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Comparative Study of Different Fuzzy Models for Gas Compressibility Factor Prediction

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Abstract: Good estimation of gas compressibility factor (z-factor) of gas is an essential key in numerous gas and oil calculations. In the absence of experimental data, the iterative methods were run to estimate the z-factor. However, these methods are more complex and have a large number of factors, which require longer calculations. In addition, the accuracy of these correlations has become insufficient for the best estimations due to their limitations. The objective of this study is to test various Fuzzy Logic (FL) technique to develop a simple and robust approach. The FL has three types: Fuzzy c-means (FCM), grid partition (GP), and sub-clustering (SC) Algorithms. The proposed FL models were compared with iterative methods to test its performance and reliability to predict z-factor. Around 6500 published and unpublished data points with a wide range of z-factor and reduced temperature and pressure were collected from several fields in the Middle East used to develop FL models. It was found that the developed FL with various cluster techniques is more precise and trustful than published empirical techniques and can be used in a wide range of pseudoreduced pressure and temperature. The obtained results show that the FL with sub-cluster technique performs well with a lower average relative per cent error of 0.13% and higher accuracy (R_2=1) than the other models. The technique presented in this work is robust, efficient, and accurate. It can be used to calculate the z-factor in the absence of experimental data.

Keywords: Artificial Intelligence; model; Fuzzy Logic; z-factor.

1. Introduction:

Gas compressibility factor is one of the most essential factors in the gas and oil industries operations. The z–factor can be used in gas processing, gas well testing, gas reserve evaluation and reservoir simulation calculations. Accordingly, searching for an accurate z - factor correlation becomes very significant.

The z - factor was defined as the ratio between the actual volume and the ideal volume of real natural gas at a given pressure and temperature (McCain, [29]):

$$Z = V_{Actual} / V_{Ideal} \quad (1)$$

The most common real gas equation is then written as:

$$PV = nZRT \quad (2)$$

Standing and Katz [35] have developed a chart (SKC) for the compressibility factor which is appropriate for gas. All gases have the same compressibility factor when they have approximately the same reduced-pressure (Pr) and reduced-temperature (Tr) (Cengel and Boles [11], Danesh [12]). Dranchuk [13] proposed pseudoreduced temperature and pressure equations that were defined as the following:

$$T_{pr} = \frac{T}{T_{pc}} \quad (3)$$

$$P_{pr} = \frac{P}{P_{pc}} \quad (4)$$

Where,

$$Z = f\,(T_{pr}, P_{pr}) \quad (5)$$

In general, the z-factor correlations of gas can be classified into direct relations such as (Standing and Katz [35], Gopal [19], Kumar [27]); and Elsharkawy [16]) and iterative relations such as Hall and Yarborough (HY), Dranchuk, Purvis and Robinson (DPR) [14] and Dranchuk and Abou Kassem (DAK). In spite of the most empirical correlations can be utilized to estimate z-factor, the accuracy of these correlations has become insufficient for accurate estimations due to their limitations or complexity of these models.

Therefore, the objective of this study is to test the three FL algorithms namely, Sub-Cluster, FCM-Cluster, and Grid Partition to develop a simplified and robust z-factor model more accurate than iterative correlations. In addition, the comparative study between the FL models and iterative methods will be done.

2. Literature Review:
Empirical Correlations:

The common methods for calculating of z-factor are HY [22], DPR [14] and DAK [13]. Hall and Yarborough [22] developed z-factor model using 1500 data sets that take out from Standing and Kats's chart. Dranchuk and Abou-Kassem applied a regression method with the same date points to modify eleven – constant of the Benedict – Webb – Rubin [10] equation of state. Dranchuk, Purvis and Robinson modified the earlier obtained DAK relation with eight constants only.

Table 1 summarized coefficients of DPR and DAK correlations. More details of these correlations will be discussed as the following:

Hall and Yarborough (HY):

$$T = \frac{1}{T_{pr}}, \quad A = 0.06125T\, e^{-1.2(1-T)^2},$$

$$B = 14.7T - 9.76T^2 + 4.58T^3$$

$$C = 90.7T - 242.2T^2 + 42.4T^3, D = 2.18 + 2.82T$$

$$-AP_{pr} + \frac{x + x^2 + x^3 + x^4}{(1-x)^3} - B + x^2 + C + x^D = 0$$

$$z = \frac{AP_{pr}}{x}$$

Dranchuk and Abou Kassem (DAK)

$$1 + R_1 x - R_2/x + R_3 x^2 - R_4 x^5 + \left[R_5 x^2 (1 + A_{11} x^2) e^{(-A_{11} x^2)}\right] = 0$$

