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Prediction of Kinematic Viscosity of Petroleum Fractions Using Artificial Neural Networks

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Abstract

In this work, artificial neural network (ANN) was utilized to develop a new model for the prediction of the kinematic viscosity of petroleum fractions. This model was generated as a function of temperature (T), normal boiling point temperature (T_b), and specific gravity (S). In order to develop the new model, different architectures of feed-forward type were examined. Finally, the optimum structure with three hidden layers was selected. The optimum structure had five, four, and two neurons in the first, second, and third layers respectively. To prevent over-fitting problem, 70% of the experimental data were used to train and validate the new model and the remaining data which did not participate in learning process was utilized to test the ability of the new model for the prediction of the kinematic viscosity of petroleum fractions. The results showed that the predicted/calculated and experimental data are in good agreement. The average absolute relative deviation (AARD) of the new model was 1.3%. Finally, the results were compared with an Eyring-based model (Soltani et al.'s work); it was shown that, based on the reported results by the authors, the accuracy of both model were in the same order.

Keywords: ANN, Kinematic Viscosity, Petroleum Fraction

1. Introduction

The kinematic viscosity of petroleum fractions is an important physical property which plays essential roles in reservoir calculations. In this regard, knowledge about this property will be helpful in production stages as well as equipment design (Aboul-Seoud and Moharam, 1999; Amin and Maddox, 1980; Fang and Lei, 1999; Mehrotra et al., 1996; Riazi, 2005). Considering the above fact, an accurate and reliable model for the prediction of the kinematic viscosity of petroleum fractions will be useful.

Inasmuch as petroleum fractions are composed of many compounds, it is difficult to find an accurate as well as simple model (Fang and Lei, 1999; Riazi, 2005). Petroleum fractions may contain thousands compounds and thus developing a new model able to include the effect of all the compounds is practically impossible; if it was possible, the calculation and modeling of the kinematic viscosity of petroleum fractions would need much time and advanced computing systems. As a result, most of the presented models have used other properties of petroleum fractions such as physical properties (normal boiling point and specific gravity) which are commonly determined easily (Amin and Maddox, 1980; Beg et al., 1988; Fang and Lei, 1999; Riazi, 2005). In recent years, numerous

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models, most of which are empirical or semi-empirical, have been developed to estimate the kinematic viscosity of petroleum fractions. Amin and Maddox (Amin and Maddox, 1980) proposed the model based on Eyring-type equation (Eyring, 1936). The adjustable parameters of their model were correlated with Watson characterization factor and average boiling point temperature; Watson characterization factor depends on average boiling point temperature and specific gravity. Beg et al. (Beg et al., 1988) also applied Eyring-type equation and developed a new model. API gravity (dependent on the specific gravity) and average boiling point temperature were utilized as the input parameters to obtain adjustable parameters. Dutt (Dutt, 1990) also developed a new model based on Antoine-type correlation. One of the adjustable parameters is constant and the other parameters of this model were regressed using average boiling point temperature. Moharam et al. (Moharam et al., 1995) employed the double-logarithmic function to model the kinematic viscosity of petroleum fractions. Normal boiling point temperature and specific gravity were used as the input parameters. Orbey and Sandler (Orbey and Sandler, 1993) also developed a new model based on alkanes absolute viscosity. They modified Rackett (Spencer and Alder, 1978) density equation for alkanes and considered a 50% boiling point temperature as the input parameter. Fang and Lei (Fang and Lei, 1999) developed their model based on the equation utilized by Amin and Maddox (Amin and Maddox, 1980) and Beg et al. (Beg et al., 1988) to model the kinematic viscosity-temperature behavior of petroleum fractions. In this model, the specific gravity at 15.6 °C and 50% boiling point were considered as the input parameters. Soltani et al. (Soltani et al., 2010) developed an equation based on the modified Eyring's theory for predicting the kinematic viscosity of petroleum fractions. The equation utilizes two reference fluids including a pair of (C6 and C10), (C10 and C14), or (C14 and C20) for the petroleum fractions having molecular weight higher than 70 and lower than 300.

The ability of artificial neural networks in modeling complex systems has attracted the attention of many researchers during recent years. Most of researchers in chemical and petroleum engineering fields have used it in the prediction of thermo-physical properties of pure components and mixtures (Dehghani et al., 2006; Eslamimanesh et al., 2011; Eslamloueyan and Khademi, 2009; Eslamloueyan and Khademi, 2010; Gharagheizi et al., 2010; Gharagheizi et al., 2011a; Gharagheizi et al., 2011b; Gharagheizi et al., 2011c; Parhizgar et al., 2012; Roosta et al., 2011).

In this work, the ANN approach has been utilized to propose a new model for the perdition of the kinematic viscosity of petroleum fractions. For this purpose, normal boiling point temperature, specific gravity, and temperature have been used as the input parameters. The methodology of ANN has been presented in section 2; finally, the results of the new model have been evaluated and compared with previous models.

2. Artificial neural networks

2.1. Theory

ANN is one of the well-known approaches in black box modeling fields, which is inspired from the architecture of human's brain (Braspenning et al., 1995; Rogers and Kabrisky, 1991; Yegnanarayana, 2004). ANN has many computational units called neurons. The connection between neurons leads to construct the network. Each network of ANN has three layers such as input, hidden, and output layer. The kind of connections between each layer causes to generate different types of structure of ANN. For example, if neurons in the input layer connect to just one hidden layer or connect to all the hidden layers, this structure is feed-forward neural network (FFNN) or cascade-forward neural network (CFNN) respectively. The most common type of ANN's is FFNN (Braspenning et al., 1995; Priddy and Paul E. Keller, 2005; Yegnanarayana, 2004). In the FFNN, the number of neurons in the input

and output layers equals input and output parameters respectively (Braspenning et al., 1995; Mohammadi et al., 2010; Mohammadi et al., 2007; Parhizgar et al., 2012; Paulraj and Sivanandam, 2009). All the signals emitted from each neuron in the input layer are summed up by the neurons in the next hidden layer, and then bias is added to be summed up value. The outputs of neurons in the hidden layer are calculated by a non-linear or linear function which is called activation function. The output neuron or neurons sum up the signals coming from neurons in the last hidden layer. This neuron returns the calculated/predicted value.

