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Prediction of Minimum Miscibility Pressure (MMP) of CO_2-Crude Oil Systems Considering the Differences of MMP in Different Experiments Based on Artificial Neural Network and Bayesian Optimization Algorithm

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ABSTRACT

In this work, considering the differences of MMP in slim tube and RBA, an ANN-based technique has been developed to estimate MMP and identify the influence of different measurement methods to the predicted MMP for the compiled 193 sets of MMP data for CO_2 and crude oil systems under various conditions. The 193 MMP datasets are collected from open literature, including 60 sets for slim tube and 134 sets for RBA. In addition to MMP, each group of the dataset mainly contains 12 influencing factors, which can be divided into the following five main categories, i.e., compositions of the injected gas (G_{CO2}, G_{N2}, G_{H2S}, G_{CH4}, and G_{HC}), reservoir temperature (T_R), molar fraction of each component in crude oil (L_{VOL}, L_{INT}, $L_{C5\text{-}C6}$, and L_{C7+}), molecular weight of C_{7+} oil components (MW_{C7+}), and the method used to measure MMP (E_M). The E_M value of 0 indicates that the MMP is obtained through the slim tube experiment, and the MMP is measured by RBA when the value of E_M is 1. To comprehensively improve the generalization ability of the model, the Bayesian optimization algorithm (BOA) was applied to optimize the model structure. Then, the developed ANN-BOA model was evaluated by comparing the prediction results with the measured MMPs and the predicted MMPs from the same model based on mixed MMP data, respectively. Compared to the existing model without taking the measurement method of MMP as input to generate the forecasting MMP data, the newly proposed model not only has the lowest overall MAPE of 6.84%, lowest overall MSE of 3.2062, and highest overall R2 of 0.9739 on the testing datasets for the three random runs, but also vividly reflect the interactive relationships of each influential factor and the MMP. Finally, the differences of MMP measured with the slim tube method and RBA method on the predicted MMP were analyzed. The results indicate that MMPs measured by RBA are generally higher than those measured by slim tube under the same reservoir conditions during pure and impure CO_2 injection process, which explains why the prediction accuracy of the newly developed ANN-BOA model considering the influences of different measurement methods on MMP prediction is higher than that of the existing model.

Keywords: artificial neural network, minimum miscibility pressure, machine learning, CO_2-Crude Oil System, bayesian optimization algorithm

1. INTRODUCTION

An increasing energy demand has urged the world to switch its focus on the enhanced oil recovery (EOR) techniques, among which CO_2 miscible flooding has proved to be one of the most effective ones due to its high displacement efficiency, relatively low cost, and storage in a depleted reservoir [1]. Physically, the minimum miscibility pressure (MMP) between CO_2 and crude oil is defined as the lowest pressure at which CO_2 and crude oil can reach miscibility via multiple contacts at reservoir temperature [2]. Due to the presence of various impurities in a CO_2 stream and complex compounds in a crude oil, it is physically difficult to determine the MMP of a CO_2-crude oil system under different reservoir conditions. Although various experimental techniques such as slim tube and rising bubble apparatus (RBA) have been developed to determine the MMP for a given system, it is time-consuming and expensive [3-4]. Therefore, rapid and accurate MMP determination is of a great and practical significance to evaluate and design a CO_2-based EOR strategy in a hydrocarbon reservoir.

In general, two inexpensive and quick methods have been proposed for estimating MMP between CO_2 and crude oil: Empirical correlations and machine learning methods. The former is easy to use with a low accuracy if the applications have different conditions from those used to develop the corresponding correlations, while the latter can achieve fast MMP prediction with a high accuracy. Such machine learning methods mainly include artificial neural network (ANN) [5-7] and support vector regression (SVR) [8-10]. However, as for the above MMP prediction models, the MMP data measured by slim-tube and rising-bubble were mixed indiscriminately to construct the database. Inevitably, such a treatment makes it detrimental to the accurate prediction of MMP. So, it is necessary to establish the MMP prediction model that can consider the impact of different measurement methods on MMP.

By collecting 193 sets of minimum miscibility pressure (MMP) data covering 60 sets for slim tube and 133 sets for RBA from the public domain, in this study, an ANN-based machine learning model has been proposed and validated to determine MMPs of pure/impure CO_2-crude oil systems. Such a developed model took measurement method of MMP as input to generate the forecasting MMP data. To comprehensively improve the generalization ability of the model, the Bayesian optimization algorithm (BOA) was applied to optimize the model structure. Then, the developed ANN-BOA model was evaluated by comparing the prediction results with the measured MMPs and the predicted MMPs from the existing model ignoring the influence of different measurement methods on MMP prediction, respectively. Finally, the difference of MMP measured with the slim tube method and RBA method on the predicted MMP was analyzed.

2. EXPERIMENTAL DATABASE

In this study, the 193 MMP datasets (see Table A-1) are collected from open literature [11-27], including 60 sets for slim tube (E_M=0), and 139 sets for RBA (E_M=1). In addition to MMP, each group of the dataset mainly contains 12 influencing factors, i.e., compositions of the injected gas (G_{N2}, G_{CO2}, G_{H2S}, G_{CH4}, and G_{HC}), reservoir temperature (T_R), molar fraction of volatiles (L_{VOL}, contains CH_4 and N_2), molar fraction of intermediates (L_{INT}, includes CO_2, H_2S and C_2-C_4), molar fraction of C_5-C_6 ($L_{C5\text{-}C6}$) and molar fraction of C_{7+} (L_{C7+}) in crude oil, molecular weight of C_{7+} oil components (MW_{C7+}), and the method used to measure MMP (E_M). The value of E_M is 0 represents the MMP of slim tube experiment, otherwise it represents the MMP of RBA when the value of E_M is 1. It was observed that the total molar fraction of different impurities in the injected gas and the total molar fraction of each component in crude oil besides C_{7+} are correlated with the molar fraction of CO_2 (G_{CO2}) and C_{7+} (L_{C7+}) respectively. To reduce this collinearity between the different features, G_{CO2} and L_{C7+} are not chosen as an input parameter to generate the MMP prediction model. By doing this, each input parameter is isolated from one another.

