# CHAPTER IV RESULTS AND DISCUSSION

### 4.1 Data Available

Data collection is the most crucial task in this research. An ANN model demands a large volume of data for training purposes and cross-validation in order to solve complex, nonlinear problems accurately. In addition, the accuracy of the correlation depends on the data used for developing correlation as well. The data employed in this research were carefully collected from the existing publications. The list of all the available data sources is shown in Table 4.1.

 Table 4.1
 List of all the available data sources

Sources	Relevant crude oil properties
Glaso (1980)	$P_b, B_{ob}, R_s$
Ostermann and Owolabi (1983)	$P_b, B_{ob}, R_s$
Al-Marhoun (1988)	$P_b, B_{ob}, R_s$
Abdul-Majeed et al. (1988)	B <sub>ob</sub> , R <sub>s</sub>
Abdul-Majeed et al. (1990)	$R_s, \mu_o$
Dokla and Osman (1991)	$P_b, B_{ob}, R_s$
Labedi (1992)	μο
Omar and Todd (1993)	$P_b, B_{ob}, R_s$
De Ghetto and Villa (1994)	$P_b, B_{ob}, \mu_o, R_s$
De Ghetto et al. (1995)	μο
Mahmood and Al-Marhoun (1996)	$P_b, B_{ob}, R_s$
Velarde et al. (1997)	$P_b, B_{ob}, R_s$
Gharbi and Elsharkawy (1997)	B <sub>ob</sub> , R <sub>s</sub>
Gharbi and Elsharkawy (1999)	P <sub>b</sub> ,
Wu and Rosenegger (1999)	P <sub>b</sub> , B <sub>ob</sub>
Isehunwa et al. (2006)	μο
Bello et al. (2008)	$P_b, B_{ob}, R_s$

Note:  $P_b$  = bubble point pressure (psia),  $B_{ob}$  = bubble point oil formation volume factor,  $R_s$  = solution gas oil ratio (scf/stb)

For  $P_b$  modeling, 764 data points with 3,820 measurements including reservoir temperature ( $T_{res}$ ), solution gas oil ratio ( $R_s$ ), gas specific gravity ( $\gamma_g$ ), oil

specific gravity ( $\gamma_0$ ), oil API gravity (API), and bubble point pressure ( $P_b$ ) in each data point were collected for this work. After removing all redundant data, the total of 757 data points with 3,785 measurements were employed for developing bubble point pressure model. The data were randomly divided into two sets. A set of 557 data points were used for developing correlation and ANN, and another set of 200 data points were used for testing the models. Table 4.2 presents the data summary for developing bubble point pressure models and Table 4.3 presents the data summary for testing bubble point pressure models.

In order to develop and test  $B_{ob}$  correlation and ANN, the total of 1,175 data points with 5,875 measurements were selected after the repeated data were removed. The crude oil data comprised reservoir temperature, solution gas oil ratio, gas specific gravity, oil specific gravity, oil API gravity and bubble point oil formation volume factor. Furthermore, the crude oil data were randomly classified into a set of 875 data points for developing  $B_{ob}$  models, and another set of 300 data points for testing  $B_{ob}$  models. The data summaries for developing and testing  $B_{ob}$  models are shown in Tables 4.4 and 4.5, respectively.

 Table 4.2 Data summary for developing Pb models (557 points)

Properties	Min	Max	AVG	S.D.	Skewness	Kurtosis
$R_s$ (scf/bbl)	8.61	3298.66	644.368	518.154	1.49876	2.81296
$T_{res}$ (°F)	74	341.6	199.587	52.4055	-0.2168	-0.4695
γ <sub>g</sub>	0.61	3.4445	1.13424	0.42862	1.60444	2.89109
API°	6	56.8	35.1157	8.32354	-1.056	1.58375
P <sub>b</sub> (psia)	79	7127	1976.5	1409.72	0.81095	0.28586

 Table 4.3 Data summary for testing Pb models (200 points)

Properties	Min.	Max.	AVG	S.D.	Skewness	Kurtosis
R <sub>s</sub> (scf/bbl)	17.21	3020	657.41	528.524	1.43495	2.55253
$T_{res}$ (°F)	80	334.4	204.357	51.8959	-0.2426	-0.1802
γ <sub>g</sub>	0.61	2.98	1.16574	0.44579	1.63334	2.9683
API°	6.3	56.5	35.972	8.41313	-1.2479	2.17911
P <sub>b</sub> psia	95	6641	1970.43	1438.43	0.72348	-0.0341

Properties	Min.	Max.	Average	S.D.	Skewness	Kurtosis
R <sub>s</sub> (scf/bbl)	0	3298.66	523.534	480.242	1.66484	3.57134
$T_{res}$ (°F)	74	593.996	187.693	54.1197	0.47773	2.71979
$\gamma_{g}$	0.511	3.4445	1.01727	0.37987	2.08889	5.32879
API°	6	59.5	32.8496	10.0429	-0.5984	-0.341
B <sub>ob</sub>	1.028	2.916	1.34781	0.28297	1.77547	4.47046

**Table 4.4** Data summary for developing B<sub>ob</sub> models (875 points)

 Table 4.5 Data summary for testing Bob models (300 points)

