Undersaturated Oil Compressibility Prediction for Mishrif Reservoir in the Southern Iraqi Oil Fields Using Artificial Neural Network

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Abstract

Coefficient of isothermal oil compressibility is required in transient fluid flow problems, extension of fluid properties from values at the bubble point pressure to higher pressures of interest and in material balance calculations [1, 2]. Coefficient of isothermal oil compressibility is a measure of the fractional change in volume as pressure is changed at constant temperature [3]. Coefficients of isothermal oil compressibility are usually obtained from reservoir fluid analysis. Reservoir fluid analysis is an expensive and time consuming operation that is not always available when the volumetric properties of reservoir fluids are needed. For this reason correlations have been developed and are being developed for predicting fluid properties including the coefficient of isothermal oil compressibility.

This paper presents an application of Artificial Neural Network (ANN) methods for estimation of isothermal oil compressibility for the Mishrif reservoir oils among of commonly available field data, according to the fact that this method is useful when relationships of parameters are too complicated. The method is proposed as a more effective prognostic tool than are currently available procedures.

In this study, back propagation (BPN) network was used to develop an ANN model to predict isothermal oil compressibility. A three layer feed-forward network has been selected which has the best correlation coefficient in testing the models. The new model of undersaturated oil compressibility in which the first

layer consists of five neurons representing the input values of pressure above bubble point, solution gas oil ratio at bubble point, oil gravity API, reservoir temperature and gas specific gravity. The second (hidden) layer contains 12 neurons, and the third layer contains one neuron representing the output values of undersaturated oil compressibility. It was found that the new model estimate undersaturated oil compressibility for Mishrif reservoir crudes in the southern Iraqi oil fields much better than the published ones. The present model predicts undersaturated oil compressibility with an average absolute relative error of 3.86% for the testing data set.

Introduction

The isothermal oil compressibility at pressure above the bubble point is defined as the fractional change in volume of oil as pressure is changed at constant temperature [4]. For crude oil system, the isothermal compressibility coefficient of the oil phase C_o is defined, for pressure above the bubble-point, by one of the following equivalent expression [3]:

$$C_O = -\frac{1}{V}\left(\frac{\partial V}{\partial P}\right)_T \qquad \text{.........1}$$

$$C_O = -\frac{1}{Bo}\left(\frac{\partial B_O}{\partial P}\right)_T \qquad \text{.........2}$$

$$C_O = \frac{1}{\rho_O}\left(\frac{\partial \rho_O}{\partial P}\right)_T \qquad \text{.........3}$$

Coefficients of isothermal oil compressibility are usually obtained from reservoir fluid analysis. Reservoir fluid analysis is an expensive and time consuming operation that is not always available when the volumetric properties of reservoir fluids are needed. For this reason correlations have been developed and are being developed for predicting fluid properties including the coefficient of isothermal oil compressibility. This study developed a mathematical model for predicting the coefficient of isothermal oil compressibility for Mishrif reservoir in the southern Iraqi oil field using artificial neural. A computer program was developed to predict the coefficient of isothermal compressibility using the developed model.

Literature Review

In the last decades, engineers realized the importance of developing and using empirical correlations for PVT properties. Studies carried out in this field resulted in the development of new correlations.

In 1980, Vasquez and Beggs [5] developed a correlation for the isothermal oil compressibility correlated with the gas solubility Rs, reservoir temperature T, API gravity, gas specific gravity γ_g and reservoir pressure. They used 4036 experimental data points and linear regression model to develop the new correlation.

In1985, Ahmed [6] used 245 experimental data points to propose a mathematical expression for the isothermal oil compressibility using the gas solubility R_S as the only correlation parameter.

In 1993 Petrosky and Farshad [7] developed a new correlation for undersaturated isothermal oil compressibility using 304 data points obtained from the Gulf of Mexico crude oils. This new correlation introduces one additional fitting parameter to the model functional form used by Vasquez and Beggs in order to increase the accuracy of the correlation.