3. METHODOLOGY

The model is run on the Tensorflow2.4 platform of Python 3.7 under Windows 10 with a processor of Intel(R) Xeon(R) Gold 6258R CPU @ 2.70GHz and 2.69 GHz, a 128 GB running memory, and a GPU of NVIDIA GeForce RTX 3090. To ensure reproducibility of results, the program is processed by the CPU.

3.1 Artificial Neural Network (ANN)

Artificial neural network (ANN) is an artificial intelligence method that mimics the human brain's operation and computation performance, and has the ability to reflect the underlying linear or non-linear relationships amongst input and target data. As shown in Fig. 1, ANN is made up of three parts, i.e., the input layer, the hidden layers and the output layer. ANN was trained using an error backpropagation training algorithm by adjusting the connection weights according to the backpropagated error computed between the observed and the estimated results. This is a supervised learning procedure that attempts to minimise the error between the desired and the predicted outputs.

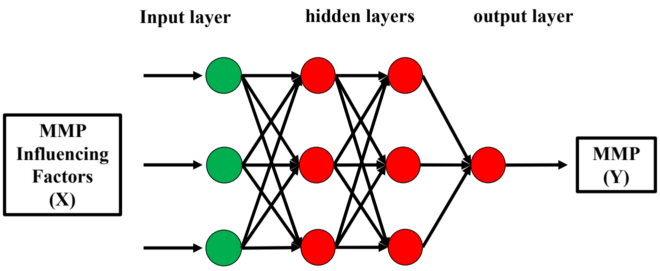

Fig. 1 The architecture for ANN

3.2 Bayesian optimization algorithm (BOA)

Hyperparameters are important for machine learning algorithms since they directly control the behaviour of training algorithms and have a significant effect on performance of the machine learning models. To solve an optimization problem of an unknown black-box function like machine learning, the BOA found to effectively outperform other global optimization algorithms on a number of challenging optimization benchmark functions [28-30].

Since the BOA is based on the Bayesian theorem, which can be expressed by the hyperparameter optimization as：

$$p\left(w=w_1 \middle| M=M_1\right)=\frac{p\left(M=M_1 \middle| w=w_1\right)p\left(w=w_1\right)}{p\left(M=M_1\right)} \tag{1}$$

where w and M are respectively the hyperparameter and error of the ANN model for MMP; $p\left(w = w_1 \middle| M = M_1\right)$ refers to the probability that the hyperparameter equals w_1 when the error of the model is M_1, i.e., the posterior probability; $p\left(M = M_1 \middle| w = w_1\right)$ denotes the probability that the error of the model is M_1 when the hyperparameter equals w_1; $p\left(w = w_1\right)$ represents the probability that the hyperparameter equals w_1; and $p\left(M = M_1\right)$ is the probability that the error of the model equals M_1, i.e., the prior probability.

The BOA is composed of the probabilistic model and the acquisition function, and the process of optimizing the hyperparameters of an ANN model is briefly described as follows:

(1) Select *n* initial values of the hyperparameter (w) and calculate their corresponding errors of the ANN model (M). Then, the initial dataset $Q=\{(w_1,M_1),(w_2,M_2),\cdots,(w_n,M_n)\}$ is established.

(2) $p\left(M = M_i\right)$, $p\left(w = w_i\right)$, and $p\left(w = w_i \middle| M = M_i\right)$ are calculated by their proportions in the sample Q; According to Equation (1), the initial probabilistic model $p\left(M \middle| w\right)$ is then created to replace the ANN model $f(w)$. The input of the probabilistic model is the hyperparameter w_i and the output is the probability of the ANN model error under the hyperparameter w_i. Based on the established probabilistic model, the probability of the ANN model error M_i under any hyperparameter w_i can be calculated.

(3) The next hyperparameter w_{n+1} most likely to reduce M is selected by the acquisition function, while the corresponding M_{n+1} is calculated by applying the ANN model. And, the initial dataset $Q=\{(w_1,M_1),(w_2,M_2),\cdots,(w_n,M_n)\}$ is updated to be the new dataset $Q=\{(w_1,M_1),\cdots,(w_n,M_n),(w_{n+1},M_{n+1})\}$.

(4) Repeat Steps #2 and #3 until the number of iterations of the BOA reaches the upper limit *N* (both *n* and *N* are manually set, in this work, according to several trial calculations, when *n* is 10 and *N* is 90, BOA can quickly find the hyperparameters with high precision.). As the BOA is continued to run, the amount of data in Q will gradually increase, making the established probabilistic model $p\left(M \middle| w\right)$ more accurate and improving the probability of finding the best hyperparameters. Finally, the BOA will choose the w with the minimum M from the dataset Q as the output result.

In this study, the hyperparameters of the ANN are optimized as follows: A is the number of hidden layers and B represents the number of nodes in each layer; The value of the Dropout in each hidden layer is set to be C; D implies the initial learning rate of the Adam optimizer. In addition, the mini-batch size (E) and the training cycle (F) are chosen as hyperparameters to be optimized.

4. RESULTS AND DISCUSSION

4.1 ANN Optimization Results

To evaluate the MMP prediction model more comprehensively, this study uses a total of three evaluation indicators, which are coefficient of determination (R^2), MSE, and mean absolute percentage error (MAPE). Mathematically, these parameters are defined below.

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2} \quad (2)$$

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 \quad (3)$$

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \quad (4)$$

where *m* is the total number of the dataset; y_i and $\hat{y}_i$ refer to the measured and the predicted values of MMP, respectively; and $\bar{y}$ and $\hat{y}_i$ refer to their respective mean.

The target of the Bayesian optimization is to minimize the mean square error (MSE) of the ANN model in the validation set. After setting the number of steps n for performing random search and the number of steps N to perform the Bayesian optimization, the best hyperparameters will be automatically searched and determined. The ranges and optimal values of hyperparameters for the ANN model are summarized in Table 1.

Table 1 The ranges and optimal values of the ANN hyperparameters

Hyperparameter	Minimum	Maximum	Integer or not	optimum
A	1	3	True	1
B	1	500	True	439
C	0	0.5	False	0.0137
D	0.0001	0.0010	False	0.0007034
E	1	115	True	48
F	100	500	True	323

After tuning the hyperparameters with the Bayesian optimization, the prediction accuracy of the ANN model for the MMP is very high in both the training and test sets with an MAPE of 2.92% and 5.68%, respectively. Fig. 2 presents the cross plot between the measured and predicted MMPs based on the BOA-optimized ANN model for the testing data. As the data points are densely distributed on both sides of the diagonal line, indicating there exists an excellent agreement between the newly proposed ANN-BOA (ANN-BOA-New) model and the experimental data, illustrating the effectiveness of the BOA.

