Using Intelligent Methods and Optimization of the Existing Empirical Correlations for Iranian Dead Oil Viscosity

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Abstract

Numerous empirical correlations exist for the estimation of crude oil viscosities. Most of these correlations are not based on the experimental and field data from Iranian geological zone. In this study several well-known empirical correlations including Beal, Beggs, Glasso, Labedi, Schmidt, Alikhan and Naseri were optimized and refitted with the Iranian oil field data. The results showed that the Beal and the Labedi methods were not suitable for estimation of the viscosity of the Iranian crudes, while the Beggs, Glasso and Schmidt methods gave reasonable results. The Naseri's correlation and their present method proved to be the best classical methods investigated in this study. Two new intelligent methods to predict the viscosity of Iranian crudes have also been introduced. The study also showed that the neural network and SVM give much better results comparing to classical correlations. It is claimed that this study may provide more exact results for the prediction of Iranian oil viscosity.

Keywords

Dead oil;
Empirical correlation;
Neural network;
SVM;
Viscosity.

1. Introduction

Middle East countries contain at least 60 percentages of the world's proved oil reservoirs. Most of these reservoirs locate in the six oil rich countries of Iran, Iraq, Saudi Arabia, Kuwait, Qatar and United Arab Emirates. As the ratio of oil production to proved reservoirs in these countries is considerably lower than other parts of the world, this share is expected to rise in the next few decades. So it is clear that the commercial oils of these countries will be more important in the future oil market and industry. The crude oil is a complicated mixture of too many components and cannot be treated like normal multi-component mixtures. In most cases, the process engineers have to calculate the various physical oil properties without even knowing the exact composition. Therefore, the conventional thermodynamic methods usually are not applied to crude oil and oil products. The physical properties of these mixtures are usually estimated by means of numerous empirical correlations based on the limited experimental laboratory or field data of certain kinds of

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crude oils or oil products. The accuracy of these empirical correlations generally depends on the degree of similarity between the sample crude oil and the original experimental data set forming the basis of the correlation. To say it in another way, if the original correlation is mainly based on the experimental data of certain kinds of crude such as West Texas Intermediate (WTI) or Brent oil of the North Sea, the estimation would be most accurate for these kinds of crude oils or some similar crude but the correlation would be expected to give poor results for a different kind of crude oil.

The composition and properties of different crude oils vary widely. Even different crudes from a unique geographical region such as Persian Gulf or Caspian Sea are different from each other but these differences are not usually so sharp. Therefore, the physical properties of the crude oils of different Middle East countries are different from each other but of course, these differences are less distinct comparing to other crudes from different geological locations such as North Sea or Venezuela. Most of the empirical correlations used in the oil industry are developed on the basis of experimental data from oil fields in the other parts of the world such as North America. Therefore, it can be expected that most of these correlations may give poor predictions of the physical properties of the Middle East crudes.

It was noted that the Middle East's global share of oil production will considerably rise in the future decades, so the commercial importance of these kinds of crude oils justifies the reconsideration and re-establishment of empirical correlations.

On the other hand, the intelligent methods have been widely used in different sectors of the oil industry in recent years. During the recent decades the petroleum industry has experienced a rapid increase in the applications of the artificial intelligence methods. Mohaghegh et al. [1] introduced a new model that used the pattern capabilities of the neural networks to characterize the reservoir heterogeneity. They used a three layer, feed forward, back propagation network and their input variables consisted of spatial coordinates, well logs and geological interpretations. Romero and Carter [2] used genetic algorithm (GA) for reservoir characterization. They applied their GA model to a realistic complex synthetic reservoir and claimed that their GA based method give better results in comparison to other conventional methods. Nikravesh and Aminzadeh [3] studied the intelligent reservoir characterization methods. They concluded that the soft computing methods including neural network, fuzzy logic, genetic algorithm and probabilistic reasoning are more tolerant than the conventional hard computing techniques and may play a key role in this field. Esmaeilzadeh and Nourafkan [4] calculated the original oil in place (OOIP) in the oil reservoirs using genetic algorithm. They used a two-stage method using the genetic algorithm in the first stage to initialize and identify the search zone. The final results were then obtained from a simplex method. They applied their technique to three different cases and concluded that this method is able to solve the problem in cases that are not solvable by conventional methods. El-Sebakhy predicted the PVT properties of crude oils by means of support vector machines (SVM). He reported that the SVM performance was more reliable and accurate in comparison with other published correlations [5]. Emera and Sarma [6] used the genetic algorithm to estimate the CO_2-Oil minimum miscibility pressure and claimed that their GA based method is superior to other methods. Alomair et al. [7] developed a new model for dead oil viscosities of Kuwaiti heavy crude oils at elevated temperatures. Hemmati-Sarapardeh et al. [8] used support vector machine (SVM) soft computing technique to provide predictive models for dead oil viscosities. Their original data bank consisted of over 1500 data sets from different geological locations.

