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Estimation of Gas Mixture Compressibility Factor and Viscosity based on AI and Experimental Data

Afife Banavand[1], Amir Sarafi *[2], and Amir Ehsan FeiliMonfared [3]

[1,2,3] Department of Chemical Engineering, Reservoir Engineering, Bahonar University, Kerman, Iran

Abstract: Compressibility factor and viscosity of natural gasses are of great importance in petroleum and chemical engineering. To calculate the natural gas properties in the pipelines, storage systems and reservoirs, the exact values of gas compressibility factor and viscosity are required. A new method that allows accurate determination of compressibility factor and gas viscosity for all types of: sweet, sour, condensate and acid gases in a wide range of pressure and temperature conditions are presented here. The sizable data base of experimental Z factor and experimental gas viscosity measurements is collected from the available related literature. This newly developed method is tested by implementation of combined fuzzy inference system and Genetic Algorithm. The natural gas compressibility factor and viscosity as a function of gas composition, pressure, temperature and molecular weight of C7+ can be predicted through this model. The accuracy of this proposed model is compared with some commonly applied empirical correlations. The average absolute relative error here is 1.28 % and 0.57% for Z factor and gas viscosity, respectively.

Keywords: Natural Gas Viscosity, Gas Compressibility Factor, ANFIS, Genetic Algorithm.

1. Introduction

In oil and gas industries, natural gas compressibility factor and viscosity are very important parameters in calculating other gas properties. Compressibility factor represents the deviation of real gas behavior from the ideal state.

Natural gas compressibility factor and viscosity depend on gas compositions, temperature and pressure. It is revealed that gas viscosity increases with an increase in temperature and pressure. In the methods in practice determination of Z factor and gas viscosity, experimental measurement is the most accurate method, while it is hard to determine the compressibility factor and viscosity for all composition states of gases at all ranges of pressure and temperature. Experimental measurement is expensive and time consuming, moreover, they are usually subject to reservoir temperature, Ahmed, (2006). The properties of viscosity prediction and compressibility factor empirical correlations can be measured with an acceptable accuracy through newly introduced methods. Correlations applied in estimating gas compressibility factor are usually too complicated, require initial value and have significant errors, Shokir, et al, (2012). A minor error in predicting Z factor will lead to a big error in predicting all other properties like gas formation volume factor, compressibility and gas in situ Mahmoud, (2013), while a small uncertainty in gas viscosity data may affect the inflow performance corelations curves et al, (2001). The objective of this study is to propose a new accurate model for prediction of gas

* **Corresponding Author.**
Authors' Email Address:
[1] **Afife Banavand** (afife.banavand@yahoo.com),[2] **Amir Sarafi** (sarafi@uk.ac.ir),
[3] **Amir Ehsan FeiliMonfared** (ehsan.monfared@outlook.com)

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compressibility factor and viscosity for all natural gas mixtures with impurities like CO_2, H_2S, and N_2 in a wide range of pressure and temperature.

1.2. Natural Gas Compressibility Factor

There exist several different correlations for predicting Z factor, mostly based on corresponding states concept Xiang, (2005). The law of corresponding states, states that all pure gases have the same Z factor at the same reduced pressure and temperature values McCain, (1990).
For the mixtures of gas types the law of corresponding states is extended and Pseudo-reduced pressure (P_{pr}) and Pseudo-reduced temperature (T_{pr}) are introduced. The Standing and Katz (1942) chart represents compressibility factors of sweet and dry natural gas as a function of Ppr and Tpr. This chart is generally valid for sweet natural gas types with low amounts of non-hydrocarbons. Beggs and Brill (1973) introduced an equation extracted from Standing and Katz Z-factor chart. This correlation is a function of (Ppr) and (Tpr). This method is not valid for (Tpr) values less than 0.92. Azizi et al. (2010) developed an equation based on linear Genetic Programming (GP) approach in order to estimate the sweet gas types compressibility factor over the specific range of (Ppr) and (Tpr). Dranchuk and Abu-Kassem(1975) provided a correlation with eleven constants for calculating the gas compressibility factor. Kumar(2004) introduced the Shell model for prediction of Z factor. Sanjari and Lay(2012) proposed an empirical correlation by applying all the experimental data in multiple regression analysis, where, Z factor is a function of Ppr and Tpr.