Properties	Min.	Max.	Average	S.D.	Skewness	Kurtosis
R <sub>s</sub> (scf/bbl)	0	3020	552.867	481.115	1.75751	4.27439
$T_{res}$ (°F)	75.002	341.6	187.153	54.102	0.08627	-0.6121
$\gamma_{ m g}$	0.525	2.98	1.03774	0.3922	2.02137	4.72544
API°	6.3	56.8	33.2908	9.72234	-0.6421	0.19895
B <sub>ob</sub>	1.028	2.903	1.36313	0.29277	2.15482	6.97319

With respect to  $R_s$  modeling, after removing redundant data, a total of 750 data points including 3,750 measurements including  $R_s$ ,  $T_{res}$ ,  $\gamma_g$ , API°, and  $B_{ob}$  for each data point were collected. Nevertheless, the entire data for  $R_s$  had resulted in high errors after being applied to some published correlations. Data filtering was required for these data sets. The data points with the majority of errors over 15% of the prediction resulted from the published correlations was removed as invalid data (Mohammadpoor et al., 2010). The correlations used in data filtering were from Standing (1947), Glaso (1980), Al-Marhoun (1988), Petrosky Jr. and Farshad (1993), and Hemmati and Kharrat (2007) as they gave reasonably good  $R^2$  value for the entire data. Finally, 254 data points with 1,270 measurements were selected as valid data. The data were randomly divided into two sets. A set of 204 data points were used in developing correlations and ANN, and another set of 50 data points were used for testing the models. Table 4.6 and 4.7 summarize the data used in developing and testing  $R_s$  models, respectively.

Properties	Min	Max	Average	S.D.	Skewness	Kurtosis
T <sub>res</sub> (°F)	74	306	177.3103	53.5355	0.25833	-0.3837
P <sub>b</sub> (psia)	133	7127	2461.832	1313.61	0.6429	0.77613
R <sub>s</sub> (scf/bbl)	39	2249	715.2556	421.813	0.86782	0.8676
$\gamma_{g}$	0.61	1.981	0.883494	0.18043	2.37246	10.1396
API°	10	56.5	35.52543	6.71268	-0.253	1.45365
γο	0.75266	0.9902	0.847988	0.03317	0.37677	1.38331

**Table 4.6** Data summary for developing R<sub>s</sub> models (204 points)

**Table 4.7** Data summary for testing R<sub>s</sub> models (50 points)

Properties	Min	Max	Average	S.D.	Skewness	Kurtosis
T <sub>res</sub> (°F)	80	305.1	179.244	56.591	0.44137	-0.2745
P <sub>b</sub> (psia)	179	6641	2318.816	1684.23	0.86365	0.39826
R <sub>s</sub> (scf/bbl)	39	2191.33	693.0238	566.516	0.98737	0.30701
γ <sub>g</sub>	0.612	1.517	0.91048	0.18985	0.94314	0.78646
API°	10.9	53	34.19725	9.04099	-0.1313	-0.0513
γο	0.771	0.93771	0.857017	0.04043	-0.1042	-0.7448

Regarding to  $\mu_0$  modeling, after removing duplicated data, 525 data points with 3,150 measurements were collected. With high errors similar to the case of R<sub>s</sub> modeling, data filtering was mandatory. 446 data points were used after being filtered with the methods presented by Beal (1946), Vazquez and Beggs (1980), Khan et al. (1987), Kartoatmodjo and Schmidt (1991), De Ghetto and Villa (1994), Petrosky and Farshad (1995), Hossain et al. (2005), Isehunwa et al. (2006), Sutton and Bergman (2006), and Abedini et al. (2010). Therefore, a set of 357 data points used for developing and another set of 89 data points used for testing the  $\mu_0$  models were selected at random. The data summaries for developing and testing  $\mu_0$  models are shown in Table 4.8 and 4.9.

Properties	Min	Max	Average	S.D.	Skewness	Kurtosis
$T_{res}$ (°F)	80.6	305.1	181.336	36.4153	0.29233	0.79745
P (psia)	242.22	7411.54	3947.64	1405.58	-0.14157	-0.3801
API°	6	56.8	27.3126	10.363	0.208	-0.61701
P <sub>b</sub> (psia)	113.129	6613.82	2618.97	1391.1	0.30147	-0.44678
μ <sub>ob</sub> (cp)	0.093	90.3	4.78695	8.69585	4.13282	28.3054
$\mu_{o}(cp)$	0.096	108.3	5.69268	10.76	4.31918	28.3166

**Table 4.8** Data summary for developing  $\mu_0$  models (357 points)

**Table 4.9** Data summary for testing  $\mu_0$  models (89 points)

Properties	Min	Max	Average	S.D.	Skewness	Kurtosis
$T_{res}$ (°F)	90.5	303.1	189.544	46.8272	0.53159	0.38161
P (psia)	351	7137.42	3845.11	1523.88	-0.09841	-0.66949
API°	7.9	51	27.8787	10.4373	0.03522	-0.74797
P <sub>b</sub> (psia)	113.129	6272.98	2739.01	1603.7	0.25018	-0.66949
μ <sub>ob</sub> (cp)	0.093	80.6	5.08887	12.1685	4.53219	22.8862
μ <sub>0</sub> (cp)	0.099	86.6	6.18115	14.4356	4.0129	17.2185

#### 4.2 Developed Correlations

The prepared data sets, presented in section 4.1 were used for developing new correlations for predicting each crude oil property by utilizing Minitab 16. A nonlinear regression was a technique used to create the correlations for the determination of each crude oil property using field parameters.

