Development of an artificial neural network model to predict CO_2 minimum miscibility pressure

A. B. Nezhad, S. M. Mousavi, and S. Aghahoseini

ORIGINAL SCIENTIFIC PAPER

Miscible gas injection is among the most widely used enhanced oil recovery techniques, and its applications are increasingly visible in oil production worldwide. Characterizing the Minimum Miscibility Pressure (MMP) as a main parameter in these projects is a problem with no direct known solution. Available experimental methods are very time-consuming and also there is no universal method. To date, investigators have tried to find parametric correlation between different direct measurable parameters such as injected gas composition, reservoir temperature and reservoir fluid composition. However, due to complex nature of the phenomena, the proposed correlations are not accurate and reliable. Attempts are made to utilize artificial neural networks (ANNs) for identification of the relationship, which may exist between MMP, gas and reservoir fluid composition and reservoir temperature. The radial basis function (RBF) neural network architecture has been used successfully in predicting the CO_2 MMP.

Key words: minimum miscibility pressure (MMP), artificial neural network (ANN), radial basis function (RBF)

1. INTRODUCTION

Miscible gas injection is among the most widely used enhanced oil recovery techniques, and its applications are increasingly visible in oil production worldwide. An important concept associated with the description of miscible gas injection processes is the minimum miscibility pressure (or MMP). At this pressure, the injected gas and the initial oil in place become multicontact miscible, and the displacement process becomes very efficient. Also the MMP is an important parameter in the design of a miscible gas injection project. The rationale behind the determination of MMP for a particular miscible gas injection project is that there is a tradeoff between achieving high oil recovery and reducing production costs. If the injection pressure is too low, the displacement would still be two-phase immiscible, and therefore the local displacement efficiency would be below the desired level. If the pressure is too high, although the displacement would become multicontact miscible, and the oil recovery would reach the desired level, the cost of pressurizing the injected gas would be larger than necessary. Hence an optimal pressure has to be found, and that pressure is MMP. Accurate prediction of MMP for a miscible gas injection process is therefore of considerable interest to the petroleum industry. Traditionally the MMP is determined either numerically or experimentally. There are several ways to measure MMPs experimentally. The slim tube test is one of the most widely used techniques and is accepted as a standard means to measure MMPs in the petroleum industry. The other experimental methods for measuring MMP are the rising bubble experiment and VIT.

Based largely on slim tube test data, a number of empirical MMP correlations has been developed.[1,9,21] The earliest contribution to the development of MMP correlations was due to Benham et al.[2] Their correlation was based on calculated critical point compositions of selected multi-component systems which were simplified into three pseudo-components. In general, MMP correlations can reproduce MMP predictions reasonably good for oil and gas composition ranges in which the correlations are developed and also MMP correlations have different forms depending on whether they are for CO_2, CH_4, N_2 or a gas mixture. There is no comprehensive MMP correlation that predicts MMPs systematically for arbitrary oil and gas mixtures.

An alternative approach to the parametric modeling approach is the application of artificial neural networks (ANNs) . In last decades, ANNs have emerged as powerful tools for modeling complex systems. These networks are non-algorithmic, analog, distributive and massively parallel information processing methods that have proven to be powerful pattern recognition tools. Since they process data and learn in a parallel and distributed fashion, they are able to discover highly complex relationships between several variables that are selected as inputs to the network. As a model-free function estimator, neural networks can map input to output no matter how complex the relationship might be. For these reasons, this technique can be used for predicting CO_2 MMP because of high complexity of nature of miscibility concepts. In the present work, measurement of CO_2 MMP in wide range of input parameter is given. The radial basis function (RBF) neural network architecture is then applied for the prediction of MMP as a function of gas composition, reservoir temperature and oil composition.

2. NEURAL NETWORK ANALYSIS

In recent years, there has been an increasing interest in studying the mechanisms and structure of the brain. This has led to the development of ANN computational models for solving complex problems. The ability of a neural network to approximate any complex functional relationship makes the selection of a suitable regression equation for particular application unnecessary. ANNs are inherently parallel and have the capability to learn non-linear relationships, which may exist between a set of inputs and output. The design of a supervised neural network may be pursued in different ways. Multilayers feed forward neural networks are the most popular ones. Ungar et al.(1990) point out that the limitations of these networks are their slow learning (large number of iterations before convergence), rapid forgetting due to seldom seen exemplars and the lack of first principle knowledge.[14]

The neural network used in this work is the RBF feed forward layered type (Figure 1). Radial basis networks can require more neurons than standard feedforward backpropagation networks, but often they can be designed in a fraction of the time it takes to train standard feedforward networks. They work best when many training vectors are available.[15]