1.3. Natural Gas Viscosity

There exist several correlations and models in predicting natural gas viscosity. Bicher and Katz (1943) developed a plot of viscosity versus molecular weight for natural gas mixtures at atmospheric pressure, in presence of non-hydrocarbon components through correction factor. Lohrenz et al (1964) proposed a correlation for viscosity of natural gases as a function of gas composition, pressure and temperature. Lee Gonzalez and Eakin (1966) carried out a project to study the viscosity of natural gas types. Temperature, density, and molecular weight of the natural gas are sufficient components in calculating the viscosity through Lee, Gonzalez, and Eakin correlation. Shokir and Dmour (2009) developed a model to determine the viscosity of pure hydrocarbon and gas mixtures. Heidaryan et al.(2010) presented an explicit equation as a function of temperature, gas density and apparent molecular weight with 10 constants to calculate the natural gas viscosity. Sanjari et al.(2011) presented an explicit equation to determine gas viscosity with two dependent variables of (Ppr and Tpr), and eleven independent variables of (α1– α11).

2. Data Gathering and the New Developed Method

In this study, a great number of data from a variety of natural gas types are applied in developing a new method for predicting gas compressibility factor and viscosity. These data contain 1500 gas compressibility factor data point of 99 different gas types: Elsharkawy and Foda, (1998), Elsharkawy, (2002), Reamer et al (1944 & 1945), Reameret al (1951), Reamer et al (1952), Reamer & Sage, (1962), Sage et al (1940); Sage and Lacey, (1950); Sage et al (1934), Simon, et al (1977), Wichert and Aziz, (1971) and 1300 gas viscosity data points . These data include mole percent of C_1 to C_{7+}, CO_2, H_2S, N_2, molecular weight of the C_{7+}, pressures, temperatures of natural gas viscosities and experimental compressibility factors. The data range applied in this study is tabulated in Table 1.
The modeling approach applied in this study is an adaptive neuro-fuzzy inference system similar to available system identification techniques. [After applying the ANFIS data to train the fuzzy inference system model]. The inputs here are gas compositions, pressure, temperature and molecular weight of C_7^+.

$$Z=f\left(y_i,P,T,MW_{C7+}\right) \tag{1}$$

$$Z=f\left(y_i,P,T,MW_{C7+}\right) \tag{2}$$

$$Z=f\left(y_i,P,T,MW_{C7+}\right) \tag{3}$$

Table 1. Data Range of Natural Gas Used in this Study

	Z factor		Viscosity	
	Min	Max	Min	Max
C_1%	19.38	97.76	57.3	90.26
C_2%	0	28.67	0.55	28.4
C_3%	0	14.15	0.5	2.7
iC_4%	0	2	0	0.4
nC_4%	0	1.07	0	0.64
iC_5%	0	1.08	0	0.214
nC_5%	0	2.85	0	0.16
C_6%	0	1.31	0	0.014
C_7^+%	0	12.68	0	6.382
CO_2%	0	67.16	0	14.28
H_2S%	0	51.37	0	2.58
N_2%	0	25.15	0	6.59
P (psia)	154	16896.9	646.86	9427.45
T (f)	40	335.57	13.73	350.33
MWc7+	0	191	0	142
Z	0.402	2.0366	—	—
μ_g(pa.s)	—	—	9.43	70.26

2.1. ANFIS

Adaptive Neuro - Fuzzy Inference System (ANFIS) creates a Fuzzy inference system (FIS) with input/output data. Fuzzy inference is the system of formulating the mapping from a given input to an output through fuzzy logic.

For a given data set, different ANFIS, can be constructed through the two different identification methods of grid partitioning and subtractive clustering, Jalalifar et al (2011). The subtractive clustering method works based on the potential of any data points in a clustered centered feature space, Chiu, (1994). Sugeno type fuzzy system is developed through a graphical ANFIS and after training it is tested for validation. This graphical inference is of the four: loading and plotting data, creating the basic structure of FIS, training FIS and validation parts. To begin the FIS training, the training data set that contains of input/output data pairs of the target system are necessary.

The Hybrid-learning rule applied for basic structure of FIS and the ANFIS is run through 60 epochs. The data set consists of two, training, (70%) and testing, (30%) sets. The FIS is generated through the sub clustering technique and a range of influence of cluster centers (r) is set for every run. When the range of influence is set at 0.38 the error is low but that is not ideal, that is, this model is not able to find the best radius for clustering when the FIS is generated. Here, when 16 radi are considered for each dimension, the error is low compared to when only one radius is applied for all dimensions. Consequently, the Genfis2 is one of the suggestions. Genfis2 and Anfis function of MATLAB programming language are applied to generate a Sugeno type of FIS with maximum efficiency. Since setting the clustering range of influence for each dimension manually by trial and error is a difficult and time consuming process, in order to find the best radiuses applying Genetic Algorithm (GA) is a better choice for optimizing performance.

