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Article

Determination of the Gas–Oil Ratio below the Bubble Point Pressure Using the Adaptive Neuro-Fuzzy Inference System (ANFIS)

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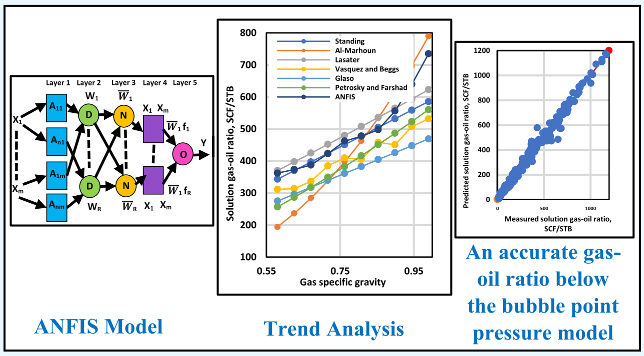
ABSTRACT: Determining the solution gas–oil ratio (R_s) below the bubble point is a vital requirement that aids in multiple production engineering and reservoir analysis issues. Currently, there are some models available for the determination of the solution gas–oil ratio under the bubble point. However, they still may prove unreliable due to the applied assumptions and their specification to operate only under a particular range of data. In this study, the neuro-fuzzy, i.e., the adaptive neuro-fuzzy inference system (ANFIS) approach, is utilized to develop an accurate and dependable model for determining the R_s below the bubble point pressure. A total of 376 pressure–volume–temperature datasets from Sudanese oil fields were used to establish the proposed ANFIS model. The trend analysis was applied to affirm the proper relationships between the inputs and outputs. Furthermore, using different statistical error analyses, the developed model was benchmarked against widely used empirical methods to evaluate the proposed method's performance in predicting the R_s at pressures below the bubble point. The proposed ANFIS model performs with an average absolute percent relative error of 10.60% and a correlation coefficient of 99.04%, surpassing the previously studied correlations.



1. INTRODUCTION

The solution gas–oil ratio (GOR) is the quantity of gas dissolved at reservoir pressures in reservoir fluids.[1] This term can also be described as the ratio of the gas volume that comes from the produced oil (or water) at atmospheric pressure—measured in standard cubic feet (SCF)—to the volume of oil produced after the dissolved gas has evolved from it at the surface, measured in STB.[2]

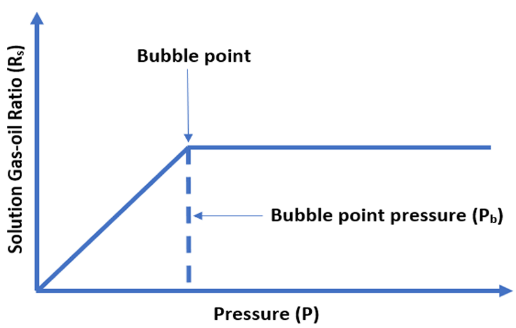


Figure 1. Typical trend of solution GOR versus pressure.[6]

The solution gas–oil ratio (R_s) tends to be higher in heavy oil when compared to light oil. A ratio value of 0 SCF/STB for dead oil (where no dissolved gas exists) is found, whereas a value in the region of 2100 SCF/STB is actual for very light oil.[3] The solution gas–oil ratio tends to increase linearly until the bubble point pressure is reached.[4] The bubble point pressure (BPP) is defined according to ref 5 as "the maximum pressure at which the first gas appears". Above the bubble point, the R_s have a constant value as no gas is released from the oil as it is still contained in the reservoir (Figure 1).

