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Permeability Prediction in One of Iraqi Carbonate Reservoir Using Hydraulic Flow Units and Neural Networks

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Abstract

Permeability determination in Carbonate reservoir is a complex problem, due to their capability to be tight and heterogeneous, also core samples are usually only available for few wells therefore predicting permeability with low cost and reliable accuracy is an important issue, for this reason permeability predictive models become very desirable.

This paper will try to develop the permeability predictive model for one of Iraqi carbonate reservoir from core and well log data using the principle of Hydraulic Flow Units (HFUs). HFU is a function of Flow Zone Indicator (FZI) which is a good parameter to determine (HFUs).

Histogram analysis, probability analysis and Log-Log plot of Reservoir Quality Index (RQI) versus normalized porosity ($ø_z$) are presented to identify optimal hydraulic flow units. Four HFUs were distinguished in this study area with good correlation coefficient for each HFU (R^2=0.99), therefore permeability can be predicted from porosity accurately if rock type is known.

Conventional core analysis and well log data were obtained in well 1 and 2 in one of carbonate Iraqi oil field. The relationship between core and well log data was determined by Artificial Neural Network (ANN) in cored wells to develop the predictive model and then was used to develop the flow units prediction to un-cored wells. Finally permeability can be calculated in each HFU using effective porosity and mean FZI in these HFUs. Validation of the models evaluated in a separate cored well (Blind-Test) which exists in the same formation. The results showed that permeability prediction from ANN and HFU matched well with the measured permeability from core data with R^2 =0.94 and ARE= 1.04%.

Key Words: Permeability Prediction, Flow Zone Indicator, Hydraulic Flow Unit, Artificial Neural Network.

Introduction

Reservoir characterization methods are very important to provide a better attributive of the flow capacities and storage of petroleum reservoir. Carbonate reservoirs show challenges in characterization because of their heterogeneity and tendency to be tight due to depositional and digenetic processes [1].

Permeability estimation in a logged but uncored wells/intervals is a generic problem to all reservoirs. Models based on HFU which is a function of FZI are more recommended to predict permeability than traditional regression because they provide more reliable accuracy and precise models for entire reservoir by dividing the reservoir into various flow units different from the other by means of characters controlling fluid flow in reservoir[2]. FZI is depending on geological description of the material and various pore geometry of rock mass (Reservoir Quality Index (RQI) and normalized porosity ($ø_z$)). FZI is a useful value that offers a relationship between petrophysical properties at the macroscopic scale like core plugs with mega scale which is represented by the wireline-log measurement scale. RQI and $ø_z$ can be determined from core permeability and effective porosity.

Recently, intelligent techniques like Artificial Neural Network (ANN) have achieved considerable attention in several areas of geosciences. The oil and gas industry has shown an interest to use these techniques to solve difficult problems and enhance the accuracy of reservoir properties prediction.

The main goal of this study is finding the best accurate model for characterization the reservoir. Values of FZI for uncored well can be calculated using ANN and well log data as input variables.

Determination of Hydraulic Flow Unit (HFU)

Hydraulic flow unit concept proposed by Amaefule et al [2] to be used as a principle for subdividing reservoir in different rock types. HFU represent volume of reservoir rock when the petrophysical and geological properties within it are different from properties of other rock volumes [3]. Each distinct reservoir flow unit has a unique FZI which represents the relationship between Reservoir Quality Index (RQI) which represent geometric distribution of pore space and the normalized porosity ($ø_z$).

$$RQI = 0.0314\sqrt{\frac{K}{øe}} \qquad \dots (1)$$

Where K is the permeability in md
RQI is Reservoir Quality Index in μm
$ø_e$ is effective porosity in fraction

$$øz = \left(\frac{øe}{1-øe}\right) \qquad \dots (2)$$

Where $ø_z$ is the pore volume to grain volume ratio or normalized porosity

The FZI is defined by

$$FZI = \frac{RQI}{øz} \qquad \dots (3)$$

Where FZI is Flow Zone Indicator in μm

Take the logarithm of both sides of equation (3)

$$\text{Log RQI}=\text{Log } ø_z+\text{Log FZI} \qquad \dots (4)$$

On a log –log plot of RQI versus $ø_z$ all samples have similar FZI values will lie on a straight line with unit slope. Samples with different FZI values will lie on other parallel lines. The intercept of the unit slope straight line at $ø_z$ =1 represents the mean value of FZI. Samples that lie on the same straight line have similar pore throat attributes and constitute a flow unit [2].

The number of hydraulic flow units Determination

In carbonate reservoirs or heterogeneous reservoirs, the data is more scattered and recognizing the straight lines and the boundaries of flow units through these scattered data and is more difficult. To determine the exact boundary of each hydraulic flow unit, three different ways were applied and compared the results that was obtained [3,4, 5, 6 and 7].

1-Histogram Analysis

The data of FZI plotted in the form of histogram, "n" number of normal distribution for "n" number of HFUs will be obtained because FZI distribution is a superposition of multiple log-normal distribution, therefore a histogram of log FZI should show "n" number of normal distribution [8].

