A NEURAL NETWORK MODEL AND AN UPDATED CORRELATION FOR ESTIMATION OF DEAD CRUDE OIL VISCOSITY

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ABSTRACT

Viscosity is one of the most important physical properties in reservoir simulation, formation evaluation, in designing surface facilities and in the calculation of original hydrocarbon in-place. Mostly, oil viscosity is measured in PVT laboratories only at reservoir temperature. Hence, it is of great importance to use an accurate correlation for prediction of oil viscosity at different operating conditions and various temperatures. Although, different correlations have been proposed for various regions, the applicability of the existing correlations for Iranian oil reservoirs is limited due to the nature of the Iranian crude oil. In this study, based on Iranian oil reservoir data, a new correlation for the estimation of dead oil viscosity was provided using non-linear multivariable regression and non-linear optimization methods simultaneously with the optimization of the other existing correlations. This new correlation uses API Gravity and temperature as an input parameter. In addition, a neural-network-based model for prediction of dead oil viscosity is presented. Detailed comparisons show that validity and accuracy of the new correlation and the neural-network model are in good agreement with large data set of Iranian oil reservoir when compared with other correlations.

KEYWORDS

dead oil viscosity; correlation; nonlinear regression; Artificial Neural Network; nonlinear optimization

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1. INTRODUCTION

Reservoir fluid properties are the key parameters in reservoir engineering calculations. PVT data are applicable in production equipment design, fluid flow in porous media and pipes, well testing and, reservoir simulation analysis.

Viscosity is defined as the resistance of fluid to flow. Increasing pressure causes the decrease in oil viscosity below the bubble point. Meanwhile, increasing pressure leads to the increase in oil viscosity above the bubble point. So oil viscosity is categorized into three types: dead, gas saturated, and under saturated oil (McCain, 1990). Figure 1 depicts a typical diagram of oil viscosity as a function of pressure at constant temperature.

Oil viscosity is measured at PVT laboratory using different techniques such as the rolling ball system, the centrifuge, and electromagnetic ones. For the calculation of a two-phase model, pressure traverse, and simulation process other temperatures are needed. Also, PVT experiments are always money and time consuming. The above mentioned reasons urge the development of a novel and accurate dead oil viscosity (μ_{od}) correlation.

Correlations are categorized into two types. The first type is the black oil model that use available field measurement parameter such as: pressure, API gravity and gas-oil ratio solutions to obtain an unknown property. The second type is the compositional model, which uses the equation of state and the law of corresponding state. This type uses, besides previous parameters, properties like: fluid composition, critical temperature, and acentric factor (Ahrabi et al., 1987; Naseri et al., 2005).

Results show that existing correlations present large error for estimation of dead oil viscosity of Iranian data due to a high dependency of oil viscosity to its nature, place, and origin. In this study, the correlations were applied to Iranian data and, subsequently, coefficients of these equations were optimized for Iranian data. However, based on nonlinear multivariable regression and nonlinear optimization involving Iranian oil reservoirs data, a novel API gravity and temperature (T) dependent correlation was developed. Results show that this correlation has

Figure 1. Oil viscosity as a function of pressure.

more accuracy if compared to other correlations.

Neural-networks have been used successfully in different fields, especially in a number of areas in petroleum industry. Neural-network models have shown great potential for generating reliable models for prediction of oil PVT properties. In this study, an Artificial Neural Network (ANN) approach for achieving a high degree of accuracy in predicting the dead oil viscosity is presented. The statistical analysis shows that ANN approach is a far more comprehensive method for use in dead oil viscosity correlations when compared to other conventional correlations.

This study was particularly conducted to develop two empirical models, a new correlation and an ANN model, to provide a quick and reliable estimate of dead oil viscosity based on Iranian reservoirs data.

2. LITERATURE REVIEW

In literature many attempts have been done to predict dead oil viscosity in various conditions. Below some of dead oil viscosity correlations are presented along with other correlations which present significant errors, considering that Iranian crude oil data are neglected:

2.1 Black oil model correlations

These correlations use reservoir temperature and API gravity of stock tank to obtain oil viscosity at atmospheric condition, known as dead oil.

