Prediction of Relative Permeability for Multiphase Flow in Fractured Oil Reservoirs by using a Soft Computing Approach

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ABSTRACT
Artificial neural networks (ANNs) are weightily parallels, distributed processors, constituting of numerous simple processing units that are used to solve the complex problems. In this paper ANN was used to present complex relation between water-oil relative permeability key points and rock and fluid properties for multiphase flow in porous media. In this research 200 relative permeability curves from Iranian carbonate were used to reach the ultimate goal. 6 key points which contains end points and the crossover points, were considered for each curve. ANN was then used to predict these key points from different rock and fluid properties. ANN presents very high correlation coefficients in the range of 0.85 to 0.95 for Kr key points. The results proved that ANN is an appropriated tool to predict water-oil relative permeability in porous media with high accuracy when the needed core and fluid properties are available.

General Terms
Artificial Intelligence, Reservoir Engineering

Keywords
Soft computing, Artificial Neural Network (ANN), Water-oil relative permeability, Multiphase flow.

1. INTRODUCTION
Relative permeability (K_r) is explained as the ratio of effective phase permeability to absolute permeability and it is expressed as a function of saturation. Relative permeability is computed from capillary pressure curves, and also it is commonly measured in laboratory by unsteady or steady state methods [1][2]. Ultimate recovery and oil production rate of reservoirs are generously affected by the relative permeability curves.
The effects of some parameters such as fluid viscosity, interfacial tension, wettability, density, displacement rate, capillary number, pore size distribution and temperature on relative permeability curves are studied which are different and even opposing in many cases [3][4][5][6].
Some mathematical models have been constructed for prediction and calculation of the relative permeability. It is just because of laboratory measurements are expensive and complex, and it is taking a long time. Diversity of correlations from simple models to classified models based on lithology, wettability and imbibitions or drainage processes were proposed [7][8][9][10][11][12].
One of the most important parameters for fluid flow calculations of the water and oil phases in the porous media is Water-Oil permeability. Prediction of K_r end points is the most importance for engineering applications. Roghanian et al. [13] used linear regression method to find credible correlations for key points of water-oil relative permeability curves from different rocks and fluid properties. This was the only approach that could predict Kr end points and provide un-normalized curves.
In this paper ANN method is used in place of linear regression to obtain relations between key points of water-oil relative permeability and rock and fluid properties. To gain this objective relative permeability curves from Iranian fractured reservoirs with different rock and fluid properties were used. Six key points, including the end points and the crossover points were determined for each curve. The data were divided into training data sets (85%) and testing data sets (15%). Relationship between key points of water oil relative permeability curves and rock and fluid properties are established by using ANN toolbox. Then full curves of the relative permeability are created very simple by having known these key points.

2. ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANNs) developed in an important manner in the mid-1980s after major developments in neuroscience. Artificial Neural Network is a computer model that is planned to mimic the behavior of the human brain in terms of the learning process and pattern recognition. Artificial neural networks are information process systems that are a rough approximation and a simplified simulation of the biological process. They have the performance characteristics similar to those of biological neural networks. In fact neural networks realize the nature of the dependency between input and output parameters and so work very well at solving problems when it is difficult to suggest extremely accurate mathematical model. A neuron is the basically processing element of a neural network. Fundamentally a biological neuron gets inputs from other sources, unites them in some way, carries out an ordinarily nonlinear operation on the results, and then outputs the results. A neuron includes dendrites, a cell body and an axon. Figure 1 shows schematic diagram of a biological neuron.

A typical ANN has three layers of neurons includes input, hidden or and output layer. Figure 2 shows a schematic diagram of three-layer artificial neural network system. Neural networks are so suitable for complex problems. They generally have large degrees of freedom, therefore they can capture the nonlinearity of the process being studied better than conventional regression methods. ANN is relatively insensitive to data noise, as they can present the underlying relationship between model inputs and outputs, resulting in good generalization capacity [14]. In predictive modeling, the performance of suggested network highly depends on correct network training choice and correct data processing [15]. A feed forward neural network is ordinarily used in different area such as petroleum engineering such as reservoir characterization, optimization of field operations and optimization of simulation treatments design [16]. Simple structure of neural network such as three layered feed-forward with back propagation can utilized for nonlinear continuous problems [17]. The mean squared error of the network is delineated as:

$$U = \frac{1}{2}\sum_{k=1}^{G}\sum_{j=1}^{m}\left(T_j(k) - Y_j(k)\right)^2 \qquad (1)$$

where U is sum of the mean squared error, m is the number of output nodes, G is the number of training samples, Tj(k) is the expected output and Yj(k) is the actual output. Data used under study is separated in two different sets, first is training data set and second is testing data set. The neuron output is "weighted" by the model in order to present results that are close to the correct outputs in the training set. The mathematical function that was described above occurs in the middle layer. Optimization set of weights in network is purpose of training process and if the number of weights in network is higher than useable data, the error in fitting the non-trained data firstly decreases, but then increases as the network become over trained and over fitting problem is occurred. An applicable ANN must be capable of predict an output with good results for data not previously seen by the network.

3. RELATIVE PERMEABILITY CURVE

In this paper unsteady state approach during the imbibition process of water-oil system is used to achieve all relative permeability curves and air permeability is assumed as the basis for all relative permeability estimations. For this study core samples from Asmari formation were used to measure the relative permeabilities. Asmari formation is located in South-West of Iran. The Oligocene Miocene Asmari formation is a thick sequence of shallow water carbonate.

The main characteristics of relative permeability curves are indicated by key points. The key points are initial water saturation (S_{wi}), maximum water saturation (S_{wmax}), oil relative permeability at S_{wi} (K_{rom}), water relative permeability at S_{wmax} (K_{rwm}), cross point saturation (S_x) and relative permeability at S_x (K_{rx}). Oil relative permeability has its maximum value at initial water saturation where the most of pores are available for the oil to flow and water relative permeability has its maximum value at maximum water saturation. A typical set of K_r curves with six key points is shown in figure 3. Core and fluid properties for each set of K_r test contain: porosity, water permeability, air permeability, pressure drop, oil and water viscosities, initial water saturation, maximum oil relative permeability, maximum water relative permeability, cross point saturation, cross point relative permeability, residual oil saturation (maximum water saturation), formation type and lithology.

Frequency and the standard deviation of these data are calculated. Data in the range of 2 times of the standard deviation around the mean was considered, which left 200 data sets of water-oil relative permeability for analysis. Summary of core and fluid properties is provided in table 1.

A parameter selection code developed in MATLAB to find effective variables for each key point calculation. This program searches for all possible combinations in input space to closely calculate key points by a well ANN architecture. The group of independent variables with the highest R^2 was considered as the most appropriate combination.

4. KNOWN KEY POINTS

4.1 Maximum water saturation (S_{wm})

Maximum water saturation in a core sample is commonly measured in spontaneous and forced water-oil capillary pressure test. It is important to know maximum water saturation in reservoir is caused by competition between capillary, viscous and gravity forces. S_{wm} varies between 25% and 95% in data bank.

4.2 Initial water saturation (S_{wi})

Distribution of S_{wi} in the reservoir condition can be determined from the resistivity logs or capillary pressure curves or both of them. When capillary and gravity forces are in balance initial water saturation is obtained in any points of reservoir. The quantity of S_{wi} is a complicated function of wattability, interfacial tension of fluids, pore geometry and their viscosities and densities. Core samples with different lithology have broad range of S_{wi} from 4.4% to 59.1%. The initial water saturation is assumed as one of the input parameters for prediction of the other key points.

5. ESTIMATION OF UNKNOWN KEY POINTS

5.1 Cross Point Saturation

Cross point saturation (S_x) is an important point in developing of a relative permeability curve. It is a point where the relative permeability curves intersect each other, that means the phase permeabilities of two phases are equal. The values of S_x in data bank vary between 19.9% and 79.7% with normal distribution. The following functionality for S_x is considered:

$$Sx = F\left(S_{wi}, \varphi, \mu_w, S_{wm}, \log\varphi, \log S_{wi}, \log K_a, \log\mu_w, \log\left[\mu_o / \mu_w\right]\right) \qquad (2)$$

Final ANN model presented high R^2=0.95 for both the training and testing data sets. Figures 4 and 5 show the cross plot of the calculated values vs. actual S_x for the training and testing data sets respectively. It is a very sufficient result that is obtained by ANN.