Notice that the expression for the net input of a *radbas* neuron is different from that of other neurons. Here the net input to the *radbas* transfer function is the vector distance between its weight vector *w* and the input vector *p*, multiplied by the bias *b*. (The || dist || box in this figure accepts the input vector *p* and the single row input weight matrix, and produces the dot product of the two.) The transfer function for a radial basis neuron is

$$Redbas(n) = e^{-n2} \quad (1)$$

The MATLAB function that is used in this work is *newrb*. The function *newrb* iteratively creates a radial basis network one neuron at a time. Neurons are added to the network until the sum-squared error falls below an error goal or a maximum number of neurons has been reached. The call for this function is

$$net = newrb(P,T,GOAL,SPREAD) \quad (2)$$

The function newrb takes matrices of input and target vectors *P* and *T*, and design parameters *GOAL* and *SPREAD*, and returns the desired network.[6]

3. ANALYSIS PROCEDURE

• *Data collection:*

To build an ANN for predicting of the CO_2-oil MMP, a data bank of the reliable experimental data is provided. The data sets are collected from papers and articles.[1,3,4,17,18,5,12,10,16,6,8,11,7,19] Finally 179 sets of data are collected and used for ANN modeling of MMP.

• *Input parameter:*

Selecting input parameters for modeling a phenomena with neural network is very critical. Inputs of a network should be selected carefully if the best results are expected to be obtained. The input variables should reflect the underlying physics of the process to be analyzed. Many researcher have discussed on the parameters that impact on the MMP and also many correlations have produced.[1,9,21,3,4,17,13,20] Therefore, on the base of literature examples and availability of data, the following parameters are chosen for using in MMP modeling with ANN: reservoir oil composition (volatile, intermediate and C_{5+} mole fractions and C_{5+} molecular weight), reservoir temperature and CO_2 gas composition(CO_2, volatile, intermediate and C_{5+} mole fractions). C_{5+} mole fraction of gas and volatile fraction of oil are ignored because they are dependent variables.

• *Network architecture:*

Figure 1 shows the architecture of the network. It is consists of three layers. The first layer is the input layer and the number of its nodes is equal to the dimension of

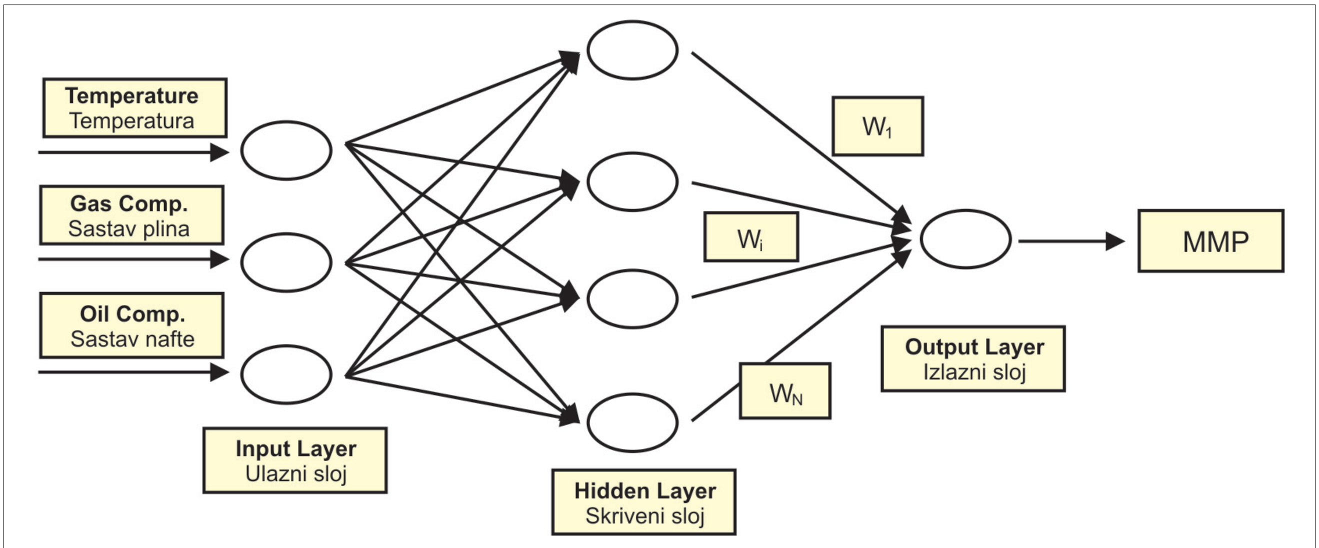

Fig. 1. The RBF network artichecture
Sl. 1. Arhitektura RBF mreže

the input vector. In this study, it is equal to 7. The second layer is a hidden layer, composed of non-linear units that are connected directly to all of the nodes in the input layer. The activation functions of the individual units in the hidden layer are defined by the Gaussian's functions. The output layer consists of a single linear unit and its output is MMP. The only parameters that need to be trained in this network are the linear weights in the output layer.