2.2. Modeling kinematic viscosity using ANN

To develop a model based on ANN for the prediction of the kinematic viscosity of petroleum fractions, three important steps must be carried out. In the first step, the input and output parameters should be specified. The output of ANN is the kinematic viscosity of petroleum fractions. The input parameters must have a theoretical relation with the output. The previous theoretical and empirical models can help a lot in this regard. Based on them, temperature (T), normal boiling point temperature (T_b), and specific gravity (S) have been selected as the input parameters. In the second step, the architecture of ANN should be identified. The structure with a high and low number of neurons leads to rising probably of over-fitting phenomena and decreasing the accuracy of the model respectively. To prevent these two problems, the optimum structure of ANN should be specified. This structure is identified by a trial-and-error procedure. For this purpose, the experimental data has randomly been divided into the training, validation, and test sets. The training and validation sets include 60% and 10% of the experimental data respectively. The training set has been utilized to determine the value of weight matrices and biases for minimizing the objective function. To find the optimum values, the Levenberg−Marquart algorithm (Levenberg, 1944; Marquardt, 1963) has been applied. The validation set has been used to identify and prevent over-fitting phenomena; the test set has been employed to check the capability of the developed model. In the third step, the objective function should be defined for the optimization procedure.

3. Results and discussion

To develop the optimum network, different structures of FFNN's have been checked; finally, the structure with three hidden layers has been selected to predict the kinematic viscosity of petroleum fractions. The first, second, and third hidden layers consist 5, 4, and 2 neurons respectively. The architecture of optimum FFNN has been shown in Figure 1. In order to identify the activation function between two layers, different activation functions such as *logsig*, *tansig*, and *linear* have been examined; finally, activation functions have been assigned as follows:

$$Output(\nu) = \sum_{n=1}^{2}\left[\left(l_n W_{l_n - m_1}\right) + b_{m_1}\right] \tag{1}$$

$$l_n = \tan sig\left(\sum_{y=1}^{4}\left[\left(k_y W_{k_y - l_n}\right) + b_{l_n}\right]\right) \tag{2}$$

$$k_y = \tan sig\left(\sum_{x=1}^{5}\left[\left(j_x W_{j_x - k_y}\right) + b_{k_y}\right]\right) \tag{3}$$

$$j_x = \tan sig\left(\sum_{p=1}^{3}\left[\left(i_p W_{i_p - j_x}\right) + b_{j_x}\right]\right) \tag{4}$$

$$\tan sig\left(x\right)=\frac{1-e^{-x}}{1+e^{-x}} \tag{5}$$

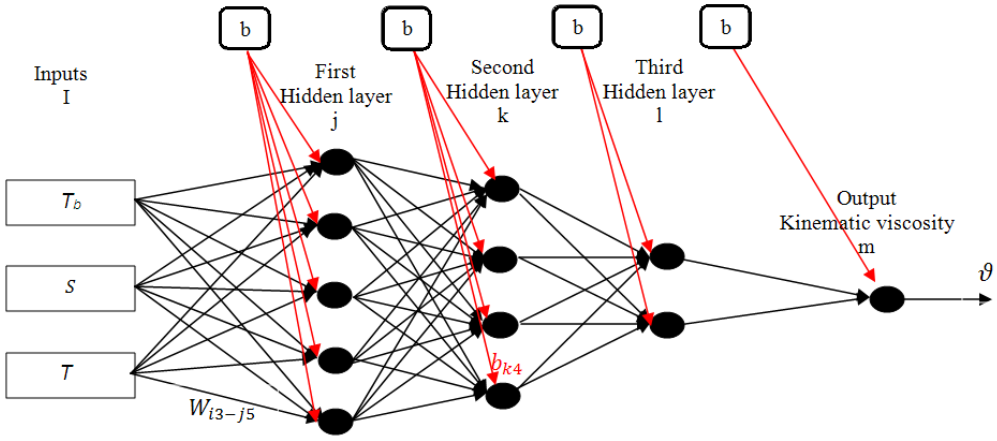

Figure 1
Neural network architecture.

where, *b* and *W* are bias and weight respectively. The weight matrix of the input layer, hidden layers, and output layer has been presented in Tables 1-4. Table 5 presents the bias of each neuron. To optimize the value of the biases and weight matrixes, 60% and 10% of the experimental data have randomly been selected to train and validate the FFNN respectively. The validation data set has been employed to prevent over-fitting problem. In general, the training and validation data sets are included in the learning data set. The remaining data (30% of the experimental data) has been utilized to test the accuracy and ability of the new model. A comparison between the results of FFNN and the kinematic viscosities data used in the learning and testing set has been shown in Figures 2 and 3 respectively. The calculated/predicted values of the kinematic viscosities of petroleum fractions have been illustrated against the experimental data in Figure 4.