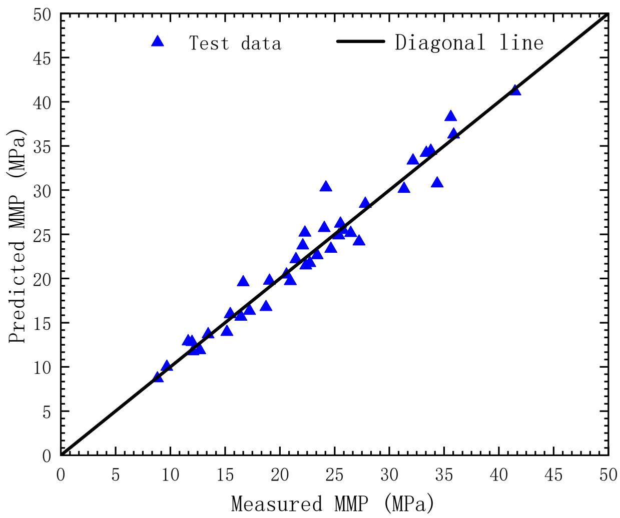

Fig 2 Cross-plot between the measured and predicted MMPs based on the BOA-optimized AAN model for test data

4.2 Model Comparison

Based on the same data, ANN and BOA have been used to develop the MMP prediction models without considering the differences of MMP in slim tube and RBA (ANN-BOA-Old). To avoid the impact of data division on the comparison results of the MMP prediction models, three random divisions of the dataset are performed. Table 2 tabulates the R^2, MSE and MAPE of these optimized models on the three random test set, respectively.

Table 2 Comparison of different MMP prediction models

Run No.	Model	R^2 Test set	MSE Test set	MAPE (%) Test set
1	ANN-BOA-New	0.9779	2.8925	5.68
	ANN-BOA-Old	0.9741	3.4968	6.73
2	ANN-BOA-New	0.9731	3.4739	8.19
	ANN-BOA-Old	0.9369	7.2817	10.50
3	ANN-BOA-New	0.9709	3.2523	6.66
	ANN-BOA-Old	0.9308	6.5572	8.22
Average	ANN-BOA-New	0.9739	3.2062	6.84
	ANN-BOA-Old	0.9473	5.7786	8.48

Compared to the ANN-BOA-Old model, it can be seen that the ANN-BOA-New model has lower MSE and MAPE and higher R^2 on the test set in each experiment (In particular, the ANN-BOA-New has the lowest overall MSE of 3.2062 and MAPE of 6.84% and the highest overall R^2 of 0.9739 for the three random runs.), indicating that the fitting ability and learning ability of ANN-BOA-New are stronger than the ANN-BOA-Old. This may be attributed to the fact that the effect of different measurement methods on MMP reduces the prediction accuracy of ANN-BOA-Old model.

4.3 Comparison of MMPs from the RBA and the Slim Tube

In this study, the differences of MMP measured with the slim tube method and RBA method on the predicted MMP during pure/impure CO_2 injection process under the same reservoir conditions for the predicted MMP are studied. As shown in Fig. 3, in this database interval, whether in slim tube or RBA, the presence of N_2 and CH_4 will increase the MMP, while H_2S and HC decrease the MMP, which is consistent with the experimental measurements documented elsewhere [15, 31]. Furthermore, it can be seen from Fig. 3 that MMPs measured by RBA are generally higher than those measured by slim-tube, which explains why the ANN-BOA-New model has a higher prediction accuracy than the ANN-BOA-Old model ignoring the influence of different measurement methods on MMP prediction in the testing set.