2.2. ANFIS-GA based Model

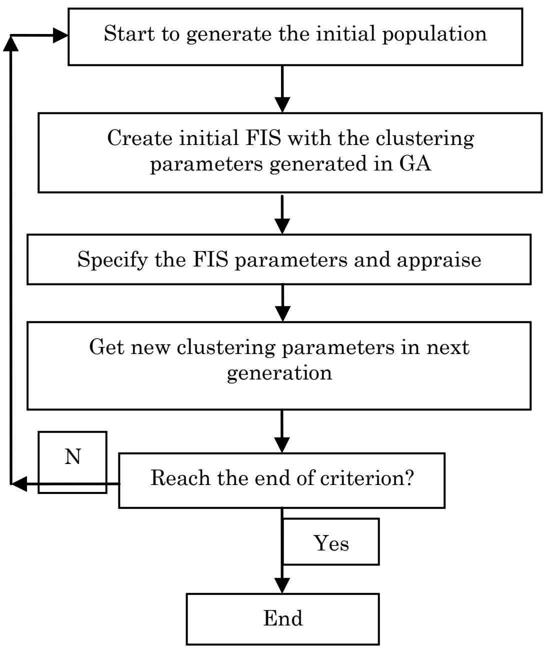
GA is known as a kind of effective and robust optimization algorithm well-suited for discontinues and multi- modal functions(Beyer, 2000). GA algorithms are special type of evolutionary algorithms which apply evolutionary biology techniques such as inheritance and mutation. The GA applies the genetically evolution as a model for solving the problem. A problem that must be resolved is the input and solutions are encoded as a function of the pattern called fitness function which evaluates each one of the most randomly selected candidate solutions.

In this study, an ANFIS and a combination of ANFIS and GA are applied. GA is highly involved in optimizing the clustering parameters like the influence range and evaluation of ANFIS fitness values through the solutions. The input parameters values applied in this study are tabulated in Table 2 and the diagram of hybrid ANFIS-GA model is presented as a flowchart in Fig. (1).

Table 2. Input Parameters Values

GA - ANFIS Model	
Train data	70%
Test data	30%
Dimension of problem	16
Maximum number of generations in GA	60
Number of populations in GA	70
Number of epoch in ANFIS	60

Figure 1. The ANFIS-GA Model flowchart



The objective of applying GA together with ANFIS model is to find the optimum cluster center's range of influence in each dimension and minimizing the fitness function. In this case the fitness function is the absolute average relative percent error of predicted outputs. Maximum number of? generation in GA is 60 and Maximum number of population is 70.

3. Results

A new compositional model for estimation of gas compressibility factor based on Fuzzy logic modeling approach and GA is proposed in this study. The data set consists of two training, (70%) and testing, (30%) sets.

Between the two methods adopted in this article, combination of GA and ANFIS, indicates a better performance with minimum average absolute relative error (AARE) in predicting gas properties, Tables 3 and 4.

The two generated methods for mapping the inputs into a single output are detailed and tabulated in Tables 3 and 4. The hybrid GA-ANFIS model is more accurate and closer to the experimental data. The number of rules in GA-ANFIS system is less than that of the ANFIS system, that is, ANFIS is more complex for modeling the gas compressibility factor and viscosity. The combination of GA-ANFIS is an efficient AI system in predicting these properties. The advantage in applying this newly introduced method is its multi-functionality, that is, no limitation in performance. The Optimum ranges of influence when GA+ ANFIS are applied for gas viscosity and compressibility factor are illustrated in bar charts in Figs (2 & 3).

The accuracy of this new model in estimating both the gas compressibility factor and viscosity are shown in Figs. (4 & 5), where a good agreement is observed between experimental data and predicted values obtained by GA-ANFIS model

Table 3. The Results of ANFIS Models against Testing Data

Properties	r	Number of Rules	AAE	AARE%
	0.4	24	0.03566	4.370
Z factor	0.35	37	0.03461	4.315
	0.3	61	0.02387	2.882
	0.4	36	0.01052	1.134
Viscosity	0.35	54	0.00828	0.972
	0.3	70	0.00824	0.936