It is often difficult to separate the overlapped individual distribution from histogram plot. Fig.1 shows log FZI histogram for well1

2-Probability Plot

The probability plot or cumulative distribution function (cdf) is the integral of probability density function (pdf) or histogram. This plot is more useful to determine HFUs because it is smoother than the histogram and identification the number of HFUs becomes easier. The number of straight lines in the probability plot is an indication of HFU in the reservoir.

Fig.2 shows the logarithm of FZI probability plot for well 1, four HFUs were distinguish.

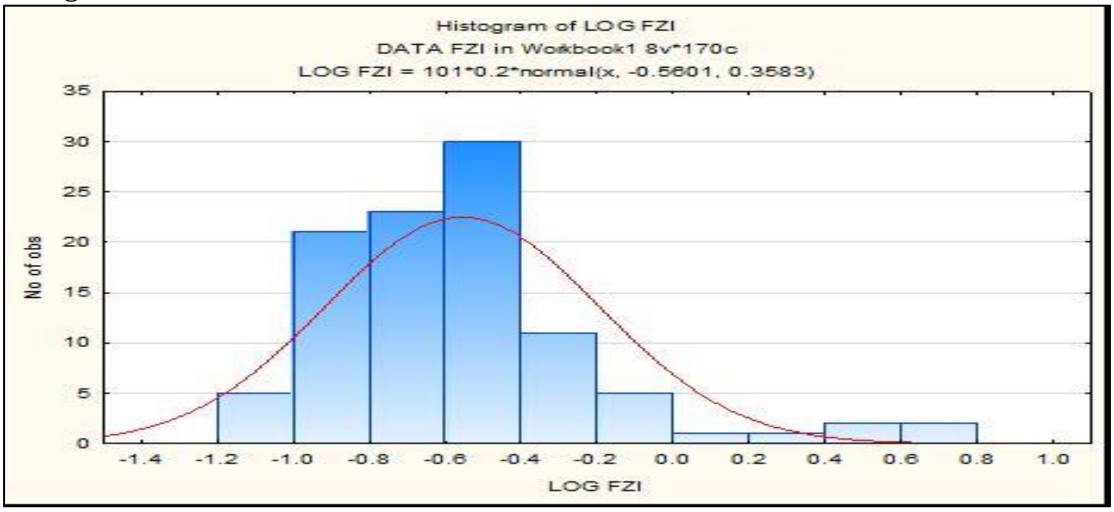

Fig. 1, log FZI histogram for well1

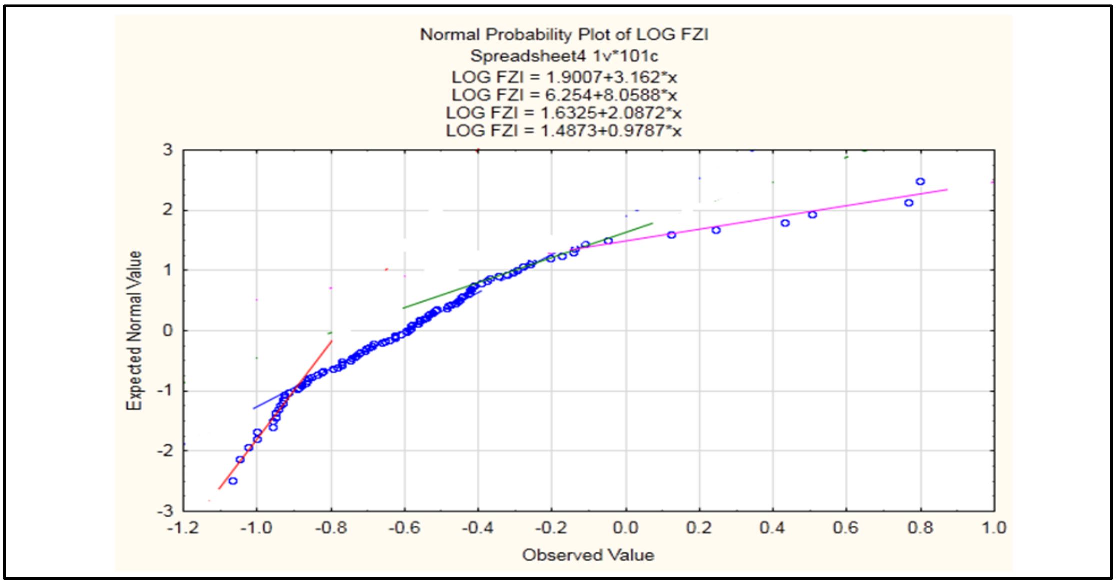

Fig.2, the logarithm of FZI probability plot for well 1

3-Log- log plot of RQI versus $ø_z$

This method is a simple analysis but in this method the number of HFUs and their boundaries is clearly not sufficient to distinguish. The log- log plot of RQI versus $ø_z$ will produce a number of parallel straight lines with a unit slope for each one. Samples that lie on the same straight line have the same pore throat attributes and thereby constitute a hydraulic unit [2].