The usual scenario experienced in most oil reservoirs is where the pressures are usually higher than the bubble point pressure. There is no evolution of gas from oil as it drops from its P_i (initial reservoir pressure) to P_b (bubble point pressure). This results in the gas solubility to remain constant. The speed at which R_s lowers and its behavior are very convoluted and are dependent on various reservoir fluid properties as proposed by many authors.[7]

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Table 1. Input Parameters Were Used to Determine the R_s for the Previous and Proposed ANFIS Models

Model	Parameters						Average absolute percent relative error (%)
	Reservoir pressure	Bubble point pressure	Oil gravity API	Gas specific gravity	Gas-oil ratio at bubble point pressure	Reservoir temperature	
Standing [8]	√		√	√		√	
Vasquez and Beggs [9]	√		√	√		√	
Glaso [10]	√		√	√		√	
Al-Marhoun [11]	√		√	√		√	
Lasater [12]	√		√	√		√	
Petrosky and Farshad [13]	√		√	√		√	
Hassan [7]	√	√	√	√	√	√	5.04
Bebaha [14]	√		√	√		√	11.93
Baniasadi et al. [15]		√	√	√			23.15
Tohidi-Hosseini et al. [16]		√	√	√		√	15.94
Bahadori [6]		√	√	√		√	1.73

2. BACKGROUND

The computation of the solution gas−oil ratio (R_s) requires first the determination of the parameters involved in generating the R_s value. This was done by reviewing past research papers to identify the most vital parameters in determining the R_s value. The previous and the proposed ANFIS models' input parameters are shown in Table 1.

Therefore, based on the above analysis, the most consistently used parameters are the reservoir pressure, oil gravity (API), gas specific gravity (γ_g), and reservoir temperature (T). Henceforth, these parameters shall be used as the input parameters to predict the R_s at pressures below the bubble point pressure.

The results of this work are compared against the previously developed models for estimating the R_s at pressures below the bubble point pressure.

Standing's[8] graphical correlation was introduced to determine the solution gas−oil ratio (R_s) using 105 experimentally obtained data points. These data points were from California crude oil and natural gases. The determination of the solution gas−oil ratio was based on pressure, γ_g, API gravity, and temperature.[8]

Lasater's[12] correlation was introduced in 1958 using 158 experimentally measured datasets. These data were obtained from systems produced in Canada, Western and the Mid-Continental United States, and South America.[12]

Vasquez and Beggs'[9] empirical correlation was presented to improve the solution gas−oil ratio (R_s) estimation using over 5000 measured solution gas−oil ratio data points from various regions of the world. The acquired data were separated based on their API gravity.[9]

Glaso's[10] correlation was developed through the study of 45 samples that were obtained from the North Sea crude. The calculated solution gas−oil ratio depends on API gravity, pressure, temperature, and specific gas.[10]

Al-Marhoun's[11] correlation was developed from 75 bottom hole fluid samples (crude oil) from 62 reservoirs in the Middle East. The development of this correlation was based on nonlinear multiple regression analysis and a trial and error method.[11]

Petrosky and Farshad's[13] correlation was developed for Gulf of Mexico crudes; here, 90 fluid samples were obtained from offshore regions in Texas and Louisiana. The development of this correlation was to take Standing's correlation mentioned earlier as the basis in the development of the coefficients for the correlation. Next, nonlinear regression gave the correlation model maximum resilience and achieved the most acceptable empirical relation possible with the data set in hand.[13]

Nowadays, AI-based models have become a hot topic in engineering applications and are efficiently applied in many petroleum engineering calculations.[14−16] Deep learning and gradient boosting methods were successfully conducted to determine complex carbonate rock's permeability, capillary pressure, relative permeability, and the optimum operational conditions for CO_2 foam enhanced oil recovery.[17−23] Adaptive neuro-fuzzy inference systems (ANFIS), artificial neural network (ANN), fuzzy logic, and group method of data handling techniques have been effective in obtaining the mineralogy of organic-rich shales, the oil formation volume factor, the fractured well productivity, the natural gas density of pure and mixed hydrocarbons, the breakdown pressure of unconventional reservoirs, and the critical total drawdown for the sand production.[24−30]