Table 4. The Results of GA-ANFIS Models against Testing Data

Properties	R	Number of Rules	AAE	AARE%
Z factor	[0.72,0.48,0.56,0.12,0.99,0.87,0.69,0.94,0.83,0.81,0.5, 0.61,0.68,0.35,0.47,0.13]	26	0.01134	1.284
Viscosity	[0.56,0.13,0.55,0.74,0.94,0.99,0.68,0.59,0.77,0.83,0.6, 0.7,0.13,0.51,093,0.31]	42	0.0017	0.576

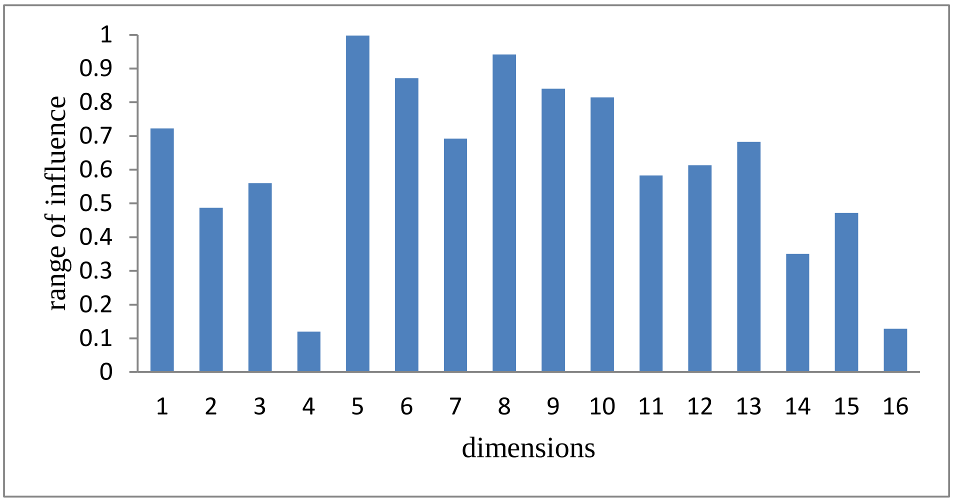


Figure2. Optimum Range of Influence through GA for Gas Viscosity

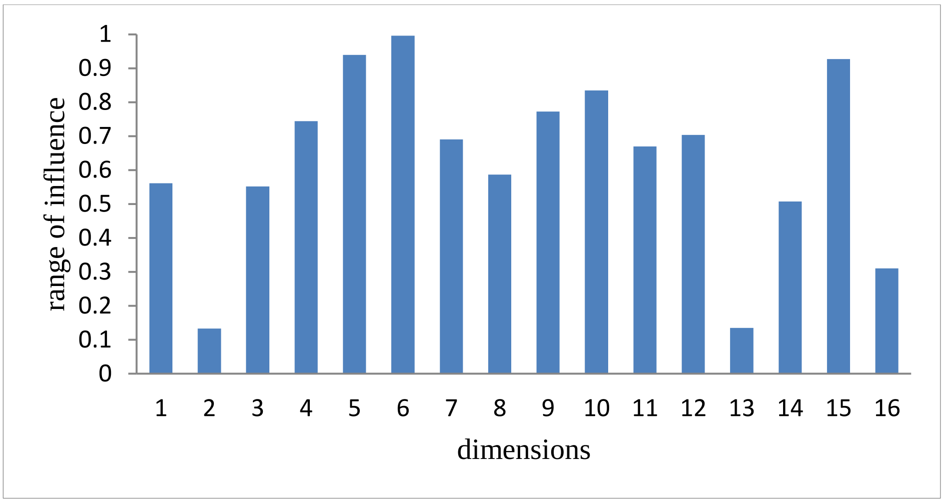


Figure 3. Optimum Range of Influence through GA for Gas Compressibility Factor

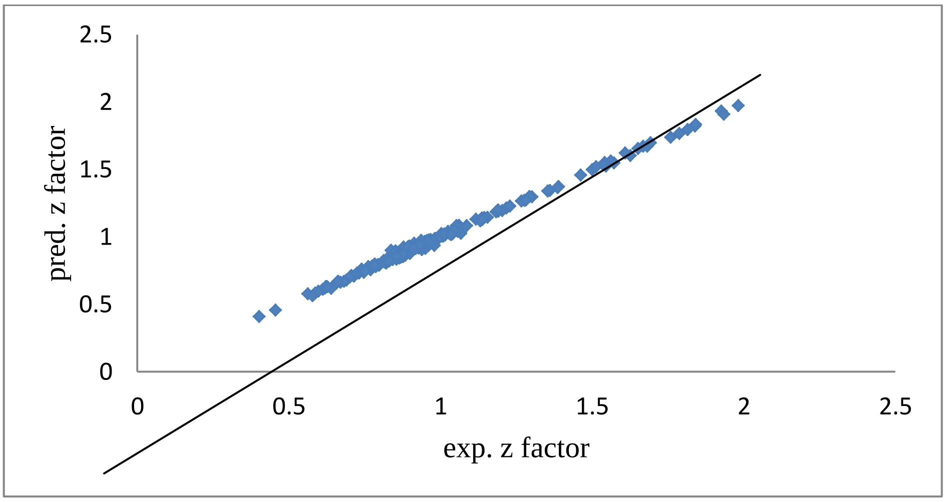


Figure 4. Comparison between the Results of GA-ANFIS Model and the Testing Data for Gas Compressibility Factor

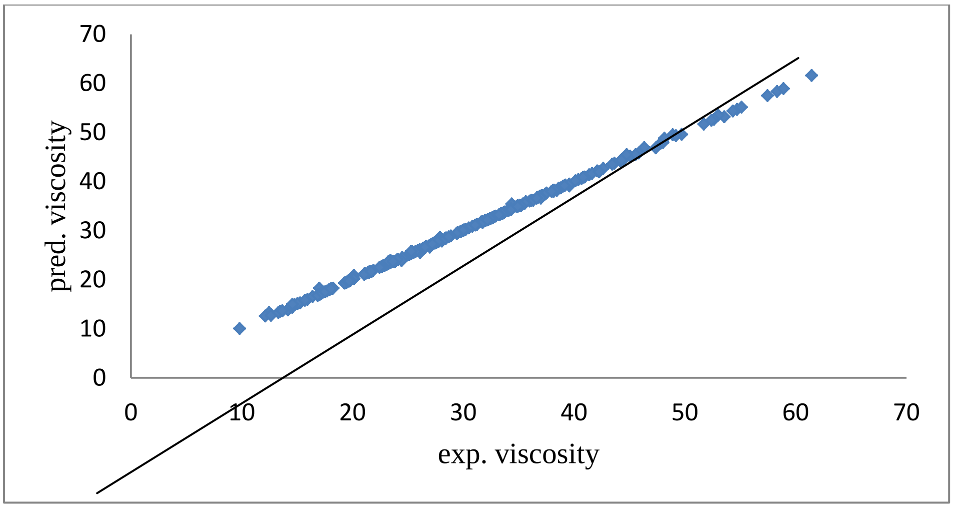


Figure 5. Comparison between the Results of GA-ANFIS Model and the Testing Data for Gas Viscosity

Table 5. The Comparison of Case Studied Gas Sample and Experimental Data with the Results of the New Model and other Methods at T=162F

Comp.	Mole%	P (psia)	Predicted z				
			Exp. Z	GA-ANFIS Model	Beggs and Brill	Shell Oil Company	Heidaryan
C_1	66.34	2899	0.819	0.822	0.768	0.768	0.828