Table 1
First layer weight functions ($W_{i_p-j_x}$).

x	*p* = 1	*p* = 2	*p* = 3
1	1.5058	-1.8218	-0.2946
2	0.7525	-0.9083	-0.0728
3	-0.1809	1.2107	-0.5446
4	-10.5391	11.2713	-0.5238
5	1.6849	-3.7855	0.1596

Table 2
Second layer weight functions ($W_{j_x-k_y}$).

y	*x* = 1	*x* = 2	*x* = 3	*x* = 4	*x* = 5
1	2.6816	-8.9732	-3.1585	-0.6463	3.1587
2	2.8586	-9.9031	-2.8996	-0.0731	0.8587
3	3.1373	-13.9889	1.468	-0.1922	9.7802
4	-1.795	4.4056	-2.1658	-0.0388	-0.432

Table 3
Third layer weight functions ($W_{k_y - l_n}$).

n	***y* = 1**	***y* = 2**	***y* = 3**	***y* = 4**
1	0.3804	0.6357	23.8956	3.1073
2	8.091	-8.1404	-0.4038	-0.2839

Table 4
Fourth layer weight functions ($W_{l_n - m_1}$).

***n* = 1**	***n* = 2**
-24.0773	15.5573

Table 5
Biases.

i	***bji***	***bki***	***bli***	***bmi***
1	1.5141	-6.3109	-19.4945	7.7438
2	-1.081	-9.9423	2.9581	
3	-1.608	-1.7821		
4	-1.5555	3.0864		
5	-1.8511			

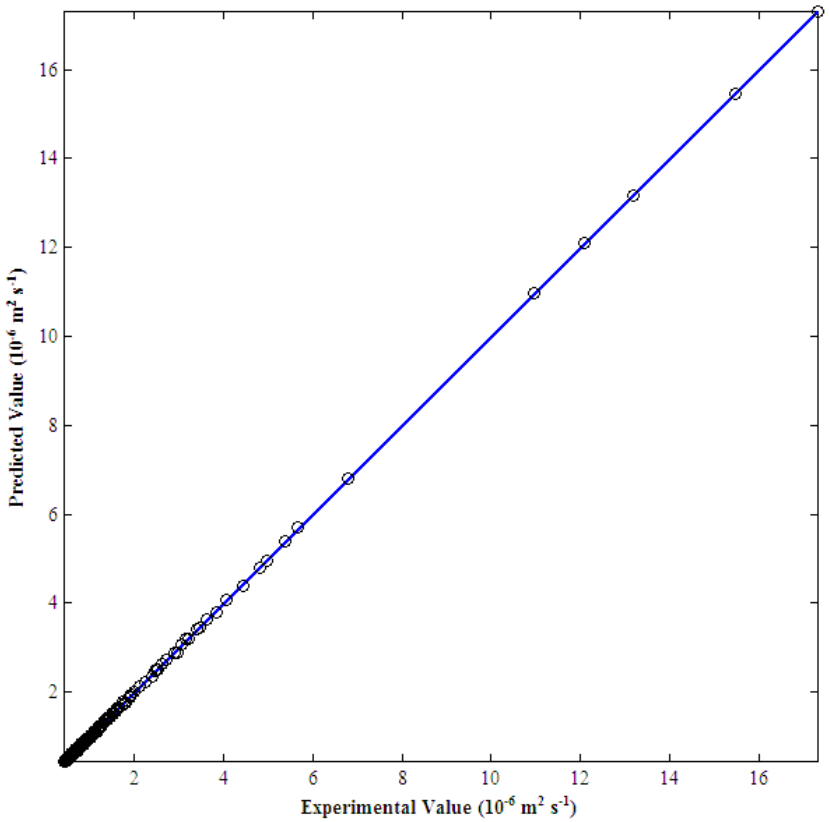

Figure 2
Kinematic viscosity predicted by ANN versus experimental data, the training data.

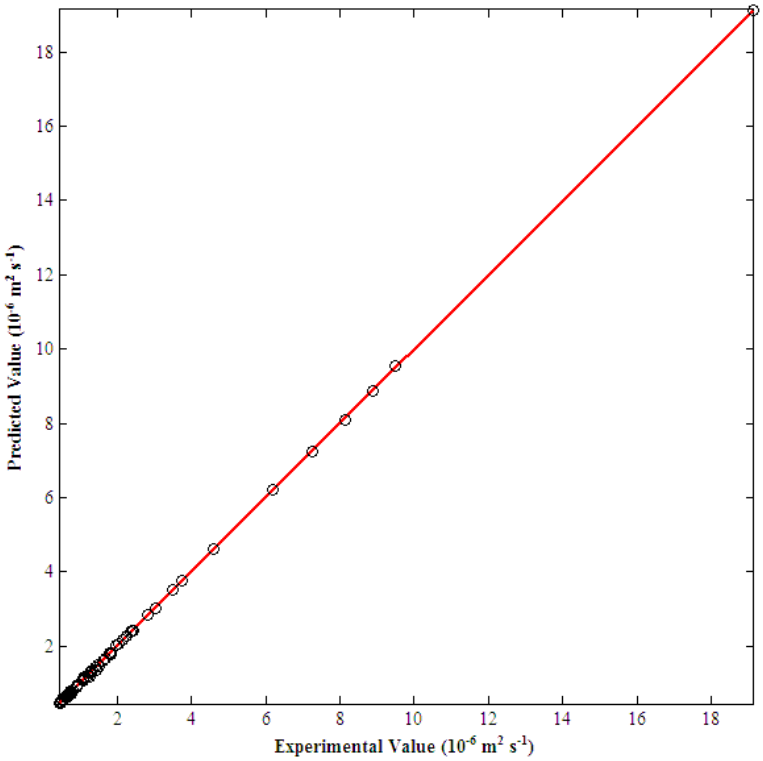

Figure 3
Kinematic viscosity predicted by ANN versus experimental data, the test data.

