

An artificial neural network structure and a new semi-empirical relation for predicting the viscosity of natural gas

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1. Introduction

Natural gas is a crucial fuel utilized across various industries for electricity and heat production, primarily due to its cost-effectiveness. Its appeal is further enhanced by significantly lower carbon dioxide emissions compared to other gases used in electricity generation, making its adoption increasingly

ABSTRACT

This study introduces a new empirical model and an artificial neural network (ANN), developed from over 3,800 experimental viscosity data points collected at various temperatures and pressures. The presented models demonstrate the ability to accurately predict the viscosity of natural gas (containing at least 80% CH₄) across a wide range of reduced pressures (from 0.01 to 21) and reduced temperatures (from 1 to 3). The dataset is divided into 70%, 20%, and 10% for the test, validation, and test phases in a 5-fold cross-validation process. The comparison highlights the advantages of both the new empirical model and the ANN method in terms of simplicity and lower deviation when compared to other methods utilized for calculating natural gas viscosity. Furthermore, the semi-empirical model has a simple structure that does not require complex calculations or extensive trial and error with a low number of parameters. This new semi-empirical model and ANN model yield Average Absolute Relative Deviation (AARD%) of 1.004% and 0.221% relative to existing experimental data.

justifiable [1, 2]. In recent years, interest has surged regarding the gas flow under relatively high pressures and temperatures. Calculating energy losses in gas flow through conduits and porous media in natural petroleum reservoirs necessitates a thorough understanding of fluid viscosity at the specific pressures and temperatures involved.

A notable study conducted by Sanaei et al. [3] Leveraged extensive data on gas pressure, density, and temperature to develop a robust and reliable equation for estimating hydrocarbon gas viscosity. This research employed artificial intelligence methods, computational

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techniques, and nonlinear optimization to achieve its objectives.

The neural network method has proven influential in analyzing laboratory data. First introduced in the late 1950s, early significant contributions to neural networks can be credited to Frank Rosenblatt et al. This foundational work paved the way for subsequent global research exploring various algorithms aimed at identifying repetitive patterns. A key advancement in this field was the introduction of the backpropagation algorithm in 1982, which marked a significant milestone in the evolution of neural networks during the 1980s. These algorithms have since evolved substantially, finding applications in diverse areas such as control modeling, optimization, device design, and financial markets [4].

In 1966, Lee et al. [5] developed a semi-empirical equation to estimate the viscosity of natural gas based on reservoir temperature, density, and molecular weight. This equation is applicable within an operational range of 311 to 444 Kelvin and pressures from 0.69 to 55.16 megapascals.

In 2004, Elasharkawy [6] modified the Lee et al. [5] equation to present a new correlation specifically for determining the viscosity of biogas.

Subsequently, in 2010, Heidaryan et al. [7] introduced an equation for estimating the viscosity of natural gas that operates effectively at higher temperatures and pressures than previous models. Building on these advancements, Sanjari et al. [8] proposed an equation in 2011 for estimating natural gas viscosity, which is valid for pressures ranging from 0.1 to 973 bar and temperatures from 240 to 598 K.

Further contributions to this field include research by Abooali and Khamsehchi [9] in 2014 and Dargahi-Zarandi et al. [10] in 2017, who achieved approximate accuracies of 2.55% using a genetic algorithm estimation method and 3.45% with a hybrid neural network approach utilizing statistical datasets, respectively.

In 2015, Hajirezaie et al. [11] presented a straightforward model for estimating the viscosity of hydrocarbon fluids based on 3,800 laboratory data points, resulting in an average absolute error of 4.9% in their calculations.

In a study conducted in 2013, Heidaryan et al. [12] derived an equation using 3,255 experimental data points, achieving a calculation accuracy of 5.89%.

In 2012, Lay et al. [13] utilized an ANN system to calculate the viscosity of natural gas, reporting a computational error of only 0.221%. This model was developed from 3,841 data points and is applicable within a temperature range of 250 to 570 Kelvin and a pressure range of 95 to 586 micropoise.

In 2011, Al-Quraishi and Shokir [14] examined two neural networks to estimate the density and viscosity of natural gas. The viscosity was calculated as a function of density, while density was estimated based on molecular weight. This study used a total of 3645 random data points, resulting in mean error accuracies of 3.65% for viscosity and 4.93% for density.

In 2024, Thomasseti et al. [15] employed a multilayer neural network model to analyze the relationship between temperature, pressure, and dynamic viscosity of GWP refrigerant liquids, achieving an estimated error of 0.86%, indicating a strong fit for this relationship.

Also in 2024, Geng et al. [16] explored machine learning techniques for predicting the deviation factor of natural gas, demonstrating that such models can effectively estimate the z-factor and related mechanical properties.

Orodu et al. [17] conducted research in 2021 on the density of hydrocarbons at high temperatures and pressures, presenting a machine-learning model that achieved an impressive accuracy of 99%. This study considered operational temperatures between 300 to 500 Kelvin and pressures from 50 to 150 megapascals, showing strong performance on the provided data.

In another study [18], by combining ANN and k-Nearest Neighbor method (kNN), a novel machine learning tool for the prediction of thermophysical properties of natural gas was developed. The authors claimed that the AARD of the combined model is less than that of the ANN and kNN models.

The effect of Hydrogen content on the natural gas properties was investigated by Abd et. al. [19]. They showed that the presence of hydrogen increases the viscosity of natural gas, which leads to increase in pressure losses in pipelines.

As a comparative research [20], the viscosity of 1602 gas components was evaluated by 36 machine learning algorithms. It was concluded that the Bayesian regularization algorithm shows the best results.