C_2	3.11	2916	0.821	0.826	0.768	0.769	0.831
C_3	1.8	2945	0.821	0.831	0.769	0.77	0.832
iC_4	0.34	2984	0.823	0.832	0.77	0.771	0.835
nC_4	0.94	3014	0.823	0.834	0.771	0.773	0.837
iC_5	0.33	3064	0.825	0.835	0.773	0.775	0.841
nC_5	0.45	3114	0.827	0.836	0.775	0.777	0.845
C_6	0.56	3214	0.831	0.839	0.779	0.782	0.853
C_7^+	1.48	3314	0.836	0.842	0.784	0.787	0.861
CO_2	2.06	3514	0.846	0.849	0.794	0.8	0.879
H_2S	12.96	4014	0.878	0.871	0.828	0.837	0.928
N_2	9.63	4514	0.916	0.916	0.868	0.882	0.984
Total	100	5014	0.958	0.947	0.911	0.929	1.043
		5514	1.003	1.001	0.955	0.979	1.106
		6014	1.048	1.053	1.001	1.03	1.172

4. Discussion

For validation of the accuracy of this method, the absolute average relative error of this new method is compared with some of the available reliable correlations. The results obtained from the comparisons made between this newly proposed model and its outperforming capabilities with respect to the available models regarding the title of this article are tabulated in tables 5 and 6. . It should be added that the previous methods have some limitation like presence of high pressure and existence of non-hydrocarbon compositions.