In 1994, De Ghetto, Paone and Villa [8] evaluated the reliability of some isothermal oil compressibility correlations and came up with some modified correlations which they reported as being more accurate. They characterized the fluid samples used in their studies as extra heavy oil (API≤10), heavy oil (10< API≤22.3), medium oil (22.3< API≤31.1) and Light oil (API>31.1). They reported that the errors on the correlation were decreased by about five percent.

In 2001, Dindoruk and Christman [9] proposed a new correlation for estimating undersaturated oil compressibility for the Gulf of Mexico. The proposed oil compressibility correlation predicts the oil compressibility values with an average absolute relative error of 6.21%.

In 2003, Al-Marhon [10] presented a new mathematical model for calculating undersaturated oil compressibility using 3412 data points from 186 Middle East PVT reports. Al-Marhon reported an average absolute relative error of 5.46%.

Artificial Neural Network

An artificial neural network is a computer model that attempts to mimic simple biological learning processes and simulate specific functions of human nervous system. It is adaptive, parallel information processing system, which is able to develop associations, transformations or mappings between objects or data. It is also the most popular intelligent technique for pattern recognition to data. The basic elements of a neural network are the neurons and their connection strength (weight). A learning algorithm takes an initial model with some "prior" connection weight (usually random numbers) and produced a final model by numerical iteration. Hence learning implies the derivation of posterior connection weights when a performance criteria is matched (e.g. the mean square error is below a certain tolerance value). Learning can be performance by "supervised" or "unsupervised" algorithm. The former requires a set of Known input-output data patterns (or training pattern). This commonly known as the feed forward model, in which no lateral or backward connections are used [11].

Data Description

Data used in this study are collected from Mishrif reservoir from the following southern Iraqi oil fields: Buzurgan (Bu), Halfaya (Hf), Fauqi (Fq), Amara (Am), Nasiriya (Ns), Rumaila Nourth (R), Rumaila South (Ru), West Qurna (WQ), Zubair (Zb) [12]. The number of data points used is 129 data sets collected from 52 oil samples. These data were divided into two groups: training group (96 data sets) and testing group (33 data sets). Table (1) presents the description of data utilized in this study with ranges of solution gas oil ratio at bubble point, reservoir temperature, gas relative density, API oil gravity, pressure above bubble point and undersaturated oil compressibility.

Table (1) Range of Data for the Mishrif Crude oil Used

Property	Minimum Value	Maximum value	Mean
P(psia)	1104.7	3257.544	2335.19983
GOR(SCF/STB)	337.0123	757.5196	556.8827
Absolute Temp. (R°)	619.47	699.75	653.707
g(air=1)γ	0.854722	1.183	0.967681
Oil API Gravity	18.5	29.3	23.8446532
Co($psia^{-1}x10^{-6}$)	5.3976	13.7898	8.17142

Development of ANN Model

In this study, back propagation (BPN) network was used to develop undersaturated oil compressibility. The undersaturated oil compressibility model in which the first layer consists of five neurons representing the input values of pressure above bubble point, solution gas oil ratio at bubble point, oil gravity API, reservoir temperature and gas specific gravity. The second (hidden) layer contains 12 neurons, and the third layer contains one neuron representing the output values of undersaturated oil compressibility. Table (2) shows the structure of the neural networks after trial and error and obtained the best performances of the ANN models. Simplified schematic of the used neural networks for undersaturated oil compressibility model is illustrated in figure (1)

Table (2) Structure of the training networks for the Co Models

element	Co model
Number of input Variable(Node)	5 (API, γ_g, T, Rs, P)
Number of output Variable	1 (Co)
Number of Hidden layer	1
Number of Neuron in Hidden layer	12
Performance goal(mse)	1.0000e-04
Learning Rate	0.9
Momentum constant	0.9
Max. Number of epoches to train	10000
Transfer functions	tansig , purelin
Train function	Trainlm
Number of Training sample	96
Number of epoches to the Best Train performance	155
Number of Testing sample	33