According to the literature, the importance of providing a more accurate model with simpler calculations is clear. In the present research, an efficient and highly accurate semi-empirical relation for calculating the viscosity of natural gas is derived by integrating the findings from previous studies along with mathematical and physical relationships. Despite the high accuracy, the proposed model has a simple structure that does not require complex calculations or extensive trial and error with a low number of parameters. Additionally, using the available database, an Adaptive Neuro-Fuzzy Inference System (ANFIS) is utilized to estimate this thermophysical parameter. After modeling with ANFIS, the results are compared with the proposed semi-empirical model.

2. Equations

In many oil and natural gas engineering calculations, the viscosity and density of fluids play a critical role in measurements, compression processes, and pipeline design. Among the various methods available for determining viscosity, such as equations of state, semi-empirical equations, and experimental data, semi-empirical equations are the simplest to use, while equations of state offer the most comprehensive approach. In general, the viscosity of natural gas can be calculated using the following function:

$$\mu_{NG} = f(P, T, y_i) \quad (1)$$

where μ is the viscosity of natural gas, P is the gas pressure, T is the gas temperature, and y_i is the molar composition of the components of natural gas.

The theory of corresponding states shows that viscosity can be uniquely defined as a function of reduced temperature and reduced pressure. The reduced temperature and reduced pressure of a gas mixture are obtained as follows:

$$T_{pr} = T/T_{pc} \quad (2)$$

$$P_{pr} = P/P_{pc} \quad (3)$$

where P_{pr} and T_{pr} are pseudo reduced pressure and pseudo reduced temperature of the mixture, and P_{pc} and T_{pc} are the critical mean pressure and temperature of the natural gas mixture, respectively, which can be calculated from the following relations [8]:

$$P_{pc} = \sum_{i=1}^n P_{ci} y_i \quad (4)$$

$$T_{pc} = \sum_{i=1}^n T_{ci} y_i \quad (5)$$

where P_{ci} is the critical pressure, T_{ci} is the critical temperature, and y_i is the mole fraction of component i .

By determining the temperature, pressure, and composition of natural gas, the reduced temperature and reduced pressure can be calculated. These values can then be applied in semi-empirical equations to accurately predict the viscosity of natural gas.

3.A semi-empirical relationship for calculating the natural gas viscosity

For this purpose, the existing experimental data from references [21-27] have been utilized and categorized. Initially, thermodynamic relations were employed, taking into account the thermophysical properties of natural gas and their relationship with viscosity. This led to the formulation of a preliminary equation with unknown constant coefficients, which can be expressed as follows:

$$\mu = \frac{(a_1 + a_2 T^{a_3})}{a_4 + a_5 T^{a_6}} \exp(a_7 \rho^{a_8}) \quad (6)$$

As seen in Eq. 6, it is expressed in terms of temperature and density. After formulating this equation, the next step involves placing it alongside the organized data into Excel, then utilizing MATLAB or SigmaPlot software for the fitting process and performing regression analysis. Following these computational operations, the software will determine the constant coefficients a_1 to a_8 . Subsequently, we will use the available laboratory data from the references one by one, substituting them into the new equation to calculate the viscosity for each data point. The calculated viscosity will then be compared with the experimental viscosity, and the absolute error will be recorded. This process must be repeated for all 3841 data points to obtain the mean absolute error. It can be

anticipated that the initially guessed equation will exhibit a high error rate. Therefore, by analyzing the "standard error" of each coefficient (a_1 to a_8) provided by the software, modifications to the equation will be necessary. After this stage, we will examine the errors in the equation based on the software's analysis results and adjust the raw equation accordingly before re-entering it into the software with unknown coefficients. This iterative process continues until the results from the equation analysis reach an acceptable state and computational errors are minimized. Through several adjustments, we can reduce the standard error of each constant coefficient. With multiple changes, based on an examination of thermodynamic properties, the absolute error of all coefficients can also be minimized. Results have indicated that decreasing the standard error for each coefficient is likely to lead to a reduction in the absolute error of the equation when applied to experimental data. However, in this research, even after achieving suitable standard errors for each fixed coefficient, further modifications were made until a final equation with very low absolute error was obtained. After completing all calculations and regression steps outlined above, an efficient equation has been derived that maintains fixed coefficients across all gases while exhibiting a lower absolute error compared to experimental data.

In many references, including [12, 28, 29], the Standing-Katz diagram has been utilized as a database. In this study, to enhance accuracy and comprehensiveness, a variety of laboratory data obtained from different sources [21-27]

spanning the years 1939 to 2009 has been incorporated.

This database comprises 3841 laboratory data points related to over 11 types of natural gas compositions. It is important to note that this equation is applicable for estimating the viscosity of all natural gases with a methane mole percentage exceeding 60%.

After organizing the data through mathematical calculations and regression analysis and applying thermodynamic principles to derive the initial form of the desired equation, several modifications were made to arrive at the final equation. Ultimately, a semi-empirical relationship for accurately calculating the viscosity of natural gas was established as follows:

$$\mu = 0.1 D_1 \exp(D_2 \rho^{D_3}) \quad (7)$$

where

$$D_1 = \frac{(a_1 + a_2 Mw) T^{a_3}}{a_4 + a_5 Mw + T^{a_6}} \quad (8)$$

$$D_2 = a_7 + a_8 Mw + \frac{a_9}{T} \quad (9)$$

$$D_3 = a_{10} - a_{11} D_2 \quad (10)$$

Here, ρ is the gas density, T is the gas temperature, and M_w is the gas molecular weight.

The constant coefficients of the equation are also obtained using the Levenberg-Marquardt algorithm, which actually minimizes the sum of the squared errors between the experimental and computational values.

In this research, calculations have been performed for 11 types of natural gas, with the general specifications presented in Table 1.

