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An Intelligent Model for Estimating Bubble Point Oil Formation Volume Factor

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Abstract

In this study, using Adaptive Neuro-Fuzzy Inference System (ANFIS) an intelligent model was developed to predict bubble point oil formation volume factor (Bob) for Middle East crudes. A total of 429 data sets, included *Bob* and conventional PVT properties, were used. Among those, 286 and 143 data sets were selected randomly for constructing and testing the model, respectively. The mean squared errors and correlation coefficient (R^2) between predicted values from the modeling and experimental values in the test data were 0.0023 and 0.9731, respectively. The model, which promptitude and save in time and costs are its advantages, is more accurate than all of the previous empirical correlations.

Keywords: PVT; oil formation volume factor; Middle East; ANFIS.

1. Introduction

The accurate determination of the PVT properties of the reservoir fluid such as bubble point pressure, solution gas oil ratio (GOR) and oil formation volume factor (*Bo*) is necessary for the formation evaluation of hydrocarbon reserves, reservoir performance, production operations and the design of production facilities [1].

Substantially, PVT properties of the crude oil are determined from the laboratory PVT tests. In addition, several correlations have been developed which can be applied for estimation of PVT properties when the laboratory determination of the properties is impossible.

Bubble point oil formation volume factor (*Bob*) is defined as the volume of reservoir oil that would be occupied at bubble point pressure and reservoir temperature by one stock tank barrel oil plus any gas dissolved in the oil at the same pressure and temperature. Its evaluation is an essential step in reservoir performance calculations and design of various stages of oil field operations [2].

For estimation of *Bob*, several correlations have been developed for different regions. The correlations are listed in Table 1. However, due to regional changes in crude oil composition, none of the correlations can be applied as a universal one. On the other hand, laboratory determination of *Bob* is very expensive and time consuming.

In this study, using Adaptive Neuro-Fuzzy inference System (ANFIS), a model was proposed to predict the *Bob* for Middle East crudes. High accuracy, promptitude and save in time and cost are the advantages of the proposed intelligent model.