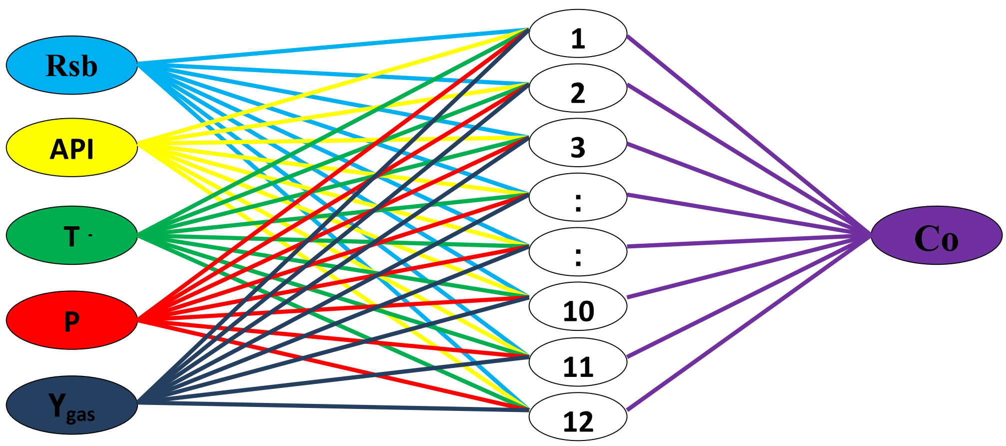

Fig. (2) Schematic Diagram of Artificial Neural Network Topology used for undersaturated oil compressibility Model

Performance Plot of the Developing ANN Model

Figure (3) shows the behavior of the model during the training period reaching to the best training performance (cross plots illustrate the number of epochs with MSE for every network). Epochs are usually increased in ANN to make the network repeatedly understand the trends of the data.

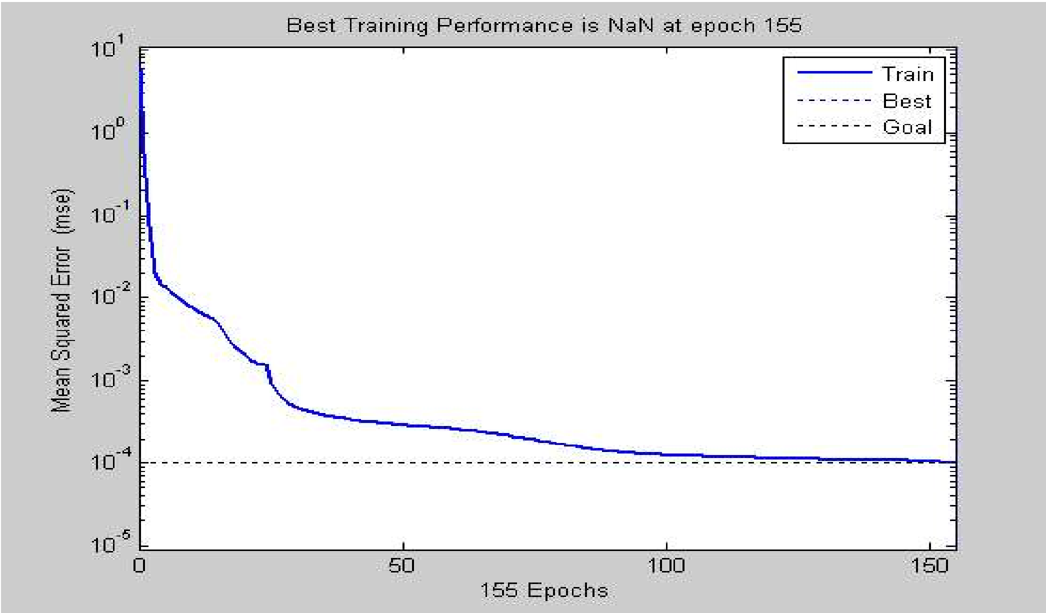

Fig. (3) Neural network Training Performance for Co Model

Statistical Analysis and Simulation of the Model

The statistical analysis of the training model is given in table (3). Figure (4) shows the simulation for the training model to compare the predicted values with measured values. The cross plot indicates the degree of agreement between the measured and predicted values.