Table. 1. General specifications of the examined natural gases

Compositions (mol %)	Minimum	Maximum	Mean
C1	30.64	100	88.29
CO2	0	50	3.4970
C2	0	64.56	2.2368
C3	0	21	0.8194
i-C4	0	0.755	0.0236
n-C4	0	0.755	0.0221
i-C5	0	0.299	0.0092
n-C5	0	0.304	0.0067
C6	0	0.058	0.0003
C7+	0	0.043	0.0004
N2	0	50	4.1563
H2	0	37.75	0.9382
Pressure (bar)	0.1	973	173.51
Temperature (K)	240	598	372.73

The benchmarks for comparing experimental and calculated values include Average Absolute Relative Deviation (AARD%), Average Relative Deviation (ARD%), and Root Mean Square Deviation (RMSD), each defined as follows:

$$AARD\% = \frac{1}{N} \sum_{i=1}^N \left| \frac{P_{i,exp} - P_{i,calc}}{P_{i,exp}} \right| \times 100 \quad (11)$$

$$ARD\% = \frac{1}{N} \sum_{i=1}^N \left(\frac{P_{i,exp} - P_{i,calc}}{P_{i,exp}} \right) \times 100 \quad (12)$$

$$RMSD = \frac{1}{N} \sqrt{\sum_{i=1}^N \left(\frac{P_{i,exp} - P_{i,calc}}{P_{i,exp}} \right)^2} \times 100 \quad (13)$$

where P can be any quantity.

As previously mentioned, the pressure and temperature deviations for a specific natural gas composition will vary uniquely for each composition. The operational range of this semi-empirical equation is defined for temperatures where $0.1 < T_{pr} \leq 0.3$ and pressures where $0.01 \leq P_{pr} \leq 15$. This equation includes 11 constant parameters (a_1 to a_{11}), and the values of these constants are presented in Table 2:

Table 2. Coefficient values.

Coefficient	Value	Standard deviation
a1	- 49.603773	0.0083742
a2	5.464866	0.0023841
a3	1.281261	0.0001123
a4	-1834.595952	0.0124101
a5	151.39159	0.0004326
a6	0.978493	0.0004236
a7	2.332756	0.0100123
a8	- 0.020092	0.0042731
a9	2058.144	0.0000112
a10	1.288751	0.0657114
a11	- 0.001598	0.0351264

As noted, these data comprise 3,841 experimental data points obtained from various sources, each potentially subject to laboratory measurement errors. The gas compositions feature molecular weights ranging from 11.3 to 30, with specific viscosities varying from 0.389 to 1.04.

4.Presentation of ANN

One of the most effective and accurate methods for calculating material properties is the use of

ANNs. To establish a relationship between input and output data derived from experimental results, a method that surpasses conventional techniques is essential. ANNs are highly efficient algorithms capable of estimating functions with a finite number of discontinuities by training the relationships between input and output vectors. The architecture of these data processing systems consists of numerous interconnected elements known as "neurons." These neurons collaborate to process data and solve problems, reflecting scientific studies that employ mathematical formulations to model neural system operations. Today, techniques derived from neural networks are successfully applied across various fields, including daily tasks, business, industry, and medicine [13].

ANNs are trained by adjusting connection weights until the network's output closely aligns with expected values. The output of a specific neuron is generated by applying a transfer function to the sum of the input weights, with these outputs serving as inputs for other neurons [13]:

$$\alpha_{jk} = F_k \left(\sum_{i=1}^{N_{k-1}} w_{ijk} \alpha_{i(k-1)} + \beta_{jk} \right) \quad (14)$$

where α_{jk} is the output of neuron j from layer k, and β_{jk} is the bias weight for neuron j in layer k. The model's adjusted parameters, w_{ijk} , are the connection weights. F_k , which are nonlinear activation transfer functions, can take various forms such as circular, Gaussian, linear functions, and so on.

During training, the biases and weights of the network are iteratively adjusted in succession to minimize the network's operational functions. One of these operational functions used for training the network is AARD%, which is obtained from the following relation [13]:

$$AARD\% = \frac{1}{N} \sum_{i=1}^N \left| \frac{z_{exp} - z_{calc}}{z_{exp}} \right| \times 100 \quad (15)$$

Among the various types of neural networks, the Back Propagation (BP) training algorithm is the most commonly used for predicting material properties. There are several methods for training the network using the BP approach, including the Levenberg-Marquardt Algorithm (LMA), Scaled Conjugate Gradient (SCG), and Pola-Ribiere Conjugate Gradient (PRCG),

among others. A review of studies on similar applications indicates that the LMA method performs exceptionally well and is particularly suitable for developing accurate neural networks. The LMA method is akin to the Gauss-Newton method, which aims to minimize the absolute error of BP outputs. Using the LM algorithm, which is recognized as the most accurate among BP methods, 70% of the total data is allocated for training, while the remaining data is reserved for evaluating the network's accuracy and stability on unseen data. To determine the optimal number of neurons in the hidden layer, various networks with different neuron counts were created, and the error rates for each configuration were calculated [13].

As mentioned, to find the optimal number of neurons in the hidden layer, an examination of different neuron counts was conducted, utilizing AARD% or RMSD as evaluation criteria, leading to optimization outcomes. The data used to construct the neural network consists of the same 3,841 experimental data points referenced earlier, obtained from various sources [21-27].

5. Results obtained from the new semi-empirical equation

To assess the predictive capability of the equation developed in this research against the experimental data from references [21-27], the values calculated using the new method are compared with the experimental values. The deviations between the calculated and experimental values are shown in Fig.1. To compare the values obtained from the proposed semi-empirical relationship with the experimental data, Fig.1 illustrates the differences between the two across all data points.

