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Compressibility factor model of sweet, sour, and condensate gases using genetic programming

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ABSTRACT

Gas compressibility factor (z-factor) is necessary in most petroleum engineering calculations. The most common sources of z-factor values are experimental measurements, equations of state (EOS) and empirical correlations. There are more than twenty correlations available with two variables for calculating the z-factor from fitting Standing–Katz chart values in an EOS or just through fitting techniques. However, these correlations are too complex, which require initial value and longer computations, and have significant error. This work presents a new model for estimating z-factors of sweet gases, sour gases and gas condensates using genetic programming (GP). The z-factor model was developed using pseudo-reduced pressure, and pseudo-reduced temperature. Moreover, two new models of pseudo-critical pressure and temperature were built as a function of the gas composition (mol percent of C_1–C_{7+}, H_2S, CO_2, and N_2) and the specific gravity of the C_{7+}. The developed new GP-based model yields a more accurate prediction of gas z-factor compared to the commonly used correlations and EOS's.

Keywords: Gas compressibility factor; Sour gas; Condensate gas; Genetic programming

1. Introduction

In the oil and gas industries, gas compressibility factor (z-factor) is one of the most important parameters in upstream and downstream operations. The importance of z-factor cannot be overemphasized in material balance, gas reserve evaluation, gas reservoir simulation, gas well testing and gas processing calculations. Occasionally, experimental data is unavailable and estimation from EOS or empirical correlations becomes a necessity. The existing methods of calculating z-factor, at significant amounts of acid gases like carbon dioxide (CO_2) and hydrogen sulfide (H_2S), incur high deviation from the actual value. Consequently, searching for a simple and an accurate model for predicting the compressibility factors of sweet, sour, lean and rich gas condensate reservoirs becomes very important.

Therefore, in this paper a new model for estimating z-factors of sweet gases, sour gases, and lean to rich gas condensates using genetic programming is presented. The new model was designed to be simpler as it eliminates the numerous computations involved in any equation of state applications. The efficiency of the developed model was tested against the most commonly used gas compressibility correlations and EOS's. In addition, risk analysis was used to demonstrate the sensitivity of the new model and the dependency extent of the compressibility factor on each of the independent variables. The z-factor model was developed using pseudo-reduced pressure, and pseudo-reduced temperature. However, the pseudo-reduced pressure and temperature are defined based on pseudo-critical pressure and pseudo-critical temperature ($P_{Pr} = P/P_{Pc}$ and $T_{Pr} = T/T_{Pc}$), respectively. Therefore, theses two

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Nomenclature

T	terminal set
F	genetic operator function
T_{Pc}	pseudo-critical temperature
P_{Pc}	pseudo-critical pressure
T_{Pr}	pseudo-reduced temperature
P_{Pr}	pseudo-reduced pressure
zC_1	mole percent of methane
zC_2	mole percent of ethane
zC_3	mole percent of propane
ziC_4	mole percent of iso-butanes
znC_4	mole percent of *n*-butanes
ziC_5	mole percent of iso-pentanes
znC_5	mole percent of *n*-pentanes
zC_6	mole percent of hexanes
zC_{7+}	mole percent of heptanes-plus
zCO_2	mole percent of carbon dioxide
zH_2S	mole percent of hydrogen sulfide
zN_2	mole percent of nitrogen
SPG C_{7+}	specific gravity of heptanes-plus
AARE	average absolute relative error, $100/N\sum_1^N \lvert(y_{calculated} - y_{measured})/y_{measured}\rvert$, %

parameters (pseudo-critical pressure and temperature) were modelled as a function of the gas composition (mol percent of C_1–C_{7+}, H_2S, CO_2, and N_2) and the specific gravity of the C_{7+}.

