A new empirical correlation for estimating bubble point pressure using the genetic algorithm

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Received: 2016-06-26; accepted: 2017-04-26

Abstract: In this paper, a new and more accurate correlation to predict bubble point pressure (P_b) for Middle East crudes by using the genetic alorithm (GA) is attempted. For this purpose, a total of 286 data sets of different crude oils from Middle East reservoirs were used as training data for constructing the correlation. The general form of the correlation was found by several regressive examinations. To improve the correlation, the genetic algorithm was applied. To validate the correlation, 143 data sets of different crudes from Middle East reservoirs which were different from the training data were used as test data for calculating mean absolute relative error (MARE) and correlation coefficient (R^2) between the predicted values from the proposed correlation and the experimental values. In addition, the MARE and R^2 were calculated for previous correlation in the test data. The results show that the proposed correlation is more accurate than all of the previous correlations exclusively for Middle East crudes.

Keywords: PVT properties, bubble point pressure, empirical correlation, Middle East, genetic algorithm

INTRODUCTION

The accurate determination of the PVT properties of the reservoir fluids, such as bubble point pressure (P_b), solution gas oil ratio (R_s) and oil formation volume factor (B_{ob}), is necessary for the formation evaluation of hydrocarbon reserves, reservoir performance, production operations and the design of production facilities (Elsharkawy et al. 1995).

The PVT properties can be obtained by laboratory PVT tests or estimated by using empirical correlations. Although laboratory results provide a better accuracy where controlled conditions are imposed, the results are heavily dependent on the validity of the reservoir fluid samples, especially when the reservoir has been depleted below the bubble point pressure (Hemmati & Kharrat 2007). In case no fluid samples are taken, the correlations can be used to estimate PVT data. This is particularly true during the early development phase where fluid properties are only available from surface flow tests (Dokla & Osman 1992). In addition, the laboratory methods are too expensive and time consuming.

The bubble point pressure (P_b) is one of the most important PVT properties. P_b evaluation is an essential step in reservoir performance calculations and the design of various stages of oil field operations.

Because the laboratory methods are sometimes impossible for many reasons, several empirical correlations have been developed for PVT properties. Especially in the recent decades, there has been an increasing interest in developing new correlations for crude oils of different regions of the worlds. A review of the published P_b correlations is summarized in Tables 1 and 2. According to Table 1, the majority of the current correlations have been proposed for specific regions. In addition, Table 2 shows that the used oil PVT properties of each region are different from those of the others.

Due to regional changes in crude oil compositions and properties, none of the correlations can be applied as an exact universal correlation. In this paper, by using the genetic algorithm, which is one the most powerful techniques of artificial intelligence in optimization, a new and more accurate correlation to predict P_b of Middle East crudes has been proposed.

