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Electrofacies Characterization of an Iraqi Carbonate Reservoir

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Abstract

Predicting peterophysical 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.
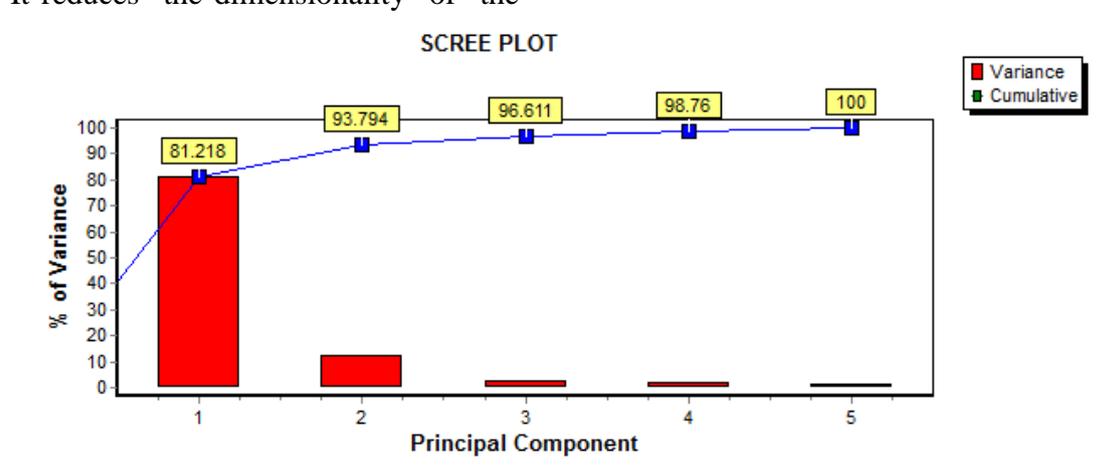

Fig. 1: Scree plot of the sample data set from Wells A,B,C and D

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 redu 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 (eigenvectors)

EV2	EV1	Variable
−0.0203	−0.406	NPHI
−0.5450	0.3403	RHOB
−0.5522	0.3422	ILD
−0.1706	0.4115	SFL
−0.5617	−0.3222	DT

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

PC1= -0.406 NPHI + 0.3403RHOB + 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)
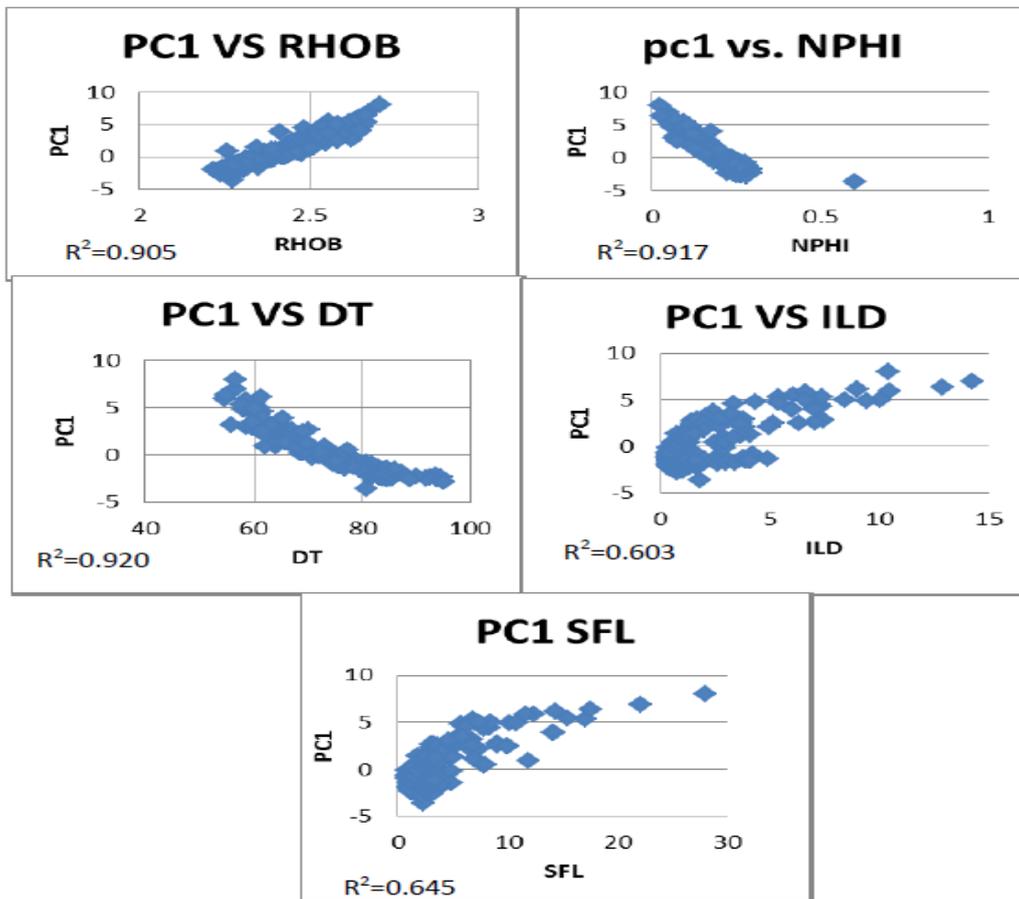

