Electrofacies Characterization of an Iraqi Carbonate Reservoir

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Abstract
Predicting petrophysical parameters and doing accurate geological modeling which are an active research area in petroleum industry cannot be done accurately unless the reservoir formations are classified into sub-groups. Also, getting core samples from all wells and characterize them by geologists are very expensive way; therefore, we used the Electro-Facies characterization which is a simple and cost-effective approach to classify one of Iraqi heterogeneous carbonate reservoirs using commonly available well logs.

The main goal of this work is to identify the optimum E-Facies units based on principal components analysis (PCA) and model based cluster analysis(MCA) depending on available well logs data for four wells from an Iraqi carbonate oil field. The optimum E-Facies units came from comparing them with geologist classification units for these four wells. Also, we conclude that the value of permeability is not important to get the optimum E-Facies units.

Several runs have been tried each with different number of units using the Electro-Facies approach. The results of the techniques show very good match of the tops for various units with the actual ones. This application also shows the power and versatility of electrofacies characterization in improving reservoir descriptions in complex carbonate reservoirs.

Keywords: electrofacies, permeability prediction, zonation methods

Introduction
Electrofacies determination method is based on attempts to identify clusters of well log responses with similar characteristics which used to perform the electrofacies classification. Efacies is a window based software for electrofacies characterization based on the multivariate analysis from well logs. Generally a suite of well logs can provide valuable but indirect information about mineralogy, texture, sedimentary structure, fluid content and hydraulic properties of a reservoir. The distinct log responses in the formation represent electrofacies that very often can be correlated with actual lithofacies identified from cores, based on depositional and diagenetic characteristics. The importance of electrofacies characterization in reservoir description and management has been widely recognized. In this software, the calculation parts are done by Fortran 77 and the graphical interface parts are done by the program C++. This classification of electrofacies in our study is done by Efacies
software which developed by Dr. A. Datta-Gupta from Texas A&M University [1, 2, and 3].

Data Preparation
The well log data considered in this analysis has been gathered from 4 wells (Well A, Well B, Well C and well D). Logs of 230 sample data from 4 well were used in this field with thier corresponding depth for characterizing the electrofacies groups. The well logs used are : resistivity (LLD) and (SFL), neutron porosity (NPHI), density (RHOB) and Sonic log (DT). These logs are considered as independent variables. The number of independent variables has been reduced to obtain the optimum results.

Principal component analysis (PCA):
Principal Component analysis (PCA) technique is a mathematical tool used for summarizing the data without losing too much information. It reduces the dimensionality of the problem by introducing principal components. Principal components are identified within the defined variable space. They provide an alternate coordinate system in multi-dimensional space for displaying data without too much lose of information. Principal components are constructed through linear combination of variables [1 and 4].

The Eigenvectors and covariance matrix provide the coefficients for principal component transformations. The total variance of the dataset is the sum of individual variances associated with each principal component. Hence addition of every principal component increases the percentage of variance explained. The maximum number of principal components equals the number of variables and all the principal components together explain 100% variance as shown in Fig. 1 below.

Principal components correlate well with the variables in the problem, PC1 correlates well with RHOB log, NPHI log and DT log as shown in Fig. 2 consecutively and PC2 may show a good correlation with SFL log and ILD log as shown in Fig. 3. This indicates that PC1 represents formation porosity while PC2 shows a stronger correlation with resistivity. Table 1 shows the eigenvectors of the covariance matrix which represent the coefficients of the PC equations for all PCs and well logs. The first few principal components often explain most of the variance in the dataset and are usually adequate to reveal the structure of the dataset without too much loss of information as shown in Fig. 1. By selecting only
the first few principal components for data analysis, one can reduce the dimensionality of the problem [3,4,5]. For example in our work, the first two principal components explain over 90% variance of the dataset then by selecting the first two principal components for cluster analysis, the dimensionality of the problem can be reduced from five to two. Every principal component is then a coordinate of the data point in a two-dimensional space Fig. 4