Table (3) Statistical accuracy of the Training model

Statistical property	Value
Average absolute relative error (AAERR)	0.4896
Correlation coefficient (R)	0.9993
Standard deviation (SD %)	0.7764

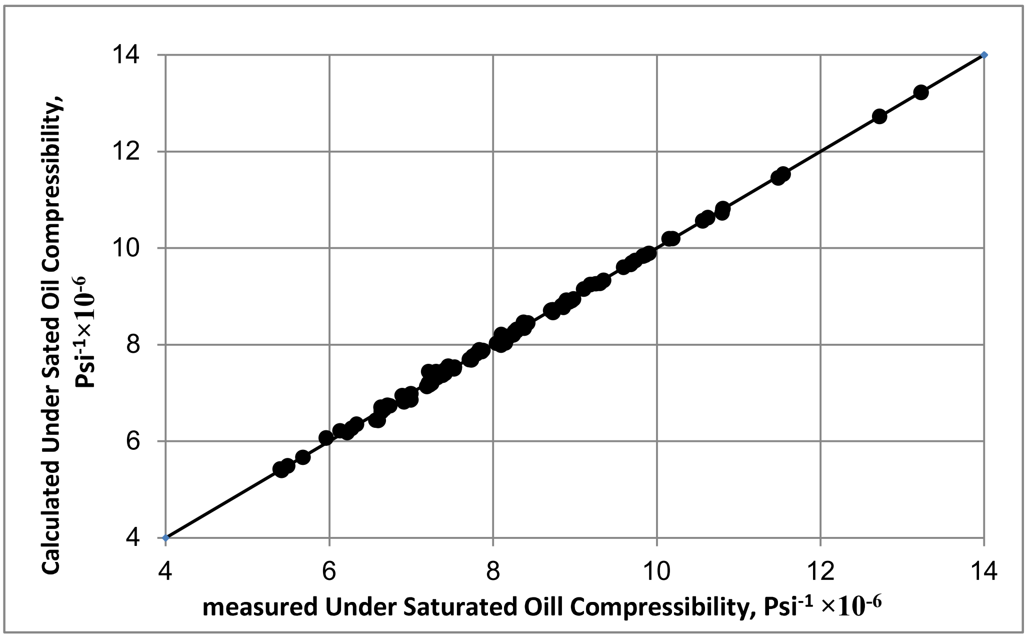

Fig. (4) Cross Plot of ANN Model for Undersaturated Oil Compressibility

Validation of the Training Models

After training the neural networks, the model becomes ready for testing and evaluation. To perform this, the last data group as shown in table (2), which was not seen by the neural network during training, was used. The statistical results of the artificial neural network model for undersaturated oil viscosity of the testing data are 3.87% and 0.979 for average absolute error and correlation coefficient respectively. Figure (5) shows acceptable agreement between predicted and measured values. Performance plots for existing correlation show in appendix-A.