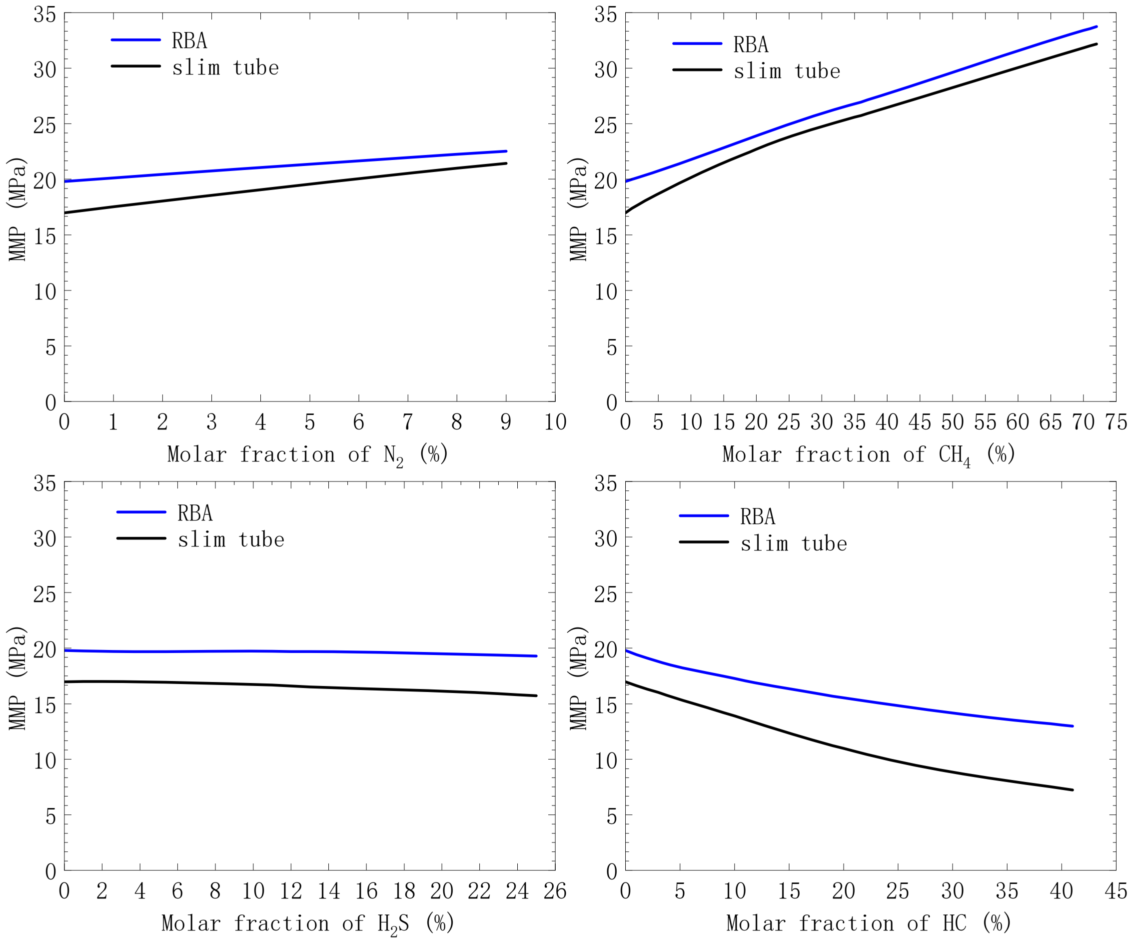

Fig. 3 Effect of N_2, CH_4, H_2S, and HC in CO_2 on MMP

5. CONCLUSIONS

Considering the differences of MMP in slim tube and RBA, this paper presents a new model for predicting the MMP of CO_2-crude oil systems based on the ANN and the BOA. Through the detailed analysis and discussions of the simulation results, the following conclusions can be drawn:

(1). With the lowest average MAPE of 6.84%, lowest average MSE of 3.2062, and highest average R^2 of 0.9739 on the testing datasets in the three experiments, the ANN-BOA-New is superior to the ANN-BOA-Old on MMP prediction, indicating that the fitting ability and learning ability of ANN-BOA-New are stronger than the ANN-BOA-Old. This may be attributed to the fact that the effect of different measurement methods on MMP reduces the prediction accuracy of ANN-BOA-Old model.

(2). MMPs measured by RBA are generally higher than those measured by slim-tube under the same reservoir conditions, which explains why the prediction accuracy of the ANN-BOA-New model considering the influence of different measurement methods on MMP prediction is higher than that of the ANN-BOA-Old model in the testing set.

(3). The differences of MMP in slim tube and RBA cannot be neglected when establishing the MMP prediction model. The measuring methods of MMP should be used as input to generate the forecasting MMP data, which has been proven to be helpful to improve the accurate prediction of MMP.

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APPENDIX

In this Appendix, the 193 MMP data covering 12 influencing factors are presented.

Table A-1 193 sets of MMP data

Appendix A

No.	Composition of the injected gas (mol%)					T_R (°C)	Component in crude oil (mol%)				MW_{C7+} (g/mol)	E_M	MMP (MPa)	reference
	G_{N2}	G_{CO2}	G_{H2S}	G_{CH4}	G_{HC}		L_{VOL}	L_{INT}	$L_{C5\text{-}C6}$	L_{C7+}				
1	0.0000	100.0000	0.0000	0.0000	0.0000	42.7800	17.0700	20.9500	7.8800	54.1000	222.00	0	10.34	Rathmell et al., 1971
2	0.0000	100.0000	0.0000	0.0000	0.0000	39.4400	27.8400	21.8100	8.2200	42.1300	223.00	0	13.79	Rathmell et al., 1971
3	0.0000	100.0000	0.0000	0.0000	0.0000	54.4400	29.4800	31.8200	8.5500	30.1500	197.40	0	11.03	Dicharry et al., 1973
4	0.0000	100.0000	0.0000	0.0000	0.0000	40.0000	24.2500	23.8500	6.8600	45.0400	221.00	0	12.40	Spence and Watkins, 1980
5	0.0000	100.0000	0.0000	0.0000	0.0000	42.8000	17.0400	17.2400	6.1800	59.5400	235.00	0	8.96	Spence and Watkins, 1980
6	9.6580	85.7570	0.0000	4.5630	0.0220	71.1100	4.4050	13.8970	11.0270	70.6710	227.94	0	20.96	Graue et al., 1981
7	0.0810	95.0160	0.0000	4.8920	0.0110	71.1100	4.4050	13.8970	11.0270	70.6710	227.94	0	14.48	Graue et al., 1981
8	0.0000	40.0000	40.0000	20.0000	0.0000	40.6000	10.5000	14.2800	10.7400	64.4800	206.00	0	12.06	Metcalfe, 1982
9	0.0000	45.0000	45.0000	10.0000	0.0000	40.6000	10.5000	14.2800	10.7400	64.4800	206.00	0	8.83	Metcalfe, 1982
10	0.0000	45.0000	45.0000	10.0000	0.0000	57.2000	10.5000	14.2800	10.7400	64.4800	206.00	0	10.38	Metcalfe, 1982
11	0.0000	50.0000	50.0000	0.0000	0.0000	40.6000	10.5000	14.2800	10.7400	64.4800	206.00	0	6.55	Metcalfe, 1982
12	0.0000	50.0000	50.0000	0.0000	0.0000	57.2000	10.5000	14.2800	10.7400	64.4800	206.00	0	8.97	Metcalfe, 1982
13	0.0000	55.0000	25.0000	20.0000	0.0000	57.2000	10.5000	14.2800	10.7400	64.4800	206.00	0	16.45	Metcalfe, 1982
14	0.0000	60.0000	20.0000	20.0000	0.0000	40.6000	10.5000	14.2800	10.7400	64.4800	206.00	0	14.07	Metcalfe, 1982
15	0.0000	60.0000	20.0000	20.0000	0.0000	57.2000	10.5000	14.2800	10.7400	64.4800	206.00	0	17.24	Metcalfe, 1982
16	0.0000	67.5000	23.0000	10.0000	0.0000	57.2000	10.5000	14.2800	10.7400	64.4800	206.00	0	12.41	Metcalfe, 1982
17	0.0000	68.0000	22.0000	10.0000	0.0000	40.6000	10.5000	14.2800	10.7400	64.4800	206.00	0	10.28	Metcalfe, 1982
18	0.0000	75.0000	25.0000	0.0000	0.0000	57.2000	10.5000	14.2800	10.7400	64.4800	206.00	0	10.35	Metcalfe, 1982
19	0.0000	75.0000	25.0000	0.0000	0.0000	40.6000	10.5000	14.2800	10.7400	64.4800	206.00	0	7.53	Metcalfe, 1982
20	0.0000	80.0000	0.0000	20.0000	0.0000	40.6000	10.5000	14.2800	10.7400	64.4800	206.00	0	14.83	Metcalfe, 1982
21	0.0000	80.0000	0.0000	20.0000	0.0000	57.2000	10.5000	14.2800	10.7400	64.4800	206.00	0	18.74	Metcalfe, 1982
22	0.0000	80.0000	0.0000	0.0000	20.0000	65.6000	34.3400	22.8200	4.4300	38.4100	200.00	0	12.88	Metcalfe, 1982
23	0.0000	80.0000	0.0000	20.0000	0.0000	40.6000	10.5000	14.2800	10.7400	64.4800	206.00	0	14.83	Metcalfe, 1982
24	0.0000	90.0000	0.0000	10.0000	0.0000	40.6000	10.5000	14.2800	10.7400	64.4800	206.00	0	11.04	Metcalfe, 1982
25	0.0000	90.0000	0.0000	10.0000	0.0000	57.2000	10.5000	14.2800	10.7400	64.4800	206.00	0	15.17	Metcalfe, 1982