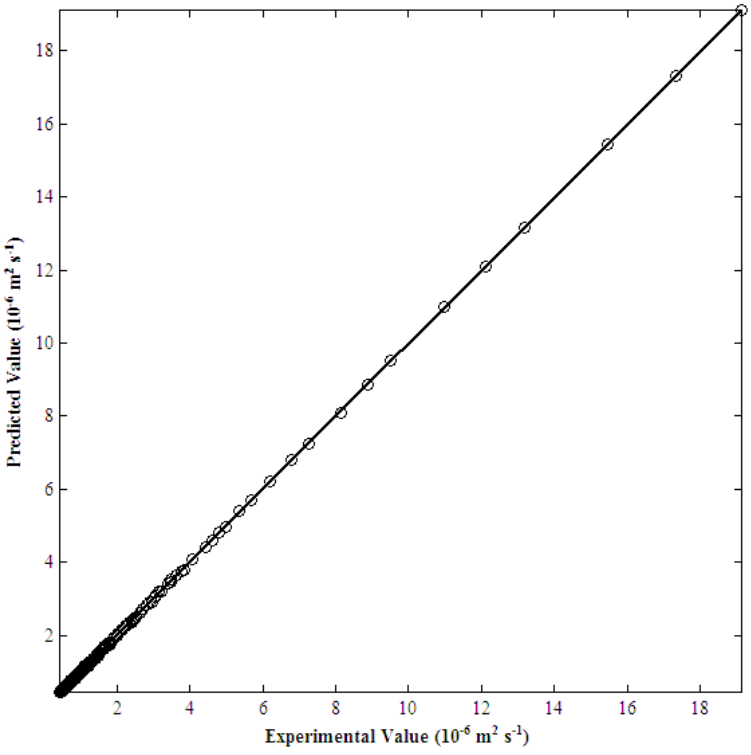

Figure 4
Kinematic viscosity predicted by ANN versus experimental data, the total data.

In Table 6, the results the proposed model based on FFNN in the prediction of kinematic viscosities of petroleum fractions of 250 data points from 15 different crude oil samples have been compared with previous models such as Amin and Maddox (Amin and Maddox, 1980), Beg et al. (Beg et al., 1988), Dutt (Dutt, 1990), Orbey and Sandler (Orbey and Sandler, 1993), Moharam et al. (Moharam et al., 1995), and Fang and Lei (Fang and Lei, 1999). The evaluation of the results has been done based on the absolute relative deviations (ARD) as well as the average absolute relative deviations (AARD) of the calculated/predicted and experimental data (Equations 6 and 7). The average absolute deviation (AAD) based on Equation 8 is also presented in Table 6. Moreno et al. investigated the efficiency of seven usual metric objective functions; their results demonstrated that the efficiency of AARD is more than other criteria. According to this work, the AARD has been selected as the objective function.

$$ARD = \sum_{i=1}^{N} \left| \frac{\nu_i^{cal} - \nu_i^{\exp}}{\nu_i^{\exp}} \right| \times 100 \tag{6}$$

$$AARD = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\nu_i^{cal} - \nu_i^{\exp}}{\nu_i^{\exp}} \right| \times 100 \tag{7}$$

$$AAD = \frac{1}{N} \sum_{i=1}^{N} \left| \nu_i^{cal} - \nu_i^{\exp} \right| \tag{8}$$

The calculated values of the kinematic viscosity of petroleum fractions of 3 samples (i.e. Arab Berri, Arab medium, and Arab heavy crude oil) have been compared with the experimental values (Figures 5-7). Similar comparisons have been depicted for the kinematic viscosity of petroleum fractions of Pennsylvania, California, Wyoming, and Oklahoma crude oil in Figures 8-11 respectively. Figure 12 compares the predicted kinematic viscosity of petroleum fractions of Iranian export crude oil with the experimental values. The details of the results demonstrate that the new model is more accurate in the case of heavy crude oils (high specific gravity and normal boiling).

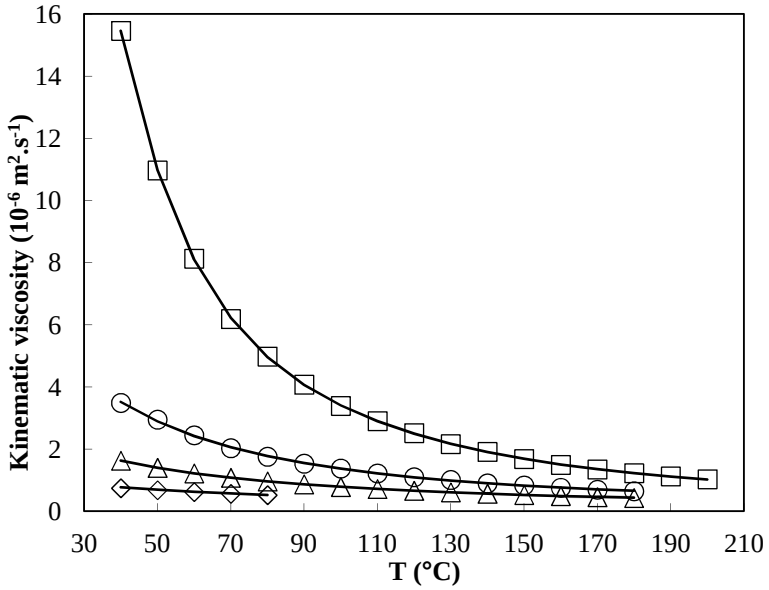

Figure 5

The experimental and calculated kinematic viscosity of petroleum fractions of the Arab Berri crude oil; Symbols show experimental data and curves illustrate the calculated values using the new model. (□) S = 0.8883 and T_b = 398.9 °C; (○) S = 0.8428 and T_b = 301.7 °C; (Δ) S = 0.8072 and T_b = 232.2 °C; (◊) S = 0.7547 and T_b = 148.9 °C.

