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

Mohammed Abdalla Ayoub Mohammed,* Fahd Saeed Alakbari, Clarence Prebla Nathan, and Mysara Eissa Mohyaldinn

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. 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.

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. The solution gas–oil ratio tends to increase linearly until the bubble point pressure is reached. 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.

Received: March 13, 2022
Accepted: April 7, 2022
Published: May 31, 2022
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 ($\gamma_g$), 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 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, $\gamma_g$ API gravity, and temperature.

Lasater's 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.

Vasquez and Beggs 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.

Glaso's 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.

Al-Marhoun's 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.
Petrosky and Farshad’s 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 Steding’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. 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 CO2 foam enhanced oil recovery.17 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 oil, and the oil formation volume factor.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 $P_d$ at the bubble point pressure (SCF/STB) based on the bubble point pressure ($P_b$), $\gamma_g$, API, and $T$ using 157 datasets from Iranian fields. Figure 1 shows the $R_1$ at and below $P_b$. The $R_1$ at $P_b$ (SCF/STB) as a function of $P_b$, $\gamma_g$, 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 $R_1$ at $P_b$ (SCF/STB).38 The novelty of this study is applying the ANFIS model with trend analysis to predict the $R_1$ 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, $\gamma_g$ and $T$ as inputs and the $R_1$ 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 $R_1$ 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.

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 factored 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 multwell field development,42 and prediction of water saturation.43

| 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 | 1391.20 | 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 | 313.64 |

| 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 | skewness |
|---------|---------|
| −0.55  | −0.43 |

The ANFIS structure introduced by Takagi-Sugeno was utilized to predict the $R_1$ at pressures below $P_b$ (SCF/STB) as a function of $P_b$, $\gamma_g$, API, and $T$ using 157 datasets from Iranian fields. Figure 1 shows the $R_1$ at and below $P_b$. The $R_1$ at $P_b$ (SCF/STB) as a function of $P_b$, $\gamma_g$, API, and $T$ was also determined, utilizing 1136 data points from the literature. The ANFIS model without utilizing the trend analysis was also utilized to determine the $R_1$ at $P_b$ (SCF/STB). The novelty of this study is applying the ANFIS model with trend analysis to predict the $R_1$ 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, $\gamma_g$ and $T$ as inputs and the $R_1$ 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 $R_1$ at pressures below $P_b$ (SCF/STB) to indicate the correct physical behavior.
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.

The MATLAB software was used to construct and develop the neuro-fuzzy model to estimate the solution gas–oil ratio 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 ($E_{\text{max}}$), minimum absolute percent relative error ($E_{\text{min}}$), and RMSE (SCF/STB) are used to evaluate the model's performance.

### Table 4. Optimized Parameters for the Proposed ANFIS Model

| parameter                   | description/value             |
|-----------------------------|-------------------------------|
| fuzzy structure             | Sugeno-type                   |
| initial FIS for training    | gensf2                        |
| 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                             |

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

| datasets | APRE (%) | AAPRE (%) | $E_{\text{max}}$ (%) | $E_{\text{min}}$ (%) | 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          |
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 Rs 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 Rs. The statistical error analysis and cross plotting indicate that the proposed ANFIS model can accurately find the Rs for training and testing datasets. The main accuracy indicators 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 Rs.

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 Rs. 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 Rs. The Rs 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 Rs. 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 Rs to prove that the proposed ANFIS can robustly predict the Rs. 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, Standing8 Vasquez and Beggs,9 Al-Marhoun,11 Lasater,12 Glaso,10 and Petrosky and Farshad13 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 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, Glaso,10 Al-Marhoun,11 and Lasater,12 have AAPRE in