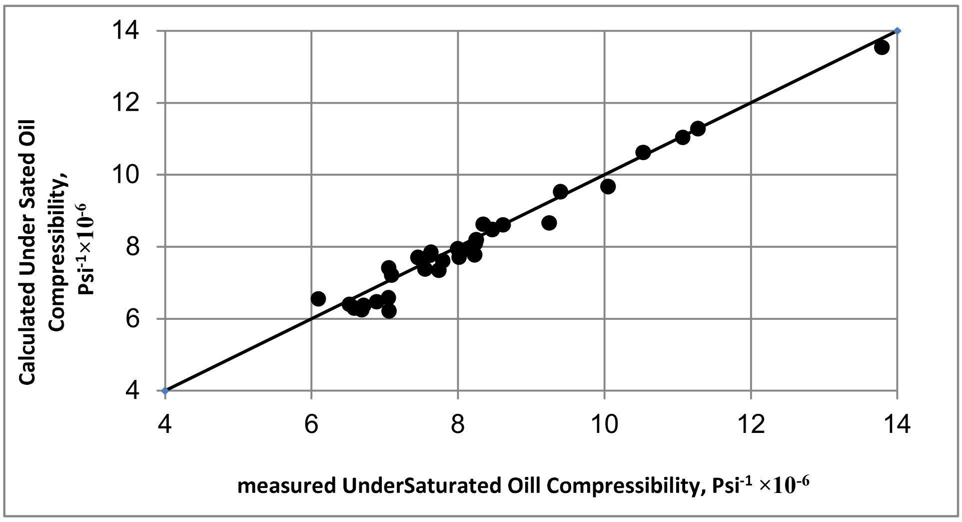

Fig. (5) Cross Plot of tested values for UnderSaturated Oil Compressibility

Results and Comparison

Table (4) shows the comparison between the published correlations and new developed ANN models. The new ANN model showed higher accuracy than published correlations in predicting undersaturated oil compressibility.

Table (4) Statistical Analysis of the Result for undersaturated oil Compressibility of Published Correlations and Developed ANN Model

Correlation	AAERR %	SD %
De Ghetto & Villa[8]	17.80	14.67
Al-Marhoun[10]	19.06	13.36
Vasquez & Beegs[5]	19.82	12.98
Petrosky& Farshad[7]	24.26	13.58
Dindoruk & Chirsman[9]	29.64	19.68
Present study ANN	**3.87**	**4.74**

Conclusions

1- Most of the published empirical correlations for predicting undersaturated oil compressibility, often do not adequately predict the behavior of crudes of Mishrif reservoir.

2- New model was developed to predict the undersaturated oil compressibility for Mishrif reservoir crudes in the southern Iraqi oil fields. The model was based on artificial neural network. The developed ANN model was tested using independent data which was not used in training this model and the results of the testing show that the developed model predicts the undersaturated oil compressibility in good accuracy with low average absolute relative error.

Nomenclature

AAERR = Average Absolute Percent Relative Error.

ANN= Artificial Neural Network.

API = American Petroleum Institute.

Bo = Oil Formation Volume, RB/STB.

Co = Isothermal Oil Compressibility, $psia^{-1}$

GOR = Gas-Oil Ratio, SCF/STB.

P = Pressure above bubble point, psia.

R = Coefficient of Correlation, %.

Rs = Solution GOR, SCF/STB.

T = Reservoir temperature, R°.

V= Volume, m^3, cm^3, ft^3, bbl.

γ_g = Gas specific gravity (air=1).

γ_o = Oil specific gravity .

γ_{API} = Oil API gravity.

PVT = Pressure-Volume-Temperature.

SD= Standard Deviation.

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Appendix A -Performance plots for existing correlation

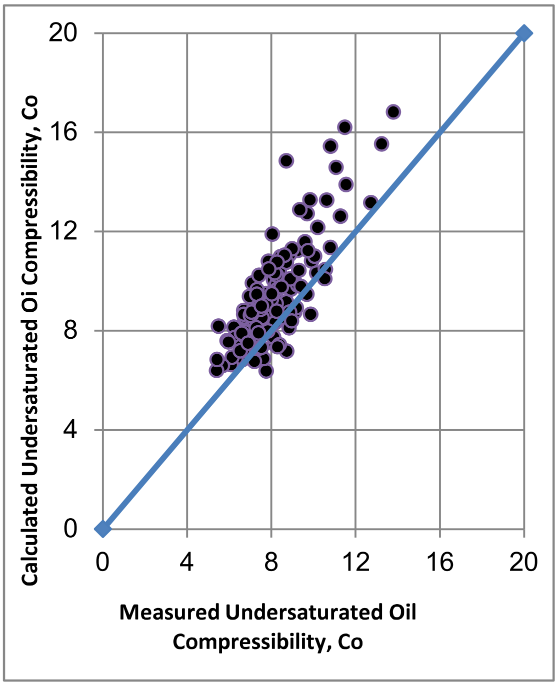

Fig. (A1) Cross Plot for Oil Compressibility, psia^{-1} × 10^{-6} (De Ghetto and Villa's Correlation[8])