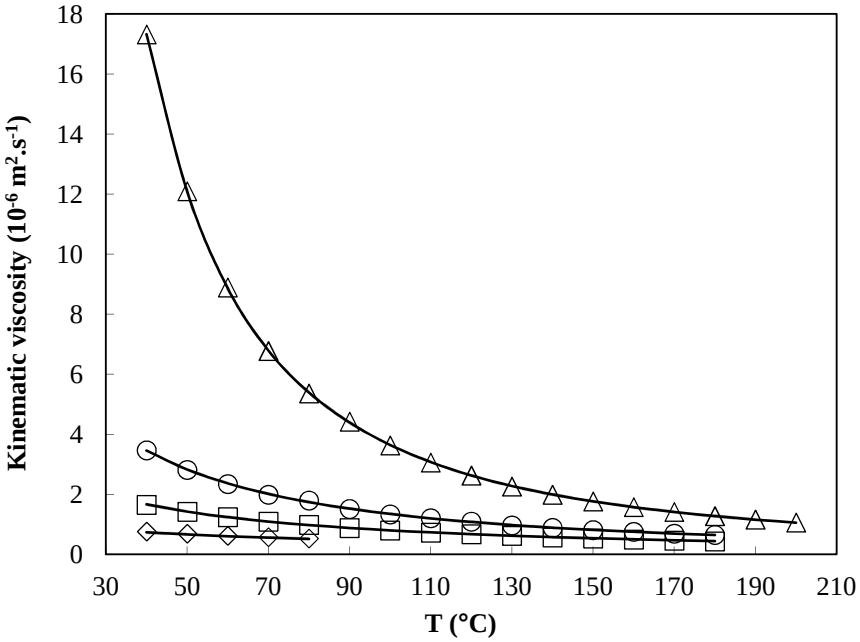

Figure 6
The experimental and calculated kinematic viscosity of petroleum fractions of the Arab medium crude oil; Symbols show experimental data and curves illustrate the calculated values using the new model. (Δ) S = 0.9003 and T_b = 398.9 °C; (○) S = 0.8474 and T_b = 301.7 °C; (□) S = 0.8096 and T_b = 332.2 °C; (◊) S = 0.7621 and T_b = 148.9 °C.

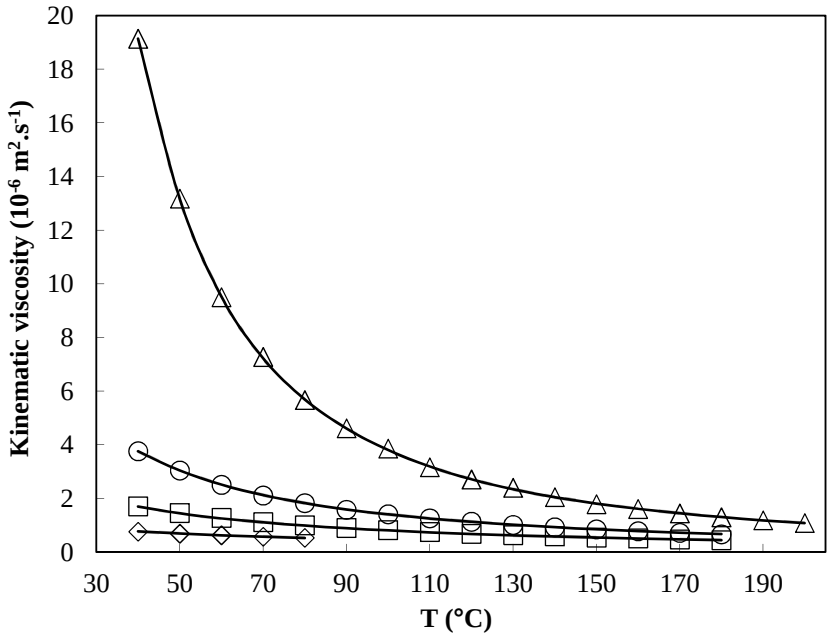

Figure 7
The experimental and calculated kinematic viscosity of petroleum fractions of the Arab heavy crude oil; Symbols show experimental data and curves illustrate the calculated values using the new model. (Δ) S = 0.9017 and T_b = 398.9 °C; (○) S = 0.851 and T_b = 301.7 °C; (□) S = 0.8103 and T_b = 232.2 °C; (◊) S = 0.7548 and T_b = 148.9 °C.

