No.13 Journal of Petroleum Research & Studies (JPR&S)

Selection of Optimum Permeability Estimation Approach in a Heterogeneous Carbonate Reservoir

Ali Mohammad Bagheri; Mohsen Saemi;

Research Institute of Petroleum Industry, Iran,

Abstract

Determination of permeability is an essential component of reservoir characterization process which is among the key input parameters into a flow simulation models. Permeability modeling in carbonate reservoirs is still a challenge in the world. Permeability is directly determined in the laboratory from core analysis. Alternatively, it can be determined by analyzing well test or well logs. Due to high cost associated with coring and some technical problems, few wells in any given field are cored whereas most wells have wire-line logs.

In this study detailed core analysis data including core porosity and core permeability supplemented by well logs and well test data to predict a continuous log derived permeability in un-cored wells in a heterogeneous carbonate reservoir in south west of Iran. The Mishrif reservoir in the studied field consists of limestone and interbedded shale. The field has 3 wells that have recovered cores. Permeability prediction was applied by several methods including: fuzzy logic, neural networks, clustering, empirical methods and regression analysis. These different methods were used to determine the optimal approach for utilizing in the field under study. To test the permeability prediction, the techniques were calibrated in 2 cored wells and blind tested in remaining cored well to see how well estimated permeability fitted the actual core permeability. Among all permeability modeling methods applied in the field, it turned out that electrofacies method and after that artificial neural network have the highest degree of association. Fuzzy logic and regression techniques are average in modeling permeability and empirical methods are not capable for predicting permeability in studied heterogeneous carbonate reservoir. The core analysis from 3 cored-wells was applied to determine permeability in 51 un-cored wells.

Keywords: Permeability, Neural Network, Fuzzy Logic, Electrofacies, Regression

Introduction

It is well known that accurate reservoir simulation and management requires a quantitative model of the spatial distribution of reservoir properties such as permeability and an understanding of the nature of reservoir heterogeneity at many scales. Permeability is directly determined in the laboratory from core analysis. Permeability estimation has presented a challenge for cases whenever no direct measurements of permeability are available. In these cases, it can be indirectly determined by analyzing well test or well logs. Typically, few wells in a field may have laboratory information such as core analysis data whereas most of wells may have electronic logs data. Wells without core are usual due to various reasons such as, time and cost associated with coring, and or impractical coring in many situations, such as in horizontal wells.

There are several methods for determination of permeability from logs, including the Flow Zone Indicator (FZI), empirical methods, fuzzy logic, neural networks, simple K versus PHI regression and facies-based permeability estimation. In Petrophysical study of the field under study, empirical methods and statistical and artificial intelligence techniques such as regression, electrofacies, fuzzy logic and neural networks were employed to identify permeability based on limited data obtained from core analysis supplemented by well log data in the Mishrif formation of a heterogeneous reservoir in Iran. FZI method was omitted because it is not possible to accurately predict FZI in un-cored wells.

The Mishrif formation in the southwest of Iran is one of the most important reservoirs in the Middle East. This formation in the studied field consists of limestone and interbedded shale.

Data Preparation

There are three cored wells available in the field. Well A and well B (Most samples) were selected and used for training and the other well (C) was sequestered for blind test.

Before implementing core data in permeability modeling, because of different measured depth between core samples and well logs, core data was depth shifted to match with well logs. Also all broken, chipped, spitted, micro-fractured, and fractured samples were excluded from the analysis.

In this study, various well logs were used as input to permeability modeling. There is no limitation on the number of input logs in electrofacies modeling and intelligent methods. However, the additions of more curves may possibly not reduce the uncertainty of the determination of permeability, but, it is important to have a consistent set of logs in all wells.

For best results, these logs should vary in some fashion with permeability. A sensitivity study was carried out based on raw original logs and also log derived properties due to their relative importance in permeability estimation. These raw logs are: gamma ray (GR), neutron porosity (NPHI), density (RHOB), sonic (DT), Photoelectric factor (PEF) and resistivity (RT). Log derived properties are porosity and water saturation. Cross plots between these logs and core permeability are shown in figure 1. Finally GR, RHOB, NPHI, DT, PEF and PHIE were selected as input of the permeability estimation models.

