An Artificial Intelligent Approach for Black Oil PVT Properties

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Abstract. In absence of experimental oil fluid samples, it is usually difficult to select the suitable correlation to estimate oil properties. However, the accuracy of these empirical correlations has become insufficient for the best calculation. The main objective of this work is to test the capability of Particle Swarm Optimization with Neural Network (PSONN) and Neuro-Fuzzy (NFuzzy) approaches to predict oil properties with simply and accurately. The proposed approaches are developed based on clustering the oil data into the three groups (light, medium and heavy light oil). Over five hundred of black oil samples were collected from Middle East Field to train the hybrid models whereas additional oil data samples were selected to validate. The developed models used to estimate bubble points pressure (Pb), solution gas oil ratio at and below Pb, undersaturated oil compressibility, saturated formation volume factor, saturated and undersaturated density. The recommended guidelines and optimal configuration of the PSONN and NFuzzy models are developed to estimate any oil property in future. Statistical error analyses show that the proposed models exhibit a robust predictive capability for estimating oil properties. The validation results show the PSONN model achieve the lowest average absolute percent relative error (0.04, 2.89 and 1.0) for estimating formation volume factor, gas oil ratio and oil compressibility respectively whereas the NFuzzy model obtains the best approximation in oil density and bubble point pressure with average absolute percent relative error (0.18 and 0.97) respectively.

1. Introduction

The oil (pressure-volume-temperature) PVT data are often necessarily used in petroleum engineering calculations, such as, production calculations, material balance computations, reserve estimation, well test, and reservoir simulations. The primary source of oil PVT data obtained from laboratory measurements on samples collected from the surface or from the bottom of the wellbore. Therefore, in the absence of experimental measurements, the oil PVT data must be obtained by correlations. In addition, multitude of empirical correlations in literature will increase the difficulty to choose the proper correlation to calculate any oil properties.

This study focuses on the capabilities of Particle Swarm Optimization (PSO) [9] with Neural Network (NN) combination and NFuzzy approaches to predict oil PVT properties with simple and
accurate. The proposed model is based on clustering the oil PVT data into the three groups (heavy, medium and light oil). The previous groups were clustered according to gas oil ratio (GOR) values. The heavy oil has GOR range between (0-500), medium oil (500-1500) and light oil (1500-3200). Clustering the oil PVT data in this procedure will make their calculations in more sense, easy and accurate.

In this work, the proposed approach have been established for predicting bubble point pressure $P_b$, solution gas oil ratio ($R_s$), saturated formation volume factor ($B_o$), oil density ($\rho_o$) and oil compressibility ($C_o$) properties. Statistical error analysis was also used to test the validity of this developed technique. To confirm the precision of developed models, the measured and predicted oil PVT data are plotted against pressure.

2. Literature Review

2.1. Artificial Neural Networks Techniques

Gharbi [15] proposed new correlations for estimating isothermal compressibility coefficient for undersaturated crude oil based on multilayer perceptron trained by back-propagation with momentum algorithm from the regions of Middle East. Elsharkawy [12] developed radial neural network model to predict different oil PVT properties. Gharbi [16] introduced new models for estimating some oil PVT properties using Middle Eastern oil data. Gharbi [17] used 5200 data sets from the worldwide data to establish a neural network (NN) for predicting bubble point pressure and formation volume factor. Elsharkawy [13] applied a NN model and regression method to estimate oil viscosity based on Kuwaiti oil crude data. Al-Shammasi [6] developed neural network model to estimate bubble point pressure and oil formation volume factor. Al-Marhoun [5] used Saudi Arabian crudes to create NN model for estimating bubble point pressure and saturated formation volume factor. Fattah [14] collected the Middle East data to develop a NN approach for predicting both bubble point pressure and saturated formation volume factor. Osman [30] published two NN models to obtain different brine properties based on 1040 published data points. Sarit [31] used Indian crude oil to apply a NN model for predicting bubble point pressure, solution gas oil ratio formation volume factor and oil viscosity. Al-Khudafi [4] used ANFIS for estimating $K$-values to predict heptane’s plus fractions using more than 1340 data points. Moreover, the different Artificial Intelligence techniques were developed to predict $z$-factor, such as Kamyab [25], Mohagheghian [27], Shateri [32], Mohamadi-Baghmolaie [28] and Azizi [7]. Hajirezaie [19, 20] presented two separated approaches to estimate of hydrocarbon fluids viscosity. Adel Salem [1] developed different intelligent models to predict gas compressibility factor. Lately, Baarimah [8] proposed fuzzy logic technique to estimate reservoir oil PVT properties. Ghorbani [18] developed different AI to predict the bubble point pressure for Ahvaz oil field (Iran).

