Rock types, Flow zone index, Fuzzy c-means

Abbreviations
ANN: Artificial Neural Network
COUCSI: Spontaneous absorption
FCM: Fuzzy c-means
FZI: Flow zone index
HFU: hydraulic flow unit
Jm: Evaluation function
RQI: Reservoir Quality Index
SCAL: Specific Core Analysis
SSE: Sum of square errors

1. Introduction

The term "*rock type classification*" was first coined by Archie (1942) and later used by many scholars and engineers. Archie first defined the classification of rock types as units of rock formed under the same sedimentary conditions. He experienced comparable diagenesis leading to a relationship between porosity-permeability and unique capillary pressure curves (Bezdek, 1981; Serra, 1984; Serra and Abbott, 1982; Wolf and Pelissier-Combescure, 1982). Hydraulic flow units (HFUs) is referred to as lateral continuity of reservoir units with consistent geological properties controlling the behavior of fluid flow in pores media (Amaefule et al., 1993; Gualda and Vlach, 2007; Kadkhodaie-Ilkhchi et al.,

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2013). Amaefule et al. (1993) defined the concept of a hydraulic flow unit (HFU) as a method for estimating permeability in a reservoir and non-reservoir zones. Gomes et al. (2008) emphasized the importance of the main facies, sedimentary environments, the process of later diagenesis, and the relationship between rock and fluid by Specific Core Analysis (SCAL) to establish relationships between geological facies, petrophysical groups, and rock classification. Their proposed method of classifying carbonate rocks solved some industrial problems and differences between geological facies and petrophysical groups (Hosseini et al., 2023a; Kianoush et al., 2022a; Kolbikova et al., 2021; Kumar et al., 2023; Tavakkoli and Amini, 2006; Yokeley et al., 2021). Kharrat et al. (2009)Kharrat et al. (2009) used ANNs and geostatistical data to model hydraulic flow units to estimate permeability and rock classification. The permeability obtained by the ANN method logically followed the changes in the properties measured by the logs where the reservoir was unavailable. Hollis et al. (2010) used the characterization of the cavity system in heterogeneous carbonates as an alternative approach to the well-known methods used to determine rock groups. The results show that the pore heterogeneity properties are critical for predicting flow behavior under reservoir conditions, and standard petrophysical parameters often need to be sound indicators. Permadi et al. (2011) conducted experiments on two models of carbonate and sandstone with different wettability. They conclude that there is a robust relationship between the microscopic geology and the geometry of the porous space, which are the layers of the rock classification.

Chandra et al. (2015) effectively integrated reservoir rock clusters and simulations using well drilling. Using rock bands determination and well drilling, the X field reservoir simulation model was improved, and therefore the accuracy of in situ fluid computation was also improved (Hosseini et al., 2023b; Hosseini et al., 2023c; Hosseinzadeh et al., 2023; Konaté et al., 2021; Valinasab et al., 2023; Yan et al., 2023). Ghadami et al. (2015) Studied Trojan-porosity modeling, the determination of reservoir rock groups, and the unification of hydraulic flow in a large carbonate reservoir. In this study, the formation was carried out using the concept of sequential stratigraphy, and the layering was divided into hydraulic flow units (HFU). In 2016, rock groups of rigid gas sandstone were determined: a case study in the Lance Formations and the Massif from the Yunus field. Four major rock groups were identified based on the particle size distribution data (Aliyev et al., 2016; Ghadami et al., 2015)

Mirzaei-Paiaman and Saboorian-Jooybari (2016) proposed a spontaneous adsorption-based method for characterizing pore structure and its application in pre-SCAL sample selection and rock group determination. They used the flow zone index (FZI) for spontaneous absorption (COUCSI). Moradi et al. (2017) identified rock groups using geological and petrophysical data in the Asmari reservoir, located in Aghajari oilfield, SW Iran. They quantified five electrophysiological counts using petrophysical logs (EF1-EF5). The best electrophysics in the Asmari reservoir of the Aghajari oil field was determined due to high porosity, permeability and RQI, and low water saturation percentage. Using data mining techniques, Gonçalves et al. (2017) predicted carbonate rock groups from NMR responses. Their experiments show that combining pre-processed strategies with classification algorithms can increase prediction accuracy to 97.4%.

Mahjour et al. (2016) used three methods of Testerman statistical zonation, flow zone index (FZI), and cluster analysis to identify flow units and estimate average porosity and permeability in the Tabnaak gas field in southern Iran. Compilation of core porosity and permeability are used to identify these units. Yasmaniar et al. (2018) utilized Artificial Neural Network (ANN) to determine the permeability of different Rock Type Using the Hydraulic Flow Unit Concept (Ding et al., 2022; Kharrat et al., 2009; Kianoush et al., 2023c; Mahadasu and Singh, 2022; Masroor et al., 2023; Rafik and Kamel, 2017). Oliveira et al. (2020) demonstrated that an inter-clustering process is recommended when selecting data points associated with representative volumes and local spots characterizing HFUs. In 2020, rock type and hydraulic flow units were used as a successful tool for reservoir characterization of the Bentiu-Abu Gabra sequence, Muglad basin, SW Sudan (El Sawy et al., 2020; Shalaby, 2021; Shoghi et al., 2020; Wu et al., 2020). Machine learning is effectively used by Man et al. (2021) to boost the prediction of permeability and reduces uncertainty in reservoir modeling. Recently, a variety of conventional methods and machine learning algorithms were investigated in determining hydraulic flow units (HFUs), and the performance of each method was evaluated (Fernandes et al., 2023a; Forbes Inskip et al., 2020; Kianoush et al., 2022b, 2023c; Kianoush et al., 2023a; Masroor et al., 2023; mohammadinia et al., 2023; Shi et al., 2023; Yu et al., 2023). Salavati et al. (2023) used hydraulic flow units, multi-resolution graph-based clustering, and fuzzy c-mean clustering methods to determine rock types. Al-Ismael and Awotunde (2023) used differential evolution optimization and two-stage clustering techniques to identify HFUs to support a critical process in reservoir characterization.

Finally, a novel approach has been done for estimating pore size distribution and capillary pressure in the hydrocarbon zone through a hydraulic flow unit framework using an NMR log. The workflow establishes a robust and cost-effective methodology for NMR T2 distribution correction in hydrocarbon zone for uncored and partially cored wells (Baykin et al., 2023; Fernandes et al., 2023a; Fernandes et al., 2023b; Jehanzaib et al., 2023; Kadkhodaie, 2021; Kianoush, 2023; Lai et al., 2023; Osinowo et al., 2023; Wang and Weijermars, 2023; Wang et al., 2023; Zhang et al., 2023b) (Abraham-A et al., 2023; Duda et al., 2012; Yu et al., 2023; Zhang et al., 2023a; Zhang et al., 2023b; Zheng et al., 2023).

The fuzzy c-means (FCM) method is an efficient tool for solving fuzzy clustering problems. The FCM clustering is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data point's membership value. This algorithm moves objects between clusters until the objective function cannot be decreased further. The result is a set of clusters that are as compact and well-separated as possible. The nature of FCM algorithm is to apply the gradient descent method to find out optimal solution, so there is a local optimization problem and the algorithm convergence speed is greatly influenced by the initial value. Evolutionary optimization methods are effective global optimization algorithm.

The FCM approach uses a fuzzy membership which assigns a degree of membership for every class. The importance of degree of membership in fuzzy clustering is similar to the pixel probability in a mixture. FCM algorithm always converges. However, unfortunately, in most cases, this convergence does not lead to the general minimum and stops at the first local minimum. For this reason, the FCM algorithm is sensitive to the selection of initial values, and therefore a random selection of initial values leads to unfavorable performance of the algorithm (Bezdek, 1981; Hosseini et al., 2023a; Jafarzadeh et al., 2019; Kadkhodaie and Amini, 2008; Kadkhodaie et al., 2006; Majdi and Beiki, 2019; Shakiba et al., 2015).

The general purpose of conducting this study is to determine the final model of reservoir modeling and sedimentary environment for the Asmari reservoir in the Mansouri field, utilizing techniques to identify rock typing, flow units, and electrofacies. It has been carried out in two stages. This manuscript is the result of the first part of the studies. In this study, to confine the number of hydraulic flow units of reservoir samples is first prepared. Then their porosity and permeability are determined by measuring devices. The flow zone index (FZI) is calculated for each sample. After determining the FZI of each sample using MATLAB software, the flow zone index logarithmic data is performed, histogram analysis is performed, and the number of hydraulic flow units is determined based on the normal distributions.

Given that these two patterns are user-friendly (depending on the number and experience of the user), there is a heightened likelihood of error in computation. The squared sum parameter to determine the number of hydraulic flow units was used to reduce the errors. The method first assumes the number of batches equal to 1 (HFU = 1) using the sum of squares of errors. It performs cluster analysis of the mean K data by MATLAB software, then linear regression analysis. On the data and calculate the sum of the squares of the errors.

The same for the number of other batches has been done, and finally, the sum of the squares of errors against the number of batches has been plotted. In these graphs, the changes in the sum of the squares of errors are not perceptible from one value to the next and can be neglected. It was the optimal number of hydraulic flow units. Hydraulic flow units were made on 280 core samples obtained from one of the drilled wells in the Mansouri field, including permeability, porosity, and formation information.

This research aims to determine the porosity and permeability parameters as essential factors for rock typing. Thus, any cluster produced during the clustering process represents a rock group. In the clustering process, each rock group will have its own characteristics of minimum, maximum, mean, median, standard deviation, and amplitude of its porosity and permeability variations, separating it from other groups. In addition, as a novelty, in cross-porosity versus permeability plates, each group is well separated from the other groups, and there is no overlap. In this case, as the first time in the Asmari Formation of the Mansouri oilfield, integrating the Fuzzu C-means and hydraulic flow unit, each rock represents a facies with a specific range of porosity and permeability. In this research, as a new approach, it has been tried to use clustering (unobserved) methods to determine the number of rock groups. The results showed that the fuzzy c-mean method not enhanced the relationship between the petrophysical parameters of the reservoir in all hydraulic flow units and caused a decrease in the relationship between porosity and permeability.

2. Geological Setting

2.1. Loaction and Structural Geology of study field

Carbonate sediments of the middle-late Cretaceous (the upper Albian, Cenomanian, Turonian, and Santonian stages), known as the Bangestan reservoir (Ilam and Sarvak formations), are among the giant oilfields in the Zagros Basin, which contain a sizeable prolific hydrocarbon reservoir. Mansouri field in the southernmost part of the north Dezful zone, about 45 kilometers south of Ahwaz, is located approximately on the border of the Arabian plateau, and quaternary alluviums represent the Zagros plateau and its surface outcrop (Fig. 1). Mansouri field is located in the north of the Ahwaz field, in the west, in the vicinity of the Abteymur and Susangerd fields, and in the northeast of the Shadegan field. The axial trend of this field is from the northwest to the southeast (the general Zagros trend) and lies between ˚48 to ˚52 east longitude and ˚30 to ˚32 north latitude (Fig. 2). Mansouri field is located in a flat zone just off the foot of the foothills and was discovered by seismic exploration in 1963. Based on the seismic and structural maps of the Mansouri field, it is an anticline with gentle and low slopes in the northwest-southeast (NW-SE) direction. The northern slopes are slightly higher than the southern slopes, respectively (AbdollahieFard et al., 2019; Motiei, 1995; Varkouhi and Wells, 2020).