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

Figure 5. Effect of reservoir pressure on GOR in the previous models and neuro-fuzzy model.
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 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.
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<sub>max</sub> (%) | E<sub>min</sub> (%) | 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<sup>8</sup>         | −0.06    | 12.02     | 41.60                | 0.702               | 15.32          | 98.79  | 9.50          |
| 3    | Vasquez and Beggs<sup>9</sup> | −8.01    | 16.35     | 44.69                | 0.065               | 20.01          | 98.02  | 11.55         |
| 4    | Glaso<sup>10</sup>           | −12.70   | 23.84     | 100.18               | 0.681               | 30.47          | 97.88  | 18.97         |
| 5    | Al-Marhoun<sup>11</sup>      | −24.83   | 26.75     | 55.68                | 0.079               | 30.86          | 97.79  | 15.40         |
| 6    | Lasater<sup>12</sup>         | 15.12    | 28.93     | 288.16               | 0.087               | 49.51          | 98.31  | 40.18         |
| 7    | Petrosky and Farshad<sup>13</sup> | 30.08    | 43.78     | 448.32               | 0.210               | 84.12          | 97.83  | 71.83         |

Notes
The authors declare no competing financial interest.

ACKNOWLEDGMENTS
The authors would like to express their profound gratitude to the Universiti Teknologi PETRONAS (UTP) for supporting this study under YUTP-Grant cost centre 015LC0-232.

REFERENCES
(1) Ahmed, T. Equations of State and PVT Analysis; Elsevier, 2013.
(2) Meehan, D. N. Advanced Reservoir Management and Engineering; Gulf Professional, 2012.
(3) Valkó, P. P.; McCain, W. D., Jr. Reservoir Oil Bubblepoint Pressures Revisited; Solution Gas−Oil Ratios and Surface Gas Specific Gravities. J. Pet. Sci. Eng. 2003, 37, 153−169.
(4) Elmabrouk, S.; Shirif, E. Prediction of Bubblepoint Solution Gas/Oil Ratio in the Absence of a PVT Analysis. Braz. J. Pet. Gas 2011, 5, 227.
(5) Ahmadi, M. A.; Zendejboudi, S.; James, L. A.; Elkamel, A.; Dusseault, M.; Chatziz, I.; Lohi, A. New Tools to Determine Bubble Point Pressure of Crude Oils: Experimental and Modeling Study. J. Pet. Sci. Eng. 2014, 123, 207−216.
(6) Bahadori, A. Fluid Phase Behavior for Conventional and Unconventional Oil and Gas Reservoirs; Gulf Professional Publishing, 2016.
(7) Hassan, O. F. Correlation for Solution Gas-Oil Ratio of Iraqi Oils at Pressures below the Bubble Point Pressure. Iraqi J. Chem. Pet. Eng. 2011, 12, 1−8.
(8) Standing, M. B. A Pressure-Volume-Temperature Correlation for Mixtures of California Oils and Gases. In Drilling and Production Practice; American Petroleum Institute, 1947.

(9) Vasquez, M.; Beggs, H. D. Correlations for Fluid Physical Property Prediction. J. Pet. Technol. 1980, 32, 968–970.

(10) Glao, O. Generalized Pressure-Volume-Temperature Correlations. J. Pet. Technol. 1980, 32, 785–795.

(11) Al-Marhoun, M. A. PVT Correlations for Middle East Crude Oils. J. Pet. Technol. 1988, 40, 650–666.

(12) Lasater, J. A. Bubble Point Pressure Correlation. J. Pet. Technol. 1958, 10, 65–67.

(13) Petrosky, G. E.; Farshad, F. Pressure-Volume-Temperature Correlations for Gulf of Mexico Crude Oils. In SPE annual technical conference and exhibition; Society of Petroleum Engineers, 1993.

(14) Bebaha, M. Estimation of GOR at Reservoir Pressures Below Bubble Point Pressure Using GMDH (Group Method of Data Handling); Universiti Teknologi PETRONAS, 2014.

(15) Baniasadi, H.; Kamari, A.; Heidaranarbi, S.; Mohammadi, A. H.; Hemmati-Sarapardeh, A. Rapid Method for the Determination of Solution Gas-Oil Ratios of Petroleum Reservoir Fluids. J. Nat. Gas Sci. Eng. 2015, 24, 500–509.

(16) Tohidi-Hosseini, S.-M.; Hajirezaie, S.; Hashemi-Doulatabadi, M.; Hemmati-Sarapardeh, A.; Mohammadi, A. H. Toward Prediction of Petroleum Reservoir Properties: A Rigorous Model for Estimation of Solution Gas-Oil Ratio. J. Nat. Gas Sci. Eng. 2016, 29, 506–516.