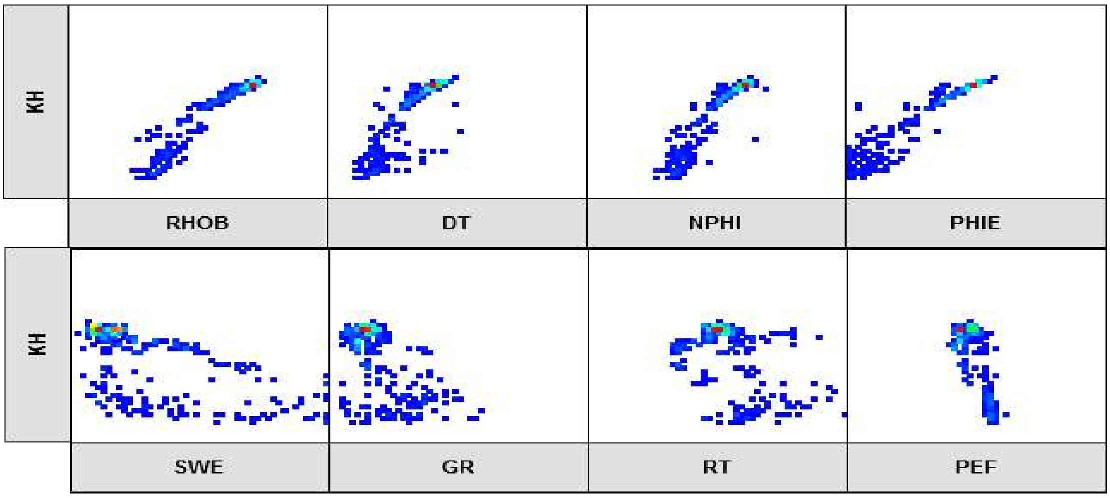

Fig.(1) Relationship between permeability and wire line logs for selection of input log for creating permeability prediction model

Regression method

In order to develop a log-derived porosity to permeability transform, multi well cross plots of permeability in logarithmic scale versus porosity in linear scale were generated (Figure 2). Then based on best fit line, permeability to porosity equation was generated. This gives a regression line on the form as shown below:

$$Kh = 10^{10.791 \times PHI - 1.524} \qquad R^2 = 0.469$$

Where Kh is horizontal core permeability and PHI is core porosity.

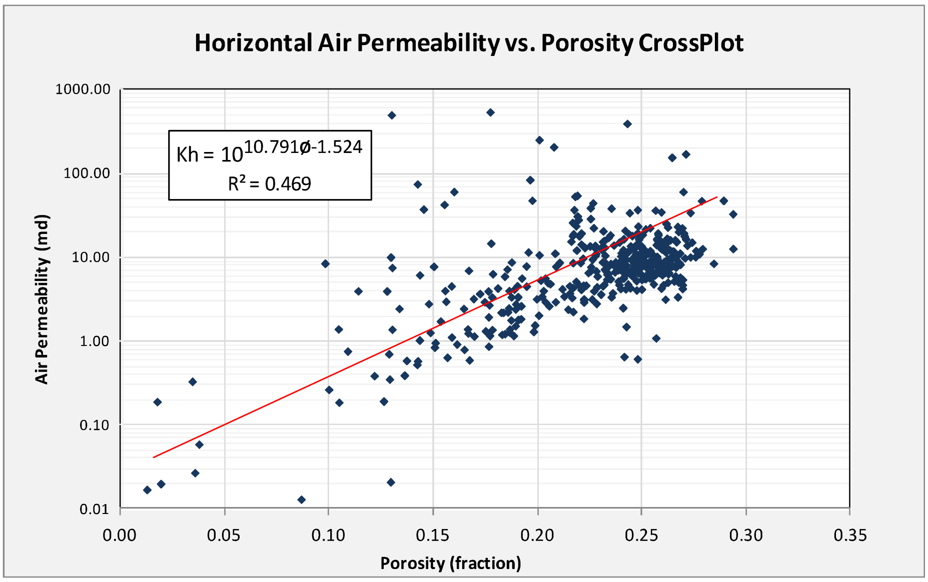

Fig. (2) Horizontal permeability vs. porosity and best fit line.

Empirical methods

In this study two common empirical equation including Timur and Coates were used to predict permeability in the field. The modified form of the Timur equation is:

$$k = \frac{c \times \varphi^d}{(S_{wirr}{}^e)^2}$$

The constant parameters for this equation were calibrated using core data of train wells in the field to be c=50, d=3 and e=1.