Furthermore, 5-6 degrees, the slope of the eastern and western slopes is about 1-5 degrees. The study of geophysical maps and the information on drilled wells show no evidence of fault or disruption in the field, and it is generally mild in structure (Fig. 1). Mansouri's field in the horizons of Asmari is about 42 kilometers long. It has a variable width of up to 6 kilometers in the middle of the field and an average of 4.5 kilometers, which decreases to the east and west slopes. The dimensions of the reservoir at the contact surface of water and oil (2272 m below sea level) are 30 km long and 3.5 km wide, stretching northwest-southeast (Aleali et al., 2013; Hosseini et al., 2023a; Kianoush et al., 2023b; Kianoush et al., 2023a; Michael and Gupta, 2022; NISCO, 2022; Sabouhi et al., 2023).

In addition to the Asmari reservoir and sandstone section of Ahwaz, the Bangestan reservoir (Ilam and Sarvak Formations) are also present in this field (AbdollahieFard et al., 2019; Motiei, 1995; Talaie et al., 2023; Tavakkoli and Amini, 2006).

Factors influencing reservoir characterizations are sedimentary environments, microfacies, diagenetic processes, and tectonic activities. Kadkhodaie and Kadkhodaie (2018) and Kiaei et al. (2015) explored that sedimentary environments and microfacies control the mineralogy and porosity of formations. Although the microfacies study helps extend researchers' knowledge about the origin and history of carbonate reservoirs, there has yet to be a detailed investigation of the seismic stratigraphy on the reservoir properties. Also, integrating the microfacies and geochemical data can help petroleum engineers and geoscientists better understand reservoir characterizations (Flügel, 2010; Kadkhodaie-Ilkhchi et al., 2013; Kadkhodaie and Kadkhodaie, 2018; Kiaei et al., 2015). Fig. 4 shows the chronostratigraphic framework of the sediments equivalent to the Bangestan reservoir (the upper Albian to Santonian) in the Zagros Basin and the Arabian Plate.

From petrographic studies of thin sections and core data, the Sarvak Formation consists of shallowing facies of rudist biostrome, back shoal, shoal, lagoon, and flat tidal facies. Also, the Ilam Formation represents open- and deep-marine facies. The Sarvak and Ilam Formations show evidence of an internal carbonate platform with an interior shelf and a carbonate ramp, respectively (Abraham-A et al., 2023; Forbes Inskip et al., 2020; Kianoush et al., 2023d; Kianoush et al., 2023a; Varkouhi and Wells, 2020).

2.2. Stratigraphy of the Asmari Formation

In the sequence of oil/gas wells, zoning is one procedure that segregates the sequence studied into zones with common conditions (geological or reservoir conditions, etc.). This section used log data to accurately represent the Asmari Formation in the Mansouri Field. The lithology was evaluated and estimated in each sequence using corrected and edited logs and lithology cross-sections (neutron-density, Rho-U plot, MID plot, and MN plot). Finally, using the probabilistic method, the petrophysical parameters were calculated in the whole sequence, and the average of these parameters was calculated in the whole well and each zone. The shear boundaries for the carbonate and sandstone sequences of the Asmari Formation are presented in Table 1. Zones with typical reservoir geology (lithology) were studied in the well sequences using read logs (Fig. 3). The Asmari Formation has been divided into five zones based on petrophysical results.

Zone 1 (3538.5-3472.5 m): This zone exists in all drilled wells. The central part of the zone consists of dolomite plus a thick layer of limestone. Limestones are mostly cream to light brown and cream to gray, semi-hard to hard, fine-grained, micro-crystalline with anhydrite, chert, mudstone argillic to packstone.
Zone 2 (3582.5-3538.5 m): This zone is present in all wells. The lithology of this zone mainly consists of dolomite and sandstone.
Zone 3 (3605-3582.5 m): Its dominant lithology includes shale, limestone, and sandstone.
Zone 4 (3715-3605 m): This zone exists in all wells, and most of it contains a barrier/ beach ridge and is likely to be associated with the Ahwaz sand dunes. Much of the lithology of this zone is sandstone and shale.
Zone 5 (3772-3715 m): This zone cannot be identified in all wells due to a lack of logging data. The main lithologies in this zone are shale, sandstone, and limestone.

3. Methodology

In this study, 280 core samples (obtained from one of the wells of Mansouri Field) were selected to determine hydraulic flow units. Furthermore, information on permeability, porosity, and structural properties was recorded. General flowchart of this study is presented in Fig. 4.

3.1. The relationship between porosity and permeability

Matrix permeability is related to porosity and the specific surface of rocks, as expressed by the Kozeny (1927) equation (Eq. (1)):

$$K = \frac{0.101\varphi^3 S^2}{r_i - \varphi^2 V} \tag{1}$$

Where K: matrix permeability (mD); φ: matrix porosity (%); S/V: specific surface of pores in rocks (cm^2/cm^3);
r_i: constitutional factor, dimensionless, related to pore geometry and fluid flowing path per length in the porous medium. Kozeny 's relation is one of the most basic and famous relations that expresses permeability as a function of the porosity and the specific surface area of the grains. In nuclear magnetic logs, applying Eq. (2), the interpretation models for rock permeability estimation are built by two methods, through analysis of the correlation between T_2 spectrum distribution and S/V .
Consider a porous sample, with cross-sectional area A and length L, consisting of n parallel straight capillary tubes, with the space between the tubes filled with cement. If the capillary tubes all have the same radius r (cm) and the same length L (cm), the flow rate q (cm^3/s) of a set of tubes is obtained according to the following Eq. (2):

$$q = \left(\frac{n\pi r^4}{8\mu}\right)\frac{\Delta P}{L} \tag{2}$$

In this relationship, the pressure drop ΔP is expressed in length L with the unit of dynes/cm^2.

3.2. Hydraulic flow units determination

A flow unit is a volume of reservoir rock that is continuous and predictable laterally and vertically, and the geological and petrophysical characteristics affecting the fluid flow within it are constant and distinctly different from other rock volumes (Bhatti et al., 2020; Kharrat et al., 2009). Hydraulic flow units are related to the distribution of geological facies, but they do not necessarily correspond to the boundaries of these facies. Therefore, these units can not be connected vertically.
Geological texture, mineralogy, sedimentary structures, layered contact surface, nature of permeable barriers, and petrophysical properties of porosity, permeability, and capillary pressure often define flow units.
The main methods for determining the number of hydraulic flow units include histogram analysis, normal probability analysis, and the sum of squares errors. These mentioned parameters will be discussed in the following section.

3.2.1. Histogram analysis

In this method of analysis, the logarithm of hydraulic flow unit values will be obtained after acquiring the FZI values of each sample, and then using the MATLAB software, the logarithmic data of the flow zone index of the histogram

analysis is performed. According to the principles of hydraulic flow units, the distribution of the logarithm of the flow zone index in each hydraulic flow unit is the normal distribution. This method applies this principle and determines the number of hydraulic flow units (Al-Rbeawi and Kadhim, 2017; Alhashmi et al., 2016; Bhattacharya et al., 2016; El-Sayed et al., 2021; El Sharawy and Gaafar, 2016; Ismail et al., 2021; Kazemzadeh et al., 2013; Kianoush et al., 2022a; Kianoush et al., 2023a; Mirkamali et al., 2016; Roslin and Esterle, 2016; Salehi et al., 2015; Shakiba et al., 2015).

3.2.2. Normal probability analysis

In this analysis, the logarithmic values of the flow zone index are obtained using MATLAB software. According to the principles of hydraulic flow units, the normal probability logarithm of the flow zone index in each hydraulic flow unit is linearly distributed. This method uses this principle and determines the number of hydraulic flow units (Davis, 2018; Heydari et al., 2012; Hosseini et al., 2023a; Madani et al., 2019; Manshad et al., 2021; Rabbani et al., 2018; Shirneshan et al., 2018; Yasmaniar et al., 2018).

3.2.3. Sum of squares errors (SSE)

In this analysis, the working method is as follows: first, the number of categories is assumed to be 1 (HFU=1), and the cluster analysis of average K data is performed by MATLAB software, then linear regression analysis is performed on the data and the value. The sum of squared errors was calculated. This work was done the same way for the number of other categories, and finally, a graph of the sum of squared errors against the number of categories was drawn. According to the diagram, with the increase in the number of hydraulic flow units, the total amount of errors decreased. However, from one value to the next, the changes in the total square of errors were not noticeable and can be ignored. This value is the optimal number of hydraulic flow units (Fernandes et al., 2023a; Olayiwola and Sanuade, 2021).

3.3. Methods for determination of rock types

After determining the number of hydraulic flow units, two methods are used to determine rock groups, which are discussed below.

3.3.1. Flow Zone Index Method

According to Zahaf and Tiab (2002)'s findings, a hydraulic flow unit is continuous throughout the specific volume of the reservoir, which practically has the physical stability of rock and fluid properties. This flow unit uniquely describes the static and dynamic interactions with the well wall. Based on microscopic measurements and core samples, El-Sayed et al. (2021) developed a method to identify and describe formations that have similar hydraulic properties or similar flow units. The hydraulic quality of rocks is controlled by pore geometry, radius, tortuosity, specific surface, mineralogy, and morphology side by side with textural parameters such as sorting, packing, grain size, and shape. The selection of samples of the same pore attributes can be clustered in a similar hydraulic unit. The boundaries of rock genetic units a geologist represents may be useful for the reservoir engineer if they coincide with unprecedented changes in flow properties (El-Sayed et al., 2021; Ji et al., 2022; Ojo et al., 2021; Shalaby, 2021).

The flow zone index method is the most commonly used method for determining rock Types. In this method, unlike other methods, the user has no role in determining the results, and all the steps are based on mathematical models.

Kozeny (1927) has extracted one of the most fundamental and famous relationships that express permeability as a function of porosity and specific surface zone. The generalized form of the Carmen-Kuzny relation is as Eq. (3):

$$K = \left(\frac{1}{f_g \tau S_{vgr}^2}\right)\frac{\varphi^3}{(1-\varphi)^2} \tag{3}$$

where K : permeability (μm^2); Ø = fractional porosity; τ is the electrical tortuosity and can be measured from electrical resistivity measurement; f_g is a shape factor.

The objective is to avoid measuring these microscopic properties by gathering these parameters into a single variable called the flow zone indicator (FZI). The previous equation can be adjusted to be Eq (4);

$$K = \left(\frac{1}{F_s \tau^2 S_{v_{gr}}^2}\right) \frac{\varphi^3}{(1-\varphi)^2} \tag{4}$$

Where Sv_{gr} is the Specific surface area of the grain (μm^{-1}).
The problem of the variability of the decomposition constant mentioned above could be solved by the following.