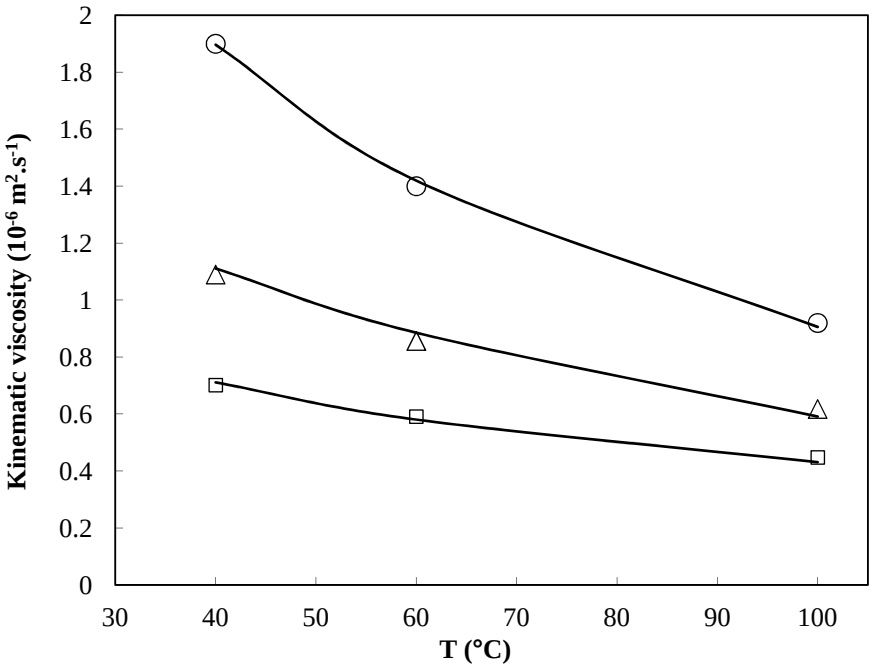

Figure 8
The experimental and calculated kinematic viscosity of petroleum fractions of the Pennsylvania crude oil; Symbols show experimental data and curves illustrate the calculated values using the new model. (○) S = 0.7972 and T_b = 237.5 °C; (Δ) S = 0.7728 and T_b = 187.5 °C; (□) S = 0.7459 and T_b = 137.5 °C.

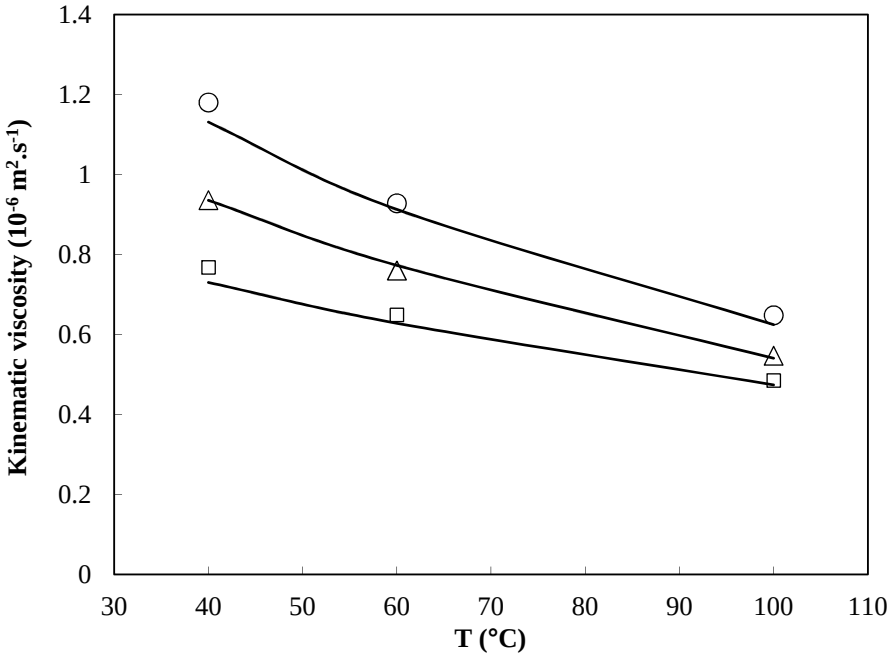

Figure 9
The experimental and calculated kinematic viscosity of petroleum fractions of the California crude oil; Symbols show experimental data and curves illustrate the calculated values using the new model. (○) S = 0.8179 and T_b = 187.5 °C; (Δ) S = 0.8049 and T_b = 162.5 °C. (□) S = 0.7818 and T_b = 137.5 °C.

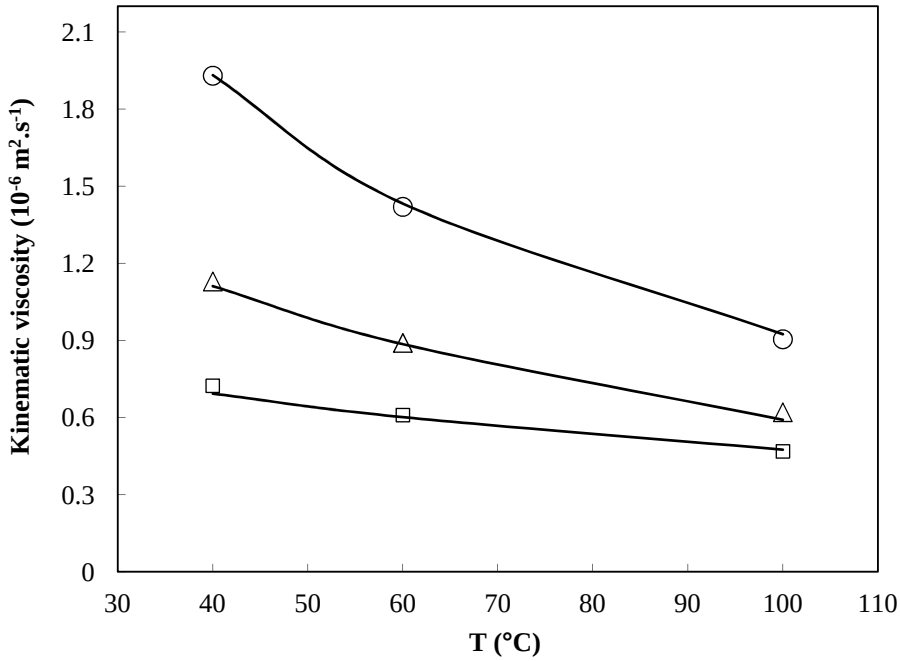

Figure 10
The experimental and calculated kinematic viscosity of petroleum fractions of the Wyoming crude oil; Symbols show experimental data and curves illustrate the calculated values using the new model. (○) S = 0.8222 and T_b = 237.5 °C; (Δ) S = 0.7728 and T_b = 187.5 °C; (□) S = 0.764 and T_b = 137.5 °C.