Also permeability was calculated from the Coates Free Fluid Index method with correlated scaling factor (c) equal to 6.

$$k = c \times \varphi^2 \times \frac{1 - S_{wirr}}{S_{wirr}{}^2}$$

Permeability modeling using Fuzzy Logic

The Fuzzy Logic inference method was applied to estimate permeability in the un-cored wells based on data from wire-line logs in the Mishrif formation.

Fuzzy logic is an extension of conventional Boolean logic (zeros and ones) developed to handle the concept of "partial truth" values between "completely true" and "completely false". In contrast to binary-valued (bivalent) logic, truth is ascribed either 0 or 1, multivalent logic can ascribe any number in the interval [0,1] to represent the degree of truth of a statement. This is a normal extension of bivalent logic, and it is a form of logic that humans practice naturally.

More common use of fuzzy logic is to describe the logic of fuzzy sets (Zadeh, 1965). These are sets that have no crisp, well-defined boundaries, and which may have elements of partial instead of full membership. For fuzzy sets, elements are characterized by a membership function that describes the extent of membership (or the degree of fit) of each element to the set. Such a membership function maps the entire domain universe to the interval [0,1]. A schematic membership function is shown in Figure 3a For each GR log value as an example, it assigns a measure of the degree of fit of that GR to the definition of the set (Permeability). This measure is called the fuzzy possibility. Note that bivalent sets are special cases of fuzzy sets, where the membership function has only two values, 0 and 1 (Figure 3b).

Permeability estimation applying the Fuzzy Logic is based on the fact that a rock with a bin of permeability can give any log reading although some readings are more likely than others. In this method several conditions based on wire-line data were applied to determine the permeability and reduce the uncertainty of the determination. The membership functions are based on measured permeability applying the wire-line data. The bin with highest membership function is won for corresponding permeability (Figure 3c). These membership functions will be applied to identify the permeability in an uncored well by means of wire-line log.

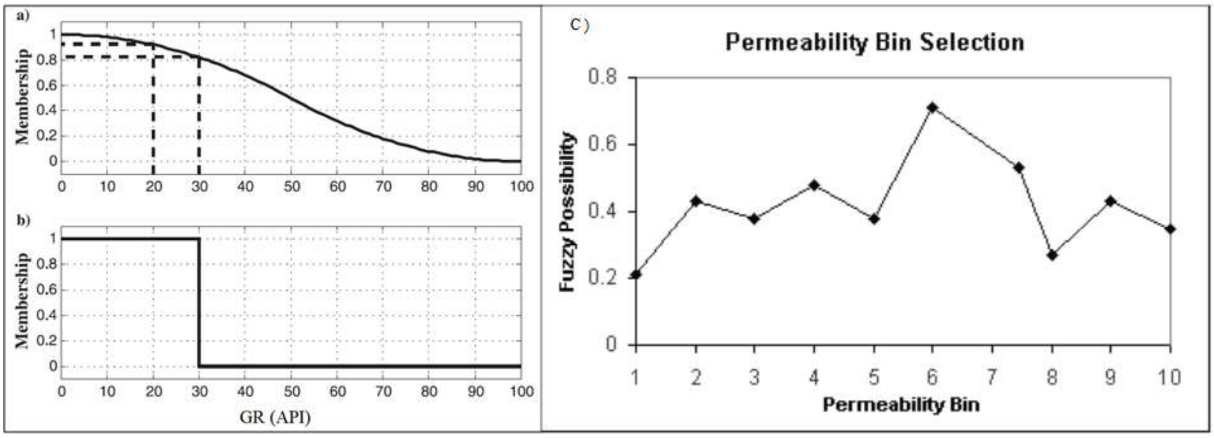

Fig. (3) Membership function for the fuzzy set of GR (a) , membership function for the bivalent set of GR (b) and Fuzzy possibility versus permeability bin (c)

Permeability modeling using Artificial Neural Network, ANN method

A feed forward, back propagation neural network (which adopts a supervised training scheme) was used for permeability estimation. This network is popular for developing highly non-linear relationships between known inputs and outputs.

During the design and development of the neural network for this study, it was determined that a Three layer network would be most appropriate (Figure 4).

It was important to train the network long enough so it would learn all the examples that were provided. It was also equally important to avoid overtraining, which would cause memorization of the input data by the network. A network that has memorized all of its training data will perform poorly when exposed to a new set of data for testing. Another important factor is local minima. During the course of training, the network is continuously trying to correct itself and achieve the lowest possible error (global minimum) for every example to which it is exposed. The neural network method is performed in two steps: training and propagation. Data is selected to use as "training" data to generate models, which may then be used in log prediction.

