The volume and weight percentage of materials used in house H2 and their contribution to particular environmental indicators is presented in Figure 3. As illustrated in Figure 3, concrete was the material with largest volume percentage (28.7 %), the calculated weight percentage reached even 56.8 %. Therefore, environmental impact of concrete structures reached the largest scale in concrete materials (PEI = 33.5 %, GWP = 39.1 % and AP = 32.6 %). Relatively large volume percentage was calculated for aerated concrete and mineral insulation with 19.9 % and 20.2 % respectively. For these materials the calculated embodied energy ranged from 13.8 to 15.6 % MJ, embodied CO_2 ranged from 12.3 to 14.8 % and AP was in range from 9.9 to 21.7 %. Contribution of wood materials to global warming reached -22.1 %.

4. Conclusions

The design of buildings is a complicated process which requires cooperation of specialists from several branches including architecture, civil engineering as well as non-technical sectors. Selection of building materials is an important stage in the design process, because this is the key factor to influence also future behaviour, including environmental performance. It is rather important to analyze the environmental performance in the early project phase to make sure that all necessary decisions and changes of the design can be taken relatively quickly and easily rather than more complicatedly in further stages.

Analysis of 2 alternatives of one building with slightly changed material basis of selected structures presented that even relatively easy changes in material composition may lead to reduction of environmental impacts. In addition, also other advantages can be achieved, e.g. increase of useful floor area what is another benefit of optimization. The results of evaluation have proven that to reduce the negative impact of construction sector further investigation in the branch of environmental engineering is necessary.

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Modelling of Crude Oil Bubble Point Pressure and Bubble Point Oil Formation Volume Factor Using Artificial Neural Network (ANN)

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Crude oil properties data were gathered from publications for modeling correlations and artificial neural networks (ANN), which could be used to predict bubble point pressure and bubble point oil formation volume factor. The data sets were screened for redundant data. Each data set was selected randomly and divided into developing, and test data sets. Nonlinear regression was the technique used to develop each correlation. For ANN development, the developing data sets were randomly divided into training, validation, and testing sets. Different network architectures and transfer functions were used for developing the best ANN models. To ensure their accuracy and applicability, the developed models were tested and compared with other published correlations using the testing data sets, which had not been used for developing correlations and ANNs. The results showed that the developed models gave better performance compared to other existing correlations.

1. Introduction

Physical properties of reservoir fluid are necessary for various field applications. These properties are essentially determined at reservoir temperature with various pressures for reservoir system studies as well as at both various parameters for wellbore calculations. It implies that the fluid properties have a profound influence on petroleum and reservoir engineering calculations (Consentino, 2001). This valuable information of reservoir fluid can be obtained through vast laboratory testing either on bottom-hole or sub-surface samples, PVT laboratory analysis and field production data. In order to acquire the accurate results from the laboratory, the reservoir fluid samples must be appropriately collected and kept for the representative quality of the original reservoir condition. Moreover, apart from the inherent difficulties of the sampling measurements, these extensive procedures are very expensive and time-consuming. Since the last century, many empirical correlations of reservoir fluid properties have been developed and used in order to solve the aforementioned obstacles. These correlations can predict fluid properties based on the measured data from various sources, but fail to predict fluid properties in a wide range of conditions due to the complexity of fluid compositions, different crude characteristics in each area or region, and insufficient information (Sutton and Farshad, 1990). Artificial neural network (ANN) can be another approach among artificial intelligence techniques for prediction of reservoir fluid properties. ANN has been involved in many studies, such as for predictions or forecasting of annulus pressure in oil well (Vega et al., 2012), diesel fuel properties (Mohler et al., 2010), plant oil properties (Fülöp and Hancsók, 2009), failure and reliability of engine systems and components (Zio et al., 2012), gas emission from boiler (Valdman et al., 2011). ANN has been incorporated with membrane study (Ibáñez et al., 2009). Moreover, ANN can be used for controlling reactors (Zakrzewska and Jaworski, 2009), or heat exchanger (Vasičkaninová et al., 2010). The objective of this work was to develop ANNs and correlations for predicting bubble point pressure and bubble point oil formation volume factor using data available in publications. Finally, the developed models were evaluated and compared with other existing correlations.