2.2. Hybrid Soft Computation Techniques

Yasin [34] proposed two models of fuzzy logic and neural network to estimate the reservoir oil viscosity using 98 data sets from Iranian reservoir data. El-Sebakhy [10] applied Neuro-Fuzzy model to predict bubble point pressure and formation volume factor based on 1225 data points. El-Sebakhy [11] used three different published oil PVT data to develop a support vector regression approach for predicting bubble point pressure. Sunday [32] applied an adaptive fuzzy inference system (ANFIS) to calculate bubble point pressure. Khoukhi [26] used genetic algorithm to optimize NN model to predict bubble point and oil formation volume factor. Al-Gathe [3] applied different hybrid AI techniques to predict bubble point pressure. Mohammad [29] used more than 750 data points to develop ANFIS models for predicting oil bubble point pressure. Hamada [21] and Al-Gathe [2] developed two separated PSONN approaches to estimate water saturation and choke size respectively.

According to the previous review, we can notice that a very few researchers developed hybrid AI techniques to estimate oil PVT properties. Also, the estimation of oil PVT properties displays the superiority of AI techniques over empirical correlations. Therefore, the objective of this study is to test
the capability of PSONN and NFuzzy approaches to predict oil PVT properties with simply and accurately. Then, the capability of these models is tested to identify which technique is the most suitable for oil PVT properties prediction.

3. Methodology

3.1. Data description
In this study, the most of experimental data collected from Middle East oil reservoir and the other from published work. Additional unpublished oil PVT data samples were selected to validate the proposed models. Table 1 shows the number data samples and the number of data points of each oil PVT properties. The input data were used to predict oil PVT properties are temperature (T), pressure (P), oil gravity, specific gravity, Rs, Bo, Pb, oil density (ρo) and oil compressibility (Co) and their ranges are summarized in Table 2. Table 3 describes additional oil PVT data that can be used to validate the developed models. These proposed models used 70% of data for training and 30% for testing. To avoid numerical difficulties during the oil PVT data computation, the data should be normalized and scaled to the range between -1 and 1 as the followed equation:

\[ Z = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \] ……… (1)

where Z is the normalized value and X is the original data and X_max, X_min are the maximum and minimum of the actual data respectively. The output data should be de-normalized to obtain the actual oil PVT data.

Table 1. Describes The Number of Oil PVT Simples.

| Property                                      | No. of samples | Data Points |
|-----------------------------------------------|----------------|-------------|
| Oil compressibility above Pb                  | 210            | 2142        |
| Oil density above Pb                          | 210            | 2142        |
| Oil density below Pb                          | 251            | 2581        |
| Undersaturated Formation volume factor        | 210            | 2142        |
| Saturated Formation volume factor             | 360            | 2910        |
| Solution gas oil ratio                        | 360            | 2910        |
| Bubble point pressure                         | 1440           | 1440        |

Table 2. Summarizes the oil PVT data Range.

