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Development of an artificial neural network model for predicting minimum miscibility pressure in CO_2 flooding

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Abstract

This paper presents the development of an artificial neural network (ANN) model for the prediction of pure and impure CO_2 minimum miscibility pressures (MMP) of oils. The pure CO_2 MMP of a reservoir fluid (live oil) is correlated with the molecular weight of C_{5+} fraction, reservoir temperature, and concentrations of volatile (methane) and intermediate (C_2–C_4) fractions in the oil. The impure CO_2 MMP factor, F_{imp}, is predicted by correlating the concentration of contaminants (N_2, C_1, H_2S and SO_2) in CO_2 stream and their critical temperatures. The F_{imp} is a correction factor to the MMP of pure CO_2. The advantage of using the ANN model is evaluated by comparing the measured MMP values with the predicted results from the ANN models as well as those from other statistical methods. The developed ANN models are able to reflect the impacts on CO_2 MMP of molecular weight of C_{5+} fraction, reservoir temperature, and solution gas in the oil. The ANN model of impure CO_2 MMP factor can distinguish the effects on MMP of different contaminants in the CO_2 stream. It can also be used to predict the CO_2 MMP of a reservoir oil and the level of contaminants in the CO_2 stream which can be tolerated for a miscible injection.

Keywords: Artificial neural network; Minimum miscibility pressure; CO_2 flooding

1. Introduction

Over the last two decades, carbon dioxide injection has become the leading enhanced oil recovery (EOR) process for light oils (Grigg and Schechter, 1997). The CO_2 injection can prolong, by 15 to 20 years, the production life of light oil fields nearing depletion under waterflood; the method could recover 15% to 25% of the original oil in place. It also brings environmental benefits by facilitating storage of CO_2 in the reservoir.

In a miscible CO_2 flood, multiple-contact miscibility between the injected CO_2 and the reservoir fluid can be achieved at pressures greater than a minimum value that is referred to as minimum miscibility pressure (MMP). The MMP is the single most important parameter in designing a miscible flood. It has been recognized that the MMP for CO_2 in a reservoir depends on oil temperature, oil composition, and CO_2 purity. The latter parameter is the only one that operators can influence. Some contaminants, mainly

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N_2 in the flue gas and CH_4 from the reservoir-produced gas, in CO_2 can either increase or reduce the CO_2 MMP. Since separation of CO_2 could be costly, reinjecting recycled CO_2 without removing hydrocarbon gases could make the process more attractive economically. Therefore, for a reservoir, the CO_2 MMP and the tolerable level of contaminants in the CO_2 stream are key parameters for design of a miscible CO_2 flood system, as well as the associated gas separation and field injection components.

Numerous empirically derived and thermodynamic models for predicting CO_2 MMP have been reported in the literature. Enick et al. (1988) provided a review of the related literature. Some of the empirical correlations disregarded the C_1 through C_4 fraction and were based only on the reservoir temperature and the molar weight of C_{5+} fraction in the oil. Alston et al. (1985) offered an empirical correlation that accounts for the effect on MMP caused by solution gas present in reservoir fluids. The minimum miscibility pressure was correlated with reservoir temperature, the oil's C_{5+} molecular weight, volatile oil fraction (CH_4+N_2), intermediate oil fraction (C_2 to C_4, H_2S, and CO_2), and composition of the CO_2 stream. More recently, Zuo et al. (1993) modified the correlation derived by Johnson and Pollin (1981) by introducing two compositional parameters: the mole fractions of the light and the intermediate components in reservoir fluids. Although these two correlations account for the effect on MMP of solution gas, it was found (Dong et al., 2000) that they could not provide satisfactory prediction of MMP for reservoir oils that had high solution-gas-to-oil ratios and high volatile-component fractions. It was realized (Dong et al., 2000) that, to improve the MMP prediction accuracy, the effects of solution gas in CO_2 (and thus the amounts of volatile and intermediate fractions in oil) should be considered.

Among the empirical models, only those of Alston et al. (1985) and Sebastian et al. (1984) took into account the effects on CO_2 MMP of contaminants in the CO_2 stream. Results of the two models were tested, with the outcomes indicating that the effects of impurities on CO_2 MMP were not effectively reflected.

The development of statistical models for CO_2 MMP prediction has been a subject that involved extensive research efforts, resulting in many publications (Cronquist, 1978; Yellig and Metcalfe, 1980; Mungan, 1981; Sebastian et al., 1984; Alston et al., 1985; Kovarik, 1985). However, the main concern with statistical techniques is the difficulties in satisfying many rigid assumptions that are essential for justifying their applications, such as those of sample size, linearity, and continuity. One alternative approach for system forecasting is the technique of artificial neural network (ANN) based on the theory of artificial intelligence. The massive interconnections in the ANN framework produces a large number of degrees of freedom, or fitting parameters, and thus may allow it to reflect the system's complexity more effectively than conventional statistical techniques. Recently, methods of artificial neural networks have been applied to petroleum engineering in a number of areas such as well-test analysis, well-log interpretation, reservoir characterization, and more recently, PVT and permeability studies for crude oils (Waller and Rowsell, 1994; Gharbi and Elsharkawy, 1996, 1999).