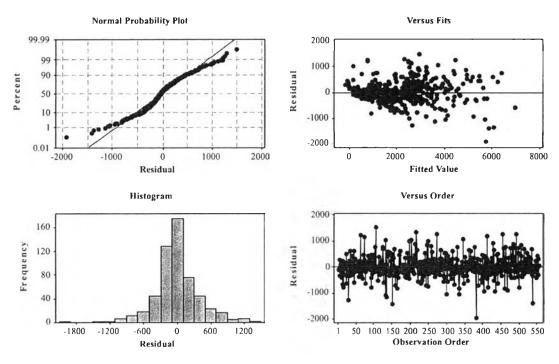
### 4.2.1 <u>Bubble Point Pressure Correlation</u>

After numerous trials using nonlinear regression technique in Minitab 16, the following equation was created to predict bubble point pressure:

$$P_b = 577.747 (R_s^{0.444689} - 4.43941) e^{(0.00252849T_{res} - 0.0217755API - 0.976346\gamma_g)}$$
(4.1)

Equation 4.1 was modified from Calhoun's correlation form (Calhoun, 1976) with the changes in coefficients. It is a function of  $R_s$ ,  $T_{res}$ , API, and  $\gamma_g$ . Residual plots of  $P_b$  obtained from Equation 4.1 are shown in Figure 4.1.

#### Residual Plots for Ph



**Figure 4.1** Residual plots resulted from developing P<sub>b</sub> correlation using nonlinear regression technique.

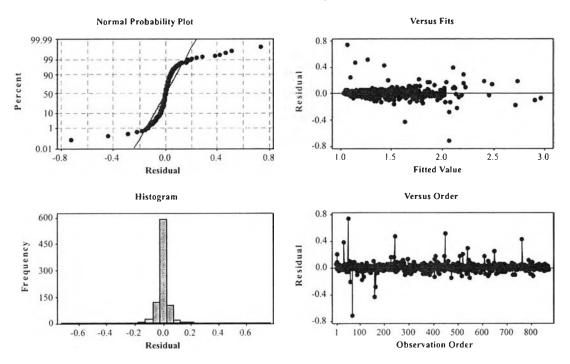
#### 4.2.2 Bubble Point Oil Formation Volume Factor Correlation

The  $B_{ob}$  expression in Equation 4.2 was developed from the data used in this work by using nonlinear regression technique. The results indicated that  $B_{ob}$ expression was a function of  $R_s$ ,  $T_{res}$ ,  $\gamma_g$ , and  $\gamma_o$ . In addition, this equation was correlated by modifying Petrosky-Farshad's correlation form (Petrosky Jr. and Farshad, 1993).

$$B_{ob} = 4.25999 \times 10^{-5} \left( R_s^{0.601715} \cdot \left( \frac{\gamma_g}{\gamma_o} \right)^{1.47844} + 0.968331 \cdot T_{res}^{0.68077} \right)^{1.99881} + 1.00387$$
(4.2)

Plus, residual plots of  $B_{ob}$  generated from Minitab resulting from developing Equation 4.2 are illustrated in Figure 4.2.

#### Residual Plots for Bub



**Figure 4.2** Residual plots resulted from developed  $B_{ob}$  correlation using nonlinear regression technique.

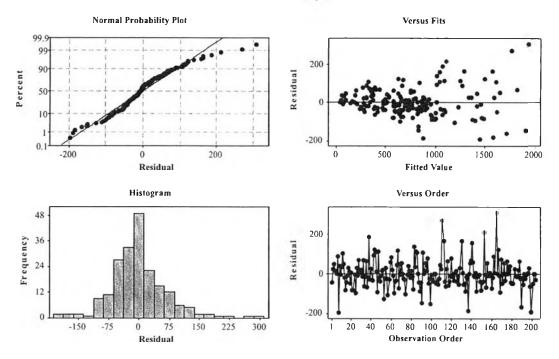
#### 4.2.3 Solution Gas Oil Ratio Correlation

After numerous trials on nonlinear regression technique with respect to the available data,  $R_s$  correlation was correlated as a function of  $\gamma_g$ ,  $P_b$ ,  $\gamma_o$ , API, and  $T_{res}$ . Therefore, Equation 4.3 was developed for predicting  $R_s$ . The equation was modified from Frashad's correlation form (Frashad et al., 1996).

$$R_{s} = \frac{0.0395338\gamma_{g}P_{b}^{1.10041}}{(1-28.7354\left(\frac{\gamma_{o}}{T_{res}}\right)) \times 10^{(0.0002.8594T_{res}-0.01575API)}}$$
(4.3)

To examine the applicability of Equation 4.3, residual plots generated from developing  $R_s$  correlation are presented in Figure 4.3.