(17) Kasha, A. A.; Sakhaee-Pour, A.; Hussein, I. A. Machine Learning for Capillary Pressure Estimation. SPE Reservoir Eval. Eng. 2022, 1–20.

(18) Mathew, E. S.; Tembely, M.; ALAmeri, W.; Al-Shahbi, E. W.; Shaik, A. R. Application of Machine Learning to Interpret Steady State Drainage Relative Permeability Experiments. In Abu Dhabi International Petroleum Exhibition & Conference; OnePetro, 2021.

(19) Mathew, E. S.; Tembely, M.; ALAmeri, W.; Al-Shahbi, E. W.; Shaik, A. R. Artificial Intelligence Coreflooding Simulator for Special Core Data Analysis. SPE Reserv. Eval. Eng. 2021, 24, 780–808.

(20) Rizk, A. S.; Tembely, M.; ALAmeri, W.; Al-Shahbi, E. W. A Critical Literature Review on Rock Petrophysical Properties Estimation from Images Based on Direct Simulation and Machine Learning Techniques. In Abu Dhabi International Petroleum Exhibition & Conference; OnePetro, 2021.

(21) Tembely, M.; ALSumaiti, A. M.; ALameri, W. S. Machine and Deep Learning for Estimating the Permeability of Complex Carbonate Rock from X-Ray Micro-Computed Tomography. Energy Reports 2021, 7, 1460–1472.

(22) Alakbari, F. S.; Mohyaldinn, M. E.; Ayoub, M. A.; Muhsan, A. S. Deep Learning Approach for Robust Prediction of Reservoir Bubble Point Pressure. ACS Omega 2021, 24199.

(23) Iskandarov, J.; Fanourgakis, G.; ALameri, W.; Froudakis, G.; Karanikolos, G. Machine Learning Application to CO2 Foam Rheology. In Abu Dhabi International Petroleum Exhibition & Conference; OnePetro, 2021.

(24) Mustafa, A.; Tariq, Z.; Mahmoud, M.; Radwan, E. A.; Abdulraheem, A.; Abouelrefesh, M. O. Data-Driven Machine Learning Approach to Predict Mineralogy of Organic-Rich Shales: An Example from Qusaiba Shale, Rub’al Khali Basin, Saudi Arabia. Mar. Pet. Geol. 2022, 105495.

(25) Alakbari, F. S.; Mohyaldinn, M. E.; Ayoub, M. A.; Muhsan, A. S.; Hussein, I. A. Development of Oil Formation Volume Factor Model Using Adaptive Neuro-Fuzzy Inference Systems ANFIS. In SPE/IATMI Asia Pacific Oil & Gas Conference & Exhibition; OnePetro, 2021.

(26) Ayoub, M. A.; Elhadi, A.; Fatherhman, D.; Saleh, M. O.; Alakbari, F. S.; Mohyaldinn, M. E. A New Correlation for Accurate Prediction of Oil Formation Volume Factor at the Bubble Point Pressure Using Group Method of Data Handling Approach. J. Pet. Sci. Eng. 2022, 208, 109410.

(27) Alakbari, F. S.; Mohyaldinn, M. E.; Ayoub, M. A.; Muhsan, A. S.; Hussein, I. A. A Robust Fuzzy Logic-Based Model for Predicting the Critical Total Drawdown in Sand Production in Oil and Gas Wells. PLoS One 2021, 16, No. e0250466.

(28) Desouky, M.; Tariq, Z.; Alkoori, H.; Mahmoud, M.; Abdulraheem, A. Development of Machine Learning Based Propped Fracture Conductivity Correlations in Shale Formations. In SPE Middle East Oil & Gas Show and Conference; OnePetro, 2021.

(29) Tariq, Z.; Aljawad, M. S.; Murtaza, M.; Mahmoud, M.; Al-Shehri, D.; Abdulraheem, A. A Data-Driven Approach to Predict the Breakdown Pressure of the Tight and Unconventional Formation. In SPE Annual Technical Conference and Exhibition; OnePetro, 2021.