This study is an extension of the previous efforts, emphasizing on the development of an ANN model for predicting CO_2 MMP. The main purpose is to examine the effects of (a) solution gas in CO_2, (b) amount of volatile and intermediate fractions in oil, and (c) their ratio on pure CO_2 MMP, through the developed ANN model. Firstly, the interrelations of pure CO_2 MMPs (of live oils) with (a) molecular weight of C_{5+} fraction, (b) reservoir temperature, (c) volatile oil fraction (methane and nitrogen gas), and (d) intermediate oil fraction (C_2–C_4 and CO_2, H_2S) will be analyzed, resulting in a trained ANN model; the trained model will then be used to predict CO_2 MMP, with the results being compared with the measured live oil MMP values reported in the literature. Secondly, the correlations between the impure CO_2 MMP factor (F_{imp}) and the contaminant concentrations (for N_2, C1, H_2S, and SO_2) in the CO_2 stream will be examined. The F_{imp} represents the effect on CO_2 MMP of contaminants in CO_2 stream. Lastly, the developed ANN models will be used to predict the variations of CO_2 MMP with MW of C_{5+} fraction, temperature of reservoir, and contaminant contents in CO_2 stream. In addition, the effectiveness of the developed ANN models will be evaluated by comparing the prediction results with (a) the measured MMP levels and (b) the prediction results from other statistical models.

ANN's main difference from statistical methods is its relinquishment in terms of strict conditions for data samples and associated assumptions. This is applicable to the existing situation of data availability for impure CO_2 MMP factors, which is not good enough for either statistical or numerical modeling. At the same time, analytical models are advantageous over the ANN in terms of its touching the detailed mechanisms of interactions among various impact factors; at the same time, such methods' limitations are also from their attempts to specify the complicated processes by detailed mathematical formulations, since many uncertain, interactive, and dynamic system components can hardly be expressed as accurate analytical formulations. Under such a situation, ANN becomes the only usable tool for analyzing the related effects and interactions; it can be used without violating either a number of prerequisites associated with statistical models or being forced to assuming unrealistic or over-simplified system conditions that are needed for analytical simulation.

2. Model development

In biology, a neural network is an array of neurons in the brain that processes information from input stimuli to produce comprehensible sensations. In the computer world, a neural network is a computer architecture that resembles its operators' process numerical inputs to generate outputs that are in some way meaningful to the user. Artificial neural networks (ANNs) are characterized as computational models with particular abilities to adapt, learn, generalize, recognize, cluster, and organize data (Dayhoff, 1990). ANNs are computing tools composed of many simple interconnected elements called neurons by analogy with neurophysiology. ANNs have a unique ability of recognizing underlying relationships between input and output events. They are well suited for modeling systems with complex relationships among incomplete or noisy data sets. Petroleum engineering applications of ANNs include areas such as well-test analysis, well-log interpretation, field development, reservoir characterization, formation damage, production, and drilling.

A typical neuron is shown in Fig. 1. A neuron has two components (Dayhoff, 1990): (1) a weighted summer which perform a weighted summation of its inputs with components (X_1, X_2, X_3, ..., X_n), i.e., $s = \Sigma w_i X_i + b$, where b is the bias of the networks; and (2) a linear, nonlinear or logic function which gives an output corresponding to s. Here, many kinds of functions can be used, including threshold (logic), sigmoid, hyperbolic tangent and Gaussian functions. In this study, each of them is examined at each neuron during the training process in order to get desired ANNs. In a typical ANN, there are three types of neurons: input neurons which may receive external data, output neurons which send data out of the ANN, and hidden neurons whose signals remain within the ANN. There are three types of layers corresponding to the types of neurons. The hidden neurons may form one or more hidden layers. The neurons in each layer are usually fully interconnected with neurons from neighboring layers. The importance of each interneuron connection is determined by its numerical value. A three-layered back-propagation network structure is depicted in Fig. 2 (Dayhoff, 1990). The ANN shown in Fig. 2 has an input layer, an output layer, and one hidden layer. The input layer contains an array of variables into which the input data of the system are read from an external source. Similarly, the predicted data or results, which can be multiple vectors, are written in the output layer. Initially, the input layer receives the input and passes it to the hidden layer. If more hidden layers exist, the processed information from the first hidden layer is then passed the next hidden layer for processing. Finally, the output layer receives information from the last hidden layers. In this study, the number of hidden layer is not fixed. The training tool will automatically

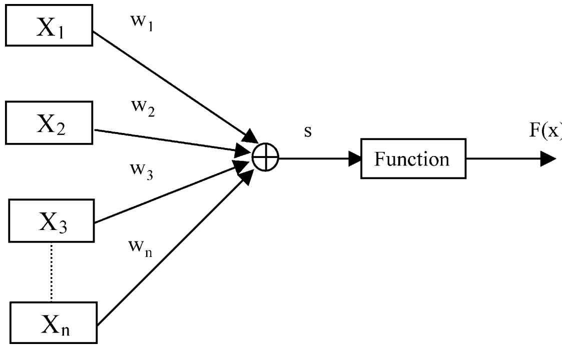


Fig. 1. Basic components of a neuron.

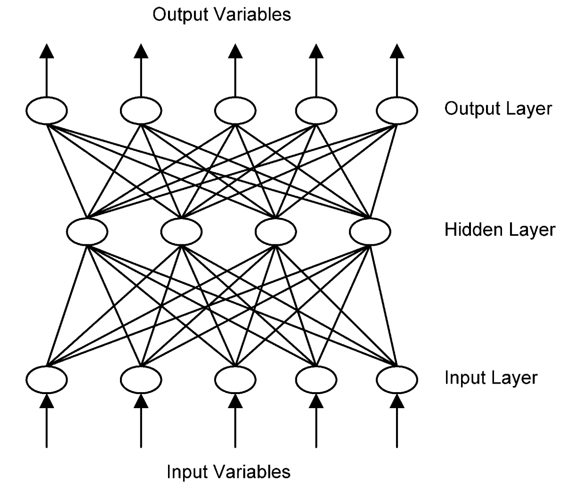


Fig. 2. A fully interconnected three-layered back-propagation network.

select suitable number of hidden layer to get the desired ANN model.