| Property                          | Unit         | Undersaturated Co, ρo and Bo | Pb and Rs |
|-----------------------------------|--------------|------------------------------|-----------|
|                                   |              | Min | Max | Min | Max |          |          |
| T                                 | °F           | 70  | 304 | 69  | 2102|          |          |
| Oil gravity                       | °API         | 10  | 53  | 6   | 57  |          |          |
| Specific gravity                  |              | 0.624 | 1.789 | 0   | 3.83|          |          |
| Rs                                | scf/STB      | 7.9 | 7804 | 0.54 | 3074|          |          |
| P                                 | psia         | 58  | 7412 | 30  | 7127|          |          |
| Bo                                | bbl/STB      | 1.034 | 4.48 | 30  | 7127|          |          |
| Pb                                | psia         | 49  | 6359 | 30  | 7127|          |          |
| ρo                                | lb/cu ft     | 0.2242 | 0.9996 |     |     |          |          |
| Co                                | Psia-1       | 1.3E-7 | 1.8E-4 |     |     |          |          |

Table 3. Shows the validated database.

| Property | No. of samples | No. data points |
|----------|----------------|-----------------|
| Co       | 9              | 91              |
| Pb       | 20             | 20              |
| Rs       | 9              | 76              |
| ρo       | 9              | 165             |
| Bo       | 8              | 139             |
The oil PVT data can be classified into three groups according to the values of gas oil ratio: the heavy oil has GOR range between (0-500), medium oil (500-1500) and light oil (1500-3200). The criteria of graphical and statistical error analysis used in this study were average absolute percent relative error (AAPRE), the root mean square error (RMSE) and the correlation coefficient (CC).

3.2. Hybrid NFuzzy Model Development
The proposed NFuzzy model was developed by Takagi and Sugeno (Jang [23]). The NFuzzy called Adaptive Neural Inference System (ANFIS) was applied on earlier database to obtain the optimum configuration model for predicting oil PVT properties. The NFuzzy is the combination of artificial neural network (ANN) and Fuzzy models in training step in order to increase the ability of learning, Jang [23], [24]. The NFuzzy modifies the inappropriate properties of ANN and fuzzy model by applying the positive features of both model. The Subtractive Clustering (ANFIS-SC) algorithm was applied to generate a FIS on the data. A set of rules were extracted by using genfis2 function to determine antecedent membership functions. The diagram of NFuzzy model is shown in Figure 1.

![Figure 1. the Basic schematic structure of NFuzzy](image)

3.3. Hybrid PSONN Model Development
Particle swarm optimization (PSO) is a strong optimization approach based on the movement and intelligence of swarms. It develops to look for the optimal solution by simulating the movement and flocking of birds. The details about PSO approach were discussed by Eberhart and Dr. Kennedy [9]. The PSONN is the combination of the Neural Network (NN) with a PSO. The PSO algorithm displayed the convergence rapidly during the initial stages of a global search, whereas around global optimum, the search process will become very slow. Consequently, integrating NN and PSO can reach faster convergent speed around global optimum and increase the convergent accuracy at the same time. The procedure of PSONN has two steps: Firstly, the optimum connection weights and thresholds of the NN were obtained by PSO algorithm. Then, the learning rule and training algorithm of NN was run to adjust the final weights. The learning steps of the PSONN approach were explained in Figure 2. For more details about PSONN approach and their description is discussed in (Hamada [21]). In this work, the parameters of NN were adjusted by the PSO approach and the adopted NN has two layers. The transfer function of the first hidden layer was (tansig) whereas the other transfer function of the second hidden layer was (purelin).
4. Results and Discussion

4.1. Hybrid NFuzzy Model

The optimum NFuzzy configuration model is chosen according to the optimal radii and number of clusters. The different values of cluster radius are proposed and the black oil PVT properties were estimated. Then, the optimal radius was specified when NFuzzy was achieved the lowest AAPRE and the highest CC. Figure 3 shows an example of how the optimal radius was selected for oil compressibility model. Consequently, the specified radius of each black oil PVT properties is summarized in Table 4. The optimal configuration of the NFuzzy model in previous Table can be used as guidelines. These guidelines should be taken in consideration into any oil PVT properties calculation. Table 5 shows statistical analysis of NFuzzy model results for each oil PVT types and properties. The results show that the AAPRE will be decreased from heavy oil, medium oil to light oil for each oil PVT properties respectively.