Viscosity is usually considered as one of the most important physical properties of crude oil. Numerous processes such as oil production and transportation, transport phenomena such as heat and mass transfer and so on depend on the precise evaluation of this property. Due to the complexity and unknown composition of crude oil and oil products, the petroleum engineer often uses the empirical correlations to predict the oil viscosity. These empirical correlations are fitted with laboratory and field data which are usually gathered from very different geological locations at the Middle-East oil producing countries. In this study, we aim to check the applicability of the common empirical correlations to estimate the viscosity of Iranian crudes. A large data bank of the viscosity of Iranian crudes was collected from different sources. The difference between the calculated and experimental results was used as a measure tool to compare the different correlations with each other. The coefficients of some well-known correlations were re-fitted using Iranian field data to improve their precision when applying to Iranian crudes. A completely new empirical correlation based on the dead oil viscosity of the Iranian crudes, was also developed. Of course this new correlation is expected to be more precise in prediction of the viscosity of Iranian and similar crudes. On the other hand, it was tried to use new intelligent methods to estimate the viscosity of the crude oils and compare their performance with the previous classical methods. These intelligent methods were trained using the collected viscosity data, so they are believed to give better results for Iranian and probably similar crudes of other Middle-East countries. It is clear that as the total share of the commercial oil production of Middle-East countries is expected to rise continuously in the next few decades, the refitted and new methods introduced in this study may be more widely used in near future. El-Hoshoudy et al. [9] used a similar procedure for prediction of viscosity and density of Egyptian oil reservoirs.

Oil viscosity is measured in four different regions which are described as follows:

1. The oil viscosity at the bubble point pressure that refers to oil at the reservoir temperature and bubble pressure. This kind of viscosity is usually called saturated crude oil viscosity.
2. The oil viscosity in a pressure lower than the bubble pressure which is called under-saturated oil viscosity. As the oil pressure decreases from the bubble pressure, the dissolved gases release from the oil and the oil viscosity changes as a result.
3. If the oil pressure falls to lower than atmospheric pressure, nearly all of the dissolved gases release from the oil and the oil is called the dead or stock oil. Dead oil viscosity is another important kind of oil viscosity and we are going to consider this kind of oil viscosity in this paper.
4. If the oil exists in a pressure higher than bubble pressure, it is called live oil and its viscosity is known as the live oil viscosity.

All of these four different kinds of oil viscosity have been studied in this research, but all of them cannot be presented in a single paper, so only the dead oil viscosity is considered here and the other three kinds of oil viscosity will be considered in other publications.

2. The Empirical Correlations for Dead Oil Viscosity

Several empirical models exist for the estimation of dead oil viscosity, some of them have been found to give reasonable results for Iranian samples. Many new empirical correlations have been introduced in recent years [10-11] but in this paper, we have focused on those empirical methods which have been tested for Iranian crudes.

In 1946, Beal introduced a graphical method for estimation of dead oil viscosity [12]. This graph was mainly based on the Californian field data. In 1981, Standing substituted the Beal's graph by the following formula:

$$\mu_{od}=\left(0.32+\frac{1.8\times10^{7}}{API^{4.53}}\right)\left(\frac{360}{T-460}\right)10^{\left(0.43+8.33/API\right)} \quad (1)$$