Beggs and Robinson (1975) developed a new formula based on crude oils of unknown location. The equations 1-4 show this correlation. **Glaso (1980)** using North Sea data, developed new correlations that are given as equations 5 and 6. **Labedi (1992)**, based on African data, developed the correlation that is shown in equation 7. This latter correlation is applicable for light crude oils, with API ranging from 32 to 48. **Kartoatmodjo and Schmidt (1994)** using a data bank developed an empirical formula. Equations 8 and 9 show this correlation. **Elsharkawy and Alikhan (1999)**, for Middle East crude oils, presented a new correlation which is given as equations 10 to 12. Table 1 summarizes more information for the proposed correlations among others relevant ones.

Beggs and Robinson correlation (**Beggs and Robinson, 1975**):

$$\mu_{od} = 10^x + a_1 \quad (1)$$

$$x = a_2 y (T_f)^{a_3} \quad (2)$$

$$y = 10^z \quad (3)$$

$$z = a_4 API + a_5 \quad (4)$$

Glaso correlation (**Glaso, 1980**):

$$\mu_{od} = a_1 (T_f)^{a_2} [\log(API)]^a \quad (5)$$

$$a = a_3 [\log(T_f)] + a_4 \quad (6)$$

Labedi correlation (**Labedi, 1992**):

$$\mu_{od} = \frac{10^{a_1}}{API^{a_2} T_f^{a_3}} \quad (7)$$

Kartoatmodjo and Schmidt correlation (**Kartoatmodjo and Schmidt, 1994**):

$$\mu_{od} = a_1 (T_f)^{a_2} [\log(API)]^x \quad (8)$$

$$x = a_3 [\log(T_f)] + a_4 \quad (9)$$

Elsharkawy and Alikhan correlation (**Elsharkawy and Alikhan, 1999**):

$$\mu_{od} = \text{anti log}_{10}(x) + a_1 \quad (10)$$

$$x = \text{anti log}_{10}(y) \quad (11)$$

$$y = a_2 + a_3 API + a_4 \log_{10}(T) \quad (12)$$

Where: a_1, a_2, a_3, a_4, a_5 are constants, shown in Table 5; T_f = temperature (°F); API= oil API gravity; T = temperature (°R); and μ_{od} = dead oil viscosity.

2.2 Compositional model correlations

These correlations use parameters other than temperature and API gravity to reduce errors. Since Black oil models are developed for a specific region, they have great error margins when applied to other locations, because oil viscosity has a strong connection with its nature and region.

Table 1. Data properties used in different correlations.

Correlation	year	Source of data	API	Temperature (F)	Dead oil viscosity (cp)
Beggs and Robinson	1975	unknown	16-58	70-295	unknown
Glaso	1980	North Sea	20-48	50-300	0.6-39
Labedi	1992	Africa	32-48	100-306	0.6-4.8
Kartoatmodjo and Schmidt	1994	data bank	14.4-59	80-320	0.5-586
Elsharkawy and Alikhan	1999	Middle East	20-48	100-300	0.6-33.7
This work	2011	Iran	16-49.2	100-292	0.4-37.2

Egbogah and Ng (1990) by adding pour point temperature modified Beal correlation (**Beal, 1946**). However, pour point temperature is neither reported in any standard PVT nor measured in the field (**Svrcek and Mehrotra, 1988**). **Mehrotra (1991)** predicted the viscosity of light and medium hydrocarbons using molar mass, normal boiling point, critical temperature, and acentric factor, despite the fact that these parameters are not available in usual PVT reports. **Johnson and Svrcek (1991)** published their correlation from corresponding state equations that use fluid composition as an input parameter. Although these compositional models are using different parameters other than temperature and API gravity, their prediction is poor (**Elsharkawy and Alikhan, 1999**).