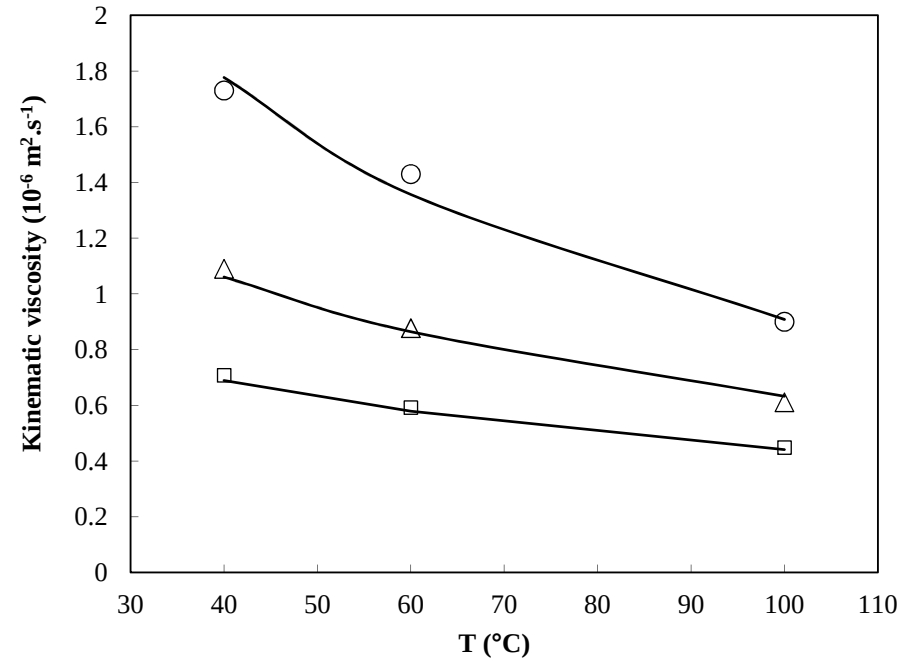

Figure 11
The experimental and calculated kinematic viscosity of petroleum fractions of the Oklahoma crude oil; Symbols show experimental data and curves illustrate the calculated values using the new model. (○) S = 0.8279 and T_b = 237.5 °C; (Δ) S = 0.7958 and T_b = 187.5 °C; (□) S = 0.7579 and T_b = 137.5 °C.

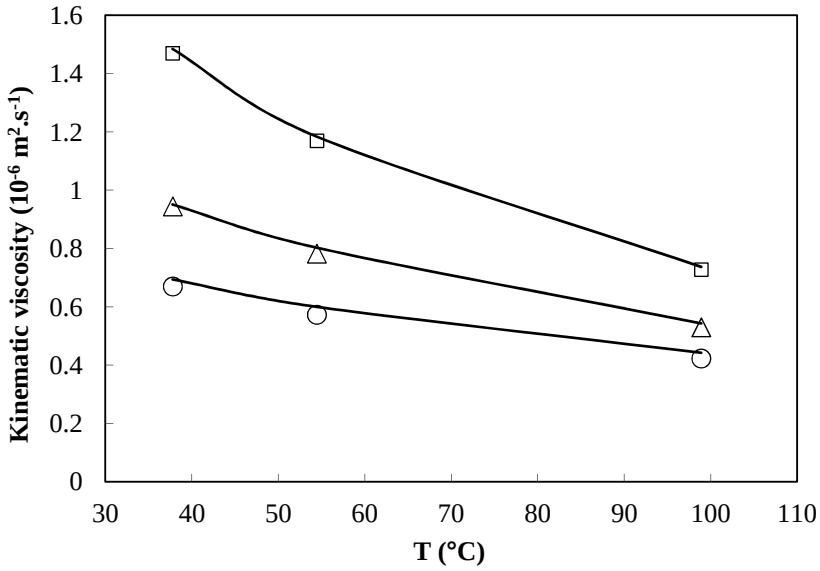

Figure 12
The experimental and calculated kinematic viscosity of petroleum fractions of the Iranian export crude oil; Symbols show experimental data and curves illustrate the calculated values using the new model. (□) S = 0.8012 and T_b = 223.3 °C; (Δ) S = 0.7805 and T_b = 178.3 °C; (○) S = 0.7569 and T_b = 135 °C.

Table 6
Comparison (AARD%) of kinematic viscosity predicted and calculated by various correlations for petroleum fractions.