In 1975 Beggs and Robinson introduced an empirical correlation to determine the dead oil viscosity [13]. This empirical method is presented in the following formulas:

$$\mu_{od}=10^{x}-1 \quad (2)$$

$$x=y(T-460)^{-1.163} \quad (3)$$

$$y=10^{z} \quad (4)$$

$$z=3.0324-0.02023API \quad (5)$$

Glaso's formulas were based on the field data of North America and can be shown by the following formulas [14]:

$$\mu_{od}=3.141\times10^{10}(T-460)^{-3.444}[\log(API)]^{a} \quad (6)$$

$$a=10.313[\log(T-460)]-36.447 \quad (7)$$

Labedi's correlation was mainly based on the field data of light crudes from North Africa, especially Lybia. [15]

$$\mu_{od}=\frac{10^{9.224}}{API^{4.7013}T_f^{0.6739}} \quad (8)$$

Kartoatmodjo and Schmidt presented the following formulas in 1994 which was based on 3588 measured viscosity data of 661 crude samples from Southwest Asia, North and South America and Middle East. [16]

$$\mu_{od}=16\times10^{8}\,T_f^{-2.8177}[\log(API)]^{x} \quad (9)$$

$$x=5.7526\log(T_f)-26.9718 \quad (10)$$

The Elsharkawy and Alikhan's formulas for estimation of dead oil viscosity can be presented as follow [17]:

$$\mu_{od}=anti\log_{10}(x)-1.0 \quad (11)$$

$$x=anti\log_{10}(y) \quad (12)$$

$$y=2.16924-0.02525API-0.68875\log_{10}(T) \quad (13)$$

Naseri et al. introduced the following formula for Iranian dead oil viscosity in 2005[18].

$$\mu_{od} = anti\log_{10}\left(11.2699 - 4.298\log_{10}(API) - 2.052\log_{10}(T_f)\right) \qquad (14)$$

There are many more correlations, but these formulas are usually used by Iranian oil experts, they have been selected to estimate the dead oil viscosity of Iranian crudes. To compare these empirical correlations, the following statistical measures have been used:

1. The average relative error (ARE) as follow:

$$ARE = \frac{100}{N}\sum_{i=1}^{N}\frac{x_{i_{cal}} - x_{i_{exp}}}{x_{i_{exp}}} \qquad (15)$$

2. The average absolute relative error as follow: (AARE)

$$(\mathrm{AARE})\ AARE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{x_{i_{cal}} - x_{i_{exp}}}{x_{i_{exp}}}\right| \qquad (16)$$

3. The standard deviation (SD) as follow:

$$SD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left\{\left|\frac{x_{i_{cal}} - x_{i_{exp}}}{x_{i_{exp}}}\right| - AARE\right\}^2} \qquad (17)$$

It is clear that the coefficients of these correlations are found by fitting curves with a certain set of the experimental data. One of the main aims of this study was to re-fit the coefficients of these correlations for Iranian samples. This re-fit was done with the aid of the collected viscosity data bank. The re-constructed correlations are given as follows:

The optimized Glaso formula was found to be:

$$\mu_{od} = 212.5(T-460)^{-0.5495}\left[\log(API)\right]^a \qquad (18)$$

$$a = 2.66381\times10^{-8}\left[\log(T-460)\right] - 4.155 \qquad (19)$$

The optimized Labedi formula is:

$$\mu_{od} = \frac{10^{10.04}}{API^{2.764}\,T_f^{2.266}} \qquad (20)$$

The Kartoatmojdo and Schmidt formula was optimized to:

$$\mu_{od} = 31.93\times10^{6}\,T_f^{-2.293}\left[\log(API)\right]^x \qquad (21)$$

$$x = -9.25\times10^{-9}\log(T_f) - 8.755 \qquad (22)$$

These statistical measures have been calculated for all of the above-mentioned correlations and the results have been summarized in Table 1 and Fig. 1.

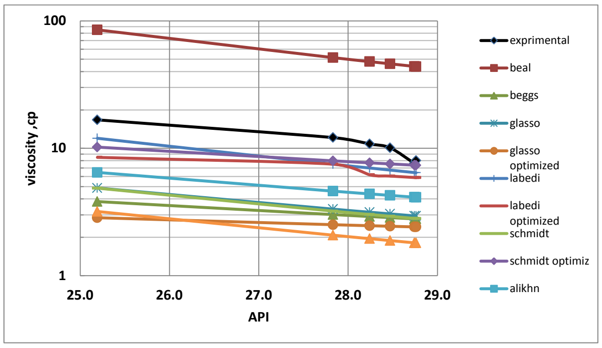

Figure 1. The comparison of different empirical prediction methods.