$$R_1 = A_1 + \frac{A_2}{T_{pr}} + \frac{A_3}{{T_{pr}}^3} + \frac{A_4}{{T_{pr}}^4} + \frac{A_5}{{T_{pr}}^5}$$

$$R_2 = \frac{0.27P_{pr}}{T_{pr}}, \qquad R_3 = A_6 + \frac{A_7}{T_{pr}} + \frac{A_g}{{T_{pr}}^2}$$

$$R_4 = A_9 \left(\frac{A_7}{T_{pr}} + \frac{A_g}{{T_{pr}}^2}\right), \qquad R_5 = \frac{A_{10}}{{T_{pr}}^2}$$

$$z = \frac{0.27P_{pr}}{XT_{pr}}$$

Table 1. Shows the DAK and DPR Correlations Coefficients

Dranchuk and Abou Kassem (DAK)	**Dranchuk, Purvis and Robinson (DPR)**
A1 = 0.3265	A1 = 0.31506237
A2 = -1.070	A2 = -1.04670990
A3 = -0.5339	A3 = -0.57832720
A4 = 0.01569	A4 = 0.53530771
A5 = -0.05165	A5 = -0.61232032
A6 = 0.5475	A6 = -0.10488813
A7 = 0.7361	A7 = 0.68157001
A8 = 0.1844	A8 = 0.68446549
A9 = 0.1056	
A10= 0.6134	
A11= 0.721	

Beggs and Brills [9] developed an explicit correlation for estimating z-factor. Elsharkawy [15] used gas condensates reservoirs data to calculate gas compressibility factor. Heidaryan [23] developed a new z-factor correlation using 1220 data points. Moreover, Azizi [6] used about 3038 data points to establish z-factor correlation. Another correlation with 16 constants was developed by Sanjari [33] for estimating z-factor using 5844 data points. Moreover, Lateef [28] linearized z-factor correlation to overcome the complicated procedure associated with the nonlinearity based on 6000 experimental data points. Ghiasi [18] developed empirical correlations to simplify the z-factor calculation whereas Vassilis [36] applied a regression method with a simple interpolation to calculate the z-factor. Abdolhossein [1] developed a hybrid group method to determine the z-factor at different conditions.

In spite of that, these correlations are more complex including a large number of factors, which required longer and more complex calculations, the previous iterative methods are still the most used and accurate than direct methods.

3. Artificial Intelligent Techniques:

Recent Artificial Intelligent models were applied in petroleum engineering calculations specifically in reservoir fluid properties such as Hajirezaie [20, 21], Al-Gathe [3, 4], and Baarimah [8]. Moreover, the Artificial Neural Network (ANN) techniques were developed to estimate z-factor, such as Kamyab [26], Mohagheghian [30, 31], Shateri [34], Mohamadi-Baghmolaei [32] and Azizi [7]. In addition, some papers focused on the use of machine learning model to estimate the z -factor, such as Fayazi [17]. Lately, Adel Salem [2] has developed different intelligent models to predict gas compressibility factor.

With regard to the previous review, we can notice that a very few researchers proposed AI techniques to estimate z-factor especially using Fuzzy model. The prediction of z-factor also shows the superiority of AI models over empirical correlations. Therefore, the objective of this study is to develop a different types of FL models. Then, the capability of these models is tested to identify which of the FL techniques is the most suitable for z-factor prediction.

4. Statement of the Problem:

Firstly, the iterative methods require initial guess value that outcome within the unacceptable root that also leads to undesirable result [Azizi [6]; Heidaryan [23]; Sanjari and Lay [33]]. Subsequently, application of these methods to the studied data points result with undesirable errors at higher pressure and temperature close to the critical temperature as shown in Figs. 1 through 3. Therefore, the precision of these iterative methods has become inadequate for estimating z-factor. In addition, the objective of this work is to develop a suitable FL model to calculate the z-factor with high accuracy.

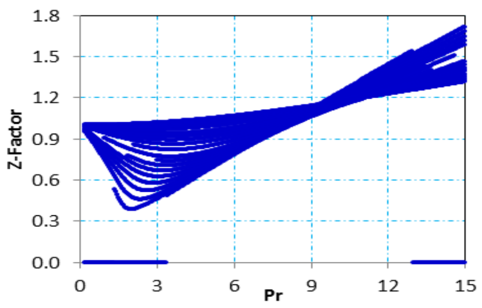

Figure 1. Shows the HY – z-factor Model versus P_r.