![Figure 2. The basic PSO/NN procedure (Al-Gathe, 2019).](image)

![Figure 3. Optimal radii for oil compressibility NFuzzy model.](image)
Table 4. Optimal radii for each oil PVT properties.

| Oil Property                  | Heavy Oil | Medium Oil | Light Oil |
|-------------------------------|-----------|------------|-----------|
| Radii                         | 0.35      | 0.17       | 0.15      |
| No. of Cluster                | 18        | 18         | 31        |
| Solution Gas Oil Ratio at Pb  | Radii     | 0.13       | 0.16      | 0.32      |
| No. of Cluster                | 45        | 22         | 19        |
| Gas oil ratio below Pb        | Radii     | 0.13       | 0.19      | 0.17      |
| No. of Cluster                | 33        | 7          | 28        |
| Oil compressibility factor    | Radii     | 0.23       | 0.13      | 0.13      |
| No. of Cluster                | 78        | 20         | 19        |
| Oil density below Pb          | Radii     | 0.15       | 0.13      | 0.23      |
| No. of Cluster                | 48        | 40         | 9         |
| Oil density above Pb          | Radii     | 0.23       | 0.13      | 0.13      |
| No. of Cluster                | 78        | 20         | 19        |
| Saturated Bo                  | Radii     | 0.2        | 0.21      | 0.19      |
| No. of Cluster                | 14        | 13         | 28        |

Table 5. Statistical accuracy of NFuzzy model.

|                | Bo     | Sat. Oil density | Rs at Pb | Rs below Pb | Pb | Co |
|----------------|--------|------------------|----------|-------------|----|----|
| Heavy Oil      | AAPRE  | 1.62             | 38.41    | 55.52       | 23.38 | 30.77 | 5.9 |
|                | RMSE   | 2.43             | 223.03   | 262.28      | 51.29 | 64.95 | 18.96 |
|                | R²     | 0.945            | 0.949    | 0.916       | 0.959 | 0.907 | 0.966 |
| Medium Oil     | AAPRE  | 2.57             | 7.51     | 13.54       | 14.31 | 16.17 | 5.8  |
|                | RMSE   | 4.27             | 15.44    | 18.63       | 20.19 | 35.72 | 8.62 |
|                | R²     | 0.932            | 0.941    | 0.809       | 0.757 | 0.804 | 0.955 |
| Light Oil      | AAPRE  | 1.64             | 4.84     | 8.04        | 3.15  | 6.52  | 2.54 |
|                | RMSE   | 3.4              | 6.79     | 11.18       | 8.44  | 12.73 | 6.55 |
|                | R²     | 0.979            | 0.919    | 0.808       | 0.956 | 0.929 | 0.999 |

4.2. Hybrid PSOnn Model

Many of black oil samples are used to estimate the optimal PSOnn configuration for calculating any oil properties according to each cluster (heavy, medium and light). The optimal configuration of PSOnn model and guidelines are developed. These guidelines should be taken into consideration in any oil properties calculation. Table 6 explains the parameters of the optimal configuration of PSOnn model. The other parameter values are summarized in the Table 7. These parameters can be varied depending on oil PVT property types.

Number of dimension in PSOnn model is refers to number of weight and bias based on the dataset and the PSOnn model architecture.

Table 6. Shows the optimal configuration of PSOnn network.

| Parameter                          | Value |
|------------------------------------|-------|
| Number of hidden layers            | 2     |
| Number of hidden neurons           | 25    |
| Number of Max iteration            | 300   |
| Number of population (number of bird) | 300 |
| Inertia weight (w)                 | 0.7   |
| Cognitive parameter (c1)           | 0.5   |
| Social parameter (c2)              | 1.0   |
Table 7. Parameters used for running PSONN model.

| Parameter              | No. of parameters | Dimension | Max. velocity |
|------------------------|-------------------|-----------|---------------|
| Oil compressibility    | 8                 | 251       | 1.5           |
| Bubble point pressure  | 4                 | 151       | 3             |
| Solution gas oil ratio | 4                 | 151       | 3             |
| Oil density            | 8                 | 251       | 1.5           |

The developed hybrid PSONN model is used to determine the oil PVT properties. The statistical analysis is also applied to check the performance of the proposed approach according to measured data as shown in Table 8. Figure 4 presents the training of the network of Pb for the light oil types. Figure 5 and Figure 6 depict AAPRE comparison for both models.

