Arab J Sci Eng (2018) 43:2491–2500
https://doi.org/10.1007/s13369-017-2589-9

RESEARCH ARTICLE - PETROLEUM ENGINEERING

# Development of a New Correlation for Bubble Point Pressure in Oil Reservoirs Using Artificial Intelligent Technique

**Salaheldin Elkatatny**[1] · **Mohamed Mahmoud**[1]

Received: 28 November 2016 / Accepted: 8 May 2017 / Published online: 19 May 2017


**Abstract** Accurate determination of the bubble point pressure (BPP) is extremely important in several applications in oil industry. In reservoir engineering applications the BPP is an essential input for the reservoir simulation and reservoir management strategies. Also, in production engineering the BPP determines the type of the inflow performance relationship that describes the reservoir production performance. Accurate estimation of the BPP will eliminate the risk of producing in two-phase region. Current correlations can be used to determine the BPP with high errors, and this will lead to poor reservoir management. Artificial intelligent tools used in the previous studies did not disclose the models they developed, and they stated the models as black box. The aim of this research is to develop a new empirical correlation for BPP prediction using artificial intelligent techniques (AI) such as artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and support vector machine (SVM). For the first time we extracted the weights and the biases from AI models and form a new mathematical model for BPP prediction. The results obtained showed that the ANN model was able to estimate the BPP with high accuracy (correlation coefficient of 0.988 and average absolute error percent of 7.5%) based on the specific gravity of gas, the dissolved gas to oil ratio, the oil specific gravity, and the temperature of the reservoir as compared with ANFIS and SVM. The developed mathematical model from the ANN model outperformed the previous AI models and the empirical correlations for BPP prediction. It can be used to predict the BPP with a high accuracy (the average absolute error (3.9%) and the coefficient of determination ($R^2$) of 0.98).

**Keywords** Bubble point pressure · Artificial intelligent · Reservoir management · Artificial neural network

## Abbreviations

| | |
|---|---|
| BPP | The bubble point pressure (psi) |
| OFVF | The oil formation volume factor |
| GG | Gas gravity |
| RS | The dissolved gas to oil ratio (scf/bbl) |
| API | The oil gravity |
| $T_f$ | The temperature of the reservoir (°F) |

## 1 Introduction

Bubble point pressure is the pressure at which the first bubble of the gas will come out of the liquid oil solution [1]. The determination of the bubble point pressure in oil reservoirs is crucial because it will determine several aspects in the reservoir management strategy. For example, several oil producers set their production strategy to produce above the bubble point to avoid multiphase flow in the reservoirs which will make the reservoir simulation process more complex. Therefore, the accurate knowledge of the reservoir bubble point pressure is very important. If the reservoir pressure declines below the bubble point, the gas will come out of solutions and form a secondary phase that will flow with the oil and occupy part of the reservoir volume. This will affect

✉ Salaheldin Elkatatny
elkatatny@kfupm.edu.sa

Mohamed Mahmoud
mmahmoud@kfupm.edu.sa

1 Department of Petroleum Engineering, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia

the oil effective permeability, and in turn the oil production will diminish. The gas will form a continuous phase, thereby leading to a decrease in relative permeability to oil. The prediction/determination of reservoir bubble point pressure is important because it will help manage the production from oil reservoirs [2,3].

The inflow performance relationship (IPR) in oil reservoirs is a strong function of the BPP. If the bottom hole pressure is greater than the BPP, the IPR can be described as straight line between the bottom hole pressure and oil flow rate. If the bottom hole pressure is lower than the BPP, the IPR in this case ceases to be straight line and will be curved and can be described by Vogel's correlation [4].

## 1.1 Artificial Intelligent Techniques

### *1.1.1 Artificial Neural Network Technique*

Artificial neural network is the most powerful statistical tool to recognize and classify complex patterns and system which human brain cannot do [5,6]. In fact, the artificial neural network technique is inspired from biological neurons that are found in human brain [7].

An ANN model consists of fundamental processing unit, termed as neurons. The neural network models are structured on three components, learning algorithm, transfer function, and network architecture [8]. The network model comprises of at least three layers, input layer, hidden layer, and output layer. Each layer connects with other layers with the help of weights. The network performance is solely based on the adjustment of weights between these layers [9,10]. Hidden layers are assigned with a transfer function, which is usually 'log-sigmoidal' or 'tan-sigmoidal.' Output layer is assigned with a 'pure linear' activation function. All the data that go into the model are normalized between −1 and 1 by default [11]. The first step of modeling with ANN is the training of the network; data are processed through the input layer to hidden layer(s) then all the way to the output layer. In the output layer, the data are compared with the actual data. The difference between actual and predicted data is transferred back to the model to update the individual weights between each connection and the biases of each layer. This process is called epoch. In this way, training continues for all the data set until the average error reduces to certain defined limit [12].

### *1.1.2 Adaptive Neuro-Fuzzy Inference System*

ANFIS has also gained importance in a petroleum industry. Many researchers used ANFIS to delineate complex concepts in the petroleum industry [13,14]. ANFIS is the combination of neural network and fuzzy logic and its very robust supervised learning technique. It is the kind of neural network that uses Sugeno fuzzy inference system [15]. ANFIS has the capability to extract the benefits of both mentioned AI techniques [artificial neural networks (ANN) and fuzzy logic (FL)] in a single platform [16]. In order to get best out of this technique one should use any evolutionary algorithm to optimize the parameters of ANFIS [16].

Fuzzy logic maps input parameters to input membership functions, followed by converting input membership functions to set of fuzzy rules and then converting set of fuzzy rules to output characteristics and followed by converting output characteristics to output membership functions, finally this membership function to one valued output or any classification based on output [17]. In ANFIS, instead of just fixing the shape of membership function, it automatically assigns the type and shape of membership function by analyzing the data [18].