When an ANN is constructed, small numbers (weights) are assigned randomly to the connections between neurons. In general, the output from neural j in layer k can be calculated by the following equation:

$$u_{jk} = F_k\left(\sum_{i=1}^{N_{k-1}} w_{ijk}u_{i(k-1)} + b_{jk}\right)$$

Coefficients w_{ijk} and b_{jk} are connection weight and bias of the network, respectively; they are fitting parameters of the model. The purpose is to obtain a mapping from an input vector to an output one. It is desired that the difference between the predicted and the observed (actual) values in the output vector be as small as possible. The fitting parameters are modified

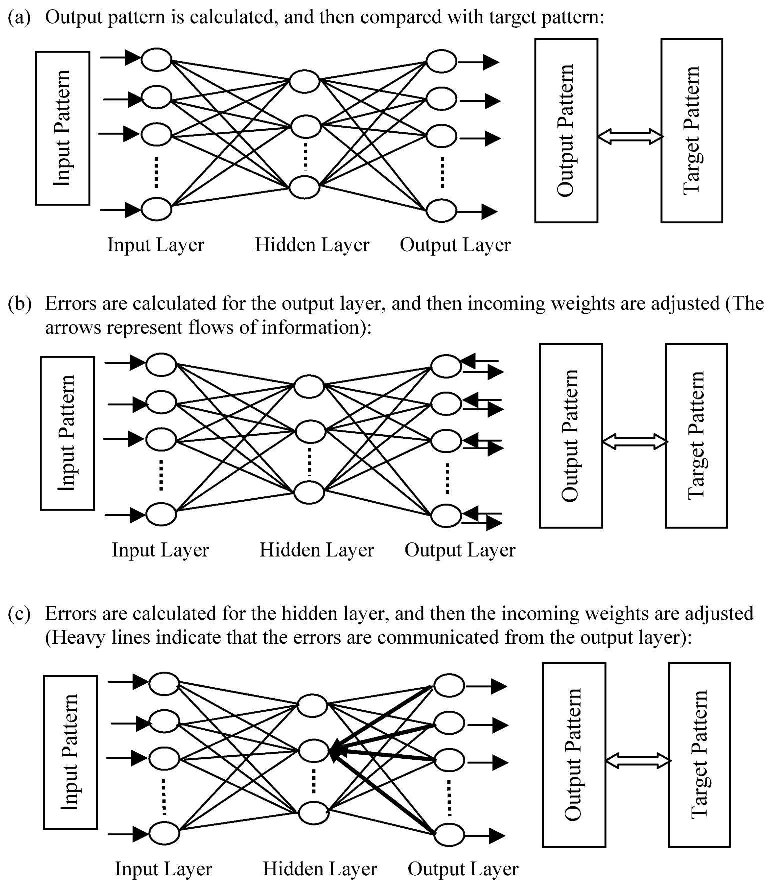


Fig. 3. Basic back-propagation dynamics.

until an error criterion between the input and the output is satisfied based on the topology of the ANN and the learning technique. The adjustment of the weights is defined as the learning process. The ANN is tested with input/output values used in training. After training and testing, the network is ready to perform tasks such as pattern recognition, classification, or function approximation. There are mainly two types of networks, feed-forward networks and recurrent networks. In this study, the back-propagation technique with momentum is used. The fitting procedure from which weights w_{ijk} are determined is performed using a least-squares minimization routine. In this routine, the sum of root-squared relative errors between the calculated and the experimental data is to be minimized. In general, the back-propagation method uses the following steps (Fig. 3):

(a) Read a specific input and calculate its corresponding output.
(b) If the error between the produced output and the desired output is acceptable, then stop.
(c) If the error is unacceptable in step (b), then the weights are adjusted for all of the interconnections that go into the output layer. Next, an error value is calculated for all of the units in the hidden layer that is just below the output layer. Then, the weights are adjusted for all interconnections that go into the hidden layer. The process is continued until the last layer of weights has been adjusted.

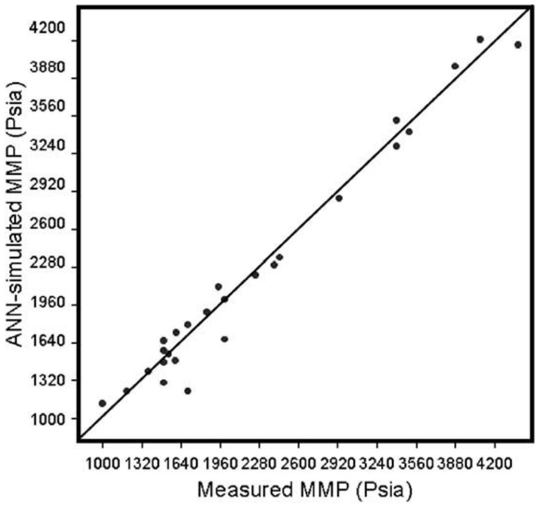


Fig. 4. The measured versus ANN-simulated MMP values (with °F for temperature).

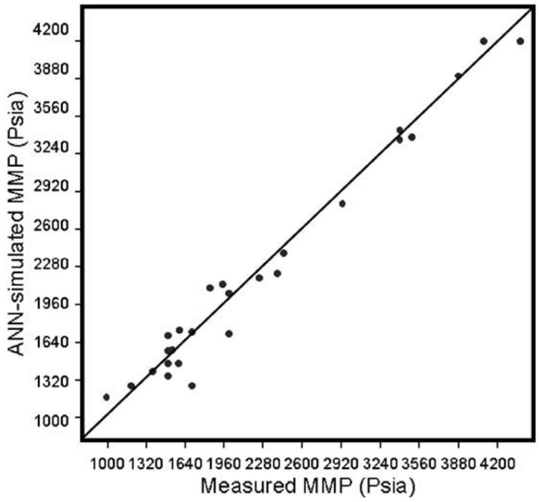


Fig. 5. The measured versus ANN-simulated MMP values (with K for temperature).