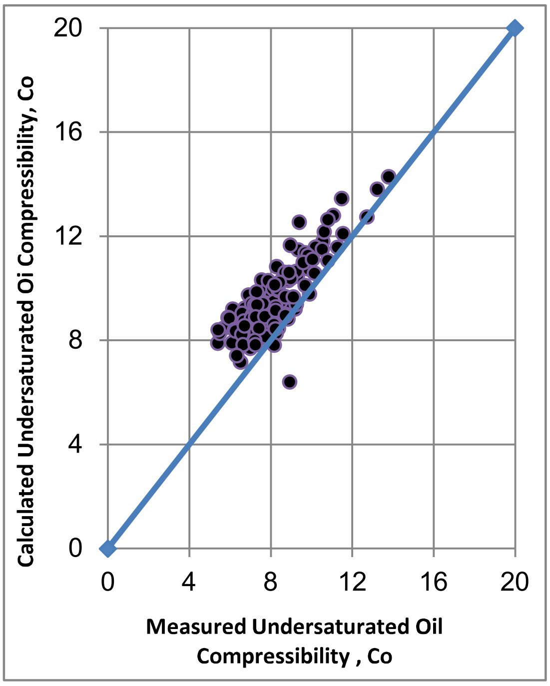

Fig. (A2) Cross Plot for Oil Compressibility, psia^{-1} × 10^{-6} (Al-Marhoun's Correlation[10])

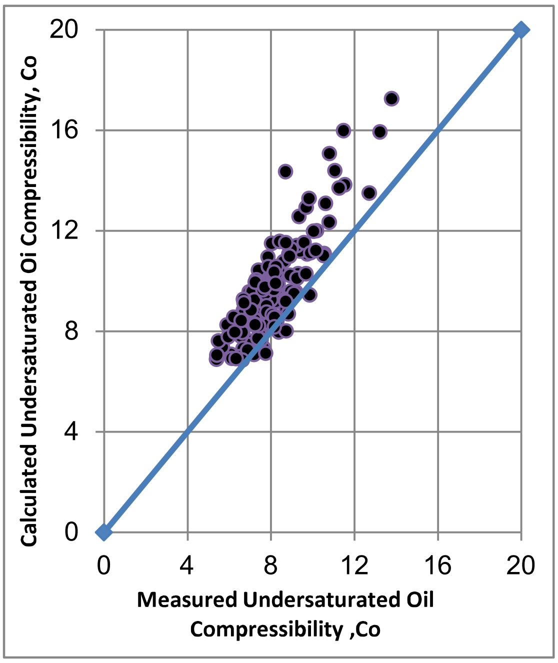

Fig. (A3) Cross Plot for Oil Compressibility, psia^{-1} × 10^{-6} (Vasquez and Beggs's Correlation[5])

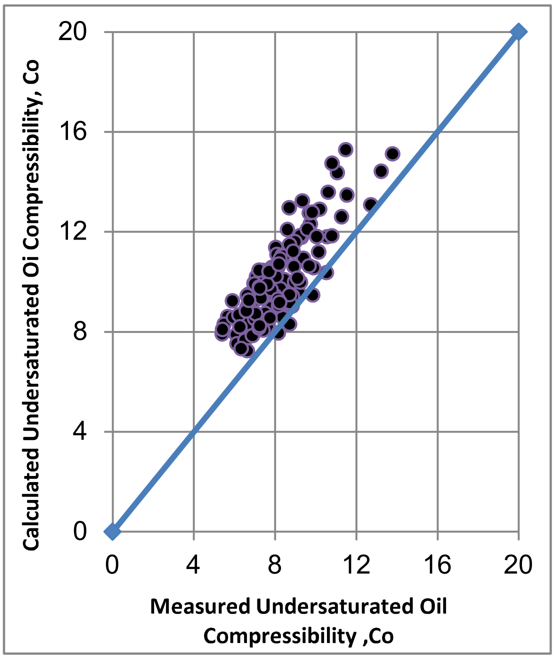

Fig. (A4) Cross Plot for Oil Compressibility, psia^{-1} × 10^{-6} (Petrosky and Farshad's Correlation[7])