3. The Neural Network Model

Neural networks generally consist of three main layers called input, hidden and output. These networks have been successfully used in many different types and architectures, and are consist of same elements such as nodes, layers and connections. Multi-layer perceptron and radial basis function are two of the most popular architectures for prediction of physical properties of fluids. It has been reported that multi-layer feed forward neural network with one hidden layer is able to approximate any complicated nonlinear function [19], thus a multi-layer feed forward perceptron neural network with two hidden layers has been used in this

Table 1. The comparison of different empirical prediction methods.

	Beal	Beggs	Glasso	Optimized glasso	Labedi	Optimized labadi	Schmidt	Optimized schmidt	Alikhan	Naseri
ARE%	**263.45**	**-36.3**	**-37.89**	**-19.6**	**32.69**	**25.06**	**-42.76**	**24.44**	**-11.25**	**-65**
AARE%	**266.81**	**52.55**	**53.21**	**45.01**	**86.76**	**65.07**	**56.52**	**41.7**	**55.32**	**69**
SD%	**369.86**	**26**	**33.14**	**32**	**116**	**77.8**	**32.92**	**35**	**47.5**	**23**

work to correlate the dead oil viscosity of Iranian crudes. Figure 2 shows the general structure of the ANN architecture used in this work.

Weight factors connect the different neurons in each layer. Except the input layer, other layers receive a sum of inputs. The sigmoid transfer function is used in this study because of easy derivation evaluation [20].

It is necessary to train an artificial neural network before being used for a specific application. This process is a step by step method for calculation of the optimized weight factors and biases. During the training, the new outputs are generated by the network, iteratively. The sequential weight/bias rule is one of the most commonly used training methods and is also applied in this study. Initial weights are first generated randomly at the first step. Then the inputs are entered into the input layer and move forward through the hidden layers of neurons to the output layer and the generated output would be compared with the experimental dead oil viscosity. Changing the weight factors may decrease the calculated errors. After the training process, the network can be used to predict the dead oil viscosity.

Scaling of the output and input values may improve the increase in the network performance. In this work both inputs and outputs are scaled between 0.1 and 0.9 as follows:

$$\text{Scaled Value} = \frac{(\text{Actual Value}) - (\text{Minimum Value})}{(\text{Maximum Value}) - (\text{Minimum Value})} \times 0.8 + 0.1 \qquad (23)$$

The dead oil viscosity data were randomly divided into two main groups which consisted 70% and 30% of the total data, respectively. The first group was used to train and the second group was used to test the trained network. The number of the neurons in the hidden layer of the neural network was found to be equal to 20. Fig. 3 shows the graphical representation of the neural network. Moreover, the characteristics of the optimized neural network are also summarized in Table 2.

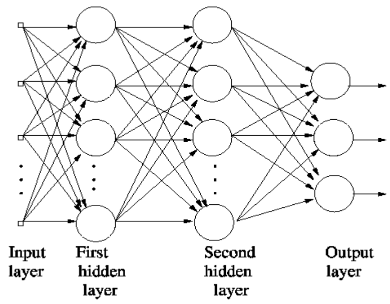

Figure 2. The general architecture of the ANN model.

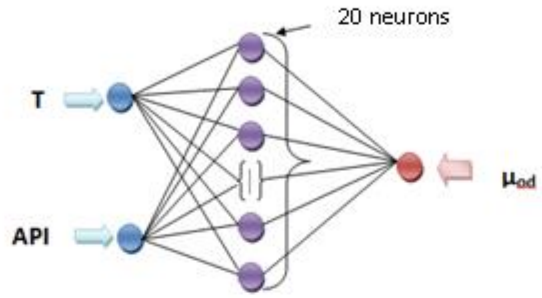

Figure 3. Graphical representation of the neural network.

Fig. 4 also compares the results of this section with the experimental data.

Mean square error has been used to compare the different prediction methods.

$$mse = \frac{\sum (x_{cal} - x_{\exp})^2}{n} \qquad (24)$$

4. Support Vector Machine

Vapnic [21] introduced the support vector machines (SVMs) in 1998. The advantage of this method is that it obtains the solution by solving the quadratic programming (QP) and avoids the local minima [22]. Obtaining the final SVM model can be very difficult because it is necessary to solve a set of nonlinear equations. A simplified version

Table 2. The characteristics of the optimized neural network for Iranian dead oil viscosity.