Typically, an application of back-propagation requires both a training set and a test set. Both the two sets contain input/output pattern pairs. While the training set is used to train the network, the test set is used to assess the performance of the network after the training is complete. To provide the best test of network performance, the test set should be different from the training set. The most successful ANN architecture is the one that has the smallest prediction error on a data set for which it was not trained. For pure CO_2 MMP modeling, the reservoir temperature T, molecular weight of C_{5+}, volatile oil fraction X_{vol}, and intermediate oil fraction X_{int} are selected as input variables. Minimum miscibility pressure (MMP) is the output variable. The data used for developing the ANN model are from Jacobson (1972), Dicharry et al. (1973), Wittstrom and Hagemeier (1978), White and Lindsay (1972), Graue and Zana (1981), Gardner et al. (1981), Frimodig et al. (1983), Cardenas et al. (1984), and Alston et al. (1985). Two scenarios of reservoir temperature are used: one with the degree Fahrenheit (°F) (Alston et al., 1985) and the other with the Kelvin (K).

For modeling the impure CO_2 MMP factor (F_{imp}), the concentrations of different components in the gas

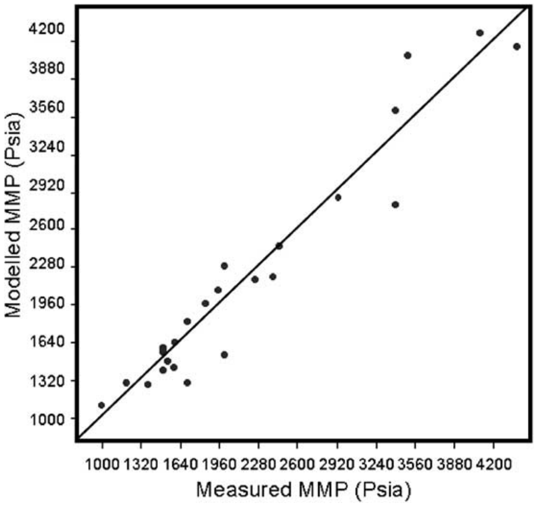


Fig. 6. The measured versus modeled MMP values (from Alston et al., 1985).

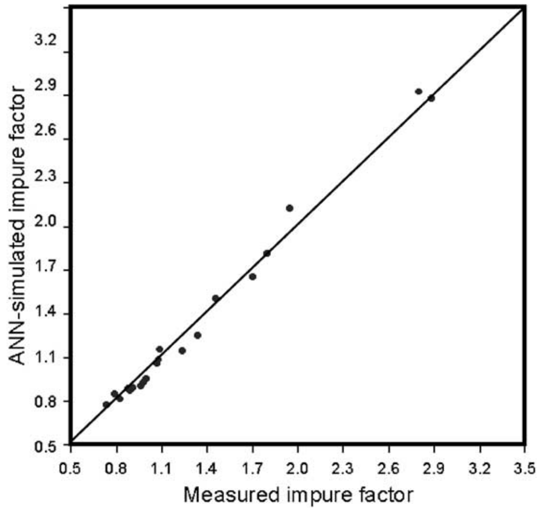


Fig. 7. The measured versus ANN–simulated impure factors.

mixture (CO_2 and contaminants) are used as input variables. Based on data availability and importance of the contaminants, N_2, CH_4, H_2S, and SO_2 are selected for the modeling study; the output variable is F_{imp}. For a pure CO_2 stream, F_{imp} is equal to 1. The value of F_{imp} for impure CO_2 is equal to the impure CO_2 MMP divided by the pure CO_2 MMP of the same oil. The data used for system training are from Alston et al. (1985) and Dong (1999).

Various neural network architectures were investigated to obtain desired models for predicting pure CO_2 MMP and impure factor (F_{imp}) as a function of selected input variables. Different scenarios on the number of hidden layers, the number of neurons in each hidden layer, and the type of transfer function for each neuron are analyzed. An architecture of one or two hidden layers is initially used, followed by the selections for the number of neurons and the types of transfer functions (logic, sigmoid, or hyperbolic tangent), with the target of obtaining the best fit to the given data.

Table 1
Statistical analysis for calibration results from the ANN and statistical models (for MMP)

Method	Average relative error (%)	Minimum relative error (%)	Maximum relative error (%)	Standard deviation (psia)	Correlation coefficient
ANN (°F)	5.91	0.08	27.30	157.57	0.987
ANN (K)	6.48	0.46	25.51	158.61	0.987
Statistical	8.88	0.33	23.34	290.05	0.963

3. The training results

The scatter plots in Figs. 4–6 provide comparisons of the measured CO_2 MMP levels with the ANN-derived ones as well as those provided by Alston et al. (1985) using statistical models. Figs. 4 and 5 present

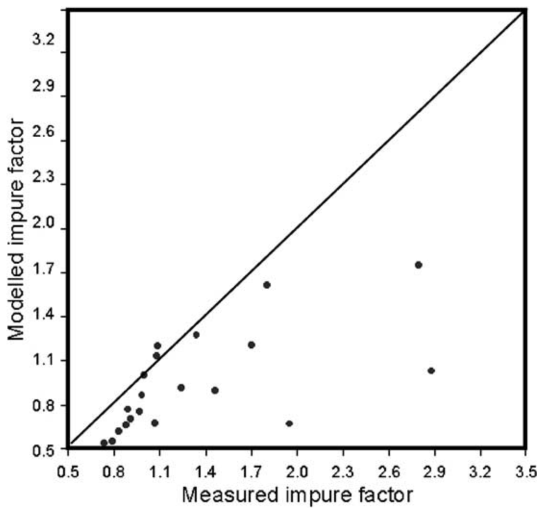


Fig. 8. The measured versus modeled impure factors (from Sebastian et al., 1984).