### *1.1.3 Support Vector Machine*

Support vector machine is the type of supervised learning that is mostly used for regression and pattern recognition purposes [19,20]. Based on soft margin hyper-plane, support vector machine was introduced as a new artificial intelligence tool framework for both classification and function approximation [21,22]. Classification is an example of supervised learning that help indicate whether the system is performing correctly or not. It somehow acts as clustering, in which the data are clustered or classified based on their types. The data can be classified or clustered based on the range; for example several correlations can be developed for different crude oils based on their density range and each range we call a class or cluster. Instead of sigmoidal type transfer function like in artificial neural network, support vector machine stands on the kernel neuron function which definitely allows projection to higher planes and is able to solve more complicated and complex highly nonlinear problems [23]. The projection feature in SVM means how similar or the parameter is and it determines the degree of overlap between the different parameters. Also, it affects the classifications and clustering process based on the degree of overlap (projections). SVM applications can be found in many fields like medical, business, civil, and electrical engineering [24].

## 1.2 Correlations for Bubble Point Pressure

Several correlations were developed to determine the oil reservoirs bubble point pressure, most of these correlations based on Standing's correlations [25]. One of the common methods used to obtain the BPP from the laboratory test data is the Y-function. This function was used by several investigators to determine the BPP to smoothen the laboratory experimental data [26,27]. The Y-function can be determined as follows:

$$Y = \frac{(\mathrm{BPP} - p)}{\left(p\left(\frac{V}{V_b} - 1\right)\right)} \quad (1)$$

where BPP is the bubble point pressure, $p$ is the pressure at any point, $V_b$ is the bubble point volume, $V$ is the two-phase volume, $V/V_b$ is the relative volume.

### 1.3 Bubble Point Pressure Prediction Using AI Techniques (Black Box)

Many empirical equations for BPP were developed depending on the data collected from specific reservoir or regions such as that developed by Gharbi and Elsharkawy [28]. They developed a neural network model to predict the bubble point pressure as a function of the specific gravity of gas, the dissolved gas to oil ratio, the oil specific gravity, and the temperature of the reservoir. They tested the developed correlations on Middle East crudes. They used two parallel neural network models to minimize the prediction error. They used 498 data points to develop their model. They compared the prediction of the bubble point pressure with three correlations [29–33], and their model yielded the least average absolute relative error (AARE) on the tested data. Their model gave 2.79% AARE, and the other three correlations gave AARE more than 4%.

Osman et al. [34] established ANN model to predict the oil formation volume factor (OFVF) using 803 published data for Middle East, Malaysia, Colombia, and Gulf of Mexico crude oil. They concluded that the ANN was able to predict the OFVF with higher accuracy as compared with the empirical equations. The average absolute error was 1.79%, and the correlation coefficient was 0.988 for the developed ANN model.

Moghadam et al. [35] concluded that the ANN technique was able to predict the PVT properties of Iranian crude oils with a correlation coefficient of 0.990 and the ANN model outperformed the traditional methods of predicting the PVT properties.

Al-Marhoun and Osman [36] used the artificial neural network to establish new equations for the crude oils at Saudi Arabia. They introduced new model to predict the BPP of the crude oils for a specific field in Saudi Arabia. They used 283 data points collected from different Saudi reservoirs. They found that the established model outperformed all previous equations in terms of predicting the bubble point pressure. The average absolute error of the developed model was 5.8%, and their study supported the development of regional correlations rather than developing universal general ones.

El-Sebakhy et al. [37] used support vector machines framework (SVM) to develop a model for BPP prediction. They concluded that the SVM model outperformed both ANN models and the common empirical correlations for BPP prediction.

Moghadassi et al. [38] stated that ANN model is one of the best model to predict the PVT properties. They optimized the number of neuron to be sixty in the hidden layer to optimize the minimum mean square error (MSE) of 0.000606.

Numbere et al. [39] used artificial neural network (ANN) approach to develop an empirical equation for the BPP for the Niger Delta crude oil. They used 1248 data points to develop their ANN model to predict the BPP, 60% of the data was used for training, 20% for validation, and the rest 20% for testing. Their ANN model outperformed the existing empirical correlations in predicting the BPP for the selected region.

Baarimah et al. [40] develop a model to estimate the BPP using fuzzy logic (FL). They used the specific gravity of gas, the dissolved gas to oil ratio, the oil specific gravity, and the temperature of the reservoir as inputs to build the BPP model. They concluded that the new fuzzy logic model can be used to predict the BPP with a correlation coefficient of 0.9995.

Adeeyo [41] used neural network to estimate the BPP and the OFVF factor for Nigerian crude oil samples. They used 2114 data points for the BPP and 2024 for the OFVF. He used several sets of the neural network design and number of neurons. He used 60% of the data for testing, 20% for validation, and 20% for testing. The prediction of his model was accurate compared to the published correlations estimation for the BPP.

It is clear from the literature that no one can apply the available AI models for new data without having these models. So, the objective of this research is to develop a mathematical model from the AI model that can be used generally without the need for the code of the AI model.

In this study, we developed a new empirical correlation to determine the BPP based on the specific gravity of gas ($\gamma_g$), the dissolved gas to oil ratio ($R_s$), the oil specific gravity (API), and the temperature of the reservoir ($T_f$). Three artificial intelligent techniques will be used to develop the BPP model such as artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and support vector machine (SVM). The obtained results of the three models will be compared, and the one that gives the highest accuracy will be used to develop the new empirical correlation for BPP prediction by extracting the weight and biases from the AI model.

**Table 1** Sample of the collected data (700 data points) for different crude

| Sample ID | Input parameters | | | | Output parameter |
|---|---|---|---|---|---|
| | Solution gas oil ratio (scf/bbl) | Gas gravity | Oil gravity (°API) | Reservoir temperature (°F) | Bubble point pressure (psi) |
| 1 | 494 | 0.677 | 44.5 | 230 | 2081 |
| 2 | 267 | 0.884 | 31.4 | 174 | 1220 |
| 3 | 956 | 0.811 | 43.2 | 226 | 2390 |
| 4 | 242 | 0.824 | 31.4 | 180 | 1302 |
| 5 | 214 | 0.664 | 31.9 | 180 | 1195 |
| 6 | 741 | 0.795 | 42 | 234 | 2562 |
| . | . | . | . | . | . |
| . | . | . | . | . | . |
| . | . | . | . | . | . |
| 699 | 274 | 1.005 | 39.8 | 150 | 790 |
| 700 | 566 | 0.817 | 45.2 | 185 | 1530 |


**Fig. 1** Relative importance of input parameters to bubble point pressure (output parameter)

## 2 Data Description and Analysis

Table 1 lists a sample of the collected data for different crudes (700 data points). These data were collected from published papers [11,42–46].