Dividing the two sides of the relationship by the porosity and taking the root of the two sides of the relation will have Eq. (5):

$$\sqrt{\frac{K}{\varphi_e}} = \left(\frac{\varphi_e}{1-\varphi_e}\right) \frac{1}{\sqrt{F_s} \tau S_{v_{gr}}} \tag{5}$$

where: K in square micrometers (μm^2).
Permeability in milliseconds, the following parameter can be introduced (Eq. (6)):

$$RQI(\mu m) = 0.0314 \sqrt{\frac{K}{\varphi}} \tag{6}$$

where: RQI is known as the Reservoir Quality Index (expressed in micrometers). It is an approximate index of the average hydraulic radius in the reservoir rock and is the key to the hydraulic units that correlate porosity, permeability, and capillary pressure.
ϕ_z is the ratio of pore volume to grain volume is defined as Eqs. (7), (8) and (9):

$$\varphi_z = \frac{\varphi_e}{1-\varphi_e} \tag{7}$$

FZI is considered an indicator of flow zone:

$$FZI(\mu m) = \frac{1}{\sqrt{F_s \tau^2 S_{v_{gr}}^2}} = \frac{RQI}{\varphi_z} \tag{8}$$

By taking the logarithm of both sides of the equation, we could write Eq. (9):

$$LogRQI = Log\varphi_z + LogFZI \tag{9}$$

Eq. (9) shows a straight line with the same slope on the logarithmic plot of RQI in terms of Φ_z. The intersection point of this straight line at $\Phi z = 1$ is the flow zone index. Samples with different FZI values correspond to other parallel lines. Samples on a straight line have similar characteristics and form a single flow unit. Straight lines with a slope equal to unity should initially be expected for sandstone formations without shale. Larger slopes characterize shale-bearing formations.
FZI flow zone index is a unique parameter that includes geological properties, rock texture, and mineralogy in its geometry and facies structure.
Generally, rocks containing detrital materials have porous layering and porous joints are filled with clays and fine graining, so they show a low FZI value. On the other hand, sands with low amounts of shale, coarse and fine graining, low specific surface area, low shape factor, and low twist degree show high FZI. Different sedimentary environments control diagenetic processes and flow zone index geometry.
Fluid flow units can be identified based on the values of the flow zone index. It is assumed that the same values of the flow zone index are assigned to the same hydraulic flow units. Therefore, for examples with similar FZIs, the logarithmic diagram of RQI vs. V will be linearly linear with the unit slope. The value of the flow zone index can be obtained from the origin of this line. Samples with different flow zone index values make another parallel line. All specimens are located on a single line and have the same bottleneck properties and thus form a single flow unit (Amraei and Falahat, 2021; Jehanzaib et al., 2023; Kadkhodaie and Kadkhodaie, 2018; Mahjour et al., 2016; Shahat et al., 2021).

3.3.2. FZI Calculation of flow unit

To obtain an equivalent value of FZI for each group according to Eq. (9) when plotting RQI in a logarithmic graph, it must obtain a line with a constant slope of 45 degrees, which is zero at (that is) the value. As a result, LogRQI equals LogFZI. This method can obtain FZI equivalent to each unit of hydraulic flow (Mahjour et al., 2016; Shalaby, 2021). The deviation formula can be used to obtain a 45-degree angle that has a high scattering point (Eq. (10)).

$$\sum Err = \sum (Y - y)^2 = S \tag{10}$$

Err = Error (deviation)
Y = RQI for all samples
y = RQI for each sample
Now consider Eq. (9) as a linear formula in which:
y = LogRQI
x = Log Φz
b = LogFZI
To reduce the deviation, we have to derive the deviation formula for a variable equal to zero, which will have Eqs. (11) and (12):

$$S = \sum (y - x - b)^2 \tag{11}$$

$$\frac{\partial S}{\partial b} = 0 \Rightarrow \sum_{i=1}^{n} 2(-1)(y - x - b) = 0$$

$$\Rightarrow \sum_{i=1}^{n} (y - x - b) = 0$$

$$\Rightarrow b = \frac{\sum y - \sum x}{n} \tag{12}$$

After obtaining b, FZI can be calculated for each unit.

3.3.3. Fuzzy C-Means Method

Clustering is the most crucial method of unsupervised learning. A *cluster data* is a set that resembles one another. Clustering seeks to divide the data into clusters that maximize the similarity between the data within each cluster and the similarity between the data within the different clusters. Clustering of numerical data forms the basis of many classification and system modeling algorithms. Traditional hard clustering analysis requires every point of the data set to be assigned into a cluster precisely. But in fact, most things exist ambiguity in the attribute, there are no explicit boundaries among the things, and no the nature of either-or. So the theory of the fuzzy clustering is more suitable for the nature of things, and it can more objective reflect the reality. Fuzzy clustering isused to partition sample points into subgroups which are characterized by cluster centers. Each data point belongs to a cluster center with a degree which is determined by the membership grade.

A fuzzy c-means clustering method has been proposed to solve the problem of assigning each data to a particular cluster in each iteration (Bezdek, 1981; Ghadami et al., 2015; Kadkhodaie-Ilkhchi et al., 2010; Kadkhodaie and Amini, 2008; Olayiwola and Sanuade, 2021; Pourreza et al., 2023; Salavati et al., 2023; Shakiba et al., 2015; Tian et al., 2016). In *fuzzy clustering*, an object can be a member of more than one cluster. For k clusters, m_1, m_2, m_3,…, and m_k is the possibility of an object I belonging to each cluster. These values are between 0 and 1, and the sum of their values is 1. For this method, membership is spread across all clusters. The advantage of this clustering is that each object does not have to reach a specific cluster, and its disadvantage is that there is so much more information to interpret. In this model, objects close to the center of a cluster with more probability belong to the cluster with a higher degree than the edge objects of the cluster (Gosain and Dahiya, 2016; Reza Keyvanpour and Shirzad, 2022; Zadeh, 1978). Sample of FCM Clustering is shown in Fig. 5.

Currently, the fuzzy c-means clustering (FCM) algorithm is the most widely used. This technique was originally introduced by Bezdek (1981) as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters.
Given n data patterns, $x_1, x_2, ..., x_n$, fuzzy clustering means grouping the data patterns into c clusters ($1 \leq c \leq m$) which centered at ci. FCM algorithm starts with an initial guess for the cluster centers (c_i.), which are intended to mark the mean location of each cluster. Additionally, the algorithm assigns every data point a membership grade, u_{ij}, for each cluster, where u_{ij} is the degree of membership of object j (x_j) in cluster i. By iteratively updating the cluster centers and the membership grades for each data point, the cluster centers are moved to the right location within a data set. The membership u_{ij} and the cluster centers ci are updated by the following equations (Bezdek, 1981; Bezdek et al., 1984; Seising, 2018; Zadeh, 1978).

In FCM, the objective is to minimize the Eq. (13):

$$J_m = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^m \left\| x_j - v_i \right\|^2 \tag{13}$$

where u_{ij} represents the membership of pixel x_j in the j_{th} cluster, v_i is the i_{th} cluster center, $\|.\|$ is a norm metric, and m is a constant. The parameter m controls the fuzziness of the resulting partition, and m=2 is used in this study.

Then, the following condition must be observed (Eq. (14)):

$$\sum_{i=1}^{C} u_{ij} = 1 \tag{14}$$

The complete procedure of this algorithm is as follows:
A) Determine the initial values for c (number of clusters), m (fuzzy value of the algorithm), and v (initial centers for each cluster).
B) Calculate the amount of belonging to each cluster concerning the Eq. (15):

$$u_{ij} = \sum_{k=1}^{c} \left(\frac{\left\| x_j - v_i \right\|}{\left\| x_j - v_k \right\|} \right)^{-2/(m-1)} \tag{15}$$

C) Calculate the number of new centers for each cluster according to the Eq. (16):

$$V_i = \frac{\sum_{j=1}^{N} \left(u_{ij} \right)^m x_j}{\sum_{j=1}^{N} \left(u_{ij} \right)^m} \tag{16}$$

This iteration is based on minimizing the following objective function that represents the distance from any given data point to a cluster center weighted by that data point's membership grade:

$$Obj.Func = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m \left\| x_j - c_i \right\|^2 \tag{17}$$

$$1 \leq i \leq c$$

$$1 \leq j \leq n$$

where m is the weighting exponent and usually set to 2. Several stopping rules can be used. One is to terminate the algorithm when the relative change in the centroid values becomes small or when the objective function cannot be minimized more.
Repeat steps two and three until the value of the difference between the u (the amount of data belonging to the cluster) in the new stage differs from the value of u in the previous step, less than a threshold value.
The output of the FCM method is the coordinates of the batch centers and the U matrix, where the membership functions of each point in each cluster are specified. In the FCM fuzzy clustering algorithm, the number and centers

of the clusters are first determined by the user. The quality of this algorithm strongly depends on the initial number of clusters and the initial location of the cluster centers (Jafarzadeh et al., 2019; Kadkhodaie-Ilkhchi et al., 2013; Kadkhodaie and Amini, 2008; Kadkhodaie and Kadkhodaie, 2018; Kadkhodaie et al., 2006; Kiaei et al., 2015).

4. Results

Results of hydraulic flow units were made based on 280 core samples and well logs obtained from one of the drilled wells in the Mansouri field, including permeability, porosity, and formation information. The integrated analysis of Fuzzy C-mean and hydraulic flow unit (HFU) clustering techniques is found useful with limited data to develop the porosity relationship to predict the rock type in un-cored wells, especially less distance offset wells. In order to determine the number of hydraulic flow units, reservoir samples were first prepared. Then their porosity and permeability were determined by measuring devices. The flow zone index (FZI) was calculated for each sample. After determining the FZI of each sample using MATLAB software, a histogram analysis was performed on the logarithmic data of the flow area index, and the number of hydraulic flow units was determined based on the obtained normal distributions. Considering that these two methods depend on the user (this number changes according to the user's opinion and experience), the possibility of making errors in the calculations is high. For this purpose, to reduce the errors, it was tried to use the sum of square errors parameter to determine the number of hydraulic flow units. In using the sum of squares of errors, the working method is as follows: first, the number of categories is assumed to be 1 (HFU=1), and the average K cluster analysis of the data was performed by MATLAB software, then the linear regression analysis was performed on It was done on the data and the sum of square errors was calculated. It was done the same way for the number of other categories, and finally, a graph of the sum of squared errors against the number of categories was drawn. In these graphs, from one value to the next, the changes in the sum of squared errors are not noticeable and can be ignored. This value is the optimal number of hydraulic flow units.

Then, considering that one of the most important parameters in determining rock type is the parameters of porosity and permeability, in this research, the definition of rock type based on these two parameters, using the fuzzy c-mean clustering method in MATLAB software environment, takes place. Thus, each cluster produced during the clustering process is considered a representative of a rock type. In the clustering process of this method, each rock type will have characteristics related to statistical parameters (the minimum, maximum, mean, median, and standard deviation) and a range of porosity and permeability changes, which separates it from another type. In addition, in the cross-plots of porosity versus permeability, each type is well separated from the other types, and there is no overlap. Obviously, in this case, any rock represents a facies with a specific range in terms of porosity and permeability.

4.1. Determination the number of hydraulic flow units

The number of hydraulic flow unit determinations results include histogram analysis, normal probability analysis, and the sum of squared errors. These three methods are studied on core data in the following section.

a) The histogram analysis results in four normal distributions representing four hydraulic flow units (Fig. 6).

The first hydraulic flow unit consists of 24 members, the second hydraulic flow unit consists of 109 members, the third hydraulic flow unit consists of 117 members, and the fourth hydraulic flow unit consists of 30 members.

b) As the normal probability analysis results, four linear distributions are obtained, representing four hydraulic flow units; therefore, this method confirms the number of hydraulic flow units obtained from the previous step.