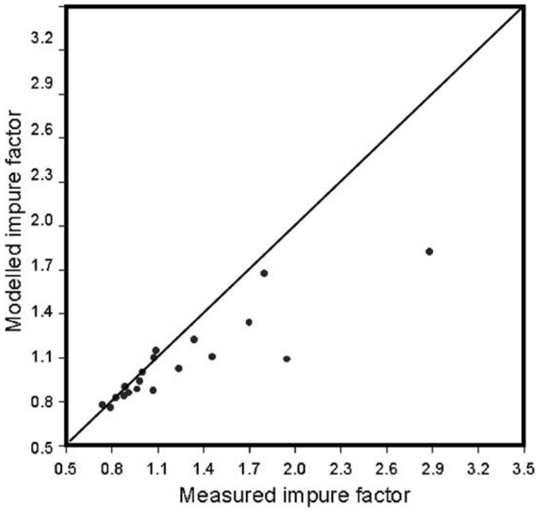


Fig. 9. The measured versus modeled impure factors (from Alston et al., 1985).

the error analysis of results with the input reservoir temperatures expressed as Fahrenheit (°F) and Kelvin (K), respectively. It is indicated that, when reservoir temperature is expressed in different units (°F and K), the related ANN inputs will be different. These different input data will then result in differences in training and calibrating processes for the ANN model, leading to varied relations between the measured and the ANN-simulated MMP values. In this study, the two sets of data were used to verify each other in order to improve the model's performance. Fig. 6 shows the error levels from the model of Alston et al. (1985) based on the same data set but a different method (statistical technique). As shown, the ANN models produce much lower error levels, compared with the statistical approach (Alston et al., 1985).

Table 1 shows the outputs of statistical analyses for calibration results from the ANN and statistical models for MMP forecasting. It is indicated that the developed ANN models have lower calibration errors than those developed by Alston et al. (1985). In detail, for the ANN model, the calibrated relative errors are 5.91% for °F and 6.48% for K, and the correlation coefficients are both 0.987. In comparison, for the statistical model (Alston et al., 1985), the calibrated relative error is 8.88%, and the correlation coefficient is 0.963.

The scatter plots as shown in Figs. 7–9 provide comparisons of the measured impure factor (F_{imp}) values with the ANN-derived ones as well as those provided by Sebastian et al. (1984) and Alston et al. (1985) based on the same data set but different statistical models. Much lower error levels were encountered from the results of the ANN model, compared with those of statistical approaches (Sebastian et al., 1984; Alston et al., 1985). Table 2 shows the outputs of statistical analyses for calibration results from the ANN and statistical models for impure factor (F_{imp}) forecasting. It is indicated that the developed ANN model has lower calibration errors than those developed by Sebastian et al. (1984) and Alston et al. (1985).

4. Application to MMP and F_{imp} forecasting

After the ANN models were established, they could then be used for MMP and F_{imp} forecasting under a variety of conditions. With measured data sets that were not used for training, the modeling outputs could then be compared with measured values to verify the model's accuracy. The data from Rhuma (1992) were used to validate the accuracy of ANN outputs for pure CO_2 MMP. ANN verifications for F_{imp} predictions were not conducted due to data unavailability. The following applications of ANN for F_{imp} forecasting were based on an assumption that its accuracy is comparable to that of MMP forecasting.

The predicted results of pure CO_2 MMP are showed in Figs. 10–12. Among them, Figs. 10

Table 2
Statistical analysis for calibration results from the ANN and statistical models (for impure factor)

Method	Average relative error (%)	Minimum relative error (%)	Maximum relative error (%)	Standard deviation	Correlation coefficient
ANN	3.83	0.12	8.87	0.07	0.99
Statistical (Alston et al.)	13.25	0.16	44.14	0.45	0.80
Statistical (Sebastian et al.)	25.25	0	65.68	0.62	0.63

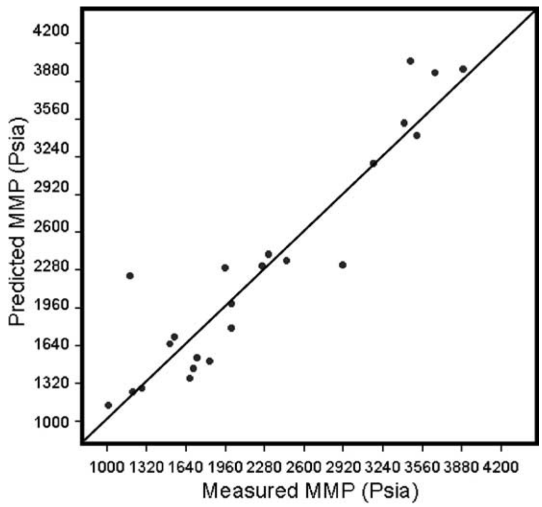


Fig. 10. The measured versus ANN-predicted MMP values (with °F for temperature).