A total of 1270 data points for a variety of natural gases, covering lean, sweet to rich and acid or sour gases (H_2S, and CO_2), were collected from literature (Buxton and Campbell, 1967; Elsharkawy, 2002, 2004; Reamer et al., 1942, 1952, 1953; Reamer and Sage, 1962; Elsharkawy and Foda, 1998; Wichert, 1970; Simon et al., 1977) to develop a new predictive model of sweet gases, sour gases, and lean to rich gas condensates z-factors. These data include gas compositions (mol percent of C_1–C_{7+}, H_2S, CO_2, and N_2), molecular weight and specific gravity of the C_{7+}, experimentally measured compressibility factors, pressures, temperatures. The corresponding pseudo-critical pressures and temperatures were calculated using mixing rule of Piper et al. (1993). Some points were discarded due to the lack of C_{7+} fraction properties (which is essential for establishing the new z-factor models). Finally, 1150 gas samples are randomly divided into two parts. The first part, contains 800 gas samples, was introduced for building the new models using genetic programming, and the second part (350 gas samples) was used for validating and testing the developed models against the other early published gas compressibility correlations and EOS's.

2. Gas compressibility factor

The ratio of the actual volume to the ideal volume of real gas "which is a measure of the amount the gas deviates from perfect behavior" is called the compressibility factor. It is also called the gas deviation factor and is denoted by the symbol z. The most common sources of z-factor values are experimental measurement, equations of state and empirical correlations. Scarcity of experimental data for the required composition, pressure, and temperature conditions arise the need for modelling. Several different correlations are available for this important parameter. The basic correlations use the corresponding states concept. The theory of corresponding states dictates that the z-factor can be uniquely defined as a function of reduced pressure and reduced temperature. The reduced pressure and reduced temperature are defined as

$$P_r = \frac{P}{P_c} \tag{1}$$

$$T_r = \frac{T}{T_c} \tag{2}$$

where P_r and T_r are reduced pressure and reduced temperature, respectively, and P_c and T_c are critical pressure and critical temperature of the gas, respectively. The values of pseudo-critical pressure and pseudo-critical temperature can be estimated from the following equations if the composition of the gas and the critical properties of the individual components are known (Kay, 1936):

$$P_{Pc} = \sum_{i=1}^{n} P_{ci} y_i \tag{3}$$

$$T_{Pc} = \sum_{i=1}^{n} T_{ci} y_i \tag{4}$$

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

For unknown composition of different gas systems, there are different correlations to predict pseudo-critical temperature and pressure from gas specific gravity like Standing (1981), Elsharkawy et al. (2001) and Sutton (2007). Standing and Katz (1942) developed an accepted chart (SKC) according to the theory of corresponding states for the z-factor. On the other hand, there are more than twenty correlations available with two variables for calculating the z-factor from fitting SKC values in an EOS as reported by Hall and Yarborough (1973), Dranchuk and Abou-Kassem (1975), Nishium and Saito (1975), Dranchuk et al. (1974), and Benedict et al. (1940) or just through fitting techniques like Gopal (1977). In addition, Brill and Beggs (1974) presented an explicit relation to estimate/predict the z-factor. They reported that 94 data points were used to establish this correlation, which yields an average absolute error of 0.19%. However, their correlation can only be used in the range of $1.2 \leq T_{Pr} \leq 2.4$ and $0 \leq P_{Pr} \leq 10$.

The above mentioned correlations are complicated in a sense of initial value availability, longer computations and/or accompanied magnitude error. Therefore, the objective of this paper is to apply GP to generate a simplified new compressibility factor model of sweet, sour, lean and rich gas condensate reservoirs as a function of the pseudo-reduced pressure and pseudo-reduced temperature. Moreover, new pseudo-critical pressure and pseudo-critical temperature models were developed using GP as function of gas compositions (mol percent of C_1–C_{7+}, H_2S, CO_2, and N_2) and the specific gravity of the C_{7+}.