5.2 Relative Permeability at Cross Point Saturation

Cross point relative permeabilities (K_{rx}) did not show a normal distribution. Their logarithmic values provided a normal distribution and were used in the analysis. K_{rx} in data bank is changed from very low values in the order of less than thousandth up to 0.2. K_{rx} values Functional relationships with R^2=0.95 and R^2=0.89 for the training and testing data sets respectively that are achieved with the following variables and by using ANN:

$$\log Krx = F\left(\varphi, \mu_w, \log\varphi, \log\mu_o, \log\Delta P, \log K_a, \log K_w, \log\left[\mu_o / \mu_w\right]\right) \qquad (3)$$

Calculated K_{rx} versus actual values for training and testing data sets are presented in figure 6 and 7 respectively. It is clear that ANN is a strong method to estimate K_{rwm} from above mentioned variables.

5.3 Water Relative Permeability at S_{wm}

Water relative permeability reaches its maximum (K_{rwm}) at S_{wm} while that of the oil decreases to zero. K_{rwm} in data bank varies from less than 0.0015 to 0.61 with normal distribution of their logarithmic values. ANN could estimate K_{rwm} with

R^2= 0.87 and R^2=0.91 for the testing and training data sets respectively. In this study K_{rwm} is considered as a function of:

$$Krwm = F\left(\varphi, Swc, \mu_o/\mu_w, \log\varphi, \log Swc, \log\left[\mu_o/\mu_w\right], \log K_w, \log K_a, \log\Delta P, \log\mu_w\right)$$

(4)

Estimated versus actual K_{rwm} for the training and testing data sets are presented in Figure 8 and 9 respectively. These figures indicate very satisfactory act of ANN model for prediction of K_{rom} from previously mentioned input core and fluids properties.

5.4 Maximum Oil Relative Permeability

Oil relative permeability has its maximum value at initial water saturation where the most of pores are valid for the oil to flow. K_{rom} in data bank is changed from less than 0.002 to 0.95 with normal distribution of their logarithmic values. Final ANN model presented high R^2=0.94 and R^2=0.93 for the training and testing data sets respectively. Selected input parameters are shown below:

$$Krom = F\left(\Delta p, \mu_o, S_{wc}, \mu_o/\mu_w, \log\left[\mu_o/\mu_w\right], \log K_w, \log K_a, \log\mu_o, \log\mu_w, \log S_{wc}\right)$$

(5)

Calculated versus actual K_{rom} for training and testing data sets are presented in figures 10 and 11 respectively. These graphs also show very well and sufficient performance of ANN model for calculation of K_{rom} from above mentioned input variables.

6. CONCLUSION AND DISCUSSION

There is no mathematical formula can exactly predict relative permeability for any specific rock and fluid system. Relative permeability is influenced by many variables such as porosity, pore geometry, wettability, interfacial tension, temperature, displacement rate, etc which are not included in Darcy's equation. It can be said that it is originally explained to extend Darcy's equation to multi-phase systems. In this paper to have a proper comparison, linear regression method is used to predict water-oil relative permeability key points from different rock and fluid properties. R^2 values in their suggested correlations for S_x, K_{rx} and K_{rwm} were in the range of 0.65 to 0.8. Also in this study, ANN is used to investigate dependency of the same key points to the porosity, initial and maximum water saturation, water and air permeability, oil and water viscosities and pressure drop. High R^2 values for S_x and K_{rx} indicate that they are mostly affected by the assumed independent parameters. However, in some manner lower R^2 for K_{rwm} indicates it possibly influenced by other parameters like wettability, interfacial tension, temperature, displacement rate and pore geometry that were not considered in this study.

Table 2 presented comparison of their R^2 values which proves higher capability of ANN in data modeling than linear regression techniques. The suggested models can be made an application for all variety of core and fluid properties which are given in table 1.

It is very simple to develop full curves of water and oil relative permeability curves by using simple polynomials and having known these 6 characteristic points where each K_{ro} and K_{rw} curve is characterized by 3 points. Such predictions are carried out for 3 core samples. The properties of each core sample are presented in table 3. Comparison between measured and estimated relative permeability of these samples are indicated in figures 12 to 14. As these figures prove, measured relative permeabilities are extremely matched by the computed curves in their un-normalized forms.

So this paper proves that the considered key points are sufficient to construct full relative permeability curves and the suggested functional relationships by ANN are extremely exact to achieve these key points from simple rock and fluid characteristics.

7. ACKNOWLEDGMENT

Authors are grateful to National Iranian Oil Company (NIOC) for providing the data.