No.	Composition of the injected gas (mol%) G_{N2}	G_{CO2}	G_{H2S}	G_{CH4}	G_{HC}	T_R (°C)	Component in crude oil (mol%) L_{VOL}	L_{INT}	L_{C5-C6}	L_{C7+}	MW_{C7+} (g/mol)	E_M	MMP (MPa)	reference
26	0.0000	100.0000	0.0000	0.0000	0.0000	32.2000	10.5000	14.2800	10.7400	64.4800	206.00	0	6.90	Metcalfe, 1982
27	0.0000	100.0000	0.0000	0.0000	0.0000	40.6000	10.5000	14.2800	10.7400	64.4800	206.00	0	8.28	Metcalfe, 1982
28	0.0000	100.0000	0.0000	0.0000	0.0000	57.2000	10.5000	14.2800	10.7400	64.4800	206.00	0	11.86	Metcalfe, 1982
29	0.0000	100.0000	0.0000	0.0000	0.0000	49.0000	34.3400	22.8200	4.4300	38.4100	200.00	0	11.04	Metcalfe, 1982
30	0.0000	100.0000	0.0000	0.0000	0.0000	65.6000	34.3400	22.8200	4.4300	38.4100	200.00	0	13.45	Metcalfe, 1982
31	9.6700	85.3200	0.0000	4.9900	0.0100	54.4400	25.5100	7.6600	4.7400	62.0900	319.70	0	33.78	Frimodig et al., 1983
32	0.1800	95.0300	0.0000	4.7800	0.0100	54.4400	25.5100	7.6600	4.7400	62.0900	319.70	0	32.06	Frimodig et al., 1983
33	0.0000	45.0000	0.0000	27.0000	28.0000	18.5500	16.4800	17.0100	7.1600	59.3500	240.00	0	10.48	Sebastian et al., 1985
34	0.0000	81.0000	0.0000	19.0000	0.0000	8.9500	16.4800	17.0100	7.1600	59.3500	240.00	0	12.51	Sebastian et al., 1985
35	0.0000	90.0000	0.0000	10.0000	0.0000	19.1500	16.4800	17.0100	7.1600	59.3500	240.00	0	10.79	Sebastian et al., 1985
36	8.0000	92.0000	0.0000	0.0000	0.0000	17.1500	16.4800	17.0100	7.1600	59.3500	240.00	0	11.65	Sebastian et al., 1985
37	0.0000	100.0000	0.0000	0.0000	0.0000	31.0500	16.4800	17.0100	7.1600	59.3500	240.00	0	8.10	Sebastian et al., 1985
38	0.0000	1.0500	0.0000	83.2100	14.3200	93.3300	54.9800	17.1800	4.9800	22.8600	209.00	0	39.99	Firoozabadi and Khalid, 1986
39	75.0000	2.9575	0.0000	0.0000	22.0425	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	41.47	Eakin and Mitch, 1988
40	75.0000	2.9575	0.0000	0.0000	22.0425	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	41.47	Eakin and Mitch, 1988
41	0.3000	3.5250	0.0000	54.3750	41.8000	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	27.23	Eakin and Mitch, 1988
42	0.3000	3.5250	0.0000	54.3750	41.8000	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	28.72	Eakin and Mitch, 1988
43	0.3000	3.5250	0.0000	54.3750	41.8000	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	22.17	Eakin and Mitch, 1988
44	0.3000	3.5250	0.0000	54.3750	41.8000	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	23.89	Eakin and Mitch, 1988
45	0.3000	3.5250	25.0000	54.3750	16.8000	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	26.92	Eakin and Mitch, 1988
46	0.3000	3.5250	25.0000	54.3750	16.8000	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	30.23	Eakin and Mitch, 1988
47	0.3000	3.5250	25.0000	54.3750	16.8000	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	25.55	Eakin and Mitch, 1988
48	0.3000	3.5250	25.0000	54.3750	16.8000	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	27.81	Eakin and Mitch, 1988
49	0.3600	4.2300	0.0000	65.2500	30.1600	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	30.44	Eakin and Mitch, 1988
50	0.3600	4.2300	0.0000	65.2500	30.1600	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	32.16	Eakin and Mitch, 1988
51	0.3600	4.2300	0.0000	65.2500	30.1600	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	24.75	Eakin and Mitch, 1988
52	0.3600	4.2300	0.0000	65.2500	30.1600	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	26.58	Eakin and Mitch, 1988
53	0.3600	4.2300	10.0000	65.2500	20.1600	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	30.44	Eakin and Mitch, 1988
54	0.3600	4.2300	10.0000	65.2500	20.1600	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	33.37	Eakin and Mitch, 1988
55	0.3600	4.2300	10.0000	65.2500	20.1600	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	25.44	Eakin and Mitch, 1988
56	0.3600	4.2300	10.0000	65.2500	20.1600	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	29.44	Eakin and Mitch, 1988
57	0.4000	4.7000	0.0000	72.5000	22.4000	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	32.78	Eakin and Mitch, 1988
58	0.4000	4.7000	0.0000	72.5000	22.4000	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	35.87	Eakin and Mitch, 1988
59	0.4000	4.7000	0.0000	72.5000	22.4000	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	27.51	Eakin and Mitch, 1988
60	0.4000	4.7000	0.0000	72.5000	22.4000	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	30.14	Eakin and Mitch, 1988
61	0.2250	5.3250	0.0000	35.9775	58.4725	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	17.51	Eakin and Mitch, 1988
62	0.2250	5.3250	0.0000	35.9775	58.4725	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	19.68	Eakin and Mitch, 1988
63	0.2250	5.3250	0.0000	35.9775	58.4725	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	20.62	Eakin and Mitch, 1988
64	0.2250	5.3250	0.0000	35.9775	58.4725	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	21.48	Eakin and Mitch, 1988
65	0.2250	5.3250	25.0000	35.9775	33.4725	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	24.13	Eakin and Mitch, 1988
66	0.2250	5.3250	25.0000	35.9775	33.4725	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	25.75	Eakin and Mitch, 1988
67	0.2250	5.3250	25.0000	35.9775	33.4725	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	23.41	Eakin and Mitch, 1988
68	0.2250	5.3250	25.0000	35.9775	33.4725	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	24.61	Eakin and Mitch, 1988