According to the figure, the closer the circular points (each representing an experimental data point) are to the diagonal of the rectangle, the smaller the error in the proposed equation's calculation of viscosity compared to the actual experimental values. As shown in the figure, a significant number of points are located at a minimal distance from the diagonal, indicating that the derived equation demonstrates excellent accuracy in estimating viscosity. To provide further assurance and facilitate a more precise comparison with other models, Table 3 presents the absolute error values for the newly proposed model alongside those of other models developed by researchers.

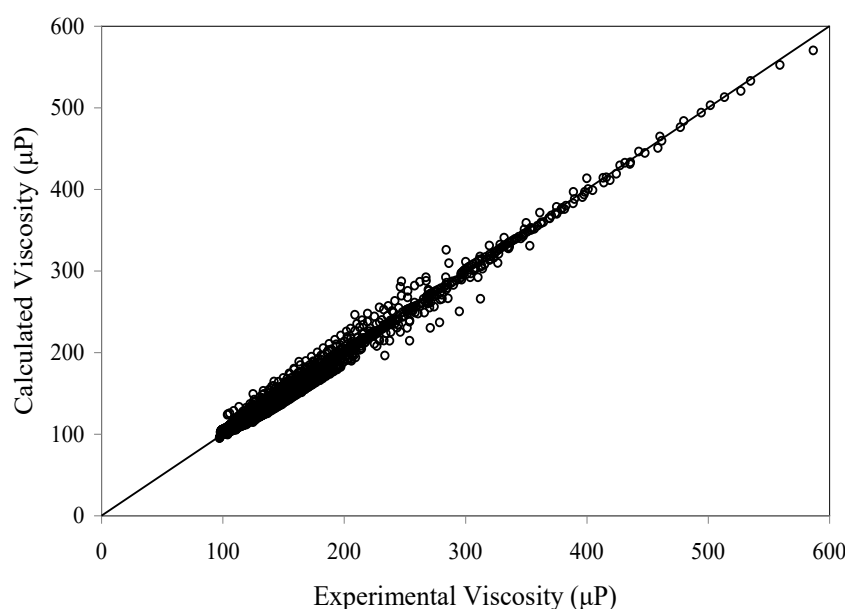


Fig.1. The accuracy of the proposed model in estimating the viscosity of natural gas (The horizontal axis represents experimental values and the vertical axis represents calculated values).

Table 3. Error rates of different compressibility factor models for each natural gas sample

Gas	Methane (%)	No. of data	Mw	Temperature range (K)	ADEL	LGE	HMS	CKB	SNP	Present work	Ref.
No.1	0.9026	248	18.41	250-450	2.027	9.584	17.407	3.766	2.476	2.123	[21]
No.2	0.8034	248	20.17	250-450	8.697	3.506	18.189	9.273	1.925	1.008	[22]
No.3	0.8470	248	19.33	250-450	4.375	7.297	19.820	9.639	2.961	1.458	[22]
No.4	0.8509	246	19.26	250-450	4.207	7.569	19.951	9.424	2.487	1.032	[22]
No.5	0.8484	40	18.21	241-455	2.441	3.595	O.R.	8.996	2.972	1.979	[23]
No.6	0.9016	45	17.81	263-303	1.545	7.727	O.R.	7.745	4.791	2.509	[24]
No.7	0.8001	34	20.75	262-304	1.391	10.77	O.R.	28.26	4.256	0.809	[24]
No.8	0.9220	45	17.50	262-304	1.020	7.162	O.R.	7.437	5.233	2.391	[24]
No.9	0.8957	224	17.99	260-320	1.834	1.937	O.R.	9.151	2.855	2.183	[25]
No.10	0.8433	224	18.4	269-320	4.443	5.921	O.R.	12.86	2.123	2.897	[25]
No.11	1.0000	2239	16.04	250-570	4.927	4.076	14.301	3.545	1.742	0.439	[26, 27]
Average		3841			4.550	4.942	18.89	5.940	2.126	1.004	

The table above displays the average absolute error values of various methods for calculating viscosity, including the relationship derived in the present work, for 11 different types of natural gas. In this table, No. 1 to No.

11 correspond to the 11 distinct natural gas compositions. The specific compositions of these 11 types of natural gas are thoroughly detailed in Tables 4 and 5.

Table 4. Composition of natural gases No.1 to No.6 studied in this work.

	No.1	No.2	No.3	No.4	No.5	No.6
Methane	84.99	90.26	80.34	84.7	85.094	84.84
Ethane	5.529	5.828	5.189	5.584	5.529	8.40
Propane	2.008	2.106	1.878	1.962	2.009	0.50
n-Butane	0.585	0.641	0.573	0.553	0.612	0
i -Butane	0.401	0.412	0.384	0.416	0.401	0
n-Pentane	0.147	0.162	0.14	0.155	0.141	0
i -Pentane	0.169	0.214	0.188	0.214	0.171	0
Hexane	0	0	0	0	0	0
Heptane	0	0	0	0	0	0
Heptane+	0.344	0.377	0.332	0.248	0.251	0
Hydrogen	0	0	0	0	0	0
Helium	0	0	0	0	0	0
Water	0	0	0	0	0	0
Argon	0	0	0	0	0	0
Nitrogen	3.496	0	6.596	3.711	3.496	5.60
Carbon dioxide	2.331	0	4.38	2.457	2.296	0.66
Benzene	0	0	0	0	0	0

Table 5. Composition of natural gases No.7 to No.11 studied in this work.