After training the models, Artificial Neural Network method was tested in well C as the blind test. Data of well C was not used in training step and it was used for checking the ability of constructed method.

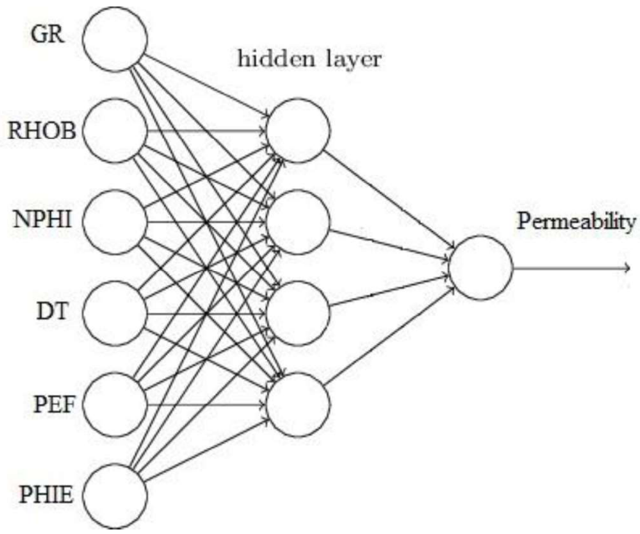

Fig. (4) Three layer feed forward, back propagation neural network

Permeability modeling using electrofacies

Electrofacies analysis consists of partitioning a set of log data into electrofacies, to present them in a way comparable to that used by geologists for either outcrop or core description.

An efficient way to perform a facies analysis is to setup a classification model that partitions the log data into sets of log responses that characterize sediment and allow the sediment to be distinguished from others, as per the definition given by Serra and Abbot (1980). In a later stage of the survey, the model is propagated over the other wells of the same field or basin area.In this studied field, well log responses by using Multi Resolution Graph Base Clustering, MRGC are portioned into distinct classes. Figure 5 shows a cross section of different wells in the field with final electrofacies model.

For estimation of permeability, above model is trained by supervised classification; on the other hand structural information (from input logs) is defined to optimize the match between the calculated output (predicted permeability) and original target (core permeability).

Same model of ANN and Fuzzy was used in electrofacies study; so input logs in model were: GR, RHOB, NPHI, DT, PEF and PHIE. Core permeability selected as output. From different optimum models of MRGC clustering, the model with highest clusters was selected in order to predict permeability smoothly. Selective model was propagated in the three wells. Correlation coefficient in training data is near to 0.9 and in test well is about 0.72. This correlation coefficient value reveals a good to very good result for permeability estimation.