3. NON-LINEAR PROGRAMMING OPTIMIZATION

Optimization is one of the most important areas of modern applied mathematics, with applications in fields from engineering and economics to medicine. The general optimization problem is shown as equations 13-15.

$$\min(\max) \quad f(x) \quad (13)$$

Subject to:

$$g_i(x) \leq 0 \quad i = 1, 2, \dots, m_1 \quad (14)$$

$$g_i(x) = 0 \quad i = m_1 + 1, \dots, m \quad (15)$$

$$(X \in R^n)$$

In particular, if $m = 0$, the problem is called an unconstrained optimization problem. If the objective function or at least one of constraints is nonlinear, the program is called a nonlinear optimization problem. Many methods can be applied to solve problem and find optimum solution. In this study LINGO software has been used to optimize dead oil viscosity correlation constants.

LINGO is a tool designed to build and solve

linear, nonlinear, and integer optimization models. LINGO provides an integrated package that includes a powerful language for expressing optimization models, a full featured environment for building and editing problems, and a set of fast built-in solvers.

For nonlinear programming models, the primary underlying technique used by LINGO's optional nonlinear solver is based upon a Generalized Reduced Gradient (GRG) algorithm. However, to help get to a good feasible solution quickly; LINGO also incorporates Successive Linear Programming (SLP) (**LINDO Systems Inc., 2011**).

4. ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial neural networks (ANNs) are massively parallels, distributed processors, constituting of numerous simple processing units, called neurons, developed by mimicking the behavior of the human brain (**Dutta and Gupta, 2010**). Neural systems are typically organized in layers. Layers are made up of a number of interconnected nodes called artificial neurons, which contain activation functions. Patterns are presented to the network via the input layer, which communicates to one or more hidden layers where the actual processing is done through a system of connections. The hidden layers then linked to the output layer (**El-M Shokir et al., 2004**). The number of neurons in the input layer is determined based on the number of the parameters in the network. The same is true for the output layer (**Mohaghegh, 2000**). Initially, the input layer receives the input and passes it to the first hidden layer for processing. The processed information from the first hidden layer is then passed to the second hidden layer for processing. Finally, the output layer receives information from the last hidden layer and sends the results to an external source. All the hidden layers have no direct connections to the outside world, and the entire processing step is hidden. (**Gharbi and Elsharkawi, 1999**). To provide an appropriate model, a Multi-layer feed-forward neural network used and several architectures with different hidden layers and different number of nodes in the hidden layers were trained and tested. Finally architecture with one input layer with 2 nodes and two hidden layer with 6, 5 nodes was selected as the best architecture. The activation function for

Figure 2. Multiple layer neural-network model.

input and output data considered Logistic. Figure 2 depicts the selected architecture containing neurons and connections between them.

In this study 120 real data from Iranian oil samples used, and mainly divided into two distinct categories: one for training (%85) and another for testing (%15). The training group comprises of two separate set of data: the first used for training the network and second, for testing the error during

the training, which is called cross validation. The testing set is used to assess the reliability and accuracy of the model. Tables 2 to 4 show the statistical comparisons for training, validation and testing data. Figure 3 indicates the confusion matrix for the ANN model. This matrix shows the correspondence between the target and output data in different ranges. The data are divided into 12 categories. For each range of data, the number of the corresponded network output with target

Table 2. Statistical analysis for training results.

	Target	Output	AE	ARE
Mean	4.434911	4.434835	0.240797	0.100577
Standard Deviation	4.242802	4.224235	0.320937	0.13262
Min	0.4781	0.841682	0.001211	0.000135
Max	21.60058	20.4472	1.736033	0.76051

Table 3. Statistical analysis for validation results.

	Target	Output	AE	ARE
Mean	5.783518	5.700524	0.548706	0.168125
Standard Deviation	3.633678	3.904789	0.472623	0.256099
Min	0.3937	0.841694	0.02528	0.004731
Max	15.7491	17.12863	1.820617	1.137907

Table 4. Statistical analysis for testing results.

	Target	Output	AE	ARE
Mean	5.304221	5.486879	0.511788	0.155168
Standard Deviation	5.94521	6.179092	0.646858	0.17294
Min	0.7461	0.667677	0	0
Max	21.60058	21.60058	2.327192	0.643968

output is shown with blue color blocks and pink or red color blocks indicate the number of non-conforming data.