Number of neurons	Learning algorithm	Transfer function of the input layer	Transfer function of the output layer	MSE
20	Sequential waight/bias rule	Sigmoid	Purelin	0.014

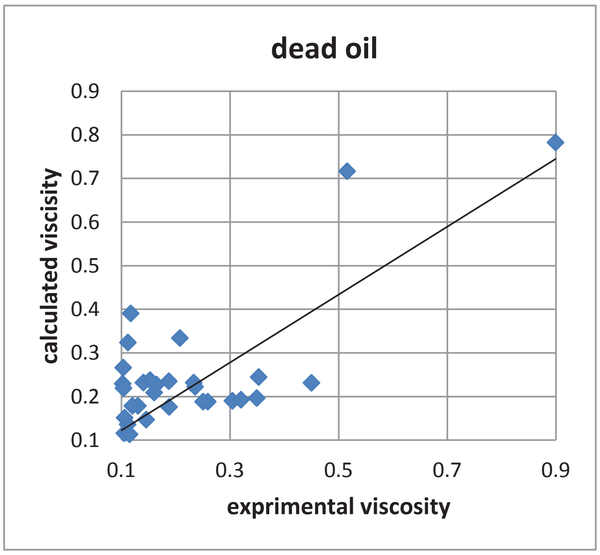

Figure 4. Experimental viscosity vs. neural network predictions.

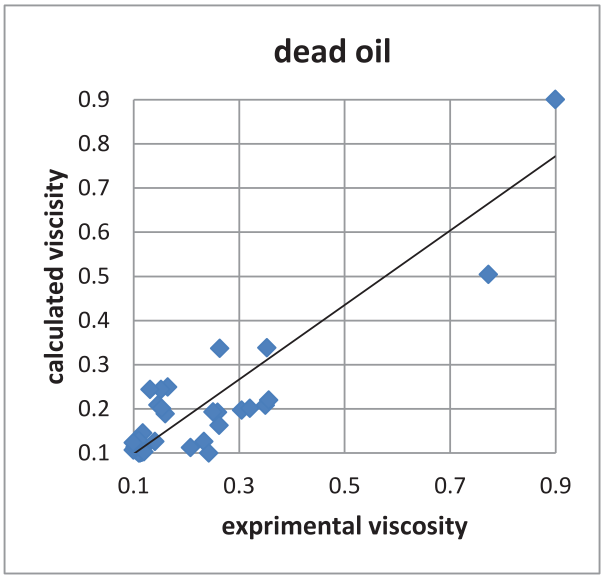

Figure 5. Experimental viscosity vs. SVM predictions.

of SVM called least square support vector machine (LS-SVM) leads to a set of linear equations. The support vector machine is also used to recognize the hidden patterns and to classify the input data by means of least square method, but SVM is more generalized in comparison to ANN. SVM is considered to belong to Kernel methods.

Given a set of training data like this:

$$\{(x_1,y_1)..(x_k,y_k)\}\subset R^N \times R^N \quad (25)$$

The following regression model is constructed by using nonlinear mapping function $\varphi(.)$:

$$y = W^T.\varphi(x)+b \quad \text{with } W\in R^N, \quad b\in R, \varphi : R^N \to R^M, M\to\infty \quad (26)$$

where b is the bias and W is the weight vector. If the least-squares support vector is used as an approximation function, a new problem has to be solved. The optimization of LS-SVM is given as:

$$\mathrm{Min}\,J(W,e) = \frac{1}{2}W^T.W + \frac{1}{2}\gamma\sum_{k=1}^{N} e_k^2 \quad (27)$$

These equations are constrained by:

$$y = W^T.\varphi(x), + b + e_k \quad k = 1...N \quad (28)$$

where, γ is the regularization parameter and e_k is the desired error. The problem may be solved by a Lagrangian function as:

$$L(W,b,e,\alpha) = J(W,e) - \sum_{k=1}^{N}\alpha_k\{W^T.\varphi(x), + b + e_k - y_k\} \quad (29)$$

where, α_k is called the support value. Partial differentiating with respect to each variable leads to the solution.

$$\frac{\partial L}{\partial W} = 0 \to W = \sum_{k=1}^{N}\alpha_k.\varphi(x_k) \quad (30)$$

$$\frac{\partial L}{\partial b} = 0 \to W = \sum_{k=1}^{N}\alpha_k = 0 \quad (31)$$

$$\frac{\partial L}{\partial e_k} = 0 \to \alpha_k = \gamma.e_k \quad k = 1,...,N \quad (32)$$

$$\frac{\partial L}{\partial \alpha_k} = 0 \to W^T.\varphi(x), + b + e_k - y_k = 0 \quad k = 1,...,N \quad (33)$$