The mean value of FZI for each HFU can be distinguished from the intercept of the unit slope straight line with $ø_z$ =1.

Fig.3 shows the plot of RQI versus $ø_z$ in logarithmic scale, four HFUs were identified which means there are four rock types exist in the studied reservoir. HFU1 with FZI mean equals 0.11, HFU2 with FZI mean equals 0.28, HFU3 with FZI mean equals 0.6 and HFU4 with FZI mean equals 3. These intercept values (FZI $_{mean}$) are used to calculated permeability from the following equation.

$$K=1014(FZI_{mean})^2(ø_e^3/(1-ø_e)^2) \quad \ldots(5)$$

The calculated permeability then plotted against the core permeability as shown in the fig.4 with Average Relative Error (ARE) equals 0.55% ARE can be calculated from equation 6 below.

$$ARE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{core\ permeability - calculated\ permeability}{core\ permeability}\right| \quad \ldots(6)$$

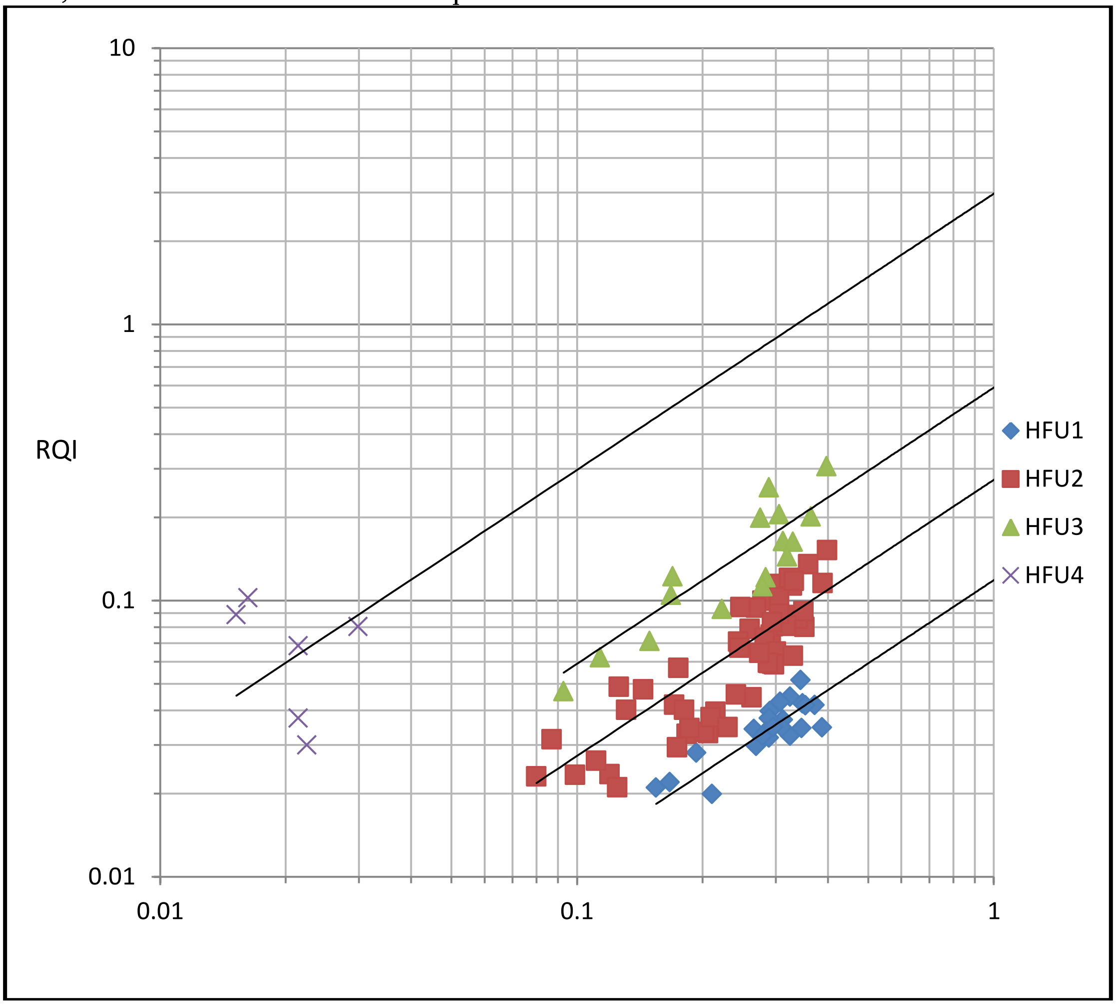

Fig. 3, the plot of RQI versus $ø_z$ for well 1

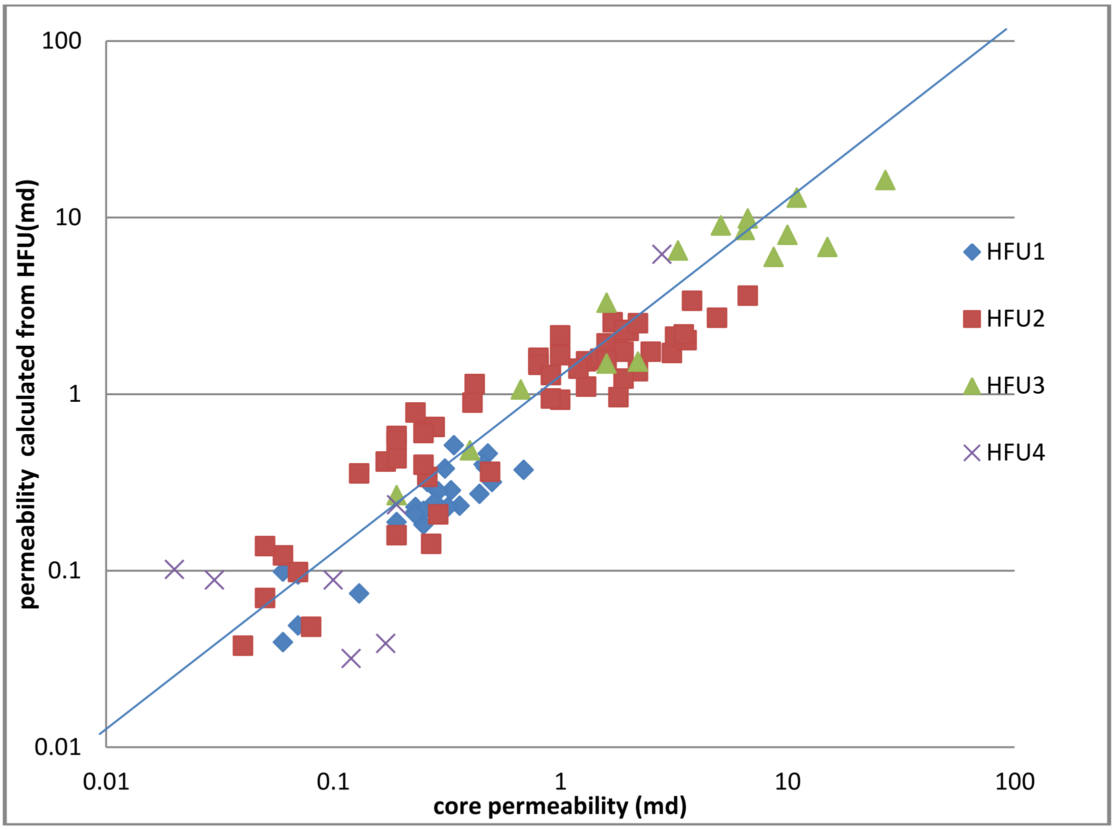

Fig. 4, permeability calculated after final HFU determination vs. core permeability for well 1.