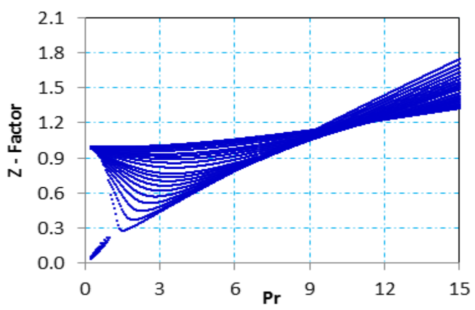

Figure 2. Shows the DAK – z-factor Model versus P_r.

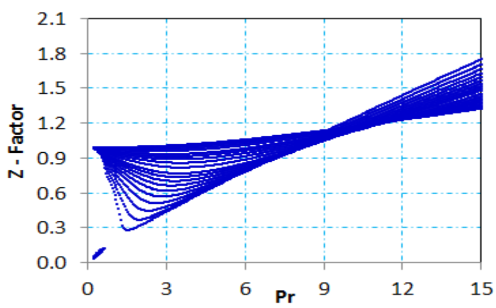

Figure 3. Shows the DPR – z-factor Model versus Pr.

5. Fuzzy Logic Model:

Adaptive Neural Inference System (ANFIS) or the FL modelling was used in this study. The ANFIS is the integration of Fuzzy and ANN techniques in the training step in order to improve the capability of learning, Jang [24, 25]. The ANFIS modifies the inappropriate properties of ANN and fuzzy model by applying the positive features of both models. In other words, Fuzzy inference system (FIS) is generated by hybrid optimization and Back propagation (BP) methods. The trial and error method was used to select a suitable configuration model depend on the minimum absolute relative percent error (ARPE) and maximum correlation coefficient (CC). The schematic structure of FL model, formulating Pr and Tr data to z-Factor, is illustrated in Fig.4.

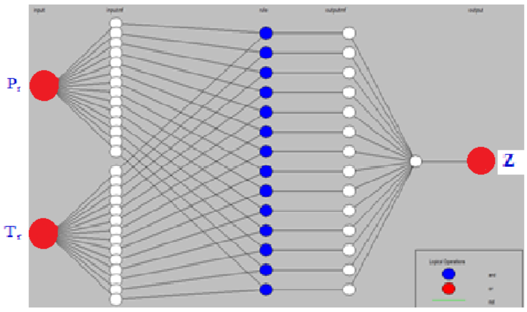

Figure 4. FL model structure for z-factor prediction

The constructed above models will be applied using Matlab software. The Matlab software generated Fuzzy Inference System (FIS) configuration from actual data using grid partition by (genfis1) function, whereas the Subtractive Clustering and FCMcluster models used (genfis2) and (genfis3) functions, respectively.

6. Data Description

About 6500 data points were used from several fields in the Middle East to develop FL models. A wide range of z-factor and reduce-pressure, and reduce-temperature were covered in this study. Most of these data were published by Al-Khamis [5]. Table 2 is summarized the overall data ranges. These proposed models used around 70% of data points for training and 30% data for testing. The data points should be normalized to avoid arithmetical difficulties during the computations.

Table 2. Summarizes the data range**.**

	Max.	**Min.**
Z-factor	1.753	0.2992
Pr	15	0.2
Tr	3	1.05

The criteria applied to test the accuracy and performance of those proposed models in this study were minimum/maximum absolute error, the root means square error (RMSE), Average per cent relative error (APRE), and the correlation coefficient (CC).

7. Results and discussion

In this study, the three iterative methods (HY, DPR and DAK) correlations were run to estimate z-factor. The result of the DPR correlation has the highest correlation coefficients and the lowest APRE in comparison with the other correlations as shown in Figs.5 and 6.