The data include bubble point pressure (BPP), gas specific gravity ($\gamma_g$), solution gas oil ratio ($R_s$), oil gravity (API), and the reservoir temperature ($T_f$).

The BPP ranges from 126 to 7127 psi. Gas gravity ($\gamma_g$) changes from 0.589 to 1.367, while the dissolved gas to oil ratio ($R_s$) ranges from 9 to 2637 scf/bbl. The API changes from 15.3 to 59.5, and the reservoir temperature ranges from 74 to 294°F.

The correlation coefficient ($R$) was determined in order to evaluate the importance of each input parameter to the bubble point pressure. Figure 1 shows that the BPP is a strong function of the dissolved gas to oil ratio, with the correlation coefficient 0.88. While the BPP is a moderate function of the specific gravity of gas, the correlation coefficient is $-0.51$. The bubble point pressure is a weak function of the oil gravity and the reservoir temperature; the correlation coefficient is 0.38 and 0.32 for the oil specific gravity and the temperature of the reservoir, respectively.

### 2.1 Building the Artificial Intelligent Models

The first step in building the AI model is to normalize all the parameters that will be used to build the model. The value of the parameters (input and output) is normalized between -1 and 1 by using two points slope, Eqs. (2, 3).

$$\frac{Y - Y_{\min}}{Y_{\max} - Y_{\min}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (2)$$

$$Y = \frac{X - X_{\min}}{X_{\max} - X_{\min}} (2) - 1 \quad (3)$$

where $Y$ is the input parameter in the normalized form, $Y_{\max} = 1$, $Y_{\min} = -1$, $X_{\max}$ is the maximum value of input data, $X_{\min}$ is the minimum value of input data, $X$ is the input parameter to be normalized. For example, the minimum value of the BPP ($X_{\min}$) is 126 psi, and the maximum value of BPP ($X_{\max}$) is 7127 psi, so for the value of BPP equal to 2000 psi, the normalized value will be equal to 0.267.

The second step is to train the model. Seventy percent of the data (490 data points) was used to train the AI models. Figure 2 shows that the ANN model was able to predict the bubble point pressure with a correlation coefficient ($R$) of 0.988 and an average absolute error of 7.5 % when comparing the actual and predicted value of the BPP. ANFIS was able to predict the BPP with a correlation coefficient ($R$) of 0.986 and an average absolute error of 11.5 when comparing the actual and the predicted values of the BPP, while SVM was able to predict the BPP with a correlation coefficient ($R$) of 0.977