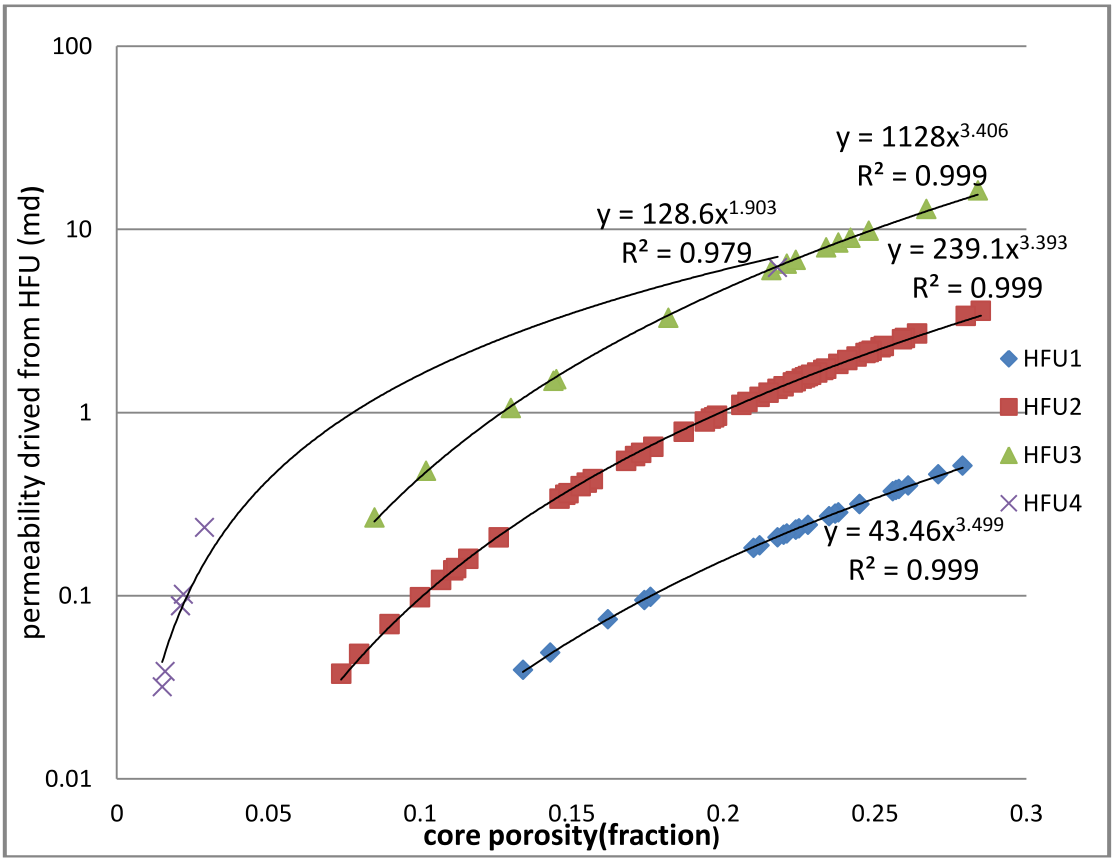

Fig. 5, Permeability vs. porosity for well 1

Table 1, reservoir rock classification by HFU method

layer	Correlation coefficient(R^2)	Relation between k and ø
HFU1	0.999	$K=43.46\ ø^{3.499}$
HFU2	0.999	$K=239.1\ ø^{3.393}$
HFU3	0.999	$K=1128\ ø^{3.406}$
HFU3	0.979	$K=128.6\ ø^{1.903}$

Fig.5 shows the relations between permeability and porosity for each HFU and table (1) summarized these relations and given an idea about the high accuracy of HFU approach in permeability correlating with porosity.

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) which is the most popular neural networks provides a flexible way to generalize linear regression because it does not require any relationships between variables [9]. ANN is arranged in multiple layers with one input layer, one output layer and one or more hidden layers. Each layer contains a number of nodes called neuron which are connected to each node in the preceding layer by simple weighted links [10]. Except for nodes in the input layer, each node multiplies its specific input value by the corresponding weight and then sums all the weighted inputs [11].

Flow Zone Indicator Determination in Uncored Wells Using Artificial Neural Network (ANN)

Conventional core analysis and well log data were obtained in well 1 and 2 in one of carbonate Iraqi oil field, data of well 1 used for building the model then the model generalized to well 2 as uncored well for determining HFUs. The Artificial Neural Network is utilized to find the most reliable approach for HFU prediction. Different models of neural networks are available and they are used for a specific purpose. In this paper feed forward back propagation neural networks technique was used. One of the major problems with this type of network is training the network using the mean square error in order to minimize the overall error. Another important issue is to find the optimal number of neurons and hidden layer and select the best appropriate function [10].

For building the model in this paper, well log data including RHOB, NPHI, PHIE, ILD, SFL and DT are required as input data for the (ANN). To make the data uniform and prevent scattering of variables the log values must be lie between 0 and 1 to become dimensionless therefore each of these data set are normalized using equation 7 below.

$$N\delta = \frac{\delta - \delta min}{\delta max - \delta min} \quad \ldots (7)$$

Where: δ is any log value.
δmin is the minimum reading of δ log
δmax is the maximum reading of δ log
$N\delta$ is the normalized δ log

The data set with 101 points from well 1 was divided into three sets 70% for training, 15% for testing and 15% for validation the model. Each set of training data, testing and validation should be included in all wells and all the sections and subsections, also the three sets of data, including permeability data of all intervals [12].

After trial and error to obtain the best performance of the ANN network, the first layer of the network (a hidden layer) consists of 20 neurons. The second layer of the network is the output layer consists of one neuron which is the logarithm of the FZI. Table (2) gives the structure of the neural network to obtain the best performances of the ANN model. Fig.6 shows the simplified schematic of the ANN used for FZI model, fig.7 shows the number of epochs with MSE during the training period (best training performance).

FZI determined from ANN model was matched to FZI that was calculated from core permeability and effective porosity with correlation coefficient (R^2) of 0.96 for training, 0.99 for validation and 0.98 for testing as shown in fig.8 then the ANN method was generalized to well 2 as uncored well to obtain FZI from only log data.

Table 2, the training networks structure for the FZI model.

Element	FZI model
The input variables	6 (RHOB, NPHI, PHIE, ILD, SFL,DT)
The output variable	1 (FZI)
The hidden layer	1
Number of neuron in hidden layer	20
Performance goal (mse)	0.0000001
Max. number of epoches to train	10000
Transfer functions	Tansig, purelin
Training function	trainlm