3. Genetic programming

GP is a recent development in the field of evolutionary algorithms, which extends the classical genetic algorithms (Reeves, 1997; Shokir et al., 2004) to a symbolic optimization technique (Koza, 1992; Shokir, 2008). It is based on so-called "tree representation". This representation is extremely flexible, because trees can represent computer programs,

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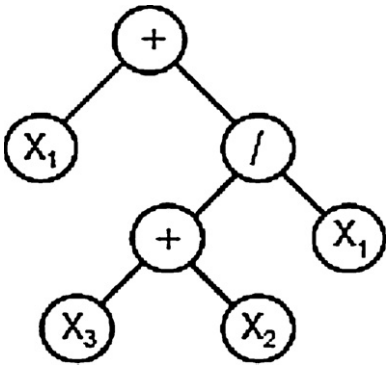

Fig. 1 – A tree structure for the model (Madar et al., 2004): $y = x_1 + (x_3 + x_2)/x_1$.

mathematical equations, or complete models of process systems. This scheme has been already used for circuit design in electronics and algorithm development for quantum computers and is suitable for generating model structures, e.g., identification of kinetic orders (Cao et al., 1999), steady-state models (McKay et al., 1997), and differential equations (Sakamoto and Iba, 2001). GP initially creates an initial population [i.e., it means generating individuals (trees) randomly to achieve high diversity]. In all iterations, the algorithm evaluates the individuals, selects individuals for reproduction, generates new individuals by mutation, crossover, and direct reproduction, and finally creates the new generation (Koza, 1992; Madar et al., 2004; Pearson, 2003; Potvin et al., 2004). Unlike common optimization methods, in which potential solutions are represented as numbers (usually vectors of real numbers), the symbolic optimization algorithms represent the potential solutions by structural ordering of several symbols, as shown in Fig. 1.

The generated potential solutions in the form of a tree structure during the GP operation may have better and worse terms (subtrees) that contribute more or less to the accuracy of the model represented by the tree structure. Using an orthogonal least squares (OLS) algorithm estimates the contribution of the branches of the tree to the accuracy of the model. Whereas, using the OLS, one can select the less significant terms in a linear regression problem. Terms having the smallest error reduction ratio could be eliminated from the tree (Pearson, 2003). Fig. 2 illustrates an example of elimination a sub-tree based on OLS. A complete explanation of the presentation of the mathematical model in GP and the OLS algorithm is found in Koza (1992) and Shokir (2008).

4. Building the gp-based pseudo-critical pressure and temperature and z-factor models

As mentioned before the data set that was used in building the new pseudo-critical pressure, pseudo-critical temperature, and z-factor models is equal to 1150 gas samples. Eight hundred data points are randomly selected from the collected data for building the pseudo-critical pressure, pseudo-critical temperature, and gas factor models, and the remaining 350 data points put aside for testing the developed models. Table 1 summarizes the minimum and maximum values of all components in the collected gases. Table 2 shows the minimum and maximum values for the used data in building the new pseudo-critical pressure and temperature models. The maximum and minimum values of the different parameters

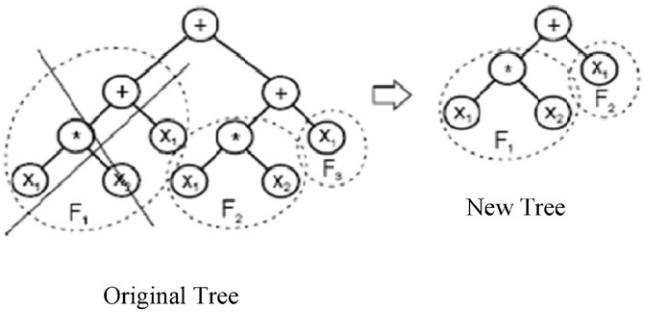

Fig. 2 – Elimination a sub-tree based on OLS (Madar et al., 2004).

constitute the limits of the developed model domains; extrapolation beyond these values could lead to unrealistic results.