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2. Methodology

2.1 Data preparation

It is essential to select the effective inputs to develop an ANN model. However, availability of data is another major factor for choosing the input parameters since ANN demands large volume of data to be used for training and cross-validation in order to solve complex, nonlinear problems accurately. In this study, PVT data were collected from available publications. Collected Data were checked based on following criteria. Redundant data points or data points with errors were removed. The data sets were divided into data sets for developing and testing the models.

2.2 Developing ANNs and correlations

The prepared data sets were utilized for developing ANNs by using neural network toolbox (nntool) embedded in Matlab software. In addition, the data sets were used for developing correlations by using nonlinear regression technique from Minitab software.

2.3 Statistical analysis

As a consequence of testing the developed models, the statistical parameters, such as minimum error (Er_{min}), maximum error (Er_{max}), average absolute error (AEr_{avg}), and coefficient of determination (R^2) were determined and compared with the results from some published correlations.

3. Results and discussion

3.1 Data available

The data used in this work were collected from publications. For bubble point pressure modelling, after removing redundant data, a total of 757 data points were selected. The crude oil data consist of reservoir temperature ($T_{res,}$ °F), solution gas oil ratio ($R_{s,}$ scf/stb), gas specific gravity (γ_g), oil API gravity (API°), and bubble point pressure ($P_{b,}$ psia). The data were randomly classified into two sets. A set of 557 data points were used in developing models, and another set of 200 data points were used for testing the models. Similarly, for the bubble point oil formation volume factor (B_{ob}) modelling, a total of 1,175 data points were selected. The crude oil data consist of T_{res}, R_s, γ_g, API, and B_{ob}. The data were randomly divided into a set of 875 data points and a set of 300 data points for developing and testing the models. The data summaries for developing and testing $P_{b \text{ and }}$ B_{ob} are shown in Tables 1-4.

Table 1: Data summary for developing P_b models (557 points)

Properties	Min	Max	AVG	S.D.	Skewness	Kurtosis
R_s (scf/stb)	8.61	3,298.66	639.685	514.78	1.52654	2.95075
T_{res} (°F)	74	341.6	197.875	52.5279	-0.2074	-0.5608
γ_g	0.61	3.4445	1.12292	0.42212	1.59279	2.86265
API°	6	56.8	34.8083	8.27712	-0.9992	1.44669
P_b (psia)	79	7127	1,978.68	1,400.58	0.84701	0.42249

Table 2: Data summary for testing P_b models (200 points)

Properties	Min	Max	AVG	S.D.	Skewness	Kurtosis
R_s (scf/stb)	17.21	3,020	657.41	528.524	1.43495	2.55253
T_{res} (°F)	80	334.4	204.357	51.8959	-0.2426	-0.1802
γ_g	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_b (psia)	95	6,641	1,970.43	1,438.43	0.72348	-0.0341

Table 3: Data summary for developing B_{ob} models (875 points)