No.	Composition of the injected gas (mol%)					T_R (°C)	Component in crude oil (mol%)				MW_{C7+} (g/mol)	E_M	MMP (MPa)	reference
	G_{N2}	G_{CO2}	G_{H2S}	G_{CH4}	G_{HC}		L_{VOL}	L_{INT}	L_{C5-C6}	L_{C7+}				
69	0.3600	5.4130	0.0000	65.2500	28.9770	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	31.34	Eakin and Mitch, 1988
70	0.3600	5.4130	0.0000	65.2500	28.9770	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	33.12	Eakin and Mitch, 1988
71	0.3600	5.4130	0.0000	65.2500	28.9770	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	25.79	Eakin and Mitch, 1988
72	0.3600	5.4130	0.0000	65.2500	28.9770	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	27.25	Eakin and Mitch, 1988
73	0.2700	6.3900	0.0000	43.1730	50.1670	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	20.62	Eakin and Mitch, 1988
74	0.2700	6.3900	0.0000	43.1730	50.1670	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	23.37	Eakin and Mitch, 1988
75	0.2700	6.3900	0.0000	43.1730	50.1670	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	22.68	Eakin and Mitch, 1988
76	0.2700	6.3900	0.0000	43.1730	50.1670	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	24.66	Eakin and Mitch, 1988
77	0.2700	6.3900	10.0000	43.1730	40.1670	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	23.41	Eakin and Mitch, 1988
78	0.2700	6.3900	10.0000	43.1730	40.1670	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	25.41	Eakin and Mitch, 1988
79	0.2700	6.3900	10.0000	43.1730	40.1670	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	23.20	Eakin and Mitch, 1988
80	0.2700	6.3900	10.0000	43.1730	40.1670	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	24.24	Eakin and Mitch, 1988
81	0.3000	6.4825	0.0000	54.3750	38.8425	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	26.48	Eakin and Mitch, 1988
82	0.3000	6.4825	0.0000	54.3750	38.8425	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	28.03	Eakin and Mitch, 1988
83	0.3000	6.4825	0.0000	54.3750	38.8425	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	22.68	Eakin and Mitch, 1988
84	0.3000	6.4825	0.0000	54.3750	38.8425	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	24.79	Eakin and Mitch, 1988
85	0.3100	6.9700	0.0000	48.5100	44.2100	103.3000	6.7400	20.5900	6.9100	65.7600	281.00	1	26.21	Eakin and Mitch, 1988
86	0.3000	7.1000	0.0000	47.9700	44.6300	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	21.13	Eakin and Mitch, 1988
87	0.3000	7.1000	0.0000	47.9700	44.6300	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	24.06	Eakin and Mitch, 1988
88	0.3000	7.1000	0.0000	47.9700	44.6300	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	22.17	Eakin and Mitch, 1988
89	0.3000	7.1000	0.0000	47.9700	44.6300	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	23.97	Eakin and Mitch, 1988
90	0.2700	7.5730	0.0000	43.1730	48.9840	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	20.02	Eakin and Mitch, 1988
91	0.2700	7.5730	0.0000	43.1730	48.9840	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	23.03	Eakin and Mitch, 1988
92	0.2700	7.5730	0.0000	43.1730	48.9840	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	21.65	Eakin and Mitch, 1988
93	0.2700	7.5730	0.0000	43.1730	48.9840	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	23.46	Eakin and Mitch, 1988
94	66.7500	8.2500	0.0000	0.0000	25.0000	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	34.58	Eakin and Mitch, 1988
95	66.7500	8.2500	0.0000	0.0000	25.0000	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	35.61	Eakin and Mitch, 1988
96	0.2250	8.2825	0.0000	35.9775	55.5150	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	17.00	Eakin and Mitch, 1988
97	0.2250	8.2825	0.0000	35.9775	55.5150	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	22.57	Eakin and Mitch, 1988
98	0.2250	8.2825	0.0000	35.9775	55.5150	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	19.99	Eakin and Mitch, 1988
99	0.2250	8.2825	0.0000	35.9775	55.5150	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	22.51	Eakin and Mitch, 1988
100	80.1000	11.0830	0.0000	0.0000	8.8170	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	40.44	Eakin and Mitch, 1988
101	80.1000	11.0830	0.0000	0.0000	8.8170	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	40.78	Eakin and Mitch, 1988
102	66.7500	11.2075	0.0000	0.0000	22.0425	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	36.65	Eakin and Mitch, 1988
103	66.7500	11.2075	0.0000	0.0000	22.0425	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	38.54	Eakin and Mitch, 1988
104	4.3000	30.0000	0.0000	45.7000	20.0000	84.4000	6.7400	20.5900	6.9100	65.7600	281.00	1	34.37	Eakin and Mitch, 1988
105	4.3000	30.0000	0.0000	45.7000	20.0000	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	35.87	Eakin and Mitch, 1988
106	4.3000	30.0000	0.0000	45.7000	20.0000	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	27.51	Eakin and Mitch, 1988
107	4.3000	30.0000	0.0000	45.7000	20.0000	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	30.61	Eakin and Mitch, 1988
108	0.0000	75.0000	0.0000	0.0000	25.0000	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	17.42	Eakin and Mitch, 1988
109	0.0000	75.0000	0.0000	0.0000	25.0000	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	20.24	Eakin and Mitch, 1988
110	0.0000	75.0000	0.0000	0.0000	25.0000	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	16.91	Eakin and Mitch, 1988
111	0.0000	75.0000	0.0000	0.0000	25.0000	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	18.86	Eakin and Mitch, 1988