The neuro-fuzzy system or ANFIS combines two intelligent systems, namely, fuzzy logic and artificial neural network. Zadeh first introduced fuzzy logic (FL) or fuzzy sets in 1965.[31] This tool can be utilized to solve highly complex problems in which the formulation of a mathematical model may prove to be too difficult or even impossible to construct.[32] Fuzzy logic expands the Boolean rationale (zeroes and ones), where it is the utilization of perceived statistical techniques. It is developed to deal with the concept of partial or incomplete truth whereby the values fall between the whole truth (one) and absolute false (zeroes).[33]

The application of the fuzzy logic in the petroleum industry can be seen in several cases, namely, in controlling the pressure of fracturing fluid in its characterization facility,[34] risk analysis for enhanced oil recovery,[35] and the petroleum separation process.[36] Zamani et al.[37] used the ANFIS method without using trend analysis to predict the R_s at the bubble point pressure (SCF/STB) based on the bubble point pressure (P_b), γ_g, API, and T using 157 datasets from Iranian fields. Figure 1 shows the R_s at and below P_b. The R_s at P_b (SCF/STB) as a function of P_b, γ_g, API, and T was also determined, utilizing 1136 data points from the literature.[38] The ANFIS model without utilizing the trend analysis was also utilized to determine the R_s at P_b (SCF/STB).[38] The novelty of this study is applying the ANFIS model with trend analysis to predict the R_s at pressures below P_b accurately and robustly. Three hundred seventy-six datasets from Sudanese oil fields include the parameters, i.e., the reservoir pressure, API, γ_g, and T as inputs and the R_s at pressures below P_b (SCF/STB) as outputs were used to develop the proposed ANFIS model. In this study, the trend analysis was used with the ANFIS model to prove the proper relationships between the inputs and the R_s at pressures below P_b (SCF/STB) to indicate the correct physical behavior.

3. METHODOLOGY

3.1. Data Collection and Pre-processing. The datasets used in this study were obtained from Sudanese oil fields. A total of 376 datasets include the parameters, i.e., reservoir pressure, psi; oil gravity, API; gas specific gravity; and reservoir temperature, °F, as inputs and the solution gas−oil ratio, SCF/STB, at a pressure below bubble point pressure as outputs. The statistical description of the collected data is shown in Table 2.

Table 2. Statistical Description of the Collected Datasets

parameter	pressure, psi	oil gravity, API	gas specific gravity	temperature, °F	solution gas−oil ratio, SCF/STB
minimum	115.80	9.50	0.5200	69.98	10.79
maximum	7126.97	53.40	1.0400	294.08	1764.04
mean	1591.20	31.51	0.7826	164.44	393.04
median	1422.00	32.20	0.7680	170.06	322.75
mode	800.02	33.00	0.7500	170.06	100.00
standard deviation	1015.65	9.53	0.0894	46.91	331.64
kurtosis	1.54	−0.37	0.3788	−0.20	1.83
skewness	0.87	−0.36	0.2436	0.39	1.29

Table 3. Statistical Description of the Clean Datasets

parameter	pressure, psi	oil gravity, API	gas specific gravity	temperature, °F	solution gas−oil ratio, SCF/STB
minimum	115.80	10.00	0.5800	80.06	16.12
maximum	4086.85	53.40	0.9900	294.08	1206.74
mean	1503.02	31.12	0.7804	164.72	357.96
median	1393.49	32.20	0.7590	170.06	297.47
mode	800.02	33.00	0.7500	170.06	47.02
standard deviation	930.03	9.60	0.0785	44.91	282.89
kurtosis	−0.55	−0.43	−0.1589	−0.17	−0.07
skewness	0.54	−0.41	0.2755	0.43	0.84

The box and whisker plotting method was applied to remove the outliers to clean the collected datasets. The box and whisker plot was explained in Alakbari et al.'s study.[22] Table 3 presents the statistical description of the clean datasets. After that, the datasets were divided into subsections: 70% training and 30% testing to build the ANFIS model.

