دانشگاه ارومیه

بسمه تعالی

جناب آقای/سرکار خانم **علی اشرف شرفخانی**

با سپاس و تشکر از همکاری علمی جنابعالی در ارائه مقاله تحقیقاتی در چهاردهمین همایش انجمن زمین شناسی ایران و بیست و هشتمین گردهمائی علوم زمین، بدینوسیله مراتب قدردانی انجمن زمین شناسی ایران، سازمان زمین شناسی و اکتشافات معدنی کشور و دانشگاه ارومیه را اعلام داشته و با آرزوی موفقیت روز افزون، امید است همواره شاهد یافته های نوین شما در زمینه های گوناگون علوم زمین باشیم.

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رئیس انجمن زمین شناسی ایران
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دبیر علمی همایش

محمد تقی کره ای
معاون وزیر صنایع و معاون
رئیس سازمان زمین شناسی و
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Electrofacies determination from well log data using cluster analysis technique for Asmari Reservoir, Hendijan Oilfield

Ali Ashraf Sharafkhani[1,3,4], Ali Kadkhodaie[2], Shervin Rasoulzadeh[3,4], Mahmud Almasian[1,] Ali Chehrazi[5]

1. Geology Department, Islamic Azad University, Tehran North Branch, Tehran, Iran
asharafkhani@fugro-jason.com; m_almasian@hotmail.com
2. Geology Department, Tabriz University, Tabriz, NW Iran
Kadkhodaie_ali@yahoo.com; Kadkhodaie_ali@tabrizu.ac.ir
3. Fugro-Middle East Co., Abu Dhabi, UAE
srasoulzadeh@fugro-jason.com
4. c/o Petrokav Energy Co., Tehran, Iran
5. Iranian Offshore Oil Company, Tehran, Iran
Chehrazi2001@yahoo.com

Abstract

Reservoir characterization is a prerequisite study for oil and gas reservoirs development. Identification of reservoir electrofacies plays an important role in petrophysical evaluation of hydrocarbon bearing intervals. In this study, electrofacies of the Asmari Reservoir in the Hendijan Oilfield was determined by utilizing cluster analysis technique. In this method, data distance was first calculated and then using linkage functions they were connected together spatially. Dendrogram function was used to extract cluster tree for Asmari Formation over the studied field.
Input Logs are PHIE, NPHI, DT, GR and RHOB which led to recognition of five reservoir electrofacies within this Formation. The results show that Cluster Analysis is a precise, rapid and cost-effective method for reservoir zonation and electrofacies determination in hydrocarbon reservoirs.

Keywords: Log data; electrofacies; cluster analysis, zonation; Asmari reservoir

Introduction

Hendijan is an offshore oilfield discovered by SIRIP and is located in the northern Persian Gulf. The field has approximately 12 Km length and 4 Km width orientating in north-south direction. The location map of the Hendijan oilfield is shown in figure 1. Multiple limestone and sandstone reservoirs have been discovered in the field. The sand reservoirs are very porous and as a result oil-in-place and recoverable oil values are relatively high. The quantities of discovered hydrocarbons have been prolific throughout multiple levels of the stratigraphic column. This field consists of four separate oil reservoirs:

a) Ghar reservoir: a clastic reservoir composed of sandstone and shale which is member of the Asmari Formation. The Ghar reservoir has been petrophysically divided into 3 zones. Each zone is separated at the base by a thin shaly layer.
b) Asmari reservoir: a carbonate reservoir overlain by the Ghar clastic sediments. This reservoir is underlain by the Jahrum carbonate formation. Asmari reservoir is divided into four different zones based on petrophysical data and reservoir properties.

c) Sarvak reservoir: composed of limestone and dolomite and underlain by the Gurpi shale and marls with an angular unconformity. In Sarvak reservoir, four different zones are distinguished based on petrophysical data and reservoir properties.

d) Kazhdumi reservoir: composed of three lithological units; the top unit consists of shale. Limestone makes up the middle unit and sandstone layers make up the lower unit. Kazhdumi formation is divided into three different zones (PPZ report, 2005).