Table 8. Training of the Network for PSONN Model.

|            | Bo | Sat. Oil density | Rs at Pb | Rs below Pb | Pb | Co |
|------------|----|-----------------|----------|-------------|----|----|
| Heavy Oil  | AAPRE | 1.42         | 20.79    | 54.33       | 20.2 | 24.54 | 1.79 |
|            | RMSE     | 2.2         | 179.8    | 349.1       | 60.3 | 56.34 | 2.72 |
|            | R²        | 0.955       | 0.989    | 0.955       | 0.975 | 0.947 | 0.997 |
| Medium Oil | AAPRE | 6.31         | 1.93     | 8.69        | 5.68 | 9.57 | 1.61 |
|            | RMSE     | 8.86        | 3.61     | 12.25       | 7.84 | 23.57 | 2.25 |
|            | R²        | 0.967       | 0.996    | 0.921       | 0.97 | 0.998 | 0.998 |
| Light Oil  | AAPRE | 0.74         | 0.92     | 0.61        | 0.84 | 1.17 | 0.79 |
|            | RMSE     | 1.02        | 1.53     | 1.38        | 1.15 | 1.86 | 1.02 |
|            | R²        | 0.998       | 0.996    | 0.998       | 0.999 | 0.998 | 1.0  |

Figure 4. Shows the training performance of PSONN model.
5. Validation

In order to examine the proposed techniques and validate its applicability, all the techniques are tested with new oil PVT samples that are not used to develop the earlier techniques.

In order to test and validate the reliability of the optimal configuration and guidelines of proposed approaches, the new available unpublished data were used. Both hybrid models (PSONN and NFuzzy) were applied to predict of the oil PVT properties. Figure 7 depicts the AAPRE of both models. These results confirm the capability of PSONN technique to estimate gas oil ratio and formation volume factor more accurate than NFuzzy model whereas the NFuzzy model was achieved the best in the rest of oil PVT properties.

For checking more the validity of these techniques, the predicted data are compared against the measured oil PVT properties. Here, only one example (oil A) was selected to explain. Figure 8 through Figure 12 compared predicted data versus actual data points. Figure 13 through Figure 16 also showed that an excellent agreement was found between the measured and the predicted values when both plot versus pressure. It is clear from the results that the two hybrid models performed better with higher CC and lower AAPRE.

**Figure 5.** Shows of AAPRE for PSONN model.  **Figure 6.** Shows of AAPRE for PSONN model.

**Figure 7.** Shows the AAPRE Error.  **Figure 8.** Comparison of actual versus predicted Co.
Figure 9. Comparison of actual versus predicted Pb values.

Figure 10. Comparison of actual versus predicted Rs values.

Figure 11. Comparison between actual and predicted density values.

Figure 12. Comparison of actual versus predicted Bo.

Figure 13. Actual and predicted Co above Pb (oil A).

Figure 14. Actual and predicted Rs (oil A).

Figure 15. Actual and predicted oil density (oil A).

Figure 16. Actual and predicted Bo (oil A).
6. Conclusions

The following conclusions can be made from this study:

1) Two hybrid approaches for predicting oil PVT properties are developed based on data clustering.
2) The proposed hybrid approaches can be programmed and integrated in any simulator to increase the accuracy of oil PVT properties.
3) The guidelines are added according to each oil PVT properties and should be taken into consideration in any oil PVT properties calculation.
4) Hybrid approaches are powerful tools which overcome imprecise, incompleteness and uncertainty existent in reservoir oil PVT parameters.
5) The hybrid techniques exhibited superior performance with lowest AAPRE and the highest correlation coefficients.

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