Table 1. Bubble point oil formation volume factor correlations

Num.	Date	Sample origin	Correlation	Author
1	1947	California, USA	$B_{ob} = a_1 + a_2\left[R_s\left(\gamma_g/\gamma_o\right)^{a_3} + a_4 T\right]^{a_5}$ $a_1 = 0.972$; $a_2 = 1.472e-4$; $a_3 = 0.5$; $a_4 = 1.25$; $a_5 = 1.175$	*Standing* [20]
2	1980	North Sea	$B_{ob} = 1 + 10^{[a_1 + a_2(\log G) - a_3(\log G)^2]}$ $G = R_s\left(\gamma_g/\gamma_o\right)^{a_4} + a_5 T$ $a_1 = -6.58511$; $a_2 = 2.91329$; $a_{3=}0.27683$; $a_4 = 0.526$; $a_5 = 0.968$	*Glaso* [13]
3	1988	Middle East	$B_{ob} = a_1 + a_2(T + 460) + a_3 M + a_3 M^2$ $M = R_s^{a_5}\gamma_o^{a_6}\gamma_g^{a_7}$ $a_1 = -0.497069$; $a_2 = 0.000862963$; $a_3 = 0.00182594$; $a_4 = 0.318099e-5$; $a_5 = 0.74239$; $a_6 = 0.323294$; $a_7 = -1.20204$	*Al-Marhoun* [8]
4	1988	–	Al -Marhoun (1988) New calculated constants $a_1 = 0.9657876$; $a_2 = 7.73e-4$; $a_3 = 4.8141e-5$; $a_4 = -6.8987e-10$; $a_5 = 1.2$; $a_6 = -0.147$; $a_7 = -5.222$	*Abdul-Majeed and Salman* [7]
5	1992	UAE	Al -Marhoun (1988) New calculated constants $a_1 = 0.0431935$; $a_2 = 0.00156667$; $a_3 = 0.00139775$; $a_4 = 0.380525e-5$; $a_5 = 0.773572$; $a_6 = 0.404020$; $a_7 = -0.882607$	*Dokla and Osman* [11]
6	1993	Gulf of Mexico	$B_{ob} = a_1 + a_2\left[{R_s}^{a_3}\left({\gamma_g}^{a_4}/{\gamma_o}^{a_5}\right) + a_6 T^{a_7}\right]^{a_8}$ $a_1 = 1.0113$; $a_2 = 7.2046e-5$; $a_3 = 0.3738$; $a_4 = 0.2914$; $a_5 = 0.6265$; $a_6 = 0.24626$; $a_7 = 0.5371$; $a_8 = 3.0936$	*Petrosky and Farshad* [19]
7	1996	Colombia	$B_{ob} = 1 + 10^{[a_1 + a_2(\log G) - a_3(\log G)^2]}$ $G = R_s^{a_4}\gamma_o^{a_5}\gamma_g^{a_6} + a_6 T$ $a_1 = -2.6541$; $a_2 = 0.5576$; $a_3 = 0.3331$; $a_4 = 0.5956$; $a_5 = 0.2369$; $a_6 = -1.3282$; $a_7 = 0.0976$	*Farshad* [12]
8	1992	Wordwide	$B_{ob} = 1 + a_1 R_s + a_2 R_s\left(\gamma_g/\gamma_o\right) + a_3 R_s(1-\gamma_o)(T-60) + a_4(T-60)$ $a_1 = 0.177342e-3$; $a_2 = 0.220163e-3$; $a_3 = 4.292580e-6$; $a_4 = 0.528707e-3$	*Al –Marhoun* [8]
9	1993	Malaysia	$B_{ob} = a_1 + a_2\left[R_s\left(\gamma_g/\gamma_o\right)^{a_3} + a_4 T\right]^{X}$ $X = b_1 + b_2\left(\gamma_{o,API}/\gamma_g\right) + b_3\gamma_g$ $a_1 = 0.972$; $a_2 = 1.472e-4$; $a_3 = 0.5$; $a_4 = 1.25$; $a_5 = 1.175$; $b_1 = 1.1663$; $b_2 = 0.762e-3$; $b_3 = -0.0399$	*Omar and Todd* [18]
10	1997	UAE	$B_{ob} = a_1 + a_2 R_s T/\gamma_o^2 a_1 = 1.22018$; $a_2 = 1.41e-6$	*Almehaideb* [20]
11	1992	Gulf of Suez ,Egypt	$B_{ob} = (a_1 + a_2 T)N$ $N = \exp[a_3 R_s + a_4(\gamma_o/\gamma_g)]$ $a_1 = 1.0031$; $a_2 = 0.0008$; $a_3 = 0.0004$; $a_4 = 0.0006$	*Macary and El – Batanoney* [17]
12	1994	Worldwide	$B_{ob} = a_1 + a_2\left[{R_s}^{a_3}\left({\gamma_{g\,100}}^{a_4}/{\gamma_o}^{a_5}\right) + a_6 T\right]^{a_7}$ $a_1 = 0.98496$; $a_2 = 0.0001$; $a_3 = 0.755$; $a_4 = 0.25$; $a_5 = 1.5$; $a_6 = 0.45$; $a_7 = 1.5$	*Kartoatmodjo and Schmidt* [16]
13	2001	Worldwide	$B_{ob} = 1 + 0.000412(R_s/\gamma_o) + 0.000650[(T-60)/\gamma_o]$	*Al-Shammasi* [9]
14	2005	Egypt	$B_{ob} = 0.0006R_{si} + 1.079$ $R_{si} = 23.94 + 1.101R_{sft}$ $R_{sft} = 69 + 1.071R_{sf1}$	*Hanafy* [14]
15	2007	Iran	$B_{ob} = 1 + 10A$ $A = -4.6862 + 1.5959\log Bob^* - 0.0566(\log Bob^*)^2$ $Bob^* = R_s\left(\gamma_g/\gamma_o\right)^{0.5946} + 1.7439T$	*Hemmati and Kharrat* [15]