Table 1. Properties of core samples

	ϕ (%)	K_a (md)	K_w (md)	μ_o (cp)	μ_w (cp)	ΔP (psi)	S_{wi} (%)	S_{wm} (%)	K_{rwm} (Frac.)	K_{rom} (Frac.)	S_x (Frac)	K_{rx} (Frac.)
No	200	200	200	200	200	200	200	200	200	200	200	200
Min	2.1	0.15	0.004	1.1	1	0.69	4.4	25	<0.0015	<0.002	19.9	<0.001
Max	30.8	2142	636	20	1.86	5245	59.1	95	0.61	0.95	79.7	0.2

Table 2. Comparison between R^2 values of linear regression and ANN data modelling

		Cross point saturation	Cross point relative permeability	Maximum water relative permeability	Maximum oil relative permeability
Linear regression		0.79	0.78	0.8	0.65
ANN	Training data sets	0.95	0.94	0.95	0.91
	Test data sets	0.95	0.93	0.89	0.87

Table 3. Properties of compared samples

sample No	ϕ (%)	Ka (md)	Kw (md)	μ_o (cp)	μ_w (cp)	Swi (%)
1	21.6	45.7	19.2	19.4	1.51	36
2	9.7	0.48	0.053	21.5	1.38	16
3	9.1	5.6	0.4	20.7	1.64	25