Table 1
A review of the published Pb correlations

Author	Correlation	Region
Standing (1947)	$P_b = 18.2[\left(\frac{R_S}{\gamma_g}\right)^{0.83} 10^{(0.00091T_F - 0.0125\gamma_o)} - 1.4]$	California, U.S.A.
Vazquez & Beggs (1980)	$P_b = [27.64\left(\frac{R_S}{\gamma_g}\right) 10^{\left(-11.172\frac{\gamma_{o(°API)}}{T_R}\right)}]^{1.0937}$. For: $\gamma_{o(°API)} \leq 30$ $P_b = [56.06\left(\frac{R_S}{\gamma_g}\right) 10^{\left(-10.393\frac{\gamma_{o(°API)}}{T_R}\right)}]^{1.187}$. For: : $\gamma_{o(°API)} > 30$	Worldwide
Glaso (1980)	$P_b = 10^{[1.7669 + 1.7447\log(G) - 0.30218(\log(G))^2]}$ and: $G = \left(\frac{R_S}{\gamma_g}\right)^{0.816} T_F^{\ 0.172}\ \gamma_{o(°API)}^{\ -0.989}$	North Sea
Al-Marhoun (1988)	$P_b = 0.00538088 R_s^{\ 0.715082}\ \gamma_g^{\ -1.877840} \gamma_o^{\ 3.1437} T_R^{\ 1.326570}$	Middle East
Dokla & Osman (1992)	Al-Marhoun (1988). New calculated constant: $P_b = 0.836386e4 R_s^{\ 0.724047}\ \gamma_g^{\ -1.01049} \gamma_o^{\ 0.107971} T_R^{\ -0.952584}$	U.A.E.
Petrosky & Farshad (1993)	Standing (1947). New calculated constants: $P_b = 112.727[\left(\frac{R_S^{0.5774}}{\gamma_g^{0.8439}}\right) 10^X - 12.340]$ $X = 0.00004561 T_F^{\ 1.3911} - 7.916e - 4\gamma_{o(°API)}^{\ 1.5410}$	Gulf of Mexico
Lasater (1958)	$P_b = P_t \frac{T_R}{\gamma_g}$ $P_t = 0.38418 - 1.20081 Y_g + 9.64868 Y_g^{\ 2}$ & $Y_g = \left(\frac{R_S}{379,3}\right) / \left[\left(\frac{R_S}{379,3}\right) + \left(\frac{R_S}{M}\right)\right]$ $M = 725.32143 - 16.03333\gamma_{o(°API)} + 0.09524\gamma_{o(°API)^2}$	Canada West and Midcontinent
Omar & Todd (1993)	Standing (1947) correlation with one change: $P_b = 18.2[\left(\frac{R_S}{\gamma_g}\right)^{X} 10^{(0.00091T_F - 0.0125\gamma_o(°API))} - 1.4]$ $X = 1.4256 - 0.2608 B_{ob} - 0.4596\gamma_g + 0.04481 B_{ob}^{\ 2} + 0.2360\gamma_g^{\ 2} - \left(\frac{0.1077}{\gamma_g B_{ob}}\right)$	Malaysia
Farshad et al. (1996) (correlation (1))	Standing (1947). New calculated constants: $P_b = 33.22[\left(\frac{R_S}{\gamma_g}\right)^{0.8283} 10^{(0.000037T_F - 0.0142\gamma_o)}]$	Colombia

***Table 1** cont.*

Farshad et al. (1996) (correlation (2))	Glaso (1980). New calculated constants: $P_b = 10^{[0.3058 + 1.9013\log G - 0.26(\log G)^2]}$ and: $G = \gamma_g^{-1.378} R_S^{1.053} 10^{(0.00069 T_F - 0.0208\gamma_o(°API))}$	Colombia
Macary & El-Batanoney (1992)	$P_b = 204.257K(R_s^{0.51} - 4.7927)$ $K = \exp[0.00077T_F - 0.0097\gamma_o - 0.4003\gamma_g]$	Gulf of Suez
Almehaideb (1997)	$P_b = -620.592 + 6.23087(R_S\gamma_o)/(\gamma_g B_{ob}^{1.38559}) + 2.89868T_F$	U.A.E.
Kartoatmodjo & Schmidt (1994)	Vazquez & Beggs (1980). New calculated constants: $P_b = \{R_S/[0.05958\gamma_g^{0.7972} 10^{(13.1405\gamma_o(°API)/TR)}]\}^{0.9986}$. For: $\gamma_{o(°API)} \le 30$ $P_b = \{R_S/[0.03150\gamma_g^{0.7589} 10^{(11.2895\gamma_o(°API)/TR)}]\}^{0.9143}$. For: $\gamma_{o(°API)} > 30$	Worldwide
Al-Shammasi (2001)	$P_b = \gamma_o^{5.527215}\exp(-1.841408\gamma_o\gamma_g)(R_S T_R \gamma_g)^{0.783716}$	Worldwide
Hanafy et al. (2005)	$P_b = 3.205R_s + 157.27$	Egypt
Hemmati & Kharrat (2007)	$P_b = 10.4566[\left(\frac{R_S}{\gamma_g}\right)^X 10^{[0.0008T_F - 0.0098\gamma_o]} - 8.6817]$ $X = 1.5897 - 0.2735B_{ob} - 0.4429\gamma_g + 0.04649\, B_{ob}^2 + 0.144\gamma_g^2 - 0.1596\,[1/(\gamma_g B_{ob})]$	Iran