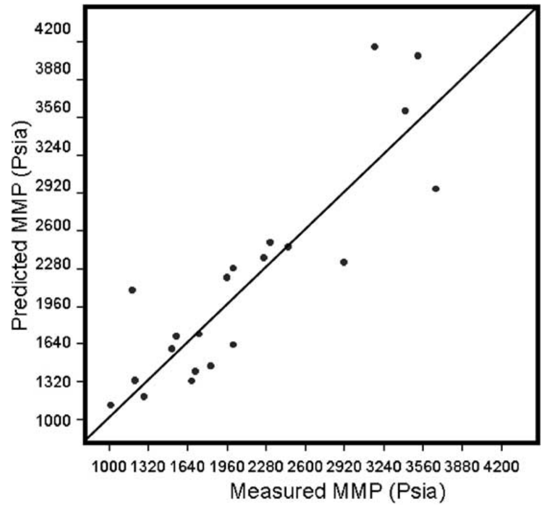


Fig. 12. The measured versus statistically predicted MMP values (from Alston et al., 1985).

and 11 are the prediction results of MMP obtained from ANN models under different reservoir temperatures (°F and K); Fig. 12 shows the results from Alston et al. (1985) using statistical methods. As shown, higher prediction accuracies were obtained by the ANN models, compared with those by statistical approaches.

Table 3 shows the results of error analyses for prediction outputs from the developed ANNs and the statistical models of Alston et al. (1985). It is indicated that outputs from the ANNs are more accurate than those from the models of Alston et al. (1985). Compared with the calibration results as shown in Table 1, the relative errors and standard deviations become higher, while the correlation coefficients are lower. In detail, the average relative errors are 12.08% for °F and 12.32% for K, and correlation coefficients are 0.936 for °F and 0.939 for K. However, the accuracy and correlation level are still much higher than those of statistical models (relative error = 17.05%, and correlation = 0.896).

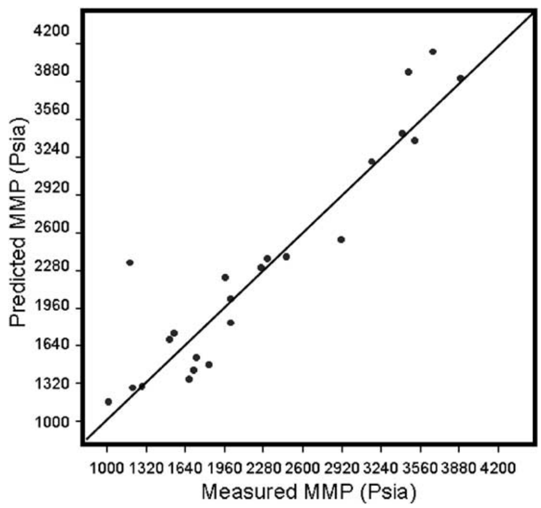


Fig. 11. The measured versus ANN-predicted MMP values (with K for temperature).

With the developed ANNs models for MMP and F_{imp} forecasting, we can further study the variations of MMP under different reservoir temperatures, C_{5+} molecular weights, volatile oil fractions, and intermediate oil fractions. According to Alston et al. (1985), if the volatile oil fraction and intermediate oil fraction vary at the same rate, the MMP will remain constant. This is because the ratio of volatile oil fraction to intermediate

Table 3
Error analysis for prediction outputs

Method	Average relative error (%)	Minimum relative error (%)	Maximum relative error (%)	Standard deviation (psia)	Correlation coefficient
ANN (°F)	12.08	0.51	86.88	333.31	0.936
ANN (K)	12.32	0.09	96.83	337.32	0.939
Statistical	17.05	0.29	76.24	552.21	0.896

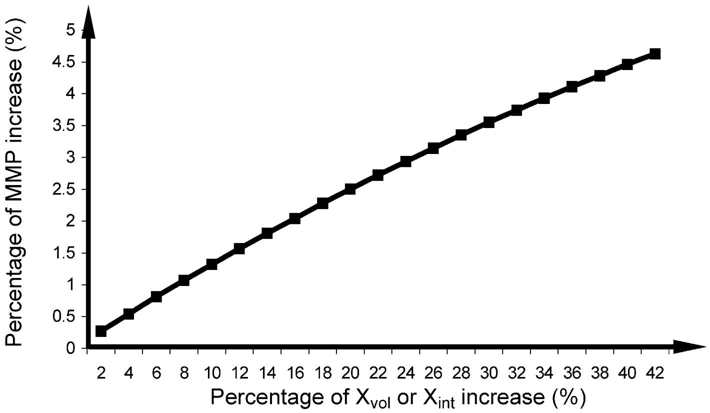
oil fraction is constant, even though the contents of solution gas are changing. In the real field, however, MMP will change even when the volatile oil fraction and the intermediate oil fraction vary at the same rate. In this study, the base points for the contents of solution gas are selected as $X_{vol}=16.09\%$ and $X_{int}=19.68\%$. Thus, the contents of solution gas will then increase with increments of 2%, 4%,. . ., of the base points. In this way, the ratio of volatile oil fraction to intermediate oil fraction will keep to be a constant, while the contents of solution gas are changing dynamically. Using the developed ANN model, variations of MMP under given reservoir temperature and C_{5+} molecular weight but varying contents of solution gas can be examined.

In general, MMP will be constant if effect of volatile-oil-fraction variation is the same as that of intermediate-oil-fraction variation. However, as shown in Fig. 13, MMP is an increasing function of the mole fractions of volatile oil and intermediate oil, even though X_{vol}/X_{int} is a constant. This indicates that the effect of X_{vol} variation is greater than that of X_{int} variation; conversely, if MMP was a decreasing function, the effect of X_{int} would be greater than that of X_{vol}. This result is consistent with the experimental results from Dong (1999).