5. METHODOLOGY

In this study a database gathered from different Iranian oil reservoirs for estimating dead oil viscosity was employed. This database contains light to heavy hydrocarbons which satisfies the range of validity for temperature, API and dead oil experimental viscosity shown in Table1.

To develop the proposed correlation multivariable regression was employed and temperature and API used as independent variables and experimental viscosity as dependant or desired variable. Afterward the best function which fits better to the experimental data between different possible function is selected. This function selected based on the Average Absolute Relative Error (AARE) and R-square.

In next stage a nonlinear programming model is solved to minimize AARE. The general form of this unconstrained model is shown in equation 16. To obtain optimized coefficients for predicting

Target output:	Network output:											
	<0.39	0.39-2.51	2.51-4.64	4.64-6.76	6.76-8.88	8.88-11	11-13.12	13.12-15.24	15.24-17.36	17.36-19.48	19.48-21.6	>21.6
0.39-2.51	0	44	1	0	0	0	0	0	0	0	0	0
2.51-4.64	0	3	21	0	0	0	0	0	0	0	0	0
4.64-6.76	0	1	3	17	1	0	0	0	0	0	0	0
6.76-8.88	0	1	0	1	11	0	0	0	0	0	0	0
8.88-11	0	0	0	0	1	3	0	0	0	0	0	0
11-13.12	0	0	0	0	0	0	5	0	0	0	0	0
13.12-15.24	0	0	0	0	0	0	0	1	0	0	0	0
15.24-17.36	0	0	0	0	0	0	0	0	2	0	0	0
17.36-19.48	0	0	0	0	0	0	0	0	0	0	1	0
19.48-21.6	0	0	0	0	0	0	0	0	0	0	1	0

Figure 3. The confusion matrix for the ANN Model.

function, LINGO software has been used. Coefficients were chosen free in sign. This model also used for optimizing the other correlations.

$$\text{Min}\left(\left|\mu_{\text{exp}} - \mu_{\text{est}}\right|/\mu_{\text{exp}}\right) \quad (16)$$

6. RESULT AND DISCUSSION

Usually, application of dead oil viscosity correlations to crude oil of different sources results in huge errors. This difference attributed to the difference in asphaltic, paraffinic and/or mixed nature of the oils (Naseri et al., 2005). So it may be useful to correct the coefficient of the existing correlations based on Iranian crude oil data. Using nonlinear optimization the coefficients were modified and the Average Absolute Relative Error (AARE) significantly decreased. Table 5 shows the optimized coefficient for each mentioned correlation, and Table 6 indicates the AARE, Average Relative Error (ARE), and Standard Deviation (SD) after optimization the correlation.

To develop new correlation, 70% of all data

chosen as training data randomly and the other 30% data were used as testing data. Non-linear multivariable regression and optimization was accomplished to obtain new formula based on training data. The proposed correlation gives an AARE of 16.75% for testing data which is an acceptable error in comparison with other ones. This correlation is given as equation 17-19.

$$\mu_{od} = 10^x - 1.12 \quad (17)$$

$$x = 10^y \quad (18)$$

$$y = 7.9684 - 2.7942 \log(API) - 1.6044 \log(T_f) - \frac{47.3757}{T_f} - \frac{165.1894}{API^2} \quad (19)$$

6.1 Validation of the new correlation

Here, the validity of new correlation, the new ANN model and previous mentioned correlations for prediction of dead oil viscosity is checked with

Table 5. Constants in the existing correlations and optimized of them.

Constants	Beggs and Robinson	Glaso	Labedi	Kartoatmodjo and Schmidt	Elsharkawy and Alikhan
a_1	-1	$3.141(10^{10})$	9.224	$16(10^8)$	-1
a_2	1	-3.444	4.7013	-2.8177	2.1692
a_3	-1.163	10.313	0.6739	5.7526	-0.02525
a_4	-0.02023	-36.447		-26.9718	-0.6887
a_5	3.0324				
Constants	Optimized Beggs and Robinson	Optimized Glaso	Optimized Labedi	Optimized Kartoatmodjo and Schmidt	Optimized Elsharkawy and Alikhan
a_1	-1.4605	118.2046	8.9458	118.2046	-1
a_2	0.6209	-0.0955	2.9336	-0.0955	11.6870
a_3	-0.8297	-9.2346	1.8533	-9.2346	-0.0262
a_4	-0.02123	12.2538		12.2538	3.9678
a_5	2.5168

Figure 4. Dead oil viscosity vs. API Gravity at 255°F.

experimental data. Figure 4 depicts that when dead oil viscosity is plotted versus API Gravity at specific temperature (255°F), the proposed correlation and the ANN model has more precision compared to other ones.