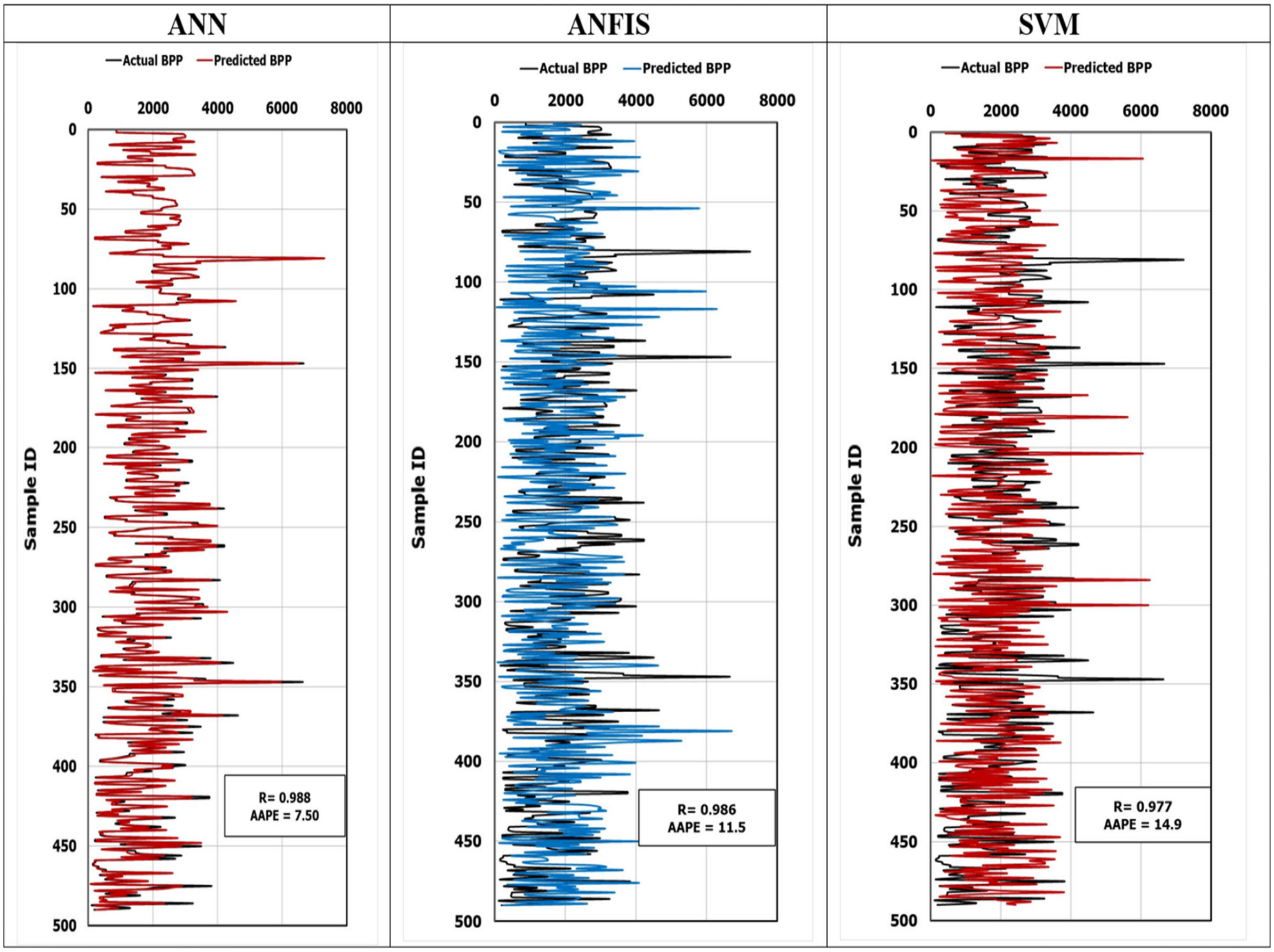


**Fig. 2** Bubble point pressure prediction using AI techniques for the training data (490 data points)

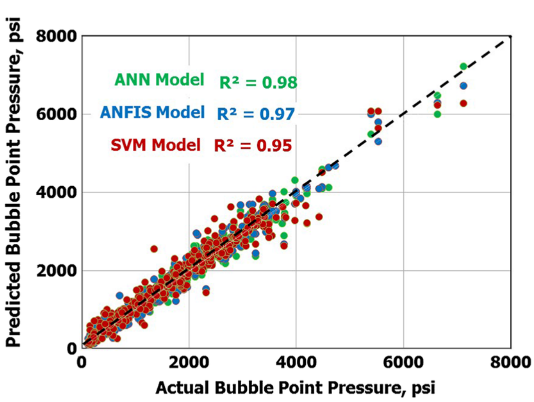


**Fig. 3** Coefficient of determination ($R^2$) for BPP prediction using AI techniques for the training data

and an average absolute error of 14.9% when comparing the actual and predicted values of the BPP, Fig. 2.

Figure 3 shows that for the training data (490 data points), the ANN yielded higher coefficient of determination ($R^2$) of 0.98 for predicting the BPP than ANFIS and SVM where the $R^2$ was 0.97 and 0.95, respectively.

The third step is to assess the developed AI models by testing the three models using unseen data (210 data points), which is 30% of the collected data. Figure 4 shows that ANN model was able to predict the BPP with a correlation coefficient of 0.987 and an average absolute error of 7.9%. ANFIS was able to predict the BPP with a correlation coefficient of 0.985 and an average absolute error of 13.1%, while SVM was able to predict the BPP with a correlation coefficient of 0.965 and an average absolute error of 17.4%, Fig. 4.

It can be concluded that ANN model was able to estimate the BPP based on the specific gravity of gas ($\gamma_g$), the dissolved gas to oil ratio ($R_s$), the oil specific gravity (API), and the temperature of the reservoir ($T_f$) with higher accuracy than ANFIS and SVM. Based on these results, ANN model was selected to develop a new empirical correlation for predicting the BPP by extracting the weights and the biases from the model to develop the mathematical model.

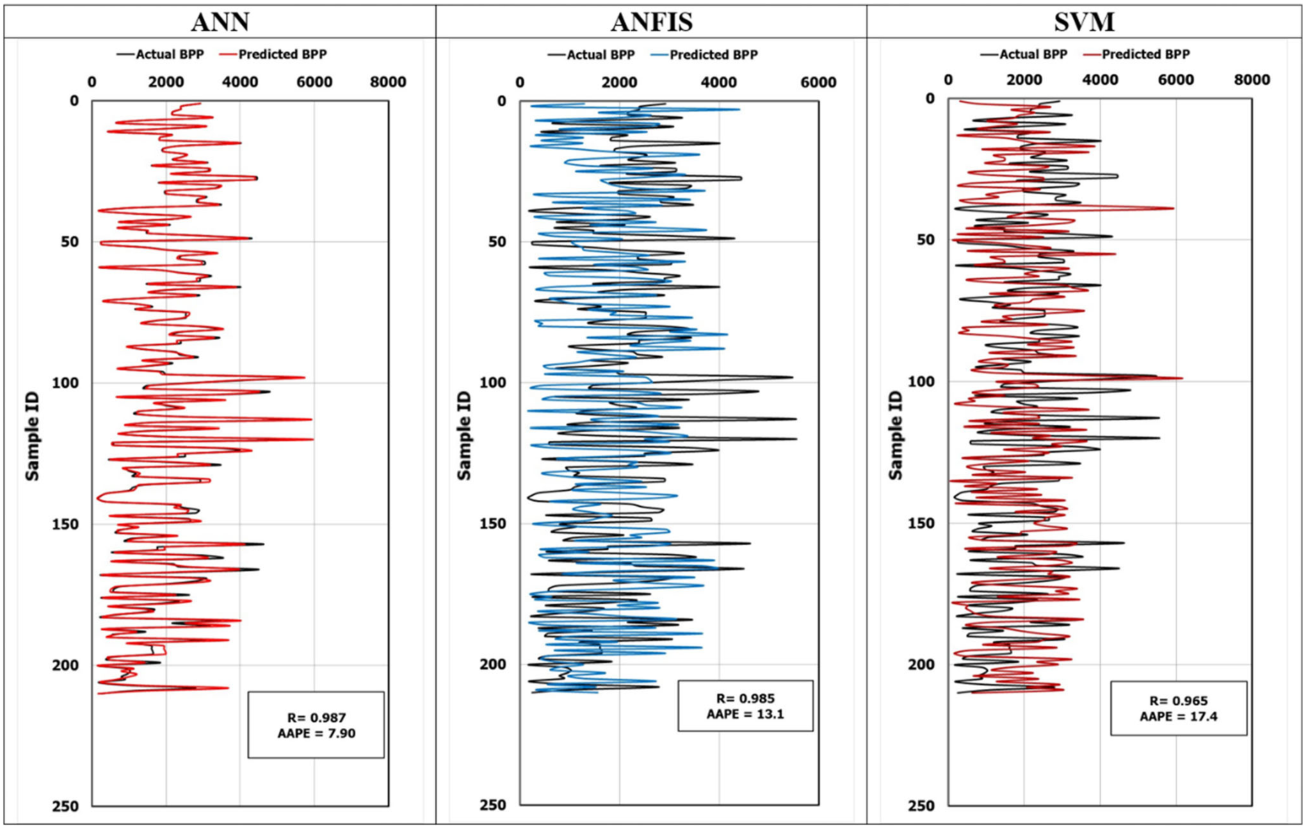


**Fig. 4** Bubble point prediction using AI techniques for the testing data (210 data points)

## 3 Development of Mathematical Model Using Artificial Neural Network

The mathematical model was driven from the artificial neural network model by extracting the weights associated with input layer/hidden layers and hidden layer/outer layer and the biases of the hidden layer and the output layer. Figure 5 shows the diagram of the developed ANN model. The weights between input layer and hidden layer are termed as $w_1$, the weights between hidden layer and outer layer are termed as $w_2$, the bias of the hidden layer is termed as $b_1$, and the bias of the output layer is termed as $b_2$, which are given in Table 2.