#### Residual Plots for R.



**Figure 4.3** Residual plots resulted from developing  $R_s$  correlation from nonlinear regression technique.

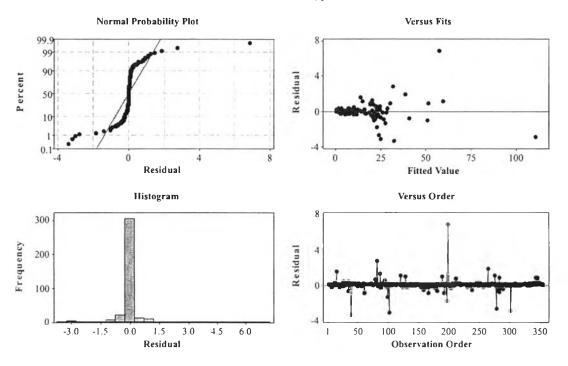
### 4.2.4 Undersaturated Oil Viscosity Correlation

For  $\mu_0$  correlation, after a number of trials, Equation 4.4 was exploited to predict  $\mu_0$  as a function of oil viscosity at bubble point ( $\mu_{ob}$ ), T<sub>res</sub>, reservoir pressure (P), and P<sub>b</sub>.

$$\mu_{\rm o} = \mu_{\rm ob} + (1.16682\mu_{\rm ob}^{1.0841052} - 0.474189) \cdot (P - P_{\rm b}) \times 10^{-4}$$
(4.4)

Finally, the residual plots resulted from developing  $\mu_0$  using Minitab are shown in Figure 4.4.

#### Residual Plots for µ<sub>a</sub>



**Figure 4.4** Residual plots for the developed  $\mu_0$  correlation resulted from nonlinear regression technique.

### 4.3 Developed Artificial Neural Networks

Both developing correlations and ANN models employed the similar developing datasets (presented in section 4.1). Neural network toolbox (nntool), which is graphical user interface (GUI) embedded in Matlab was used to develop the ANN models. In this research, 70% of the developing data were randomly used for training, and 30% were used for validation and testing each network. Feed-forward, back-propagation neural network with one hidden-layer was applied to each model. Gradient descent with momentum (GDM) training algorithm and Levenberg-Marquardt (LM) learning algorithm were adopted in each model. Hyperbolic tangent sigmoid transfer function (Tansig) was used for the calculation between input layer and hidden layer, while linear transfer function (Purelin) was chosen to calculate the output from the hidden layer to the output layer.

#### 4.3.1 <u>Bubble Point Pressure Neural Network</u>

From 557 data points out of the data set for developing P<sub>b</sub> model (see section 4.1), 389 data points were randomly selected for training. 84 data points were also randomly selected for validation and another 84 data points were used for testing the network. Four input parameters including R<sub>s</sub>,  $T_{res}$ ,  $\gamma_g$ , and API were used as input parameters, while P<sub>b</sub> is the target for the developing P<sub>b</sub> ANN. After numerous trials, a neural network with 10 neurons in the hidden layer was recognized as the best model in training, validation, and testing the ANN. In other words, the 4-10-1 (i.e., input layer - hidden layer - output layer) neural network architecture was selected. The neural network architecture for the developed P<sub>b</sub> ANN is illustrated in Figure 4.5.

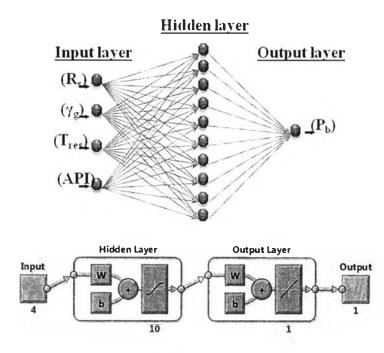


Figure 4.5 The architecture of the developed  $P_b$  ANN.

Regression plots resulted from the developed network outputs with respected to targets for training, validation, and testing the developing data set are shown in Figure 4.6. The regression plots gave reasonably good performance for all data sets with correlation coefficient (R value) above 0.96 for the total response in each case. Performance plots, shown in Figure 6.9, gave the best validation performance at iteration  $14^{th}$  with the mean square error (MSE) of 1,177,883.51. The training results, which are connection weight ( $W_{ji}$ ) and bias ( $b_j$ ) between each layer of  $P_b$  neural network, are shown in table 6.9.

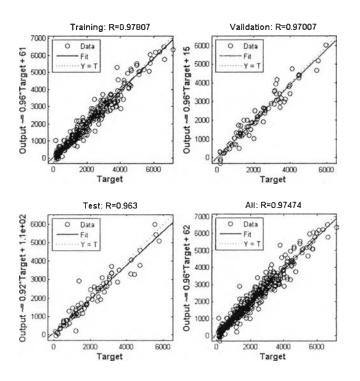


Figure 4.6 Regression plots of the P<sub>b</sub> neural network outputs.

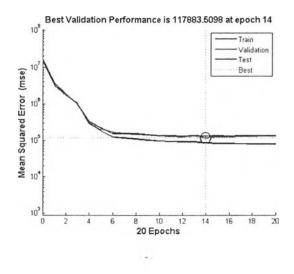


Figure 4.7 Performance plots of the developed P<sub>b</sub> ANN.