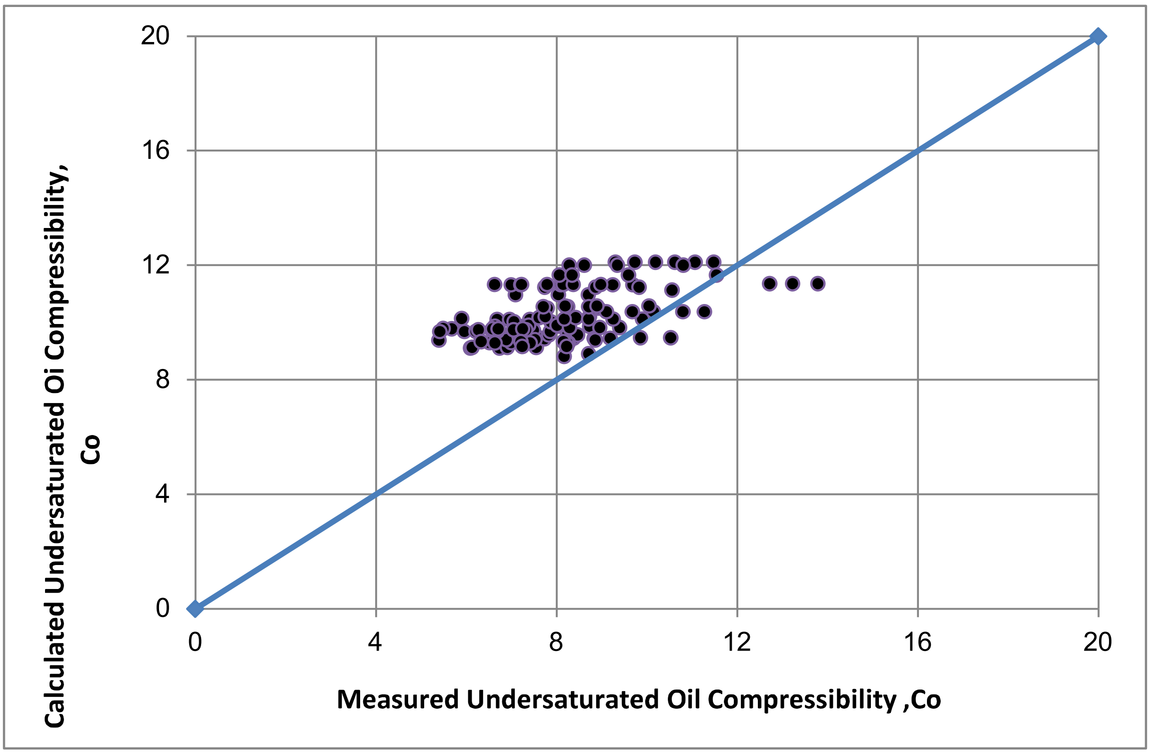

Fig. (A5) Cross Plot for Oil Compressibility, psia-1 × 10-6 (Dindoruk and Chirstman's Correlation9)

Appendix B-Definitions of Statistical Parameters

There are four main statistical parameters that being considered in this study. These parameters help to evaluate the accuracy of predicted fluid properties obtained from the black oil correlations.

Average Percent Relative Error (AERR)

This is an indication of the relative deviation in percent of the estimated values from the experimental values and is given as:

$$E_r = \left(\frac{1}{n_d}\right) \sum_{i=1}^{n_d} E_i \quad \text{.......... } B_1$$

E_i is the relative deviation in percent of an estimated value from an experimental value and is defined by:

$$\boldsymbol{E_i} = \left(\frac{x_{est}-x_{exp}}{x_{est}}\right)_i \times 100, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots B_2$$

Where: $\boldsymbol{x_{est}}$ and $\boldsymbol{x_{exp}}$ represent the estimated and experimental values, respectively.

Average Absolute Percent Relative Error (AAERR)

This parameter is to measure the average value of the absolute relative deviation of the measured value from the experimental data. The value o f AAERR is expressed in percent. The parameter can be defined as:

$$\boldsymbol{E_a} = \left(\frac{1}{n_d}\right) \sum_{i=1}^{n_d} |\boldsymbol{E_i}| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots B_3$$

And indicated the relative absolute deviation in percent from the experimental values, a lower value of AAERR implies better agreement between the estimated and experimental values.