(30) Tariq, Z.; Hassan, A.; Waheed, U. B.; Mahmoud, M.; Al-Shehri, D.; Abdulraheem, A.; Molkeimer, E. M. A. A Data-Driven Machine Learning Approach to Predict the Natural Gas Density of Pure and Mixed Hydrocarbons. J. Energy Resour. Technol. 2021, 143, 92801.

(31) Zadeh, L. A. Fuzzy Sets, Fuzzy Logic, and Fuzzy Systems: Selected Papers by Lotfi A Zadeh (Advances in Fuzzy Systems-Applications and Theory); World Scientific: 1996; pp 394–432.

(32) Gray, A.; MacDonell, S. Applications of Fuzzy Logic to Software Metric Models for Development Effort Estimation. In 1997 Annual Meeting of the North American Fuzzy Information Processing Society-NAFIPS (Cat. No. 977782977); IEEE, 1997; pp 394–399.

(33) Abdulraheem, A.; Sabakh, E.; Ahmed, M.; Vantala, A.; Raharja, P. D.; Korvin, G. Estimation of Permeability from Wireline Logs in a Middle Eastern Carbonate Reservoir Using Fuzzy Logic. In SPE middle east oil and gas show and conference; OnePetro, 2007.

(34) Rivera, V. P. Fuzzy Logic Controls Pressure in Fracturing Fluid Characterization Facility. In Petroleum Computer Conference; OnePetro, 1994.

(35) Chung, T.-H.; Carroll, H. B.; Lindsey, R. Application of Fuzzy Expert Systems for EOR Project Risk Analysis. In SPE Annual Technical Conference and Exhibition; OnePetro, 1995.

(36) Liao, R. F.; Chan, C. W.; Hromek, J.; Huang, G. H.; He, L. Fuzzy Logic Control for a Petroleum Separation Process. Eng. Appl. Artif. Intell. 2008, 21, 835–845.

(37) Zamani, H. A.; Rafiee-Taghanaki, S.; Karimi, M.; Arabloo, M.; Dadashi, A. Implementing ANFIS for Prediction of Reservoir Oil Solution Gas-Oil Ratio. J. Nat. Gas Sci. Eng. 2015, 25, 325–334.

(38) Nabipour, N.; Baghban, A. Rigorous Model for Determination of PVT Properties of Crude Oil in Operational Conditions. Energy Sources, Part A 2019, 1–7.

(39) Vieira, J.; Dias, F. M.; Mota, A. Neuro-Fuzzy Systems: A Survey. In 5th WSEAS international conference on neural networks and applications; Udine, Italia; 2004; pp 87–92.

(40) Singh, S. Permeability Prediction Using Artificial Neural Network (ANN): A Case Study of Uinta Basin. In SPE annual technical conference and exhibition; OnePetro, 2005.

(41) Mohaghegh, S.; Arefi, R.; Ameri, S.; Aminian, K.; Nutter, R. Petroleum Reservoir Characterization with the Aid of Artificial Neural Networks. J. Pet. Sci. Eng. 1996, 16, 263–274.

(42) CentiIlmen, A.; Ertekin, T.; Grader, A. S. Applications of Neural Networks in Multiwell Field Development. In SPE annual technical conference and exhibition; OnePetro, 1999.

(43) Mardi, M.; Nurozi, H.; Edalatkhah, S. A Water Saturation Prediction Using Artificial Neural Networks and an Investigation on Cementation Factors and Saturation Exponent Variations in an Iranian Oil Well. Pet. Sci. Technol. 2012, 30, 425–434.

(44) Bradford, I. D. R.; Fuller, J.; Thompson, P. J.; Walsgrove, T. R. Benefits of Assessing the Solids Production Risk in a North Sea Reservoir Using Elastoplastic Modelling. In SPE/ISRMP rock mechanics in petroleum engineering; Society of Petroleum Engineers, 1998; DOI: 10.2118/47360-MS.

(45) Jang, J.-S. ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Trans. Syst. Man Cybern. 1993, 23, 665–685.