			÷		w <sub>ji</sub>						bj
j∖i	1	2	3	4	5	6	7	8	9	10	
First	layer	· · ·									
1	-0.13712	-0.33441	1.4863	0.50169							2.1933
2	-1.4088	-4.6959	-2.4845	-0.1808							-0.10565
3	-2.2805	7.9196	-4.4596	1.5205							1.1446
4	-2.5518	-3.1182	-0.92311	4.5653							-1.0879
5	0.2058	2.061	2.8962	2.0211							-0.50916
6	2.8641	-0.86916	0.88196	4.2808							1.0816
7	-1.3071	-1.2768	1.4905	9.278							1.598
8	2.8033	-0.81956	-0.098831	-2.8951							3.615
9	6.5022	-0.73523	-0.087034	-2.4325							3.5421
10	2.0283	-0.0106	1.0566	0.41804							3.179
Seco	nd layer (ou	tput layer)									
1	-2.7849	-0.28332	0.053302	0.14211	-0.26872	-0.049906	-0.10666	0.085681	0.09737	1.1821	0.94689

**Table 4.10** Connection weights and biases for the developed  $P_b$  neural network

#### 4.3.2 Bubble Point Oil Formation Volume Factor Neural Network

In case of  $B_{ob}$  neural network model, four input parameters (i.e.,  $R_s$ ,  $T_{res}$ ,  $\gamma_g$ , and  $\gamma_o$ ) were used for  $B_{ob}$  prediction. From 875 data points used for developing the  $B_{ob}$  model (see section 4.1), 613 data points were employed for training purposes. 131 data points were selected randomly for validation and another 131 data points were assigned to test the neural network. After various iterations, the 4-12-1 neural network architecture was chosen for  $B_{ob}$  prediction as shown in Figure 4.8.

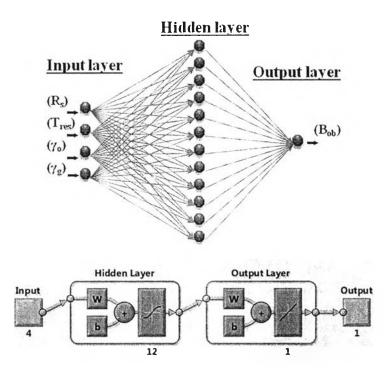


Figure 4.8 The architecture of the developed B<sub>ob</sub> ANN.

Figure 4.9 presents the regression plots as a result of the outputs of the  $B_{ob}$  ANN comparing to the targets used for training, validation, and testing. The value of the MSE resulted from validation performance of the developed  $B_{ob}$  ANN is 0.0039261 at 4 epochs as depicted in Figure 4.10. Although, the MSE resulted from training the  $B_{ob}$  ANN is relatively low, the range of the  $B_{ob}$  value used in this work are generally in between 1.0 to 3.0. Moreover, the connection weights and biases, which are the results of the  $B_{ob}$  ANN are shown in table 4.11.

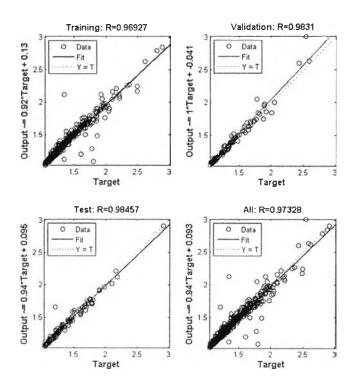


Figure 4.9 Regression plots of the B<sub>ob</sub> ANN outputs.

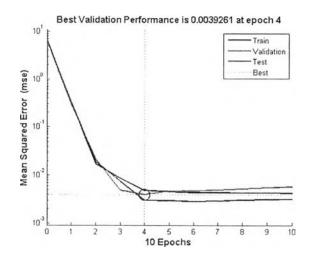


Figure 4.10 Performance plots of the developed  $B_{ob}$  ANN.

						w <sub>ji</sub>							bj
j∖i	1	2	3	4	5	6	7	8	9	10	11	12	
First	t layer												
1	-3.7885	-0.73268	-0.1973	-2.5793									4.3068
2	-1.578	3.0598	1.9243	-0.20581									3.8808
3	-1.6512	-0.53053	-1.2049	-0.7897									0.43339
4	0.74874	0.52802	0.1475	3.909									1.4545
5	2.243	0.42189	1.5931	0.53994									2.0292
6	0.36368	0.99081	-0.6465	-0.61309									0.32125
7	0.7214	-3.2948	0.22585	-0.54945									0.58692
8	-0.3878	-1.6791	-1.2342	1.4284									0.06498
9	2.1128	0.86987	-0.3278	1.0708									1.462
10	-1.2871	1.6473	1.6813	0.090412									-1.0217
11	-2.1487	-0.0099892	-0.323	-0.18022									-1.9552
12	1.0879	1.3284	-2.2623	0.4335									2.6979
Seco	ond layer (ou	utput layer)											
I	0.84657	0.01734	-1.5198	0.018101	0.12476	0.14344	-0.053519	0.047158	0.060627	-0.062205	-0.21342	0.28169	-0.32992

**Table 4.11** Connection weights and biases for Bob neural network model

4.3.3 Solution Gas Oil Ratio Neural Network

For  $R_s$  neural network model, four input parameters, which are  $P_b$ ,  $\gamma_g$ , API, and  $T_{res}$  were used. After numerous trials, a 4-11-1 neural network architecture (as shown in Figure 4.11) was selected to be the best model for determining  $R_s$ .

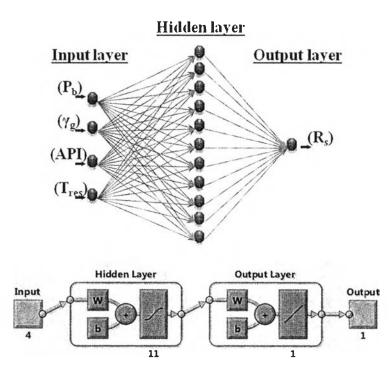


Figure 4.11 The architecture of the developed R<sub>s</sub> ANN.