In this method, normal probability analysis is performed on the logarithmic data of the flow zone index, and four linear distributions are obtained, representing four hydraulic flow units and, thus, the number of hydraulic flow units obtained from the previous stage. The first hydraulic flow unit consists of 24 members, the second hydraulic flow unit consists of 109 members, the third hydraulic flow unit consists of 117 members, and the fourth hydraulic flow unit consists of 30 members. (Fig. 7).

c) Table 2 shows the value of the sum of squared errors (SSE) calculated according to the number of hydraulic flow units. As Table 1, the value of SSE in the presence of a hydraulic flow unit is equal to 0.92, which clearly shows the inadequacy of classical methods and the existence of several fluid behaviors in the tank. By adding the number of HFUs, the number of SSEs decreases. However, as continue to add HFUs, the amount of SSE reduction becomes less and less, and SSE, in this case, is used as a criterion to determine the optimal number of hydraulic flow units in the reserve, reaching the lowest value of SSE at 0.02 in 4 known HFU units. As Fig. 8 , increasing the number of HFUs

causes insignificant changes in the SSE value. Fig. 9 shows all four hydraulic units' normal porosity versus rock quality index (RQI). Furthermore, Table 3 shows the average FZI values for each hydraulic flow unit in the studied well. According to the results obtained from these three methods, the sum of squared errors method is optimal for determining the number of hydraulic flow units because it is independent of the user and has a higher accuracy in determining the number of categories.

4.2. Comparison of rock types determination methods

Two methods of flow zone index and fuzzy c-means (FCM) are used to determine rock types in the study wells. In this section, the proposed approaches are compared:

a) Ideally, the reservoir quality index and porosity ratio values are drawn in a log-log scale. In that case, the data with the same flow area index values are placed on a line with a single slope, and the samples with different flow area index values are placed on parallel lines. The samples on the same line have the same pore throat properties, forming a hydraulic flow unit. Each line defines a unique HFU, and the width from the origin of the lines at $\Phi z=1$ shows the average value for that unit. Initially, both methods of rock type determination were implemented in-depth. The wells studied have four hydraulic flow units. If each unit has maximum coupling, its coupling number is 1, and when it has minimum coupling, its coupling number is zero. Four hydraulic flow units have maximum coupling, their total coupling number is 4, and for any of these four units, there is no correlation between their data. Their total correlation number becomes zero.

b) the fuzzy c-mean algorithm divides the data set into four similar fuzzy clusters with different numbers of members. In this diagram, each cluster is displayed with a different color, and the centers of each cluster are marked with a black square. The first cluster with blue has 77 members, the second with red has 42 members, the third with green has 87 members, and the fourth with pink has 74 members.

As seen in Table 4, the fuzzy c-means tries to minimize Jm with successive iterations until a significant improvement is achieved. Furthermore, as seen in Fig. 10, the algorithm divides the fuzzy c-means of the dataset into four identical fuzzy clusters with different members. In this graph, each cluster is represented by a single color, and the centers of each cluster are marked with a black square. The first cluster is blue, with 77 members. The second cluster is red, with 42 members, and the third is green, with 87 members. Furthermore, the fourth cluster is pink, with 74 members.

5. Discussion

5.1. Determining Rock type

In this research, two methods of flow zone index and Fuzzy C-mean (FCM) have been used to determine the rock types in the studied well. In this section, solutions are proposed to compare these methods, which are mentioned below:

Both methods of determining rock types in depth were implemented, as shown in figures (Fig. 11a and Fig. 11b). The studied well information showed four hydraulic flow units. If each unit has maximum continuity, its continuity number is one; if it has minimum continuity, its continuity number becomes zero. Suppose four hydraulic flow units have maximum continuity. In that case, their total continuity number becomes 4, and if each of these four units has no continuity between their data, their total continuity becomes zero.

First, the data of the flow zone index (FZI) method have been implemented in-depth. The continuity number for the first hydraulic flow unit is 0.66. The second hydraulic flow unit is 0.79, the third hydraulic flow unit is 0.76, and the fourth hydraulic flow unit is 0.53. Finally, summing the continuity numbers of these three units, the total continuity number becomes 2.7672 (Table 5).

Then the data obtained from the fuzzy c-means method has been implemented in-depth. The continuity number for the first hydraulic flow unit is 0.87. The second hydraulic flow unit is 0.61, the third hydraulic flow unit is 0.89, and the fourth hydraulic flow unit is 0.72. Finally, by summing the continuity numbers of these three units, the total continuity number is 3.1153 (Table 6).

According to the obtained results, the total continuity number of the fuzzy c-mean method is higher than the total continuity number of the flow zone index in-depth, and it shows more continuity in depth.

5.2. Changes in the porosity diagram according to permeability

Usually, permeability-porosity diagrams in heterogeneous carbonate reservoirs are usually scattered and show poor correlation (Fig. 12a) but correlate with the classification and arrangement of data regarding hydraulic flow units. Permeability is observed in each hydraulic flow unit (Fig. 12b to Fig. 13d). Table 7 and Table 8 show the correlation coefficients of porosity with permeability for all samples and four units of hydraulic flow in the well-studied.

The correlation coefficient for all samples is equal to 0.552. However, the correlation coefficient obtained in the flow zone index method for the first hydraulic flow unit is 0.809. The second hydraulic flow unit is 0.939, the third hydraulic flow unit is 0.845, and the fourth hydraulic flow unit is 0.94, which indicates the improvement of the relationship between permeability and porosity in all hydraulic flow units compared to the general state for all samples.

Furthermore, the correlation coefficients obtained in the fuzzy c-mean for the first hydraulic flow unit is 0.195, for the second hydraulic flow unit is 0.094, for the third hydraulic flow unit is 0.171, and for the fourth hydraulic flow unit is 0.05-e8, which These results show that the correlation coefficients obtained using the fuzzy c-mean method in all four hydraulic flow units are lower than the correlation coefficient in the general case.

Based on these results, the flow zone index method improved the correlation coefficients between permeability and porosity in all hydraulic flow units relative to the correlation coefficients in the general states for all samples. However, the fuzzy centrifugal method not only improved the relationship between the petrophysical parameters of the reservoir in all hydraulic flow units relative to the general states but also reduced the porosity-permeability relationship. Furthermore, According to the results, the total fidelity of the fuzzy c-means method is greater than the total fidelity of the flow zone index at depth and shows greater consistency at depth.

According to these results, the flow zone index method has improved the correlation coefficients in the relationship between permeability and porosity in all hydraulic flow units compared to the correlation coefficients in general cases for all samples. However, the fuzzy c-mean method not improved the relationship between the petrophysical parameters of the reservoir in all hydraulic flow units compared to the general conditions; furthermore, it also caused a decrease in the relationship between porosity and permeability. The log of changes in petrophysical parameters versus depth in the studied well includes the depth column, porosity change column, permeability change column, hydraulic flow unit column, and rock types change column is shown in Fig. 14.

6. Conclusions

Regarding the determination of hydraulic flow units on 280 core samples of the Mansouri field, using three different methods, the obtained result can be surmised as blew:

Four hydraulic flow units were determined for the studied data after classifying FZI values by histogram analysis, normal probability analysis, and the sum of squares errors. If the number of hydraulic flow units is at most their optimum, the results will not improve significantly, making the calculations more difficult and complex. Because the SSE method has lower error rates than the other two methods, this method can be optimal for determining the number of hydraulic flow units. In the flow zone index method, the reservoir quality index values and the oscillation ratio are plotted on a logarithmic scale, the data having the same flow zone index values are aligned on a single slope line having the same pore throat properties, and they make a hydraulic flow unit. Mean FZI values were calculated at 0.19 for the first hydraulic flow unit, 0.31 for the second hydraulic flow unit, 0.63 for the third hydraulic flow unit, and 1.44 for the fourth hydraulic flow unit in the studied well. The fuzzy c-means clustering method divides the data set into four identical fuzzy clusters with different member numbers by minimizing the evaluation function (Jm). Flow zone index and fuzzy c-means were used to determine rock types in the studied well. According to the results obtained from implementing these two methods in depth and applying the correlation index, the total correlation number in the method of flow zone index is 2.7672, and the total continuity number is calculated in the fuzzy c-means method as 3.1153. Therefore, the fuzzy c-means method shows more consistency in-depth than the flow zone index method. The flow zone index method improves and enhances the correlation coefficients of porosity relation with permeability in each hydraulic flow unit.

In contrast, in the fuzzy c-means method, the correlation coefficient is lower in all hydraulic flow units than in the general state. FZI lines in low porosity are approximated in analyzing permeability graphs regarding porosity. Therefore, at a fixed porosity, samples with higher FZI have higher permeability, so that FZI values can be a good criterion for pore correlations, and the higher this permeability, the more rock permeability increases. The porosity and permeability values of different reservoir rock samples are highly dispersed, and using hydraulic flow units

dramatically improves the relationship between these two parameters. In this study, the correlation coefficient between porosity and permeability ranged from 0.552 for all samples to 0.809 in the first hydraulic flow unit, 0.939 in the second hydraulic flow unit, 0.845 in the third hydraulic flow unit, and 0.94 increase in the fourth hydraulic flow unit were since samples with similar flow characteristics were placed in a single hydraulic flow unit.

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Conflict of Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availibility Statement

The following datasets generated and/or analyzed during the current study are available in the **Mahmoud Memariani** repository, http://dx.doi.org/10.13140/RG.2.2.19913.31847. The other datasets generated and/or analyzed during the current study are not publicly available due to not permitted to share by National Iranian Oil Company Exploration Directorate (NIOC-EXP) request but are available from the corresponding author on reasonable request.

Tables

Parameter	Type	Cut off (%) CARBONATE	Cut off (%) SANDSTONE
PHIE	≥	4.5	8
SWE	≤	50	50
Vsh	≤	20	30

Table 1 Cutting limits for carbonate and sandstone sections.

No. of HFU	Sum of Squared Error (SSE)
1	0.921313
2	0.144515
3	0.08462
4	0.021707
5	0.013309
6	0.002989

Table 2. The value of the error calculated for the number of hydraulic flow units.

Hydraulic Flow Unit	Flow Zone Index (FZI)
1	0.1899
2	0.3117
3	0.6345
4	1.4459

Table 3. FZI value for each hydraulic unit

Iteration count	obj. function
1	8.8759
2	6.9395
3	6.6943
4	5.8739
5	4.9493
6	4.3072
7	3.8888
8	3.7368
9	3.6962
10	3.6846
11	3.6806

Table 4. Evaluation function values in consecutive iterations

Flow Unit no. 1	Flow Unit no. 2	Flow Unit no. 3	Flow Unit no. 4	Total cohesion
0.6666	0.7981	0.7692	0.5333	2.7672

Table 5. Continuity numbers in hydraulic flow units in the flow zone index (FZI) method.

Flow Unit no. 1	Flow Unit no. 2	Flow Unit no. 3	Flow Unit no. 4	Total cohesion
0.8701	0.6190	0.8965	0.7297	3.1153

Table 6. Continuity numbers in hydraulic flow units in Fuzzy C-mean (FCM) Method.

all samples	Flow Unit no. 1	Flow Unit no. 2	Flow Unit no. 3	Flow Unit no. 4
0.552	0.809	0.939	0.845	0.94

Table 7. Correlation coefficients of porosity with permeability in flow zone index method.

all samples	Flow Unit no. 1	Flow Unit no. 2	Flow Unit no. 3	Flow Unit no. 4
0.552	0.195	0.094	0.171	0.00008

Table 8. Correlation coefficients of porosity with permeability in fuzzy c-means.