	No.7	No.8	No.9	No.10	No.11
Methane	90.16	80.0079	92.2045	89.57	84.33
Ethane	6.3077	9.3063	4.3373	6.1464	3.4085
Propane	0.801	4.963	0.5396	1.2532	0.6023
n-Butane	0.0643	1.2791	0.0771	0.1924	0.1282
i -Butane	0.0446	0.7188	0.2562	0.2857	0.1033
n-Pentane	0.0044	0.2499	0.0198	0.0324	0.035
i -Pentane	0.0054	0.2556	0.0468	0.0565	0.0375
Hexane	0.0014	0.1793	0.0606	0.0572	0.0388
Heptane	0.0005	0.101	0.0364	0.034	0.0174
Heptane+	0.0001	0.0621	0.0091	0.0095	0.0072
Hydrogen	0	0.001	0.0005	0.0007	0.0005
Helium	0.0068	0.0084	0.0168	0.0137	0.052
Water	0.0006	0	0	0	0
Argon	0.0514	0	0	0.0419	0.01
Nitrogen	0.7587	0.6601	1.3916	1.5324	9.752
Carbon dioxide	1.7947	2.1902	1.003	0.774	1.4523
Benzene	0.0002	0.0173	0.0007	0	0.025

As shown in the tables above, the derived relationship exhibits significantly higher accuracy compared to most of the examined models, including the CKB, LGE, ADEL, HMS, and SNP models. No other model demonstrates a lower error rate than the proposed model.

Table 6 presents the various computational error rates for all available data calculated by the proposed semi-empirical model. The results of this table indicate the high accuracy of the proposed model.

Two notable advantages of the proposed model are its low number of parameters and its straightforward calculation process. The equation consists of only 11 fixed coefficients, meaning that for each calculation of the compressibility factor, we only need the 13 constant parameters listed in the table. Furthermore, this model has a simple structure that does not require complex calculations or extensive trial and error; it can even be used to

calculate the viscosity of natural gas with basic engineering calculators. To perform calculations using this relationship, only the temperature, molecular weight, and density of the gas are required.

Results obtained from the ANN

As previously mentioned, to determine the optimal number of neurons in the hidden layer, an examination of various neuron counts was conducted, utilizing AARD% or RMSD as evaluation criteria. The results of this optimization are presented in Fig.2. The dataset is divided by 70%, 20% and 10% for the test, validation, and test phases in a 5-fold cross-validation process. In this phase of modeling, 37 different neural network structures were created, ranging from 4 to 40 neurons, and the absolute error for each configuration was calculated separately and summarized in Fig. 2.

Table 6. Types of errors in the new model.

Error type	Value
Average Absolute Relative Deviation (AARD%)	1.004
Absolute Relative Deviation (ARD%)	-0.002
Average Absolute Deviation (AAD%)	0.856
Root-Mean-Square Deviation (RMSD%)	1.437

In this chart, the horizontal axis represents the number of neurons or nerves, and the vertical axis shows the standard absolute error. As shown in Fig.2, the neural network structure with 29 neurons has the lowest RMSD for calculating the overall thermal conductivity, which is equal to 0.221%.

Figure 3 shows the structure of a neural network with a hidden layer of 29 neurons and its inputs and outputs. The data used to create the neural network is the same data used in the

previous section, which includes 3841 experimental data points obtained from references.

Figure 4 illustrates the reduction in mean squared error (MSE) during the training, validation, and evaluation phases when developing the neural network structure for this research, which used 29 neurons. This value was consistently less than 10^{-6} for all stages (training, validation, and evaluation).

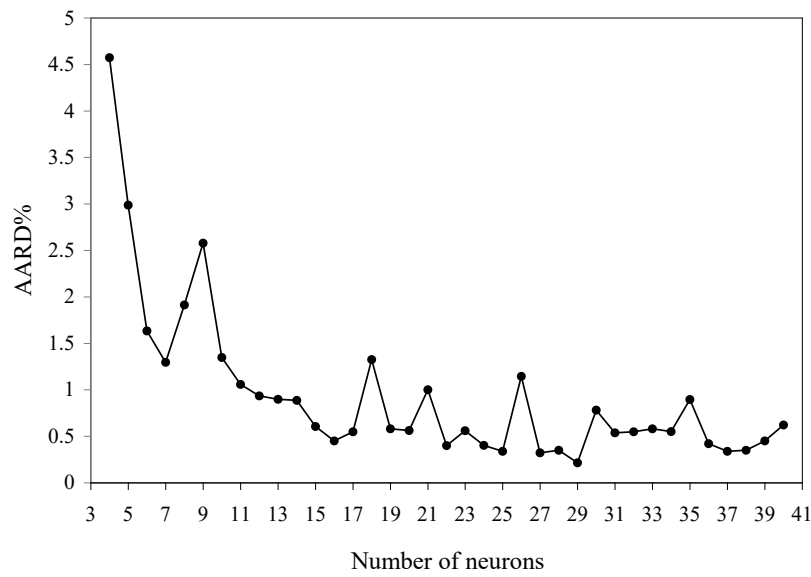


Fig.2. Error rates of different networks by varying numbers of neurons.

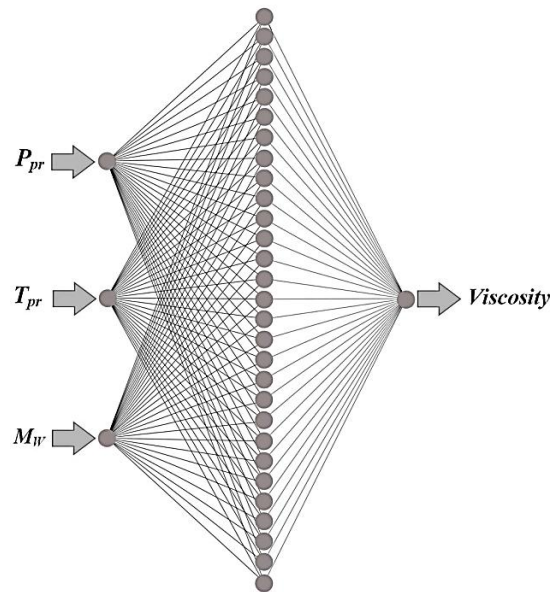


Fig. 3. A schematic of the optimized neural network created using 29 neurons.