The Karush-Kuhn-Trucker (KKT) system is obtained as the variable w and e are removed:

$$\begin{bmatrix} 0_{1\times N} & 1_{1\times N} \\ 1_{N\times 1} & Z+\gamma^{-1}.I \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \quad (34)$$

with

$$y = [y_1,...,y_N] \quad (35)$$

$$1 = [1,...,1] \quad (36)$$

$$0 = [0,...,0] \quad (37)$$

$$\alpha = [\alpha_1, \ldots, \alpha_N]$$
$$z = \{Z_{kj} \mid k, j = 1, \ldots, N\}, \tag{38}$$

$$Z_{kj} = \varphi(x_k)^T . \varphi(x_j) =$$
$$K(x_k, x_j)\ j = 1, \ldots, N \tag{39}$$

where, $k(x_k, x_j)$ is called the RBF kernel function.

$$K(x, x_k) = \exp\left(-\frac{\|x - x_k\|^2}{\delta^2}\right) \tag{40}$$

The LS-SVM regression model can be shown as:

$$y(x) = \sum_{k=1}^{N} \alpha_k . K(x, x_k) + b \tag{41}$$

where (b, α) can be found by solution of Eq. 27.

The experimental data were divided randomly into two different groups as for neural networks model. 70% of the experimental data were used for training and the remaining for testing the trained SVM. All of the figures were normalized into [0.1, 0.9] range to eliminate the effect of the figures' magnitude on their real value. The results of the SVM regression for Iranian dead oil viscosity are summarized in the Table 3 and Fig. 5.

Table 3. The characteristics of the optimized SVM for Iranian dead oil viscosity.

Type of Kernel function	γ	σ	MSE
Radial	100	1.3096	0.0063

5. Comparison of the Methods

Figure 6 compares the experimental data with the predictions of the different methods.

This figure is arranged in term of API of the samples and clearly shows that the different prediction methods behave differently for Iranian crude samples. Most of the prediction methods except the Beal's, under-predict the viscosity and it is clear that the optimized correlations are generally more accurate than the original ones. The least square error of the different methods used in this study is also listed in the Table 4. The results of this table show that the Beal and the Labedi methods are not suitable for estimation of the viscosity of the Iranian crudes. While the Beggs, Glasso and Schmidt methods give reasonable results. The least square errors of the Neural Network and SVM methods are much less than the classical methods.

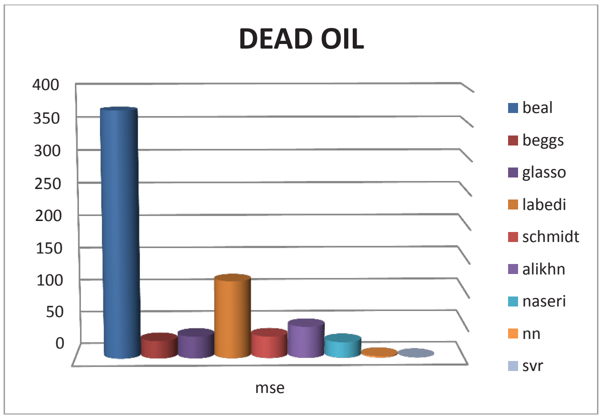

Figure 6. Comparison of different correlations for prediction of Iranian dead oil viscosity.

From comparing these two last methods with each other, it is clear that the SVM method is more exact than the neural network model.

6. Conclusions

The results of this study show that the classical correlations give huge errors for Iranian dead oil viscosity. Optimization of the original classical methods always gives better estimations and this technique may be extended to other physical properties. The study also showed that the statistical methods of neural network and SVM give much better results comparing to the classical correlations. The results in Table 4 showed that the Naseri's equation is better than the other empirical equations which may be due to the fact that it was originally based on the Iranian dead oil viscosities. On the other hand intelligent methods are more accurate than classical methods and this research implies that the SVM

Table 4. Comparison of the different methods.

Method	Beal	Beggs	Glasso	Labedi	Schmidt	Alikhn	naseri	N.N.	SVM
Minimum least square Error	369.86	26.54	33.14	116.9	32.92	47.56	23.78	1.959	0.0739

method is much more accurate than the neural network model.

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