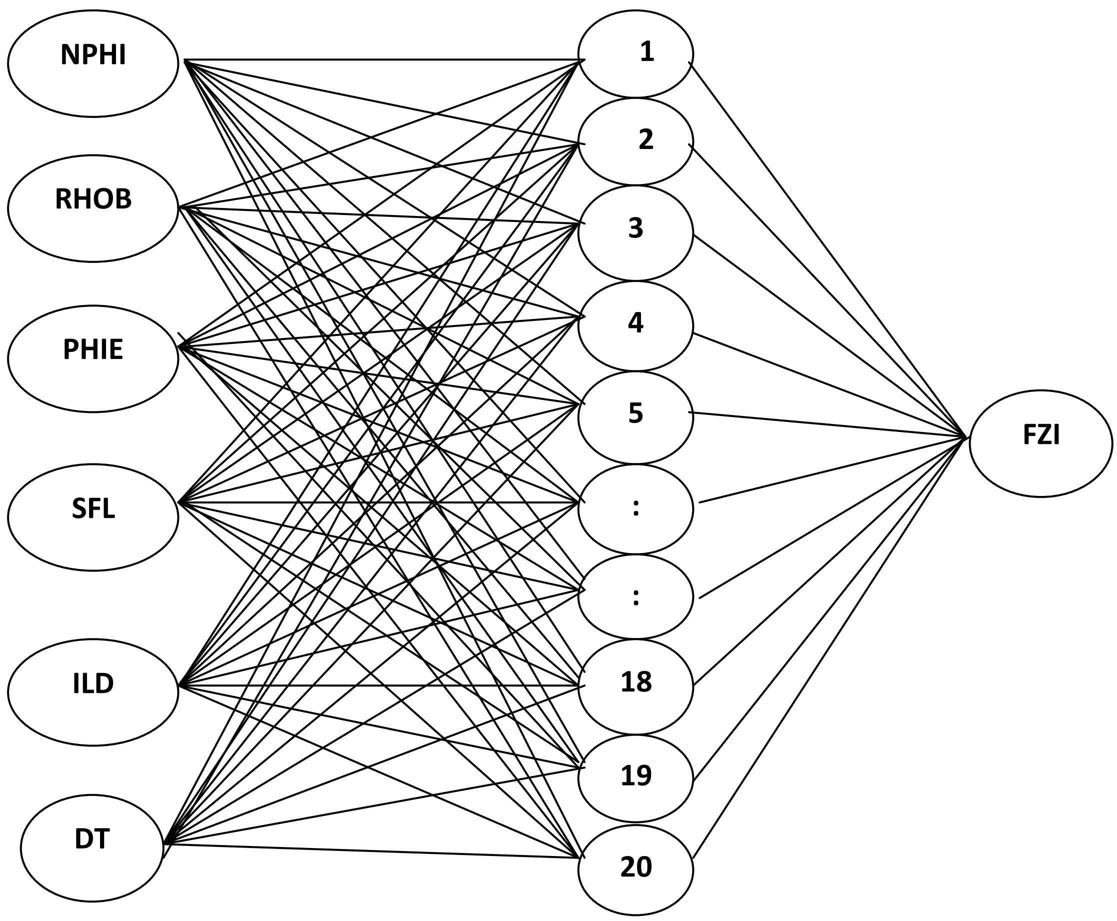

Fig. 6, Schematic diagram of ANN used for FZI model.