Standard Deviation (SD)

Standard deviation, SD, of the estimated values with respect to the experimental values can be calculated using the following equation:

$$\boldsymbol{SD} = \left[\left(\frac{1}{n_d-1}\right) \sum_{i=1}^{n_d} (\boldsymbol{E_i} - \boldsymbol{E_r})^2\right]^{0.5} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots B_4$$

The accuracy of the correlation is determined by the value of the standard deviation, where a smaller value indicates higher accuracy. The value of the standard deviation is usually expressed in percent.

Correlation Coefficient(R)

The purpose of performing correlation coefficient calculation is to describe the extent of the association between two variables namely experimental and calculated values obtained from the correlation. The value of the correlation coefficient varies from zero to (1.0). A coefficient of zero indicates no relationship between experimental and calculated values. A (1.0) coefficient indicates a perfect positive relationship. The correlation coefficient can be calculated using the following equation:

$$\mathbf{R} = \left[1 - \left(\frac{\sum_{i=1}^{n_d}((x_{est}-x_{exp})_i)^2}{\sum_{i=1}^{n_d}((x_{exp}-\bar{x})_i)^2}\right)\right]^{0.5} \quad \ldots\ldots B_5$$

Where: $\bar{x}$ is the average value of the experimental PVT parameter, which can be calculated using the following equation:

$$\bar{x} = \left(\frac{1}{n_d}\right)\sum_{i=1}^{n_d}\left(x_{exp}\right)_i \quad \ldots\ldots B_6$$

Appendix C- Undersaturated oil Compressibility Correlations used for Comparison:

1. Vasquez and Beggs (1980)

$$Co=\frac{-C_1+5R_{sb}+C_2(T-460)-C_3\,\gamma_{gs}+C_4\,^{\circ}API}{10^5\,P} \quad \ldots\ldots C_1$$

Where:

$C_1=-1433$ $C_2=17.2$ $C_3=1180$ $C_4=12.61$

2. Ahmed (1985)

$$Co=\left[\frac{C_1+C_2\left[R_s\left(\frac{\gamma_g}{\gamma_o}\right)^{0.5}+1.25(T-460)\right]^{1.175}}{C_4\gamma_o+C_5\,R_s\gamma_g}\right]e^{(C_3\,P)} \quad \ldots\ldots C_2$$

Where:

$c_1=1.026638$ $c_2=0.0001553$ $c_3=-0.0001847272$ $c_4=62400$ $c_5=13.6$

3. Petrosky and Farshad (1993)

$$C_O=1.0705*10^{-7}\,R_{sb}^{\ 0.69357}\,\gamma_g^{\ 0.1885}\,API^{0.3272}\,T^{0.6729}\,P^{-0.5906} \quad \ldots\ldots C_3$$

4. Dindoruk and Christman (2010)

$$Co=(C_1+C_2\,A+C_3\,A^2)10^{-6} \quad \ldots\ldots C_4$$

Where:

$C_1=4.487462368$ $C_2=0.00519704$ $C_3=0.00001258$

$$A=\frac{\left[\frac{R_s^{a1}\,\gamma_g^{a2}}{\gamma_o^{a3}}+a_4(T-60)^{a5}-a_6\,R_s\right]^{a7}}{\left[a_8+(T-60)\,\frac{2\,R_s^{a9}}{\gamma_g^{a10}}\right]^{2}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots C_5$$

a_1=0.980922372 **a_2=0.021003077** **a_3=0.338486128** **a_4=20.00006358**

a_5=0.300001059 **a_6=0.876813622** **a_7=1.759732076** **a_8=2.749114986**

a_9=-1.713572145 **a_{10}=9.999932841**

5. Al-Marhon (2003)

$$\ln C_O = -14.1042+\frac{2.7314}{\gamma_{ob}}+\frac{-56.0605\times10^{-6}(P-P_b)}{\gamma_{ob}^{\,3}}+\frac{-580.8778}{(T+460)} \quad \ldots\ldots\ldots\ldots\ldots\ldots C_6$$