The GP-OLS technique was applied to generate the new pseudo-critical pressure and pseudo-critical temperature models for sweet, sour, lean and rich condensate gas reservoirs, using Matlab software. On the basis of the input data, the GP identified the model equation. During the identification process, the function set F contained the basic arithmetic operations $F = (+, -, \times, /)$ and the terminal set T contained repressor variables

$$T = zC_1 + \ldots, zC_{7+}, zN_2 + zH_2S + zCO_2, \mathrm{SPG}\,C_{7+} \quad (5)$$

The OLS evaluation is inserted into the fitness evaluation step. Before calculation of the fitness value of the tree, the OLS calculates the error reduction ratio of the branches of the tree, and the terms that have an error reduction ratio below a threshold value are eliminated from the tree. With the help of the selected branches, the OLS estimates the parameters of the model represented by the tree. After that, this new individual proceeds on its way in the GP algorithm (fitness evaluation, selection, etc.). Table 3 summarizes the final GP parameters that were used in building the new pseudo-critical pressure and temperature models.

The resulted new pseudo-critical temperature is:

$$T_{Pc} = A + B + C + D + E + F \quad (6)$$

where

$$A = 0.90802((ziC_4 - ziC_4ziC_5)(zC_3 + zH_2S + (znC_4zCO_2))) + 0.50786((zH_2S + zC_2)znC_4)$$

$$B = -2.123366(ziC_4(zH_2S + zC_2)) + 1.159927zC_3 - 2.071292zC_1 - 69.070023(ziC_5\mathrm{SPG}\,C_{7+}^2)$$

$$C = -2.996917zN_2 - 8.917447zC_{7+} + 21.072914ziC_4 - 1.422166\mathrm{SPG}_{7+} + 0.35641(znC_4C_2)$$

$$D = 3.83187(zC_6zC_{7+}) - 3.81694znC_5 - 7.13966znC_4 + 1.2344zH_2S + 13.2054(\mathrm{SPG}\,C_{7+}zC_{7+})$$

$$E = -0.308395(\mathrm{SPG}\,C_{7+}zH_2S) - 0.012482(zN_2zH_2S) + 64.093536(\mathrm{SPG}\,C_{7+}ziC_5)$$

$$F = 0.724091ziC_5 + 3.57128zC_6 - 1.47642(znC_4ziC_5) + 19.845762(ziC_4znC_5) - 0.024106zCO_2 + 550.092621$$

Table 1 – The minimum and maximum values of all components in the collected gases.

	C_1 (mol%)	C_2 (mol%)	C_3 mol%	i-C_4 (mol%)	n-C_4 (mol%)	i-C_5 (mol%)	n-C_5 (mol%)	C_6 (mol%)	C_{7+} (mol%)	N_2 (mol%)	CO_2 (mol%)	H_2S (mol%)	SPG C_{7+}	Mw C_{7+}	T (°F)	P (psi)	P_{Pc}	T_{Pc}	z factor
Min.	17.3	0	0	0	0	0	0	0	0	0	0	0	0	0	39	150	640	345	0.456
Max.	97.5	28.67	13.16	1.07	1.8	1.59	0.79	1.31	6.18	25.15	54.5	73.85	0.91	150	299	7040	1170	602	1.361

Table 2 – The minimum and maximum values for the used data in building the new pseudo-critical pressure and temperature models.

	C_1 (mol%)	C_2 (mol%)	C_3 (mol%)	i-C_4 (mol%)	n-C_4 (mol%)	i-C_5 (mol%)	n-C_5 (mol%)	C_6 (mol%)	C_{7+} (mol%)	N_2 (mol%)	CO_2 (mol%)	H_2S (mol%)	SPG C_{7+}	T (°F)	P (psi)	P_{Pc}	T_{Pc}
Min.	17.27	0	0	0	0	0	0	0	0	0	0	0	0	39	150	640	345
Max.	97.48	28.67	13.16	1.07	1.8	1.59	0.79	1.31	6.18	25.15	54.46	73.85	0.91	299	7040	1170	602

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Table 3 – GP parameters used in building the new pseudo-critical pressure and temperature models.