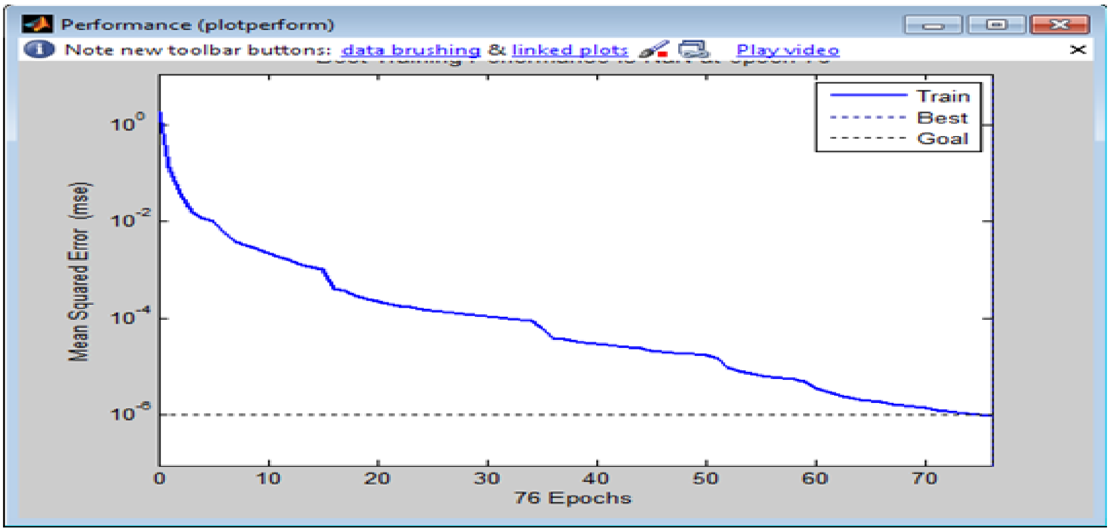

Fig. 7, ANN training performance for well 1

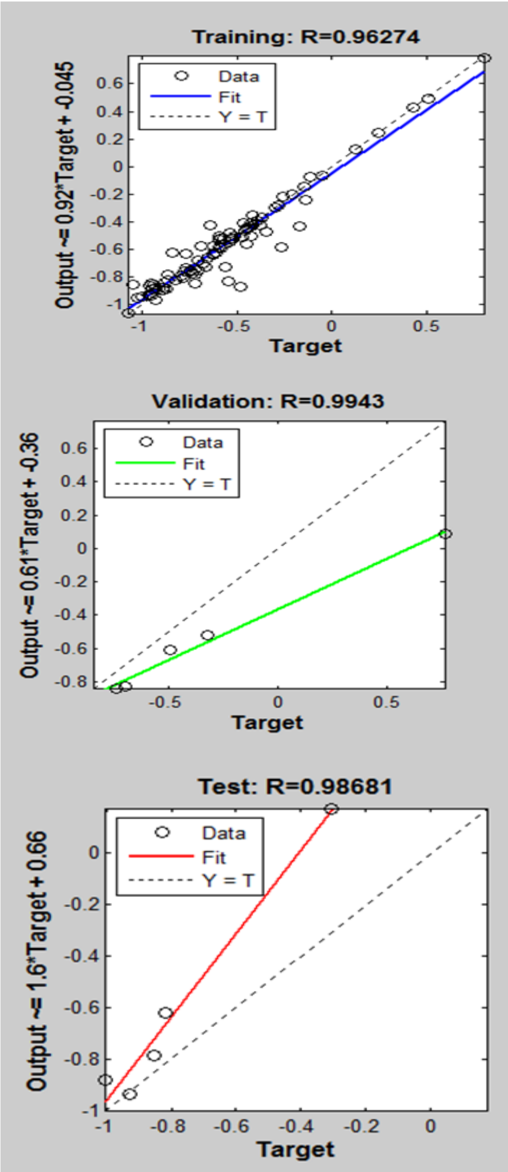

Fig. 8, training, validation and testing the ANN model for FZI values in well 1.

Permeability determination in uncored wells with ANN model

After calculating FZI in uncored well having effective porosity from well logs and using ANN method, permeability can be determined for each HFU using equation 5.

Fig.(9) shows the results of calculated permeability and core permeability with depth. The correlation between