2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) is one of the techniques of intelligent systems. It is a combination of fuzzy logic and neural networks which combines the advantages of both systems. For example, when the number of training pairs is small, the results from neural network system may be poor. In such conditions, if fuzzy systems are combined with neural network system, the results can improve [3]. An ANFIS system, which was first introduced by Jang in 1993, constructs a FIS whose membership function parameters are adjusted using a back propagation algorithm either alone or in combination with a least-squares type of method. This adjustment allows the fuzzy systems to learn from the data that they are modeling [4]. ANFIS is capable of mapping unseen inputs to their outputs by learning the rules from the previously seen data [5]. An ANFIS system has five layers including an input layer, an input MFs layer (for fuzzification of inputs), a rule layer, an output MFs layer (for defuzzification of outputs) and an output layer. Figure 1 shows the structure of an ANFIS system.

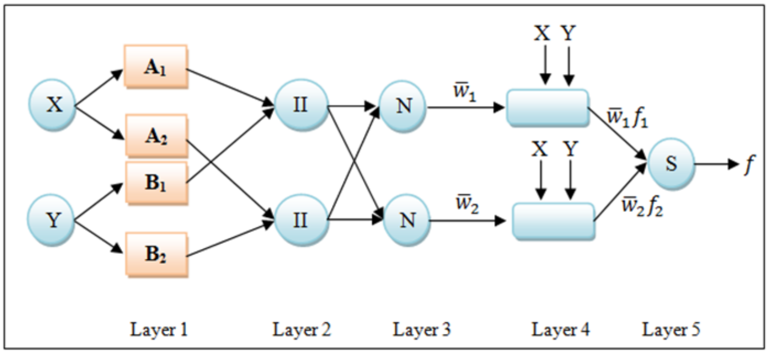

Figure 1. Structure of a simple ANFIS system

3. Data analysis

Different Middle East oil fields were selected for this study. From these oil fields, 429 laboratory PVT analyses were obtained and used to develop an intelligent model for prediction of bubble point oil formation volume factor for Middle East crude oils. The data consist of the reservoir temperature (T), gas specific gravity (γ_g), solution gas oil ratio (Rs) etc within the range as shown in Table 2.

Table 2. PVT properties of samples used in this study

Number of Points	PVT Property	Mean	Range
429	Tank Oil Gravity (°API)	31.7281	6 to 56.8
429	Reservoir Temperature (°F)	141.8338	59 to 306
429	Solution Gas Oil Ratio (SCF/STB)	635.4519	8.61 to 3298.7
429	Bubble Point Oil FVF (bbl/STB)	1.3834	1.032 to 2.887
429	Gas Gravity (air=1)	0.9980	0.624 to 1.789

The obtained correlation from different fluid property point of view was compared with previously published *Bob* Correlations. Range of input data used by each author in developing the correlations is provided in Table 3.

Table 3. PVT properties of samples used in published correlations for bubble point oil FVF.