Fig. 2: Scatter plot (PC1 VS NPHI, RHOB, DT, ILD and SFL) of the sample data set from Wells (A,B,C and D)
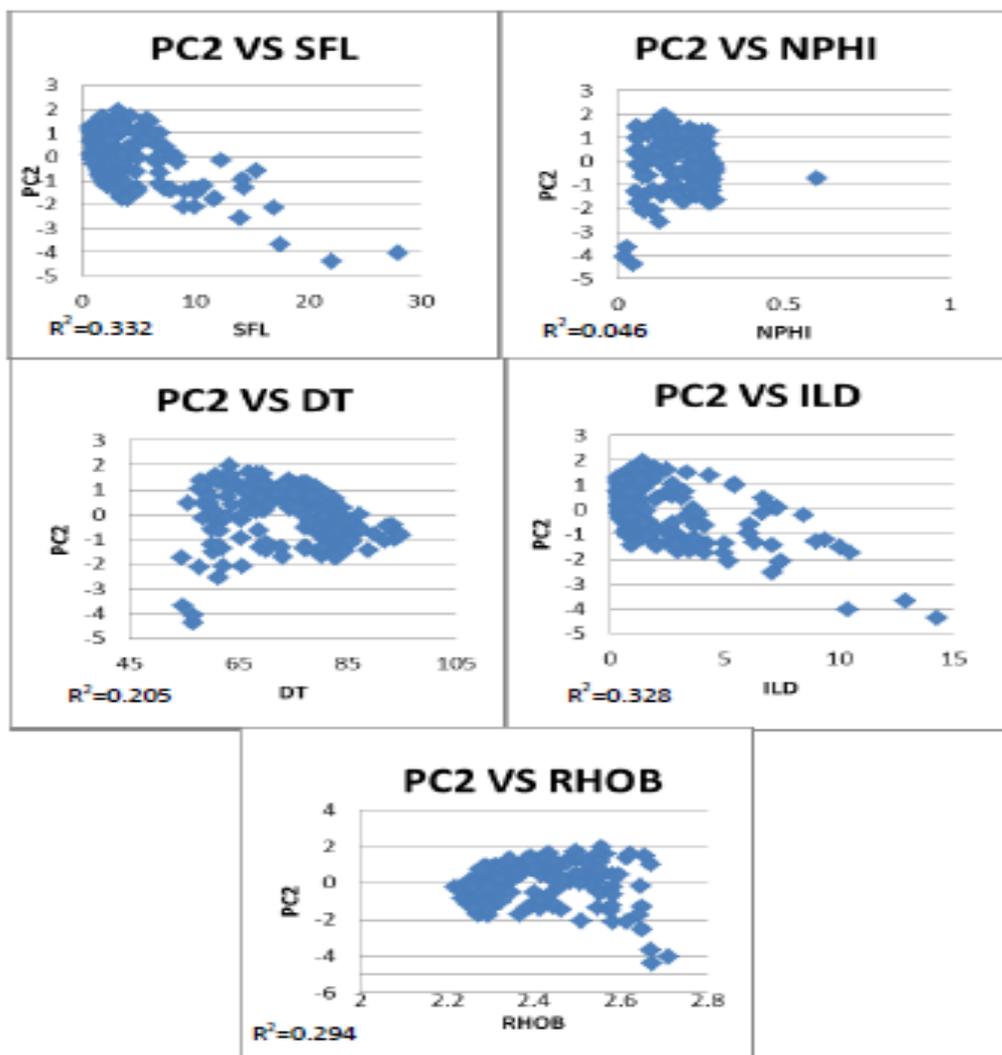
Fig. 3: Scatter plot (PC2 VS NPHI, RHOB, DT, ILD and SFL) of the sample data set from Wells (A,B,C and D)
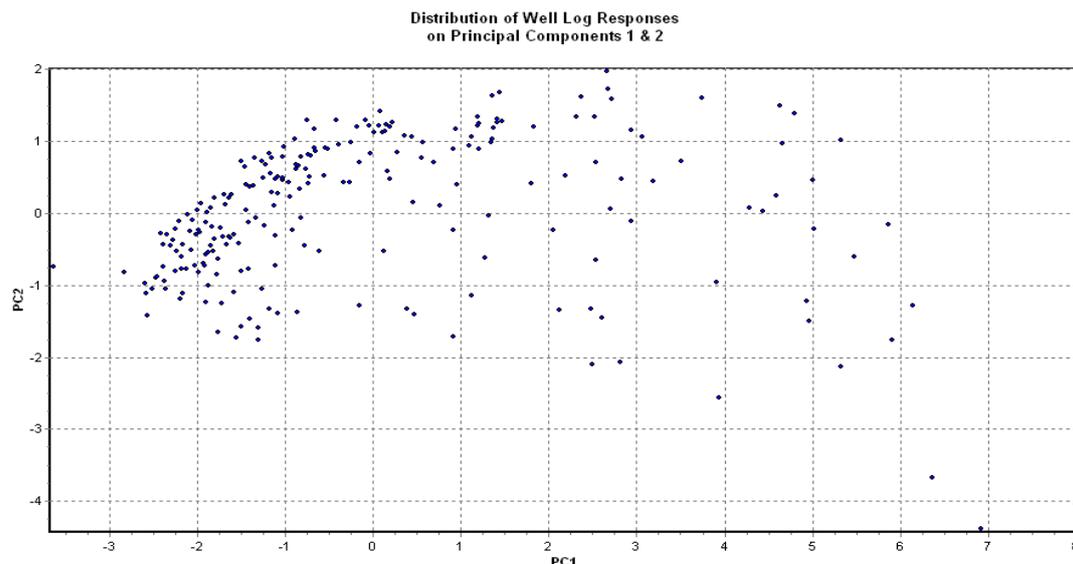