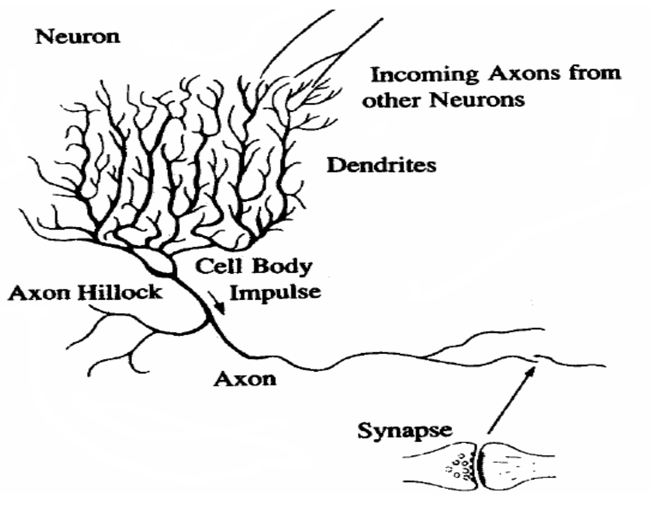

Fig 1: Schematic diagram of a biological neuron

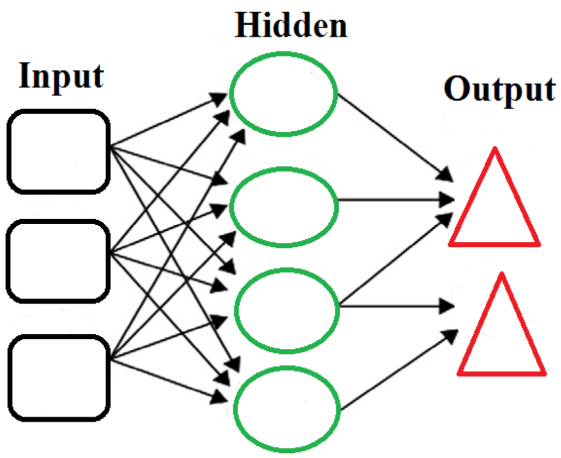

Fig 2: schematic diagram of three-layer artificial neural network system

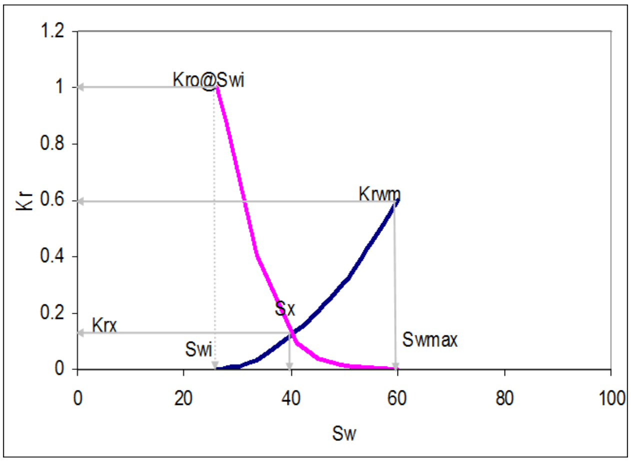

Fig 3: A typical water-oil relative permeability curve

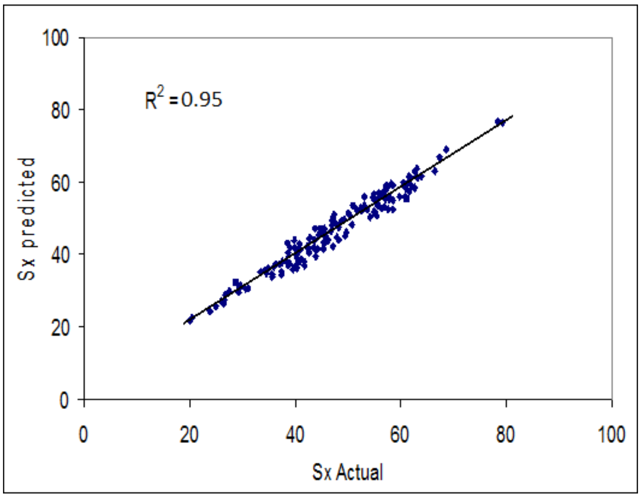

Fig 4: Crossover saturation point for training data set

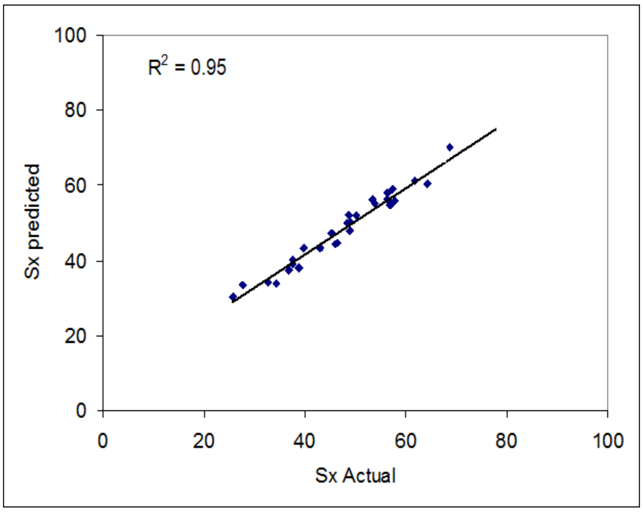

Fig 5: Crossover saturation point for testing data set