3.2. Neuro-Fuzzy Approach. The neuro-fuzzy approach can be further divided into several systems; however, for this research paper, the ANFIS structure introduced by Takagi-Sugeno that falls under the hybrid neuro-fuzzy is used. The structure of ANFIS usually consists of five layers (Figure 2). The input variables are mapped relative to each membership function in the first layer. The second layer is where the operator T-norm is fixated to calculate the antecedents of the rules. The rule strength is normalized in the third layer, while the fourth layer determines the consequents of the rules. The fifth and last year, also called the output layer, determines the overall output as the summation of all incoming signals.[39]

The ANN, on the other hand, can be described as a conceptual model inspired by the structure and behavior of neurons of the human brain.[40] The composition of this network includes a large number of highly interconnected elements working as one to solve a particular problem. Added on by 40 on the ANN "is an information-computing system with particular performance characteristics in conjunction with biological neural networks". The application of the artificial neural network in the oil and gas industry can be seen in several instances, namely, petroleum reservoir characterization,[41] multiwell field development,[42] and prediction of water saturation.[43]

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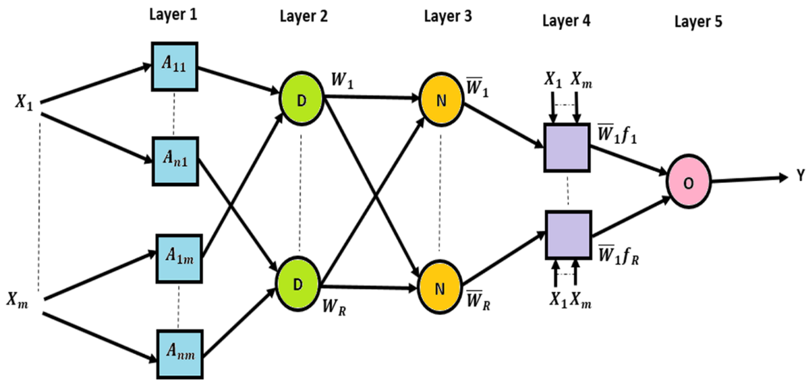

Figure 2. ANFIS structure.

Table 4. Optimized Parameters for the Proposed ANFIS Model

parameter	description/value
fuzzy structure	Sugeno-type
initial FIS for training	genfis2
membership function type	dsigmf
cluster center's range of influence	0.459
number of inputs	4
number of outputs	1
optimization method	hybrid
number of fuzzy rules	10
training epoch number	44
clustering radius	0.43200002
step size decrease rate	0.2
step size increase rate	2

The intelligent techniques presented previously, namely, the FL and ANN, are suited for particular problems but not for others when acting individually. For instance, the ANN excels in identifying patterns but fails to explain how the specific decision was made. On the other hand, the FL excels when working with inaccurate data and explaining how the decision was reached. However, the rules used in making those decisions cannot be obtained automatically. Therefore, to overcome these limitations, the development of intelligent hybrid systems combines two or more intelligent techniques. Thus, the combination of the ANN and FL intelligent techniques gives idealistic prediction and is called a neuro-fuzzy system used for this research study.[44] Figure 2 shows the ANFIS structure.[45]

The MATLAB software was used to construct and develop the neuro-fuzzy model to estimate the solution gas—oil ratio(R_s) under the bubble point pressure.

The redistributed PVT datasets were first trained to understand the connection or relationship among the input parameters to reach a particular output.

The developed training model was then tested with data that the model had not encountered during the training phase. This testing dictates the model's performance and allows the authors to assess its performance.

The following training options have to be optimized to develop the optimal model. This is a trial and error process whereby different combinations of the training options may be required to arrive at the best possible model (Table 4).

3.3. Trend Analysis. The effects of each parameter on the solution gas—oil ratio under the bubble point are assessed by keeping the other parameters constant. This study can be termed trend analysis, and the purpose of conducting this analysis is to ensure whether the developed model corresponds to the correct pattern.