P_b – bubble point pressure, Psi
R_s – solution gas oil ratio, SCF/STB
T_F – reservoir temperature, Fahrenheit degree
T_R – reservoir temperature, Rankin degree
γ_o – specific oil gravity
γ_g – specific oil gravity, air = 1
$\gamma_{o(°API)}$ – specific oil gravity, API degree
B_{ob} – bubble point oil formation volume factor, bbl/STB

Table 2
Data used in the development of published Pb correlations

Author	**Number of used data**	**Bubble point pressure [Psi]**	**Reservoir temperature [°F]**	**Solution gas oil ratio [SCF/STB]**	**Tank oil gravity [°API]**	**Gas gravity (air = 1)**
Standing (1947)	105	130–7000	100–258	20–1425	16.5–63.8	0.59–0.95
Vazquez & Beggs (1980)	6004	15–6055	75–294	0–2199	15.3–59.3	0.51–1.35
Glaso (1980)	41	165–7142	80–280	90–2637	22.3–48.1	0.65–1.28
Al-Marhoun (1988)	160	20–3573	74–240	26–1602	19.4–44.6	0.75–1.37
Dokla & Osman (1992)	51	590–4640	190–275	181–2266	28.2–40.3	0.80–1.29
Farshad et al. (1996)	43	32–4138	95–260	6–1645	18.0–44.9	0.66–1.7
Lasater (1958)	158	48–5780	82–272	3–2905	17.9–51.1	0.57–1.2
Macary & El-Batanoney (1992)	90	1200–4600	130–290	200–1200	25–40	0.70–1.00
Petrosky & Farshad (1993)	90	1574–6523	114–288	217–1406	16.3–45.0	0.58–0.85
Omar & Todd (1993)	93	790–3851	125–280	142–1440	26.6–53.2	0.612–1.32
Kartoatmodjo & Schmidt (1994)	5392	15–6055	75–320	0–2890	14.4–58.9	0.38–1.71
Almehaideb (1997)	62	501–4822	190–306	128–3871	30.9–48.6	0.75–1.12
Al-Shammasi (2001)	1709	0–6613.8	58–341	6–3298	6–63.7	0.511–3.445
Hanafy et al. (2005)	741	36–5003	107–327	7–4272	17.8–47.7	0.633–1.627
Hemmati & Kharrat (2007)	287	248–5156	77.5–290	125–2189.25	18.8–48.34	0.523–1.415

METHODOLOGY

In this study, the genetic algorithm (GA) was used as the main tool for developing the correlation. The genetic algorithm is one of the powerful techniques of artificial intelligence in terms of optimization. Optimization is the process of adjusting the inputs to or characteristics of a device, mathematical process, or experiment to find the minimum or maximum output or results (Alenoghena et al. 2013). GA, which is based on the genetic process of biological organisms, is used to find a solution to a problem called objective function. A generated solution by the GA is called a chromosome and a collection of chromosomes is called a population. A chromosome is composed of genes. These chromosomes will undergo a process, which is called fitness function, to measure the suitability of the solution generated by GA with the problem. Some chromosomes in the population will mate through a process called crossover thus producing new chromosomes named offspring which its genes composition is the combination of their parent. In a generation, a few chromosomes will undergo mutations in their gene. The chromosome in the population, which has a higher fitness value will have a greater probability of being selected again in the next generation. After several generations, the chromosomes value will converge to a certain value which is the best solution for the problem (Mitchell 1999). Figure 1 shows the flowchart of the genetic algorithm.

The GA could be used for solving both constrained and unconstrained optimization problems (Karimnezhad et al. 2014). Furthermore, it can be applied to solve a variety of optimizations of problems that are not well suited for standard optimization algorithms (especially, problems in which the objective function is highly nonlinear).

In this paper, GA is applied to minimize the objective function to improve the accuracy of the proposed correlation. The proposed correlation is described in section "Verification of correlation".