Figure Captions

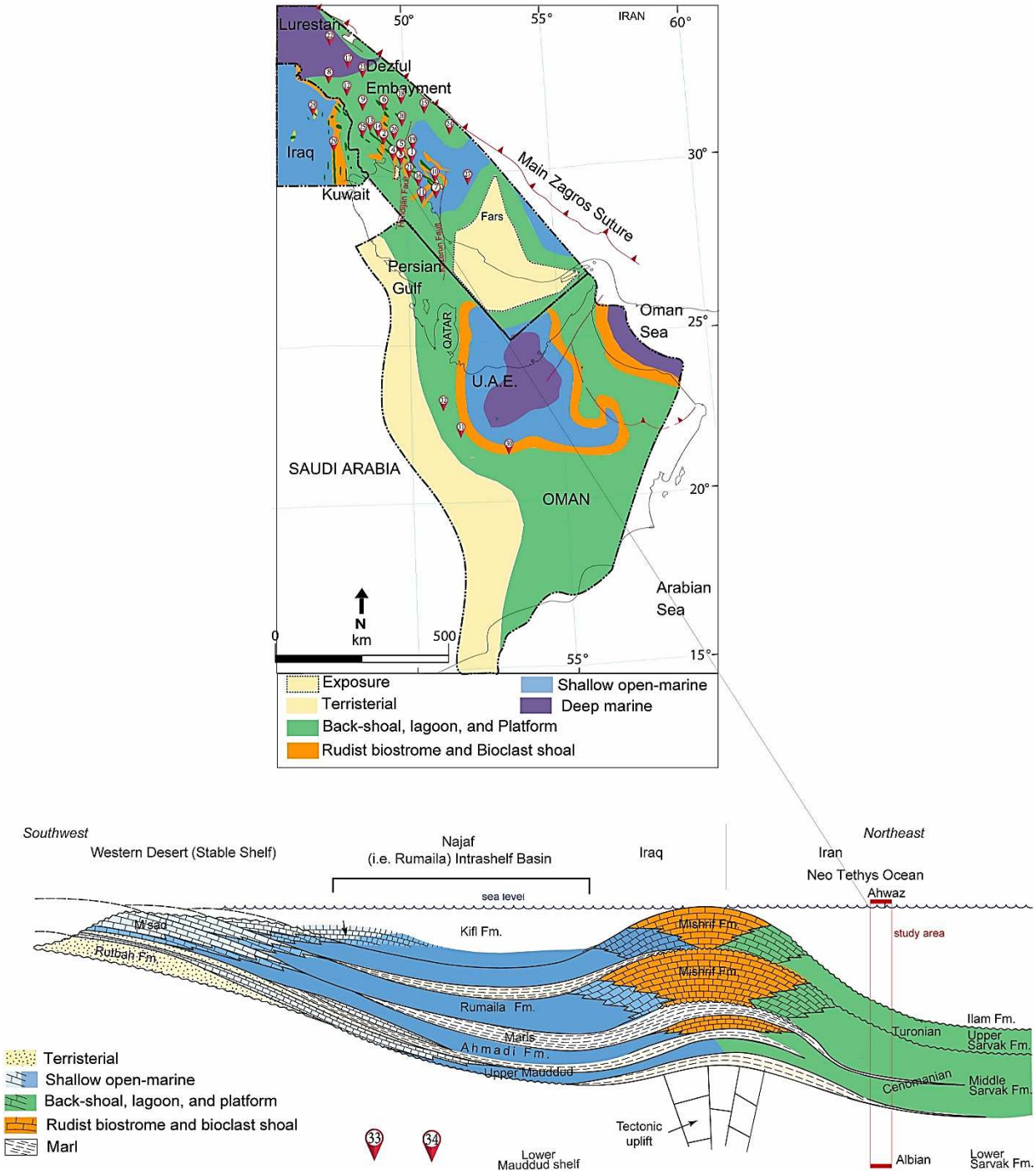

Fig. 1. The proposed depositional environment of the Zagros and adjacent basins in the middle Cretaceous (Khoshnoodkia et al., 2022; Mirkamali et al., 2016).

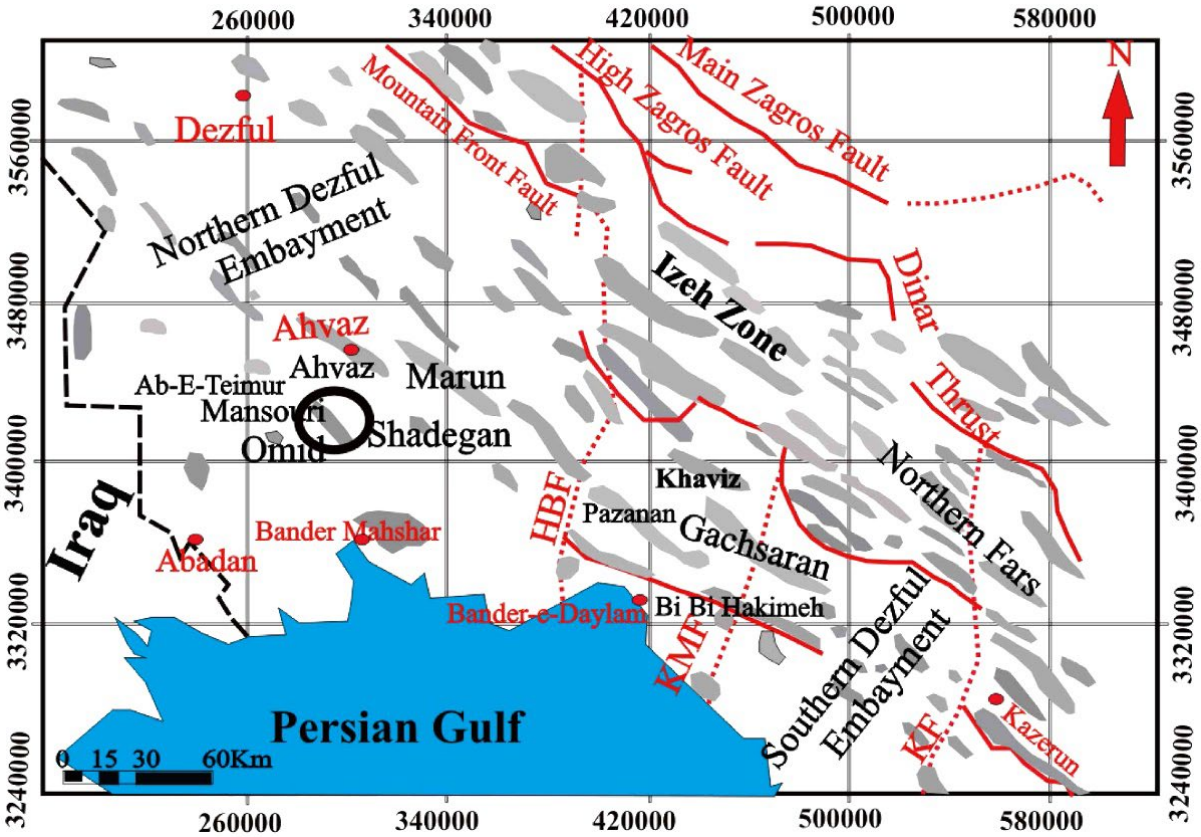

Fig. 2 The Mansouri oilfield and adjacent fields (Sherkati and Letouzey, 2004).

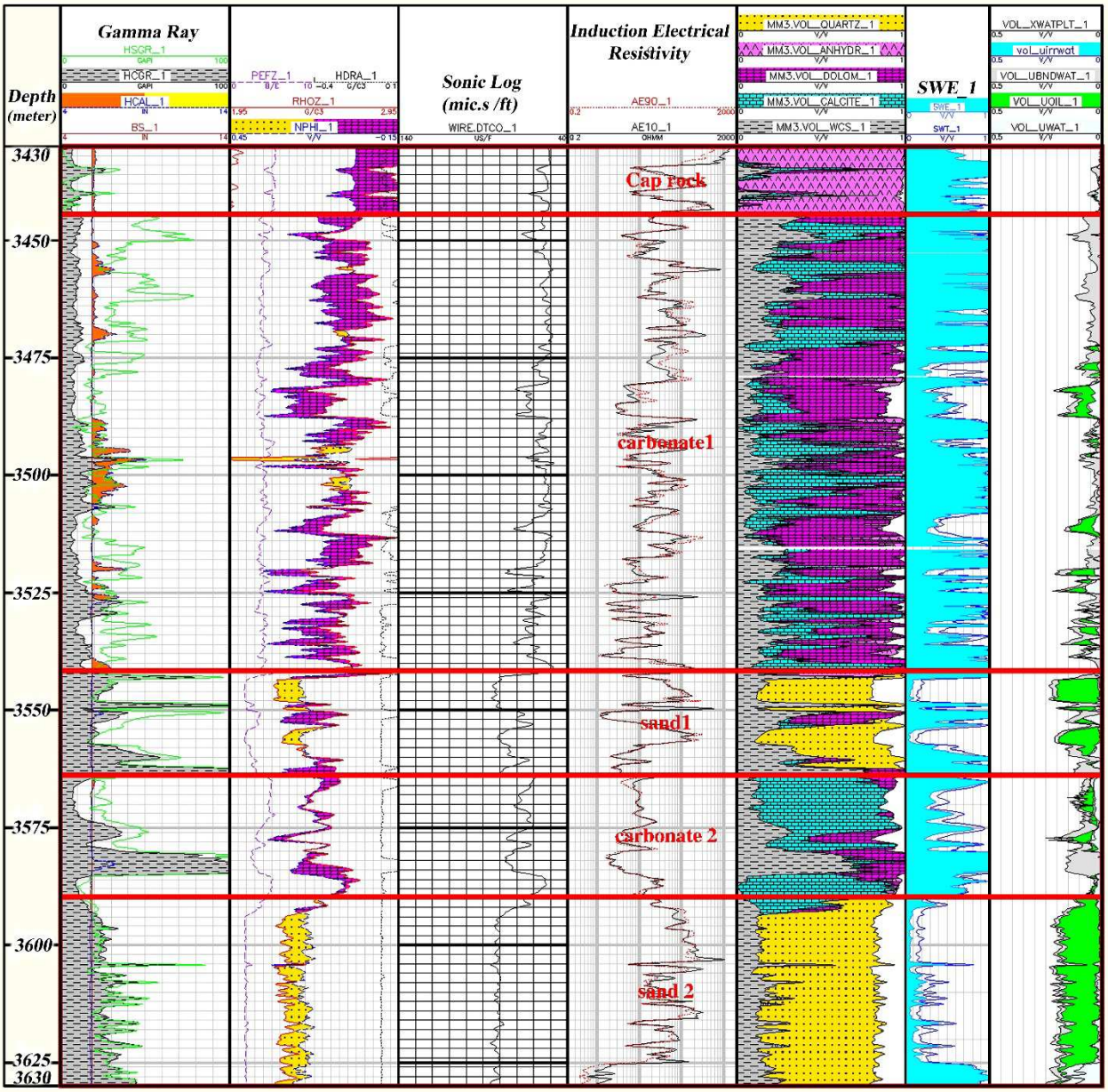

Fig. 3 Reservoir zonation sequences of the Asmari Formation based on lithological alteration in the studied well.