The clastic Ghar and the carbonate Asmari reservoir layers are the main subject of this study. Well logs from seven available wells were used to identify reservoir electrofacies by implementing the cluster analysis technique

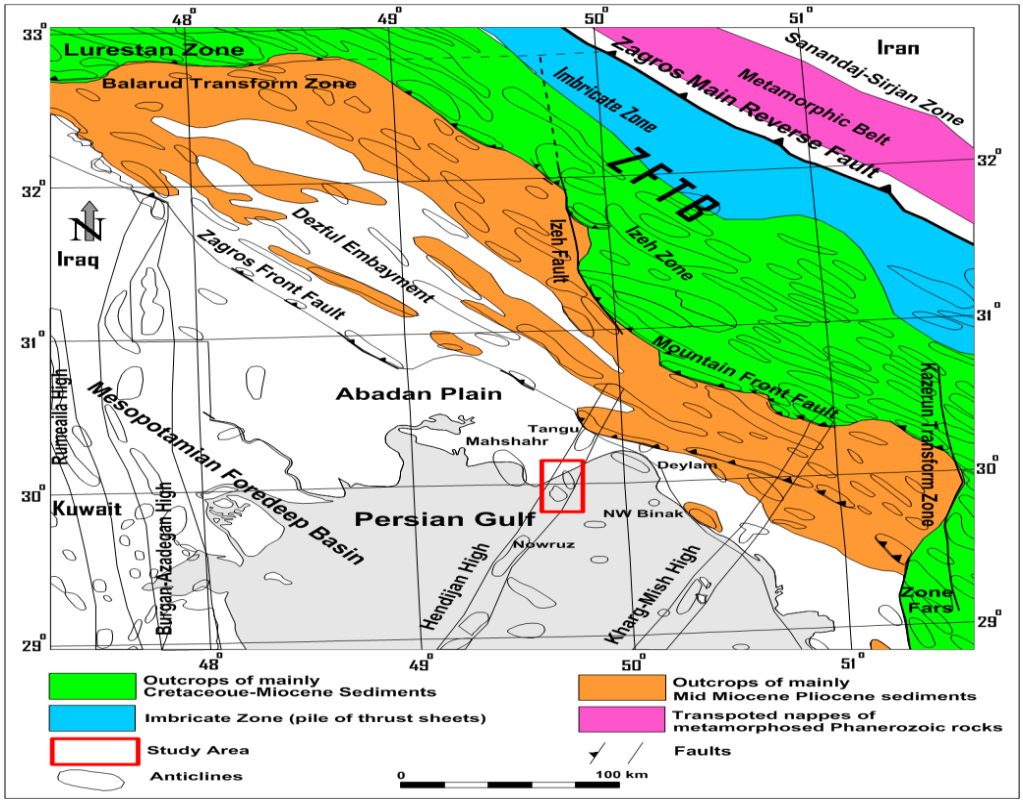


Figure 1. Generalized geological map showing study area and major structural elements (Abdollahie Fard, 2006).

Methodology

In this study cluster analysis technique was applied for grouping data and identifying reservoir electrofacies. Cluster analysis is the classification of objects into different groups, or more precisely, the partitioning of a data set into subsets (clusters), so that the data in each subset (ideally) share some common trait - often proximity according to some defined distance measure. Data clustering is a common technique for statistical data analysis, which is used in many fields, including machine learning, data mining, pattern recognition, image analysis and bioinformatics. Besides the term data clustering (or just clustering), there are a number of terms with similar meanings, including cluster analysis, automatic classification, numerical taxonomy, botryology and typological analysis (Jain et al, 1999).

1- Finding distance between data object

An important step in any clustering is to select a distance measure, which will determine how the similarity of two elements is calculated. This will influence the shape of the clusters, as some elements may be close to one another according to one distance and further away according to another. For example, in a 2-dimensional space, the distance between the point (x=1, y=0) and the origin (x=0, y=0) is always 1 according to the usual norms, but the distance between the point (x=1, y=1) and the origin can be 2,$\sqrt{2}$ or 1 if you take respectively the 1-norm, 2-norm or infinity-norm distance.