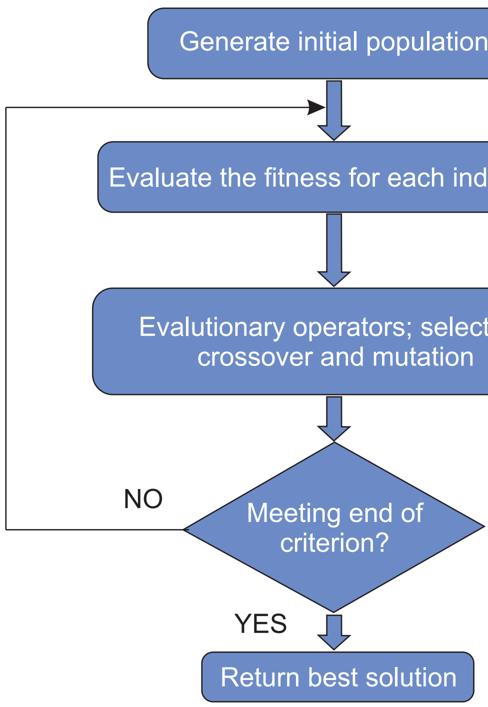

Fig. 1. *Genetic algorithm flowchart (Ravandi et al. 2014)*

DEVELOPMENT OF THE NEW CORRELATION

Different Middle East oil fields were selected for this study. From these oil fields, 429 laboratory PVT analyses data were obtained and used.

Table 3
Range of the data used

PVT property	Number of data		Range		Mean	
	training data	test data	training data	test data	training data	test data
Tank oil gravity [°API]	286	143	6.3–56.8	6–52.03	31.78	31.61
Reservoir temperature [°F]	286	143	62.6–297	59–306	143.43	186.64
Solution gas oil ratio [SCF/STB]	286	143	17.21–3020	8.61–3298.66	636.4	633.58
Bubble point pressure [Psi]	286	143	130–6613.82	107.33–6358.55	2126.83	2157.25
Gas gravity (air = 1)	286	143	0.649–1.789	0.624–1.53	1.00	0.982

The data sets were extracted from various papers (Glaso 1980, Al-Marhoun 1988, Dokla & Osman 1992, Ghetto et al. 1994, Gharbi & Elsharkawy 1997). The data sets were divided into two groups: one group including 286 data sets used as training data for constructing the correlation, and the other including 143 data sets used as test data for the correlation validation. The training and test data were selected randomly. The data consists of the reservoir temperature, bubble point pressure, oil and gas specific gravity and solution gas oil ratio within the ranges as shown in Table 3.

Bubble point pressure (P_b) is a function of solution gas oil ratio (R_s), temperature (T), oil gravity (γ_o) and gas gravity (γ_g); in other words:

$$P_b = f(T, R_s, \gamma_o, \gamma_g) \tag{1}$$

For constructing an appropriate correlation, the training data sets were used. Several cases were examined to find an appropriate correlation between these parameters for P_b prediction. After several regressive examinations, it was found that there is a powerful relationship between the independent parameters (T, R_s, γ_o, γ_g) and P_b as equation (2) (Fig. 2):

$$P_b = 7.9522[R_s \cdot (\gamma_o/\gamma_g) + T_R \cdot (\gamma_g/\gamma_{o(°API)})]^{0.8747} \tag{2}$$

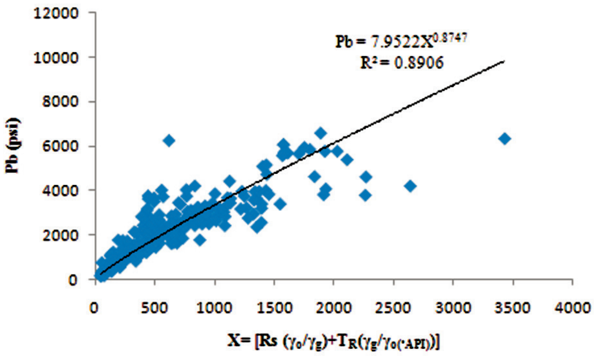

Fig. 2. *Relationship between the independent parameters (T, R_s, γ_o, γ_g) and P_b (training data)*