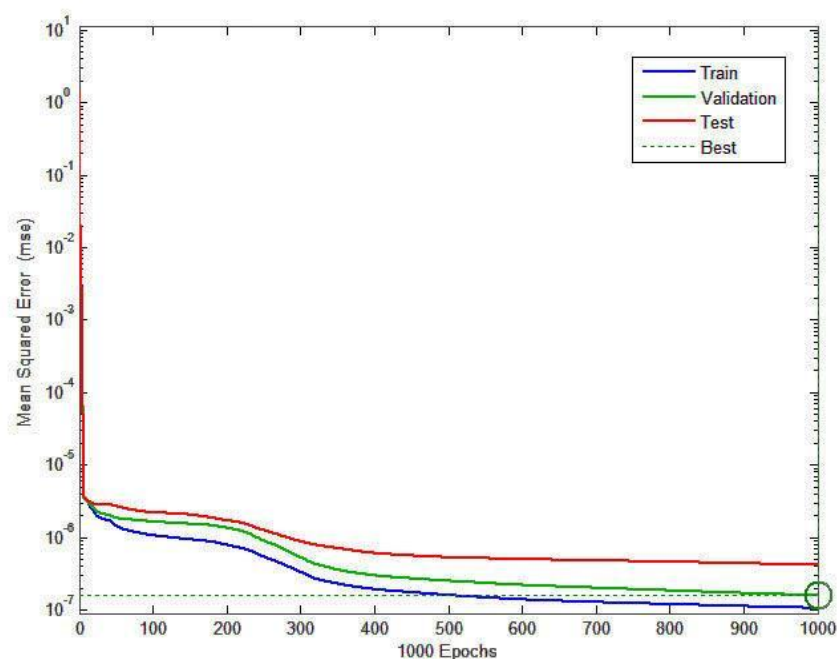


Fig.4. Changes in mean squared error during training, validation, and testing operations.

Viscosity calculations for the natural gases, based on the specified experimental data, were performed, and the error was precisely calculated for each point. Figure 5 shows the differences between the artificial neural network's predictions and the experimental data for all data points.

As shown in Fig.5, the closer the data points (represented by circular points) are to the rectangle's diameter, the lower the error in the neural network's viscosity calculation compared to the experimental value. The figure shows that many points are very close to the diameter, indicating high accuracy in the network's viscosity estimation for natural gas.

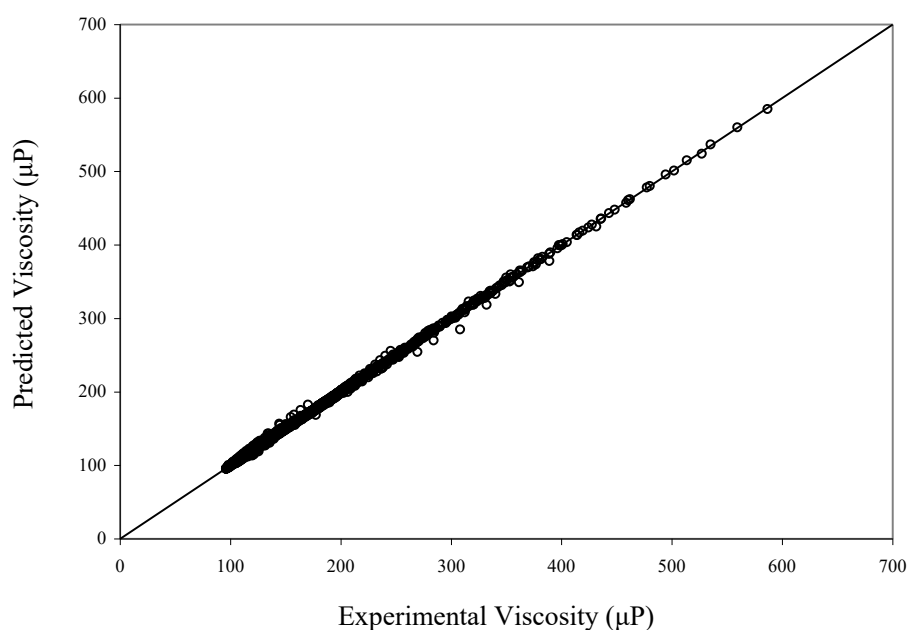


Fig.5. Deviation of calculated values from experimental values for the neural network model.

For greater confidence and a more precise comparison with other models, Table 7 presents the absolute error values for previous models (ADEL, LGE, HMS, CKB, and SNP) and the semi-empirical model and ANN, alongside those of existing experimental data.

In Table 7, O.R. (Out of range) signifies a high computational error (over 20%) when using that equation. The viscosity calculation results for 11 natural gases, obtained using the equation

presented in this work, have been thoroughly compared with results from other models. These comparisons demonstrate the presented equation's significantly higher accuracy. Another method for comparing models involves examining the cumulative frequency of deviations. Figure 6 illustrates the cumulative frequency of the AARD% for all models, including the newly proposed equation discussed in this work.