Population size	160
Maximum generation	250
Type of selection	Tournament[a]
Type of mutation	Point-mutation
Type of crossover	One-point (2 parents)
Type of replacement	Elitist[b]
Generation gap (P_{gap} parameter)[b]	0.8
Probability of crossover	0.7
Probability of mutation	0.4
Probability of changing terminal – non-terminal nodes (vica versa) during mutation	0.25
Maximum tree depth	7

[a] This method chooses each parent by randomly drawing a number of individuals from the population and selecting only the best of them.
[b] Before new individuals inserted to the population, it is necessary to 'kill' the old individuals. Elitist *replacement* strategy was applied in order to keep the best solutions with a 'generation gap' P_{gap} parameter. E.g., the P_{gap} = 0.8 means that 80% of population is 'killed' and the only the best 20% will survive.

Table 4 – The minimum and maximum values for the used data in building the new z-factor model.

	T_{Pr} (mol%)	P_{Pr} (mol%)	z-Factor
Min.	1.967	0.17	0.456
Max.	0.974	10.2	1.361

The resulted new pseudo-critical pressure is:

$$P_{Pc} = A + B + C + D + E + F \quad (7)$$

where

$$A = 0.007417(((zCO_2 + ziC_5) + 2zH_2S)(zC_1(zC_{7+} - SPG\,C_{7+})))$$

$$B = -1.15556((zH_2S(znC_5 + ziC_5))((znC_6SPG\,C_{7+}) + SPG\,C_{7+}))$$

$$C = 2.5781((znC_5 + zC_{7+}) - (zCO_2zC_6)) - 2.3518zCO_2 - 5.9904zC_2 - 16.0772znC_4 + 0.05118(zN_2 + znC_4)(H_2S + znC_5)$$

$$D = -8.30318zN_2 - 0.16079(zH_2SzCO_2SPG\,C_{7+}) - 1.01137ziC_4 + 13.5415(SPG\,C_{7+}ziC_4)$$

$$E = -6.39055zC_1 + 22.30057(SPG\,C_{7+}ziC_5) - 50.32981(zC_{7+} - SPG\,C_{7+}) - 1.90345(zH_2SzC_6)$$

$$F = -6.90457zC_3 - 0.54279(zC_1SPG\,C_{7+}) + 24.59715zC_{7+} + 8.27392zC_6 + 0.303324znC_5 - 9.24827ziC_5 + 1306.82706$$

The developed GP-based pseudo-critical pressure and pseudo-critical temperature models were used to calculate the pseudo-reduced pressure and pseudo-reduced temperature for each gas samples which used for building the new GP-based gas z-factor model. The minimum and maximum values for the used data in building the new z-factor model are shown in Table 4. The above mentioned procedures of GP-OLS were used in developing the new z-factor model. Table 5 summarizes the final GP parameters that were used in building the new z-factor model.

Table 5 – GP parameters Used in building the new z-factor model.

Population size	110
Maximum generation	350
Type of selection	Tournament[a]
Type of mutation	Point-mutation
Type of crossover	One-point (2 parents)
Type of replacement	Elitist[b]
Generation gap (P_{gap} parameter)[b]	0.8
Probability of crossover	0.8
Probability of mutation	0.7
Probability of changing terminal – non-terminal nodes (vica versa) during mutation	0.25
Maximum tree depth	6

[a] This method chooses each parent by randomly drawing a number of individuals from the population and selecting only the best of them.
[b] Before new individuals inserted to the population, it is necessary to 'kill' the old individuals. Elitist *replacement* strategy was applied in order to keep the best solutions with a 'generation gap' P_{gap} parameter. E.g., the P_{gap} = 0.8 means that 80% of population is 'killed' and the only the best 20% will survive.

The resulted new z-factor model is:

$$\text{z-factor} = A + B + C + D + E \quad (8)$$

where

$$A = 2.679562\frac{(2T_{Pr} - P_{Pr} - 1)}{[(P_{Pr}^2 + T_{Pr}^3)/P_{Pr}]}$$

$$B = -7.686825\left[\frac{P_{Pr}T_{Pr} + P_{Pr}^2}{T_{Pr}P_{Pr} + 2T_{Pr}^2 + T_{Pr}^3}\right]$$

$$C = -0.000624(T_{Pr}^2P_{Pr} - T_{Pr}P_{Pr}^2 + T_{Pr}P_{Pr}^3 + 2T_{Pr}P_{Pr} - 2P_{Pr}^2 + 2P_{Pr}^3)$$