4. RESULTS AND DISCUSSION

4.1. Model for Solution Gas—Oil Ratio below Bubble Point Pressure. The main aim of this study is to build a model that can generate the solution gas—oil ratio under the bubble point pressure for oil fields that match those obtained through experimentation. Statistical error analysis such as AAPRE, average percentage relative error (APRE), maximum absolute percent relative error (E_{max}), minimum absolute

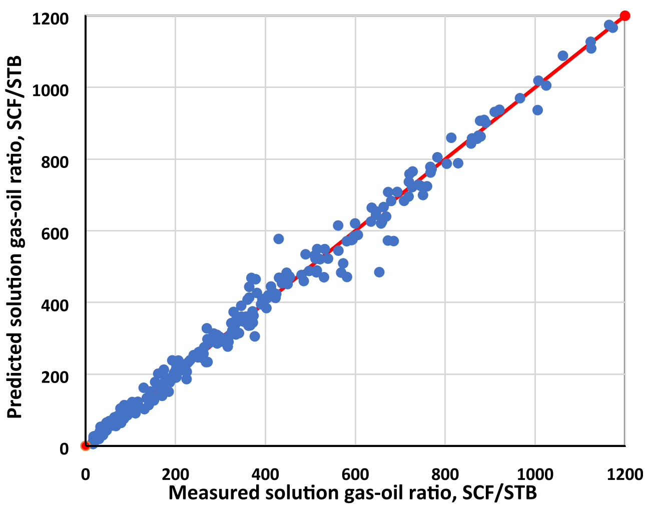

Figure 3. Cross plot of training datasets using the proposed ANFIS model.

Table 5. Statistical Error Analysis of the ANFIS Model for Predicting R_s

datasets	APRE (%)	AAPRE (%)	E_{max} (%)	E_{min} (%)	RMSE (SCF/STB)	R (%)	STD (SCF/STB)
training	0.45	9.44	169.25	0.020	17.30	99.41	14.49
testing	0.09	10.60	43.77	0.194	13.70	99.04	8.68

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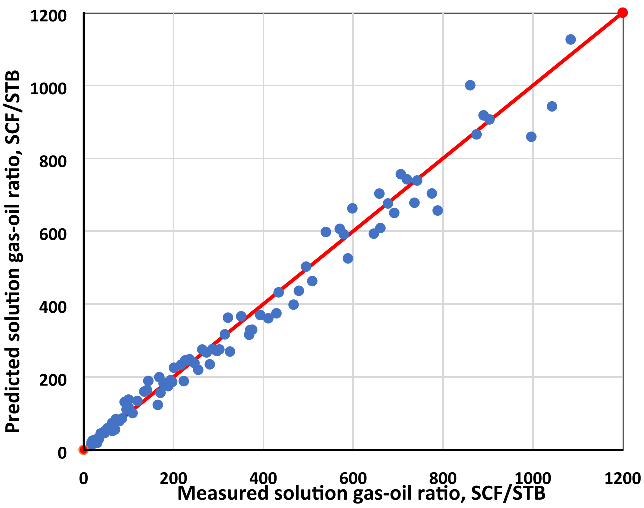

Figure 4. Cross plot of testing datasets using the proposed ANFIS model.

percent relative error (E_{min}), root-mean-square error (RMSE), standard deviation (SD), and (R) have been conducted to assess the ANFIS model. As shown in Table 5, the proposed ANFIS model can estimate the R_s with high accuracy for the training and testing datasets. Figures 3 and 4 show the cross plotting for the training and testing ANFIS model datasets, and it is apparent that there is a high match between the observed and predicted values of the R_s. The statistical error analysis and cross plotting indicate that the proposed ANFIS model can accurately find the R_s for training and testing datasets. The main accuracy indictors are AAPRE and R and are closed for the training and testing datasets to overcome the overfitting and underfitting issues. The proposed ANFIS model has AAPRE of 9.44 and 10.60% and R of 99.41 and 99.04% for training and testing datasets, respectively. As a result, the performance of the proposed ANFIS model was improved to determine the R_s.