Common distance functions are as below:

a) Euclidean distance: $d_{rs}^2 = (x_r - x_s).(x_r - x_s)'$ Eq. (1)

b) Standardized Euclidean distance: $d_{rs}^2 = (x_r - x_s)D^{-1}(x_r - x_s)'$ Eq. (2)

Where D is the diagonal matrix with diagonal elements given by, which denotes the variance of the variable Xj over the m objects.

c) Mahalanobis distance: $d_{rs}^2 = (x_r - x_s)V^{-1}(x_r - x_s)'$ Eq. (3)

Where V is the sample covariance matrix.

d) City Block metric: $d_{rs} = \sum_{j=1}^{n} |x_{rj} - x_{sj}|$ Eq. (4)

e) Minkowski metric $d_{rs} = \left\{ \sum_{j=1}^{n} |x_{rj} - x_{sj}| \right\}^{(1/p)}$ Eq. (5)

2- Linking between distance data

Usually the distance between two clusters s and r is one of the following:

a) The maximum distance between elements of each cluster (also called complete linkage clustering):

$$d(r,s) = \max(dist(x_{ri}, x_{sj})), i \in (i,...,n_r), j \in (1,...,n_s)$$ Eq.(6)

b) The minimum distance between elements of each cluster (also called single linkage clustering):

$$d(r,s) = \min(dist(x_{ri}, x_{sj})), i \in (i,...,n_r), j \in (1,...,n_s)$$ Eq. (7)

c) The mean distance between elements of each cluster (also called average linkage clustering):

$$d(r,s) = \frac{1}{n_r n_s} \sum_{i=1}^{n_r} \sum_{j=1}^{n_s} dist(x_{ri}, x_{sj})$$ Eq. (8)

d) The distance between centroid elements of each cluster (also called centroid linkage clustering):

$$d(r,s) = d(\bar{x}_r, \bar{x}_s)$$ Eq. (9)

3- Dendrogram generation

A Dendrogram consists of many U-shaped lines connecting objects in a hierarchical tree. The height of each U represents the distance between the two objects being connected. If there were fewer data points in the original dataset, each leaf in the Dendrogram corresponds to one data point. If there

were more data points, the complete tree can look crowded, and Dendrogram collapses lower branches as necessary, so that some leaves in the plot correspond to more than one data point. A schematic diagram of a cluster tree or Dendrogram is shown in figure 2.

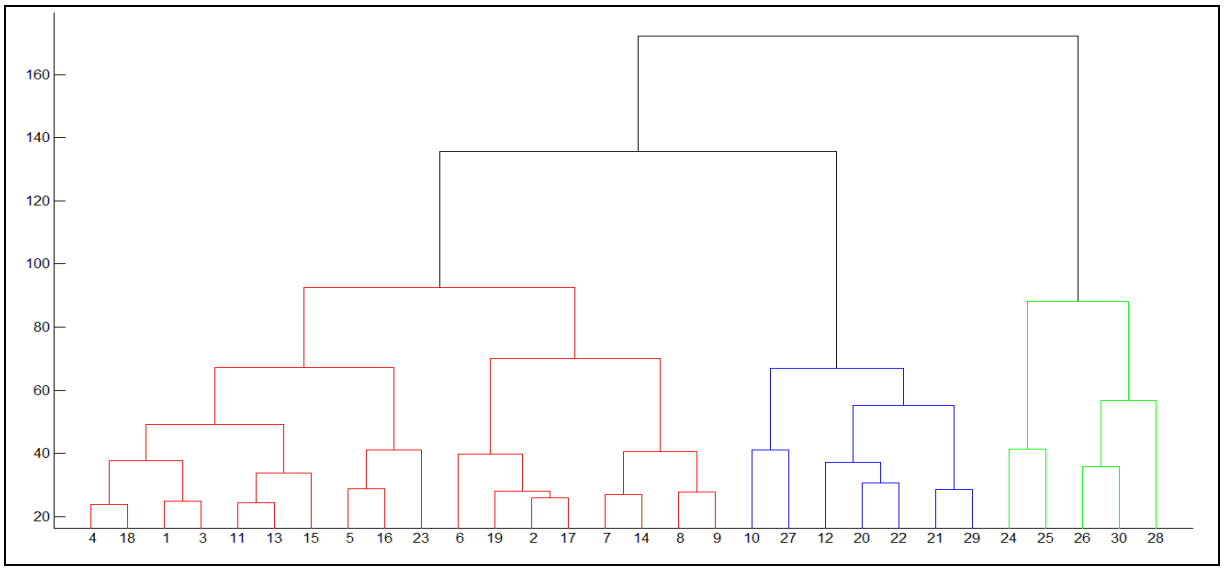


Figure 2. Extracted Dendrogram for Asmari Reservoir color display in Hendijan Oilfield

4- Cluster generation

The final step in cluster analysis is generation of data cluster using a set of cut-off values. In present research, several groups of data clusters were generated by identifying different cut-off values or thresholds. An examination based on trial and error revealed that the case of extracting five clusters is more compatible with previous petrographic studies result. In the mean time, identifying more clusters will complicate facies analysis and their modeling and less clusters cannot cover the entire domains (reflect the reservoir heterogeneity). So, cluster generation function was run and five cluster representing five electrofacies were extracted over the seven wells penetrating into Asmari reservoir.