Equation 4 can be used to predict the BPP in normalized form as a function of the specific gravity of gas ($\gamma_g$), the dissolved gas to oil ratio ($R_s$), the oil specific gravity (API), and the temperature of the reservoir ($T_f$). To obtain the denormalized form of the BPP, Eq. 4 can be used.

$$\mathrm{BPP}_n = \left[\sum_{i=1}^{N} w_{2_i}\left(\frac{2}{1+\mathrm{e}^{-2\left(w_{1_{i,1}}R_{sn}+w_{1_{i,2}}\mathrm{GG}_n+w_{1_{i,3}}\mathrm{API}_n+w_{1_{i,4}}\mathrm{T}_{fn}+b_{1_i}\right)}}\right)\right]+b_2 \tag{4}$$

$$\mathrm{BPP} = \frac{(7127-126)\,(Pb_n+1)}{2}+126 \tag{5}$$

where $R_{s_n}$ is the normalized value of the solution gas oil ratio, $\mathrm{GG}_n$ is the normalized value of the gas specific gravity, $\mathrm{API}_n$ is the normalized value of the oil gravity, $T_{f_n}$ is the normalized value of the reservoir temperature, N is the number of neurons (the number of neurons should be optimized to have good match with less error); $w_1$ is weight of hidden layer; $w_2$ is weight of the output layer; $b_1$ is bias of the hidden layer, and $b_2$ is bias of the output layer. Table 2 lists the input parameters for Eq. (4).

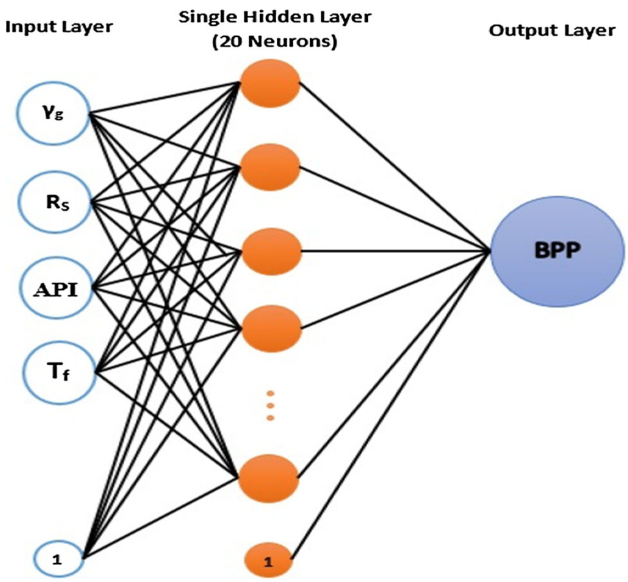


**Fig. 5** ANN diagrams show the inputs, output, hidden layer, and number of neuron

The number of neuron was optimized to be 20 to give the highest accuracy between the estimated and actual values of the bubble point pressure.

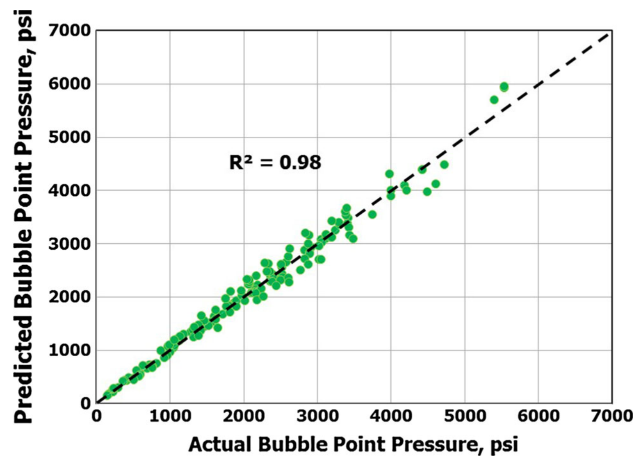


**Fig. 6** Coefficient of determination ($R^2$) for BPP prediction using Eq. 5

## 4 Validation of the Developed Mathematical Model

To assess the developed equation, 30% of the data (210 data points) which was unseen by ANN model was used to calculate the BPP using Eq. 7. Figure 6 shows that the developed equation (Eq. 5) was able to predict the BPP with a coefficient of determination ($R^2$) of 0.98 when comparing the actual and calculated values of the BPP.

**Table 2** Weights and biases for BPP prediction, Eq. 4

| Input layer weight matrix $W_1$ | | | | Input layer bias vector $b_1$ | Hidden layer weight vector $W_2$ | Output layer bias vector $b_2$ |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | | | |
| −2.3248 | 2.4608 | −2.0104 | −5.2317 | −0.1354 | 5.1937 | −0.2966 |
| −7.3692 | −1.2562 | 1.3131 | −2.3560 | 0.8256 | −1.4706 | |
| 3.9584 | −5.5817 | 7.7670 | 3.8646 | 0.1137 | −5.4995 | |
| −1.9146 | −1.2198 | 2.2708 | 0.5839 | 0.3471 | 0.3738 | |
| 3.4328 | 0.3899 | −0.3055 | 1.5746 | −1.3133 | 2.3265 | |
| −10.0962 | −1.6637 | 3.1283 | −3.3665 | −0.6302 | −1.9974 | |
| 4.7945 | −1.3479 | 2.7555 | −4.4916 | −0.0972 | −3.7194 | |
| −2.6018 | −0.1854 | 0.2493 | −1.3114 | −1.8183 | −1.7052 | |
| −1.2289 | 8.2957 | 5.2978 | −0.0575 | −1.3804 | −0.4322 | |
| 1.4999 | 0.0844 | −1.3773 | −0.3384 | 0.8569 | −0.0429 | |
| 1.4657 | −8.1862 | −5.3571 | 0.1018 | −1.3891 | 0.6172 | |
| 2.9561 | −3.6712 | 2.1439 | −5.6756 | −0.0851 | 1.3972 | |
| −0.4082 | 1.4761 | 1.0359 | 2.0513 | −1.7523 | −0.5735 | |
| 1.1950 | −2.0113 | 6.3937 | 1.3641 | 0.0687 | −0.1036 | |
| −4.6161 | 2.0524 | −2.7155 | 4.6920 | −0.0773 | −2.6209 | |
| 0.1657 | 1.4925 | −2.5912 | −0.5166 | −0.2125 | −0.7838 | |
| −3.4169 | 0.3328 | −1.6494 | 1.1327 | −0.2330 | −3.8676 | |
| −4.0265 | 1.4697 | 3.1386 | 5.1145 | −0.2537 | −6.3839 | |
| −0.3942 | 1.5115 | 0.9122 | 1.9610 | 1.8640 | −0.6851 | |
| 0.5939 | −1.0508 | 1.1340 | 0.2161 | −0.3469 | 1.4986 | |