Fig. 4: Scatter plot (PC1 Vs PC2) of the sample data set from Wells (A,B,C and D)

Model Based Cluster Analysis (MCA)

Cluster analysis is done for 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 petro physical 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.
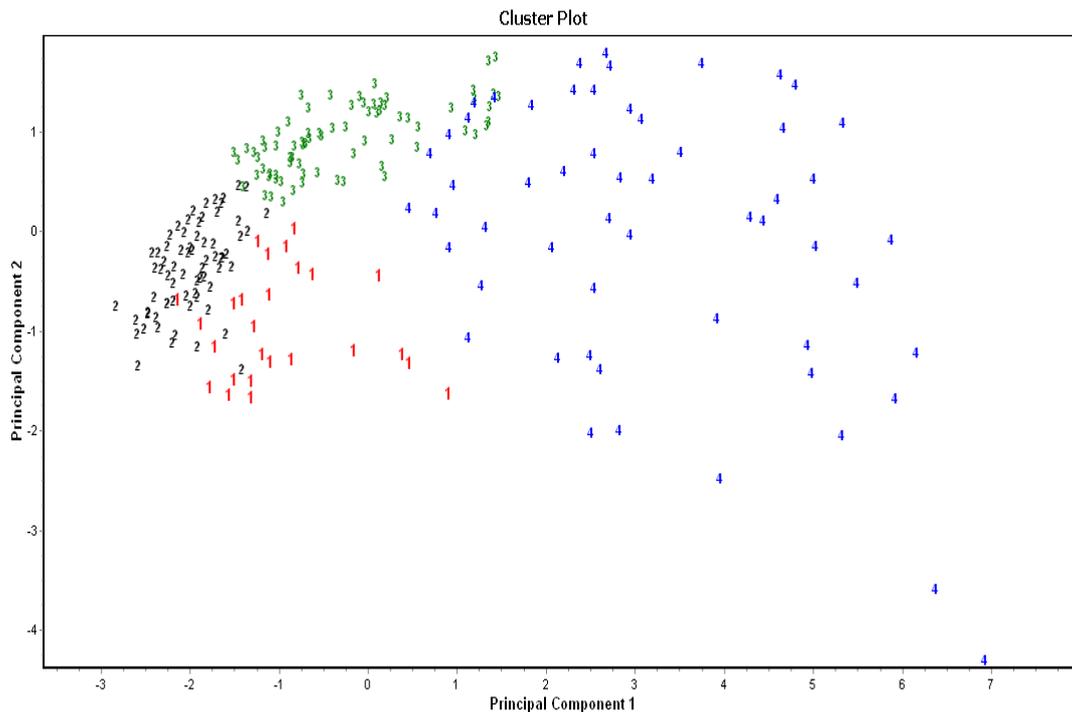