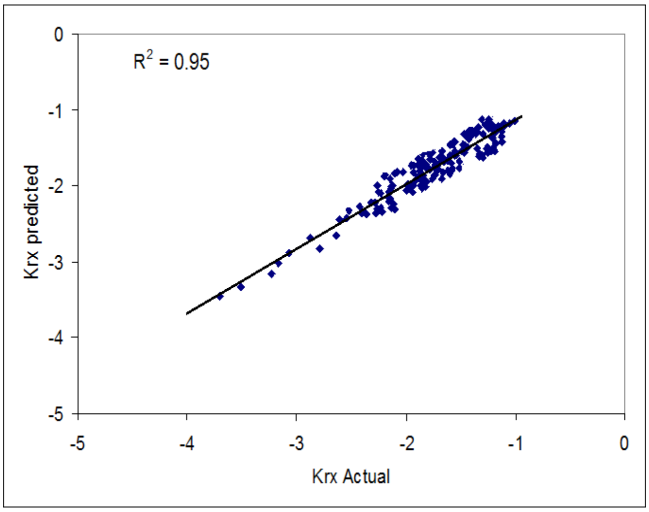

Fig 6: relative permeability for training data set

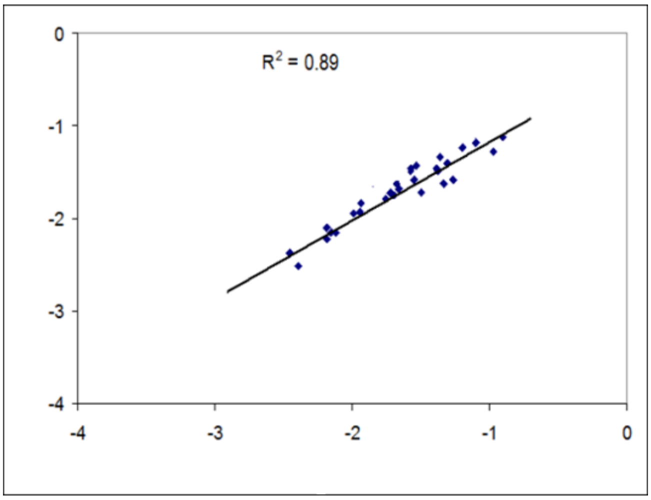

Fig 7: Crossover relative permeability for testing data set

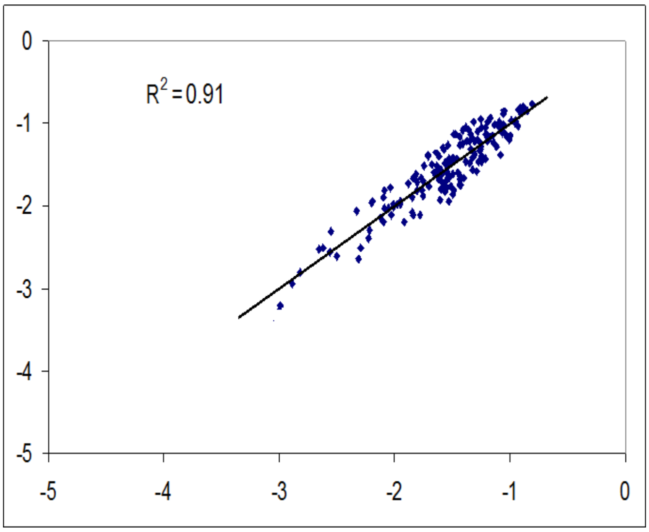

Fig 8: Maximum water relative permeability for training data set

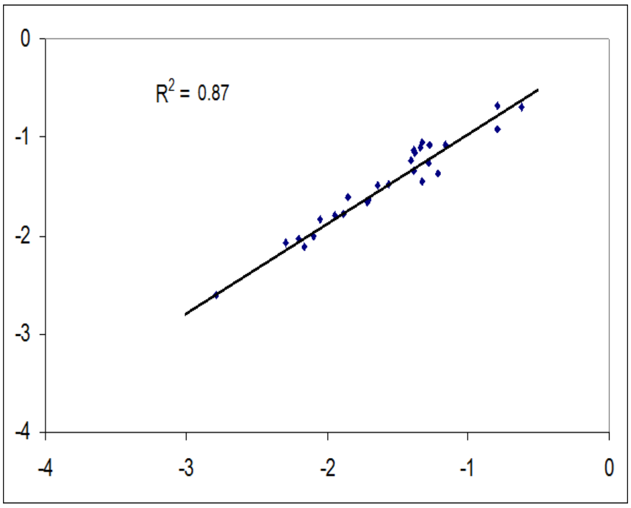

Fig 9: Maximum water relative permeability for testing data set

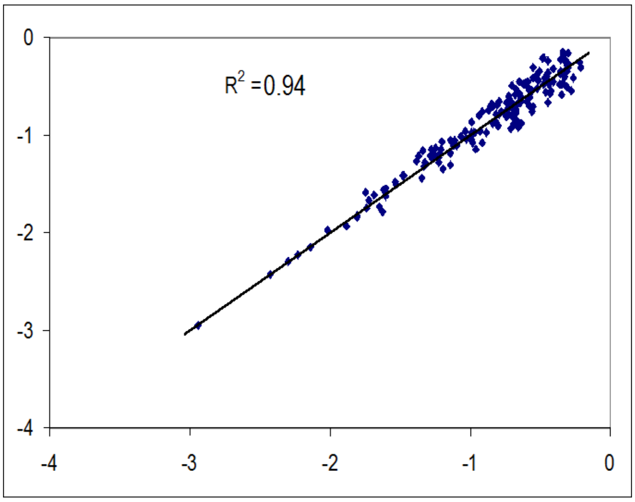

Fig 10: Maximum oil relative permeability for training data set