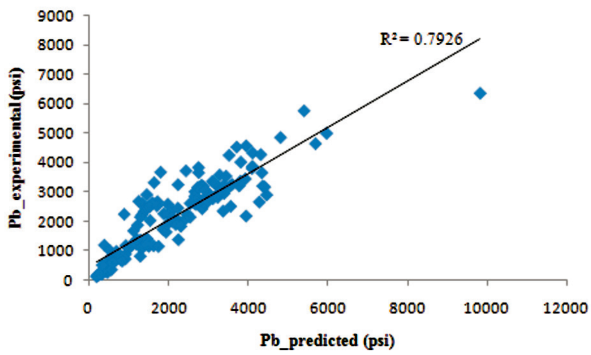

Fig. 3. *The correlation between experimental P_b values and predicted P_b values from equation (2) (test data)*

The correlation between experimental values and predicted values from equation (2) in the test data has been shown in Figure 3.

By the trial and error method, it was found that the accuracy of the equation (2) can improve if it is rewritten as equation:

$$P_b = a_1[R_S^{a_2}(\gamma_o/\gamma_g)^{a_3} + T_R^{a_4}(\gamma_g/\gamma_{o(°API)})^{a_5}]^{a_6} \tag{3}$$

It is obvious that the accuracy of correlation (3) will be maximized if the constants a_1 through a_6 are optimal. To determine the constants a_1 through a_6 optimally, GA was applied. GA is one of the artificial intelligence techniques which can be used for both linear and nonlinear optimizations. GA minimizes the objective function. Objective function (or fitness function) is the function that must be optimized.

Table 4
Parameters used in the GA

GA parameter	GA parameters that used for prediction of P_b
Population	Population type: double vector; population size: 55; initial range: [0;1]
Fitness scaling	Scaling function: rank
Selection	Selection function: roulette
Reproduction	Elite count: 3; crossover fraction: 0.85
Mutation	Mutation function: Gussian; shrink value: 1; scale: 0.1
Crossover	Crossover function: scattered
Migration	Direction: forward; fraction: 0.8; interval: 40
Hybrid function	Hybrid function: fminsearch
Algorithm setting	Initial penalty: 100; penalty factor: 980
Stopping criteria	Generation: 1000; time limit: inf; fitness limit: inf; stall generation: 1000; stall time limit: inf

To determine the constants a_1 to a_6 using GA, the fitness function is defined as equation:

$$\text{Fitness function} = \text{Mean Absolute Relative Error (MARE)} = \frac{\sum_{i=1}^{n} ARE}{n} \tag{4}$$

where:

$$ARE = \frac{abs(P_{b\_experimental} - P_{b\_predicted})}{P_{b\_experimental}} =$$

$$= \frac{abs(P_{b\_experimental} - a_1[R_S^{a_2}(\gamma_o / \gamma_g)^{a_3} + T_R^{a_4}(\gamma_g / \gamma_{o(°API)})^{a_5}]^{a_6})}{P_{b\_experimental}}$$

In equation (4), $P_{b\_experimental}$ and $P_{b\_predicted}$ are the experimental P_b and the predicted P_b by equation (3), respectively. Moreover, n is the number of the used data, a_1 to a_6 are the constants which are predicted by the GA.

Parameters used to perform genetic algorithm are listed in Table 4.

The constants a_1 to a_6 were defined as vectors in order to accelerate the algorithm performance. In this case, the fitness function is called once instead of being called for each member and, therefore, its performance accelerates. The "fminsearch" which is a hybrid function was used to improve results obtained from the GA. After the end of the GA, the "fminsearch" which is an optimizer function uses genetic algorithm end point as its own starting point and is executed. This function improves the results.

Training data were used as input of GA to determine the constants a_1 through a_6. After adjusting the algorithm, it was run and the parameters were obtained as follows:

$$a_1 = 6.15, a_2 = 1.015, a_3 = 1.05, a_4 = 1, a_5 = 1.5, a_6 = 1.$$

Figure 4 shows the experimental and predicted P_b from correlation (3) versus oil gravity in the training data. According to Figure 4, performance of the correlation (3) is not acceptable when the oil gravity is more than 27°API. To solve this problem, the training data were divided into two groups based on the value of the oil gravity; one group included the training data sets with an oil gravity less than 27°API, and the other included the training data sets with oil gravity more than 27°API. Then, the GA were reused to determine the constants a_1 through a_6 for training data sets with oil gravity more than 27°API. The final results are listed in Table 5.