No.	Composition of the injected gas (mol%)					T_R (°C)	Component in crude oil (mol%)				MW_{C7+} (g/mol)	E_M	MMP (MPa)	reference
	G_{N2}	G_{CO2}	G_{H2S}	G_{CH4}	G_{HC}		L_{VOL}	L_{INT}	L_{C5-C6}	L_{C7+}				
112	0.0000	75.0000	25.0000	0.0000	0.0000	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	21.20	Eakin and Mitch, 1988
113	0.0000	75.0000	25.0000	0.0000	0.0000	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	23.82	Eakin and Mitch, 1988
114	0.0000	75.0000	25.0000	0.0000	0.0000	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	21.13	Eakin and Mitch, 1988
115	0.0000	75.0000	25.0000	0.0000	0.0000	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	23.37	Eakin and Mitch, 1988
116	0.0000	77.9575	0.0000	0.0000	22.0425	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	16.31	Eakin and Mitch, 1988
117	0.0000	77.9575	0.0000	0.0000	22.0425	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	21.89	Eakin and Mitch, 1988
118	0.0000	77.9575	0.0000	0.0000	22.0425	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	18.03	Eakin and Mitch, 1988
119	0.0000	77.9575	0.0000	0.0000	22.0425	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	21.68	Eakin and Mitch, 1988
120	0.0000	90.0000	0.0000	0.0000	10.0000	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	17.86	Eakin and Mitch, 1988
121	0.0000	90.0000	0.0000	0.0000	10.0000	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	23.72	Eakin and Mitch, 1988
122	0.0000	90.0000	0.0000	0.0000	10.0000	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	16.65	Eakin and Mitch, 1988
123	0.0000	90.0000	0.0000	0.0000	10.0000	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	21.30	Eakin and Mitch, 1988
124	0.0000	90.0000	10.0000	0.0000	0.0000	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	22.74	Eakin and Mitch, 1988
125	0.0000	90.0000	10.0000	0.0000	0.0000	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	25.79	Eakin and Mitch, 1988
126	0.0000	90.0000	10.0000	0.0000	0.0000	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	22.37	Eakin and Mitch, 1988
127	0.0000	90.0000	10.0000	0.0000	0.0000	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	24.03	Eakin and Mitch, 1988
128	0.0000	91.1830	0.0000	0.0000	8.8170	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	19.34	Eakin and Mitch, 1988
129	0.0000	91.1830	0.0000	0.0000	8.8170	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	24.06	Eakin and Mitch, 1988
130	0.0000	91.1830	0.0000	0.0000	8.8170	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	19.06	Eakin and Mitch, 1988
131	0.0000	91.1830	0.0000	0.0000	8.8170	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	22.75	Eakin and Mitch, 1988
132	0.0000	100.0000	0.0000	0.0000	0.0000	82.2000	6.7400	20.5900	6.9100	65.7600	281.00	1	21.99	Eakin and Mitch, 1988
133	0.0000	100.0000	0.0000	0.0000	0.0000	115.6000	6.7400	20.5900	6.9100	65.7600	281.00	1	25.55	Eakin and Mitch, 1988
134	0.0000	100.0000	0.0000	0.0000	0.0000	82.2000	32.9900	42.4400	4.9800	19.5900	216.00	1	21.34	Eakin and Mitch, 1988
135	0.0000	100.0000	0.0000	0.0000	0.0000	115.6000	32.9900	42.4400	4.9800	19.5900	216.00	1	25.30	Eakin and Mitch, 1988
136	0.0000	93.2100	0.0000	6.7900	0.0000	85.6500	17.3610	12.9190	1.9090	67.8110	282.00	0	25.79	Zou et al., 1993
137	0.0000	100.0000	0.0000	0.0000	0.0000	85.6500	17.3610	12.9190	1.9090	67.8110	282.00	0	20.61	Zou et al., 1993
138	0.4900	1.8200	0.0000	81.3900	16.3000	114.3000	46.3000	19.4800	5.2000	29.0200	216.04	0	37.60	Jaubert et al., 2002
139	0.4700	2.2500	0.0000	85.3400	11.9400	100.6000	7.3000	58.1500	5.6100	28.9400	217.29	0	33.50	Jaubert et al., 2002
140	0.0000	4.3500	0.0000	81.1400	14.5100	120.0000	31.2800	22.8300	9.1100	36.7800	201.48	0	29.60	Jaubert et al., 2002
141	0.0000	4.3500	0.0000	81.1400	14.5100	120.0000	32.2480	23.1790	9.1030	35.4700	208.07	0	26.25	Jaubert et al., 2002
142	0.4800	4.9600	0.0000	58.0500	36.5100	101.7000	23.1000	22.2100	10.6900	44.0000	257.72	0	22.10	Jaubert et al., 2002
143	0.4800	4.9600	0.0000	58.0500	36.5100	98.9000	23.8400	21.8800	8.4800	45.8000	254.44	0	23.50	Jaubert et al., 2002
144	0.1900	87.3800	0.0000	7.6700	4.7600	60.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	11.99	Bon et al., 2006
145	0.1900	87.3800	0.0000	7.6700	4.7600	80.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	13.06	Bon et al., 2006
146	0.1900	87.3800	0.0000	7.6700	4.7600	100.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	13.87	Bon et al., 2006
147	0.1900	87.3800	0.0000	7.6700	4.7600	60.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	8.85	Bon et al., 2006
148	0.1900	87.3800	0.0000	7.6700	4.7600	80.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	9.69	Bon et al., 2006
149	0.1900	87.3800	0.0000	7.6700	4.7600	100.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	10.70	Bon et al., 2006
150	0.1900	87.3800	0.0000	7.6700	4.7600	60.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	12.71	Bon et al., 2006
151	0.1900	87.3800	0.0000	7.6700	4.7600	80.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	14.06	Bon et al., 2006
152	0.1900	87.3800	0.0000	7.6700	4.7600	100.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	15.48	Bon et al., 2006
153	0.1900	89.0800	0.0000	7.8200	2.9100	60.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	9.16	Bon et al., 2006
154	0.1900	89.0800	0.0000	7.8200	2.9100	80.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	10.36	Bon et al., 2006