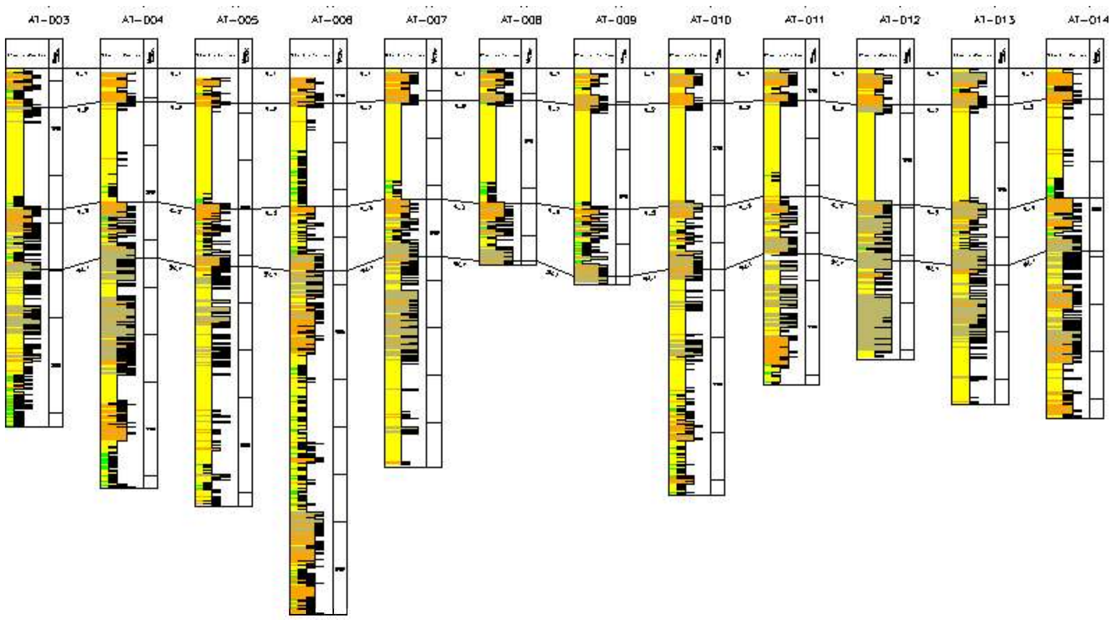

Fig.(5) Section of different wells with final electrofacies model

Results and conclusion

To test the permeability prediction, the techniques were calibrated in 2 cored wells and blind tested in remaining cored well to see how well estimated permeability fitted the actual core permeability. The core data in this latest well was applied for a comparison with the result from the estimation methods (Figure 6). The correlation between predicted permeability and MDT results in three wells was also considered as another verification of the trained model.

Among all permeability modeling methods applied in the field, it turned out that electrofacies modeling method and after that artificial neural network have the highest degree of association. Fuzzy logic and regression techniques are average in modeling permeability and empirical methods are not capable for predicting permeability in studied heterogeneous carbonate reservoir. Empirical methods applied in this field are very sensitive to irreducible water saturation and doesn't give reasonable results in transition zone and water bearing intervals.

As indicated in figure 7, correlation from Coates equation is almost half of correlation from electrofacies method.

The core analysis from 3 cored-wells was applied to determine permeability in 51 un-cored wells. These permeability determinations were combined with the geometry of the reservoir to construct a representation of the initial (static) state of the reservoir, having a specified resolution, quality and accuracy.

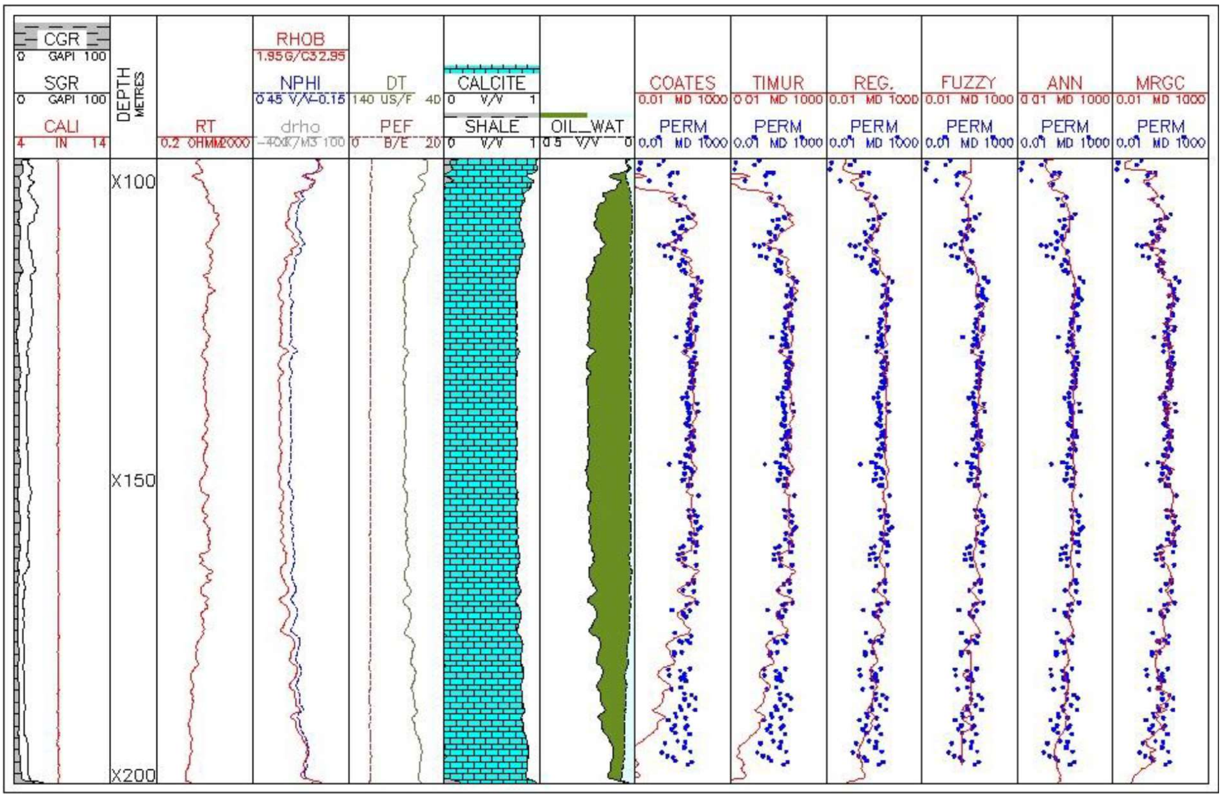

Fig.(6) Comparison between core permeability and estimated permeability by different methods