**Table 3** Comparison of the developed mathematical model for BPP prediction with previous models

| | BPP prediction | | | | | | Average absolute error % | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Actual BPP (psi) | New Eq. | Gharbi [47] | Al-Marhoon [11] | Standing [13] | Glaso [43] | New Eq. | Gharbi [47] | Al-Marhoon [11] | Standing [13] | Glaso [43] |
| 1 | 408 | 405 | 422 | 418 | 468 | 445 | 0.8 | 3.4 | 2.5 | 14.7 | 9.1 |
| 2 | 804 | 752 | 773 | 853 | 1199 | 1446 | 6.4 | 3.9 | 6.1 | 49.1 | 79.9 |
| 3 | 1257 | 1134 | 1188 | 1088 | 1047 | 1180 | 9.8 | 5.5 | 13.4 | 16.7 | 6.1 |
| 4 | 1625 | 1615 | 1780 | 1836 | 2329 | 2492 | 0.6 | 9.5 | 13.0 | 43.3 | 53.4 |
| 5 | 1890 | 1859 | 1977 | 1925 | 1741 | 2159 | 1.6 | 4.6 | 1.9 | 7.9 | 14.2 |
| 6 | 2020 | 1956 | 2082 | 1794 | 1670 | 1775 | 3.2 | 3.1 | 11.2 | 17.3 | 12.1 |
| 7 | 2200 | 2125 | 1718 | 1517 | 1616 | 1721 | 3.4 | 21.9 | 31.0 | 26.5 | 21.8 |
| 8 | 2430 | 2401 | 2281 | 2062 | 1940 | 2135 | 1.2 | 6.1 | 15.1 | 20.2 | 12.1 |
| 9 | 2650 | 2510 | 3887 | 3580 | 2586 | 2918 | 5.3 | 46.7 | 35.1 | 2.4 | 10.1 |
| 10 | 2845 | 2863 | 2749 | 3427 | 2606 | 3017 | 0.6 | 3.4 | 20.5 | 8.4 | 6.0 |
| 11 | 3057 | 2940 | 3132 | 2971 | 2866 | 3284 | 3.8 | 2.5 | 2.8 | 6.2 | 7.4 |
| 12 | 3320 | 3125 | 3828 | 3111 | 3610 | 4021 | 5.9 | 15.3 | 6.3 | 8.7 | 21.1 |
| 13 | 3442 | 3265 | 3319 | 4081 | 3298 | 3563 | 5.2 | 3.6 | 18.6 | 4.2 | 3.5 |
| 14 | 3647 | 3421 | 3782 | 4457 | 4798 | 4989 | 6.2 | 3.7 | 22.2 | 31.6 | 36.8 |
| 15 | 3870 | 4000 | 3861 | 3964 | 4319 | 4198 | 3.4 | 0.2 | 2.4 | 11.6 | 8.5 |
| 16 | 4011 | 3792 | 3680 | 3988 | 3713 | 4125 | 5.5 | 8.3 | 0.6 | 7.4 | 2.8 |
| 17 | 4215 | 4013 | 3470 | 2737 | 3517 | 3975 | 4.8 | 17.7 | 35.1 | 16.6 | 5.7 |
| 18 | 4432 | 4375 | 3777 | 2656 | 3165 | 3504 | 1.3 | 14.8 | 40.1 | 28.6 | 20.9 |
| 19 | 4640 | 5119 | 4248 | 5568 | 6077 | 5941 | 10.3 | 8.4 | 20.0 | 31.0 | 28.0 |
| 20 | 5405 | 5411 | 5416 | 5922 | 7537 | 6843 | 0.1 | 0.2 | 9.6 | 39.4 | 26.6 |
| 21 | 6358 | 6456 | 6604 | 10,412 | 9502 | 7860 | 1.5 | 3.9 | 63.8 | 49.4 | 23.6 |
| Average absolute error percentage = | | | | | | | 3.9 | 8.9 | 17.7 | 21.0 | 19.5 |

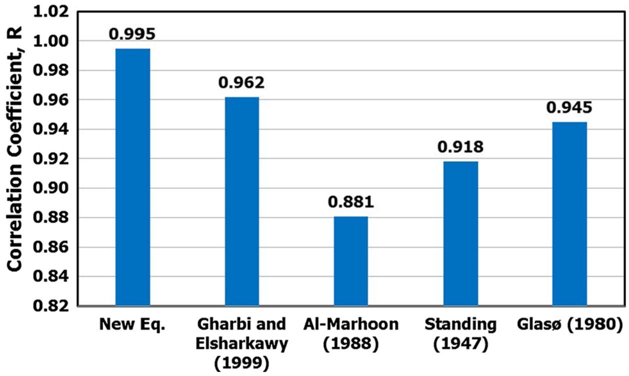


**Fig. 7** The developed equation yields the highest correlation coefficient for BPP prediction as compared with the previous models