4.2. Trend Analysis Results. Figures 5−8 show the reservoir pressure, oil gravity, gas specific gravity, and reservoir temperature trend analysis for the proposed ANFIS model. As displayed in Figure 5, increasing the reservoir pressure increases the R_s. All models follow the correct trend of the reservoir pressure. The proposed ANFIS model also applied the proper relationship between the reservoir pressure and the R_s. The R_s was increased by expanding oil gravity to show the adequate trend analysis for all published models and the proposed ANFIS model (Figure 6). All published models and the proposed ANFIS model also follow the correct gas specific gravity trend analysis (Figure 7). However, Figure 8 displays the trend analysis of the reservoir temperature. As seen in the figure, growing the reservoir temperature decreases the R_s. All previous models and the proposed ANFIS model indicate the proper reservoir temperature trend. Therefore, all previously studied correlations, i.e., Standing,[8] Al-Marhoun,[11] Lasater,[12] Vasquez and Beggs,[9] Glaso,[10] and Petrosky and Farshad,[13] and the proposed ANFIS model are following the correct reservoir pressure, oil gravity, gas specific gravity, and reservoir temperature trends analyses. The study of the trend analyses indicates the proper relationships between all inputs and the R_s to prove that the proposed ANFIS can robustly predict the R_s. In conclusion, the trend analysis study evaluates the proposed ANFIS model to increase its performance.

4.3. Comparison of the New Model to the Previous Correlations. The testing datasets of the neuro-fuzzy model were compared against six widely used correlations, namely, Standing,[8] Vasquez and Beggs,[9] Al-Marhoun,[11] Lasater,[12] Glaso,[10] and Petrosky and Farshad[13] correlations (Table 6). The statistical error analyses were computed to compare the best-selected correlations and proposed ANFIS models. The models are ranked based on the AAPRE, i.e., from low to high values, and R, i.e., from high to low values. The first rank model is the proposed ANFIS model with the lowest AAPRE of 10.60% and the highest R of 99.04%. The second rank model is Standing[8] correlation with an AAPRE of 12.02% and an R of 98.79%. The Petrosky and Farshad correlation has the highest AAPRE in the region of 43.78% and an R of 97.83%, and it fails to predict the solution gas−oil ratio with acceptable accuracy. The other correlations, namely, Vasquez and Beggs,[9] Glaso,[10] Al-Marhoun,[11] and Lasater,[12] have AAPRE in

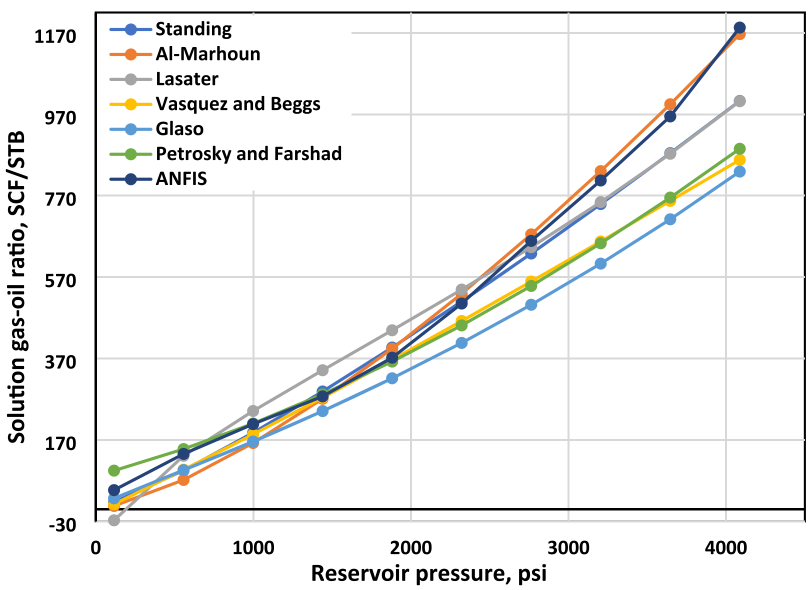

Figure 5. Effect of reservoir pressure on GOR in the previous models and neuro-fuzzy model.