$$D = 3.067747\frac{(T_{Pr} - P_{Pr})}{(P_{Pr}^2 + T_{Pr} + P_{Pr})}$$

$$E = \left[\frac{0.068059}{T_{Pr}P_{Pr}}\right] + 0.139489T_{Pr}^2 + 0.081873P_{Pr}^2 - \left[\frac{0.041098T_{Pr}}{P_{Pr}}\right] + \left[\frac{8.152325P_{Pr}}{T_{Pr}}\right] - 1.63028P_{Pr} + 0.24287T_{Pr} - 2.64988$$

4.1. *Validation of the new Gp-based models*

To validate the new pseudo-critical pressure and temperature models, the randomly stored 350 points from the original database were used for that propose. The minimum and maximum values for these test data parameters are shown in Table 6. The results of the new pseudo-critical pressure and temperature models show a good accuracy as well as a low average absolute relative error (AARE) equals to 0.04% and 0.03%, respectively (Figs. 3 and 4).

On the other hand, the performance and the accuracy of the developed GP-based model to predict the z-factors for sweet gases, sour gases, and lean to rich gas condensates were tested and validated by comparing the predicted z-factor with those

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Table 6 – The minimum and maximum values for the used data in testing the new pseudo-critical pressure and temperature models.

	C_1 (mol%)	C_2 (mol%)	C_3 (mol%)	i-C_4 (mol%)	n-C_4 (mol%)	i-C_5 (mol%)	n-C_5 (mol%)	C_6 (mol%)	C_{7+} (mol%)	N_2 (mol%)	CO_2 (mol%)	H_2S (mol%)	SPG C_{7+}	T (°F)	P (psi)	P_{Pc}	T_{Pc}	Z factor
Min.	20.2	0	0	0	0	0	0	0	0	0	0	0	0	39	154	640	345	0.48
Max.	97.48	28.67	13.16	1.07	1.8	1.59	0.79	1.31	6.18	25.15	54.46	70.03	0.905	279	7026	1170	602	1.28

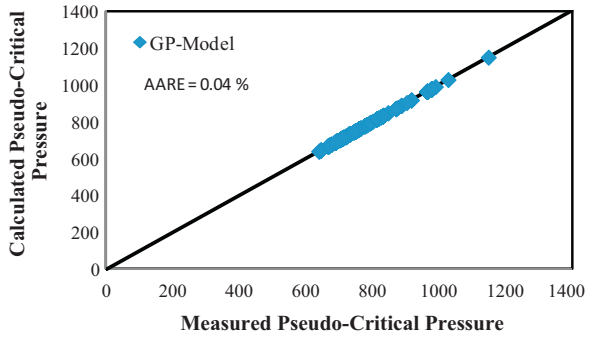

Fig. 3 – Cross plot of the predicted pseudo-critical pressures from the new GP-based model versus the calculated values from Piper et al. (1993) correlation.

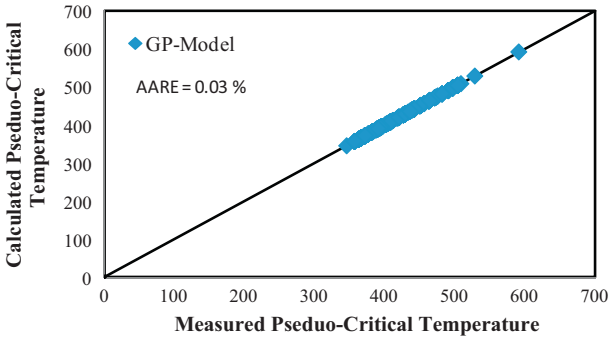

Fig. 4 – Cross plot of the predicted pseudo-critical temperature from the new GP-based model versus the calculated values from Piper et al. (1993) correlation.