core permeability versus the permeability values predicted from ANN for the selected model was shown in fig.(10). Good matching and good correlation were observed with correlation coefficient (R^2) equals 0.94 and Average Relative Error (ARE) equals 1.04%. The predicted permeability profile for well 2 determined from ANN model by assuming that well logged only then this well was used as a blind well for validation the model.

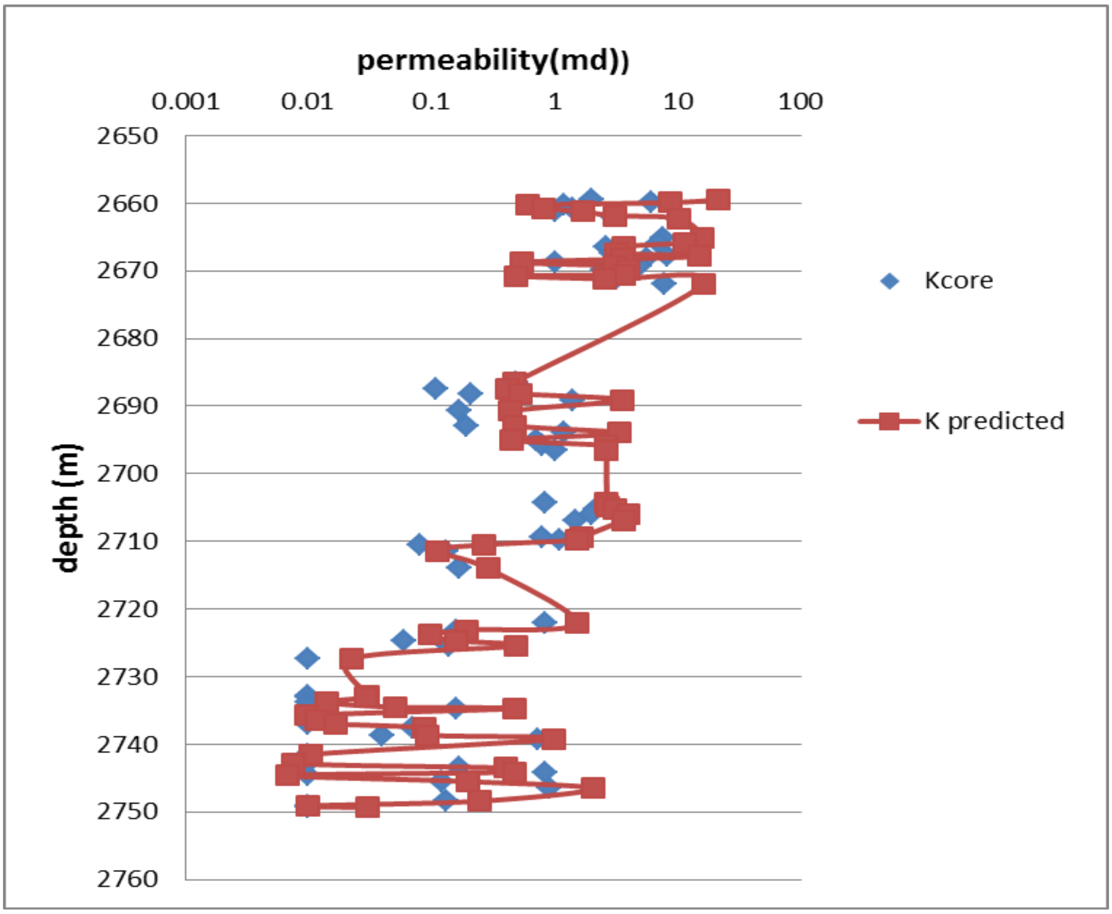

Fig. 9, Permeability predicted from ANN versus core permeability for well 2.