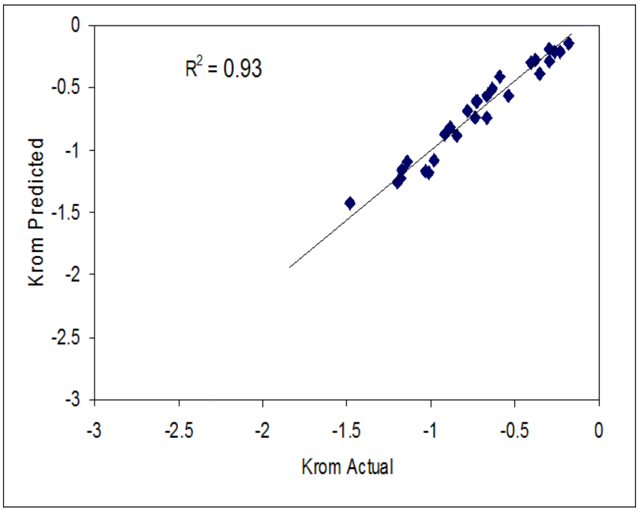

Fig 11: Maximum oil relative permeability for testing data set

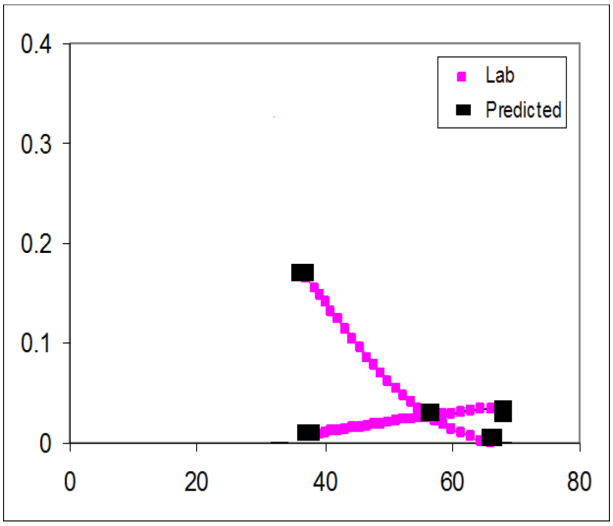

Fig 12: A comparison between measured and predicted K_r for core sample.1

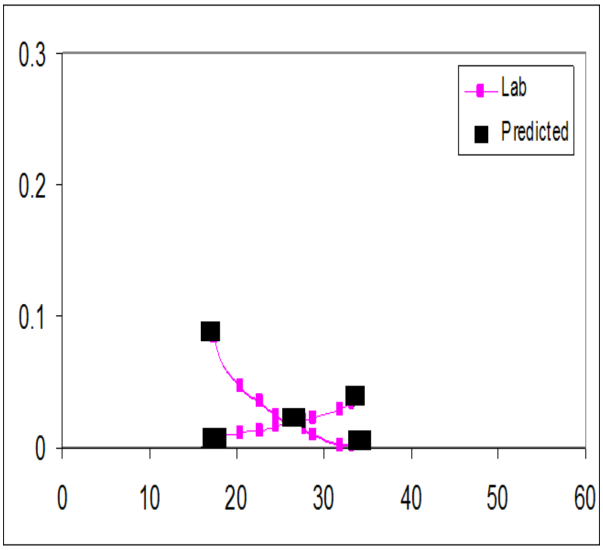

Fig 13: A comparison between measured and predicted K_r for core sample.2

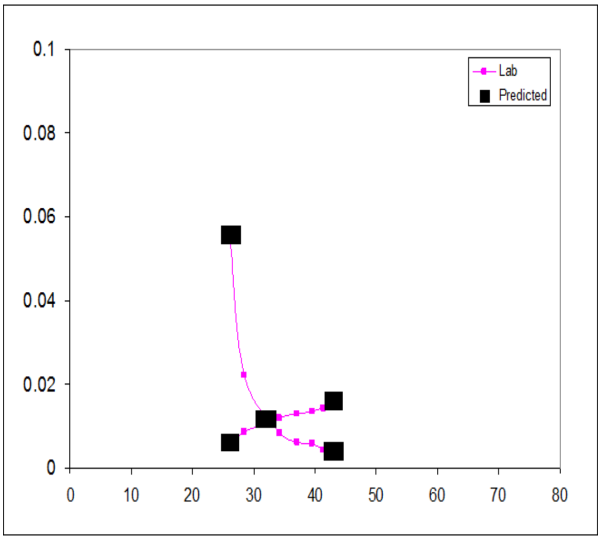

Fig 14: A comparison between measured and predicted K_r for core sample.3

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