Table 7. Error rates of different viscosity models for natural gas samples

Gas	Methane (%)	No. of data	Mw	Temperature range (K)	ADEL	LGE	HMS	CKB	SNP	Semi-empirical results	ANN
No.1	0.9026	248	18.41	250-450	2.027	9.584	17.407	3.766	2.476	2.123	0.2274
No.2	0.8034	248	20.17	250-450	8.697	3.506	18.189	9.273	1.925	1.008	0.0994
No.3	0.8470	248	19.33	250-450	4.375	7.297	19.820	9.639	2.961	1.458	0.1162
No.4	0.8509	246	19.26	250-450	4.207	7.569	19.951	9.424	2.487	1.032	0.1523
No.5	0.8484	40	18.21	241-455	2.441	3.595	O.R.	8.996	2.972	1.979	2.0496
No.6	0.9016	45	17.81	263-303	1.545	7.727	O.R.	7.745	4.791	2.509	0.7616
No.7	0.8001	34	20.75	262-304	1.391	10.77	O.R.	28.26	4.256	0.809	0.6745
No.8	0.9220	45	17.50	262-304	1.020	7.162	O.R.	7.437	5.233	2.391	0.4739
No.9	0.8957	224	17.99	260-320	1.834	1.937	O.R.	9.151	2.855	2.183	0.3435
No.10	0.8433	224	18.4	269-320	4.443	5.921	O.R.	12.86	2.123	2.897	0.139
No.11	1.0000	2239	16.04	250-570	4.927	4.076	14.301	3.545	1.742	0.439	0.1931
Average		3841			4.550	4.942	18.89	5.940	2.126	1.004	0.221

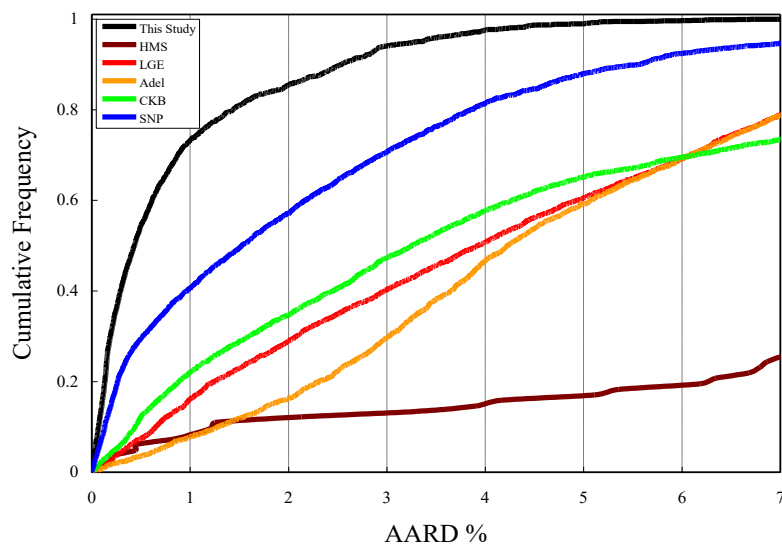


Fig. 6. Cumulative frequency in terms of AARD% for different models in viscosity calculation.

Figure 6 and the preceding tables demonstrate that the present model exhibits significantly lower error compared to all examined equations. The proposed model estimates 74% of the laboratory data with less than 1% absolute error and 85% with less than 2%, enhancing the model's credibility and accuracy. Only 2% of the data showed an error exceeding 5% with this model. In contrast, the SNP state equation, previously considered the most accurate semi-empirical equation for gases at medium pressures, estimated only 40% of the data with less than 1% absolute error and 56% with less than 2%. The CKB equation, the most accurate method before the SNP model, had an error of less than 1% for just 22% of the experimental data and less than 2% for 36%.

The various comparisons of natural gas viscosity calculations demonstrate that the model presented here exhibits lower error than all mentioned and validated models, with an average absolute error of approximately 1% and a mean squared error of 1.437%, indicating high accuracy.

To further evaluate the neural network's performance on unseen data, this section presents a case study using laboratory data from a natural gas sample, obtained at three temperatures by researchers. The viscosity of this gas, with compositions listed in Table 8,

was calculated using all models from this research, and the deviations from the experimental data are shown in Figs. 7 through 9. In these figures, the circular points represent the experimental data, and the curves represent the results of the semi-empirical equations.

Table 8. Composition of the sample natural gas.

mol%	
0.84990	Methane
0.05529	Ethane
0.02008	Propane
0.00401	i-Butane
0.00585	n -Butane
0.00169	i-Pentane
0.00147	n -Pentane
0.00152	n -Octane
0.00090	Toluene
0/00102	Methylcyclopentane
0.03496	Nitrogen
0.02331	Carbon dioxide

Figures 7 to 9 demonstrate a strong agreement between the artificial neural network's results and the laboratory data. As shown, the black curve representing the ANN closely aligns with the experimental data (gray circular points), indicating high calculation accuracy.

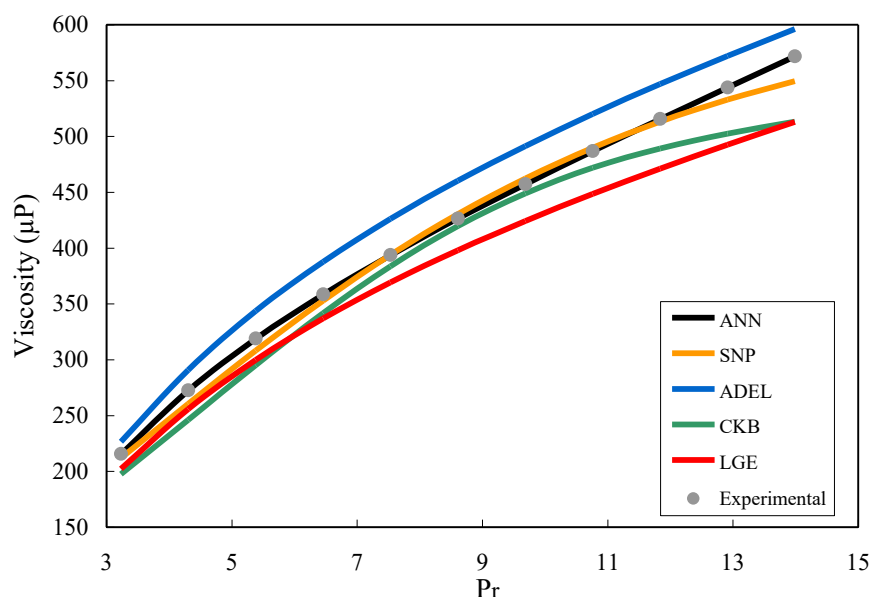


Fig.7. New experimental data and neural network results along with other previous models at a temperature of 270 K.