Author	Bubble Point Oil FVF (bbl/STB)	Reservoir Temperature (°F)	Solution Gas Oil Ratio (SCF/STB)	Tank Oil Gravity (°API)	Gas Gravity (air=1)
Standing [20]	1.0240 to 2.150	100 to 258	20 to 1425	16.5 to 63.8	0.59 to 0.95
Glaso [13]	1.032 to 2.588	80 to 280	90 to 2637	22.3 to 48.1	0.65 to 1.28
Al-Marhoun [8]	1.032 to 1.997	74 to 240	26 to 1602	19.4 to 44.6	0.75 to 1.37
Abdul-Majeed [7]	1.028 to 2.042	75 to 290	0 to 1664	9.5 to 59.5	0.51 to 1.35
Dokla and Osman [11]	1.216 to 2.493	190 to 275	181 to 2266	28.2 to 40.3	0.80 to 1.29
Al-Marhoun [19]	1.010 to 2.960	75 to 300	0 to 3265	9.5 to 55.9	0.575 to 2.52
Farshad *et al.* [12]	1.060 to 2.064	95 to 260	6 to 1645	18.0 to 44.9	0.66 to 1.7
Macary [8]	1.20 to 2.00	130 to 290	200 to 1200	25 to 40	0.70 to 1.00
Petrosky [18]	1.118 to 1.623	114 to 288	217 to 1406	16.3 to 45.0	0.58 to 0.85
Omar and Todd [20]	1.085 to 1.954	125 to 280	142 to 1440	26.6 to 53.2	0.612 to 1.32
Kartoatmodjo [17]	1.007 to 2.144	75 to 320	0 to 2890	14.4 to 58.9	0.38 to 1.71
Almehaideb [16]	1.142 to 3.562	190 to 306	128 to 3871	30.9 to 48.6	0.75 to 1.12
Al-Shammasi [9]	1.011 to 2.916	58 to 341	6 to 3298	6 to 63.7	0.511 to 3.445
Hanafy [14]	1.032 to 4.35	107 to 327	7 to 4272	17.8 to 47.7	0.633 to 1.627
Hemmati [15]	1.091 to 2.54	77.5 to 290	125 to 2189.25	18.8 to 48.34	0.523 to 1.415

4. Constructing the intelligent model

Appropriate assigning of input and output parameters is the first step in any modeling process with intelligent systems. In this study, because *Bob* determination is the objective, *Bob* was assigned as the output parameter. *Bob* is a function of the reservoir temperature, *T*, gas specific gravity, γ_g, solution gas oil ratio, *Rs*, and tank oil gravity, °*API* [6]. Therefore, reservoir temperature and gas specific gravity, solution gas oil ratio and tank oil gravity were assigned as input parameters. Figure 2 shows the schematic of the output and input parameters.

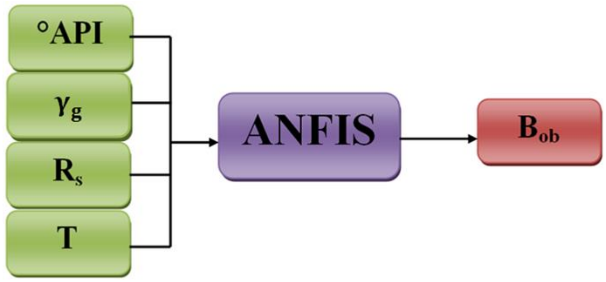

Figure 2. Schematic of the output and input parameters of the system (ANFIS).

A total of 429 data sets, including the input and output parameters, were used. These data were divided into two groups; one group included 286 data sets, which were selected randomly, were used for constructing the model, and the other included 143 data sets were used for the model testing.

To generate the structure of Fuzzy Inference System (FIS), there are three methods including Genfis1 and Genfis2 and Genfis3. Genfis1 and Genfis2 generate Sugeno-type FIS structure and use "grid partition" and "subtract clustering" for data clustering, respectively. Genfis3 could generate either Sugeno-type or Mamdani-type FIS structure. It uses the "fuzzy c-means (FCM)" method for data clustering. In this study, for *Bob* prediction, all of the methods (Genfis1 and Genfis2 and Genfis3) are evaluated, and it was found that the Genfis2 is the best for this purpose. Properties and parameter values of the constructed model are listed in Table 4 and Table 5, resp. Figure 3 shows the structure of the constructed model.