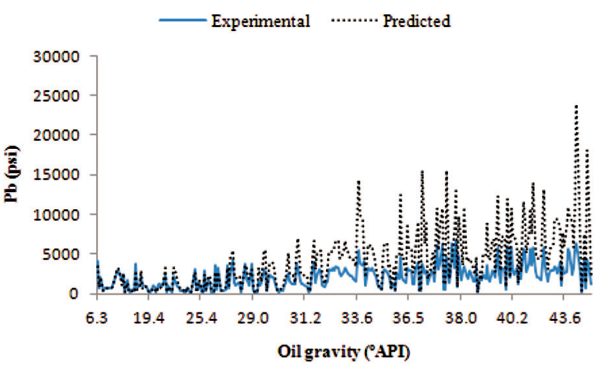

Fig. 4. *Experimental and predicted P_b from equation (3) versus oil gravity (training data)*

Table 5
The final proposed correlation and its constants

Constant	$P_b = a_1[R_S^{a2}(\gamma_o/\gamma_g)^{a3} + T_R^{a4}(\gamma_g/\gamma_{o(°API)})^{a5}]^{a6}$	
	API ≤ 27	API > 27
a_1	6.15	17.8
a_2	1.015	0.735
a_3	1.05	1.25
a_4	1	0.9
a_5	1.5	2
a_6	1	1.01

Figure 5 shows the experimental and predicted P_b from the proposed correlation (based on the constants a_1 through a_6 which are listed in Table 5) versus oil gravity in the training data.

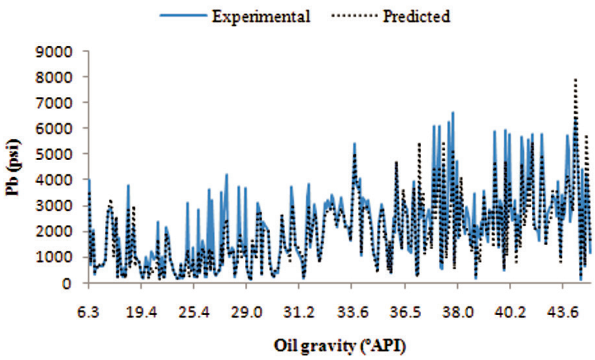

Fig. 5. *Experimental and predicted P_b from correlation (3) (based on the constantsa$_1$ through a_6 which are listed in Table 5) versus oil gravity (training data)*

VERIFICATION OF CORRELATION

For the verification of the proposed correlation, test data including 143 data sets were used. Figure 5 shows the experimental and predicted P_b from the proposed correlation (based on the constants a_1 through a_6 which are listed in Table 5) versus oil gravity in the test data. In addition, the correlation between experimental values and predicted values from the correlation in the test data is shown by Figure 6. According to the results presented in Figures 6 and 7, it seems that there is an acceptable agreement between predicted P_b values from the proposed correlation and the experimental P_b values.

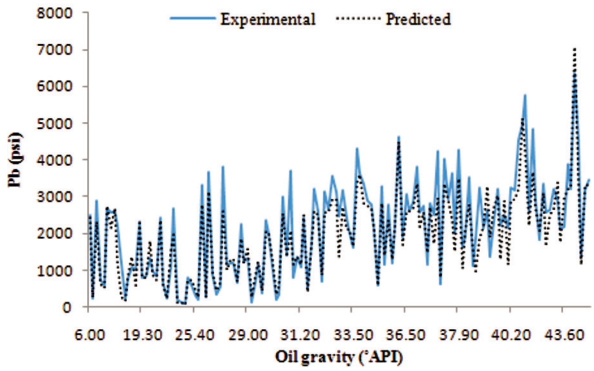

Fig. 6. *Experimental and predicted P_b from correlation (3) (based on the constants a_1 through a_6, (listed in Table 5) versus oil gravity (the test data)*