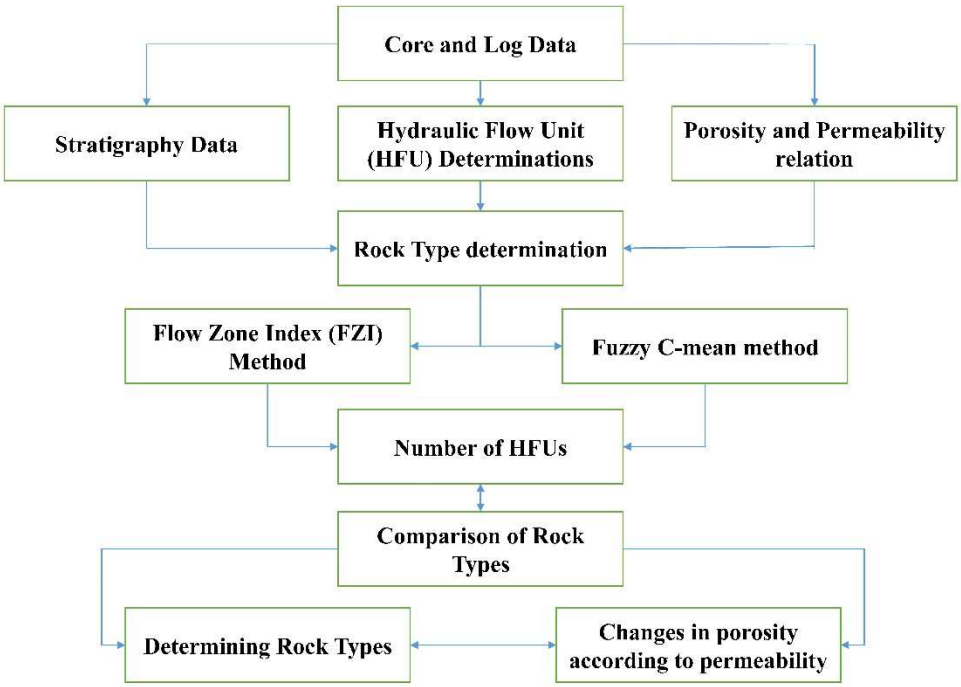

Fig. 4 General Flowchart of study based on core and log data in the studied well.

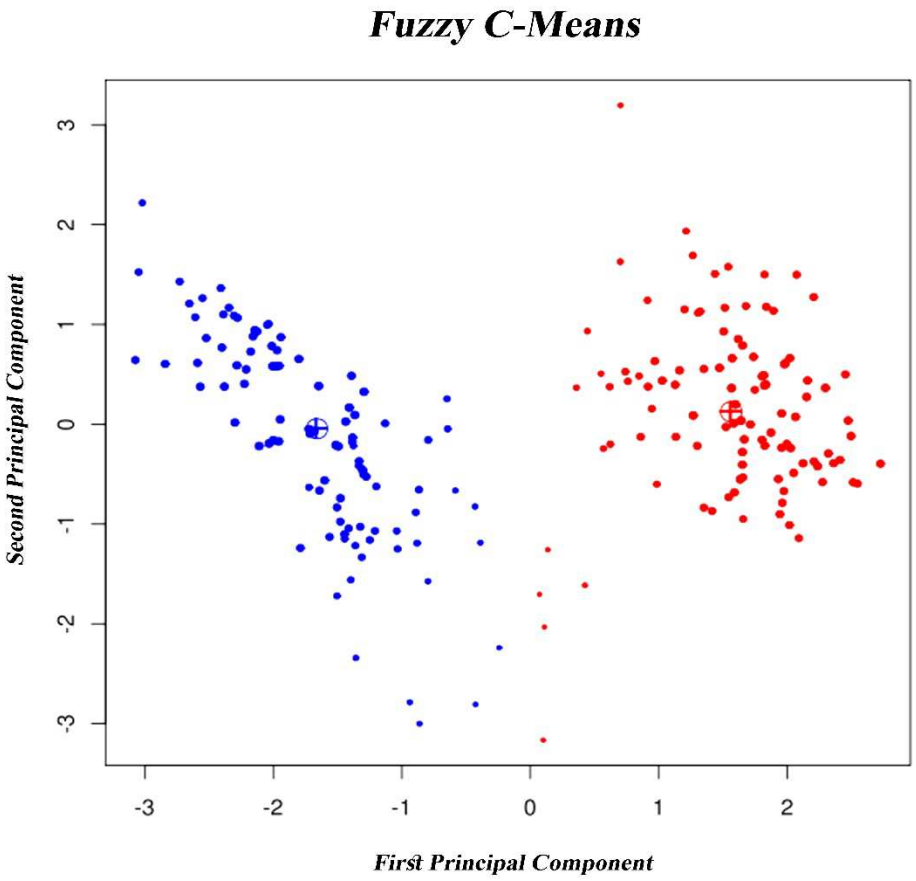

Fig. 5. Sample of FCM Clustering method (Majdi and Beiki, 2019; Salavati et al., 2023).

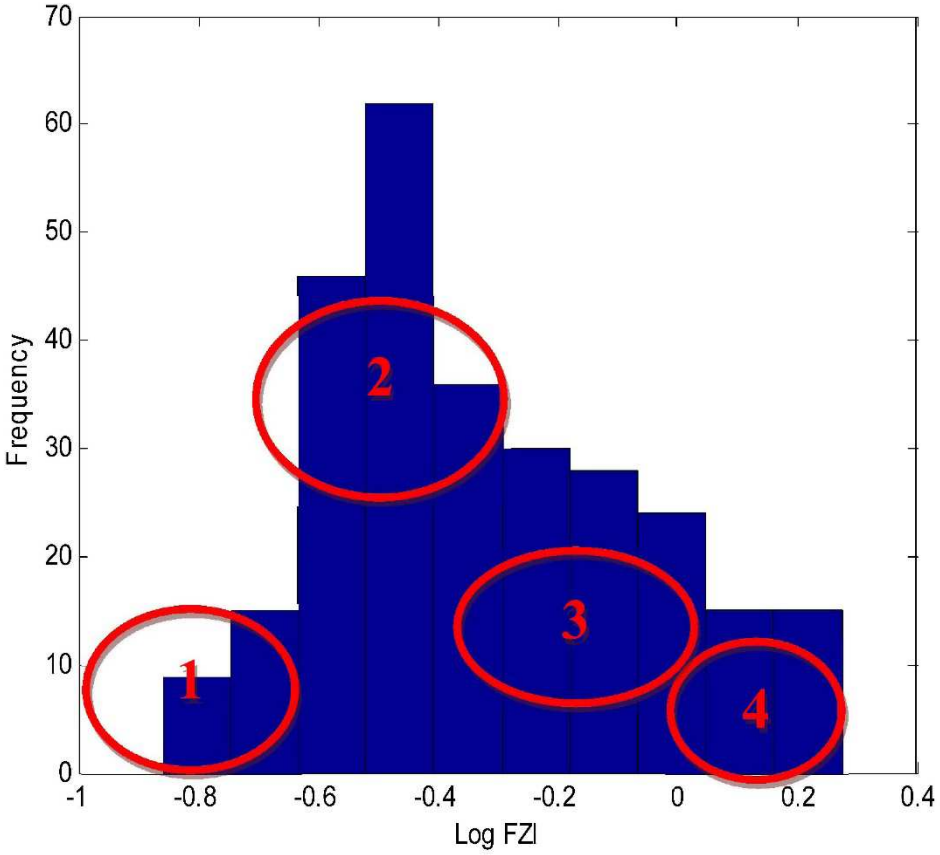

Fig. 6. Histogram analysis on logarithmic data of flow zone index.

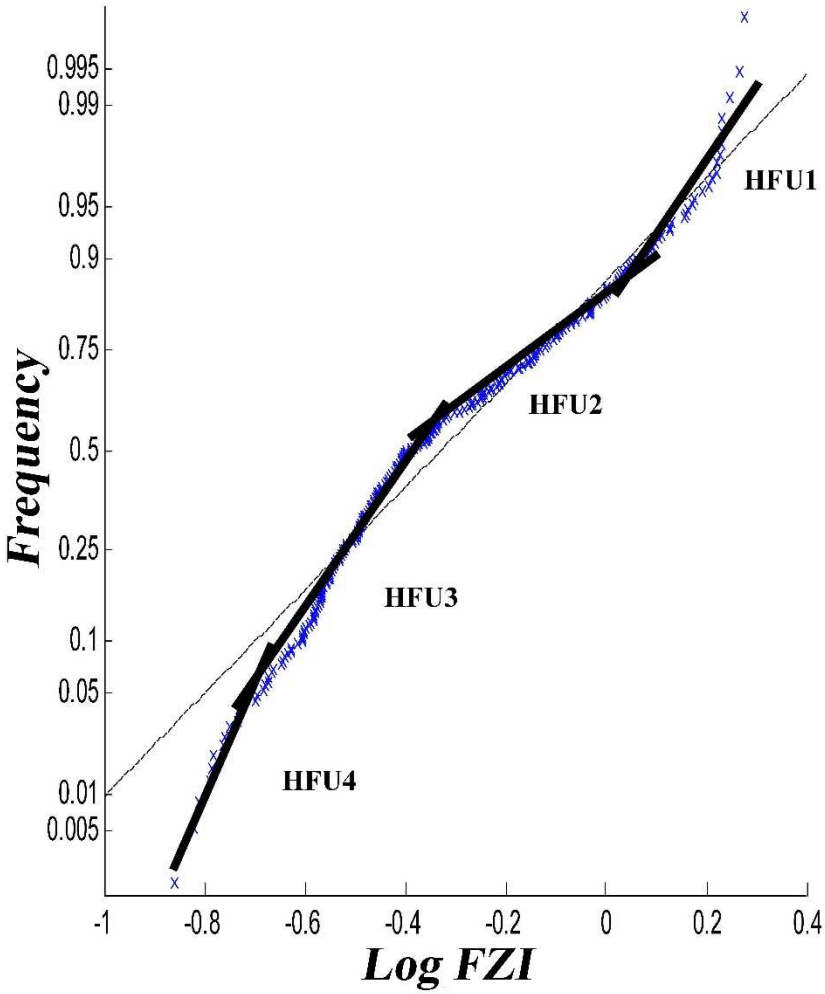

Fig. 7. Normal probability analysis on logarithmic data of flow zone index.