Tab. 4. Values of parameters of the constructed model (Genfis2)

Inference type	Method
AND	prod
OR	probor
Implication	prod
Aggregation	max
Difuzzification	wtaver

Tab. 5 Values of parameters of the constructed model (Genfis2)

Parameter	Value
cluster radius	0.4
Epoch	100
Squash factor	1.25
Accept ratio	0.05
Reject ratio	0.015

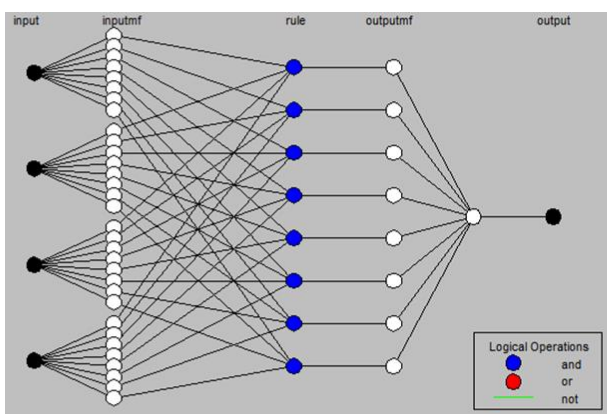

Figure 3. ANFIS structure for formulating input data

5. Results and discussion

In this study, the Adaptive Neuro-Fuzzy Inference System (ANFIS) were applied for prediction of *Bob*. The ANFIS is one of the techniques of artificial intelligence which is a combination of fuzzy logic and neural networks and combines the advantages of the both systems. After constructing and running the model, the mean squared errors (MSEs) in the test data were calculated for evaluation of the model accuracy. The MSE was calculated using Eq. (1). The MSE in the test data was 0.0023.

$$\text{Mean Square Error (MSE)} = \sum_{i=1}^{n}\left[(Bob)_{experimenal} - (Bob)_{predicted}\right]^2/n \qquad (1)$$

where $(Bob)_{experimenal}$ and $(Bob)_{predicted}$ and n are the *Bob* values that obtained from laboratory methods, *Bob* values that obtained from ANFIS, and number of data, respectively.

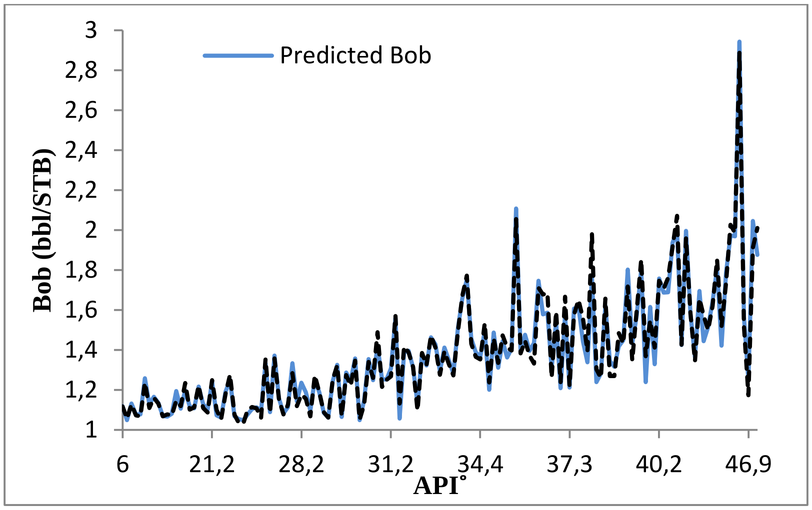

Fig. 4. Comparison between the experimental values and the predicted values from ANFIS in the test data

A comparison between the experimental values and the predicted values from ANFIS in the test data is shown in Figure 4. The R^2 between predicted values from the intelligent model, ANFIS, and experimental values of *Bob* for the test data was 0.9731 (Figure 5). According to the obtained results from the intelligent model and Table 6, it is revealed that the model is more accurate than all of the conventional correlations. In addition, the model is very fast and much cheaper than laboratory methods for *Bob* prediction. Therefore, when laboratory determination of *Bob* is impossible, the proposed model can be applied as an accurate substitute.