• *Network training:*

In this work, MATLAB toolbox is used for modeling of *MMP* with RBF algorithm. The function that is used for modeling is *newrb*. The parameters of network are set manually to decrease Average Relative Error (*ARE*) and Average Absolute Relative Error (*AARE*) and improve Correlation Coefficient, *R*. The final network parameters are set as follows:

- number of neuron in hidden layer is 100,
- the *SPREAD* of radial basis function is 41 and
- the *GOAL* is 10^{-6}.

$$ARE = \frac{1}{n}\sum\left(\frac{MMP_{Predicted} - MMP_{Exprimental}}{MMP_{Exprimental}}\times 100\right) \qquad (3)$$

$$AARE = \frac{1}{n}\sum\left(\left|\frac{MMP_{Predicted} - MMP_{Exprimental}}{MMP_{Exprimental}}\right|\times 100\right) \qquad (4)$$

As usual, the available experimental data sets are randomly partitioned into two sets. About 25 data sets are set aside to be used for testing the network integrity and robustness after training. The remaining data are used to train the network for the unknown weight vector. Once the weight vector is calculated, the most important remaining task is to determine how good the network performs at the completion of the training. Checking the performance of a trained network involves the following two main criteria:

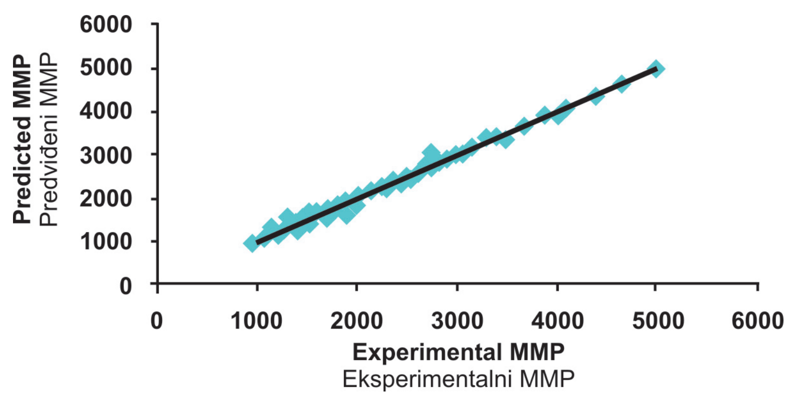

Fig 2. Results of network training.
Sl.2. Rezultati uvježbavanja mreže

1. How well the neural network recalls the output vector from the data set used to train the network

2. How well the network predicts responses for test data sets that were not used in training.

Also for comparing the result of network with classicla linear correlations (regression) as it is applied in[1,9,21] some GUI - graphical user interface) are designed and programmed with MATLAB.

4. RESULTS AND DISCUSSION

The result of ANN in simulating the train and test data are reported in Table 1 and Figures 2 and 3. The results of calculation of MMP by correlations are reported in Table 2.

As shown in Tables 1 and 2, the ANN model for MMP has the better result (*ARE*,*AARE*,*R*) than correlations used in this work. The ANN model is got 6.61 in *AARE* and 0.96 in correlation factor but for statistical correlations the 53.03 is *AARE*.

By comparing the results of correlation and also the previous researches on the MMP with Neural Network Systems, the results of this work are acceptable.[17,13]

Table 1. Neural network results and error of estimation

	ARE	*AARE*	Correlation Coefficient (*R*)
Training Data	0.162 614	2.433 171	0.994 987
Testing Data	-0.071 18	6.613 956	0.954 987

Table 2. Correlation results and error of estimation

Correlation		*ARE*	*AARE*	Correlation Coefficient (*R*)
Alston et al.	Training Data	3.737 107 8	22.977 177	0.767 814
	Test Data	-12.005 88	20.252 608	0.917 055
Glaso	Training Data	-112.208 9	112.259 27	0.664 883
	Test Data	-99.988 42	100.335 12	0.861 566
Yuan et al.	Training Data	-50.279 18	55.326 692	0.341 611
	Test Data	-30.980 48	38.531 976	0.730 303

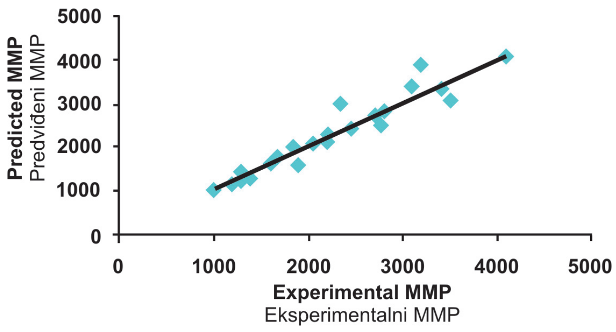

Fig. 3. Testing data results by ANN.
Sl. 3. Rezultati podataka provjere korištenjem ANN

5. OVERALL CONCLUSIONS

The following conclusions are obtained from this work:

- A model is developed for predicting CO_2 MMP with Artificial Neural Network
- The stepwise procedure for modeling of network is established.
- The available CO_2 MMP's are programmed by MATLAB to ease comparing their results with ANN results.
- The average absolute relative error with ANN for test data is 6.61, for correlations 53.03 averagely.
- By comparison of results of ANN model and correlations, it is proved that Intelligence regression methods like ANN can be used for predicting complex phenomena in petroleum industry such as miscibility pressure that depend on several factors and mechanisms better than routine statistical regression methods.

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