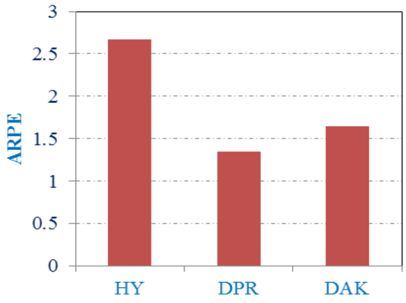

Figure 5. Shows ARPE of three iterative methods

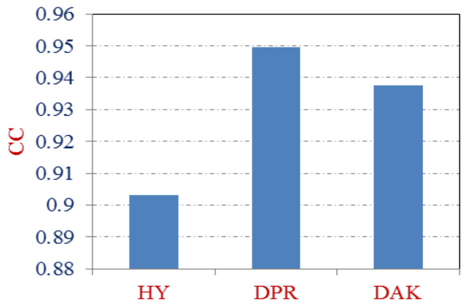

Figure 6. Shows CC of three iterative methods

Along with iterative methods, fuzzy logic (FL) is also used in this study. As it is known, FL has three types: grid partition, Fuzzy c-means clustering and sub-clustering. There are many differences between these types. The grid partition depends on the type of membership functions (MFs) that are used to get optimal results. The grid partition model always needs to select the suitable input functions (gbellmf, pimf, gaussmf, dsigmf, pimf, gauss2mf and No. of function) and output data either linear or constant. All options of this model were applied and the optimal option was chosen. The results show the (gaussmf) is the optimal function to achieve this task with higher CC and lower APRE as shown in Fig.s7 and 8. In addition, it takes a much longer time compared to the other cluster types.

The FCMcluster does not take much time to run in comparison with the grid partition model. The best result of this type depended on optimal number of clusters. To achieve the optimal result, the different numbers of clusters were proposed then the best number of cluster is determined with minimum APRE and maximum correlation coefficient. Fig.9 shows the number of cluster (14) was the best.

The last sub-cluster type achieves the best model according to optimal cluster radii. In this type, the different radii were proposed to estimate the z-factor. Then, the optimal radii and model were achieved with minimum APRE and maximum CC. It is clearly observed that the optimal clustering radius was specified (0.10), whereas the sub-cluster technique's error reaches its minimum value, as shown in Fig.10.

Comparisons are also provided for the three cluster algorithms that show the Sub-Cluster (SC) algorithm is achieved the best one with the highest CC and the lowest APRE and RMSE as shown in Figs.11 through 13. According to the data presented in **Table** 3 and **Table** 4, the sub-cluster model yielded better performance and more accuracy than the other cluster models.

The sub-cluster has the highest number of rules (118), whereas the FCMcluster has the lowest with 14 rules. Finally, Fig.14 and Fig.15 show a good agreement between the experimental and Sub-Cluster z-factor models in 3D dimension plots.

Figure 7. Performance of Input MFs versus CC

Figure 8. Performance of Input MFs versus ARPE

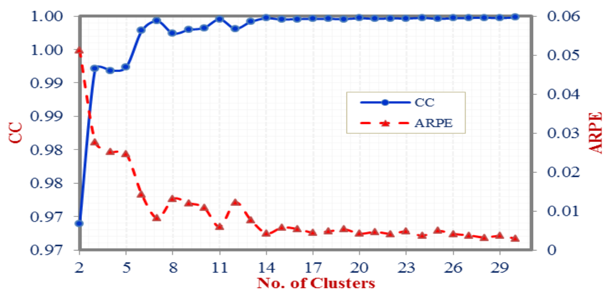

Figure 9. Optimal No. of Cluster for FCMcluster

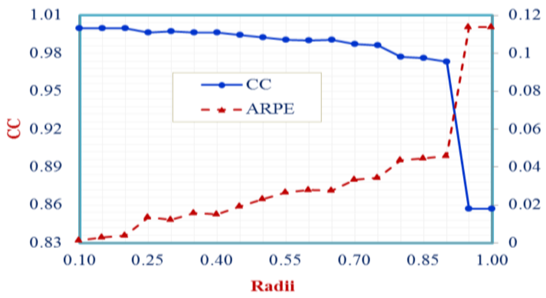

Figure 10. Optimal Radii for Sub-Cluster using CC and ARPE

Table 3. Summarizes the accuracy analysis of the three Fuzzy Algorithms

	RMSE		CC		ARPE	
	Train	***Test***	***Train***	***Test***	***Train***	***Test***
Sub-Cluster	0.21	0.21	1	1	0.13	0.13
FCM Cluster	0.64	0.63	0.9997	0.9997	0.43	0.42
Grid Partition	0.90	0.77	0.9994	0.9995	0.50	0.44