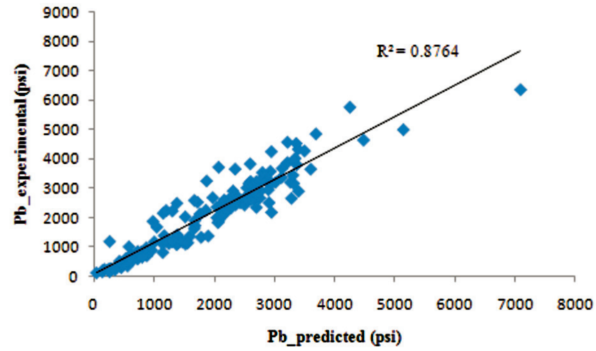

Fig. 7. *The correlation between experimental values and predicted values from correlation 3 (based on the constants a_1 through a_6 listed in Table 5 (test data))*

RESULTS AND DISCUSSION

In this study, a new emprical correlation was proposed to predict the bubble point pressure (P_b) for Middle East crude oils. The genetic algorithm (GA) is the dominant tool used for developing the correlation. GA is a tool, which can be used for both linear and nonlinear optimizations. The initial form of the correlation was obtained by regressive examinations (Fig. 2). To improve the accuracy of the proposed correlation, training data were divided into two groups based on their oil gravity (one group included the training data sets with oil gravity less than 27°API, and the other included the training data sets with oil gravity more than 27°API) and the GA was used for optimization the constants of the correlation (constants a_1 through a_6). The proposed correlation and its obtained constants are listed in Table 5.

The correlation coefficient (R^2) between the experimental values and the predicted values from the proposed correlation in the test data was 0.874, which reveals an acceptable agreement between the predicted and experimental values (Fig. 7). To evaluate the accuracy of the proposed correlation, Mean Absolute Relative Error (MARE) was also calculated. The MARE of the correlation in the test data was 0.1624. In addition, the MARE and R^2 were calculated for previous correlation in the test data (Tab. 6). A comparison between the MARE and R^2 of the proposed correlation and previous correlations shows that the proposed correlation is much more accurate than all of the previous correlations.

The proposed correlation was developed for Middle East crudes. However, because it is more accurate than all of the previous correlations, it could be used as a universal correlation for the prediction of bubble point pressure.

Table 6
Mean Absolute Relative Error (MARE) and correlation coefficient (R^2) for different correlations

Author	Year	MARE	R^2
Standing	1947	0.5366	0.7375
Petrosky & Farshad	1993	0.24095	0.8245
Lasater	1958	0.3978	0.8131
Vazquez & Beggs	1980	0.946	0.7440
Glaso	1980	0.3445	0.7616
Al-Marhoun	1988	0.382	0.7778
Dokla & Osman	1992	0.301	0.7858
Farshad et al. (correlation (1))	1996	0.2329	0.8467
Farshad et al. (correlation (2))	1996	0.3802	0.8052
Macary & El-Batanoney	1992	0.2335	0.812
Omar & Todd	1993	0.9497	0.7907
Kartoatmodjo & Schmidt	1994	0.27	0.7687
Almehaideb	1997	1.703	0.7778
Al-Shammasi	2001	0.2623	0.8172
Hanafy et al.	2005	0.3327	0.71843
Hemmati & Kharrat	2007	0.4438	0.7718

CONCLUSIONS

1. In this study, a new empirical correlation has been proposed to predict the bubble point pressure (P_b) for Middle East crude oils. The genetic algorithm (GA), which is one of the most powerful techniques of the artificial intelligence in optimization, has been used to develop the correlation.
2. The proposed correlation is a nonlinear function of temperature, solution gas oil ratio, and oil and gas gravity. To evaluate its accuracy, the Mean Absolute Relative Error (MARE) and correlation coefficient (R^2) between predicted values from the proposed correlation and experimental values in the test data were calculated. The MARE and R^2 in the test data were 0.1624 and 0.874, respectively.
3. The comparison between the MARE and R^2 of the proposed correlation and previous correlations shows that the proposed correlation is more accurate than all of the previous correlations.
4. The correlation was developed exclusively for Middle East crudes. However, because it is more accurate than all of the previous correlations, it could be used as a universal correlation for the prediction of P_b.

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