Fig. 5: Cluster plot of the first twoPrincipal components after model based cluster analysis

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.
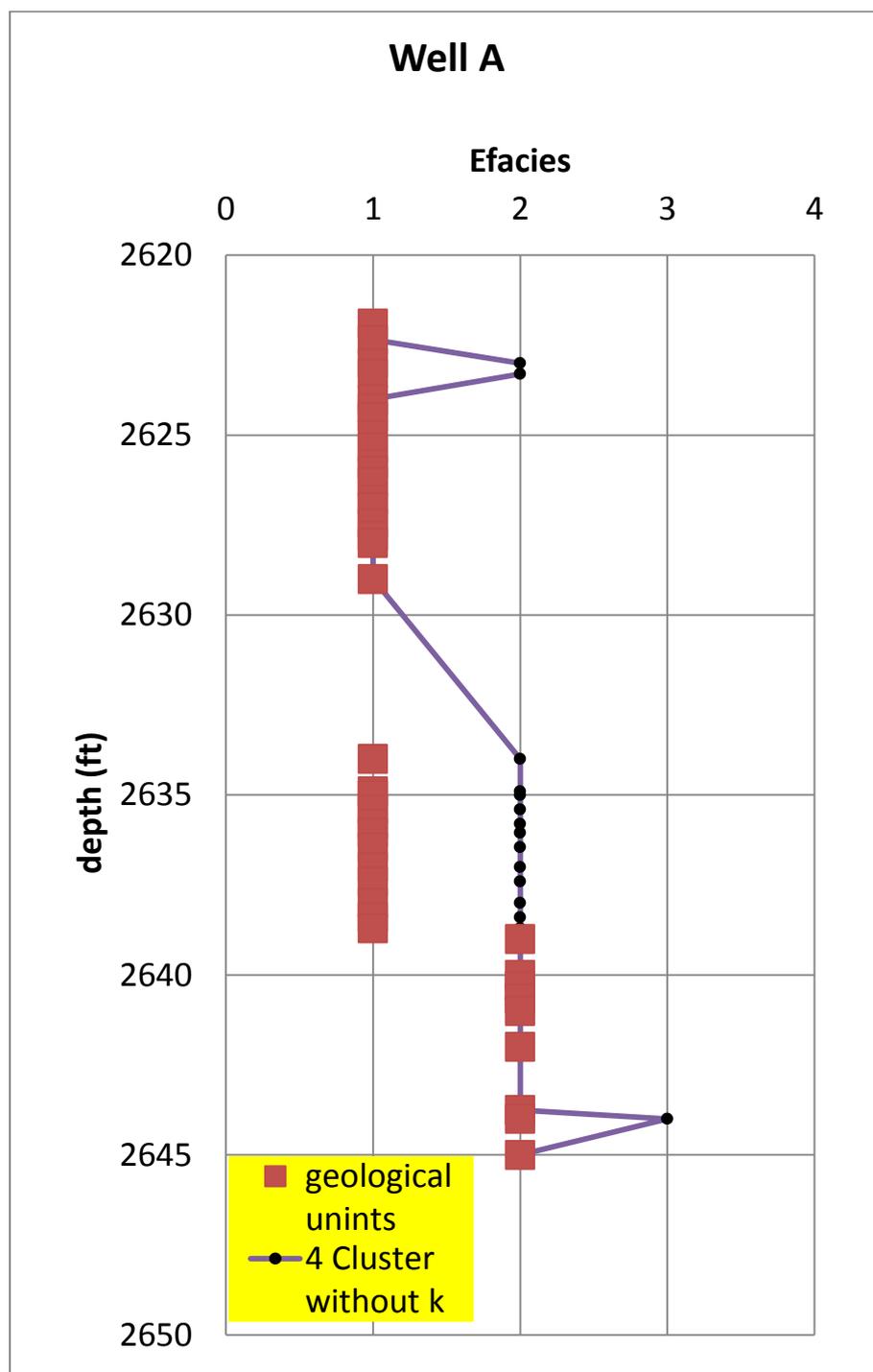
Fig. 6: A Comparison between distribution of the four electrofacies groups with respect to depth and geological units for well A