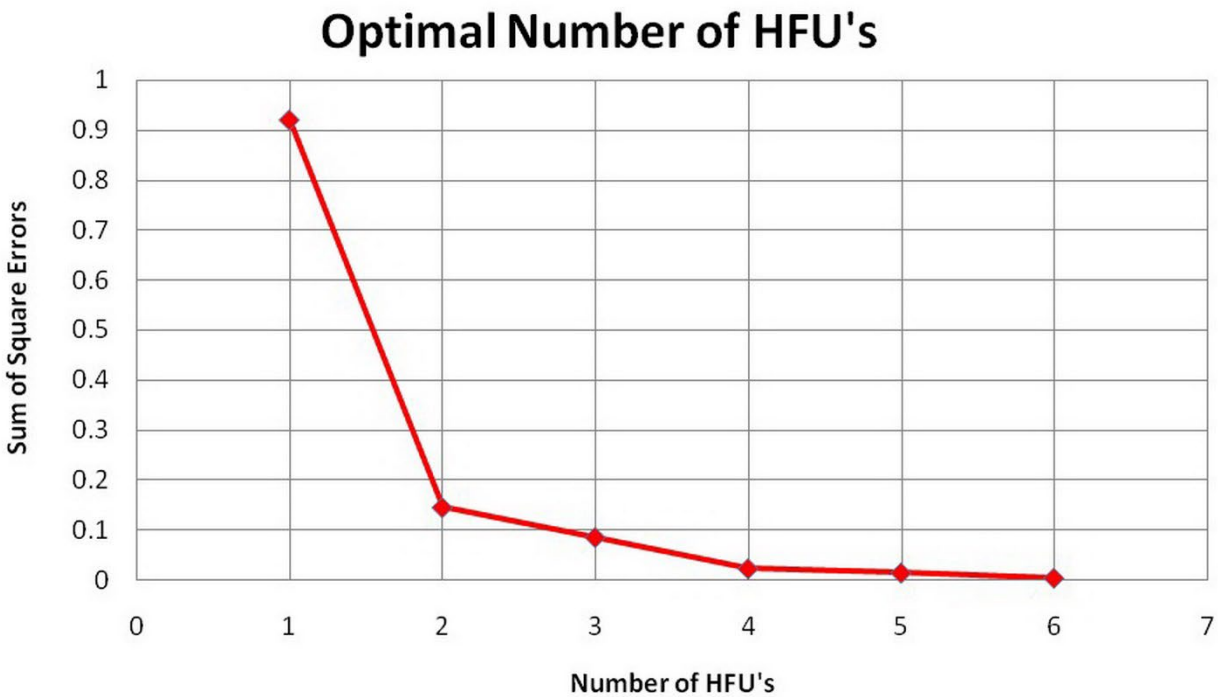

Fig. 8. Diagram of the sum of squares of errors versus the number of hydraulic flow units.

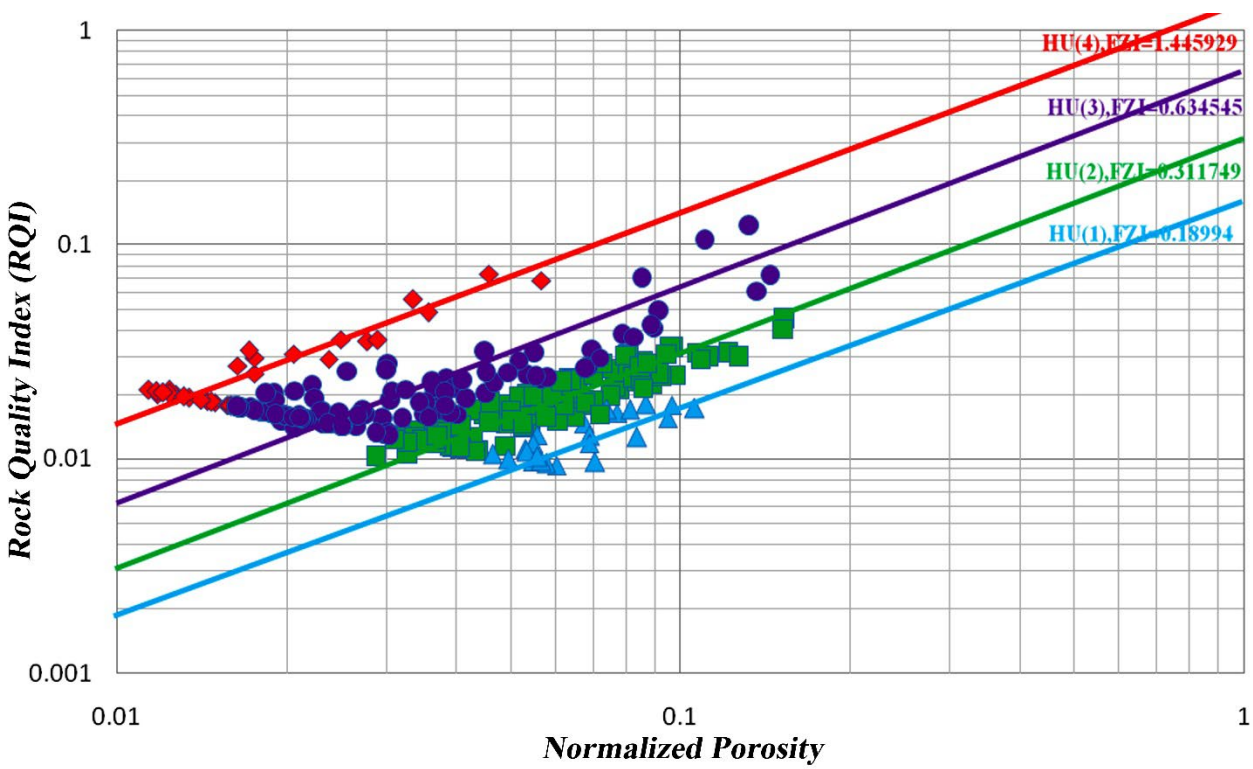

Fig. 9. FZI of each flow unit.

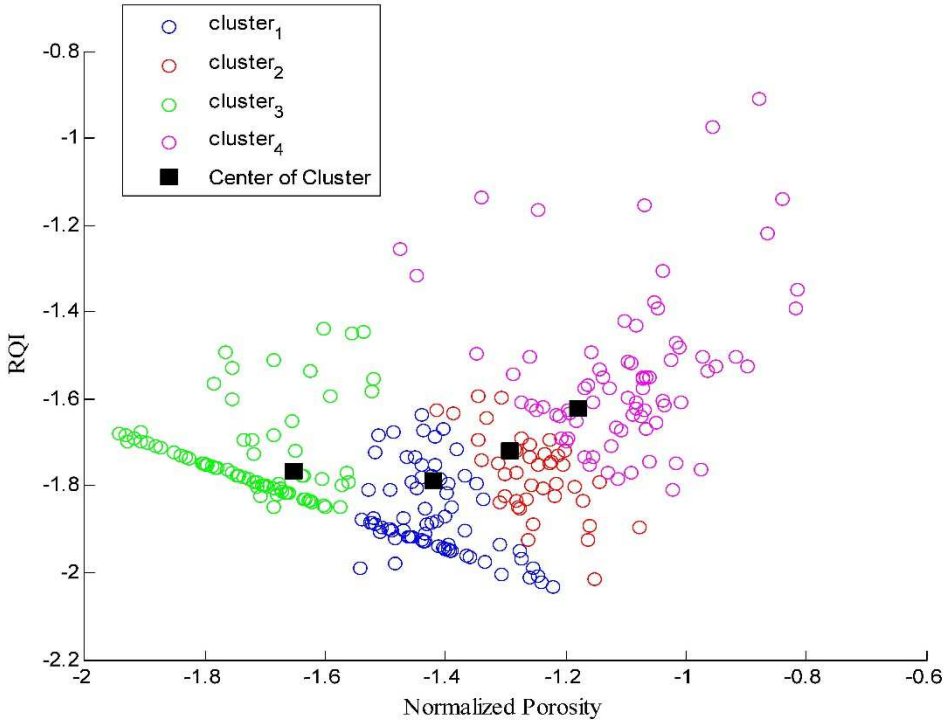

Fig. 10. Fuzzy c-means method.

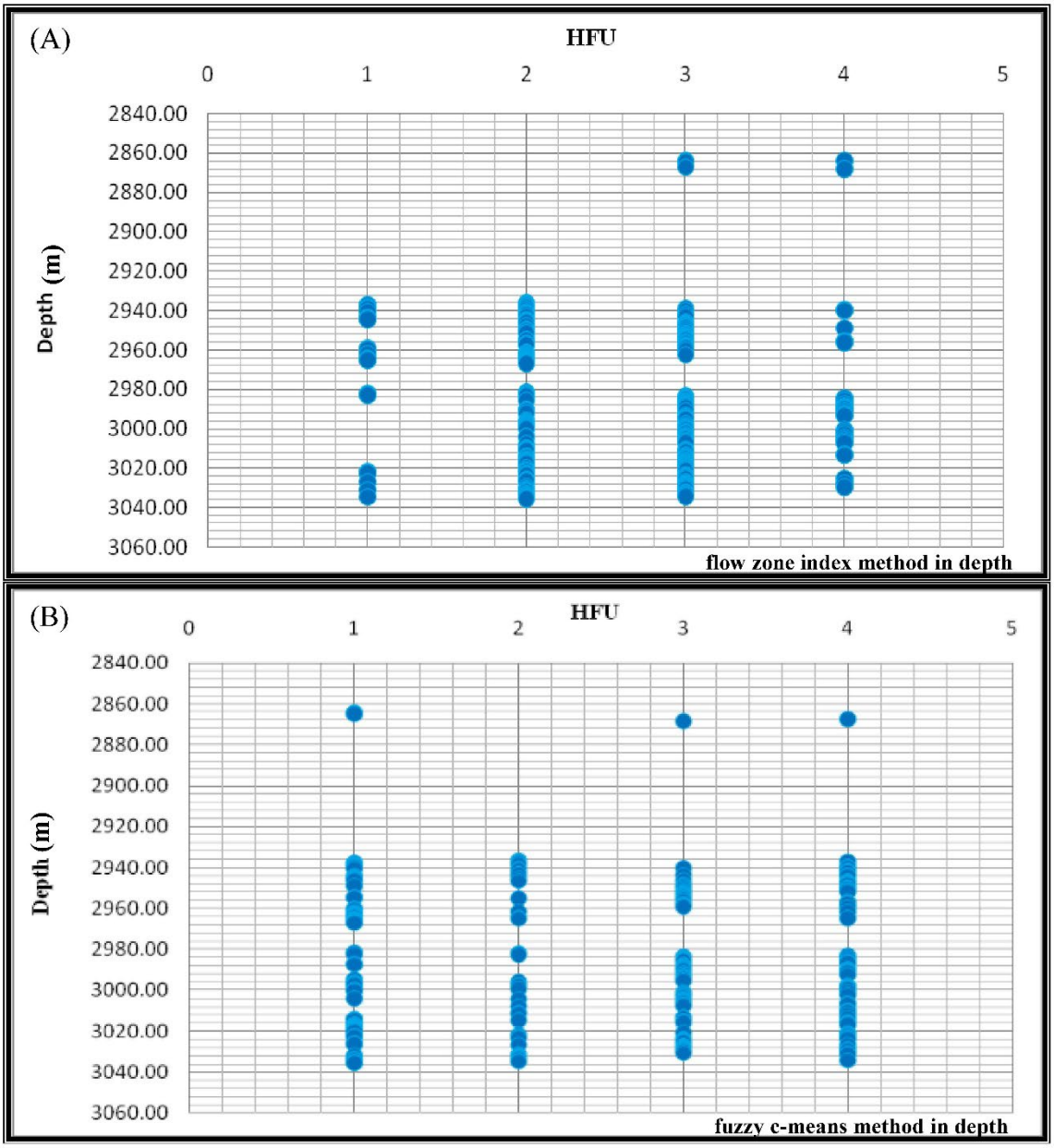

Fig. 11. Implementation of a) flow zone index method in depth, b) fuzzy c-means method in depth.