Through the developed ANN models, variations of CO_2 MMP under different reservoir temperatures and C_{5+} molecular weights can be examined, with the volatile oil fraction (X_{vol}) and the intermediate oil fraction (X_{int}) being fixed at 10.5% and 14.28%, respectively. Figs. 14 and 15 show that the MMPs increase with reservoir temperature and C_{5+} molecular weight. The relation between MMP and reservoir temperature is close to linear when the level of C_{5+} molecular weight is high. For many reservoir oils with nearly equal values of volatile and intermediate fractions, the developed ANNs can be used to quantify the relation between CO_2 MMP and reservoir temperature under different C_{5+} molecular weights, such that forecasting of CO_2 MMP becomes possible.

It is generally recognized that the effect of an impurity (or contaminant) on CO_2 MMP depends on whether the impurity can enhance the CO_2's solubility. This idea of the solubility was used to estimate the effects of impurities on CO_2 MMP by Alston et al. (1985) and Sebastian et al. (1984), where they incorporated an average critical temperature of the gas mixture within the correlations. It was indicated that solvency could be improved if CO_2 was diluted with an impurity whose critical temperature was higher than that of CO_2. However, the solvency deteriorated if CO_2 was diluted with an impurity with a lower critical temperature. In general, the effects of H_2S and SO_2 on MMP are less dramatic than those of CH_4 and N_2.

Fig. 7 shows an excellent agreement between predicted and measured F_{imp} values. Thus, the



Note: (1) The base points of volatile and intermediate oil fractions are: X_{vol} = 16.09% and X_{int} = 19.68%;

(2) The percentage of X_{vol} increase = the percentage of X_{int} increase.

Fig. 13. Variations of MMP with solution-gas contents (at $T=316$ K and $M_{C5+}=196.1$).

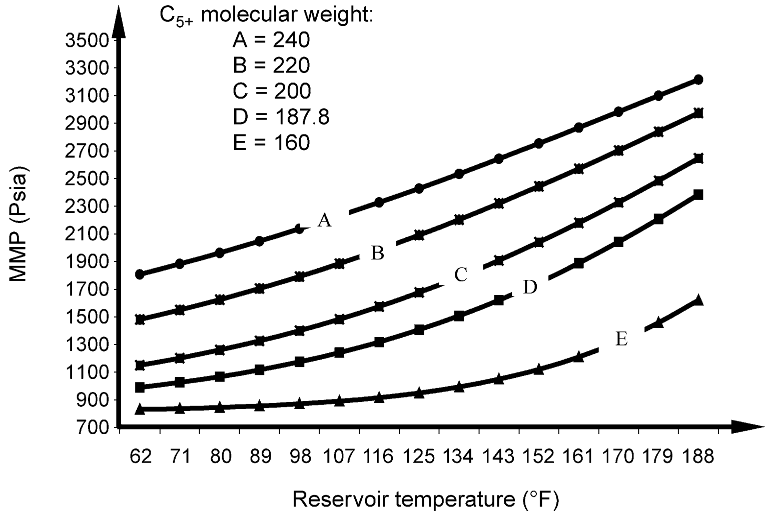


Fig. 14. Variations of MMP with temperature and C_{5+} molecular weight (at $X_{int} = 10.5\%$ and $X_{vol} = 14.28\%$) (with °F for temperature).

effects of each impurity (N_2, C_1, H_2S or SO_2) in the CO_2 stream on the MMP can be examined by simulating F_{imp} levels under different mole fractions using the developed ANN model. The results are shown in Fig. 16, indicating that N_2 has the most significant effect; a small variation in N_2 content could result in a great fluctuation in CO_2 MMP level. The content of C_1 is also an increasing function of CO_2 MMP level, with a less significant effect. In comparison, the contents of H_2S and SO_2 are slightly decreasing functions of MMP. Therefore, N_2 is the most important impurity which should be well considered before the recycled CO_2 is reinjected.

In Fig. 16, MMP is an increasing function of N_2 concentration. The MMP increases rapidly when the N_2 concentration is between 4% and 9%. Thus, keeping N_2 concentration lower than 4% would be a desired strategy. Attempts to reduce N_2 concentration to lower than 4% could lead to low efficiencies and

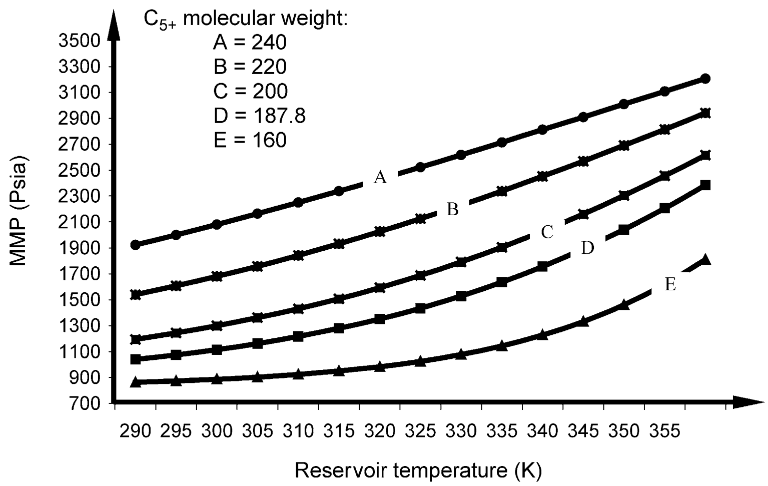


Fig. 15. Variations of MMP with temperature and C_{5+} molecular weight (at $X_{int} = 10.5\%$ and $X_{vol} = 14.28\%$) (with K for temperature).