Table 4. Summarizes the accuracy of the three iterative methods

	ARPE	R2
HY	2.674	0.9032
DPR	1.349	0.9495
DAK	1.642	0.93751

Figure 11. Dipects the RMSE of three Fuzzy models

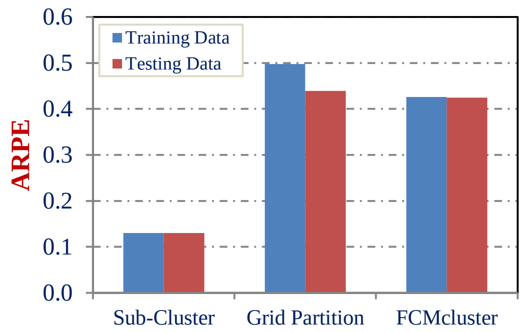

Figure 12. Dipects the ARPE of three Fuzzy models

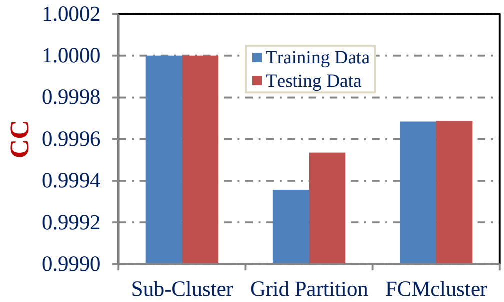

Figure 13. Depicts the CC of three Fuzzy models

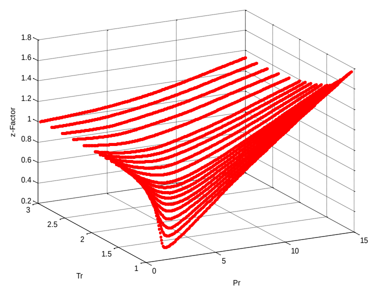

Figure 14. Experimental z-factor plot in 3D

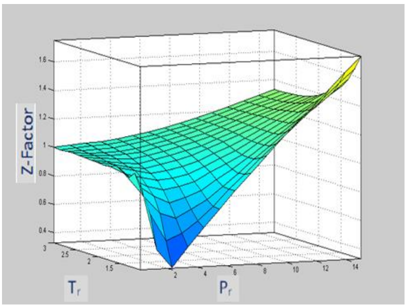

Figure 15. FL z-factor plot in 3D

Conclusions:

In this study, a robust and accurate technique is applied to predict the z-factor. Our conclusions are written as the following:

- Combination of the FL with the learning power of ANN can alleviate the problems associated with each of these techniques.
- FL System was proposed to estimate the z-factor of natural gases as a function of P_r and T_r.
- The developed FL with varies cluster techniques is more reliable and accurate than published empirical correlation and can be used in wide range of P_r and T_r.
- The FL technique improves the calculation of gas compressibility factor, especially at lower pseudo-reduced pressure values.
- The results show that the Fuzzy Logic with sub-cluster technique perform well with lower error (ARPE=0.13) and higher accuracy (R2=1) than the others.

Nomenclature:

P	Pressure,
T	Temperature,
V	Volume,
R	Universal gas constant,
Tc	Critical temperature,
Pc	Critical pressure,
Tpr	Pseudo-reduced temperature,
Ppr	Pseudo-reduced pressure,
Z	Compressibility factor,
n	Number of moles of the gas,
N	Number of data points

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دراسة مقارنة بين الأنظمة المنطقية الضبابية في حساب معامل انضغاطية الغازات

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الملخص: يعد حساب معامل انضغاطية الغاز (z-factor) من العوامل الأساسية في معظم حسابات النفط والغاز .ونظرا لغياب المعلومات تستخدم طرائق التكرار في حساب معامل انضغاطية الغازات. ولكن هذه الطرائق تعد أكثر تعقيدا ولها معاملات كثيرة والتي تحتاج الي خطوات حسابية كثيرة. إضافة لذلك فإن الدقة لهذه الطرائق تصبح غير كافية لحساب معامل انضغاط الغاز. إن الهدف من هذه الدراسة هو اختبار أنواع مختلفة من المنطق الغامض للحصول علي طريقة سهلة وأكثر دقة. المنطق الغامض لديه ثلاثة أنواع من خوارزمية التصنيف وهى,(Fuzzy c-means (FCM و Grid Partition (GP) و .(Sub-Clustering (SC هذه الخوارزميات للمنطق الغامض تم مقارنتها مع الطرائق التكرارية لاختبار ادائها ومقدرتها على حساب معامل انضغاط الغاز. ولأجل هذه الدراسة تم جمع 6500 نقطة من حقول مختلفة من الشرق الأوسط بعضها تم نشرها وبعضها الاخر لم تنشر. لقد لوحظ أن الأنواع المختلفة من المنطق الغامض المطور أكثر مقدرة ودقة على حساب معامل انضغاطية الغاز مقارنة مع الطرائق التكرارية وباستخدام مدى كبير للضغوط ودرجات الحرارة الزائفة. النتيجة توضح ان المنطق الغامض باستخدام خوارزمية (SC)حقق أفضل أداء بأقل متوسط خطأ نسبي يساوي (0.13%) واعلى معامل ارتباط ويساوي (1).

كلمات مفتاحية: الذكاء الصناعي ، المنطق الضبابي ، انضغاطية الغازات.