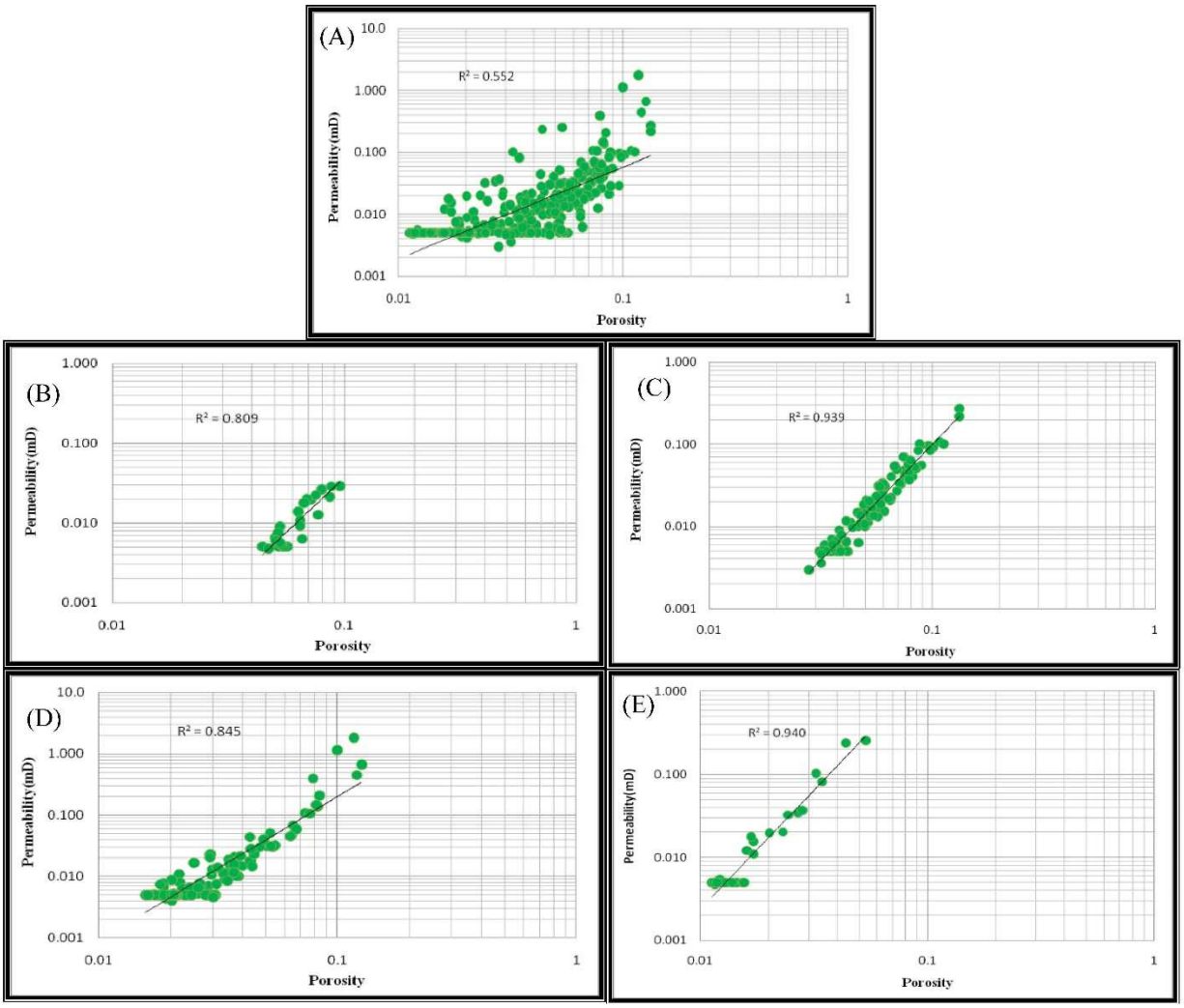

Fig. 12 Porosity relationship with permeability using flow zone index method for a) all samples, b) unit No. 1, c) unit No. 2, d) unit No. 3, e) unit No. 4.

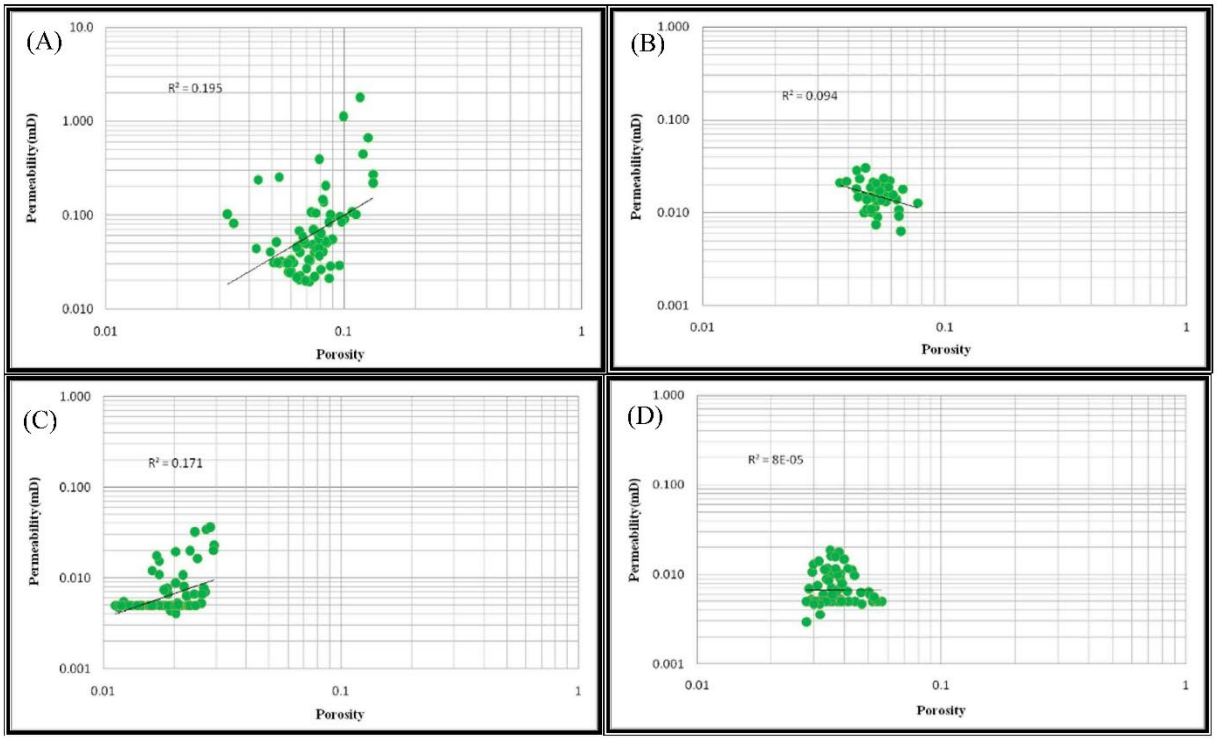

Fig. 13 Porosity relationship with permeability for flow unit using fuzzy c-means method for a) unit No. 1, b) unit No. 2, c) unit No. 3, d) unit No. 4.

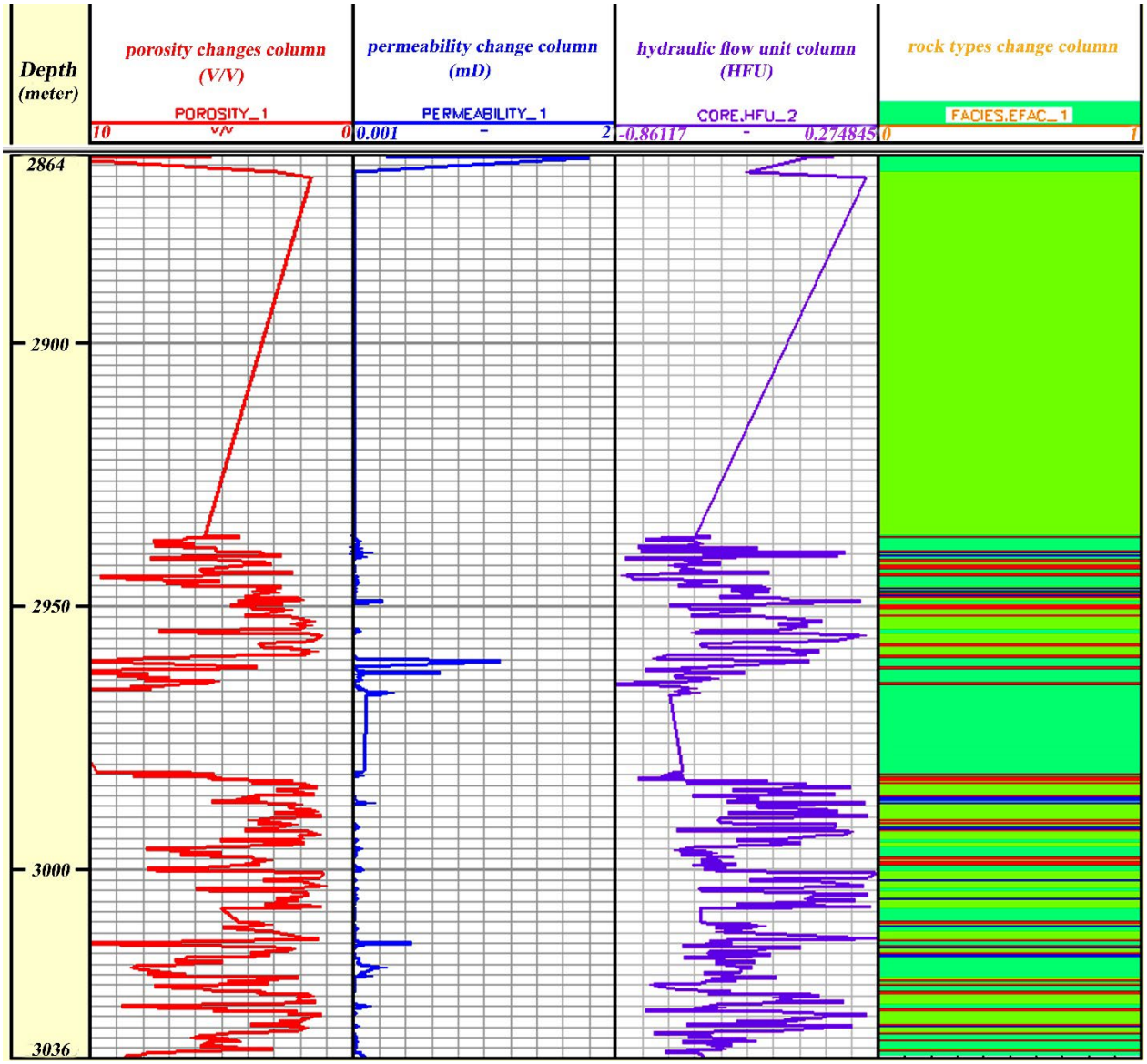

Fig. 14 The log of changes in petrophysical parameters versus depth in the studied well includes the depth column, porosity change column, permeability change column, hydraulic flow unit column, and rock types change column.

References

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