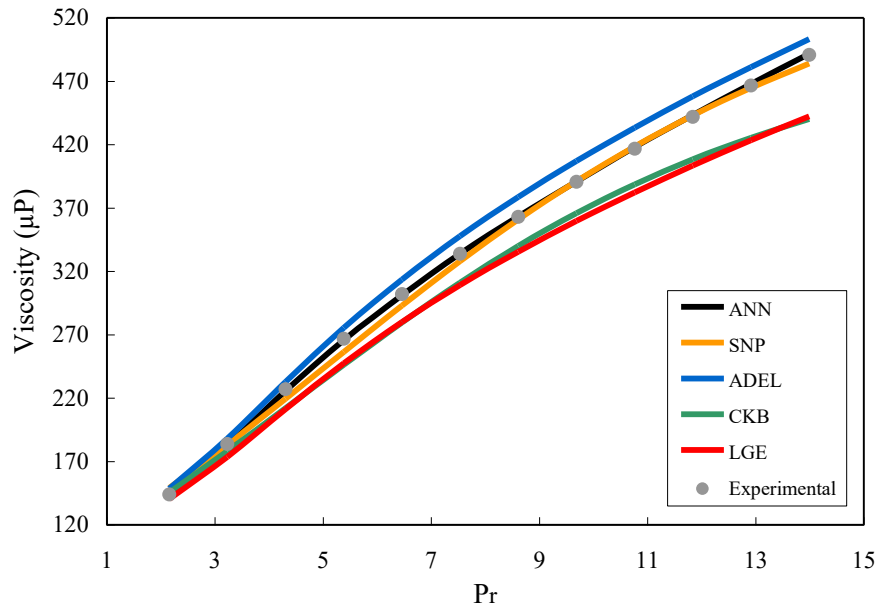


Fig. 8. New experimental data and neural network results along with other previous models at a temperature of 300 K.

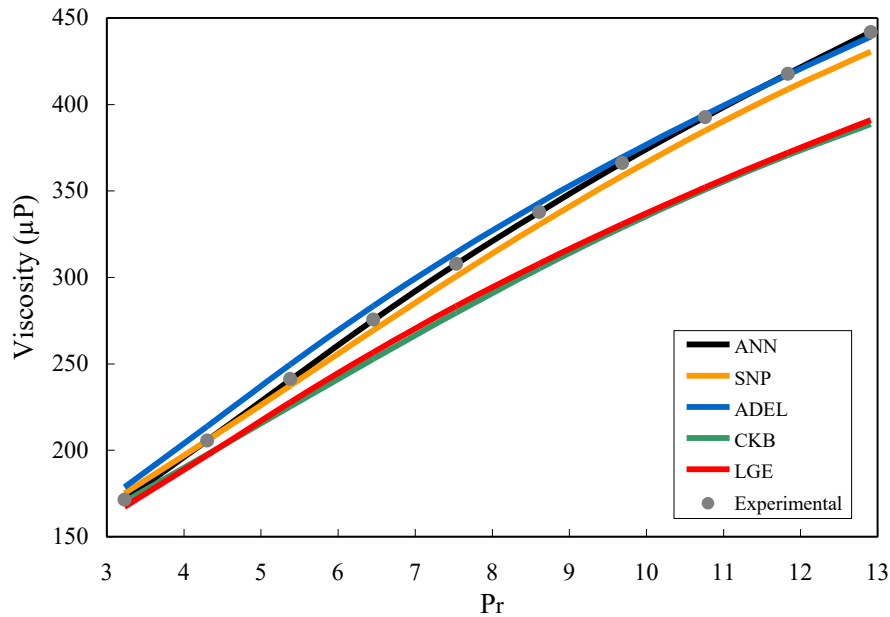


Fig.9. New experimental data and neural network results, along with other previous models at a temperature of 330 K.

4. Conclusion

This paper estimates natural gas viscosity as a function of density, temperature, and molecular weight by developing both a semi-empirical relationship and an Artificial Neural Network (ANN) model.

Cumulative frequency analysis showed the proposed model estimated 74% of experimental data with an absolute error of $< 1\%$ and 85%

with an absolute error of $< 2\%$, bolstering the model's credibility and accuracy. Only 2% of the data had an error $> 5\%$. The semi-empirical model presented in the current study has an Average Absolute Relative Deviation (AARD) of 1.004% and a Root Mean Squared Deviation (RMSD) of 1.437%, revealing that the present model exhibits significantly lower error compared to the existing equations. To illustrate, the SNP equation of state estimated

40% of the data with an error greater than 1% and 56% with an error less than 2%. The CKB equation has an error of less than 1% for 22% of the experimental data and an error of less than 2% for 36% of the experimental data.

Another method addressed in this paper is the ANN method. In this modeling, the Levenberg–Marquardt (LM) algorithm, which is the most accurate among Back Propagation (BP) methods, is used, with 80% of the total data for training and the remaining data for evaluating the accuracy and stability of the network for data not used in network construction. The dataset is divided into 70%, 20%, and 10% for the test, validation, and test phases in a 5-fold cross-validation process. Initially, to find the optimal number of neurons in the neural network, calculations indicate that a network with 29 neurons in its hidden layer structure has less error compared to other similar neural networks. AARD and RSMD are 0.221% and 0.338%, respectively.

In the present work, 11 different natural gas compositions have been investigated. It is suggested that a broader range of compositions with wider pressure and temperature ranges be investigated in future work.

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