In addition, the regression plots and performance plots resulted from training the  $R_s$  ANN are depicted in Figure 4.11 and 4.12. The R values resulted from training the  $R_s$  ANN have the value above 0.96 for all the responses, while the MSE value validated from the  $R_s$  ANN is 8,709.68 at epoch 4. The connecting weights and biases of the  $R_s$  ANN are shown in Table 4.12.

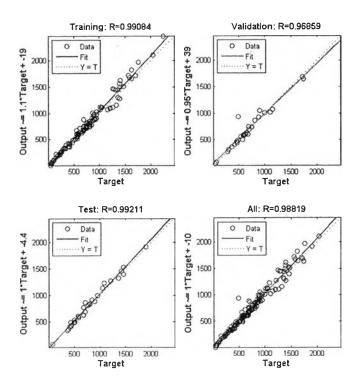


Figure 4.12 Regression plots of the R<sub>s</sub> ANN outputs.

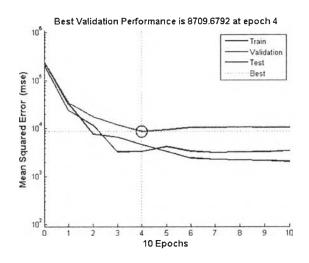


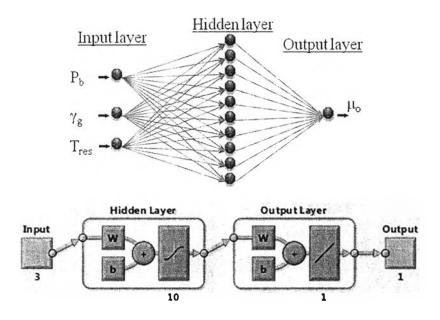
Figure 4.13 Performance plots of the developed R<sub>s</sub> ANN.

						W <sub>ji</sub>						bj
j/i	1	2	3	4	5	6	7	8	9	10	11	-
Firs	st Layer											
1	0.99236	-0.73559	1.0989	1.9376								-1.782
2	-1.5706	-1.3857	-0.94633	1.0411								1.855
3	0.68951	1.7531	-1.4553	1.068								-1.594
4	0.14542	1.4121	1.7477	-0.51542								-1.019
5	-1.941	1.7102	0.38953	0.40357								0.3890
6	-0.63523	-1.3448	0.45067	2.0518								-0.1127
7	-1.1727	1.402	0.61674	-0.34716								-1.261
8	-0.017742	1.3448	-0.47845	-2.2416								0.8961
9	-0.41216	0.39466	-0.63146	2.7098								-0.9066
10	-0.11717	-0.13075	2.4864	1.0164								-1.69
11	-1.3167	-2.0174	-0.84977	0.26514								-1.64
Sec	ond layer (d	output layer	.)									
1	0.1471	-0.15453	0.26219	1.9826	-0.047412	-0.051181	-0.76391	-0.066245	-0.085887	-0.85449	-0.47645	1.246

Table 4.12 Connection weight and biases for the developed  $\mathsf{R}_{\mathsf{s}}$  neural network model

#### 4.3.4 Undersaturated Oil Viscosity Neural Network

In order to develop  $\mu_0$  ANN, three input parameters, which are P<sub>b</sub>,  $\mu_{0b}$ , and P were used. 357 data points used for developing the ANN model (see section 4.1) were randomly divided into a set of 249 data points for training. A set of 49 data points was randomly selected for validation and another set of 49 data points was employed for testing the model. Finally, the 3-10-1 neural network architecture, shown in Figure 4.14, was selected for  $\mu_0$  prediction.



**Figure 4.14** The architecture of the developed  $\mu_0$  ANN.

Figure 4.15 illustrates the regression plots resulted from the outputs of the  $\mu_0$  ANN which compare to the targets for training, validation, and testing. The graphical representation gave good-fitting results with the R value exceeding 0.99 for each response. The value of the MSE obtained from the validation performance of the developed  $\mu_0$  ANN was 0.32241 at 26 epochs as shown in Figure 4.16. The connection weights and biases of the developed  $\mu_0$  ANN are shown in Table 4.13.

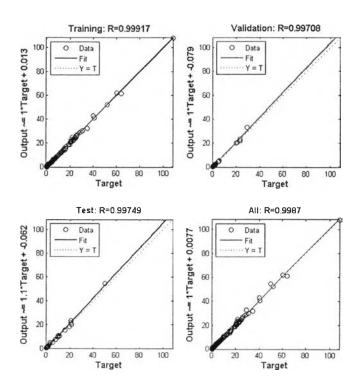


Figure 4.15 Regression plots of the  $\mu_0$  ANN outputs.

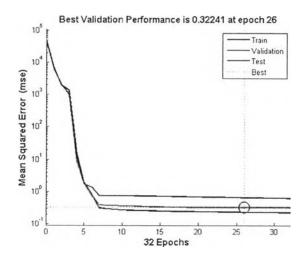


Figure 4.16 Performance plots of the developed  $\mu_0$  ANN.