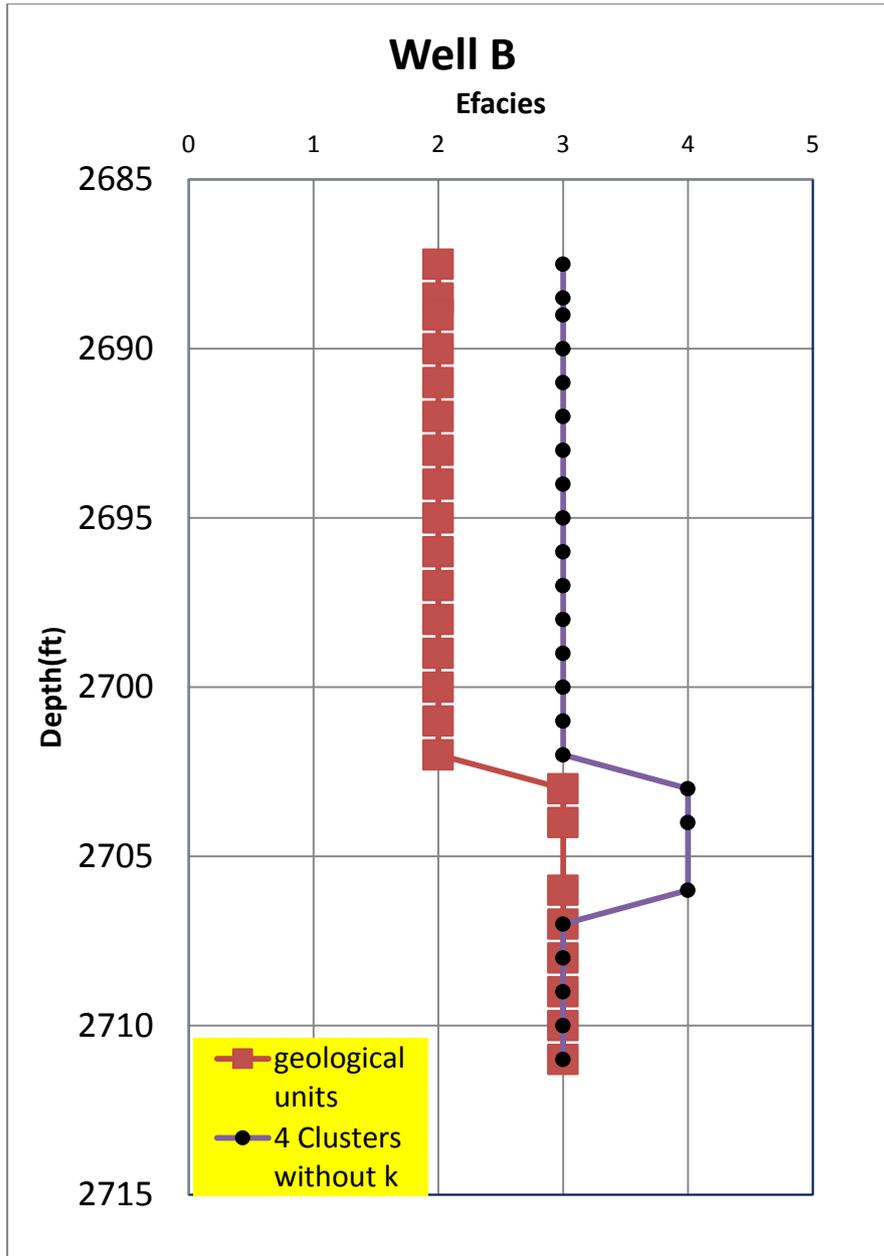
Fig. 7: A Comparison between distribution of the four electrofacies groups with respect to depth and geological units for well B
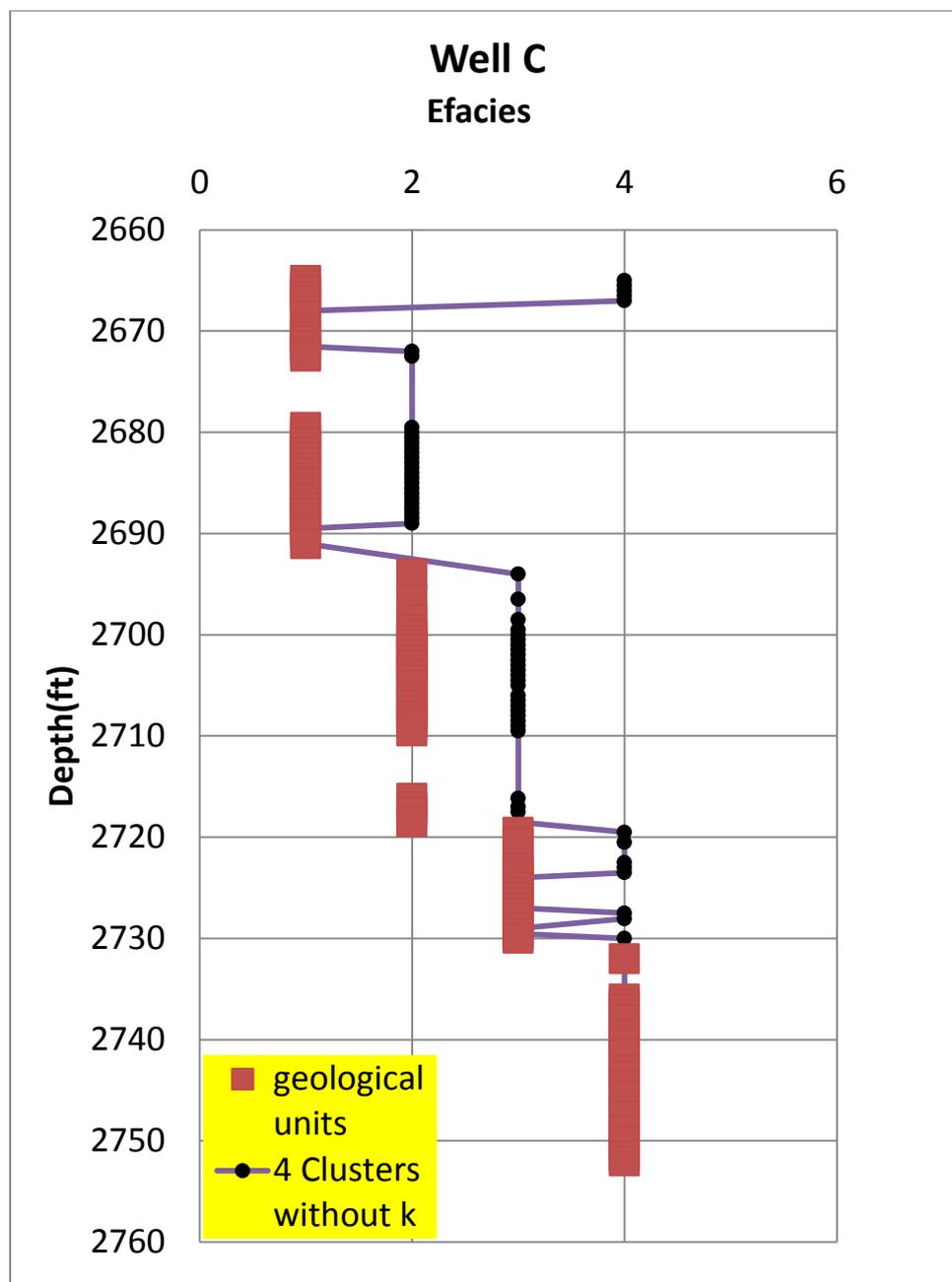