Results and discussion

Five logs (PHIE, NPHI, DT, GR and RHOB) selected from seven wells of the Hendijan field were analyzed in this study. Cityblock function of MATALB was used to calculate the distances of the data. The *Complete* linkage function, Eq. 6, was used to link among distances. The clustering tree was generated to identify the number of proper clusters. Figure 2 shows the acquired Dendrogram from the Hendijan wells. Five clusters were identified in the tree. The identified clusters were controlled by plotting against the available logs at the wells. As an example, figure 3 represents the resulted electrofacies for well HD-03. The electrofacies have been plotted as stair diagram and color map at columns 6 and 7, respectively. The presented logs are from the left: effective porosity, total porosity, Sonic, Gamma Ray and density logs.

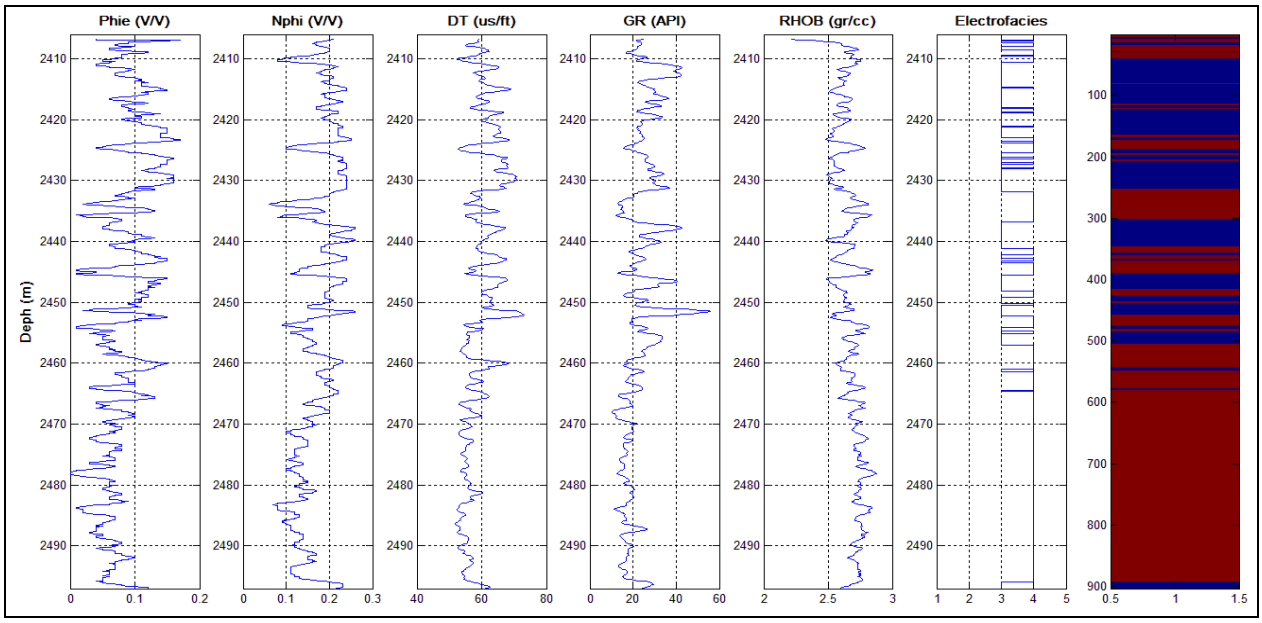


Figure 3. Electrofacies plot along with input well log data for Asmari Reservoir, HD-03

The process was repeated for all available seven wells and the results are compared in figure 4. As it is shown the cluster analysis has helped to differentiate log groups in each well which could be referred to as electrofacies.