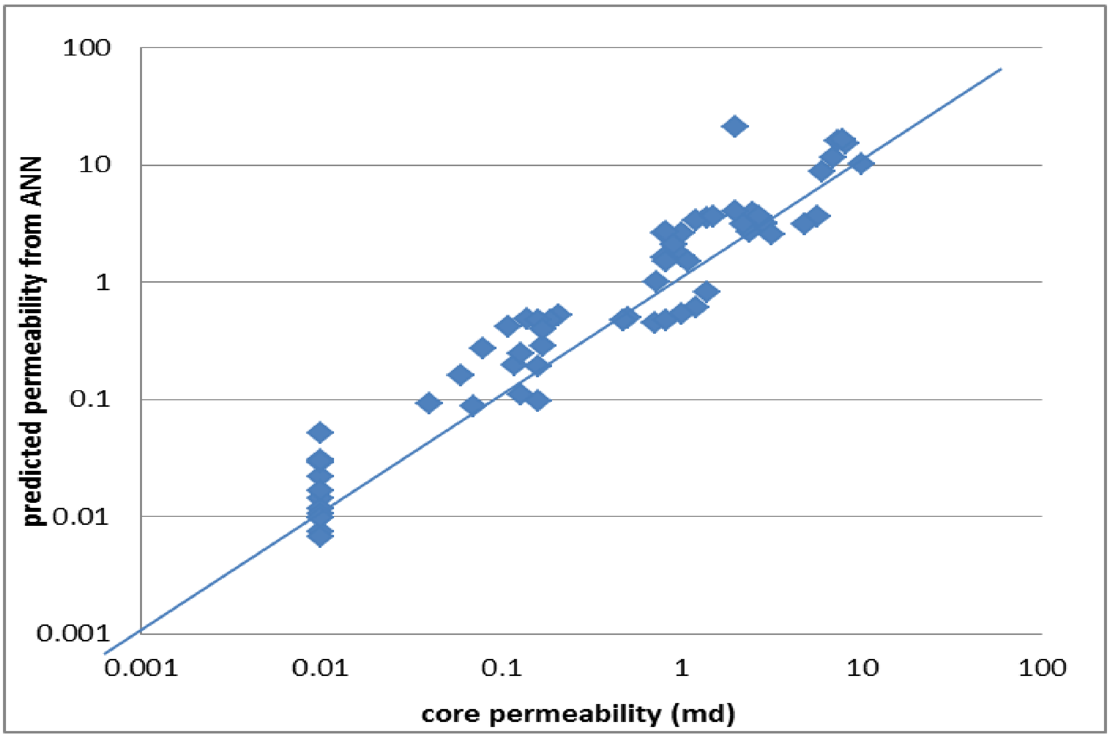

Fig. 10, Permeability predicted from ANN versus permeability measured from core well 2.

Conclusions

1- Flow Zone Indicator (FZI) is an effective and suitable parameter in correlating rock properties and for determining Hydraulic Flow Units (HFUs). These HFUs represent the different rock types in the studied formation.
2- Using probability plot and log-log plot of RQI versus Φ_z methods to determine the number of HFUs and their boundaries is more reliable than histogram analysis.
3- Four HFUs was obtained with high correlation coefficient R^2 for each HFU when relate the permeability that was derived from HFU with core porosity.
4- Good Average Relative Error (ARE) equals 0.55% was obtained between core permeability and permeability calculated from HFU.
5- Good correlation coefficient R^2 = 0.96 was obtained between FZI derived from ANN and FZI that was calculated from HFU which is an indication for accuracy of this method.
6- Artificial Neural Network model provides a good and accurate results for predicting permeability in uncored well with R^2 =0.94 and ARE= 1.04%.
7- Permeability profile predicted by ANN model using well log data and HFUs agree well with core permeability which clarify the applicability of this method.

Nomenclature

ANN: Artificial Neural Network
ARE: Average Relative Error
DT: sonic transient time, µsec/ft
FZI: Flow Zone Indicator, µm
HFU: Hydraulic flow unit
HFUs: Hydraulic flow units
ILD: deep lateral log, Ωm
NPHI: neutron log derived porosity, fraction
PHIE: effective porosity, fraction
RHOB: density log, gm/cc
RQI: Reservoir Quality Index, µm
SFL: spherically focused log, Ωm

Symbols

K: permeability, md
N: number of variables
R^2: correlation coefficient
$ø_z$: normalized porosity, fraction
$ø_e$: effective porosity, fraction
ø: porosity, fraction
δ: Any log value
$N\delta$: Normalized δ log

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