No.	Crude oil	50% boiling point range(°C)	No. of fractions	Data points	Amin and Maddox[a]	Beg et al.[a]	Dutt[a]	Orbey and Sandler[a]	Moharam et al.[a]	Fang and Lei[a]	This work	
											AARD	AAD
1	Arab Berri	148.9–398.9	4	52	9.6	8.2	3.9	6	3.6	2.9	0.693	0.0104
2	Arab medium	148.9–398.9	4	52	11.6	6.1	5.3	6.3	5.1	3.1	0.764	0.0104
3	Arab heavy	148.9–398.9	4	52	12.1	6.7	6.7	6	4.8	3.5	0.577	0.0099
4	Pennsylvania	137.5–237.5	3	9	9.7	10.6	5.2	3.1	10.2	8.9	2.181	0.0167
5	California	137.5–187.5	3	9	17.6	20.9	10.3	8.2	2.2	4	2.514	0.0196
6	Wyoming	137.5–237.5	3	9	9	7.9	7.3	4.2	5.2	3.1	1.891	0.0147
7	Oklahoma	137.5–237.5	3	9	10	4.9	4.4	3.1	3.3	2	2.536	0.0256
8	Minas Sumatra	149.4–211.1	2	5	11	4.8	1.5	3.8	5.7	3.3	3.251	0.0266
9	Safania(Saudi Arabia)	143.9–201.1	2	5	5.9	10.5	5.4	6.2	9.7	8.4	4.661	0.0425
10	Stabilized Arabian	118.3–196.1	3	8	13	2.2	3.1	5.2	4.8	3.6	2.106	0.0139
11	Boscan	182.2–290.0	3	8	11.6	8.1	13.2	14.9	4.7	6.6	0.996	0.0129
12	Iranian Export	90.0–223.3	4	11	15.5	3.9	5	8.3	5.8	4.4	2.345	0.0150
13	Waxy	124.4–217.2	3	6	8.8	2.5	1.6	3.7	7.1	11.3	4.558	0.0379
14	Light Valley	159.4–252.8	3	7	3.5	2.2	9.7	7	9.4	8	1.682	0.0193
15	Midway special	100.0–245.0	3	8	7.2	9.3	15.8	13	9.4	9.3	0.889	0.0073
	Overall AARD %	**90.0–398.9**	**47**	**250**	**10.9**	**7.2**	**6**	**6.4**	**5.2**	**4.2**	**1.297**	

[a] Quoted in Wenjun Fang and Qunfang Lei

Table 7
Comparison between the new model and Soltani et al.'s (2010) model.

						New model			Soltani et al. (2010) model		
No.		**T_b(°C)**	**S**	**T(°C)**	**υ_{exp}**	**υ_{cal}**	**ARD%**	**AD**	**υ_{cal}**	**ARD%**	**AD**
157	Pennsylvania crude oil	137.5	0.7459	40	0.702	0.7111	1.30	0.009	0.701	0.14	0.001
158				60	0.591	0.5804	1.79	0.011	0.579	2.03	0.012
159				100	0.448	0.431	3.79	0.017	0.425	5.13	0.023
160		187.5	0.7728	40	1.09	1.111	1.93	0.021	1.113	2.11	0.023
161				60	0.857	0.8853	3.30	0.028	0.879	2.57	0.022
162				100	0.618	0.5909	4.39	0.027	0.599	3.07	0.019
163		237.5	0.7972	40	1.9	1.8965	0.18	0.003	1.831	3.63	0.069
164				60	1.4	1.4189	1.35	0.019	1.392	0.57	0.008
165				100	0.92	0.9053	1.60	0.015	0.887	3.59	0.033
184	Oklahoma crude oil	137.5	0.7579	40	0.708	0.6889	2.70	0.019	0.712	0.56	0.004
185				60	0.592	0.5792	2.16	0.013	0.588	0.68	0.004
186				100	0.448	0.4411	1.54	0.007	0.432	3.57	0.016
187		187.5	0.7958	40	1.09	1.0606	2.70	0.029	1.146	5.14	0.056
188				60	0.877	0.8645	1.43	0.013	0.906	3.31	0.029
189				100	0.611	0.633	3.60	0.022	0.617	0.98	0.006
190		237.5	0.8279	40	1.73	1.7765	2.69	0.047	1.603	7.34	0.127
191				60	1.43	1.3566	5.13	0.073	1.447	1.19	0.017
192				100	0.9	0.9079	0.88	0.008	0.921	2.33	0.021
193	Minas (Sumatra) crude	149.4	0.7531	37.78	0.792	0.8099	2.26	0.018	0.799	0.88	0.007
194				54.44	0.653	0.6757	3.48	0.023	0.672	2.91	0.019
221	Iranian export crude oil	135	0.7569	37.78	0.67	0.6934	3.49	0.023	0.713	6.42	0.043
222				54.44	0.573	0.5997	4.66	0.027	0.606	5.76	0.033
223				98.89	0.423	0.4425	4.61	0.020	0.429	1.42	0.006
						Overall	**2.65**	**0.021**		**2.84**	**0.026**

4. Conclusions

In the current work, the ANN has been employed to develop a new model for the prediction of the kinematic viscosity of petroleum fractions. Normal boiling point temperature, specific gravity, and temperature has been utilized as the input parameters. For this purpose, the experimental data of the kinematic viscosities of 47 fractions from 15 world crude oils have been investigated. The new model has been learned by 70% of the experimental data, which are selected randomly; the remaining data are utilized to test the new model. The results of the proposed model demonstrate that the calculated results are in good agreement with the experimental data. The results are compared with previous models and it is found that the proposed model is more accurate in prediction. The average absolute relative deviations of the new model is 1.3%. Moreover, our results show that the results of this work and Eyring-based model are in the same order. Finally, the results of this model demonstrate that

neural network modeling approach can be employed for describing complex systems such as petroleum fractions. Furthermore, neural network model can recognize the pattern of the system.

Nomenclature

AAD%	: Average absolute deviations
AARD%	: Average absolute relative deviations
ANN	: Artificial neural network
ARD%	: Absolute relative deviations
CFNN	: Cascade-forward neural network
FFNN	: Feed-forward neural network
M	: Molecular weight
N	: Number of experimental data
S	: Specific gravity
T	: Temperature (°C)
Greek Symbols	
v	: Kinematic viscosity
Subscripts	
b	: Normal boiling point
Superscripts	
exp	: Experimental data
cal	: Calculation data

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