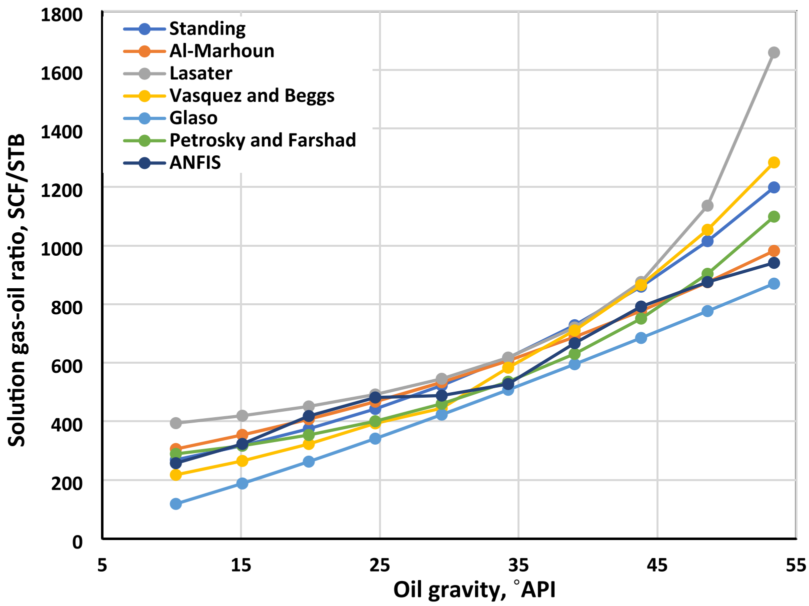

Figure 6. Effect of oil gravity on GOR in the previous models and neuro-fuzzy model.

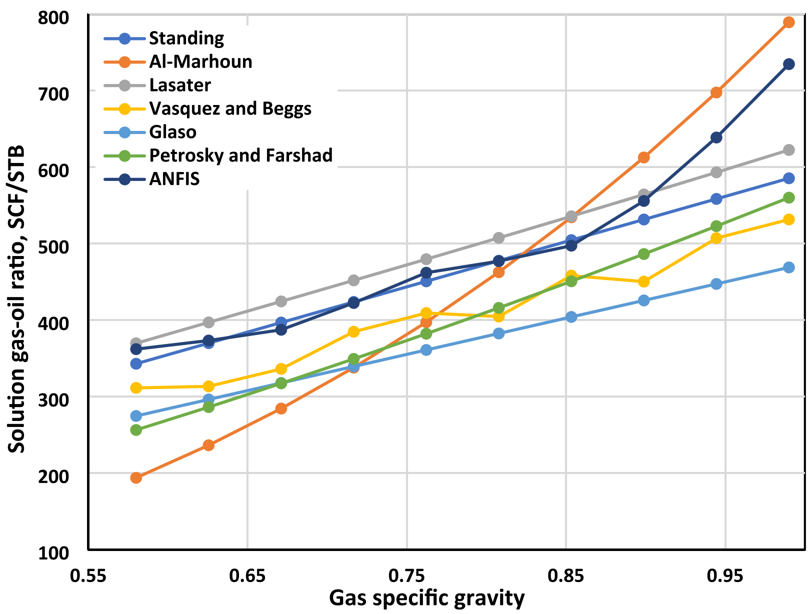

Figure 7. Effect of gas specific gravity on GOR in the previous models and neuro-fuzzy model.

(16.35−28.93)%, which provides a better estimation than the Petrosky and Farshad correlation but still falls short when compared to the neuro-fuzzy model. It can be concluded that the proposed ANFIS model can produce results with higher accuracy than the other correlations presented in this study.