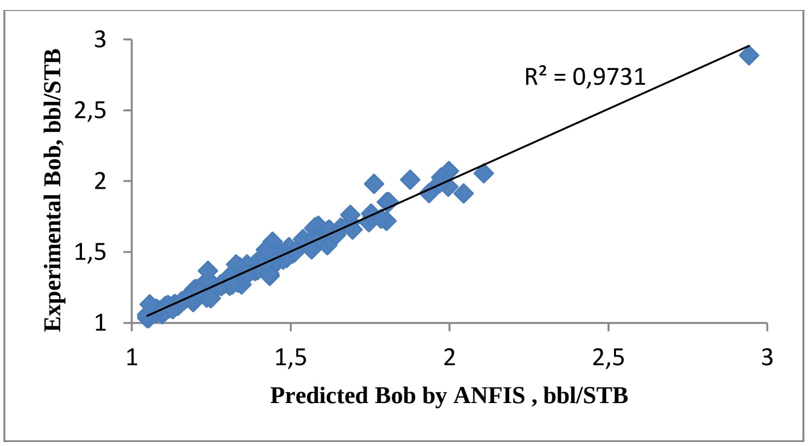

Fig. 5. Correlation between the experimental values and the predicted values from ANFIS in the test data

Table 6. Mean Squared Error (MSE) and correlation coefficient (R^2) for different correlations

Correlation	MSE	Correlation coefficient (R^2)
Standing [20]	0.0036	0.9611
Glaso [13]	1.077	0.9582
Al-Marhoun [8]	0.00552	0.9638
Abdul-Majeed [7]	0.0997	0.8527
Dokla and Osman [11]	0.00813	0.9495
Al-Marhoun [19]	0.00617	0.9554
Farshad [12]	1.4694	0.8968
Macary [8]	0.0231	0.9211
Petrosky [18]	0.00455	0.9534
Omar and Todd [20]	0.00458	0.9622
Kartoatmodjo [17]	0.00612	0.9635
Almehaideb [16]	0.0258	0.8053
Al-Shammasi [9]	0.00334	0.9642
Hanafy [14]	0.0118	0.9376
Hemmati [15]	0.00403081	0.9607

6. Conclusion

For several reasons laboratory determination of PVT properties (including bubble point oil formation volume factor, *Bo*, *Pb*, *Rs* etc.) of crude oils can be limited. In this study, using ANFIS an intelligent model was presented for *Bob* prediction of Middle East crudes. For evaluation of the model accuracy, the mean squared errors (MSEs) and the correlation coefficient (R^2) between the predicted data and experimental data were calculated. The MSE and R^2 in the test data were 0.0023 and 0.9731, respectively. From the results of this study, it can be pointed out that, the developed intelligent model can be used as an accurate substitute method to predict the *Bob* for Middle East crudes when the laboratory determination of the *Bob* is not possible.

Nomenclature

API	*Stock-tank oil gravity, °API*
B_{ob}	*Bubble point oil formation volume factor, bbl/STB*
$(B_{ob})_{experimenal}$	*Experimentally determined bubble point oil formation volume factor, bbl/STB*
$(B_{ob})_{predicted}$	*Bubble point oil formation volume factor predicted by the correlation*
f	*function*
FVF	*Formation volume factor*
GOR	*Gas oil ratio, SCF/STB*
MSE	*Mean squared error*
n	*number of data*
Pb	*Bubble point pressure, psia*
PVT	*Pressure-volume-temperature*
Rs	*Solution gas-oil ratio, SCF/STB*
Rsi	*Initial gas oil ratio, SCF/STB*
Rsf1	*The first stage separator gas oil ratio, SCF/STB*
Rsft	*Total separator gas oil ratio, SCF/STB*
T	*Temperature, °F*
γ_g	*Gas specific gravity (air=1)*
γ_o	*Oil specific gravity (water=1)*

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