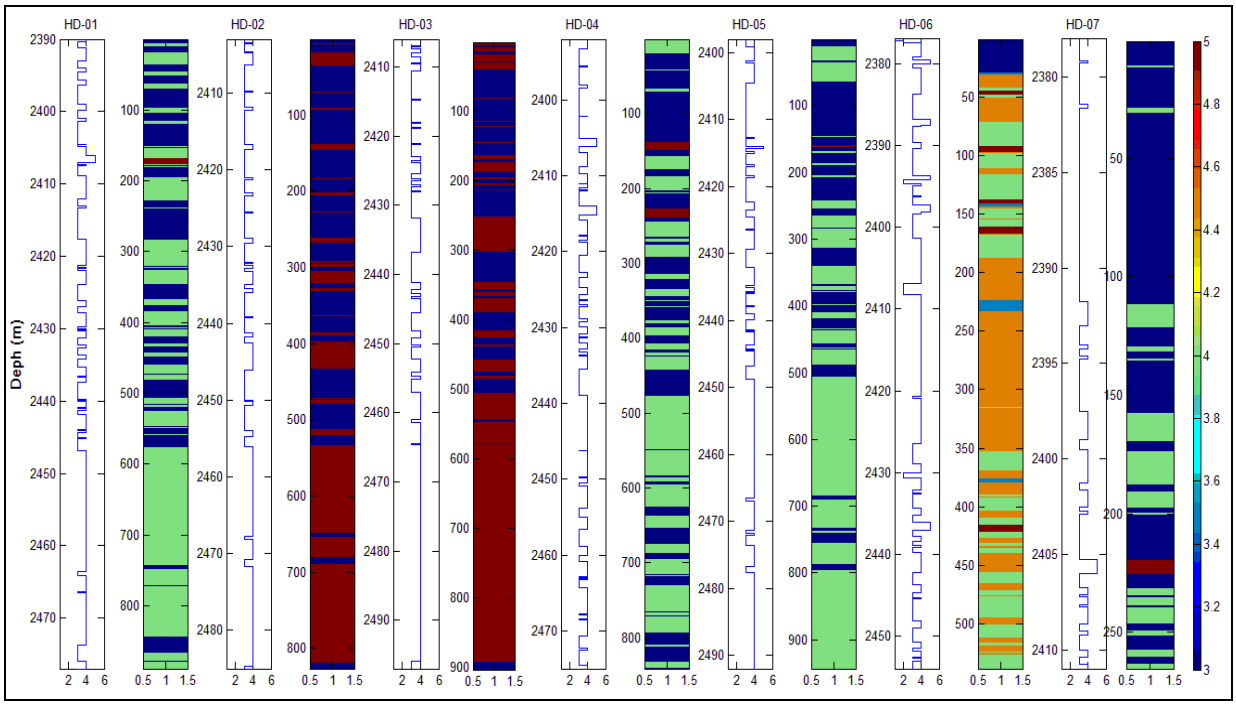


Figure 4. Electrofacies color map for Asmari Reservoir in wells HD-01 to HD-07

In order to correlate the resulted electrofacies to reservoir zones, average of well log properties were calculated individually for each electrofacies and compared to the identified electrofacies (table 1).

Table 1. Average log properties for extracted Electrofacies in Asmari Reservoir

rank	PHIE	NPHI	DT	GR	RHOB	Electrofacies code
1	0.17	0.22	107.81	22.11	2.26	2
2	0.10	0.43	160.35	14.13	1.59	1
3	0.11	0.18	64.02	31.37	2.60	3
4	0.09	0.24	86.35	71.27	2.33	5
5	0.09	0.14	59.81	19.16	2.67	4

Based on the results presented in Table 1, electrofacies No. 2 has the first rank due to representing better reservoir properties (higher effective porosity, sonic transit time, lower density and shale content). The other priorities from the reservoir quality point of view are electrofacies 1, electrofacies 3, electrofacies 5 and electrofacies 4.

Conclusion

In this study a cluster analysis technique was applied for identification of the reservoir electrofacies for the Asmari reservoir. The results obtained indicate five electrofacies could better represent the reservoir heterogeneity. It is a fast, robust, accurate and cost-effective method for electrofacies determination and reservoir zonation. The results and methodology of this study could be generalized and implemented for the other hydrocarbon fields of Iran. The outputs of this study will be used as inputs for facies modeling. Our research in this area is ongoing…

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