No.	Composition of the injected gas (mol%)					T_R (°C)	Component in crude oil (mol%)				MW_{C7+} (g/mol)	E_M	MMP (MPa)	reference
	G_{N2}	G_{CO2}	G_{H2S}	G_{CH4}	G_{HC}		L_{VOL}	L_{INT}	L_{C5-C6}	L_{C7+}				
155	0.1900	89.0800	0.0000	7.8200	2.9100	100.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	11.63	Bon et al., 2006
156	0.1900	89.0800	0.0000	7.8200	2.9100	60.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	13.01	Bon et al., 2006
157	0.1900	89.0800	0.0000	7.8200	2.9100	80.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	14.69	Bon et al., 2006
158	0.1900	89.0800	0.0000	7.8200	2.9100	100.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	16.07	Bon et al., 2006
159	0.1900	89.0800	0.0000	7.8200	2.9100	60.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	12.62	Bon et al., 2006
160	0.1900	89.0800	0.0000	7.8200	2.9100	80.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	13.72	Bon et al., 2006
161	0.1900	89.0800	0.0000	7.8200	2.9100	100.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	14.76	Bon et al., 2006
162	0.2000	90.8400	0.0000	7.9700	0.9900	60.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	14.11	Bon et al., 2006
163	0.2000	90.8400	0.0000	7.9700	0.9900	80.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	16.29	Bon et al., 2006
164	0.2000	90.8400	0.0000	7.9700	0.9900	100.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	17.77	Bon et al., 2006
165	0.2000	90.8400	0.0000	7.9700	0.9900	60.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	15.18	Bon et al., 2006
166	0.2000	90.8400	0.0000	7.9700	0.9900	80.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	16.13	Bon et al., 2006
167	0.2000	90.8400	0.0000	7.9700	0.9900	100.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	16.88	Bon et al., 2006
168	0.2000	90.8400	0.0000	7.9700	0.9900	60.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	9.85	Bon et al., 2006
169	0.2000	90.8400	0.0000	7.9700	0.9900	80.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	11.47	Bon et al., 2006
170	0.2000	90.8400	0.0000	7.9700	0.9900	100.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	13.45	Bon et al., 2006
171	0.2000	91.7500	0.0000	8.0500	0.0000	60.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	16.21	Bon et al., 2006
172	0.2000	91.7500	0.0000	8.0500	0.0000	80.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	17.24	Bon et al., 2006
173	0.2000	91.7500	0.0000	8.0500	0.0000	100.0000	12.1500	2.6300	4.4700	80.7500	173.80	1	18.48	Bon et al., 2006
174	0.2000	91.7500	0.0000	8.0500	0.0000	60.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	11.03	Bon et al., 2006
175	0.2000	91.7500	0.0000	8.0500	0.0000	80.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	12.69	Bon et al., 2006
176	0.2000	91.7500	0.0000	8.0500	0.0000	100.0000	13.5300	26.7600	11.1900	48.5200	155.90	1	14.63	Bon et al., 2006
177	0.2000	91.7500	0.0000	8.0500	0.0000	60.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	15.13	Bon et al., 2006
178	0.2000	91.7500	0.0000	8.0500	0.0000	80.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	17.15	Bon et al., 2006
179	0.2000	91.7500	0.0000	8.0500	0.0000	100.0000	24.6800	39.3700	6.7900	29.1600	153.90	1	18.65	Bon et al., 2006
180	0.0000	100.0000	0.0000	0.0000	0.0000	66.0000	25.0100	11.5300	2.2700	61.1900	402.70	0	20.00	Sun et al., 2006
181	0.0000	100.0000	0.0000	0.0000	0.0000	106.0000	24.1500	7.8900	3.6500	64.3200	233.00	0	26.00	Sun et al., 2006
182	0.5700	0.5900	0.0000	57.2200	41.6200	76.1100	26.5400	18.9800	8.5200	45.9600	290.00	0	31.03	Al-Ajmi et al.,2009
183	0.0000	100.0000	0.0000	0.0000	0.0000	90.5600	40.0800	18.7600	5.5500	35.6200	256.14	0	27.68	Al-Ajmi et al.,2009
184	0.0000	59.6600	0.0000	10.3000	30.0400	77.2500	21.9500	19.5590	8.6430	49.8480	291.00	0	15.79	Al-Ajmi et al.,2011
185	0.0300	59.7000	0.0000	10.9000	29.3700	80.5500	36.3570	20.9060	7.4400	35.2970	262.00	0	17.10	Al-Ajmi et al.,2011
186	0.0000	100.0000	0.0000	0.0000	0.0000	101.6000	28.8900	4.3500	3.4700	63.2900	310.00	0	31.30	Li et al., 2012
187	0.0000	100.0000	0.0000	0.0000	0.0000	99.0000	18.7100	11.7830	3.9490	65.5580	265.00	0	22.30	Li et al., 2012
188	0.0000	100.0000	0.0000	0.0000	0.0000	108.4000	26.8200	6.8000	3.2010	63.1790	293.00	0	27.90	Li et al., 2012
189	0.0000	100.0000	0.0000	0.0000	0.0000	101.6000	17.3000	13.6400	3.4800	65.5800	275.00	0	24.10	Li et al., 2012
190	0.0000	100.0000	0.0000	0.0000	0.0000	130.0000	44.6000	24.5000	7.0000	23.8700	269.86	0	24.21	Heidary et al., 2016
191	0.2900	0.7200	0.0000	84.0300	14.9600	83.8500	43.0300	19.3400	5.3300	32.3000	265.00	0	38.91	Moosazadeh et al., 2017
192	0.0000	100.0000	0.0000	0.0000	0.0000	83.8500	43.0300	19.3400	5.3300	32.3000	265.00	0	24.40	Moosazadeh et al., 2017
193	0.0000	100.0000	0.0000	0.0000	0.0000	81.8500	10.9000	17.2100	6.1000	65.7900	390.90	0	25.38	Moosazadeh et al., 2017