Table (1) PCA Transformation Coefficients

<table>
<thead>
<tr>
<th>Variable</th>
<th>EV2</th>
<th>EV1</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPHI</td>
<td>-0.0203</td>
<td>-0.406</td>
</tr>
<tr>
<td>RHOB</td>
<td>-0.5450</td>
<td>0.3403</td>
</tr>
<tr>
<td>ILD</td>
<td>-0.5522</td>
<td>0.3422</td>
</tr>
<tr>
<td>SFL</td>
<td>-0.1706</td>
<td>0.4115</td>
</tr>
<tr>
<td>DT</td>
<td>-0.5617</td>
<td>-0.3222</td>
</tr>
</tbody>
</table>

The PC transformation coefficients for the first two PCs are given in eq.(1) and eq.(2) as:

PC1 = -0.406 NPHI + 0.3403 RHOB + 0.3422 ILD + 0.4115 SFL - 0.3222 DT ...(1)

PC2 = -0.0203 NPHI - 0.5450 RHOB - 0.5522 ILD - 0.1706 SFL - 0.5617 DT ...(2)

Fig. 2: Scatter plot (PC1 VS NPHI, RHOB, DT, ILD and SFL) of the sample data set from Wells (A,B,C and D)
Fig. 3: Scatter plot (PC2 VS NPHI, RHOB, DT, ILD and SFL) of the sample data set from Wells (A,B,C and D)

Fig. 4: Scatter plot (PC1 Vs PC2) of the sample data set from Wells (A,B,C and D)

Model Based Cluster Analysis (MCA) classifying a data set into groups that are internally homogeneous and externally isolated on the basis of a
measure of similarity and dissimilarity between groups. In this study, model-based clustering technique is used. This approach can give much better performance than traditional procedures of clustering techniques, which are often fail to identify groups that are either overlapping or of varying sizes and shapes. Another advantage of model-based approach is that there is an associated Bayesian criterion for assessing the model. This provides a means of selecting not only the parameterization of the model, but also the number of the clusters without the subjective judgments [1, 5 and 6].

Cluster analysis aims to classify data points into groups based on the unique characteristics of the well log measurements, where input is in the form of petrophysical properties measured at every depth, a cluster represents a collection of samples with similar petrophysical properties which are considerably different from the petrophysical properties of the samples from another cluster.

Cluster analysis was applied to the first two principal components for classifying the data into clusters, as shown in figure 5. The first two principal components PC1 and PC2 show the existence of 4 clusters (E-facies). The E-facies that was obtained in Well A are 1, 2 and 3. In Well B only two E-facies 3 and 4 was noticed, while in the wells C and D the E-facies are 1, 2, 3 and 4.

Fig. 5: Cluster plot of the first two principal components after model based cluster analysis

Comparison with geological units

Results that obtained from E-facies characterization were compared with the geological units which also divided the formation into four units (a,b,c and d). The top for each unit that was obtained from the E-Facies characterization seems to be too close to the geological units as seen from Figures 6, 7, 8 and 9.
Fig. 6: A Comparison between distribution of the four electrofacies groups with respect to depth and geological units for well A.
Fig. 7: A Comparison between distribution of the four electrofacies groups with respect to depth and geological units for well B
Fig. 8: A Comparison between distribution of the four electrofacies groups with respect to depth and geological units for well C
Conclusions

- In electrofacies determination by E-Facies Software, the PCA analysis gives convenient visual information for identifying the important components. The first two principal components explain around 90% variation of the whole sample data set. The first principal component PC1 shows a strong correlation with RHOB, DT log and NPHI log readings where PC2 shows good correlation with SFL log, ILD log and RHOB log readings.
- PC1 and PC2 are used in MCA model-based cluster analysis. The whole data set divided into

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four cluster groups by the MCA. Each cluster can be treated as an individual electrofacies groups.

- The results of the Electrofacies Characterization show very good match of the tops for various number of units with the actual ones.
- Electrofacies Characterization is a powerful tool to predict lithofacies at wells without core data.

Nomenclature

- **DT**: sonic transient time, µsec/ft
- **EV**: eigenvectors
- **ILD**: deep lateral log, Ωm
- **K**: permeability, md
- **MCA**: model based clustering
- **NPHI**: neutron log derived porosity, fraction
- **PC**: principal component
- **PCA**: principal component analysis
- **SFL**: spherically focused log, Ωm
- **RHOB**: density log, gm/cc

References