The capability of this new method for calculating the compressibility factor and gas viscosity is assessed through the test data, which is not applied during the process of model development. As observed in Tables (7 & 8), this developed hybrid GA-ANFIS model is much more accurate than other empirical methods for prediction of a natural gas properties containing non-hydrocarbon components at high pressures and temperatures.

Table 6. The Comparison of Case Studied Gas Sample and Experimental Data with the Results of the New Model and other Methods at T=350.33F

Comp.	Mole%	P (psia)	Exp.μ (Pa.S)	Predicted μ			
				GA-ANFIS model	Heidaryan	Sanjari	LGE
C_1	88.04	1450.38	17.13	17.08	17.7	17.45	21.72
C_2	0.55	2175.56	18.46	18.42	18.66	18.72	23.16
C_3	2	2900.75	19.96	19.80	19.79	19.84	24.92
iC_4	0.4	3625.9	21.61	21.54	21.13	21.32	27.03
nC_4	0.62	4351.13	23.35	23.38	22.7	23.07	30.19
iC_5	0.171	5076.32	25.13	25.24	24.51	25.48	32.38
nC_5	0.14	5801.5	26.92	26.95	26.59	26.76	33.56
C_6	0	6526.7	28.71	28.73	28.97	28.53	36.42
C_7^+	0.24	7251.89	30.47	30.38	31. 7	31.48	39.14
CO_2	2.3	7977.07	32.2	32.24	34.81	34.05	41.61
H_2S	1.99	8702.26	33.9	33.69	38.38	36.71	44.3
N_2	3.5	9427.45	35.56	35.45	42.46	38.95	47.58
Total	100						

Table 7. Average Absolute Relative Error for each Compressibility Factor Method versus Experimental Data

Ref.	Method	Range of Application	AARE%
Beggs and Brill	correlation	sweet gasses , Tpr>0.92	5.49
Shell oil company	correlation	for low and moderate pressures	3.80
Heidaryan et al.	correlation	1.2<Tpr<3 , 0.2<Ppr<15	3.54
Azizi et al.	correlation	sweet gasses	3.92
Sanjari and Lay	correlation	1.01<Tpr<3 , 0.01<Ppr<15	3.76
This study	ANFIS-GA	___	1.28

Table 8. Average Absolute Relative Error for each Gas Viscosity Method versus Experimental Data

Ref.	Method	Range of Application	AARE%
LGE	correlation	10< P(psi) <8000 , 100< T(F) <340	9.33
Heidaryan et al	correlation	116 < P(psi) <9580 , 77.7< T(F) <340	5.61
Sanjari and Lay	correlation	1.01<Tpr<3 , 0.01<Ppr<15	3.76
This study	ANFIS-GA	___	0.57

5. Conclusion

There exist several empirical correlations for predicting natural gas properties where are more accurate than the others. Most of the presented correlations for compressibility factor are based on Standing-Katz chart and this is the reason why they show some error compared to experimental data. There exist some limitation(s) of application in these methods, while this new developed model has no limitation in applying any type of gas mixture. A new method is developed based on the experimental data capable of predicting the compressibility factor and natural gas viscosity with more accuracy than the previous methods. Based on the obtained results, it is concluded that the developed GA-ANFIS system is more successful compared to Genfis2+ANFIS and exhibits a higher accuracy and a low absolute average relative percent error in predicting these properties of gas.

Appendix

Eq. (A.1) $\text{Average error} = \sum_{i}^{N} \left(\frac{Z_i\text{exp-}Z_i\text{pre}}{N} \right)$

Eq. (A.2) Average absolute error =

$$\frac{1}{N}\sum_{i}^{N}\left(\left|Z_i\text{exp-}Z_i\text{pre}\right|\right)$$

Eq. (A.3) Average absolute relative error %

$$= \left(\frac{100}{N}\right)\sum_{i}^{N}\left(\left|\frac{Z_i\ \text{exp -}Z_i\text{pre}}{Z_i\ \text{exp}}\right|\right)$$

Nomenclature

Ppr	Pseudo-reduced pressure
Tpr	Pseudo-reduced temperature
GP	Genetic Programming
GA	Genetic Algorithm
ANFIS	Adptive Neuro-Fuzzy Inference System
FIS	Fuzzy Inference System
Mw_{C7+}	Molecular weight of heptane-plus fraction
AARE	Average absolute relative error
AAE	Average absolute error
Pred	Predicted
Exp	Experimental
r	Range of influence

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