predicted from the early published correlations (Elsharkawy, 2004; Dranchuk and Abou-Kassem, 1975; Hall and Yarborough, 1973; Gopal, 1977; Brill and Beggs, 1974; Dranchuk et al., 1974), and EOS's (Lawal et al. (LLS-EOS), 1985; Peng and Robinson (PR-EOS), 1976; Redlich and Kwong (RK-EOS), 1949). Cross-plot of the predicted z-factor values from the GP-based model versus the experimental values is shown in Fig. 5. This cross-plot shows the degree of agreement between the experimentally measured data and the predicted z-factor values. The new z-factor model yields the closest match between the predicted and the measured z-factor. It is clear from Table 7 that the new GP-based model presented in this study for calculating gas compressibility factor has the smallest average relative errors (ARE), smallest average absolute relative errors (AARE), and the highest coefficient of correlations (COC) for all types of natural gases considered. Table 7 also indicates that the new

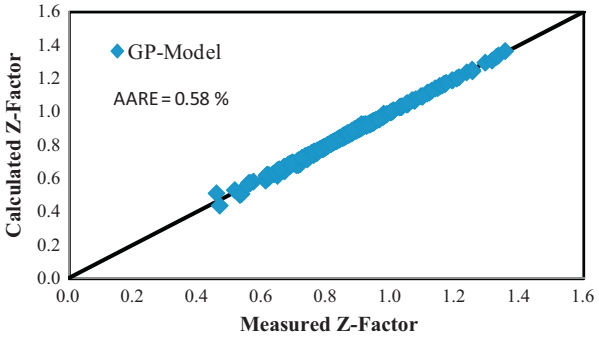

Fig. 5 – The predicted z-factor values from the new GP-based model versus and the experimental measured values.

Table 7 – Comparison between the accuracy of different methods in predicting the gas compressibility factors of different types of natural gases.

	ARE (%)	AARE (%)	COC (%)
GP-based model	−0.02	0.58	99.88
Elsharkawy (2004)	−0.57	2.34	95.14
Gopal (1977)	5.15	5.22	89.55
Dranchuk and Abou-Kassem (1975)	−3.34	4.53	90.19
Dranchuk et al. (1974)	4.50	4.63	90.04
Brill and Beggs (1974)	4.70	4.79	88.80
Hall and Yarborough (1973)	1.62	3.66	97.09
Lawal et al. (1985)	4.33	4.33	94.15
Peng and Robinson (PR-EOS) (1976)	−5.03	5.77	95.02
Redlich and Kwong (RK-EOS) (1949)	2.20	2.77	95.53

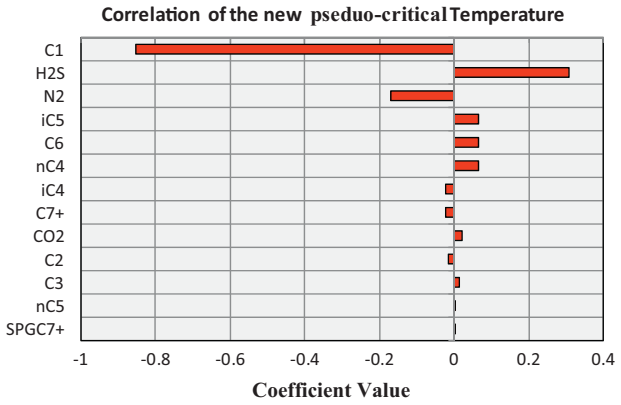

Fig. 6 – Sensitivity analysis of the new pseudo-critical temperature model and its dependence on each independent variable.

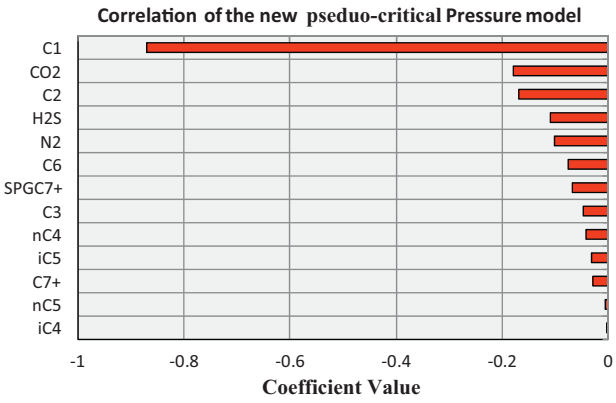

Fig. 7 – Sensitivity analysis of the new pseudo-critical pressure model and its dependence on each independent variable.