5. CONCLUSIONS

In conclusion, this research has proven the capability of the neuro-fuzzy (ANFIS) model to deliver accurate determination of the solution gas−oil ratio (R_s) at pressures below the bubble point. This model can produce results with an AAPRE of 10.60% and a correlation coefficient of 99.04%, surpassing the results produced by the best-in-industry correlations investigated in this study. This has provided validation of the capability of the neuro-fuzzy model to map the relationship between the input parameters and the output (R_s) successfully. Furthermore, the model has also been proven to be physically sound as the trend analysis conducted using the model matches those generated using correlations. The trend analysis study demonstrates the correct relationships between all inputs and the output, i.e., R_s at pressures below the bubble point to represent the proper physical behavior. The statistical error analyses for the training and testing datasets indicate that the proposed ANFIS model has high accuracy and no fitting associated issues to predict the R_s accurately and robustly.

This model is recommended to be applied within the same range of data input to develop the model with matching geological properties. Using this model for the first well for a particular virgin field would not be advisable since developing the neuro-fuzzy model requires calibration with actual field data.

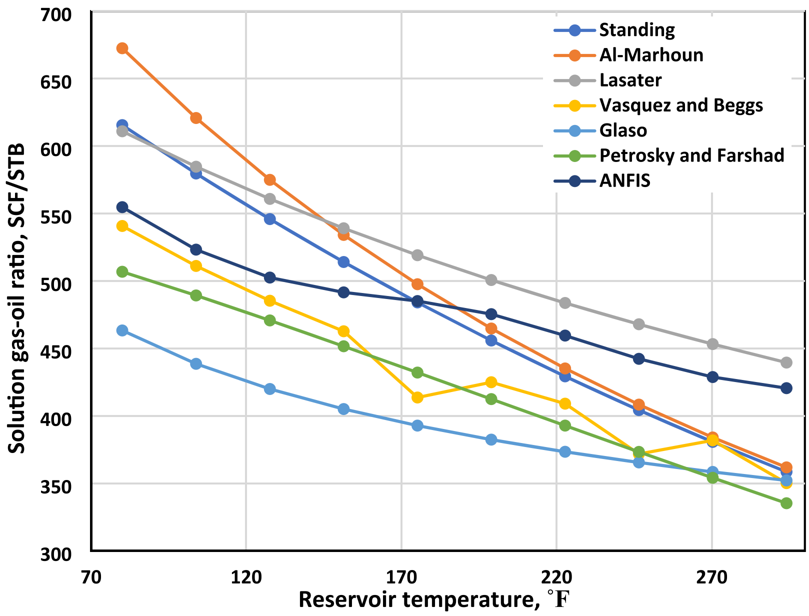

Figure 8. Effect of reservoir temperature on GOR in the previous models and neuro-fuzzy model.

Table 6. Comparison of the Proposed ANFIS Model and the Previously Used Correlations

rank	model	APRE (%)	AAPRE (%)	E_{max} (%)	E_{min} (%)	RMSE (SCF/STB)	R (%)	STD (SCF/STB)
1	ANFIS	0.09	10.60	43.77	0.194	13.70	99.04	8.68
2	Standing[8]	−0.06	12.02	41.60	0.702	15.32	98.79	9.50
3	Vasquez and Beggs[9]	−8.01	16.35	44.69	0.065	20.01	98.02	11.55
4	Glaso[10]	−12.70	23.84	100.18	0.681	30.47	97.88	18.97
5	Al-Marhoun[11]	−24.83	26.75	55.68	0.079	30.86	97.79	15.40
6	Lasater[12]	15.12	28.93	288.16	0.087	49.51	98.31	40.18
7	Petrosky and Farshad[13]	30.08	43.78	448.32	0.210	84.12	97.83	71.83

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsomega.2c01496.

Statistical error analysis equations (PDF)

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Notes

The authors declare no competing financial interest.

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