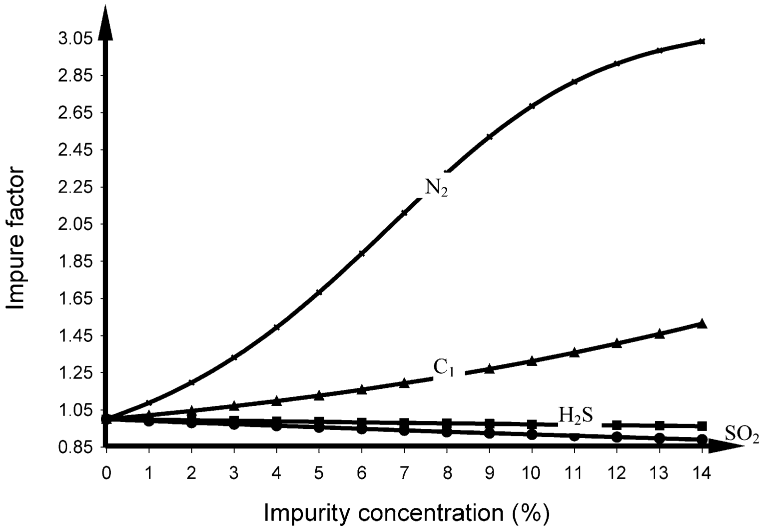


Fig. 16. The predicted values of impure factor as functions of impurity concentrations.

high costs. This information is important for determining the desired removal rate of N_2 in the recycled CO_2 stream.

5. Discussion

Conventional pressure, volume and temperature (PVT) simulation techniques can directly address complexities associated with factors that affect the MMP level. However, such simulation efforts often suffer from problems of data unavailability for specifying complicated state equations and quantifying interrelationships among various system components. This might lead to over simplification of the related processes and thus reduced prediction accuracy. On the other hand, although statistical models have lower requirements in terms of data availability, the associated difficulties in satisfying many rigid assumptions that are essential for justifying their applications have affected their performances.

In this study, the ANN approach is for the first time used to predict MMP and F_{imp}. The results demonstrate that, under conditions with limited field information, the ANN approach could produce a higher accuracy than statistical models.

Prediction of CO_2 MMP is critical for CO_2 flooding in enhanced oil recovery processes. An inaccurate prediction may result in significant consequences. For example, recommendation for a too high operating level of MMP may result in greatly inflated operation costs as well as occupational health concerns. On the other hand, if the suggested MMP is too low, the miscible displacement process would become ineffective, leading to a high risk of system failure. Thus, a higher prediction accuracy would bring significant economic benefits.

In the last few years, more and more attentions have been paid on the use of recycled CO_2 for enhanced oil recovery, because of the worldwide concern on the issue of greenhouse gas emissions. In the recycled CO_2 stream, however, a variety of impurities exist and may significantly affect the MMP. At the same time, it is costly to purify the CO_2 stream. Therefore, identification of a suitable level of impurity removal rate (and thus a suitable level of impurity contents in the CO_2 stream which can be tolerated for miscible injections) is desired. The developed ANN model for F_{imp} forecasting can supply such information in terms of the relations between F_{imp} levels and impurity contents in the CO_2 stream, and thus help to identify an optimum removal rate. Thus, the chance of economic losses due to either unnecessarily too high removal rate (and thus an increased operating costs) or too low rate (and thus a raised risk of inflated MMP) can be minimized.

6. Conclusions

In this study, ANN models for predicting CO_2 minimum miscibility pressures (MMP) and impure CO_2 MMP factor (F_{imp},) have been developed. The interrelations of CO_2 MMPs with molecular weight of C_{5+} fraction, reservoir temperature, volatile oil fraction, and intermediate oil fraction have been analyzed, resulting in a trained ANN model. Moreover, correlations between the impure CO_2 MMP factor (F_{imp}) and the contaminant concentrations in the CO_2 stream have been examined. The developed ANN models have been used then to predict the variations of CO_2 MMP with MW of C_{5+} fraction, temperature of reservoir, and contaminant contents in CO_2 stream. The effectiveness of the developed ANN models was also evaluated by comparing its prediction results with measured MMP levels and prediction results from other statistical models. The modeling results indicate that reasonable predictions have been generated. Especially, under conditions with limited field information, the ANN approach could produce a higher accuracy than statistical models.

In this study, the ANN approach is for the first time used to predict MMP and F_{imp}. With the increased prediction accuracy, the developed models can help to identify the desired operating levels of MMP and the suitable levels of impurity removal rates in enhanced oil recovery processes. Pool operators can thus optimize the injection gas to improve the process economics. This provision of effective decision support would bring tremendous economic efficiencies for oil industries. In practical applications of the model, continuous updates of the modeling system are recommended as long as new field operation data become available. The developed ANN models are user-friendly and can be easily utilized by engineers in petroleum industry.

The ANN method has been utilized in a number of applications in petroleum industry. This study is an extension of the previous efforts. It is the first attempt in using ANN to facilitate forecasting of CO_2 minimum miscibility pressures (MMP) and impure CO_2 MMP factors. When applying the ANN to this new area, a number of innovative considerations need to be made to effectively reflect the effects of many impact factors and their interactions. For example, the interrelations of CO_2 MMPs with molecular weight of C_{5+} fraction, reservoir temperature, volatile oil fraction, and intermediate oil fraction, as well as the correlations between the impure CO_2 MMP factor and the contaminant concentrations in the CO_2 stream, have been examined through the developed ANN framework. These interrelationships could hardly be addressed through traditional approaches, while the ANN approach shows advantages in reflecting such complex uncertainty and nonlinearity.

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