					$w_{ji}$						bj
j∖i	1	2	3	4	5	6	7	8	9	10	
Firs	t layer									· · · · · · · · · · · · · · · · · · ·	
1	50.6069	-4.1999	-8.5235								-21.2024
2	2.0448	-3.0648	-1.5013								-4.9377
3	12.4152	-10.2516	-6.3569								-4.2787
4	-0.91043	0.47302	1.8279								2.9978
5	-0.059353	0.050421	0.76089								0.0068025
6	2.0083	2.454	5.8789								11.9947
7	-0.52828	0.80617	-1.7411								-0.29849
8	-2.0051	2.791	4.4742								2.789
9	1.893	1.2556	6.8942								-6.5685
10	-2.3809	-0.34968	6.2977								8.0729
Sec	ond layer (out	put layer)									
1	0.00035858	5.4837	0.0025817	-0.20914	2.4453	1.5075	0.35764	-0.03868	-0.19741	0.013542	4.1268

# Table 4.13 Connection weights and biases for the developed $\mu_o$ neural network

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### 4.4 Testing Results

The developed correlations and ANNs were tested against published correlations using the data sets for testing (the published correlation methods used for testing the developed models are summarized in Appendix A). The statistical results from the predictions of  $P_b$ ,  $B_{ob}$ ,  $R_s$  and  $\mu_o$  using published correlations and the developed models are shown in Tables 4.11-4.14. As for the visual aid, the graphical plots for the testing results are also illustrated in Appendix B.

Method	Er <sub>min</sub>	Er <sub>max</sub>	%AEr <sub>avg</sub>	%AEr <sub>max</sub>	R <sup>2</sup>
Standing (1947)	-3139.93	1579.84	25.69	372.01	0.88929
Calhoun (1976)	-1882.76	1654.84	53.76	614.80	0.86888
Glaso (1980)	-4181.29	1228.53	27.62	247.00	0.87955
Vazquez and Beggs (1980)	-3869.91	1307.29	30.15	403.90	0.88920
Al-Marhoun (1988)	-4049.08	1894.29	23.20	131.62	0.83649
Petrosky Jr. and Farshad (1993)	-3035.26	1521.86	86.39	766.86	0.90579
Dokla and Osman (1991)	-1830.10	2243.37	29.80	206.23	0.79883
Kartoatmodjo and Schmidt (1991)	-4685.30	1179.75	34.54	487.43	0.87637
De Ghetto and Villa (1994)	-2617.00	1624.93	30.22	466.61	0.89587
Frashad et al. (1996)	-1620.52	1624.93	39.08	230.77	0.88458
Almehaideb (1997)	-3979.12	1724.54	34.32	427.18	0.82125
Velarde et al. (1997)	-1611.32	2117.66	21.12	110.45	0.87761
Hanafy et al. (1997)	-1882.76	1645.84	53.77	614.80	0.86888
Al-Shammasi (1999)	-1862.15	1642.29	18.09	105.65	0.89788
Valkó and Mccain Jr (2003)	-1566.93	1829.55	18.76	112.73	0.91467
Dindoruk and Christman (2004)	-1314.32	2703.91	25.94	152.31	0.80465
Nikpoor and Khanamiri (2011)	-2731.29	2077.11	20.72	115.40	0.85476
$P_b$ correlation (Equation 4.1)	-1633.87	1693.76	22.36	185.92	0.91846
P <sub>b</sub> ANN (this work)	-1519.51	1512.67	21.32	240.19	0.93176

## Table 4.14 Statistical results of Pb using testing data

Method	Er <sub>min</sub>	Er <sub>max</sub>	%AEr <sub>avg</sub>	%AEr <sub>max</sub>	$\mathbb{R}^2$
Standing (1947)	-0.0214	1.5944	16.70	54.92	0.81238
Glaso (1980)	-0.1674	0.2695	2.84	11.61	0.97351
Al-Marhoun (1988)	-0.1014	0.2821	1.99	10.90	0.98026
Al-Marhoun (1992)	-0.0726	0.5773	3.56	20.00	0.97846
Omar and Todd (1993)	-0.0015	1.6115	17.87	55.51	0.84345
Petrosky Jr. and Farshad (1993)	-0.2337	0.1530	2.46	15.08	0.97582
Almehaideb (1997)	-0.2062	0.3171	4.23	17.73	0.93238
Hanafy et al. (1997)	-01.268	0.1512	7.97	43.93	0.93602
Al-Shammasi (1999)	-0.2136	0.4123	3.06	16.66	0.95197
Hemmati and Kharrat (2007)	-0.1789	0.1805	1.89	11.53	0.98179
Nikpoor and Khanamiri (2011)	-0.1421	0.4129	2.00	14.30	0.97513
B <sub>ob</sub> correlation (Equation 4.2)	-0.1377	0.2189	1.67	8.21	0.98395
B <sub>ob</sub> ANN (this work)	-0.1951	0.1876	2.13	9.67	0.98134

Table 4.15 Statistical results of  $\mathrm{B}_{\mathrm{ob}}$  using testing data