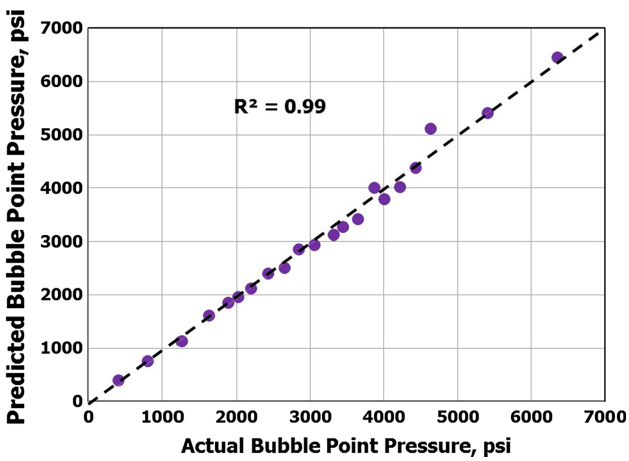


**Fig. 8** Prediction of BPP for the published data [47] using Eq. 5

For further validation, another set of data (21 data points) was used to compare the developed mathematical equation with previous ANN model [47] and other empirical equations (Standing, [31], Al-Marhoun [29], Glasø [43]) as listed in Table 3.

Table 3 confirms that the developed mathematical model for BPP prediction yielded the lowest average absolute error (3.9%) when compared with the previous models.

Figure 7 shows that the developed equation for BPP prediction (Eq. 5) yields the highest correlation coefficient as compared with the previous models.

Figure 8 shows that Eq. 5 was able to predict the BPP with a coefficient of determination ($R^2$) of 0.99 for unseen published data [47].

## 5 Conclusions

Three AI models were developed to estimate the BPP as a function of the specific gravity of gas ($\gamma_g$), the dissolved gas to oil ratio ($R_s$), the oil specific gravity (API), and the temperature of the reservoir ($T_f$). Based on the results obtained, the following conclusion can be drawn:

1. Artificial neural network is the best AI technique to be used to predict the bubble point pressure as a function of the gas specific gravity, the solution gas oil ratio, the oil gravity, and the reservoir temperature.
2. ANN model has a correlation coefficient of 0.988 and an average absolute error of 7.5% when it was used to predict the BPP.
3. The developed mathematical equation from the ANN model outperformed the previous models for BPP prediction.
4. The developed correlation of the BPP from the ANN model can be used to predict the BPP with high accuracy ($R^2 = 0.98$)

A new empirical correlation for the BPP was developed based on the weights and biases from the ANN model. This will eliminate the need for special software or equipment to run the model. The developed equation can be run on Excel. This development will help the reservoir engineer to better manage the reservoir and predict the BPP.

## References


1. McCain Jr., W.D.: The Properties of Petroleum Fluids, 2nd edn. PennWell Publishing Co., Tulsa (1990)
2. Coats, K.H.; Smart, G.T.: Application of a regression based equation of state PVT program to laboratory data. SPE Reserv. Eng. J. **1**(3), 277–299 (1986). SPE 11197-PA.
3. Hosein, R.; Dawe, R.A.: A parametric methodology in tuning the Peng–Robinson (PR) equation of state for gas condensate systems. Pet. Sci. Technol. **32**, 662–672 (2014)
4. Vogel, J.V.: Inflow performance relationship for solution-gas drive wells. Trans. AIME **243**, 83–92 (1986)
5. Huang, Z.; Shimeld, J.; Williamson, M.; Katsube, J.: Permeability prediction with artificial neural network modeling in the Venture gas field, offshore eastern Canada. Geophysics **61**, 422–436 (1996). doi:10.1190/1.1443970
6. Álvarez del Castillo, A.; Santoyo, A.; García-Valladares, E.: A new void fraction correlation inferred from artificial neural networks for modeling two-phase flows in geothermal wells. Comput. Geosci. **41**, 25–39 (2012). doi:10.1016/j.cageo.2011.08.001
7. Graves, M.; Liwicki, S.; Fernandez, R.; Bertolami, H.; Bunke, J.; Schmidhuber, : A novel connectionist system for improved unconstrained handwriting recognition. IEEE Trans. Pattern Anal. Mach. Intell. **31**(5), 855–868 (2009)
8. Lippmann, R.P.: An introduction to computing with neural nets. IEEE ASSP Mag. **4**(2), 4–22 (1987)
9. Hinton, G.E.; Osindero, S.; Teh, Y.: A fast learning algorithm for deep belief nets. Neural Comput. **18**(7), 1527–1554 (2006)
10. Mohaghegh, S.; Ameri, S.: Artificial neural network as a valuable tool for petroleum engineers. In SPE Paper 29220-Prepared at Consolidated Paper for SPE (1995)
11. Niculescu, S.P.: Artificial neural networks and genetic algorithms in QSAR. J. Mol. Struct. Theochem. **622**, 71–83 (2003)