6.2 Accuracy of new correlation

In this part, the accuracy of new correlation, ANN model, mentioned correlations and optimized of them, is investigated. For this purpose 120 real cases data series of Iranian oil Reservoirs are used. Figure 5 and Table 6 show the results of this work and other correlations. This figure shows that the proposed correlation and the ANN model have the smallest error than other ones. For example Figure 5 indicates that there is a significant deviation from 45 degree straight line for the existing correlations applied to Iranian crude oil data comparing the developed correlation (more conformances to this straight line results in more agreement between the experimental and calculated dead oil viscosity value). For statistical comparison between new correlation, the ANN model and other mentioned correlations, Table 6 is presented. Results confirm that proposed correlation has the smallest ARE, AARE, SD among the other correlations, also the ANN model has the most accurate prediction. (Statistical parameters are defined in equations 20-

22). Although the ANN model has lower AARE than the proposed correlation but, in some predictions it shows huge errors which causes it's ARE to be more than the proposed correlation. As indicated in Figure 5 it can be inferred that using the ANN model may cause to wrong prediction in some cases. Thus, the new correlation is more preferable to predict dead oil viscosity for Iranian oil Reservoir data. It is obvious that applicability of this correlation to other locations must be checked.

$$ARE = \frac{100}{N} \sum_{i=1}^N \frac{X_{i_{cal.}} - X_{i_{exp.}}}{X_{i_{exp.}}} \quad (20)$$

$$AARE = \frac{100}{N} \sum_{i=1}^N \left| \frac{X_{i_{cal.}} - X_{i_{exp.}}}{X_{i_{exp.}}} \right| \quad (21)$$

$$SD = \sqrt{\frac{1}{N-1} \sum_{i=1}^N \left(\left| \frac{X_{i_{cal.}} - X_{i_{exp.}}}{X_{i_{exp.}}} \right| - AARE \right)^2} \quad (22)$$

Where: N= number of data points, X_i = generic dependant variable.

Figure 5. Scatter diagram of viscosity predicted for dead oil viscosity correlations.

Table 6. Accuracy of proposed correlation and other correlations for testing data.

Correlation	AARE%	ARE%	SD
Beggs and Robinson	25.97	10.02	39.77
Optimized Beggs and Robinson	20.17	-4.92	36.51
Glaso	35.70	25.51	42.64
Optimized Glaso	22.11	-6.77	40.74
Labedi	218.83	215.51	196.32
Optimized Labedi	19.80	-5.17	36.10
Kartoatmodjo and Schmidt	39.50	26.86	51.19
Optimized Kartoatmodjo and Schmidt	22.11	-6.77	40.74
Elsharkawy and Alikhan	61.23	-61.23	125.28
Optimized Elsharkawy and Alikhan	19.21	-6.31	35.63
ANN model	12.17	-7.166	23.51
This work	16.75	-4.29	31.10

7. CONCLUSIONS

Generally the most common method for viscosity calculation of crude oils is correlations. The main purpose of this study was to develop a reliable black oil model viscosity correlation and a neural-network based model for estimation of dead crude oils for Iranian oil Reservoirs. On the other hand, optimized models of the other correlations were presented based on Iranian crude oil data. The new proposed correlation was developed by the aid of non-linear multivariable regression and optimization based on extensive data bank that covers all Iranian oil Reservoirs. Input parameters for this new formula are API Gravity and temperature that are always available in field. The proposed correlation and the proposed ANN model yield accurate predictions with the least ARE, AARE and SD among the other mentioned correlations and even the proposed optimized correlations. However, employing this new correlation and ANN model for other boundary limits may result in huge errors and should be reconstructed again.

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