 Table 4.16
 Statistical results of Rs using testing data

Method	Er <sub>min</sub>	Er <sub>max</sub>	%AEr <sub>avg</sub>	%AEr <sub>max</sub>	$R^2$
Standing (1947)	-180.39	259.66	8.81	26.97	0.9848
Glaso (1980)	-220.49	589.67	14.64	50.02	0.9549
Al-Marhoun (1988)	-718.44	1335.15	19.62	200.83	0.7780
Petrosky Jr. and Farshad (1993)	-130.96	345.64	35.26	300.63	0.9835
Hemmati and Kharrat (2007)	-332.79	1424.27	11.85	100.14	0.8360
R <sub>s</sub> correlation (Equation 4.3)	-206.15	254.68	6.88	20.50	0.9840
R <sub>s</sub> ANN (this work)	-234.65	85.48	7.47	55.67	0.9909

Method	Er <sub>min</sub>	Er <sub>max</sub>	%AEr <sub>avg</sub>	%AEr <sub>max</sub>	R <sup>2</sup>
Beal (1946)	-7.34	1.79	4.01	15.85	0.9979
Vazquez and Beggs (1980)	-3.08	11.91	12.77	39.74	0.9934
Khan (1987)	-0.27	10.05	3.37	15.97	0.9966
Kartoatmodjo and Schmidt (1991)	-7.36	1.64	4.54	21.35	0.9981
Petrosky and Farshad (1995)	-0.29	25.70	5.93	38.54	0.9664
Isehunwa et al. (2006)	-0.34	8.90	3.36	17.05	0.9974
Abedini et al. (2010)	3.28	-3.53	6.86	57.83	0.9969
$\mu_0$ correlation (Equation 4.4)	-0.80	3.56	3.79	24.88	0.9992
$\mu_0$ ANN (this work)	-27.51	1.62	13.97	81.67	0.9789

Table 4.17 Statistical results of  $\mu_0$  using testing data

According to the P<sub>b</sub> prediction results, presented in Table 4.11, the developed P<sub>b</sub> ANN provided competitive performance compared to some of the published correlations. The developed P<sub>b</sub> ANN had the best fit with the highest R<sup>2</sup> value (0.93176), where the R<sup>2</sup> value of the developed P<sub>b</sub> correlation (Equation 4.1) had the second best result (0.91846). The developed P<sub>b</sub> ANN gave 21.32 % AEr<sub>avg</sub>, which is somewhat higher than several methods; however, the developed P<sub>b</sub> ANN had the narrowest range of error (Er<sub>min</sub> = -1519.51 psia, Er<sub>max</sub> = 1512.67 psia, and range = 3032.18 psia). For the range of error of the developed P<sub>b</sub> correlation, it is broader than the results obtained from the P<sub>b</sub> ANN and Frashad's approach (Frashad et al., 1996).

In case of the  $B_{ob}$  prediction results, the developed  $B_{ob}$  correlation (Equation 4.2) outperformed other methods with the highest R<sup>2</sup> value of 0.98395, the lowest AEr<sub>avg</sub> of 1.67 %, and the lowest AEr<sub>max</sub> of 8.21 %. Moreover, the developed B<sub>ob</sub> had the narrowest range of error (Er<sub>min</sub> = -0.1951, Er<sub>max</sub> = 0.2189, and range = 0.3827). The developed B<sub>ob</sub> ANN had the second lowest result in terms of AEr<sub>max</sub> (9.67 %). Also, other results from B<sub>ob</sub> ANN including the R<sup>2</sup> value, the AEr<sub>avg</sub>, and the range of

error are noticeably competitive to the Hemmati-Kharrat's approach (Hemmati and Kharrat, 2007).

For the prediction results of  $R_s$ , as shown in Table 4.13, the developed  $R_s$  correlation (Equation 4.3) and the  $R_s$  ANN gave competitively lower values of AEr<sub>avg</sub> (7.47 % AEr<sub>avg</sub> for the developed correlation and 6.88 % AEr<sub>avg</sub> for the  $R_s$  ANN) than other methods. Meanwhile, the developed  $R_s$  correlation exhibited the lowest AEr<sub>max</sub> (20.5 %), but the  $R_s$  ANN gave higher AEr<sub>max</sub> (55.67 %) than the developed  $R_s$  correlation (AEr<sub>max</sub> = 20.5 %) and some existing approaches (i.e., Standing (1947) and Glaso (1980)). However, in terms of the  $R^2$  value and the range of error, there are insignificant statistical outcomes compared to those from Standing's method and the  $R_s$  ANN.

For the prediction of  $\mu_0$ , as presented in Table 4.14, the developed  $\mu_0$  correlation (Equation 4.4) gave the highest R<sup>2</sup> value of 0.9992 and the narrowest range between  $\text{Er}_{min}$  (-0.8 cp) and  $\text{Er}_{max}$  (3.56 cp) with competitive performance compared to the published correlations by Beal (1946), Vazquez and Beggs (1980), Khan (1987), and Isehunwa et al. (2006). Although, the developed  $\mu_0$  ANN had a good result in developing process (see section 4.3.2), it gave poor performance when using the testing data set with the highest range between  $\text{Er}_{min}$  and  $\text{Er}_{max}$ , highest AEr<sub>avg</sub> and AEr<sub>max</sub>, and lowest R<sup>2</sup>. Thus, in order to check the applicability of an ANN, the ANN should be evaluated with different data set, and the appropriate size of the data set for developing process is also necessary.

Since the correlation approach does not need a computer, the correlation approach is therefore easier to be used. However, ANN approach can be quickly retrained using new data sets (i.e. regional data). ANN can also be practically applicable as long as the computer is accessible.