Fig. 8: A Comparison between distribution of the four electrofacies groups with respect to depth and geological units for well C
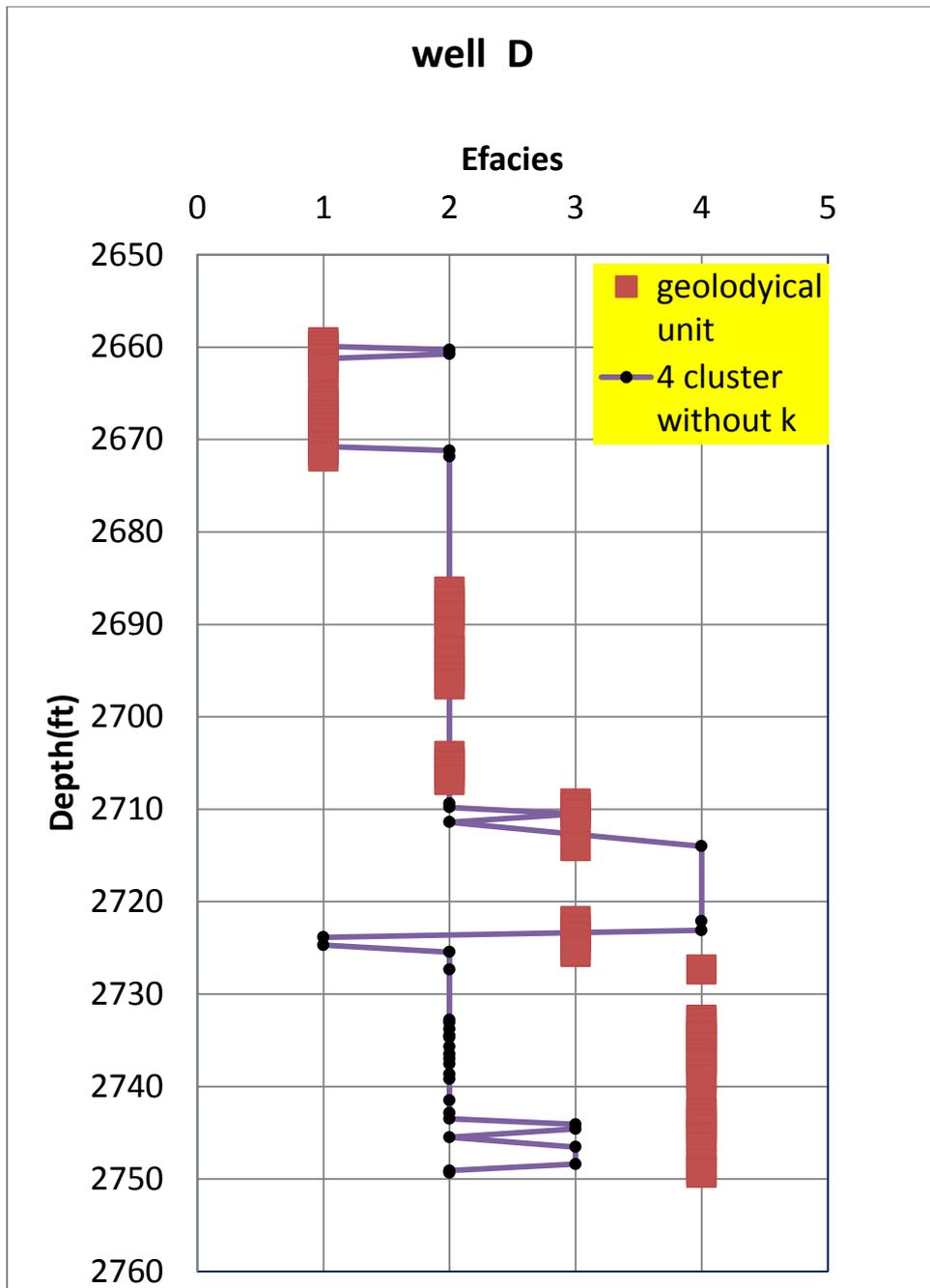
Fig. 9: A Comparison between distribution of the four electrofacies groups with respect to depth and geological units for well D

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

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

- The results of the Electrofacies Characterization show very goodmatch 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

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