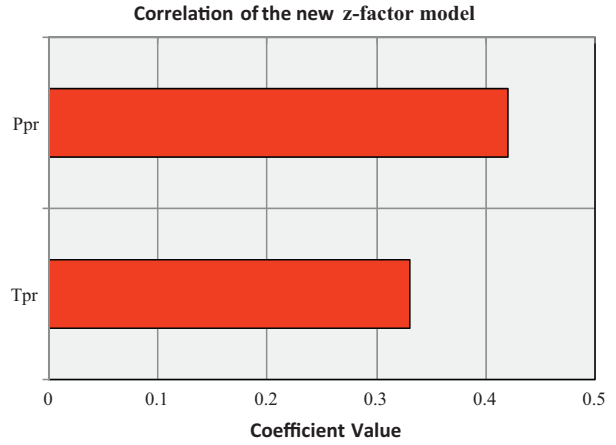

Fig. 8 – Sensitivity analysis of the new z-factor model and its dependence on each independent variable.

method shows superiority over all the correlations and EOS(s) considered in this study.

5. Sensitivity analysis

The influence of the individual independent variables on the new pseudo-critical pressure and temperature, and z-factor models were tested using MonteCarlo simulation software (@risk, 2008). This software was used to demonstrate the effect of all input variables on the depended predicted variable of each model. Figs. 6–8 show the results of sensitivity analysis of the new pseudo-critical pressure and temperature, and z-factor models. These figures show the rank correlation coefficients that were calculated between the output variable and the samples for each of the input parameters. In general, as the correlation coefficient between any input variable and output variable increases, the influence of that input in determining the output's value increases.

These figures indicate the following:

- From Figs. 6 and 7, it is obvious that the mole percent of C_1 component has the major impact on both the pseudo-critical pressure and temperature. The pseudo-critical pressure and temperature decreases as a function of increasing mole percent of C_1. Decreasing the pseudo-critical temperature with increasing mole percent of C_1 may be attributed to negative value of the pseudo-critical temperature of the pure C_1 and also the higher percent of this component in the gas mixture. On the other hand, decreasing the pseudo-critical pressure with increasing mole percent of C_1 may be attributed to the higher compressibility of the C_1 component.
- Fig. 6 also shows that pseudo-critical temperature decreases significantly if the mole percent of N_2 increases. This observation is also attributed to the higher negative value of the pseudo-critical temperature of the pure N_2 component. On the other hand, the results of sensitivity analysis of the new z-factor model are shown in Fig. 8. It shows that the z-factor increases with increasing the pseudo-reduced pressure and temperature. Fig. 6 also shows that pseudo-critical temperature decreases significantly if the mole percent of H_2S increases. This observation is also attributed to the higher negative value of the pseudo-critical temperature of the pure N_2 component.
- Fig. 8 shows that the z-factor increases with increasing the pseudo-reduced pressure and pressure temperature.

6. Conclusions

1. New models of the compressibility factor and pseudo-critical pressure and temperature for sweet gases, sour gases, and gas condensates were developed using genetic programming.

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2. The comparison between the new GP-based model of the gas compressibility factor and the early published correlations and EOS's of the compressibility factor indicated that the new model is more accurate than the other tested correlations and EOS's. Therefore, the new model can be considered an alternative method to estimate the compressibility factor of lean and rich gas condensates, sweet gases, and sour gases, when the experimentally measurement is not available.
3. Sensitivity analysis using MonteCarlo simulation was used to examine the impact of different parameters on the predicted gas compressibility factor and pseudo-critical pressure and temperature for lean and rich gas condensates, sweet gases, and sour gases. The results were matched with the physical interrelationship between the input and output variables.

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