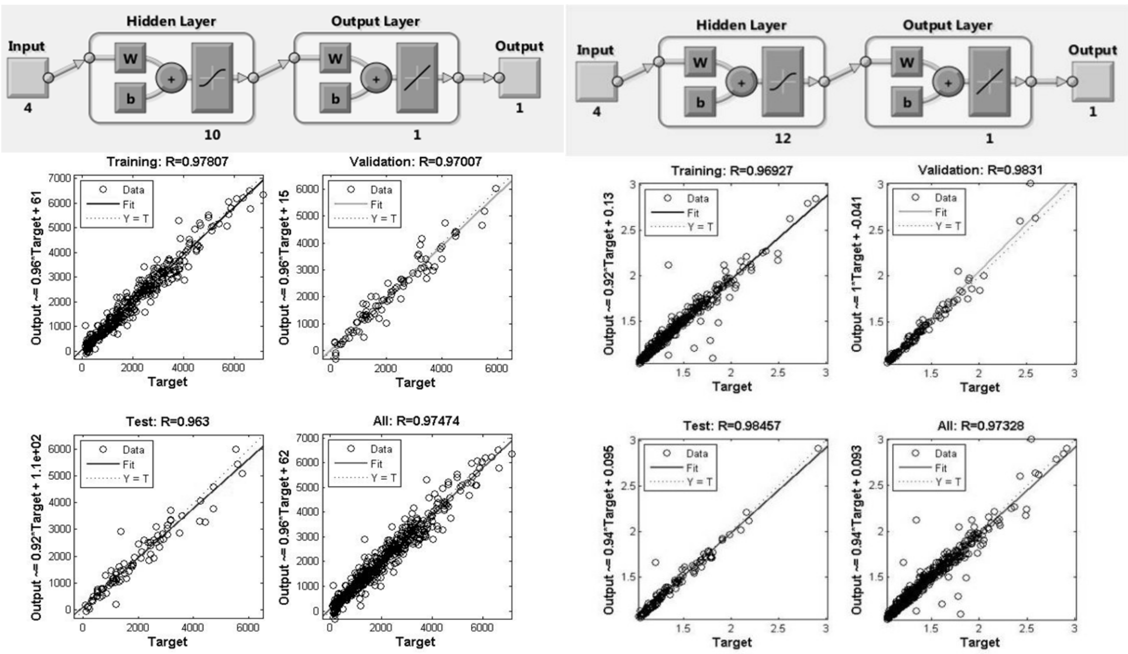
Properties	Min	Max	AVG	S.D.	Skewness	Kurtosis
R_s (scf/stb)	0	3,298.66	523.534	480.242	1.66484	3.57134
T_{res} (°F)	74	593.996	187.693	54.1197	0.47773	2.71979
γ_g	0.511	3.4445	1.01727	0.37987	2.08889	5.32879
API°	6	59.5	32.8496	10.0429	-0.5984	-0.341
B_{ob}	1.028	2.916	1.34781	0.28297	1.77547	4.47046

Table 4: Data summary for testing B_{ob} models (300 points)

Properties	Min	Max	AVG	S.D.	Skewness	Kurtosis
R_s (scf/stb)	0	3,020	552.867	481.115	1.75751	4.27439
T_{res} (ºF)	75.002	341.6	187.153	54.102	0.08627	-0.6121
γ_g	0.525	2.98	1.03774	0.3922	2.02137	4.72544
APIº	6.3	56.8	33.2908	9.72234	-0.6421	0.19895
B_{ob}	1.028	2.903	1.36313	0.29277	2.15482	6.97319

3.2 Developed ANNs

The developing data sets as used for developing correlations were also used for developing ANNs. In this work, 70% of the developing data were randomly used for training, and 30% were used for validation and testing each ANN. Feed-forward, back-propagation neural network with one hidden-layer was used for each ANN. Gradient descent with momentum (GDM) training algorithm and Levenberg-Marquardt (LM) learning algorithm were used for developing the ANNs. Hyperbolic tangent sigmoid transfer function (TANSIG) was used for 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. For P_b ANN, four input parameters including R_s, T_{res}, γ_g, and API were used. The ANN with 10 neurons in the hidden layer was regarded as the best model with the mean square error (MSE) for validation performance of 1,177,883.51. In other words, the 4-10-1 (input layer-hidden layer-output layer) ANN architecture was selected. For B_{ob} ANN, four input parameters, which are R_s, T_{res}, γ_g, and γ_o, were used for B_{ob} prediction. The 4-12-1 ANN architecture was chosen for B_{ob} prediction. A value of the MSE for validation performance of B_{ob} ANN is 0.0039261. The ANN architectures and the regression plots resulted from the developed network outputs with respect to targets for training, validation, and testing the developing data sets for P_b ANN and B_{ob} ANN are shown in Figure 1.



a) b)

Figure 1: ANN architectures and regression plots resulted from the developed ANNs: a) P_b ANN, b) B_{ob} ANN

3.3 Developed correlations

After numerous trails on nonlinear regression technique in Minitab software using the developing data sets, the P_b correlation was developed by modifying Calhoun's correlation (Calhoun, 1976), as expressed in Eq.(1).

$$P_b = 577.747(R_s^{0.444689} - 4.43941)e^{(0.00252849T_{res} - 0.0217755API - 0.976346\gamma_g)} \quad (1)$$

