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3D modeling of reservoir electrofacies using integration clustering and geostatistic method in central field of Persian Gulf

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ABSTRACT

Description and distribution of reservoir rock characterization in 3D space are challenging issues in study of heterogeneous reservoirs. In order to obviate these complications, a static model based on reservoir and geology characterization is created.

Well log data has been using to extract reservoir properties. Analyzing a large volume of well log data in order to extract reservoir properties by manual approaches is difficult and time consuming. Therefore, reservoir properties can be determined by simultaneous process of several logs. The simultaneous process to classify well log data based on similar response is called electrofacies (EF). Electrofacies analysis is used to determine reservoir properties based upon lithology, porosity and permeability.

This study consists of three steps. Initially, based on similarity in well log response and geological characteristics, electrofacies were created by unsupervised clustering approach in one well. These approaches include hierarchical cluster analysis (HCA), multi resolution graph based clustering (MRGC) and Self-Organizing Maps (SOM). Afterward, the clusters were generalized to all wells by supervised clustering approach. Finally, geostatistical simulation was applied to generate a 3D spatial model of reservoir electrofacies.

According to the results, the hierarchical clustering has performed as a robust and more effective approach in clustering of data based on silhouette validity tests and geological information. Application of sequential indicator simulation (SIS) algorithms to estimate EF 3D model was successfully tested in the study area.

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1. Introduction

Understanding the distribution of geological and petrophysical properties such as facies, porosity and permeability in a carbonate reservoir is essential to build a robust static model. Traditionally, reservoir properties can be determined from cores which these core results have high accuracy. Nevertheless, core data is costly and extrapolating it to non-cored wells is difficult. Moreover, petrophysic is another way to determine reservoir properties, but this method is not useful for sedimentary studies, separation and zoning of reservoirs, and geological properties.

Researchers have used well logs to determine reservoir and geological properties. However, it is difficult to manually analyze a large digitized amount of well log data. The use of electrofacies is a very effective alternative. Serra and Abbott (1982) defined electrofacies as a set of log responses that characterizes a bed and permits it to be distinguished from other beds. Electrofacies are usually assigned to one or more properties of a reservoir, because log responses are measurements of the physical properties of rock.

Clustering is an effective method of data exploration and determining electrofacies. Several algorithms for clustering large data sets have been proposed that use different methodologies to detect arbitrary shapes (Yu et al., 2005). After clustering log data, the log response must be generalized to the overall reservoir. Log data represents a few inches of the surrounding well. The best method to determine the properties of the reservoir by well log data is Geostatistic simulation. Sequential indicator simulation (SIS) has emerged as a powerful tool for stochastic imaging of earth science phenomena and is commonly used for fast

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Nomenclature

AHC	analysis hierarchical cluster
EF	electrofacies
GR	gamma ray
MRGC	multi resolution graph based clustering
NPHI	neutron porosity
PNN	probabilistic neuron network
RHOB	bulk density
SIS	sequential indicator simulation
SOM	Self-Organizing Maps

simulation algorithms (Caers, 2000).

2. Area of study

The Zagros Mountains in southwestern Iran along the Persian Gulf are one of the most productive basins in the world. They contain 8.6% of proven oil and gas proven reserves (R.I.P.I. and N.I.O.C., 2010). Central field of Persian Gulf is located in the interior of the Arabian plate and stretches north, south-northeast and southwest of the Qatar-Fars arc (Motiee, 1990; Darvishzadeh, 2004). One important formation in the central field of Persian Gulf is the Dariyan formation, which is part of the Khami group. The Dariyan is an Aptian formation that consists of shallow water limestone. The upper contact boundary of the Dariyan formation with the overlying Kazhdumi formation is sharp and, in places, an unconformity. The lower contact with the Gadvan formation is gradational (Ghazban, 2007).

The Dariyan formation can be divided into three parts, but the current study focuses on the upper Dariyan formation. This upper part consists of brown limestone with crystals having pyrite, glauconite and iron oxide coatings and is strongly oil-stained. In central field of Persian Gulf, the thickness of this part is 43–61.5 m. The area under study comprises 12 horizontal wells and two vertical wells that display the alteration of the upper Dariyan.

3. Methodology

Three steps are proposed to design a model for reservoir electrofacies (EFs). The first is clustering digitized well log data into a number of EFs using hierarchical cluster analysis (HCA), multi-resolution graph-based clustering (MRGC) and Self-Organizing Maps (SOM). Next, the results are compared and method with the highest validity is chosen to cluster log data into EFs. The reservoir properties of each EF are then extracted and assigned a code. The second step is the use of an artificial neural network (ANN) to identify EFs in other wells in similar proportions to each cluster obtained from the source well. In the third step, 3D models of the EFs are built using EF code and the geostatistical simulation approach.

3.1. Determining electrofacies

3.1.1. HCA

Since EF classification is based on similarity of log response, log responses in the same cluster should be similar and log responses in different clusters should differ. HCA was done on a data set using the statistical functions in MATLAB (The MathWorks, 2010) in the following steps:

(1) Calculate pairwise distances of objects in the data set. Some functions support several ways to compute this measurement.
(2) Group the objects into a hierarchical cluster tree by linking pairs of objects in close proximity using linkage functions. This step uses the distance information generated in Step 1 to determine the proximity of objects to each other. The objects are paired into clusters and the newly-formed clusters are grouped into larger clusters until a hierarchical tree is formed.
(3) Determine where to cut the hierarchical tree into clusters.

In the present study, the cophenetic correlation coefficient was used to validate the three steps. This coefficient uses different distances and linkage methods to create a tree to better represent the original distances (The MathWorks, 2010).

The main input data to HCA was the log data that controls the reservoir lithology and porosity (GR, NPHI, PEF, RHOB logs). To minimize the effect of scale and unit of the log variables, the logs were standardized as

$$Z = (X - \mu)/\sigma \tag{1}$$

where X is the log value, μ is the mean of X, and σ is the standard deviation.

After analysis of the functions for Steps 1 and 2, the Euclidean distance and ward linkage functions were obtained. The cophenetic correlation coefficient was calculated to be 80%.

The function of clustering is to determine the optimum number of EFs. This is normally controlled by geological heterogeneities of the reservoir. The more heterogeneous the reservoir, the greater the number of clusters (Sfidari et al., 2012). The silhouette value is used for each point as a measure of how similar that point is to other points in its cluster and to points in other clusters. The silhouette value ranges from -1 to $+1$ (Kaufman and Rousseeuw, 2009). The silhouette value for the i^{th} point, S_i, is defined as

$$S_i = \frac{(b_i - a_i)}{\max(a_i, b_i)} \tag{2}$$

where a_i is the average distance from the i^{th} point to the other points in the same cluster and b_i is the minimum average distance from the i^{th} point to points in a different cluster, minimized over clusters.

The average silhouette values were plotted for different clusters to determine the optimum number of clusters. Fig. 1 indicates that a decrease in the silhouette value decreased the optimum number of EFs. In this figure, points 2, 3 and 5 have the highest values. Fig. 2 is a silhouette plot of these points. Fig. 3 identifies the three clusters that were more consistent with previous geological studies and validity testing. Fig. 4 is an extracted dendrogram of the HCA.

3.1.2. MRGC

Determining the number of cluster without an a priori data structure is a problem for clustering. HCA shows the number of clusters obtained using geological studies and validity testing, but it is essential to find a method to determine the number of EFs without a priori geological information. MRGC derives the number of clusters from the structure of the data itself. MRGC is a multidimensional dot-pattern recognition method based on the non-parametric k-nearest-neighbor and graph data representation. The underlying structure of the data is analyzed and natural data

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