12. Liew, S.S.: An optimized second order stochastic learning algorithm for neural network training. Neurocomputing (2015). doi:10.1016/j.neucom.2015.12.076i
13. Rammay, M.H.; Abdulraheem, A.: Automated history matching using combination of adaptive neuro fuzzy system (ANFIS) and differential evolution algorithm. In: Paper SPE 172992 Presented at the SPE Large Scale Computing and Big Data Challenges in Reservoir Simulation Conference and Exhibition held in Istanbul (2014)
14. Nooruddin, H.A.; Anifowose, F.; Abdulraheem, A.: Applying artificial intelligence techniques to develop permeability predictive models using mercury injection capillary-pressure data. In: Paper SPE 168109 Presented at SPE Saudi Arabia Section Technical Symposium and Exhibition, Al-Khobar (2013)
15. Jang, J.S.R.: ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans. Syst. Man Cybern. **23**(3) (1993). doi:10.1109/21.256541
16. Tahmasebi, P.A.: Hybrid neural networks-fuzzy logic-genetic algorithm for grade estimation. Comput. Geosci. **42**, 18–27 (2012)
17. Klir, G.; Yuan, B.: Fuzzy Sets and Fuzzy Logic: Theory and Applications. Prentice-Hall, Englewood Cliffs (1995)
18. Kaydani, H.; Mohebbi, A.; Baghaie, A.: Neural fuzzy system development for the prediction of permeability from wireline data based on fuzzy clustering. J. Pet. Sci. Eng. **30**(19), 2036–2045 (2012)
19. Burbidge, R.; Trotter, M.; Buxto, B.: Drug design by machine learning: support vector machines for pharmaceutical data analysis. Comput. Chem. **26**(1), 5–14 (2001)
20. Ben-Hur, A.H.; David, S.H.; Vapnik, V.: Support vector clustering. J. Mach. Learn. Res. **2**, 125–137 (2001)
21. Jeng, J.T.; Chuang, C.C.; Su, S.F.: Support vector interval regression networks for interval regression analysis. Fuzzy Sets Syst. **138**(2), 283–300 (2003)
22. William, H.; Teukolsky, S.A.; Vetterling, W.T.; Flannery, B.P.: Support Vector Machines. Numerical Recipes: The Art of Scientific Computing, 3rd ed. Cambridge University Press, New York (2007) ISBN 978-0-521-88068-8
23. Trontl, K.; Smuc, T.; Pevec, D.: Support vector regression model for the estimation of $\gamma$-ray buildup factors for multi-layer shields. Ann. Nucl. Energy **34**(12), 939–952 (2007)
24. Gholami, R.; Shahraki, A.R.; Jamali P.M.: Prediction of hydrocarbon reservoirs permeability using support vector machine. Math. Prob. Eng. (2012). doi:10.1155/2012/670723
25. Standing, M.B.: Volumetric and Phase Behavior of Oil Field Hydrocarbon Systems. Reinhold Publishing Corporation, New York (1952)
26. Amyx, J.W.; Bass, D.M.; Whiting, R.L.: Petroleum Reservoir Engineering Physical Properties. McGraw Hill Inc, New York (1960)
27. Craft, B.C.; Hawkins, M.F.: Applied Petroleum Reservoir Engineering. Prentice-Hall Inc, Englewood Cliffs (1959)
28. Gharbi, R.B.; Elsharkawy, A.M.: Neural network model for estimating the PVT properties of middle east crude oils. In: Paper SPE 37695 Presented at the Middle East Oil Show and Conference, 15–18 March, Bahrain (1997)
29. Al-Marhoun, M.A.: PVT correlations for middle east crude oils. J. Petrol. Technol. **40**(5), 650–666 (1988)
30. Al-Marhoun, M.A.: New correlation for formation volume factors of oil and gas mixtures. J. Can. Pet. Technol. **31**(3), 22–26 (1992)
31. Standing, M.B.: Pressure–Volume–Temperature Correlation for Mixtures of California Oils and Gases. Drilling and Production Practice. API, New York (1947)
32. Standing, M.B.: Oil-system correlations. In: Frick, T.C. (ed.) Petroleum Production Handbook, pp. 1–42. SPE, Richardson (1962)
33. Standing, M.B.: Volumetric and Phase Behavior of Oil Field Hydrocarbon Systems. Millet Print Inc., Dallas (1977)
34. Osman, E.A., Abdel-Wahhab, O.A.; Al-Marhoun, M.A.: Prediction of oil PVT properties using neural networks. In: Paper SPE 68233 Presented at the SPE Middle East Oil Show held in Bahrain, 17–20 March (2001)
35. Moghadam, J.N.; Salahshoor, K.; Kharrat, R.: Introducing a new method for predicting PVT processing of iranian crude oils by applying artificial neural network. Petrol. Sci. Eng. **29**(10), 1066–1079 (2001)
36. Al-Marhoun, M.A.; Osman, E.A.: Using artificial neural networks to develop new PVT correlations for saudi crude oils. In: Paper SPE 78592 Presented at the 10th Abu Dhabi International Petroleum Exhibition and Conference (ADIPEC), October 8–11, Abu Dhabi (2002)
37. El-Sebakhy, E.A.; Sheltami, T.; AL-Bokhitan, S.Y.; Shaaban, Y.; Raharja, P.D.; Khaeruzzaman, Y.: Support vector machines framework for predicting the PVT properties of crude oil systems. In: Paper SPE 105698 Presented at the SPE Middle East Oil and Gas Show and Conference, 11–14 March, Manama (2007)
38. Moghadassi, A.R.; Parvizian, F.; Hosseini, S.M.; Fazali, A.R.: A New Approach for Estimation of PVT Properties of Pure Gases Based on Artificial Neural Network Model. Brazilian Journal of Chemical Engineering Department, Faculty of Engineering, Arak University (2009)
39. Numbere, O.G.; Azuibuike, I.I.; Ikiensikimama, S.S.: Bubble point pressure prediction model for Niger delta crude using artificial neural network approach. In: Paper SPE 167586, Presented at the SPE Nigeria Annual International Conference and Exhibition, 5–7 August, Lagos (2013)
40. Baarimah, S.O.; Gawish, A.A.; BinMerdhah, A.B.: Artificial intelligence techniques for predicting the reservoir fluid properties of crude oil systems. Int. Res. J. Eng. Technol. **2**(7), 373–382 (2015)
41. Adeeyo, Y.A.: Artificial neural network modelling of bubble point pressure and formation volume factor at bubble point pressure of nigerian crude oil. In: Paper SPE 184378 Presented at the SPE Nigeria Annual International Conference and Exhibition, 2–4 August, Lagos, (2016)
42. Katz, D.L.: Prediction of Shrinkage of Crude Oils. Drilling and Production Practice. API, New York (1942)
43. Glasø, O.: Generalized pressure–volume–temperature correlations. J. Pet. Technol. **32**(5), 785–795 (1980)
44. Vazquez, M.E.; Beggs, H.D.: Correlation for fluid physical property prediction. J. Pet. Technol. **32**(6), 968–970 (1980)
45. Omar, M.I.; Todd, A.C.: Modified black oil correlation for malaysian crudes. In: The 1993 SPE Asia Pacific Asia Pacific Oil & Gas Conference and Exhibition, Feb. 8–10, Singapore, SPE 25338, pp. 211–219 (1993)
46. Ghetto, G., Aone, D.F.; Villa, M.: Reliability analysis on PVT correlation. In: Paper SPE 28904 Presented at the SPE European Petroleum Conference, October 25–27, London (1994)
47. Gharbi, R.B.; Elsharkawy, A.M.: Neural network model for estimating the PVT properties of middle east crude oils. SPE Reserv. Eval. Eng. **2**(3), 255–263 (1999)