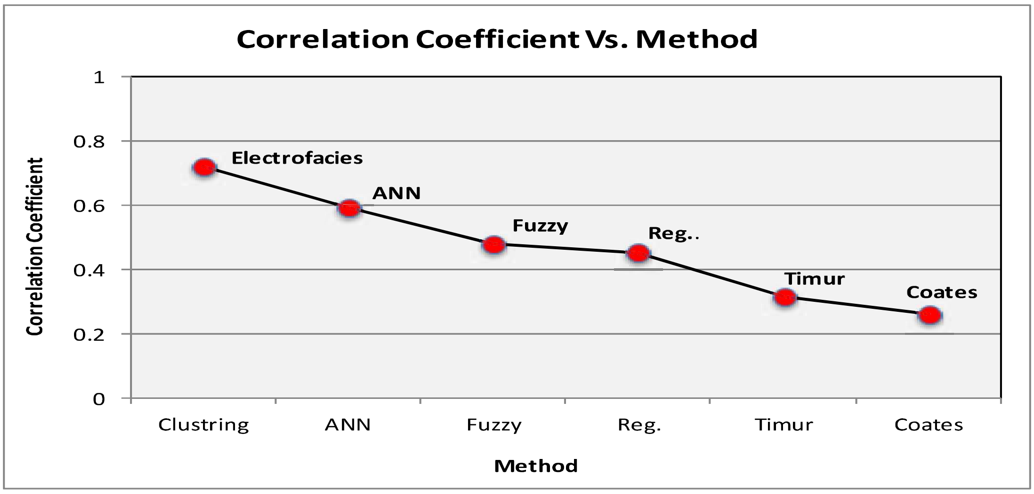

Fig.(7)Permeability prediction correlation vs. method applied. Correlation from Coates equation is almost half of correlation from clustering method

Reference

1- D. Xie, D. Wilkinson, T. Yu, S. Ramon, Permeability estimation using a hybrid genetic programming and fuzzy/neural inference approach, Proceeding of SPE Annual Technical Conference, Dallas, Texas. (2005) SPE 95167.

2- G.R. Coates, and J.L. Dumanoir,: "A New Approach to Improved Log Derived Permeability", The Log Analyst (Jan – Feb) 1974, pp.17.

3- J.L Lin, and H.A. Salisch,: "Determination from Well Logs of Porosity and Permeability in a Heterogeneous Formation", SPE 28792, presented at the SPE Asia Pacific Oil & Gas Conference, Melbourne, Australia, Nov. 7-10, 1994.

4- L. Quintero, and A. Boyd,: "Comparison of Permeability from NMR and Production Analysis in Carbonate Reservoirs", paper SPE 56798 presented at the SPE Annual Technical Conference held in Houston, TX, Oct. 1999.

5- M.E Semmelbeck,. et al.: "Invasion based method for estimating permeability from logs", paper SPE 30581 presented at SPE Annual Technical Conference & Exhibition held in Dallas, U.S.A., 22-25 Oct., 1995

6- S.J. Cuddy, Litho-Facies and Permeability Prediction from Electrical Logs Using Fuzzy Logic, SPE Reservoir Evaluation and Engineering. 4 (2000) 319-324.

7- S.-J. Ye, P. Rabiller, "A New Tool for electrofacies Analysis: Multi-Resolution Graph-Based Clustering",SPWLA, 41st Annual Logging Symposium Transaction.

8- W.W. Johnson,: "Permeability Determination From Well Logs and Core Data", paper SPE 27647 presented at the SPE Permian Basin Oil and Gas Recovery Conference held in Midland, TX, 16-18 March, 1994.

9- Y.J. Zhang, and P.A. Lollback,: "A Methodology for Estimating Permeability From Well Logs in a Formation of Complex Lithology", SPE 37025, presented at the SPE Asia Pacific Oil & Gas Conference, Adelaide, Australia, Oct. 28-31,1996.