Likewise, the B_{ob} expression in Eq(2) was correlated using Petrosky Jr. and Farsahd's correlation form (Petrosky Jr. and Farshad, 1993).

$$B_{ob} = 4.25999 \times 10^{-5} \cdot \left(\frac{R_s^{0.601715} \gamma_g^{1.47844}}{\gamma_o^{1.47844}} + 0.968331 \cdot T_{res}^{0.68077} \right)^{1.99881} + 1.00387 \quad (2)$$

3.4 Testing results

The developed models were tested against published correlations using data sets for testing. The testing results from P_b and B_{ob} predictions are shown in Tables 5-6. Regarding the P_b prediction results, the developed P_b ANN gave competitive performance compared to other correlations. Although the AEr_{avg} (21.32 %) from the developed P_b ANN was higher than some published correlations, the developed P_b ANN had the highest R^2 of 0.93176 with the narrowest range between Er_{min} (-1,519.51) and Er_{max} (1,512.67). The developed P_b correlation Eq(1) also gave competitive performance for P_b prediction compared to most of the published correlations with R^2 of 0.91846. For the prediction of B_{ob}, both developed B_{ob} correlation Eq(2) and B_{ob} ANN outperformed the published correlations in term of AEr_{max}, which are 8.21 % for B_{ob} correlation and 9.67 % for B_{ob} ANN. Moreover, the result from the developed B_{ob} correlation was slightly better than B_{ob} ANN in term of R^2 (0.98134) and AEr_{avg} (1.67 %).

Table 5: Statistical results of P_b using testing data

Method	Er_{min}	Er_{max}	AEr_{avg} (%)	AEr_{max} (%)	R^2
Standing (1947)	-3,139.93	1,579.84	25.69	372.01	0.88929
Calhoun (1976)	-1,882.76	1,654.84	53.76	614.80	0.86888
Glaso (1980)	-4,181.29	1,228.53	27.62	247.00	0.87955
Vazquez and Beggs (1980)	-3,869.91	1,307.29	30.15	403.90	0.88920
Al-Marhoun (1988)	-4,049.08	1,894.29	23.20	131.62	0.83649
Petrosky Jr. and Farshad (1993)	-3,035.26	1,521.86	86.39	766.86	0.90579
Dokla and Osman (1991)	-1,830.10	2,243.37	29.80	206.23	0.79883
Kartoatmodjo and Schmidt (1991)	-4,685.30	1,179.75	34.54	487.43	0.87637
De Ghetto and Villa (1994)	-2,617.00	1,624.93	30.22	466.61	0.89587
Frashad et al. (1996)	-1,620.52	1,624.93	39.08	230.77	0.88458
Almehaideb (1997)	-3,979.12	1,724.54	34.32	427.18	0.82125
Velarde et al. (1997)	-1,611.32	2,117.66	21.12	110.45	0.87761
Hanafy et al. (1997)	-1,882.76	1,645.84	53.77	614.80	0.86888
Al-Shammasi (1999)	-1,862.15	1,642.29	18.09	105.65	0.89788
Valkó and McCain Jr (2003)	-1,566.93	1,829.55	18.76	112.73	0.91467
Dindoruk and Christman (2004)	-1,314.32	2,703.91	25.94	152.31	0.80465
Nikpoor and Khanamiri (2011)	-2,731.29	2,077.11	20.72	115.40	0.85476
P_b correlation (this work)	-1,633.87	1,693.76	22.36	185.92	0.91846
P_b ANN (this work)	-1,519.51	1,512.67	21.32	240.19	0.93176

Table 6: Statistical results of B_{ob} using testing data

Method	Er_{min}	Er_{max}	AEr_{avg} (%)	AEr_{max} (%)	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_{ob} correlation (this work)	-0.1377	0.2189	1.67	8.21	0.98395
B_{ob} ANN (this work)	-0.1951	0.1876	2.13	9.67	0.98134

4. Conclusions

The developed P_b ANN and the P_b correlation could competitively predict P_b when compared to the other published correlations. On the other hand, the developed B_{ob} ANN and B_{ob} correlation could be satisfactorily employed in the prediction of B_{ob} under an acceptable range of data. This can be concluded that ANN technique is another possible candidate for crude oil properties approximation.

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